Precision Agriculture (2023) 24:2566–2591
https://doi.org/10.1007/s11119-023-10053-5

Precision nitrogen management in rainfed durum wheat cultivation: exploring synergies and trade-offs via energy analysis, life cycle assessment, and monetization

Michele Denora[1] · Vincenzo Candido[2] · Paola D'Antonio[2] · Michele Perniola[1] · Andi Mehmeti[2,3]

Accepted: 12 July 2023 / Published online: 10 August 2023

Abstract
Fertilization with variable rate technology (VRT) is a pivotal technique of precision agriculture proposed for eco-friendly farming practices. Yet the magnitude of environmental benefits is often not well known or is highly variable. This study used a multi-indicator model and life cycle-based indicators to compare the performance of rain-fed durum wheat production using uniform (UA) and variable N fertilization (VRT). Two functional units were used: 1 ha of cultivated wheat and 1 ton of wheat produced. The energy analysis indicated that VRT increases energy use efficiency and productivity by 13.3%, reduces specific energy and total energy input by 11.7%, and increases net energy gain by 15.3%. The life cycle assessment (LCA) analysis indicated that for some environmental impacts, VRT had minor negative effects due to the comparable yield performance with UA. Yet, the VRT had a noteworthy positive impact on global warming, fine particulate matter formation, stratospheric ozone depletion, terrestrial acidification, and marine eutrophication, generating a final environmental benefit of 12.2% for 1 ton of product and 13.3% for 1 ha of land. Economic valuation or monetization of LCA results using monetization weighting factors indicated indirect economic benefits of VRT can be up to 6.6% for 1 ton of product and

✉ Andi Mehmeti
mehmeti@iamb.it

Michele Denora
michele.denora@unibas.it

Vincenzo Candido
vincenzo.candido@unibas.it

Paola D'Antonio
paola.dantonio@unibas.it

Michele Perniola
michele.perniola@unibas.it

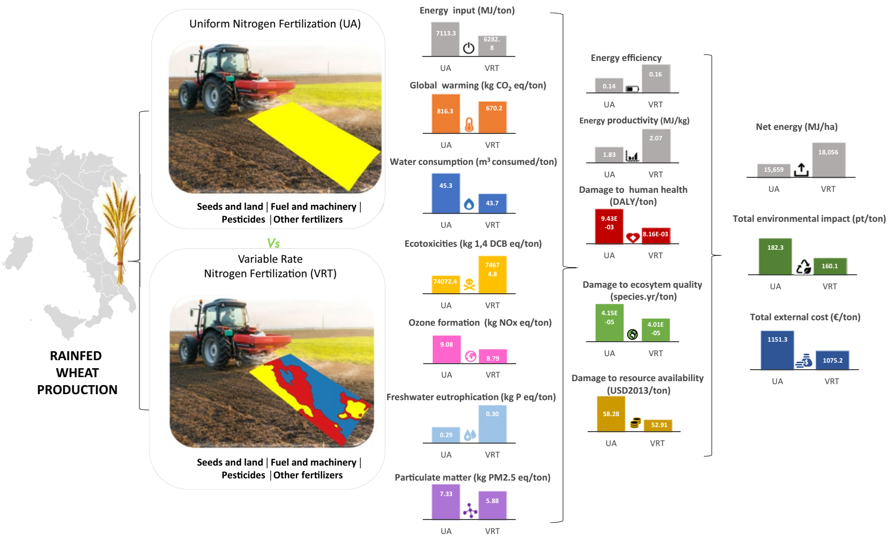
[1] Department of European and Mediterranean Cultures, Environment and Cultural Heritage, University of Basilicata, 75100 Matera, Italy

[2] School of Agricultural, Forestry and Environmental Sciences, University of Basilicata, Viale dell'Ateneo Lucano 10, 85100 Potenza, Italy

[3] Mediterranean Agronomic Institute of Bari, Via Ceglie 9, 70010 Valenzano, Italy

7.7% for 1 ha of land. Our findings support the use of nitrogen fertilization with VRT for sustainable extensification and improved eco-efficiency of wheat production in a Mediterranean context. As a result of our research, we conclude that future case studies on annual crops with moderate land requirements should employ multiple metrics and functional units, as well as the concepts of monetization and life cycle assessment, to investigate trade-offs between yield, economic, and environmental benefits and to aid decision-making about the true sustainability of proposed farming technologies.

Graphical abstract



Keywords Life cycle assessment (LCA) · Precision agriculture · Site-specific input management · Nitrogen variable rate application · External cost

Abbreviations

N	Nitrogen
PA	Precision agriculture
UA	Uniform management
LCA	Life cycle assessment
LCIA	Life cycle impact assessment
VRT	Variable rate technology
PMPF	Fine particulate matter formation
FFP	Fossil resource scarcity
FETP	Freshwater ecotoxicity
FEP	Freshwater eutrophication
GWP	Global warming
HTPc	Human carcinogenic toxicity
HTPnc	Human non-carcinogenic toxicity
IRP	Ionizing radiation
LU	Land use

METP	Marine ecotoxicity
MEP	Marine eutrophication
MRS	Mineral resource scarcity
HOFP	Human health ozone formation
EOFP	Ecosystem ozone formation
ODP	Stratospheric ozone depletion
TAP	Terrestrial acidification
TETP	Terrestrial ecotoxicity
WCP	Water consumption

Introduction

Agriculture and food systems are confronted with daunting and complex challenges, not the least of which is the ongoing effort to increase food production by 25–70% above current levels while maintaining and enhancing ecosystem resilience (Hunter et al., 2017). Traditional farming practices, on the other hand, are still used to manage an agricultural field uniformly, ignoring the inherent variability in topography, soil, crop growth conditions, and other agronomic factors (Neupane & Guo, 2019). As a result, the excessive and inappropriate use of agrochemicals, fossil fuels, natural resources, and machinery is jeopardizing the ecological integrity of agroecosystems (Singh & Singh, 2017). The prevailing discourse on the future of agriculture calls for food production to increase while becoming more environmentally sustainable (Hunter et al., 2017). Sustainable intensification is emerging as the most frequently referenced new paradigm to produce more from the same area of land by increasing efficiency, reducing waste, conserving resources, reducing negative impacts on the environment, and enhancing the provision of ecosystem services (Wezel et al., 2015). Sustainable intensification is achieved through increased inputs, improved agronomic practices, improved crop varieties, and other innovations (Tilman et al., 2011).

Precision agriculture (PA) is widely acknowledged as a contributor to farming efficiency and environmentally friendly farming practices, and it is essential to long-term intensification (Lindblom et al., 2017). It assists farmers in making precise and optimized use of crop-specific inputs, resulting in lower production costs and a lower environmental impact (Bacenetti et al., 2020; Canaj et al., 2021). Nitrogen (N) is an essential and often the most yield-limiting nutrient for winter wheat production. However, often N fertilization in wheat is commonly based on yield goals, derived by applying uniform rates without considering the spatial and temporal variability (Gobbo et al., 2022). As a result, the N supply and crop demand are misaligned, resulting in low time and space efficiency (Denora et al., 2022) and economic and environmental losses (Fiorentino et al., 2020; Gobbo et al., 2022). The precise management of N fertilizer application is essential for improving crop productivity, use efficiency and environmental sustainability. Variable-rate technology (VRT) is a pivotal technology in PA, aiming to perform site-specific chemical, lime, gypsum, irrigation water, and other farm input management across a field (Vatsanidou et al., 2020). Because it tackles in-field heterogeneity in soil N availability and crop response, variable rate fertilization provides a technique for more effective site-specific management (Stamatiadis et al., 2018). The empirical findings suggest that variable-rate fertilizer application can have both environmental and economic benefits. Many studies, however, fail to investigate the links between the environment and production, as well as the environmental and economic implications of the product's life cycle. Precision agriculture frequently necessitates the use of advanced machinery and technological systems, the construction, maintenance, and use of which may reduce the potential environmental and economic benefits of its implementation (Bacenetti et al., 2020).

The life cycle thinking has been considered one of the most fitting methodologies to deal with farming sustainability. Life cycle assessment (LCA) is widely regarded as the most effective method for assessing the impact of crop production-related emissions and resource consumption. It generates a better understanding of the energy, water, and material inputs and evaluates the output impacts of any production system from a life cycle perspective. LCA has been carried out on various precision agriculture applications, including irrigation (Canaj et al., 2021; Fotia et al., 2021); fertilization (Bacenetti et al., 2020; Jovarauskas et al., 2021; Li et al., 2016; Meza-Palacios et al., 2020; Sanches et al., 2021; Vatsanidou et al., 2020); mechanized field operations (Ashworth et al., 2022; Lagnelöv et al., 2021; Lovarelli & Bacenetti, 2017); and land leveling (Nguyen-Van-Hung et al., 2022). It is applied to olives in Greece (Fotia et al., 2021; van Evert et al., 2017), zucchini in Italy (Canaj et al., 2021), rice in Italy (Bacenetti et al., 2020) and Asia (Nguyen-Van-Hung et al., 2022), pear orchards in Greece (Vatsanidou et al., 2020), nectarines in Greece (Núñez-Cárdenas et al., 2022), corn in the USA (Li et al., 2016), vineyards in Greece (Balafoutis et al., 2017; Pradel et al., 2022), wheat in Lithuania (Jovarauskas et al., 2021) and sugarcane in Brazil (Sanches et al., 2021) and South Africa (Van Der Laan et al., 2015). Previous LCA studies in wheat production (Fabiani et al., 2020; Jovarauskas et al., 2021; Kazlauskas et al., 2021; Medel-Jiménez et al., 2022; Scuola et al., 2017) found that variable fertilization rates may reduce overall energy consumption and greenhouse gas (GHG) emissions. However, other direct and indirect environmental benefits from the reduction of synthetic resources in crop production could be realized. Understanding how alternative agricultural input efficiency, such as variable rate fertilization, contributes to a variety of environmental effects is essential for reducing crop production's environmental impact. This study applied life cycle energy analysis (LCEA) and a multi-indicator life cycle assessment (LCA) to evaluate the energy performance, environmental impact, and external environmental costs of durum wheat production in southern Italy by using different N fertilization strategies: variable rate technology (VRT) and uniform application (UA). The findings provide the first detailed assessment of the energy and environmental benefits that can be realized when precision farming technologies are used to support N fertilization in rainfed wheat production in a Southern Mediterranean context. Moreover, the study is the first of its kind to estimate the indirect economic benefits of variable rate fertilization in cereal crops by monetizing the LCA results.

Material and methods

Case study and system description

The data for this study were retrieved from field data collected in 2018–2019 at Genzano di Lucania (Potenza province, Basilicata region), latitude: 40.82° N, longitude: 16.08° N. The Basilicata region primarily produces cereals, accounting for 72% of arable land. The experimental field had a total area of 4.07 ha. The area is located on the clayey hills of the Bradanica grave and the basin of Sant'Arcangelo (Fig. 1).

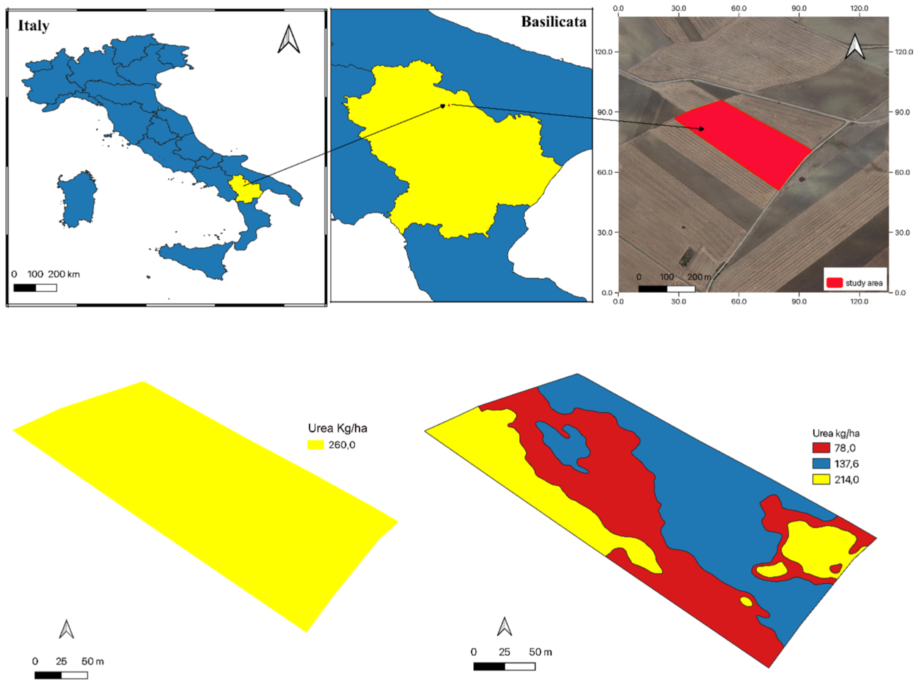


Fig. 1 Location of the study site and delineated maps of N fertilization in uniform management and variable-rate application

Across the whole field, wheat was sown with a row spacing of 0.13 m, and 250 kg ha^{-1} of seeds were used. Soil tillage consisted of a 40 cm deep plowing (August 28, 2018) and two harrowings (November 11, 2018, and December 5, 2018). Pre-sowing fertilization was broadcast applied with 92 kg ha^{-1} of P_2O_5 and 36 kg ha^{-1} of N. A dose of 35 kg ha^{-1} of N (Urea 46%) was spread in pre-sowing over the entire field. In the uniform application (UA) plots, we applied a dose of N equal to 85 kg ha^{-1}, which corresponds to the amount generally applied by the farmer, and slightly over the average, the dose of N applied in the three zones. The amount of nitrogen fertilizer to be applied by VRT was calculated based on estimated crop nitrogen uptake and soil characteristics of the area determined by electrical resistivity (Denora et al., 2022). Crop potential N uptake was estimated using the previous year's crop yield in each homogeneous area, and was corrected to account for the N contribution provided to the crop by organic matter mineralization. Soil property maps derived from low induction electromagnetic measurements were used to calculate N balances for a field application of VRT nitrogen fertilization. A low-induction electromagnetic mini explorer (GF Instruments Brno-CZ) was used to investigate the spatial variability of the soil. For the variable rate nitrogen treatments, the final prescription map was created using the QGIS 2.18.4 software, and N doses were applied in each homogeneous area using a Kuhn Axis-40–2-w fertilizer spreader mounted on a John Deere 6910 tractor.

LCA modeling

This LCA study was based on the LCA framework's four main phases: goal and scope definition, life cycle inventory, life cycle impact assessment, and life cycle interpretation of results.

Goal and scope

In this study, a cradle-to-farm gate LCA study was performed. Crop cultivation started with tillage for seeding; after that, seeding occurred, plant protection and fertilization were performed for crop growth, and at the last stage, harvesting took place. A flow chart of the system boundary is shown in Fig. 2. The analysis also takes into account the production of seeds, fertilizers, pesticides, fuel, tractors, and human labor within the system boundary. We distinguished foreground (direct) and background (indirect) systems when analyzing datasets. Direct field and farm emissions are substances emitted from an agricultural area or directly from the farm. In our model, we accounted for foreground emissions due to agricultural operations (fuel combustion and tyre wear), fertilizer application, and emissions of pollutants (ammonia volatilization, nitrous oxide emissions, nitrate leaching, and phosphorus compound emissions). Indirect emissions denote emissions that occur in upstream processes, such as purchased inputs used in agriculture or transportation (production of seeds, fertilizers, pesticides, fuel, lubricants, and tractor units). Both hectare (1 ha) and ton of grain (1 ton) production were used as functional units to highlight possible contrasting results on crop yield and the effect of agricultural intensification. No allocation criteria were used for allocating the impacts because it was assumed that straw was left on the field.

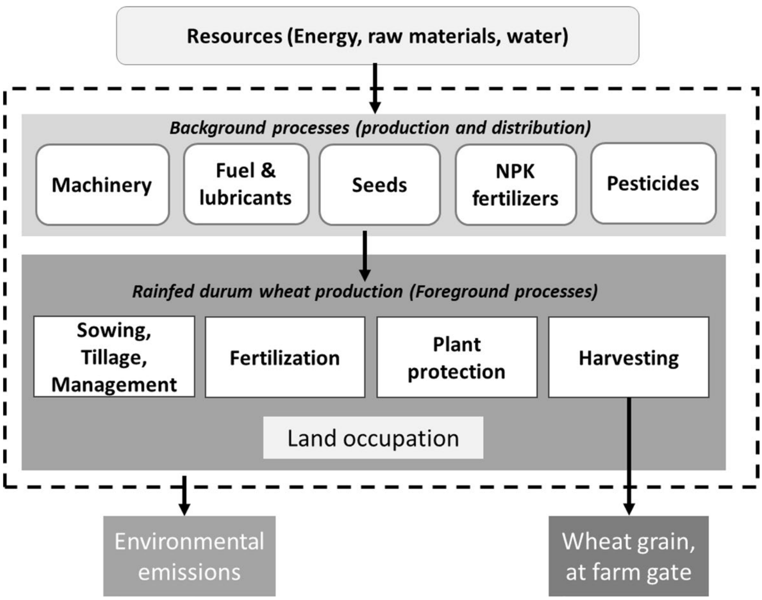


Fig. 2 A flow chart diagram for the system boundary for wheat production

Table 1 Inventory data for 1-ton wheat production under uniform (UA) and variable rate fertilization (VRT)

Parameter	Process modeled/Compartment	Unit	Uniform N application (UA)	Variable rate N application (VRT)
Inputs				
Seeds for sowing	Market for wheat seed, for sowing	kg t^{-1}	93.98	95.05
Nitrogen fertilizer	Market for urea, as N	kg N t^{-1}	46.1	34.82
Phosphorus fertilizer	Market for phosphate fertiliser, as P_2O_5	kg P_2O_5 t^{-1}	34.59	34.98
Pesticides, unspecified	Market for pesticide, unspecified	kg t^{-1}	0.432	0.437
Diesel fuel	Diesel, burned in building machine	MJ t^{-1}	1283	1298
Tractor machinery	Market for tractor, 4-wheel, agricultural	kg t^{-1}	3.75	3.80
Lubricating oil	Market for lubricating oil	kg t^{-1}	0.748	0.757
Land occupation	Occupation, arable, non-irrigated	m^2 t^{-1}	3383.5	3422
Human labor		h t^{-1}	3.38	3.94
Outputs				
Crop yield	Wheat grain, at the farm exit gate	t ha^{-1}	2.66	2.63
Ammonia	Emission to air, low population density	kg t^{-1}	8.39	6.35
Dinitrogen monoxide	Emission to air, low population density	kg t^{-1}	0.94	0.63
Nitrogen oxides	Emission to air, low population density	kg t^{-1}	0.15	0.12
Nitrates	Emission to water, groundwater	kg t^{-1}	40.45	7.65
Carbon dioxide, fossil	Emission to air, low population density	kg t^{-1}	72.31	54.74
Ammonia	Emission to air, low population density	kg t^{-1}	5.99E−04	6.06E−04
Benzo(a)pyrene	Emission to air, low population density	kg t^{-1}	8.99E−07	9.10E−07
Cadmium	Emission to air, low population density	kg t^{-1}	3.00E−07	3.04E−07
Carbon dioxide, fossil	Emission to air, low population density	kg t^{-1}	9.37E+01	9.47E+01
Carbon monoxide, fossil	Emission to air, low population density	kg t^{-1}	3.41E−01	3.45E−01
Chromium	Emission to air, low population density	kg t^{-1}	1.50E−06	1.52E−06
Copper	Emission to air, low population density	kg t^{-1}	5.09E−05	5.15E−05
Dinitrogen monoxide	Emission to air, low population density	kg t^{-1}	3.59E−03	3.63E−03

Table 1 (continued)

Parameter	Process modeled/Compartment	Unit	Uniform N application (UA)	Variable rate N application (VRT)
Tetrachlorodibenzo-p-dioxin	Emission to air, low population density	kg t^{-1}	1.80E−12	1.82E−12
Methane, fossil	Emission to air, low population density	kg t^{-1}	4.81E−03	4.87E−03
Nickel	Emission to air, low population density	kg t^{-1}	2.10E−06	2.13E−06
Nitrogen oxides	Emission to air, low population density	kg t^{-1}	1.32E+00	1.34E+00
NMVOC	Emission to air, low population density	kg t^{-1}	1.55E−01	1.57E−01
Polycyclic aromatic hydrocarbons	Emission to air, low population density	kg t^{-1}	1.01E−04	1.02E−04
Particulates, < 2.5 um	Emission to air, low population density	kg t^{-1}	1.21E−01	1.22E−01
Particulates, > 10 um	Emission to air, low population density	kg t^{-1}	8.06E−03	8.15E−03
Particulates, > 2.5 um, and < 10 um	Emission to air, low population density	kg t^{-1}	5.38E−03	5.44E−03
Selenium	Emission to air, low population density	kg t^{-1}	3.00E−07	3.04E−07
Sulfur dioxide	Emission to air, low population density	kg t^{-1}	3.03E−02	3.06E−02
Zinc	Emission to air, low population density	kg t^{-1}	3.00E−05	3.04E−05
Phosphate	Emission to water, groundwater	kg t^{-1}	0.1206	0.1209
Phosphorus	Emission to water, surface water	kg t^{-1}	0.636	0.644
2,4-D	Emission to soil/agricultural	kg t^{-1}	7.9E−06	5.6E−05
Chloridazon	Emission to soil/agricultural	kg t^{-1}	4.2E−06	2.9E−05
Chlormequat	Emission to soil/agricultural	kg t^{-1}	2.2E−05	1.5E−04
Choline chloride	Emission to soil/agricultural	kg t^{-1}	8.9E−06	6.2E−05
Cyprodinil	Emission to soil/agricultural	kg t^{-1}	5.6E−06	3.9E−05
Fenpropidin	Emission to soil/agricultural	kg t^{-1}	3.0E−06	2.1E−05
Glyphosate	Emission to soil/agricultural	kg t^{-1}	1.5E−05	1.1E−04
Isoproturon	Emission to soil/agricultural	kg t^{-1}	3.4E−06	2.4E−05
MCPA	Emission to soil/agricultural	kg t^{-1}	6.8E−06	4.7E−05
Mecoprop	Emission to soil/agricultural	kg t^{-1}	3.7E−06	2.6E−05

Table 1 (continued)

Parameter	Process modeled/Compartment	Unit	Uniform N application (UA)	Variable rate N application (VRT)
Metsulfuron-methyl	Emission to soil/agricultural	kg t^{-1}	7.5E−08	5.2E−07
Picoxystrobin	Emission to soil/agricultural	kg t^{-1}	1.5E−07	1.1E−06
Pyraclostrobin (prop)	Emission to soil/agricultural	kg t^{-1}	5.9E−07	4.2E−06
Bromoxynil	Emission to soil/agricultural	kg t^{-1}	6.94E−06	1.83E−05
Fluroxypyr	Emission to soil/agricultural	kg t^{-1}	7.23E−06	1.90E−05
Ioxynil	Emission to soil/agricultural	kg t^{-1}	7.09E−06	1.86E−05
Metaldehyde	Emission to soil/agricultural	kg t^{-1}	7.73E−06	2.03E−05
Propiconazole	Emission to soil/agricultural	kg t^{-1}	5.16E−06	1.36E−05

Life cycle inventory (LCI)

The inventory data are summarized in Table 1. The direct agricultural input data (foreground system), such as seed rate for sowing, plant protection product, fertilization amount and types, fuel consumption, and machinery working hours, were collected at the farm during field tests and surveys. Nitrogen emissions (nitrate leaching, ammonia volatilization, and nitrous and nitrogen oxide emissions in the atmosphere), phosphate emissions in water, and fossil CO_2 emissions to the atmosphere were calculated using Koeble (2014) and Nemecek et al. (2020) guidelines. N_2O emissions from atmospheric deposition of N on soils and water surfaces and emissions from N leaching and runoff were included in the indirect emissions. Direct N_2O emissions were equivalent to 1% of the amount of N applied as fertilizer (0.01 kg N_2O–N). Ammonia volatilization was considered to be 0.1 kg NH_3–N per kg of N. The indirect N_2O from atmospheric deposition was 0.01 kg N_2O–N per kg of NH_3–N whereas the indirect N_2O from leaching/runoff was 0.0075 kg N_2O–N per kg of NO_3–N. The nitrate–nitrogen leaching loss was considered 0.22 kg NO_3–N per kg of N for UA and 0 for VRT. In the VRT strategy all the N given with the fertilizer was taken up by the crop, whereas in the UA strategy, only 22% was lost. For urea, the emission is 1.57 kg CO_2 per kg Urea–N. The secondary emissions of the inputs during the production stage, including fertilizer, agrochemicals, machinery, and infrastructure production, were retrieved from the Ecoinvent database (Ecoinvent Database 3.1 2014).

Energy analysis and life cycle impact assessment

The performance assessment included energy input-output and a series of life-cycle environmental impacts. To evaluate the energy performance, various energy indices such as energy consumption, energy use efficiency (EUE), net energy gain (NEG), energy productivity (EP), and specific energy (SE) were used (Table 2). The energy input was obtained as a product of each input and its corresponding energy coefficient. It was classified into

Table 2 The average value of energy equivalent coefficient of inputs and outputs

Parameter	Energy equivalents (MJ unit^{-1})	Unit	Category of input	Source of energy	References
Human labor	1.96	h	Direct	Renewable	Ilahi et al. (2019)
Seeds	13	kg	Indirect	Renewable	Ilahi et al. (2019)
Nitrogen-based fertilizers	78.1	kg	Indirect	Non-renewable	Ilahi et al. (2019)
Phosphorus based fertilizers	15.28	kg	Indirect	Non-renewable	Ilahi et al. (2019)
Pesticide, unspecified	101.2	kg	Indirect	Non-renewable	Taki et al. (2018)
Diesel fuel, tractor	47.8	kg	Direct	Non-renewable	Ilahi et al. (2019) and Taki t al. (2018)
Tractor, module manufacturing	132	kg	Indirect	Non-renewable	Ilahi et al. (2019)
Wheat, yield	13	kg	-	-	Ilahi et al. (2019)

direct and indirect, and renewable and non-renewable. The total energy input was calculated as the sum of all energy inputs for all resources used in crop production. The output energy was obtained as a product of yield and its equivalent energy representative.

Energy use efficiency (EUE) was calculated from the ratio of energy output and energy input (Eq. 1). An increase in the ratio indicates an improvement in energy efficiency.

$$\text{Energy use efficiency} = \frac{\text{Energy output (MJ ha}^{-1})}{\text{Energy input (MJ ha}^{-1})} \quad (1)$$

Energy productivity (EP) was measured from the ratio of crop output of wheat and energy input (Eq. 2). An increase in the indicator denotes high EP and vice versa.

$$\text{Energy productivity (kg MJ}^{-1}) = \frac{\text{Crop output (kg ha}^{-1})}{\text{Energy input (MJ ha}^{-1})} \quad (2)$$

Specific energy (SE) was estimated from the ratio of energy input and crop output (Eq. 3). An increase in the indicator denotes lower energy efficiency and vice versa.

$$\text{Specific energy (MJ kg}^{-1}) = \frac{\text{Energy input (MJ ha}^{-1})}{\text{Crop output (kg ha}^{-1})} \quad (3)$$

Net energy gain (NEG) was approximated by the deduction of input energy from output energy (Eq. 4).

$$\text{Net energy}\left(\text{MJ ha}^{-1}\right) = \text{Energy output}\left(\text{MJ ha}^{-1}\right) - \text{Energy input}\left(\text{MJ ha}^{-1}\right) \quad (4)$$

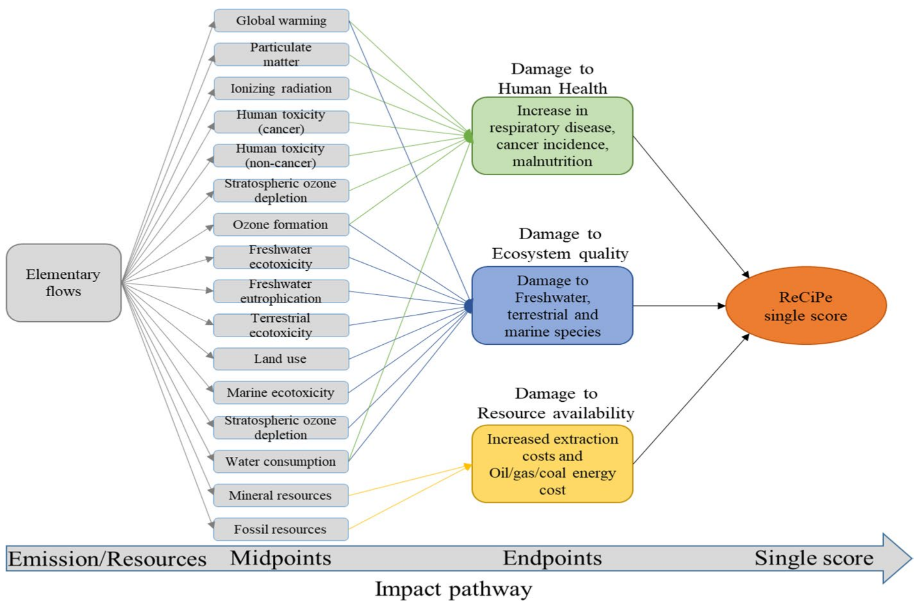


Fig. 3 ReCiPe 2016 impact pathway from inventory to aggregation to a single score

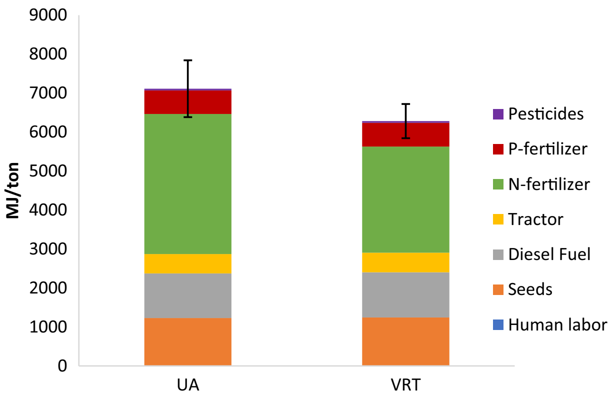


Fig. 4 Process input energy required for rainfed durum wheat production using uniform (UA) and variable rate fertilization

Table 3 Indicators of energy performance for wheat production with uniform (UA) and variable rate fertilization

Item	Unit	Wheat (UA)	Wheat (VRT)	Δ VRT/UA
Energy use efficiency (EUE)	–	1.83	2.07	+ 13.2%
Energy productivity (EP)	kg MJ^{-1}	0.14	0.16	+ 13.2%
Specific energy (SE)	MJ kg^{-1}	7.11	6.28	– 11.7%
Net energy gain (NEG)	MJ ha^{-1}	15 659	18 056	+ 15.3%
Direct energy (DE)	MJ ha^{-1}	1153.0	1169.1	+ 1.4%
Indirect energy (IE)	MJ ha^{-1}	5960.3	5113.7	– 14.2%
Renewable energy (RE)	MJ ha^{-1}	1229.2	1246.2	+ 1.4%
Non-renewable energy (NRE)	MJ ha^{-1}	5884.1	5036.6	– 14.4%

The life cycle impact (LCIA)-model ReCiPe 2016 (Huijbregts et al., 2017) was used to analyze environmental performance. We calculated twenty-one (21) environmental indicators (Fig. 3): eighteen (18) at the midpoint level (e.g., global warming, acidification, eutrophication, and toxicities) and three (3) at the endpoint level (human health, ecosystem quality, and resources). Midpoints were used for a more specific and detailed analysis, whereas endpoints were used to communicate the results obtained to a broader, non-expert audience. To easily compare the environmental impact of fertilization strategies, a single score index was calculated by aggregating environmental impacts into a single score expressed in a physical value (ReCiPe single score) (Fig. 3). Afterward, the computed environmental impacts were converted into externalities (environmental costs) by applying monetization weighting factors (Canaj et al., 2021). Monetizing LCA results is one way of expressing environmental impacts in terms of costs. The openLCA 1.10.3 software (https://www.openlca.org/) was used to model the study system and to calculate the selected performance indicators. The standard deviation of the impact categories was simulated as a function of seed rate (± 10%), crop yields (± 10%), diesel fuel (± 10%), and fertilization rates (± 10% and ± 20%).

Result and discussion

Energy performance indicators

Figure 4 and Table 3 show the results of the energy analysis for wheat production. The energy input was calculated to be 7113.3 ± 729.3 MJ t^{-1} and 6282.8 ± 438 MJ t^{-1} for UA and VRT, respectively. Fertilization used the most energy (Fig. 4), accounting for 59% and 53% of total energy consumption for UA and VRT, respectively. In rain-fed wheat production, chemical fertilizers are one of the top contributors to total energy consumption and environmental footprint (Canaj & Mehmeti, 2022; Ilahi et al., 2019; Taki et al., 2018).

Table 3 presents the energy use efficiency (EUE), net energy gain (NEG), energy productivity (EP), and specific energy (SE) scores. In wheat production with UA, the EUE, SE, EP, and NEG were calculated as 1.83 ± 0.18, 7.11 ± 0.73 MJ kg^{-1}, 0.14 ± 0.014 kg MJ $^{-1}$, and 15 659 ± 3325 MJ ha^{-1}, respectively. The values for wheat with VRT were 2.07 ± 0.14, 6.28 ± 0.44 MJ kg^{-1}, 0.16 ± 0.011 kg MJ^{-1}, and 18 084 ± 730.7 MJ ha^{-1}. Accordingly, VRT increased EUE and EP by 13.3%, reduced SE and total energy inputs by 11.7%, and increased NEG by 15.3%. Both systems relied on non-renewable energy sources (> 80%). The fossil energy dependence was found to decrease in VRT, as the use of non-renewable energy decreased by 14.4% from 5884.1 MJ ha^{-1} to 5036.6 MJ ha^{-1}.

Our results agree with the findings of other studies (Fabiani et al., 2020; Jovarauskas et al., 2021; Kazlauskas et al., 2021; Scuola et al., 2017), in which VRT technology improves energy performance indicators of wheat production. Kazlauskas et al. (2021) demonstrated that using VRT technology could save 5.2% of energy input (12 059 vs. 12 726 MJ ha^{-1}) in wheat production in Lithuania. Jovarauskas et al. (2021) estimated that VRT reduced total energy input by 10.46% in Lithuanian winter wheat production, which resulted in approximately 9% higher energy efficiency (4.58 vs. 4.18) and productivity (0.327 ± 0.015 kg MJ^{-1} vs. 0.299 ± 0.012 kg MJ^{-1}). In Central Italy, Scuola et al. (2017) estimated a 30.15% (12 732 vs. 18 228 MJ) reduction in non-renewable energy consumption. Fabiani et al. (2020) discovered that using VRT applications in Greek wheat production could increase EUE by 14% (2.51 vs. 2.21) and decrease SE by 12% (5.7 vs. 6.56 MJ kg^{-1}) compared to the Czech Republic, where the authors estimated marginal effects with less than 2% benefits.

Environmental performance at the midpoint and endpoint level

Table 4 shows the results of impact category indicators at the midpoint level for 1 hectare and 1 ton of product. The findings show that VRT had a negligible impact on many environmental impacts (such as mineral resource scarcity, ozone formation, human toxicity, water consumption, and so on), with benefits of less than 5%. The VRT demonstrated a general reduction in potential impacts for 1 ha of wheat cultivated. For one ton of wheat, the VRT had a minor negative impact on freshwater eutrophication, freshwater, marine, and terrestrial ecotoxicity, and land use. In our study, the yield of wheat with VRT was slightly lower than in UA. Nevertheless, our model results show that the application of the VRT for a precise N-fertilization system allows reducing several environmental impacts, such as global warming (− 17.9%), fine particulate matter formation (− 19.7%), stratospheric ozone depletion (− 28.7%), terrestrial acidification (− 22.3%), and marine eutrophication (− 87.8%). These environmental impacts were mitigated by reducing on-farm

Table 4 Average cradle-to-farm gate midpoint environmental impacts of wheat production with uniform (UA) and variable rate fertilization (VRT)

Indicator	Abbreviation	Unit	1 ton			1 ha		
			UA	VRT	Δ VRT/UA	UA	VRT	Δ VRT/UA
Fine particulate matter formation	PMPF	kg PM2.5 eq	7.33	5.88	− 19.7%	19.5	15.5	− 20.6%
Fossil resource scarcity	FFP	kg oil eq	147.6	133.5	− 9.5%	392.5	351.0	− 10.6%
Freshwater ecotoxicity	FETP	kg 1,4 DCB eq	452.9	457.2	+0.9%	1204.8	1202.4	− 0.2%
Freshwater eutrophication	FEP	kg P-eq	0.29	0.30	+0.3%	0.784	0.777	− 0.8%
Global warming	GWP	kg CO_2 eq	816.3	670.2	− 18.0%	2171.39	1762.73	− 18.9%
Human carcinogenic toxicity	HTPc	kg 1,4 DCB eq	14.3	13.7	− 4.0%	38.0	36.0	− 5.1%
Human non—carcinogenic toxicity	HTPnc	kg 1,4 DCB eq	483.3	465.4	− 3.7%	1285.6	1223.9	− 4.8%
Ionizing radiation	IRP	kBq Co-60 eq	40.1	38.9	− 3.1%	106.7	102.2	− 4.2%
Land use	LU	m^2a crop eq	7056.5	7136.6	+1.1%	18 770.27	18 769.30	− 0.01%
Marine ecotoxicity	METP	kg 1,4 DCB-eq	691.7	698.2	+0.9%	1839.91	1836.31	− 0.2%
Marine eutrophication	MEP	kg N eq	3.1	0.4	− 87.8%	8.23	0.99	− 88.0%
Mineral resource scarcity	MRS	kg Cu eq	6.49	6.37	− 1.9%	17.3	16.7	− 3.0%
Human health ozone formation	HOFP	kg NOx eq	2.76	2.68	− 3.1%	7.35	7.04	− 4.2%
Ecosystem ozone formation	EOFP	kg NOx eq	6.32	6.12	− 3.2%	16.8	16.1	− 4.3%
Stratospheric ozone depletion	ODP	kg CFC11 eq	0.0119	0.01	− 28.7%	0.03	0.02	− 29.5%
Terrestrial acidification	TAP	kg SO_2 eq	45.36	35.26	− 22.3%	120.7	92.7	− 23.2%
Terrestrial ecotoxicity	TETP	kg 1,4 DCB-eq	72 430	73 040	+0.8%	192 664	192 096	− 0.3%
Water consumption	WCP	m^3 consumed	45.3	43.7	− 3.7%	120.6	114.8	− 4.8%

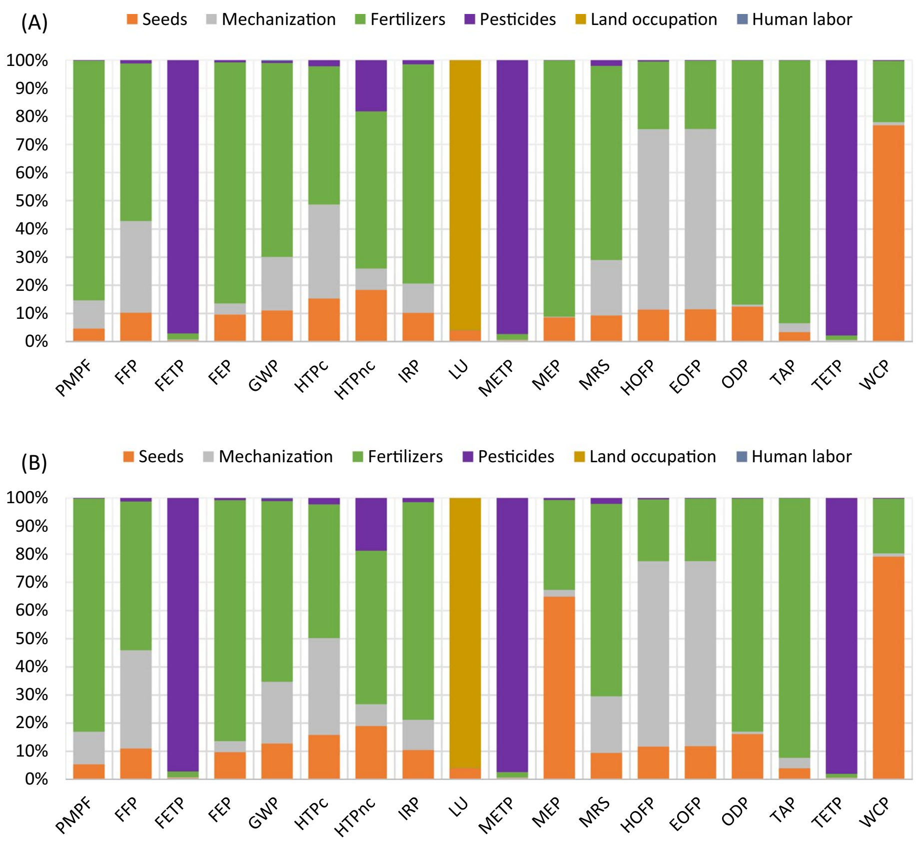


Fig. 5 Contribution of agricultural inputs and processes to the environmental impacts of wheat production: **A** UA, **B** VRT

(foreground) emissions. The higher land application of N compounds as chemical fertilizers had a negative influence on the environment through the release of N-containing gases such as NH_3 and N_2O, and nitrate (NO_3^-) losses via leaching and runoff. Further, the use of every kg of urea essentially induces CO_2 emissions after its usage. The reduction of soil N_2O emissions and CO_2 releases after urea applications reduced global warming. Reduction of ammonia (NH_3) volatilization and nitrogen oxide (NOx) emissions had the greatest impact on fine particulate matter formation and terrestrial acidification. Marine eutrophication occurred due to the nitrate originating from agricultural runoff and leaching (waterborne N-emissions).

The relative contribution of the agricultural inputs to the environmental impacts of wheat is presented in Fig. 5. For both UA and VRT, fertilizers had the greatest environmental impact (12 out of 18). Photochemical ozone formation was greatly affected by mechanized field operations (i.e., diesel fuel emissions), whereas pesticide use caused freshwater, marine, and terrestrial ecotoxicity. The greatest impact on water consumption was caused by seed production.

Figure 6 depicts the numerical endpoint scores for 1 ton of product. The benefits of VRT to areas of protection (human health, ecosystems, and resources) ranged from 3.3% to

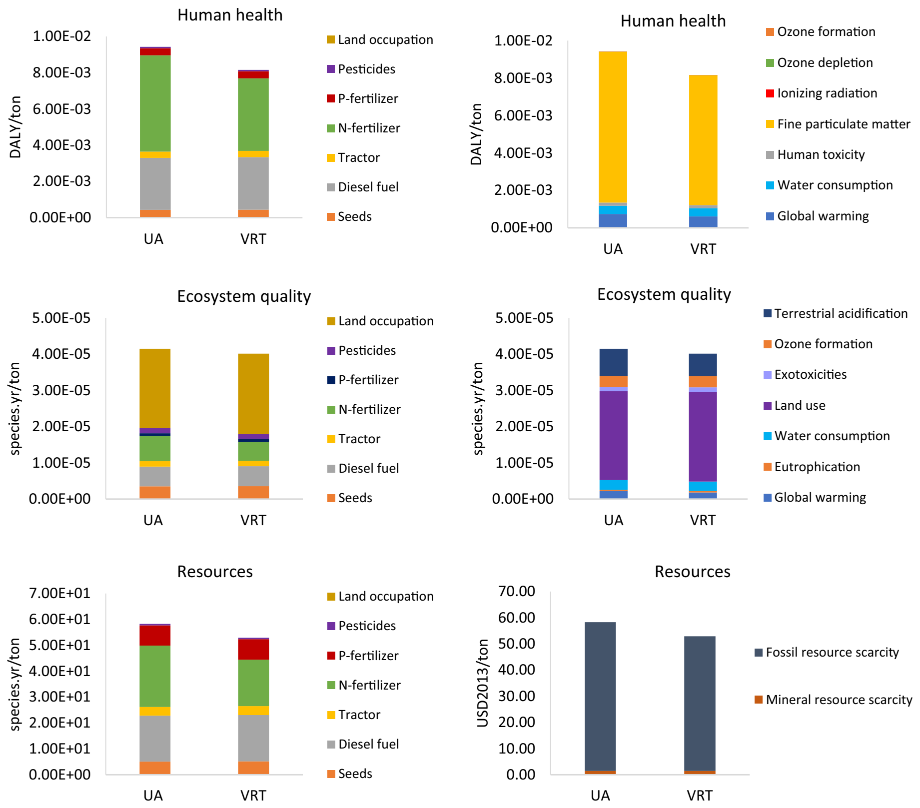


Fig. 6 Scores for human health, ecosystem quality, and resource availability in wheat production using uniform (UA) and variable rate fertilization (VRT), with input/process and indicator contributions

13.5% for 1 ton of product and from 4.4% to 14.2% for 1 ha of land. For UA, the damage to human health, ecosystem quality, and resource availability was 9.43E−03 ± 9.77E−04 DALY t^{-1}, 4.15E−05 ± 4.6E−06 species.yr t^{-1} and 58.28 ± 6.53 USD2013 t^{-1}, respectively. For VRT, the damage to human health, ecosystem quality, and resource availability was 8.16E−03 ± 5.52E−04 DALY t^{-1}, 4.01E−05 ± 1.9E−06 species.yr t^{-1} and 52.9 ± 2.9 USD2013 t^{-1}, respectively. The aggregation of the weighted results into a single score showed that damage to human health is controlled by fine particulate matter formation, which is due to the volatilization of ammonia (NH_3). In terms of ecosystem quality, agricultural land occupation accounted for more than 47% of the footprint. The scarcity of fossil fuels is the primary determinant of resource availability.

LCA single score analysis (physical weighting)

Figure 7 depicts the aggregated single-score indicator, expressed as a physical value (ReCiPe single score). Wheat production with UA and VRT was estimated to have an environmental footprint of 182.3 ± 18.8 and 160.1 ± 11.2 points ton^{-1} respectively. The footprint for 1 ha was 484.9 ± 49.9 points and 421.1 ± 29.4 points for UA and VRT, respectively.

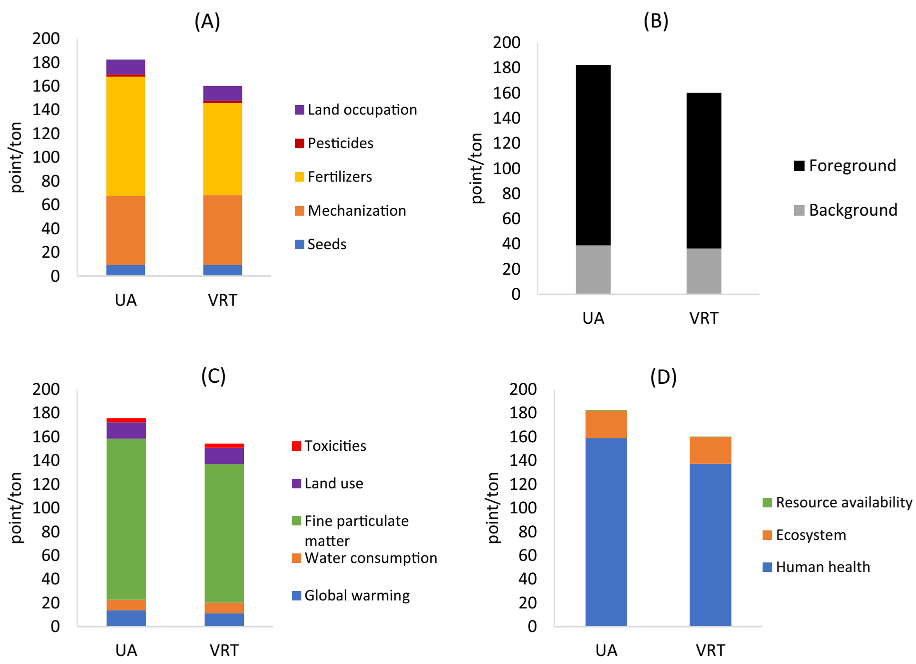
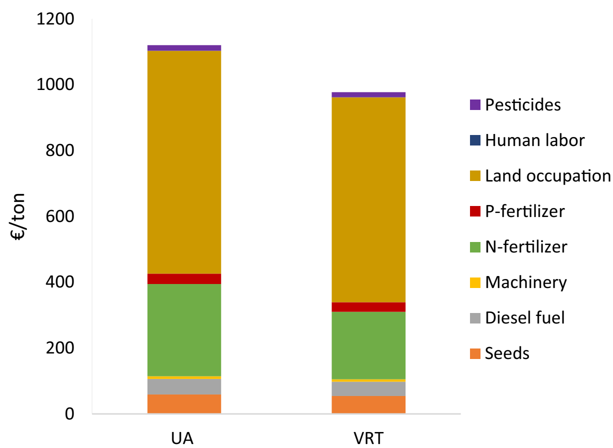


Fig. 7 Single score environmental impact of wheat production with uniform (UA) and variable rate fertilization (VRT). **A** Process contribution; **B** Subsystem contribution; **C** Midpoint impact contribution; **D** Endpoint impact contribution

Fig. 8 The external environmental cost of wheat production under uniform (UA) and variable rate fertilization (VRT)



With VRT, the fertilization environmental footprint of wheat production was reduced by 23%, from 100.7 points per ton to 77.6 points per ton. Considering the cradle-to-farm gate perspective, VRT could reduce the total environmental footprint by 12.2% per ton of product or 13.1% per hectare cultivated. The background subsystem (production and transport of N-fertilizers) was responsible for about 6% of the reduction, while the foreground subsystem was responsible for 14% (application of N-fertilizers). The highest benefits were due to the reduction of fine particulate matter formation as a result of NH_3 reduction.

LCA single score analysis (external environmental cost)

Figure 8 depicts the aggregated single-score indicator, which is expressed in monetary value (EURO) and represents the external environmental cost. Wheat production with UA and VRT has external environmental costs of 1151.3 ± 80.4 and 1075.2 ± 73.2 Euros ton^{-1}, respectively. Considering the cradle-to-farm gate perspective, wheat with VRT can reduce the external environmental cost by 6.6% for 1 ton of product and 7.7% for 1 ha of land. Differently from physical weighting, money gives more value to land occupation, an indicator that is related mainly to crop yield and no farm inputs. Production of wheat crops needs adequate land requirements (Romano et al., 2021). Land use is the main driver of global biodiversity loss, and its environmental relevance is widely recognized in research on LCA (De Baan et al., 2013), as there are external costs associated with biodiversity loss associated with land use (De Bruyn et al., 2018). The economic analysis literature indicates that the production costs of wheat production in southern Italian regions were 992 EUR ha^{-1} (Pazienza & Zanni, 2009), 512.52 to 693.96 EUR ha^{-1} (Tiberti, 2013), 379 and 784.1 EUR ha^{-1} (Todorović et al., 2018) and 926.5 to 1023.8 EUR ha^{-1} (Bux et al., 2022). These figures show that indirect costs can be as high as or higher than production costs. This confirms that the true cost performance of variable rate technology will be greatly underestimated if the environmental cost is not considered. Environmental impact monetization could be considered in cost–benefit analyses as a further evaluation attempt.

Comparison of our findings with other studies

Several LCA studies on wheat production have been conducted, but with a limited focus on the benefits of variable fertilization (Jovarauskas et al., 2021; Kazlauskas et al., 2021; Medel-Jiménez et al., 2022; Scuola et al., 2017). As a result, we provided an overview and compare findings with other several other LCA studies on variable rate fertilization that have been published internationally (Table 5).

Jovarauskas et al. (2021) and Kazlauskas et al. (2021) found that variable-rate fertilization on wheat production could reduce the GHG emissions by 5.2% to 9.5%. Scuola et al. (2017) estimated a 32% lower carbon footprint in the cultivation of bread wheat through precision agriculture in Central Italy. Further reductions were estimated for blue water, acidification, and eutrophication potential. Medel-Jiménez et al. (2022) estimated an 8.6% reduction in the climate change impact by using the ground-based optical crop sensor for variable rate nitrogen application in Austrian conditions. Other remarkable benefits were observed for freshwater eutrophication (− 21.23%), human toxicity (−20.20%), and marine eutrophication (− 9.05%). According to Van Der Laan et al. (2015), total energy input and GHG emissions in sugarcane production in Brazil could be cut by 20% and 25%, respectively. According to Li et al. (2016), sensor-based nitrogen application in corn production in the USA could reduce life cycle non-renewable energy consumption, global warming, acidification potential, and eutrophication potential by 7, 10, 22, and 16%, respectively. Variable rate nutrient application, according to Balafoutis et al. (2017), could reduce the carbon footprint of the vineyard in Northern Greece by 28.3% when compared to conventional production. Vatsanidou et al. (2020) demonstrated the environmental benefit

Table 5 Literature LCA studies on variable rate fertilization

Author	Geographical scope	Crop	Main findings on precision agriculture/variable rate fertilization
Van Der Laan et al. (2015)	Brazil	Sugarcane	VRA reduced energy input by 20% and GHG by 25%
Li et al. (2016)	USA	Corn	Precision application of N is predicted to have reduced soil NO emissions by 10%, volatilized NH loss by 23%, and NO leaching by 16%, which in turn reduced life cycle nonrenewable energy consumption, GWP, acidification potential, and eutrophication potential by 7, 10, 22, and 16%, respectively
van Evert et al. (2017)	Greece and Netherlands	Olive	Variable rate application for side-dress N (SN) can lead to a reduction of nitrogen fertilizer use of 15%. The externality of GHG emissions is reduced from 136 € ha^{-1} to 124 € ha^{-1} (a 9% reduction). VRA for SN also reduces eutrophication by 17%
Balafoutis et al. (2017)	Greece	Vineyard	Precision viticulture led to a PCF reduction of 28.3% compared to conventional production
Scuola et al. (2017)	Italy	Bread wheat (Triticum aestivum L.)	Precision agriculture under integrated farming (IFPA) in the cultivation of bread wheat (Triticum aestivum L.) improved global warming, blue water, non-renewable energy consumption, acidification, and eutrophication potential
Vatsanidou et al. (2020)	Greece	Pear Orchard	The environmental benefit of using the variable rate fertilization with a reduction of almost 50% of air emissions from fertilizer application in pear orchards
Bacenetti et al. (2020)	Italy	Paddy rice	Variable-rate fertilization allowed for reducing the environmental impact by 11.0% to 13.6% as compared to uniform N application
Meza-Palacios et al. (2020)	Mexico	Sugarcane	The decision support system for NPK fertilization could reduce on average damage to human health by 11%, damage to ecosystem quality by 9%, climate change impact by 14.5%, and resources by 11.5%
Núñez-Cárdenas et al. (2022)	Spain	Nectarine	Variable rate drip irrigation and fertigation can significantly reduce the CO_2 equivalent emissions generated during grape production by over 50% and increase water use efficiency by over 30% (for traditional nutrient and water management)
Casson et al. (2022)	Italy	Vineyards	Variable rate drip irrigation and fertigation can significantly reduce the CO_2 equivalent emissions generated during grape production by over 50%
Sanches et al. (2021)	Brazil	Sugarcane	N and P applications were reduced using VRT, allowing the production of a similar yield with the saving of inputs
Jovarauskas et al. (2021)	Lithuania	Wheat	GHG emissions were 9.4% lower than when variable rate fertilization was used
Kazlauskas et al. (2021)	Lithuania	Wheat	Variable rate fertilization on wheat production allowed reducing the GHG emissions by 5.2%

Table 5 (continued)

Author	Geographical scope	Crop	Main findings on precision agriculture/variable rate fertilization
Medel-Jiménez et al. (2022)	Austria	Wheat	A crop sensor for nitrogen fertilization could reduce the global warming potential of fertilization by 8.6%, freshwater eutrophication by 21.23%), human toxicity by 20.20%, and marine eutrophication (-by 9.05%)

of variable rate fertilization by reducing air emissions from fertilizer application in pear orchards in Greece by nearly 50%. Variable-rate fertilization could reduce the environmental impact of rice production in Italy by up to 13.6% when compared to uniform N application (Bacenetti et al., 2020). Meza-Palacios et al. (2020) showed that a decision support system for NPK fertilization in sugarcane farms could reduce on average damage to human health by 11%, damage to ecosystem quality by 9%, climate change impact by 14.5%, and resource availability by 11.5%. Sanches et al. (2021) estimated that applying fertilizer at variable rates in sugarcane production could reduce climate change by 3.4% and fossil fuel depletion by 4.2% per ton of product. According to Núñez-Cárdenas et al. (2022), using precision agriculture practices in Spanish conditions could reduce the carbon footprint of nectarine production per kg of fresh fruit at the farm's gate by 20.5%. Casson et al. (2022) found that variable-rate drip irrigation and fertigation in Italian grape farms can significantly reduce the CO_2-eq emissions generated during grape production by over 50%. In general, the majority of LCA studies show that variable-rate fertilizer application has environmental benefits. These benefits of VRT technology vary from study to study depending on data availability and accuracy, system boundaries, modeling approach, functional unit, and life cycle impact assessment method. Future case studies are thus required to test new indicators, new LCIA methods, and their outcomes.

Discussion

Fertilization is an essential crop input for wheat production; however, improper N application rates can result in serious environmental concerns from fertilizer production and application. Precision farming has been widely expected to show environmental benefits; however, the magnitudes of these effects are largely uncertain and case-dependent (Finger et al., 2019). Here, using a multi-indicator life cycle impact assessment model, we compared the energy and environmental impacts of wheat production under uniform and variable rate fertilization strategies. VRT resulted in a 25% reduction in nitrogen fertilizer with the same level of yield as UA. This level of nitrogen efficiency provided environmental benefits on air-related environmental indicators of particulate matter formation, global warming, and terrestrial acidification, which depended on emissions of ammonia (NH_3), nitrogen oxide (NOx), and nitrous oxide (N_2O). Our model results showed that the reduction of NH_3 had a greater influence on the final environmental benefits of wheat production. Similar previous findings (Medel-Jiménez et al., 2022) have revealed that the amount of applied N fertilizer has a greater influence on NH_3 and NO_3 indirect soil emissions than on direct N_2O emissions. Fine particulate matter formation is an indicator of air pollution that causes primary and secondary aerosols in the atmosphere and can have a substantial negative impact on human health (Huijbregts et al., 2017). For some environmental impacts, a minor negative effect was observed due to the effect of crop yield. According to the single-score analysis, wheat production with VRT has lower pollution-related environmental impacts per unit of product and land area. The findings, which are consistent with previous energy-related (Fabiani et al., 2020; Jovarauskas et al., 2021; Scuola et al., 2017) and LCA research (Bacenetti et al., 2020; Medel-Jiménez et al., 2022; Vatsanidou et al., 2020), highlight the value of VRT in input management to reduce nitrogen application rates while maintaining crop productivity and providing energy as well as numerous environmental benefits. Yet, our study highlighted that the overall expected benefits of smart agricultural technologies in annual crops are not always straightforward due to trade-offs between environmental indicators. In this study, land-use impacts that are not controlled by crop yield rather than fertilization had a significant effect on the overall co-benefits or co-damages of wheat production. This suggests that the consideration of multiple metrics needs to simultaneously explore trade-offs that may exist between productivity and environmental sustainability. Higher grain yields are expected to have a lower impact on land occupation; thus, the environmental benefits of VRT could be maximized by simultaneously increasing grain yield and optimizing the fertilizer rates. Understanding the spatial and temporal interactions between soil–plant-atmosphere is required for the successful implementation of site-specific N management (Basso et al., 2016). It is demonstrated that soil type, meteorological conditions, and N fertilizer rate and type have significant implications for N availability and crop uptake (Pampana & Mariotti, 2021) and crop yield, energy performance, and economic efficiency (Jovarauskas et al., 2021). Therefore, to realize the full potential of VRT, weather, soil, and landscape data should be combined when implementing variable rate treatments.

The decision to use variable rate fertilization would be based on economic performance. Until now, literature has produced contradictory results on the profitability of such concept. Farm sizes and the level of efficiency of the "business-as-usual scenario" influence the economic impact of the VRT (Fabiani et al., 2020). To be profitable, variable rate N management must accurately match N requirements to crop N demands (Long et al., 2015). Even with an increase in yield and cost savings on crop production inputs, using VRT technology may result in high costs, especially in small-scale farming systems (Späti et al., 2021). For the first time, this paper introduces the concept of monetization life-cycle assessment results to estimate the indirect cost of wheat production under the precision management of fertilizers. Our research found that VRT can have indirect economic benefits because the indirect costs (environmental externalities as external costs) are lower than with uniform management. Thus, we emphasize that a more comprehensive LCA that includes these environmental impact monetizations is required to investigate the "true cost" performance of VRT by quantifying the cost of environmental impacts and directly integrating them with economic costs.

Conclusion

This study used a multi-indicator model and lifecycle-based indicators to compare the performance of rainfed wheat production using uniform (UA) and variable N fertilization (VRT). According to our model results, the VRT can reduce indirect energy inputs while increasing energy efficiency and productivity by at least 10%. The LCA findings show that there is a range of potential environmental benefits associated with VRT on wheat cultivation, including reductions in global warming, fine particulate matter formation, stratospheric ozone depletion, terrestrial acidification, and marine eutrophication. Our model indicated that fertilizer use efficiency drives on-farm environmental benefits (reduction of N losses due to leaching, denitrification, ammonia volatilization, and fossil CO_2 emissions) more than indirect benefits (emissions that come from the manufacture of synthetic N fertilizer). Aggregating the results into a single score demonstrated that physical environmental benefits can be up to 12.2% and indirect economic benefits (hidden environmental costs) can be up to 7.7%. These results outline that VRT is a promising option for sustainable extensification and improved eco-efficiency of wheat production in a Mediterranean context.

As a result of our research, we conclude that for annual crops, multiple metrics need to be considered to explore the full range of trade-offs and synergies between different environmental indicators. The analysis shall include mass-based and land-use-based functional units to capture trade-offs between environmental performance, land use, and productivity. It is necessary to improve the methodology by combining life cycle assessment, monetization, and life cycle costing to explore the connection between direct and indirect financial implications and environmental benefits in a life cycle context. This would be a great step for the to support decision-making regarding the "true" sustainability of VRT.

Acknowledgements This work was funded in part by the Basilicata Region's project "CERESO" - Optimization of inputs for the sustainability of Lucanian Cereal cropping systems (DBA.AD002.241).

Funding Open access funding provided by Università degli Studi della Basilicata within the CRUI-CARE Agreement.

References

Ashworth, A. J., Putman, W. B., Kharel, T., Thoma, G., Shew, A., Popp, M., & Owens, P. (2022). Environmental impact assessment of tractor guidance systems based on pasture management scenarios. *Journal of the ASABE, 65*(3), 645–653. https://doi.org/10.13031/ja.14930

Bacenetti, J., Paleari, L., Tartarini, S., Vesely, F. M., Foi, M., Movedi, E., et al. (2020). May smart technologies reduce the environmental impact of nitrogen fertilization? A case study for paddy rice. *Science of the Total Environment, 715*, 136956. https://doi.org/10.1016/j.scitotenv.2020.136956

Balafoutis, A., Koundouras, S., Anastasiou, E., Fountas, S., & Arvanitis, K. (2017). Life cycle assessment of two vineyards after the application of precision viticulture techniques: A case study. *Sustainability, 9*(11), 1997. https://doi.org/10.3390/su9111997

Basso, B., Dumont, B., Cammarano, D., Pezzuolo, A., Marinello, F., & Sartori, L. (2016). Environmental and economic benefits of variable rate nitrogen fertilization in a nitrate vulnerable zone. *Science of the Total Environment*. https://doi.org/10.1016/j.scitotenv.2015.12.104

Bux, C., Lombardi, M., Varese, E., & Amicarelli, V. (2022). Economic and environmental assessment of conventional versus organic durum wheat production in Southern Italy. *Sustainability (switzerland), 14*(15), 1–14. https://doi.org/10.3390/su14159143

Canaj, K., & Mehmeti, A. (2022). Analyzing the water-energy-environment nexus of irrigated wheat and maize production in Albania. *Energy Nexus, 7*(May), 100100. https://doi.org/10.1016/j.nexus.2022.100100

Canaj, K., Parente, A., D'Imperio, M., Boari, F., Buono, V., Toriello, M., et al. (2021). Can precise irrigation support the sustainability of protected cultivation? A life-cycle assessment and life-cycle cost analysis. *Water, 14*(1), 6. https://doi.org/10.3390/w14010006

Casson, A., Ortuani, B., Giovenzana, V., Brancadoro, L., Corsi, S., Gharsallah, O., et al. (2022). A multidisciplinary approach to assess environmental and economic impact of conventional and innovative vineyards management systems in Northern Italy. *Science of the Total Environment, 838*(May), 156181. https://doi.org/10.1016/j.scitotenv.2022.156181

De Baan, L., Alkemade, R., & Koellner, T. (2013). Land use impacts on biodiversity in LCA: A global approach. *International Journal of Life Cycle Assessment*. https://doi.org/10.1007/s11367-012-0412-0

De Bruyn, S., Bijleveld, M., de Graaff, L., Schep, E., Schroten, A., Vergeer, R., & Ahdour, S. (2018). *Environmental prices handbook EU28 version—Methods and numbers for valuation of environmental impacts*. *CE Delft*.
Denora, M., Amato, M., Brunetti, G., De Mastro, F., & Perniola, M. (2022). Geophysical field zoning for nitrogen fertilization in durum wheat (*Triticum durum* Desf.). *PLoS ONE, 17*(4), e0267219. https://doi.org/10.1371/journal.pone.0267219
Ecoinvent Database 3.1. (2014). Ecoinvent Database 3.1. *Ecoinvent Centre*. https://doi.org/10.4018/978-1-59140-342-5.ch003
Fabiani, S., Vanino, S., Napoli, R., Zajíček, A., Duffková, R., Evangelou, E., & Nino, P. (2020). Assessment of the economic and environmental sustainability of Variable Rate Technology (VRT) application in different wheat intensive European agricultural areas. A Water energy food nexus approach. *Environmental Science and Policy*. https://doi.org/10.1016/j.envsci.2020.08.019
Finger, R., Swinton, S. M., & BenniEl Walter, N. A. (2019). Precision farming at the Nexus of agricultural production and the environment. *Annual Review of Resource Economics*. https://doi.org/10.1146/annurev-resource-100518-093929
Fiorentino, C., Donvito, A. R., D'Antonio, P., & Lopinto, S. (2020). Experimental methodology for prescription maps of variable rate nitrogenous fertilizers on cereal crops. *Lecture Notes in Civil Engineering*. https://doi.org/10.1007/978-3-030-39299-4_93
Fotia, K., Mehmeti, A., Tsirogiannis, I., Nanos, G., Mamolos, A. P., Malamos, N., et al. (2021). LCA-based environmental performance of olive cultivation in Northwestern Greece: From rainfed to irrigated through conventional and smart crop management practices. *Water, 13*(14), 1954. https://doi.org/10.3390/w13141954
Gobbo, S., Morari, F., Ferrise, R., De Antoni Migliorati, M., Furlan, L., & Sartori, L. (2022). Evaluation of different crop model-based approaches for variable rate nitrogen fertilization in winter wheat. *Precision Agriculture*. https://doi.org/10.3920/978-90-8686-916-9_4
Huijbregts, M. A. J., Steinmann, Z. J., Elshout, P. M. F., Stam, G., Verones, F., Vieira, M. D. M., et al. (2017). *ReCiPe 2016 v1.1 A harmonized life cycle impact assessment method at midpoint and endpoint level Report I: Characterization. RIVM Report 2016–0104a*. https://www.rivm.nl/sites/default/files/2018-11/ReportReCiPe_Update_20171002_0.pdf
Hunter, M. C., Smith, R. G., Schipanski, M. E., Atwood, L. W., & Mortensen, D. A. (2017). Agriculture in 2050: Recalibrating targets for sustainable intensification. *BioScience*. https://doi.org/10.1093/biosci/bix010
Ilahi, S., Wu, Y., Raza, M. A. A., Wei, W., Imran, M., & Bayasgalankhuu, L. (2019). Optimization approach for improving energy effciency and evaluation of greenhouse gas emission of wheat crop using Data Envelopment Analysis. *Sustainability (switzerland)*. https://doi.org/10.3390/SU11123409
Jovarauskas, D., Steponavičius, D., Kemzūraitė, A., Zinkevičius, R., & Venslauskas, K. (2021). Comparative analysis of the environmental impact of conventional and precision spring wheat fertilization under various meteorological conditions. *Journal of Environmental Management*. https://doi.org/10.1016/j.jenvman.2021.113150
Kazlauskas, M., Bručienė, I., Jasinskas, A., & Šarauskis, E. (2021). Comparative analysis of energy and ghg emissions using fixed and variable fertilization rates. *Agronomy*. https://doi.org/10.3390/agronomy11010138
Koeble, R. (2014). The Global Nitrous Oxide Calculator—GNOC—Online Tool Manual. *Joint Research Centre of the European Commission*, *1.2.4*, 40. http://gnoc.jrc.ec.europa.eu/
Lagnelöv, O., Larsson, G., Larsolle, A., & Hansson, P. A. (2021). Life cycle assessment of autonomous electric field tractors in Swedish agriculture. *Sustainability (switzerland)*. https://doi.org/10.3390/su132011285
Li, A., Duval, B. D., Anex, R., Scharf, P., Ashtekar, J. M., Owens, P. R., & Ellis, C. (2016). A case study of environmental benefits of sensor-based nitrogen application in corn. *Journal of Environmental Quality*. https://doi.org/10.2134/jeq2015.07.0404
Lindblom, J., Lundström, C., Ljung, M., & Jonsson, A. (2017). Promoting sustainable intensification in precision agriculture: Review of decision support systems development and strategies. *Precision Agriculture*. https://doi.org/10.1007/s11119-016-9491-4
Long, D. S., Whitmus, J. D., Engel, R. E., & Brester, G. W. (2015). Net returns from terrain-based variable-rate nitrogen management on dryland spring wheat in Northern Montana. *Agronomy Journal*. https://doi.org/10.2134/agronj14.0331

Lovarelli, D., & Bacenetti, J. (2017). Bridging the gap between reliable data collection and the environmental impact for mechanised field operations. *Biosystems Engineering*. https://doi.org/10.1016/j.biosystemseng.2017.06.002

Medel-Jiménez, F., Piringer, G., & Gronauer, A. (2022). Modelling soil emissions and precision agriculture in fertilization life cycle assessment—A case study of wheat production in Austria. *Journal of Cleaner Production*. https://doi.org/10.1016/j.jclepro.2022.134841

Meza-Palacios, R., Aguilar-Lasserre, A. A., Morales-Mendoza, L. F., Rico-Contreras, J. O., Sánchez-Medel, L. H., & Fernández-Lambert, G. (2020). Decision support system for NPK fertilization: A solution method for minimizing the impact on human health, climate change, ecosystem quality and resources. *Journal of Environmental Science and Health, Part A, 55*(11), 1267–1282. https://doi.org/10.1080/10934529.2020.1787012

Nemecek, T., Bengoa, X., Rossi, V., Humbert, S., Lansche, J., & Mouron, P. (2020). *World Food LCA Database: Methodological guidelines for the life cycle inventory of agricultural products*. *World Food LCA Database (WFLDB)*.

Neupane, J., & Guo, W. (2019). Agronomic basis and strategies for precision water management: A review. *Agronomy*. https://doi.org/10.3390/agronomy9020087

Nguyen-Van-Hung, Balingbing, C., Sandro, J., Khandai, S., Chea, H., Songmethakrit, T., et al. (2022). Precision land leveling for sustainable rice production: case studies in Cambodia, Thailand, Philippines, Vietnam, and India. *Precision Agriculture*. https://doi.org/10.1007/s11119-022-09900-8

Núñez-Cárdenas, P., Diezma, B., San Miguel, G., Valero, C., & Correa, E. C. (2022). Environmental LCA of precision agriculture for stone fruit production. *Agronomy, 12*(7), 1545. https://doi.org/10.3390/agronomy12071545

Pampana, S., & Mariotti, M. (2021). Durum wheat yield and N uptake as affected by N source, timing, and rate in two mediterranean environments. *Agronomy*. https://doi.org/10.3390/agronomy11071299

Pazienza, M., & Zanni, G. (2009). Fare i conti per decidere se seminare il grano duro. *Informatore Agrario*.

Pradel, M., de Fays, M., & Séguineau, C. (2022). Comparative life cycle assessment of intra-row and inter-rows weeding practices using autonomous robot systems in French Vineyards. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4068293

Romano, E., De Palo, P., Tidona, F., Maggiolino, A., & Bragaglio, A. (2021). Dairy buffalo life cycle assessment (LCA) affected by a management choice: The production of wheat crop. *Sustainability (switzerland)*. https://doi.org/10.3390/su131911108

Sanches, G. M., Magalhães, P. S. G., Kolln, O. T., Otto, R., Rodrigues, F., Cardoso, T. F., et al. (2021). Agronomic, economic, and environmental assessment of site-specific fertilizer management of Brazilian sugarcane fields. *Geoderma Regional*. https://doi.org/10.1016/j.geodrs.2021.e00360

Scuola, R. V., Sant'anna, S., Bosco, S., Sant'anna, S. S., Dragoni, F., Scuola, C. T., et al. (2017). Improving resource efficiency in the cultivation of bread wheat through precision agriculture. In *Atti del XI Convegno della Rete Italiana LCA. Resource Efficiency e Sustainable Development Goals: il ruolo del Life Cycle Thinking* (pp. 159–165). Siena.

Singh, R., & Singh, G. S. (2017). Traditional agriculture: A climate-smart approach for sustainable food production. *Energy, Ecology and Environment*. https://doi.org/10.1007/s40974-017-0074-7

Späti, K., Huber, R., & Finger, R. (2021). Benefits of increasing information accuracy in variable rate technologies. *Ecological Economics*. https://doi.org/10.1016/j.ecolecon.2021.107047

Stamatiadis, S., Schepers, J. S., Evangelou, E., Tsadilas, C., Glampedakis, A., Glampedakis, M., et al. (2018). Variable-rate nitrogen fertilization of winter wheat under high spatial resolution. *Precision Agriculture*. https://doi.org/10.1007/s11119-017-9540-7

Taki, M., Soheili-Fard, F., Rohani, A., Chen, G., & Yildizhan, H. (2018). Life cycle assessment to compare the environmental impacts of different wheat production systems. *Journal of Cleaner Production*. https://doi.org/10.1016/j.jclepro.2018.06.173

Tiberti, M. (2013). Production costs of soft wheat in Italy. In *Between crisis and development: Which role for the bio-economy* (Vol. 1, pp. 1–22).

Tilman, D., Balzer, C., Hill, J., & Befort, B. L. (2011). Global food demand and the sustainable intensification of agriculture. *Proceedings of the National Academy of Sciences of the United States of America*. https://doi.org/10.1073/pnas.1116437108

Todorović, M., Mehmeti, A., & Cantore, V. (2018). Impact of different water and nitrogen inputs on the eco-efficiency of durum wheat cultivation in Mediterranean environments. *Journal of Cleaner Production, 183*, 1276–1288. https://doi.org/10.1016/j.jclepro.2018.02.200

Van Der Laan, M., Jumman, A., & Perret, S. R. (2015). Environmental benefits of improved water and nitrogen management in irrigated sugar cane: A combined crop modelling and life cycle assessment approach. *Irrigation and Drainage*. https://doi.org/10.1002/ird.1900

van Evert, F. K., Gaitán-Cremaschi, D., Fountas, S., & Kempenaar, C. (2017). Can precision agriculture increase the profitability and sustainability of the production of potatoes and olives? *Sustainability (switzerland)*. https://doi.org/10.3390/su9101863

Vatsanidou, A., Fountas, S., Liakos, V., Nanos, G., Katsoulas, N., & Gemtos, T. (2020). Life cycle assessment of variable rate fertilizer application in a Pear Orchard. *Sustainability, 12*(17), 6893. https://doi.org/10.3390/su12176893

Wezel, A., Soboksa, G., McClelland, S., Delespesse, F., & Boissau, A. (2015). The blurred boundaries of ecological, sustainable, and agroecological intensification: A review. *Agronomy for Sustainable Development*. https://doi.org/10.1007/s13593-015-0333-y

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.