



Prifysgol Cymru

Y Drindod Dewi Sant

University of Wales

Trinity Saint David

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Student Name: Tasin Islam

Student Number: 2435184

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Lecturer: Dr Aliyu Sambo

Supervisor: Nouh Elmitwally

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Abstract

In crop yield forecasting, accuracy can be seen as a key part of creating a climate-resilient agricultural plan given the rise of variable and unpredictable climatic conditions. The use of conventional approaches to crop yield estimation is most commonly achieved through a single data source. This may not be adequate compared to crop yield prediction using advancements in deep learning technologies and spatio-temporal modeling and their accuracy. There are still some difficulties and challenges associated with creating a spatio-temporal model and successfully aligning different sources of data.

This paper proposes a spatio-temporal crop yield forecasting and climate resilience planning framework, which utilizes multi-data sources related to agricultural and climate conditions, and an adaptive brain imaging registration technology. Based on the popular medical image registration technique, which can register diverse brain imaging modalities, this paper advances an innovative spatial alignment and temporal correspondence process to improve the regularization of features across satellite images, climate conditions, and past crop yields. This paper utilizes multi-temporal satellite images, meteorological conditions, soil indices, and ecosystem variables through a deep learning-based spatiotemporal learning.

The proposed framework is likely to enhance the accuracy, reliability, and interpretability of the forecasts, as well as facilitate climate-resilient decision-making at the farm and regional levels. Some of the possible outcomes expected from the proposed framework's application include improved performance in forecasting, as well as comprehension and insights about climate-related yield variation. The brain imaging and agricultural analytics techniques integrated in this research provide the unique interdisciplinary perspective envisioned in this intelligent agriculture and climate resilient planning study.

Introduction

Agriculture remains one of the climate-sensitive sectors where crop production is directly impacted by changes in temperature, precipitation, and soil conditions, among other extreme weather events. Crop yield forecasting is very important to food security, economic stability, and management of resources on a sustainable basis. In recent years, expanding satellite imagery, climate datasets, and agricultural records have promoted the adoption of AI and deep learning methods for crop yield forecasting. Despite these advances, achieving reliable spatio-temporal forecasts under dynamic climate conditions is still a major research challenge.

Most of the current crop yield forecasting methods are limited to a few data sources or simplified temporal modeling, which restrains their capability to capture the interactive complexity of environmental factors with crop growth processes. Works like Gong et al. (2025), and Menon et al. (2025) illustrate the performance of deep learning models using multi-temporal satellite imagery. However, many approaches still face difficulties related to spatial misalignment, temporal inconsistencies, and heterogeneity in data. Likewise, spatiotemporal modeling techniques have been successfully applied within related applications, such as crop disease analysis and ecosystem monitoring, but their complete potential for integrated climate-resilient planning has not yet been fully exploited.

An important shortcoming of the available literature is the scarcity of effective spatiotemporal registration mechanisms, which can facilitate the registration of diverse data sources in a timely manner. Satellite images, climatic data, and yield data are not always of the same scale, causing inconsistencies within data, which is very detrimental to the overall performance of the model. Interestingly, the domain of medical image analysis, particularly for brain image analysis, has already addressed such challenges through image registration mechanisms, where different images are correlated very effectively. Brain image registration measures have been used to enhance analytical precision.

Motivated by these promising results, the present work sets out to investigate the application of a new brain imaging registration method, which can enhance the integration of agricultural and climate data. This study focuses on the implementation of a spatio-temporal deep learning model, which has the potential to address the concerns of long-term dependencies and regional interactions, observed and affected by climate.

The main aim of this study is to propose a spatio-temporal AI-based framework that can improve the accuracy of crop yield prediction while ensuring the climate resilience plan. The specific objectives of this study are to (i) integrate different datasets from satellite images, climate, and agriculture, (ii) implement advanced registration techniques for spatio-temporal data, and (iii) conceive the performance of the framework for crop yield prediction under different climate scenarios. The expected contributions of the work are two-fold: (i) this study is a cognitive advancement of AI techniques that transfer knowledge from brain imaging to crop assessment usually not easy to implement, while (ii) practically speaking, this is beneficial to policymakers, farmers, and planners to derive useful information for climate-resilient agriculture.

In conclusion, it can be said that the study uses spatiotemporal deep learning together with novel registration approaches in a bid to address significant white spaces in crop yield prediction studies to achieve sustainable crop yield prediction despite climate changes through scalable and robust solutions.

Literature Review

Agriculture is a climate-sensitive area, where the production of crops is directly influenced by temperature, rainfall, soil type, and other extreme weather events. Hence, crop yield prediction is a critical requirement for agricultural security, economic sustainability, and resource management. In recent years, the availability of satellite images, climate data, and agricultural records has fueled the use of AI and deep learning techniques for crop yield prediction. Yet, precise spatio-temporal prediction in a dynamically changing climate is still a significant challenge.

The existing crop yield prediction techniques employ a few data sources or a simplified temporal model, which fails to represent the intricate relationship between environmental variables and crop growth. For instance, Gong et al. and Menon et al. in their research have demonstrated how deep learning models can be used to predict crop yield at the farm level using multi-temporal satellite images. However, existing solutions still suffer from issues of spatial mismatch, temporal incongruence, and data diversity. Spatio-temporal modeling has been successfully employed in other related domains such as crop disease assessment and ecosystem studies, but the true potential of this technology for comprehensive climate-resilient planning has yet to be fully harnessed [6].

One of the major drawbacks of the existing system is the absence of efficient spatio-temporal registration methods. The satellite images, climatic information, and past crop yield information are not always in the same resolution. This leads to inconsistencies in the data, which is harmful to the model. Image registration methods have been employed to overcome such difficulties in medical image analysis, particularly in brain image analysis. Brain image registration enables the development of accurate correlations among various images, which enhances the accuracy of analysis. For instance, Colliot, Olivier, Machine Learning for Brain Disorders and Varatharaj & Radhakrishnan have demonstrated the effectiveness of sophisticated registration methods in improving the accuracy of medical imaging results.

Encouraged by such promising outcomes, the current study aimed to apply a novel brain imaging registration technique to enhance the integration of crop and climatic information. This proposed research will be able to identify long-term dependencies and interactions among regions through the application of a spatio-temporal deep learning model. The effects of climatic variability and environmental factors will be examined in this context.

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Based on the encouraging outcomes of such research, the proposed study aims to apply a novel brain image registration technique to enhance the integration of crop and climatic information [1][2]. This proposed research will be able to identify long-term dependencies and interactions at the regional level by implementing a spatio-temporal deep learning model. The effect of climatic variability and environmental conditions will be examined in this context.

The spatio-temporal AI model will be trained by combining satellite images, IoT sensor information, climatic information, and past crop yield information. The AI model will be able to forecast crop yield based on climate conditions such as drought, flood, or heatwave. The AI model will not only be used for forecasting but also as a climate-resilient decision support system to offer feasible suggestions to policymakers and farmers.

The primary objective of this research work is to introduce a spatio-temporal AI-based framework that will enhance the accuracy of crop yield forecasting and ensure climate-resilient planning.[3] The specific objectives include: (i) combining satellite images, climatic information, and agricultural data, (ii) synchronizing spatio-temporal data using sophisticated registration methods, and (iii) testing the framework performance under climate conditions.

The significance of this research work is significant in two ways. Firstly, it is the cognitive development of AI models, which is novel in crop yield forecasting by applying knowledge from brain imaging. Secondly, its application will help policymakers, farmers, and agricultural planners make climate-resilient agricultural decisions. Furthermore, the integration of multi-source data and spatio-temporal modeling will enhance the efficiency of crop yield forecasting.

Previous research works like Gong et al., S Menon et al., Xu et al., Spatial-temporal analysis and trend prediction, and A Spatio-Temporal AI Framework for Ecosystem Monitoring have proved that multi-temporal satellite images, AI, and spatio-temporal modeling are highly significant for crop yield prediction [1]. But the use of brain-inspired registration methods for crop and climate data integration to fill this research gap is still unexplored [4]. This would help to make a significant contribution to agricultural planning in the UK and worldwide.

This literature review clearly proves that the combination of multi-source data integration, spatio-temporal modeling, and brain-inspired registration methods leaves a significant research gap in crop yield prediction. The proposed framework will fill this gap, ensuring climate-resilient, scalable, and robust crop yield prediction, which is highly significant for sustainable agriculture.

Methods

The proposed research will create a Spatio Temporal AI framework that will enable crop yield prediction and climate resilience planning based on multi-source data. The research will be conducted in five major steps.

First, data will be gathered from satellite images, climatic data (temperature, rainfall, humidity), and crop yield data. Public domain agricultural data will be utilized if needed.

Second, data preprocessing and cleaning will be conducted. As the data from various sources is of different spatial resolutions and temporal scales, normalization, interpolation, and missing data treatment will be required.

Third, data from various sources will be synchronized using a spatiotemporal registration approach modeled after brain imaging. Satellite images, climatic data, and crop yield data will be combined into a unified spatial-temporal framework using transformation and feature registration techniques similar to those used in medical image registration.

Fourth, a spatio-temporal model using deep learning (for example, CNN-LSTM or a Transformer model) will be designed and trained. This model will be able to learn long-term temporal dependencies and spatial interactions.

Fifth, the training and testing sets will be split for the evaluation of the model. The accuracy of the model predictions will be verified under different climate conditions (for example, drought or heavy rainfall).

Although other approaches, such as statistical regression or single-source modeling, can be used, the integration of multiple sources and brain-inspired registration techniques will be reasonably proven to be more accurate.

Expected Results

Though the final results are yet to be obtained, it is expected that the proposed model will give a more accurate estimation of crop yield compared to the conventional approaches.

The data collected will be numerical (temperature and rainfall), image data (satellite images), and tabular data (agricultural data). Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R^2 score will be used for statistical analysis.

Moreover, the stability of the predictions will be analyzed based on climate conditions. It is expected that the proposed advanced registration technique will help in better alignment of data and hence improve the performance of the proposed model.

Evaluation

The potential impact of this research is significant. It will assist policymakers, farmers, and agricultural planners in making climate-resilient decisions. The integration of multi-source data and brain-inspired registration can provide a new methodological contribution to agricultural research.

However, there are some limitations to this research. First, the collection of high-quality datasets can be time-consuming. Second, the computational complexity can be high, especially in training deep learning models. In addition, the research may be limited to a certain region or crop, which may affect generalization.

These limitations are justifiable in light of the time constraints and the nascent stage of development of the research field. However, the proposed research is expected to make a significant contribution to the development of climate-resilient sustainable agriculture.

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