Wheat Yield Prediction Using Soil Drought Index-based Machine/Deep Learning

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**ABSTRACT:** In recent years, the food crisis has become more pronounced due to climate change and extreme weather events, such as extreme temperature fluctuations and severe droughts. Wheat is one of the crucial economy crops in Kinmen, and its growth and harvest are highly contingent on the soil moistures in the farmland. Both excessive and insufficient rainfall can severely impact yields, highlighting the vital importance of maintaining a balanced soil moisture environment to ensure the prosperous cultivation of wheat. In this research, three soil drought indices, namely the Perpendicular Drought Index (PDI), Modified PDI (MPDI), and Vegetation-Adjusted PDI (VAPDI), and two vegetation indices, including the Normalized Difference Vegetation Index (NDVI) and Perpendicular Vegetation Index (PVI), were calculated from the monitoring data by UAV multispectral imagery to predict wheat yields using three learning model, including Support Vector Machine (SVM) regressor, Gradient Boosting (GB) regressor, and Convolutional Neural Network (CNN) regressor. The experimental results indicate that the accuracy of the three learning models for wheat yield estimation is comparable, with the CNN learning model offering a slightly higher accuracy compared to the other two. The CNN learning model can attain a validation accuracy exceeding 90% when predicting wheat yields during years characterized by relatively consistent wheat yields. Furthermore, the model has demonstrated its capacity to provide early warnings of reductions in wheat yield.

# Introduction

In recent years, extreme weather has transitioned into the new normal, marked by frequent instances of record-setting high and low temperatures, along with severe droughts. These shifts in climate have resulted in a decline in soil fertility, further exacerbating the ongoing food security crisis. Agriculture, an industry particularly vulnerable to the impacts of climate change, incurs economic losses accounting for approximately 25% of the total effects caused by climate change (Baas *et al*., 2015). Within the sphere of agriculture, the soil moisture content (SMC) emerges as a pivotal variable demanding both consideration and study, as it plays a pivotal role in enhancing both crop quality and yields. Maintaining an optimal soil moisture percentage not only facilitates the optimization of plant growth, but also amplifies nutrient absorption, encourages beneficial microbial growth, and simultaneously allows for the regulation of soil temperature (Casamitjana *et al*., 2020). From a chemical standpoint, ensuring an adequate SMC is crucial in enabling the process of photosynthesis in plants (Li *et al*., 2004).

Drought-induced natural hazards, as classified by meteorological, agricultural, hydrological, and socio-economic parameters (UNISDR, 2009), engender a intricate interplay of interconnected environmental and socio-economic repercussions. Among these categorizations, agricultural drought assumes paramount significance owing to its direct impact on plant growth during pivotal developmental phases, primarily attributed to soil moistures. Due to the strong correlation between agricultural drought and soil moisture, the integration of soil moisture observations or pertinent indicators becomes imperative in assessing the severity of drought. This methodology not only furnishes pivotal data for the design of early warning systems tailored to drought scenarios but also offers insights into the prevailing agricultural growth conditions (Farhan & Al-Bakri, 2019).

As drought influences land cover, soil moisture, and surface roughness, while impacting energy and water exchange among vegetation, soil, and air, these effects manifest through phytophysical factors such as vegetative indices, albedo, and surface temperature. At present, several researches had substantiated the efficacy of the normalized difference vegetation index (NDVI) in effectively gauging drought severity resulting from variations in rainfall and soil water content using time-series telemetry data (Di *et al*., 1994; Kogan, 1990). Regarding the development of agricultural drought monitoring indicators, it indeed provides robust drought monitoring capabilities for bare soil. However, the monitoring of soil moisture within vegetation cover across diverse ecosystems has captured the attention of those involved in precision agriculture. Ghulam *et al*. (2007a) harnessed the reflective and absorptive properties of vegetation canopy and bare soil within the red and near-infrared light spectrum to introduce the concept of a perpendicular drought index (PDI), which has proven to be highly effective. Nevertheless, certain limitations still persist in the performance of the PDI for estimating soil moisture in agricultural regions characterized by varying surface cover types, ranging from bare soil to vegetated cover, as well as in regions featuring uneven topography and distinct soil types. In light of this, Ghulam *et al*. (2007b) introduced an enhanced version of PDI termed Modified PDI (MPDI). In MPDI, the influence of vegetation cover on the mixed pixel effect of bare soil spectrum reflection has been eradicated. In comparison to the original PDI, the drought monitoring performance yields significantly improved accuracy. Recently, numerous studies have been dedicated to evaluating and monitoring topsoil soil moisture, employing the foundation of MPDI (Zhang *et al*., 2015; Farhan & Al-Bakri, 2019; Nie *et al*., 2020; Tao *et al*., 2021).

The greater the PDI value, the drier the soil tends to be. Another index being normal to PDI is referred to as the perpendicular vegetation index (PVI), which responses the density of vegetation covering the surface. When the PVI value is larger, it indicates a denser presence of vegetation. Li & Tan (2013) presented the vegetation-adjusted perpendicular drought index (VAPDI) based on the foundations of PDI and PVI. Nie *et al*. (2020) employed PDI, MPDI, and VAPDI in their study of SMC estimation and discovered that both MPDI and VAPDI exhibit a higher accuracy than PDI.

In this research, two wheat fields located in Jinsha Township, Kinmen, were selected as our study site. Three machine/deep learning technologies: Support Vector Machine (SVM), Gradient Boosting (GB), and Convolutional Neural Network (CNN) were employed to develop the regressors for estimating wheat yield. Throughout the wheat growth cycle, unmanned aerial vehicle (UAV) aerial photography was conducted to acquire multispectral images. From these images, we computed five index maps, i.e., PDI, MPDI, VAPDI, NDVI, and PVI. By learning relationships between the index values and the wheat yields per unit area, the regressors were trained to predict the overall wheat yield of the experimental fields. Finally, the accuracies of the yield estimates produced by the three learning models were assessed.

# Study sites

We selected two wheat fields situated in the Jinsha Township of Kinmen, identified by parcel numbers (PNs) 713 and 253, as depicted in Figure 1. These parcels cover approximately 0.2 and 0.16 hectares, respectively. Our selection of study sites was based on two key geographical considerations: accessibility to irrigation water and terrain conditions. PN 713 enjoys proximity to water bodies, enabling the application of artificial irrigation during crop growth. In contrast, PN 253 is situated far from water bodies, relying solely on natural precipitation for irrigation. As a result, PN 713 boasts a more reliable irrigation water source compared to PN 253. Regarding terrain, PN 253 has slightly higher elevation than PN 713, and its soil has generally superior permeability. This topographical advantage allows water to flow naturally downhill from the farmland due to gravity. Consequently, SMC in PN 253 tends to be lower, indicating higher drought stress compared to PN 713. Nevertheless, it's worth noting that sustained precipitation over several days or weeks may elevate SMC in PN 713, potentially leading to reduced wheat yields.

|  |  |
| --- | --- |
| **Kinmen**  Jinsha Township | **PN 713** |
| **PN 253** |

Figure 1. Study sites.

# Data acquisition and Preprocessing

The DJI P4 Multispectral unmanned aerial vehicle (UAV) system was employed, developed by Da-Jiang Innovations in Shenzhen, China, to acquire the multi-temporal monitoring images. From Dec. 2021 to Apr. 2023, we obtained a total of fifteen UAV images for PN 713 and fourteen for PN 253. The DJI P4 Multispectral system is equipped with five lenses to capture images in the blue (B: 450 ± 16 nm), green (G: 560 ± 16 nm), red (R: 650 ± 16 nm), red-edge (RE: 730 ± 16 nm), and near-infrared (NIR: 840 ± 26 nm) spectral bands, as well as a lens for visible light images. To ensure a fine ground sampling distance of 1 cm per pixel, we set a low flying altitude of 20 meters and included 85% end-lap and side-lap in the UAV mission plan. To mitigate the effects of shadows caused by a low solar altitude angle, the UAV imaging was scheduled between 10:00 am and 2:00 pm. Moreover, we established ground control points (GCPs) around the study sites. We obtained information regarding the interior orientation parameters of the sensor using Pix4D software. This information, coupled with aerial triangulation involving the GCPs, enabled us to achieve geometrically corrected results with residual errors of less than one pixel, equivalent to 1 centimetre.

While the atmospheric scattering effect on UAV images is relatively limited, it's essential to acknowledge the persistent atmospheric scattering interference between the sensor and the Earth's surface (Shoshany *et al*., 2019). Thus, the correction of digital number (DN) values in UAV imagery must be conducted using a standard module calibrated for surface reflectance (Lu *et al*., 2020). In this study, a standard module with well-defined radiometric reflectance value was used. To ensure consistency and accuracy across all UAV images acquired at different time points, normalization was performed using the standard module for DN values within the images. To achieve image normalization, Equation (1) was employed to calculate the normalized pixel value based on the measured DN influenced by the incident light in the reference area, corresponding to the standard module area. Within Equation (1), *DNn* signifies the normalized pixel value, *DNm* denotes the original measured pixel value prior to normalization, *DNR* represents the known pixel value corresponding to reflectance level of the standard module, and *DNstd.\_m* represents the pixel value measured during image acquisition when utilizing the standard module.

(1)

# Methodology

## Soil Drought Indices

PDI, MPDI, and VAPDI all belong to soil drought indices and were developed from the soil line theory (Richardson & Wiegand, 1977). These indices can be calculated using the following formulas:

(2)

(3)

(4)

(5)

(6)

(7)

The DNs (Digital Numbers) for red and NIR (Near-Infrared) spectral reflectance are denoted as Rred and RNIR, respectively. *s* represents the slope of the soil line, while *i* represents its interception on the vertical axis. The DNs of red and NIR spectral reflectance for vegetation are denoted as Rv,red and Rv,NIR, respectively. PDI(A) represents the PDI corresponding to the largest PVI (PVI(A)). *fv* varies within a range of 0 (indicating bare soil) to 1 (representing full vegetation cover).

## Learning Models by Regression

In this study, three learning methods—SVM, GB, and CNN—were employed to establish the regressors. These methods facilitate the acquisition of data characteristics from the index map and the subsequent establishment of a relationship between these index-based data characteristics and the wheat yield per unit area. Currently, these three learning methods have found application in the analysis of telemetry image data, effectively addressing both classification and regression problems. Shun *et al*. (2022) introduced an Asymmetric Convolution-CBAM (AC-CBAM) module, which is an extension of the Convolutional Block Attention Module, designed for remote sensing image segmentation. Ghimire *et al*. (2022) introduced a hybrid deep learning method, CNN-REGST, which combines a CNN with a dual-stage Stacked Regression framework. This framework includes a Level-O Learner and a Level-O predictor, further augmented by a SVM as the Level-1 Learner. The hyperparameters of the SVM were optimized using the HyperOpt function. This hybrid approach demonstrates significant accuracy in predicting daily global solar radiation. Panahi *et al*. (2020) developed groundwater potential maps using a machine learning algorithm and a deep learning algorithm, specifically the support vector regression and convolution neural network functions, respectively. Yang *et al*. (2023) used deep learning and optimized shallow machine learning (Random Forest, XGBoost and Gradient Boosting) based on multi-sensor images from satellite and UAV platforms to construct multiple retrieval models of water quality parameters. The three learning models (SVM, GB, and CNN) by regression established in this research are described as follows:

### **SVM Regressor**:

SVM Regression, also referred to as SVR, is a derivative of the SVM framework. SVM aims to maximize the distance between the support vectors and the hyperplane, whereas SVR focuses on minimizing the distance between the support vectors and the hyperplane. The SVR optimization goal is

(8)

*xi* and *yi* are input sample and prediction sample, respectively. *w* means weight, and *b* is bias. is a threshold, i.e., the distance between the support vectors and the hyperplane. No loss is estimated for samples that are within the distance () on either side of the hyperplane. The samples positioned at a distance of ε from the hyperplane are referred to as support vectors. The above optimization problem is solved by a linear model. However, many practical classification or regression problems are nonlinear. In order to address linear optimization problems, SVR utilizes masks (kernels) to nonlinearly transform samples (*xi*) from the sample space into a higher-dimensional feature space. In this paper, the kernel of radial basis function (Gaussian) was used and is

. (9)

### **GB Regressor**:

GB can be viewed as an enhanced iteration of Random Forest (RF), effectively harnessing the strengths of bagging present in RF alongside the principles of boosting. This amalgamation serves to rectify erroneous predictions stemming from earlier recursive decision tree generations within subsequent recursions. Consequently, the difference from RF is that the decision trees generated across distinct iterations of GB maintain an inherent interrelation, in contrast to the independent nature of RF. This interdependence is helpful to accelerate the learning gradient with each iteration, thereby effectively reducing computation time. GB, also referred to as additive training, involves the summation of the prediction outcome from the prior recursive decision tree with that of a new decision tree *ft*(**x***i*) (as demonstrated by Equation (10)). This combined prediction contributes to the outcome of the *t*-th recursion. The decision of the new decision tree *ft*(**x***i*) must rely on the minimization of the loss objective function (shown as Equation (11)), so that the learning gradient can be rapidly improved.

(10)

(11)

Here, *yi* is true value and Ω is to measure the complexity of the regression model. To avoid overfitting of the regression model, Ω(*fm*) is

(12)

T denotes the number of leaves within the decision tree, while *w* corresponds to the weight assigned to each leaf. Thus, by training Equation (11), the first and second differentials of the Taylor polynomials are obtained as follows:

. (13)

*gi* and *hi* are the first and secondary differentials of the loss objective function, respectively. This research trained the ensemble of boosted regression trees using least-squares boosting.

### **CNN Regressor**:

In this study, the wheat yield was sampled in six one-square-meter areas within each of the two wheat fields during the mature stage of wheat growth. Given the spatial resolution of the image at 0.01 meters, the image size of the index map corresponding to each wheat yield sampling area consists of 101 x 101 pixels (including the central pixel). In a single wheat yield survey, a total of 61,206 (1012 6) index values could be obtained. In this research, the index map was subdivided into 25 smaller index maps, each containing 21 21 pixels. This preprocessing technique serves the purpose of data augmentation, enabling the CNN regressor to learn wheat yield per unit area associated with a more extensive set of index features. This approach not only helps address the issue of data imbalance but also contributes to learning convergence during network training.

The CNN learning model established in this study is shown in Figure 2. "3 × 3 Conv., 8" indicates the use of 8 convolution masks (kernels) with dimensions of 3 × 3. The activation function applied in this model is ReLU (Rectified Linear Unit). Subsequently, a max-pooling operation is performed as part of the subsequent convolutional stage, and ultimately, the learning outcomes are obtained through the fully connected layer. For network training, we employed the Adam optimizer. The training process consisted of a maximum of 30 epochs, with a mini-batch size set to 2. Initially, the learning rate was configured at 0.001. Furthermore, a learning rate drop factor of 0.2 was applied, and this adjustment took place after 20 epochs.

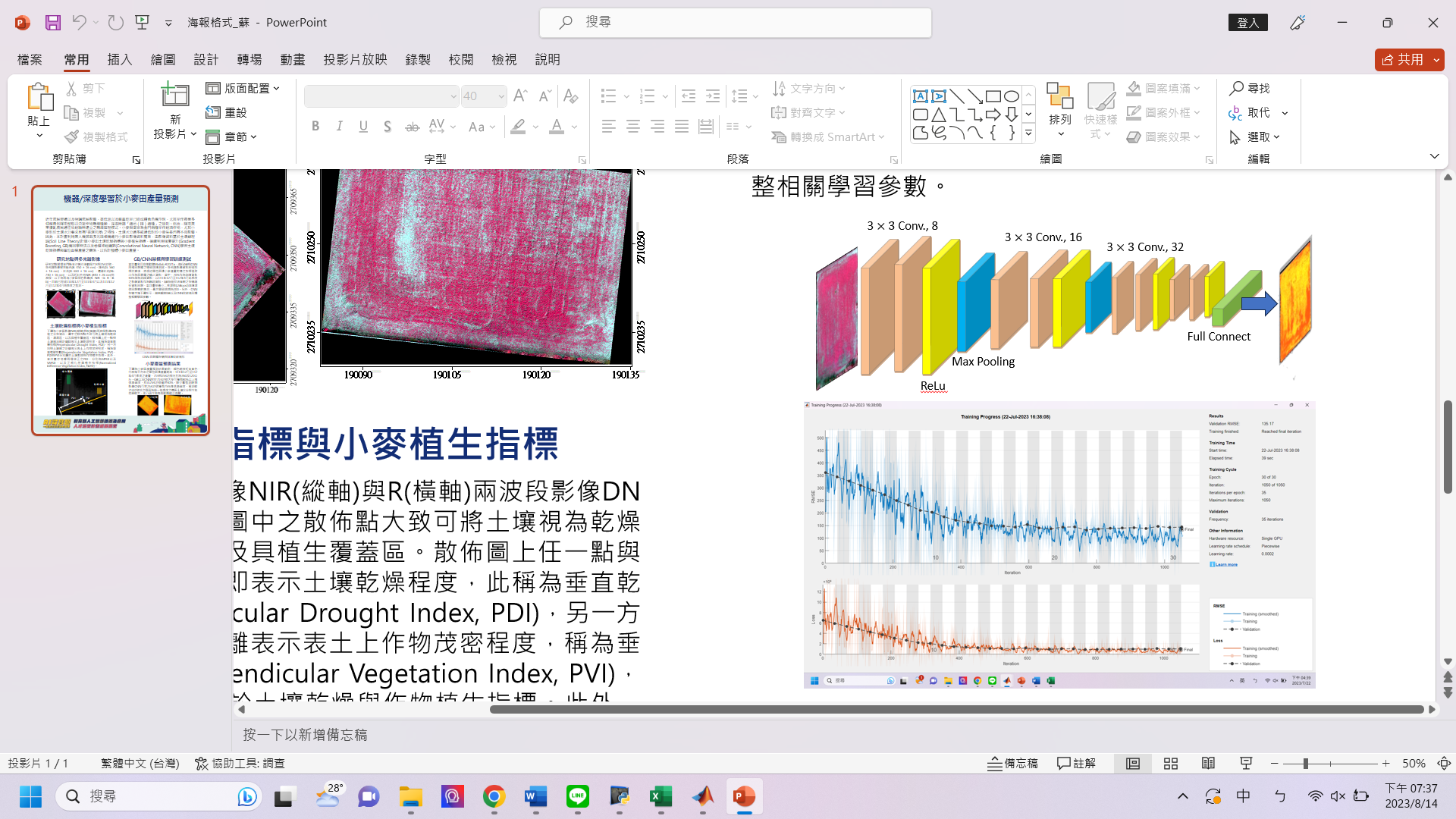


Figure 2. CNN regressor architecture and training convergence.

# Results and discussion

PNs 713 and 253 have approximately 1.6 × 107 and 1.2 × 107 pixels, respectively. In order to organize the learning for GB or SVM, we randomly selected 70% of the 61,206 index values as the training dataset, while the remaining 30% as the testing one. CNN learning requires input data in array format. To facilitate this, we randomly selected 80 frames out of the 150 (25 × 6) index maps for the training dataset, with the remaining 70 frames designated for testing.

The three learning models were trained based on the index dataset computed from the UAV monitoring images acquired in 2021 to predict the wheat yield per unit area. Subsequently, the trained models were applied to estimate and validate the yield using the index dataset from 2022. The verification results for PNs 713 and 253 are presented in Tables 1 and 2, respectively. The predicted yield (*WYP*) was calculated using

. (14)

denotes the estimated wheat yield per unit area (g/m2) corresponding to an element within the index map; represents the summation of estimated wheat yield per unit area obtained from all elements within the index map; signifies the conversion factor that relates the actual field size to the image size. and mean the farmland area and the number of elements within the index map, respectively. The unit of the calculated *WYP* is kg. A positive error value signifies an underestimation of wheat yield, whereas a negative value indicates an overestimation.

For PN 713, the three learning models reached an accuracy exceeding 90% across the various monitoring dates. This demonstrates the robust performance of the learning models in predicting wheat yield for this farmland. On the contrary, in PN 253, with the exception of the CNN learning model achieving higher accuracy on certain monitoring dates, most of the accuracies are merely between 20% and 30%. As shown in Table 2, it is obvious that the wheat yield estimation for PN 253, based on the monitoring data from 2021 to predict the wheat yield in 2022, is inaccurate. The error values in this case are approximately 2 to 3 times the actual yield.

Table 1. Comparison of three learning models for estimation and validation of wheat yield in 2022 based on monitoring data of PN 713 in 2021

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Learning model | Date | Used index | Predicted yield (kg) | Error (kg) | Accuracy (%) | Remark |
| GB | 20221210 | PDI | 721.82 | 38.18 | 94.98 | Actual yield of 760 kg |
| 20230111 | NDVI | 703.88 | 56.12 | 92.62 |
| 20230219 | NDVI | 776.64 | -16.64 | 97.86 |
| 20230305 | PVI | 655.52 | 104.48 | 86.25 |
| 20230318 | PVI | 621.68 | 138.32 | 81.80 |
| 20230331 | VAPDI | 773.46 | -13.46 | 98.26 |
| 20230414 | NDVI | 537.90 | 222.10 | 70.78 |
| CNN | 20221210 | VAPDI | 766.38 | -6.38 | 99.17 |
| 20230111 | NDVI | 695.38 | 64.62 | 91.50 |
| 20230219 | VAPDI | 765.26 | -5.26 | 99.31 |
| 20230305 | PVI | 763.66 | -3.66 | 99.52 |
| 20230318 | PDI | 754.40 | 5.60 | 99.26 |
| 20230331 | PVI | 655.12 | 104.88 | 86.20 |
| 20230414 | PDI | 920.30 | -160.30 | 82.58 |
| SVM | 20221210 | NDVI | 758.42 | 1.58 | 99.79 |
| 20230111 | PVI | 830.70 | -70.70 | 91.49 |
| 20230219 | VAPDI | 789.42 | -29.42 | 96.27 |
| 20230305 | NDVI | 680.28 | 79.72 | 89.51 |
| 20230318 | PDI | 860.14 | -100.14 | 88.36 |
| 20230331 | VAPDI | 817.66 | -57.66 | 92.95 |
| 20230414 | VAPDI | 738.18 | 21.82 | 97.13 |

Table 2. Comparison of three learning models for estimation and validation of wheat yield in 2022 based on monitoring data of PN 253 in 2021

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Learning model | Date | Used index | Predicted yield (kg) | Error (kg) | Accuracy (%) | Remark |
| GB | 20221210 | NDVI | 403.28 | -283.28 | 29.76 | Actual yield of 120 kg |
| 20230111 | MPDI | 430.10 | -310.10 | 27.90 |
| 20230219 | NDVI | 411.95 | -291.95 | 29.13 |
| 20230305 | PVI | 408.37 | -288.37 | 29.39 |
| 20230318 | PVI | 396.90 | -276.90 | 30.23 |
| 20230331 | VAPDI | 384.32 | -264.32 | 31.22 |
| 20230414 | NDVI | 396.06 | -276.06 | 30.30 |
| CNN | 20221210 | VAPDI | 430.86 | -310.86 | 27.85 |
| 20230111 | PDI | 159.47 | -39.47 | 75.25 |
| 20230219 | PVI | 402.69 | -282.69 | 29.80 |
| 20230305 | PVI | 379.01 | -259.01 | 31.66 |
| 20230318 | PVI | 386.21 | -266.21 | 31.07 |
| 20230331 | VAPDI | 201.92 | -81.92 | 59.43 |
| 20230414 | NDVI | 358.70 | -238.70 | 33.45 |
| SVM | 20221210 | NDVI | 510.03 | -390.03 | 23.53 |
| 20230111 | MPDI | 448.96 | -328.96 | 26.73 |
| 20230219 | PDI | 513.84 | -393.84 | 23.35 |
| 20230305 | VAPDI | 511.63 | -391.63 | 23.45 |
| 20230318 | VAPDI | 509.41 | -389.41 | 23.56 |
| 20230331 | MPDI | 494.64 | -374.64 | 24.26 |
| 20230414 | NDVI | 444.99 | -324.99 | 26.97 |

Due to the inadequate learning models developed by training with the monitoring data from 2021, the research subsequently utilized the monitoring data from 2022 to retrain the learning models and tested their capacities in predicting the wheat yield in PN 253. The accuracies of wheat yield estimation are presented in Table 3. It is found that a significant reduction in the error values in the retrained models. Specifically, the SVM learning model achieved the estimation accuracies exceeding 90% for February 19 and March 18, 2023. The reliable verification results for PN 713, as compared to PN 253, can be attributed to the insignificant difference, as determined by a two-tailed test, in wheat yield per unit area between the two years (2021 and 2022). Nevertheless, PN 253 was demonstrated a significant difference in wheat yield per unit area between the two years. The significant difference hampers the wheat yield estimation in 2022 for PN 253 by the learning model, based on the monitoring data from 2021.

Among the learning models, the CNN model offered the highest accuracy, with most of the estimations above 70%. Figures 3 and 4 are the thematic maps illustrating the wheat yield predicted for PNs 713 and 253 through the CNN model coupled with the used indices in Tables 1 and 3, respectively. The closer the area is to the golden-yellow hue, the higher the estimated wheat yield for the area at the date. It is noticed that the image acquired for PN 713 on March 31, 2023, could not be completely stitched due to unmatched feature points. Figure 5 displays the boxplots representing the predicted wheat yields illustrated in Figures 3 and 4. Most of the median values for the predicted wheat yields in PN 713 are approximately 400 g/m2 (the survey *in situ* is 361.8 g/m2), whereas for PN 253 are merely at around 100 g/m2 (the survey *in situ* is 101.7 g/m2). This result demonstrates that the wheat yield estimations derived from the CNN learning model well align with the survey *in situ*.

Tables 1 through 3 are seen that the presented methodology, relying on index data from various monitoring dates, can derive the approximately equivalent accuracies of wheat yield estimation. This result demonstrates that the acquisition of UAV multispectral imagery, conducted during the early stages of wheat growth, and the subsequent input of the index map calculated from UAV imagery into the established prediction model, effectively facilitate the estimation of the final wheat yield. Hence, if the initial monitoring data for the wheat field in a given year indicates that the yield deviates from expectations, an early warning should be started. PN 253 for instance, while this study failed to obtain the final wheat yield data for this farmland in 2021, the wheat yield estimated for 2022, derived from the 2021 monitoring data in Table 2, indicates an expected range of 350 to 500 kg. However, the actual yield is only 120 kg. It is noticed that the verification result of the CNN learning model on January 11, 2023, as presented in Table 2, demonstrates an estimated yield of 159.47 kg. Moreover, upon relearning the index data in 2022 (refer to Table 3), the estimated yield is 160.10 kg. The estimations from both CNN learning models are approximately consistent, verifying that the wheat yield of PN 253 in 2022 is indeed lower than that in 2021. The early warning of wheat yield reduction can be started in January 2022.

Table 3. Comparison of three relearning models for estimation and validation of wheat yield in 2022 based on monitoring data of PN 253 in 2022

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Learning model | Date | Used index | Predicted yield (kg) | Error (kg) | Accuracy (%) | Remark |
| GB | 20221210 | VAPDI | 181.20 | -61.20 | 66.23 | Actual yield of 120 kg |
| 20230111 | NDVI | 186.93 | -66.93 | 64.20 |
| 20230219 | PDI | 187.60 | -67.60 | 63.97 |
| 20230305 | NDVI | 185.02 | -65.02 | 64.86 |
| 20230318 | VAPDI | 185.49 | -65.49 | 64.69 |
| 20230331 | MPDI | 181.86 | -61.86 | 65.98 |
| 20230414 | PVI | 183.04 | -63.04 | 65.56 |
| CNN | 20221210 | VAPDI | 167.52 | -47.52 | 71.63 |
| 20230111 | PDI | 160.10 | -40.10 | 74.95 |
| 20230219 | VAPDI | 170.42 | -50.42 | 70.41 |
| 20230305 | NDVI | 157.54 | -37.54 | 76.17 |
| 20230318 | PDI | 182.42 | -62.42 | 65.78 |
| 20230331 | PDI | 166.77 | -46.77 | 71.96 |
| 20230414 | PDI | 172.82 | -52.82 | 69.44 |
| SVM | 20221210 | VAPDI | 218.96 | -98.96 | 54.80 |
| 20230111 | PDI | 192.11 | -72.11 | 62.46 |
| 20230219 | PDI | 128.85 | -8.85 | 93.13 |
| 20230305 | PVI | 248.18 | -128.18 | 48.35 |
| 20230318 | MPDI | 125.79 | -5.79 | 95.40 |
| 20230331 | PDI | 212.26 | -92.26 | 56.53 |
| 20230414 | PVI | 206.24 | -86.24 | 58.18 |

Mar. 5, 2023

Feb. 19, 2023

Jan. 11, 2023

Dec. 10, 2022

|  |  |  |  |
| --- | --- | --- | --- |
| Mar. 18, 2023 | Mar. 31, 2023 | Apr. 14, 2023 |  |
|  |  |  |  |

Figure 3. Thematic maps illustrating wheat yield predicted for PN 713.

|  |  |  |  |
| --- | --- | --- | --- |
| Mar. 18, 2023 | Mar. 31, 2023 | Apr. 14, 2023 |  |
|  |  |  |  |

Figure 4. Thematic maps illustrating wheat yield predicted for PN 253.

Mar. 5, 2023

Jan. 11, 2023

Feb. 19, 2023

Dec. 10, 2022

|  |  |
| --- | --- |
|  |  |

Figure 5. Boxplots of predicted wheat yield; a) PN 713; b) PN 253.

a

b

# conclusions

In this study, UAV multispectral imagery was employed to monitor the growth of two wheat fields in Jinsha Township, Kinmen from 2021 to 2022. Based on the soil line theory, we calculated the relevant soil drought indices and the wheat vegetation indices from the UAV imagery. These calculated index maps were subsequently input into the machine/deep learning models, including SVM, GB, and CNN, to estimate wheat yield and assess the accuracy of the predictions. The experimental results reveal that the accuracy of the three learning models for wheat yield estimation is comparable, with the CNN learning model offering a slightly higher accuracy compared to the other two. The model training for the wheat field of PN 713 used the monitoring data from 2021, and the yield estimation by the 2022 monitoring data verified an accuracy exceeding 90%. In spite of that, for PN 253, the verification accuracy is only within the range of 20 to 30%. However, following the retraining of the wheat yield estimation model based on the monitoring data from 2022 for PN 253, the estimation accuracy can be improved to above 70%. This study further identified that the wheat yield for PN 253 in 2021 was indeed lower than that observed in 2022. Additionally, the CNN learning model demonstrated its capability to offer an early warning of wheat yield reduction.

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**References**

Baas, S., Trujillo, M., & Lombardi, N., 2015. *The Impact of Disasters on Agriculture and Food Security*. Food and Agriculture Organization of the United Nations.

Casamitjana, M., Torres-Madroñero, M.C., Bernal-Riobo, J., & Varga, D., 2020. Soil moisture analysis by means of multispectral images according to land use and spatial resolution on andosols in the Colombian Andes. *Applied Sciences*, 10(16), 5540.

Di, L., Rundquist, D.C., & Han, L., 1994. Modelling relationships between NDVI and precipitation during vegetative growth cycles. *International Journal of Remote Sensing*, 15(10), pp. 2121-2136.

Farhan, I.A., & Al-Bakri, J., 2019. Detection of a real time remote sensing indices and soil moisture for drought monitoring and assessment in Jordan. *Open Journal of Geology*, 9(13), pp. 1048-1068.

Ghimire, S., Nguyen-Huy, T., C Deo, R., Casillas-P´erez, D., Salcedo-Sanz, S., 2022. Efficient daily solar radiation prediction with deep learning 4-phase convolutional neural network, dual stage stacked regression and support vector machine CNN-REGST hybrid model. *Sustainable Materials and Technologies*, 32, e00429.

Ghulam, A., Qin, Q., & Zhan, Z., 2007a. Designing of the perpendicular drought index. *Environmental Geology*, 52, pp. 1045-1052.

Ghulam, A., Qin, Q., Teyip, T., & Li, Z.-L., 2007b. Modified perpendicular drought index (MPDI): a real-time drought monitoring method. *ISPRS Journal of Photogrammetry & Remote Sensing*, 62(2), pp. 150-164.

Kogan, F.N., 1990. Remote sensing of weather impacts on vegetation in non-homogeneous areas. *International Journal of Remote Sensing*, 11(8), pp. 1405-1419.

Li, S., Pezeshki, S.R., & Goodwin, S., 2004. Effects of soil moisture regimes on photosynthesis and growth in cattail (Typha latifolia). *Acta Oecologica*, 25(1-2), pp. 17-22.

Li, Z., & Tan, D., 2013. The second modified perpendicular drought index (MPDI1): A combined drought monitoring method with soil moisture and vegetation index. *Journal of the Indian Society of Remote Sensing*, 41, pp. 873-881.

Lu, F., Sun, Y., & Hou, F., 2020. Using UAV visible images to estimate the soil moisture of steppe. *Water*, 12, 2334.

Nie, Y., Tan, Y., Deng, Y., & Yu, J., 2020. Suitability evaluation of typical drought index in soil moisture retrieval and monitoring based on optical images. *Remote Sensing*, 12(16), 2587.

Panahi, M., Sadhasivam, N., Pourghasemi, H.R., Rezaie, F., & Lee, S., 2020. Spatial prediction of groundwater potential mapping based on convolutional neural network (CNN) and support vector regression (SVR). *Journal of Hydrology*, 588, 125033.

Richardson, A.J., & Wiegand, C.L., 1977. Distinguishing vegetation from soil background information. *Photogrammetric Engineering and Remote Sensing*, 43, pp. 1541-1552.

Shoshany, M., Spond, H., & Bar, D.E., 2019. Overcast versus clear-sky remote sensing: Comparing surface reflectance estimates. *International Journal of Remote Sensing*, 40, pp. 6737-6751.

Shun, Z., Li, D., Jiang, H., Li, J., Peng, R., Lin, B., Liu, Q., Gong, X., Zheng, X., & Liu, T., 2022. Research on remote sensing image extraction based on deep learning. *Peer J Computer Science*, 8, e847.

Tao, L., Ryu, D., Western, A., & Boyd, D., 2021. A new drought index for soil moisture monitoring based on MPDI-NDVI trapezoid space using MODIS data. *Remote Sensing*, 13(1), 122.

UNISDR., 2009. *Drought Risk Reduction Framework and Practices: Contributing to the Implementation of the Hyogo Framework for Action*. United Nations Secretariat of the International Strategy for Disaster Reduction, in Partnership with the National Drought Mitigation Center, Geneva, 3-8.

Yang, W., Fu, B., Li, S., Lao, Z., Deng, T., He, W., He, H., & Chen, Z., 2023. Monitoring multi-water quality of internationally important karst wetland through deep learning, multi-sensor and multi-platform remote sensing images: A case study of Guilin, China. *Ecological Indicators*, 154, 110755.

Zhang, J., Zhou, Z., Yao, F., Yang, L., & Hao, C., 2015. Validating the modified perpendicular drought index in the north China region using *in situ* soil moisture measurement. *IEEE Geoscience and Remote Sensing Letters*, 12(3), pp. 542-546.