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An operational workflow to assess rice nutritional status based on satellite imagery and smartphone apps

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ABSTRACT

Nitrogen fertilization plays a key role in rice productivity and environmental impact of rice-based cropping systems, as well as on farmers' income, representing one of the main cost items of rice farming. Average nitrogen use efficiency in rice paddies is often very low (about 30%), leading to groundwater contamination, greenhouse gases emission, and economic losses for farmers. The resulting pressure on many actors in the rice production chain has generated a need for operational tools and techniques able to increase nitrogen use efficiency. We present an operational workflow for producing nitrogen nutritional index (NNI) maps at sub-field scale based on the combined use of high-resolution satellite images and ground-based estimates of Leaf Area Index (LAI) and plant nitrogen concentration (PNC, %) data collected using smart apps. The workflow was tested in northern Italy. The analysis reveals that vegetation indices are satisfactorily correlated with LAI ($r^2 > 0.77$, $p < 0.01$) and PNC ($r^2 > 0.55$, $p < 0.01$); whereas most patterns of NNI maps are coherent with the available information on soil texture and performed agro-practices. Key features of the proposed approach are (i) the time- and cost-effectiveness for producing NNI maps even in operational contexts and (ii) the full exploitation of smart scouting techniques to drive field data acquisitions using smartphones as sensors. The use of operational, free-of-charge products from Sentinel-2 for real-time field monitoring to potentially support variable rate fertilizations is also discussed.

1. Introduction

Nitrogen (N) is a key element for plant growth, being a fundamental component of many cell structures such as proteins, chlorophylls and nucleic acids. Its concentration in plant tissues is the highest among those of the three main nutritional elements for plants (N, phosphorus [P] and potassium [K]). For instance, Sukristiyonubowo et al. (2012) measured N, P and K contents in rice (*Oryza sativa* L.) grains corresponding to 1.28%, 0.15% and 0.32% on dry matter basis, respectively. For these reasons, rice N demand is high and deficiencies rapidly decrease yields (Huang et al., 2015), because of reduced tillering, lower number of spikelets per panicle and decreased photosynthetic rate (Mae, 1997). However, rice yields are also threatened by N excess, because of the increased plant susceptibility to diseases (Long et al., 2000) and lodging (Shimono et al., 2007). The high impact of N availability on yields and the low efficiency in its use due to the special water management practices applied to rice paddies, make it crucial for paddy rice farmers to match plants needs with supply in terms of both timing and amounts.

Concerning the low N use efficiency, most of the N supplied to paddies can be lost via denitrification because of the redox conditions of flooded soils, ammonia volatilization, and—especially in case of dry sowing and delayed flooding on non-puddled soils—nitrate leaching (Confalonieri et al., 2006; Ke et al., 2017). According to published data, N use efficiency in rice paddies range from about 60% at best (Li et al., 2017) to 12% in the worst cases (Singh et al., 1999), with common values reported to be around 30% (e.g., Confalonieri et al., 2006). These low efficiencies lead to eutrophication, groundwater contamination, greenhouse gases emission and air pollution. In order to mitigate these impacts and to avoid excessive fertilization, the EC Nitrate Directive (91/676/EEC) focuses on encouraging a more strict and mindful application of nitrogen.

Another crucial factor relevant to the low N use efficiencies often observed in paddy fields is related to the impact on farmers' income,

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since fertilization is a major cost in rice farming. For example in Italy, a major rice producer in Europe, the cost for fertilizers in a medium-size rice farm (150 ha) represents almost 40% (~ 370 €/ha) of the total cost for input factors, with agrochemicals, seeds and water accounting only for 26%, 16%, and 20%, respectively (Camera di Commercio Vercelli, 2013). This further underlines how fertilizers management is of fundamental importance for farm economic balance.

In this context, operational solutions able to optimize the use of N fertilizers are increasingly needed to implement sustainable agro-practices and maximize farmers' income, in other words, to increase the efficiency of rice-based cropping systems. A promising approach to face this challenge is precision farming, i.e., the exploitation of multi-source information in a decision support system to improve the efficiency of farm management (Blackmore, 1994).

1.1. Precision farming and variable rate technologies for fertilization

The use of variable rate (VR) fertilization maps rather than fertilizing homogeneously the whole field is considered a promising approach to face some of the criticalities involved with N use efficiency and represents the basis for the implementation of rationale top-dressing fertilization (Basso et al., 2016). Indeed, the capacity to assess, understand and manage the within-field variability is a prerequisite to define sustainable agro-practices able to reduce farming cost and environmental impact (Stroppiana et al., 2009). Different methodologies were proposed in recent years, some of them being operationally adopted in real farming practices to create variability maps. These methodologies can be grouped in two categories: (i) based on the analysis of static information from data acquired during previous cropping season(s) and (ii) based on the near-real-time dynamic monitoring of crop conditions exploiting direct/indirect measurements.

A common approach for supporting the creation of VR maps is to exploit different thematic layers as input to a clustering process, in order to generate a map of management unit zones (MUZ) where each zone represents an area with uniform condition of soil fertility to be appropriately managed (Fridgen et al., 2004). Spatially-distributed inputs for MUZ definition can refer to every kind of information related to plant growth and considered important for yield determination (Casa and Morari, 2016). For instance, MUZ can be identified through the analysis of soil properties either derived from (i) interpolation of geo-located ground data of "stable" soil parameters, like texture, organic matter content, available phosphorus, and exchangeable potassium (Casa and Castrignanò, 2008; Casa and Morari, 2016) and/or (ii) indirectly estimated from the analysis of remote sensing data (e.g., Agbu et al., 1990) or ground measurements (e.g., soil electrical conductivity; Grisso et al., 2009). Alternatively, yield maps produced in previous years (Stafford et al., 1999) or archives of remote sensing (RS) data can also be used to define patterns of constant intra-field variability (Busetto et al., 2017; Casa et al., 2017). The definition of MUZ can be continuously updated to account for new information made available by new technologies (e.g., new satellites, drones, new sensors) or by more recent yield maps.

Another approach for static VR fertilization is based on compiling a simplified nutrient balance (Grignani et al., 2003). This can be performed by analyzing yield maps from previous seasons to get spatially-distributed estimates of the uptake of main nutrients (N, P, K), as well as inferring the other items of the balance, such as residuals from previous organic fertilizations, inputs from dry and wet depositions, losses from leaching and so on (Casa et al., 2011). The fertilization for the current season can be then modulated based on the expected crop needs (Casa et al., 2011). Compared to the approaches previously described, for which fertilizer amounts can be quantified only via expert-knowledge, the nutrient balance approach allows mapping explicitly the quantity of fertilizers, although it requires more inputs.

Dynamic monitoring for VR fertilization is instead based on the near-real-time collection of data able to provide information on crop development and nutrition status. For this approach, ground, proximal and remote sensing measurements are usually exploited to analyze the within-field variability in a qualitative or quantitative way. One of the main constraints in using optical sensors to map nutritional status is the fact that N content is not an optically discernible variable in green plants, because nitrogen absorption features are obscured by water (Chen, 2015). Therefore, it cannot be estimated directly from RS. However, it is possible to assess N concentration thanks to its direct relationship with chlorophyll content that has well-known spectral features in visible and Red-Edge bands. For this reason, chlorophyll-related indicators can be used as proxies of crop nitrogen concentration (Guerif et al., 2007).

A qualitative approach to support in-season VR fertilization can rely on the analysis of spatially distributed information (from the interpolation of field measurements or from proximal/remote sensing images) in order to identify field regions characterized by different crop vigor. In this sense, recent approaches are driven by sensors mounted directly on the operating tractor (e.g., GreenSeeker active canopy sensor; Trimble, Sunnyvale, CA, USA), or by the analysis of earth observation (EO) data acquired by sensors on drones, aircraft or satellites (Casa and Morari, 2016). According to the within-field variability in crop vigor, N application can be modulated either (i) using cultivar-specific empirical equations (Xue and Yang, 2008; Pahlmann et al., 2017) or (ii) adapting the average prescription (based on expert-knowledge) in the different zones according to the relationship between local crop vigor and field average (Busetto et al., 2017). These approaches are already provided by operational services exploiting commercial devices such as those proposed by Oklahoma State University for GreenSeeker (Raun et al., 2005) or by Nebraska University for Crop Circle (Holland and Schepers, 2010).

Other approaches for dynamic VR fertilization are more quantitative and provide a direct support to farmer by diagnosing the actual crop N nutritional status. A widely recognized approach is the one based on the estimation of N nutritional index (NNI) (Lemaire et al., 2008). NNI is the ratio between actual (PNC, %) and critical (Nc, %) plant N concentration, with the latter being the minimum N concentration below which crop growth is reduced and the former is the plant nitrogen concentration (Confalonieri et al., 2011). Nc is often estimated as a function of aboveground biomass (AGB) using the dilution curve approach (Salette and Lemaire, 1981; Ata-Ul-Karim et al., 2013), with its value decreasing during the crop cycle because of the reallocation of N-rich compounds from senescent tissues and of the relative decrease in N-rich organs during crop aging (less leaves, more stems) (Confalonieri et al., 2011). Other approaches derive Nc curves as a function of development stage indices (Williams et al., 1989; Hansen et al., 1991). In any case, the effectiveness of these methods for diagnostic purposes is partly limited by the procedures needed to determine their driving variables (AGB or development stage indices). To overcome this limitation, a recent approach was proposed to derive Nc curves as a function of Leaf Area Index (LAI) (Confalonieri et al., 2011), easily obtainable using indirect, non-destructive methods (e.g., LAI-2000; (Stroppiana et al., 2006)) without the need for defining sample size, sampling/drying/weighing plants (as for AGB determination), or performing calculations based on heat units (as for development stage indices). As for LAI, instruments are available for non-destructive PNC estimates (through related index and dedicated calibration curves (Varinderpal et al., 2011)). Examples range from inexpensive plastic strips with different green shades (leaf color charts; (Alam et al., 2005)) to optical instruments able to estimate plant chlorophyll content alone (e.g., SPAD 502, Konica Minolta Inc., Tokyo, Japan; (Peng et al., 1996)) or in addition to other variables related to the relationship between primary and secondary metabolism (flavonoids content) to derive a N balance index (Dualex 4, Force-A, Orsay, France; (Cerovic et al., 2012)). Other approaches were proposed based on the exploitation of hyper-spectral proximal sensing measurements (Stroppiana et al., 2009).

Recently, new approaches were proposed to estimate both LAI