92. A statistical test to evaluate the relevance of auxiliary time series to predict another time series

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Abstract

This article introduces an application of the Granger causality test in precision agriculture. Originally developed to address economic issues, this statistical test aims at determining whether one time series is useful to forecast another time series. In this study, the test was applied to two time series of data available at within field level in viticulture: sentinel-2 satellite images and Apex growth monitoring (iG-ApeX method). Results show that time series obtained by Sentinel-2 satellite imagery can be used to predict vegetation growth both at the field scale and at the within-field scale. The Granger causality test could find many applications in precision agriculture, especially with the development of high temporal resolution data acquisition methods.

Keywords: NDVI, Water stress, Viticulture, Forecast, Granger test

Introduction

Over the past few decades, new data sources have emerged in precision agriculture, particularly new sensors (Jawad et al. 2017) and new remote sensing tools (Sishodia et al. 2020). These new data sources have enabled acquisitions with better temporal resolution making it easier to monitor agronomic variables over the time. As a result, spatialized time series are becoming more and more common in precision agriculture. Analysing these time requires suitable methods to account for their temporal structure. Several methods, specifically dedicated to time series analysis, have been proposed and successfully applied in precision agriculture for example to evaluate soil erosion (Meinen & Robinson 2021) or for irrigation management (Kashyap et al. 2021). However, most of these methods are often complex, difficult to implement or require significant computational capabilities. Another limitation of these approaches is their lack of generality as they are implemented in a specific context to answer a specific problem.
Other fields of application have long been confronted with temporal series of observations. For example, in economy where many methods have already been proposed to model, analyse, estimate and predict the temporal evolution of economic variables (Hamilton, 1994). Among these methods, the Granger causality test (Granger, 1969) has been designed to determine whether one time series is useful for better predicting another one. This statistical test is, in the authors' opinion, of most interest for applications in agriculture. Indeed, the Granger causality test uses a linear model to detect whether a time series improves the prediction of another time series values. This test, initially developed in the field of economics, relies on a general formalism which has allowed its application in other disciplines such as ecology (Detto et al., 2012) or medicine (Grande et al., 2022) among others. Like any statistical test, its usefulness to the practitioner is to produce a probability with a first and second order risk of error, which is interesting information for

decision making on variable selection. To the authors' knowledge, the Granger causality test has never been applied to agriculture and precision agriculture questions.
The objective of this paper is to evaluate the interest of the Granger causality test in the precision agriculture context. This study proposes an application of the test to a case study to identify if remote sensing NDVI time series can be used to improve the prediction of vine growth measurements in the field, vine growth measurements being used as a surrogate to estimate the spatial variability of plant water restriction. The objective is also to test Granger causality test at two different spatial scales (field and within-field scale) on a vineyard field in the South of France.

Materials and methods

The Granger causality test

The notion of causality introduced by Wiener (1956) and Granger (1969) is one of the foundations of the analysis of dynamic relationships between time series. The basic idea of the Granger causality is that a time series X would cause another series Y, when the knowledge of the past values of X leads to a better prediction of Y than that based only on the past values of Y. In other words, the series X "Granger-causes" the series Y, if conditionally on the past values X_{t-j} ($j \geq 1$), the mean square prediction error of Y_t is smaller than that obtained without the information about the past values X_{t-j}. j represents the time lag between X_{t-j} and Y_t. Granger-causality is tested in the context of linear regression models (Granger, 1969). The main idea is to fit a linear model for Y_t based on the p past values X_{t-j} and Y_{t-j} ($j=1, ..,p$), and to test whether the coefficients associated with the variables X_{t-j} are zero or not with a Fisher test. A model selection criteria, such as the BIC (Bayesian Information Criterion) or the AIC (Akaike Information Criterion) can be used to determine the appropriate model order p.
To properly use the Granger test, it is required that time series share the same spatial footprint and temporal resolution. In this study, the Granger causality test was applied to the prediction of vine growth with NDVI obtained from remote sensing and with the derivative of NDVI times series. p was set at 1 as the degrees of freedom were not sufficient to test higher values. The Granger causality test was performed with the "grangertest" function, provided in the "lmtest" R-package (Zeilis and Hothorn, 2002).

Experimental data

Experimental data were collected in 2020 on a 0.8 *ha* non-irrigated Syrah grapevine field (Figure 1.A) in South of France (latitude=43.1777, longitude= 2.5903, WGS 84) under Mediterranean climate. The vine field was planted in 1995 with a plantation density of 4000 $vines.ha^{-1}$.. The northern part of the field presented a higher elevation and a higher proportion of missing vines (Figure 1.B).
Vine shoot growth was measured on 101 sampling sites using index of Growing Apex (iG-Apex). The sampling sites location were based on set of 10 consecutives vines every 15 vines. As missing vines were not considered, the distribution of the measurement sites on the field was not regular (Figure 1.B). iG-Apex was measured by observing 5 apex per vine for a total of 50 apex per sampling site. The iG-Apex index varies from 1 (full shoot growth) to 0 (total cessation of shoot growth) and is considered as a surrogate for vine water restriction (Rodriguez Lovelle et al., 2009; Pichon et al. (2021)).
Observations were collected by a single operator using the ApeX-Vigne smartphone application (Brunel et al., 2019). Sampling sites were georeferenced by recording the

position of the central vine using a GNSS receiver (R1, Trimble, Sunnyvale, USA) with a SBAS/EGNOS correction service. Observations were carried out weekly at every sampling site from flowering (week 24) to veraison (week 34).

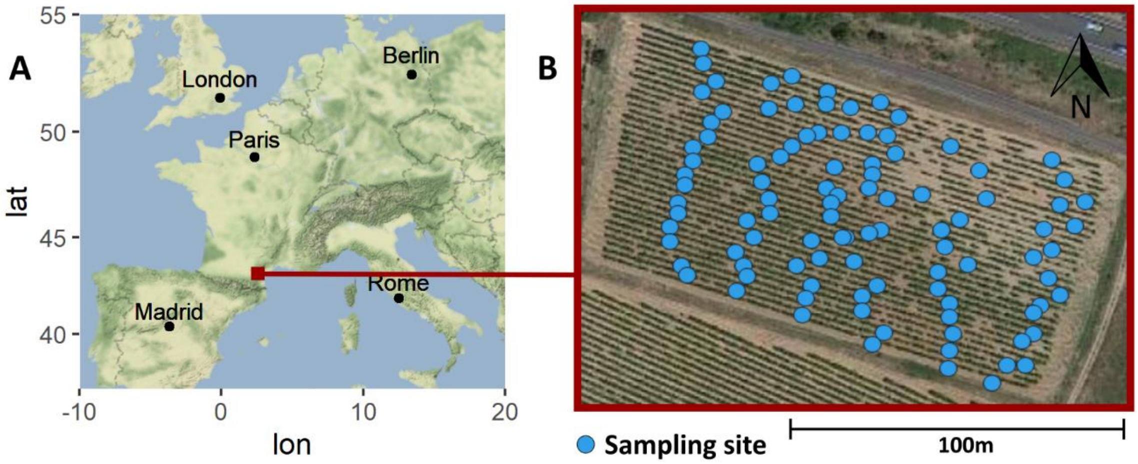

Figure 1. Location of the fields in southern France (A) and location of iG-APEX sampling points within the fields (B)

Normalized Difference Vegetation Index (NDVI) was computed based on Band-4 (664.5nm) and Band-8 (835.1nm) reflectance from the Sentinel-2 Multispectral Imager. Images were extracted and processed with Google Earth Engine (GEE) (Gorelick et al. 2017). The spatial resolution was $10m$ and the total number of pixels covering the study field was 53. Images obscured by clouds were filtered via GEE Javascript API using decision trees and Bayesian models proposed by Hollstein et al. (2016). 17 images out of 48 potentially available were used after the filtering.

Spatial interpolation

The aim of spatial interpolation was to obtain the same spatial footprint for both iG-Apex and NDVI data. iG-Apex observations were downscaled to NDVI observations spatial grid. Interpolation was performed with inverse distance weight method. It was implemented using R 4.0.0 with the “idw” function from the “gstat” package (Pebesma, 2004).

Temporal interpolation

The objective of temporal interpolation was to obtain times series that share the same observation dates and time intervals between two observations. NDVI and its local derivative value were estimated at each dates on which iG-Apex was measured. To obtain these values, two interpolation methods were tested.

The first one, called linear interpolation, consisted in a direct linear interpolation between each pair of observations. The NDVI values at a given date were interpolated from the equation of the line connecting the previous observation to the next observation. The derived value at the same date was the slope of the line. The NDVI was not interpolated on dates where it was already measured. The linear interpolation is therefore not derivable at these dates. In these cases, the value used as derivative was the slope between the previous and the next observation. For clarity purpose, these values for linear interpolation are still improperly called derivative hereafter.

A second interpolation method was introduced in order to catch the general trend of the time series by removing the noise that could arise from the variability of the satellite images acquisition conditions. This second method, called "locfit" interpolation, is based on polynomial functions fitted to the neighbourhood of each observation. This interpolation is easily derivable and has a continuous derivative. It has been implemented with the R package locfit (Loader, 2020). Polynomials were chosen of degree 3 and the smoothing parameter based on nearest neighbours (nn) was set at 0.7. These values provided a convincing fit of the interpolation to the observed data. The two interpolations method were both applied to the field mean and to each pixel of the NDVI time series. Resulting time series had the same time steps as those of iG-Apex with one measurement per week. The Granger causality test was then applied to these time series to test whether NDVI was informative to predict an iG-Apex time series.
A common variographic analysis was performed afterward to evaluate the spatial autocorrelation of the Granger test results. The nugget-to-sill ratio was used to describe the proportion of spatially unstructured variability compared to the total variability.

Results

For every pixel of the field, NDVI value increased during the season (Figure 2.A). It started from around 0.2 in May, at the beginning of the vegetative season, and reached the value of 0.45 in late September, after the harvest. The difference between highest and lowest NDVI values also increased over the season, indicating an increase in the within-field variability. iG-Apex decreased during the season for every observation site (Figure 2.B). It started from 1 in early June, indicating a full vegetative growth, towards around 0.15 in mid-August, indicating a total cessation of growth at this date. This decrease in growth is strongly related to the occurrence of the water restriction during the summer period.

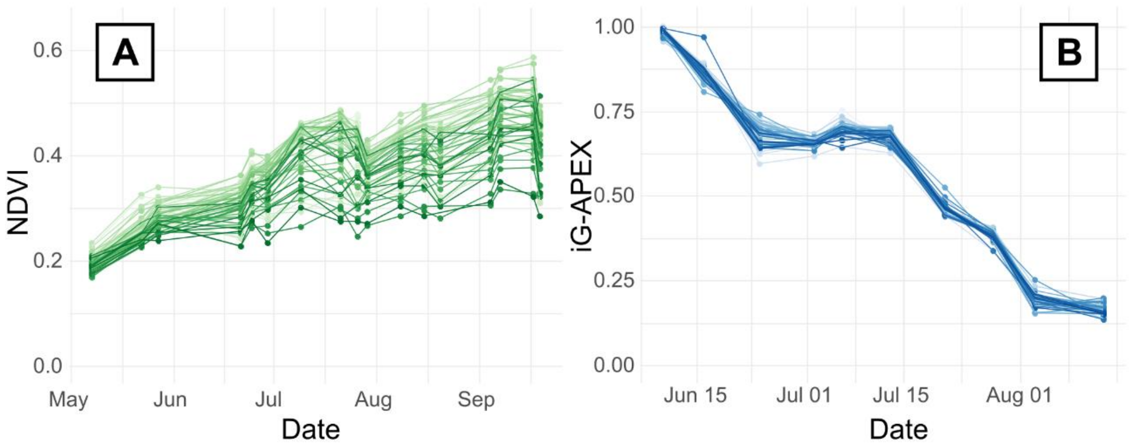

Figure 2. Time series of NDVI (A) and iG-Apex (B) over the season. Each time series represent one Sentinel2 pixel. NDVI is increasing while iG-Apex is decreasing.

When interpolating NDVI time series, the linear interpolation goes through all observations and connects them in a linear way without any smoothing (Figure 3). The locfit interpolation, based on polynomial functions, is smoothed and does not necessarily include all points. It thus reflects the general trend of the time series (Figure 3).

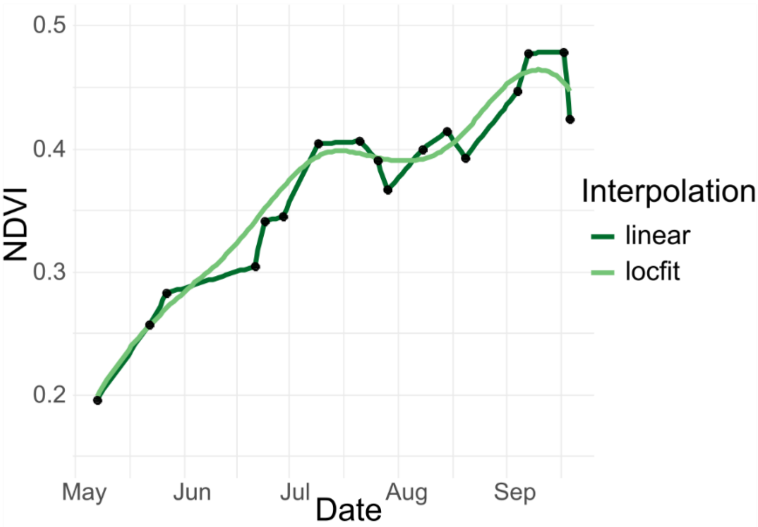

Figure 3. Example of temporal interpolation result with the mean field NDVI times-series.

According to the Granger causality test, at the field scale, NDVI does not provide significant information for the prediction of iG-Apex time series regardless of the time-interpolation method (Table 1). However, with the derivative of NDVI, the test is significant at $p<0.05$ with the linear interpolation and significant at $p< 0.1$ with the locfit interpolation. The derivative of NDVI therefore Granger-causes iG-Apex and may be relevant to forecast its values.

Table 1. p-values of the Granger causality test applied at the field level (pixels mean). NDVI was interpolated with both linear and locfit interpolation methods. Significance (p-value <0.05) in bold font. Best significance is achieved for the NDVI derivative values.

Interpolation method	With NDVI	With NDVI derivative
Linear	0.8611	**0.0083**
Locfit	0.9869	0.0771

When performed at the within field scale (Figure 4), the test is more significant when the NDVI time series derivatives (B and D) are used to forecast the iG-Apex time series at the pixel scale. The tests based on the NDVI values (A and C) are almost all non-significant for all the within field pixels. The largest number of significant pixels is obtained with linear interpolation derivative values (Figure 4B). On this map, the p-values obtained with the Granger test are spatially structured (nugget-to-sill ratio = 0). The most significant pixels are concentrated in the South-West and in the center of the field, while the pixels in the North-East have higher p-values. This phenomenon is also found, to a lesser extent, with the locfit interpolation (Figure 4D).

Discussion

The decrease of the iG-Apex time series observed is coherent and highlights the occurrence of a water restriction that affects vine growth over the summer: plant vines go from a period of strong growth at the end of spring to a near-stop of growth a few weeks before harvest (Pichon et al. 2021; Martinez-De-Toda et al. 2010). At the same time, the NDVI increases irregularly. The variability coming from these irregularities is shown in the linear interpolation method, while the general trend of the time series is better reflected in the locfit interpolation.

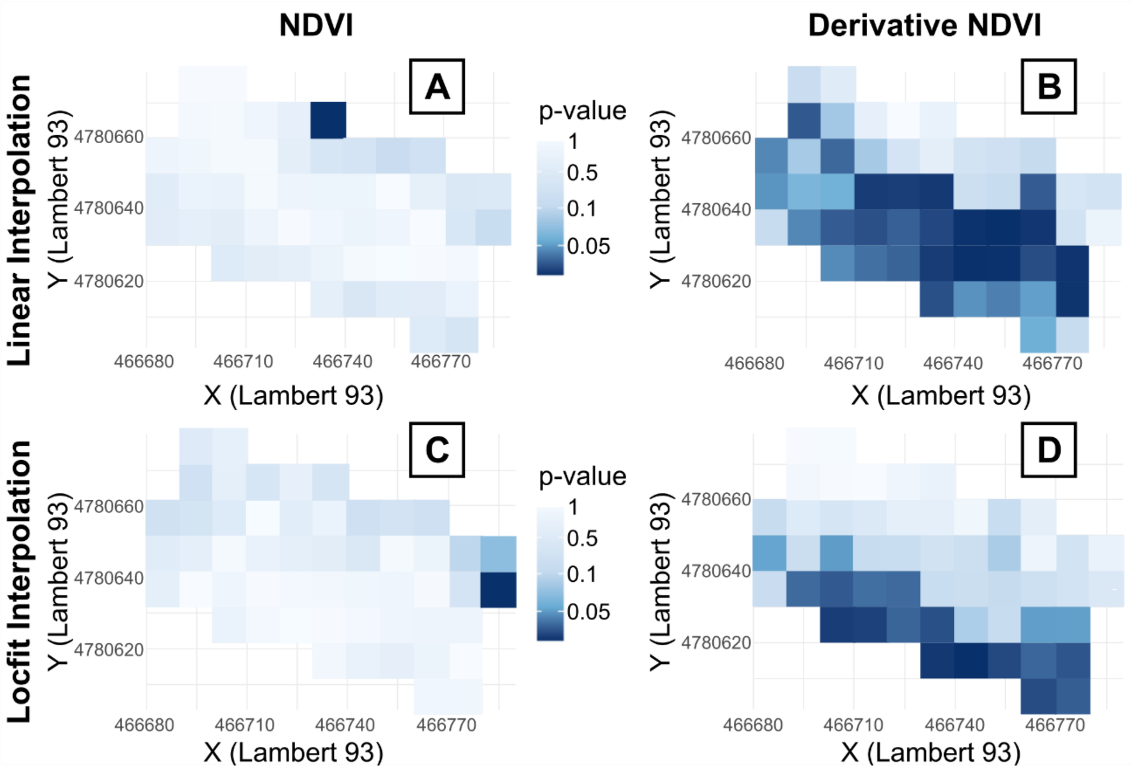

Figure 4. Application of the Granger causality test to the prediction of iG-Apex time series from Sentinel-2 images time series at the within field level. Information extracted from Sentinel-2 images are NDVI (A and C) and its derivative (B and D) interpolated in time using linear (A and B) and locfit (C and D) interpolations.

In this case-study, the test does not show Granger causality between NDVI and iG-Apex. The vegetation index values at one date do not provide information about the growth index. In contrast, the derivative of NDVI is significant in predicting iG-Apex according to the Granger test. With locfit interpolation, the test is significant for about one-third of the pixels in the field. This shows that the global trend of the NDVI derivative provides valuable information for predicting the iG-Apex. This result is robust to variations in the choice of parameters for the locfit interpolation (results not shown). Best results are obtained with linear interpolation. It shows that part of the information is also contained in small variations of the NDVI derivative observed between two close dates.
The Granger causality test states that this derivative can be used to improve the prediction of iG-Apex. It is also possible to interpret this result from an agronomic point of view. Indeed, the NDVI is often considered as a surrogate for the vine canopy volume (Campos et al. 2021). When the vine is growing (high iG-Apex), the vine produces new shoots and leaves and the canopy volume (NDVI) increases. Its derivative is therefore expected to be positive and higher with a higher vine growth. Conversely, if the growth index is low, there is little or no canopy development and the derivative of NDVI is expected to be low. The spatial organization of p-values for the Granger causality test (Figure 4.B) might also be interpretable. The band of insignificant pixels observed in the north-eastern zone of

the field presents the highest proportion of missing vines (Figure 1B). The lower number of “active” plant vines leads to lower NDVI values on this zone over the whole season. In these conditions, the magnitude of variation of NDVI values over the season may not be high enough to allow any relationship between the dynamics of the two variables (NDVI-iG-Apex) to be detected. In other words, the NDVI signal-to-noise ratio being very low in this zone, it becomes difficult for the granger test to detect any significant relationship between the two time series under study. Another hypothesis related to the difference in elevation could explain the differences in Granger test conclusions since it could result in different growing conditions (thinner soil, lower water reserve etc.).
This case-study illustrates the potential of the Granger causality test in precision agriculture. Its easy implementation makes it possible to quickly identify relationships between one or more time series that may be of different natures. In a context where more and more time series are available (Sishodia et al. 2020), this test could constitute a relevant first step to identify the potential of new information before considering more ambitious research in precision agriculture. Returning to the case study, the Granger causality test highlights promising results since NDVI changes can be related to iG-Apex evolution in our Mediterranean context. Remote sensing temporal series could therefore be an interesting covariate to interpolate the iG-Apex point observations. This result highlights the complementarity between spatially exhaustive data and specific point data for mapping vine water restriction at different spatial scales.

Conclusions

The application of the Granger causality test shows that the derivative of remotely sensed NDVI time series can be used to improve the prediction of a growth index on the studied field. In this study, the test gives promising results both at the field scale and at the within-field scale where p-values reflect the spatial organisation of the field. These results illustrate the opportunity that the Granger causality test represents in precision agriculture. With its quick and easy implementation, it could be considered as first relevant step before more complex exploratory analyses by identifying the causal relations that may exist between several time series.

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