Article:

Zhang, Y., Wang, X., Liu, T. et al. (4 more authors) (2023) Sustainable fertilisation management via tensor multi-task learning using multi-dimensional agricultural data. Journal of Industrial Information Integration. 100461. ISSN 2452-414X

https://doi.org/10.1016/j.jii.2023.100461

Journal Pre-proof

Sustainable Fertilisation Management via Tensor Multi-task Learning using Multi-dimensional Agricultural Data

Yu Zhang , Xulong Wang , Tong Liu , Ruijing Wang , Yang Li , Qing Xue , Po Yang

PII: S2452-414X(23)00034-1
DOI: https://doi.org/10.1016/j.jii.2023.100461
Reference: JII 100461

To appear in: *Journal of Industrial Information Integration*

Received date: 1 October 2022
Revised date: 24 February 2023
Accepted date: 1 April 2023

Please cite this article as: Yu Zhang , Xulong Wang , Tong Liu , Ruijing Wang , Yang Li , Qing Xue , Po Yang , Sustainable Fertilisation Management via Tensor Multi-task Learning using Multi-dimensional Agricultural Data, *Journal of Industrial Information Integration* (2023), doi: https://doi.org/10.1016/j.jii.2023.100461

Sustainable Fertilisation Management via Tensor Multi-task Learning using Multi-dimensional Agricultural Data

Index Terms—**Precision fertilisation, real-world agricultural data, multi-task learning, spatio-temporal tensor, tensor decomposition**

Yu Zhang[1], Xulong Wang[1], Tong Liu[1], Ruijing Wang[2], Yang Li[3], Qing Xue[3], Po Yang[1*]

***Abstract*—Precision fertilisation is crucial to agricultural system, which enables to balance soil nutrients, save fertiliser, reduce emissions, and increase crop yield productivity. Due to the low-level sensor and network technologies on most farms, it is difficult to acquire diverse and comprehensive agricultural data. Hence, the absence of agricultural data becomes a major obstacle to the applications of machine learning techniques in precision fertilisation. In this work, we investigate a newly acquired real-world agricultural dataset collected from four genuine winter wheat farms in the United Kingdom, which covers various sorts of agricultural information, such as climate, soil nutrients, and crop yield. To deal with the spatio-temporal characteristics of the agricultural dataset, we propose a novel multi-task learning (MTL) approach that utilises a tensor created from original data to efficiently predict the amount and timing of base fertiliser and topdressing. Specifically, the agricultural measurements (such as climatic data, soil nutrients, etc.) are encoded into a three-dimensional tensor, and tensor decomposition is utilised to extract a series of interpretable temporal and spatial latent factors from the raw data. The latent factor is then utilised as a multi-task relationship to train the spatio-temporal tensor prediction model. The temporal latent factor can be regarded as a temporal pattern shared by different farms on the fertilisation operation of the same crop, and the spatial latent factor can be regarded as the influence of different farm locations on the fertilisation operation of the same crop. Extensive experiments are carried out to evaluate our proposed method utilising the real-world agricultural dataset, in comparison to the standard regression models. Results show that our proposed method provide superior accuracy and stability in fertilisation prediction. Moreover, we have constructed a precision fertilisation system that integrates the proposed algorithm and multi-dimensional agricultural data to assist farms in achieving intelligent, precise and personalised farm management and fertilisation decisions.**

1

[1] Department of Computer Science, University of Sheffield, Sheffield, UK
[2] The Institute of Intelligent Machines, Chinese Academy of Sciences, Hefei, China
3. AntData Ltd, Liverpool, UK.

*Corresponding author: Dr. Po Yang (po.yang@sheffield.ac.uk)

I. Introduction

SUSTAINABLE fertiliser management and reducing farming emissions have become high priority agricultural issues in recent decades. The excessive use of chemical fertilisers and pesticides is causing damage to the soil and ecosystem, as well as hazards to human health (Sharma and Singhvi, 2017). Many countries have given strong support for innovating artificial intelligence (AI) assisted smart farming technologies to enhance production and reduce emissions. For example, there are farming, seeding, and selecting intelligent robots (Fue et al., 2020) (Sowjanya et al., 2017), as well as intelligent detection systems, such as intelligent soil detection, disease and insect pest detection, and climatic disaster warning (Ray, 2017) (Shi et al., 2019). Besides, smart wearable products for poultry and cattle are widely employed in the livestock breeding business (Halachmi et al., 2019) (Neethirajan, 2017). These AI-assisted techniques significantly improve the yield productivity and operational intelligence.

Despite the above achievements, the use of AI in precision fertilisation is still largely under studied. Fertilisers are materials of natural or synthetic origin that are applied to soil or to plant tissues to supply nutrients. For good nutrient management, the total supply of nutrients from all these sources must meet, but not exceed crop demand. Applying the correct amount of nitrogen at the correct time is an essential feature of good crop management. For most fertiliser applications, however, soil does not always provide the best nutrients for crops, and farmers must rotate their crops on a regular basis. Traditionally, this is achieved by using human experts and prior knowledge. Based on the first-principle, the nutrient balance model (Bindraban et al., 2000) and fertiliser effect function model (He et al., 2011) are two classic methods for estimating fertiliser application rates. The nutrient balance method is typically computationally expensive due to the large number of involved factors, and it heavily relies on human experts and prior knowledge. The fertiliser effect function method requires the fitting of ternary quadratic equations using massive experimental data. Such function fitting is normally poor due to the low-quality of data. Hence, these mechanism models are not

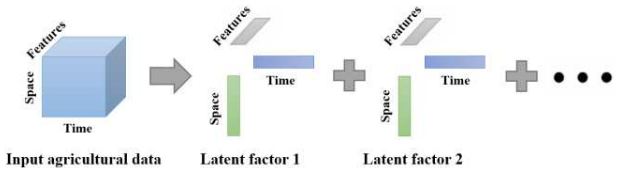


Fig. 1. CP decomposition is signified by a tensor based on the input agricultural data.

applicable to precision fertilisation. An alternative way is to employ data-driven techniques using machine learning models. However, high-quality data acquisition from farms is a difficult task. Large amounts of data in the domains of agronomy, remote sensing, and plant breeding are collected by national and international agricultural research agencies, which can theoretically support machine learning models. However, these data are often non-reusable, non-interpretable or non-discoverable (Tzachor et al., 2022). The incomplete and skewed agricultural data directly leads to the poor decision making in fertilisation, hence causing the overuse and waste of fertilisers in farms. To the best of our knowledge, a complete agricultural dataset has not been established so far for smart fertiliser study. More critically, the development of machine learning model driven by agricultural data for precision fertilisation is still a vacant research field.

To fill this research vacancy in smart agriculture community, this paper proposes a novel MTL approach for precision fertilisation utilising newly acquired real-world agricultural data. This dataset was collected from four genuine winter wheat farms in the United Kingdom, which covers various sorts of agricultural information, such as climate, soil nutrients, and crop yield. Due to the different farm locations and acquisition time, the obtained dataset exhibits strong spatio-temporal characteristics, which is difficult to mine for traditional machine learning models. Our proposed tensor-based MTL model can effectively capture spatio-temporal characteristics of the agricultural data, thus enabling accurately predicting the fertiliser amount and time for different farms. As is known, standard machine learning regression models aim to optimize a certain metric of a single task, which fails to capture the related information from other learning tasks (Zhou et al., 2011). By sharing joint representations among related tasks, MTL allows to make full utilise of information from other tasks, thus improving the achievable performance (Zhang and Yang, 2021). It should be noted that integrating spatio-temporal information from different farms into MTL framework for precision fertilisation is a challenging task. First, it is difficult to collect agricultural data and fertiliser application records from various farms and digitizing them into a AI-model-friendly dataset. Second, it is challenge to integrate both temporal and spatial information into the MTL model with a tensor representation. Third, traditional MTL correlations are based on various assumptions made by task models, such as low rank assumption (Kumar and Daumé, 2012) and temporal

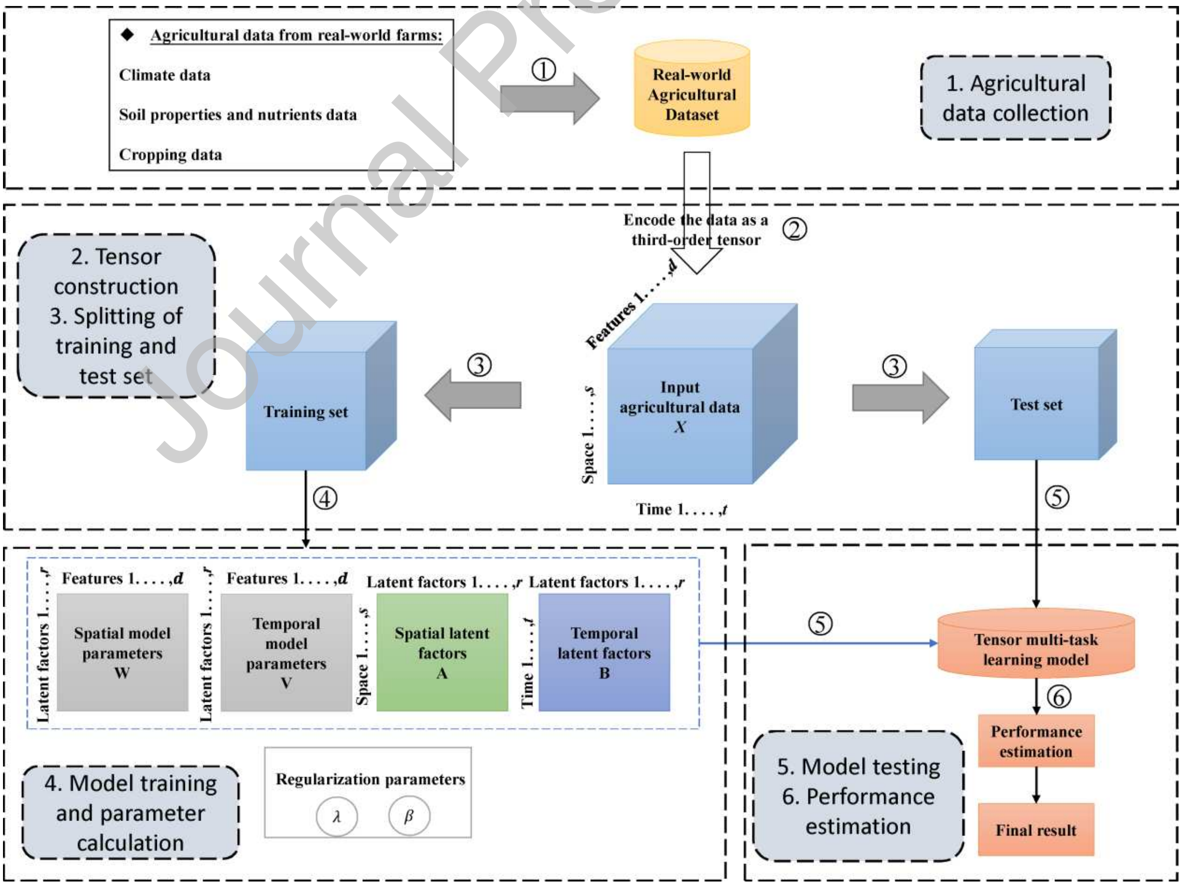


Fig. 2. Overview of the presented spatio-temporal tensor multi-tasking regression framework.

smoothing assumption (Zhou et al., 2013), but how to define tasks and correlations among tasks remains a problem when combining spatio-temporal tensor with MTL model.

To address above-mentioned problems, a real-world agricultural dataset from four genuine winter wheat farms, containing a variety of agricultural features such as climate, soil nutrients, crop yield, and fertilisation records, is first formed for smart fertiliser study. To deal with the spatio-temporal characteristics of this dataset, we propose a novel MTL method by integrating a three-dimensional tensor created from raw data to accurately predict the amount and timing of base fertiliser and topdressing. Specifically, a third-order spatio-temporal tensor is utilised to represent real-world agricultural data from various farms. Space (i.e., the various farms), time (i.e., from September to August the following year), and features (i.e., various input agricultural information) denote three dimensions of the tensor. Based on CANDECOMP/PARAFAC (CP) approach (Kolda and Bader, 2009), the proposed model decomposes tensors and extracts a series of rank-one latent factors from the original data. The agricultural spatio-temporal data can be decomposed into multiple rank-one tensors, with each rank-one tensor generated utilizing the outer product of three rank-one latent factors (Fig. 1). Since each latent factor can be characterized in terms of space, time, and feature dimensions, an interpretable approach for describing the latent factors that govern data variability is proposed. Fertiliser application prediction for different months and different farms are the tasks in this research, the spatial (farm) and temporal (month) latent factors obtained from the raw agricultural data combined with tensor decomposition are the multi-task relationships in the model. The latent factors can be utilised as predictors to train a MTL model that aggregates the outputs of the spatial and temporal models to generate final predictions while incorporating sparsity-inducing norms as additional constraints to prevent overfitting and improve model interpretability.

The main contributions of this paper are as follow:

1) A real-world agricultural dataset from four genuine winter wheat farms is established for smart fertiliser study. This provides a desirable platform for machine learning assisted precision fertilisation.

2) To exploit the spatio-temporal information reside in the agricultural data, the original data is encoded into a third order tensor. Followed by this, a novel tensor-based MTL framework is proposed for precise fertilisation. It employs tensor decomposition to learn task correlations from raw data and seamlessly integrates temporal and spatial latent factors in the model to improve fertilisation prediction accuracy and stability.

3) Extensive experiments are carried out to evaluate our proposed method utilising the real-world agricultural dataset, in comparison to the standard regression models. Moreover, important factors that influence the nitrogen fertilisation process is identified and analyzed.

The rest of the paper is organized as follows: Section II introduces the literature review. The proposed Tensor MTL model for precision fertilisation research is presented in Section III. Our real-world agricultural dataset, preprocessing steps, and experimental steps are presented in Section IV. Section V provides the experimental results for the agricultural dataset, which were utilised to validate the performance of the proposed prediction model, as well as a discussion of the important features and discoveries for our proposed approach. Section VI introduces our precision fertilisation system, which integrates the proposed algorithm and multi-dimensional agricultural data. The paper is concluded in Section VII.

II. Literature Review

Precision agriculture is a system that uses information technology to perform a comprehensive set of modern agricultural operation technology and management based on geographical variation at a defined time, location, and quantitatively (Zhang et al., 2002). Its core concept is to modify crop inputs based on soil parameters, mobilise soil production, and produce the same or higher revenue with the least amount of input while improving the environment (Chen et al., 2014). A new pattern of agriculture that blends information technology and agricultural production in a holistic approach is efficient use of diverse agricultural resources. Precise agricultural technology concentrates on decision-making and precision fertilisation. To optimise fertiliser utilisation, decision-making and precision fertilisation technologies are based on soil nutrient conditions, crop fertiliser requirements, and goal yield to modify fertiliser quantity, nitrogen, phosphorus, and potassium ratios, and fertilisation duration (Shafi et al., 2019). Maximize the utilisation of land resources, achieve the best yield and economic advantages using a reasonable amount of fertiliser, and safeguard the agricultural ecological environment and natural resources (Gebbers and Adamchuk, 2010). Decision-making and precision fertilisation technologies can help conserve fertiliser while increasing crop yield and balancing soil nutrients. The major technologies for decision-making and precise fertilisation include realizing accurate soil nutrient testing and crop nutrition diagnosis based on the spatial variability of soil nutrients in the fertilising area (Cox, 2002); determining appropriate fertilisation models to achieve reasonable fertilisation decisions (Pierpaoli et al., 2013); and adopting reasonable fertilisation methods to achieve precise fertiliser application (Maes and Steppe, 2019).

Decision-making initially means the process or solution that necessitates human decision-making. Noises such as ability experience, knowledge level, and mental feeling will invariably disrupt it because it is something that needs to be defined by humans (Das, 2016). As a result, data collecting and visual analysis informatization seeks to give data and theoretical support for decision-making, promoting the most efficient decision-making in the most effective method at the appropriate time. Practical application scenarios frequently require making multiple decisions in multiple aspects and levels, that is, based on multiple decision results in the previous step, and then making each decision in the next step, and repeating the above process according to the continuous acquisition new data to complete the entire application process decisions and actions (Jarrahi, 2018), the participation of people and the key decision-making role have divided the entire process into multiple divisible sections. Artificial intelligence can produce unambiguous decision-making findings and conduct appropriate actions based on those decisions, allowing decision-making, thinking, and action to be fully integrated and finished without the need for human intervention; the entire process is completely automated.

Traditional decision-making is based on rules, which necessitates artificially establishing preconditions and guide the actions of machines when those criteria are satisfied. Artificial intelligence decision-making is data-driven decision-making. In other words, machines can synthesise rules from data and generalise knowledge that can be applied to real-world circumstances, and it is based on data and the machine's experience. All of its expertise is based on real-world data and scenarios (Jarrahi, 2018). It can cope with a variety of complicated problems, diverse specific conditions, and make more accurate judgements to optimise the system than traditional decision-making.

Several prior research have proposed a variety of models and methods to be used in precision fertilisation with machine learning. In 2001, Pokrajac and Obradovic (2001) developed a neural network-based precision fertilisation decision support system. Yu et al. (2010) presented a neural network ensemble technique in which the K-means clustering method is used to individually choose optimum networks and a Lagrange multiplier is used to aggregate these chosen networks to calculate the fertilisation rate more precisely. For oil crop fertilisation, Zheng et al. (2013) presented a hybrid multiobjective fireworks optimization method that considers not only crop production and quality but also energy consumption and environmental implications. Dong et al. (2020) presented a wavelet-BP neural network-based technique for precision maize fertilisation. For fertilisation prediction applications, the preceding models and algorithms can produce acceptable results. However, the aforementioned study did not utilise both the temporal and spatial information of the data in the algorithm in order to increase the accuracy and stability of the prediction.

In order to overcome the above issues, we utilise the notion of multi-task learning to include both the temporal and spatial information in the data into the algorithm to enhance the accuracy, stability and generalisation of the model. The premise behind multi-task learning is that there is an underlying connection between various data recordings from subjects, and that capturing the intrinsic correlation can enhance the generalisation of the final prediction model (Zhang and Yang, 2021). The typical focus of a traditional machine learning prediction method is on optimising specific metrics using a model or a mix of models (Das and Behera, 2017). Although the strategy can typically generate adequate results, it primarily concentrates on a single task, causing the model's relationships to be overlooked. In contrast to traditional single-task learning, multi-task learning allows information and knowledge from other tasks to be fully utilised and shared, thus improving achievable performance and enhancing the generalisability of the algorithm. By sharing the representation between related tasks, MTL can assist the model better summaries the original task. The MTL technique focuses on how to define tasks and the relationship between tasks. Low-rank assumptions (Chen et al., 2011), parameter sharing (Evgeniou and Pontil, 2004), novel regularisation (Cao et al., 2017) (Wang et al., 2019) are utilised to establish task relevance in existing MTL techniques, and the addition of the kernel method allows the algorithm to fit non-linear connections (Cao et al., 2018) (Peng et al., 2019).

III. Proposed Approach

A. Denotation

For brevity, we represent tensors as italic capital letters, such as *X* or *Y*, and matrices by capital letters, such as A or B. Vectors are denoted by lowercase letters such as x whereas Scalars are denoted by italic lowercase letters such as *a*.

B. Tensor Decomposition

The proposed tensor MTL framework's training and prediction stages are depicted in Fig. 2. Understanding the latent factors in the spatio-temporal tensor of farm measurement data is required for our proposed method. These latent factors are represented by factor matrices A and B, which can be generated utilising tensor decomposition techniques. Two typical techniques for decomposing the tensor are Tucker and CANDECOMP/PARAFAC (CP) decompositions (Kolda

Table 1 Nitrogen application timing for winter wheat from the real-world agricultural dataset.

Farms	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug
Farm 1	0	0	0	0	0	Base fertiliser	1st Top dressing	2nd Top dressing	3rd Top dressing	0	4th Top dressing	0
Farm 2	0	0	0	0	0	0	Base fertiliser	1st Top dressing	2nd Top dressing	0	0	0
Farm 3	0	0	0	0	0	0	Base fertiliser	1st Top dressing	0	0	2nd Top dressing	0
Farm 4	0	0	0	0	0	Base fertiliser	1st Top dressing	2nd Top dressing	0	0	0	0

Table 2 Structures of the winter wheat real-world agricultural dataset.

Winter Wheat Dataset	Agricultural feature			Range of target values (kg/ha)
	Climate data	Soil properties and nutrients data	Cropping data	
Nitrogen fertiliser	Mean daily temperature (℃) Monthly rainfall (mm) Monthly solar radiation (TJ/ha)	Soil pH value Soil water holding capacity (mm) Soil phosphorus content (mg/l) Soil potassium content (mg/l) Soil magnesium content (mg/l)	Potential grain yield (t/ha) Seeds sown per m^2 Working ha	0 – 126.99

and Bader, 2009). The Tucker decomposition divides the tensor into the product of the core tensor and each mode's factor matrix. Although it presents a more complete statement, the latent factors are harder to understand since the number of latent factors differs between models (Xu et al., 2019). In contrast, CP decomposition decomposes a tensor into a sum of rank-one tensors. i.e., $X \approx [\![\mathrm{A} \times \mathrm{B} \times \mathrm{C}]\!] = \sum_{i=1}^{r} \mathrm{a}_i \circ \mathrm{b}_i \circ \mathrm{c}_i$, where $\circ$ denote the outer product operation between two vectors, while $\mathrm{a}_i, \mathrm{b}_i$ and c_i correspond to the vectors related with the i-th latent factor. Given a tensor X of the size $n_1 \times n_2 \times n_3$, the size of matrix A, B and C is $n_1 \times r, n_2 \times r$ and $n_3 \times r$ respectively.

C. *Spatio-temporal tensor multi-task regression*

To predict the precise amount and timing of fertilisation during a twelve-month period. Consider a tensor multi-task regression problem with s training samples (farms) and t time points (months) of d features (agricultural input information). Let $X \in \mathbb{R}^{s\times t\times d}$ be the input tensor from diverse farms, $\mathrm{Y} \in \mathbb{R}^{s\times t}$ be the targets. Since fertiliser application is a multistep concept including numerous processes (e.g., base fertiliser and top dressing), the objectives are presented as a set of twelve-month time series, allowing us to determine how much fertiliser should be applied in given months. Table 1 shows the winter wheat fertilisation target.

The objective function of the proposed method can be stated as follows:

$$\min_{\mathrm{W,V,A,B,C}} \frac{1}{2}\left\|\hat{\mathrm{Y}} - \mathrm{Y}\right\|_{\mathrm{F}}^{2} + \frac{\lambda}{2}\|X - [\![\mathrm{A, B, C}]\!]\|_{\mathrm{F}}^{2} + \Omega_m(\mathrm{W, V}) + \Omega_l(\mathrm{A, B, C})$$

$$\hat{y}_{st} = (\mathrm{AW}^{\mathrm{T}} + \mathrm{BV}^{\mathrm{T}})\mathrm{x}_{st}^{\mathrm{T}} \tag{1}$$

where the first term calculates the empirical error for the training data. $\hat{\mathrm{Y}} \in \mathbb{R}^{s\times t}$ are the predicted values (Fertiliser application time and amount), $\mathrm{A} \in \mathbb{R}^{s\times r}$ is the spatial latent factor matrix and $\mathrm{B} \in \mathbb{R}^{t\times r}$ is the temporal latent factor matrix, $\mathrm{W} \in \mathbb{R}^{d\times r}$ is the spatial model parameter matrix and $\mathrm{V} \in \mathbb{R}^{d\times r}$ is the temporal model parameter matrix with r latent factors, λ is regularization parameter. Ω_l are regularization terms for latent factors and Ω_m are regularization terms for model parameters, the Ω_l and Ω_m are utilised to limit the size of the parameters to prevent overfitting and perform feature selection. Obtain latent factors by optimising objective function $\left\|X - [\![\mathrm{A, B, C}]\!]\right\|_{\mathrm{F}}^{2}$, where $X = [\![\mathrm{A, B, C}]\!] = \sum_{i=1}^{r} \mathrm{a}_i \circ \mathrm{b}_i \circ \mathrm{c}_i$, where $\circ$ denote the outer product operation between two vectors.

By iteratively optimising the objective function for each set of variables for which a solution is sought, the latent factors A, B, and C, as well as the model parameters W and V, can be learned. We utilise the proximal gradient descent approach to solve each subproblem in this study since not all components of the objective function are differentiable. In the MTL model, the proximal approach is commonly utilised to construct the proximal solution for the non-smooth objective function (Zweig and Weinshall, 2013) (Zhao et al., 2015) (Han and Zhang, 2015) (Gong et al., 2014), that is, by replacing the smooth function with the quadratic function, the sum of the smooth and non-smooth functions. Stated that non-differentiable function f(x), which can be factored into the smooth differentiable function d(x) and the non-smooth function n(x), i.e., f(x) = d(x) + n(x). The model parameters can be iteratively updated utilising proximal gradient descent approach:

Algorithm 1: Pseudocode for Spatio-temporal tensor multi-task regression

---

Input:
  X: Spatio-temporal tensor
  Y: Twelve-month targets
  A: Spatial latent factors
  B: Temporal latent factors
  C: Feature latent factors
  W: Spatial model parameters
  V: Temporal model parameters
Output:
  $\hat{\mathrm{Y}}$: Twelve-month predicted values
Parameter: λ, β
1: **if** (number of iterations < maximum iterations) **or** ($\left\|\hat{\mathrm{Y}} - \mathrm{Y}\right\|_{\mathrm{F}}^{2}$ > optimization tolerance) **then**
2: Solve A, B, C, W, V by optimizing (1) with the training set
3: **end if**
4: Utilise A, B, W, V to calculate $\hat{\mathrm{Y}}$ with the test set
4: **return** $\hat{\mathrm{Y}}$

Fig. 3. Pseudocode for Spatio-temporal tensor multi-task regression.

Table 3
Comparison of the results from our proposed methods with standard methods for nitrogen fertilisation prediction with real-world winter wheat dataset. The best results are bolded.

Methods	rMSE	R^2
Ridge regression	25.9331±4.4030	0.3733±0.2056
Lasso regression	25.7061±4.3802	0.3622±0.2225
Elastic-Net	29.3327±6.3230	0.2028±0.1440
Bayesian ridge regression	30.7387±5.9796	0.1340±0.1585
Bayesian automatic relevance determination regression	25.8242±3.9310	0.3187±0.2554
Linear support vector regression	36.3096±6.4595	0.1514±0.1797
Sigmoid kernel support vector regression	35.2318±7.3093	0.1750±0.1360
Regression based on k-nearest neighbors	34.1705±8.8471	0.1928±0.1775
Decision tree regressor	26.9973±8.0372	0.3338±0.6233
Multi-layer perceptron regressor	32.1934±6.9039	0.2067±0.1302
TMTR-b	22.7924±4.2660	0.5122±0.1878
TMTR-s	28.7313±4.3463	0.2362±0.1352
TMTR-t	**20.8125±3.1875**	**0.5649±0.1131**

$$\mathrm{x}^{(s)} = \mathbf{prox}_{z_s,\mathrm{n}}\left(\mathrm{x}^{(s-1)} - z_s \nabla \mathrm{d}\left(\mathrm{x}^{(s-1)}\right)\right) \tag{2}$$

where $\mathrm{x}^{(s)}$ is the parameter to be estimated at step s. $\mathbf{prox}_{z_s,\mathrm{n}}$ is proximal operator for non-differentiable function n, $\nabla \mathrm{d}\left(\mathrm{x}^{(s-1)}\right)$ is the gradient for the smooth function d, $\mathrm{x}^{(s-1)}$ and z_s is the step size for gradient descent update. The proximal operator for $\ell 1$-norm function is the soft-thresholding operator (Parikh and Boyd, 2014) as follows:

$$\mathbf{prox}_{\xi,\mathrm{n}}(\mathrm{v}) = (\mathrm{v} - \xi)_+ - (-\mathrm{v} - \xi)_+ \tag{3}$$

where ξ is the threshold parameter. Iteratively updating the parameters involves computing the gradient on the smooth section of the objective function and then using the soft-thresholding operation (proximal mapping function for $\ell 1$-norm) to determine its next value. A line search technique can be utilised to evaluate the step size. This strategy can improve an optimization process's convergence time or make the design of distributed optimization algorithms easier. The pseudocode is depicted in the Fig.3.

IV. Experimental Settings

A. Dataset

In collaboration with the UK agricultural company, we have collected a real-world agricultural dataset containing various agricultural factors from four genuine winter wheat farms, this dataset is non-public but can be requested from the corresponding author for research purposes. Farms include a wide range of information for agricultural data, and our chosen factors must meet two conditions: first, it can affect the crop's growth and yield from an agronomic standpoint. Second, it is a parameter that can be determined prior to the fertilisation stage. Specifically, our dataset has three categories of data.

The first is climate data, which can be collected from a weather forecast tool, and we have three factors: mean daily temperature, monthly rainfall, and solar radiation.

The second sort of content is soil properties and nutrients data, which can be collected by soil analysis. We have two variables for soil properties: soil pH value and soil water holding capacity, and three variables for soil nutrients: soil phosphorus, potassium, and magnesium content. Soil analysis enables farmers to optimise yields by adjusting their fertiliser requirements to the needs of their plants, while minimizing environmental risks. It can also be utilised to assess the texture, moisture and strength characteristics of the soil.

The third type of content is cropping data, which can be collected through cropping records, and we have four parameters: potential grain yield, seeds sown per m^2, and working ha.

There are 11 agricultural input features in total for fertilisation prediction. For the prediction target, nitrogen fertiliser is the sole fertiliser that all farms use once the crops are planted, and it is the most frequently manufactured and used fertiliser on the planet. The right quantity of nitrogen fertiliser can help increase crop yields and improve the quality of agricultural goods. As a result, the research concentrates on nitrogen fertilisation prediction. The structures of the winter wheat dataset are summarised in Table 2.

B. Evaluation metrics

Based on the tensor of input agricultural data, we propose a prediction model for nitrogen fertilisation prediction. We utilised data from three of the farms for model training and the remaining one for testing due to the limited number of farms and the difficulties of gathering agricultural data. Since regularisation parameters and the number of latent factors r must be set during the training phase, we use 2-fold cross-validation on the training data to determine model parameters.

In this study, the root mean square error (rMSE) is utilised as the prime evaluation metric to assess the accuracy of different prediction algorithms. For overall regression performance, we utilise R squared (R^2), which evaluates how well the predicted value matches the actual value. The R^2 ranges from $-\infty$ to 1, with the closer the number to 1, the greater the prediction result. The following are the definitions of rMSE and R^2:

$$\mathrm{rMSE}(\mathrm{y}, \hat{y}) = \sqrt{\frac{\|\mathrm{y} - \hat{\mathrm{y}}\|_2^2}{\mathrm{n}}} \tag{4}$$

$$\mathrm{R}^2 = 1 - \frac{\sum_i (\mathrm{y}_i - \hat{\mathrm{y}}_i)^2}{\sum_i (\mathrm{y}_i - \bar{\mathrm{y}})^2} \tag{5}$$

where for the R^2, y_i is the ground truth of target at number *i* and

$\hat{y}_i$ is the corresponding prediction from a prediction model, $\bar{y}$ is the average of the true y values. For the rMSE, y is the target's ground truth in the matrix and $\hat{y}$ is the corresponding prediction by a prediction model. The mean and standard deviation of 20 iterations of tests on different data splits are reported.

C. *Tensor multi-task regression and its variants*

In our studies, we examine the predictive accuracy of tensor multi-task regression utilising both spatial and temporal latent factors, as well as spatial latent factors or temporal latent factors alone supplemented with a ℓ_1-norm regularisation term to ensure model sparsity. Specific tensor multi-tasking regressions and their variants are shown below.

Tensor multi-task regression contains both spatial and temporal model parameter and corresponding latent factors (TMTR-b):

$$\min_{W,V,A,B,C} \frac{1}{2}\left\|\hat{Y} - Y\right\|_F^2 + \frac{\lambda}{2}\|X - [\![A,B,C]\!]\|_F^2 + \beta\|W,V,A,B,C\|_1$$
$$\hat{y}_{ij} = \sum_{i=1}^{s}\sum_{j=1}^{t}(A_i W^T + B_j V^T)\, x_{ij}^T \tag{6}$$

Tensor multi-task regression contains spatial model parameter and corresponding latent factors (TMTR-s):

$$\min_{W,A,B,C} \frac{1}{2}\left\|\hat{Y} - Y\right\|_F^2 + \frac{\lambda}{2}\|X - [\![A,B,C]\!]\|_F^2 + \beta\|W,A,B,C\|_1$$
$$\hat{y}_{ij} = \sum_{i=1}^{s}\sum_{j=1}^{t} A_i W^T x_{ij}^T \tag{7}$$

Tensor multi-task regression contains temporal model parameter and corresponding latent factors (TMTR-t):

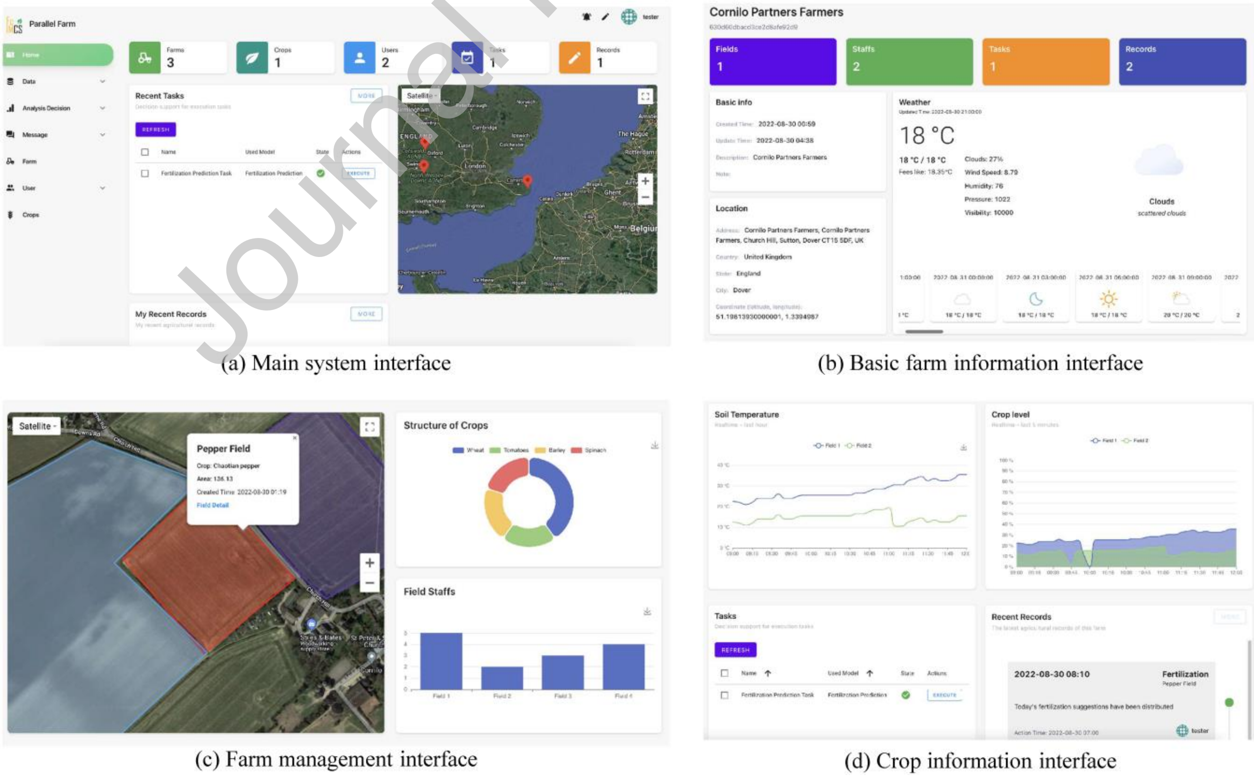
$$\min_{V,A,B,C} \frac{1}{2}\left\|\hat{Y} - Y\right\|_F^2 + \frac{\lambda}{2}\|X - [\![A,B,C]\!]\|_F^2 + \beta\|V,A,B,C\|_1$$
$$\hat{y}_{ij} = \sum_{i=1}^{s}\sum_{j=1}^{t} B_j V^T x_{ij}^T \tag{8}$$

V. Experimental Results And Analysis

A. *Comparison with standard regression methods*

We utilised the real-world winter wheat dataset to evaluate the precision fertilisation prediction performance of the proposed tensor multi-task regression and its variants with the following standard regression methods. The dataset is represented as a third-order tensor for our proposed tensor multi-tasking approach. The dataset is represented as a matrix with dimensions of months x features for the standard regression models used for comparison. Table 3 shows the experimental results for nitrogen fertilisation prediction.

- Ridge regression (Hoerl and Kennard, 1970)
- Lasso regression (Tibshirani, 1996)
- Elastic-Net (Zhou and Hastie, 2005)
- Bayesian ridge regression (Minka, 2000)
- Bayesian automatic relevance determination regression (Rudy and Sapsis, 2021)
- Linear support vector regression (Smola and Schölkopf, 2004)
- Sigmoid kernel support vector regression (Smola and Schölkopf, 2004)
- Regression based on k-nearest neighbors (Song et al., 2017)
- Decision tree regressor (Dobra, 2002)
- Multi-layer perceptron regressor (Ramchoun et al.,



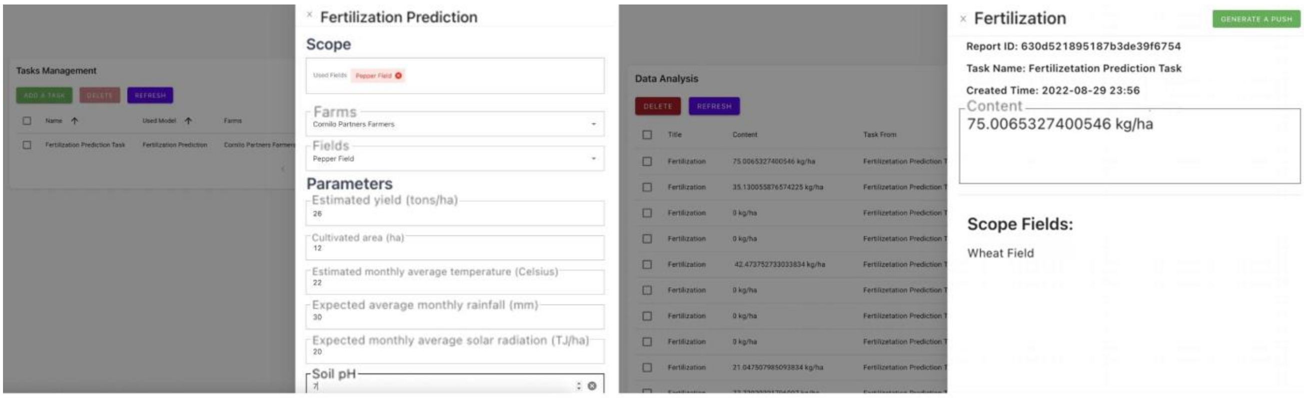
(a) Main system interface

(b) Basic farm information interface

(c) Farm management interface

(d) Crop information interface

Fig. 4. Precision fertilisation system.



(a) Target farm information input

(b) Precision fertilisation prediction output

Fig. 5. Algorithm integration interface.

2016)

Our observations are as follows:

1) The presented tensor multi-task regression algorithms outperform standard regression methods in the winter wheat dataset, validating the utilisation of the temporal and spatial latent factor hypothesis and multi-task learning concept in our regression formulation.

2) TMTR-t delivered the best performance. Due to the difficulty of a small dataset, information in the spatial dimension does not perform well, and experiments have shown that utilising only latent factors in the temporal dimension in the algorithm produces superior results.

3) The presented tensor multi-tasking regression model enhances prediction stability substantially. The standard deviation of the 20 iterative experiments was lower than the standard comparison methods. That may be due to the inclusion of temporal latent factors in the prediction algorithm to improve stability. In other words, all farms share a set of temporal patterns for the fertilisation operation in a multi-task learning manner, thus improving the generalisation and stability of the model.

B. *Interpretability*

The rank of features was listed in descending order of weight parameter values for the proposed TMTR-t model (i.e., the best performing model) in Table 4. The higher rank indicates the greater impact on the final prediction.

From the results presented in Table 4, we can observe that 11 agricultural factors can be divided into three levels according to importance for winter wheat nitrogen fertilisation. The first level is ranked 1 to 4, which can be regarded as having an important impact on the nitrogen fertilisation of winter wheat. Two of them are weather factors, namely monthly solar radiation and monthly rainfall, and the remaining two are soil pH value and potential grain yield. For solar radiation, it is necessary to apply more nitrogen fertiliser in places with good sunshine conditions, which can promote the vegetative growth and reproductive growth of crops, while in places with poor sunshine conditions, less nitrogen fertiliser should be applied to prevent crops from maturing late (Caviglia and Sadras, 2001). For rainfall, it has a great influence on the degree of nitrogen

Table 4 The rank of Agricultural features according to the weight parameter values for the proposed TMTR-t model on Nitrogen fertilisation.

Rank	Agricultural feature	Weight parameter value
1	Monthly solar radiation (TJ/ha)	0.9559
2	Soil pH value	0.8671
3	Monthly rainfall (mm)	0.8650
4	Potential grain yield (t/ha)	0.8215
5	Mean daily temperature (℃)	0.6795
6	Working ha	0.6258
7	Soil phosphorus content (mg/l)	0.6087
8	Soil magnesium content (mg/l)	0.3545
9	Soil water holding capacity (mm)	0.3290
10	Seeds sown per m^2	0.1605
11	Soil potassium content (mg/l)	0

loss. The nitrogen loss caused by rainfall is an important factor of farmland pollution and the higher the fertilisation rate, the more serious the nitrogen loss (Monjardino et al., 2013). For soil pH value, the most direct impact on the fertilisation effect is to affect the solubility of soil nutrients. In addition, it will also affect the life activities of soil microorganisms, thereby indirectly reducing the effectiveness of soil nutrients (Cameron et al., 2013). For potential grain yield, good nitrogen fertiliser utilisation promotes crop growth and development, resulting in higher yields and improved quality (Kindred et al., 2008).

The second level is ranked 5 to 7, which can be seen as having a moderate effect on nitrogen fertilisation in winter wheat. The third level is ranked 8 to 11, which had little or no effect on nitrogen fertilisation in winter wheat.

VI. PRECISION FERTILISATION SYSTEM

The above proposed spatio-temporal tensor multi-task regression algorithm for fertilisation prediction and multi-dimensional agricultural data are integrated in a precision fertilisation system (dev-cms.fcimcs.com). The system requires an authorization to utilise, please contact the corresponding author for further information. The system is an intelligent, real-time, precise and personalised life-cycle planting decision tool, dedicated to solving the core needs of low-cost farming and high efficiency output.

The system is utilised to assist farmers or farm managers with farm information inspecting and management, environmental information query, crop information management, fertiliser application process management and recording, and fertiliser application decision guidance. Fig. 4 shows the application interface of the system and Fig. 5 shows the interface of the integrated fertilisation prediction algorithm. The main system interface allows the user to monitor and manage crop records, geographic location, staff and various information for all farms. The basic farm information interface allows users to monitor and manage individual farm information, including climate, geographic location, staff and fertilisation tasks. The farm management interface allows users to manage information for different fields and crops on the farm. The crop information interface allows users to manage specific field soil information, fertilisation tasks and records for different crops. The user can utilise our proposed precision fertilisation algorithm in the algorithm integration interface, where the user has to input various environmental information of the farm and field, then the system will output the exact month and amount of fertiliser to be applied.

VII. CONCLUSION

This research gathers agricultural data from various farms and integrates it into a real-world agricultural dataset, and then we present a multi-task learning approach for precision fertilisation prediction based on Spatio-temporal tensor. The method builds a prediction model based on spatio-temporal input information from individual farms and presents multi-task regression utilising the spatio-temporal latent factors obtained from tensor decomposition as multi-task relationships to achieve the final prediction results. The predictive model can be utilised to compute the optimal amount and time of application of various types of fertilisers, therefore preventing environmental harm caused by over-fertilisation. The experiment results indicate that multi-task learning employing spatio-temporal tensors can increase the accuracy and stability of agricultural fertiliser application prediction. It can help farmers and managers use fertilisers more rationally and productively, reducing fertiliser pollution while maintaining or boosting agricultural production. Moreover, we have constructed a precision fertilisation system that integrates the proposed spatio-temporal tensor multi-task regression algorithm for fertilisation prediction and multi-dimensional agricultural data to effectively support real-world farms in achieving the goals of low-cost farming and high efficiency output.

REFERENCES

Bindraban, P.S., Stoorvogel, J.J., Jansen, D.M., Vlaming, J., Groot, J.J.R., 2000. Land quality indicators for sustainable land management: proposed method for yield gap and soil nutrient balance. ELSEVIER Agriculture, Ecosystems and Environment. 81(2), 103-112.

Cameron, K.C., Di, H.J., Moir, J.L., 2013. Nitrogen losses from the soil/plant system: a review. Annals of Applied Biology. 162(2), 145-173.

Cao, P., Liu, X., Yang, J., Zhao, D., Huang, M., Zaiane, O., 2018. $\ell_{2,1} - \ell_1$ regularized nonlinear multi-task representation learning based cognitive performance prediction of Alzheimer's disease. ELSEVIER Pattern Recognition. 79, 195–215.

Cao, P., Shan, X., Zhao, D., Huang, M., Zaiane, O., 2017. Sparse shared structure based multi-task learning for MRI based cognitive performance prediction of Alzheimer's disease. ELSEVIER Pattern Recognition. 72, 219–235.

Caviglia, O.P., Sadras, V.O., 2001. Effect of nitrogen supply on crop conductance, water- and radiation-use efficiency of wheat. ELSEVIER Field Crops Research. 69(3), 259-266.

Chen, C., Pan, J., Lam, S.K., 2014. A review of precision fertilization research. Springer Environmental Earth Sciences. 71, 4073–4080.

Chen, J., Zhou, J., Ye, J., 2011. Integrating low-rank and group-sparse structures for robust multi-task learning. KDD'11. 42-50.

Cox, S., 2002. Information technology: the global key to precision agriculture and sustainability. ELSEVIER Computers and Electronics in Agriculture. 36(2-3), 93-111.

Das, T.K., 2016. Intelligent Techniques in Decision Making: A Survey. Indian Journal of Science and Technology. 9(12), 1-6.

Das, K., Behera, R.N., 2017. A survey on machine learning: concept, algorithms and applications. International Journal of Innovative Research in Computer and Communication Engineering. 5(2), 1301-1309.

Dobra, A., 2002. Classification and Regression Tree Construction. Citeseer. 1-18.

Dong, Y., Fu, Z., Peng, Y., Zheng, Y., Yan, H., Li, X., 2020. Precision fertilization method of field crops based on the Wavelet-BP neural network in China. ELSEVIER Journal of Cleaner Production. 246, 1–13.

Evgeniou, T., Pontil, M., 2004. Regularized Multi–Task Learning. KDD'04. 109–117.

Fue, K.G., Porter, W.M., Barnes, E.M., Rains, G.C., 2020. An Extensive Review of Mobile Agricultural Robotics for Field Operations: Focus on Cotton Harvesting. AgriEngineering. 246, 150–174.

Gebbers, R., Adamchuk, V.I., 2010. Precision agriculture and food security. Science. 327, 828–831.

Gong, P., Zhou, J., Fan, W., Ye, J., 2014. Efficient multi-task feature learning with calibration. KDD. 761–770.

Halachmi, I., Guarino, M., Bewley, J., Pastell, M., 2019. Smart Animal Agriculture: Application of Real-Time Sensors to Improve Animal Well-Being and Production. Annual Review of Animal Biosciences. 7, 403–425.

Han, L., Zhang, Y., 2015. Learning multi-level task groups in multi-task learning. AAAI. 2638–2644.

He, J., Wang, J., He, D., Dong, J., Wang, Y., 2011. The design and implementation of an integrated optimal fertilization decision support system. ELSEVIER Mathematical and Computer Modelling. 54, 1167–1174.

Hoerl, A., Kennard, R., 1970. Ridge Regression: Biased Estimation for Nonorthogonal Problems. Technometrics. 12, 55-67.

Jarrahi, M.H., 2018. Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. ELSEVIER Business Horizons. 61(4), 577-586.

Kindred, D.R., Verhoeven, T.M.O., Weightman, R.M., Swanston, J.S., Agu, R.C., Brosnan, J.M., Sylvester-Bradley, R., 2008. Effects of variety and fertiliser nitrogen on alcohol yield, grain yield, starch and protein content, and protein composition of winter wheat. ELSEVIER Journal of Cereal Science. 48(1), 46-57.

Kolda, T.G., Bader, B.W., 2009. Tensor Decompositions and Applications. SIAM Review. 51, 455–500.

Kumar, A., Daumé III, H., 2012. Learning task grouping and overlap in multi-task learning. International Conference on Machine Learning. 1-8.

Maes, W.H., Steppe, K., 2019. Perspectives for Remote Sensing with Unmanned Aerial Vehicles in Precision Agriculture. ELSEVIER Trends in plant science. 24(2), 152–164.

Minka, T.P., 2000. Bayesian linear regression. Citeseer. 1-13.

Monjardino, M., McBeath, T.M., Brennan, L., Llewellyn, R.S., 2013. Are farmers in low-rainfall cropping regions under-fertilising with nitrogen? A risk analysis. ELSEVIER Agricultural Systems. 116, 37-51.

Neethirajan, S., 2017. Recent advances in wearable sensors for animal health management. ELSEVIER Sensing and Bio-Sensing Research. 12, 15–29.

Parikh, N. and Boyd, S., 2014. Proximal algorithms. Foundations and trends® in Optimization. 1(3), 127-239.

Peng, J., Zhu, X., Wang, Y., An, L., Shen, D., 2019. Structured sparsity regularized multiple kernel learning for Alzheimer's disease diagnosis. ELSEVIER Pattern Recognition. 88, 370–382.

Pierpaoli, E., Carli, G., Pignatti, E., Canavari, M., 2013. Drivers of Precision Agriculture Technologies Adoption: A Literature Review. ELSEVIER Procedia Technology. 8, 61–69.

Pokrajac, D., Obradovic, Z., 2001. Neural network-based software for fertilizer optimization in precision farming. International Joint Conference on Neural Networks. 2110–2115.

Ramchoun, H., Idrissi, M.A.J., Youssef, G., Mohamed, E., 2016. Multilayer Perceptron: Architecture Optimization and Training. International Journal of Interactive Multimedia and Artificial Intelligence. 4(1), 26-30.

Ray, P.P., 2017. Internet of things for smart agriculture: Technologies, practices and future direction. Journal of Ambient Intelligence and Smart Environments. 9, 395–420.

Rudy, S.H., Sapsis, T.P., 2021. Sparse methods for automatic relevance determination. ELSEVIER Physica D: Nonlinear Phenomena. 418, 1-16.

Shafi, U., Mumtaz, R., García-Nieto, J., Hassan, S.A., Zaidi, S.A.R., Iqbal, N., 2019. Precision Agriculture Techniques and Practices: From Considerations to Applications. Sensors. 19(3796), 1–25.

Sharma, N., Singhvi, R., 2017. Effects of Chemical Fertilizers and Pesticides on Human Health and Environment: A Review. International Journal of Agriculture, Environment and Biotechnology. 10, 675–679.

Shi, X., An, X., Zhao, Q., Liu, H., Xia, L., Sun, X., Guo, Y., 2019. State-of-the-Art Internet of Things in Protected Agriculture. Sensors. 19, 1–24.

Smola, A.J., Schölkopf, B., 2004. A tutorial on support vector regression. Springer Statistics and Computing. 14, 199-222.

Song, Y., Liang, J., Lu, J., Zhao, X., 2017. An efficient instance selection algorithm for k nearest neighbor regression. ELSEVIER Neurocomputing. 251, 26-34.

Sowjanya, K.D., Sindhu, R., Parijatham, M., Srikanth, K., Bhargav, P., 2017. Multipurpose Autonomous Agricultural Robot. International Conference on Electronics, Communication and Aerospace Technology. 696–699.

Tibshirani, R., 1996. Regression shrinkage and selection via the lasso. J. R. Stat. Soc. Ser. B Methodol. 58, 267–288.

Tzachor, A., Devare, M., King, B., Avin, S., hÉigeartaigh, S.Ó., 2022. Responsible artificial intelligence in agriculture requires systemic understanding of risks and externalities. Nature Machine Intelligence. 4, 104-109.

Wang, M., Zhang, D., Shen, D., Liu, M., 2019. Multi-task exclusive relationship learning for alzheimer's disease progression prediction with longitudinal data. ELSEVIER Medical Image Analysis. 53, 111–122.

Xu, J., Zhou, J., Tan, P., Liu, X., Luo, L., 2019. Spatio-temporal Multi-task Learning via Tensor Decomposition. IEEE TRANSACTIONS ON KNOWLEDGE AND DATA ENGINEERING. 1–12.

Yu, H., Liu, D., Chen, G., Wan, B., Wang, S., Yang, B., 2010. A neural network ensemble method for precision fertilization modeling. ELSEVIER Mathematical and Computer Modelling. 51, 1375–1382.

Zhang, N., Wang, M., Wang, N., 2002. Precision agriculture—a worldwide overview. ELSEVIER Computers and Electronics in Agriculture. 36(2-3), 113–132.

Zhang, Y., Yang, Q., 2021. A Survey on Multi-Task Learning. IEEE Transactions on Knowledge and Data Engineering. 1–20.

Zhao, L., Sun, Q., Ye, J., Chen, F., Lu, C., Ramakrishnan, N., 2015. Multi-task learning for spatio-temporal event forecasting. KDD. 1503–1512.

Zheng, Y., Song, Q., Chen, S., 2013. Multiobjective fireworks optimization for variable-rate fertilization in oil crop production. ELSEVIER Applied Soft Computing. 13, 4253–4263.

Zhou, H., Hastie, T., 2005. Regularization and variable selection via the elastic net. J. R. Statist. Soc. B. 67(2), 301-320.

Zhou, J., Liu, J., Narayan, V.A., Ye, J., 2013. Modeling disease progression via multi-task learning. ELSEVIER NeuroImage. 78, 233–248.

Zhou, J., Yuan, L., Liu, J., Ye, J., 2011. A Multi-Task Learning Formulation for Predicting Disease Progression. ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. 814–822.

Zweig, A., Weinshall, D., 2013. Hierarchical regularization cascade for joint learning. The 30th International Conference on Machine Learning. 28, 37–45.

Declaration of interests

☐The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☒The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Po Yang reports financial support was provided by The University of Sheffield.

Credit Author Statement

Yu Zhang[1]: Investigation, Formal Analysis, Draft Writing

Tong Liu[1], Conceptualization Methodology, Investigation,

Ruijing Wang[2], Supervision, Funding Acquisition, Conceptualization, Investigation.

Yang Li[3], Supervision, Funding Acquisition,

Qing Xue[3], Supervision, Data curation, review & editing

Po Yang[1,] Supervision, Funding Acquisition, Conceptualization, Investigation.

Highlights

- A real-world agricultural dataset collected from real winter wheat farms in the UK.
- Spatio-temporal tensor multi-task learning for precision fertilisation prediction.
- Important factors influencing nitrogen fertilisation process were identified and analysed.
- A precision fertilisation system has been constructed for intelligent farm management