Extrapolation spatialisée d'une mesure locale de l'état hydrique de la vigne à partir de données auxiliaires

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Par:

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Ce mémoire de doctorat est présenté sous la forme d'une introduction générale en Français et de cinq chapitres en anglais correspondant aux cinq publications réalisées dans le cadre de ce travail.

L'objectif de l'introduction générale est de présenter le contexte et la question scientifique générale dans lequel s'inscrit le présent document. Son objectif est également de mettre en évidence la cohérence des différents chapitres relativement à la question scientifique posée.

Valorisation scientifique des résultats obtenus:

Articles (dans des revues à comité de lecture)

ACEVEDO-OPAZO, C., TISSEYRE, B., OJEDA, H., ORTEGA-FARIAS, S. and GUILLAUME, S. (2008) Is it possible to assess the spatial variability of vine water status?. ***Journal International des Science de la Vigne et du Vin, 42*** *(n°4)*, 203-219.

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ACEVEDO-OPAZO, C., TISSEYRE, B., GUILLAUME, S. and OJEDA, H. (2009) Spatial extrapolation of the vine (Vitis vinifera L.) water status: a first step towards a spatial prediction model. ***Irrigation Science****, In Press (DOI: 10.1007/s00271-009-0170-3)*.

TAYLOR, J.A., ACEVEDO-OPAZO, C., OJEDA H. and TISSEYRE B. (2009) Identification and significance of sources of spatial variation in grapevine water status. ***Australian Journal of Grape and Wine Research****, In Press (DOI 10.1111/j.1755-0238.2009.00066.x).*

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Communication à des congrès

ACEVEDO-OPAZO, C., TISSEYRE, B., GUILLAUME, S. and OJEDA, H. (2007) Test of NDVI information for a relevant vineyard zoning related to vine water status, *Proceedings of the 6th European Conference on Precision Agriculture (ECPA),* 547-554.

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TABLE DE MATIÈRES

LISTE DES FIGURES

LISTE DE TABLES

INTRODUCTION GÉNÉRALE

L'évolution de l'état hydrique de la vigne tout au long de son cycle de croissance annuel a un effet direct sur la composition du raisin et sur la qualité de la récolte. Cet effet s'explique par l'influence de l'état hydrique de la plante sur la croissance végétative, la croissance des fruits, le rendement, le microclimat de la canopée et le métabolisme des fruits (Ojeda et al., 2002, 2004; Dry and Loveys 1998; Champagnol 1984; Seguin 1983).
La connaissance de l'état hydrique de la vigne constitue une information déterminante pour la conduite du vignoble. Le suivi de l'état hydrique de la vigne dans le temps est très important afin de raisonner, entre autres, la conduite de la canopée et l'irrigation en fonction d'une qualité des baies recherchée à la récolte (Choné et al. 2001a; Naor et al. 1997).
Pour les vignobles irrigués, cette connaissance constitue un élément essentiel pour déterminer si la pratique de l'irrigation est nécessaire (Girona et al., 2006; Olivo et al., 2009) ou éventuellement pour déterminer les niveaux d'irrigation à apporter (doses ou fréquence d'apport). Pour les vignobles non irrigués, il permet d'appréhender le potentiel qualitatif d'un millésime (Van Leeuwen et al., 2009), il permet également d'ajuster les pratiques culturales (enherbement, gestion de la canopée, fertilisation, etc.) d'un groupe de parcelles, d'une parcelle ou même d'une zone se situant à l'intérieur d'une parcelle.
La connaissance de l'état hydrique des plantes revêt donc une importance particulière pour la conduite des vignobles et la gestion de la qualité de la vendange. Elle peut être nécessaire à des échelles spatiales très différentes :

- A petite échelle, il s'agit des bassins versants, petite région ou périmètre irrigué, l'information sur l'état hydrique des plantes doit permettre d'anticiper et d'optimiser la gestion de l'eau surtout lorsqu'il y a conflit sur l'usage de cette ressource entre plusieurs utilisateurs.
- A plus grande échelle, domaine viticole, groupe de parcelles, parcelle ou même zones à l'intérieur des parcelles, la connaissance de l'état hydrique va permettre d'adapter les itinéraires techniques à la qualité recherchée.
- Enfin, il existe une échelle spatiale intermédiaire (cave coopérative, winery) pour laquelle, la connaissance du « parcours » hydrique des plantes peut constituer une aide à la décision pour sélectionner les parcelles en fonction de leur potentiel qualitatif (sélection parcellaire).

La variabilité temporelle de l'état hydrique de la vigne est classiquement prise en compte pour étudier ou caractériser le « parcours hydrique » d'une plante ou d'une parcelle (Deloire et al. 2003). Le stade physiologique de la vigne associé aux niveaux de contrainte hydrique ainsi que la durée des différents régimes hydriques sont déterminants pour caractériser la qualité du raisin obtenu (Deloire et al. 2003). Par exemple, une contrainte moyenne (potentiel hydrique de base compris entre −0.3 MPa et −0.4 MPa) ou élevée (<−0.4 Mpa) pendant la période comprise entre la floraison et la véraison induit une réduction irréversible de la taille des baies, car elle réduit le volume moyen des cellules du péricarpe (pulpe + pellicule), la multiplication cellulaire n'est pas affectée (Ojeda et al., 2001). Ce même niveau de contrainte hydrique peut être recherché, après la véraison, pour stimuler la production d'anthocyanes et pour limiter la taille des baies (Ojeda et al., 2002). Cette réduction de la taille des baies influence le rapport pellicule/volume fonctionnel lors de l'extraction pendant la vinification (Matthews *et al*., 1987b. Medrano *et al.*, 2003 ; Ginestar *et al*., 1998).

Depuis les dix dernières années, l'avènement et l'adoption de technologies telles que le GPS, la télédétection ou les capteurs embarqués sur machines viticoles rendent accessible l'information sur la variabilité spatiale des systèmes de production en viticulture. L'utilisation de ces technologies sur lesquelles nous reviendrons plus tard dans cette introduction, est désignée par le terme de Viticulture de Précision (VP ou PV : Precision Viticulture en anglais).

Grâce à ces technologies, de nombreux auteurs ont ainsi montré que la plupart des parcelles viticoles présentent une grande variabilité spatiale des facteurs tels que le rendement (nombre et poids de grappe), la croissance végétative (surface du couvert végétal, poids de bois de taille), la teneur en sucre du raisin et certains composants de la qualité des baies (Ortega et al., 2003; Bramley and Hamilton, 2004; Taylor et al., 2005). Il a également été démontré que l'état hydrique de la vigne présente une amplitude de variation importante même à l'intérieur d'une parcelle viticole (Tisseyre et al., 2005; van Leeuwen et al., 2006). Cette variabilité est particulièrement importante à la fin de l'été en conditions non irriguées où une contrainte hydrique particulièrement importante peut-être observée (Ojeda et al., 2005a). Ces mêmes auteurs ont observé, sur une parcelle de petite taille (1 hectare), une amplitude de variation du potentiel hydrique de base des plantes de 1,6 MPa au cours de la saison. En fin de saison, ces mêmes travaux ont montré qu'une amplitude de variation de 1,2 MPa entre plantes à l'intérieur d'une même parcelle pouvait être observée. A une même date, l'amplitude de variation spatiale représente dans ce cas, 75 % de la variation temporelle observée sur une saison.

Cette variabilité spatiale est peu prise en compte. En règle général, les protocoles de mesure visent au contraire à lisser la variabilité spatiale en préconisant un échantillonnage et en calculant une moyenne sur les mesures effectuées (Ruffo et al., 2005). Ce raisonnement peut conduire à des actions ou des conclusions inadaptées sur certaines parties, voire sur l'ensemble du domaine considéré (parcelle, groupe de parcelle, vignoble). Par exemple, la moyenne de l'état hydrique des plantes mesurée sur une parcelle constituée de deux sols très distincts, l'un profond et l'autre superficiel, peut conduire à estimer une valeur moyenne alors que la restriction hydrique pourrait être très forte sur le sol superficiel et faible sur le sol profond. Le résultat d'une action basée sur une telle information (la moyenne) risque de n'être adapté pour aucune des zones de la parcelle.
Il apparaît donc important de s'intéresser à la variabilité spatiale. Cette connaissance permet de d'établir des stratégies ciblées spatialement telles que : (i) l'identification de zones à risque avec apparition d'une contrainte hydrique trop importante à un stade phénologique clé, (ii) la mise en œuvre d'actions correctives ciblées spatialement, par exemple, l'effeuillage, l'irrigation ou la vendange sélective (iv) le raisonnement des observations et contrôles.

Historiquement, la caractérisation de la variabilité spatiale en agriculture et en viticulture nécessitait la mise en œuvre de campagnes d'observations et de mesures souvent manuelles et géo-localisées particulièrement lourdes et coûteuses. C'est certainement la raison pour laquelle elle s'est souvent limitée à des études à de petites échelles (région, appellation) faisant intervenir des observations ou des mesures avec une faible résolution. En viticulture, ces études se sont focalisées sur l'étude des sols, de la géologie et du climat pour définir de grandes unités homogènes (Carey et al., 2008, Vaudour, 2003).

Depuis quelques années cette situation a changé. De nouveaux outils de mesures spatialisées donnant des informations souvent indirectes sur l'état des plantes ou sur le sol sont apparus dans le cadre du concept d'agriculture de précision ou de viticulture de précision. Ces technologies font largement appel à la localisation par satellite en mode naturel ou différentiel, à la télédétection aérienne ou satellitaire, à la proxi-détection ou à l'utilisation de systèmes de mesures spécifiques embarqués sur machine ou piéton (Tisseyre *et al.*, 2007). Ces nouvelles technologies ont été appliquées avec succès dans le domaine de la viticulture. Elles ont la particularité de produire un volume d'information géo-localisée avec une résolution spatiale jamais atteinte jusqu'à présent. En effet, selon le capteur utilisé et la mesure mise en œuvre, la résolution des informations obtenues peut être très importante, de l'ordre du mètre et parfois inférieure. La plupart des systèmes de mesure utilisés en viticulture de précision, se basent sur des principes physiques relativement simples. Une analyse détaillée des principes et capteurs utilisés en viticulture de précision a été proposée par Tisseyre et al. (2007). L'obtention d'une information avec une haute résolution spatiale suppose de pouvoir réaliser un grand nombre de mesures rapidement sur une surface donnée. Les contraintes de coût, de non-destruction, etc., liées à une utilisation sur des vignobles en production, limitent les principes physiques des capteurs et les grandeurs mesurées qui en résultent. Si l'on excepte les capteurs spécifiques embarqués sur les machines à vendanger (rendement, sucre, acidité), les principes physiques des capteurs utilisées en viticulture de précision reposent généralement sur la mesure de deux types d'informations :

- le rayonnement électromagnétique (mesure de la réflexion),
- des grandeurs électriques ou électromagnétiques (résistivité ou conductivité électrique souvent appliquées à l'étude des sols),

Bien qu'offrant des perspectives intéressantes pour caractériser la variabilité spatiale des systèmes de production, les technologies issues de la viticulture de précision ne fournissent pas d'information directement utilisable pour la conduite de ces systèmes. Par exemple, une image aérienne multispectrale permettra de produire un indice de biomasse tel que le NDVI (Normalised difference vegetative index), elle permettra ainsi d'en caractériser la variabilité spatiale. La mesure effectuée reste toutefois éloignée des grandeurs de référence telles que la surface foliaire exposée (SFE), la surface foliaire totale (SFT), etc. utilisées pour caractériser et/ou piloter la culture de la vigne. Un autre exemple est relatif au sol ; les capteurs utilisés pour en caractériser la variabilité spatiale ne fournissent pas, à l'heure actuelle, de mesures directes des propriétés utilisées classiquement telles que la texture, la teneur en eau, la profondeur, le pH, etc.
Certains auteurs (Johnson et al., 2003) ont démontré qu'il était possible de convertir les informations « brutes » fournies par ces techniques nouvelles en information élaborée et utilisable directement. Ces approches visent à proposer un modèle simple capable d'estimer, localement, un paramètre utile par une grandeur physique mesurée. Le modèle monovariable est étalonné sur un nombre limité de sites et peut ensuite être utilisé sur l'ensemble du domaine couvert par la grandeur mesurée avec une haute résolution (image multispectrale, mesure de résistivité apparente des sols, etc.).
D'autres auteurs ont proposé l'utilisation combinée de différentes sources d'information à haute résolution spatiale telle que des images aériennes multi-spectrales, les propriétés électriques des sols et/ou l'altitude pour définir des zones de fonctionnement à

l'intérieur des vignobles (Ortega et al., 2003; Bramley and Hamilton, 2004; Taylor et al., 2005). Ces approches sont souvent basées sur des classifications non-supervisées. Les classes ainsi mises en évidence correspondent à des zones de vigueur distinctes définies très souvent par la variabilité du sol (profondeur, texture, altitude, etc.). Ces différences de vigueur entraînent des différences sur l'ensemble des paramètres de production (rendement, teneur en sucre, acidité, anthocyanes) (Kliewer et al., 1983, Matthews and Anderson, 1989; Goodwin, and Jerie 1992; Ginestar et al., 1998). D'autres expérimentations (Tisseyre et al., 2008; Bramley, 2005) ont permis de montrer le caractère stable des zones et de la variabilité spatiale ainsi mise en évidence. En condition non-irriguée, ce caractère stable a surtout été mis en évidence pour les paramètres quantitatifs tels que la vigueur et le rendement. Cette stabilité temporelle s'explique i) par le caractère pérenne de la vigne (Tisseyre et al., 2008) mais aussi vraisemblablement ii) par la stabilité des paramètres du milieu (texture du sol, profondeur du sol, altitude, etc.) qui déterminent ces différences de vigueur. En condition méditerranéenne et sur vignoble non irrigué, l'accès à l'eau est le facteur limitant qui pourrait expliquer les zones de différente vigueur (Pellegrino, 2004). Dans ces conditions, les données à haute résolution relatives à l'état de la plante, mais aussi au sol pourraient constituer des données auxiliaires du plus grand intérêt pour estimer la variabilité spatiale de l'état hydrique des plantes.

D'un point de vue scientifique, la question est originale. En effet, elle doit proposer une approche basée sur des informations indirectes pour produire l'estimation d'une grandeur qui varie à la fois dans l'espace et dans le temps. Cette approche ne se limite donc pas à la caractérisation d'une corrélation entre une variable d'intérêt (l'état hydrique dans notre cas) et des variables auxiliaires à haute résolution spatiale pour estimer spatialement les valeurs de la variable d'intérêt, à une date donnée. De telles approches ont déjà été proposées dans la littérature, surtout dans le domaine de la pédologie, une synthèse des méthodes utilisées a été proposée par (McBratney et al., 2003).
Ces considérations amènent à une question intéressante : est-il possible d'estimer la variabilité spatiale des valeurs d'état hydrique de la vigne sur la base d'observations à haute résolution relatives à l'estimation de la vigueur de la vigne (indice de biomasse) ou certaines propriétés du sol (résistivité ou conductivité apparente) ?

L'originalité de l'approche à mettre en œuvre réside dans l'estimation de fonctions localisées qui, en chaque site du domaine considéré, vont permettre de produire une estimation de la variable d'intérêt à toutes les dates possibles. Ainsi l'estimation de la variabilité spatiale des valeurs d'état hydrique de la vigne à partir d'information à haute résolution pose une question scientifique originale : est-il possible d'estimer, à partir d'informations indirectes à haute résolution, des fonctions localisées qui, en chaque site d'un domaine considéré permettent d'estimer l'état hydrique des plantes à toutes les dates possibles. Ainsi, l'originalité de notre question scientifique réside dans l'objectif de produire un outil de pilotage où la dynamique de la variable d'intérêt est à prendre en compte.

Ce travail de thèse se propose donc de répondre à la question scientifique relative à : **la possibilité de proposer une approche qui intègre des données auxiliaires, peu coûteuses, et à haute résolution pour estimer spatialement l'état hydrique d'un vignoble**.

Ce travail est organisé en cinq chapitres qui correspondent à des articles scientifiques. Quatre de ces articles ont déjà été publiés.

La réponse aux questions scientifiques identifiées a nécessité la mise en œuvre d'un dispositif expérimental sur la station expérimentale INRA de Pech-Rouge (Gruissan, Aude, France) dont nous présentons les principales caractéristiques.

I. Description succincte du dispositif expérimental

Le station expérimentale INRA de Pech-Rouge a été choisie pour i) les facilités qu'elle propose en terme de suivi d'expérimentations, mais aussi pour ii) sa localisation géographique et le climat qui en résulte, en effet, le déficit hydrique estival important est représentatif des systèmes viticoles méditerranéens, iii) la diversité des cépages et des modes de conduite qui y sont présents , iv) l'absence d'irrigation et v) un parcellaire morcelé avec une surface moyenne des parcelles (~0,8 hectares) représentative du sud de la France.
La contrainte hydrique estivale, sur ce vignoble non-irrigué est très importante (Ojeda et al., 2005; Tisseyre et al., 2005). Le potentiel hydrique de base peut atteindre des valeurs de l'ordre de –2 MPa à la fin de l'été. Une caractéristique intéressante de ce vignoble est la présence de 3 unités pédologiques marquées sur une étendue restreinte (~170 ha). Le climat est considéré comme relativement homogène sur l'ensemble de ces unités. Dans la suite du document, ces unités pédologiques sont dénommées Littorale, Clape et Colombier. L'unité Littorale est située pratiquement au niveau de la mer et se caractérise par un sol de sable très profond avec la présence d'une nappe d'eau superficielle. L'unité Clape est constituée de Calcaire avec des alternances de marnes. Enfin l'unité Colombier est principalement constituée de marnes avec un colluvionnement provenant des falaises calcaires. Chacune des unités décrites présente donc des spécificités induisant des contraintes hydriques différentes mais aussi une variabilité spatiale importante.
Ainsi le sol plus profond de la zone littorale entraîne des contraintes hydriques plus faibles que dans les autres unités et la présence d'une couche d'argile de profondeur variable entraîne une variabilité spatiale importante de la contrainte hydrique. Le calcaire de La Clape entraîne des contraintes hydriques très importantes et l'alternance de calcaire et de marne une variabilité spatiale importante. Une variabilité spatiale importante est également observée sur l'unité des Colombier.

Les mesures de potentiel hydrique de base ont été recueillies sur neuf parcelles à deux dates en 2006 et quatre dates en 2007. Les neuf parcelles suivies sont réparties sur les trois grandes unités pédologiques décrites précédemment (trois parcelles sur chacune des unités pédologiques). A l'intérieur de chacune des parcelles, trois placettes de mesure ont été définies sur la base de connaissances expertes ou de données auxiliaires (images multispectrales). Chacune des placettes correspond à des situations de contrainte hydrique attendue (faible, moyenne ou forte). Les placettes sont constituées de 5 souches.
Ce dispositif nous a permis de collecter 810 mesures de potentiel hydrique de base au cours des étés 2006 et 2007. Cette base de données a été utilisée :

a) pour identifier les principales sources de variabilité au cours de la saison (inter-pied, intra-parcellaire, inter-parcellaire, inter-unité pédologique),

b) pour valider le lien entre données auxiliaires et état hydrique des plantes. A cette fin, de nombreuses mesures complémentaires ont été réalisées soit spécifiquement sur les placettes considérées, soit sur l'ensemble du domaine (images multi-spectrales, résistivité électrique apparente des sols, conductivité électrique apparente du sol, observations manuelles de l'expression végétative de la vigne, circonférence des ceps, rendement et paramètres de la qualité des baies).

Une deuxième base de donnée, acquise antérieurement à la thèse a également été utilisée dans ce travail. Il s'agit de potentiels hydriques de base mesurés sur deux parcelles, au niveau intra-parcellaire sur 49 placettes et à plusieurs dates. Cette base de donnée a été utilisée pour :

a) identifier et tester la fonction d'extrapolation présentée équation 1,
b) tester l'introduction de données auxiliaires spatialisées.

II. Chapitre I : Vers un modèle spatialisé d'estimation de l'état hydrique de la vigne

Le premier chapitre de cette thèse est un état de l'art sur les mesures actuellement disponibles ou en cours de développement pour estimer l'état hydrique des plantes et de la vigne en particulier. Dans un premier temps, l'objectif de ce chapitre est d'identifier clairement les grandeurs physiques utilisées pour mesurer ce que nous avons désigné par le terme général d' « état hydrique ». Dans un deuxième temps, pour chacune des méthodes identifiées, ce chapitre analyse i) le principe physique des mesures mises en œuvre, ii) le dispositif technique et/ou la méthode utilisés et iii) l'intérêt et les limites relatives à leur utilisation pour mesurer/estimer spatialement l'état hydrique des plantes.

Trois méthodes sont présentées pour mesurer l'état hydrique des plantes. En fait, beaucoup d'autres existent qui ne sont pas présentés. (i) la conductance stomatique, (ii) le rapport isotopique du carbone C^{13}/C^{12} et (iii) le potentiel hydrique de la plante (Scholander et al., 1965). Cette dernière méthode peut être mise en œuvre à des moments différents de la journée et avec différents protocoles ce qui permet de définir trois type de potentiels: le potentiel hydrique de feuille (PHF), le potentiel hydrique de tige (PHT) et le potentiel hydrique de base (PHB) (Schultz, 1996; Choné et al., 2000; Choné et al., 2001; Lampinen et al., 2001; Ojeda et al., 2002; Carbonneau et al., 2004; Ortega-Farías et al., 2004b; Acevedo et al., 2005; Girona et al., 2006, Sibille et al., 2007).
Ce chapitre met évidence l'intérêt de ces mesures puisqu'elles fournissent des informations de référence à partir desquelles il est possible de « piloter » le vignoble. Toutefois, elles nécessitent la mise en œuvre d'équipements parfois lourds et une préparation manuelle minutieuse des échantillons. Ces contraintes techniques rendent difficile voire impossible leur utilisation pour fournir une information avec une résolution spatiale et temporelle adaptée au pilotage de la culture.
Pour pallier le problème de la résolution temporelle, ce chapitre montre que d'autres approches ont été proposées dans la littérature.
Une première approche est basée sur l'utilisation de capteurs positionnés sur la plante (capteurs de flux de sève, capteur dendromètrique) ou dans le sol (tensiomètres, sondes TDR, etc.) (Fernández et al., 2001; Cifre et al., 2005; Naor and Cohen, 2003; Topp et al., 1980; McCarthy, 1997; Pellegrino et al., 2004). L'intérêt de ces systèmes est de

fournir en continu, la mesure d'une grandeur physique en relation avec la contrainte hydrique subie par la plante. Toutefois, ils ne fournissent qu'une information indirecte telles que le flux de sève, l'amplitude de contraction du tronc ou du rameau ou une grandeur électrique en relation avec la teneur en eau du sol. Ces informations doivent nécessairement être reliées aux mesures de références par un étalonnage local. De plus, leur intérêt pour estimer l'état hydrique des plantes avec une bonne résolution, est considérablement limité. En effet, le coût et la maintenance des équipements nécessaires, que ce soit le capteur, le système d'acquisition ou de transmission de l'information limitent considérablement le nombre de points de mesure. L'utilisation de ces systèmes pour caractériser la variabilité spatiale de l'état hydrique des plantes est donc contrainte par le nombre de dispositifs qu'il est possible d'installer.
Une deuxième approche est basée sur l'utilisation de données climatiques. Son intérêt est d'utiliser les informations collectées régulièrement par une station météorologique. Cette approche vise à estimer l'évapotranspiration des plantes à partir du rayonnement, de la température, de l'humidité, de la vitesse du vent, etc. Il s'agit de méthodes basées sur la notion de bilan qui, en fonction des caractéristiques du sol (principalement la notion de réserve utile) permettent d'estimer la contrainte hydrique subie par les plantes. Ce type d'approche est couramment utilisé dans toutes les régions du monde pour piloter l'irrigation des cultures. D'un point de vue spatial, elle présente toutefois des limites importantes puisqu'elle suppose un climat et une réserve utile du sol homogènes sur une zone donnée. Remarquons qu'en fonction de la zone géographique et de la résolution spatiale des informations météorologiques, l'hypothèse d'homogénéité du climat peut être plus ou moins acceptable.

L'état de l'art de ce premier chapitre de thèse se termine par l'analyse de technologies plus récentes permettant de caractériser l'état des plantes ou le sol avec une haute résolution (de l'ordre du m²). Il s'agit de systèmes actuellement commercialisés qui permettent, avec un coût limité, de caractériser la variabilité spatiale des systèmes de production. Ces informations ont déjà été mentionnées dans cette introduction, elles sont basées sur de l'imagerie multi-spectrale ou des propriétés électriques des sols (Bramley, 2001; Hall et al., 2002; Johnson et al. 2003; Taylor and Bramley, 2005; Tisseyre el al. 2007). Une analyse de ces informations montre que, dans un contexte non-irrigué, elles sont susceptibles de mettre en évidence des zones correspondant à des contraintes hydriques différentes. Cette analyse montre l'intérêt que pourrait présenter ces informations pour estimer la variabilité spatiale de l'état hydrique des plantes. Elles présentent toutefois une limite importante puisqu'elles ne sont qu'indirectement reliées à l'état hydrique de la vigne.

Ce chapitre met donc en évidence ; i) la possibilité d'obtenir des mesures de référence de l'état hydrique des plantes avec une faible résolution spatiale (S) et temporelle (T), ii) l'existence de systèmes ou de méthodes permettant d'estimer l'état hydrique des plantes avec une haute résolution T mais inadaptés pour une résolution S élevée, iii) l'existence d'informations avec une haute résolution S mais indirectement reliées à la variable d'intérêt.
Ce constat nous a amené à proposer une approche combinant information de référence et informations spatiales indirectes pour produire une estimation spatialisée de l'état hydrique des plantes. L'équation 1 résume l'approche proposée. Elle consiste, sur une région ou une zone de l'espace D , à effectuer une estimation $z(s_i,t_j)$ de l'état hydrique des plantes en un site s_i de D et à une date t_j à partir i) d'une mesure de référence $z(s_{re},t_j)$ réalisée sur un site de référence s_{re}^{n} appartenant à D et à la même date t_j et ii)

une fonction d'extrapolation f_D , définie sur D, qui permet d'extrapoler la mesure de référence à partir de plusieurs informations auxiliaires $(q_m(s_i))_{m=1...M}$ disponibles avec une haute résolution spatiale et dont la valeur est connue sur chacun des sites s_i de D.

$$\hat{z}\ (s_i,t_j) = f_D(q_1(s_i),q_2(s_i),..., q_M(s_i),\ z(s_{re},t_j)) \qquad (1)$$

Afin d'en démontrer l'intérêt, cette approche a été mise en œuvre avec succès à l'échelle d'une parcelle et avec un nombre limité de données auxiliaires. La proposition formalisée par l'équation 1 soulève des questions que la suite de ce travail se propose d'explorer.

Question a

Comment définir la région sur laquelle une fonction d'extrapolation pourrait être définie ?. Le domaine *D* correspond à une unité de gestion, et la définition de *D* nécessite une expérimentation rigoureuse visant à étudier la variabilité spatiale de l'état hydrique des plantes. Elle nécessite en effet de vérifier i) si la variabilité spatiale de l'état hydrique des plantes est structurée dans l'espace, ii) d'identifier les éléments (pédologie, parcelles, cépage, etc.) qui conditionnent cette structure spatiale et iii) de vérifier si ces éléments jouent le même rôle quel que soit le niveau de contrainte hydrique observé.

Question b

Les données à haute résolution actuellement disponibles sont-elles pertinentes pour estimer l'état hydrique des plantes spatialement ? Dans la littérature, il a en effet été montré que ces informations pouvaient localement être reliées à des paramètres précis du sol (pour les données de conductivité ou de résistivité électrique) ou bien de la canopée (images multispectrales) (Bramley, 2001; Hall et al., 2002; Johnson et al. 2003; Taylor and Bramley, 2005; Tisseyre el al. 2007). Dans une situation où le principal facteur limitant est l'accès à l'eau, il est probable que le développement de la canopée (vigueur, expression végétative, surface totale de feuillage) soit la principale caractéristique affectée. Ainsi la croissance de la canopée induite par un déficit plus ou moins important en eau pourrait être cartographiée par un indice de biomasse. De la même manière, il est probable que les principaux facteurs induisant une variabilité spatiale de l'état hydrique des plantes soient liés aux caractéristiques du sol. Des cartes de conductivité ou de résistivité électrique apparente des sols pourraient mettre en évidence une structure spatiale en cohérence avec la variabilité spatiale de l'état hydrique des plantes.

Bien que réalistes, ces relations entre état hydrique des plantes et données à haute résolution ne sont qu'hypothétiques, elles n'ont fait l'objet d'aucune étude spécifique dans la littérature et méritent d'être analysées de manière rigoureuse.

Question c

Comment définir la fonction d'extrapolation f_D introduite à l'équation 1 ? Rappelons que cette fonction d'extrapolation définit la relation qui existe entre l'état hydrique d'un site (plante ou groupe de plantes) de référence et un site du domaine *D*. Rappelons que cette fonction n'est définie que localement, sur le domaine *D* et qu'elle ne dépend pas du temps, en d'autres termes, qu'elle est définie uniquement par les caractéristiques

locales du site à estimer. La variation temporelle de l'état hydrique étant pris en compte par la mesure sur le site de référence.
Cette approche, intéressante d'un point de vue opérationnel, n'a jamais été testée. Il convient donc d'en vérifier la pertinence. Il convient également d'identifier la forme de la fonction d'extrapolation (type de fonction) afin de proposer une mise en œuvre du modèle proposé.

Les chapitres 2, 3 et 4 se proposent de répondre aux questions scientifiques a, b et c respectivement.

III. Chapitre 2: Identification et importance des facteurs induisant une variabilité spatiale de l'état hydrique de la vigne.

Les informations générées à partir du dispositif expérimental présenté nous ont permis de répondre en premier lieu à la question liée à la définition du domaine spatial *D*. Ainsi cet article a eu pour objectif d'examiner l'amplitude de variation de l'état hydrique des plantes à plusieurs échelles au sein du vignoble et à plusieurs dates correspondant à des niveaux de contrainte hydrique différents. Ce chapitre vise à vérifier si la variabilité spatiale de l'état hydrique est aléatoire ou spatialement structurée, il vise également à identifier les facteurs qui expliquent la variation spatiale de l'état hydrique des plantes.

La méthode utilisée consiste, pour chaque date de mesure, à analyser la variance observée en i) variance entre plantes voisines (σ^2_P) au sein d'une placette, ii) variance intra-placette (σ^2_S), iii) variance intra-parcellaire (σ^2_B) et iv) variance sur l'ensemble du vignoble (σ^2_V). Cette analyse permet d'identifier la part de la variance correspondant à un phénomène aléatoire (non structuré dans l'espace). Un algorithme de partitionnement récursif (arbre de régression) a été utilisé pour hiérarchiser les facteurs de variation pour chacune des dates de mesure. Chaque date a été traitée de manière indépendante avec les mesures individuelles de potentiel hydrique comme variable dépendante et les variables cultivar, type du sol et expression végétative, comme variables explicatives.
Les résultats de ce travail montrent que plus la contrainte hydrique moyenne est élevée sur le domaine, plus la variabilité qui y est observée est importante. Parallèlement à l'augmentation de la contrainte hydrique, une diminution de la part du phénomène aléatoire (non structuré dans l'espace) est observée. Ce résultat met en évidence l'intérêt de prendre en compte la variabilité spatiale de l'état hydrique des plantes, surtout lorsque la contrainte hydrique devient importante.
A la mi-saison (vers floraison), lorsque le contrainte hydrique est faible (valeurs de potentiel hydrique de base supérieures à -0,4 MPa), le partitionnement récursif a identifié le cépage comme principal facteur discriminant. Pour des contraintes hydriques modérées, l'expression végétative a été identifiée comme le facteur dominant. Enfin, en fin de saison (août), lorsque la contrainte hydrique devient importante, le principal facteur discriminant est l'unité pédologique suivie de l'expression végétative.

Les résultats de ce chapitre constituent une aide à la décision pour définir un schéma d'échantillonnage spatial de l'état hydrique des plantes. Lorsque la contrainte hydrique est faible, un échantillonnage peu dense peut-être réalisé, la répartition des échantillons peut-être aléatoire au niveau des parcelles. Lorsque la contrainte hydrique augmente, la variabilité spatiale augmente également, cette variabilité spatiale tend à se structurer en fonction des zones de vigueur identifiées au sein de chaque parcelle. L'échantillonnage

spatial doit donc être raisonné en conséquence. Lorsque la contrainte hydrique devient très importante, la variabilité spatiale est structurée en fonction des grandes unités pédologiques puis au sein de chacune de ces unités, en fonction des zones de vigueur. Un échantillonnage basé sur les unités pédologiques, puis au sein de chaque unité pédologique, en fonction des niveaux de vigueur observés devra être proposé.
Ce chapitre permet de répondre à certaines questions initiales ; la variabilité spatiale de l'état hydrique de la vigne est clairement structurée dans l'espace (pour des potentiel hydrique de base inférieurs à -0.4 MPa). La structure spatiale est définie par les unités pédologiques et vraisemblablement par la variabilité (sol, altitude, etc.) au sein de chacune d'elles. La définition des domaines *D* doit donc être réalisée prioritairement en prenant en compte l'unité pédologique.

IV. Chapitre 3: Pertinence des informations auxiliaires à haute résolution pour définir des zones de fonctionnement hydrique?

Ce chapitre a pour objectif d'étudier l'intérêt des informations à haute résolution spatiale, fournies notamment par les images aériennes et les capteurs de propriétés électriques du sol, pour définir des zones de restriction hydrique stables dans le temps. Compte tenu du chapitre précédent, ce travail s'intéressera particulièrement à la définition de zones au niveau de chaque domaine *D* (définis par les unités pédologiques). Afin de prendre en compte les recherches et développements actuellement réalisés dans le domaine des capteurs embarqués (Goutouly et al., 2006a, 2006b), d'autres informations relatives à la plante et à la canopée ont été prises en compte : épaisseur et hauteur de la canopée, circonférence du ceps, rendement. Naturellement, ces informations ont été mesurées manuellement avec une résolution spatiale moindre (de 5 à 30 placettes mesurées par parcelle). Toutes les informations auxiliaires ont été analysées en relation avec les mesures d'état hydrique des plantes (potentiel hydrique de base). L'analyse des résultats a été conduite avec des méthodes classiques d'analyse de données (analyse en composante principale) et des tests statistiques (analyse de la variance non paramétrique).
Les résultats obtenus mettent en évidence une corrélation négative entre le potentiel hydrique de base et l'ensemble des paramètres en relation avec la canopée des plantes (indice de biomasse issu des images aériennes -NDVI-, épaisseur, hauteur de la canopée, diamètre des troncs). Sur l'ensemble des unités pédologiques du vignoble expérimental, l'indice de biomasse (NDVI), suffit pour identifier les placettes correspondant à des états hydriques différents.
Des observations complémentaires semblent montrer que ce résultat est stable dans le temps. En effet, ce résultat a été validé en considérant plusieurs mesures de potentiel hydrique de base à des dates différentes et plusieurs acquisitions d'images réparties sur trois années différentes (1999, 2006, 2007). De plus, une corrélation entre les mesures de NDVI et un paramètre intégratif comme la circonférence des ceps a été mise en évidence.
Une analyse plus fine des résultats (analyse de la variance) montre toutefois que l'utilisation d'un indice de biomasse, comme le NDVI, n'est pertinente que si la situation est contrastée. En effet, cet indice s'est avéré moins discriminant sur la zone littorale où les différences de contraintes hydriques entre placettes sont les moins marquées.
En ce qui concerne les propriétés électriques des sols, les résultats mettent en évidence un effet marqué (attendu) des unités pédologiques. Par exemple, pour la Clape,

l'alternance de calcaire et de marne entraîne une amplitude de variation très importante entre zones à forte contrainte hydrique et zones à faible contrainte hydrique. Cette amplitude de variation est beaucoup moins marquée sur la zone littorale. Ces résultats montrent que les propriétés électriques du sol peuvent présenter un intérêt pour définir des zones de contrainte hydrique à l'intérieur des parcelles. Toutefois, une telle utilisation nécessite impérativement une expertise préalable sur les caractéristiques des principales unités de sol.

Le résultat de ce chapitre permet de mettre en évidence l'intérêt et la pertinence des données à haute résolution (images multispectrales, propriétés électriques des sols) pour définir des zones d'état hydrique des plantes stables dans le temps. Rappelons que ces résultats ont été obtenus sur une situation particulière: climat méditerranéen entraînant des contraintes hydriques très élevées sur un vignoble non irrigué. Dans ces conditions, nos résultats ne font que valider des liens de causalité suivants:

- la croissance de la vigne est principalement limitée par la disponibilité en eau,
- la variabilité spatiale de la canopée (surface, volume), observée par imagerie aérienne, est donc le reflet de la disponibilité en eau,
- la disponibilité en eau est déterminée par les caractéristiques du sol, que ce soit à petite échelle (unité pédologique) ou à grande échelle (variabilité du sol constaté au sein de chaque unité pédologique),
- les propriétés électriques des sols peuvent mettre en évidence cette variabilité, toutefois, une expertise préalable est nécessaire pour une interprétation correcte des données mesurées.

Dans toute autre situation où le facteur limitant n'est pas l'eau, les résultats de ce chapitre ne sont pas nécessairement transposables.

V. Chapitre 4 : validation de l'existence et détermination de la forme de la fonction d'extrapolation,

Ce chapitre a pour objectif de montrer l'existence de la fonction d'extrapolation f_D introduite au niveau du premier article de la thèse (équation 1). Il a également pour objectif de proposer et de valider la forme de la fonction mathématique permettant de modéliser f_D. L'étude a été réalisée en considérant un domaine D limité à la parcelle. Ce choix permet de ne s'intéresser, dans un premier temps, qu'à un domaine où la variabilité de l'état hydrique des plantes est principalement liée au milieu (sol). En effet, les sources de variabilité inter-parcellaires liées au cépage, au porte-greffe, à l'année de plantation, au mode de conduite, etc. ne seront pas prises en compte.
Afin de valider notre approche dans des conditions différentes, deux domaines ont été pris en compte. Ils correspondent à deux parcelles d'une surface de 1,2 et 1,7 ha plantées avec de la Syrah (D_1) et du Mourvèdre (D_2), respectivement. Ces deux cultivars ont été choisis pour leurs réponses différentes aux contraintes hydriques. La Syrah est plus sensible aux contraintes hydriques tandis que le Mourvèdre l'est moins (Schultz, 2003; Ojeda et al. 2005b). Ces deux parcelles sont situées sur l'unité pédologique de la Clape et présentent une variabilité spatiale de l'état hydrique importante.
Cette étude a mobilisé une base importante de mesures de potentiels hydriques de base. Cette base a été collectée dans un contexte préalable à la thèse. Sur chaque domaine, 49 sites de mesure (s_1, s_2, ..., s_i: i = 1, 2, ..., 49) sont répartis sur une grille régulière. Sur

chacun des sites, des mesures de potentiel hydrique de base ont été effectuées au cours de deux saisons. Pour le domaine D_1, sept dates de mesure ont été considérées en 2003 et six dates en 2004. Pour le domaine D_2 six dates ont été considérées en 2005 et trois dates en 2006. Ce dispositif représente donc un ensemble de 637 mesures de potentiel hydrique de base sur le domaine D_1 et de 441 mesures sur le domaine D_2.
Ce jeu de données permet d'étudier très finement, sur chacun des domaines, la variabilité spatiale et temporelle de l'état hydrique des plantes. Il nous a permis de proposer une forme simple de fonction d'extrapolation basée sur des relations linéaires. Le modèle est présenté dans l'équation 2.

$$\hat{z}(s_i, t_j) = a_{s_i} \; x \; z_{re}(s_{re}, t_j); \; s_{re} \in \mathrm{D}, \; \forall s_i \in \mathrm{D}, \; a_{s_i} \in \Re \qquad (2)$$

Dans l'équation 2, afin simplifier les notations, la lettre D désigne le domaine de validité de la fonction d'extrapolation. Dans notre cas, D désigne alternativement l'une des deux parcelles (D_1 ou D_2). L'équation 2 montre que la fonction d'extrapolation est paramétrée par une collection de coefficients (a_{s_i}) locaux et spécifiques à chaque site s_i. Ces coefficients définissent la relation qui existe entre une mesure d'état hydrique en un site de référence s_{re} et chacun des sites s_i de D pour une date donnée. Ces coefficients locaux ne varient pas dans le temps et sont donc uniquement dépendants des caractéristiques du site s_i considéré (capacité de stockage d'eau dans le sol, texture du sol, profondeur du sol, topographie, etc). Rappelons que dans cette approche, la variabilité temporelle de l'état hydrique est prise en compte par une mesure de référence.

Afin de valider l'approche proposée, les mesures réalisées ont été utilisées pour étalonner deux modèles (un modèle pour D_1 et un modèle pour D_2). Cet étalonnage a été réalisé par une méthode classique des moindres carrés. La partie résultat de ce chapitre présente la qualité des résultats obtenus pour les deux modèles : erreur d'étalonnage, erreur de prédiction dans le temps, erreur de prédiction dans l'espace et sensibilité au choix du site de référence. L'ensemble des résultats obtenus ne sera pas détaillé ici. D'une manière générale, ces résultats montrent que les modèles permettent d'expliquer une part d'autant plus importante de la variabilité spatiale que le niveau de contrainte hydrique est élevé (moyenne de la parcelle <-0,4 MPa). Cette observation corrobore les résultats obtenus dans l'article 2. Lorsque la contrainte hydrique est élevée, l'approche proposée permet d'expliquer une part importante de la variabilité spatiale de l'état hydrique des plantes ($r^2 = 0.7$).

Les résultats présentés dans ce chapitre permettent de répondre aux questions initialement posées. Ils valident l'approche proposée qui consiste à extrapoler spatialement l'état hydrique des plantes à partir d'une mesure de référence. Ils ont permis, sur des domaines restreints, de valider l'approche générale proposée équation 2. Accessoirement ces résultats ont permis de mettre en évidence la faible sensibilité du modèle lié au choix du site de référence.
Le modèle présente une forme simple paramétrée par une collection de coefficients linéaires locaux. Cette forme simple s'explique certainement par le choix d'un domaine d'étude restreint correspondant à la parcelle. Les sources de variabilité, bien qu'importantes, y sont limitées aux facteurs du milieu. Cette échelle de travail constitue une première étape de validation du modèle d'extrapolation. A terme, d'autres sources

de variabilité devront être intégrées afin de proposer une extrapolation sur un domaine plus vaste.
D'un point de vue opérationnel, l'approche mise en œuvre dans ce chapitre n'est pas réaliste. En effet, elle requiert l'élaboration d'une base de données importante pour étalonner chaque modèle. Pour des raisons de coût et de main d'œuvre disponible, une telle approche n'est pas transférable à l'échelle d'un domaine viticole. D'un point de vue pratique, cette approche ne présente un intérêt, que s'il est possible d'étalonner les paramètres du modèle avec des informations mesurables avec une haute résolution et à moindre coût.

VI. Chapitre 5: extrapolation spatiale de l'état hydrique des plantes sur la base de données auxiliaires à haute et moyenne résolution.

Ce chapitre propose l'intégration, dans le modèle défini au chapitre précédent, de données auxiliaires à haute et moyenne résolution identifiées dans l'article 3. L'approche proposée consiste à estimer la collection de coefficients locaux a_{s_i} par des données auxiliaires. Afin de rester dans un cadre linéaire permettant l'étalonnage du modèle par une méthode classique des moindres carrés, il a été proposé de travailler avec une combinaison linéaire des variables auxiliaires. L'approche testée est présentée dans l'équation 3.

$$\hat{z}\,(s_i,t_j) = \left(b_0 + b_1 \times q_1(s_i) + b_2 \times q_2(s_i) + \ldots + b_K \times q_K(s_i)\right) x \; z_{re}\;(s_{re},t_j) \quad (3)$$

$avec \quad s_{re}\in D,\ \forall s_i \in D,\ q_k(s_i), k=1,\ldots,K \in \Re$ et $b_k, k=0,\ldots,K \in \Re$,

L'équation 3 présente la même forme générale que l'équation 2. Le terme a_{s_i} y a été remplacé par le terme $\left(b_0+b_1\times q_1(s_i)+b_2\times q_2(s_i)+\ldots+b_K\times q_K(s_i)\right)$. Chaque site s_i y est donc décrit par un vecteur $\boldsymbol{q}^i$, $\boldsymbol{q}^i=[q_1(s_i),q_2(s_i),\ldots,q_K(s_i)]$, correspondant aux valeurs des informations auxiliaires mesurées en ce site. K est le nombre d'informations auxiliaires disponibles et les coefficients b_0, b_1, b_2, b_3,…, b_K représentent les coefficients à déterminer. Remarquons que ces coefficients ne sont pas spécifiques au site considéré mais au domaine D sur lequel la mesure de référence sera extrapolée. Ainsi, l'étalonnage de la fonction présentée équation 3 revient à déterminer un vecteur $\boldsymbol{b}$= [b_0, b_1, b_2, b_3,…, b_K] sur l'ensemble d'un domaine D.
Cette approche a été mise en œuvre et testée sur le même jeu de données et les mêmes domaines que ceux utilisés au chapitre 4. Deux modèles ont donc été déterminés sur deux domaines différents, l'un pour la parcelle Syrah (D_1) et l'autre pour la parcelle Mourvèdre (D_2). Pour chacun des deux domaines, plusieurs données auxiliaires mesurées avec une haute résolution spatiale ont été utilisées, il s'agit de mesures de conductivité électrique apparente des sols et de plusieurs séries d'images multispectrales qui ont permis de calculer des indices de végétation (NDVI). L'essentiel de ces données à haute résolution spatiale a été acquis dans le cadre de la thèse et donc, à des dates postérieures aux dates de mesures d'état hydrique des plantes. Une image multispectrale d'archive acquise à une date antérieure a également été utilisée. Afin de bénéficier de données auxiliaires acquises approximativement aux mêmes dates que les mesures d'état hydrique des informations auxiliaires mesurées manuellement et avec une plus faible résolution spatiale ont été prises en compte (Surface Foliaire Exposée, circonférence des troncs). Bien que plus difficiles à mesurer et plus coûteuses, ces

informations ont quand même été introduites parce qu'elles correspondent à des grandeurs potentiellement accessibles avec des capteurs existants ou en cours de développement.

L'étalonnage correspondant à la détermination du vecteur $\boldsymbol{b}= [b_{0,} b_1, b_2, b_3,\ldots, b_K]$ pour chacun des domaines considérés, a été réalisé par une méthode classique de moindres carrés, en deux étapes. Une première étape a été introduite pour sélectionner, pas à pas, les variables auxiliaires les plus pertinentes. Une deuxième étape a permis d'estimer, pour chacun des deux domaines, le vecteur $\boldsymbol{b}$ avec les variables auxiliaires sélectionnées. La partie résultat présente les variables auxiliaires qui ont été retenues pour chacun des deux domaines ainsi que la qualité des résultats : erreur d'étalonnage, erreur de prédiction dans le temps, erreur de prédiction dans l'espace et sensibilité au choix du site de référence.

Les résultats de ce chapitre montrent que l'approche proposée dans l'équation 3 est pertinente pour estimer l'état hydrique. Conformément aux conclusions des chapitres précédents, le modèle spatialisé permet une amélioration de la prédiction pour des contraintes hydriques élevées (potentiel hydrique de base <-4 MPa). Cette méthode a été mise en œuvre et validée sur deux parcelles. Comparée à une approche classique similaire à l'estimation de la moyenne, elle permet d'expliquer une part importante de la variabilité spatiale de l'état hydrique des plantes ($r^2 = 0.7$) lorsque la contrainte hydrique est élevée. Les variables auxiliaires sélectionnées sont au nombre de deux et sont les mêmes pour les deux domaines d'étude. Il s'agit des mesures de Surface Foliaire exposée et de circonférence des troncs. Cette sélection, une information de la vigueur de l'année et une donnée plus intégrative comme la circonférence du tronc montre que les données auxiliaires relatives à la vigueur des plantes sont pertinentes dans nos conditions. Cette sélection met également en évidence la stabilité temporelle du phénomène puisqu'une information comme la circonférence du tronc est intégrative depuis la date de plantation. Afin de tester l'introduction de variables auxiliaires à haute résolution moins coûteuses en main d'œuvre, l'approche a également été testée en introduisant uniquement les valeurs de NDVI. Les résultats montrent que cette approche reste pertinente même si elle aboutit à des prédictions de moindre qualité ($r^2 = 0.55$).

D'un point de vue opérationnel, l'approche mise en œuvre dans ce chapitre n'est pas réaliste. En effet, comme pour l'approche présentée au chapitre 4, elle requiert l'élaboration d'une base de données importante pour étalonner chaque modèle. Toutefois, les résultats obtenus aboutissent à un modèle relativement simple nécessitant, pour chaque domaine D, la détermination de seulement trois paramètres $b_{0,} b_1, b_2$, voire seulement deux paramètres ($b_{0,} b_1$) si l'on ne considère qu'une donnée auxiliaire comme le NDVI. L'étalonnage d'un tel modèle pourrait donc être conduit avec seulement 2 ou trois mesures d'état hydrique réalisées sur des sites différents et à des dates différentes. Cet étalonnage pourrait tout à fait s'inscrire dans une campagne classique de suivi de l'état hydrique des plantes. Les résultats obtenus avec un étalonnage réalisé à partir de seulement trois mesures réparties dans l'espace du domaine D et réparties dans le temps. Ce protocole a permis d'étalonner un modèle dont la pertinence est présentée et est tout à fait similaire au modèle précédent ($r^2 = 0.7$).

CONCLUSION GÉNÉRALE

Ce travail de thèse s'est intéressé à l'estimation spatialisée de l'état hydrique de la vigne. Son objectif est de proposer et de valider une approche permettant de prendre en compte la variabilité spatiale d'une zone définie afin d'y estimer au mieux l'état hydrique des plantes à une date donnée.

D'un point de vue scientifique, notre travail apporte des connaissances intéressantes pour modéliser la variabilité spatiale de l'état hydrique des plantes. Il montre que, pour des contraintes modérées à élevées, il s'agit d'un phénomène structuré dans l'espace. Il montre également que toute information, qu'elle soit experte, issue de mesures indirectes à haute résolution ou d'une combinaison des deux, peut permettre la définition de zones (domaine) au comportement plus homogène relativement à l'état hydrique des plantes. La structure spatiale est déterminée par des paramètres environnementaux stables dans le temps et elle peut être mise en évidence par des données à haute résolution. Ce constat a permis de proposer une approche opérationnelle qui combine données de référence avec données indirectes pour estimer spatialement l'état hydrique des plantes. Il est toutefois nécessaire de rappeler certaines caractéristiques de notre étude qui limitent la portée de nos conclusions. L'étendue de notre zone d'étude est restreinte, le climat peut raisonnablement y être considéré comme uniforme, il s'agit d'un vignoble non irrigué avec un climat caractérisé par un fort déficit hydrique estival. Ces caractéristiques entraînent des contraintes hydriques très importantes et l'effet des facteurs du milieu qui déterminent l'accès à l'eau y est certainement exacerbé. Dans une autre situation où l'accès à l'eau serait moins limitant, l'effet de ces facteurs, pourrait être plus difficile (voire impossible) à mettre en évidence.
Le modèle d'extrapolation proposé, a été validé et mis en œuvre sur des domaines limités à la parcelle. L'amplitude de variation observée au niveau intra-parcellaire, est, dans notre cas très importante et permet de valider l'approche proposée. Toutefois, certaines simplifications et hypothèses ont été réalisées, elles méritent une attention particulière pour les investigations futures. Les paragraphes suivants ont pour objectif de soulever les principales interrogations et éventuellement les questions scientifiques sous-jacentes.

a. Domaine de validité de la fonction d'extrapolation

La fonction d'extrapolation a été testée et validée à un niveau intra-parcellaire. Ce domaine spatial a permis de s'affranchir des sources de variabilité inter-parcellaires liées au mode de conduite, au cépage, au porte-greffe, etc. A l'échelle d'un domaine viticole, cette approche reste très contraignante puisqu'elle suppose la réalisation d'une mesure sur un site de référence pour chaque parcelle et pour chaque date. Le nombre de mesures de référence à réaliser doit être limité. La fonction d'extrapolation doit être utilisable sur l'ensemble des parcelles d'un domaine viticole, voire sur des groupes de parcelles préalablement réunies en fonction des unités pédologiques. Cette contrainte soulève le problème de l'extrapolation d'une mesure de référence à un ensemble de parcelles qui présentent des caractéristiques différentes en terme de densité de plantation, de cépage, de mode de conduite, etc. La fonction d'extrapolation proposée devra certainement être adaptée pour prendre en compte ce phénomène. Une démarche similaire à celle que nous avons présenté pourra être adoptée pour valider et tester la pertinence du modèle proposé.

b. L'étalonnage de la fonction d'extrapolation

Le problème de l'étalonnage de notre approche reste un point crucial pour un transfert éventuel vers des vignobles en production. D'un point de vue théorique, l'intérêt de notre approche réside dans le faible nombre de mesures de référence nécessaires pour étalonner le modèle. Il a d'ailleurs été montré qu'un étalonnage avec un nombre de mesures très limité permettait d'obtenir un modèle pertinent. Toutefois, la définition d'un protocole d'échantillonnage optimal dans l'espace et dans le temps mérite d'être étudié. Certaines informations auxiliaires peuvent être utilisées pour définir des mesures orientées dans l'espace et dans le temps. Cet aspect constitue une question scientifique intéressante et appelle des expérimentations et/ou à des simulations destinées à formaliser l'établissement d'un protocole d'échantillonnage permettant de minimiser le coût et le temps nécessaire à l'étalonnage du modèle.

c. Le choix des variables auxiliaires

Le choix et la disponibilité des informations auxiliaires est déterminant. De nouvelles informations auxiliaires seront certainement disponibles dans les prochaines années (analyse d'images, lidar, infra-rouge thermique, capteurs de sol, etc.). Le choix des informations auxiliaires devra nécessairement être raisonné en fonction de leur pertinence dans un contexte local, mais aussi en fonction de contraintes pratiques liées aux modes de conduite, à l'entretien du sol, et naturellement en fonction des contraintes économiques. Il est difficile de proposer une aide à la décision générique pour orienter ce choix. Il est probable que des tests préalables seront nécessaires pour valider le choix des données auxiliaires adaptées aux spécificités locales (au moins régionales).
Remarquons toutefois qu'une approche mixte, que nous n'avons pas considérée dans notre travail, peut être envisagée. Une telle méthode consisterait à caractériser la structure spatiale de l'état hydrique des plantes avec une autre mesure de référence plus simple à échantillonner et intégrative comme le $\delta^{13}C$. Cette mesure pourrait également être utilisée comme une donnée auxiliaire introduite dans la fonction d'extrapolation. Une telle approche mériterait d'être étudiée pour son caractère plus général, elle présente l'intérêt de baser l'extrapolation sur une grandeur homogène avec la grandeur à estimer.

d. La résolution temporelle

Ce travail s'est intéressé à l'estimation spatiale de l'état hydrique des plantes. L'approche proposée ne résout pas le problème de la résolution temporelle, en effet, cette dernière est déterminée par la fréquence des mesures réalisées sur le site de référence. D'un point de vue opérationnel, il s'agit d'une contrainte importante, surtout lorsque certaines opérations comme l'irrigation, nécessitent une connaissance fine de la variabilité temporelle de l'état hydrique des plantes. Il s'agit d'une question scientifique intéressante qui nécessite l'intégration de données auxiliaires à haute résolution temporelle (capteurs sur les plantes, capteurs continus dans le sol, données climatiques, etc.). L'approche que nous proposons devrait évoluer vers une approche plus globale de coopération entre données de référence et données auxiliaires indirectes i) à haute résolution spatiale d'une part et ii) à haute résolution temporelle d'autre part. Une première approche prometteuse a été proposée et mise en œuvre par Taylor et al. (2009) (annexe 1) sur la base de données climatiques.

e. Le transfert de notre approche à d'autres conditions

Enfin, notre étude s'est focalisée sur un vignoble non irrigué dans des conditions climatiques favorisant l'apparition de contraintes hydriques fortes. L'adaptation de notre approche aux vignobles irrigués soulève des questions. Dans le cas de l'irrigation, plusieurs phénomènes sont susceptibles de modifier l'interaction milieu/état hydrique des plantes et de limiter la pertinence de l'approche proposée. Parmi ces phénomènes, notons i) l'application modulée des doses d'irrigation par un système d'irrigation, ii) l'incidence de conduites d'irrigation gravitaires particulières avec mise en œuvre de buttage, iii) la présence simultanée de zones sèches et humides au niveau des racines induites par une irrigation localisée comme le goutte à goutte, iv) des pratiques d'irrigation alternées sur les rangs par exemple le partial root-zone drying. D'une manière, plus générale, l'irrigation limite l'effet des facteurs du milieu sur l'état hydrique des plantes. La structure spatiale induite par ces facteurs risque d'être plus difficile à mettre en évidence par les données auxiliaires. Remarquons que ce constat est également vrai pour les vignobles septentrionaux caractérisés par des contraintes hydriques modérées.

L'utilisation de notre approche à des vignobles irrigués nécessite de choisir la mesure de référence adaptée, en effet, le potentiel hydrique de base proposé dans notre travail risque de ne pas être adapté aux irrigations localisées. Elle nécessite également de choisir judicieusement les informations auxiliaires à utiliser et d'en tester la pertinence. Enfin, la forme linéaire de la fonction d'extrapolation devra nécessairement être confirmée par des expérimentations.

Une expérimentation réalisée au Chili sur vignoble irrigué permet d'apporter quelques éléments de réponses prometteurs (annexe 2). Cette expérimentation a pour objectif d'adapter l'approche utilisée en considérant une autre mesure de référence : la conductance stomatique. Une base de données intra-parcellaire a permis de montrer la possibilité d'extrapoler la conductance stomatique sur l'ensemble de la parcelle. Cette extrapolation est réalisée avec une mesure de référence et une collection de relations linéaires estimés grâce à la base de donnée. S'agissant d'un contexte irrigué, les contraintes hydriques sont plus faibles et la qualité des prédictions est moindre que dans nos conditions. Toutefois, ces résultats montrent que notre approche reste tout à fait transposable à un contexte irrigué et avec des mesures de référence différentes.

CHAPTER I

Chapter 1: Is it possible to assess the spatial variability of vine water status?

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Abstract

Aims:
Plant water status monitoring during the vineyard growth cycle constitutes a basic parameter for both harvest quality and vineyard management. Unfortunately, the plant water status measurement requires skills and heavy devices which drastically limit the number of repetitions either in space or in time. Moreover, due to the significant spatial variability in viticulture, extrapolation of one local measurement to a larger scale, vine field or vineyard, is difficult. Therefore, the design of tools and methods to characterize and to assess the spatial variability of plant water status constitutes a big challenge. The aim of this paper is to propose an approach allowing the spatial variability of the plant water status to be assessed.

Methods and results:
This work proposes a complete literature review of previous works using different approaches to assess the vine water status. Based on this review, it leads to a conceptual approach considering the Spatial (S) and Temporal (T) variability of the plant water status assessment at a whole vineyard scale. This paper is divided into three sections: (i) description of plant water status reference methods based on direct measurements on the plant, (ii) plant water status assessment methods based on auxiliary information (i.e. weather, soil and plant vegetative expression), and finally (iii) a proposal for combining local reference measurement and auxiliary information to characterize the spatial variability of the vine water status at the vineyard scale.

Conclusion:
Taking into account restrictive assumptions, this paper points out the possibility to provide relevant spatial assessment of the vine water status. This possibility is illustrated with a simple example.

Significance and impact of the results:
This work gives an answer to the significant problem of vine water status assessment over space. It proposes an approach based high spatial resolution auxiliary information to extrapolate a measurement (PLWP or SWP) made at a given time on a reference site. This proposal determines the different steps for further investigations aiming at proposing a spatial model of vine water status.

Keywords: grapevine, vine water status, spatial and temporal variability, water restriction zones.

Résumé
Objectif:
L'évolution de l'état hydrique de la plante au cours du cycle végétatif est un paramètre important pour la gestion du vignoble et de la qualité de la vendange. Malheureusement, cette mesure fait appel à des dispositifs spécifiques particulièrement contraignants ce qui limite fortement le nombre de mesures réalisables. La résolution spatiale et temporelle des mesures d'état hydrique est donc généralement faible. Compte tenu de la forte variabilité spatiale observée en viticulture, l'extrapolation de quelques mesures ponctuelles à une zone plus large peut s'avérer délicate. La conception d'outils et de méthodes qui permettent de caractériser cette variabilité constitue à la fois un enjeu et un défi. L'objectif de ce travail est de proposer une approche permettant d'estimer la variabilité spatiale de l'état hydrique des plantes.
Méthodes et résultats:
Cette proposition s'appuie sur un état de l'art exhaustif des principes de mesures et envisage une approche de modélisation. L'article est divisé en trois parties : (i) une description des méthodes de référence, mesures directes effectuées sur la plante, (ii) une revue des méthodes d'évaluation indirecte, basées sur des informations auxiliaires (climat, sol, expression végétative) et finalement, (iii) une proposition de combinaison des deux approches en vue de caractériser la variabilité de l'état hydrique des plantes à l'échelle du vignoble.
Conclusion:
Ce travail ouvre des perspectives relatives à l'utilisation de données auxiliaires à haute résolution spatiale pour estimer la variabilité spatiale de l'état hydrique des plantes. Cette perspective est illustrée à travers un exemple simple. Ce travail met également en évidence les limites et les hypothèses de base à formuler pour mettre en œuvre l'approche proposée.
Signification et impact de l'étude:
Ce travail propose une réponse au problème de l'estimation de l'état hydrique des plantes à l'échelle d'un domaine. Il envisage une approche basée sur l'utilisation de données à haute résolution pour extrapoler une mesure de référence (potentiel hydrique de base ou potentiel hydrique de tige) réalisée à un moment donné sur un site particulier. Cette proposition permet de mettre en évidence toutes les étapes de recherche nécessaires afin d'arriver à un véritable modèle spatial d'estimation de l'état hydrique des plantes.
Mots clés: vigne, état hydrique de la vigne, variabilité spatiale et temporelle, zones de restriction hydrique.

Introduction

Several researchers have shown that changes in grapevine water status have a direct effect on grape composition and quality through its influence on vegetative growth, fruit growth, yield, canopy microclimate, and fruit metabolism (van Leeuwen and Seguin, 1994; Dry and Loveys, 1998; Ojeda *et al.,* 2002; Trégoal *et al.,* 2002). Therefore, spatial and temporal knowledge of changes in vine water status is important for deciding several managements inside the vineyard (i.e. harvest from different section of a vineyard block, leaf area, crop load, root stocks selection, etc). However, from an irrigation point of view, the vine water status is of critical importance for deciding whether or not irrigation practice is required at a given time. Adequate irrigation management can be performed using vine water status monitoring over time. Depending on the accuracy of the method used, vine water status monitoring can lead to the development of a relevant decision support tool, which could enable grape growers to optimally manage vineyards for vegetative and fruit growth.

As well, many authors have shown that the majority of vineyards present a great spatial variability in the following factors: yield (number and size of bunches), vegetative growth (canopy density), sugar and grape quality components (Ortega *et al.,* 2003; Bramley and

Hamilton, 2004; Taylor *et al*., 2005). It has also been shown that vine water status presents a significant magnitude of variation even in a single field (Tisseyre *et al.* 2005; van Leeuwen *et al.,* 2006). This vine water status variability is especially evident at the end of summer when significant water restriction is found under non-irrigated conditions (Ojeda *et al.* 2005a). Ojeda et al. 2005a showed that in a single field the magnitude of variation of the predawn leaf water potential was of -1.6 MPa over the time and more than -1.2 MPa at the within field level. Therefore, in addition to temporal water status monitoring, spatial variability of vine water status also needs to be considered.

Spatial variability of vine water status can occur on very different scales depending on the driving factor. Climate variability may mainly explain differences on large scales. Soil and meso-climate variability may explain differences between blocks, even within a given field. The variation in soil components can sometimes be discerned within a-meter-scale (Hellebrand and Umeda, 2004). Since soils are the main substrate for plants, their variations in water holding capacity, induced by variations in texture and soil depth, within a whole field may induce high variability in vine water status (Tisseyre *et al.,* 2005; Ojeda *et al.,* 2005a).

The most appropriate method for monitoring vine water status would then require taking into consideration both sources of variability: (i) the evolution of vine water status over time (T) (growing period), and (ii) spatial variability (S). Therefore, an efficient decision support tool must be based on a Spatio-Temporal (S-T) vine water status monitoring system. This means a system which is able to provide maps or snapshots of plant water status variability in the whole vineyard during the entire growing season.

Most past research on vine water status monitoring have focused on temporal variability (T). Mainly with the practical goal to define the opportune moment for irrigation, maximizing water use efficiency and improve the wine grape quality. These studies aimed at providing efficient and accurate tools to assess plant water status. Thus, different sensing systems and methods have been developed to offer the best estimation of vine water status. This research has supplied sensors that allow the plant water status to be measured very accurately at the leaf level or at the plant level. It has also considered different approaches which take into consideration weather and/or soil data to generate empirical models to estimate the indirect effect of plant water restriction over time (Goodwin and Macrae, 1990; Jensen *et al*., 1990; Allen *et al.,* 1998; Ortega *et al.,* 2000; Lebon *et al.,* 2003).

Very few authors have focused on spatial variability. Therefore, more relevant tools for growers need to be considered for the large amount of variability in water status within a vineyard and its effect on grape quality and yield (Ortega *et al.,* 2003; Bramley and Hamilton, 2004; Taylor *et al*., 2005).

It is fundamental to explain that two spatial scales are simultaneously and independently considered in this study. The first spatial scale to be considered deals with the area over which the data provided by a sensor or a measurement is valid. Most of the methods dedicated to the assessment of plant water status are punctual. That means, they provide information only about the specific site where the assessment is carried out. However, depending on the sensing systems and the type of measurement, a large variability can occur even at the site of measurement. That means a method based on leaf measurement necessarily presents a larger variability than a method based on the stem or the whole canopy.

The second spatial scale to be considered deals with the management scale. It has a much more complex definition, since it refers to an area over which climate, soil characteristics and the resulting vine response imply similar types of management practices (training systems, fertilization, irrigation, etc.). These areas (or zones) are sometimes defined by soil units based on expert analysis of auxiliary information (i.e. elevation, soil depth, soil colour, or other knowledge). Figure 1 shows an example of such a definition. It considers a whole vineyard (D) which constitutes the study area. It assumes homogeneous weather conditions over D. Conversely, different types of soil were observed; for example, deep sandy soils on D_1, limestone on D_2,…, etc. $(D_n)_{n\ =\ 1\ldots N}$ can be considered as sub-areas or sub-zones of D. Characteristics of each sub-zones determine management practices (choice of variety and rootstock, density, training systems, etc.). A sub-zone may present very similar characteristics, but this does not mean it is homogeneous. For example, differences in soil depth can be found in D_1 even if the soil is mainly sandy, regular changes in limestone layers can be observed in D_2 inducing a large variability of vine response within D.

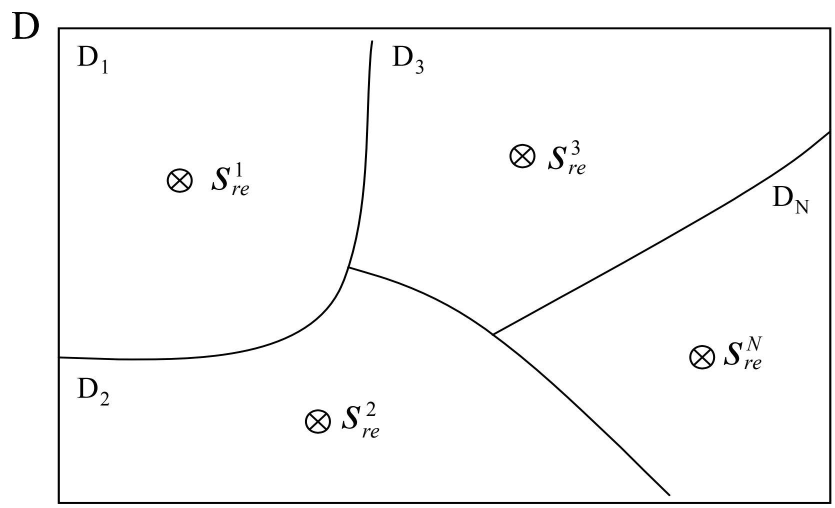

Fig 1. Illustration of a sub-zones D_n at a vineyard spatial scale. D constitutes the study area (the vineyard) and $(D_n)_{n\ =\ 1\ldots N}$ are the sub-zones belonging to D. s^n_{re} is considered as a reference site for D_n ($s^n_{re} \in D_n$). Definition of a reference site is introduced latter in the paper.

The aim of this paper is to propose a complete literature review of previous methods to assess the vine water status. For each method, this paper focuses mainly on (i) a brief description of the principle, (ii) the meaning of the measurement and its relevance towards plant water status estimation, (iii) the practical implementation of the method and its ability to provide measurements either over S or T and, (iv) the underlying assumptions which are considered either in the S or in the T data collection. Based on this review, this paper presents a relevant approach to take into account the spatial and the temporal variability in vine water status assessment at a within vineyard scale. Table 1 provides a summary of the information presented in the following sections.

1. Plant level measurement

In recent years, plant-based measurements have been proposed to assess and quantify the level of water restriction affecting the plants. Consequently, due to their accuracy, some growers are currently using plant-level measurements techniques practically as the unique method to monitor plant water status. These methods provide a direct measurement of plant physical and physiological parameters to assess water status.

An accurate method of vine water status measurement should be one which responds quickly to change in vine water restriction, soil water availability, soil hydraulic conductivity and the ability of the vine to transport water from the soil to the atmosphere (Choné *et al.* 2000; Choné *et al*. 2001). A subdivision of these methods based on data collection techniques can be presented as: reference measurements, used to measure the effect of a determined level of water restriction on the vine (usually manual methods), and the plant water status monitoring systems which can collect a large number of measurements over a short period of time.

1.1 Reference measurements

1.1.1 Stomatal conductance (g_s)

Stomatal conductance (g_s) consists in measuring the water vapour pressure gradient (air flow) between the vine leaf and the atmosphere (water diffusion through vine leaf stoma). g_s is the first factor to be affected by either water stress or high atmospheric demand due to the effect of plant stomatal regulation (Cifre *et al.,* 2005). A high correlation between g_s and plant water potential and/or relative water content has been observed in some grapevines under specific conditions (Bravdo and Naor, 1996; Cifre *et al.,* 2005). According to Flexas *et al.,* (2002) and Cifre *et al.,* (2005) g_s can be considered as an integrative parameter reflecting the severity of water restriction on different grapevine cultivars. Thus, as plant water restriction increases due to high atmospheric demand and/or soil water deficit, it results in reduced g_s and leaf transpiration rates (Loveys *et al.,* 2001).

Frequently, stomatal conductance and transpiration rate measurements are made at the leaf scale using porometer and gas exchange instrumentation. However, g_s monitoring data are characterized by a high degree of variability between measurements. Therefore, this method requires a great number of single point measurements to be able to accurately characterize variability in the whole canopy of the grapevine. Sampling becomes even more critical when it deals with the assessment of a whole field. For example, in their particular conditions, Loveys *et al.,* (2005) defined an optimum sampling strategy to obtain a relative standard error of 5% at the field scale. This strategy required the sample of 32 vines with 4 measurements per vine which lasts 3 hours per field (Loveys *et al.,* 2005).

1.1.2 Plant water potential

Many authors have proposed the use of the pressure chamber method (Scholander *et al.* 1965) as an excellent tool to measure vine water status under irrigated and non-irrigated conditions (McCutchan and Shackel 1992; van Leeuwen and Seguin, 1994; Naor *et al.,* 2001; Ojeda *et al.,* 2002). Vine water status can be assessed using different pressure chamber approaches such as: (i) Leaf water potential (LWP), (ii) Stem water potential (SWP), and (iii) Predawn leaf water potential (PLWP) (Schultz, 1996; Choné *et al*., 2000; Choné *et al*., 2001; Ojeda *et al.,* 2002; Carbonneau *et al.,* 2004; Girona *et al.,* 2006; Sibille *et al.,* 2007).

Leaf Water Potential (LWP)

LWP is commonly used as an auxiliary tool in irrigation scheduling (Loveys *et al.,* 2001). It is made on leaves that are extracted and measured in-situ (without waiting for any process of plant stabilization). It is commonly done at the time of the day when the evaporative demand by the atmosphere is maximum. However, the main disadvantage of this method is that the values of water potential are highly variable between leaves and between plants due to differences in the transpiration rate of the canopy (which depends on stomatal behaviour) (van Leeuwen *et al.,* 2007). Thus, LWP represents only the leaf water potential without any kind of plant integration.

Stem Water Potential (SWP)

A pressure chamber can be used to measure SWP and the procedure involves covering a leaf with an aluminium foil bag coated with plastic to stop leaf transpiration (Begg and Turner 1970). With the transpiration close to zero, leaf water status equilibrates with the stem of the vine. Therefore, the values of water potential measured in the chamber represent SWP (McCutchan and Shackel, 1992). Unlike the LWP, the SWP represents the water potential of the whole vine plant. The midday SWP corresponds to measurements of this parameter at the time of day when the evaporative demand by the atmosphere is maximum (Prichard and Verdegaal, 2001). Various authors have proposed midday SWP as a sensitive physiological indicator of the water status for fruit trees under irrigated conditions (McCutchan and Shackel, 1992; Naor *et al.,* 2001; Choné *et al.,* 2001).

Predawn Leaf Water Potential (PLWP)

PLWP assesses the plant water potential measured with a pressure chamber between 3:00 and 5:00 a.m. Thus, PLWP measures the plant water status with zero water flux through the plant and provides information about soil water status close to the root-zone (Katerji and Hallaire, 1984). Indeed, PLWP is considered to be a surrogate for soil matrix potential since during the night, when stomata are closed and transpiration pressure is low, leaf water potential becomes equilibrated with the water potential in the soil. However, PLWP represents the soil water potential in the most humid soil layer and might thus not be representative of average soil water potential when soil water is heterogeneous (Ameglio *et al.,* 1999).

Which Plant Water Potential to Use?

The selection of the appropriate method (LWP, SWP or PLWP) depends on the conditions in which the measurements are made. These conditions can be described by the irrigation method used and the water restriction level. Thus, Sibille *et al*., (2007) showed that in the case of vine water status under high-water restriction conditions to extreme water restriction conditions (PLWP < -1.0 MPa), the PLWP was a better option than SWP. To the contrary, LWP and SWP present a higher sensitivity in the low water restriction level ($-0.4 <$ PLWP) (irrigated conditions) compared to PLWP (Sibille *et al.,* 2007). Furthermore, PLWP gives a good estimation of vine water status in the case of homogeneous distribution of water in the soil (flood irrigation or rain feed crops). However, it does not behave in the same way for heterogeneous soil water conditions (partial root-zone drying irrigation and more generally all sorts of drip irrigation) where the use of this indicator is questionable (Améglio and Archer, 1996). PLWP is not a good indicator for irrigation when drip irrigation is implemented (Ameglio *et al.,* 1999).

It is important to consider that depending on the method used, it is possible to make different physiological interpretations from the values obtained. For example, in the case of LWP and SWP, the stomatal behaviour has a strong effect on measurement results. This is mainly due to the direct dependency of LWP and SWP on the stomatal behaviour and water vapour transport processes through the leaf. For this reason, it is more complex to compare values of SWP or LWP between near-isohydric and anisohydric behaviour cultivars, especially when a high water restriction condition is reached (PLWP ≤ -0.8 MPa) (Sibille *et al.,* 2007; Ojeda *et al.,* 2005b; Shultz, 2003). Moreover, in the case of the PLWP the stomatal behaviour of the variety is less important, since this method directly gives the soil water status. Therefore, the values of PLWP between different varieties would be comparable, especially if the vines are under strong water restrictions and on the condition that soil humidity is homogeneous (Sibille *et al.,* 2007).

1.1.3 Carbon isotope composition measurement (δ13C)
The carbon 13 isotopic discrimination method is another physiological indicator that is able to integrate the water regime applied to grapevines from veraison to harvest. This method is based on the following known facts: (i) the ^{13}C represents 1.1% of carbon in the CO_2 atmospheric concentration and (ii) the ^{12}C (lighter than ^{13}C) is preferentially used during the photosynthesis. Thus, when soil water availability decreases, leaf water potential also decreases causing partial stomata closure. The later process reduces CO_2 exchange between the leaf and the atmosphere (coupled with water diffusion through the stomata), limiting the isotropic discrimination. The ratio $^{13}C/^{12}C$ (denoted $\delta^{13}C$) comes close to the described condition compared to the atmospheric CO_2. Therefore, an integrated indicator of water restriction has been based on this isotropic relation. The period that this indicator considers is the synthesis of sugar in berries, which is from veraison to harvest. The $\delta^{13}C$ is expressed in ‰ compared to a standard (Pee Dee Belemnite standard, Farquhar *et al.,* 1989) and values can range from -20 to -26‰, where -20‰ indicates a strong water restrictions and -26 ‰ an absence of water restriction (Gaudillère *et al.,* 2002). The interest in assessing plant water stress based on this indicator resides in two main advantages: i) samples for $\delta^{13}C$ measurements are only required during berry maturation (van Leeuwen *et al.,* 2001); ii) a single sampling time allows monitoring a large number of fields, which is not possible using other water-stress assessment methods, such as the pressure chamber.

1.2 Plant water status monitoring system
These methods are characterized by continuous monitoring of the physical and physiological parameters of the plant using data loggers. The main advantage of these systems is their ability to take a large number of measurements in a short period of time, making it possible to assess temporal changes in the plant parameters that can occur on a relatively short time scale.

1.2.1 Transpiration measurements (Sap flow sensors)
Sap flow sensors measure the rate at which sap ascends the stem using heat as a tracer (Huber, 1932). The main methods to measure sap flow velocity are: (i) heat balance, (ii) heat-pulse velocity and (iii) thermal dispassion (Granier, 1985). These methods allow transpiration rate estimation for the whole plant (Fernández *et al.,* 2001; Giorio and Giorio, 2003).

A decrease in soil water availability induces a reduction in g_s and decreases plant transpiration (Davies *et al.,* 2002). Escalona *et al.,* (2002) have demonstrated a very high correlation between single leaf g_s and the instantaneous sap flow in a water-restricted potted grapevine.

Sap flow measurements give reliable, direct estimates of plant water loss without disturbing the leaf environment conditions (Fernandez *et al.,* 2001; Cifre *et al.,* 2005). Therefore, a direct measurement of real vine water use can be obtained without considering water evaporation from the soil (Escalona *et al.,* 2002; Yunusa *et al.,* 2000). Under irrigation conditions, sap flow measurement has proved to be a good tool for estimating canopy transpiration (Yunusa *et al.,* 2000; Cifre *et al.,* 2005). Thus, this method can be used as an auxiliary tool for irrigation scheduling. However, this method is difficult to adapt to adult vine with a thick trunk.

1.2.2 Trunk diameter fluctuations monitoring (Dendrometry)
The shrinking and the swelling of the extensible plant tissues provide an indirect measurement of the transpiration streams during daylight periods, and is related to changes in water content and turgor of plants. Therefore, diurnal stem diameter contraction monitoring has been proposed in the past as a means to monitor plant water status, which can be related to plant

growth and water-use (Naor and Cohen, 2003; Cifre *et al.,* 2005). Trunk diameter has been shown to be indirectly related to plant water status, as is LWP (Naor and Cohen, 2003).

Maximum Daily trunk Shrinkage (MDS) was proposed as a plant water stress indicator suitable for irrigation scheduling purposes because it was found to be highly sensitive to changes in soil water availability (Naor and Cohen, 2003). MDS is closely related to plant water status in deficit irrigation treatments due to a strong relationship between the stress imposed and the relative MDS. Weather conditions influence MDS causing greater MDS on hot days characterized by high evaporative demand compared to milder days (Loveys *et al.,* 2001). Nevertheless, in grapevines MDS is only representative until veraison. After this period the important production of bark in the trunk makes non-sensible this measurement. Therefore, the sensor must be moved to one of the shoots and then the information generated is difficult to compare whit previous data. Furthermore, the shoot may not represent the water status of the whole plant.

1.2.3 Leaf and canopy temperature

It has been long recognized that leaf and canopy temperature is highly dependent on the transpiration rate and can therefore be used as a stomatal behaviour indicator (Sinclair *et al.* 1984). Remote infrared sensing of canopy temperature (as a surrogate for g_s) has become an established technique for plant water status assessments (Idso, 1982; Jones, 1999). Infrared Thermography (IRT) has been proposed as an appropriate method for assessing grapevine water status reducing the high variability associated with single point measurements using IRT (Jones *et al.,* 2002).

The increasing availability of infrared imaging analysis tools opens up the possibility of high-resolution studies of stomatal behaviour variations over leaf surfaces. By measuring canopy temperature, using the IRT technique and the index of canopy conductance (I_g) proposed by Jones (1999), it is also possible to integrate a large number of leaves into the measurement, effectively reducing the error associated with leaf to leaf or vine to vine variation.

1.3 Technical and spatial consideration

The main advantage of the methods presented in sections 1.1 and 1.2 is to provide a relevant assessment of the plant water status on the plant basis. This means that the real response of the plant to water restriction is taken into account. Nevertheless, each of these methods presents significant drawbacks, which limits the number of field measurements.

In the case of plant water potential (Scholander *et al.,* 1965), the measurement requires an expensive heavy device which has to be brought into the field. Moreover, measurements are manual and time consuming; they sometimes have to be done at dawn (for PLWP), which constitutes a significant constraint for labor management and limits the number of samples measured each day. For g_s estimation, the technical constraints are similar since manual measurements using a porometer or a gas exchange chamber are required in that case. These constraints constitute strong limitations in the use of reference methods. Nevertheless, g_s estimation and plant water potential are supposed to provide the best estimation of plant water status.

Considering the $\delta^{13}C$ method, it requires a high initial and running investment (associated instrumentation and laboratory analysis). This drawback could drastically limit the spatial resolution of the measurements since an important number of samplings and analyses within the vineyard is required to highlight the spatial variability of the vine water restriction. Another significant drawback of the method, in the frame of this work, is due to the technical characteristics of the $\delta^{13}C$ technique which gives an information of the water restriction experienced by the vines after harvest (berry collection during harvest). Obviously, this information is to late for irrigation scheduling management during the season. However, we will see later in this paper, that the $\delta^{13}C$ could provide relevant information of the plant water status spatial variability. Assuming spatial patterns highlighted by this technique are time stable, the $\delta^{13}C$ could constitute a relevant auxiliary information to model the spatial variability of the plant water status in association with other measurements.

The development of plant water status monitoring systems allows this problem to be partly addressed. These methods can provide an estimate of this measurement with a high temporal resolution since a data logger is used to monitor plant water status. Nevertheless, these methods also present significant limitations:

- the measurements provided by trunk diameter sensors or sap flow sensors have to be carried out on the same plant. The relevance of such information is mainly due to its dynamic variation over the season; different plants can show different responses at different times of the season complicating data interpretation.

- the cost and the maintenance of the system limits the number of devices that it is possible to use at the vineyard scale. The amount of available information in terms of space is consequently small, limiting the knowledge of the spatial variability of plant water status.

- For each system (trunk diameter sensors, sap flow sensors or infra-red thermography) the measurement does not provide any direct estimation of the plant water status. For irrigation scheduling, these monitoring systems can constitute a relevant decision support system. Nevertheless, for other purposes, if a reference measurement is required, a calibration model provided by previous experiments performed on the same location has to be defined. Such models developed on specific locations have already been proposed in the literature for sap flow (Escalona *et al*., 2002), trunk diameter (Naor and Cohen, 2003) or canopy temperature measurements (Jones, 1999, Möller *et al.*, 2006). These studies show that a relation between monitoring systems and reference measurement is possible locally. However, they require extensive experimentation.

2. Plant water status assessment based on auxiliary information

There are indirect methods based on mathematical models that can be used to estimate plant water status. These models use auxiliary information like weather and/or soil variables to provide an indirect plant water status assessment. Therefore, these methods are widely used for irrigation scheduling design. Depending on the auxiliary information used, such methods can provide estimation on very different spatial scales. Thus, the study of water transport through the soil-plant-atmosphere continuum provide the standardization of critical parameters to represent plant water status. After identifying these critical parameters a validation process is made comparing them with physiological reference measurement (see section 1).

Over the last years many new technologies have been developed and adopted in agriculture such as: Global Positioning Systems (GPS), on-board crop and soil measurement systems and reliable devices to store and exchange/share information, among others. These new technologies applied to viticulture produce a large amount of auxiliary information easily available at a high-spatial resolution (i.e. remote sensing and soil electrical property maps), which can be used to define different water restriction zones at the vineyard scale (Acevedo-Opazo *et al.,* 2007).

2.1 Climate

A large number of more or less empirical methods have been developed over the last 50 years by numerous scientists and specialists worldwide to estimate evaporation from an open water surface from different climatic variables. These methods classically combine the energy balance with the mass transfer method and derive an equation to compute the evaporation from standard climate records of sunshine, temperature, humidity and wind speed. They are used to provide an assessment of the water consumption of the plants which, in addition with soil average characteristics (water holding capacity), are widely used for irrigation scheduling design.

Available methods and indices used to estimate vine water consumption based on weather variables can be summarized as: (i) methods to estimate the crop evapotranspiration like the Penman-Monteith method recommended by the FAO (Food and Agriculture Organization of the United Nations) (Allen *et al.,* 1998; Bois *et al.,* 2008a; Bois *et al.,* 2008b), (ii) methodologies to estimate the plant water status (crop and soil water stress indices).

Crop evapotranspiration (ETc), or water consumption of the plants, is determined using empirical models (Penman-Monteith, Blanney-Criddle, Radiation and Class A evaporation pan). Accurate results can be obtained using the Penman-Monteith method for non-stressed plants due to the incorporation of the canopy resistance parameter (r_c). Various models have been proposed to estimate r_c using weather variables (Allen *et al.,* 1989; Pereira *et al.,* 1999).

Others approaches have been developed to assess and quantify the stress level in vines at different phenological stages to maximize crop water use efficiency in order to control vigour harvest quality and yield. The most common one implies the use of the Crop Water Stress Indices (CWSI). This approach is based on the crop evapotranspiration estimations corrected by infrared thermometry and Vapour Pressure Deficit (VPD) to construct a plant water stress index which was related to the plant water potential (Idso *et al.,* 1981; Sammis *et al.,* 1988; Goodwin and Macrae, 1990; McCarthy, 1997).

For all these methods, weather information is the key parameter to estimate the vine water consumption derived from evaporation models. The advantage of these approaches relies on the ability to record the information with a high temporal resolution by means of automatic weather stations. Such systems have been available for a long time and as a result have a wide adoption by growers. Moreover climatological records are assumed reliable over a large area (at least the vineyard). However, depending on the topographic conditions, the area over which climatological data are relevant may vary drastically, this last point is still under research (Stahl *et al.,* 2006, Martinez-Cob *et al.,* 1996). In the rest of this review, the study area (D) will be considered small enough to assume homogeneous climate.

2.2 Soil

The soil is the main substrate for the plants; its variation in water holding capacity, induced by variations in texture and soil depth at the field scale may induce a high variability in plant water status (Tisseyre *et al.,* 2005; Ojeda *et al.,* 2005a; van Leeuwen *et al.,* 2006; van Leeuwen *et al.,* 2007). Thus, soil variability may explain differences at the within field level as well as between fields. There are different approaches which take into consideration the soil data to estimating the effect of water restriction on plants over time. One of the most studied approaches is based on evaluation of the soil water resource and its influence on plant water status (McCarthy, 1997; Peregrino *et al*., 2004; Loveys *et al*., 2005).

There are many methods available for soil moisture monitoring, nevertheless, they are quite expensive and tend to be used at only a few points. Some methods like tensiometers are based on soil water potential measurement other methods are based soil water content assessment, this is the case of neutron moisture probes, TDR probes and capacitance sensor, among others). Both methods are commonly used in vine irrigation scheduling. The tensiometers are mainly used to control the size and the depth of humid soil in drip irrigation, The other methods measure the punctual Soil Water Content (SWC) with relatively little disruption (Topp *et al.,* 1980; Ortega-Farías and Acevedo, 2004). These sensors assess SWC indirectly by different principles such as: pressure indicator, soil electrical resistance assessment, and measuring the travel time through the soil of a short pulse of electromagnetic energy, among others.

Plant water restriction can be monitored using soil moisture measurements during the season. Locally, soil moisture can be correlated to evapotranspiration (Stevens *et al.,* 1995; McCarthy, 1997). This allows the creation of Soil Water Stress Indices (SWSI), which are based on soil water content measurements close to the root-zone (McCarthy, 1997; Colaizzi *et al*., 2003). The use of these SWSI in irrigation scheduling programs has allowed, for example, the grape and wine quality to be improved for the cv. Cabernet Sauvignon (Ortega-Farías *et al.,* 2004b).

Soil water status and the relationship with the plant water status are commonly evaluated to obtain plant water stress diagnosis. This method uses the Fractions of Transpirable Soil Water (FTSW) to characterize the soil water deficit experienced by the plant (Lebon *et al.,* 2003; Pellegrino *et al.,* 2004). Lebon *et al.,* (2003), showed that FTSW is linked to several variables describing vegetative growth in vines growing in pots. These results show that FTSW is sensitive to quantify the soil water deficit experienced by a crop. However, the positioning of soil moisture probes is critical to get representative information about soil water status for crops using trickle irrigation (Li *et al.,* 2002; Fuentes *et al.,* 2004). A probe located in a dry spot in the soil will give underestimated soil moisture values while another located in a non-representative wet soil will generate an overestimated one.

2.3 High-spatial resolution information

No sensor providing a direct assessment of the plant water status with a high spatial resolution is currently commercially available. The most promising technology is infra-red thermography to derive plant water status and stomatal conductance from the canopy temperature. Many authors investigated this way at the leaf and the plant level (Jackson *et al.,* 1981; Sepaskhah and kashefipour, 1994). It was more recently applied with infra red camera at the vine level (Jones, 1999; Jones *et al.,* 2002; Möller *et al.,* 2006). This approach is interesting, however, (i) it requires temperature calibration with field measurements during image acquisition, (ii) in the field, (proximal) sensors are still very expensive which reduces the potential number of measurement sites, (iii) and finally resolution of thermal images provided by satellites is still too low for vine applications.

Therefore, an alternative approach to characterize spatial variability would be based on low cost complementary information that is easy to get at a high-spatial resolution (for example multispectral images from airborne or satellites, soil electrical conductivity maps) to define time stable zones with different water restriction (Taylor *el al.,* 2004; Tisseyre *et al.,* 2007; Acevedo-Opazo *et al.,* 2007, 2008). The following sections provide a brief description of possible high resolution information sources and then detail their potential and limits to characterize spatial variability of plant water status. Table 1 summarizes the information presented in the following sections.

2.3.1 Plant variability

Airborne Imagery

Optical remote sensors detect and record sunlight reflected from the surface of objects on the ground. The ability of a sensor to detect object reflectance is quantified in terms of the spatial and spectral resolution of the sensor (Hall *et al*., 2002). Airborne imagery is currently dominated by multi-spectral sensors due to their low cost and easy operability (Blue, Green, Red and Near Infra-Red wavelengths). For viticulture purposes, the required spatial resolution of an image is generally about 1-3m^2 per pixel. This resolution is applicable to the inter-row width (densities between 3,000 and 4,000 vines ha^{-1}) (Tisseyre *et al.,* 2007). However airborne imagery may also be used at larger scale to provide information at the regional scale; for example Montero *et al.* (1999) used satellite images to provide an assessment of vine development according to available water resources at a regional scale corresponding to La Mancha in Spain.

Since the collected information contains mixed pixels, which includes reflectance from the vines and the soil, images are generally processed to produce indices, such as NDVI (Normalised Difference Vegetative Index) or Plant Cell Density (PCD) for every pixel (Tisseyre *et al.,* 2007). These indices are generally used as a vigour assessment. In viticulture, vigour generally refers to the vine growth rate (of shoots). Whereas, in remote sensing, vigour refers to a combination of plant biomass (vine size) and photosynthetic activity, termed the "photosynthetically active biomass" (PAB) (Bramley, 2001). The computed index (either PCD or NDVI) can be related to vigour, since vigorous vines are characterised by larger and denser canopies than vines of lower vigour. Many authors have shown relationships between NDVI and Leaf Area Index (LAI) (Johnson *et al.,* 2003), annual pruning weight (Dobrowski *et al.,* 2003) and other vine parameters (Lamb *et al.,* 2004) at the vineyard scale. Therefore, the use of remote sensing data often constitutes a relevant and low cost information source to perform vigour zoning at the field scale (Hall *et al.,* 2002; Bramley *et al.,* 2005).

In conditions where water is the limiting parameters, vigour is strongly related to soil water availability; therefore NDVI maps may provide relevant information to zone the vineyard according to water restriction (Tisseyre *et al.,* 2007; Acevedo-Opazo *et al.,* 2007).

Despite its relevancy, this information presents some analytical challenges for the considered application. Canopies are highly discontinuous in viticulture, especially in the case of vertical shoot positioning systems where large areas of soil appear between vine rows. To cope with this problem, a moving averaged window of NDVI calculation can be used. This solution leads to mixed pixels where soil, cover grass along the inter-row, training systems and summer trimming operations may affect the NDVI values. Most of these problems are overcome with an image acquired in the late summer (after veraison), when growth has stopped and the canopy has achieved its maximum size. Under non-irrigated Mediterranean conditions this solution is also convenient to overcome the problem of cover crop since grass is dry, thus minimizing the effect on NDVI values. Under other conditions (irrigated or humid areas), inter-row cover crop may remain a significant problem, leading to more sophisticated image processing. In that case, image resolution has to be high enough (less than 30 cm pixel^{-1}) to segment vine rows from inter-rows to analyze NDVI information from vines (Da Costa *et al.,* 2006; Hall *et al.*, 2003; Homayouni *et al.,* 2008).

Ground-based sensors

In order to cope with the issues of remote sensing problems due vertical shoot positioning, ground-based monitoring systems have been developed to assess and map canopy properties

(plant biomass, vine size and photosynthetic activity). These systems avoid background noise problems due to mixed pixels containing soil, grass and vine canopy, which is an advantage over remote sensing technologies. Some of these systems are based on digital imaging, which provides the measurement of several parameters such as canopy height and canopy porosity (Praat *et al.,* 2004; Tisseyre *et al.,* 1999). Others systems are based on ground-based NDVI measurement (GreenSeeker^{TM}). It has been shown that the information provided is strongly related to VLAI (Vertical Leaf Area Index) and canopy porosity (Goutouly *et al.,* 2006).
These ground-based systems are designed to be mounted on existing machinery, allowing the acquisition of spatial information during the daily management of the vineyard (trimming and spraying, among others). They allow the spatial variability of the vigour to be characterized with a resolution never before achieved. Again, in areas where water availability constitutes the main constraint, these systems could be useful to characterize spatial variability due to different levels of water restriction at the vineyard scale.

2.3.2 Soil variability

Section 2.2 showed the main punctual methods for soil water content assessment, which is a fundamental information for water management at the vine field scale. In complement, this section introduces new technologies that allow the soil physical properties to be characterized with a high spatial resolution. These sensors are based on the soil di-electric or electro-magnetic properties. The soil Apparent Electrical Conductivity (EC_a) is a quick, reliable measurement for the spatial characterization of edaphic (i.e. salinity, water content and texture, among others) and anthropogenic properties (Corwin and Lesch, 2005; Samouëlian *et al.,* 2005). Spatial EC_a measurements have become a common method used for field and landscape-scale studies related to soil properties. This method offers a very attractive tool for describing the soil properties with a small number of soil observations. There are two types of EC_a sensors available: (i) Electrical Resistivity (ER) sensors that use invasive electrodes and (ii) non-invasive Electromagnetic Induction (EMI or EM) sensors (Tisseyre *et al.,* 2007). Invasive ER and non-invasive EM are the most frequently used sensors as they have been widely commercialized.

Both technologies (ER and EM) have been widely implemented in viticulture. Barbeau *et al.,* (2005) used ER to compare the effect of rows with and without grass cover on soil water distribution. Bramley (2005) used such soil information to determine different soil zones within fields. High resolution EC_a was used to delineate zones with different water availability (Taylor, 2004). Taylor (2004) also proposed an estimation of soil water holding capacity based on EC_a measurement over a whole vineyard. This estimation required the calibration of a transfer function allowing the soil water holding capacity to be derived from EC_a values. This work required a large data base of known points to calibrate the model. Obviously, this approach is hardly tractable for commercial vineyards, however, it shows the relevance of EC_a information to delineate zones where water restriction experienced by the plants may be significantly different. We (Acevedo-Opazo *et al.,* 2007, 2008) showed that extreme care must be taken in using this information to highlight zones with difference in plant water status. An expert delineation of the main soil types should better be considered before using EC_a information directly. We mainly focused on electrical parameters since they are used for a long time, however, depending on the location, many others technology like ground penetrating radar or gamma radiometre may be helpful to provide relevant soil variability maps.

2.4 Technical and spatial considerations of auxiliary information

Focusing first on methods based on weather information, it has been shown that they are widely used. They are usually used on large scale studies, such as the whole vineyard, or a complete region. It is important to consider that these methods do not take into account the spatial variability which is usually encountered at the field scale. Moreover, these methods need to be calibrated on field conditions by comparing their estimates with physiological reference measurements (i.e. plant water potential or stomatal conductance).

Soil moisture monitoring systems require the consideration of a series of technical details, such as: (i) the choice of the appropriate method among all the available ones for soil moisture monitoring, (ii) they are all quite expensive leading to use them on a few selected sites. This last point is critical since spatial variability in soil depth, texture and other properties might not be taken into account properly. Although pedological maps or elevation information might constitute a relevant support to help in deciding the sensor locations, soil water holding capacity may vary over small spatial range (even within a same pedological unit) leading to weak spatial relevance of the soil moisture measurements. Thus, soil water monitoring does not allow flexibility in measurement sites once the access tubes or probes are put in place.

The main advantage of airborne imagery and soil electrical survey is that they can bring high resolution information that can reach more than 2000 measurements per hectare. Both information are able to provide information on plant and soil variability with a resolution achieved never before. In addition to spatial resolution, a significant advantage of remote sensing technology remains the spatial support of the information since one acquisition (or one fly) may cover several hundred hectares of vines. Soil conductivity remains a punctual information which requires an exhaustive soil survey. Depending on the required resolution and the field distribution, 40 hectares to more than 100 hectares might be analysed in a day. Data need also to be processed (krigging) to provide the information on a regular grid. Apart from these spatial considerations, the use of multispectral imagery or soil apparent conductivity in zoning vineyard according to plant water status raises several problems.
Considering multispectral airborne imagery:

- The canopy architecture and the resulting information can vary drastically between fields due to different training system (Johnson *et al.,* 2003). This means that indices derived from remote sensing images like NDVI can be helpful in analyzing variability when homogeneous training systems are encountered (at field level). However, care must be taken when assessing vigour variability between areas where different training systems may be encountered.

- NDVI is presented as a possible way to map variations in vine water status. This might be true in un-irrigated vineyards in dry climates, where the main factor inducing differences in NDVI is vine water status. However, in many cases NDVI varies rather with the nitrogen offer of the soil. When soil is moved during soil preparation before plantation, zones with low organic matter content are easily created. Vigour is generally low in these zones because of low nitrogen status of the vines. On the others hand Johnson *et al.,* (1996) shown that canopy diseases/pests problems or nutritional deficiencies also induce great changes in NDVI values. Obviously, missing vines also bias this information.

Considering soil apparent conductivity (or resistivity):
- This method integrates many soil parameters (i.e. salinity, water content, texture, among

others), which makes its interpretation difficult (Corwin and Lesch, 2005; Samouëlian *et al.,* 2005). Obviously, the same conductivity value may be observed for two different soil types. To cope with this problem, a rough soil delineation based on expert analysis (i.e. elevation, soil depth, soil color or other knowledge) may be done. The area under study is then divided in simple soil units leading to a more simple analysis of soil apparent conductivity data. Figure 1 (see page 21) shows an example where the study area is divided in different soil units. Soil conductivity remains interesting to characterise soil variability (texture, depth, etc.) within each soil unit.

- As said previously, the investigation depth depends on sensor characteristics. It is limited to 1 to 2 m for most available systems. Depending on the situation, this depth may not fit with vine rooting system. Therefore, information derived from EC_a survey may be weakly linked to the water really available for the plant roots.

Table 1 summarizes main specificities of the different methods presented section 1 and section 2. For each method, table 1 particularly focuses on spatial characteristics and in a less extend on temporal characteristics. Quick analysis of table 1 highlights the lack of ideal system allowing the plant water status to be known with a high spatial resolution. This conclusion leads to consider cooperation between different information sources to provide an assessment of plant water status over large area. Such a cooperation needs to take into account the spatial variability which may be encountered.

3. Toward the spatial modelling of vine water status

This section aims at presenting an approach based on reference measurements and other spatial information. Obviously, depending on the location and the available information, many particular methods may be relevant. This is the reason why this section focuses on an approach as general as possible trying to encompass most of particular cases.
Let us remind the reader of the problem under consideration. Let's consider a whole vineyard (D) which constitutes the study area. D is small enough to assume homogeneous weather conditions. This last point means that climate (rainfall, temperature,…) can be characterised by only one weather station over D and also that climate variables affect plants and soil homogeneously over D. Spatial modelling of the plant water status aims at providing an estimate $\hat{z}(s_i,t_j)$ of the plant water status $z(s_i,t_j)$ at time t_j and location s_i belonging to the study area D. Depending on the training system, the irrigation system and measurements usually carried out, $z(s_i,t_j)$ can refer either to the PLWP or to the SWP. The rest of the section considers that z is a common reference measurement that management practices or irrigation scheduling can be based on.

Table 1. Summary of plant water status measurement methods and their spatial and temporal characteristics.

Method	Type measurement	Record	Time resolution	Spatial resolution of the measure	Spatial validity of the measure	Area covered by day
Plant based methods						
Stomatal conductance	direct	manual	low	within leaf (~cm²)	leaf (cm²)	< 50 plants
Leaf Water Potential	direct	manual	low	leaf (~dm²)	leaf (dm²)	< 50 plants
Stem Water Potential	direct	manual	low	stem (~dm²)	plant (dm²)	< 50 plants
Carbon isotope composition	indirect	manual	low (at harvest)	cluster (~cm²)	plant (m²)	< 100 plants
Predawn leaf Water Potential	direct	manual	low	plant (~m²)	depend on soil variability	< 50 plants
Sap flow	indirect	automatic	high (every day or more)	plant (~m²)	plant (m²)	1 plant
Dendrometry	indirect	automatic	high (every day or more)	plant (~m²)	plant (m²)	1 plant
Canopy temperature	indirect	automatic manual	high (every day or more) low	plant (~m²)	plant (m²) or several plants	< 100 plants
Auxiliary methods						
Crop Evapotranspiration	indirect	automatic manual	high (every day or more)	punctual (soil and weather station)	soil and climate unit	several ha
Soil moisture sensors	indirect	automatic manual	high (every day or more) low	punctual (~m²)	soil unit	punctual
Airborne imagery	indirect	automatic	low	(0 cm²-3m²)	(0 cm²-3m²)	several ha
Apparent soil conductivity survey (EC_a)	indirect	automatic	low	~ m²	~ m²	several ha

3.1. Considering a unique zone

A classical approximation considers that all locations $(s_i)_{i=1 \ldots I}$ on D presents approximately the same water status. Plant water status is then measured on an appropriate reference site s_{re} to provide the value $z(s_{re},t_j)$ at time t_j. As summarized by Equation 1, $z(s_{re},t_j)$ is then considered as the estimate of the plant water status on D at t_j. This approach ignores the spatial variability.

$$\hat{z}\,(s_i,t_j) = z\,(s_{re},t_j)\ , \quad \forall\ s_i \in \mathrm{D} \qquad \textit{(Equation 1)}$$

where
s_{re} is the location (or the set of locations) where the reference measurement of the plant water status (PLWP or SWP) is performed on.

When plant monitoring systems (sap flow, trunk diameter or canopy temperature) or soil monitoring systems are available on D, a similar reasoning is possible. In that case, a calibration function $f_{(D,K)}$ determined on D, may be used to derive reference plant water status from x_K, the measurement provided by the monitoring system. The site of reference s_{re} is then the location (or the set of locations) of the monitoring system(s). Considering that all locations $(s_i)_{i=1 \ldots I}$ on D presents approximately the same water status leads to provide an estimate over D as presented by Equation 2.

$$\hat{z}\,(s_{re},t_j) = f_{(D,K)}(x_K(\mathrm{s}_{re},t_j)) \ \Leftrightarrow\ \hat{z}\,(s_i,t_j) = f_{(D,K)}(x_K(\mathrm{s}_{re},t_j))\ , \forall\ s_i \in \mathrm{D} \qquad \textit{(Equation 2)}$$

where:
$x_K(\mathrm{s}_{re},t_j)$ is the value provided by the monitoring systems at time t_j on the location s_{re}.

$f_{(D,K)}$ models the relation between z and x_K on D. Several authors proposed such a relation in the literature either with plant monitoring systems (Bravdo and Naor, 1996; Cifre *et al.,* 2005) or weather data (Allen *et al*., 1989; Pereira *et al.,* 1999). K refers to the type of measurement performed on the reference site (stomatal conductance, sap flow, trunk diameter or canopy temperature).

Equations 1 and 2 highlight several problems in spatial estimation of the plant water status. The choice of s_{re} (or set of s_{re}) is critical since it determines the plant water status over the whole vineyard. Although, variability which happens from leaf to leaf or vine to vine may be smoothed by considering average values over a small area around s_{re}, meso-scale variability (mainly due to soil and elevation) may not be taken into account. For plant monitoring systems the problem of the choice of s_{re} may be of greater importance since the value comes from the vine located at s_{re} during the whole season. This means that the estimation over D can be systematically over estimated or under estimated. In summary, plant based measurements certainly provide the best assessment of the plant water status. They provide an assessment of the real response of the plant. Nevertheless, for each method the values always come from a small sampling area which is extrapolated to the whole vineyard. Depending on the spatial variability, the measurement should be considered as relevant only on a defined area centered around the measurement site (s_{re}). In practice, end users do no have a reliable picture of the spatial variability. The information measured at the reference site has then to be used with extreme care.

3.2 A set of zones

In order to cope with limitations detailed in the previous section, a simple approach may consist in zoning the study area D in sub-areas with more or less homogeneous characteristics (figure 1). Let's call this sub-areas $(D_n)_{n=1\ldots N}$. The N sub-areas (or zones) may be defined according to soil units based on expert analysis of auxiliary information (i.e. elevation, soil depth, soil colour, soil sample among others). The reasoning presented in the previous section is then applied to each sub-areas. All locations $(s_i)_{i=1\ldots I}$ on D_n are assumed to presents approximately the same water status. Plant water status is then measured on an appropriate site s_{re}^n considered as a reference site for D_n ($s_{re}^n \in D_n$). The measurement provides the value $z(s_{re}^n, t_j)$ at time t_j which is then used to assess the plant water status over D_n. When reference measurement is used, this leads to a very similar case as the one presented in Equation 1. Equation 3 summarizes the principle of this approach in the case with plant monitoring system.

$$\hat{z}\,(s_i, t_j) = f_{(D_n, K)}(x_K(s_{re}^n, t_j)) \qquad \textit{(Equation 3)}$$

$\forall\, s_i \in D_{n,\, n=1\ldots N}$, with $s_{re}^n \in D_n$ and $D_n \subset D$,

where:
s_{re}^n belonging to sub-area D_n of D.

$f_{(D_n, K)}$ models the relation between z and x_K specifically on D_n.

The approach presented in this section is interesting since it takes into account the macro-scale variability due to soil for example. It may be applied at various scale, however, it is commonly used on large areas to provide advice on irrigation management. An approach based on remote imagery like the one proposed by Montero et al. (1999) could be used to design such large zones. D_n are usually large zones and depending on the method used to their delineation, some locations may be attributed to two or more zones. As a result, a significant spatial variability may remain in each zones. This means that at the within zone level, all the problems presented section 3.1. may remain significant. Obviously, this approach leads to increasing number of reference sites since a minimum of one measurement site is required for each zone. Therefore it increases the number of measurements or the number of plant and soil monitoring systems. Obviously, for practical considerations, this approach cannot be extended to characterize small scale spatial patterns.

3.3. Maps of spatial variability

The next step is to design an approach that integrates reference measurements and high resolution information sources (HRIS) to maximise quality of information for management. Equation 4 summarizes the principle of such an approach.

$$\hat{z}\,(s_i, t_j) = f_{D_n}(q_1(s_i), q_2(s_i), \ldots, q_M(s_i), z(s_{re}^n, t_j)) \qquad \textit{(Equation 4)}$$

$\forall\, s_i \in D_{n,\, n=1\ldots N}$, with $s_{re}^n \in D_n$ and $D_n \subset D$, In equation 4, f_{D_n} can be seen as a function that allows the extrapolation of the measurement of reference ($z(s_{re}^n, t_j)$) over D_n according to spatial variability characterised by the different HRIS ($(q_m(s_i))_{m=1...M}$).

HRIS might then improve significantly the spatial prediction of the plant water status. Each location $(s_i)_{i=1...I}$ of D_n will then be characterised by additional information $(q_m(s_i))_{m=1...M}$. Depending on the available HRIS or depending on the local specificities, the number M of variables may be more or less important. Note that the date of acquisition is not taken into account. This means that HRIS only provide information on the spatial structure which drives the plant water status. This spatial structure is then assumed to be time-stable. Obviously, to be able to provide an estimate $\hat{z}(s_i,t_j)$ of the plant water status at time t_j, HRIS require additional information to take into account the level of water restriction at t_j. As shown Equation 4, interaction between HRIS and plant water status measurements is then necessary to provide $\hat{z}(s_i,t_j)$. In order to simplify the formulation, Equation 4 only considers the case where $z(s_{re}^n, t_j)$ is the reference measurement. Regarding Equation 3, it is easy to modify Equation 4 so that to consider the case with a plant monitoring system.
As seen in previous sections, it is possible to use information which provides knowledge on plant water status spatial variability like:

(i) plant vigour and canopy size (multispectral imagery) which are affected by plant water restriction,
(ii) soil depth, soil water content, texture (soil conductivity) and elevation that the spatial variability induces difference in plant water restriction.
(iii) water regime applied to grapevines during the whole season, the $\delta^{13}C$ technique also can be used as complementary information. However, despite its relevance, note that $\delta^{13}C$ method is based on sampling. Obviously this drawback strongly limits the spatial resolution of this information.

Therefore, under assumptions which will be detailed further, these high resolution information sources (HRIS) may be useful to:

(i) delineate the D_n zones more accurately,

(ii) improve the spatial prediction of the plant water status within each zone.

Obviously, equation 4 makes reasonable assumptions:

(i) the approach assumes that HRIS are available at each location s_i.
(ii) the study area (D_n) is small enough to assume homogeneous weather conditions. Temporal variability of the plant water status is only taken into account with the measurement of reference $z(s_{re}^n, t_j)$.
(iii) training system, disease infestation and other similar parameters that can affect plant response are assumed to have the same effect over D_n.

3.4. Example of a very simple spatial model
In order to illustrate the approach, Figure 2 and 3 provide an example from real data at the within field level. The goal is only to show an example for a better understanding of the proposed approach. The case study is just a first attempt; therefore the model is very simple.

Calibration step and coefficients are not thoroughly detailed and the results will only be analysed qualitatively. A more precise presentation of this case study will be presented in a next paper.

Figure 2a presents the 1.2 ha study area (D_n) under consideration, it corresponds to a grape field. 49 sites $(s_i)_{i=1...49}$ are defined on D_n. Figures 2b and 2c represent the high resolution information sources (HRIS) available on D_n. HRIS correspond to canopy area (q_1) and soil apparent resistivity (q_2) for Figures 2b and 2c respectively. Each site $(s_i)_{i=1...49}$ of D_n is then characterized by two types of HRIS $[q_1(s_i);q_2(s_i)]$ which bring additional local information at each site (s_i). The plant water status is measured at time t_j, only on one location considered as the reference site (s_{re}^n). The approach presented in Equation 4 was applied to the set of data with a very simple model presented Equation 5.

$$\hat{z}(s_i,t_j) = \left(a_1 \times q_1(s_i) + a_2 \times q_2(s_i) + a_3\right) \times z(s_{re}^n, t_j) \qquad \textit{(Equation 5)}$$

with a_1, a_2 and $a_3 \in \Re$,

Equation 5 models a cooperation between the plant water status on the reference site s_{re}^n at time t_j and the HRIS to assess the plant water status on each site of D_n.

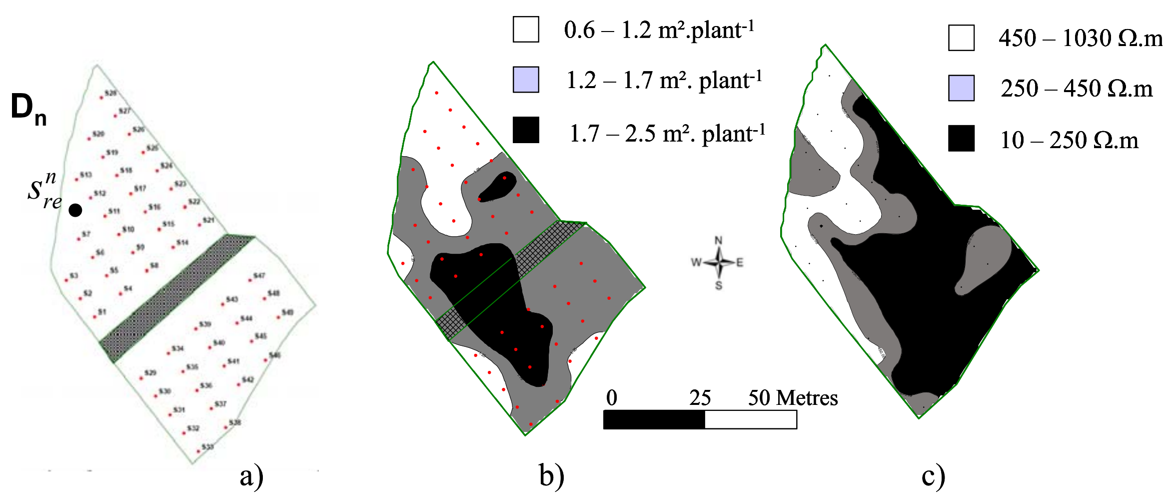

Fig 2. (a) example of a zone (D_n) corresponding to a grape field with 49 sites $(s_i)_{i=1...49}$ and a reference site (s_{re}^n). (b) and (c) represent two High resolution information sources $[q_1(s_i);q_2(s_i)]$ which characterize each site (s_i) of D_n. (b) and (c) correspond to canopy area and soil apparent resistivity respectively.

Figure 3 a) shows a map of the Predawn leaf water potential realised at the end of the summer on the grape field. Figure 3 b) shows the PLWP prediction map obtained from the model presented in Equation 5. The calibration of the model was realised from a data base of PLWP measured over two different years. Figure 3 a) highlights the significant variability of the plant water status observed at the within field level. Assessment of the plant water status without any spatial consideration would have lead to affect an average PLWP of -0,9 MPa to the whole field. Obviously the spatial variability allows the consideration of very different zones with very different vine water status. Comparison of Figure 3 a) and b) points out the relevance of the model to provide an assessment of the plant water status variability. Note that this map results from only one measurement at a reference site and the HRIS (once the model has been calibrated).

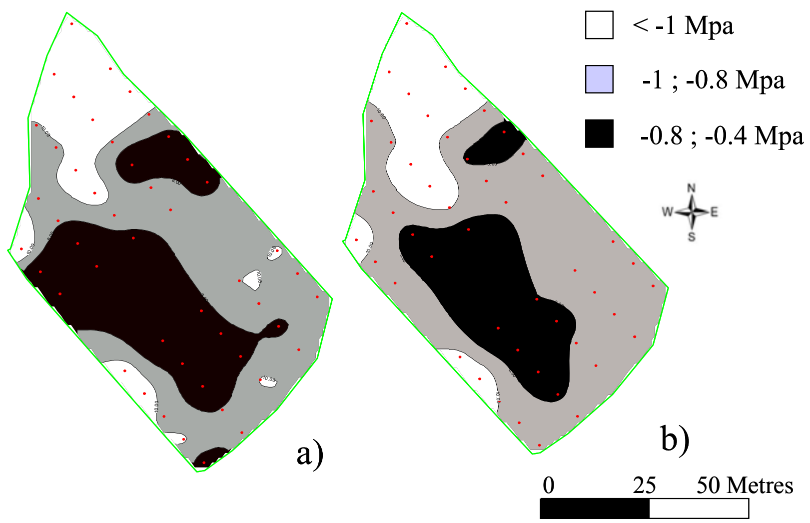

Fig 3. maps of plant water status at the end of the summer (predawn leaf water potential). a) map resulting from measurements on 49 sites with a Scholander pressure chamber, b) Map of estimations of the plant water status (PLWP) resulting from the model presented Eq. 5.

Obviously this field is small which leads to a very simplistic model. However this example shows that such an approach is possible. Extension to other fields and larger area will probably lead to more advanced models.

Conclusions

The majority of vineyards present a great spatial variability in yield (number and size of bunches), vegetative growth (canopy density), sugar and grape quality components and also in vine water status. This vine water status variability is especially evident at the end of summer, when significant water restriction is found under non-irrigated conditions. Therefore, in addition to temporal water status monitoring, spatial variability of vine water status also needs to be considered.

Many approaches are now available to provide a measurement of the plant water status. They are based either on direct or indirect methods. The first methods use plant-based measurements (reference measurements) to provide a relevant and accurate assessment of the plant water status at the plant scale. Nevertheless, each of these methods requires an expensive heavy device, such as a pressure chamber and porometer sensors to be brought to the field for the manual measurements. Moreover, measurements are time consuming, which constitutes a significant constraint for labour management and significantly limits the number of measurements either in time or in space.

Other plant based systems deliver continuous information. The relevance of such information is mainly due to its dynamic variation over the season; different vines can show different responses at different times in the season complicating data interpretation. This means that absolute values provided by these sensors do not bring any direct estimation of plant water status. Indeed, the cost and the maintenance of the system limit the number of devices that it is possible to use at the vineyard scale. The amount of available spatial information is consequently quite small, limiting the knowledge about the spatial variability of plant water status.

Plant water status may also be assessed using indirect methods based on weather and/or soil information. These methods are widely used on large scale studies, the whole vineyard or a complete region. However, they do not take into account the spatial variability which is usually encountered at the vine field scale. Moreover, these methods need to be calibrated for field conditions comparing their estimates with physiological reference measurements (i.e. plant water potential and stomatal conductance).

Finally, information provided by sensing systems developed in the framework of precision viticulture can give useful information, allowing the spatial variability of plant water status to be characterized at a fine scale. However, it does not provide any information on the plant water status itself. It only gives knowledge about the spatial variability of parameters which are affected by differences in water availability (vigour, canopy size), or which induce differences in plant water regimes (soil variability in depth, water content, texture and elevation). These parameters can only be considered as auxiliary information allowing the spatial variability to be modeled. This means that using this information to provide an estimate of the vine water status over space and over time in a study area will necessarily require a reference measurement (PLWP or SWP) made at a given time on one or more reference sites. In such an approach, auxiliary information measured with a high resolution over the study area may be used to extrapolate the reference measurement.

Nevertheless, it is important to say that this approach assumes significant restrictive hypothesis. It refers mainly to the study area over which the model has to be relevant (homogeneous climate conditions, relevancy of auxiliary information, etc.). This work proposes a formalization of a possible approach allowing the spatial variability of plant water status to be characterized. This formalization shows that scientific problems still have to be addressed in order to build up such a spatial model. The first point deals with the selection of the best auxiliary information allowing the vine water status to be spatially estimated for different conditions of training systems and soil types. Obviously best auxiliary information may change from region to another. The second point deals with the model determination. This point aims at testing and proving the relevancy of this approach. It requires a large and complete database aiming at having high spatial and temporal resolution plant water status measurements over several years for a single study area. The third point deals with the introduction of auxiliary information (selected during step 1) within the model in order to compute the model parameters according to the encountered spatial variability.

These points will constitute our further investigations aiming at proposing a spatial model of plant water status.

CHAPTER II

Chapter 2: Identification and significance of sources of spatial variation in grapevine water status

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Abstract

Background and Aims: Water stress in grapevines is directly linked to grape quality. Differential vine water management should therefore be strongly linked to the water stress in the vine. To do this, an understanding of the dominant drivers and indicators of vine water status are needed from a sub-block to whole vineyard level. This understanding will help generate effective vine water status models for variable rate irrigation systems.
Methods and Results: Two blocks in a vineyard in southern France was sampled for pre-dawn leaf water potential (Ψ_{PD}) at several dates during the growing season for two consecutive years. Sampling was stratified by soil types and relative within-block vegetative expression. A recursive partitioning analysis identified that cultivar had a dominant effect at low water stress while vegetative expression and then soil unit effects became dominant as water restriction increased. Variance in Ψ_{PD} was calculated at difference scales (plant, site, block and vineyard) and Fairfield Smith's heterogeneity law used to evaluate the scalar nature of Ψ_{PD} variance. Spatial heterogeneity increased as the season and water restriction increased.
Conclusion: Variance in Ψ_{PD} changed temporally through a season and the dominant drivers/indicators also changed. The opportunity to spatially manage water stress (irrigation) increased as water restriction increased.
Significance of Study: Managing vine water stress helps optimise production and a Ψ_{PD} model would be a useful addition to a viticulture decision support system. This study identified how the variance in Ψ_{PD} evolved during a season and the best ancillary indicators of Ψ_{PD} for spatial and temporal modelling.

Abbreviations

Ψ Grapevine (plant) water status; Ψ_{PD} Pre-dawn leaf water potential; INRA Institut National de la Recherche Agronomique; NDVI Normalised Differences Vegetative Index; b' Fairfield Smith's coefficient of spatial heterogeneity, VPD vapour pressure deficit

Keywords: precision viticulture, predawn leaf water potential, regression trees, scalar variance, stratified sampling

Introduction

Several researchers have shown that changes in grapevine water status (Ψ) have a direct effect on grape composition and quality by influencing vegetative growth, fruit growth, yield, canopy microclimate, and fruit metabolism (see among others, Trégoat et al. 2002, Dry and Loveys 1998, Van Leeuwen and Seguin 1994, Seguin 1983, Ojeda et al. 2002). The recent introduction and adoption of irrigation into Mediterranean viticulture has seen many studies focus on vine water status as a method for assisting irrigation and agricultural development (Patakas et al. 2005, Sousa et al. 2006). Despite this, the relative contribution of environmental and vine traits in determining Ψ are not clearly understood, particularly at a block/vineyard level. If, for example, the spatial Ψ response was to be considered in the redevelopment of a vineyard, should designers focus on the spatial variation in soil type, within-block canopy response (vegetative expression and/or vigour) of the existing vines or assume that variations in Ψ are driven primarily by cultivar differences?. Within the literature clues to this can be found. For example, van Leeuwen et al. (2004) have shown that Ψ is greatly dependant upon climatic and soil factors and much less so on the cultivar, Koundouras et al. (2006) reported that mean Ψ was strongly correlated to vineyard location (soil type) for the cultivar Agiorgitiko, while Guix-Hébrarda et al. (2007) linked Ψ in vines to water table levels at the landscape scale. However, no direct study has been undertaken on the relative contribution of genotypic (cultivar) and environmental factors (soil type) to the observed variation in Ψ at the block and vineyard level.

Recent studies have also shown that Ψ exhibits a significant magnitude of variation in a single block (Tisseyre et al. 2005, Acevedo-Opazo et al. 2007, Acevedo-Opazo et al. 2008b) without directly linking this variance to driving factors. This variability in Ψ was especially evident at the end of summer when significant water restriction was found under non-irrigated conditions (Ojeda et al. 2005a, Tisseyre et al. 2005). While these studies have concentrated on within-block variation, spatial variation of Ψ can occur at different scales (plant, block, vineyard, catchment, etc) depending on the driving factor. To our knowledge there has been no direct analysis of how Ψ varies at different scales and, in particular, how within-block variance compares to the total variance across a vineyard, which will have implications for management. A high ratio of within-block variance to total variance would indicate that the grower should focus on block management, while a low ratio would lead a grower to investigate and manage variation within blocks.

Since viticulture systems vary markedly around the world, the size (spatial) terminology used in this paper will be based on the conditions of the French vineyard in the analysis. Block therefore refers to a discrete production unit under a single cultivar and trellising system. In this vineyard the blocks were ~0.8 ha in size, which is typical in France but small for many other countries. The term vineyard refers to all the blocks that make up the estate. The size of the blocks in this analysis needs to be taken into account when considering the implications of this analysis in other production systems where block size may be larger.

Given the recent interest in developing point (Pellegrino et al. 2006) and spatial (Acevedo-Opazo et al. 2008a) models of Ψ and the potential for future spatio-temporal models, a better understanding of which factors are determinants or indicators of Ψ will help researchers to properly construct and populate models with relevant and available ancillary data. This knowledge should also be of assistance in designing stratified sampling schemes to monitor Ψ for both general vineyard management and for generating data to calibrate and populate these models of Ψ.

This paper aims to fill an existing knowledge gap by a) investigating the magnitude of variation in Ψ at different scales within a vineyard and at different stages of the growing season, and b) identification of the dominant factors contributing to spatial Ψ variation.

Materials and Methods

The study was undertaken on a vineyard at the INRA's Experimental Unit of Pech Rouge, Gruissan, in the south of France (43°10'N, 3°06'E). The vineyard consists of 45 blocks (parcelles), with an average block area of ~0.8 ha. The blocks are not contiguous and are spread over an area of ~170 ha, which encompasses three broad pedological units, Littorale, Clape and Colombier that are derived from sand, limestone and marlstone parent material respectively (Fig. 1). The Littorale unit is located near sea-level and is characterised by a very shallow water-table. Thus, although it has a sandy texture, the watertable is often located within the vadose zone and water supply to the vines is greatest in this unit. The Clape and Colombier units are located on the side of the Clape Massif (a local geological feature) and the dominant soil characteristic is a variable rooting depth. The vineyard grows a range of red and white grape varieties on several different rootstocks.

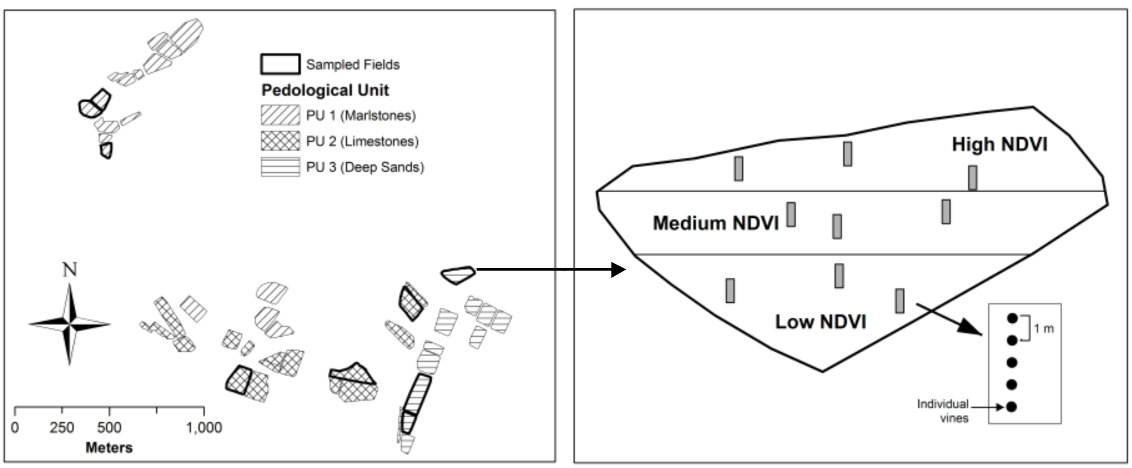


Figure 1 Schematic of the sampling design. The top image shows the geographical layout of the vineyard highlighting the soil units and the blocks sampled. The bottom image shows a stylised schematic of the within-block sampling with the block split into thirds based on vegetative expression (NDVI), with 3 sites allocated within each third and 5 (or 9) consecutive vines measured at each site. (PU 1 = Colombier, PU 2 = Clape and PU 3 = Littorale for the top legend)

The pre-dawn plant leaf water potential (Ψ_{PD}) was measured using a pressure chamber (Scholander et al. 1965) as an estimation of the Ψ of the vines. There are various possible methods for measuring Ψ. The pressure chamber was used as this is generally considered the most accurate method, even though it is laborious (Katerji and Hallaire, 1984, Choné et al. 2001, Ojeda et al. 2002, Sibille et al. 2007). Predawn measurements were preferred as the plant is believed to be in equilibrium with the soil conditions at this time (Katerji and Hallaire, 1984, Tardieu et al. 1990). Measurements taken during the day (for example at solar noon) involve effects pertaining to the climatic conditions (particularly temperature) at sampling

(Carbonneau et al. 1994). Predawn measurements also minimise known problems with the use of a pressure chamber on leaves under high levels of water stress (Sibille et al. 2007). For these reasons, Ψ_{PD} is the recommended methodology for measuring Ψ under non-irrigated conditions when high water stresses are expected at the end of a season (Sibille et al. 2007).

The Ψ_{PD} data was collected from 9 blocks within the vineyard at 2 dates in 2006 and 4 dates in 2007. The 9 blocks were split between the Littorale:Clape:Colombier soil units in the ratio of 3:3:3 and encompassed 6 cultivars (Syrah, Carignan, Grenache Noir, Muscat, Petit Verdot and Mourvèdre). The relationship between the cultivars and soil units is shown in Table 1. Note that not all cultivars are represented on all the soil units. Sampling for Ψ was based on a randomized stratified design. A mid-season Normalised Differences Vegetative Index (NDVI) map was obtained for each block in July 1999 during the period of full vine canopy expansion (NDVI data not shown). The NDVI map was divided into 3 equal quantiles (tiertiles), representing low, medium and high vegetative expression, and a site was selected within each tiertile. At each selected site there were 9 individual measurements taken from consecutive vines in 2006 and 5 measurements in 2007. Thus, within each block there were 27 measurements in 2006 and 15 measurements in 2007 at each date. In total there were 1026 measurements taken across the 6 dates. On each vine, a pressure chamber measurement of Ψ_{PD} was taken from 1 mature but non-senescing leaf from the central third of a shoot using the methodology outlined in Choné et al. (2001).

The NDVI stratification was utilised to ensure the within-block variation in vegetative expression was taken into account during sampling to achieve a good estimation of the block mean. Although the NDVI image is not taken from a year when Ψ was measured, NDVI images have been shown to be temporally stable for areas of relatively high, medium or low response (Acevedo-Opazo et al. 2008b).

The date, vine cultivar, vegetative expression tiertile (High, Medium or Low) and soil unit (Littorale, Clape or Colombier) were recorded in a spreadsheet with each of the 1026 measurements. As specified in the introduction, an aim of this work was to identify drivers of variation in Ψ, and these three factors - cultivar, soil unit and vegetative expression - formed the basis for this analysis. The cultivar and soil units were block level measurements but relate to genotype and environmental differences respectively. The label 'cultivar' was used here but it is important to realise that the genotype response in a block was also related to the rootstock used and to some extent affected by management, in particular vine density and trellis type (Katerji et al. 1994, Santiago et al. 2007). For this analysis, these effects were assumed to be components of the cultivar effect. Genotype (cultivar) governs the potential water use efficiency of the plant, its ability to explore the soil environment, its behaviour under water restriction (Schultz 2003, Ojeda et al. 2005b) and its ambient vapour pressure deficit (VPD) (Soar et al. 2006). The soil at a site or within a block determines the amount of water that is available to the plant (from the soil moisture-holding capacity and the potential for root development) (Guswa 2005, Acevedo-Opazo et al. 2008b). The vegetative expression factor incorporated vine response to the local environment and was a sub-block factor. However, with the sampling scheme outlined above, each tiertile contained one-third of the point Ψ data. The vegetative expression factor allowed a contrast between intra- and inter-block effects. It tests the hypothesis that Ψ is related to canopy development, rather than broad soil or genotypic effects. Canopy response is a function of growth conditions at a site, thus the sub-block variation in vegetative expression will, in part, also be related to sub-block variations in environmental factors including soil properties.

Table 1. Relationship between the pedological units and vine cultivars within the experimental design.

Field ID	Cultivar	Soil Unit	Parent Material	Area (ha)
11	Petit Verdot	Littorale	Sands	0.58
22	Syrah	Littorale	Sands	1.58
61	Carignan	Littorale	Sands	0.95
63	Syrah	Clape	Limestone	1.13
69	Mourvedre	Clape	Limestone	1.33
76	Syrah	Clape	Limestone	1.26
90	Muscat	Colombier	Marlstone	0.34
95	Carignan	Colombier	Marlstone	0.71
96	Grenache	Colombier	Marlstone	0.63

Data Analysis

Scalar variance

The first analysis of the data examined the relationship between variance in Ψ at different spatial scales. This provided information on whether the variance in Ψ is potentially manageable or a stochastic effect in the vineyard.

From the collected data it was possible to determine the variance of Ψ at 4 different scales for each date; a) between adjacent plants (σ^2_P), b) at each site (9 or 5 vines) (σ^2_S), c) within each block (27 or 15 vines) (σ^2_B) and, d) across the vineyard (243 or 135 vines) (σ^2_V).

The spatial footprint for these variance estimations were; a) 2.5 m² (2.5 m row spacing by 1 m vine spacing), b) 15 m² (which is an approximation based on 2.5 m row spacing between either 9 vines (2006) (22.5 m²) or 5 vines (2007) (12.5 m²)), c) 9460 m² which is the mean block size for the 9 blocks and, d) 346200 m² which is the total area of the blocks in the vineyard.

Alternatives existed for the total area. This could be considered just the area of the 9 blocks (~85000 m²) or the entire area of the vineyard estate. The first was not used as the measurements, with the stratification, were an estimation of total population variance, not just the target blocks. The total area of the estate included a large area of protected forest and areas which were unsuitable for vineyards thus this was an over-estimation of area.

The semi-variance equation (Eqn. 1) was used to provide an estimation of σ^2_P. This is a commonly used equation in geostatistics to determine (semi) variance between data points separated by a defined distance (lag). A lag of 1 was chosen as vines are separated by 1 m spacings. Similarly, a lag tolerance of 25% was used to ensure that only adjacent vines were considered. This therefore provides an estimation of variance between neighbouring vines, rather than the variance between all the vines at a site.

$$\sigma^2_P = \frac{1}{2N(\boldsymbol{h})} \sum_{i=1}^{N(\boldsymbol{h})} [Z(\boldsymbol{u}_i) - Z(\boldsymbol{u}_i + \boldsymbol{h})]^2 \qquad \text{Equation 1}$$

where Z is the attribute of interest, $\boldsymbol{u}_i$ = is the vector of spatial coordinates of the ith individual and $\boldsymbol{h}$ is a separation distance (1 m in this case).

The estimation of the site variance (σ^2_S) was performed by averaging the variance at each site for a given date.

$$\sigma^2_S = \frac{1}{N}\sum_{i=1}^{N}\sigma_i^2 \qquad \text{Equation 2}$$

where σ_i^2 is the variance at each site i and N is the number of sites across all the blocks.

The mean variance per block (σ^2_B) was estimated by averaging variance across the blocks (σ_i^2 = block variance in Eqn. 2 and N = 9). The total variance, using all the data for a particular date, was calculated as an estimation of σ^2_V.

The ratio between σ^2_S and σ^2_B was computed for each date. The σ^2_S is an estimation of the variance caused by intrinsic stochastic short-range variation and measurement error, and corresponds to the variation in the data that can be considered unmanageable (Pringle et al, 2003). Thus the relationship between σ^2_S and σ^2_B provided an indication of how much of the variation at the block level is potentially unmanageable.

Previous work (Fairfield Smith, 1938, Pringle et al. 2003) has shown that the spatial heterogeneity of yield data within a block can be assessed by examining the variance per unit area. For yield data Fairfield Smith (1938) demonstrated that variation per unit area decreases linearly according to the function;

$$\mathrm{Log}_{10}V_x = \log_{10}V_1 - b` \cdot \log_{10}x \qquad \text{Equation 3}$$

where x = the area of the plot, V_x = the variance of yield per unit of area x, V_1 = the variance of yield per unit area for the smallest plot (i.e. the intercept), and b` = the absolute value of the relation's gradient.

The gradient b` in this relationship provides an indication of the spatial heterogeneity in data. As the value of $b$` increases the noise (variance) at fine scales increases. Smaller values indicate macro-scale variation as being dominant. This statistic therefore provided an indication of how Ψ responded to increasing spatial scales. The collected data was used to estimate the V1 and b` value at each measurement date. Model fitting was done using the Non-Linear fitting function in JMP v7.02 (SAS Institute, 2007)

All the data (date, mean Ψ, σ^2_P, σ^2_S, σ^2_B, σ^2_V, the ratio σ^2_S:σ^2_B, and b`) were tabulated. The actual variance values are presented here not the log transformations or variance by area values used in Eqn 3.

Drivers of variance at the block/vineyard level

A recursive partitioning algorithm, sometimes referred to as a regression tree, was used as a data mining tool to identify the dominant factors that explain the observed variation in the Ψ data at the vineyard level. The recursive partitioning was performed using the JMP v7.02 statistical package (SAS Institute, 2007). Each date was treated independently with the individual Ψ measurements as the dependent variable and the categorical variables, cultivar, soil unit and vegetative expression, were the independent variables in the model. This approach helped determine whether variance in Ψ was explained by differences in genotype (cultivar), crop growth (vegetative expression) or the soil type.

The partitioning is binary. With a continuous response variable (Ψ), the variable to be split and the cutting level (or grouping of the factors in the split variable) are determined by the LogWorth statistic, which is defined as the negative base 10 logarithm of the p-value calculated from the sum of squares due to the differences in means from the two groups formed from the split (Su et al. 2009). LogWorth values of 1.3 and 2 relate to p-values of 0.05 and 0.01 respectively.

The recursive partitioning function in JMP permitted splitting to be done automatically, based on the largest LogWorth value, or the partitioning can be forced along a particular node (or branch) by the operator. For each date the initial split was performed automatically. Since the splitting was binary, and each variable has more than two factors, the second split was forced on the node that contained two or more variables. Subsequent splitting was done by the operator, using the same approach. Splitting was terminated after all three variables had been assigned along a branch or when a variable recurred after another variable was chosen. The fit (r^2) of the partitioning was recorded for the whole model and for the first factor.

Results and Discussions

Scalar variance

The results from the variance calculations and Fairfield Smith's equation are shown in Table 2. The rows are ordered according to increasing water restriction (decreasing mean Ψ). As expected, the actual variance increased as the support (area) over which the data was collected increased whilst the variance per unit area decreased.

Table 2. The mean Ψ_{PD} response, the scalar variances and Fairfield smith *b'* values calculated from Ψ_{PD} sampling. Rows arranged in order of increasing water restriction.

Date	Mean ψ_{PD} (MPa)	σ^2_P	σ^2_S	σ^2_B	σ^2_V	Ratio σ^2_S:σ^2_B	*b'*
June 14, 2007	-0.163	9.96e-4	1.34e-3	1.85e-3	2.68e-3	0.537	0.924
July 9, 2007	-0.340	7.86e-3	9.22e-3	2.01e-2	2.74e-2	0.392	0.891
July 18, 2006	-0.362	4.66e-3	5.20e-3	1.35e-2	2.68e-2	0.345	0.851
July 31, 2007	-0.469	7.74e-3	1.08e-2	4.36e-2	6.04e-2	0.177	0.818
Aug. 22, 2007	-0.638	8.30e-3	1.07e-2	6.92e-2	1.41e-1	0.120	0.749
Aug. 10, 2006	-0.701	1.29e-2	1.34e-2	4.23e-2	9.60e-2	0.305	0.826

The total variance (σ^2_V) in the system showed an increasing trend as water restriction increased, whilst the ratio σ^2_S:σ^2_B, which indicates the amount of variation at the block level is potentially manageable, showed a definite decreasing trend at the same time. The inference associated with this is important. When water is non-limiting, the variance in Ψ at a site accounts for approximately half the variance in a block but the amount of variance in the vineyard is lower. As the system dried out, the variances in Ψ at all scales increased, but the variance at a site became a much smaller percentage of the overall block variance (12 - 30 %). This concurs with a previous more intensive, block-based study that visually showed a more pronounced spatial patterning in Ψ as the global mean Ψ decreased (Acevedo-Opazo et al.

2007). The implication is that as water restriction increased the opportunity to undertake a spatial, differential intervention increased.

The *b'* values also reflected this with macro-scale variation (lower *b'* values) becoming more dominant as Ψ decreased. The measurements early in the season displayed a high level of noise in the data. The *b'* values recorded here are generally higher than those observed for yield data by Fairfield Smith (1938) and Pringle et al. (2003). A *b'* value of 0.7 – 0.9 in these previous studies was related to noisy responses. However, these reports have focused on yield variance and are calculated on individual blocks (single cultivars). The *b'* values calculated here include an inter-cultivar effect, thus they are not a true uniformity trial as expounded by Fairfield Smith (1938), which will inflate the spatial heterogeneity in the data.

The exception to these trends was the result for August 10th 2006. Although this had the highest water restriction (lowest Ψ), neither the ratio nor the *b'* values changed significantly from the mid (July 18th) to late (August 10th) measurement. The reasons for this become clearer and are discussed in the next section.

Despite the result on August 10th, 2006, the trend observed in the ratio and *b'* values indicated that there is potentially a better opportunity for spatial management of Ψ at more negative Ψ_{PD} values. This concurs with the period of production when correct and timely management of Ψ is most beneficial for production i.e. the time when the opportunity to spatially manage Ψ is optimised coincides with the time when water management is most critical. The term 'potentially' is important here. As Pringle et al. (2003) discussed, the *b'* value and the ratio used here do not directly address the issues of whether the magnitude of variation was large enough nor if the variation was spatially structured enough to permit zone- or site-specific management practices.

Drivers of variance at the block/vineyard level

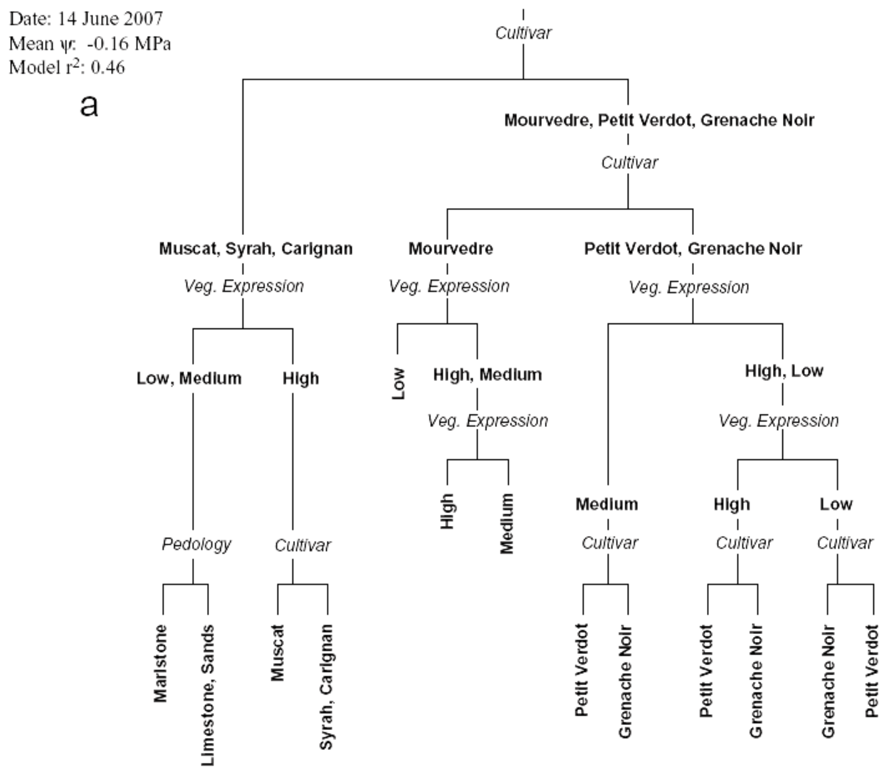
The results from the recursive partitioning are summarised in Table 3. Again the rows in the table are ordered by decreasing Ψ. The factors responsible for the first and second splits in the tree are recorded along with the whole model fit and the fit for the first factor. The regression trees for three of the dates – June 14th, July 31st and Aug 22nd 2007 – representing early, mid and late season measurements are depicted in Fig. 2. For the early season (June 14th) data (Table 3 and Figure 2a), with the highest (least negative) mean Ψ, the recursive partitioning identified cultivar as the dominant factor. It is well known that different cultivars exhibit different vegetative expression and have differential timing of budburst and growth early in the season. The second level was split on vegetative expression (Figure 2) and then again into cultivars. The soil type is redundant in this model. It appears that the differences in Ψ across the vineyard were driven by cultivar effects early in the season and to a lesser extent differences in vegetative expression (timing of bud burst and early season vigour). However, the fit to cultivars was not strong (r^2 = 0.18) nor was the full model fit (r^2 = 0.46) when compared to later models.

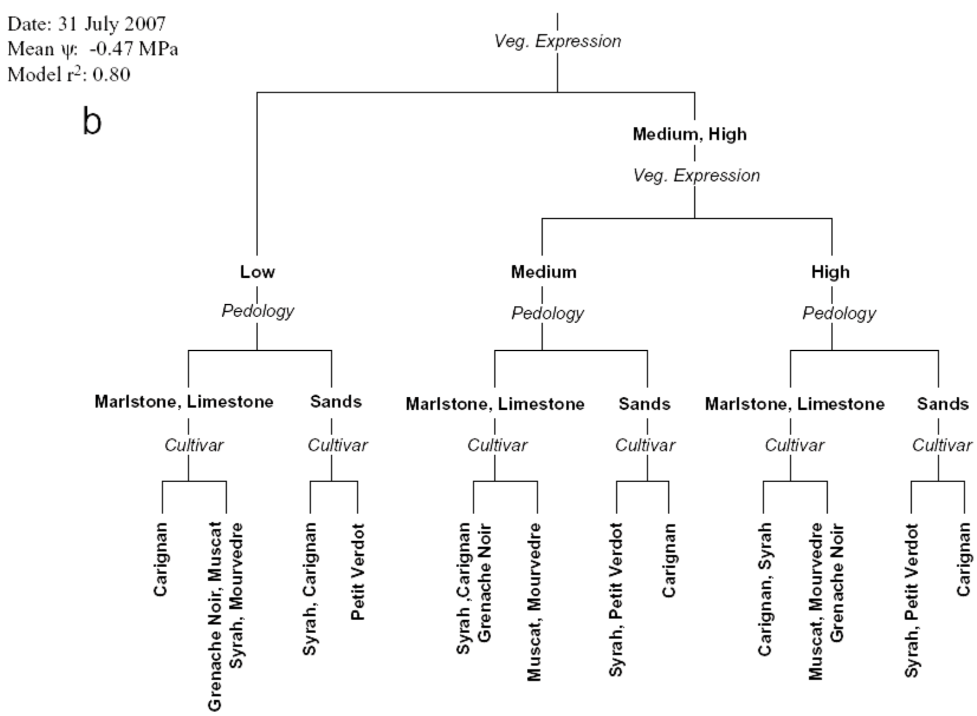
Table 3. Summary of the model fits and dominant splitting factors for the recursive partitioning trees for each date. Rows arranged in same order as Table 2.

Date	Factor of 1st Split	Fit (r^2) of 1st Split	Factor of 2nd Split	Full Model fit (r^2)	$\sigma^2_S:\sigma^2_B$ * + Model r^2
June 14, 2007	Cultivar	0.18	Vegetation	0.46	0.96
July 9, 2007	Vegetation	0.23	Soil	0.61	0.95
July 18, 2006	Soil	0.35	Mixed	0.70	0.89
July 31, 2007	Vegetation	0.38	Soil	0.80	0.98
Aug. 22, 2007	Soil	0.39	Vegetation	0.86	0.93
Aug. 10, 2006	Soil	0.46	Mixed	0.77	0.91

* Value from Table 2

For the late season (August) measurements (Table 3 and Figure 2), when water stress was the strongest, the primary factor identified was pedology. For both late season regression trees (August 10th, 2006 and August 22nd, 2007) subsequent levels after the first split were mixed showing both vegetative expression and cultivar effects. However, the trend was the same in both trees with the Clape and Colombier units split according to vegetative expression response, while the Littorale unit was split by cultivar. An ANOVA of the mean Ψ response by soil type for each date showed that vines on the Littorale unit had the highest Ψ values (least water restriction, data not shown). The Littorale response was not significantly different ($p<0.05$) from the other two pedological units on June 14th and July 9th, however as the season progressed, and water restriction increased, the Ψ on the Littorale (sand) unit did not decrease as rapidly as the other units. It had a lowest mean block value of -0.45 MPa (August 10th, 2006) and for all other dates the mean Ψ was < -0.4 MPa, which is considered the threshold where Ψ becomes limiting to production (Carbonneau, 1998, Sibille et al. 2007). The splitting of the Littorale by cultivar at all dates mirrored the response from the early season (June 14th) measurements and reinforced the observation that when water is non-limiting, cultivars are a bigger source of variance in Ψ than plant vegetative expression or soil effects.


Date: 14 June 2007
Mean ψ: -0.16 MPa
Model r²: 0.46
a
Cultivar
Mourvedre, Petit Verdot, Grenache Noir
Cultivar
Muscat, Syrah, Carignan
Veg. Expression
Mourvedre
Veg. Expression
Petit Verdot, Grenache Noir
Veg. Expression
Low, Medium
High
Low
High, Medium
Veg. Expression
High, Low
Veg. Expression
Pedology
Cultivar
High
Medium
Medium
Cultivar
High
Cultivar
Low
Cultivar
Marlstone
Limestone, Sands
Muscat
Syrah, Carignan
Petit Verdot
Grenache Noir
Petit Verdot
Grenache Noir
Grenache Noir
Petit Verdot


Date: 31 July 2007
Mean ψ: -0.47 MPa
Model r²: 0.80
b
Veg. Expression
Medium, High
Veg. Expression
Low
Pedology
Medium
Pedology
High
Pedology
Marlstone, Limestone
Sands
Marlstone, Limestone
Sands
Marlstone, Limestone
Sands
Cultivar
Cultivar
Cultivar
Cultivar
Cultivar
Cultivar
Carignan
Grenache Noir, Muscat
Syrah, Mourvedre
Syrah, Carignan
Petit Verdot
Syrah ,Carignan
Grenache Noir
Muscat, Mourvedre
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Carignan, Syrah
Muscat, Mourvedre
Grenache Noir
Syrah, Petit Verdot
Carignan

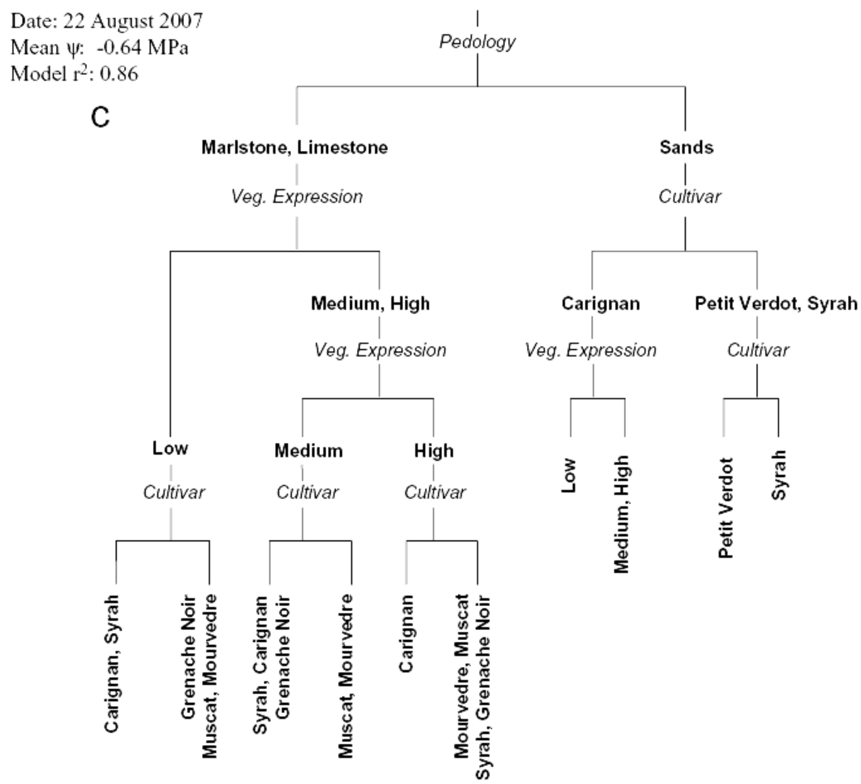

Figure 2 Three of the regression trees from the survey showing the response to Ψ_{PD} early (a), mid (b) and late (c) season in 2007. The date, mean Ψ_{PD} and r² for the whole model fit are shown on the left hand side of each tree. The summary of these three regression trees and the other three regression trees are given in Table 3.

Under high water restriction in 2007, the mean Ψ response between Colombier and Clape was not significantly different. This relationship was also observed in July 2006. However, in August 2006, the Colombier response was significantly different to the Clape unit and closer to Littorale (least water restriction). The reason for this was uncertain but may be due to localised rainfall prior to measurement over the Colombier area, which is geographically separated from the other units by ~1.5 km (Fig. 1). Unfortunately, meteorological observations for the vineyard were confined to a single location so it was not possible to validate this hypothesis. Whatever the reason, the Colombier unit was significantly less stressed in August 2006 when compared to the Clape unit, whilst at all other dates the two units showed no significant difference in response ($p>0.05$). The lower water restriction in the Colombier was also associated with a lower variance in Ψ, leading to the higher *b'* values and ratio observed in the previous section for the August 10th data.

With the three mid-season measurements (mid Ψ_{PD} levels), two of the dates (July 9th and 31st, 2007) showed vegetative expression to be the dominant factor, whilst the third (July 18th, 2006) showed pedology (Table 2). For the two that split initially on vegetative expression, the second level of the tree was univariate and split on pedology. The model fit (r²) after the first split and for the total model (Table 3) showed that both vegetative expression and pedology are making significant contributions to the model. The data from July 18th followed the same branching of the later August measurements, with the Littorale unit split on cultivar and the Clape/Colombier split on vegetative expression for the same reasons explained previously.

The absence of a soil effect on early season Ψ when water restriction was non-limiting, was also noted by Koundouras et al. (2006), although this data was confined to a single cultivar (cv. Agiorgitiko). As the season and water restriction progressed, statistical differences in Ψ were observed between vines planted on different soil types (Koundouras et al. 2006).

The final column in Table 3 sums the fit of the recursive partitioning model with the ratio derived in Table 2. The ratio can be considered the percentage of block variance that is associated with a site, whilst the model fit (r^2) can be considered the percentage of variance explained by the variates at the block level i.e. the stochastic (unmanageable) and spatial (potentially manageable) portions of the variance. For all dates ~90 – 95 % of variance in the data is explained. If the cultivar effect is removed from the recursive partitioning model, these values drop to 77.5 – 81 % (data not shown and data for June 14th not included as cultivar is dominant at this date).

Implications for sampling and modelling

Directly monitoring Ψ is the most effective way of determining irrigation requirements (Choné et al. 2001, Sousa et al. 2006, Ojeda, 2007). It has also been shown that Ψ is an effective predictor of the end quality of production (Ollat et al. 2002, Ojeda et al. 2002, Pellegrino et al. 2006). For these reasons alone there has been a renewed effort in the past 5 years to investigate options for monitoring and modelling vine water status. There is also a realisation that vine water status exhibits spatial variation, even within small (<1 ha) blocks (Acevedo-Opazo et al. 2008a). Therefore, correct decision-making relies on correct observations and this needs an effective sampling system. The results from this study have some clear inferences for designing sampling schemes. Firstly, when water restriction is low, variance in Ψ is low and fewer samples are needed at this time to estimate the mean block or zone Ψ. As water restriction increases, variance in Ψ also increases and the required sampling density increases.

Secondly, if a stratified sampling system is to be used, stratifying based on soil type is most effective when water restriction is high (and information on Ψ most beneficial for management decisions). Stratifying on vegetative expression can be effective at sub-block levels but is less effective than soil type over larger areas (the vineyard scale here but possibly at a block scale in larger production systems) if large pedological differences occur across this larger area. Cultivar effects on Ψ are minor at high water restriction. If information on Ψ is needed at low water restriction, then cultivar effects appear to be dominant in defining mean block Ψ values. Some research has shown that early season water deficit has a beneficial effect on grape quality parameters (Koundouras et al, 2006) however, the authors cannot envisage many scenarios where information on Ψ when water is non-limiting (Ψ_{PD} > -0.4 MPa) is valuable for management.

Thus in commercial situations, when there are clear and distinct pedological units in the vineyard and an assessment of the mean Ψ for a vineyard is required, stratification should be based on cultivar at low water restriction, vegetative expression at medium water restriction and soil type for high water restriction. For the latter situation it is advisable to stratify samples on vegetative expression within each pedological unit particularly under conditions of high water restrictions. This approach also provides information on the mean Ψ response within pedological units. For vineyards or individual blocks with (relatively) homogenous soil, stratification based on vegetative expression is likely to be appropriate at both intermediate and high water restrictions. A similar approach should be considered for any plant monitoring system, such as sap flow sensors and dendrometers, not just for Ψ. This will help ensure that any limited spatial point sampling network generates the best quality information on the vineyard system.

As indicated in the introduction, this analysis was undertaken in a French viticulture production system, which is characterised by small blocks (~1 ha). In many other countries, such as Australia, block size can be considerably larger (> 10 ha). In these larger blocks, a larger amount of soil heterogeneity is likely (though not necessarily) to be found. When transferring the results from this analysis to larger, more edaphically heterogeneous blocks the influence of intra-block soil variation, which may be similar to the inter-block soil variation observed in this system, needs to be taken into consideration.

The increased variance at high water restriction is also accompanied by an increase in spatial heterogeneity. Thus stratified sampling appears to be more important, to take into account the spatial heterogeneity, at high water restrictions.

Conclusions

This analysis indicated that as overall water restriction increased in a vineyard, the response of the vines was driven mainly by environmental parameters rather than genetic effects. The dominant environmental effect appeared to be soil type and then vegetative expression. When water is non-limiting, cultivar (genotype) differences were the dominant drivers of variation in Ψ response, however a lot of the variance at this time was stochastic in nature. The spatial heterogeneity of Ψ also increased as water restriction increases and with it the percentage of variance that was not associated with stochastic variance. Thus, as the overall variance increased, the percentage of variance that is potentially manageable also increased.

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CHAPTER III

Chapter 3: The potential of high spatial resolution information to define within-vineyard zones related to vine water status

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Abstract

The goal of this study was to test the usefulness of high-spatial resolution information provided by airborne imagery and soil electrical properties to define plant water restriction zones within-vineyards. The main contribution of this is to propose a study on a large area representing the regions' vineyard diversity (different age, different varieties and different soils) located in southern France (Languedoc-Roussillon region, France). Nine non-irrigated plots were selected for this work in 2006 and 2007. In each plot, different zones were defined using the high-spatial resolution (1m2) information provided by airborne imagery (Normalised Difference Vegetation Index, NDVI). Within each zone, measurements were conducted to assess: (i) vine water status (Pre-dawn Leaf Water Potential, PLWP), (ii) vine vegetative expression (vine trunk circumference and canopy area), (iii) soil electrical resistivity and, (iv) harvest quantity and quality. Large differences were observed for vegetative expression, yield and plant water status between the individual NDVI-defined zones. Significant differences were also observed for soil resistivity and vine trunk circumference, suggesting the temporal stability of the zoning and its relevance to defining vine water status zones. The NDVI zoning could not be related to the observed differences in quality, thus showing the limitations in using this approach to assess grape quality under non-irrigated conditions. The paper concludes with the approach that is currently being considered: using NDVI zones (corresponding to plant water restriction zones) in association with soil electrical resistivity and plant water status measurements to provide an assessment of the spatial variability of grape production at harvest.

Keywords: vine water status, vineyard spatial variability, water restriction zone, soil electrical resistivity, airborne imagery

Introduction

Many authors have shown that grapevine water status has a direct effect on grape quality through its influence on vegetative and fruit growth (Dry and Loveys 1998, Ojeda et al. 2002). This has led to the increased implementation of irrigated viticulture to alleviate grapevine water stress (Naor et al. 2001, Ortega-Farías et al. 2004, Girona et al. 2006). Yet, viticulture in the southern region of France is carried out using non-irrigated practices (Ojeda et al. 2005, Tisseyre et al. 2005) which adds to the challenges faced by wine producers when trying to maintain the high quality requirements in wine production (AOC Appellation d'Origine

Controlée). Thus, vineyard zoning based on relevant vine water status information could lead to a practical decision support tool. Such zoning would require the assessment of plant water status using high spatial resolution imagery to capture the vineyard scale.

Several researchers have proposed the use of pressure chamber methodology (Scholander et al. 1965) as an excellent tool to measure vine water status under irrigated and non-irrigated conditions (Naor et al. 2001, Ojeda et al. 2002, Tisseyre et al. 2005). Being a manual technique, vine water status assessment using Pre-dawn Leaf Water Potential (PLWP) or other plant water potential measurement is difficult to perform, time consuming and can only be done practically at low spatial and temporal resolutions. A more practical and representative tool would require an assessment of vine water status with high spatial resolution during the growing period, especially at the end of summer when significant water restrictions are experienced under non-irrigated conditions (Ojeda et al. 2005, Tisseyre et al. 2005, 2007).

Currently, no sensor providing direct assessment of plant water status with a high spatial resolution is easily available for wine-growers to monitor plant water status. The most promising technology is certainly based on thermal infra-red technologies to derive the plant water status and the stomatal conductance from the canopy temperature. Many authors have investigated these technologies at the leaf and the plant level (Idso 1982, Jackson et al. 1981, Moran et al. 1994, Sepaskhah and Kashefipour, 1994). It was more recently applied to vine with infra-red cameras (Jones 1999, Jones et al. 2002, Fuentes et al. 2005, Stoll and Jones, 2007). This approach is interesting to monitor plant water status over time, nevertheless it remains time consuming to provide information with a high spatial resolution. Other approaches based on satellite or airborne thermal images have been proposed (Tilling et al. 2007). However, applying these technologies to vineyards on large scales still raises scientific and technical problems like the incidence of bare soil and grass cover, the cost and the resolution of the data which does not necessary fit with cooperative or winery requirements.

An alternative approach could then be based on the analysis of surrogate information that is easily available at high resolution, such as multi-spectral images and soil electrical properties mapping, to define different zones (Taylor and Bramley 2004, Tisseyre et al. 2005, 2007). An example of remote sensing has been the use of airborne imagery to map relative differences in vine canopies which is used to characterize grapevine canopy shape and vegetative expression throughout a vineyard (Hall et al. 2002). The combination of the two is taken as an estimate of vigour (Bramley 2001, Hall et al. 2002), whereas Johnson et al. (2003) used high-spatial resolution imagery to map vine leaf area converting normalized difference vegetation index (NDVI) maps into leaf area index (LAI) maps. In non-irrigated conditions, vigour is strongly related to soil water availability, thus NDVI maps could constitute relevant information to propose different water restriction zones in the vineyard.

Studies of soil physical properties, such as soil texture and its relationship with the general condition of the vines have demonstrated that significant variations may exist within single vineyards (Hall et al. 2002, Taylor and Bramley 2004). Thus, Taylor and Bramley (2004) studied the spatial variability of soils, specifically in the adoption of soil apparent electrical conductivity and GPS-based elevation surveys prior to vineyard design. Barbeau et al. (2005) used soil electrical resistivity to compare the effect of rows with and without grass cover on soil water distribution. Bramley (2005) used such soil information to determine different soil zones within fields. This type of information can be considered relevant to characterize the spatial variability of plant water status at a within-vine field scale. It is important to note that there is no clear relation between soil electrical conductivity and soil depth or soil water availability. This is mainly due to the complexity of the relations between electrical soil properties and other soil parameters such as salinity, water content and texture, among others (Corwin and Lesch 2005, Samouëlian et al. 2005). However, In addition to airborne imagery, an electrical soil survey could provide relevant information to zone a vineyard according to water restriction.

In the light of previous research, the goal of the present study is to test the potential of high spatial resolution information provided by multi-spectral airborne imagery to define plant water restriction zones at a within-vineyard scale. The potential of soil electrical properties to provide supporting information was also considered in order to verify its relevance in delineating zones of different plant water restriction resulting from differences in soil characteristics. The originality of this study is to propose an approach which may be used by wine-growers and co-operatives in a very short timescale. Therefore, high resolution information used in this study fits with practical constraints in terms of cost, resolution and commercial availability. Another originality of this study is the scale of investigation; many experiments in precision viticulture have presented the use of high resolution information to provide within-field zones (Bramley 2001, Tisseyre et al. 2005) on particular fields. This study focuses on a decision scale which fits with the requirements of co-operatives and wineries. It aims to consider within-field variability but also the effect of different locations, different soil types and different training systems which may be met in the region. Finally, the originality of this approach is also based on the parameter that the zoning is based on. In our conditions, plant water status is one of the most important parameters which drive vigour, yield and quality. Potential of high spatial resolution information to define within vineyard zones related to vine water status has never been investigated in our conditions. As far as we know, many studies investigated the relation between high resolution information (NDVI and electrical soil survey) with vigour, LAI and yield, but not with plant water status.

Materials and Methods

Experimental fields

Experiments were carried out on 41.7 ha in the experimental vineyard of Pech-Rouge (INRA-Gruissan), during the 1999, 2006 and 2007 growing seasons. The experimental vineyard is located N 43º08'47'', E 03º07'19'' WGS84, in the Languedoc-Roussillon region (Aude department) of France. The experimental centre of Pech-Rouge produces white and red grapevine varieties (see Table 2) on three different soil units: (i) Colombier (Col), predominately characterized by calcareous soil, (ii) Clape (Cla), characterized by calcareous soil with an irregularly stony profile of 40 cm depth, and (iii) the Littorale (Lit), characterized by an arenosol (thick sandy soil). These soil types were not only chosen because they are representative of the vineyards in the area but because the Colombier (Col) and Clape (Cla) represent profiles with low soil water availability compared to the Littorale (Lit). Pech-Rouge vineyard has a Mediterranean climate with a strong maritime influence, the mean annual rainfall is about 600 mm. This climate is characterized by a dry summer.

Seasonal climatic characterization

Experiments were carried out during three different years with different climatic conditions. The dryness index (DI), proposed by Tonietto and Carbonneau (2004) was used to characterize the seasonal potential soil water balance. It is an indicator of the dryness level calculated on a 6-month period from April 1st to September 30th. Based on the DI value, four classes are usually considered: humid (wet climate with DI > 150 mm), sub-humid (DI $\in$] 50 ; 150 mm]), moderately dry (DI $\in$] -100 ; 50 mm]) and very dry (DI < -100 mm). Last two classes represent conditions of medium to high levels of water restriction for the vine.

Table 1. Summary of the main climatic variables (period April-September) characterizing growing conditions during the three years of experimentation.

Year	C.Pp (mm)	C.ET_0 (mm)	DI (mm)
1999	363	799	55
2006	144	869	-82
2007	242	801	-27

C.Pp: Cumulated precipitation
C.ET_0: Cumulated reference evapotranspiration
DI: Resulting Dryness Index

Table 1 presents accumulated precipitation (C.Pp), accumulated reference evapotranspiration (C.ET_0) and dryness index (DI) values calculated for each experimental year. Season 1999 presents the lowest DI (DI = 55 mm) corresponding to a sub-humid climate. Seasons 2006 and 2007 present DI corresponding to a moderately dry climate, with 2006 DI value close to very dry climate (DI = -82). The experiment covered years with different climatic conditions. Year 2006 and, to a lesser extent year 2007, should lead to high vine water restriction.

High-spatial resolution information

Airborne imagery

The methods used for image acquisition and image processing followed well-established methods for vines (Lamb *et al.,* 2004). Three multi-spectral airborne images, with 1m resolution, were acquired during the full vine canopy expansion period (July 1999, August 2006 and August 2007). The trial site image was collected by two different companies: 'IFN Inventaire Forestier National' in 1999 and 'L'avion Jaune' in 2006 and 2007. Images were acquired at 4000m and 3200m elevation respectively, under clear sky and dry soil conditions. The spectral regions contained in the images were: (i) blue (445-520 nm), (ii) green (510-600 nm), (ii) red (632-695 nm) and (iv) near-infrared (757-853 nm). The software package Matlab v7.0 (Mathworks, Inc.) was used for image processing and analysis. The image information was used to estimate the Normalised Difference Vegetation Index (NDVI) (Hall et al. 2002, 2003) and to generate relative biomass maps. This index was calculated by transforming each multi-waveband image pixel according to equation (1).

$$NDVI = \frac{(NIR) - (R)}{(NIR) + (R)} \quad \text{(Equation 1)}$$

where NIR is near infrared and R is red. Both variables corresponded to their respective reflectance in the light band (Rouse et al. 1973).

The three images (1999, 2006 and 2007) were used to check the time stability of the zones derived from the images.

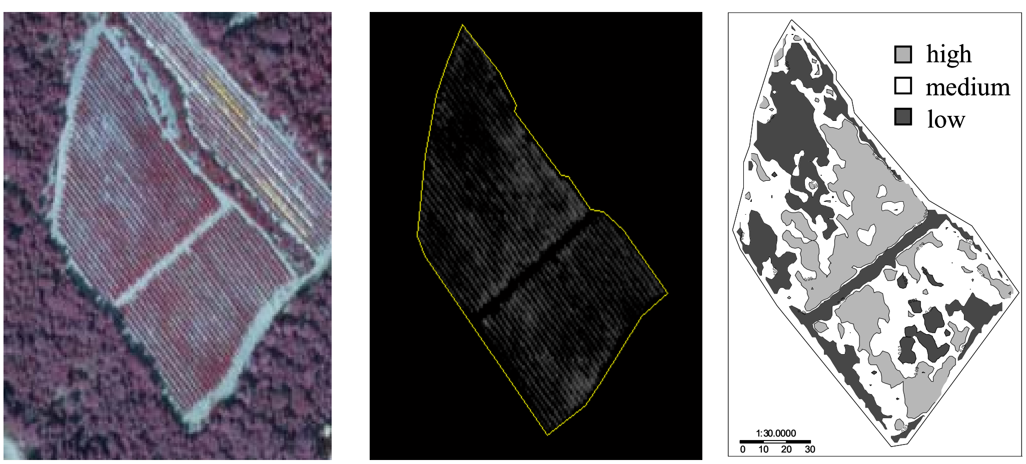
Soil physical properties

Measurement of soil electrical resistivity (SE_Resistivity) with invasive electrodes was obtained using a SE_Resistivity survey sensor (Wenner 4 electrode device). The purpose of this sensor is to determine soil resistivity distribution from a determined soil volume. The method consists of the application of artificially generated direct electric currents to the soil and measuring the resulting differences in potential. The potential difference patterns were used to characterize sub-surface heterogeneities and electrical properties (Samouëlian et al.

2005), as the depth of exploration of the soil profile is proportional (for homogeneous materials) to the distance between probes. In this study, the soil information was obtained to a depth of 1m. Measurements were made manually on specific zones defined according to NDVI information (see section sampling site determination). Five repetitions were systematically made on each measurement site and it was assumed that SE_Resistivity varies mainly with soil water availability.

Image processing

For each individual field, the image processing was performed using a Matlab script developed at the Agricultural Engineering University of Montpellier. The images were first geo-referenced using relevant points on the image such as field corners or obvious end of row. The co-ordinates of these features were determined using a DGPS (Differential Global Positioning System) (Leica Geosystems company, model GS 50 with differential correction OMNISTAR) according to the French system (Datum RGF93, projection Lambert93). Images were geo-referenced using a Helmert transformation. Considering the average slope of the fields and the elevation of the acquisition, image ortho-rectification was not necessary in this study. The next step consisted of selecting pixels belonging to the field; this was achieved using the field boundary as determined with a DGPS (see Figure 1b). Finally, the calculation of NDVI was made pixel-by-pixel (equation 1) based on image digital numbers. Image calibration was not considered in the first approach since only relative differences in NDVI were considered for each field. To avoid the effect of canopy cover discontinuity due to the vine training system (simple trellis), an averaged NDVI calculation was made using a 3x3 pixel-moving average window (area of 9 m^2). This 9 m² moving average window was chosen according to vine plantation density (1x2.5 m) in order to make sure to have NDVI values from plants. NDVI values from plants are significantly higher than from bare soil. Therefore, within-field variation of NDVI caused by soil variability was considered as insignificant compared to variation of NDVI values due to plant variability.



(a) **(b)** **(c)**

Fig 1. Different steps of the image processing: (a) original image (B, G, R and NIR), (b) extraction of the boundary of the field and calculation of NDVI within the field, (c) NDVI map after applying a 3x3 pixel moving average window, with low (dark grey), medium (white) and high (light grey) NDVI values.

Spatial analysis and field selection

The NDVI calculation was performed on the whole vineyard, a set of 24 non-irrigated fields. However, only nine of these fields trained in a simple trellis system were selected (Table 2) on the basis of their spatial structure and their NDVI variation magnitude. For each field, NDVI values were used to compute geo-statistical information, such as: the variogram and its related parameters (nugget effect C0, sill C1 and range r), and the trend. This information was used to compute the Opportunity Index of site specific management (O_i) introduced by Pringle et al. (2003). The O_i parameter provides separate measurements of magnitude of variation (CV_a) and the size of the spatial structure (S) of the within field variability (Pringle et al. 2003). Originally, Pringle et al. (2003) presented the problem of quantifying the opportunity of site-specific management based on yield monitor data. They suggested that a pertinent opportunity index has to take into account both the magnitude of the yield variation and the arrangement in space of this variation. They have proposed a SSCM (Site-Specific Crop Management) Opportunity Index (O_i) which takes into account these two components:

$$O_i = M \times S \qquad (\textit{Equation 2})$$

where M is the magnitude of data variation and S is the spatial structure of data variation.

In Eq. 2 the magnitude of field variation is assessed by the areal Coefficient of Variation (CV_a). The spatial structure of field variation (S) is assessed by the proportion of total variance explained by a trend surface of field data and the integral scale of the trend surface residual. Pringle et al., (2003) have shown that O_i was reasonably successful in ranking the fields from the most suitable to the least suitable to site-specific management. In our case, the O_i was used to choose fields which present large zones with significant differences in NDVI values. It was then used as an objective information to select the most opportune fields for our experimentation and to avoid fields with only random variation. We used the O_i to rank the grape fields from the less opportune to the more opportune in each soil unit. Nine fields were chosen among the higher values of O_i, three in the Colombier (Col), three in the Clape (Cla) and three in the Littorale (Lit) in order to consider the different soil units. Table 2 presents a summary of the 9 grape-fields used in this study.

Table 2 Summary of the selected fields, crop variety, age, field area, vine and row spacing, areal coefficient of variation (CV_a), spatial structure statistic (S) and opportunity index (O_i) present in the dataset collected for this study.

Soil unit	Field ID	Cultivar	Age (years)	Field area (ha)	Vine spacing (m)	Row spacing (m)	CV_a	S	O_i
Col	P90	MU	39	0.42	1.5	2.25	0.045	0.14	0.006
	P95	CA	40	0.81	1.5	2.25	0.033	0.20	0.007
	P96	GN	40	0.70	1.5	2.25	0.053	0.19	0.010
Cla	P63	SY	16	1.14	1.1	2.5	0.066	0.47	0.032
	P69	MO	17	1.65	1.0	2.5	0.026	0.46	0.012
	P76	SY	15	1.33	1.0	2.5	0.062	0.33	0.021
Lit	P11	PV	10	0.70	1.0	2.5	0.045	0.30	0.013
	P22	SY	11	1.72	1.0	2.5	0.054	0.62	0.034
	P61	CA	19	1.05	1.0	2.5	0.041	0.50	0.020

Soil unit: Col, Colombier; Cla, Clape; Lit, Littorale.
Variety: MU, Muscat; CA, Carignan; GN, Grenache Noir; SY, Syrah; MO, Mourvèdre; PO, Portan; PV, Petit Verdot.

Note in table 2, that O_i values are very low. The opportunity index was originally designed for yield values. In the case of NDVI information, the CV_a values are very low due to the small magnitude of variation (NDVI $\in$ [0,1]) for all the fields. Conversely, the S components are spread over a wide range of values (from 0 to 62% of the within-field variability). Since the O_i results from a multiplication of both components (CV_a and S), observed O_i values are very low in the case of NDVI values. However, S remained very different depending on the considered field and the resulting O_i remained relevant in ranking the fields.

This result raises the problem of O_i as defined by Pringle et al. (2003), which could be adapted for other types of data such as NDVI. In this particular case, another recent index (Tisseyre & McBratney 2008) could have been more appropriate.

Sampling site determination

In each field, sampling site determination was based on the NDVI information. Fields selected according to the O_i were assumed to present significant spatial patterns. The field zoning process aimed at considering two zones per grape field in order to verify whether NDVI variation was significantly related to other parameters, especially the plant water status. For each field, the zoning was carried out by considering three classes of NDVI; high, medium and low, where the low class corresponded to 0-33% quantile, the medium class corresponded to 33-67% quantile and the high class corresponded to 66-100% quantile. It is important to note that this classification is relative to each selected field from Table 2. Classes of NDVI were mapped. Two sampling sites per grape field were then determined taking into account two criteria: (i) they had to be located in two significant classes (zones) of NDVI (high and low), (ii) the zones of high or low NDVI had to present a significant area on the field (>100 m^2). The last criterion was considered mainly for practical reasons, to ensure the number of vines on each zone is relevant for further analysis. Medium zones of NDVI were never considered in this study, they were considered as transition zones (buffer zones) between low and high zones. Moreover, taking into account the inaccuracy of the geo-referenced data and the positioning system, the transition zone allowed us to confidently locate the sample sites within high and low NDVI zones.

Parameter measurement

Two ground-based measurement sites of 40 m^2 in high and low NDVI zones were chosen in each of the 9 fields. Several measurements were carried out to verify the relevance of the zoning (Table 3). In this table, a distinction is made based on the type of the variables, the number of acquisitions, the date of acquisitions and the number of repetitions (Number of vines per zone).

Although the soil electrical resistivity variable was measured manually (inter-row) with low spatial-resolution in this study, this parameter was treated as high resolution data since soil electrical survey is available and currently performed on many vineyards with embedded sensors.

Additional direct measurements were also made on the vines in each zone, including: pre-dawn leaf water potential (PLWP) at three different dates (July and August 2006 and August 2007), vine vegetative expression (canopy height (cm), canopy thickness (cm) and vine trunk circumference (mm)). In order to avoid vine age effects, the calculation of the trunk growth rate (G_rate) was considered using the ratio vine trunk circumference/age of the vine. At harvest, different variables were also measured to characterize the production (yield per plant) and berry quality parameters. Quality measurement was based on samples of 10 clusters (of different plants) collected in the center of each sampling site (high and low NDVI). Soluble solids concentration (using a thermo-compensated refractometer), total acidity (g L^{-1} of sulphuric acid) and pH were measured at berry maturity. To evaluate berry composition, measurements of total polyphenols index were assessed at harvest using the methodology proposed by Iland et al. (2000).

Table 3 Summary of the variables measured on the selected fields, number of acquisitions, date of acquisitions, number of repetitions per zone and name of the variables.

Variables	#Acquisitions	Acquisition dates	#Repetitions	Nomenclature
High spatial resolution information				
NDVI	1	July 1999	1	NDVI_a
NDVI	1	August 2006	1	NDVI_b
NDVI	1	August 2007	1	NDVI_c
Soil electrical resistivity	1	March 2006	5	SE_resistivity
Quantitative measurement				
PLWP	1	July 2006	9	PLWP1
PLWP	1	August 2006	9	PLWP2
PLWP	1	August 2007	9	PLWP3
Vine trunk circumference	1	March 2006	40	------
Canopy height	1	August 2006	10	C_height1
	1	August 2007	10	C_height2
Canopy thickness	1	August 2006	10	C_thick1
	1	August 2007	10	C_thick2
Vine growth rate	1	March 2006	40	G_rate
Yield per plant	1	September 2006	10	Yield
Berry composition				
Sugar percentage (ºBrix)	1	September 2006	----	Brix
pH	1	September 2006	----	pH
Titratable acidity	1	September 2006	----	T_acidity
Total polyphenols index	1	September 2006	----	TPI

Data analysis and data mapping

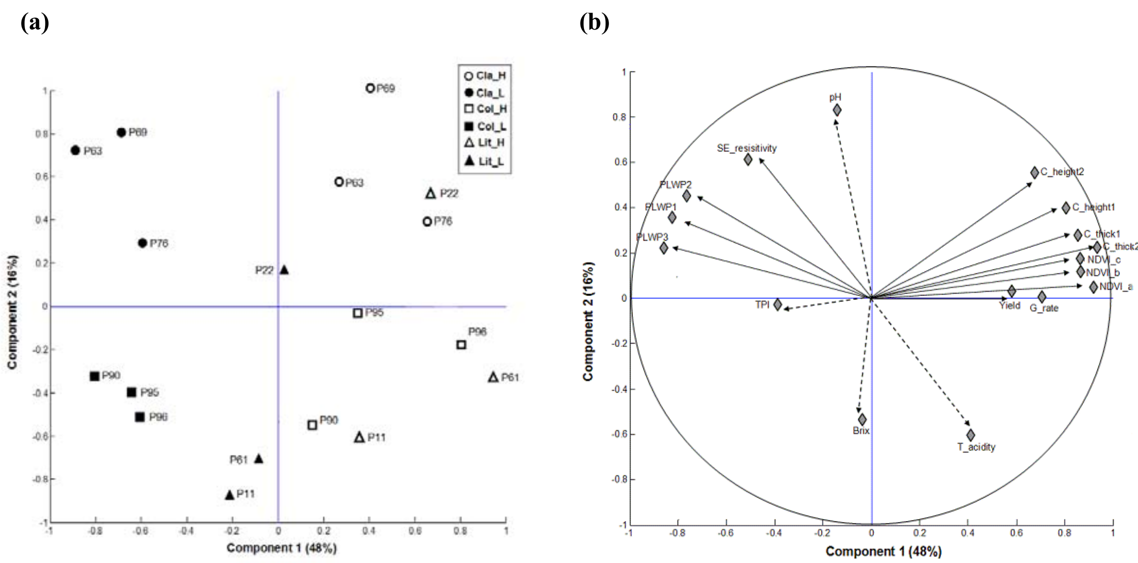
Principal Component Analysis (PCA) was carried out on the data. This study allowed analysis of the whole data set, including all the sampling sites and all the parameters. Indeed, with the aim to check significant differences between both zones (high and low NDVI), a classical statistical analysis was undertaken. Thus, the comparison of mean values between NDVI zones was performed using the Kruskal-Wallis non-parametric test. This test was selected instead of the classical analysis of variance (ANOVA) because ANOVA normality assumptions were not met with our data.

Data mapping was performed using the 3DField software (Version 2.9.0.0, Copyright 1998-2007, Vladimir Galouchko, Russia). The interpolation method used in this study was based on a deterministic function (inverse distance weighting).

Results and Discussion

General analysis

The PCA results are presented in Figure 2 and for each zone (Lit, Col and Cla), the low NDVI sample sites are represented by the closed symbols (Cla_L, Col_L, Lit_L), while high NDVI sampling sites are represented by open symbols (Cla_H, Col_H, Lit_H). When several measurements were available on each sampling site, the average was computed. In the PCA, components 1, 2, and 3 represent 48%, 16% and 11% of the variation, respectively, accounting for 75% of the total variability. It can be seen in Figure 2b, where component 1 is strongly correlated with NDVI for the three dates (NDVI_a, NDVI_b, NDVI_c), with canopy thickness (C_thick), canopy height (C_height), trunk growth rate (G_rate) and yield per plant. These last two variables constituted a smaller percentage in component 1. Conversely, component 1 is negatively correlated with pre-dawn leaf water potential (expressed in absolute values) at the three dates (PLWP1, PLWP2 and PLWP3) and with total polyphenols index (TPI). Low NDVI sites are located on the left part of the scatter plot while all the high ones are on the right side (Figure 2a). Component 1 can be related to the plant vegetative expression differences driven by plant water status, underlying the relevance of NDVI information for vineyard zoning according to plant water status.



(c) **(d)**

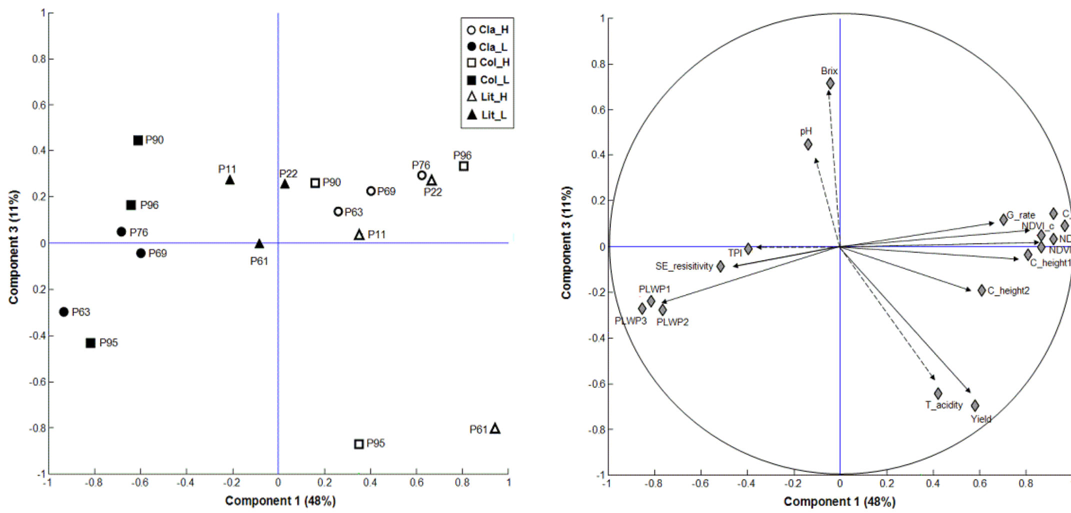


Fig 2. Principal component analysis (PCA) performed on the data set from 1999, 2006 and 2007. Each point of the PCA represents a within field measurement of high-NDVI (H) and low-NDVI (L) in each Colombier (Col), Clape (Cla) and Littorale (Lit) soil units. Projection of single individuals on the plane formed by the first and second component (**a**) and the plane formed by first and third component (**c**). Projection of variables on the plane made by the first and second component (**b**) and the plane made by first and third component (**d**). Dotted lines characterize vegetative expression and vine water potential variables, and dashed lines characterize berry quality variables. Variables are abbreviated as in Table 3.

Component 1 shows a strong correlation between NDVI information measured in 1999, 2006 and in 2007. This indicates a relative temporal stability of this information which may be related to parameters such as soil depth, soil characteristics, elevation and the resulting soil water availability. Note that in this study, the temporal stability does not mean that zones present the same values over the years. It only means that low zones remain low and high zones remain high over the three years of the study (see Figure 3). Figure 3 illustrates the temporal stability of NDVI zones observed on two fields in 1999 (a1 and b1), 2006 (a2 and b2) and 2007 (a3 and b3). For the six maps, NDVI data were mapped in 33% quantiles for each year which removes absolute differences between years due to climate, canopy management and conditions of image acquisition. For each map of the figure 3, the class "very small" (dark grey) corresponds to the 0-33 % quantile, the class "medium" (white) corresponds to the 33-67 % quantile and the class "high" (light grey) corresponds to 67-100 % quantile of the NDVI values. Figure 3 shows that low or high NDVI are consistently located in the same part of the field in 1999, 2006 and 2007. These results highlight the incidence of perennial parameters like soil depth, soil texture and slope among others which drive NDVI within-field variability. However, depending on the climate of the year, significant differences in NDVI values, PLWP, yield and vigour were observed on the same zone from one year to another.

Figure 2b shows a correlation between trunk growth (G_rate) and NDVI. Considering G_rate as an indicator of average vine vigour since establishment, this result confirms the temporal stability of the zones under consideration.

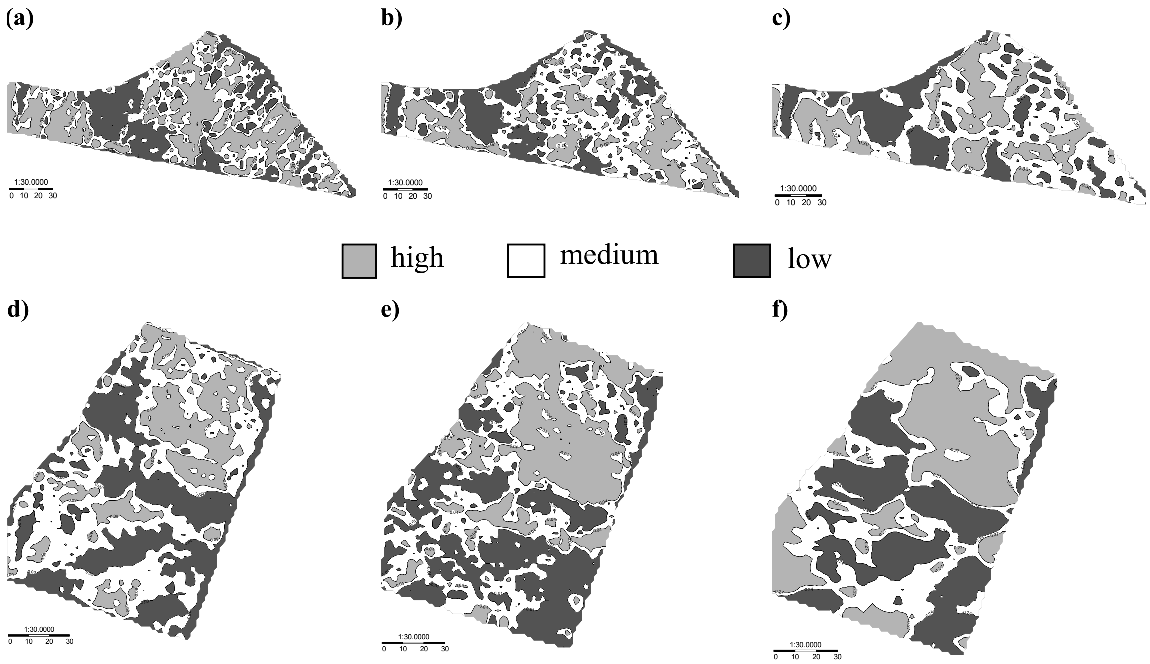


Fig 3. Maps of normalised difference vegetation index (NDVI) estimated at different seasons, July 1999, August 2006 and August 2007: (**a**), (**b**), (**c**) in Mourvèdre (P69) and (**d**), (**e**), (**f**) in Syrah (P63). NDVI data were mapped in 33% quantiles. The class "very low" (dark grey) corresponds to the 0-33 % quantile, the class "medium" (white) corresponds to the 33-67 % quantile and the class "high" (light grey) corresponds to 67-100 % quantile of the NDVI values.

Component 2 is strongly correlated with the pH and, to a lesser extent, with the berry total acidity (T_acidity) and Brix. Finally, Component 3 (Figure 2d) is correlated with the berry composition parameters (pH, T_acidity and Brix). Thus, considering sampling sites (Figure 2), most of the quality parameters (Brix, pH and T_acidity) did not show any linear relationship with the vegetative growth parameters and plant water status. These results are in accordance with those obtained by Peterlunger et al. (2002) and Ojeda et al. (2005) who found that a non-linear approach was required in order to relate the berry quality parameters with plant water status. This relationship requires a temporal approach which considers the level of water restriction in association with the variety and the phenological stage of the vine. Indeed, considering sampling sites, the total acidity (T_acidity) and yield measurements are explained principally by the values obtained by the high NDVI values of P95 and P61 fields (Figure 2d), which presented the higher yields and the higher berry total acidity with regard to the other sampling sites. Thus, the behaviour of these two variables were not observed in the rest of the sampling sites analyzed.

Figure 2 highlights obvious links between PLWP and quantitative parameters. As the water deficit increases (lower vine water potential values), the values of harvest parameters decrease. Regarding yield, this reduction is mainly due to a reduction in the individual berry weight. This means that severe water restrictions (particularly in the high water restriction zones) can cause a strong attenuation of the vine growth. In 2006, water stress occurred very early in the season reaching strong to severe levels for vines located in the Colombier and Clape zones. These results are in accordance with those by Schultz and Matthews (1988) and Ginestar *et al.* (1998) who found that vine growth is the first factor affected by water restriction. These results show the relevance of using NDVI to zone the vineyards according to water restriction. Results also showed that such a zoning seems to be stable over the years.

Considering Figure 2a and 2b, SE_resistivity is a variable whose behaviour is peculiar to our conditions. It showed no significant representation in either component 1 or component 2:

(i) it is correlated with the plant water status. This correlation shows that differences between plant water status are mainly explained by differences in soil conditions.

(ii) it also explains the important extent of variation that exists between the Cla (positive values on PCA, Figure 2a) from Lit and Col, both with negative values (on the PCA).

This result demonstrates the limitation of using SE_resistivity to zone the vineyard without any other considerations. SE_resistivity is an integrating parameter that characterises soil properties according to many different phenomena (such as salinity, water content, texture, amongst others) (Corwin and Lesch 2005, Samouëlian *et al.* 2005). In our conditions, variability due to the different soil types (Col, Cla and Lit soil units) is significant compared to the within-field variability. For example, presence of limestone layers on the Cla soil unit leads to high soil resistivity values for this part of the vineyard. To summarize, SE_resistivity can be used to delineate within-field plant water restriction zones, but this information needs to consider a previous expert delineation of the main soil types to be relevant.

Thus in our conditions, the soil (different zones of study) is the main influential factor on vine vegetative expression and plant water status. The soil hides even the influence of the variety maturity date. For example Syrah and Mouvèdre (P63 and P69 respectively, Figure 2a) are two varieties which show very distinct behaviour in terms of date of maturity (early and late varieties, respectively). Nevertheless, both varieties appear in the same zone of the PCA (in the upper part of the scatter plot) which corresponds to the Clape zone, showing that the type of soil is the main factor to consider in this analysis.

The above ground biomass production and plant water status parameters are mainly influenced by soil water content. Therefore, NDVI information offers an accurate representation of growth behaviour of vineyards affected by water restriction in our conditions.

<u>Vine water status</u>
Figure 4 shows pre-dawn leaf water potential (PLWP) values measured at two different growing periods, post-setting (a) and post-veraison (b) (July and August 2006, respectively). Each bar represents a within-field measurement of high and low NDVI zones. Figure 4 shows that significant differences in PLWP occurred between high and low vegetative expression zones (NDVI), for almost all experimental fields. The exceptions were field P22 for both periods and field P11, which presented significant statistical differences only in post-veraison.

The lowest PLWP values found in the Cla soil unit were from vines subject to higher water restrictions, especially for the P63 and P76 fields; PLWP = -1.48 MPa and PLWP= -1.36

MPa, respectively, for post-veraison. These values are mainly explained by the limestone layers and the resulting low soil water availability. The highest PLWP values were found in the Lit soil unit (between -0.34 and -0.57 MPa for the post-veraison). The Col presented intermediary values. Similar results were observed with SE_resistivity. Thus, the Cla showed higher soil resistivity compared to Col and Lit.

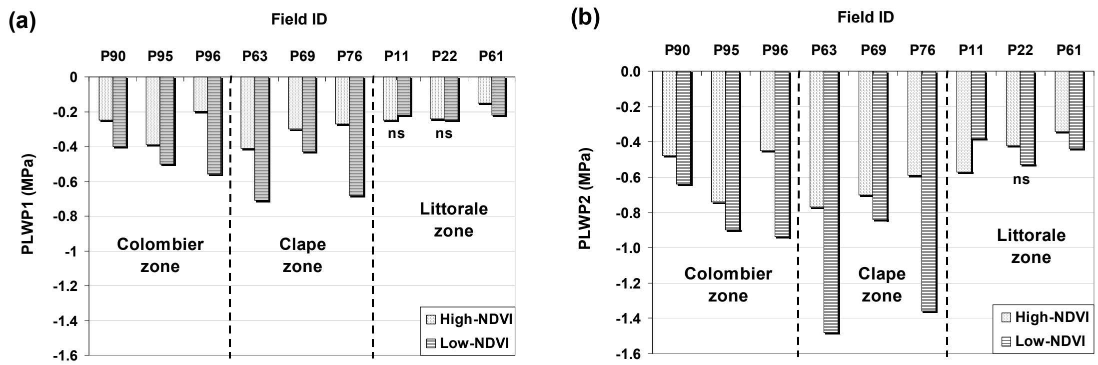


Fig 4. Pre-dawn leaf water potential measurements (PLWP1 and PLWP2) for two different growing periods: (a) post-setting (July 2006) and (b) post-veraison (August 2006). Each bar represents a within-field measurement of high and low NDVI zones (Vine vegetative expression). Values followed by '**ns**' are not significantly different (Kruskal-Wallis $p \leq 0.05$). Each value represents an average of nine plants.

The particular results observed for Lit can be explained. This soil unit presents particular conditions: deep sandy-loam soils with higher water storage capacity compared to Cla and Col soil units. This fact explains the low SE_resistivity values observed for the fields in the Lit soil unit. In these fields, water is not a limiting factor for vegetative growth. These fields developed the highest canopy area and also the highest evaporative demand. Later in the summer (August), sectors with the higher vegetative growth have the highest water consumption leading to water restriction symptoms (lower PLWP). This phenomenon can be seen as an induced water restriction.

This result is of importance since it demonstrates the limit of our approach. It shows that NDVI information and soil electrical resistivity may be relevant to define water restriction zones. However, such information needs to consider a previous delineation of the main soil types.

Other measured variables

The majority of the vegetative growth variables (canopy height, canopy thickness, canopy area and trunk circumference) showed significant differences between zones of high and low NDVI (Table 4). The major plant growth differences were observed in the fields located in the Cla and Col. These results are in agreement with PLWP values and soil electrical resistivity (Table 4). Large variations of vegetative expression are related with large differences in soil electrical resistivity.

It is important to mention that the major differences in vegetative growth variables (trunk circumference and plant canopy area) were observed in fields located in the Cla and Col, which were correlated to PLWP values (described previously). Furthermore, minor differences in both variables (vegetative growth and PLWP) were observed in the Littoral. Thus, Table 4 shows very similar results. Trunk circumference integrates information of vine growth from establishment, therefore, zones identified by trunk circumference can be considered as stable on this non-irrigated vineyard.

Table 4. Summary of ground-based measurements in the dataset collected for this study (14 March, 04 July and 06 August 2006).

	14 March		04 July			06 August		
Fields ID	Trunk circumference (mm)	SE_resistivity (ohm)	Canopy height (cm)	Canopy thickness (cm)	Canopy area (m^2/pl)	Canopy height (cm)	Canopy thickness (cm)	Canopy area (m^2/pl)
Colombier:								
P90:								
Low	241.95	4.76	113.8	49.5	1.19	108.8	51.6	1.12
High	268.36	2.59	135.1	54.6	1.94	140.0	59.3	2.09
Sign.[y]	p≤0.001	P≤0.01	p≤0.001	p≤0.05	p≤0.001	p≤0.001	p≤0.001	p≤0.001
P95:								
Low	228.81	1.70	115.2	45.4	1.34	108.7	44.5	1,09
High	291.50	1.85	138.4	62.5	2.49	133.5	62.0	2.52
Sign.	p≤0.001	n.s	p≤0.001	p≤0.001	p≤0.001	p≤0.001	p≤0.001	p≤0.001
P96:								
Low	270.33	2.65	91.0	49.8	0.86	92.0	50.9	0.84
High	395.86	1.93	133.0	77.7	2.67	128.3	78.9	2.60
Sign.	p≤0.001	P≤0.01	p≤0.001	p≤0.001	p≤0.001	p≤0.001	p≤0.001	p≤0.001
Clape:								
P63:								
Low	107.16	59.50	97.0	46.0	1.89	91.5	41.7	1.38
High	133.97	16.44	143.0	64.5	3.03	149.5	69.9	3.20
Sign.	p≤0.001	p≤0.01	p≤0.001	p≤0.001	p≤0.001	p≤0.001	p≤0.001	p≤0.001
P69:								
Low	142.1	72.36	105.5	47.2	2.23	103.5	49.1	2.04
High	210.03	10.76	160.5	67.3	3.72	152.0	68.6	3.39
Sign.	p≤0.001	p≤0.01	p≤0.001	p≤0.001	p≤0.001	p≤0.001	p≤0.001	p≤0.001
P76:								
Low	105.32	14.30	99.0	55.1	1.91	97.0	53.7	2.01
High	136.30	5.16	156.5	84.3	3.63	145.0	75.4	3.34
Sign.	p≤0.001	p≤0.01	p≤0.001	p≤0.001	p≤0.001	p≤0.001	p≤0.001	p≤0.001
Littorale:								
P11:								
Low	117.08	3.47	96	44.5	1.82	102.5	45.8	2.17
High	111.80	3.26	111.5	61.0	2.61	114.5	59.5	2.68
Sign.	n.s	P≤0.05	p≤0.001	p≤0.001	p≤0.001	p≤0.05	p≤0.001	p≤0.001
P22:								
Low	115.04	3.39	130.5	50.3	2.45	89.3	43.6	1.79
High	128.24	3.81	146	64.7	3.36	113.5	57.3	2.68
Sign.	p≤0.001	n.s	p≤0.01	p≤0.001	p≤0.01	p≤0.001	p≤0.001	p≤0.01
P61:								
Low	220.76	3.95	95.5	47.3	1.41	96.5	49.0	1.42
High	246.85	2.34	149.5	68.4	3.49	153.0	68.0	3.53
Sign.	p≤0.001	p≤0.01	p≤0.001	p≤0.001	p≤0.001	p≤0.001	p≤0.001	p≤0.001

[y]Values followed by 'ns' are not significantly different (Kruskal-Wallis $p \leq 0.05$).

The results obtained in SE_Resistivity also presented strong similarities with trunk circumference measurements. This indicates that the variability in vegetative expression may often be stable and dependent on soil variability. This effect highlights the relevance of soil electrical resistivity for zoning purposes (but not on all the soil units considered).

Conclusions

This experiment showed that the information provided by airborne imagery and soil electrical resistivity is relevant to characterize the spatial variability of plant water status at a within-vineyard scale. However, it also highlights the necessity to consider each soil unit separately since NDVI or electrical resistivity may exhibit different spatial phenomena depending on the particular part of the vineyard. To be applied to the whole vineyard, this approach has to integrate additional information such as soil units based on expert analysis or auxiliary information (such as elevation, soil depth, soil colour or other knowledge).

The results showed that zones based on NDVI information either in 1999, 2006 or in 2007 exhibited significant differences in vine vegetative expression, yield and plant water status. Moreover, the results observed in soil electrical resistivity and vine trunk circumference prove the temporal stability of the zoning (at least over the 3 experimental years), its link with soil variables (soil depth, water availability) and its relevance to define vine water restriction zones. Unfortunately, quality differences were barely exhibited between the NDVI zones. This result shows the limits of this approach for grape quality assessment in non-irrigated conditions. It highlights the necessity to develop a more comprehensive approach to provide an assessment of the quality parameters based on this type of information. High spatial resolution information like airborne imagery and soil electrical resistivity offer great promise to characterize within-field variability in yield, vegetative expression and water restriction. Thus, this type of information constitutes relevant decision support to design zones of different water restriction.

Acknowledgements

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CHAPTER IV

Chapter 4: Spatial extrapolation of the vine (*Vitis vinifera* L.) water status: a first step towards a spatial prediction model.

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Running title: Spatial extrapolation of vine water status

Abstract
The goal of this paper is to propose a model that allows for spatial extrapolation of the vine water status over a whole field from a single reference site. The precision of the model was tested using spatial plant water status data from a commercial vineyard block located in Languedoc-Roussillon Region, France. Observations of plant water status were made on 49 sites (three vines per site) on a regular grid at various times in the growing seasons over two non-irrigated fields planted with Shiraz and Mourvèdre cultivars. Plant water status was determined by measuring predawn leaf water potential (PLWP). Results showed a significant within-field variability of PLWP over space and time, and the existence of significant linear relationship among PLWP values measured at different dates. Based on these results, a linear model of spatial extrapolation of PLWP values was proposed. This model was able to predict spatial variability of PLWP with a spatial and temporal mean error less than 0.1 MPa on Shiraz as well as on Mourvèdre. This model provides maps of spatial variability in PLWP at key phenological stages on the basis of one measurement performed on a reference site. The model calibration is, in its current state, based on a significant data base of PLWP measurements. This makes unrealistic its application to commercial vineyards. However, the approach constitutes a significant step towards the spatial extrapolation of vine water status. Finally, the paper mentions alternative ways to build up such models using auxiliary information such as airborne imagery (NDVI), apparent soil conductivity (ECa) and easily measured vine/canopy development parameters.

Keywords: predawn leaf water potential, spatial prediction model, spatial and temporal variability, vine water status, grapevine.

Introduction
The evolution of vine water status throughout the vineyard growth cycle has a direct effect on grape composition and harvest quality through its influence on vegetative growth, fruit growth, yield, canopy microclimate, and fruit metabolism (Tisseyre et al. 2005; Ojeda et al. 2002, 2004; Dry and Loveys 1998; Champagnol 1984; Seguin 1983). Therefore, it is important to monitor vine water status to either predict expected harvest quality or as an important source of critical information for on-farm management such as irrigation strategies,

canopy management, etc (Choné et al. 2001; Naor et al. 1997). From an irrigation point of view, the vine water status is of critical importance for deciding whether or not irrigation practice is required at a given time (Girona et al. 2006; Olivo et al. 2009). Adequate irrigation management can be performed using vine water status monitoring over time. Depending on the accuracy of the method used, vine water status monitoring can lead to the development of a relevant decision support tool, which could enable grape growers to optimally manage vineyards for vegetative and fruit growth (Van Leeuwen and Seguin 1994; Naor et al. 2001; Ojeda et al. 2002).

Several methods of reference have been proposed to measure plant water status, such as Leaf Water Potential (LWP), Stem Water Potential (SWP), and Predawn Leaf Water Potential (PLWP) (Schultz 1996; Choné et al. 2001; Ojeda et al. 2002; Carbonneau et al. 2004; Girona et al. 2006; Sibille et al. 2007). Therefore these methods are widely used and constitute reference measurements of vine water status, from low to very high levels of water restriction (Ojeda et al. 2002; Tisseyre et al. 2005; Sibille et al. 2007). However, plant water status measurements are not easy to obtain, since they are manual techniques, requiring pressure chamber devices, nitrogen bottles and a certain level of skill in collecting the data (Sibille et al. 2005, 2007; Carbonneau et al. 2004; Ojeda et al. 2002, 2004; Gaudillère et al. 2002).

Obviously, these constraints make systematic Spatio-Temporal (S-T) vine water status measurements difficult to perform and time consuming. This explains the reason that this type of measurement has mainly been dedicated for monitoring the temporal change in vine water status. As a result, these measurements are usually reported with low spatial resolution (S), and there is often an assumption that vine water status is homogeneous over the area that the measurements are performed on (i.e. a site, a block or even a vineyard).

However, many authors have shown that most vineyards present a significant spatial variability at the within-field scale (Ortega et al. 2003; Bramley and Hamilton 2004; Taylor et al. 2005). This variability has been observed on many different variables (i) vegetative growth (number of shoots and canopy density), (ii) sugar and grape quality components and (iii) yield (Bramley and Hamilton 2004; Taylor et al. 2005). One of the main influencing factors is non-uniform soil water availability, due to differences in soil depth and soil physical properties. Significant variability of the vine water status within vineyards has already been shown by some authors under irrigated and non-irrigated conditions (Tisseyre et al. 2005; Ojeda et al. 2005a), especially at the end of the summer, when vines are subjected to significant water restriction levels.

These results support the need to study and consider the spatial variability of plant water status for a complete S-T analysis to help growers to manage irrigation, canopy architecture and grape quality more efficiently either under irrigated or non-irrigated conditions. An efficient decision support tool should be based on a S-T monitoring system of vine water status. It should be able to provide maps or snapshots of the spatial variability of plant water status over the whole vineyard at each of the key stages of the growing season. This spatial overview would permit suitable managerial decisions according to the spatial importance of the studied phenomena (vine water status) (Acevedo-Opazo et al., 2008b).

This work is a preliminary study towards a spatial prediction model of vine water status. The aim of this work is to test the feasibility of extrapolating single vine water status measurements to several unsampled locations. The aim is also to establish and to test a model of spatial extrapolation which will constitute a basis for further improvements. This paper presents: (i) a formalization of the model proposed and the underlying assumptions, (ii) the database used to calibrate and validate the model and, (iii) results obtained on the database as well as a discussion on the limits of the proposed approach, and, finally, (iv) further possible improvements.

Theory

Model description and assumptions

In the following sections, $z_{re}(s_{re}, t_j)$ is used to denote the reference measurement at s_{re} the reference site and at time t_j. The goal of the model is to extrapolate plant water status measured at time t_j, from the reference point $z_{re}(s_{re}, t_j)$ to a domain scale (D) at the same time (t_j). The location s_{re} belongs to D, and D can be either a block or a set of blocks or a whole vineyard depending on characteristics which will be detailed later. The model provides an estimation of the predicted plant water status value $\hat{z}\,(s_i, t_j)$ on the location s_i (with $s_i \in \mathrm{D}$ and $s_i \neq s_{re}$) at time t_j, from $z_{re}(s_{re}, t_j)$. Let's note g_{s_i} the site i related function. The model has been summarized in equation (1):

$$\hat{z}\,(s_i, t_j) = g_{s_i} \cdot \left[z_{re}\,(s_{re}, t_j) \right];\; s_{re} \in \mathrm{D},\; \forall s_i \in \mathrm{D} \tag{1}$$

The model (1) can be seen as a collection of site-specific functions $(g_{s_1}, g_{s_2}, g_{s_3}, \ldots, g_{s_i} : i = 1,2,3, \ldots, n)$ on each location into D. Such a definition of the model leads to several considerations:

(i) The model only focuses on spatial variability. Temporal evolution of plant water status is only taken into account through the reference measurement $z_{re}(s_{re}, t_j)$. To model spatial variability at a given date t_j, the model requires a reference measurement at the same date.

(ii) Each function g_{s_i} is assumed to be only dependent on differences in local attributes that determine soil water availability (soil properties, soil depth, topography, etc.) between location s_i and location s_{re}. These differences in local attributes are assumed to be time stable: can be used, whatever the date on which the extrapolation is performed.

(iii) The incidence of the climate and the resulting temporal variability on the plant water status is only taken into account through z_{re}. This means that the D area has to be small enough to neglect climate variability. In other words, climate is assumed to be homogeneous over D.

(iv) Vine variety, rootstock, date of plantation, training system, disease infestation and other parameters that can affect plant response are assumed to be the same over D or to have a small effect on the plant water status.

Model selection and model computation

This study aimed at verifying whether the proposed approach was relevant to provide a spatial estimation of the plant water status. As a first approach, it focused on a simple model, which was easy to set up and to calibrate with experimental data.

In this work, the domain D was considered as a vine field and g_{s_i} functions reduced to a collection of linear coefficients. Thus equation (1), can be rewritten as:

$$\hat{z}\,(s_i, t_j) = a_{s_i} \cdot z_{re}\,(s_{re}, t_j);\; s_{re} \in \mathrm{D},\; \forall s_i \in \mathrm{D},\; a_{s_i} \in \Re\,, \qquad (2)$$

Equation (2) assumes that there is a collection of site-specific coefficients a_{s_i} that are able to model the difference in plant water status between each location s_i and the location s_{re} of D. Therefore, a_{s_i} coefficients is considered dependant on differences in permanent attributes between location s_i and location s_{re}. These attributes would be also need to be constant over time or their change predictable.
The test protocol includes the following steps:

(i) to choose one or several domains D to carry out the tests,
(ii) to build up a data base of plant water status values with a high spatial and temporal resolution,
(iii) to choose a reference site (s_{re}) for each considered domain,
(iv) to determine the collection of a_{s_i} coefficients over each D,
(v) to compute, from the model and the reference measurement, the predicted plant water potential values over D for each available date,
(vi) to test the ability of the model to predict vine water status at unsampled locations. Two kinds of prediction errors need to be considered; the prediction error for each location (s_i) over the time and the prediction error for each available date (t_j).
(vii) and finally, to test the sensitivity of the model to the choice of the reference site (s_{re}).

The methods used to fulfil these requirements are detailed in the following section.

Materials and methods

Experimental field and plant material description

Experiments were carried out on the experimental vineyards of Pech-Rouge (INRA-Gruissan, N 43º08'47'', E 03º07'19'' WGS84, Languedoc-Roussillon region, France). Two fields (two domains) were selected for the experiments. These two domains of 1.2 and 1.7 ha were planted with Shiraz and Mourvèdre cultivars respectively. These two cultivars were chosen because they may present different responses to water restriction. Shiraz is more susceptible to water restriction than other varieties (i.e. Mourvèdre, Grenache, among others) (Schultz 2003; Ojeda et al. 2005b). Note that the goal of the study is not to compare these two cultivars. These two cultivars were chosen to test the relevance of the proposed approach with different conditions. Both domains are non-irrigated and were established in 1990. They were planted on a limestone plateau (shallow soil with superficial clayey colluvial soils) and were trained in a vertical shoot positioning system with spacing of 1 m between vines and 2.5 m between rows. Within each domain, 49 measurement sites ($s_1, s_2, ..., s_i$: i= 1, 2, ..., 49) were defined on a regular grid. Figure 1a and 1b show the fields and sample grids location. Domain contours and within domain sites locations were geo-referenced with a Differential Global Positioning System (DGPS) (Leica Geosystems Ltd., model GS 50 with OMNISTAR differential correction) according to the French system (Datum RGF93, Projection Lambert93) allowing mapping and spatial analysis.

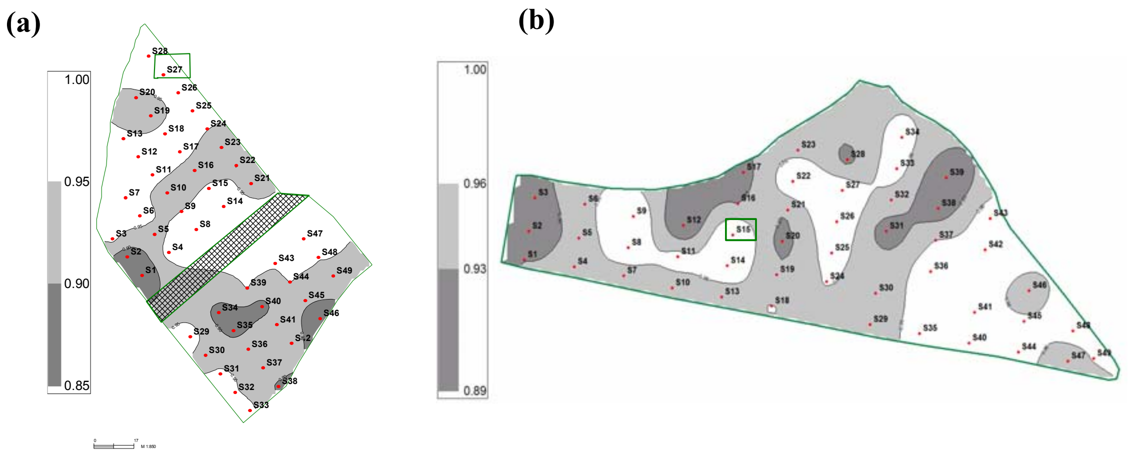


Figure 1. Correlation map of all the sites with the reference site (site 27 on the Shiraz (a) and site 15 on the Mourvèdre (b), both in a frame), in white correlation higher than the median, in grey correlation lower than the median, in dark grey the lowest correlations.

Both domains are located on soil derived from interbedded micritic limestone with important accumulations of red clay in some parts of the field. These accumulations impact variability.
The soil at a site or within a block determines the amount of water that is available to the plant (both from a moisture–holding capacity % and potential for root development) (Guswa 2005; Acevedo-Opazo et al. 2008b). Since each block is assigned to a broad soil type, the within block differences in vegetative expression are related, in part, to variation in soil within the block. Figure 2a and 2b show Normalized Difference Vegetation Index (NDVI) maps (during the full vine canopy expansion period), from an airborne image acquired in August 2006. These maps highlight the spatial patterns of canopy development in relation with soil water availability (Acevedo-Opazo et al. 2008a). The observed variability may be related to soil variability, especially in this non-irrigated conditions.

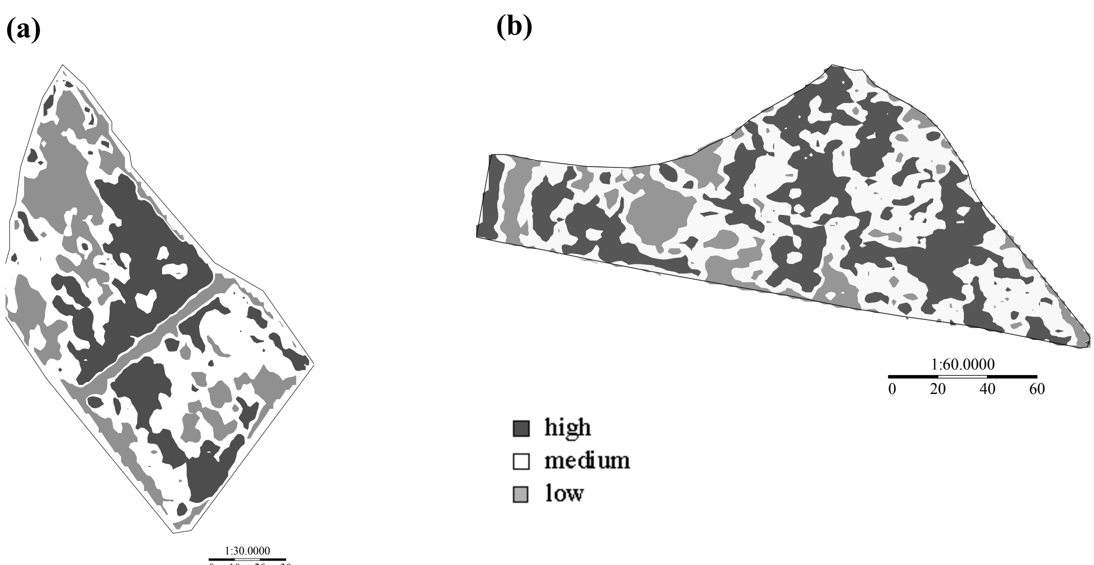


Figure 2 Maps of normalized difference vegetation index (NDVI) estimated at August 2006: (**a**) on Shiraz and (**b**) on Mourvèdre. NDVI data were mapped in 33% quantiles. The class "very low" (light grey) corresponds to the 0-33 % quantile, the class "medium" (white) corresponds to the 33-67 % quantile and the class "high" (dark grey) corresponds to 67-100 % quantile of the NDVI values.

Variables of interest

Data was collected in non-irrigated conditions with a climate leading to high to very high water restriction. In these particular conditions, PLWP is considered the best reference measure to highlight spatial variability under high water restriction conditions (Sibille et al. 2007). PLWP measurements were carried out between 3:00 and 5:00 a.m. with a pressure chamber (Scholander et al. 1965). A PLWP value at site s_i at time t_j ($z(s_i,t_j)$) corresponded to the average of three measurements on three representative vines for each of the 49 measurement sites.

In order to test the temporal consistency of this approach, within field PLWP measurements were performed during two years for each domain. On each of the 49 sites, PLWP was measured at seven dates in 2003 and six dates in 2004 on the Shiraz, six dates in 2005 and three dates in 2006 on the Mourvèdre. Figure 3 summarises the different dates of the measurement.

Seasonal dryness characterization

Experiments were carried out during four different years with different climatic conditions. The dryness index (DI), proposed by Tonietto and Carbonneau (2004), was used to characterise the seasonal potential soil water balance. This index is based on Riou's index (Riou et al. 1994) and acts as an indicator of the level of dryness calculated on a 6-month period from April 1st to September 30th. Based on the DI value, four classes are usually considered: (i) humid (wet climate with DI > 150 mm), (ii) sub-humid (150 > DI > 50 mm), (iii) moderately dry (50 > DI > -100 mm), and (iv) very dry (DI < -100 mm). These last two classes present conditions where vines potentially face a moderate to significant level of water restriction.

Data mapping and preliminary data analysis

Data mapping was performed using the 3Dfield software (Version 2.9.0.0, Copyright 1998-2007, Vladimir Galouchko, Russia). The interpolation method used in this study was based on a deterministic function (inverse distance weighing).

The classes used to build up the map corresponded to expert classes proposed by Ojeda et al 2005a. The software package Matlab® v7.0 (Mathworks, Inc.) was used for data analysis and model programming. PLWP values of each domain were subjected to linear coefficient of correlation analysis and covariance analysis between two sites (s_i and s_k) over time as indicated by equations (3) and (4).

The regression coefficient between two measurement sites ($s_i \neq s_k$) was then determined as follows:

$$r = \frac{cov\left[z(s_i), z(s_k)\right]}{\sigma s_i \cdot \sigma s_k} \tag{3}$$

where σ_{s_i} (respectively σ_{s_k}) corresponds to standard deviation of PLWP values observed on each location s_i (resp. s_k) over the time.

$$cov\left[z(s_i), z(s_k)\right] = \frac{1}{m}\sum_{j=1}^{m}\left[\left(z(s_i,t_j) - \overline{z(s_i)}\right)\cdot\left(z(s_k,t_j) - \overline{z(s_k)}\right)\right] \tag{4}$$

where $\overline{z(s_i)}$ (respectively $\overline{z(s_k)}$) corresponds to the mean of the values measured on the site s_i (resp. s_k) for all the available dates m (m = 13 for Shiraz and m = 9 for Mourvèdre).

Model computation

As mentioned previously, the model computation requires several steps to be completed.

Step 1: selecting a reference site (s_{re}) for each domain D

This reference site selection is important since s_{re} provides the reference PLWP which will be extrapolated over D. This choice, as well as the number of reference sites raise many questions and require specific experiments and work on itself. In order to cope with this problem, in a first part the reference sites were randomly selected for each domain. Figure 1a and 1b shows within a frame, the locations of s_{re} for the Shiraz (site 27) and the Mourvèdre (site 15).

For each field, values of PLWP measured on s_{re}, at all the dates, were removed from the data base to generate the $\boldsymbol{r_{ef}}$ vector (5):

$$\left(\boldsymbol{r}_{ef}\right)^{\mathrm{T}} = \left[z\left(s_{re},t_1\right), z\left(s_{re},t_2\right), z\left(s_{re},t_3\right),\ldots, z\left(s_{re},t_m\right)\right], \tag{5}$$

Step 2 : determination of the collection of coefficients over D

The matrix of PLWP values of all sites (except s_{re}) for each domain and for all the dates can be represented as $\mathbf{Z}$:

$$\mathbf{Z}=\begin{bmatrix} z(s_1,t_1) & z(s_1,t_2) & z(s_1,t_3) & \cdots & z(s_1,t_m) \\ z(s_2,t_1) & z(s_2,t_2) & z(s_2,t_3) & \cdots & z(s_2,t_m) \\ z(s_3,t_1) & z(s_3,t_2) & z(s_3,t_3) & \cdots & z(s_3,t_m) \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ z(s_n,t_1) & z(s_n,t_2) & z(s_n,t_3) & \cdots & z(s_n,t_m) \end{bmatrix}, \tag{6}$$

This step consists in finding the vector $\boldsymbol{a}$ (coefficients) to provide an estimation $\hat{\mathbf{Z}}$ for PLWP values over D, such as the indicated by the following relation:

$$\hat{\mathbf{Z}} = \boldsymbol{a}\cdot\left(\boldsymbol{r}_{ef}\right)^{\mathrm{T}}, \tag{7}$$

with,

$$\boldsymbol{a}=\begin{bmatrix} a_{s_1} \\ a_{s_2} \\ a_{s_3} \\ \vdots \\ a_{s_n} \end{bmatrix} \quad \text{and} \quad \hat{\mathbf{Z}}=\begin{bmatrix} \hat{z}(s_1,t_1) & \hat{z}(s_1,t_2) & \hat{z}(s_1,t_3) & \cdots & \hat{z}(s_1,t_m) \\ \hat{z}(s_2,t_1) & \hat{z}(s_2,t_2) & \hat{z}(s_2,t_3) & \cdots & \hat{z}(s_2,t_m) \\ \hat{z}(s_3,t_1) & \hat{z}(s_3,t_2) & \hat{z}(s_3,t_3) & \cdots & \hat{z}(s_3,t_m) \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ \hat{z}(s_n,t_1) & \hat{z}(s_n,t_2) & \hat{z}(s_n,t_3) & \cdots & \hat{z}(s_n,t_m) \end{bmatrix}, \tag{8}$$

The least square error method was used to determine the vector $\boldsymbol{a}$ as follows:

$$\boldsymbol{a} = [\boldsymbol{Z}] \cdot \boldsymbol{r}_{ef} \cdot \left[\left[\boldsymbol{r}_{ef} \right]^T \cdot \left[\boldsymbol{r}_{ef} \right] \right]^{-1} \tag{9}$$

<u>Model evaluation</u>

The precision of the model was assessed using the Standard Error of Calibration (*SEC*) which was computed as follow:

$$SEC = \sqrt{\frac{\sum_{i=1}^{n}\sum_{j=1}^{m}\left(E\left(s_i,t_j\right)\right)^2}{(n.m)-1}} \text{ , with } E\left(s_i,t_j\right) = \left(\hat{z}(s_i,t_j) - z(s_i,t_j)\right) \tag{10}$$

Where n is the number of sites on D and m is the number of available dates.

The ability of the model to predict values of PLWP was assessed using a "leave-one-out" validation procedure (Saporta 1990). The database was divided into 'm' subsets (k_1, k_2, k_3,…, k_m) corresponding to the m measurement dates. Similarly, the reference measurements obtained on the reference site (s_{re}) were divided into m singletons. Thus, m different models were assessed, leaving out one of the subsets k_1, k_2,…, k_m and only using the omitted subset to compute the error. Two types of prediction errors were computed: (i) the standard error of prediction at a given time t_j ($SEPt_j$) and (ii) at a given site s_i ($SEPs_i$), equations (11) and (12):

$$SEPt_j = \sqrt{\frac{\sum_{i=1}^{n}\left(E\left(s_i,t_j\right)\right)^2}{n-1}} \tag{11}$$

$$SEPs_i = \sqrt{\frac{\sum_{j=1}^{m}\left(E\left(s_i,t_j\right)\right)^2}{m-1}} \tag{12}$$

<u>Sensitivity to the choice of the reference site</u>

The sensitivity of the model to the choice of the reference site was undertaken by calibrating the model for all reference sites at all dates. For each case, the SEC (equation 10) was computed in order to analyse the error distribution caused by the choice of the reference site.

Results and discussion

<u>Spatial and temporal analysis of plant water status</u>

Table 1 presents the results of DI calculated for each of the 4 years of experiments. Season 2003 presented the lowest DI (DI = -128 mm) corresponding to a very dry climate. Seasons 2004, 2005 and 2006 presented DI corresponding to moderately dry climate. However, 2006 presented low DI (DI = -92) close to very dry climate. These results show that drastic to very drastic water deficits were experienced during the four years of the experiments. According to these results, in 2003 and to a lesser extent in 2006, very high vine water restriction was expected. This was only partially the case in 2006 due to a 45 mm rainfall event recorded in mid-august, which drastically reduced plant water restriction on the vine at the end of summer.

Table 1 Summary of the main climatic parameters characterizing growing conditions during the four years that experiment was carried out: cummulated precipitation (Pp), cummulated reference evapo-transpiration (ET_0) and resulting Dryness Index (DI).

Year	Pp (mm)	ET_0 (mm)	DI (mm)
2003	154	882	-128
2004	306	851	-64
2005	318	867	-8
2006	159	873	-92

Figures 3a and 3b, show changes in overall mean PLWP values over time for the Shiraz field and the Mourvèdre, respectively. At each date, mean PLWP was calculated from the 49 sites of measurements. In both domains, and for all the years studied, mean PLWP decreased during summer. PLWP ranges from -0.18 to -0.92 MPa in 2003, from -0.1 to -0.72 MPa in 2004 for the Shiraz and from -0.17 to -0.78 MPa in 2005 for the Mourvedre. For the latter domain, changes were less obvious in 2006 due to the rainfall of 45 mm observed seven days before the last PLWP measurement.

(a) **b)**

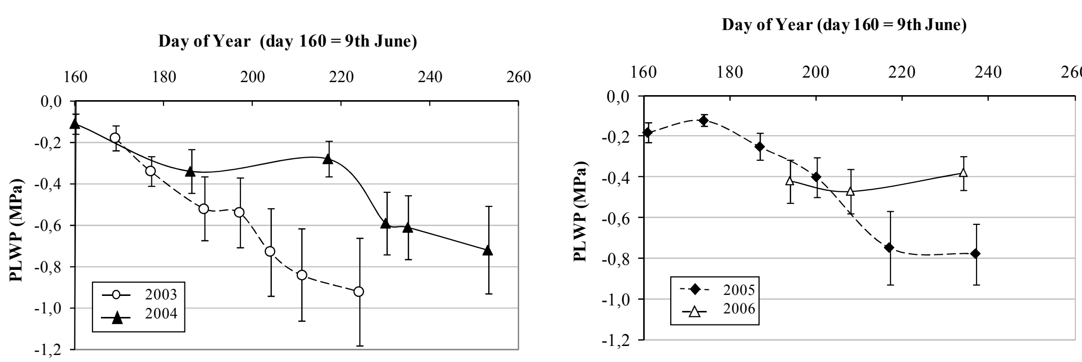


Figure 3 Mean domain predawn leaf water potential (PLWP) changes during summer 2003-2004 on the Shiraz (**a**) and 2005-2006 on the Mourvèdre (**b**). Vertical bars represent the standard deviation (SD).

Figure 3 also show the standard deviation (SD) of PLWP values within a whole domain for the Shiraz and Mourvèdre. In the case of Shiraz, SD increased from 0.06 MPa for the earliest measurement to almost 0.260 MPa for the last measurement in 2003. A similar tendency was observed in 2004 for this domain. For Mourvèdre, SD of PLWP values also increased from 0.047 to 0.148 MPa in 2005. Once again, due to the particular climate conditions, SD of PLWP values remained almost constant during summer 2006. Note (Table 2) that the standard deviation (SD) versus the mean value (coefficient of variation CV) is relatively stable. CV does not increase throughout the season showing that the SD is inscreasing with the mean of the field.

These preliminary results point out the significant PLWP within field variability observed in the domains, especially at the end of the summer. Simultaneous analysis of Figures 3a and 3b shows that within domains, the SD of PLWP values increased with increasing water restriction. Results show that (i) within field variability is significant; (ii) magnitude of variation changes over the time and (iii) a decision (for example irrigation) based on the mean domain water restriction may be inappropriate for a significant part of the field, if the variability is spatially structured.

Spatial analysis of the plant water status

Figures 4a, b and c, show three examples of linear relations between PLWP measured on reference site (s_{re}) and three other sites over two years (2003-2004) within the Shiraz. The worst, the best and the median correlation coefficients (r) were chosen to illustrate the dispersion of the linear relations observed between s_{re} and all the other sites on this domain. The worst linear relation presented a correlation coefficient of r = 0.77 (site 1), the best relation (site 25) presented an r = 0.99 and the intermediate site, which corresponds to the median of the correlation coefficient, presented an r = 0.95 (site 42). Spatial distribution of these correlation coefficients for the Shiraz is shown in Figure 1a.

Very similar results were observed over years 2005 and 2006 for the Mourvèdre. The lowest r was of 0.87 (site 38) while the highest was of 0.99 (site 22) in this domain. The results of linear relations are not presented, however Figure 1b shows the spatial distribution of correlation coefficients obtained over this domain.

The results presented in Figure 4 show that the spatial trend of plant water status is linear, which allows to propose a linear model to spatially predict vine water status (equation 2) across a vine field, using a reference measurement of PLWP. Despite the significant spatial variability observed in vine water status, the results highlight a strong linear relation of PLWP among all domain sites although the slope of the relationship is not spatially constant. Thus, Given PLWP at a reference site $z_{re}(s_{re}, t_j)$ at time t_j, and a specific a_{s_i} that represents the relationship of site s_i to s_{re}, it is possible to provide an assessment of $z(s_i, t_j)$ at the same time, using this approach.

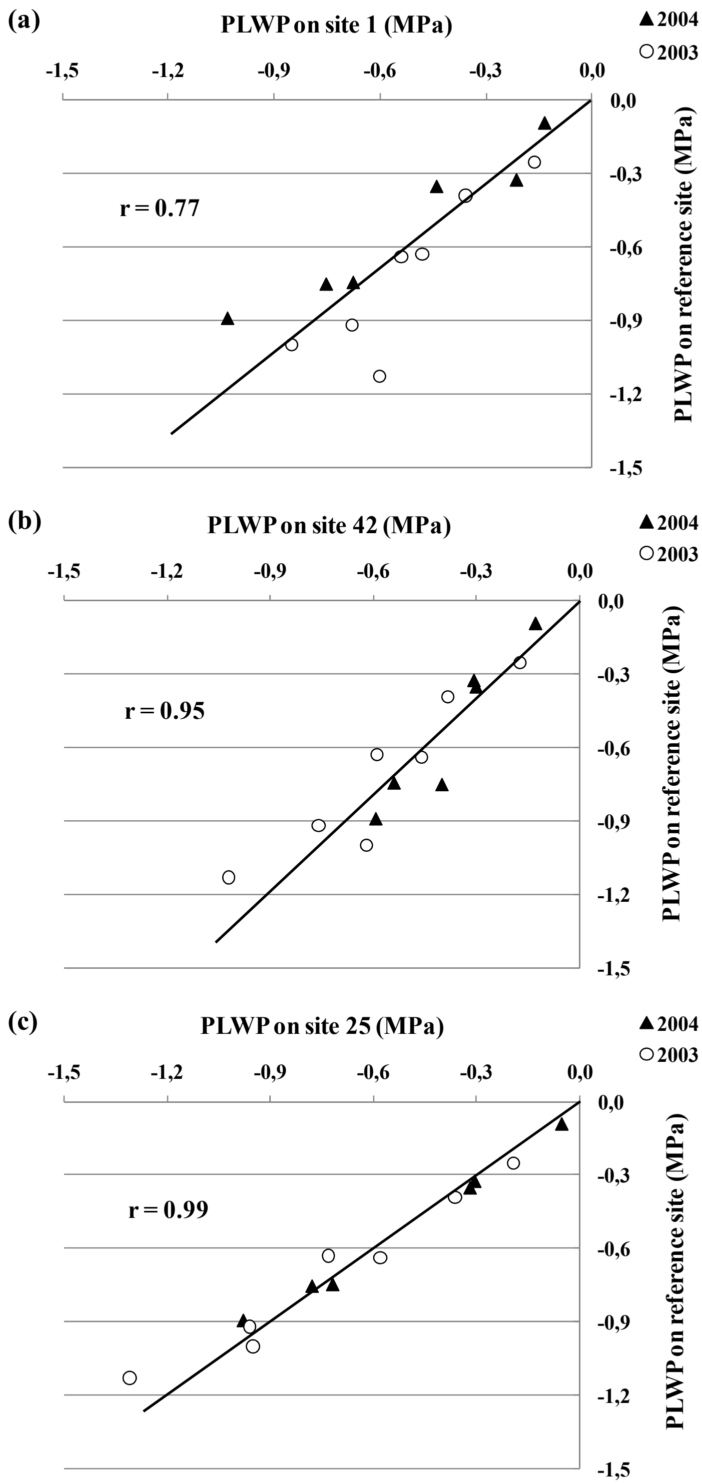


Figure 4 Example of linear relations between PLWP measured on the reference site (s_{re}) and three other sites over two years (2003-2004) within the Shiraz, (**a**) the worst relation between s_{re} and site 1, (**b**) the median relation between s_{re} and site 42 and (**c**) the best relation between s_{re} and site 25.

<u>Results of model calibration</u>

The Error of Calibration (SEC) of the model was 0.090 and 0.087 MPa on the Shiraz and Mourvèdre, respectively. Based on the range of values used by the viticulturists and wine growers to make an irrigation decision (± 0.2 MPa) (Ojeda et al. 2005a), the model was considered relevant and precise enough for management (note a more detailed analysis of the model precision will be based on the error of prediction in the next section).

Maps of the vector ***a*** after calibration of the model, for both domains are shown in Figures 5a and 5b. In order to simplify the reading, a_{si} were interpolated over the domains and four classes, based on the magnitude of observed variation, were defined. An increment of 0.2 units and 0.12 units were considered for the Shiraz and the Mourvèdre respectively. For the Shiraz and Mourvédre (Figure 5), the light grey areas represent the highest a_{si} values ($1.1 < a_{si} < 1.3$) on Shiraz and ($0.8 < a_{si} < 1$) on Mourvèdre. In Figure 5, the white zones systematically presented PLWP values higher than the reference site (s_{27}) in Shiraz and approximately the same PLWP values as the reference site (s_{15}) in Mourvèdre. Conversely, the black areas represent the lowest a_{si} values ($0.4 < a_{si} < 0.7$) for Shiraz and for Mourvèdre. These black areas present PLWP values lower than the reference site. Light grey areas represent zones where the PLWP response is similar to the reference site.

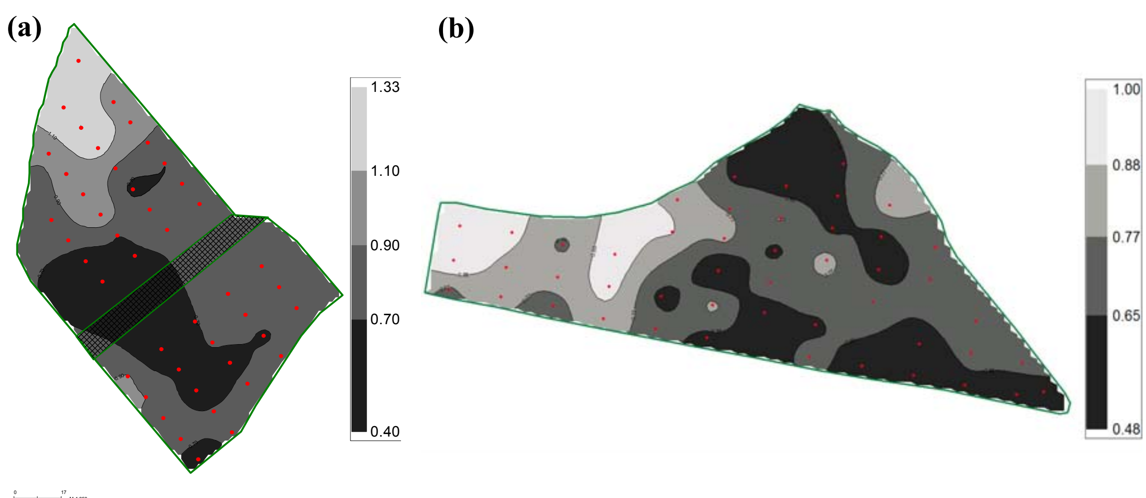


Figure 5. Maps of linear regression coefficients between the reference site (site 27 on the Shiraz (**a**) and site 15 on the Mourvèdre (**b**)) and the other sites of each domain ('vector ***a***' of the model).

The maps presented in Figure 5a and 5b summarizes the temporal and spatial behaviour of plant water status for each domain, relative to the site of reference. It is interesting to note that the maps provide information with a significant spatial organization. Indeed, for Shiraz (Figure 5a) white and light grey zones are located on the northern part of the field while the black area is located in the centre of the domain. This spatial organisation is less obvious for Mourvèdre, though light and dark zones seem to be organized along a west-eastern direction. The comparison of the within field variability between both fields as well as the analysis of vector ***a*** in relation with other parameters is not the purpose of this paper. However, Figure 2 and 5 show very similar pattern which supports the hypothesis that a_{si} is function of local environmental conditions (soil type, soil depth, water availability, etc.).

Table 2. Standard Error of Prediction at different time ($SEPt_j$) with the standard deviation of the field (SD), mean predawn leaf water potential (PLWP) and the percentage of variance explained by the model (r^2) and coefficient of variation (CV).

Shiraz

	2003							2004					
Date	18 jun	26 jun	08 jul	16 jul	23 jul	30 jul	12 aug	09 jun	05 jul	05 aug	18 aug	23 aug	10 sep
Time	t_1	t_2	t_3	t_4	t_5	t_6	t_7	t_1	t_2	t_3	t_4	t_5	t_6
$SEPt_j$	0.060	0.065	0.096	0.092	0.117	0.124	0.119	0.064	0.095	0.092	0.114	0.103	0.137
SD	0.060	0.072	0.157	0.167	0.210	0.222	0.260	0.050	0.106	0.083	0.152	0.155	0.209
PLWP	-0.18	-0.34	-0.52	-0.54	-0.73	-0.84	-0.92	-0.11	-0.34	-0.28	-0.59	-0.61	-0.72
CV (%)	33	21	30	30	28	26	28	45	31	29	25	25	29
r^2 (model)	0. 22	0.40	0.62	0.75	0.71	0.70	0.80	0.01	0.49	0.08	0.53	0.59	0.65

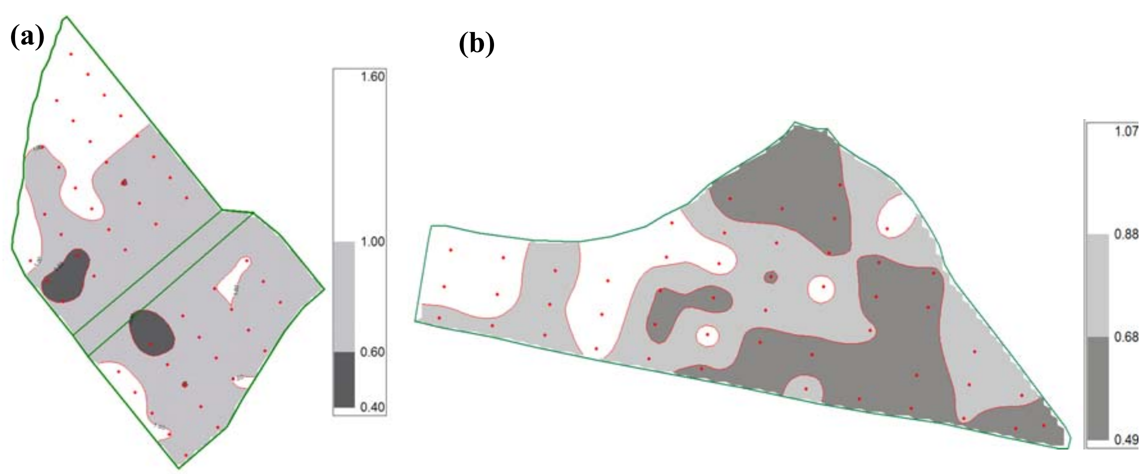
Mourvèdre

	2005						2006		
Date	10 jun	23 jun	06 jul	19 jul	05 aug	25 aug	13 jul	27 jul	22 aug
Time	t_1	t_2	t_3	t_4	t_5	t_6	t_1	t_2	t_3
$SEPt_j$	0.059	0.062	0.061	0.054	0.125	0.140	0.089	0.094	0.133
SD	0.047	0.031	0.065	0.097	0.180	0.148	0.105	0.108	0.085
PLWP	-0.17	-0.12	-0.25	-0.41	-0.75	-0.78	-0.42	-0.46	-0.38
CV (%)	27	25	26	23	24	19	25	23	22
r^2 (model)	0.05	0.08	0.22	0.77	0.74	0.58	0.43	0.38	0.14

Standard error of prediction over time ($SEPt_j$)
The $SEPt_j$ never exceeded 0.15 MPa (Table 2) for each domain. These results fit with management application requirements which require an accuracy of ±0.2 MPa. However, Table 2 shows that $SEPt_j$ is not constant over time. It increases with the SD through the seasons. For the Shiraz in 2003, $SEPt_j$ varied from 0.06 MPa, at the first date of measurement, to 0.119 MPa for the last date, which corresponded to the highest water restriction on the Shiraz. For the same domain and during the same period of time, SD for PLWP values varied from 0.06 MPa to 0.26 MPa. Similar results were observed in 2004 on the Shiraz and for both seasons on the Mourvèdre.

The percentage of variability explained by the model (r^2) was computed (Table 2) at all dates for both domains. It showed that whatever the case, r^2 increased significantly throughout the season. For the Shiraz in 2003, it increased from 0.2 to almost 0.8 for the date with the highest water restriction. Similar tendencies were observed in 2004, 2005 and 2006; the percentage of variability explained by the model never reached values higher than that found in 2003. Results presented in Table 2 show that the model became more and more relevant at high water restriction levels. This result seems logical, since significant spatial variability was previously shown to occur at high water restriction levels.

Examples of measured and predicted maps for a specific date (t_7 in 2003 and t_5 in 2005) are shown Figures 6a and 6b, and 6c and 6d, respectively. For all maps a common legend based on the ranges of PLWP currently used by viticulturists was used. These examples show that zones with significant water restriction (less than -1.0 MPa) located in the northern part of the Shiraz and in the western part of the Mourvèdre were accurately predicted. Similarly, zones with medium water restriction values were also accurately predicted in both domains.



(c) (d)

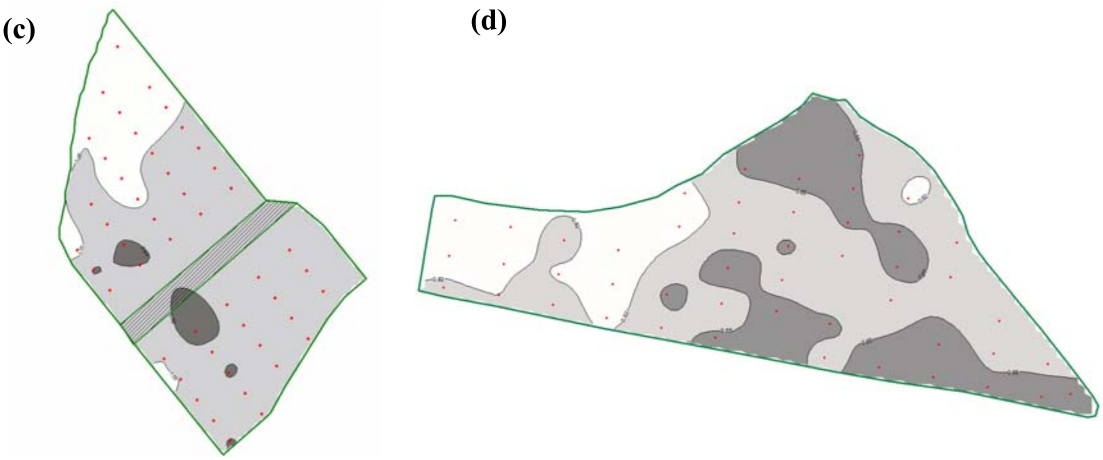


Figure 6 Maps of predawn leaf water potential at the date t_7 in 2003 on Shiraz and at the date t_5 in 2005 on Mourvèdre; (**a**) and (**b**) measured data on the Shiraz and the Mourvèdre, respectively; (**c**) and (**d**) predicted data from the model on the Shiraz and the Mourvèdre respectively. Very high water restriction (PLWP < -1.0 MPa); high water restriction (-1.0 < PLWP < -0.6 MPa); and medium water restriction (-0.6 < PLWP < -0.4 MPa).

Spatial Error of Prediction ($SEPs_i$)

The Spatial Error of Prediction ($SEPs_i$) was computed in order to check the spatial relevancy of the model. Figure 7a and 7b show maps of $SEPs_i$ for the Shiraz and Mourvèdre respectively.

Figure 7 shows that the error was low (<0.1 MPa) on approximately 70% of the area for both domains. Higher errors occurred only at two and three particular locations for Shiraz and Mourvèdre, respectively. Very high errors only occurred on one location in the Shiraz domain. These results show that the model provides relevant information on the major part of the domains.

(a) (b)

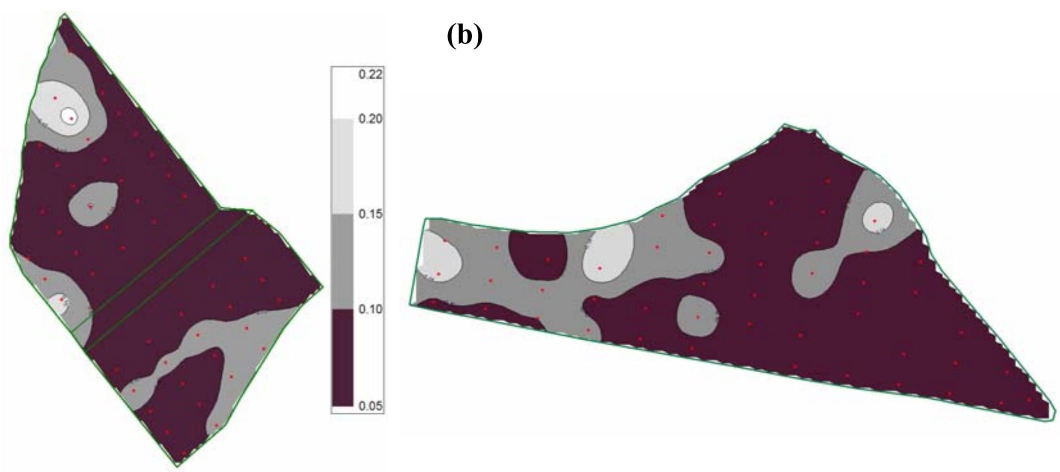


Figure 7 (**a**) and (**b**) map of standard spatial error of prediction ($SEPs_i$) on the Shiraz and the Mourvèdre, respectively. Low errors (0.05 to 0.1 MPa), medium errors (0.1 to 0.15 MPa); high errors (0.15 to 0.2 MPa) and very high errors (> 0.2 MPa).

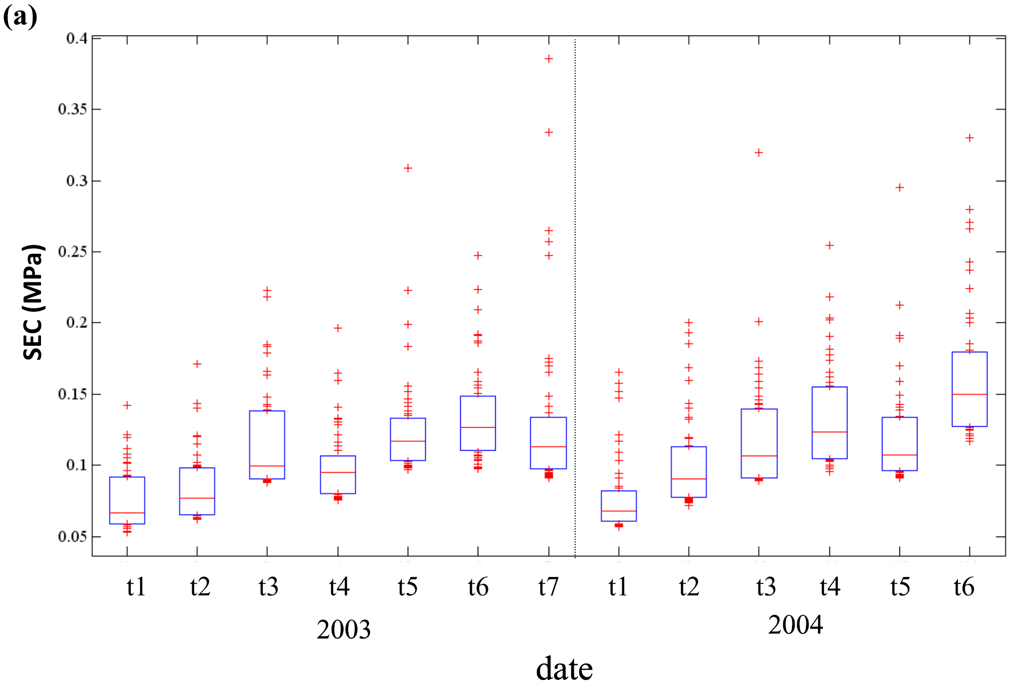
Maps presented in Figure 7 can be seen as an assessment of the spatial accuracy of the proposed model. It also gives the spatial uncertainty of predictions. White and light grey zones represent locations where low confidence is expected from extrapolation. For example, Figure 7a shows that predicted PLWP values were less reliable in the northern part and on the eastern side of the Shiraz field.

Figure 7 also shows a spatial structure in the zone of high spatial prediction error within the range of 0.15-0.22. This trend agrees with the spatial pattern observed in the zone with high water restriction (1.0-1.6 MPa) in Figure 6. However, this pattern in spatial error is not obvious in the zones where medium and low range of spatial error were observed, which correspond to almost 90% of the total surface in study. These last results show the ability of the reference site, in association with the model, to predict PLWP values over the whole field and not only on sites surrounding of the reference site.

Sensitivity to the choice of the reference site

An analysis of the sensitivity in the choice of the reference site was conducted for both fields and all the possible dates. Figures 8a and 8b present, for each of the dates, the distribution of the Standard Error of calibration (SEC) for Syrah and Mourvèdre, respectively. Figure 8 show that whatever the date, the mean SEC remains smaller than 0.15 MPa. As expected, the SEC due to the choice of the reference site increases with the mean water restriction of the field. Note also that the distribution of the SEC is larger for dates with high water restriction. This result is obvious for Syrah where SEC higher than 0.3 MPa are observed at dates t_5, t_7 in 2003 and t_3, t_6 in 2004. This observation is less significant for Mourvèdre and may be due to lower water restrictions observed for this field in 2005 and 2006. However, a higher distribution of SEC values is notable for higher water restrictions corresponding to dates t_5 in 2005 and t_3 in 2006. The choice of the reference site thus impacts more on the estimations performed at dates corresponding to high water restriction. To study this effect, a specific analysis was conducted at t_7 for Syrah in 2003 and t_5 for Mourvèdre in 2005. Figure 9 shows the Standard Error of Calibration (SEC) of the model with each site considered as a reference site.

(a)



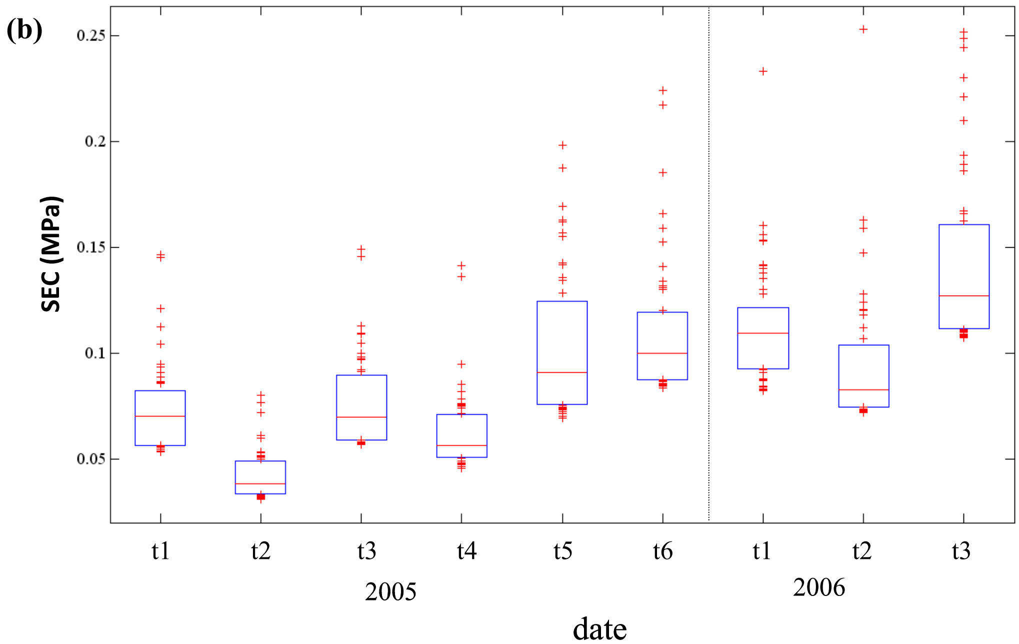


Figure 8 (**a**) and (**b**) incidence of the choice of the reference site on the standard error of calibration (SEC) of the model respectively for Shiraz and Mouvèdre and for all the dates. The limit of the box corresponds to the quartiles and the horizontal line to the median.

For Shiraz (Figure 9a) the majority of the sites lead to a SEC ranging from 0.07 MPa to 0.18 MPa showing their ability to predict the plant water status. However, 5 sites present a high SEC and can be considered as outliers. Three of them (s_1, s_2, s_5) were located in the western border of the field leading to a possible "interaction" with the nearby forest. The other two outliers (s_{34} and s_{15}) are located close to the border (track). For Mourvèdre, the SEC of the model was less than 0.2 MPa for almost all the sites (Figure 9b). Only two sites (s_{49} and s_{28}) present a SEC close to 0.2 MPa and again, these are points near to the edge of the field.

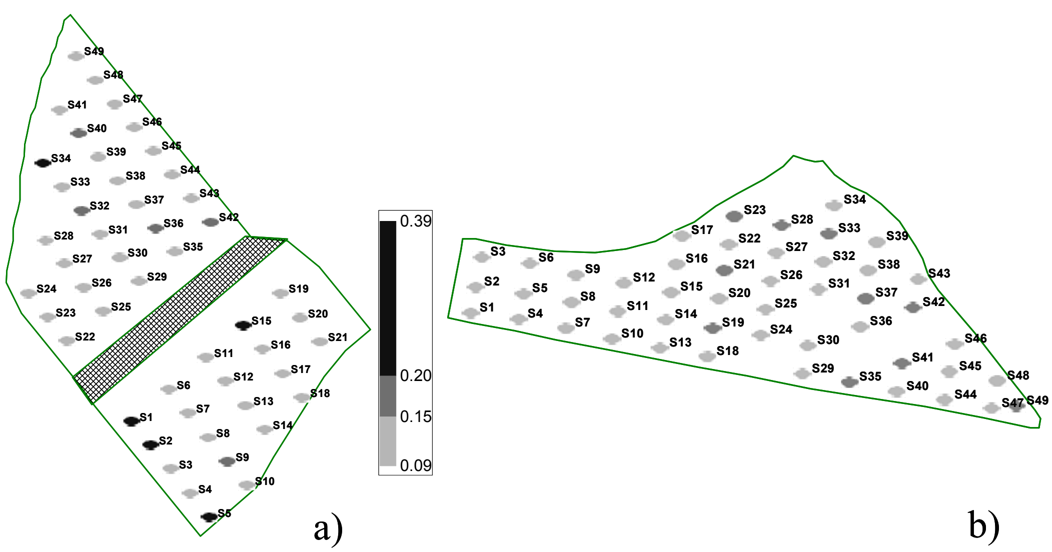


Figure 9 (**a**) and (**b**) maps showing the incidence of the choice of the reference site on the standard error of calibration (SEC) of the model respectively for Shiraz in 2003 (date 7) and Mouvèdre (date 5) in 2005.

Discussion on the practical application of the approach

The error of prediction of the model remained low compared to the SD. In this study, SD could be seen as the error resulting from a classical sampling procedure. When comparing SD with $SEPt_j$ it shows the relevance of a spatial model over a classical method (i.e. the mean of the field). Considering low water restriction (PLWP >-0.4 MPa), the SD values remained very similar when compared to $SEPt_j$ (Table 2). This shows that the spatial model was not able to provide additional information when compared to the mean value of the domain (computed from 49 samples). In some cases, results from the model were less representative than the mean value of the domain (some dates at the Mourvèdre field). These sub-optimal results at low water restriction may be explained by the fact that only one value (s_{re}) was used to predict the 48 remaining values. Therefore, considering low water restrictions, the method proposed may amplify the error made on the measurement at s_{re}. For higher water restriction levels (PLWP < -0.4 MPa), Table 2 shows that $SEPt_j$ values remained lower than SD. Therefore, when water restriction increases, the within-field variability of water restriction also increases due to the expression of other environmental variations on the plants access to water (i.e. soil variability). This result highlights the advantage of taking into account the spatial variability and therefore, the relevance of the proposed model for high water restriction (PLWP < -0.4 MPa).

On a practical point of view, this study shows that the approach was not so sensitive to the choice of the reference site. Obviously, slight differences in accuracy may be observed but, except in rare cases associated with edge effects, the choice of the reference site did not change much the quality of the model. The choice of the reference site and the number of reference sites obviously require further study to better analyse its effect on the quality of the model. However, from the results of this study, it is possible to consider simple recommendations to drive this choice like avoiding the field borders, unhealthy plants, etc.

As stated previously, the approach used in this paper is not realistic for commercial vineyards mainly because of the amount of data required to calibrate the model. However, it constitutes a significant step towards a spatial model of extrapolation since the principle of the model is now established. It is based on a collection of constant site-specific linear coefficients (Equation 2). Knowing the characteristics of the model, it is now possible to consider a relevant simplification of the calibration procedure. This simplification has to decrease significantly the number of plant water status measurements by using auxiliary information. Acevedo-Opazo et al. (2008b) showed that some low cost and easy to get auxiliary information (i.e. airborne imagery, soil apparent conductivity, canopy area) was relevant to zone vineyards according to the plant water status. These auxiliary information ($q_1(s_i); q_2(s_i); q_3(s_i)...q_k(s_i)$) may bring additional local information at each site (s_i). They can be used to provide estimates of the site-specific coefficient established in this work. Equation 13 presents the possible approach which will be tested in a further step:

$$\hat{z}\,(s_i, t_j) = \left[\left(a_1 \cdot q_1(s_i) + a_2 \cdot q_2(s_i) + \ldots + a_k \cdot q_k(s_i) + a_{k+1}\right)\right] \cdot z(s_{re}, t_j) \qquad (13)$$

with $a_1, a_2, \ldots, a_k \in \Re$,

Conclusion

This work is a preliminary study towards a spatial prediction model of vine water status. It shows the possibility to extrapolate the vine water status (PLWP) at several unsampled locations from one measurement performed on a reference site. The proposed spatial model is based on site-specific linear coefficients allowing extrapolation to the whole domain (vine fields in this case). This study also proposed a validation of the approach based on two fields planted with different varieties over several years. The proposed model improved significantly the prediction of the plant water status. It was shown to be robust to the choice of the reference site. The results also highlight the range of water restriction values over which our approach is relevant. Compared to a classical approach, the spatial model improves significantly the plant water status prediction under conditions of high water restriction (PLWP < -0.4 MPa). This last result points out the interest of such an approach as a decision-making tool. In particular, it could constitute a significant improvement of irrigation management by proposing a more reliable estimation of the plant water status over the whole vineyard.

However, on a practical point of view, the calibration of the model needs simplification to be fully operational in commercial vineyards. We intend to improve our approach in further works by using high resolution auxiliary information (i.e. airborne imagery, soil apparent conductivity, etc.). These spatial data may constitute relevant surrogates to provide an assessment of the collection of linear coefficient for plant water restriction extrapolation.

CHAPTER V

Chapter 5: Spatial prediction model of the vine (Vitis vinifera L.) water status using high resolution ancillary information

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Abstract
This paper aims to set up and test a model to spatially extrapolate vine water status across a vineyard block. The approach used was hypothetically introduced and justified in previous work, however it has never been tested formally. The proposed spatial model extrapolates Predawn Leaf Water Potential (PLWP), measured at a reference location, to other unsampled locations using a linear combination of spatial ancillary information sources (AIS) and the reference measurement. In the model, the value of the reference value accounts for temporal variability and the AIS account for spatial variability of vine water status, which allows extrapolation over the whole domain (vine fields in this case) at any time when a reference measurement is made. The spatial model was validated on two fields planted to different cultivars over several years in a vineyard in the south of France. The proposed spatial model significantly improved the prediction of the vine water status, especially under conditions of high water restriction (PLWP < -0.4 MPa), compared with a non-spatial model. The model was shown to be robust to the choice of reference site. The results also highlighted that AIS pertaining to canopy growth are the most relevant variables for predicting PLWP under these experimental conditions. Preliminary results showed the potential to calibrate the model from a limited number of field measurements, making it a realistic option for adoption in commercial vineyards. The success of the spatial model in improving the quality of prediction of PLWP means it could be incorporated into a decision-support tool to improve irrigation management within a vineyard.

Introduction

In a recent review paper, Acevedo-Opazo *et al.* (2008a) discussed the importance of methods for spatially monitoring the water status of vines. Furthermore, they proposed a conceptual spatial model to predict the water status of vines across a given domain (vineyard block, vineyard, region etc). The proposed model predicts vine water status by combining local reference measurements, to take into account the temporal variability, and ancillary information sources (AIS), to characterize the spatial variability of the vine water status. Acevedo-Opazo *et al.* (2008a) hypothesised that with denser ancillary information it may be possible to model the relative difference in vine water status between a reference point and all other sites across the domain. They demonstrated in a subsequent paper (Acevedo et al, 2009) that this relative difference was linear in nature and temporally stable. A spatial model of vine water status using AIS may be of interest for commercial vineyards as it can be easily calibrated (since it is not reliant on a full descriptive model of the vineyard environment) and spatial predictions can be easily generated from singular reference points. By coupling high quality, high cost punctual vine measurements with low cost medium-high density ancillary data sources, the model would provide quick estimations of vine water status at spatial resolutions that are cost prohibitive to generate with punctual measurements.

To illustrate the concept, Acevedo-Opazo *et al* (2008a) presented a brief case study with the use of multi-spectral imagery and soil apparent electrical resistivity (ER). However, Acevedo-Opazo *et al.* (2008) only justified the hypothetical relevance of the model. Neither an analysis of inputs, nor a validation on a significant data set were proposed. They also only considered data from what they termed "high resolution information sources" (HRIS). This negates the use of medium-density manually-sampled spatial data sets that may provide valuable information in the model. For this reason the term ancillary information sources (AIS) is preferred here to describe potential model inputs. The goal of this paper is therefore to present a formal solution to the proposed model and investigate its feasibility, including the selection of suitable AIS, and the efficacy of prediction both spatially and temporally.

The proposed conceptual model, as defined by Acevedo-Opazo et al (2008a), is shown in Equation 1.

$$\hat{z}(s_i,t_j) = f_D(q_1(s_i),q_2(s_i),\ldots,q_K(s_i),\, z(s_{re},t_j)) \;,\ \forall\ s_i \in \mathrm{D} \text{ with } s_{re} \in \mathrm{D} \qquad (1)$$

The model requires the measurement of a reference value of vine water status $z_{re}(s_{re},t_j)$ at site s_{re} and time t_j. The goal is to extrapolate the reference value $z_{re}(s_{re},t_j)$ using a function f_D, which relates $z_{re}(s_{re},t_j)$ to the AIS, over a domain scale (D) at the same time (t_j). AIS are available at each location s_i across D and the location s_{re} is a site within D, where D can be either a block or a set of blocks or a whole vineyard. In equation 1, $q_k(s_i)$ corresponds to the value of AIS k obtained at site s_i. If multiple AIS are available, then site s_i is characterised by a vector $\boldsymbol{q}$, $\boldsymbol{q}=[q_1(s_i),q_2(s_i),\ldots,q_K(s_i)]$. K denotes the number of available AIS on s_i .
In their case study, Acevedo-Opazo et al. (2008a) proposed to model the f_D function using a linear combination of AIS with the reference value $z_{re}(s_{re},t_j)$. Equation 2 can then be expressed as :

$$\hat{z}(s_i,t_j) = \left(b_0 + b_1 \times q_1(s_i) + b_2 \times q_2(s_i) + \ldots + b_K \times q_K(s_i)\right) x\ z_{re}(s_{re},t_j) \qquad (2)$$

$$\textit{with} \quad s_{re} \in \mathrm{D},\ \forall s_i \in \mathrm{D},\ q_k(s_i), k = 1,\ldots,K \in \Re \text{ and } b_k, k = 0,\ldots,K \in \Re\,,$$

If, as suggested, multiple AIS are available and characterised by a vector $\boldsymbol{q}$ at each site, then the corresponding linear coefficients associated with each AIS (b_0, b_1, b_2, b_3,…, b_K) can be characterised by a vector $\boldsymbol{b}$. The model can therefore be optimised by finding the vector $\boldsymbol{b}$ which minimises the prediction error at each site (s_i).

To test this linear model the following methodology was followed:

(i) Selection of an area (vineyard block), D over which the model is tested, two distinct D domains will be considered,
(ii) Collection of a database of vine water status values with a high spatial and temporal resolution using a pressure chamber for model calibration and validation.
(iii) Selection of a reference site (s_{re}) from the assembled database.
(iv) Collection of available AIS for the domain and stepwise determination of the best AIS, $(q_k(s_i))_{k=1,\ldots,K})$ for use in the model.
(v) Determination of the coefficients $(b_k)_{k=0\ldots K}$ for each selected AIS in relation to the reference point for each considered domain.
(vi) Computation, from the model and the reference measurement, of the predicted vine water potential values over D for each available date,

In addition, a sensitivity analysis on the choice of reference site for the model was undertaken. The methods used to fulfil these requirements are detailed in the following section.

Materials and methods

Site description

The study domains were a 1.2 ha Syrah block and a 1.7 ha Mourvèdre block at the experimental vineyard of INRA Pech-Rouge (Gruissan, Aude, France). These two cultivars were selected as they present different responses to water restriction, with Syrah being more susceptible to water restriction than most other varieties, including Mourvèdre (Schultz 2003; Ojeda et al. 2005b). These cultivars were chosen to test the relevance of the proposed approach on cultivars with different genetic traits, not with the intention of directly comparing the two cultivars.
Both fields are non-irrigated, established in 1990 with 1 m spacing between vines and 2.5 m inter-rows and trained in a vertical shoot positioning system. Both fields exhibit significant soil variability. Their geological formation is composed of interbedded micritic limestone with important accumulations of red clay in some parts of the field (Coulouma et al., *in press*), which induces differences in soil water availability and vine growth.

Vine water status measurement

Vine water status was measured as predawn leaf water potential (PLWP). Spatial measurements were carried out on 49 sites within each field between 3:00 and 5:00 a.m. using a pressure chamber (Scholander *et al.,* 1965). A mature non-senescing leaf located in the middle third of a shoot was selected from each vine for analysis. Three consecutive vines were measured at each site and averaged to obtain a site value (s_i). The sampling scheme is indicated in Figure 1 and sites were geo-referenced with a stand-alone GPS receiver (Garmin Etrex). This sampling was done for seven dates in 2003 and six dates in 2004 on the Syrah block and six dates in 2005 and three dates in 2006 on the Mourvèdre block to test the stability in spatial patterns over time.

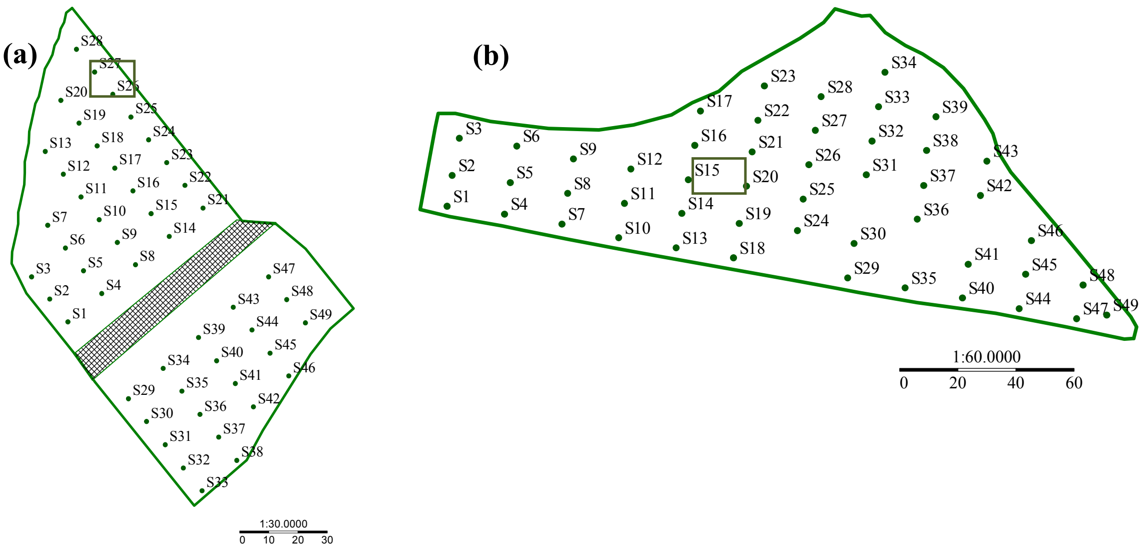


Fig. 1 Locations of measurement sites within the study area (s_i), and reference site (s_{re}) on Syrah (site 27) and on Mourvèdre (site 15) within a frame.

<u>Ancillary information sources</u>

The selected blocks are part of a research vineyard and a wide variety of spatial ancillary data on soil and canopy conditions were available from periods before, during and after the vine water status measurements. The resolution of available spatial data varied from high-spatial resolution imagery (> 1000 points ha^{-1}) to manual, medium-spatial resolution measurements at the sample sites (30-40 points ha^{-1}). There was no attempt at the start of the process to exclude spatial ancillary data on the basis of the date of collection or the time taken to collect the data. Previous work (Tisseyre et al. 2008; Martinez-Casanovas et al., 2009) has indicated that temporal patterns of canopy vigour and yield are stable in Mediterranean environments (excluding extraneous management and climatic effects). Likewise, spatial patterns for some soil physical properties tend to be temporally stable. The adoption of a model, such as the one proposed here, into commercial situations is dependent on the ability to collect spatial information in a timely and cost effective manner. Some of manual spatial data, for example pruning weight data, collected at the research vineyard station is time (and cost) prohibitive in commercial situations. However, these data are retained for this analysis as sensors that provide the same (or very similar) information are either in development or commercially available. The methods of collection and types of available AIS are summarised in Table 1 and described below.

Airborne imagery

Three multi-spectral (4-band: B, G, R and NIR) airborne images, with 1 m resolution, were acquired under clear skies and dry soil conditions during the period of full vine canopy expansion (July 1999, August 2006 and August 2007). Images were collected by Inventaire Forestier National (IFN) (Nogent sur Vernisson, Loiret, France) in 1999 and L'avion Jaune (Montpellier, Hérault, France) in 2006 and 2007. The 1 m image pixels were aggregated into 3m pixels, which approximate the "mixed pixel" row spacing approach of Lamb et al. (2004), using the methodology outlined in Acevedo-Opazo et al. (2008b). The Normalized Differences Vegetation Index (NDVI) (Rouse et al., 1973) was derived for each image and the NDVI value extracted at each of the vine sampling points (s_i) (49 per field).

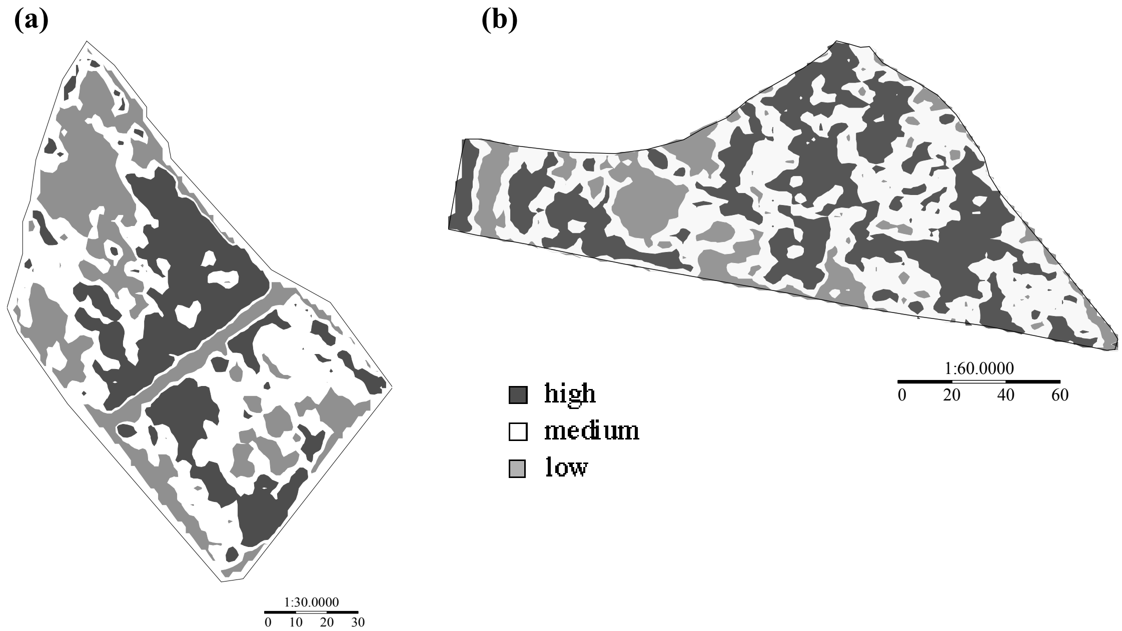


Fig. 2 Maps of Normalised Differences Vegetation Index (NDVI), August 2006 for the Syrah left) and Mourvèdre (right) domains. NDVI data were mapped in 33% quantiles. The class "low" (light grey) corresponds to the 0-33 % quantile, the class "medium" (white) corresponds to the 33-67 % quantile and the class "high" (dark grey) corresponds to 67-100 % quantile of the NDVI values.

Soil physical properties

Measurements of apparent soil electrical resistivity (ER_a) were obtained using a MEGGER ET3 4 electrode sensor (Meggar Ltd, Dallas, TX, USA). Measurements were made manually at each sample site in March 2005. Electrodes were spaced at both 1 m and 2 m spacings to measure ER_a to a depth of 0.5 m and 1 m respectively (Samouëlian et al. 2005). ER_a is the inverse of the more common soil apparent electrical conductivity (EC_a) and is affected by variations in the same soil properties as EC_a, primarily texture, clay content, salinity and soil moisture (Corwin and Lesch 2005, Samouëlian et al. 2005).

Vine measurements

Within-field manual measurements of vegetative growth were performed to measure vine size and vigour. This was done by estimating the exposed leaf area (ELA) and the thickness of the canopy (CT) using the method of Murisier and Zufferey (1997), measuring the weight of the pruned wood (PW) and measuring the trunk circumference (TC) at 10 cm above the graft of each target vine. Manual yield (ton ha^{-1}) measurements were also collected at each site.

Since many of these vine data were legacy data from previous precision viticulture studies it is important to note that exactly the same data are not available for both fields. More measurements were also temporally repeated on the Syrah block.

Table 1 Summary of the variables measured on the selected fields, nomenclature, acquisition dates, cultivar and units.

AIS	Acquisition dates	Nomenclature	Cultivar	Units
High Density Data				
NDVI	July 1999	$NDVI_{99}$	SY, MO	dimensionless
NDVI	August 2006	$NDVI_{06}$	SY, MO	dimensionless
NDVI	August 2007	$NDVI_{07}$	SY, MO	dimensionless
Medium Density Data				
Apparent Soil electrical resistivity	March 2006	ER_a	SY, MO	Ω m^{-1}
Trunk Circumference	March 2006	TC	SY, MO	cm
Exposed leaf area	August 2003	ELA_{03}	SY	m^2
Exposed leaf area	August 2006	ELA_{06}	SY	m^2
Exposed leaf area	August 2007	ELA_{07}	SY, MO	m^2
Canopy thickness	August 2006	CT_{06}	SY	cm
Canopy thickness	August 2007	CT_{07}	SY, MO	cm
Weight of pruned wood	December 2003	PW_{03}	SY	g vine^{-1}
Weight of pruned wood	December 2004	PW_{04}	SY	g vine^{-1}
Yield	October, 2003	Y_{03}	SY	kg vine^{-1}
Yield	October, 2004	Y_{04}	SY	kg vine^{-1}
Yield	October, 2005	Y_{05}	MO	kg vine^{-1}

Cultivars: SY, Syrah ; MO, Mourvèdre

Data mapping
Mapping was done with the 3Dfield software (Version 2.9.0.0, Copyright 1998-2007, Vladimir Galouchko, Russia). Interpolation was performed using a deterministic function (inverse distance weighing) as there were only a limited number of data (49) per field. The map legends were based on the PLWP classes defined by Ojeda et al. (2005a): (i) no water restriction (0 > PLWP > -0.2 MPa), (ii) low water restriction (-0.2 > PLWP > -0.4 MPa), (iii) medium water restriction (-0.4 > PLWP > -0.6 MPa), (iv) high water restriction (-0.6 > PLWP > -1.0 MPa), and (v) severe water restriction (PLWP < -1.0 MPa).

Model computation
The model computation requires several steps to be completed.

Choice of a reference site (s_{re}) for each domain D
For the proposed model the choice of reference site may have a large bearing on the accuracy of prediction. In previous analysis on this PLWP data set, Acevedo-Opazo et al. (2009) demonstrated that their randomly selection of the reference sites did not adversely affect their model output, these same reference sites have been retained for this analysis. The locations of the reference sites are shown in Fig. 1. To reconfirm the validity of these locations, and to

investigate the effect of the choice of reference site on the model performance, a similar sensitivity analysis to that of Acevedo et al. (2009) was also performed with this spatial model. For each field, values of PLWP measured on s_{re}, at all the dates, were removed from the data base.

Modelling without ancillary information
In the absence of any ancillary data Equation 2 is expressed as:

$$\hat{z}\,(s_i, t_j) = (b_0) \times z_{re}\,(s_{re}, t_j) \quad (3)$$

Equation 3 generates a constant value at each site in the field and the optimum mean prediction is proportional to the reference measurement at the same date. Thus, if the reference measurement corresponds to the mean PLWP of the field, then $b_0 = 1$. However, since the reference site was chosen randomly for each field, b_0 may differ to 1. This simple model will constitute the basic model. For both experimental fields, results obtained from spatial models with ancillary information will be compared to this simplistic model, allowing the assessment of prediction quality provided by AIS.

Considering the ancillary information
Available AIS were combined with the PLWP of the reference site to obtain a matrix **Q** (Eq. 4). Note that **Q** is a (*n* x *m)* lines and (*k*+1) column matrix (*k* being the number of AIS):

$$\mathbf{Q} = \begin{bmatrix} \mathbf{Q}_{t1} \\ \mathbf{Q}_{t2} \\ \ldots \\ \mathbf{Q}_{tm} \end{bmatrix}, \quad (4)$$

with,

$$\mathbf{Q}_{tj} = \begin{bmatrix} z(s_{re}, t_j), q_1(s_1).z(s_{re}, t_j), \ldots, q_k(s_1).z(s_{re}, t_j) \\ \ldots \\ z(s_{re}, t_j), q_1(s_n).z(s_{re}, t_j), \ldots, q_k(s_n).z(s_{re}, t_j) \end{bmatrix}$$

Determination of the coefficients over D
This step consisted of finding the vector **b** (coefficients as presented Eq. 2) to provide the vector of estimation $\hat{\mathbf{z}}$ for PLWP values over D at each date. Note that $\hat{\mathbf{z}}$ is a (*n* x *m)* lines vector. This estimation is run as indicated in the following equation:

$$\hat{\mathbf{z}} = \mathbf{Q} \times \mathbf{b} \quad (5)$$

with,

$$\mathbf{b}=\begin{bmatrix} b_0 \\ b_1 \\ b_2 \\ \vdots \\ b_k \end{bmatrix} \quad \text{and} \quad \hat{\mathbf{z}}=\begin{bmatrix} \hat{z}(s_1,t_1) \\ \hat{z}(s_2,t_1) \\ \hat{z}(s_3,t_1) \\ \ldots \\ \hat{z}(s_n,t_1) \\ \hat{z}(s_1,t_2) \\ \hat{z}(s_2,t_2) \\ \ldots \\ \hat{z}(s_i,t_j) \\ \\ \hat{z}(s_{n-1},t_m) \\ \hat{z}(s_n,t_m) \end{bmatrix},$$

The least square error method was used to determine the vector **b** as follows:

$$\mathbf{b} = \mathbf{Q}^{-1} \times \mathbf{z} \qquad (6)$$

where $\mathbf{Q}^{-1}$ is the pseudo-inverse matrix of **Q**.

Selection of optimum ancillary variables

The determination of the best AIS, $(q_k(s_i))_{k=1\ldots K})$, was done using a forward stepwise approach. At the first step, each AIS was introduced independently into the basic model (Eq. 4) and the AIS which maximised the proportion of variance (r^2) explained by the one-parameter model was selected. At the second step, each remaining AIS were added independently to the one-parameter model and again the model with the highest r^2 value was selected and assessed against the threshold. This processed continued until all AIS were added or the difference between the fit (r^2) between the *n* and (*n*+1) (where $n = 0$ at this first step) parameter model was less than 0.01 (1 % of the total variance). In the latter case the iteration was halted and the *n* parameter model was selected.

Model evaluation

The accuracy of the selected model was evaluated on each field using the proportion of variance (r^2) explained by the model across all the dates, while the accuracy of the calibration was estimated across all sites and dates using the standard error of calibration (*SEC*). The *SEC* was computed as follow:

$$SEC = \sqrt{\frac{\sum_{i=1}^{n}\sum_{j=1}^{m}\left(E(s_i,t_j)\right)^2}{(n \times m)-1}} \text{, with } E(s_i,t_j) = \left(\hat{z}(s_i,t_j) - z(s_i,t_j)\right) \qquad (7)$$

Where *n* is the number of sites on D and *m* is the number of available dates,

The ability of the model to predict values of PLWP was assessed using a "leave-one-out" cross-validation (LOOCV) procedure. In previous analysis on this PLWP data set, Acevedo-Opazo et al. (2009) showed that the spatial variability was significant for high water restriction (PLWP < -0.4 MPa). Therefore, for the LOOCV, the data was subset into two scenarios; (a) under conditions of no to low water restriction (0 > PLWP > -0.4 MPa) and (b) under conditions of medium to high water restriction (- 0.4 > PLWP > -1.0 MPa). These intervals of decision were selected to show the aptitude of the proposed model at non-critical and critical periods for irrigation management.

The LOOCV was performed both temporally and spatially. For the temporal LOOCV, i.e. a leave-one-date-out cross-validation, the database was divided into *m* subsets $(k_1, k_2, k_3, \ldots k_m)$ corresponding to the *m* measurement dates. Each date was sequentially omitted and the remaining data used to generate a model to predict at each site for the omitted date (t_j) using the reference value at t_j ($z(s_{re},t_j)$). The standard error of prediction for t_j was determined by;

$$SEPt_j = \sqrt{\frac{\sum_{i=1}^{n}\left(E\left(s_i, t_j\right)\right)^2}{n-1}} \qquad (8)$$

The spatial LOOCV, i.e. a leave-one-site-out cross-validation, was performed by sequentially omitting each site at all dates and using the remaining data to generate a model to predict at the omitted site at each date. The standard error of prediction at a given site (s_i) was calculated as;

$$SEPs_i = \sqrt{\frac{\sum_{j=1}^{m}\left(E\left(s_i, t_j\right)\right)^2}{m-1}} \qquad (9)$$

The $SEPt_j$ indicated how well the model on average predicts across the domain at a given time when a reference measurement was taken, while the $SEPs_i$ indicated how well each point was predicted and identified areas in the domain that were correctly or poorly predicted. Thus the first indicated whether the model is valid temporally, and the second the spatial pattern of prediction in the domain and areas where larger prediction errors occurred.

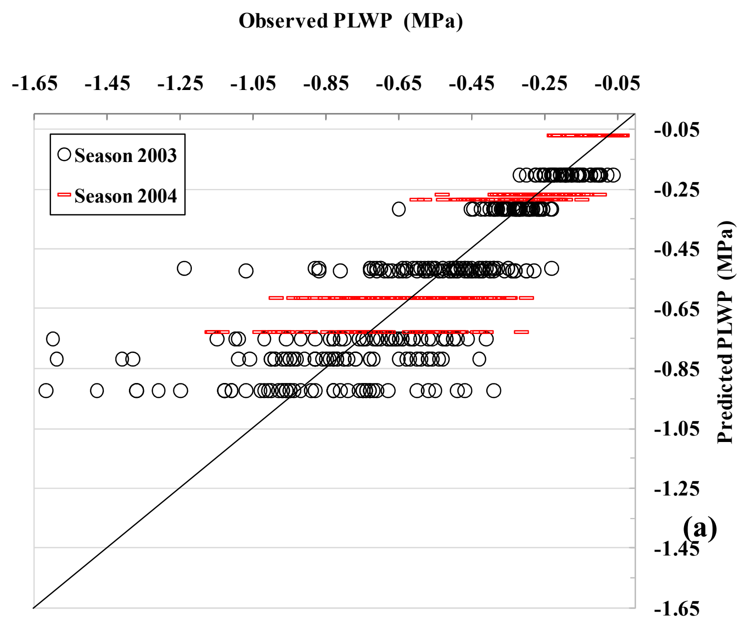
Reference site sensitivity analysis

To verify the selection of reference points used, the models (one for each block) were rerun in each block, at each date, substituting each sampling point sequentially into the models as the reference point. The SEC (Eq. 7) was calculated for each iteration, and a box plot generated for each date in each block. A point map of the spatial distribution of the SEC was also generated for late season (August) measurements in both blocks.

Results and discussion

Results of the Non-Spatial (basic) model

The predictions from the non-spatial (basic) models described in (Eq. 4) are presented in Fig. 3. Within each block, the different years are represented by distinct signs. The model parameters obtained and the r^2 fits are detailed in Table 4. For the non-spatial model a mean field value is predicted at each date. In Fig. 3, it is clear that the range (and variance) of measured PLWP increased as water restriction increased, and this increase was greater in the Syrah block. This observation was important. Firstly, it indicated that an irrigation decision late in the season (when the timing of irrigation is more critical), which is based on a single measurement or the average of the field, may be inappropriate for a significant part of the field. Secondly, it demonstrated the difference between conditions where water was non-limiting (> -0.4 MPa) and limiting (<-0.4 MPa), and the relevance of analysing the two scenarios independently. Table 4 therefore presents the full model fits as well as fits for the two ranges -0.4<PLWP<0 MPa and PLWP<-0.4 MPa. These ranges were also retained for the analysis of the spatial model. As expected, the increased variance when water is limiting resulted in a poorer fit for a predicted mean value (Table 2). When water was non-limiting, the non-spatial model accounts for > 50 % of variance in both fields, and it may be argued that these fits are sufficient for management.



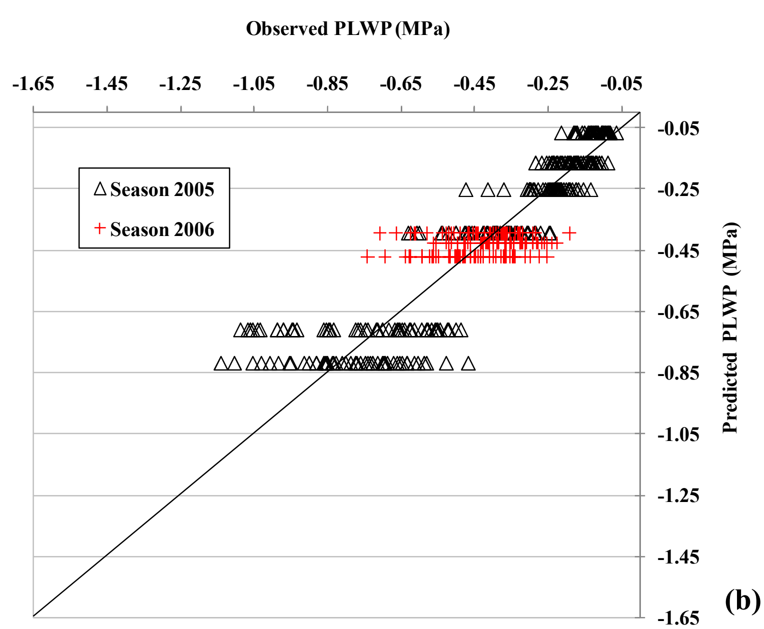


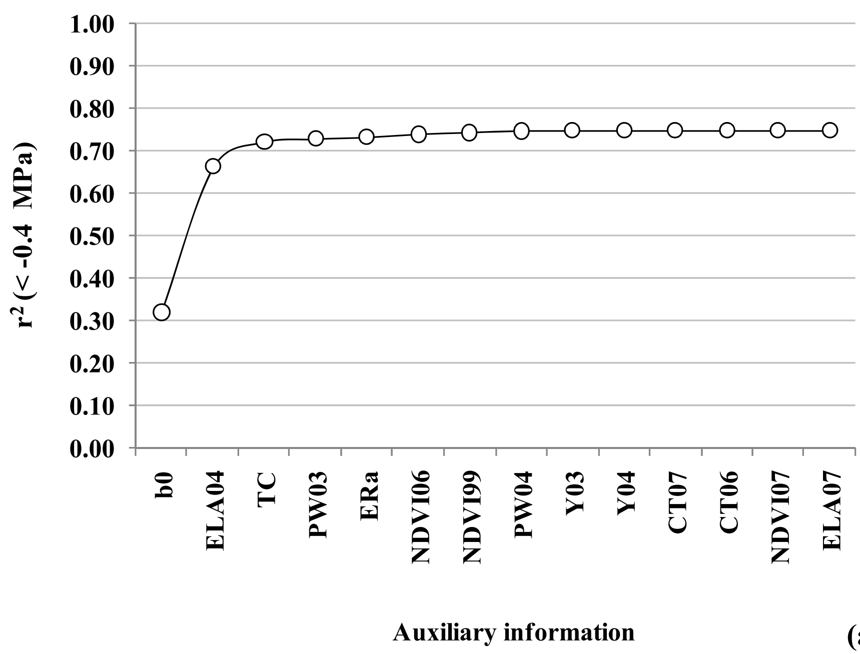
Fig. 3 (**a**) and (**b**) Prediction results of PLWP values from the non-spatial basic model (without ancillary information) for the Syrah (O 2003, — 2004) (top) and Mourvèdre (Δ 2005, + 2006) (bottom) domains.

Table 2 Predicted intercept and model fits (r² and SEC) of the non-spatial model for the two domains. Fits are shown for all the data and also for two intervals corresponding with (i) no to low water restriction (PLWP > -0.4 MPa) and (ii) medium to high water restriction (-0.4 MPa > PLWP).

Cultivars	Model	PLWP (all data)		PLWP > -0.4 MPa		PLWP < -0.4 MPa	
		r^2	**SEC**	**r^2**	**SEC**	**r^2**	**SEC**
Syrah	$b_0 = 0.818$	0.68	0.17	0.55	0.09	0.32	0.2
Mourvèdre	$b_0 = 1.093$	0.72	0.12	0.78	0.07	0.51	0.14

Results of the Spatial model with AIS

Figure 4 shows the fit (r²) of the model for data corresponding to medium to high water stress (PLWP < -0.4 MPa) as each stepwise selected AIS is introduced into the model. The first point on the abscissa is the intercept value (b_0) or the non-spatial model. Subsequent labels indicate the variable added to the model (not the actual model). For both fields the fit was significantly improved with the addition of the first two AIS, after which the addition of further AIS was non significant. For both fields these first two AIS were identical, ELA and TC. The r² increased respectively from 0.32 to 0.74 and from 0.5 to 0.72 between the intercept and 2-parameter model for the Syrah and Mourvèdre fields.



(a)

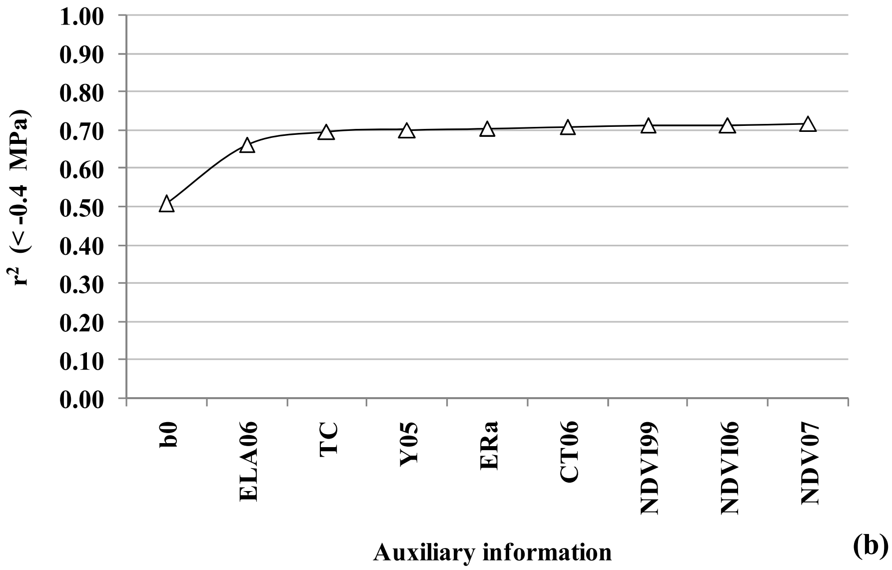


Fig. 4 Results of model calibration with the introduction of each new ancillary information source (step by step) for PLWP < -0.40 MPa values on the Syrah (top) and Mourvèdre (bottom) domains.

For each field, the optimum model with the available AIS is:

$$\hat{z}(s_i,t_j) = \left(b_0+b_1\times q_1(s_i)+b_2\times q_2(s_i)\right)\times z_{re}(s_{re},t_j) \quad (10)$$

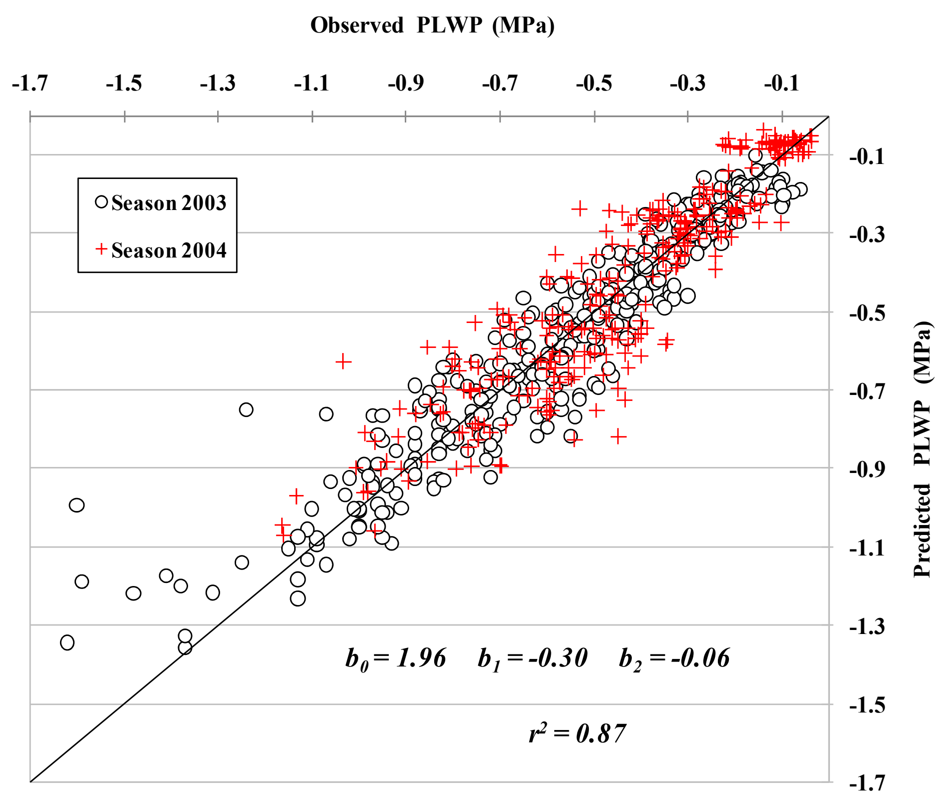
where q_1 = ELA and q_2 = TC

The results of applying this model are shown in Table 3 and Fig. 5. Under conditions of medium to high water restriction (-0.4 MPa> PLWP), significant gains in model fit and SEC were made compared to the non-spatial model (Table 2). The Error of Calibration (SEC) of the spatial model for this range (-0.4 > PLWP) was 0.12 and 0.11 MPa on the Syrah and Mourvèdre domains respectively. This was much lower than the range of values used by the viticulturists and wine growers to make irrigation decisions (± 0.2 MPa) (Ojeda et al. 2005), which indicated that the model is relevant and accurate enough for management. A more detailed analysis of the model accuracy, based on the error of prediction is carried out in the next section.

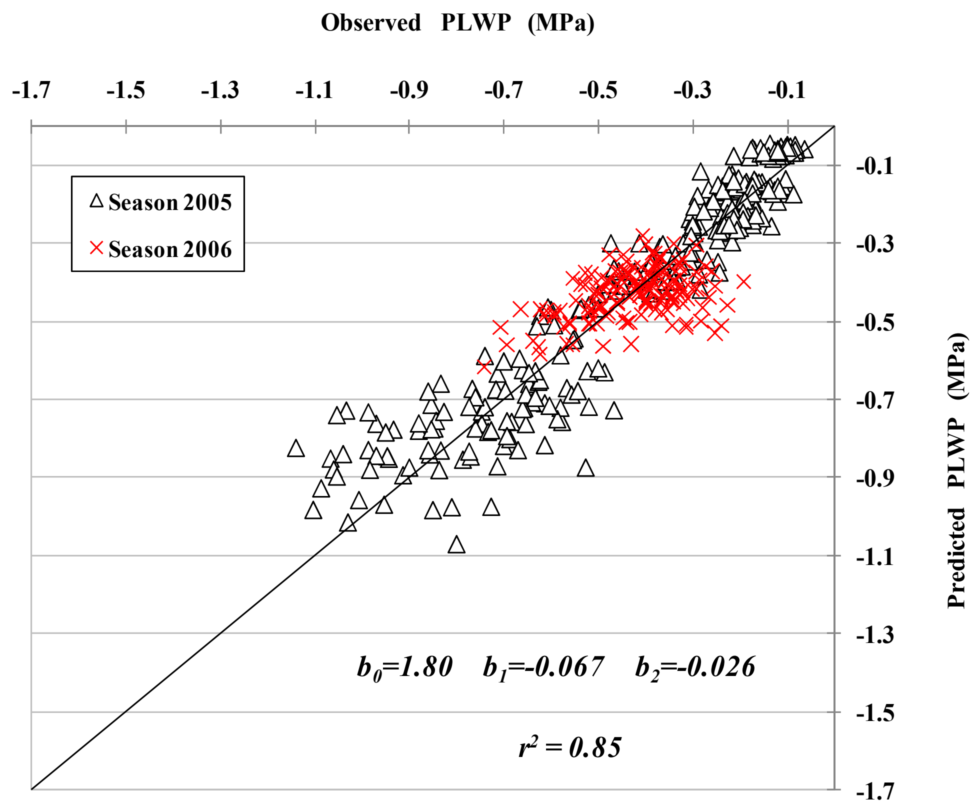
Table 3 Results of the model (r^2 and SEC) with the introduction of two AIS (q_1 = ELA and q_2 = TC) on Syrah and on Mourvèdre for two vine water potential intervals: (i) no water restriction to low water restriction (-0.4MPa < PLWP < 0) and (ii) medium to high water restriction (-0.4 > PLWP > -1.0MPa).

Cultivars	Model	PLWP (all data)		PLWP > -0.4 MPa		PLWP < -0.4 MPa	
		r^2	**SEC**	**r^2**	**SEC**	**r^2**	**SEC**
Syrah	b_0 = 1.96 b_1 = -0.3 b_2 = -0.06	0.87	0.088	0.65	0.07	0.72	0.12
Mourvèdre	b_0 = 1.80 b_1 = -0.067 b_2 = -0.026	0.86	0.07	0.72	0.07	0.69	0.11

The plot of model predictions against observed values is shown in Fig. 5. This figure has to be compared with Fig 3. Considering all available measurements, the model r² values are respectively 0.87 and 0.86 (0.71 and 0.72 if only PLWP < -0.4 MPa values are considered) for the Syrah and Mourvèdre fields. The addition of spatial information into the model has considerably reduced the dispersion of the predicted values, particularly during periods of higher water restriction. However, note that for very high water restriction (PLWP <-1.3 MPa) on the Syrah field (Fig. 5a), the linear relationship between the AIS values and the PLWP seems to be no longer valid. This phenomenon will be discussed in the spatial error of prediction section.



(a)



(b)

Fig. 5 Plots of the actual vs. predicted PLWP values for the spatial model (Eq. 11) for the Syrah (O 2003, + 2004) (top) and Mourvèdre (Δ 2005, × 2006) (bottom) domains. Intercept, coefficients and r² for all data are shown on the plots.

Examples of a measured and predicted map for a specific date, t_7 in 2003 on Syrah and t_5 in 2005 on Mourvèdre, are shown in Fig. 6a and 6b. A common legend has been used to permit a direct comparison between the predicted and measured maps. Visually, the predicted maps follow the same trends as the measured maps for both domains and, in particular, clearly identify the same areas of high water restriction.

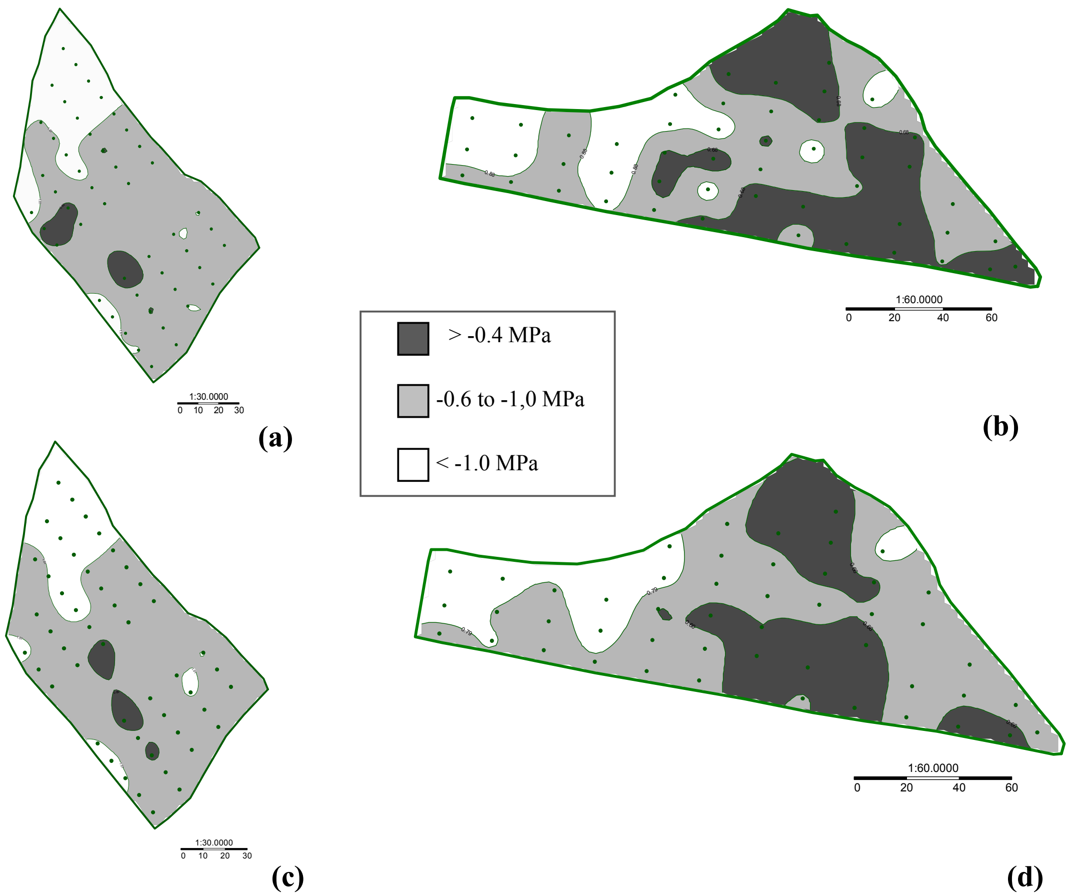


Fig. 6 Maps of predawn leaf water potential at t_7 for Syrah in 2003 (left-hand side) and t_5 for Mourvèdre in 2005 (right-hand side). The top row maps (**a** and **b**) are interpolated from physical measurements while the bottom row maps are interpolated from point predictions using the spatial model.

<u>Discussion on the AIS selected</u>

Despite inter-domain differences in location (soil and landscape), cultivar, management and the climatic conditions between years when measurements were taken, the stepwise approach yielded identical bivariate models for both blocks. The complete order of AIS (Fig. 4) did differ between the two domains however this is to be expected since identical data sets were not available and all subsequent AIS after the first two variates were non-significant. The stepwise selection of the same two AIS (ELA and TC) on two independent data sets strongly indicates that vine vigour is of particular significance for modelling PLWP. This result concurs with previous work on zoning vineyards according to vine water status (Acevedo-Opazo et al. 2008b). These two parameters present a seasonal (ELA) and historical (TC) indication of vine vigour. Vine vigour integrates genotypic, environmental and interaction effects at the site and will be related to water availability and soil fertility among other things. However, the influence of soil properties on vine vigour appears to be more relevant to the prediction model than direct measurements of soil properties (such as the ER_a measurements used here). One reason for the lack of fit of the ER_a data may be the depth of measurement, which does not necessarily correspond to the depth of exploration by vine roots. The two selected parameters are both medium density measurements. Results with faster and less intensive data to acquire (NDVI) are presented in the discussion section.

Analysis of the quality of the spatial model prediction

Standard error of prediction over time (SEPtj)

The *SEPtj* never exceeded 0.15 MPa (Table 4) for either domain. These results fit with management application requirements which require an accuracy of ±0.2 MPa. However, Table 4 shows that *SEPtj* was not constant over time. It increased as the σ of PLWP increased. For Syrah in 2003, *SEPtj* varied from 0.06 MPa, at the first date of measurement, to 0.13 MPa at the last measurement date, which corresponded to the highest water restriction. For the same domain and during the same period of time, σ of PLWP values varied from 0.06 MPa to 0.26 MPa. Similar results were observed in both years for the Mourvèdre domain. At higher water restriction levels (PLWP < -0.4 MPa), Table 4 shows that *SEPtj* values were always less than σ. This confirms the advantage of taking into account the spatial variability of PLWP and the relevance of the proposed model.

Table 4 Summary of different dates of the measurement, standard error of prediction at different time (*SEPtj*) and mean predawn leaf water potential (PLWP) on the Syrah and Mourvèdre fields.

Syrah

	2003							**2004**					
Date	18 jun	26 jun	08 jul	16 jul	23 jul	30 jul	12 aug	09 jun	05 jul	05 aug	18 aug	23 aug	10 sep
Time	t_1	t_2	t_3	t_4	t_5	t_6	t_7	t_1	t_2	t_3	t_4	t_5	t_6
$SEPt_j$	0.06	0.06	0.10	0.10	0.13	0.12	0.11	0.06	0.10	0.08	0.12	0.12	0.14
SD PLWP	0.06	0.07	0.16	0.17	0.21	0.22	0.26	0.05	0.11	0.08	0.15	0.15	0.21
Mean PLWP	-0.18	-0.34	-0.52	-0.54	-0.73	-0.84	-0.92	-0.11	-0.34	-0.28	-0.59	-0.61	-0.72

Mourvèdre

	2005						**2006**		
Date	10 jun	23 jun	06 jul	19 jul	05 aug	25 aug	13 jul	27 jul	22 aug
Time	t_1	t_2	t_3	t_4	t_5	t_6	t_1	t_2	t_3
$SEPt_j$	0.06	0.06	0.06	0.07	0.14	0.14	0.08	0.09	0.12
SD PLWP	0.05	0.03	0.06	0.10	0.18	0.15	0.11	0.11	0.08
Mean PLWP	-0.17	-0.12	-0.25	-0.41	-0.75	-0.78	-0.42	-0.46	-0.38

Spatial Error of Prediction (SEPsi)

The Spatial Error of Prediction (*SEPsi*) was computed to determine if there was any residual spatial patterning in the model. A perfect spatial model would produce a random spatial distribution of the error. Maps of *SEPsi* for the Syrah and Mourvèdre are shown in Fig. 7. The error was low (< 0.1 MPa) on approximately 70% of the sites for both domains. Higher errors (*SEPsi* > 0.15) occurred on only three locations in the Syrah block, with only one location having a very high errors (*SEPsi* > 0.2). For Mourvèdre, the spatial error never exceeded 0.15 MPa. The white and light grey zones represent locations where low confidence in prediction was observed. Fig. 7 also indirectly validates the choice of reference sites. The spatial error shows no pattern associated with the reference sites, illustrating the ability of the model to predict over the entire domain and not only on the area surrounding the reference sites.

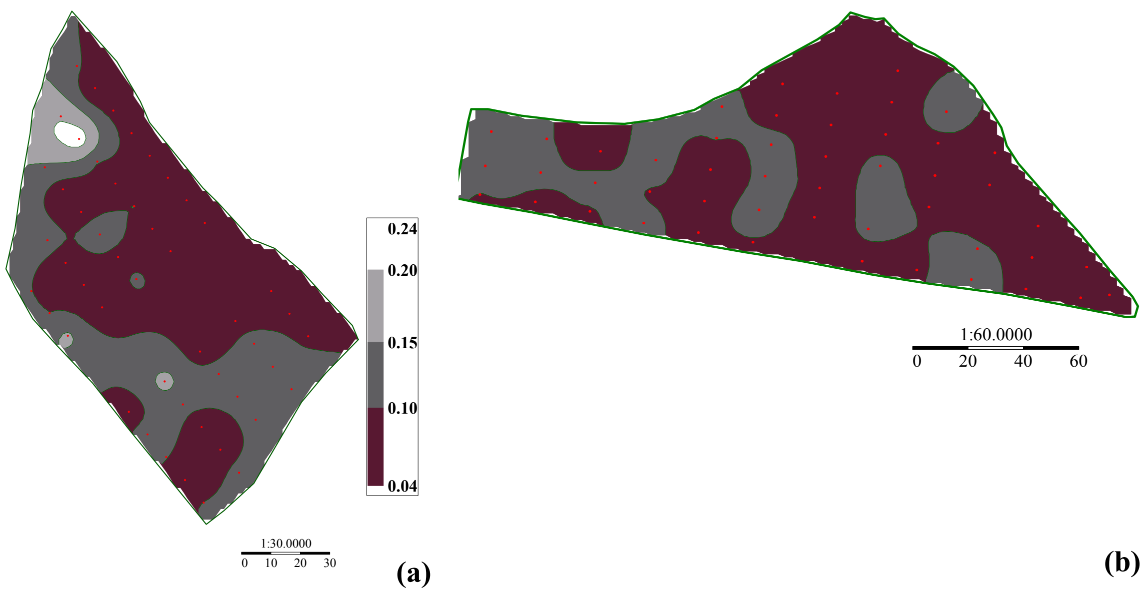


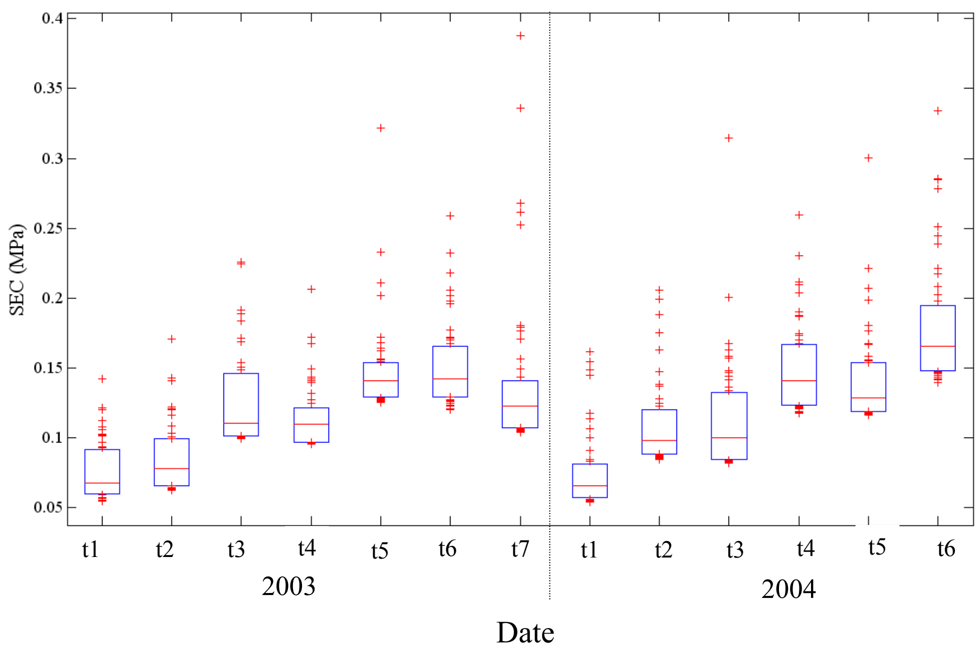
Fig. 7 (**a**) and (**b**) map of standard spatial error of prediction (*SEPsi*) on the Syrah and the Mouvèdre, respectively. Low errors (0.04 to 0.1 MPa) in black, medium errors (0.1 to 0.15 MPa) in dark grey, high errors (0.15 to 0.2 MPa) in light grey, and very high errors (> 0.2 MPa) in white

Although the *SEPsi* is generally low, there are some residual spatial patterns in the *SEPsi* maps. These patterns indicate that information is still missing to properly characterise the spatial variation in PLWP. This missing spatial information may involve more sophisticated parameters than AIS based on simple observation or measurements, for example, the interaction with the nearby forest may explain the pattern along the northern edge of the Syrah domain. Given that the current fit of the model is already strong, it is questionable whether the cost and effort needed to identify and measure this missing information can be justified.

In the Syrah domain, there is one site that presents a very high error (*SEPsi* > 0.2). This error is not an outlier caused by measurement error as the *SEPsi* takes into account all available dates. This site presents a unique behaviour with a very high water restriction (less than -1.6 MPa at date t_7 in 2003). As expected, its AIS values (ELA and TC) are low, but not extremely low when compared to other sites that exhibit a medium to high water restriction. This site may be considered as the limit where the linear relationship between the AIS values and the PLWP is no longer valid.

Sensitivity analysis of the choice of reference site

An analysis of the sensitivity in the choice of the reference site was conducted for both fields across all the measurement dates. The distribution of the Standard Errors of Calibration (SEC) from each possible model is shown in Fig. 8 for both domains. The median SEC remained lower than 0.15 MPa for all dates. As expected, the median SEC and range of SEC values increased as the mean water restriction of the field increased, indicating that a poor choice of reference site is likely to have a larger impact on prediction quality as water restriction increases. This result is obvious for Syrah, where SECs higher than 0.3 MPa are observed at dates t_5, t_7 in 2003 and t_3, t_6 in 2004. It is less significant for Mourvèdre and may be due to the lower water restrictions observed for this field in 2005 and 2006. However, a higher distribution of SEC values is noticeable for higher water restrictions corresponding to dates t_5 and t_6 in 2005 and t_3 in 2006. To visualize the influence of reference site on prediction quality, a specific analysis was conducted at t_7 for Syrah and t_5 for Mourvèdre. The Standard Error of Calibration (SEC) associated with each point if it is considered the reference site is shown in Fig. 9.



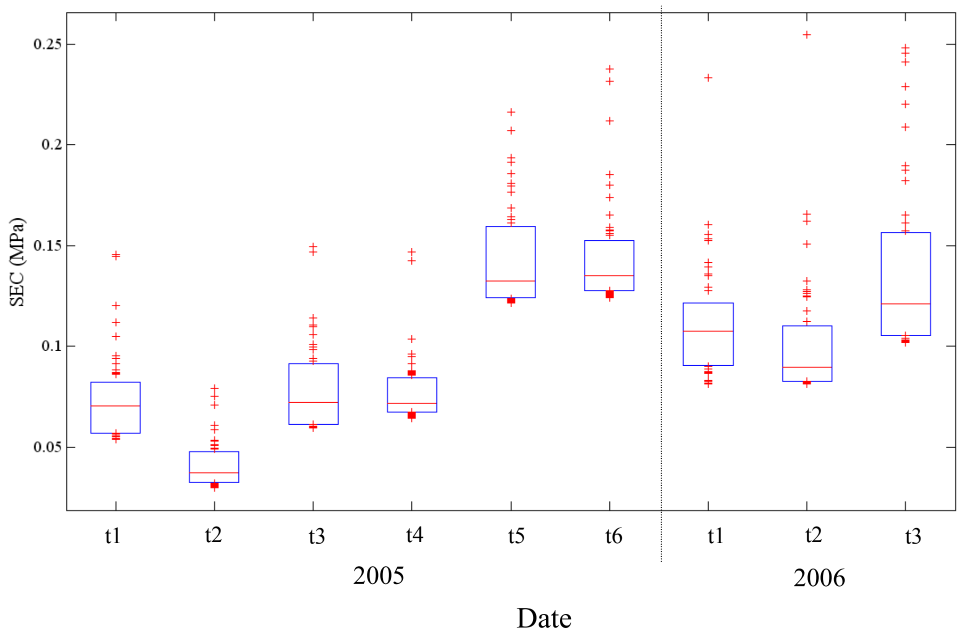


Fig 8. (**a**) and (**b**) incidence of the choice of the reference site on the calibration (SEC) of the model respectively for Syrah and Mouvèdre and for all the the dates. The limits of the box corresponds to the quartiles and the horizontal line to the median.

For Syrah (Fig. 9a) the SEC for the majority of the sites ranged from 0.10 MPa to 0.18 MPa indicating an ability to predict vine water status with suitable accuracy for management. However, 5 sites present a high SEC and can be considered as outliers. Three of them (s_1, s_2, s_5) were located along the western border of the field leading to a possible "interaction" with the nearby pine forest that adjoins the block. The other two outliers (s_{34} and s_{15}) were located along side the internal track that bisects the field, again indicating an edge-effect. For Mourvèdre, the SEC of the models was less than 0.2 MPa for almost all the sites (Fig. 9). Only two sites (s_{49} and s_{28}) had a median SEC close to 0.2 MPa. Again one of these (s_{49}) had a specific location close to the pine forest on the eastern border of the field. The reason for the high response at the second site s_{28} was unclear.

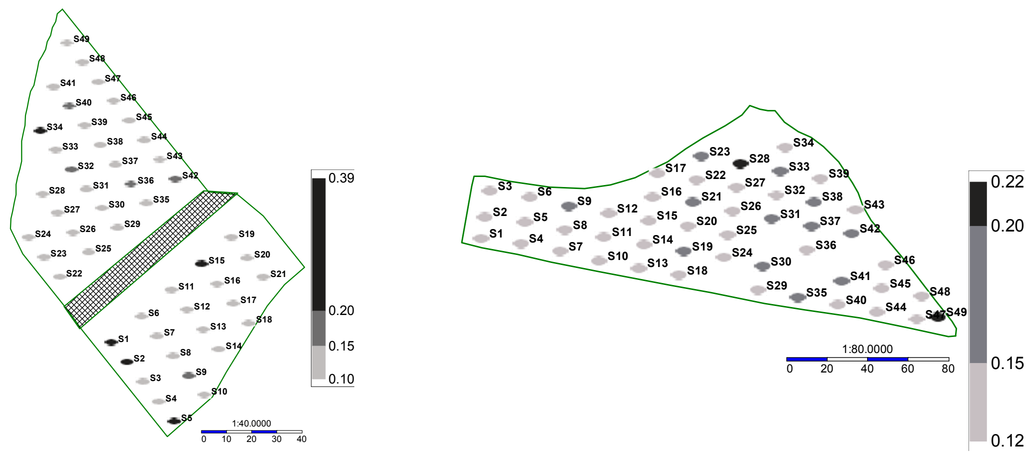


Fig 9. Point maps showing the effect of the choice of the reference site on the calibration error (SEC) of the model for Syrah at t_7 (left) and Mouvèdre at t_5 (right).

Discussion on the practical implementation of the approach

From a practical point of view, this analysis has shown that the model was not very sensitive to a sensible choice of reference site. Obviously, slight differences in accuracy may be observed but, except in rare cases, the choice of the reference site did not alter the quality of prediction. More detailed investigations into the choice and number of reference sites will provide a better understanding of these effects on prediction quality. However, from the results of this study, it is possible to consider some simple recommendations to ensure the good selection of a reference site, such as avoiding field borders and unhealthy vines.

The choice of the AIS information was also of importance. In these conditions, AIS relating to seasonal (ELA) and historical (TC) indications of vine vigour were the most relevant. The two selected parameters are both medium density measurements. In a commercial situation, using NDVI information derived from multispectral aerial images is more convenient as it is faster and less labour intensive to acquire. Several reasons may explain the non-selection of NDVI information in this study: (i) the correlation of NDVI with canopy parameters leading to redundant information and the non selection of NDVI information in the stepwise algorithm, (ii) The processing and the resolution of the NDVI images, which results in some non-vine information in the signal and a spatial footprint that encompasses several vines i.e. the image value will not be specific to the sampled vine and iii) the absence of NDVI imagery in years when PLWP was measured. Despite the strong spatial stability of canopy vigour observed in vineyards (Tisseyre et al., 2008, Martinez-Casanovas et al., 2009), the NDVI imagery cannot account for slight seasonal differences in climate and management that may affect canopy development. Since it would be preferable to use the NDVI data, the spatial model was also run using only NDVI as an AIS. Selection of the best NDVI information among years 1999, 2006 and 2007 the forward stepwise approach used previously. For both fields, $NDVI_{06}$ presented the best fit (r^2) for data corresponding to medium to high water stress (PLWP < -0.4 MPa). The results of the models are shown in Table 5.

Table 5 Results of the models (r^2 and SEC) with the introduction of $NDVI_{06}$ information ($q_1 = NDVI_{06}$) on Syrah and on Mourvèdre for two vine water potential intervals: (i) no water restriction to low water restriction (0 > PLWP > -0.4MPa) and (ii) medium to high water restriction (-0.4 > PLWP > -1.0MPa).

Cultivars	Model	PLWP (all data)		PLWP > -0.4 MPa		PLWP < -0.4 MPa	
		r^2	**SEC**	**r^2**	**SEC**	**r^2**	**SEC**
Syrah	$b_0 = 0.95$ $b_1 = -2.26$	0.79	0.13	0.59	0.08	0.54	0.15
Mourvèdre	$b_0 = 1.43$ $b_1 = -2.02$	0.82	0.08	0.76	0.07	0.56	0.13

Across the entire range of PLWP values, the $NDVI_{06}$ model increased the r² from 0.68 to 0.79 and from 0.72 to 0.82 for the Syrah and Mourvèdre fields respectively, when compared to the non-spatial basic model. The Error of Calibration (SEC) and dispersion of predicted values was also decreased for both fields. This result shows that using NDVI data does improve the prediction of spatial variability of vine water status, however, the improvement of the prediction is not as significant as with ELA and TC parameters.

Soil information (ER_a) was not relevant in this case. However, in other situations this information, as well as elevation data, may be relevant and should not be immediately discarded. Further investigations at other experimental sites will answer this question. While vine vigour was dominant here, this may not be the case in other regions. Before implementing this model in another vineyard, the local factors that most strongly influence vine water status need to be considered. This expert analysis (from a pedologist and/or a viticulturist) should provide some assistance in choosing relevant AIS given the particularity of the location and practical constraints of AIS acquisition, such as cost, spatial resolution, and timeliness.

The amount of PLWP data used to calibrate this model was large and not realistic for commercial vineyards. However, the selected model has only three unknown values (b_0, b_1, and b_2). Therefore, theoretically, only 3 measurements of PLWP, in addition to the reference site, are necessary to calibrate the model. To illustrate this, the combined PLWP data for the Syrah domain was stratified into low, medium and high groups and a value randomly selected from each group. There was no restriction on date applied to the selection. The location and date of the selected values are shown in Fig. 10. The model was then calibrated using these three points and the original reference site. The plot of actual vs. predicted values with the model parameters is shown in Fig. 10b. The result showed that with 3 sites and 2 dates, it is possible to calibrate the spatial model with an accuracy (r² = 0.87, SEC = 0.08) as good as calibration with the full dataset (49 sites and 13 dates). The potential to validate the model from a limited number of dates will considerably reduce the time required for acquiring measurements. This is only a quick illustration of the concept and the surprisingly good fit was unexpected. A more detailed analysis is required to address the questions of how to choose the sites and the dates for sampling that generate the most robust prediction model, while minimising the time and cost of data acquisition. On a spatial perspective, high resolution information like NDVI or ER_a/EC_a might constitute good surrogates for determining the best sites to sample. This aspect will be investigated further in future work.

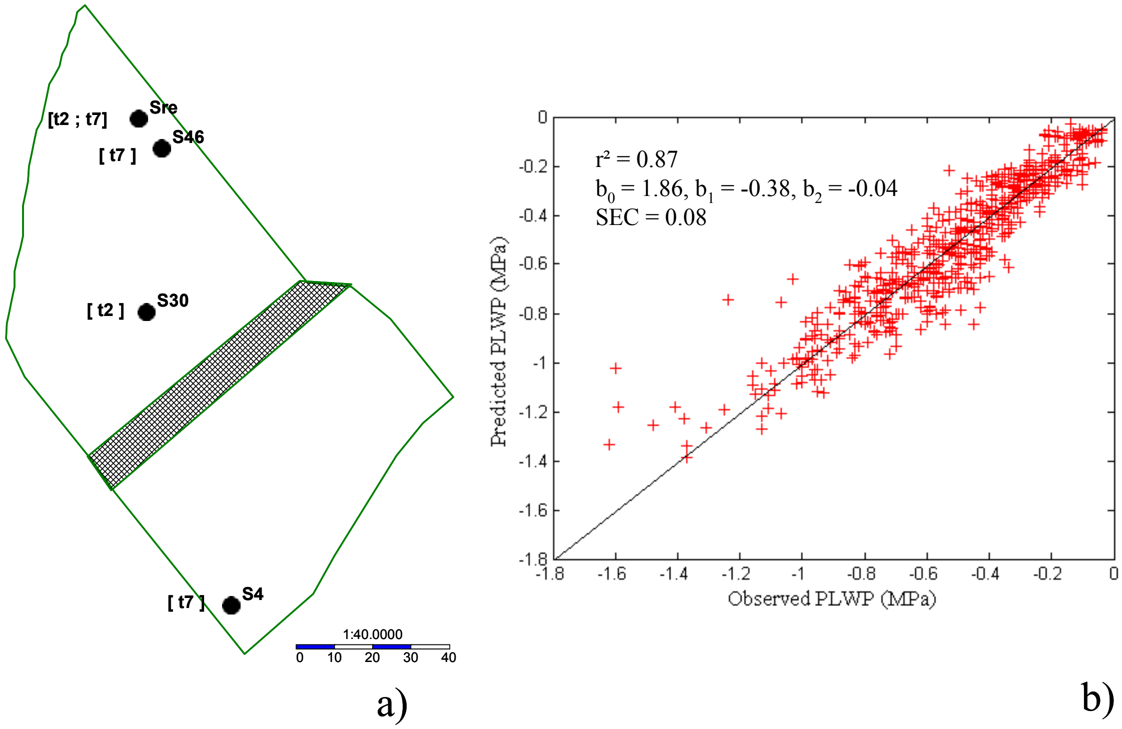


Fig. 10 (a) Location and dates of PLWP dataset used to calibrate the spatial model on Syrah field and (b) Prediction results of PLWP values from the spatial model computed with vine ancillary information (q1 : exposed leaf area, q2 : trunk circumference) on Syrah. r² and SEC are computed for the full model.

Conclusions

This work has shown the possibility of extrapolating vine water status (PLWP) to unsampled locations from a measurement performed on a reference site and ancillary information sources (AIS) located at the unsampled locations. The proposed spatial model is based on a function which uses a linear combination of AIS with the reference value. Therefore, in the model, the value of the reference value accounts for temporal variability and the AIS account for spatial variability of vine water status, which allows extrapolation over the whole domain (vine fields in this case).

This model was validated on two fields planted to different cultivars over several years. The proposed spatial model significantly improved the prediction of the vine water status, especially under conditions of high water restriction (PLWP < -0.4 MPa), compared with a non-spatial model. The model was shown to be robust to the choice of reference site. The results also highlighted relevant AIS for predicting PLWP under these experimental conditions. The success of the spatial model in improving the quality of prediction of PLWP means it could be incorporated into a decision-support tool to improve irrigation management within a vineyard.

However, the calibration of the model still needs some simplification to be fully operational on commercial vineyards. The main issue is a need to significantly decrease the number samples required to calibrate the model. We intend to improve our approach in further works by proposing decision rules using high resolution auxiliary information (i.e. airborne imagery, soil apparent conductivity, etc.) and other information sources to design the best sampling scheme.

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ANNEXES

Annexe 1: Field-scale model of the spatio-temporal vine water status in a viticulture system

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Abstract
The water status of a vine during the season is an important indicator and determinant of final grape quality. Using data collected from temporal measurements of pre-dawn vine water status from multiple locations in a field over two consecutive seasons, a field scale spatio-temporal model of vine water status has been constructed. The model uses climatic variables to temporally model mean field values for vine water status, then readily measured vine and soil parameters to model a spatial error component at any given time. The spatial component significantly improved the fit of the temporal model to the data, especially at higher water stresses when information is more important for decision making. Spatial patterns associated with management decisions were similar between the modelled and interpolated data sets. Results are very encouraging and further model development and refinement will continue to make the model more for application across different fields and varieties.

Introduction
Grape production, particularly grape quality, is strongly influenced by the level of water stress that the vine undergoes during production. Optimum quality is usually achieved through imparting some minor to moderate water stress during the reproductive phase (Dry and Loveys, 1998). However, too much stress at this stage can be detrimental to production. Consequently, growers, particularly in irrigated production systems, are very keen to have information – both spatial and temporal – on the change in plant water status (ψ) in their vineyards. However, this information is difficult to obtain due to the cumbersome and expensive nature of directly measuring ψ (Jones, 2007). Direct measurements are often limited to only a few sites, which gives poor spatial resolution. Many producers opt to measure the soil moisture potential instead, as a surrogate for plant water potential, and adjust irrigation according to soil conditions. In non-irrigated vineyards, a knowledge of ψ can also assist with management to conserve soil moisture and canopy management to optimise harvest quality. Acevedo-Opazo et al., 2007 illustrated a simple spatial model for extrapolating plant water status (ψ) across a vineyard. This was based on a demonstrated linear relationship between $\psi_{re,j}$, a reference plant water status value at a given point Sre, at a particular time j, and other measured locations in the field at the same time $\psi_{m,j}$. In their study, Acevedo-Opazo et al., 2007 had 1 reference site (ψ_{re}) and 48 measurement sites (denoted by the vector Ψ_m). Acevedo-Opazo et al 2007 hypothesis that this derived relationship can be used to predict the plant water status at some future time, h, at the measurement sites from a single reference measurement taken at time h.
While this demonstrated simple relationship is encouraging, application of the spatial model is labourious and problematic. Firstly, the spatial model depends on a linear relationship between ψre and Ψ_m. This is not a universal relationship and must be established for each individual site, even within single blocks. This involves multiple manual measurements of ψ (at both reference

and measurement sites) during the growing season to gather the required data to derive the linear relationship. Secondly, the model can only be applied to sites that are members of Ψ_m. Predictions cannot be made at locations where ψ has not been previously measured (the vector of unmeasured sites is denoted by u), thus $\psi_{u,h}$ must be spatially interpolated (e.g. by kriging or nearest neighbour interpolation) from $\Psi_{m,h}$. This imposes limitations on the minimum size and the spatial location of Ψ_m if a map of ψ is the desired outcome. Lastly, the proposed model is also purely a spatial model and limited to times when a reference measurement is obtained.

There are several potential approaches to constructing a spatio-temporal model (e.g. 3D kriging, regionalised autoregressive models, Bayesian maximum entropy models). The intention of the current project is to investigate the suitability and applicability of these and other methods for a spatio-temporal model of plant water status. As a starting point, a temporal model with a spatial error correction is presented here. The proposed model utilises a temporal component to estimate a mean ψ at a given time h ($\overline{\psi_h}$) then uses a spatial component, derived from crop and environmental parameters, to spatially correct $\overline{\psi_h}$ for every site in the block/vineyard. The derivation of the temporal and spatial error components will be presented independently before being joined in the overall model.

Site Description

A full description of the site is given in Acevedo et al, 2008. Briefly, the vineyard is located near Narbonne, southern France. The study sites consist of a 1 ha block of Syrah grapes where 49 sites were monitored for predawn vine water status (ψ) during two growing seasons – 2003 (18/06, 26/06, 8/07, 16/07, 23/07, 30/07 and 12/08) and 2004 (09/06, 05/07, 18/08, 23/08, 10/09). Values of ψ at each site were derived from the mean of three readings. Various other data (both point and surfaces) have been collected between 1999 and 2007 for the vineyard and are introduced below.

Available spatial data: Filtered and smoothed aerial NDVI images from 1999, 2006 and 2007 were extracted onto a 2.5 m square grid. The three NDVI layers were transformed into a relative NDVI (Eqn. 1) and then compressed by averaging each grid point to give a mean relative NDVI (MR-NDVI). In addition point measurements were made at the sample vine sites. A wenner array was used to measure soil resistivity to 0.5 m and 1 m depth ($ER_{0.5}$ and ER_1 respectively) at each measurement site (n = 49). Trunk circumference (TC), Yield (M) and the weight of pruned wood (PW) post-harvest was also measured at each site. An estimation of the surface area of the canopy (SFE) was made mid season 2003. All the point (sample site) data was interpolated onto the same 2.5 m square grid using ordinary global kriging with Vesper (Minasny et al, 2007). Conversely, the ECa, DEM and NDVI data were extracted to each measurement site.

$$\{[NDVI - Min(NDVI)]/[Max(NDVI) - Min(NDVI)]\}*100 \qquad \text{Equation 1}$$

Available temporal data: Daily precipitation, evaporation and temperature (mean, minimum and maximum) data was available for 2002 to 2004. Cumulative precipitation (P_c) and evaporation (E_c) were recorded daily and the difference ($P_c - E_c$), an estimation of cumulative water supply (WS_c) at each day calculated. P_c, E_c and WS_c were calculated from November 1st from the previous year till September 30th.(the end of the production season). Cumulative growing degree days (GDDs) were also calculated for the growing season (April 1st to Sept 30th) using a base temperature of 10°C (Gladstones, 1992).

$$GDD = [(T_{MAX} - T_{MIN})/2] - T_{BASE} \qquad \text{Equation 2}$$

where T_{MAX} and T_{MIN} are the maximum and minium daily temperature and T_{BASE} is a threshold temperature below which plants are considered inactive. For vines this is considered to be 10°C.

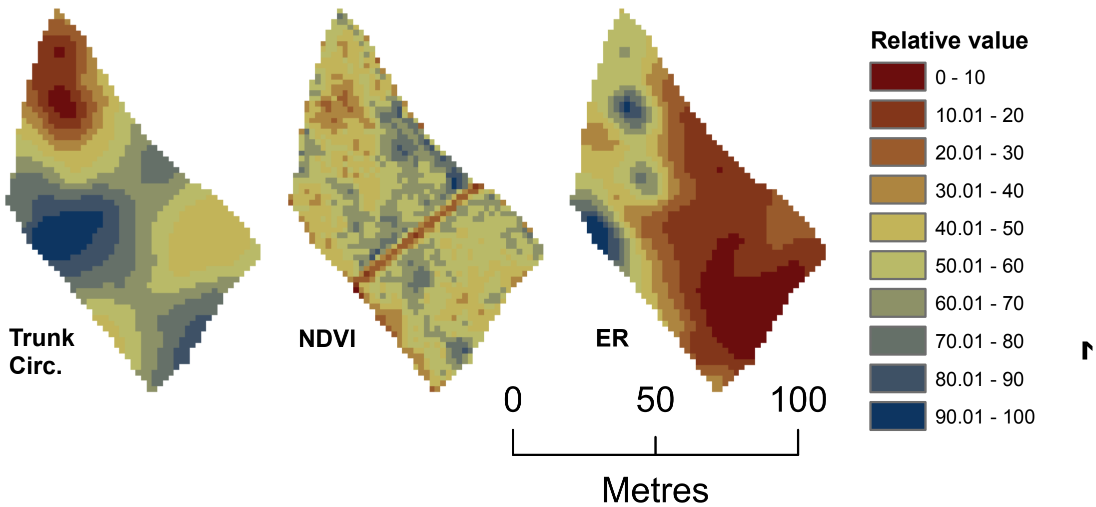


Figure 1. Maps of trunk circumference (left), NDVI (middle) and soil electrical resistivity (right) expressed as relative values for the experimental field

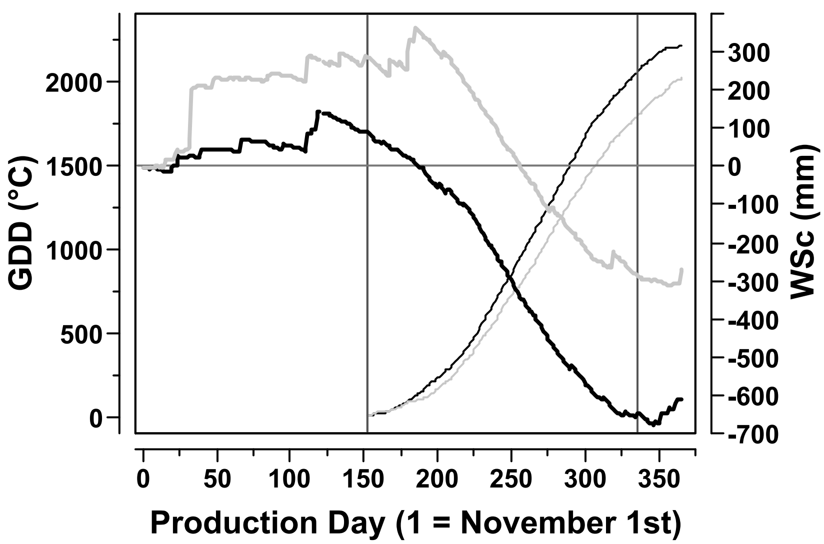


Figure 2. Climatic data for the two years showing the growing degree days (left axis and dashed lines) and cumulative water supply (deficit) (right axis and solid lines). Data for 2003 are grey lines, 2004 are black lines.

A (predictive) Spatio-temporal model of ψ

The temporal component

In non-irrigated production systems the temporal evolution of ψ is driven by climatic variables that relate to moisture availability i.e. precipitation, evaporation and transpiration. Figure 2 shows that the climate for the two years was different. 2004 was hotter (higher GDDs) and had greater water stress than 2003. There are sufficient GDDS for vine growth in both years (GDD > 1700, Gladstones (1992)). Plots of the mean field ψ ($\bar{\psi}$) vs. WS_c for each year showed strong linear responses within years, however the slope and intercept between the two years was very different (data not shown). A linear regression model was fitted to the combined ψ data from the two years using WS_c , GDD and an interaction term. The GDD and interaction term were included to see if differences in a heat index explained the slope and intercept differences between years. A good fit ($r^2 = 0.94$, intercept = -0.3, m = 0.94) across the two years was found (bearing in mind the climatic differences between years) (Fig. 3)

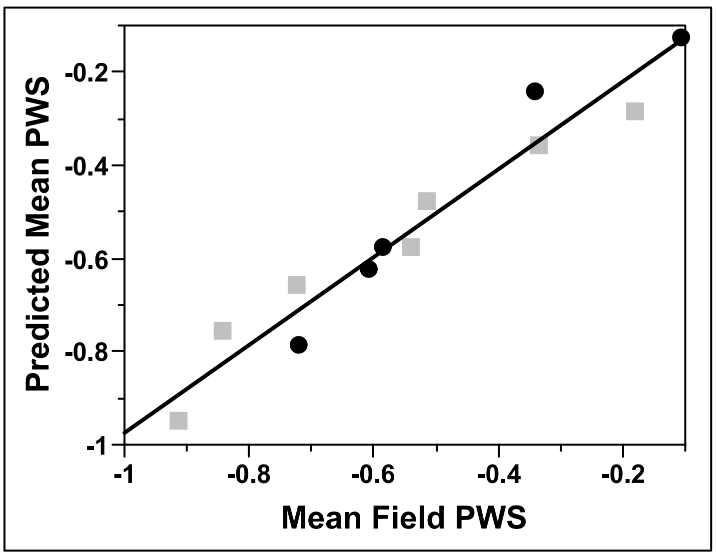


Figure 3. Regression fit of climatic variables to ψ across two years. Dots indicate 2004 data and squares 2003 data. (Regression equation is PWS = 0.888 [-0.00427*GDD] + [0.00686*WS_c] + 0.00000697[(GDD - 1015.6083)*(WS_c + 233.5083)])

The spatial error component

The temporal relationships provides a good mean prediction for a given date ($\bar{\psi}_h$). The next step is to spatially assign the mean data within the production system or rather spatially correct the error between the mean ψ at a given time h ($\bar{\psi}_h$) and ψ at each locale (**u**) in the field at time *h* ($\psi_{(u,h)}$).

Previous spatial modelling indicates that information pertaining to canopy and vine size (SFE, TC, PW) and soil variation (EC_a and ER) are all predictors of $\psi(s_u,t_h)$. Consequently they should be predictors of the spatial error ($\bar{\psi}_t - \psi_{(u,h)}$) denoted ($\varsigma_{(\mathbf{u},h)}$). However, many of these parameters are site-specific and their properties are particular to the production system – for example TC depends on vine age whilst PW and SFE will be strongly influenced by different trellising and management regimes. The intention of the project, of which this work is a part, is to develop a spatio-temporal model which is robust enough to permit the resolution of prediction to be up- or down-scaled and applied across different regions with a minimum of effort. Previous studies have indicated that the spatial pattern of NDVI imagery and EC_a surveys in vineyards tends to be temporally stable even though the absolute value of NDVI and EC_a may change from year to year (Tisseyre et al., 2008). Temporal fluctuations in absolute values will be influenced (among aother things) by time of acquisition (growth stage), sensor type and calibration and canopy management in the case of NDVI, and changes in soil moisture, sensor type and calibration , ground cover and time of collection (particularly seasonal influences) in the case of ER (EC_a). Thus, while absolute values may not be useful in a temporal setting, a relative value is, as the same locations tend to have higher (or lower) NDVI and EC_a responses over time.

The spatial correction model uses relative surrogate inputs for canopy size and soil typewhich can be rapidly sensed or measured. Thus SFE was replaced by the MR-NDVI and Relative Trunk Circumference whilst the ER_1 and $ER_{0.5}$ were converted into a relative value using equation 1 and averaged. 5NB ER and ECa are the inverse of each other)

The spatial error (ϑ_u) model can be described as;

$$\varsigma_{(\mathbf{u},h)} = \left(\overline{\psi}_t - \psi_{(u,t)}\right) \sim f(\text{MR-NDVI, R-ER, R-TC}) \qquad \text{Equation 3}$$

The overall model

An estimation of ψ at a given time and location can therefore be determined by summing the temporal and spatial error components. From the data (Fig. 4), it is known that the variance of ψ within a field is related to the mean ψ. Therefore the influence of the spatial error can be weighted by a co-efficient related to the expected variance for a given $\overline{\psi}_t$. The weighting function (α_ψ) is also shown in Fig 4.

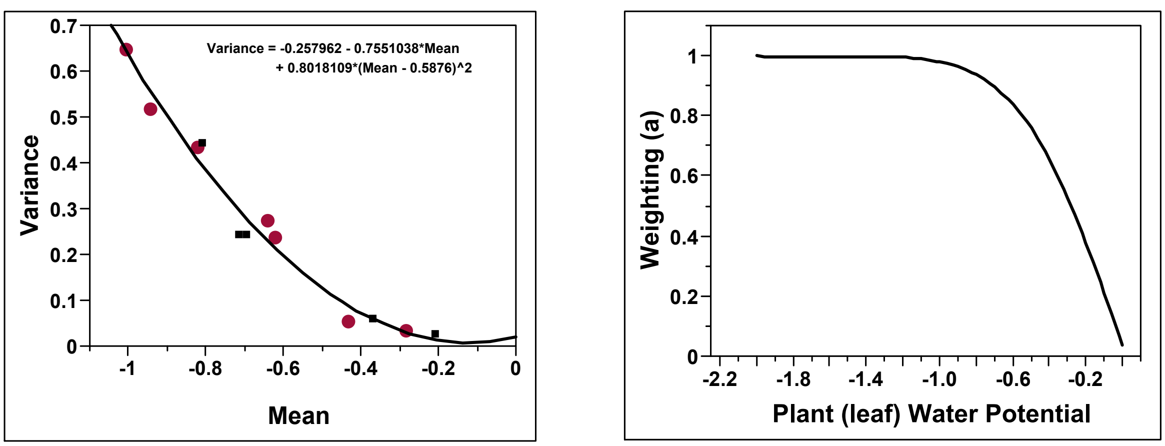


Figure 4. Relationship between mean and variance of ψ (left) and subsequent weighting function (α_ψ) applied to the spatial error component

The ST model can therefore be written as.

$$\psi_{(u,t)} \sim \overline{\psi}_t + \alpha_\psi * \vartheta_u + \varepsilon \qquad \text{Equation 4}$$

where ε is the error term

Since the independent variables in the spatial error component are not temporally variable, this (simple) model will produce the same spatial pattern at each given date. The α_ψ coefficient should dampen the response of this spatial pattern when ψ is not impacting on vine growth/production.

Validation

Two validations were performed, a global validation and an individual date validation.

Validation A – The combined 2003 and 2004 data was subset randomly into a calibration (80%) and validation (20%) set. The calibration set was used to generate a linear model to predict ϑ_u using MR-NDVI, R-ER and R-TC. The model was applied to the validation set and was evaluated using the r², Li's ρ and RSMSE. The performance of the base temporal component (i.e. prediction of a mean value for the block) and the ST model without the α_t weighting were also evaluated.

Validation B – A leave-one-date out cross validation. Each date of measurement was sequential removed from the dataset, then the three models, temporal, ST and ST + a were generated on the remaining data before being validated on the omitted data. The RMSEs from the validation set were generated and plotted against the $\overline{\psi}$.

The results from the global model were mapped and compared with maps derived from interpolation (kriging) of the 49 sample sites. The maps were displayed using threshold values related to vine irrigation management. The most critical level is -0.4 MPa, below which the vine is considered understress.

Results and Discussion

The statistical results from the Validation A are shown in Figure 5. The predicted maps from the global calibration are shown in Figure 6. The results from Validation B are shown in Figure 7.

The incorporation of the spatial component improved both the general fit (r²) and the fit to the 1:1 line (Li's ρ) compared to the temporal model. The use of the variance weighting factor (α_ψ) did not improve the temporal model in this case.

The threshold maps (Fig. 6) from the model (Eqn 3) provided similar spatial patterns to maps derived from interpolation of the raw data. This indicates that the model will be useful for management. The RMSE from the leave one date out indicated that the temporal model performed better at low $\overline{\psi}$. However the spatio-temporal model was more effective (lower RMSE) as $\overline{\psi}$ increased.

From an irrigation or vine management perspective, good information at low $\overline{\psi}$ is not necessary as no decision is required when water is non-limiting. Information becomes more valuable as a stress is applied. The results from the leave-one-date out modelling indicate that a temporal model is sufficient at the start of the season to predict how $\overline{\psi}$ is performing. Once $\overline{\psi}$ approaches the critical level of –0.4 MPa the spatio-temporal model and predictions of $\psi_{(u,h)}$ become more useful for management.

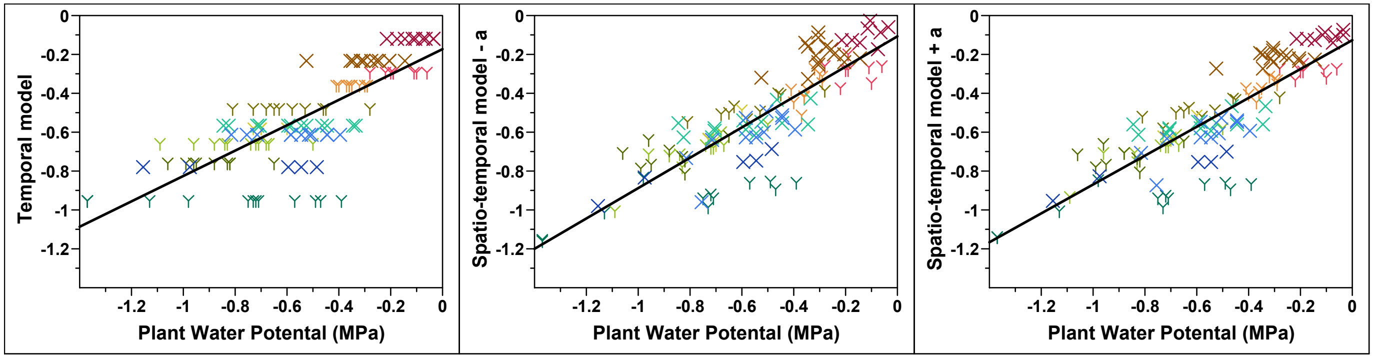
The model proposed here is a first step in the evolution of a spatio-temporal model of vine water status. Further adaptation and validation are planned, in particular approaches to make the spatial error component temporally dynamic using within season temporal data.

Conclusions

Spatial management of the temporal evolution of vine water stress will help grapegrowers optimise quality (and quantity) within their systems. A simple temporal model with a spatial correction component has been proposed and shown to perform better than the stand-alone temporal model. The patterns derived from the model follow those observed in interpolated maps and are encouraging for further model development and application.

Acknowledgements

The authors would like to acknowledge the assistance of Dr. Hernán Ojeda and his team at INRA Pech-Rouge during the collection of the data. Dr Taylor's work in France is funded by The Agropolis Foundation.



RSquare	0.62	0.75	0.75
Li's ρ	0.59	0.74	0.72
RMSE	1.13	0.94	0.94

Figure 5. Plots of actual vs. fitted for the calibration data set. From left to right models are the stand-alone temporal model, the basic spatio-temporal model and the spatio-temporal model with the weighting factor (α_ψ) X indicates 2003 data and Y 2004 data. Statistics of each fit are shown below the plots.

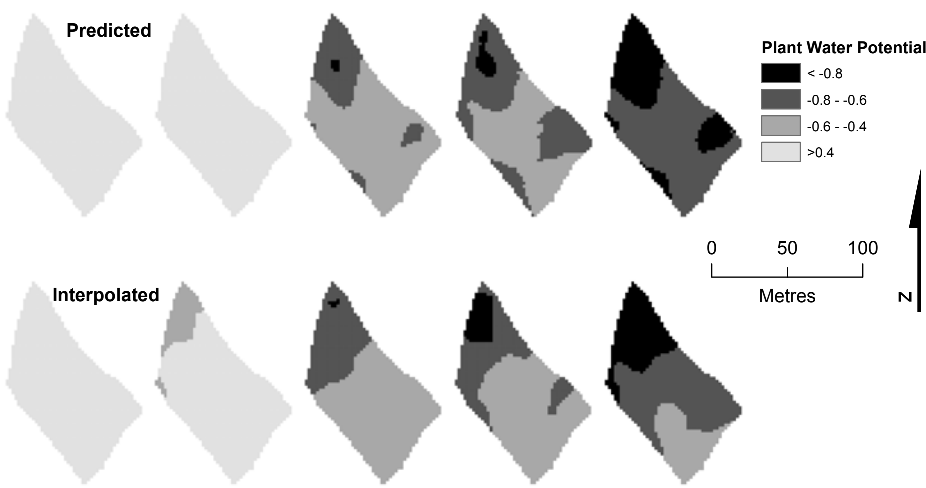


Figure 6. Threshold maps for 2004. Top line is the model derived data and the bottom line interpolated maps. Data is in increasing date of measurment from left to right and shown on the same scale

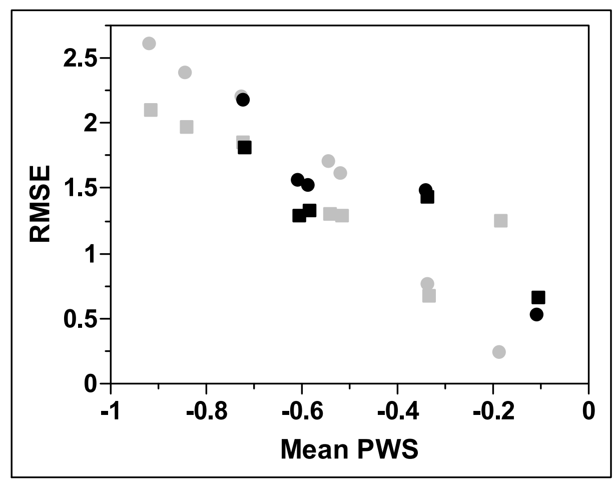


Figure 7. RMSE for leave-one-date out analysis vs $\overline{\psi}$. Squares indicate the spatio-temporal model, circles the temporal mode

Annexe 2: Preliminary model for spatial extrapolation of leaf stomatal conductance on grapevines (Vitis vinifera, L.)

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Abstract
The results of this paper show the development of a preliminary model that uses a single stomatal conductance (g_s) measurement taken on a reference site in order to predict g_s and its spatial variability over the whole vine field. An experiment to develop and test the model was carried out over a commercial vineyard (var. Merlot) located in the Maule Region of Chile, during the 2007/08 growing season. Results showed a significant within-field variability of g_s over space and time, and the existence of significant linear relations among g_s values. The model was able to predict spatial variability of g_s with a spatial and temporal mean error of 48.4 and 51.4 mmol m^{-2} s^{-1} respectively. Further studies will aim to confirm the relevancy of this approach for different seasons and locations.

Keywords: Grapevines, extrapolation, stomatal conductance, spatial model, spatial and temporal variability.

Introduction
Stomatal conductance (g_s) is a variable normally used in models to estimate plant water requirements. Since g_s is the first factor to be affected either by water stress or high atmospheric demand due to the effect of plant stomatal regulation, it can be used as an integrative tool to represent the severity of grapevine water restriction (Flexas *et al.* 2002; Cifre *et al.* 2005). Unfortunately, g_s measurements are hard to perform, require specific technical skills from the operator, it is time consuming and measurements have low spatial and temporal resolution, since it is a manual technique. Furthermore, many authors have shown that the majority of vineyards present considerable spatial variability of productivity variables, such as: vegetative growth, maturity indices, yield and grape quality components (Ortega *et al.* 2003; Bramley and Hamilton, 2004; Taylor *et al.* 2005). These effects in productivity variables are a direct result of the significant variation usually found in physiological variables (i.e. leaf g_s) within a single vine and within the field. This variability is especially evident in summer, when significant vine water restrictions are present under irrigated and non-irrigated conditions (Ojeda *et al.* 2005; Tisseyre *et al.* 2005, 2007). Frequently, g_s and transpiration rate (E) measurements are taken at the leaf scale using a porometer or gas exchange devices (Loveys *et al.* 2005; Cifre *et al.* 2005). However, g_s and E data from these sources are characterized by a high degree of variability among measurements within the same plant. Therefore, this method

requires a great number of single point measurements to be able to accurately characterize variability in the whole grapevine canopy (Loveys *et al.* 2005). Variations of g_s and E in the field can be mainly related to changes in soil physical characteristics, assuming uniformity of plant material and the irrigation system. Therefore, in addition to temporal water status monitoring it is necessary to consider a spatial variation assessment. Extrapolation of a few measurements to a vine sector or a vine field without considering any representative scaling up or modelling technique can hardly be representative. Consequently, an efficient decision support tool to estimate vine water status must be based on a Spatio-Temporal (S-T) monitoring system, which would be able to provide maps or snapshots of g_s to assess its variability over the whole vineyard during the entire growing season. This paper proposes decreasing drastically the number of g_s sampling points in space allowing reasonable sampling frequency over time. This approach necessarily requires a representative extrapolation of the g_s on unsampled sites for each date of measurement. Thus, the main aim of this paper was to propose a preliminary model that uses only a single measurement performed on a reference site in order to predict g_s and its spatial variability over the whole vine field. The features of the model proposed and its relevancy will give the future steps for developing a more advanced model.

Materials and methods

Experimental field and plant material description

The experiment was carried out on the commercial vineyard "Calina" (S 35º25'9.87'', W 71º33'2.81'' WGS84, Maule region, Chile) during the 2007/08 season. The vineyard was established on a clay loam soil (Talca series) and consists in a drip-irrigated Merlot field of 2.3 ha. The 9 year-old vines were trained in a vertical shoot-positioned system planted at 1.5 m x 2.5 m. Forty sites of measurements ($s_1, s_2, ..., s_i$: i= 1, 2, ..., 40) were defined on a regular grid within the field. The contour and the site locations were geo-referenced with a Differential Global Positioning System (model Pathfinder ProXRS, Trimble, Sunnyvale, CA, USA) allowing the analysis and mapping of the variables studied.

Variables measured

A steady state porometer (model PMR5, PP-System, Amesbury, Massachusetts, USA) was used to measure g_s within the regular grid from 13:00 to 15:00 h for the measurement dates. Therefore, $z\ (s_i,t_j)$ corresponds to the average of two measurements of g_s on the site s_i at time t_j to performed on one representative vine along the row. Measurements were obtained from 7 dates in the 2007/08 season. Additionally to measure plant water status, midday stem water potential *(SWP)* was obtained using the pressure chamber method (PMS Instrument Co., model 600, Corvallis, Oregon, USA) (Scholander *et al.* 1965; Choné *et al.* 2001). The SWP measurements were performed in the same dates that the g_s measurements.

Data mapping and data analysis

Data mapping was performed using the 3Dfield software (Version 2.9.0.0, Copyright 1998-2007, Vladimir Galouchko, Russia). The interpolation method used in this study was based on a determinist function (inverse weighting distance). The classes used to build up the g_s map corresponded to expert classes proposed by Cifre *et al.* (2005). Data analysis was done using Matlab® v.7.0 (Mathworks, Inc.). This study was conducted with a correlation coefficient analysis deduced from the variance-covariance matrix. Thus, the exploratory study was conducted on the correlation analysis of sites (spatial) over time.

Model description

The model proposes an extrapolation of g_s over a field area (D) from leaf g_s values $z_{re}(s_{re}, t_j)$ measured at time t_j and on the location s_{re}. In the following sections, $z_{re}(s_{re}, t_j)$ is also called reference measurement and s_{re} reference site, considering the location s_{re} belonging to D. The model provides an estimation $\hat{z}(s_i, t_j)$ from $z_{re}(s_{re}, t_j)$ where $\hat{z}(s_i, t_j)$ is the predicted g_s value on the location s_i (with $s_i \in \mathrm{D}$ and $s_i \neq s_{re}$) at time t_j. To compute this extrapolation, a function g_{si}, which allows the estimation of $\hat{z}(s_i, t_j)$ from $z_{re}(s_{re}, t_j)$, must be developed. The model can be summarized in follow expression:

$$\hat{z}(s_i, t_j) = g_{s_i}(z_{re}(s_{re}, t_j)); \quad s_{re} \in \mathrm{D}, \forall s_i \in \mathrm{D} \qquad (1)$$

The model (1) can be represented as a collection of site specific functions ($g_{S1}, g_{S2}, g_{S3}, \ldots, g_{Si} : i = 1,2,3,\ldots,n$) on each location into D. Each of these g_{si} functions provides an estimation of the g_s. In this preliminary step, D was considered as the field and g_{si} functions were chosen as a collection of linear coefficients. A simplified expression of the model (1) is presented in equation (2).

$$\hat{z}(s_i, t_j) = a_{s_i} \times (z_{re}(s_{re}, t_j)); \quad s_{re} \in \mathrm{D}, \ \forall s_i \in \mathrm{D}, \ a_{s_i} \in \Re, \qquad (2)$$

Equation (2) assumes that there are a collection of site specific coefficients a_{si} which allow to model the differences in g_s between the locations s_i and s_{re} within D. Therefore, the coefficients a_{si} are only dependant on differences in permanent attributes between locations s_i and s_{re}. These assumptions are considered constant over the time.

Model computation:

Model computation requires several steps to be completed.

Step1: selecting a reference site (s_{re})

This reference site selection is important since s_{re} provides reference g_s which will be extrapolated over D. In this particular study, the reference site was selected by a spatial correlation analysis method that shows the site which was better correlated with all other sites in D. Figure 2 shows within a frame the location of s_{re} for the Merlot field (site 7). Values of g_s measured on s_{re} at all the dates were removed from the data base to generate the $\boldsymbol{r_{ef}}$ vector:

$$(\boldsymbol{r_{ef}})^{\mathrm{T}} = [z(s_{re}, t_1), z(s_{re}, t_2), z(s_{re}, t_3), \ldots, z(s_{re}, t_n)], \qquad (3)$$

Step 2: determination of the collection of coefficients over D

The matrix of g_s values of all sites (except s_{re}) and for all the dates can be represented as **Z**:

$$\mathbf{Z} = \begin{bmatrix} z(s_1,t_1) & z(s_1,t_2) & z(s_1,t_3) & \cdots & z(s_1,t_m) \\ z(s_2,t_1) & z(s_2,t_2) & z(s_2,t_3) & \cdots & z(s_2,t_m) \\ z(s_3,t_1) & z(s_3,t_2) & z(s_3,t_3) & \cdots & z(s_3,t_m) \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ z(s_n,t_1) & z(s_n,t_2) & z(s_n,t_3) & \cdots & z(s_n,t_m) \end{bmatrix}, \qquad (4)$$

The model consists in finding the vector $\boldsymbol{a}$ (collection of coefficients) to provide an estimation $\hat{\mathbf{Z}}$ for g_s values over D, such as the indicated by the following relation.

$$\hat{\mathbf{Z}} = \boldsymbol{a} \times \left(\boldsymbol{r_{ef}}\right)^{\mathrm{T}}, \tag{5}$$

with,

$$\boldsymbol{a} = \begin{bmatrix} a_{s_1} \\ a_{s_2} \\ a_{s_3} \\ \vdots \\ a_{s_n} \end{bmatrix} \quad \text{and} \quad \hat{\mathbf{Z}} = \begin{bmatrix} \hat{z}(s_1,t_1) & \hat{z}(s_1,t_2) & \hat{z}(s_1,t_3) & \cdots & \hat{z}(s_1,t_m) \\ \hat{z}(s_2,t_1) & \hat{z}(s_2,t_2) & \hat{z}(s_2,t_3) & \cdots & \hat{z}(s_2,t_m) \\ \hat{z}(s_3,t_1) & \hat{z}(s_3,t_2) & \hat{z}(s_3,t_3) & \cdots & \hat{z}(s_3,t_m) \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ \hat{z}(s_n,t_1) & \hat{z}(s_n,t_2) & \hat{z}(s_n,t_3) & \cdots & \hat{z}(s_n,t_m) \end{bmatrix}, \tag{6}$$

The least square method was used to determine the vector $\boldsymbol{a}$ as follows:

$$\boldsymbol{a} = \left[\boldsymbol{Z}\right] \times \boldsymbol{r_{ef}} \times \left[\left[\boldsymbol{r_{ef}}\right]^{T} \times \left[\boldsymbol{r_{ef}}\right]\right]^{-1}, \tag{7}$$

Model evaluation

The accuracy of the model was assessed using the Standard Error of Calibration (*SEC*) which was computed as follow:

$$SEC = \sqrt{\frac{\sum_{i=1}^{n}\sum_{j=1}^{m}\left(E\left(s_i, t_j\right)\right)^2}{\left(n \times m\right) - 1}}, \text{ with } E\left(s_i, t_j\right) = \sqrt{\left(\hat{z}(s_i, t_j) - z(s_i, t_j)\right)^2}, \tag{8}$$

where n is the number of sites on the field and m is the number of available dates.

The ability of the model to predict values was assessed using a "leave-one-out" validation procedure. The database was divided into m subsets ($k_1, k_2, k_3, \ldots k_m$) corresponding to the m measurement dates.

Similarly, the reference measurements obtained on the reference site (s_{re}) were divided into m singletons. Thus, m different models were then trained leaving out one of the subsets k_1, k_2,…or k_m from training, but using only the omitted subset to compute the error. Two types of prediction errors were then computed: (i) the standard error of prediction at a given time t_j ($SEPt_j$) and (ii) at a given site s_i ($SEPs_i$):

$$SEPt_j = \sqrt{\frac{\sum_{i=1}^{n}\left(E\left(s_i, t_j\right)\right)^2}{n-1}} \qquad SEPs_i = \sqrt{\frac{\sum_{j=1}^{m}\left(E\left(s_i, t_j\right)\right)^2}{m-1}} \tag{9}$$

Results and discussion

Spatial analysis of g_s

Three examples were chosen to illustrate the dispersion of linear relations between s_{re} and all measurement sites of the studied field over the 2007/08 season. The best relation presented a r of 0.94 (site 10, Figure 1a) and the worst linear relation presented a r of 0.39 (site 36, Figure 1c).

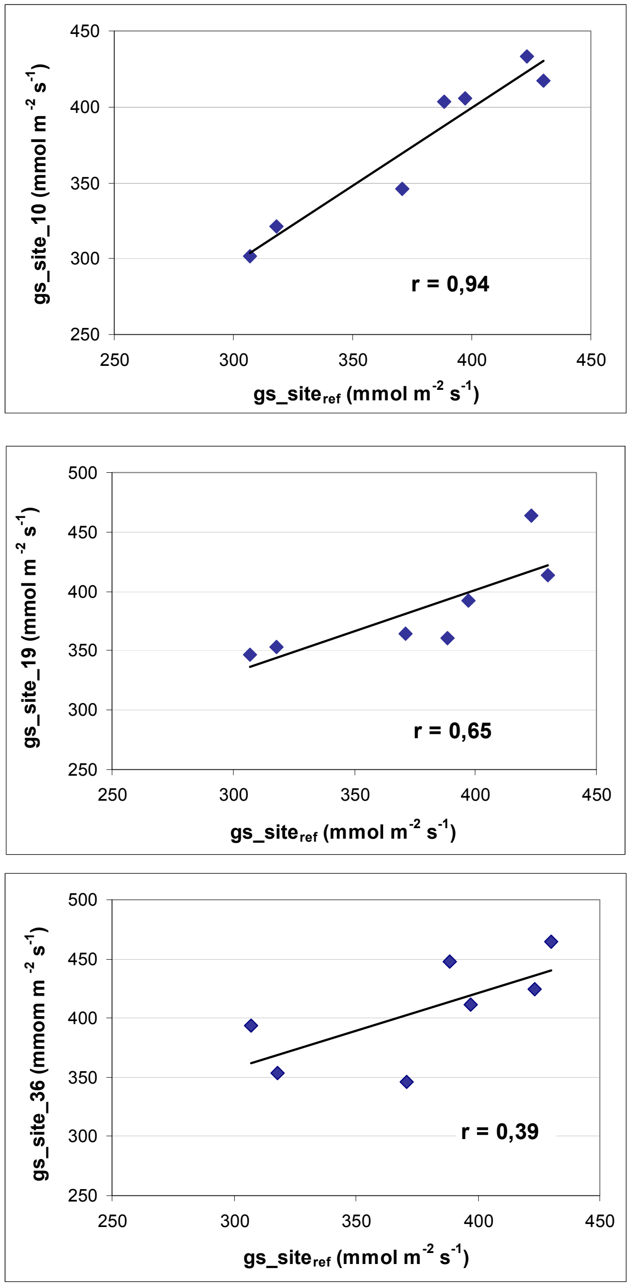

Fig 1. Example of linear relations between g_s measured on reference site (s_{re}) and three other sites over the 2007/08 growing season. (**a**) Relation between g_s from s_{re} and site 10 which presents the best correlation (r = 0.94), (**b**) relation between g_s from s_{re} and site 19 which corresponds to the median correlation coefficient (r = 0.66) and (**c**) relation between g_s from s_{re} and site 36 which presents the worst correlation coefficient (r = 0.39).

Spatial distribution of the r for the field is showed in Figure 2. The results obtained showed the relevance of the approach proposed in equation (2). Despite significant spatial variability observed in g_s, there was an acceptable linear relation between g_s from measurement sites and reference site. Knowing the g_s value z_{re} (s_{re} , t_j) and a_{si} should then provide a relevant estimation of z (s_i , t_j).

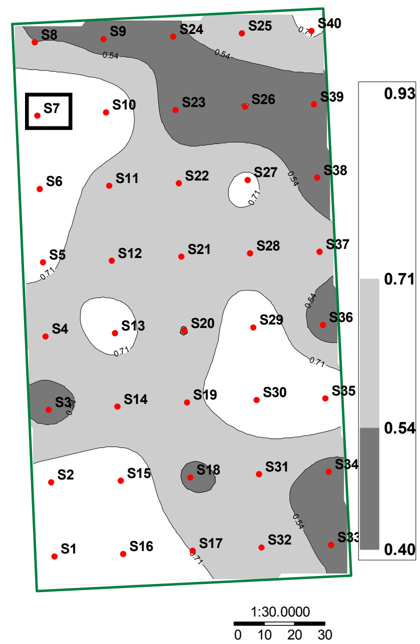

Fig 2. Correlation map from all sites compared with the reference site (site 7). High (white), medium (grey) and low correlations (dark grey) are mapped.

Model calibration

The map for vector "***a***" of the model is showed in Figure 3. In order to simplify the visualization and interpretation, a_{si} were interpolated over the field and four classes (with the same magnitude of variation) were defined.

For the studied field (Figure 3), the white pattern represents the highest a_{si} values ($a_{si} \in$ [1.11; 1.21]). Therefore, these zones systematically presented g_s values higher than the reference site. On the contrary, black pattern represents the lowest a_{si} values ($a_{si} \in$ [0.84; 0.93]) for field zones which systematically presented g_s values lower than the reference site. Light grey pattern represents field zones with similar g_s values as the reference site.

The error of calibration (SEC) of the model was 27.3 mmol m^{-2} s^{-1} on the field. Based on the range of values found in literature (± 30 mmol $m^{-2}s^{-1}$ for woody plants, Calvet et al., 2004), the model could be considered relevant and accurate enough.

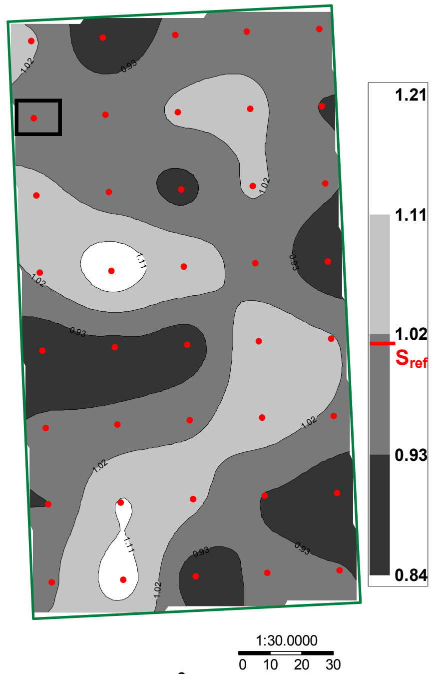

Fig 3. Map of collection of the linear r^2 between the reference site (s_{re}, site 7) and the rest of sites on the field (vector "***a***" of the model).

Standard error of prediction over time ($SEPt_j$)

$SEPt_j$ was not constant over time and varied from a minimum value of 34.1 mmol m^{-2} s^{-1} to a maximum of 63.5 mmol m^{-2} s^{-1} for the dates of the study (Table 1). It is important to notice that SWP over whole experimental period varied from -0.74 to -1.01 MPa. This variation is not significant regarding the precision considered by recommendations to vine-growers to take an irrigation decision (± 0.2 MPa) (Ojeda *et al*. 2005). Therefore, these SWP values indicated that the vineyard was under moderate water restrictions (Cifre et al., 2005; Williams and Araujo, 2002).

Table 1. Standard Error of Prediction at different times ($SEPt_j$) with mean *SWP* (MPa), mean g_s (mmol m^{-2} s^{-1}), coefficient of variation (C.V.) and the percentage of variance explained by the model (R^2) at different dates (Time).

Date	07 jan	21 jan	28 jan	05 feb	11 feb	25 feb	10 mar
Time	T_1	T_2	T_3	T_4	T_5	T_6	T_7
Mean *SWP*	-0.89	-1.01	-0.74	-0.91	-0.79	-0.94	-0.97
Mean g_s	389.0	399.5	420.5	393.3	370.4	333.5	303.4
C.V. (%)	19.0	13.5	9.3	12.8	18.0	12.2	19.3
$SEPt_j$	63.5	49.3	34.1	47.2	59.7	51.6	47.8
R^2	0.60	0.55	0.50	0.46	0.48	0.44	0.47

The percentage of variability explained by the model (R^2) at each date varied from 0.44 to 0.60 (Table 1) with a variation coefficient about 20%. The model proposed in this study could be improved having plants under a significant magnitude of variations of SWP (extreme values). Previous studies have shown that the methodology proposed in this paper was relevant to model plant water status under very contrasting soil water conditions (Acevedo et al. 2007).

Measured and predicted g_s maps for a specific date (T_1) are shown in Figure 4. These maps considered ranges of g_s currently used in literature to represent plant water stress levels (Cifre *et al*. 2005). Zones with slight [<375 mmol m^{-2} s^{-1}], medium [375 - 515 mmol m^{-2} s^{-1}] and high [> 515 mmol m^{-2} s^{-1}] g_s were accurately predicted (Fig 4).

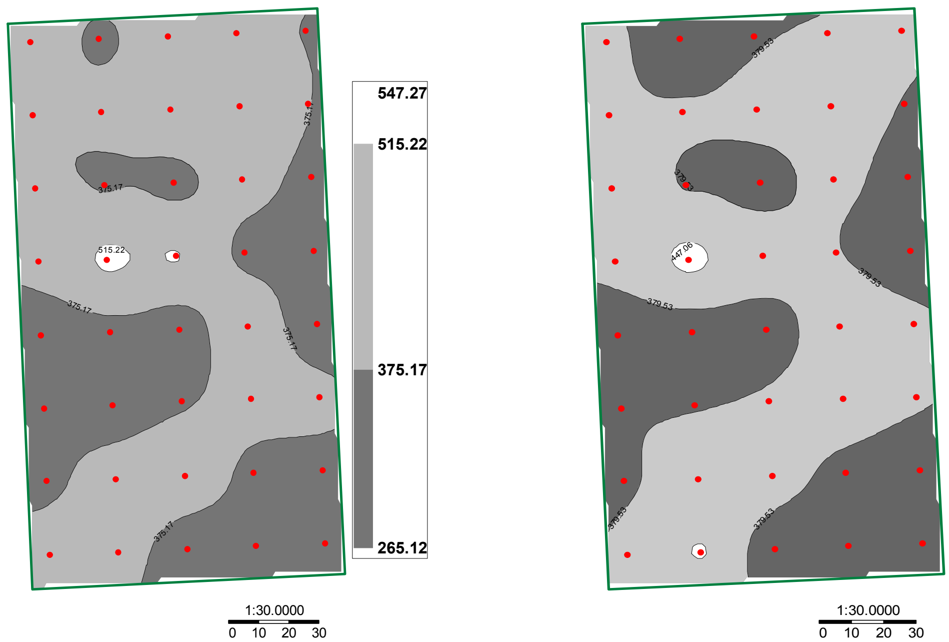

Fig 4. Maps of g_s at the date T_1 in the 2007/08 growing season, representing measured g_s data (**a**) and predicted g_s data (**b**) from the model. Three ranges of g_s currently were considered: slight to medium g_s (<375 mmol m^{-2} s^{-1}; in grey); medium g_s (375; 515 mmol m^{-2} s^{-1}; in light grey) and high g_s (>515 mmol m^{-2} s^{-1}; in white).

Spatial Error of Prediction ($SEPs_i$)

The Spatial Error of Prediction ($SEPs_i$) was computed in order to check the spatial relevancy of the model (Figure 5). Here, $SEPs_i$ was interpolated and four classes of error were considered: (i) low error [10.0; 39.5 mmol m^{-2} s^{-1}] (ii) medium error [39.5; 62.1 mmol m^{-2} s^{-1}] , (iii) high errors [62.1; 83.6 mmol m^{-2} s^{-1}] and (iv) very high errors ($SEPs_i$ > 83.6 mmol m^{-2} s^{-1}). This figure shows that the $SEPs_i$ was low on approximately 80% of the study area. High errors occurred only in seven particular locations and very high errors only occurred on one location. These results show that the model proposed provides relevant information for the majority of the field area studied.

Maps of $SEPs_i$ can be considered as an assessment of the spatial accuracy of the model proposed. It also gives information on the spatial uncertainty of predictions. White and light grey zones represent locations where low confidence is expected from the extrapolation.

Fig 5. Map of standard spatial error of prediction (SEPs_i). Low errors (10.0; 39.5 mmol m^{-2} s^{-1}; in black), medium errors (39.5; 62.1 mmol m^{-2} s^{-1}; in dark grey), high errors (62.1; 83.6 mmol m^{-2} s^{-1}; in light grey) and very high errors (> 83.6 mmol m^{-2} s^{-1}; in white).

Figure 5 shows that predicted g_s values were less reliable in the north and east side of the field and more reliable in the rest of the field. It also shows that there was no obvious spatial organization of the prediction error for the field. These results highlight the ability of the reference site, in association with the model, to predict properly g_s values over the whole field and not only on the surroundings of the reference site.

Further research

Future research will include the application of the model proposed in this paper using canopy conductance (g_c), obtained using infrared thermography (IRT), as a physiological parameter representing canopy conductance rather than leaf g_s. These measurements are based in the close relationship between canopy temperature and g_s (Jones *et al*. 2002; Fuentes *et al*. 2004). This method will reduce the variability commonly found in leaf g_s measurements within the canopy. This approach may also be improved by: (i) Selection of the reference site using auxiliary information (soil, vigour, expert knowledge of the vine field). (ii) The use of auxiliary high resolution information (airborne imagery, soil apparent conductivity, elevation) to compute the collection of linear coefficients (a_{si}). These points will be investigated in future studies with the potential application to model spatial variability for other variables of interest, such as: as leaf area, vine transpiration, among others.

Conclusion

This work was a preliminary study towards a spatial prediction model for g_s. The model was able to predict spatial variability of g_s with acceptable spatial and temporal mean error (48.4 and 51.4 mmol m^{-2} s^{-1}, respectively). Therefore, it was possible to extrapolate leaf g_s to several unsampled locations from a single measurement performed on a reference site once the model was calibrated. A limitation of this approach is that not all locations in the field are predicted with the same accuracy level.

Extrapolation spatialisée d'une mesure locale de l'état hydrique de la vigne à partir de données auxiliaires

Résumé: Ce travail de thèse est relatif à l'estimation spatialisée de l'état hydrique de la vigne. Son objectif est de proposer et de valider une approche permettant de prendre en compte la variabilité spatiale d'une zone définie afin d'y estimer au mieux l'état hydrique des plantes à une date donnée. Suite à un état de l'art des outils et méthodes existants pour estimer l'état hydrique des plantes, cette thèse a mis en évidence, d'une part, la possibilité d'obtenir des mesures de référence de l'état hydrique des plantes avec une faible résolution spatiale et d'autre part, l'existence d'informations avec une haute résolution spatiale mais indirectement reliées à la variable d'intérêt. Ce constat a conduit à proposer une approche collaborative entre mesures de référence et données auxiliaires à haute résolution. Elle propose une fonction d'extrapolation de l'état hydrique qui permet de prendre en compte la variabilité spatiale caractérisée par les données auxiliaires sur une région définie (domaine de validité). Une telle approche n'a jamais été proposée dans la littérature. Pour répondre aux questions posées et valider l'approche proposée, un dispositif expérimental a été mis en œuvre sur neuf parcelles viticoles du domaine INRA de Pech-Rouge (Gruissan France). Une base de données pré-existante à la thèse, a également été utilisée. Ces données ont permis d'identifier l'intérêt et les limites d'une estimation spatialisée de l'état hydrique des plantes.

Pour des contraintes hydriques modérées à fortes (<-0,4 MPa), la variabilité spatiale de l'état hydrique de la vigne est déterminée par certains facteurs du milieu. Le principal facteur identifié est le sol. Lorsque les unités de sol sont caractérisées, la variabilité spatiale est structurée en fonction de la vigueur des plantes. L'étude des informations à haute résolution telles que les images aériennes et les propriétés électriques du sol a montré l'intérêt de ces informations pour caractériser la variabilité spatiale de l'état hydrique des plantes.

L'étape de modélisation s'est concentrée sur un domaine spatial correspondant à la parcelle. Pour une première approche, cette échelle de travail a permis de minimiser les sources de variabilité inter-parcellaires liées au cépage, au mode de conduite, à l'âge de plantation, etc. Un modèle d'extrapolation de l'état hydrique a été proposé et validé sur deux bases de données. Ce modèle repose sur l'estimation d'une collection de coefficients locaux et constants. Chaque coefficient local, permet de modéliser la relation linéaire qui existe entre l'état hydrique mesuré sur un site de référence, et l'état hydrique sur un site donné, quelle que soit la date considérée. Lorsque la contrainte hydrique est élevée, l'approche proposée permet d'expliquer une part importante de la variabilité spatiale de l'état hydrique des plantes (r^2 = 0,70). L'identification de ce modèle général, a permis de proposer une méthode pour introduire les données auxiliaires. Comparée à une approche classique similaire à l'estimation de la moyenne, elle permet d'expliquer une part importante de la variabilité spatiale de l'état hydrique des plantes (r^2 = 0,71) lorsque la contrainte hydrique est élevée. Au niveau intra-parcellaire, les variables auxiliaires retenues sont relatives à la vigueur des plantes.

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159 Pages, 28 Figures, 15 Tables, 2 Annexes.

Mots-clés
Vigne, viticulture de précision, état hydrique de la vigne, variabilité spatiale du vignoble, potentiel hydrique de base, expression végétative, zones de restriction hydrique, arbres de régression, résistivité électrique du sol, image aérienne, modèle de prédiction spatial.

Spatial extrapolation of a punctual vine water status measurement using ancillary information

Abstract: This thesis focused on the spatial estimation of vines water status. Its objective was to propose and validate an approach to take into account the spatial variability in order to better estimate the plant water status at a given date. After a state of the art showing tools and methods exist for estimating the water status of plants, this thesis showed, firstly, the availability of measurements of reference to estimate the plant water status with a low spatial resolution and secondly, the existence of information with high spatial resolution but indirectly related to the variable of interest. This state of art led to propose a collaborative approach between reference measurements and auxiliary data at high resolution. It considers a function of extrapolation of the water status which allows to take into account the spatial variability characterized by the auxiliary data on a defined area (zone of validity). Such an approach has never been proposed in the literature. In response to questions and to validate the proposed approach, experiments were carried out in nine fields of vineyard INRA Pech-Rouge (Gruissan France). A database of pre-existing thesis was also used. A database developed by the thesis was also used.
These data have identified the advantages and limitations of a spatial estimation of plant water status.
For moderate to severe water restriction (<-0.4 MPa), spatial variability of vines water status is determined by certain environmental factors. The main factor identified is the soil. When the soil units are characterized, spatial variability is structured according to plant vigor. The study of information such as multispectral airborne images and the soil electrical properties showed the benefit of this information to characterize the spatial variability of plant water status.
The modeling stage focused on a spatial domain corresponding to the block. For a first approach, this scale of work permits to minimize inter-block sources of variability like variety, training system, date of plantation, etc. An extrapolation model of plant water status has been proposed and validated in two databases. This model is based on a collection of site specific coefficients which are constant over time. Each coefficient, models the linear relationship between plant water status measured on a reference site, and the plant water status at a given site, regardless of date. When water restriction is large, the proposed approach can explain a significant proportion of the spatial variability of plant water status ($r^2 = 0.70$). The identification of this general model, gave the formalism to take into account the auxiliary data. Compared to a classical approach similar to the estimation of the mean field, the model with auxiliary data explains a significant part of the spatial variability of plant water status ($r^2 = 0.71$), when water restriction is large. At the within-field level, selected auxiliary information refers mainly to plant vigor.

159 Pages, 28 Figures, 15 Tables, 2 Appendices.

Keywords
Grapevine, precision viticulture, vine water status, vineyard spatial variability, predawn leaf water potential, vegetative expression, water restriction zones, regression trees, soil apparent resistivity, airborne imagery, spatial prediction model.

Extrapolación espacial de una medición puntual del estatus hídrico de la viña utilizando datos auxiliares

Resumen: Este trabajo de tesis se focaliza en la estimación espacial del estatus hídrico de la viña. Tiene por objetivo proponer y validar una metodología que considera la variabilidad espacial del cuartel vitícola, de manera de estimar lo mejor posible el estatus hídrico de la planta en una fecha determinada. Posterior a una revisión exhaustiva de literatura de las principales herramientas y métodos existentes para estimar el estatus hídrico de las plantas, este trabajo puso en evidencia, por un lado, la posibilidad de utilizar mediciones de referencia para estimar el estatus hídrico de planta con una baja resolución espacial y por otro, la posibilidad de utilizar información auxiliar de alta resolución espacial que está relacionada indirectamente a la variable de interés. Este trabajo propone una metodología conjunta entre las mediciones de referencia y la información auxiliar de alta resolución, la cual es original y jamás propuesta hasta ahora en la literatura. Así, se propone una función de extrapolación del estatus hídrico que considera la variabilidad espacial sobre un área determinada (zona de validación) la cual es caracterizada por datos auxiliares. Para responder a las preguntas científicas y validar la metodología propuesta, se planificó un dispositivo experimental que comprendió nueve cuarteles vitícolas de la estación experimental del INRA de Pech-Rouge (Gruissan, Francia) que permitió crear una importante base de datos. Además se utilizó una base de datos pre-existente a la tesis. Estos datos permitieron identificar las ventajas y las limitaciones de una estimación espacial del estatus hídrico de las plantas.

Para restricciones hídricas moderadas a fuertes (<-0,4 MPa), la variabilidad espacial del estatus hídrico de la viña está determinada por ciertos factores ligados al medioambiente. Así, el principal factor identificado fue el suelo. Una vez que las unidades pedológicas han sido caracterizadas, la variabilidad espacial se presentó estructurada en función del vigor de las plantas. Además, el estudio de la información auxiliar tal como, imágenes aéreas y propiedades eléctricas de suelo, mostró las ventajas de esta información para caracterizar la variabilidad espacial del estatus hídrico de las plantas.

Las etapas de modelización fueron concentradas a la escala del cuartel. Así, en una primera etapa, esta escala de trabajo permitió minimizar las fuentes de variabilidad entre cuarteles vitícolas ligadas al cultivar, sistema de conducción, edad de plantación, etc. Un modelo de extrapolación del estatus hídrico fue propuesto y validado sobre dos bases de datos. Este modelo fue basado sobre una colección de coeficientes sitio-específicos locales y constantes. Cada coeficiente local, permitió modelar la relación lineal existente entre el estatus hídrico medido en un sitio de referencia y el estatus hídrico medido en cualquier otro sitio al interior del cuartel, sin importar la fecha de medición. Bajo condiciones de restricción hídrica elevada, el modelo permitió explicar una parte importante de la variabilidad espacial del estatus hídrico de la planta (r^2=0,70). La identificación de este modelo general, permitió proponer una metodología para introducir datos auxiliares. Comparado con un método clásico de estimación, esta última permitió explicar una parte importante de la variabilidad espacial del estatus hídrico de las plantas (r^2=0,71) en condiciones de restricción hídrica elevada. A nivel de cuartel, las variables auxiliares seleccionadas están relacionadas principalmente al vigor de las plantas.

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159 Páginas, 28 Figuras, 15 Tablas, 2 Anexos.

Palabras clave
Viña, viticultura de precisión, estatus hídrico de la viña, variabilidad espacial del viñedo, potencial hídrico de hoja antes del amanecer, expresión vegetativa, zonas de restricción hídrica, árbol de regresión, resistividad eléctrica de suelo, imagen aérea, modelo de predicción espacial.