May smart technologies reduce the environmental impact of nitrogen fertilization? A case study for paddy rice

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Abstract

Precision agriculture is increasingly considered as a powerful solution to mitigate the environmental impact of farming systems. This because of its ability to use multi-source information in decision support systems to increase the efficiency of farm management. Among the agronomic practices for which precision agriculture concepts were applied in research and operational contexts, variable rate (VR) nitrogen fertilization plays a key role.

A promising approach to make quantitative, spatially distributed diagnoses to support VR N fertilization is based on the combined use of remote sensing information and few smart scouting-driven ground estimates to derive maps of nitrogen nutrition index (NNI). In this study, a new smart app for field NNI estimates (PocketNNI) was developed, which can be integrated with remote sensing data. The environmental impact of using PocketNNI and Sentinel 2 products to drive fertilization was evaluated using the Life Cycle Assessment approach and a case study on rice in northern Italy. In particular, the environmental performances of rice fertilized according to VR information derived from the integration of

PocketNNI and satellite data was compared with a treatment based on uniform N application. Primary data regarding the cultivation practices and the achieved yields were collected during field tests.

Results showed that VR fertilization allowed reducing the environmental impact by 11.0% to 13.6% as compared to uniform N application. For Climate Change, the impact is reduced from 937.3 to 832.7 kg CO_2 eq/t of paddy rice. The highest environmental benefits – mainly due to an improved ratio between grain yield and N fertilizers – were achieved in terms of energy consumption for fertilizer production and of emission of N compounds. Although further validation is needed, these preliminary results are promising and provide a first quantitative indication of the environmental benefits that can be achieved when digital technologies are used to support N fertilization.

Keywords

Impact assessment, Life Cycle Assessment, Nitrogen Nutrition Index, PocketNNI, Precision Agriculture, Sentinel.

1. Introduction

Precision agriculture (PA) – i.e., the use of multi-source information in decision support systems to increase the efficiency of farm management (Blackmore, 1994; Bouma et al., 1999) – is increasingly catalysing the attention of scientists and farmers because of its potential to reduce environmental pollution while increasing farm profits and product quality (Srinivasan, 2006). The adoption of PA techniques proved to enhance the economic return of farming activities by improving the efficiency in the use of technical inputs (Balafoutis et al., 2017a; van Evert et al., 2017), although to a different extent according to the crop, the technical input considered, and the cost of the technology used to implement PA principles (Lowenberg-DeBoer and Erickson, 2019, Griffin and Lowenberg-DeBoer, 2005). In practical terms, PA aims at managing variability in space and time (McBratney et al., 2005), that is, doing the right thing in the right place at the right time, and in the right way (Pierce et al., 1994). A variety of studies confirmed the positive expectations behind the application of PA techniques, for both herbaceous (e.g., Basso et al., 2016) and tree species (e.g., Balafoutis et al., 2017b; van Evert et al., 2017). However, PA often requires the adoption of advanced machineries and technological systems, whose construction, maintenance and use could, to a certain extent, reduce the potential environmental and economic benefits deriving from its implementation (Sadler et al., 2005). As an example, the application of PA principles to water management normally requires the use of drip irrigation (e.g., Smith and Baillie, 2009; Mafuta et al., 2013; Prathyusha et al., 2013; Kisekka et al., 2017), which may have a higher environmental impact (evaluated through LCA) compared to less sophisticated irrigation systems characterized by lower water use efficiencies (Guiso et al., 2015) because of the production, laying and disposal of part of the plastic pipes.

These considerations are far from being aimed at casting a shadow over PA and, in general, over technology. They rather underline the need of evaluating in a quantitative way the actual economic and environmental impacts of technologies in specific production contexts. Among agricultural practices, variable rate (VR) nitrogen (N) fertilization is likely one of those for which the largest number of studies was performed (e.g., Basso et al., 2016). VR fertilization can be based (i) on static information derived from soil data (e.g., Grisso et al., 2009), remote sensing (Casa et al., 2017) or yield maps from previous years (e.g., Stafford et al., 1999), or (ii) on dynamic crop monitoring using real-time or near-real-time information (Nutini et al., 2018). The latter refers to topdressing N fertilization and can be based on sensors mounted on the operating tractor (e.g., GreenSeeker, Trimble, CA, USA; Raun et al., 2005), on remote sensing information (Schwalbert et al., 2019), or on diagnostic portable instruments (Rogovska et al., 2019).

The most quantitative approaches for dynamic VR fertilization are based on the combined use of remote sensing information and smart scouting-based ground data collection for estimating N nutrition index (NNI) (e.g., Chen, 2015; Huang et al., 2015; Ata-Ul-Karim et al., 2014; Nutini et al., 2018), the latter being defined as actual (PNC) to critical (Ncrit) plant N concentration ratio (Lemaire et al., 2008). The integration of few ground measurements and remote sensing information allows obtaining spatially distributed maps of NNI (i) with a limited effort compared to using only ground data and (ii) with a quantification of crop needs more reliable compared to the sole use of remote sensing data (Nutini et al., 2018).

Besides the need of species- or cultivar-specific calibration curves to derive PNC values from indirect proximal or remote estimates (Varinderpal et al., 2011), obstacles to the adoption of systems to support VR fertilization deal – like for many decision support systems (Rose et al., 2016) – with their time- and cost-effectiveness and usability (Korsaeth and Riley, 2006). A system to support VR topdressing fertilization based on smart apps – PocketN (Confalonieri et al., 2015) for PNC estimates and PocketLAI (Confalonieri et al., 2013) to derive Ncrit according to Confalonieri et al. (2011) – and satellite data was recently proposed and evaluated for rice (Nutini et al., 2018). The system is scientifically sound (based on the NNI concept) and inexpensive, being based on free-of-charge Sentinel 2 products and smartphones for ground data collection.

This study aimed at (i) evaluating a new smart app for determining NNI (PocketNNI) under operational farming conditions, and (ii) evaluating with a dedicated case study the environmental performances of fertilization strategies based on the integration of PocketNNI and satellite data for VR fertilization in rice as compared to adopting standard N management. Given PocketNNI allows to explicitly account for crop N nutritional status while applying VR top-dressing fertilizations, it has the potential to increase N use efficiency and, in turn, the environmental sustainability of rice-based cropping systems. PocketNNI (**Figure 1**) integrates PocketLAI, PocketN and the calibration curves to derive PNC from PocketN readings developed for European rice cultivars by Paleari et al. (2019). Being estimates geo-referenced, PocketNNI can be easily coupled to satellite data or used as a standalone tool in case of production contexts characterized by small fields. PocketNNI is the first standalone tool able to directly estimate NNI without the need of integrating readings from different instruments and without the need of transforming variables in external environments. Moreover, this is the first time LCA was performed to evaluate VR fertilization in rice, the only two studies available – to our knowledge – being for pear orchards (Vatsanidou et al., 2017) and maize (Li et al., 2016).

2. Material and Methods

2.1 The smart app PocketNNI

PocketNNI (**Figure 1**) estimates the actual (PNC) to critical (Ncrit) plant N concentration ratio (NNI) by integrating the algorithms of the smart apps PocketLAI (Confalonieri et al., 2013) and PocketN (Confalonieri et al., 2015), the calibration curves needed to estimate PNC values from PocketN readings (Paleari et al., 2019), and the model to derive Ncrit as a function of leaf area index (LAI) (Confalonieri et al., 2011).

Figure 1 – Around here

PocketN derives an index that quantifies leaf greenness (dark green colour index, DGCI, unitless; Karcher and Richardson, 2003) by using the hue (H), saturation (S) and brightness (B) values (HSB colour space) of a 25-pixel portion of leaf images acquired on a dedicated expanded polyvinyl chloride background panel that flats reflectance across the visible spectrum. This allows characterizing leaf greenness on images acquired under consistent exposure regardless of the illumination conditions.

$$DGCI = \frac{\frac{H-60}{60}+2-S-B}{3} \quad \text{(Eq. 1)}$$

In PocketNNI, *DGCI* is automatically converted into PNC values by using the calibration curves developed for European rice varieties by Paleari et al. (2019).

Ncrit is estimated according to the model proposed by Confalonieri et al. (2011), which uses the inverse of the fraction of radiation intercepted by the canopy to reproduce the dilution of N in plant tissues due to the remobilization of N from senescent leaves (Eq. 2):

$$N_{crit} = \frac{N_{mat}}{1-e^{-k \cdot LAI}} \quad (2)$$

The parameter Nmat (%) represents the value of Ncrit at maturity, and k (-) is the extinction coefficient for solar radiation. As in Confalonieri et al. (2011), Nmat and k were set to 1% and 0.5, respectively. Within PocketNNI, LAI is derived by implementing the algorithms of PocketLAI (Confalonieri et al., 2013). According to this method, the gap fraction (P_0) is estimated through the automatic segmentation of images acquired at 57.5° zenith angle from below the canopy while the user is rotating the smartphone along its main axis. The 57.5° angle is identified in real time, by applying plain vector algebra to the components of the g vector provided by the 3-axis accelerometer of the device. LAI values are then derived by inverting the light transmittance model proposed by Baret et al. (2010) (Eq. 3):

$$LAI = -\left[\frac{cos(57.5°)}{0.5}\right] log[P_0(57.5°)] \quad (3)$$

This model uses the gap fraction estimated at 57.5° because it has been proved that the information acquired from this particular view angle are independent from the leaf angle distribution (Baret et al., 2010).

Further details on PocketLAI, PocketN and on the PocketN calibration curves are provided as supplementary material (Figure S1, S2 and Table S1) and by Confalonieri et al. (2013, 2015) and Paleari et al. (2019).

2.2 Description of the field experiment

Rice (*Oryza sativa* L., cv. Volano) was scatter seeded on 7 May 2018 in a 2 ha field in Gaggiano (Milan province; 45°23'N, 9°02'E, 126 m a.s.l.) and grown under continuous flooding conditions. Rice was grown in the field since the last decade, reflecting the high level of specialization of rice farms in Northern Italy. The site is representative of the conditions experienced by rice in the eastern part of the main European rice district. Soil was silt loam (USDA), subacid, with medium organic matter content and cation exchange capacity, and unlimiting values for available P and exchangeable K. Crop management allowed a complete control of weeds, pests and diseases.

In general, temperatures during the 2018 rice season were in line with the 10-year average in the site (Figure S3) and, despite mean daily temperatures during summer months were sometimes higher than the average, they never exceeded the optimal range for rice (Sanchez et al., 2014). The 2018 season was consistent with mean climatic conditions in the study area also in terms of precipitations (Figure S4), with spring and autumn rainfall peaks, and drier conditions during summer.

Two different fertilization strategies were considered (**Table 1**), each applied to half of the field, with the latter divided along the same direction of a fertility gradient generated by the union of two fields and by the levelling of the resulting one. In the first fertilization strategy (Baseline Scenario - BS), topdressing N fertilization was applied based on the standard farming practices in the study area and on the farmer's perception of crop needs. For this scenario, N was distributed without differentiating the dose in the different parts of the field.

In the second strategy (Alternative Scenario - AS), PocketNNI and satellite data were used to derive spatially distributed estimates of NNI, whose values were grouped in five classes: (i) severe N stress ($NNI < 0.7$), (ii) light N stress ($0.7 \leq NNI < 0.9$), (iii) neutral ($0.9 \leq NNI \leq 1.1$), (iv) light luxury consumption ($1.1 < NNI \leq 1.3$), and (v) severe luxury consumption ($NNI > 1.3$). The membership of field portions to the NNI classes was used by the farmer to define the N dose corresponding to each portion (i.e., prescription map), in light of the fertilization strategy adopted (how many fertilization events), of the cultivar features and of his knowledge of the specific field (e.g., soil drainage, organic matter content). As demonstrated and discussed by Paleari et al. (2019), indeed, differences in cultivar features, and the variability in soils properties and management strategies mostly prevent using constant relationships to derive N doses from NNI values.

The clustering of Sentinel 2 NDRE (Normalized Difference Red-Edge) images acquired before the topdressing fertilizations allowed driving ground data collection with the aim of finding the best compromise between the need of properly capturing field variability and the need of keeping to the minimum the number of ground measurements (Nutini et al., 2018). In practice, one site in the field was identified for each of six NDRE clusters, and PocketNNI readings were taken at each site.

In case of directly spatializing NNI values via relationships with vegetation indices (Fitzgerald et al., 2010; Cao et al., 2013), NNI values provided by PocketNNI can be directly used. In this study, we chose to indirectly estimate NNI values at pixel level (Huang et al., 2015) based on NDRE-PNC and NDVI-LAI relationships derived using ground PNC and LAI values provided by PocketNNI at the six scouting sites (Nutini et al., 2018). These relationships were then used to estimate PNC and LAI values for each pixel, with PNC values derived with the calibration curve implemented in PocketNNI for cv. Volano: $PNC = 6.77 \cdot PocketN\ index - 2.25$ (Paleari et al., 2019). LAI was converted into Ncrit by using the approach described above (Confalonieri et al., 2011), and the NNI map was derived from pixel-level PNC to Ncrit ratios.

Details on management practices – including those not related with N fertilization – are provided in **Table 1**.

At harvest, yield of the Baseline and Alternative scenario was determined with a combined harvester, sampling eleven subplots along each half of the field.

2.3 Life cycle assessment

The Life Cycle Assessment (LCA) approach is a holistic method defined by two ISO standards (ISO, 2006a; ISO, 2006b) to evaluate the potential environmental impacts related to a product or a service throughout its entire life cycle.

2.3.1 Goal and scope

In this study, LCA was applied to rice production in Northern Italy in order to compare two different fertilization strategies: one based on conventional practices in the area (uniform N distribution according to farmer's perception of crop needs), the other based on the combined use of a new smart app and of satellite data to get a spatially-distributed, real-time diagnosis of N nutritional status. In developed countries, the outcomes of this study can support rice growers in increasing nitrogen use efficiency and policymakers in defining public subsidy frameworks targeting the reduction of the environmental impacts of rice-based cropping systems.

Specifically, this LCA study was aimed at:

- evaluating the potential environmental impact of rice production in a case study carried out in Northern Italy during 2018,
- quantifying the potential environmental benefits achievable by applying VR fertilization through the combined use of satellite data and of a new smart app developed to quantify NNI.

2.3.2 Functional unit

According to ISO standards, the functional unit (FU) is defined as the main function of the system expressed in quantitative terms (ISO, 2006a). In this study, it was considered as 1 t of rice grain at the commercial moisture (86% of dry matter). The choice of the FU is in agreement with previous studies on rice in Italy (Fusi et al., 2014; Bacenetti et al., 2016a; Bacenetti et al., 2016b), Iran (Khoshnevisan et al., 2014), USA (Brodt et al., 2014, Fertitta-Roberts et al., 2019), Korea (Jeong et al., 2018), Japan (Hokazono and Hayashi, 2012), Thailand (Thanawong et al., 2014), and Brazil (Coltro et al., 2017), thus allowing a direct acomparison of results.

2.3.3 System boundary

A "from cradle to farm gate" approach was applied in this study. The system boundary includes all the activities carried out from the extraction of the raw materials to the drying of rice grains. In particular, the following stages of the production process were considered: i) extraction of raw materials (e.g., fossil fuels, metals and minerals); ii) manufacture, maintenance and disposal of the capital goods (e.g., tractors, agricultural machines, shed and grain dryer); iii) production of the different inputs (fertilizers, pesticides, electricity, diesel, etc.); iv) emissions related to the use of input factors (e.g., emissions due to fertilizers application, diesel fuel emissions related to diesel combustion in the tractor engine).

Distribution, processing, packaging, use and end-of-life were excluded from the system boundary because they are the same in the two scenarios. Allocation was not applied since straws are left into the field in both scenarios.

Figure 2 shows the system boundary for the rice production process.

Figure 2 – Around here.

2.3.4 Inventory data collection

Two different types of inventory data were used: primary data directly collected at the farm during field tests and surveys and secondary data retrieved from databases, literature or estimated using specific models. The collected primary data refer to the consumption of the different inputs (e.g., diesel for the different field operations and for drying, seeds, fertilizers, plant protection products, machinery and tractors, infrastructures such as the dryer and the sheds for equipment). **Table 1** reports the main data concerning the cultivation practice.

Table 1 – Around here

Secondary data were instead considered for the emissions of methane and nitrogen and phosphorous compounds. For the emissions of methane in atmosphere, the IPCC model (IPCC, 2006) was used and different scaling factors (for pre- and in-season water management, application of organic fertilizer and soil type) were applied to the baseline emission value for continuously flooded field without organic amendments (1.3 kg CH_4 ha^{-1} day^{-1}). **Table 2** reports the main information used for the estimation of methane emissions. Although the cultivation practice is the same, the AS showed a slightly higher methane emissions per unit area (113.0 and 122.7 kg CH_4 ha^{-1} day^{-1}, in BS and AS, respectively) because of a higher amount of straw[1] produced and incorporated into the soil.

Table 2 – Around here.

Nitrogen emissions (nitrate leaching; ammonia volatilization, and nitrous oxide emissions in atmosphere) were computed following the IPCC Guidelines (2006), whereas the phosphate emissions in water (leaching to groundwater and surface runoff) were calculated following Prahsun (2006).

Pesticide emissions were estimated according to the Product Category Rules for Arable Crops (Environdec, 2013) and, consequently, the active ingredient of pesticides was considered totally released into the soil.

Background data regarding the production of the different inputs (fertilizers, pesticides, diesel, electricity, tractors and agricultural machines, dryer) were retrieved from the Ecoinvent database® v.3.5 (Weidema et al., 2013; Moreno Ruiz et al., 2018). **Table 3** reports the list of different Ecoinvnet® processes used and highlights the changes made.

Table 3 – around here

[1] The mass of the straw has been assessed considering a Harvest Index of 0.55

2.3.5 Impact assessment

Using the characterisation factors reported by the midpoint ILCD method (ILCD, 2011), the following impact categories were considered: Climate change (CC), Ozone depletion (OD), Human toxicity, cancer effects (HTc), Human toxicity, non-cancer effects (HTnoc), Particulate matter formation (PM), Photochemical oxidant formation (POF), Terrestrial acidification (TA), Freshwater eutrophication (FE), Terrestrial eutrophication (TE), Marine eutrophication (ME), Freshwater ecotoxicity (FEx), Mineral fossil and renewable resource depletion (MFRD).

The ILCD (2011) Midpoint method was released by the European Commission Joint Research Centre and supports the correct use of the characterisation factors for impact assessment as recommended in the ILCD guidance document "Recommendations for Life Cycle Impact Assessment in the European context - based on existing environmental impact assessment models and factors" (Hauschild et al., 2011).

3. Results and Discussions

3.1 PocketNNI/satellite-driven N management

The combined use of PocketNNI and satellite data allowed to effectively explore the in-field variability of PNC, Ncrit, and NNI (**Figure 3**).

In general, the observed within-field heterogeneity in N nutritional status was representative of intensive rice-based cropping systems, with most NNI values close to 1 even before top-dressing fertilizations (Paleari et al., 2019). The real-time diagnosis of N nutritional status via the combined use of PocketNNI and satellite data allowed capturing the spatial variability in NNI and, thus, to fine tune N distribution in the different areas of the field. This turned into a 12.8 % higher grain yield for AS as compared to BS, with only 2% more N applied (**Table 1**), thus demonstrating the system effectiveness in preventing both N stress (decreasing yield potential) and luxury consumption.

Figure 3 – around here

The increase in productivity is similar to what reported for cereals by other authors (Koch et al., 2004; Biermacher et al., 2006; Sharf et al., 2011), although it is likely larger than what could be achieved on average for rice in the area because of the pronounced heterogeneity that characterized the experimental field, in turn due to the fertility gradient generated by the union of two smaller fields. This – as mentioned in the description of the field experiment –may have increased the positive effect of VR N fertilization. The total amount of N applied for AS was slightly higher (+3 kg ha^{-1} over the entire season). This is probably due to the tendency of many Italian formers to limit N fertilization to reduce the risk of increasing the susceptibility to fungal pathogens, given tricyclazole – a fungicide widely used to tackle rice blast disease since many years – has been recently banned (Titone et al., 2015).

Besides the potential for increasing productivity and N use efficiency, other advantages of PocketNNI derive from its technological features. Indeed, although other methods are available to support topdressing N fertilization based on the NNI concept (e.g., Huang et al., 2015, Chen, 2015), PocketNNI is the first tool able to provide directly NNI as output, without the need for dedicated instruments and for data export and analysis in external environments. This allows farmers being independent in assessing N nutritional status, with clear advantages in terms of cost-effectiveness and timeliness of the analysis. Moreover, when coupled with satellite data and smart-scouting techniques (Nutini et al., 2018), PocketNNI allows deriving high resolution NNI maps with just few ground measurements. The system is scientifically sound, being based on the NNI concept, and the information provided (NNI) is easy to interpret. All these aspects make the proposed system highly promising for overcoming most of the barriers that limit the adoption of PA techniques in operational contexts (Lowenberg-DeBoer and Erickson, 2019).

3.2 Life Cycle Assessment

Figures 4 and **5** show the relative contributions to the overall environmental impact of the production factors and of the emissions sources for BS and AS, respectively.

Figure 4 and **Figure 5** – Around here

Different main contributors (namely "environmental hotspots") were identified for the different impact categories:

- the main responsible of CC were the emissions of methane and dinitrogen monoxide from the soil (44-45% of the total impact). Methane emissions contributed also to POF (7.9% and 8.4% in BS and AS, respectively);
- the emissions related to the fertilization were the main hotspot for PM, TA and ME. In particular, ammonia emission was responsible for PM, TA and ME, nitrate leaching for ME and phosphorous run-off for FE;
- the mechanisation of field operations was the responsible for HT-noc, mainly due to the emissions of pollutants (e.g., hydrocarbon, nitrogen oxides) in the exhaust gas of the tractor engine and POF, mainly because of the consumption of diesel and the emission of non-methane volatile organic compound (NMVOC);
- fertilizers production was the main responsible of MFRD, given the high energetic cost for the production of N fertilizers;
- the impact of seed and pesticides production was lower than 10% for all the evaluated impact categories but OD (mainly due to herbicides production), HT-c, FE and FEx (seed production);
- for FEx, it was related to the emissions of pesticides into the soil (about 35%) to the production of fertilizers (about 30%).

Despite the main contributors to the overall environmental impact were similar in the two scenarios, some differences can be highlighted:

- for OD, the grain drying was responsible for 27.8% of the impact in BS, whereas its contribution was larger in AS (32.4%) because of the higher transpiration (768 kg in BS and 956 kg in AS) due to the higher crop growth, which – beside the final yield - affected the amount of transpiring tissues;
- the impact related to transport was higher (both in relative and absolute terms) in AS because of the higher biomass produced.

Table 4 reports the absolute environmental impact for the two scenarios, **Figure 6** shows the comparison between the two scenarios. Regardless of the evaluated impact categories, AS showed the best results, with impact reduction ranging from 11.0% for OD to 13.6% for MFRD. The impact reduction, mainly due to the yield increase (7.97 and 8.99 t ha^{-1} at commercial moisture in BS and AS, respectively), was considerable and it was only related to the combined use of PocketNNI and satellite data. This reduction was larger for the impact categories more affected by the energy consumption for fertilizer production (MFRD) and by the emissions of N compounds due to fertilization (TA, TE, FE and ME). The impact reduction was lower for:

- OD, the impact category mainly affected by grain drying, because of the higher amount of water to be removed given the higher yield;
- CC, since the higher yield involves a higher production of straw that, being incorporated into the soil, leads to higher methane emissions.

Figure 6 – Around here

Table 4 – Around here

3.2.1 Uncertainty analysis

To test the robustness of the results achieved while comparing the two scenarios, a quantitative uncertainty analysis was carried out by using Monte Carlo techniques as sampling method (1,000 iterations and a confidence interval of 95%). The results are reported in **Figure 7**. The bars represent the probability that the environmental impact of BS is higher than (or equal to) the one of AS. The uncertainty due to selection of the data from databases, partial model adequacy and variability of data does not significantly affect the quantification of the environmental impact for all the categories, the only exception being the toxicity related ones.

Figure 7 – Around here

4. Conclusions

Among the different agricultural activities, fertilisation is responsible of serious environmental concerns because of the impacts deriving from the processes of fertilizer production (especially for N-based ones) and from the emissions of nitrogen and phosphorous compounds in ground- and surface water and in the atmosphere. This context is generating a growing demand for smart solutions able to drive the timing of fertilisation events and the amounts of products distributed.

In this study, a VR fertilization strategy based on PocketNNI (a new smart app for NNI estimates) and satellite data was compared – in terms of environmental performances – with a strategy based on the uniform distribution of N according to standard practices in the area. The combined use of PocketNNI and remote sensing products allowed achieving a considerable increase in yield at the cost of a negligible increase in the amount of nitrogen fertilisers consumed, thus reducing the amount of N used per unit of product. This, from an environmental point of view, leads to a double benefit: the reduction of the impact for all the categories considered due to the increase in productivity and – especially for acidification and eutrophication – the reduction of the emissions of N compounds.

In terms of economic sustainability, the proposed system has both direct (higher yield to fertilizer ratio) and indirect (lower risk of losses due to diseases and lodging) benefits. Future development will refer to the automatic integration and processing of satellite data.

Despite the analysis was performed using data from only one growing season, the achieved results are promising and highlight how the environmental impact of agricultural activities can be effectively reduced by using smart technologies (cost-effective and familiar for potential users) to improve fertilisation efficiency.

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Table 1 – Cultivation practice: Field operations and production factors consumed

Subsystem	Field Operation	Operative machine	Tractor		Fuel Cons.	Input		Working Time
			kW	kg	$kg \cdot ha^{-1}$	Product	Amount ($\cdot ha^{-1}$)	$h \cdot ha^{-1}$
Soil tillage and sowing	Harrowing	Rotary harrow	91	5000	19.5			1.70
	Mineral fertilization	Fertilizer spreader	91	5000	3.5	Potassium chloride	152.9 kg	0.25
	Flooding							
	Sowing	Fertilizer spreader	91	5000	8.4		229.3 kg	0.30
Crop Management	Mineral fertilization	Fertilizer spreader	91	5000	3.5	Biammonic phosphate	138 kg	0.25
	Weed control pre seeding	Sprayer	91	5000	3.0	Rifit (pretilachlor) Cadou (flufenacet) Ronstar (Oxadiazon)	1.52 kg 0.61 kg 0.61 kg	0.20
	Weed control pre seeding	Sprayer	91	5000	3.0	Glyphosate Ronstar (Oxadiazon)	3.06 kg 0.30 kg	0.20
	Weed control post germination	Sprayer	91	5000	3.0	Tripion (MCPA) Viper (Penoxsulam) Gulliver (azimsulphuron) Contest (alpha-cypermethrin)	1.53 kg 1.53 kg 0.024 kg 0.12 kg	0.20
	Mineral fertilization	Fertilizer spreader	91	5000	3.5	Urea	153 kg in BS 156 kg in AS	0.25
	Mineral fertilization	Fertilizer spreader	91	5000	3.5	23-0-30	138 kg	0.25
	Disease control	Sprayer	91	5000	3.0	Azbany (alpha-cypermethrin) Opinion (propiconazole)	1 L 0.5 L	0.20
	Disease control	Sprayer	91	5000	3.0	Azbany Siapton (alpha-cypermethrin)	1 L 1.5 L	0.20
Harvesting & Storage	Harvest	Combine harvester	335	12000	39.1		6.85 t in BS 7.73 t in AS	0.80
	Transport	Trailer	91	5000	11.5			0.80
	Transport	Trailer	100	5050	13.5			0.80
	Drying	Dryer				Diesel	Moisture from 21% to 14%	-

Table 2 – Main information regarding water and straw management.

Parameter	Date
Date of sowing	7 May
Beginning of flooding	2 April
End of flooding	21 August
Straw incorporation into the soil	28 February
Number of aerations	2
Days of flooding	141

Table 3 – List of processes retrieved from the Ecoinvent database v. 3.5

Ecoinvent® 3.5 Process	Used for	Modifications
Diesel {RER}| market group for | APOS, U	Diesel fuel consumed during field operations	Emissions related to diesel combustion were included [1]
Tractor, 4-wheel, agricultural {GLO}| market for | APOS, U	Tractors used during field operations	A life span of 12 years was considered[2]
Agricultural machinery, tillage {GLO}| market for | APOS, U	For ploughing and harrowing	A life span of 8 years was considered for the machinery used for soil tillage[2]
Agricultural machinery, unspecified {GLO}| market for | APOS, U	For field operations excluding soil tillage	The following life span were considered: 6 years for sprayer, 8 years for fertiliser, 12 years for farm trailers and 10 years for combine harvester[2]
Transport, tractor and trailer, agricultural {GLO}| processing | APOS, U	Transport of paddy rice from the field to the farm	n/a
Rice seed, for sowing {GLO}| market for | APOS, U	Crop sowing	No uptake of heavy metals and CO_2 were considered. 7.7 t/ha (14% of moisture) was considered as yield
Urea, as N {GLO}| market for | APOS, U	Mineral fertilization application	n/a
Nitrogen fertiliser, as N {RER}| diammonium phosphate production | APOS, U		
Potassium chloride, as K2O {GLO}| market for | APOS, U		
Pesticide, unspecified {RER}| production | APOS, U	For the application of pesticides	For the emissions into the soil the specific active ingredient (pretilachlor, flufenacet, oxadiazon, azoxystrobin and tricyclazole) was considered.
Glyphosate {RER}| production | APOS, U	Weed control	
Cypermethrin, at plant/RER Mass		

Shed {CH}| construction | APOS, U	For all the different field operations	n/a
Drying of bread grain, seed and legumes {CH}| processing | APOS, U	For drying of the harvested paddy rice	The fuel consumption was modified considering primary data. Italian electricity mix was considered for the electric energy consumption
Electricity, medium voltage {IT}| market for | APOS, U	Electricity consumed during drying	n/a

[1] Bacenetti et al., 2018. [2] Lovarelli and Bacenetti (2017).

Table 4 – Absolute environmental impact for the two scenarios (FU = 1 t of rice grain at commercial moisture; Δ = impact variation of AS respect to BS).

Impact Category	BS	AS	Δ
CC	937.3 kg CO_2 eq	832.7 kg CO_2 eq	-11.2%
OD	49.27 mg CFC-11 eq	43.83 mg CFC-11 eq	-11.0%
HT-noc	$1.66 \cdot 10^{-4}$ CTUh	$1.46 \cdot 10^{-4}$ CTUh	-12.2%
HT-c	$2.11 \cdot 10^{-5}$ CTUh	$1.87 \cdot 10^{-5}$ CTUh	-11.3%
PM	0.439 kg PM2.5 eq	0.383 kg PM2.5 eq	-12.8%
POF	2.13 kg NMVOC eq	1.86 kg NMVOC eq	-12.8%
TA	8.89 molc H+ eq	10.20 molc H+ eq	-12.9%
TE	41.00 molc N eq	35.63 molc N eq	-13.1%
FE	0.154 kg P eq	0.134 kg P eq	-12.5%
ME	6.68 kg N eq	5.81 kg N eq	-13.0%
FEx	5091 CTUe	4423 CTUe	-13.1%
MFRD	27.52 g Sb eq	23.79 g Sb eq	-13.6%

FIGURE CAPTIONS

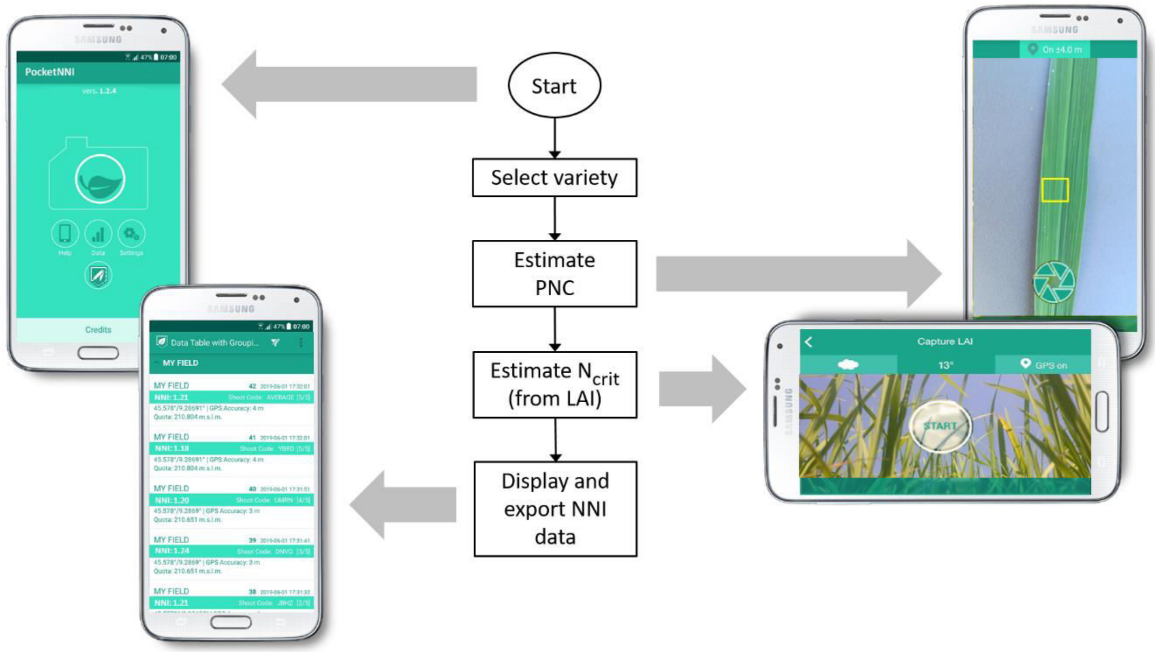

Figure 1 – Flowchart of the app PocketNNI. Actual plant N content (PNC) is estimated based on Confalonieri et al. (2015), whereas critical N content (Ncrit) is derived from leaf area index estimates (Confalonieri et al., 2013), in turn used to derive Ncrit based on Confalonieri et al. (2011). N Nutritional Index (NNI) is calculated as PNC to Ncrit ratio. NNI estimates are stored in an internal database together with GPS coordinates, and they can be exported in different formats (e.g., .csv, .shp).

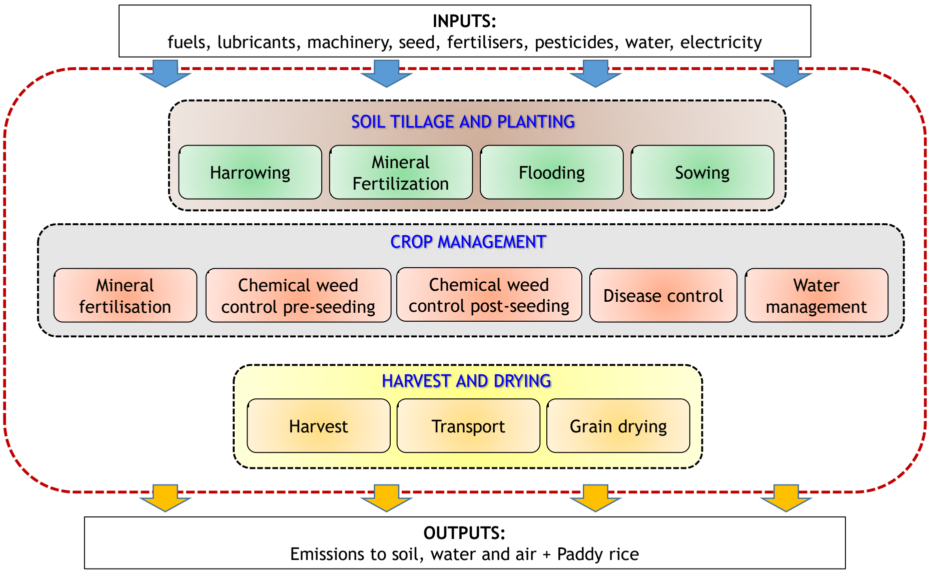

Figure 2 – System boundary for the two evaluated scenarios.

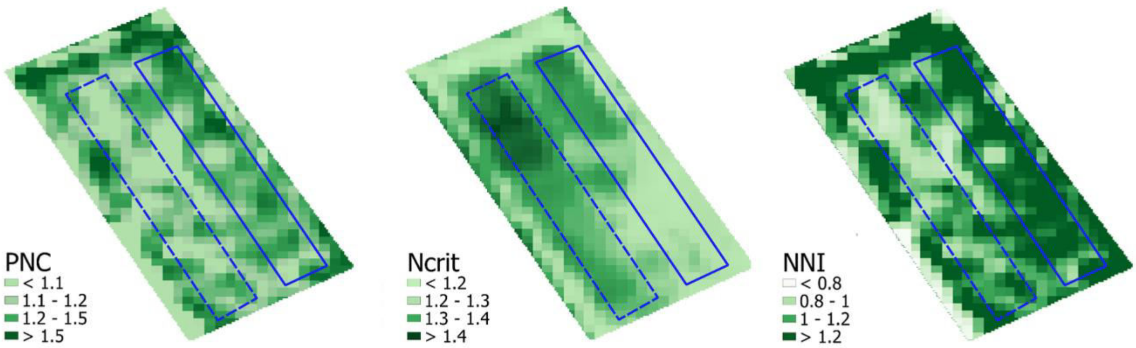

Figure 3 - Plant Nitrogen Content (PNC), Critical Nitrogen (N_{crit}), and Nitrogen Nutrition Index (NNI) maps derived by integrating Sentinel 2 data (NDRE and NDVI) and PocketNNI readings few days before the second top-dressing fertilization. The two fertilization strategies "baseline scenario" (BS, with uniform N distribution) and "alternative scenario" (AS, with PocketNNI-driven variable rate N application) were applied, respectively, in the areas bordered with dotted and continuous lines.

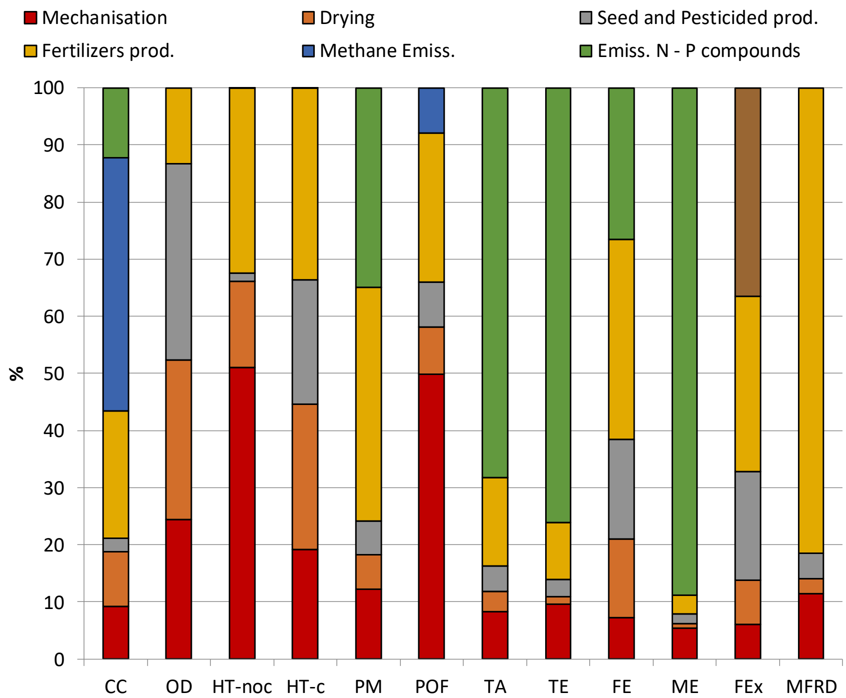

Figure 4 – Relative contributions to the overall environmental impact for the baseline scenario

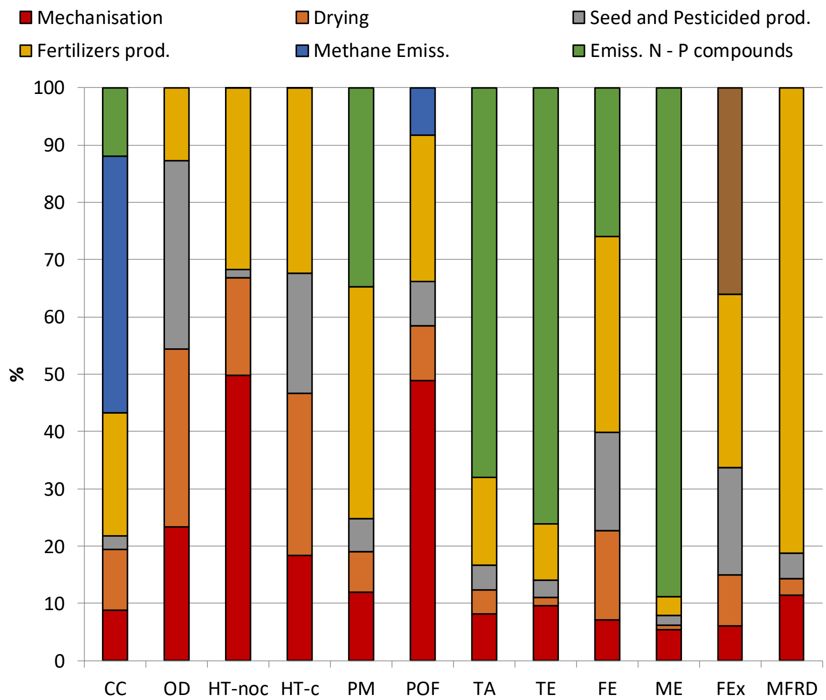

Figure 5 – Relative contributions to the overall environmental impact for the alternative scenario

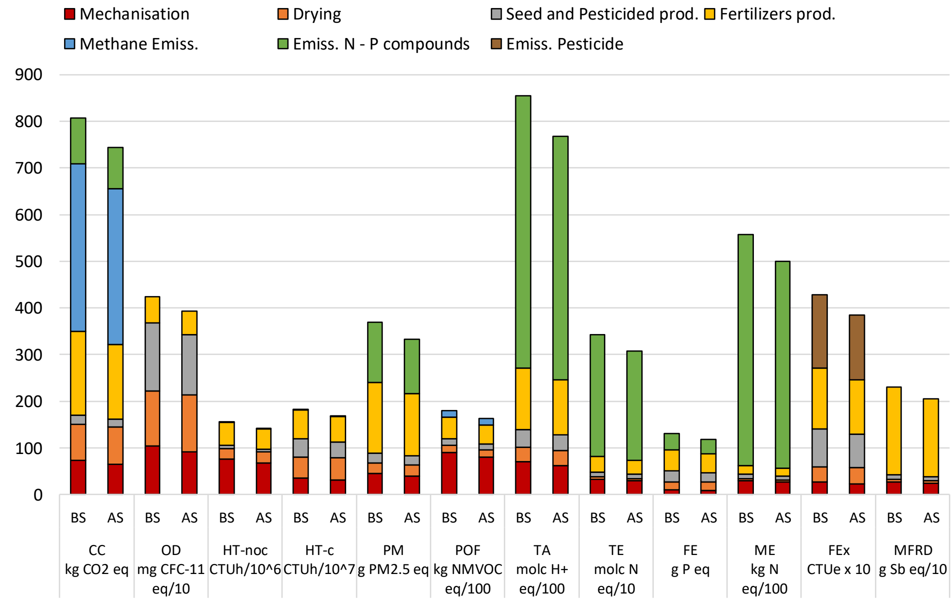

Figure 6 – Comparison between the two scenarios. BS: baseline scenario; AS: alternative scenario (Note: for graphical reasons, for some impact categories, the absolute value has been multiplied or divided by 10 or multiple. For all the evaluated impact categories the unit of measure is reported in the X-axis).

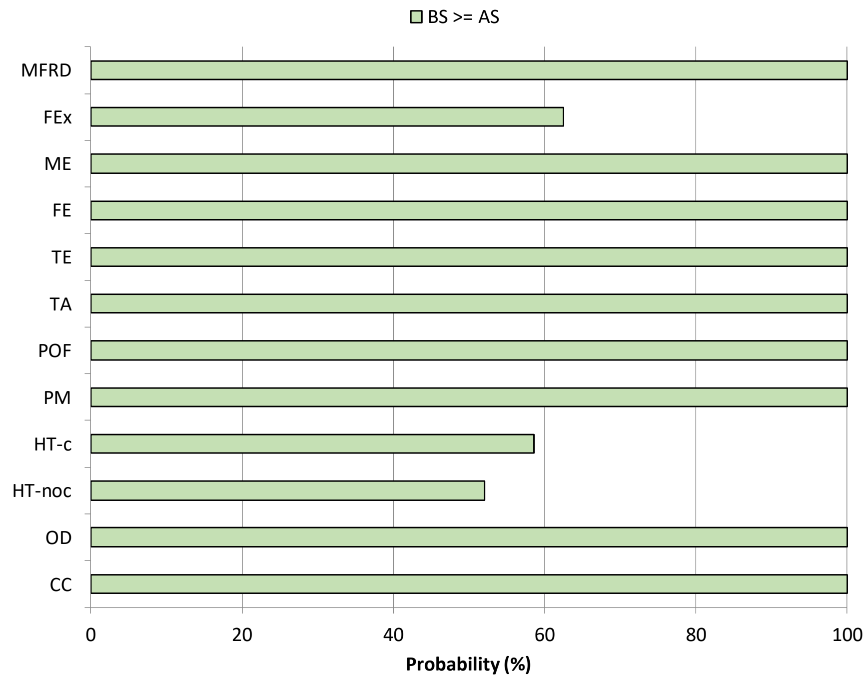

Figure 7 – Uncertainty analysis results regarding the comparison between Baseline Scenario and Alternative Scenario.

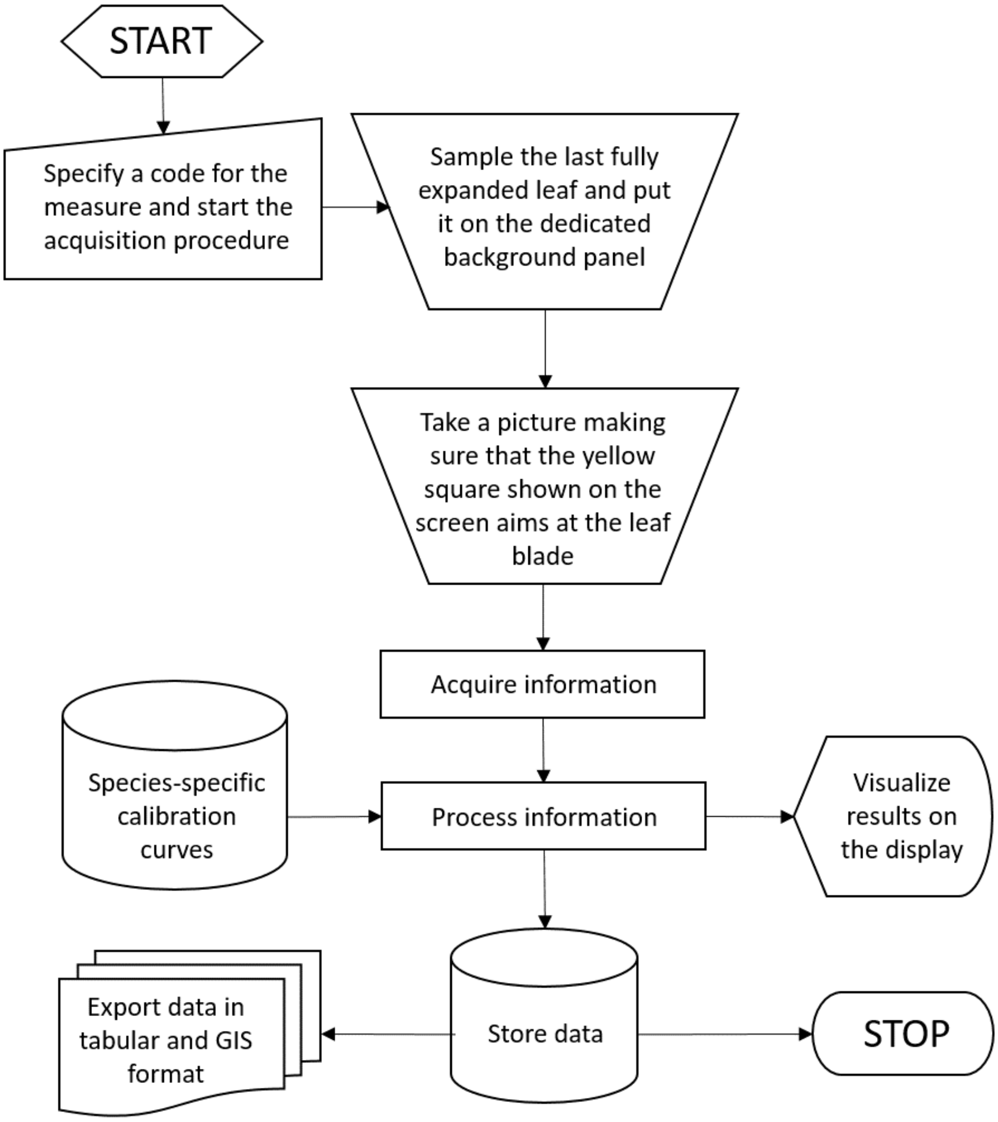

Figure S1. Flowchart of the app PocketN (Confalonieri et al., 2015) showing the functioning of the app. Tutorials on the use of the app PocketN can also be found at www.cassandralab.com. When used within PocketNNI, at the end of the PocketN acquisition the PocketLAI app is automatically opened.

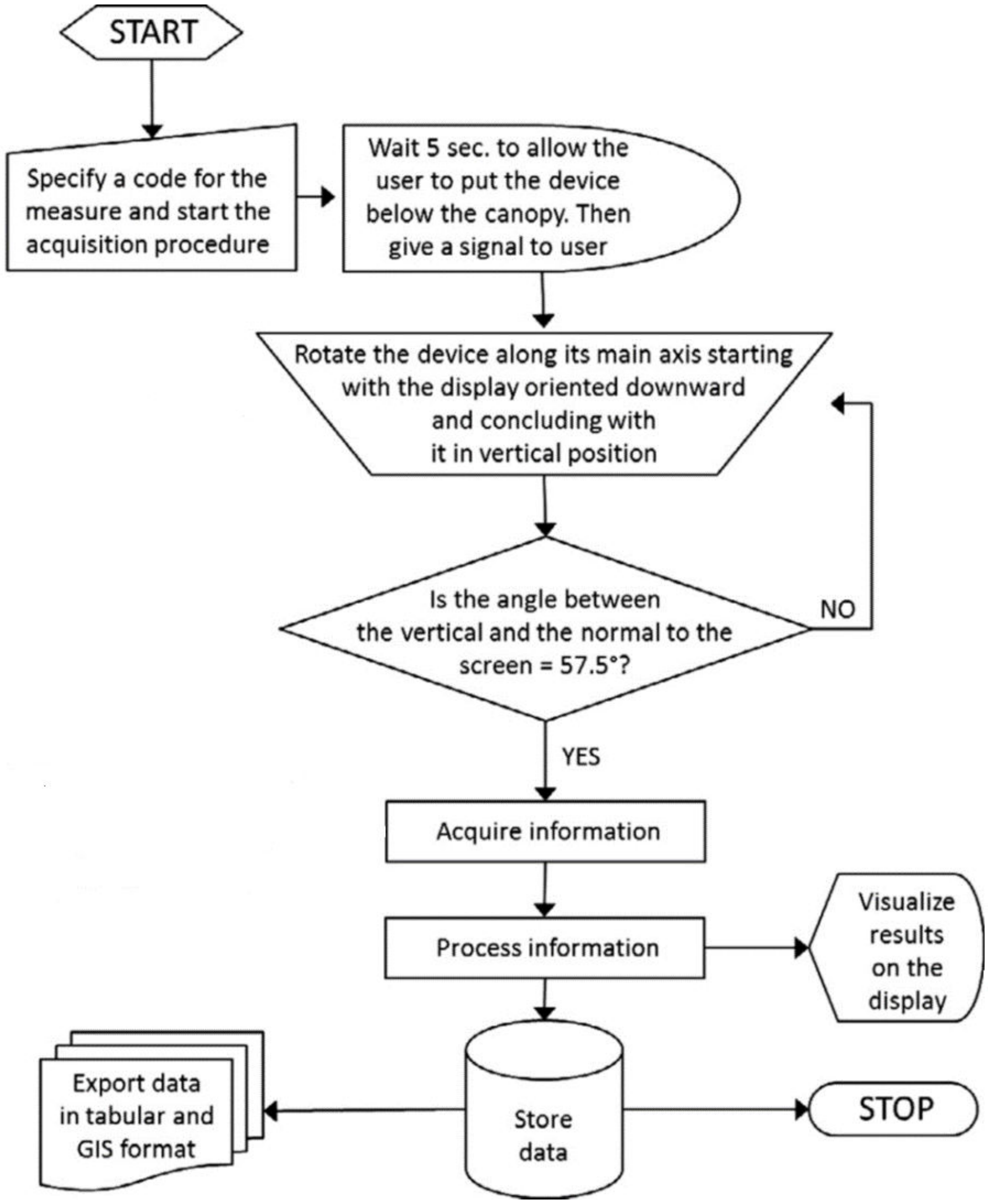

Figure S2. Flowchart of the app PocketLAI (redrawn from Confalonieri et al., 2013). Tutorials on the use of the app PocketLAI can also be found at www.cassandralab.com. When used within PocketNNI, the PocketLAI app is automatically opened at the end of the PocketN measure. In this case there is no need to specify again the code for the measure, being the same entered for the PocketN acquisition.

Table S1. Calibration curves for the main rice varieties grown in Italy, to convert PocketN readings (–) into plant nitrogen content (PNC, %) values (from Paleari et al., 2019). Rice varieties belonging to each cluster and corresponding cluster-specific calibration curves are reported.

Cluster	**Cultivars**[a]	**Calibration Curve Parameters** [b]		**R^2**	***p*-value**
		a	**b**		
1	Centauro, Ellebi, Leonardo, Opale	5.42	−1.24	0.76	<0.001
2	Brio, Carnise, Dardo, Meco	10.90	−4.02	0.85	<0.001
3	Galileo, Gladio	17.22	−7.03	0.83	0.002
4	Cammeo, Generale	9.97	−3.43	0.50	0.051
5	Carnaroli, Gloria, LunaCL®, Puma, SoleCL®	7.99	−2.87	0.95	<0.001
6	Augusto, Caravaggio, Crono, MareCL®, Mirko, Thaibonnet,	9.04	−2.79	0.79	<0.001
7	Balilla, Fedra, Onice, Ronaldo, Volano	6.77	−2.25	0.91	<0.001
8	Arborio, Baldo, Carnise Precoce, Karnak, Loto, SirioCL®, Ulisse, Vasco	11.25	−4.19	0.79	<0.001

[a] Aiace, BaroneCL®, Cerere, Cleopatra, CRLB1, Keope, and Selenio cultivars are not included in any cluster, see Paleari et al., 2019 for cultivar-specific calibration curves. [b] Calibration curves defined as PNC = a PocketN index + b.

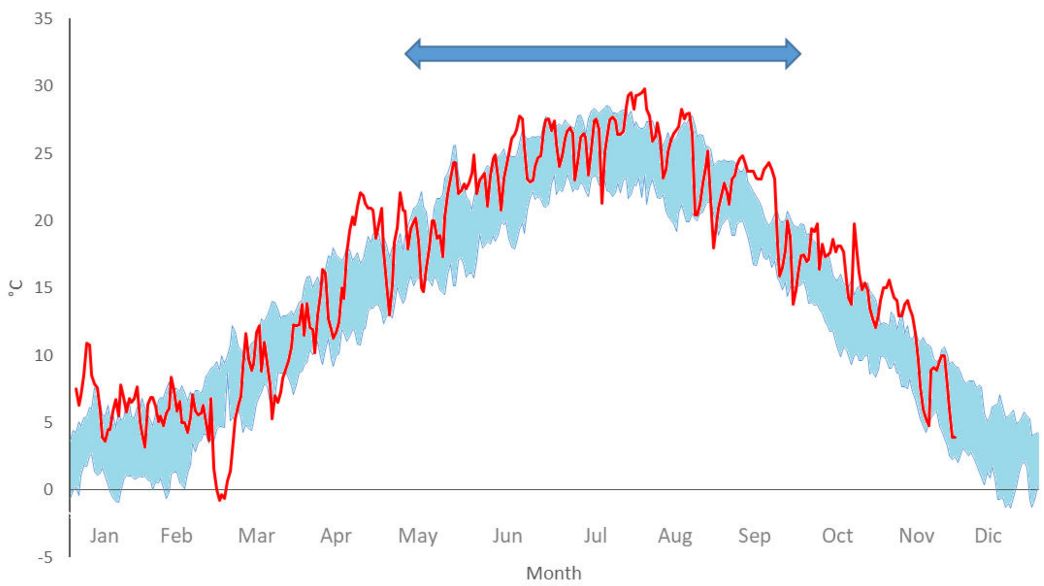

Figure S3. *Mean daily temperature (°C) characterizing the study area (Gaggiano, Italy). The red line indicates temperatures measured during the 2018, whereas the blue area refers to the mean ± 1 standard deviation for the 10-year average. The blue arrow indicates the rice campaign.*

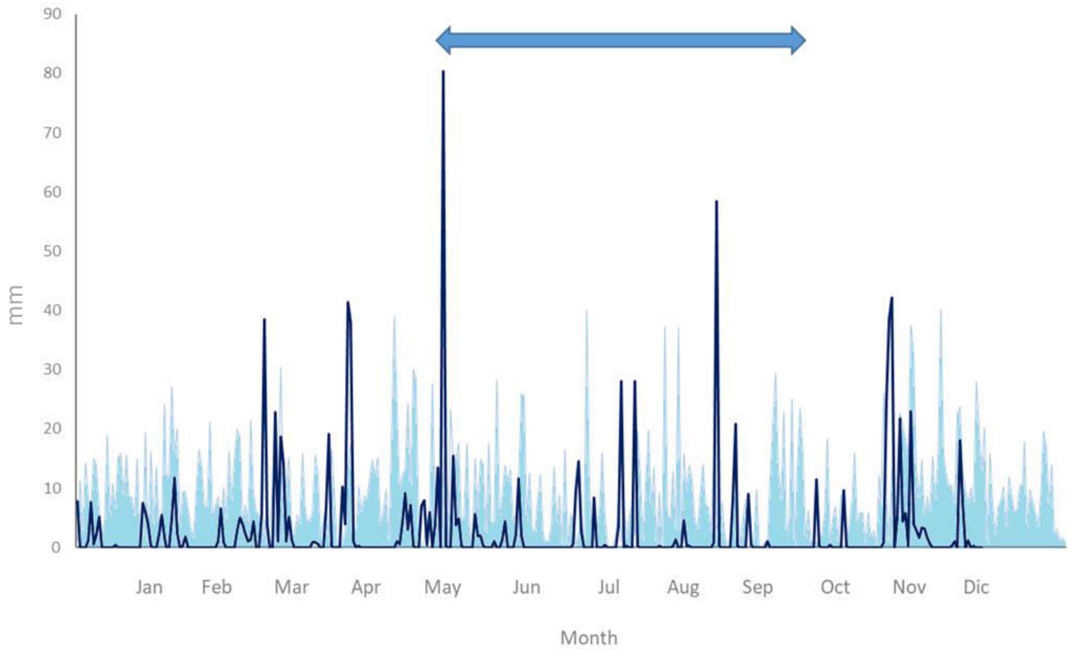

Figure S4*. Precipitation distribution at the study area (Gaggiano, Italy). The dark blue line indicates the daily rainfall (mm) recorded during the 2018, whereas the light blue area refers to the mean + 1 standard deviation for the 10-year average. The blue arrow indicates the rice campaign.*