



Precision application of combined manure, compost and nitrogen fertilizer in potato cultivation using online vis-NIR and remote sensing data fusion

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ABSTRACT

This study evaluates the agronomic, economic and environmental impacts of precision nutrient management through variable rate (VR) application of chicken manure, compost and nitrogen (N) fertilizer compared to the uniform rate (UR) application in potato (*Solanum tuberosum* L.) cultivation on two Fluvisol fields (Cayenne, 6.85 ha; Dzhond, 7.15 ha) in Belgium. Soil spectral data were collected at a 20 cm depth using an online visible and near infrared (vis-NIR) spectroscopy multi-sensor platform. Partial least squares regression models were established to predict soil pH, total carbon (TOC), extractable phosphorus (P), potassium (K), magnesium (Mg), calcium (Ca) and cation exchange capacity (CEC). Management zones (MZs) were delineated by integrating Sentinel-2 derived normalized difference vegetation index (NDVI) with the online PLSR predicted soil data using raster and k-means cluster analysis. MZs were classified into high fertile (H), medium-high fertile (MH), medium fertile (M), medium-low fertile (ML) and low fertile (L) zones. A parallel strip trial compared VR application (with nutrient rates adjusted as VR-H: -50 %, VR-MH: -25 %, VR-M: 0 %, VR-ML: +25 %, VR-L: +50 % relative to UR) against UR application of chicken manure, compost, and N fertilizer. Results showed that, in Cayenne, VR-M, VR-ML and VR-L zones exhibited significant ($P \leq 0.05$) yield increases of 14.30 %, 9.16 % and 8.89 %, respectively, compared to the UR treatment, whereas crop yield in VR-H and VR-MH zones decreased. In Dzhond, VR-H and VR-ML zones achieved yield increases of 14.85 % and 18.0 %, respectively, whereas VR-M, VR-MH, and VR-L zones showed yield decreases of 5.66 %, 3.00 %, and 11.0 %, respectively. The VR application led to net reductions in nitrogen ($\Delta N = 17.54$ kg/ha for Cayenne, and 4.24 kg/ha for Dzhond) and phosphorus ($\Delta P = 10.08$ kg/ha for Cayenne, and 1.74 kg/ha for Dzhond), which resulted in increased relative gross margins of €142.11/ha for Cayenne and €269.50/ha for Dzhond. This study concludes that site-specific nutrient management improved yields, nutrient use efficiency, and profitability, while reducing N and P inputs, supporting sustainable agriculture. Future research should refine MZ delineation with inclusion of soil nitrate and soil biological data.

1. Introduction

Global population growth projected to exceed 9.7 billion by 2050 [1], which intensifies the demand for sustainable agricultural practices to ensure food security while addressing the climate challenge. Synthetic nitrogen (N) fertilizers and organic amendments like manure are essential for meeting global food demands, yet their use contributes to environmental issues, including greenhouse gas emissions, soil degradation, and nutrient leaching [2–4]. Optimizing fertilizer use efficiency through innovative approaches is critical to balancing the productivity and environmental sustainability.

Manure and compost, while sustainable alternatives to synthetic

fertilizers, contribute to methane and nitrous oxide emissions and can introduce contaminants such as heavy metals and antibiotics into the soils [5,6]. Over- or under-application of these inputs, common in conventional uniform rate (UR) fertilization, leads to environmental issues like eutrophication, soil fertility loss and excessive resource use, while yield penalties could take place in under-fertilised zones in a field [7–9]. These challenges highlight the need for precision management strategies to optimize nutrient application when and where it is needed in order to maximize crop yield, and minimize environmental impacts.

Potato (*Solanum tuberosum* L.), the third most consumed food crop globally is cultivated on over 19 million hectares, with significant economic importance in regions like Flanders, where it occupies 8.2 % of

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agricultural land [10,11]. Potato production is highly sensitive to soil and crop variability, with key soil properties such as texture, pH, and organic matter content directly influencing yield and quality [12–14]. Effective management of these variables is essential for optimizing productivity, improving nutrient use efficiency, and reducing environmental impacts in potato cropping systems. Precision agriculture (PA) offers a modern solution to these challenges. By leveraging advanced sensing and control technologies based on machine learning and geostatistical modeling approaches, PA enables site-specific management of farm input at the field scale. This approach termed variable rate (VR) application, ensures right farming inputs are applied precisely in the right amount, at the right time, and in the right place to match the specific needs of the crops at different location in a field [15]. For implementation, high resolution data is required to map the spatial variations in soil fertility to optimize the recommendation for VR applications. Previous works on VR N (VR-N) fertilization and manure application were carried out using management zones (MZ) maps delineation by fusion of data mainly on soil and crop [16,17]. The MZ maps divide a field into sub-regions (zones) with comparable soil or crop conditions [18]. However, most of previous studies utilized low density soil data collected by traditional laboratory methods to delineate MZ maps, which can compromise the quality of MZs and decision for VR recommendations development [19].

Proximal soil sensing with spectroscopy has significantly improved soil analysis by enabling faster, more affordable, and highly accurate assessments [20]. This technique provides real-time, high-resolution measurements (≈ 2000 samples/ha) of soil properties [21,22]. By integrating visible and near infrared (vis-NIR) spectroscopy-based high-resolution soil data with remote sensing-derived crop information, the accuracy of MZ maps can be significantly improved, leading to

more effective VR recommendations compared to traditional approaches relying on sparse soil samples [18]. Previous research has demonstrated the benefits of VR fertilisation in various crops. For instance, VR manure application in wheat increased gross margins by 40.06 EUR/ha compared to UR application [17], while VR-N fertilization in wheat reduced N use by 19.4 % and improved gross margins by up to 148.78 EUR/ha [23]. Additionally, VR cattle manure application in maize enhanced soil organic matter and water-holding capacity without additional environmental risks [24]. However, research on VR application in potatoes is limited and most of the previous research on VR has focused on cereal crops [25–29]. A study in Flanders, Belgium, found that VR N management in potato using soil apparent electrical conductivity (ECa) and Sentinel-2 derived crop vegetation indices for MZ delineation reduced nitrate leaching in low-productivity zones with lower N rates, without yield loss, though zone instability led to recommendations for UR fertilization to avoid under-fertilization risks [30]. However, to the best of our knowledge, no study has explored the combined application of VR-N fertilization and manure in potato cropping using MZ maps, derived from the fusion of high-resolution soil fertility and crop data. This study aims to examine the potential agronomic, environmental and economic benefits of employing combined VR-N fertilization, compost and manure application in potato cropping, utilizing MZs delineated through the fusion of high resolution soil data and crop characteristics.

2. Materials and methods

2.1. Experimental field location

Current study was conducted in two fields, namely, Cayenne (6.85

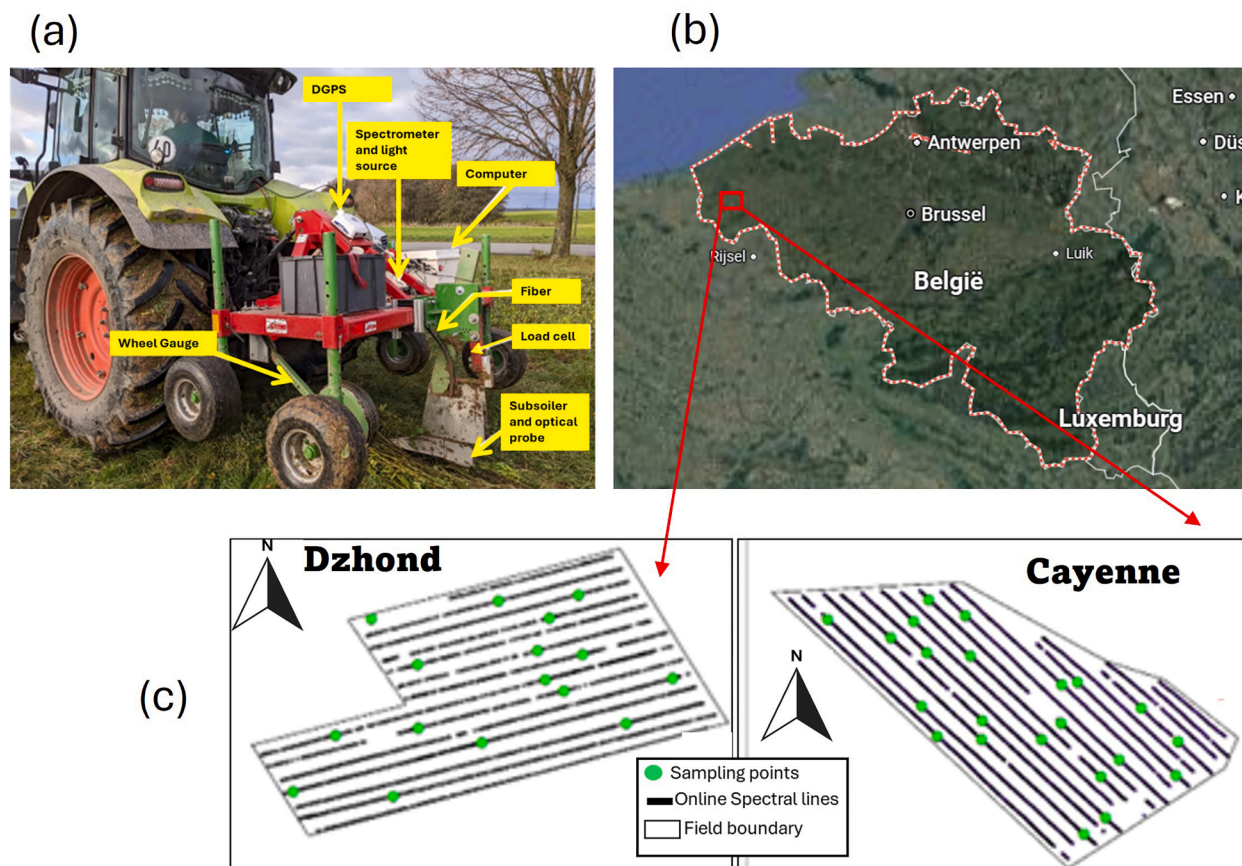


Fig. 1. Experimental field locations (Dzhond: 51°01'40.4"N 2°32'49.2"E; Cayenne: 50°59'29.1"N 2°32'20.7"E) in Belgium. (a) Online sensing platform, (b) Map of Belgium indicating field location and (c) Field boundaries showing online sensing transects and soil sampling points.

ha) and Dzhond (7.15 ha) in a commercial farm located in northwestern region of Belgium near the French boarder (Cayenne: 50°59'29.1"N 2°32'20.7"E; Dzhond: 51°01'40.4"N 2°32'49.2"E) (Fig. 1a). In this area, the average yearly temperature falls between 6 and 10 °C, with an average annual rainfall varying from 700 to 850 mm. Soil texture in Cayenne is a clay loam and in Dzhond is a sandy loam determined by following the Robinson-Kohn pipette method (ISO 11,277) at Soil Service of Belgium (BDB Heverlee, Belgium). Soil type in both fields was Fluvisols (IUSS, 2014). In both fields, in past six years no deep tillage was performed. Instead shallow tillage as disk harrowing is performed at depth of 10 to 15 cm every year before planting to incorporate crop residues and to prepare seedbed for potato cultivation. In both fields, the land surface features a flat topography with minimal undulation, with an altitude ranging from −1 to −2 m. Field trial was conducted in 2023, prior to which the Cayenne field was cultivated with Barley (*Hordeum vulgare*) and Dzhond field with wheat (*Triticum aestivum*). The typical crop rotation consists of barley, wheat, maize, potato and intermediate cover crop. The step-by-step methodology followed in this study is illustrated in Fig. 2.

2.2. Online soil sensing

Field scanning for online measurement of soil spectra was conducted in March 2023, before potato seeding by using an online vis-NIR multi-sensor system [31] (Fig. 1b). This sensor platform comprises a subsoiler attached to a metal frame that can be connected to the three-point linkage of a tractor. The subsoiler generates trenches reaching depths of 15–20 cm, with their bases leveled by the downward pressure exerted on the subsoiler chisel. An optical probe, hosted within a mild steel lens

holder, is affixed to the rear side of the subsoiler heel. Soil reflectance spectra are recorded in real-time as the tractor moves at a speed of 3.5 km/h, using a fiber-type spectrophotometer (CompactSpec Tec5 Technology, Germany), with a spectral range of 305–1700 nm and 1 nm resolution. A ceramic disk with a diameter of 50 mm, entirely made of ceramic, was utilized as a white reference. The reference was recalibrated every 30 min. Soil spectra positions were recorded using a differential global positioning system (DGPS) (Trimble AG., Trimble Navigation Ltd., Sunnyvale, Canada). Each soil spectrum, along with its geographical coordinates, was recorded at a rate of 1 Hz on a laptop using Tec5 Technology's MultiSpec Pro-II software.

The sensing system travels along parallel transects spaced 12 m apart. Typically, the datalogger recorded >800 soil spectra per hectare. During field scanning, 23 soil samples from the Cayenne field and 16 soil samples from the Dzhond field were randomly collected from the bottom of trench at 20 cm soil depth and stored in plastic zipper bags. We integrated these soil samples with selected samples from our spectral library to develop calibration models for different soil properties.

2.3. Laboratory analysis

Soil samples were mixed thoroughly and cleaned to remove any visible non-soil object such as plant roots and stones. Every soil sample was ground to pass through a 2 mm sieve. Using the quartering method introduced by Mukhopadhyay and Maiti [32], each sample was divided into three 150 g subsamples: one for chemical laboratory analysis, another for vis-NIR measurement in the laboratory, and the third was dried at room temperature for additional vis-NIR measurement on the dry sample. Oven-dry method was utilized to measure soil moisture

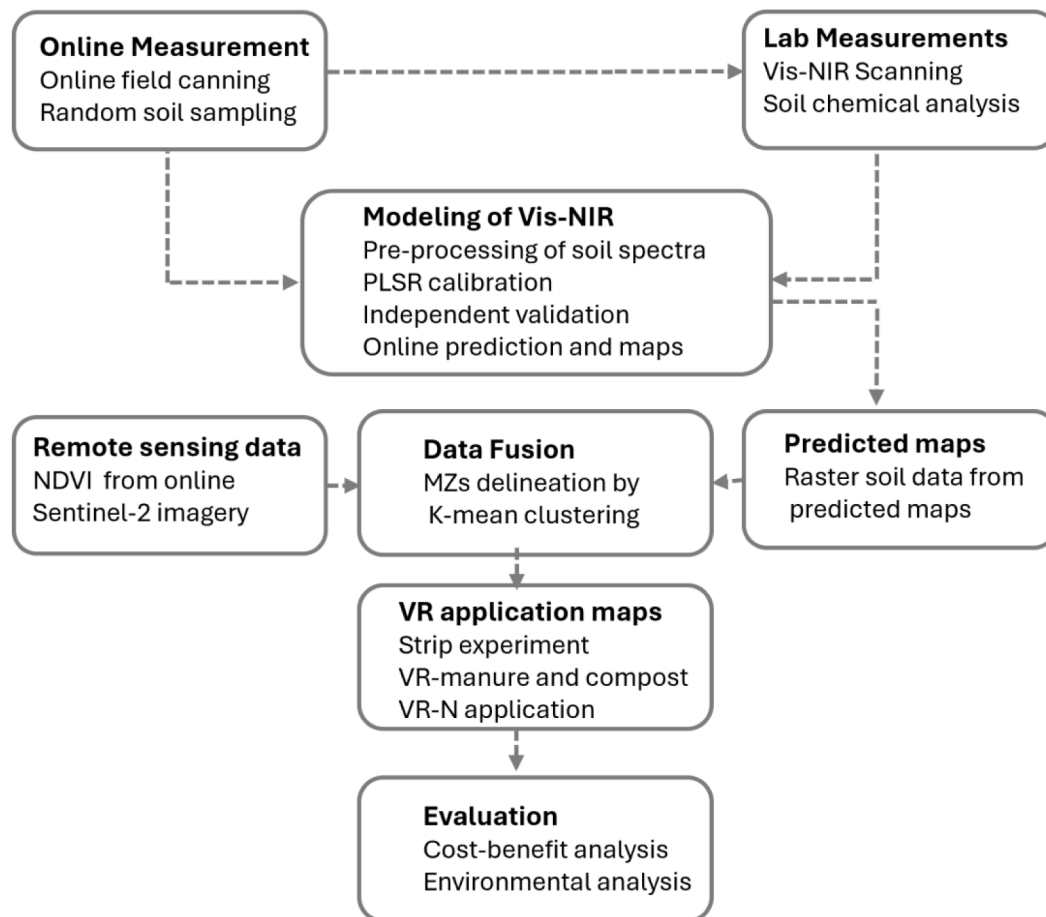


Fig. 2. Schematic diagram of methodology followed in this study. Visible–near infrared, Vis-NIR; Partial least squares regression, PLSR; Normalized difference vegetation index, NDVI; Management zones, MZs; Variable-rate, VR; Variable-rate nitrogen, VR-N.

content (MC) at 105 °C for 24 h. Chemical analysis of soil were conducted in soil laboratory at Soil Service of Belgium (Hevelee, Belgium) following the standard protocol (Table 1). Soil pH was measured in a 1:2.5 soil-to-water suspension. Soil total organic carbon (TOC) was evaluated via dry combustion following the Dumas principle, with subsequent elimination of inorganic carbon through HCl treatment. The extractable soil potassium (K), phosphorus (P), magnesium (Mg), and calcium (Ca) were analyzed within an ammonium lactate extract using inductively coupled plasma atomic emission spectroscopy [33]. Cation exchange capacity (CEC) was calculated based on base cations (K^+ , Mg^{2+} , Ca^{2+} , Na^+) following the method suggested by Gupta and Gupta [34]. The N and P (P_2O_5) content in compost were 16.1 kg/t and 15.7 kg/t, respectively, and in poultry manure were 9.30 kg/t and 6.10 kg/t, respectively, according to the analyses by the Soil Service of Belgium (BDB, Heverlee, Belgium).

2.4. Online soil prediction models and maps

Prediction models for soil MC, pH, TOC, P, K, Mg, Ca and CEC were calibrated by using partial least squares regression (PLSR) in R studio (RStudio Inc, USA) with freely accessible libraries. A total of 90 samples were utilized for calibration models, comprising 23 soil samples from Cayenne, 16 soil samples from Dzhond, and the remaining samples were sourced from the spectral library, collected from different fields within the same farm with similar soil types, land use history, and management practices to ensure spectral and compositional compatibility. The spectral library samples were selected ensuring similarity in soil properties (e.g., MC, pH, TOC, P, K, Ca, Mg) variation range of the field samples. Spectral modelling commenced with terminating the noisy edge followed by preprocessing employing various algorithms and most effective preprocessing combination was selected (Table 2). Spectra were split into calibration (70 %) and prediction (30 %) sets using the Kennard-Stone algorithm with Mahalanobis distance metric, to ensure representative coverage of spectral and chemical variability. Spectral jump correction was performed at 1045 nm according to Mouazen et al. [35]. PLSR analysis with leave-one-out cross-validation (LOOCV) was performed on the calibration dataset using the caret package in R studio, testing up to 20 components (latent variables). The number of PLSR components was optimized by selecting the model with the lowest root mean square error (RMSE) to avoid overfitting. and the resulting models were validated using the prediction set. Models accuracy was assessed by the coefficient of determination (R^2), root mean square error (RMSE), ratio of prediction to deviation (RPD), and ratio of performance to inter-quartile distance (RPIQ). Chemometric analysis and PLSR analysis were done by using a package "pls" [36] available on R CRAN. The

models that demonstrated the highest accuracy with the prediction set were employed to predict the named soil fertility parameters using all vis-NIR spectra collected during online field scanning. Following the successful prediction of soil properties using the online soil spectra, the online predicted values including DGPS coordinates were compiled into a file used to generate online maps for predicted soil attributes. The creation of high-resolution maps involved fitting a semi-variogram model, followed by interpolation using ordinary kriging (OK) accessible in ArcGIS (ESRI ArcGIS v10.7, Redlands, CA, USA).

A spatial weights matrix was constructed based on the 8 nearest neighbors of each sampling location using Euclidean distance to define local spatial relationships. The matrix assigns a weight of 1 to the 8 closest neighbors of each location and 0 to others, supporting the analysis of spatial patterns. This framework enables the computation of local and global bivariate Moran's I statistics, which evaluate the spatial correlation between measured and predicted soil properties, aiding in understanding spatial relationships and assessing prediction accuracy. The spatial weights matrix $W=[w_{ij}]$ is defined as:

$$w_{ij} = \begin{cases} 1 & \text{if } j \in 8 \text{ nearest neighbors of } i \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

where w_{ij} indicates the spatial weight between locations i and j [38].

To assess spatial agreement between measured and predicted soil properties, we calculated both local and global bivariate Moran's I statistics [39].

Local Bivariate Moran's I was computed as:

$$I_i = z_i \sum w_{ij} z_j \quad (2)$$

where z_i and z_j are the standardized values of measured and predicted variables at locations i and j , respectively, and w_{ij} are spatial weights. This local statistic quantifies the spatial association between measured and predicted values within each neighborhood.

Global bivariate moran's I was calculated as:

$$I = \frac{\sum_i \sum_j w_{ij} (x_i - \bar{x})(y_j - \bar{y})}{\sqrt{\sum_i (x_i - \bar{x})^2 \sum_j (y_j - \bar{y})^2}} \quad (3)$$

where x_i and y_j are measured and predicted values, respectively, $\bar{x}$ and $\bar{y}$ are their means, and w_{ij} are spatial weights. This global statistic evaluates the overall spatial covariance between measured and predicted variables. Local bivariate Moran's I values were normalized and visualized using spatial maps to highlight regions of strong positive or negative local spatial association. The maps were generated using the ggplot2 package with the viridis color scale to improve perceptual

Table 1
Summary statistics of soil properties measured in the laboratory for the Cayenne and Dzhond fields.

Experimental sites	Soil properties	Min	Max	Median	Mean	SD	Range	SKewness	Kurtosis
Cayenne	MC	9.82	29.60	19.97	19.84	5.56	19.78	0.06	-1.21
	pH	5.60	7.20	6.80	6.70	0.43	1.60	-1.12	0.73
	TOC	5.10	14.20	9.40	9.60	2.71	9.10	0.10	-1.29
	P	9.00	22.00	15.00	15.40	3.28	13.00	0.08	-0.81
	K	25.00	57.00	40.00	39.30	8.03	32.00	0.03	-0.44
	Mg	40.00	86.00	71.50	68.50	13.08	46.00	-0.55	-0.73
	Ca	530.00	2600.00	1070.00	1088.00	435.25	2070.00	1.71	3.96
	CEC	31.00	138.50	60.10	61.40	22.38	107.56	1.63	3.79
Dzhond	MC	4.94	8.71	6.71	6.81	1.23	3.77	0.17	-1.45
	pH	7.60	7.80	7.60	7.65	0.07	0.20	0.96	-0.85
	TOC	0.89	1.67	1.27	1.30	0.24	0.78	0.05	-1.41
	P	21.00	39.00	29.50	30.00	5.23	18.00	0.27	-0.99
	K	8.00	35.00	11.00	12.62	6.63	27.00	2.32	5.19
	Mg	40.00	49.00	44.50	44.50	2.50	9.00	0.04	-1.00
	Ca	2800.00	4400.00	3950.00	3812.00	500.50	1600.00	-0.67	-0.99
	CEC	143.80	224.30	202.00	195.00	25.10	80.56	-0.69	-0.95

Number of soil samples (n): Cayenne $n = 23$; Dzhond $n = 16$. Standard deviation, SD; moisture content, MC; total organic carbon, TOC; phosphorus, P; potassium, K; magnesium, Mg; calcium, Ca; cation exchange capacity, CEC.

Table 2

Parameters used in various algorithms for preprocessing visible and near-infrared spectra of different soil properties.

Field	Data set formation (C + L = D)	Order →	Moving average	Normalization	SG Derivative			GS Derivative		Smoothing				Effective range
		Soil properties	w	Type	w	p	m	m	w	s	w	p	m	
Cayenne	23+69 = 92	pH	5	0 to 1	3	2	1	–	–	–	–	–	–	406–1680 nm
		P, K, Mg, Ca, CEC	9	0 to 1	3	2	1	–	–	–	–	–	–	406–1680 nm
		TOC, MC	13	0 to 1	3	3	1	–	–	–	–	–	–	406–1680 nm
Dzhond	16+76 = 92	K	5	0 to 1	3	1	0	1	5	3	5	2	0	407–1665 nm
		TOC, MC	13	0 to 1										405–1680 nm
		Mg	3	0 to 1	3	2	1	1	5	3	5	2	0	402–1680 nm
		P	3	0 to 1	3	2	0	1	7	3	3	2	0	398–1680 nm
		pH	3	0 to 1	7	2	1	–	–	–	–	–	–	399–1680 nm
		Ca, CEC	5	0 to 1	–	–	–	1	7	3	–	–	–	402–1680 nm

Abbreviations: Savitzky and Golay, SG [37]; gap segment, GS; size of the moving window, w; degree of polynomial fitting, p; order of derivatives, m; gap size, s; D, dataset used for modeling; C, number of samples from current field; L, number of spiked from spectral library; moisture content, MC; total organic carbon, TOC; phosphorus, P; potassium, K; magnesium, Mg; calcium, Ca; cation exchange capacity, CEC. The right arrow (→) indicates the sequential pre-processing steps, moving from the left with the moving average towards the right with smoothing.

uniformity (Figure S2).

2.5. Management zones and application maps

Management zones (MZ) were created to generate VR maps for N, compost, and manure applications. This was achieved through the fusion of Sentinel-2 derived crop NDVI data with online predicted soil attributes. The NDVI for the previous cropping season was computed for both fields. A single cropping season NDVI data was accounted for, assuming that this layer of data might not be comparable across multiple years due to interannual variability in the environmental conditions, crop type and management practices driven by crop rotation [17,40]. To minimize this variability effect on the MZ quality, the NDVI data of maize of 2022 was used. Analysing a single year's data avoids complications introduced by interannual variability in weather, soil conditions, crop type and/or management practices, enabling clearer interpretation of crop response. However, accounting for the NDVI for the potato crop in current cropping season was impossible due to the need to apply nitrogen during seeding. To compute the NDVI, Band 4 (B4) and Band 8 (B8) data from multi-band images obtained from the Sentinel-2 open data hub were employed [41], using the following equation:

$$NDVI = \frac{(B8 - B4)}{(B8 + B4)} \quad (4)$$

Before delineating the MZ maps for both fields, a raster analysis was conducted to generate a common grid data matrix with a resolution of 5 by 5 m. This facilitated the resampling of various layers of predicted soil attributes and NDVI data to match the same resolution. Following the raster analysis, a cluster analysis was performed on normalized data layers of soil and crop to divide the field into a limited number of clusters using the K-means clustering algorithm in RStudio (RStudio Inc., USA). Each zone exhibits comparable soil and crop attributes. To ensure that the resulting MZs were both data-driven and practically meaningful for VR fertilization, zones were initially delineated based on the normalized layers of predicted soil properties and NDVI using K-means clustering. The optimal number of clusters ($k = 5$) was determined based on the Elbow method, which assesses the total within-cluster sum of squares (WCSS) for different values of k and identifies the point where increasing k no longer results in a substantial decrease in variance (Figure S2). Compact letter displays (CLDs) were generated to visually interpret statistically significant differences among clusters using annotated boxplots. To validate the statistical distinctiveness of the clusters, one-way analysis of variance (ANOVA) was conducted for each soil fertility variable. Tukey's honestly significant difference (HSD) test was used for post-hoc comparisons (Figure S5 and S6). For each cluster j , a composite fertility index (FI) was calculated to summarize the soil fertility status using the following formula [42]:

$$FI_j = \frac{1}{n} \sum_{i=1}^n \bar{X}_{ij} \quad (5)$$

Where $\bar{X}_{ij}$ is the mean normalized value of soil or NDVI variable i in cluster j , and n is the number of variables. Fertility rank bar plots are shown in Figure S4 in supplementary dataset.

However, we acknowledge that the clustering was based on a single-season dataset, which may not fully capture long-term spatial variability. Moreover, field-specific knowledge such as historical yield patterns and micro-topography, which were not available in the dataset, can influence practical fertilisation needs. Therefore, to refine the cluster-based rankings and improve their usability for VR fertilization, we consulted the farmer to re-rank the five delineated MZs into fertility classes. The farmer's knowledge, based on years of experience with his fields and its varying fertility status across different zones, was valuable in refining the MZs for VR applications. This classification was based on-line predicted soil attributes and NDVI maps. Following the discussion with farmer, the five delineated MZs were categorized into five fertility classes of high fertility (VR-H), medium-high (VR-MH), medium (VR-M), medium-low (VR-ML) and low fertility (VR-L).

In traditional farming, N is uniformly applied across the field based on a composite soil sample, considering nitrate levels and soil texture. For Cayenne, 100 L/ha of N fertilizer (39 % N) was applied, along with 10 t/ha of compost and 5 t/ha of poultry manure, which were used for the UR treatment. Similarly, for Dzhond, the N and compost rates were the same as for Cayenne, while the poultry manure application was increased to 15 t/ha. In both fields, liquid N fertilizer was applied using a John Deere's boom sprayer equipped with section control technology for map-based N application (John Deere, Moline, Illinois, US). A parallel strip map was produced for each field to compare the VR-N, -compost and -poultry manure (PM) application and UR treatment, by using fishnet function in ArcGIS software (Esri, Redlands, CA). For both fields, these treatments designated as VR and UR, were randomly distributed over the parallel strips. Treatments were randomly assigned to strips, ensuring that each treatment was exposed to a variety of environmental conditions across the study area. The random distribution of strips as independent replications helps minimize any potential spatial bias that could arise from environmental gradients. To avoid pseudoreplication, we carefully selected independent sampling units for yield data collection within each strip, ensuring that replicates were sufficiently distanced to represent independent observations in our statistical analysis. Each strip was parallel to the tramline, with a width of 20 m and a length equal to the field length. The UR treatment received the recommended rate of N, compost and manure by the farmer, whereas for the VR treatment Robin Hood principle was followed [18,23], suggesting higher application rates for low fertile zones and vice versa for the high fertile zones. The need for the Robin Hood approach was attributed to

the absence of an on-line sensor that enables the measurement of soil nitrate and N mineralization rate at high sampling resolution, like the online vis-NIR sensor used in the current study to measure OC, Mg, pH, P, K, and Ca (but not nitrate and mineralization rate). Both nitrate and mineral N rate are essential parameters for accurate calculation of recommendation for N fertilization rate, using the N-balance equation [43]. Therefore, an alternative solution for precision fertilization was necessary as high resolution data is required. The Robin Hood approach was introduced by Nawar et al. [18], as an alternative when no data with high sampling resolution could be obtained on nitrate and mineralization rate. According to this principle, fertilizer input rates were adjusted based on soil fertility levels in different MZs. In order to see differences between UR and VR fertilization, extreme low and high rates need to be tested to evaluate the crop response to each scenario. Specifically, VR-L (variable rate low fertility) and VR-ML (variable rate medium-low fertility) zones received 50 % and 25 % more fertilizer, respectively, compared to the medium fertility (M) and uniform rate (UR) zones (actually the farmer used rates). Meanwhile, VR-H (variable rate high fertility) and VR-MH (variable rate medium-high fertility) zones received 50 % and 25 % less fertilizer, respectively, than the UR zone (Fig. 3). This study was conducted on a commercial farm where the farmer did not allow unfertilized plots, as this could risk under-fertilization and yield loss. The UR treatment served as the control in our study, whose fertilizer rate was determined according to the Soil Service Belgium (BDB, Heverlee, Belgium). In fact, BDB collects about 1 soil sample per ha or per field at three depths of 0–30 cm, 30–60 cm and 60–90 cm, which are analyzed for nitrate and soil texture by feeling to determine N and manure fertilization rate for a specific crop.

2.6. Crop management and yield measurement

In this study, standard crop management practices commonly used in potato production were implemented. According to MZs recommendation, compost and poultry manure were applied before seedbed preparation using a rear-discharge commercial manure spreader equipped with a Trimble's VR control system and a GPS (Rolland Trailer, Finistere, France). Liquid nitrogen fertilizer with a nitrogen concentration of 39 % was applied at varying rates based on the recommendations of MZs after crop germination on May 12, 2023. In both fields the consumption potato was cultivated and seeding rate was set at 2200 kg/ha, and various herbicide and fungicide were applied throughout the growing season. In Dzhond, the potato cultivar Hermes was planted, while in Cayenne, the cultivar Fontaine was planted. No irrigation was applied to Dzhond field, whereas the Cayenne field underwent four irrigation events throughout the cropping season by using a gun-type sprinkler irrigation system, with approximately 30 mm of water applied during each session.

Potato tuber yield was harvested manually according to method described by Munaf et al [44]. In each field, within every treatment replication polygon, 20 sampling points in Dzhond and 27 sampling points in Cayenne field were designated for harvest, from each of which 11 plants were manually harvested. Subsequently, the yield was calculated per plot, considering the area covered by 11 plants, and then extrapolated to the strip and treatment levels. Before weighing, potatoes were cleaned well manually and rotten potatoes were removed.

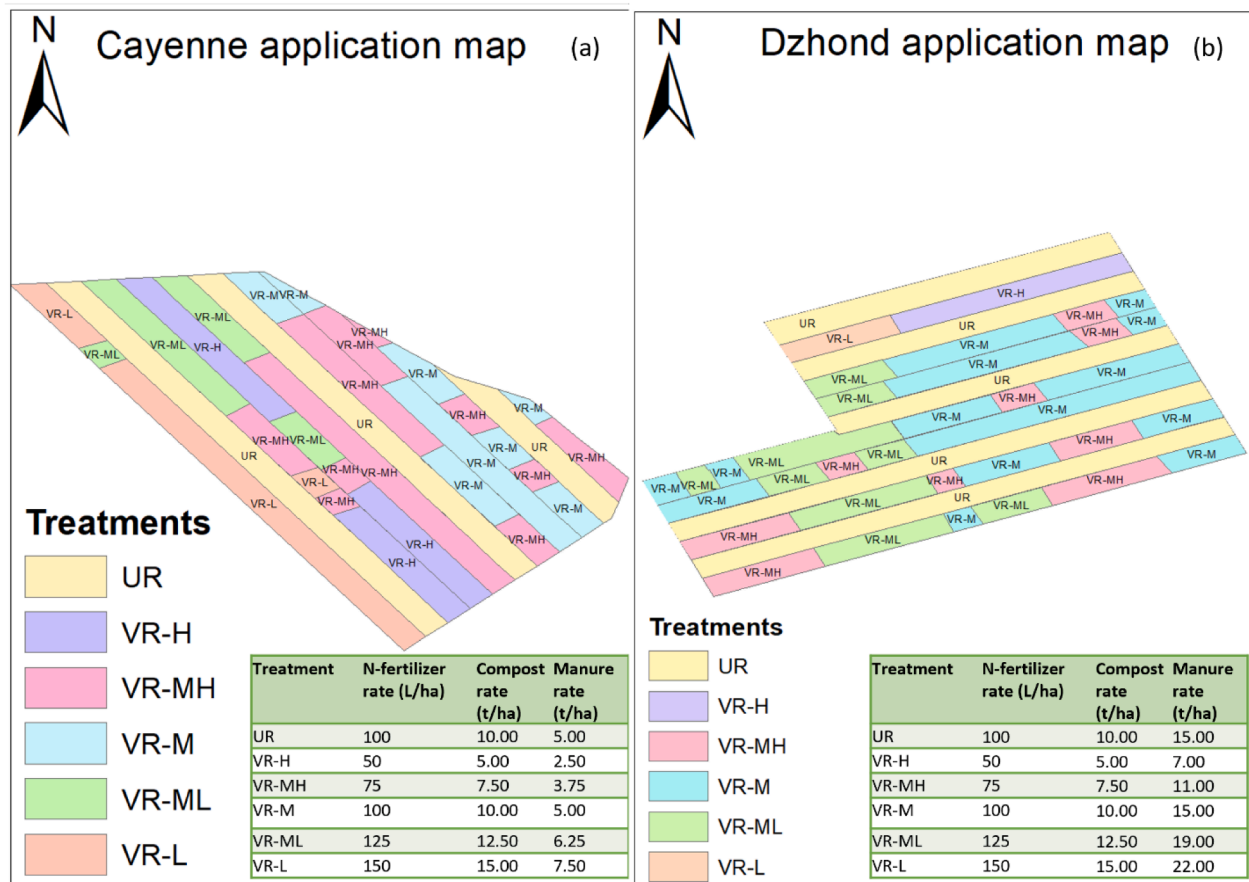


Fig. 3. Strip experiment maps comparing variable-rate (VR) treatments with uniform rate (UR) treatments in Cayenne (a) and Dzhond (b) fields. VR-H, variable-rate high fertile zone; VR-MH, VR medium-high fertile zone; VR-M, VR medium fertile zone; VR-ML, VR medium-low fertile zone; VR-L, VR low fertile zone.

2.7. Economic and environmental analysis

Cost-benefit analyses were conducted based on the expenses incurred for manure, compost, and N fertilizer, as provided by the farmer. The cost of spreading both manure and compost was €12 per ton. The cost of N fertilizer was €400 per ton, calculated based on the current fertilizer price and the N percentage in the fertilizer. The area for each treatment was determined using field map in the ArcGIS software (ESRI ArcGIS v10.7, Redlands, CA, USA). The current potato prices were €200 per ton for Dzhond and €225 per ton for Cayenne, as provided by the farmer. The profitability (gross margin) was calculated by subtracting the variable costs related to fertilizer, compost, and manure from the revenue generated from selling potato tubers (based on the current market price of potatoes). In this study, the expense of field scanning was not included, as the cost of soil scanning, assessed at €25 per year, should be allocated across multiple VR applications of agricultural inputs (such as manure, fertilization, seeding, irrigation, and tillage). Simulated profit was made for whole field assuming VR application in the whole field.

The yield response index (YRI) was also consider in this work, which quantifies the relative yield response to a VR application in comparison to a UR application. YRI was computed using the following equation.

$$YRI = \frac{\text{Yield with VR input}}{\text{Yield with UR input}} \quad (6)$$

Environmental analysis regarding N and P usage was conducted by calculating N use efficiency (NUE) and PUE, respectively, which measure how efficiently N and P were utilized by the crop in relation to crop yield. NUE and PUE were calculated by using following equations, respectively [45].

$$NUE = \frac{\text{Crop yield}}{\text{total N input}} \times 100 \quad (7)$$

$$PUE = \frac{\text{Crop yield}}{\text{total P input}} \times 100 \quad (8)$$

Net N and P impacts were calculated as the change in N and P input, respectively, between the VR and the UR treatments.

2.8. Statistical analysis

Measured soil properties were statistically analyzed to detect outliers and assess the overall quality of soil data using R Studio (RStudio Inc, USA). We evaluated significant differences among the different treatments regarding crop yield through ANOVA, followed by a post hoc Tukey's HSD test at a significance level of $P \leq 0.05$. Before performing ANOVA, the underlying assumptions of normality and homogeneity of variance were checked. Normality of residuals was assessed using the Shapiro-Wilk test, while homoscedasticity (equal variance) among treatment groups was tested using Levene's test (centered at the median). For both datasets (Dzhond and Cayenne), residuals satisfied the normality assumption (Shapiro-Wilk test $p > 0.05$) and showed no significant deviation from homogeneity of variances (Levene's test $p > 0.05$), supporting the validity of ANOVA results. In this study, to identify optimal nitrogen input rates balancing crop yield (Y) and NUE, we calculated the Pareto frontier, which represents the set of solutions where improvement in one objective cannot be achieved without compromising the other [46]. Formally, a nitrogen rate x_i with corresponding values (Y_i , NUE_i) is considered Pareto optimal if there is no other nitrogen rate x_j such that: $Y_j \geq Y_i$ and $NUE_j \geq NUE_i$, with at least one inequality being strict. In other words, the point x_i is not dominated by any other point x_i in terms of both yield and NUE.

We implemented this by comparing each nitrogen rate's yield and NUE against all other rates in the dataset. Points that were not dominated by any others were identified as members of the Pareto frontier. This allows to highlight nitrogen input rates that offer the most efficient trade-offs between maximizing crop yield and NUE, facilitating more

informed nutrient management decisions.

3. Results

3.1. Performance of online prediction models

The results showed that the prediction accuracy varies between Cayenne and Dzhond fields and across different soil properties (Table 3). The PLSR models showed reliable performance in both calibration and prediction phases in both study areas. At the Cayenne site, in the calibration set, RPD values ranged from 1.88 (Mg) to 6.52 (Ca and CEC), while RPIQ values ranged from 2.58 (Mg) to 9.82 (Ca). In the prediction set, RPD values ranged from 1.74 (Mg) to 2.22 (Ca), and RPIQ ranged from 0.38 (TOC) to 4.40 (Ca). Similarly, at the Dzhond site, RPD values in the calibration set ranged from 2.18 (Mg) to 5.04 (CEC), and RPIQ values ranged from 2.69 (MC) to 7.75 (CEC). In the prediction set, the highest RPD value was 4.49 for pH, while the lowest was 1.82 for MC and Mg. RPIQ values in the prediction set ranged from 1.48 (pH) to 3.64 (K). Notably, the online prediction accuracy for most soil properties was slightly better at the Cayenne site compared to the Dzhond site.

3.2. Within field spatial variability and delineation of management zone maps

In both Cayenne and Dzhond fields, substantial variability in soil properties was found (Table 1). Spatial autocorrelation analysis using global and local bivariate moran's I revealed varying levels of spatial agreement between measured and predicted soil property values across the study sites (Figure S2). In Cayenne, the strongest spatial concordance was observed for Mg, with a global moran's I of 0.62, followed by CEC ($I = 0.56$), K ($I = 0.41$), TOC ($I = 0.38$), pH ($I = 0.23$), and ($I = 0.03$). In contrast, in Dzhond, the highest spatial agreement was found for phosphorus (P; $I = 0.45$), followed in descending order by Mg, CEC, TOC, K, and pH. These results indicate that the degree of spatial correspondence between measured and predicted values varied by both site and soil property, reflecting site-specific prediction performance and spatial structure. Maps of online predicted soil properties and NDVI exhibited noticeable spatial differences in both fields (Fig. 4 and 5). At the Cayenne site, the southwestern edge of the field exhibited lower levels of soil pH, TOC, P, K, Mg, and CEC, indicating poor soil fertility (Fig. 4). This was partially supported by the NDVI map, which showed a corresponding indication of poor fertility in that part. In the middle part of the field, soil pH, TOC, P, and K levels were higher, classifying it as a fertile zone. The northeastern part of the field was classified as a medium fertility zone, as concentrations were moderate compared to other parts of the field. At the Dzhond site, soil pH exhibited a pattern similar to P and CEC distribution, with lower levels observed in the northern part of the field, indicating a zone of poor fertility (Fig. 5). The northeast part of the field showed the highest concentration of TOC, K, and to some extent NDVI, classifying it as a fertile zone. Based on the normalized mean plot, the five MZs were ranked into H (dark brown), MH (green), M (light blue), ML (orange), and L (pink) fertility for Cayenne (Fig. 4b) and Dzhond field (Fig. 5b). For both fields, the MZs effectively captured the spatial variability patterns observed in soil properties and NDVI.

3.3. Potato yield response to variable-rate application

The VR application of manure, compost, and N fertilizer significantly influenced potato yield in both fields (Table 4). At the Cayenne site, compared to the UR treatment, the VR-ML treatment, which received 25 % more inputs, and the VR-L treatment, which received 50 % more inputs, resulted in yield increases of 9.16 % and 8.89 %, respectively. Interestingly, the VR-M treatment, which received the same input rates as the UR treatment and smaller rates than both VR-ML and VR-L, showed a 14.3 % yield increase compared to the UR treatment. Meanwhile, the VR-H and VR-MH treatments, which received 50 % and 25 %

Table 3

Results of online predictions of different soil properties using the partial least squares regression (PLSR) models for Cayenne and Dzhond fields.

Experimental sites	Soil properties	Calibration (70 %)					Independent validation (30 %)				
		R ²	RMSEC	RPDC	RPIQC	LV _C	R ²	RMSEP	RPDP	RPIQP	LV _P
Cayenne	MC	0.79	3.32	2.24	3.38	6.00	0.77	2.57	2.13	3.76	6.00
	pH	0.74	0.26	2.00	2.27	6.00	0.68	0.29	1.80	2.93	6.00
	TOC	0.95	0.88	5.00	7.50	6.00	0.68	1.96	1.80	0.38	6.00
	P	0.87	3.67	2.79	3.87	3.00	0.77	3.87	2.15	2.32	3.00
	K	0.91	3.71	3.47	6.19	5.00	0.77	6.46	2.14	2.05	5.00
	Mg	0.71	6.67	1.88	2.58	3.00	0.66	6.92	1.74	1.01	3.00
	Ca	0.97	270.70	6.52	9.82	6.00	0.78	935.97	2.22	4.40	6.00
Dzhond	CEC	0.97	13.40	6.52	9.72	6.00	0.78	46.77	2.21	4.35	6.00
	MC	0.84	0.56	2.53	2.69	11.00	0.68	0.91	1.82	2.63	11.00
	pH	0.89	0.14	3.22	4.82	5.00	0.95	0.07	4.49	1.48	5.00
	TOC	0.87	0.13	2.85	5.12	9.00	0.71	0.17	1.95	3.45	9.00
	P	0.85	3.93	2.60	4.06	4.00	0.72	4.58	1.94	3.54	4.00
	K	0.83	2.52	2.47	3.95	10.00	0.71	4.25	1.93	3.64	10.00
	Mg	0.78	2.63	2.18	3.13	9.00	0.68	2.49	1.82	2.60	9.00
	Ca	0.96	250.64	5.02	7.71	10.00	0.70	696.5	1.87	3.16	10.00
	CEC	0.96	12.54	5.04	7.75	10.00	0.70	34.71	1.89	3.19	10.00

Abbreviations: LV, latent variables; moisture content, MC; total organic carbon, TOC; phosphorus, P; potassium, K; magnesium, Mg; calcium, Ca; cation exchange capacity, CEC; coefficient of determination, R²; root mean square error of calibration, RMSEC; ratio of performance to deviation for calibration, RPDC; ratio of performance to interquartile range of prediction, RPIQP.

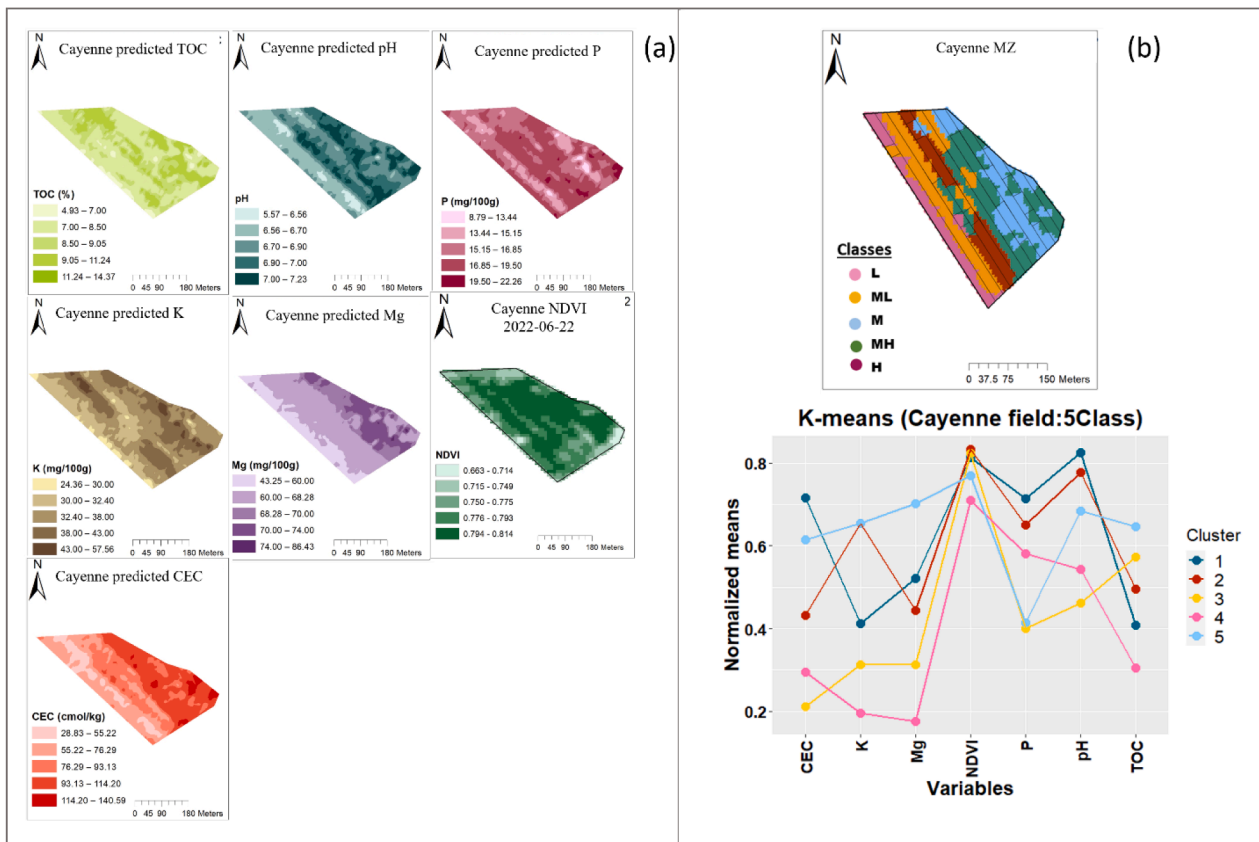


Fig. 4. Maps of online predicted soil total organic carbon (TOC), pH, phosphorous (P), potassium (K), magnesium (Mg) and cation exchange capacity (CEC) and sentinel-2 derived crop normalized difference vegetation index (NDVI) (a) and management zone (MZ) maps developed by K-mean clustering analysis, and classified to high (H), medium h (MH), medium (M), medium low (ML) and low (L) fertility classes (b) for Cayenne field.

less compost, manure, and N, respectively, decreased crop yield by 5.31 % and 11.61 % compared to the UR treatment.

At the Dzhond site, the VR-H and VR-ML treatments resulted in a 14.85 % and 18 % yield increase, respectively, compared to the UR treatment. In contrast, the VR-L treatment, despite receiving 50 % more manure, compost, and N than the UR treatment, showed an 11 % yield decrease. The crop yield also slightly decreased in the VR-M and VR-MH treatments by 5.66 % and 3.00 %, respectively, compared to the UR

treatment.

3.4. Economic and environmental evaluation

In both fields, the VR treatments increased gross margin compared to the UR treatment (Table 4). In the Cayenne field, the higher crop yield in VR-M, VR-ML, and VR-L compared to UR, led to a positive relative gross margin of 142.11 EUR/ha and a simulated field gross margin of 973.45

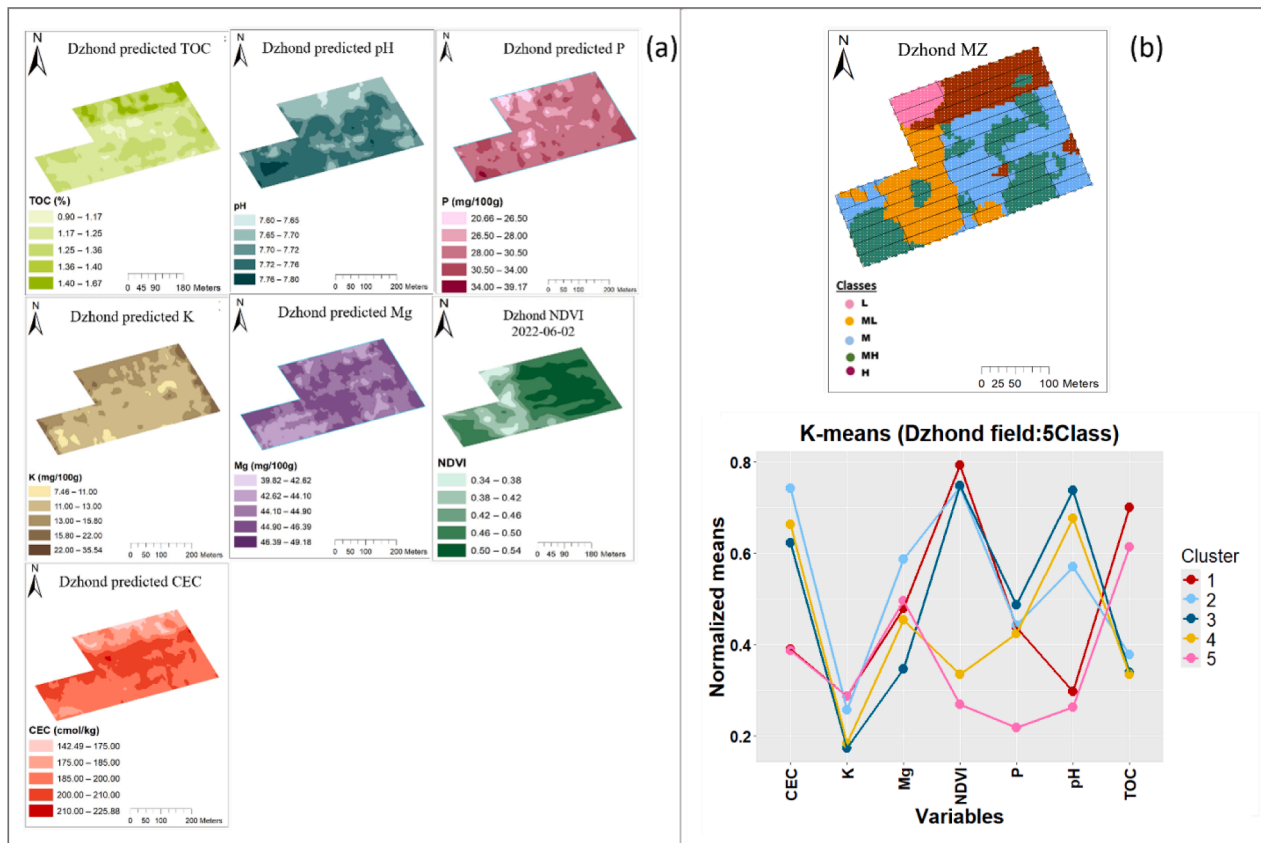


Fig. 5. Maps of online predicted soil total organic carbon (TOC), pH, phosphorous (P), potassium (K), magnesium (Mg) and cation exchange capacity (CEC) and sentinel-2 derived crop normalized difference vegetation index (NDVI) (a) and management zone (MZ) maps developed by K-mean clustering analysis, and classified to high (H), medium-high (MH), medium (M), medium-low (ML) and low (L) fertility classes (b) for Dzhond field.

EUR. Reducing inputs by 25 % (VR-MH) and 50 % (VR-H) resulted in decreased crop yield, negatively affected profitability. In the Dzhond field, the significant increase in crop yield in VR-H, and VR-ML treatments led to an overall increase in relative gross margin of 269.50 EUR/ha and a simulated field gross margin of 1926.92 EUR.

In Cayenne field, the highest YRI was found in VR-M (1.15), followed successively in descent order by VR-L (1.09), VR-ML (1.09), VR-H (0.95), and VR-MH (0.88). Overall, the YRI for VR was positive (1.01). The NUE increased by 89.28 %, 17.80 %, and 14.55 % in VR-H, VR-MH, and VR-M treatments, respectively, while it decreased in VR-ML (12.46 %) and VR-L (26.72 %). Similarly, PUE increased in VR-H, VR-MH, and VR-M by 89.56 %, 17.73 % and 14.47 %, respectively, while it decreased in VR-ML and VR-L compared to UR. Net nitrogen (ΔN) and phosphorus (ΔP) values were positive ($\Delta N = 17.54$, $\Delta P = 10.08$) in this field, indicating that VR treatments used less N and P compared to UR treatments.

In the Dzhond field, the highest YRI was observed in VR-ML (1.18), followed successively in descent order by VR-H (1.15), VR-MH (0.97), VR-M (0.94), and VR-L (0.89). Both NUE and PUE were increased in VR-H and VR-MH and decreased in VR-M, VR-ML, and VR-L compared to UR (Table 5). Both ΔN and ΔP values were positive in this field ($\Delta N = 4.24$ and $\Delta P = 1.74$), they were smaller than those in the Cayenne field ($\Delta N = 17.54$, $\Delta P = 10.08$).

Pareto frontier analysis revealed the optimal N input rate for maximum yield is 246.50 kg/ha in Cayenne and 426.70 kg/ha in Dzhond (Fig. 6). These rates represent the set of solutions where an increase in one objective (e.g., yield) cannot be achieved without a decrease in the other objective (e.g., NUE), illustrating the trade-off between maximizing yield and resource efficiency. Despite similar precision treatments, economic and environmental benefits differed

(Fig. 7). Overall, compared to the UR treatment, the input cost for Cayenne and Dzhond was reduced by 4.87 % and 0.59 %, respectively. Total inputs of N and P were reduced and NUE and PUE were increased compared to the UR treatment (Fig. 7).

4. Discussion

4.1. Online soil model prediction accuracy

This study demonstrated that the prediction accuracy differs between Cayenne and Dzhond fields and also varies across different soil properties (Table 3). These findings align with previous studies utilizing the same online vis-NIR sensing system, as the one used in the current work. For example, Munnaf et al. [22] reported RPD values of different soil properties to range from 3.5 for CEC to 1.69 for K in the calibration set and from 2.89 for Ca and 1.68 for K in the online prediction set. In both fields, the prediction accuracy for most soil properties met the standards outlined by Maleki et al. [47], indicating the necessity to have R^2 values > 0.70 for successful VR applications. The differing accuracies between the two sites could be attributed to variations in soil types and spatial differences in soil properties within each field [48]. It is reported that a diverse dataset with a wide range of variation can offer more insights during model training, potentially resulting in more accurate predictions. However, if the variations are too extreme, they may introduce noise, making it challenging for the model to identify meaningful patterns [49].

For both fields, the present models demonstrated superior predictive accuracy compared to those used in other VR applications employing the same online vis-NIR sensing system. For example, Zhang et al. [17] and Guerrero et al. [23] effectively implemented VRM and VR-N

Table 4
Calculation of cost-benefit (marginal) analysis for variable-rate (VR) of manure, compost and nitrogen (N) fertilizer application in Cayenne and Dzhond fields for potato.

Experimental field	Treatment	Area (ha)	N-fertilizer application rate (N kg/ha)	Compost application (tons/ha)	Manure application (tons/ha)	Cost of N-fertilizer €/treatment	Cost of compost €/treatment	Cost of Manure (€/treatment)	Total input cost (€/ha)	*Yield (ton/ha)	Revenue (€/ha)	Gross margin (€/ha)	Relative gross margin (€/ha)	Simulated Field relative Gross Margin (€)	YRI
Cayenne	UR	1.83	39.00	10.00	5.00	28.59	219.93	109.97	195.60	53.46 c	12,027.4	11,831.84			
	VR-H	0.84	19.50	5.00	2.50	6.54	50.27	25.14	97.80	50.63 d					0.95
	VR-MH	1.64	29.25	7.50	3.75	19.20	147.68	73.84	146.70	47.20 e					0.88
	VR-M	1.04	39.00	10.00	5.00	16.27	125.16	62.58	195.60	61.27 a					1.15
	VR-ML	0.65	48.75	12.50	6.25	12.67	97.49	48.75	244.50	58.51 b					1.09
	VR-L	0.84	58.50	15.00	7.50	19.76	152.03	76.02	293.40	58.37 b					1.01
	Total VR	5.02	37.10	9.51	4.76		344.67	517.00	186.07	54.04	12,160.0	11,973.95	142.11	973.45	1.01
Dzhond	UR	2.87	39.00	10.00	15.00	44.81	18.58	26.01	315.60	60.73 b	12,145.5	11,829.7			1.15
	VR-H	0.31	19.50	5.00	7.00	2.42	75.37	110.54	151.80	69.75 a					0.97
	VR-MH	0.84	29.25	7.50	11.00	9.80			233.70	58.91					
	VR-M	1.90	39.00	10.00	15.00	29.64	228.02	342.03	315.60	57.27 c					0.94
	VR-ML	1.09	48.75	12.50	19.00	21.20	163.04	247.82	397.50	71.77 a					1.18
	VR-L	0.15	58.50	15.00	22.00	3.44	26.49	38.85	467.40	54.03 d					0.89
	Total VR	4.28	38.3	9.96	14.89				313.74	62.07	12,413.1	12,099.4	269.5	1926.92	1.02

Abbreviations: UR, uniform rate; VR-H, variable-rate high-fertilizer; VR-MH, VR medium-high; VR-M, VR medium; VR-ML, VR medium-low; VR-L, VR low-fertilizer zones; YRI, yield response index. * Different alphabet letters beside mean yield values indicate significant differences ($P \leq 0.05$) based on the Tukey's HSD test for Cayenne and Dzhond field.

applications, respectively, using similar online vis-NIR models, reporting R^2 values ranging from 0.51 to 0.81. Similarly, Mouazen and Kuang [50] documented successful site-specific P management using the same online vis-NIR sensor, with an R^2 value of 0.60, whereas the P model in the current study achieved higher R^2 values of 0.77 at Cayenne site and 0.72 at Dzhond site (Table 3). Therefore, it can be confirmed that the current vis-NIR models provide sufficient accuracy for defining MZ maps accurately, to ensure successful VR-M, -N and -compost application.

4.2. Within field spatial variability and quality of management zone maps

Both fields showed noticeable spatial variability in soil properties and crop NDVI (Fig. 4 and Fig. 5). At the Cayenne site, the southwestern edge of the field exhibited lower soil fertility and it was also partially supported by NDVI map. The middle part of the field was classified as fertile zone and the northeastern part of field was classified as medium fertile zone, as it contains moderate level of soil nutrients as compared to the other parts of the field (Fig. 4).

Similar to Cayenne, at the Dzhond field, the northern part of the field showed lower pH, P and CEC, indicating poor soil fertility, however, this observation was not true for NDVI map (Fig. 5). The impact of soil pH is vital for the availability in P, whose uptake can be restricted in both acidic and alkaline soils. In alkaline soil ($pH > 7.5$), P tends to precipitate as calcium phosphate such as dicalcium phosphate ($CaHPO_4$), whereas in acidic soils (pH below 5.5) soil P becomes less soluble as iron and aluminum phosphate [51]. The northeast part of the field was considered the fertile zone with high soil fertility, partially supported by NDVI. However, MZ classification, based on soil fertility and farmer experience, was subjective due to the absence of yield data. Indeed, the MZ in both fields captured spatial variability in soil properties and NDVI. However, using NDVI alone is unreliable for MZ delineation due to discrepancies with soil fertility maps and dissimilarities with yield patterns [52,53]. Due to unavailable historic yield data, NDVI was used as a yield proxy alongside soil properties to classify MZs into five fertility classes, namely, high (H, dark brown), medium-high (MH, green), medium (M, light blue), medium-low (ML, yellow), and low (L, pink), an approach validated in prior VR manure studies [17,50].

4.3. Evaluation of variable-rate application

Variable-rate (VR) application of manure, compost, and N fertilizer significantly influenced potato yields, with notable variability. In Cayenne, VR-M, VR-ML, and VR-L increased yield by 14.3 %, 9.16 % and 8.89 %, respectively, outperformed UR, reflecting effective nutrient targeting in zones of varying fertility (Table 4). In Dzhond, VR-H and VR-ML increased yields by 14.85 % and 18 %, respectively, whereas VR-L, despite applying 50 % higher inputs, resulted in 11 % yield decrease. The reason could be that the 50 % increase in the nutrient input applied was either not sufficient to meet the crop actual needs, or leached in the northern zone's sandy soils, having low-CEC values (Fig. 5). The limited microbial activity in sandy soils may well be the third reason, which may result in reducing organic matter decomposition, exacerbated by unmeasured factors. This results overall in reducing yields due to poor retention and raising concerns about nutrient imbalances and environmental risks, potentially driven by higher microbial activity and TOC [54], though this requires further investigation. A critical limitation is the absence of post-harvest soil nutrient data, which restricts our ability to confirm leaching or imbalances in Dzhond's VR-L zones. Future studies should incorporate post-harvest sampling, as demonstrated by Tsibart et al. [55], to map residual nutrients and optimize VR strategies. However, in Cayenne, the 50 % higher VR-L inputs in the southwestern zone was sufficient to address nutrient deficiencies (Fig. 4), enhancing uptake resulting in increasing yield [56]. Mechanistically, VR's success in Cayenne likely stems from aligning inputs with crop demand, enhancing uptake in fertile zones (e.g., 14.55 % NUE and 14.47 % PUE increases in VR-M; Table 5).

Table 5

Environmental assessment of variable rate (VR) manure, compost and nitrogen (N) application in Cayenne and Dzhond fields for potato.

Field	Treatment	N from manure (kg/ha)	N from compost (kg/ha)	P from manure (kg/ha)	P from compost (kg/ha)	Total N input (kg/ha)	Total P input (kg/ha)	NUE (%)	PUE (%)	Net N impact ΔN (kg/ha)	Net P impact ΔP (kg/ha)
Cayenne	UR	46.05.00	161.00	30.50	157.00	246.50	187.50	21.69	28.51		
	VR-H	23.25	80.50	15.25	78.50	123.25	93.75	41.08	54.01	123.25	93.75
	VR-MH	34.88	120.75	22.88	117.75	184.88	140.63	25.53	33.56	61.63	46.88
	VR-M	46.50	161.00	30.50	157.00	246.50	187.50	24.85	32.68	0.00	0.00
	VR-ML	58.13	201.25	38.13	196.25	308.13	234.38	18.99	24.97	-61.63	-46.88
	VR-L	69.75	241.50	45.75	235.50	369.75	281.25	15.79	20.75	-123.25	-93.75
	Total VR	44.23	153.16	29.01	149.35	234.49	178.37	23.05	30.30	12.01	9.13
Dzhond	UR	139.50	161.00	91.50	157.00	339.50	248.50	17.89	24.44		
	VR-H	65.10	80.50	42.70	78.50	165.10	121.20	42.25	57.55	174.4	127.30
	VR-MH	102.30	120.75	67.10	117.75	252.30	184.85	23.35	31.87	87.20	63.65
	VR-M	139.50	161.00	91.50	157.00	339.50	248.50	16.87	23.05	0.00	0.00
	VR-ML	176.70	201.25	115.90	196.25	426.70	312.15	16.82	22.99	-87.20	-63.65
	VR-L	204.60	241.50	134.20	235.50	504.60	369.70	10.71	14.61	-165.1	-121.20
	Total VR	138.52	160.29	90.85	156.31	337.64	247.17	18.38	25.11	1.86	1.33

Abbreviations: UR, uniform rate; VR-H, variable-rate high-fertile; VR-MH, VR medium-high; VR-M, VR medium; VR-ML, VR medium-low; VR-L, VR low-fertile zones; YRI, NUE, nitrogen use efficiency; PUE, phosphorus use efficiency; $\Delta N = N$ input in UR – N input in VR; $\Delta P = P$ input in UR – P input in VR.

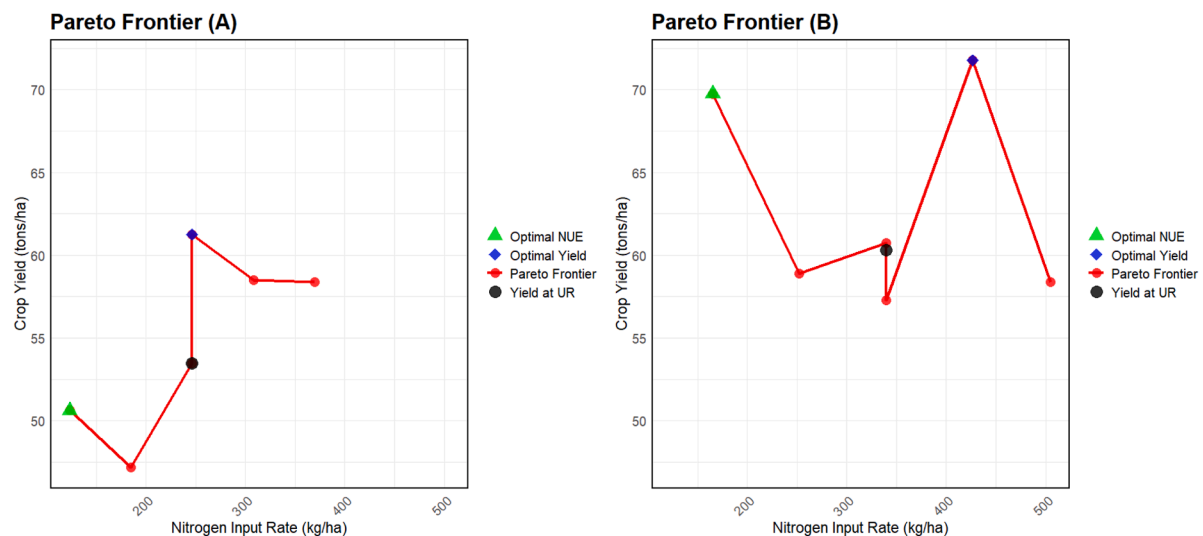


Fig. 6. Pareto frontier of optimal nitrogen rate, optimizing trade-offs between crop yield, nitrogen use efficiency (NUE) and N rates. Red line indicates Pareto frontier, blue dot indicates optimal crop yield and black dot indicates yield at uniform rate and green triangle indicates optimal NUE based on variable rate (VR) treatment in Cayenne (a) and Dzhond (b).

At the Dzhond site, the VR-H treatment produced a higher yield of 14.85 % than the UR treatment. This result supports the Robin Hood approach of feeding less to the high fertile zones and more to the less fertile zone to maximize the yield and minimize the input [40]. This outcome aligns with previous VR-N application studies, reporting that despite lower N input in the VR-H fertility zones, crop yield was higher compared to UR applications (e.g., Munna et al. [52]). High fertile soil can exhibit high nutrient retention capacities owing to elevated TOC, enhanced soil structure, and increased microbial activity [57,58]. These factors collectively facilitate improved nutrient absorption by crops, even with reduced application rates of manure and N fertilizer. However, the VR-ML treatment resulted in the maximum increase in yield of 18 % compared to the UR treatment (Table 4). Additional manure can improve soil nutrient retention capacity and microbial activity [59,60]. In conventional farming, farmers often apply farm inputs like N fertilizer and manure uniformly across their fields, neglecting spatial variability, which can harm crop productivity [61]. Nitrogen is crucial for crop growth, but it's often applied uniformly and in excess, leading to issues like wheat lodging, as reported in previous studies [62]. To maximize crop yield, it's essential to apply the right amount of manure and synthetic N fertilizers, ensuring proper plant growth and productivity [63].

Using MZ defined by high-resolution soil and remote sensing crop data for VR application of combined inputs (e.g., N, manure and compost) boosts profitability by increasing yield and reducing excessive input use, results which are consistent with previous studies on VR N fertilization [64] and VR manure application [17]. The VR fertilization relative gross margins of €142.11/ha in Cayenne and €269.50/ha in Dzhond compared to UR (Table 4) is in line with findings by Basso et al. [65]. However, these must be weighed against costs of soil scanning, precision application equipment, and data management. In Cayenne, the 14.3 % yield increase in VR-M contributed to profitability; however, in fields with low spatial variability, the economic benefits of precision equipment and soil mapping may be limited. Bullock et al. [66] highlight that the value of VR technology depends heavily on field heterogeneity, implying that in more uniform fields or for smallholders, the costs may outweigh the benefits, underscoring the need for careful economic evaluation before adoption.

Environmentally, VR enhanced NUE and PUE in high-fertility zones e.g., by 89.28 % and 89.56 %, respectively, in Cayenne's VR-H (Table 5), suggesting reduced leaching and runoff, whereas VR-L and VR-ML showed decreases, reflecting inefficiencies in low-fertility zones. In Dzhond, the VR-L yield drop and lower ΔN (4.24) and ΔP (1.74)

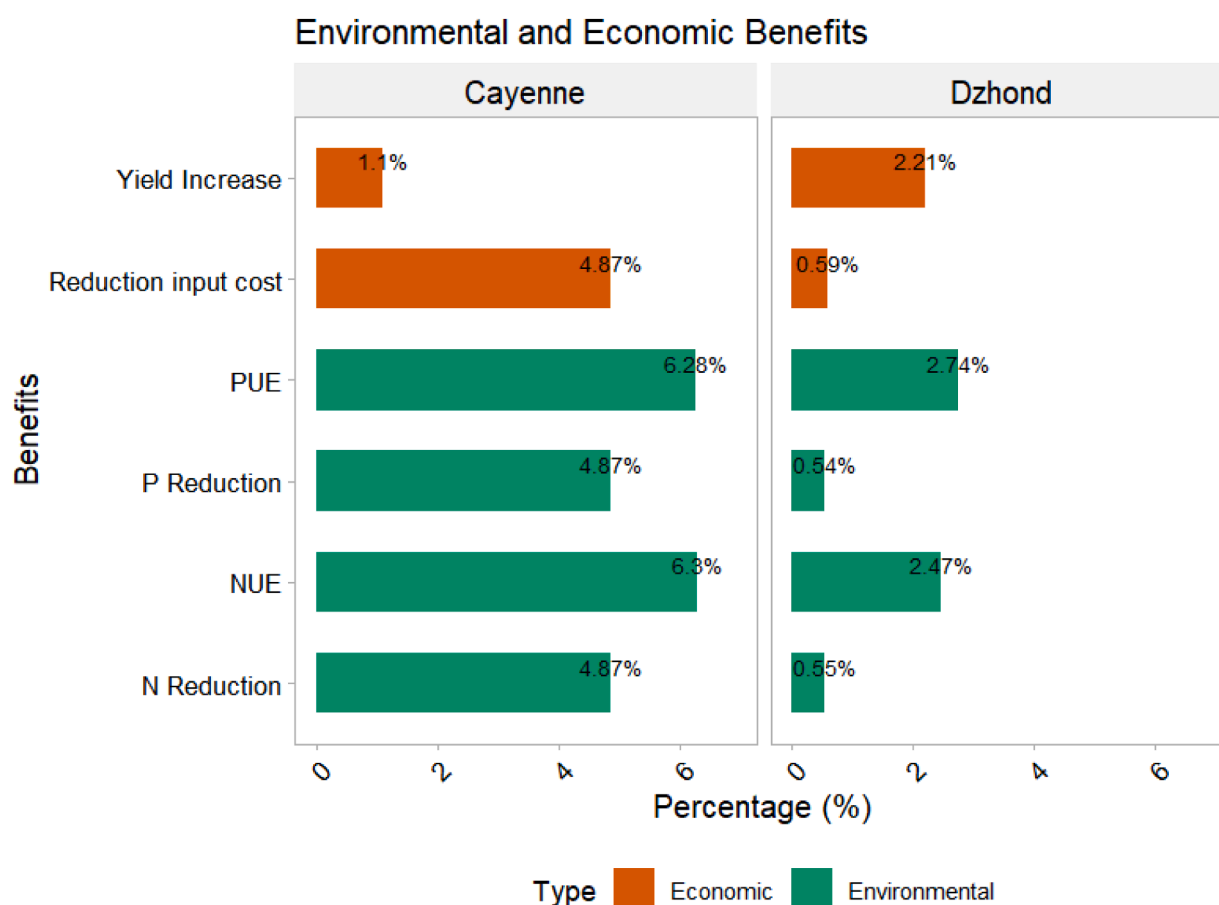


Fig. 7. Economic and environmental benefits of variable-rate (VR) of manure, compost and nitrogen (N) application in Cayenne (a) and Dzhond (b) fields. Nitrogen use efficiency, NUE; phosphorus use efficiency, PUE.

compared to Cayenne ($\Delta N = 17.54$, $\Delta P = 10.08$) indicate potential losses in sandy soils. Without quantified runoff data, field-scale significance is limited. Future studies should measure nutrient losses to link VR to water quality and sustainability goals. However, the positive ΔN and ΔP values in both fields, showing the difference in N and P input between VR and UR treatments, indicate that VR treatments used less N and P compared to UR (Table 5). This indicates VR provides economic savings, support sustainability [67], without compromising crop yield, leading to reduced emissions, improved soil health, and efficient resource use.

Furthermore, Pareto frontier analysis offers valuable insights into optimizing N input rates based on current VR to achieve both maximum yield and NUE in both fields (Fig. 6). By balancing agronomic performance with environmental sustainability, the Pareto frontier aids informed decision-making and resource management practices for sustainable crop production [46,68]. In this study, the optimal N input rate for maximum attainable yield was found to be 246.50 kg/ha in Cayenne and 426.70 kg/ha in Dzhond (Fig. 6). The substantial difference in N requirements between the two fields highlights site-specific variability in soil fertility, N mineralization potential, and crop response to fertilization. Such variation underscores the necessity of precision N management to prevent over-application, which can lead to N losses, reducing NUE and increasing environmental risks [69,70].

The economic and environmental benefits of VR treatments varied between fields (Fig. 7), likely due to differences in potato cultivars (Hermes in Dzhond vs. Fontaine in Cayenne) and soil fertility, with Dzhond requiring higher N inputs (426.70 kg/ha vs. 246.50 kg/ha in Cayenne, Fig. 6), underscoring the need for VR strategies. Therefore, it can be concluded that the benefits of precision fertilization of N, manure and compost depend not only on the precision application methods but

also on other agronomic factors, such as crop type and cultivar.

In this study, we used the Robin Hood scheme to guide precision management of manure and mineral N fertilizer. This was based on previous studies showing that the Robin Hood approach improves agronomic, environmental and economic benefits compared to the UR [17,40]. However, the Robin Hood principle, which allocates higher inputs to low-fertility zones and lower inputs to high-fertility zones [40], failed in Dzhond's VR-L zone, where excessive inputs in sandy, low-CEC soils likely caused leaching, as seen in the northern zone (Fig. 5), rather than yield gains. This failure highlights the principle's limitation in overlooking temporal variability as low-fertility zones may improve with organic amendments or vary seasonally. Fixed constraints (e.g., soil structure) may not always limit yield potential.

The contrasting VR-L yield responses highlight the critical role of soil properties and nutrient dynamics in VR efficacy. High-resolution post-harvest soil sampling and advanced sensing (e.g., vis-NIR for N mineralization [71], electrochemical sensors for nitrate [72]) could address limitations and enhance precision. Economically, adoption of VR's in low-variability fields or for resource-limited farmers should not be made without cost-benefit analysis [66]. Environmentally, VR improves NUE and PUE in high-fertility zones, but quantifying nutrient losses is essential to validate sustainability benefits [56]. VR should target fields with high spatial variability, supported by robust soil data and economic assessments, to optimize agronomic, economic, and environmental outcomes.

5. Conclusion

Variable-rate (VR) application of compost, manure, and nitrogen fertilizer based on fertility MZ delineated from high-resolution soil data

and crop NDVI determined by Sentinel-2 satellite images, improved potato yields and profitability compared to uniform rate (UR) application. In the VR-L zone, a 50 % increase in inputs boosted yield in Cayenne but reduced it in Dzond, likely due to soil property differences (i.e., soil texture and CEC), emphasizing the need for more precise nitrogen recommendations based on high-resolution, cost-effective data, including N mineralization rates to ensure the accurate calculation of fertilizer recommendations for precision nutrient management. Overall, the VR approach improved NUE and PUE, while reducing inputs and increasing yield. These findings suggest that VR fertilization using precision agricultural technologies is economically and environmentally beneficial, though the “Robin Hood principle” showed limitations in low-fertility zones, but outcomes may vary depending on cultivar, soil fertility, and field variability. Future studies should incorporate soil N and historical crop yield data to optimize VR fertilization and tailor recommendations to specific crop needs.

Ethical statement

This research was conducted in accordance with ethical standards, with no human or animal subjects involved, and there are no conflicts of interest.

CRediT authorship contribution statement

Muhammad Qaswar: Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Abdul Mounem Mouazen:** Writing – review & editing, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Conceptualization.

Declaration of competing interest

The authors declare no conflicts of interest.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at [doi:10.1016/j.atech.2025.101328](https://doi.org/10.1016/j.atech.2025.101328).

Data availability

The authors do not have permission to share data.

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