Available water capacity from a multidisciplinary and multiscale viewpoint. A review

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REVIEW ARTICLE

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Isabelle Cousin[1] · Samuel Buis[2] · Philippe Lagacherie[3] · Claude Doussan[2] · Christine Le Bas[4] · Martine Guérif[2]

Abstract

Soil–plant–atmosphere models and certain land surface models usually require information about the ability of soils to store and release water. Thus, a critical soil parameter for such reservoir-like models is the available water capacity (AWC), which is usually recognized as the most influential parameter when modeling water transfer. AWC does not have a single definition despite its wide use by scientists in research models, by regional managers as land-management tools and by farmers as decision-aid tools. Methods used to estimate AWC are also diverse, including laboratory measurements of soil samples, field monitoring, use of pedotransfer functions, and inverse modeling of soil-vegetation models. However, the resulting estimates differ and, depending on the method and scale, may have high uncertainty. Here, we review the many definitions of AWC, as well as soil and soil–plant approaches used to estimate it from local to larger spatial scales. We focus especially on the limits and uncertainties of each method. We demonstrate that in soil science, AWC represents a capacity—the size of the water reservoir that plants can use—whereas in agronomy, it represents an ability—the quantity of water that a plant can withdraw from the soil. We claim that the two approaches should be hybridized to improve the definitions and estimates of AWC. We also recommend future directions: (i) adapt pedotransfer functions to provide information about plants, (ii) integrate newly available information from soil mapping in spatial inverse-modeling applications, and (iii) integrate model-inversion results into methods for digital soil mapping.

Keywords Inverse modeling · Digital soil mapping · Geophysics · AWC · Soil–plant–atmosphere

Content

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1 Introduction

At the interface between the atmosphere and geosphere, soils play an essential role in ecosystem services. They are reservoirs that store fresh water and control how much water is available to plants (i.e., "green water") (Schyns et al. 2015). Characterizing them at local and regional scales is critical for understanding crop-environment interactions (e.g., Folberth et al. 2016).

In tools such as SWAT (Soil & Water Assessment Tool) and in crop models, water balance in the soil–plant system is often modeled using a reservoir-type representation of the soil, whose hydraulic properties are described by the available water capacity (AWC). These models can range from complex representations of plant growth and soil water balance to more simplified models for end-users. In both cases, AWC theoretically represents the maximum quantity of water available for plant growth, as defined by Veihmeyer and Hendrickson (1927). It is thus an integrated value determined over the entire soil thickness, from water content at field capacity (FC) to that at the permanent wilting point (PWP). These two water content limits are empirical concepts and may have different meanings and values depending on the discipline (e.g., soil, plant or climate science). Along with AWC, the literature describes other concepts: soil scientists may use "water holding capacity" or "soil holding capacity" (Lebon et al. 2003), "soil water reservoir" (Ratliff et al. (1983) or "soil water availability" (Brillante et al. 2016), while agronomists and forest scientists may use "apparent available water content" (Cabelguenne and Debaeke 1998), "relative available soil water" (Zhang et al. 2015), "plant available water capacity" (Jiang et al. 2007), "root zone available water capacity" (Lo et al. 2017), or "transpirable or extractable soil water" (Klein et al. 2014). The number of articles that mention these keywords continues to increase (Fig. 1), which emphasizes the need to clarify these concepts.

AWC is considered the most influential parameter in watershed or irrigation models (Barker et al. 2018; Shivhare et al. 2018). AWC is also a main source of uncertainty in outputs of land-surface and crop models (Dewaele et al. 2017; Eitzinger et al. 2004), especially when used over large regions in the context of climate change (Wang et al. 2018).

Many methods to estimate AWC have been developed: a soil-based approach by soil scientists, and a soil–plant-based approach by agronomists (Fig. 2). Both approaches have limits, and a combined approach would help to analyze
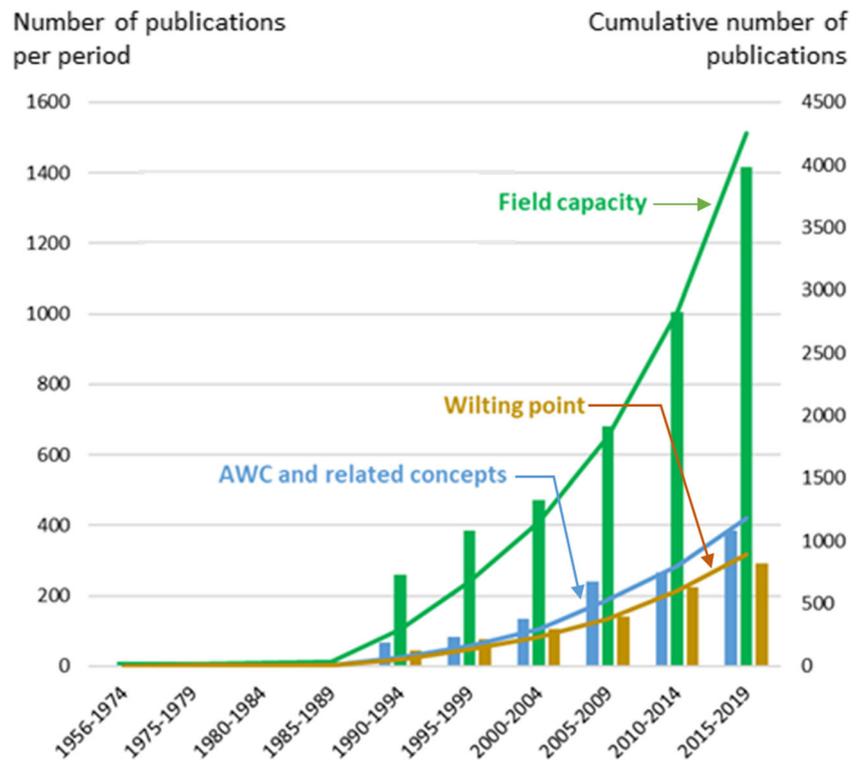
advantages and limitations of different methods and to develop new strategies to estimate AWC.

In this review, we (i) describe and develop the concepts related to AWC and its components, (ii) present the methods used to estimate AWC using soil-based and soil–plant-based approaches, and (iii) after a critical analysis of each approach, provide insights for developing improved methods to estimate AWC that are relevant for a given spatial scale and with the data available. At each stage, we focus specifically on limitations of the methods and uncertainties in the estimates.

2 The capacity of soil to store and release water: definitions and concepts

2.1 Concepts related to AWC and transpirable soil water content

2.1.1 Historical and current concepts related to AWC

The AWC concept describes the soil as a "bucket" that contains soil water between an upper limit, FC, and a lower limit,

Fig. 2 Examples of different approaches for estimating available water capacity (AWC) at different scales: **a** Soil-based approach with local measurements (photo UMR EMMAH). **b** Indirect estimation at field scale of AWC combining geophysics and soil types characterization (reproduced from Seger et al. 2016). **c** Plant-based approach using crop growth estimation and status (normalized difference vegetation index—NDVI images here) combined with variation in soil water or inversion of crop models to estimate AWC.
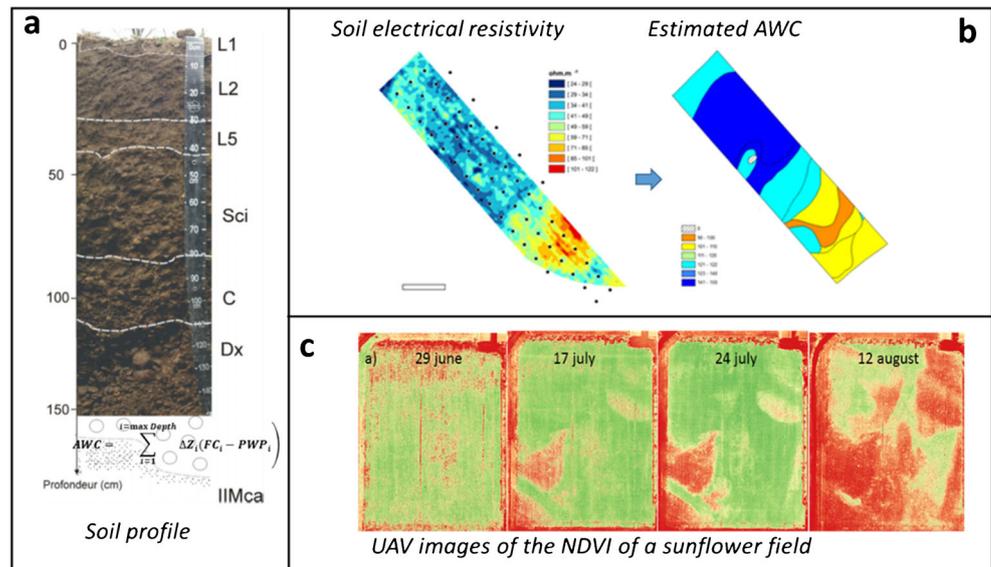
PWP. This original definition of AWC of Veihmeyer and Hendrickson (1927, 1931) is included in the current definition of the INSPIRE Directive (http://inspire.ec.europa.eu/codelist/SoilDerivedObjectParameterNameValue/availableWaterCapacity): "the amount of water that a soil can store that is available for use by plants, based on a potential rooting depth. It is the water held between field capacity and the wilting point, adjusted downward for rock fragments and for salts in solution." AWC was initially defined as total available water (TAW). To avoid confusion, we do not use this term. The AWC is thus the water quantity summed over horizons of the soil profile down to rooting depth:

$$AWC = \sum_{i=1}^{i=\text{maxDepth}} \Delta Z_i(FC_i - PWP_i) \qquad (1)$$

where *maxDepth* is the maximum soil depth or rooting depth, ΔZ is the horizon thickness, and i is the number of soil horizons.

AWC is usually expressed in $cm^3\ cm^{-3}$, but can also be expressed in $g\ g^{-1}$ or $mm\ cm^{-1}$. It can be determined from laboratory measurements and, under certain conditions discussed later, from field measurements.

In the definition of Veihmeyer and Hendrickson (1927), AWC is a plant-oriented parameter that defines the capacity of a soil to store water that can be extracted by plant roots. Consequently, *maxDepth* (Eq. 1) is the rooting depth. However, the rooting depth varies because it depends on the plant species or genotype and the stage of plant development. Some authors, especially those who map soils, consider that *maxDepth* refers to total soil depth. Unfortunately, the definition of the INSPIRE Directive does not clear up the ambiguity because it introduces the concept of "potential rooting depth." We discuss this challenging issue related to depth in detail later (Section 2.3).

2.1.2 Extractable or transpirable soil water content

Monitoring of water content in the field indicates that plants may take up less (rarely more) water than the AWC measured in laboratory experiments (Cabelguenne and Debaeke 1998; Ritchie 1981). Based on Ritchie (1981), some authors defined the plant available water capacity (PAWC), (total) extractable soil water content, or (total) transpirable soil water (TTSW) content as the difference between the field-measured drained upper limit—equal to FC—and a "(crop) lower limit" (CLL). Sinclair and Ludlow (1986) defined the latter limit as the "soil water content when transpiration of the drought-stressed plants decreased to 10% or less of that of well-watered plants." This limit can be reached during dry years or by depriving the soil of water (e.g., using rain shelters; Burk and Dalgliesh (2013)). By monitoring water content in the field, some authors defined a part of this TTSW as the fraction of transpirable soil water (FTSW), which is commonly used in

irrigation or drought studies (Abreu et al. 2015; Bindi et al. 2005; Casadebaig et al. 2008; Gaudin and Gary 2012; Lebon et al. 2003; Zhang et al. 2015). It is a relevant parameter for assessing the hydric functioning of the soil–plant system, especially for plants whose rooting depth is difficult to estimate (e.g., trees). TTSW and FTSW always refer to field measurements and are always associated with both a soil and a plant. Because this lower limit is not always the same as PWP, TTSW is not the same as AWC (Section 2.2.2).

2.1.3 AWC: available water content or available water capacity?

Based on historical and current definitions, AWC is conceptualized as the maximum quantity of water that soil, considered as a bucket, can theoretically store which is a *capacity*. It differs from the quantity of water that is actually stored at any one time, which is the *content*. Since AWC was first defined, confusion between "capacity" and "content" remains in the acronym; both are widely used in the literature and are rarely defined precisely. This confusion is maintained by that between AWC and TTSW; for the latter, field monitoring provides the soil water content. In the sections that follow, AWC refers to "available water capacity."

2.2 Two characteristic points of water content used to estimate AWC

2.2.1 Field capacity

In many handbooks dealing with AWC, the current definition of water content at FC, which has not changed since first defined, corresponds to the soil water content after rapid drainage, linked to dominance of gravity over capillary forces, has ceased (Briggs and MacLane 1910; Ottoni et al. 2014; Veihmeyer and Hendrickson 1927). FC water content thus corresponds to the maximum amount of water that a soil can store, which is assumed to be available to plants. Over temporal scales of plant growth, and depending on the climate, plants capture only a small amount of the water contained in the porosity drained by gravity (McDonnell 2014), but this assumption is debated (de Jong van Lier 2017; Logsdon 2019). FC is thus related to a physical process—gravity drainage—and should not vary among crops for a given type of soil, as demonstrated by Ratliff et al. (1983).

Veihmeyer and Hendrickson (1931) stated that FC is reached when the change in water content "reaches a negligible flow." The Soil Science Society of America (1984) considers 2–3 days for drainage to become negligible when determining FC; however, some authors suggested different durations: 2–12 days (Ratliff et al. 1983), 50–450 h (Jabro et al. 2009), a few hours to several months due to hydraulic conductivity and the climatic demand (Assouline and Or 2014),

6–24 h for coarse textured soils (Cassel and Sweeney 1974) and several weeks for fine textured soils (Davidson et al. 1969). Some authors recommend defining FC based on dynamics of the soil water content. While Ratliff et al. (1983) recommend that the change in soil water content should be 0.1–0.2% vol. per day at FC, Assouline and Or (2014) demonstrated that no standard change can be found in the literature. These criteria, based either on a duration after the end of rainfall or irrigation, or water content dynamics, are controversial; thus, some authors recommend setting FC as a given matric potential. Colman (1947) recommended a value of − 33 kPa, which has remained a reference value since then (Nachabe 1998); however, several authors recommended different values: − 20 kPa (Salter and Haworth 1961), − 10 kPa (Romano and Santini 2002), − 5 kPa (Nemes et al. 2011), and

− 6 kPa (Toth et al. 2015). Assouline and Or (2014) demonstrated that soil texture influences this value strongly. However, − 10 kPa or the original − 33 kPa value are the most common values currently found throughout the literature to describe FC.

The water content at FC depends strongly on soil characteristics, especially soil texture and structure. This is visible, for example, when examining volumetric water contents estimated from measurements of undisturbed soil aggregates equilibrated at − 10 kPa, from the UNSODA database (Nemes et al. 2001) and the EU-HYDI database (Weynants et al. 2013) (Fig. 3a), which gather mostly soils from temperate climate (see Table 1, Nemes et al. 2001). The − 10 kPa FC water contents differ strongly within and among texture classes, with a mean of 0.14 (± 0.07) cm^3 cm^{-3} for sandy soils and 0.44 (± 0.08) cm^3 cm^{-3} for clayey soils. Other

Fig. 3 Water content at − 10 kPa (**a**) and − 1500 kPa (**b**), determined on undisturbed soil samples using different laboratory protocols (mainly measurements on plate apparatus), according to the USDA textural classes. The data are collected from the UNSODA database and EU-HYDI database in which recordings without any information about the method or about the texture have been removed.
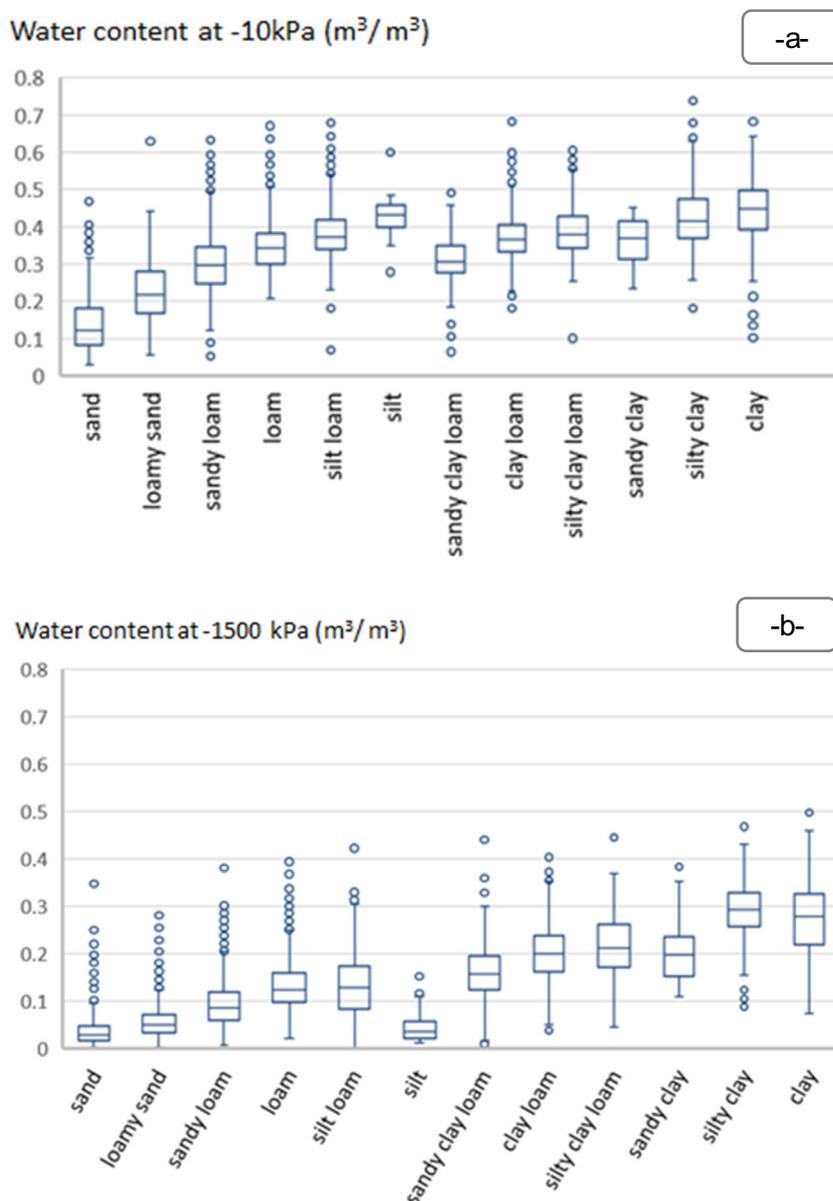
Table 1 Examples and characteristics of soil-vegetation models used in inversion to estimate AWC components.

Model type and main characteristics	Model sub-type and main characteristics (by increasing complexity)	Model name/Reference
Soil water focused models Mechanistic modelling of water transfers in the soil (Darcy-Richards equation) Aerial part poorly described More or less complex description of root water uptake	Lumped root sink term	Hydrus (Simunek et al. 2016)
	Water potential gradient from root to leaves	(Konrad and Roth-Nebelsick 2011)
	Root system architecture	(Doussan et al. 2006) R-SWMS (Javaux et al. 2008)
Vegetation focused models More precise description of plant functioning (aerial parts), simulation of biomass accumulation / LAI evolution Water transfers in the soil often described with bucket analogy	Simple Water Budget Simple description of soil and plant	SIYM (Morgan et al. 2003; Jiang et al. 2008) HYDRUS-1D (Schelle et al. 2013)
	SVAT–LSM Detailed description of water and carbon fluxes	JULES (Bandara et al. 2015) MIKE SHE–SW-ET (Ridler et al. 2012) Noah (Santanello et al. 2007; Gutmann and Small 2007, 2010) SEtHyS (Coudert et al. 2008) SWAP (Jhorar et al. 2002, 2004; Das et al. 2008; Ines and Mohanty 2008; Singh et al. 2010; Charoenhirunyingyos et al. 2011; Shin et al. 2013) WAVE (Ritter et al. 2003)
	Forest	3-PG (Coops et al. 2012)
	Crop models	APSIM (Florin et al. 2011) CERES (Link et al. 2006; Braga and Jones 2004; Dente et al. 2008) CropGro (Irmak et al. 2001; Ferreyra et al. 2006) STICS (Guérif et al. 2006; Varella et al. 2010a, 2010b; Jégo et al. 2012, 2015; Sreelash et al. 2012, 2017; Yemadje-Lammoglia et al. 2018)
Coupled soil-vegetation models	Agro-hydrological models	TNT2 (Ferrant et al. 2016)

reference values, including the influence of structure expressed by the bulk density, can be found in articles that address point pedotransfer functions (PTFs) (e.g., Al Majou et al. 2008).

2.2.2 Permanent wilting point

The original definition of PWP, for plants in pots, is the water content which induces a plant water deficit that results in leaf wilt that cannot reversed when the plant is placed in a water-saturated atmosphere (Briggs and Shantz 1912). PWP represents the inability of roots to extract water from soil with low water content, which induces wilting. This biological definition of PWP has been refined over time by defining standardized situations and conditions (Furr and Reeve 1945; Taylor et al. 1934). However, PWP is also influenced by the soil/root profile, plant stage, transpiration rate, and osmotic adjustment, which resulted in recognizing that PWP is not a single value but one that may vary within a certain range (Taylor et al. 1934). This biological estimate of PWP is relatively laborious and time consuming. It was

replaced with a water content at a fixed matric potential, as earlier scientists found that soil type influenced PWP more than environmental variables such as potential evapotranspiration (Briggs and Shantz 1911; Briggs and Shantz 1912; Taylor et al. 1934; Veihmeyer and Hendrickson 1948). Richards et al. (1949), Richards and Weaver (1943, 1944), and Sykes (1964) showed that PWP determined from plant experiments yielded matric potentials of -10 to -20 bars (-1000 to -2000 kPa), with a mean of -15 bars (-1500 kPa). As wilting can occur due to plant or soil conditions, depending on the thermodynamic equilibrium of the soil–plant system (Czyz and Dexter 2012), the water content at -1500 kPa is widely used as the operational estimate of PWP, at least for annual crops in temperate climates (Ratliff et al. 1983). Some authors (e.g., Toth et al. 2015) also used a matric potential of -1580 or -1600 kPa, but due to the steepness of the retention curve at these potentials, their water content differs little from that at -1500 kPa; in any case, the logarithm of PWP is always ca. 4.2. Nevertheless, the matric potential at PWP can vary greatly among plant species, ranging from as low as $-$

16,000 to − 3500 kPa for xerophilic species to higher than − 1000 kPa for hydrophilic species (Gobat et al. 2004). The water content at − 1500 kPa can thus differ from that "at the lowest limit in the field," as used in the definition of TTSW (Ratliff et al. 1983). The amount of water released at potentials lower than − 1500 kPa are however generally low.

To aggregate cumulative effects on crop water uptake related to soil water and its dynamics, aeration, but also mechanical resistance due to soil type and crop management, some authors introduced the concept of "least limiting water range" (daSilva and Kay 1997; Leao et al. 2006). This concept should not be confused with the PWP.

Using a reference potential of − 1500 kPa provides average ranges of PWP water content, which varies from 0.05 (± 0.04) cm^3 cm^{-3} for sandy soil to 0.28 (± 0.07) cm^3 cm^{-3} for clayey soil (Fig. 3b). Other reference potentials can be found in articles that address pedotransfer functions (e.g., Al Majou et al. 2008; Toth et al. 2015).

2.2.3 Wilting point or permanent wilting point?

From a plant-use viewpoint, not all the water stored in AWC is equally available to plants for uptake. This fact was strongly debated in the 1950s between initial findings of Veihmeyer and Hendrickson (1927, 1948) and experiments of Richards and Wadleigh (1952): the latter showed that plants begin to wilt and restrict their growth well before the soil water content reaches PWP. Many experiments that followed demonstrated that Richards and Wadleigh's view was accurate. When the matric potential in soil falls below a certain value, a plant's stomata begin to close to prevent dehydration, and transpiration decreases below maximum transpiration (determined by the climate and plant stage). The soil water content, at which the ratio of actual evapotranspiration to maximum evapotranspiration falls below one, is called the temporary wilting point (TWP), and the water content between FC and the TWP is called readily available water (Brisson et al. 1992). It defines the amount of soil water necessary for the plant to avoid suffering from a water deficit. TWP water content depends strongly on the species considered, its resistance to drought, and the amount of potential evapotranspiration (Allen et al. 1998). Some irrigation decision tools use the readily available water content in order to trigger irrigation when water content falls below it.

2.3 The depth used to estimate AWC: soil depth or rooting depth?

As mentioned, *maxDepth* (Eq. 1) is a key factor in soil AWC estimation, but it remains difficult to define and estimate. In its original definition, AWC defines two properties: (i) the ability of soil to store water and (ii) the capacity of plants to collect water from this soil water stock. Depth can mean the maximum soil depth or the rooting depth, depending on the objective of using the AWC concept and the relative importance of these two aspects in the definition. Thus, ambiguity remains about which depth to use when estimating AWC. The term "maximum soil depth" itself can be misleading when (i) roots colonize the saprolite layers located between the bottom of the soil and the bedrock (e.g., vineyard, forest) and (ii) a soil horizon becomes an obstacle to roots.

2.3.1 Estimating soil depth

Many studies have defined AWC for a given soil, regardless of the crop. Consequently, *maxDepth* (Eq. 1) was considered the soil depth or maximum soil depth. Specifications of the GlobalSoilMap program (Arrouays et al. 2014) considered "depth to the bedrock" (i.e., either "hard" bedrock—an indurated or cemented layer—or "soft" bedrock that meets the consistency requirements for paralithic contact (Soil Survey Division Staff 1993)). This depth represents the "potential rooting depth" mentioned by the INSPIRE Directive that considers potential rooting in saprolite layers and obstacles caused by certain soil layers.

In addition to these definition issues, soil depth remains difficult to estimate. The (maximum) soil depth can be underestimated for deep soils if the real soil depth exceeds the maximum observation depth (i.e., "right-censored" soil depth) (Chen et al. 2019).

2.3.2 Estimating rooting depth

If specific crops are considered when estimating AWC, *maxDepth* should be the rooting depth, as it influences estimates of AWC strongly. For example, given an elementary AWC for 1 cm of soil of 1–2.5 mm cm^{-1} soil depth, a 10 cm error in rooting depth and a measurement accuracy of water contents at FC and PWP of ca. 0.01 m^3 m^{-3} (as an estimate for laboratory measurement), the total resulting error in AWC over a 100 cm homogeneously rooted soil horizon would range from 17 to 29 mm, of which 58–87% would originate from the 10 cm error in rooting depth.

Despite its relevance for estimating AWC, maximum rooting depth is rarely measured in the field as it is time consuming; thus, it is usually estimated from tabulated values (e.g., Allen et al. 1998). In this case, a range of maximum and minimum values is generally provided, and the difference between them ranges from 0.2 m to more than 1 m depending on the species, as rooting depth varies greatly among cultivars and soil conditions (e.g., water, nutrients). Thus, measuring rooting depth in the field can provide a more accurate estimate of AWC. Unfortunately, no consensus exists on which measurement to use as the rooting depth, such as the deepest visible root or 95% of the cumulative root distribution (Combres et al. 1999). Moreover, although rooting is relatively spatially homogeneous in the upper soil layer, root heterogeneity increases greatly with depth (Hodge et al. 2009; Fig. 4). This heterogeneity can influence water uptake

Fig. 4 Vertical soil profile with root impacts. **a** Picture of the field setting for examining 2D distribution of root impacts with a grid. **b** Resulting distribution of root impacts under 3 rows for 82-day-old maize. The horizontal dotted blue line shows the depth of the cumulative 95% of root impacts. (C. Doussan, unpublished results).
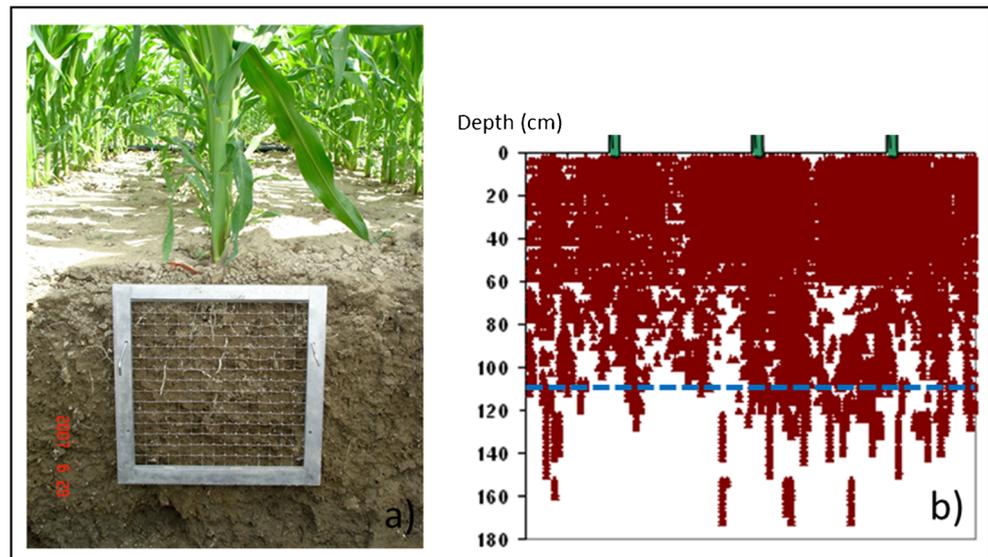
greatly due to the explored soil volume and local variability in soil hydraulic properties (Beudez et al. 2013), and challenges the idea of AWC when roots are assumed to be equally efficient throughout the entire rooting depth. For forest soils, several authors showed that knowing the AWC for some of the rooting depth is sufficient to estimate tree transpiration or growth, even if roots are observed at greater depths (Algayer et al. 2020; Tanaka et al. 2004). Cabelguenne and Debaeke (1998) reported on field experiments in which several annual crops (i.e., maize, sorghum, soybean, sunflower, and wheat) could withdraw all extractable water, even at a matric potential lower than − 1500 kPa in the near-surface layer, whereas not all of the water stored in deeper soil layers was captured, due to lower root density. Droogers et al. (1997) stressed that "the amount of available soil water" should not be confused with "water accessibility" to roots; the latter depends strongly on soil structure and may differ in compacted and uncompacted soils, even in the case, which is theoretically possible depending on the stress value, when they have the same AWC.

The concept of TTSW aggregates differences in the rooting and extraction potential among plant species throughout the rooting depth. TTSW refers to a given crop, in a given soil, and under given climate conditions. Agronomists sometimes use TTSW to quantify water uptake instead of AWC (Pellegrino et al. 2004; Ratliff et al. 1983), but it is applied only at the local scale as it requires data on field water content. The issue of rooting depth remains a challenge for modeling soil–plant functioning over large regions.

2.4 AWC in heterogeneous soils: how to address rock-fragment content and pedological heterogeneities

Some horizons have structural heterogeneities, such as irregular horizon boundaries (e.g., tongues) or rock fragments, that

must be considered when estimating AWC. A common practice is to estimate the nominal AWC for each component of the soil horizon and then sum these values for an overall estimate of AWC at the horizon or profile scale.

As a porous medium, rock fragments can store and release water. AWC has the same definition for rock fragments as for fine earth: the difference between water content at FC and PWP. The elementary AWC of a stony horizon ($AWC_{horizon}$) is thus estimated as follows:

$$AWC_{horizon} = w.AWC_{RockFragment} + (1-w).AWC_{FineEarth} \quad (2)$$

where $AWC_{RockFragment}$ and $AWC_{FineEarth}$ represent the AWC of rock fragments and fine earth, respectively, and w is the volumetric proportion of rock fragments in the horizon.

Tetegan et al. (2011) demonstrated that, depending on their lithological type, sedimentary rock fragments can contribute 2% (for flint) to 60% (for weathered limestone) to the soil horizon AWC. In a case study of a calcareous soil, Cousin et al. (2003) demonstrated that ignoring the rock-fragment content would underestimate annual water percolation by ca. 15%, and that considering their volume but ignoring their hydraulic properties would overestimate annual percolation by 15%. Algayer et al. (2020) observed a significant increase in the correlation between tree growth and AWC when the AWC of rock fragments was included in the estimated AWC of forest soil.

The same may apply to other types of soil heterogeneity. For an Albeluvisol with white silty-loam tongues in a red clay-loam horizon, Frison et al. (2009) demonstrated that PWP water content was lower and FC water content was higher for the white soil volumes than for the red soil volumes. AWC was thus significantly higher in tongues than in the bulk soil horizon, with differences ranging from 0.055 to 0.144 cm^3 cm^{-3}. Considering the contribution of tongues to the horizon

AWC resulted in AWC of 0.171–0.228 cm^3 cm^{-3}, depending on the proportions of white and red soil volumes.

2.5 Limits of this review: non-limiting water range and saline soils

Some authors introduced an alternative and more integrated concept of AWC and TTSW, the "non-limiting water range," which describes the range of soil water contents in which water, oxygen, and mechanical resistance do not limit plant growth. This concept lies outside the scope of this review. As mentioned in the INSPIRE Directive's definition of AWC, salt content in the soil solution must be considered as it alters interfacial tensions in the soil porous media and the osmotic conditions under which plants can withdraw water from the soil. Thus, the general concept of AWC cannot be considered valid for saline or sodic soils, which require site-specific studies (e.g., Wang et al. 2011; Abd El-Mageed and Semida 2015). Specifically, current PTFs (Section 3.2.2) lie outside the range for these soil types.

3 Estimating AWC from a soil viewpoint: current approaches and their limits

For decades, soil scientists have determined AWC, FC, and PWP based on the assumption that soil can be described as a vertical succession of soil horizons with different properties, especially hydraulic ones. Laboratory measurements, field monitoring, estimates using PTFs, and soil mapping are thus usually conducted at the horizon scale and summed over the soil profile down to the soil depth and, if the estimate has a spatial dimension, over the soil mapping unit.

3.1 Estimating local AWC components

3.1.1 Estimating AWC components from laboratory measurements of soil samples

AWC is usually estimated from laboratory measurements of disturbed or undisturbed soil samples (ca. 10 cm^3 in volume) collected in each soil horizon of the soil profile, and then equilibrated at pre-determined matric potentials using a Richards pressure-plate apparatus (for 5–7 days, according to ISO norm 11274 (2019)). To determine their gravimetric water content, soil samples are weighed (i) immediately after removal from the pressure-plate apparatus, to record their moisture weight, and (ii) after they have been dried at 105 °C for 48 h, to record their dry weight. As mentioned, this usually uses either a value of − 33 kPa determined by Colman (1947) or a value of − 10 kPa assumed

to be closer to the matric potential in the field (Bruand et al. 2004). For PWP, the traditional value of − 1500 kPa of Richards and Weaver (1943) is usually used. For laboratory measurements, the terms "field capacity" and "permanent wilting point" are not completely appropriate, as soil samples are not subjected to drainage dynamics or to wilting plants.

Due to the usual hysteretic form of the water retention curve, the water content measured at − 33 or − 10 kPa may depend on the initial water content of the soil sample before it was placed on the pressure plate, and whether a wetting or a drying process was used to obtain equilibrium. The standard procedure according to the ISO 11274 (2019) norm requires sampling undisturbed soil clods near FC to ensure that PWP is measured during drying. To measure FC, the undisturbed clods should be gently re-saturated before they are placed on the pressure plate to ensure that they are also drying. Conversely, due to the pore sizes involved in water retention at PWP, PWP can be measured from disturbed or sieved samples.

Because water contents measured at FC and PWP in the laboratory are based on sample weights, they are first expressed as gravimetric water contents. As traditional estimates of AWC are based on volumetric water contents, however, they usually also require estimating the bulk density. Bulk density can be estimated from the soil samples used to estimate FC and PWP or from direct measurement of soil horizons. The latter is recommended for estimates at the profile scale, especially for stony soil horizons in which the contribution of rock fragments to AWC must be included at the horizon or profile scale.

Uncertainties in measuring AWC in the laboratory are due to (i) uncertainties in the matric potential in the pressure-plate apparatus (which is related to the laboratory's maintenance protocol), (ii) lack of hydrostatic equilibrium in pressure plate (depending on soil type), (iii) uncertainties in the measured weight as a function of the precision of the scale, and (iv) intrinsic variability in the texture and structure of the soil horizon. Intrinsic variability is expressed by the standard deviation of the gravimetric water content for all of the samples used. For estimates of FC, undisturbed soil samples are more representative than disturbed or sieved soil samples, as they maintained their structure. All types of uncertainties can be considered by providing a mean and standard deviation of water content. For example, in the SOLHYDRO database (Bruand et al. 2004), the mean gravimetric water content at − 33 kPa for clayey soils and sandy soils is 0.22 and 0.07 g g^{-1}, respectively, whereas the mean standard deviation associated with this mean is 0.062 and 0.027 g g^{-1}, respectively. Estimated volumetric water content must include uncertainties in estimated bulk density to estimate the total uncertainty in AWC.

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3.1.2 Estimating AWC components from in situ soil water content monitoring

In the field, the water content of soil horizons can be monitored by sensors, such as time-domain reflectometry or neutron probes (Ritchie 1981), from the surface down to the potential rooting depth or a reasonable investigation depth. Ideally, several sensors are installed in each soil horizon to capture its heterogeneity.

For FC, field monitoring must be conducted on bare soil, preferably in winter, to obtain a soil water content high enough to be near the FC and to avoid high evaporation rates (which can even be more limited if the soil is covered) (Ottoni et al. 2014). The objective is to follow dynamics of the water content profile over several drying sequences from an almost saturated state, which occurs after heavy rainfall or irrigation. FC is thus estimated by analyzing the water content time series to obtain a value that does not change by more than 0.1–0.2% vol. in a single day (Ratliff, 1981), which is assumed to represent the transition between fast drainage and a quasi-steady-state of water content. The duration of the monitoring and the frequency of the measurements must be adapted to the texture of the soil horizons, but the transient fast drainage is generally assumed to last 48 h or more (Section 2.2.1). An important point of caution is the potential for ascending water fluxes due to capillary rise when the water table is near the soil surface. These fluxes do not have to be considered when estimating AWC although they contribute to the water supply of plants when they occur, and can lead to a wrong estimation of FC.

Several technical and environmental factors influence the uncertainty in FC estimated from field measurements. First, the uncertainty in measurements using water-content sensors usually varies from ca. 1–4% vol. (Robinson et al. 2008), depending on sensor technology, installation, and calibration; careful calibration, especially for soil bulk density may be needed (Huang et al. 2004). Second, spatial variability in soil texture or structure can introduce as much uncertainty in mean measured values as sensor uncertainty can (Vandervaere et al. 1994), depending on the number of sampling sites and knowledge of the field site. The temporal and spatial distribution of measurements can also introduce biases into the estimation of FC. Measuring for too short a period may miss favorable climatic conditions that lead to FC conditions in the field. The influence of the length of the time series with favorable conditions is also related to the measurement frequency (from hourly logging to weekly or less frequent manual measurements), which must be high enough to determine whether FC has been reached. Estimating FC water content down to the soil depth or the potential rooting depth requires installing and calibrating sensors in each soil horizon. This can be difficult, but is sometimes feasible, in stony soils (Coppola et al. 2013) or when roots colonize cracks in hard horizons or regolith. Finally, the number of measurements to make over the soil profile depends on its structuring. If the succession of soil horizons is not known, water content should be recorded along the entire soil profile (e.g., with probes in tubes) instead of measuring it at a few depths, in order to obtain a realistic vertical average.

PWP is also traditionally estimated from the time series of water content, but in cropped situations (Section 4.1.2), which estimates AWC from a soil–plant viewpoint.

3.1.3 Estimating AWC components by inverting soil models

Inverse modeling has long been an alternative and indirect way of estimating soil hydraulic properties. It has been widely used at the horizon scale using data from experiments on drainage or evaporation in soil column samples (e.g., single or multistep outflow experiments (Vereecken et al. 1997; Vrugt et al. 2001), wind evaporation experiments (Tamari et al. 1993)). It consists of adjusting the parameters of soil-water transfer models to simulate observations of the system (e.g., fluxes, soil water content, matric potential) as accurately as possible. As specific points on the water retention curve, water contents at FC and PWP can then be estimated using inverse modeling, which selects ad hoc matric potentials.

In wind evaporation experiments, Mohrath et al. (1997) demonstrated that inversion can have low error, except when soil samples are layered. Using more recent methods, such as generalized likelihood uncertainty estimation, Yan et al. (2017) highlighted that the quality of inversion depends strongly on the parameters of the inversion method itself (i.e., hyper-parameters). Uncertainties in properties estimated from model inversion may depend on many factors. Their estimation is feasible but their relevance can be questionable and they can hardly be validated. A detailed discussion on this issue is given Section 4.2.3.

3.2 Spatial estimation of AWC from the field scale to the regional scale

The locations of available soil observations and measurements used to estimate AWC in the previous methods represent only a small fraction of total soil cover. Therefore, for most large areas, AWC must be determined at unvisited locations. At the field scale, a geophysical survey can serve as a proxy for the AWC or its components when mapping at high spatial resolution. At larger scales, soil mapping techniques are used that require easily available soil properties (e.g., particle-size distribution, soil thickness) observed at enough locations to be interpolated. For AWC in particular, laboratory and field measurements are too expensive and time consuming to use at a large number of locations. This issue is usually addressed by combining soil mapping techniques with PTFs that relate AWC to basic soil properties (Bouma and van Lanen 1987). These approaches are detailed below.

### 3.2.1 Using geophysics to estimate AWC at the field scale

Agricultural geophysics involves measurement techniques based on physical processes to provide information about soil properties. These methods are generally non-invasive and use proximal soil sensors which, when placed on vehicles, can be used to create high-precision soil maps of the field (e.g., Samouelian et al. 2005). The most common geophysical methods that can sense soil down to the rooting depth are resistivity sounding and electromagnetic induction, which map the soil's electrical conductivity (ECa) or resistivity averaged over different depths. Since the 2000s, an increasing number of studies have used ECa as a proxy for soil texture (often the clay content) and water content (Heil and Schmidhalter 2017) for non-saline soils. Based on this information, FC and PWP water contents, as well as AWC, can be estimated in several ways. In some cases, a map of soil texture is derived from relationships between ECa and soil texture; the latter is then transformed into AWC using PTFs (Section 3.2.2) (Abdu et al. 2008; Fortes et al. 2015) (Fig. 5). When ECa correlates well with soil parameters (especially texture and soil depth), ECa mapping can be used to delineate homogeneous zones of soil functioning or contrasting soil types. These zones can generate an optimized sampling scheme for estimating AWC (Genere et al. 2015), and a single AWC from laboratory measurements can be used for each zone (Hedley and Yule 2009; Ortuani et al. 2016). This also sometimes enables direct regression analyses between ECa and laboratory measurements of FC and PWP water contents (Jiang et al. 2007).

Due to the high sensitivity of ECa to water content (Besson et al. 2010), some authors suggest using ECa as a proxy for water content only at FC. AWC maps are thus produced using

a mixed approach that includes field estimates of FC and laboratory estimates of PWP (Hezarjaribi and Sourell 2007; Lo et al. 2017). In several studies, the R^2 of observed site-specific relationships between ECa and AWC or AWC components ranged from 0.20 to 0.80 (Abdu et al. 2008; Fortes et al. 2015; Hedley and Yule 2009; Heil and Schmidhalter 2017; Hezarjaribi and Sourell 2007; Jiang et al. 2007; Ortuani et al. 2016). However, the quality of the relationship may depend on soil depth: for deep soil layers, weak correlations between ECa and AWC components (Ortuani et al. 2016) and inconsistent patterns (Ortega-Blu and Molina-Roco 2016) have been observed. This can be due to (i) the date of measurement (dry or wet season), which can enhance or blur the relationship, depending on soil type; (ii) the relationship between the depth and sensitivity of the geophysical method; or (iii) the vertical arrangement of soil horizons.

Gooley et al. (2014) and Priori et al. (2019) suggested adding gamma-ray spectroscopy to ECa measurements to map AWC at the plot scale. Viscarra Rossel et al. (2017) developed a comprehensive integrated soil core sensing system that included a gamma-ray densitometer and digital cameras in the visible to near-infrared spectrum to estimate several soil characteristics, including AWC, rapidly. In all of these approaches, however, errors in estimated AWC or FC and PWP water contents still need to be estimated (Gooley et al. 2014).

In addition to using proximal data from geophysical tools, remote-sensing information can be used to estimate AWC. However, as it is used mainly during the growing season, this approach is not considered here as a "soil approach" (Section 4.1.3). Nevertheless, in specific situations without vegetation, remotely sensed data can be used to provide high-resolution information about bare soils and help determine soil characteristics (Gomez et al. 2012; Pasquier et al.
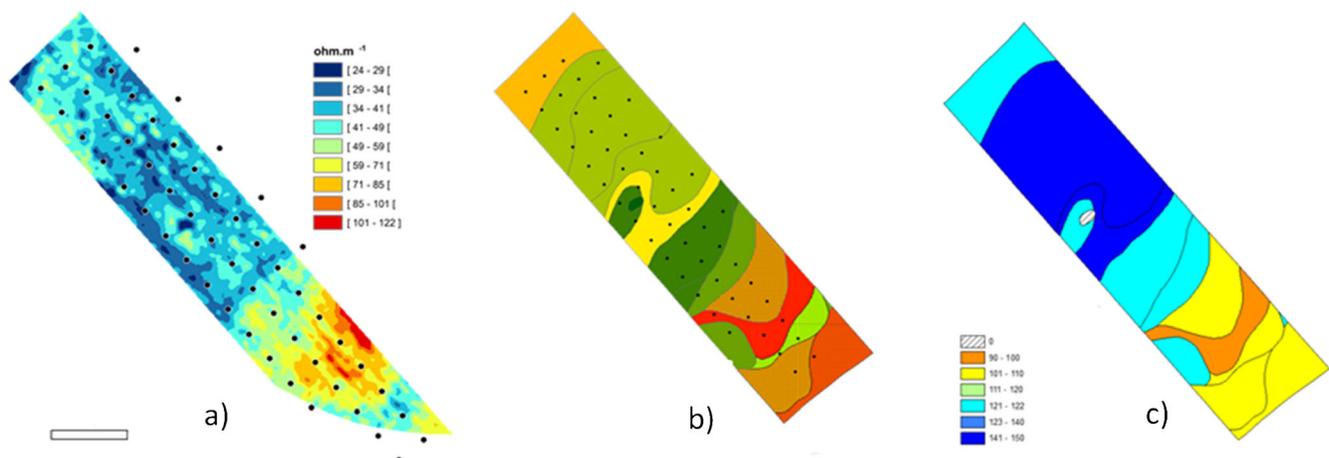
Fig. 5 Evaluation of Available Water Capacity (AWC) from electrical resistivity measurements in an agricultural plot in Central France (Villamblain). **a** Channel 3 of the electrical resistivity prospecting by the ARP device (Dabas, 2009), and locations of sampling for soil characteristics determinations (particle size distribution, organic carbon content, pH, CaCO3 content). **b** Soil types derived from the electrical resistivity device and the soil characteristics. **c** Available water capacity (mm) map derived from laboratory measurements of water contents at − 10 kPa and − 1500 kPa in each soil horizon of the soil types. Adapted from Seger et al. (2016).

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2016; Vaudour et al. 2019). Remotely sensed data can also be used in digital soil mapping (DSM) approaches (Section 3.2.4).

3.2.2 Using pedotransfer functions to estimate AWC

PTFs predict soil properties that are not easily available (e.g., soil water properties) from more readily available soil properties (e.g., particle-size distribution, soil organic carbon content) (Bouma 1989). See the review of Van Looy et al. (2017) for more information about PTFs. Soil water properties are the most important set of PTFs (Pachepsky and Rawls 2004; Wösten et al. 2001), and they are continually improved (e.g., Castellini and Iovino 2019; Szabo et al. 2019; Dharumarajan et al. 2019; Roman Dobarco et al. 2019b). Two main types of PTFs are usually defined: (i) point PTFs, which estimate water content at a given matric potential for a group of soils, and (ii) parametric PTFs, which estimate parameters of a model of the water-retention curve. PTFs are developed using a variety of statistical methods, from linear or nonlinear regressions (e.g., Romano and Palladino 2002) to artificial intelligence (e.g., Haghverdi et al. 2012; Nemes et al. 2006; review of Vereecken et al. (2010)). The best predictors for the water retention curve are those with physical significance related to water retention (Minasny and Hartemink 2011). Texture and particle-size distribution are the most commonly used predictors in PTFs (Jamagne et al. 1977; Rawls et al. 1982), but soil organic carbon content (Arrouays and Jamagne 1993; Batjes 1996) and bulk density (Al Majou et al. 2008; Vereecken et al. 1989) are also frequently used to improve their quality (Vereecken et al. 2010). PTF predictors must be adapted to the target of interest, and should differ when estimating FC and PWP, as different pore sizes are involved in water retention at these two potentials (Tomasella et al. 2003). Thus, specific PTFs have been developed for FC (Ottoni et al. 2014) and for PWP (Czyz and Dexter 2013).

The efficiency of PTFs was first considered by Pachepsky and Rawls (1999), who distinguished accuracy (i.e., the difference between measured and estimated data for the datasets used to develop a PTF) from reliability (i.e., the difference between measured and estimated data for datasets other than those used to develop a PTF). For most published point PTFs, accuracy is provided as the mean and standard deviation of water content for each soil group considered and/or some measure of goodness-of-fit, such as the root mean square error (RMSE). For example, Wösten et al. (2001) and Vereecken et al. (2010) compared the performances of a large set of PTFs and reported respectively an RMSE of 0.02–0.11 $m^3\ m^{-3}$ and a mean adjusted RMSE of 0.017 $m^3\ m^{-3}$ as measures of accuracy. For parametric PTFs, authors usually provide metrics of reliability, such as mean errors of prediction, root mean square errors of prediction, and/or standard errors of prediction, along with means of AWC or its components.

Regardless of the predictors chosen, some variance remains unexplained by PTFs (Vereecken et al. 2010). The accuracy and reliability of PTFs can be increased first by enlarging the database used to calibrate them. However, it should not generate harmonization problems (e.g., multiple protocols used to measure hydraulic properties, soil predictors and hydraulic properties measured from different samples). While the calibration database is of prime importance, accuracy can increase by stratifying data into different subsets (e.g., by soil type, parent material, horizon depth, or texture group) (e.g., Al Majou et al. 2008).

Good practices for selecting a relevant PTF include choosing a PTF that is (i) published with its uncertainties (Minasny and McBratney 2002); (ii) developed using soils similar to those to which it is applied (Wösten et al. 2001), for example by comparing ranges of their textural characteristics (Minasny and Hartemink 2011; Roman Dobarco et al. 2019b); and (iii) developed at a scale similar to that at which it is applied (Stoorvogel et al. 2019; Van Looy et al. 2017). In addition, sets of PTFs can be used, for example to estimate soil properties over large regions, as recommended by Dai et al. (2019).

3.2.3 Conventional soil mapping techniques applied to AWC

The traditional method for mapping AWC is to use soil maps produced by conventional soil surveys. For the latter, an area is separated into mapping classes, each of which is usually characterized by a representative soil profile or information about the variability in soil properties (i.e., minimum, mean/mode, maximum). Soil properties measured in the representative profiles or represented by modes or means are generally assumed to apply to the entire soil class and entire surface area. Many maps of AWC or its components have been produced using this conventional approach, especially for large spatial extents (e.g., Dejong and Shields 1988; Batjes 2016).

This conventional approach is limited by the precision of soil map delineation, which is related to the map scale. Leenhardt et al. (1994) investigated the precision of predicted AWC and its components estimated from soil maps at three scales (1:10,000, 1:25,000, 1:100,000). AWC estimates were relatively inaccurate regardless of the scale ($R^2 = 0.40$) due to the propagation of uncertainty in soil depth, which was poorly estimated ($R^2 < 0.20$). Although these results were obtained in a specific pedological context and could thus differ from soil maps with different spatial soil structure, they provided insight into the advantages and limitations of such approaches.

Other limitations are due to errors in characterizing soil classes. AWC is usually not measured from representative profiles, but is inferred from PTFs, which results in high uncertainties (Section 3.2.2). AWC is often estimated from small-scale soil maps (1:250,000 and lower) that delineate complex soil mapping units that have more than one soil class. This makes selecting a single representative profile difficult. Aggregation methods are necessary to obtain a single value

per mapping unit (e.g., weighted mean, dominant class). However, estimates of AWC at a given location may be irrelevant if this location does not represent the dominant soil class or if the agronomic context is too specific.

3.2.4 Digital soil mapping applied to AWC

DSM was developed in the 1990s as an alternative to conventional soil surveys for mapping soil properties at lower cost (Lagacherie and McBratney 2007; McBratney et al. 2003; Minasny and McBratney 2016). McBratney et al. (2003) developed the equation S = f(s,c,o,r,p,a,n) to summarize the general principle of DSM: a soil property (S) can be predicted using a spatial inference function (f) that uses as input existing soil information (s); spatial covariates that map factors of soil formation, defined by Jenny (1941) (c,o,r,p,a, standing for climate, organisms, relief, parent material, and age, respectively) and geographic location (n), which can highlight spatial trends missed by the other covariates. Many soil-sensing products that estimate soil properties at multiple unvisited sites can also be associated with DSM protocols, such as visible to short-wave-infrared remote sensing (Lagacherie and Gomez 2018), electrical resistivity (Ben-Dor et al. 2009), or electromagnetic induction combined with remotely sensed images (Sommer et al. 2003). Remote-sensing data that assess soil-vegetation-atmosphere functioning could also be useful in DSM approaches (Maynard and Levi 2017; Taylor et al. 2013). Although DSM has as many limitations as conventional soil surveys due to the availability of existing soil information, it has several advantages: (i) it benefits from a wide range of spatial landscape data provided by the spatial data infrastructure; (ii) it can provide local estimates of uncertainty in predictions, which enables realistic use of outputs; and (iii) its outputs can be updated easily to improve precision if new data are collected.

Despite its relevance for users, until 2009, AWC had fewer DSM applications than many other soil properties: only 5 of the 90 DSM articles reviewed by Grunwald (2009) focused on AWC. DSM has been increasing applied to AWC in recent years (Hong et al. 2013; Jin et al. 2018; Levi et al. 2015; Roman Dobarco et al. 2019a; Szabo et al. 2019; Zare et al. 2018), and several articles include pioneer considerations of rooting depth and gravel contents (Leenaars et al. 2018). Styc and Lagacherie (2019) showed that performances of AWC mapping were influenced strongly by the order in which "combining primary soil properties," "aggregating soil layers across depths," and "mapping" are executed to provide the targeted AWC.

To date, it has been difficult to determine whether the new DSM techniques predict AWC more accurately than conventional soil mapping, as the literature contains no full validation of AWC predictions, such as that performed by Leenhardt et al. (1994) for conventional soil surveys. However, several estimates of DSM accuracy for AWC components exist, with R^2 of ca. 0.20–0.30 for FC and PWP and ca. 0.10–0.40 for soil

depth (Hong et al. 2013; Mulder et al. 2016; Roman Dobarco et al. 2019b; Shangguan et al. 2017). Based on analysis of the limitations of using DSM to map soil properties related to AWC, the density of sites with measured soil properties is likely a major limiting factor, and is thus the main factor that influences variation in the accuracy of predictions across case studies (Vaysse and Lagacherie 2015).

4 Estimating AWC from an agronomic viewpoint: incorporating the influence of plants in experimental and inverse-modeling approaches

4.1 Using a soil–plant approach to estimate AWC

4.1.1 The plant in soil–plant hydric functioning

Plants take up water through their root system to meet the climatic demand until the water is too tightly retained by soil particles, which stops transpiration and causes them to start suffering from severe drought, inducing wilting. At this point, as mentioned, the water content should be close to PWP. Consequently, monitoring plant physiological parameters (e.g., transpiration, leaf water potential) over time could reveal soil hydraulic properties and PWP attributes. A decrease in a plant's relative transpiration or predawn leaf potential indicates that the readily available soil water (Section 2.2.3) is depleted (e.g., Feddes and Raats 2004), while a near zero relative transpiration, or nearly null difference between midday and predawn leaf water potentials, indicates that soil water is close to PWP. Water limitations also influence crop growth (e.g., biomass, leaf area index), and the reduction is related directly to the decrease in relative evapotranspiration and use of soil available water. Vegetation features (e.g., a uniformly managed sunflower field) may reflect soil hydraulic properties and soil depth strongly, especially when exposed to water limitations in the absence of other stresses (Fig. 6).

4.1.2 Field monitoring of soil water content in a vegetated soil and estimation of PWP water content

Field estimates of PWP water content are based on sensor measurements of the soil profile of a vegetated area, as well as on analysis of the water content time series. PWP is considered to be the lowest water content of cultivated soil after plants have stopped extracting water and are at or near premature death or have become dormant due to water stress (e.g., Ratliff et al. 1983; Kunrath et al. 2015). These conditions can occur in dry seasons without irrigation (Nielsen and Vigil 2018) or depriving soil of water, such as by using rain shelters (Burk and Dalgliesh 2013). Close monitoring is thus needed to detect changes in soil water content, and wilting can be associated with measurements of low transpiration or visual signs of unrecoverable wilting. PWP can
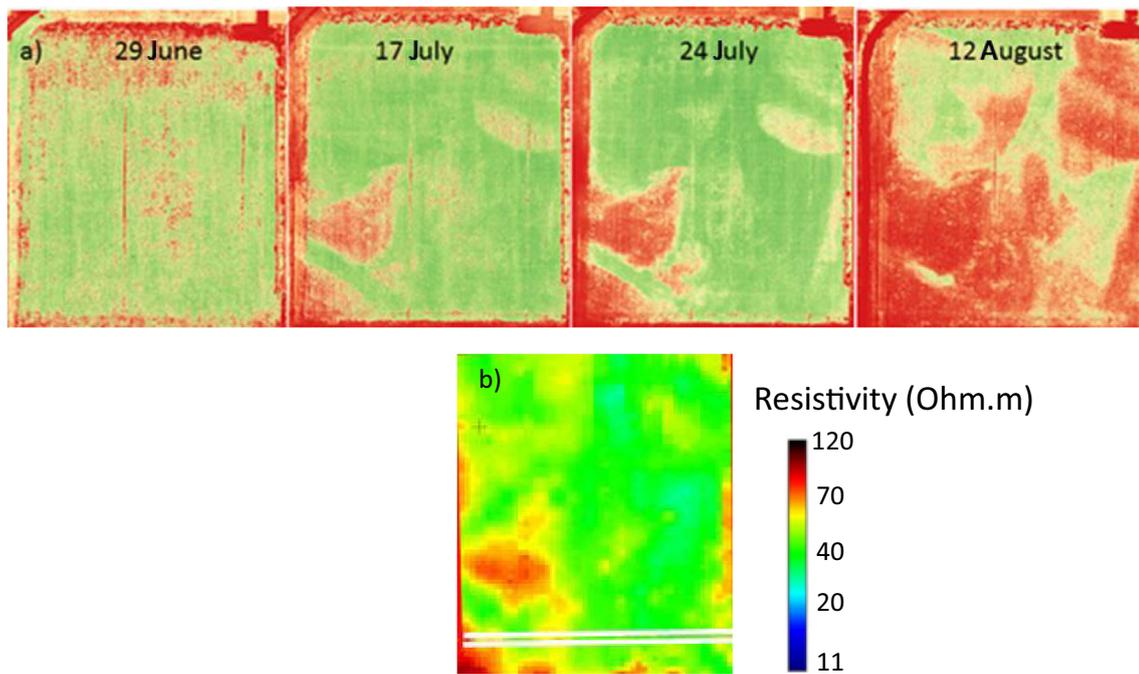
Fig. 6 Effect of available water capacity (AWC) on vegetation growth (sunflower at the Avignon INRA site, France, in 2015). **a** Four UAV (unmanned aerial vehicle) images of NDVI (normalized difference vegetation index) of a sunflower field exposed to increasing water stress showing the evolution of the vegetation from early growth (sowing was achieved on late May) to senescence (harvest occurred on mid-September), with large within-field heterogeneity; green zone correspond to high NDVI and high level of green leaf area; red zones correspond to low NDVI and low level of green leaf area. **b** Map of soil electrical resistivity over 0–2 m on the same field as (**a**) revealing the soil depth heterogeneity; the red zones correspond to high electrical resistivity values for shallow soil depths (80–90 cm); the greener zones correspond to lower electrical resistivity for soil depths deeper than 2 m. Crop heterogeneity appears to be due to AWC heterogeneity, especially soil depth.

become more difficult to estimate, especially in shallow soil or near-surface layers, when soil evaporation is counterbalanced by water supply from deeper soil layers due to capillary rise. Plants can use this ascending water to limit wilting. This process, which is included in the transpirable soil water content and PAWC (Section 2.1.2), is sometimes incorrectly used for PWP water content when field monitoring is involved.

4.1.3 Including remotely sensed vegetation data to estimate AWC or its components

Remotely sensed images of vegetated plots reflect crop development throughout the growing season. Analyses of images of rainfed agricultural areas can be used to estimate AWC, as demonstrated by Araya et al. (2013) using normalized difference vegetation indexes (NDVI) from MODIS images. Remotely sensed data have been used for several decades to estimate AWC or its components directly. See the study of Dewaele et al. (2017) for recent examples.

4.2 Inverting soil–plant models to estimate AWC

Inverse modeling has been used to predict hydraulic properties of soil–plant systems based on the influence of soil hydraulic parameters on plant variables (e.g., growth, transpiration, leaf water

potential) (e.g., Hupet et al. 2005; Konrad and Roth-Nebelsick 2011; Sreelash et al. 2017). Comparing soil/crop variables predicted by an adequate model to observations of the same variables can be used to estimate values or probability distributions of certain AWC components from the distance between these predicted and observed values using optimization (Dente et al. 2008; Timlin et al. 2001) or Bayesian methods (Das et al. 2008). A conceptual diagram of model inversion process shows how it can be used to estimate AWC components (Fig. 7).

4.2.1 Models and data used in inverse-modeling approaches

The complexity of models used to estimate AWC depends on their original objectives. Soil-vegetation models inverted to estimate AWC components differ in the detail with which they describe soil-water transfers and plant functioning (Table 1). These characteristics influence their suitability and ease of application for the soil-vegetation system considered.

The observations used in the inversion process are diverse and depend on the field of application, the model used and the spatial scale of interest. A wide variety of observations are used, from field measurements of hydrological or vegetation variables to remote-sensing products (Table 2). In recent decades, several studies used satellite products due to their advantages for spatial applications. Some studies have shown

Fig. 7 General description of the model inversion process applied to the estimation of Available Water Capacity (AWC) components.
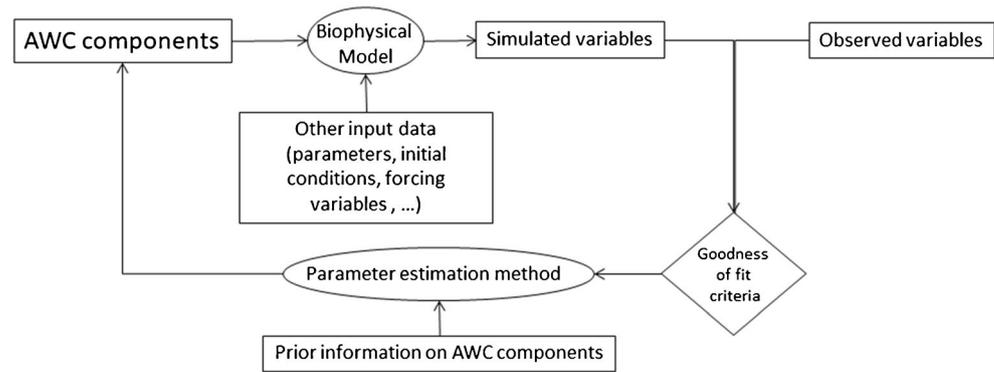
the utility of combining other types of observations of hydraulic properties of the surface and deeper root zone (Charoenhirunyingyos et al. 2011; Sreelash et al. 2012).

The components of AWC that are predicted by inverse soil–plant modeling differ depending on the model used. AWC or FC/PWP water contents can be predicted from models based on the bucket analogy, while the entire soil water retention curve (usually parameterized using the van Genuchten model) can be estimated from models based on the Darcy-Richards equation. Bulk density can also be estimated when FC and PWP are expressed gravimetrically in the inversed model; in practice, however, they are often set at measured or a priori values.

Soil depth or maximum rooting depth is often assumed to be known, and usually only soil hydraulic properties are estimated by the inversion. However, several studies have estimated depth (Irmak et al. 2001; Link et al. 2006; Ridler et al. 2012; Sreelash et al. 2012; Sreelash et al. 2017; Varella et al. 2010a; Varella et al.

2010b). Some authors also estimated root distribution parameters (e.g., Hupet et al. 2003; Schelle et al. 2013).

As mentioned, rock fragments can influence soil hydraulic functioning strongly and thus AWC or its components. To our knowledge, however, inversion of soil–plant models does not consider the influence or properties of rock fragments when estimating AWC.

Describing the complexity of the soil profile in the inversed model is an important issue. The soil can be represented as (i) a single layer (Jhorar et al. 2002), with the estimated soil hydraulic properties thus assumed to represent those of multiple soil horizons, or (ii) multiple layers, which increases the number of parameters to be estimated (e.g., each layer's thickness and water contents at FC and PWP) (Seki et al. 2015). Some authors showed that, regardless of model complexity, using multiple layers provides better performance than a single homogenous layer, except for soils with low heterogeneity (Schneider et al. 2013; Thomas et al. 2017).

Table 2 Examples of observation types used in soil-vegetation models inversion to estimate AWC components. Bold references refer to studies that used observations derived from satellites products.

Type of observation used		Reference
Hydrologic variables	Soil moisture or hydraulic heads at different depths	Ritter et al. 2003; Braga and Jones 2004; Qu et al. 2014; Hou and Rubin 2005; Chen and Yin 2006 2019; Schneider et al. 2013; Seki et al. 2015; Thomas et al. 2017
	Surface soil moisture	**Santanello et al.** 2007; **Das et al.** 2008; **Ines and Mohanty** 2008 ; **Ridler et al.** 2012; **Shin et al.** 2013; **Bandara et al.** 2015
	Drainage	Schelle et al., 2012, Schelle et al. 2013
Vegetation variables	Evapotranspiration/surface temperature	Burke et al. 1998; Jhorar et al. 2002, 2004; **Gutmann and Small** 2007, 2010; Coudert et al. 2008; **Singh et al.** 2010; **Charoenhirunyingyos et al.** 2011; **Ridler et al.** 2012; **Shin et al.** 2013
	LAI	Guérif et al. 2006 ; **Dente et al.** 2008; Varella et al. 2010a, 2010b; **Charoenhirunyingyos et al.** 2011; **Coops et al.** 2012; **Jégo et al.** 2012, 2015 ; **Ferrant et al.** 2016; **Yemadje-Lammoglia et al.,** 2018
	Yield	He et al. 2001; Timlin et al. 2001; Morgan et al. 2003; Braga and Jones 2004; Ferreyra et al. 2006; Link et al. 2006; Jiang et al. 2008; Florin et al. 2011; Yemadje-Lammoglia et al., 2018
	Plant nitrogen content	Varella et al. 2010a, 2010b

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4.2.2 Local or spatial model inversion

Inverse modeling is a natural way to estimate suitable soil parameters at the resolution of the measurements used as input data. It is also considered a powerful method for upscaling (Mohanty 2013; Vrugt et al. 2008). As such, it is a multiscale method. A local inversion (i.e., applied to a single location) estimates AWC components for the spatial (horizontal) support of the observations used. Alternately, a spatial inversion (i.e., applied to a heterogeneous landscape using spatially comprehensive observations of the soil-vegetation system) predicts spatial distribution of AWC components. Spatial inversions can be performed using either a multi-local configuration (i.e., independent inversions of the observed locations) or inversion of a spatial model over the area considered.

Local applications are generally restricted to methodological studies and are performed for well-described experimental sites with many types of data and for specific experiments, such as infiltration experiments (e.g., Russo et al. 1991; Simunek et al. 1998). In comparison, spatial applications for areas of a few hundred m^2 to a few km^2 can benefit from adequate knowledge of the modeled situation, especially the availability of in situ measurements and prior information, low uncertainty in model inputs, and a model that is adequate for the situations considered. Most applications described in the literature focus on precision agriculture (e.g., Braga and Jones 2004; Florin et al. 2011; Link et al. 2006; Morgan et al. 2003; Timlin et al. 2001). Their objective was to assess variability in soil properties to optimize crop management (e.g., irrigation, fertilization) at the intra-field scale. The authors usually used multi-local crop-model inversion along with observations obtained from in situ yield-monitoring systems with a resolution of a few m^2. High spatio-temporal resolution satellites (e.g., Sentinel-1, Sentinel-2) are promising sources of observations for these applications (Ferrant et al. 2016; Yemadje-Lammoglia et al. 2018).

Large-scale applications, mostly based on bucket analogy for soil water, have high uncertainty in model inputs and prior information (Jégo et al. 2015) due to limited access to in situ measurements and less adequate models due to their potentially high variability. For example, satellite data with medium pixel resolution (100–300 m) have been used over areas larger than 100 km^2 to provide spatial information about the status of soil and/or vegetation (Coops et al. 2012; Dente et al. 2008).

4.2.3 Errors and uncertainties in AWC estimated by inverse modeling

Relatively few studies directly estimate the error in AWC components predicted by model inversion, instead doing so indirectly for variables of interest simulated by the models, such as soil water content, water fluxes, yield, or leaf area index (e.g., Charoenhirunyingyos et al. 2011; Shin et al. 2013; Singh et al. 2010). As the inversion configurations

(i.e., models, observation systems, parameters estimated) often differ among studies, few objective elements are available to analyze and quantify the accuracy of the AWC components estimated by inverting soil–plant models. However, a few studies estimated errors in estimates of AWC components, which ranged from 10 to 18% for FC, 15–20% for PWP, and 10–30% for AWC (Dente et al. 2008; Jégo et al. 2012; Jiang et al. 2008; Morgan et al. 2003; Sreelash et al. 2017; Todoroff et al. 2010).

Model inversion has many sources of uncertainty due to model structure, input data, and the measurements used for inversion. Most inversion methods can consider at least some of these uncertainties and provide information about the uncertainty in the estimated soil parameters (Morgan et al. 2003). For example, Bayesian methods provide a joint posterior distribution, which allows a variety of criteria to be calculated to quantify their uncertainty (e.g., standard deviation, confidence intervals, correlations) (Scharnagl et al. 2011). However, the reliability of the uncertainties calculated may be questionable, as they are often based on assumptions about model and observation errors that are rarely checked due to a lack of information. These criteria should be validated by estimating the percentage of "true" values that fall within the limits of uncertainty (Shrestha and Solomatine 2006). To our knowledge, AWC components estimated from inverse modeling have never been validated in this way, as doing so would require estimating these uncertainties for many sites/pixels (usually several hundred) and relevant measurements of soil properties.

4.2.4 Limits of using inverse modeling to estimate AWC components

Inversion methods can estimate AWC components spatially without requiring heavy in situ measurement systems, but their practical application faces limits that continue to restrict their use. For example, they face the inherent limitation in the ability to solve inverse problems of complex nonlinear models. The complexity of the relationships modeled between inversed observations and estimated AWC components makes it difficult to identify the amount and type of observations required to estimate a given set of components (or, conversely, the set of components that could be estimated from a given amount and type of available observations), with an associated level of uncertainty. The amount of information obtained through inversion to estimate parameters depends on the sensitivity of the observed variables to variations in the model's parameters. This sensitivity depends strongly on the agro-pedo-climatic context studied (e.g., the occurrence of water stress) (Jhorar et al. 2002; Sreelash et al. 2017; Varella et al. 2010a). The observation system should provide a sufficient level of independent information about the estimated parameters; if not, the inversion often results in equifinality

or non-identifiability issues, which increases the uncertainty and interdependence of the estimated parameter (e.g., Jhorar et al. 2002; Ferrant et al. 2016). The small amount of information available without using heavy in situ measurement systems explains why, in general, only a few AWC components are estimated and simplified vertical representations of the soil are often used.

Spatial applications at extents of a few hundred m² to a few km² may benefit from knowledge of the modeled situation: availability of in situ measurements, low uncertainty in model inputs, and prior information strongly influenced by errors in observations and in the model. Inversion can automatically compensate for biases in observations or in the model by using non-physical values of the estimated parameters (e.g., Florin et al. 2011; Jiang et al. 2008). Model errors also include structural errors due to processes that the models do not consider but which often influence soil–plant functioning, such as pests, disease, or runoff. They may influence inversion results greatly in certain situations (Jiang et al. 2008). Errors in inverse modeling also include propagation of input errors (e.g., in non-estimated parameter values, initial conditions, forcing), which may be particularly large for applications at a large spatial scale. Ferreyra et al. (2006) showed that high-quality data may be required to invert spatially coupled crop-models, and that using one-dimensional uncoupled models is preferable when the data are of lower quality. This requires a compromise between a realistic model and the need for data, depending on the situation studied.

5 Comparing and reconciling soil approaches and soil–plant approaches

5.1 Comparing approaches for estimating AWC components

As described in the previous sections, the main characteristics of soil- and plant-based approaches for estimating AWC vary. In the Table 3 (described in the following paragraphs), we compare the different approaches to assess the advantages and disadvantages of each.

5.1.1 Different types and numbers of AWC components can be estimated (Table 3(a and c))

Local estimation methods are based on soil profiles and/or augering, which can provide estimates for nearly all AWC components (Table 3(a)). For heterogeneous horizons, laboratory measurements are recommended to estimate AWC rather than using field monitoring. The water content or matric potential measured in situ in stony or glossy horizons vary greatly and would be difficult to interpret from continuous field monitoring due to problems in sensor calibrations, except if

gravimetric water content and bulk density can be measured from soil samples frequently collected in situ (Table 3(c1)). As mentioned, the maximum rooting depth is rarely measured in the field; instead, a range of depths is often used (Section 2.3.2).

When considering spatial estimation methods within an agricultural field, a soil depth map may be available, for example from maps of electrical resistivity (Bourennane et al. 2017). Soil depth maps are less common at larger scales, but GlobalSoilMap products include information about depth, along with its associated uncertainty (Arrouays et al. 2014). Depending on the input and external data, however, the variability in rooting depth may be difficult to consider over these areas.

When inverting soil-vegetation models, to improve formulation of the problem and address equifinality issues, the maximum rooting depth is usually assumed to be known and is not included in the set of parameters to be estimated. At the local scale, at which information in addition to the observed data (e.g., soil texture in each horizon) is available, the inversion can estimate each horizon's FC and PWP water contents, as well as its depth. At larger scales, with less external information, it is difficult to estimate more than the equivalent FC and PWP water contents of a virtual soil layer at a given soil depth. When depth is estimated, the sensitivity of vegetation variables to the maximum rooting depth may be strongly correlated with FC and PWP water contents in the rooting zone and, consequently, the estimated depth and water content are dependent (Varella et al. 2010a). Therefore, accurate prior information about the parameters may avoid estimating inaccurate values.

5.1.2 The spatial support can differ between the different AWC measurements and the inversion (Table 3(b))

Laboratory and field estimates of AWC usually differ (Asgarzadeh et al. 2014), especially for soils with low AWC (Morgan et al. 2001) (Table 3(b)). Volumes of soil on which measurements are made differ and may or may not represent the behavior of the soil horizon. Laboratory measurements are performed on undisturbed soil clods or aggregates of known volume. When the size of the soil aggregate is a representative elementary volume of the soil horizon, laboratory measurements are considered to represent the horizon. Depending on field conditions and the sensor volume of measurements, water content from field monitoring may be difficult to relate to a given horizon. For inverse modeling, the spatial support of estimated AWC components is related to the footprint of the observations used as inputs. Consequently, comparisons of AWC measurements and inversion results should be considered with caution, and validating one method with the other is not always relevant.

Table 3 Comparisons between soil-based approaches and plant-based approaches for the evaluation of AWC or AWC components. Three class descriptions (indicated by +, ++, +++) were developed for each of 11 characteristics. Note that these should not be considered as scores reflecting relative strength, as the relative strengths of the classes could depend on the intended application. (a) +++: many components (FC, PWP of heterogeneous horizons , depth), + : few components (effective values for FC, PWP). (b) +++: centimetric, ++: metric, +: kilometric, (c1) +++: soil horizon heterogeneities, ++: real soil horizons, +: virtual layers, , - : non applicable. (c2) +++: representation of non equilibrium and water movement, ++: representation of non- equilibrium, +: representation of water bucket at equilibrium only; w.r.t. (c3) +++: taking into account real-time, +: constant over time. (d1) +++: legacy soil map or satellite data; ++: spatial database of soil property measurements and covariates; +: field and/or laboratory measurements. (d2) +++: no external knowledge and data required, ++: small amount of external knowledge and data, e.g. PTF, +: large amount of external knowledge and data, e.g. models and their parameters + PTF. (d3) +++: negligible costs, ++: moderate costs, +: high costs. (e1) +++: close to reference, ++: moderate accuracy, +: low accuracy. (e2) +++: high, ++: medium, +: low, −: not applicable. (e3) +++: large, ++: large but non exhaustive, +: small. (e4) +++: provided, +: not provided.

Methods	Number of attainable components of AWC (a)	Spatial support (b)	Accuracy of representation of... (c)			Low cost of ... (d)			Output quality (e)			
			Soil geometry/ Soil depth (c1)	Processes (c2)	Temporal variability (c3)	Input data (d1)	External knowledge/ data (d2)	Processing (d3)	Estimation Accuracy (e1)	Spatial description (e2)	Extent (e3)	Uncertainty representation (e4)
Local soil-based approaches												
In situ sampling and laboratory measurements	+++	+++	+++	+	+	+	+++	+	+++	−	+	+++
Soil water monitoring (FC)	+	+	++	+++	+++	+	++	+	+++	−	+	++
Inversion of soil models from local measurements	++	++	++	+++	+	+	+	+++	+++	−	+	++
Spatial soil-based approaches												
Use of geophysics at the field scale	++	++	+	+	+	++	+	+++	++	+++	++	+
Using legacy soil maps and PTF	+	+	++	+	+	+++	++	+	+	+	+++	+
Using Digital Soil Mapping and PTF	++	+	++	+	+	++	+	++	++	++	+++	+++
Plant-based approaches												
Soil water monitoring (PWP)	+	+	++	+++	+++	+	++	+	+++	−	+	++
Inversion of soil-plant models	+ to ++	+ to ++	+	+ to +++	+ to+++	++ to +++	+	+++	+ to ++	++ to +++	++	+++

5.1.3 Differences in descriptions of soil-water transfer and the soil (Table 3(c2))

The accuracy with which soil-water transfer is represented depends on whether measurement conditions (or model equations, in inverse modeling) represent the reality of water transfer. Representing the physics of water transfer raises two issues: (i) equilibrium vs non-equilibrium approaches and (ii) limits of the bucket analogy.

(i)   Equilibrium vs non-equilibrium approaches

To measure AWC in the laboratory, soil samples are brought to a given matric potential in a pressure-plate apparatus, assuming that each sample has a matric potential equilibrium. For matric potential near PWP, however, samples can have such a low hydraulic conductivity that they never equilibrate, even after many days on the plate (Gee et al. 2002). Due to their structure, some pores in the aggregates on the pressure plate may become disconnected from the water-percolation path (i.e., "hydraulic cut-off"; Czyz and Dexter 2012). Evidence of non-equilibrium has been shown by simultaneous measurements with pressure plates and psychrometers, and differences in water content between the two methods can reach 0.1 cm^3 cm^{-3} (Bittelli and Flury 2009; Klein et al. 2006). Laboratory measurements are usually conducted at equilibrium, especially those for matric potentials close to FC. Conversely, the matric potential is rarely fixed in in situ monitoring, and field measurements are usually performed out of matric potential equilibrium.

Because PTFs are usually developed from laboratory measurements, their estimates can be considered to describe soil hydraulic functioning "at equilibrium" (Section 3.2.2). Nevertheless, development of large databases that include data from multiple acquisition methods, such as those of UNSODA or EU-HYDI (Nemes et al. 2001; Weynants et al. 2013), challenges this assertion. PTF users must therefore consider the conditions under which a given PTF should be used. Gribb et al. (2009) used a PTF estimate of soil hydraulic properties to describe dynamics of field soil water content and found little agreement between field data and PTF estimates.

(ii)   Limits of the bucket analogy for water fluxes

As expressed in the definition of the INSPIRE Directive, AWC is defined by describing soil horizons as buckets, which can be filled and drained by the downward movement of water from rainfall or irrigation. In many situations, water is available to plants from water ascending from deeper areas of the vadose zone, either capillary rise from more saturated zones or hydraulic lift. In certain hydrological contexts, capillary rise can provide 30–60% of the water needed by crops (Vergnes et al. 2014). Water that is redistributed along the soil profile

due to hydraulic lift from deep roots can provide 7% of the water needed by crops (Doussan et al. 2006); however, this contribution remains poorly understood and rarely quantified (Prieto and Ryel 2014). When water flows upward from deep reservoirs, estimating plant available water using "at equilibrium" methods, such as laboratory measurements or traditional PTFs, is inadequate, which challenges the utility of the AWC. Conversely, estimates that use field monitoring data or model inversion consider all water fluxes, upward or downward, and thus can determine relevant parameters for modeling. The latter estimate is not strictly equivalent to the AWC defined by the bucket analogy because it considers all water fluxes and is estimated in an "out-of-equilibrium" state. As it was not defined by modeling, this unnamed AWC-equivalent parameter can be considered equivalent to TTSW. Estimating this unnamed AWC-equivalent parameter over successive seasons could provide a distribution of AWC (and its uncertainty) relevant for a given soil-climate-plant context.

5.1.4 Differences in the temporal variability of AWC in soil or soil–plant approaches (Table 3(c3))

Among AWC components, *maxDepth* (Eq. 1) is one of the most influential. In a soil-based approach, a *maxDepth* that represents soil depth can be considered constant over time (Table 3(c3)); consequently, AWC would be stable for several years. Conversely, the AWC-equivalent parameter estimated by inverting a soil–plant model depends strongly on the rooting depth, which is strongly influenced by weather dynamics during a crop's growing season for a given soil (Table 3(c3)). Multi-annual estimates for a given crop type are recommended to provide a mean value of this parameter, whose annual variation would represent the uncertainty. FC water content can also change over time due to its sensitivity to soil structure, which can vary over short time scales in the surface horizon due to the climate, biological activity (e.g., root activity, animal bioturbation) and human actions (e.g., tillage). Developing temporal PTFs, including predictors of soil structure dynamics, would improve their utility (Van Looy et al. 2017; Vereecken et al. 2010), especially for studies that address climate change and/or changes in land use or management that require long-term modeling.

5.1.5 Costs of input and external data, knowledge level and processing time: suggestions for choosing a compromise (Table 3(d))

Evaluating the feasibility of methods is an important issue. Laboratory measurements are highly time-consuming, as they include digging a soil pit, sampling soil in the field, and performing the measurements themselves, while using remote-sensing data requires less measuring effort, and data are available at high spatial resolution and high temporal frequency

due to the development of Sentinel products (Bousbih et al. 2017) (Table 3(d1 to d3)). However, laboratory measurements of AWC provide an independent assessment, with no need for external knowledge or data, and use simple calculations. Conversely, inverse modeling approaches that use remotely sensed information require large amounts of external knowledge and data. Users must be familiar with the model and its parameterization, and must be expert enough to provide relevant values for non-estimated parameters or the *a priori* information required for inversion.

5.1.6 The quality of the estimated AWC (Table 3(e))

Among the attributes of quality, accuracy is challenging to assess as it requires a reference (Table 3(e1)). Whereas local estimates do not provide AWC estimations over a large extent and with a high precision of spatial variability (Table 3(e2 and e3)), we considered them as the most accurate and compared them to the estimates of other methods for spatial entities characterized well by the local measurements. This characteristic is strongly correlated with spatial attributes (e.g., resolution, extent). Another important attribute of output quality is a representation of an estimate's uncertainty, regardless of the estimate's accuracy. For local methods, uncertainty can be assessed by the repeatability of the measurements (laboratory) and by investigating different agro-climatic conditions (soil monitoring) (Table 3e4). For spatial or multiscale methods, assessment depends on the types of input data and statistical processing.

Summarizing the most important characteristics of these approaches highlights their differences (Fig. 8). This comparison also highlights that there is no perfect method for estimating soil AWC and that no method has better qualities than another (Table 3). The advantages and limitations of each method are well known and can be considered by users. Considering that they are complementary to some extent, combining them could improve their performance greatly.

5.2 Combining soil and soil–plant approaches to improve AWC estimates

5.2.1 Improving soil-based estimates of AWC using inverse-modeling information or information about plants

As AWC represents the quantity of water available to plants, the main input from inverse modeling of crop or soil–plant system models should be a realistic rooting depth, depending on the soil type and crop. This information should be available at the local scale, for which a variety of accurate information and adequate models can be included in the inversion process. In databases such as GlobalSoilMap products in which AWC is provided for multiple soil depths, users can choose the most appropriate depth for their applications. The next step in

developing PTFs for estimating AWC would be to provide information about plants, as suggested by Van Looy et al. (2017). Similar to how class PTFs are usually defined for a texture class, new types of PTFs could be defined for combinations of texture and plant classes. To our knowledge, the first authors to do so were Levi et al. (2015), who introduced remotely sensed information from Landsat to produce functional spatial PTFs for AWC, which differ significantly locally from traditional PTFs. Similarly, Basile et al. (2019) highlighted the effectiveness of NDVI data to estimate PTFs.

5.2.2 Using soil information to improve inverse-modeling estimates of the AWC-equivalent parameter

Improving inverse-modeling estimates of AWC could involve integrating the available information from soil mapping approaches into the inversion process, as shown by Scharnagl et al. (2011) and Scholer et al. (2011). Existing information about soils, which varies according to the context, could be used more widely to constrain inversions by providing direct information about the parameters to be estimated. GlobalSoilMap products could be a particularly relevant source of information in this context as an operational open-access product that provides the associated uncertainties. For spatial applications, such as in hydrology, Finsterle and Kowalsky (2008) and Mariethoz et al. (2010) included a priori information about the spatial dependence of the estimated parameters—obtained from soil geophysical measurements—to constrain model inversions.

5.2.3 Improving spatial estimates of AWC over large regions

DSM techniques based on sites with known AWC components and model inversion using remote-sensing data are still limited in extent and precision for mapping AWC. However, they are complementary approaches that could be used synergistically to improve AWC mapping. Using DSM outputs to constrain model inversions can be the first step toward such synergy. The next step is to re-use in DSM the outputs of punctual model inversions performed in situations that maximize the information about the parameters to be estimated (i.e., for which model error is low and uncertainties in DSM output are high). Approaches that combine different soil inputs have been developed to combine soil property measurements and spectroscopy imagery estimates (Lagacherie et al. 2012; Walker et al. 2017). For soil–plant model inversions, considering these outputs as pseudo-measurements of AWC parameters significantly increases the density of sites with known values of these parameters, which may increase the accuracy of DSM predictions. The challenge is to develop DSM models that can use traditional AWC measurements and model-inversion outputs as input.
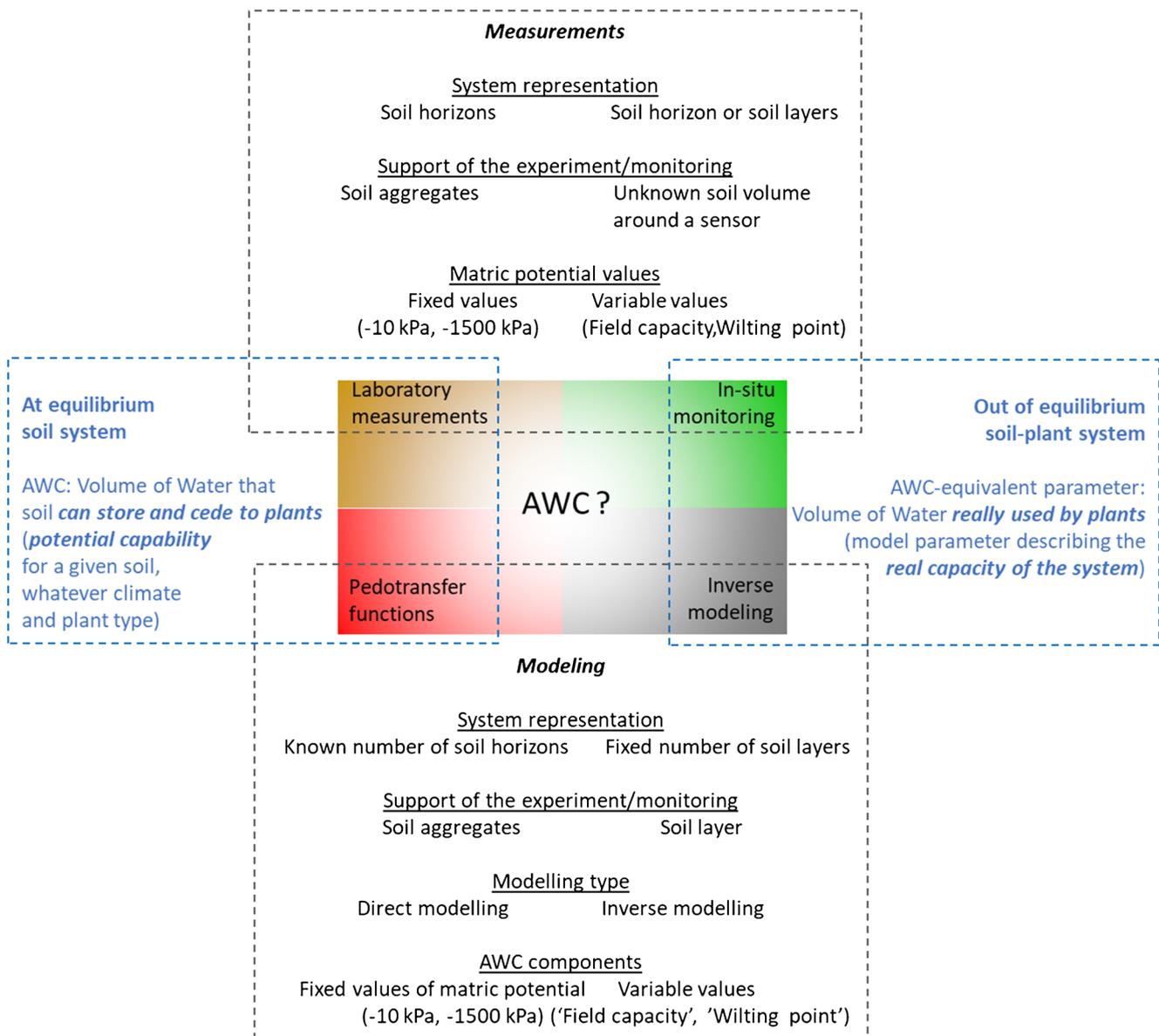
Fig. 8 Comparisons between the different methods presented in this paper to evaluate Available Water Capacity (AWC) and related definitions.

6 Conclusion: toward new definitions of AWC?

The objective of this review was to identify the concepts that underlie estimates of AWC and to clarify the methods used in the literature to estimate this fundamental parameter of soil–plant–atmosphere models at different scales. Soil-based approaches are usually based on measuring the water content of soil samples at equilibrium at a given matric potential, or on empirical models based on basic soil characteristics, such as particle-size distribution or bulk density, whether for estimates using PTFs or in DSM approaches. These soil-based approaches thus correspond well to the original and current definitions of AWC and represent a capacity (i.e., the maximum amount of water that soils can store to sustain plant transpiration). Conversely, soil–plant-based approaches are usually based on non-equilibrium approaches, which are based on field measurements of soil water content or plant characteristics when plants are dynamically subjected to climate variations. Estimating AWC directly from field measurements or inverse estimates of soil-vegetation models, whose input data are local field measurements or remotely sensed images of vegetation growth, may not indicate the soil's capacity to store water. Instead, it indicates the quantity of water that the plant takes up from the soil (i.e., an ability). AWC in this case should be called PAWC. Depending on the climate conditions, this plant AWC-equivalent parameter can differ strongly from the AWC estimated using soil-based approaches. In certain situations, it can be similar to the readily available water content. Despite these differing definitions, estimating AWC and AWC-based parameters can be

improved by hybridizing soil-based approaches and soil–plant-based approaches to create high-resolution maps of this hydraulic parameter. Among potential improvements in the near future, we emphasize three. First, estimates of AWC would likely benefit from developing new types of functional PTFs that include not only soil information but also plant-functioning information, especially from remote-sensing data. Second, including available soil data from monitoring systems when inverting models would improve estimates of AWC. GlobalSoilMap products would be particularly relevant to address the difficulty in estimating depth and the influence of uncertainties. Third, a close relationship between soil-based (laboratory-based) AWC measurements and AWC model-inversion outputs would help to develop improved soil mapping products to estimate AWC accurately. These developments in AWC could benefit farmers, who could use them as decision tools in precision agriculture, as well as scientists who use land surface models at the global scale to assess effects of global changes.

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Declarations

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