Journal of Engineering, Innovation and Sustainability (JEIS)

DEVELOPMENT OF A PREDICTIVE DECISION SUPPORT SYSTEM FOR CROP GROWTH AND MANAGEMENT OF SELECTED CROPS IN THE TROPICS

Timothy Denen Akpenpuun[1], Reginald Gbenga Azuatalam[1*], Abdulmaleek Adedapo Olaifa[1], Quam Akanji Akolade [1], Abdulgafar Usman[2], Hamidu Oladimeji Sanusi[1]

[1]Department of Agricultural and Biosystems Engineering, University of Ilorin, Ilorin, Nigeria.
[2]Department of Agricultural and Biosystems Engineering, Joseph Sarwuan Tarka University, Makurdi, Nigeria.

[*]Corresponding author: reginaldazuatalam@gmail.com

Abstract

Management of crops is critical in maximising agricultural production, particularly in the face of climate variability. In this research, a Crop Decision Support System (CDSS) is presented to utilize the concept of Growing Degree Days (GDD) to forecast crop stages and plan resource allocations. This CDSS features a user-friendly interface for calculating GDD, water requirements, and predictive models for various crops, including maize, tomatoes, rice, beans, and millet. Real-time and historical weather data were obtained using the Open-Meteo API and the Nigerian Meteorological Agency (NiMet). GDD and crop development were estimated by using ridge regression. The backend was developed using Python (Flask), and the frontend was built using Next.js. This system was tested by comparing the predicted phenological stages against literature-reported observations. Data reliability was supported by the fact that the results of statistical analysis (ANOVA) revealed no significant differences between NiMet and API temperature datasets. This CDSS generated accurate phenological forecasts and provided adequate decision support for irrigation and pest control. The work is a contribution to the development of scalable, data-driven crop management, with a future focus on the application of machine learning and remote sensing technologies.

Keywords:
Crop Decision Support System, Growing Degree Days, Predictive Modelling, Precision Agriculture, Remote Sensing, Phenological Stages

1. Introduction

Agriculture forms a fundamental part of food security and economic growth in the world. Nevertheless, due to rising climate variations, scarcity of resources and the need to increase food supply, there has been a need to change farming practices to data-driven agriculture practices. Of particular importance is precision agriculture that helps to increase productivity and make agriculture more sustainable and resource-efficient, linked to the employment of technologies (Bullock et al., 2019).

Among the tools facilitating precision agriculture, Crop Decision Support Systems (CDSS) have taken centre stage due to their ability to make informed decisions in crop management promptly. These are systems in which environmental and agronomic data are combined to aid in planting schedules, irrigation, fertilising, pest control of pests, and the harvest. The Growing Degree Days (GDD) is one of the most common measures in the field of CDSS, representing a temperature-based index that predicts plant phenological stages (Sha & Zhang, 2007; McMaster & Wilhelm, 1997). Growing degree days (GDDs) are a measure of heat accumulation over a growing season, which is essential for crop growth and development. Growing degree days (GDD), also called growing degree units, are dependent upon the minimum and maximum temperatures which affect the plant's growth (Akyuz, Kandel, & Morlock, 2017).

The effectiveness of GDD has been corroborated by its scientific usefulness, its applicability in streamlining crop growth projection and resource distribution (Angel et al., 2017; Keramitsoglou et al., 2023). Higher GDDs can lead to higher crop yields, as warmer temperatures and increased light intensity can enhance crop photosynthesis and accelerate crop growth. Higher GDDs can also lead to increased water use efficiency, as warmer temperatures can result in higher evapotranspiration rates, thereby reducing the amount of water lost to the atmosphere. According to Parthasarathi, Velu, and Jeyakumar (2013) the number of growing degree days can be used to ascertain a region's suitability for producing a specific crop, determine the crop's growth stage, determine the best time to apply fertilizer, herbicide, and plant growth regulators, estimate heat stress on crops, predict physiological maturity and harvest dates, and more. Each plant species has a different base air temperature, a threshold below which growth is limited. However, farmers in less developed areas seldom have access to affordable, easy-to-access, and data-driven decision support or decision tools, caused in part by digital illiteracy, expensive technology, and the lack of access to real-time weather information.

To address these challenges, this study proposes the development of a Crop Decision Support System (CDSS) that integrates temperature-based indicators and predictive modelling. Specifically, the CDSS utilises Growing Degree Days (GDD) and a ridge regression technique to predict the stages of phenological development for selected crops, thereby assisting in data-driven agricultural management operations. The system is designed to enable farmers to access real-time, localized information, making it easier for them to make informed decisions under variable climatic conditions.

2. Theoretical Analysis

The Crop Decision Support System (CDSS) was developed based on two conceptual models: Ridge Regression and the Growing Degree Days (GDD) model. The two models operate together to provide predictive analytics about the phase of crop growth.

1. GDD, or Growing Degree Days Model

The Growing Degree Days index, based on temperature readings and thermal units amassed, is taken as a prediction tool for the developmental pattern of crops. Estimation of the index requires using equations 1 and 2. To determine the developmental stages, cumulative Growing Degree Days are matched against standards specific to a given crop. Equation 3 is used to determine cumulative GDD.

$$T_{meam}=\frac{T_{max}+T_{min}}{2} \quad (1)$$

$$GDD = T_{meam}-T_{base} \quad (2)$$

where,

T_{BASE} = base temperature of the specific crop below which the crop grows slowly.
T_{max} and T_{min} = maximum and minimum daily temperatures

$$\text{GDD cumulative over n days} = \Sigma\ GDD \quad (3)$$

2. Using Ridge Regression for Temperature Predictions

A statistical approach called ridge regression is utilised to reduce overfitting and deal with the problem of multicollinearity commonly found with environmental data sets, as well as to estimate missing or future temperature values. Two different models were formulated for Tmax and Tmin. These predictions give the overall temperature information required for the determination of GDD. Equation 4 was used to determine β, the regression coefficient and equation 5 is the model equation.

The Ridge Regression estimator is as $\hat{\beta}=\frac{1}{(X^T+\lambda I)}X^T$ (4)

$$y = X\beta + \varepsilon \quad (5)$$

where,

y is the target variable (either Tmax or Tmin in the future).
X is the predictor matrix of meteorological variables from previous time intervals.
($\lambda > 0$) represents the regularization parameter; I is the identity matrix; ε is the error term.

3. Material and Methods

3.1 Data Collection and Sources

This study utilised both past and current meteorological data in creating a Crop Decision Support System (CDSS). The daily temperature data, including the highest temperature and the lowest temperature, was obtained using two major sources, the Nigerian Meteorological Agency (NiMet) and the Open-Meteo API (https://archive-api.open-meteo.com). These records were used to compute Growing Degree Days (GDD), a crop-based agroclimatic index to assess crop growth in terms of developmental stages.

The agronomic information related to crops, such as thresholds in terms of phenology together with the GDD requirements, was sourced from peer-reviewed studies and crop farming databases. This data was necessary in calibrating the system to the specific physiological traits of maize, rice, tomatoes, beans, and millet.

3.2 System Architecture and Model Design

The CDSS is designed to be a modular web-based system that will serve to give real-time assistance to farmers as far as decision-making is concerned. The backend was implemented in Python (v3.9) using the Flask framework to manage data processing and predictive computations. NEXT.JS was used to create a frontend that was responsive and accessible across multiple devices.

The prediction quality was enhanced by using ridge regression to model the dependence between the temperature inputs and the crop growth output. This regularised regression process is quite effective in countering multicollinearity problems that are usually high in environmental statistics.

To address potential data quality issues such as missing or noisy temperature readings, the CDSS includes the following pre-processing mechanisms: interpolation to fill missing values and smoothing statistics-based operations to overcome anomalies. Additionally, data in the NiMet and Open-Meteo datasets are cross-validated. If the deviation exceeds the threshold, a fallback is performed, and the historical average is used to provide robustness to the calculation of GDD.

Figure 1 illustrates the system architecture, which involves the use of external weather information sources, internal GDD calculators, machine learning modules, and their interfaces. The architecture is scalable and can be modified to new crops and areas.

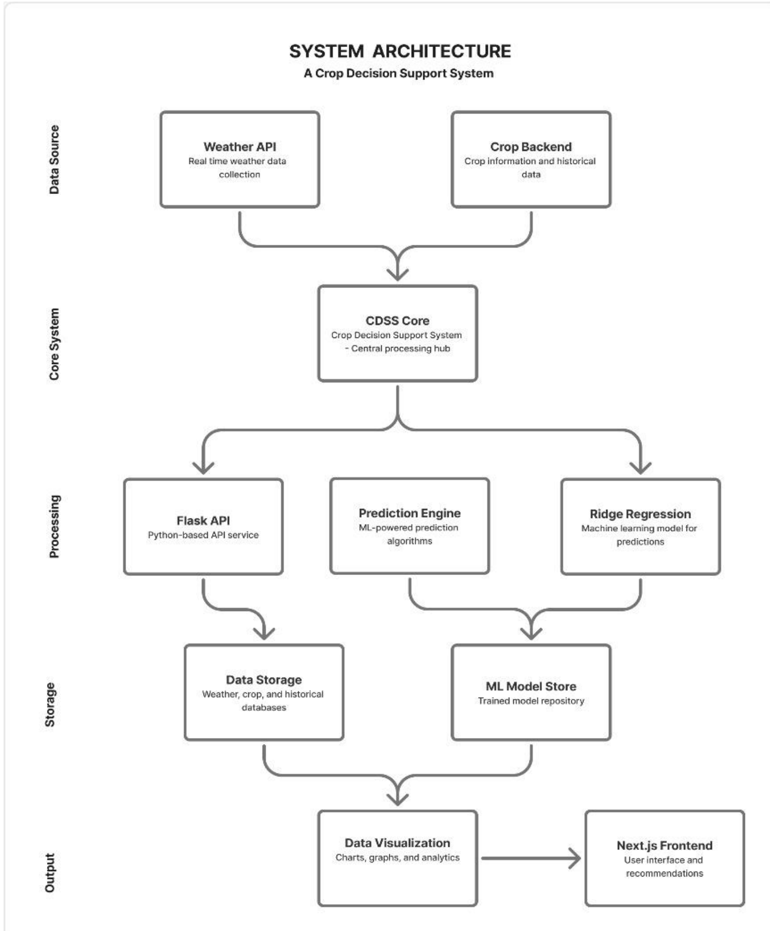

Figure 1. System Architecture of the Crop Decision Support System (CDSS).

3.3 Experimental Setup and Simulation

The CDSS was running on a cloud-based server with specifications including an 8-core virtual processor, 32 GB of memory, and the Ubuntu 20.04 (64-bit) operating system. Weather data at real-time was accessed via an API interface with caching facilities that guarantee minimum latency in data processing.

Simulations of all five crops have been utilised to measure the system performance. Users could enter the type of crop, geographical location, and the system would provide time-sensitive advice on when to irrigate, fertilise, and harvest. Secondary data gathered from publicly available sources of agricultural research and open-source agronomic datasets were used to validate the reliability of predictions. These materials presented reported phenological observations of phenological portions, i.e., flowering and maturity duration, of maize, rice, tomatoes, beans, and millet in Nigerian agro-ecological zones. This methodology enabled a literature-guided comparison of the predicted and observed values, which were remarkably close to the recorded crop development trends. Furthermore, a comparison between NiMet and Open-Meteo data was carried out using descriptive statistics and ANOVA, which validated the data obtained from the API.

3.4 Decision Support Components and Agricultural Profiles

To provide useful information beyond phenological forecasting, the CDSS incorporates modules tailored to each crop. Each module includes estimates of water requirements (per hectare), pest incidence windows (connected to GDD), and development stages calibrated by GDD, guaranteeing that recommendations are crop-specific and stage-specific.
For instance, maize normally reaches maturity between 2,100 and 2,700 growing degree days (GDD) and starts flowering (silking) between 1,300 and 1,700 GDD (Dong et al., 2021; Bonea and Dunăreanu, 2021).

For tropical cultivars of rice, flowering is between 1,300 and 1,500 GDD (Anju et al., 2018). Such thresholds are used to accurately monitor all the supported crops' growth stages as they are embedded into the Crop Decision Support System (CDSS).
The pest module links important pests with the corresponding Growing Degree Days (GDD) stages when they cause the most damage. In the list are Fall Armyworm (Spodoptera frugiperda) damaging maize between 0–2,700 GDD (FAO, 2020), the Rice Stem Borer (Scirpophaga incertulas) damaging rice between 200–1,900 GDD, and the Millet Stem Borer (Coniesta ignefusalis) damaging millet between 160–1,000 GDD (Kalaisekar, 2016; Gahukar and Reddy, 2019). Each of the pests covered in the system provides information on symptoms and integrated control measures that include biological controls (including Trichogramma spp.), resistant varieties of crops, as well as various cultural measures.
Using estimations based on FAO CROPWAT, the water requirement module offers stage-adjusted irrigation instructions. Millet's seasonal requirements are from 6,500 to 9,000 m³/ha, while rice's range is 10,500 to 14,000 m³/ha (FAO, 2025).

4. Results and Discussion

4.1 System Implementation and User Interface

The Crop Decision Support System (CDSS) was successfully developed and implemented. Users can enter the crop type and geographical coordinates to receive GDD-based directives on irrigation timing, phenological stage prediction, and harvest time. Figures 2 and 3 present the system dashboard and result interface, respectively.

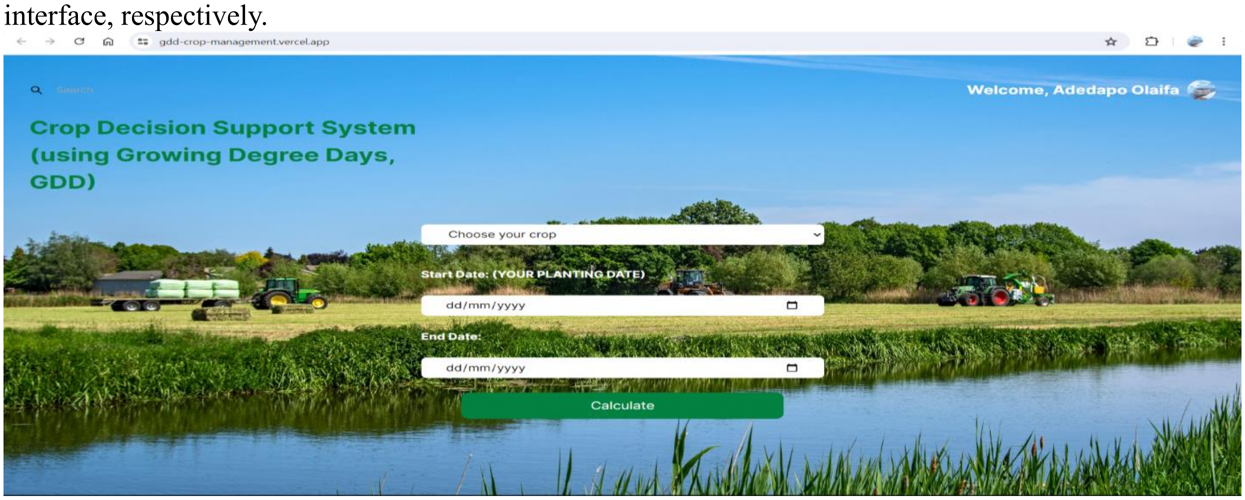

Figure 2. User dashboard of the CDSS

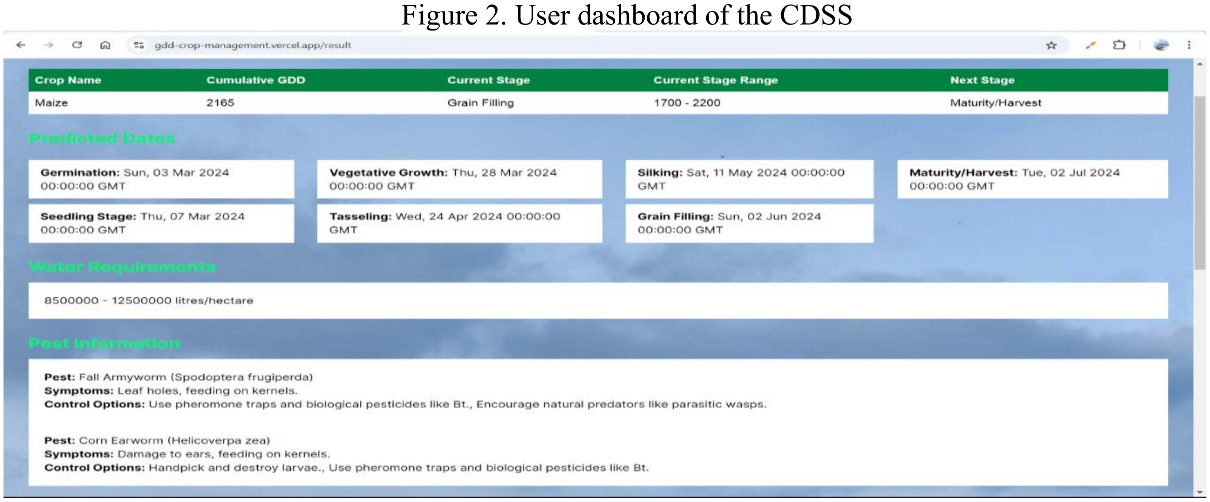

Figure 3. CDSS result interface

Figure 4 presents the monthly and cumulative Growing Degree Days (GDD) values from March to June 2024, illustrating the thermal accumulation essential for phenological predictions. The monthly GDD, represented by orange bars, demonstrates a steady heat accumulation of approximately 500 units each month, with minor fluctuations throughout the period. The cumulative GDD, represented by a blue line, begins at a low value in March and steadily increases, reaching approximately 2000 units by June, reflecting the ongoing accumulation of thermal energy.

This visualisation emphasises a stable monthly GDD contribution, indicating consistent temperature conditions that are conducive to plant development throughout the season. The upward trend in cumulative GDD signifies a continuous increase in heat units, which is crucial for forecasting phenological events such as flowering and growth stages. Overall, the chart effectively illustrates the progression of thermal accumulation over time, offering valuable insights for agricultural planning in 2024.

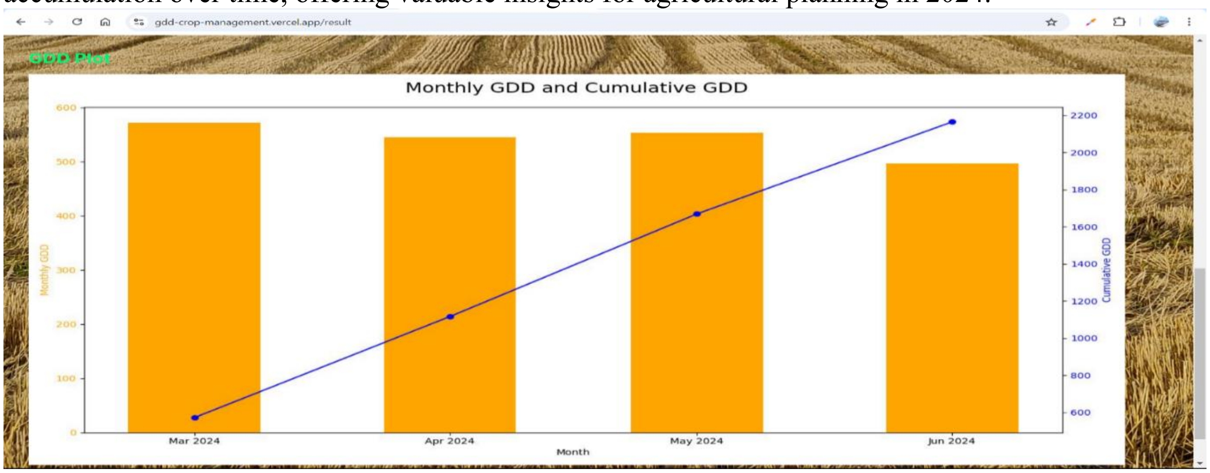

Figure 4. Monthly Growing Degree Days (GDD) and Cumulative GDD from March to June 2024

4.2 GDD-Based Prediction Validation

The phenological stages for five crops, maize, rice, tomato, beans, and millet, predicted by the GDD-based model were tested against empirical data from the field to assess the model-based prediction reliability. In conjunction with the actual true ranges recorded through field trials, Table 1 presents a summarised version of the dates for the predicted flowering and maturation dates. There was a clear match between the model predictions and the actual recorded data. For example, the model's prediction for the flowering time for maize as 35 days corresponds with the range that was recorded as between 28 to 35 days. In the same way, the flowering time for tomato was predicted as 36 days, corresponding with the normal range of between 20 to 40 days.

Common quantitative error measures such as the Coefficient of Determination (R^2), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE) were used to assess model performance alongside qualitative validation. The reference value taken for every combination of crop stage we tested in this analysis was the midpoint of the range we were phenologically able to observe. Then the predictions for the flowering phase achieved an RMSE of 5.17 days, an MAE of 4.80 days, and an R^2 of 0.93, corresponding to the high level of model precision portrayed in Table 2. Conversely, because long-term temperature predictions and durations to maturity are highly unpredictable aspects, the predictions for maturity stages achieved relatively high RMSEs (10.44 days), MAEs (8.60 days), and R^2 values (0.82).

These findings validate that crucial phenological stages, particularly those dominated by thermal time accumulation, can be reliably estimated using the CDSS. Users can better plan and modify cultivation practices under different climate scenarios thanks to the predictive capability.

Table 1: The phenological stages of a few chosen crops as predicted and as observed.

Crop	Predicted Flowering (Days)	Observed Flowering Range (Days)	Predicted Maturity (Days)	Observed Maturity Range (Days)
Maize	35	28 - 35	120	90 - 120
Rice	76	69 - 87	114	105 - 150
Tomato	36	20 - 40	84	65 - 80
Beans	25	20 - 40	62	55 - 65
Millet	35	20 - 35	76	60 - 90

Table 2: Overall prediction accuracy metrics across all crops.

Stage	RMSE (Days)	MAE (Days)	R^2
Flowering	5.17	4.80	0.93
Maturity	10.44	8.60	0.82

4.3 Accuracy of Crop-Specific Prediction

Prediction errors were evaluated separately for flowering and maturity events to further investigate the accuracy of the CDSS across crops and developmental stages. To compute the Mean Absolute Error (MAE) for each crop-stage combination, the midpoint of the observed phenological range was used as the reference point. This method provides a consistent and interpretable measure of deviation between predicted and expected crop behaviour.

The MAE for each crop at the flowering and maturity phases is presented in Table 3. The model performed a very good fit for short-term predictions, with the highest MAE accuracy for millet maturity (MAE = 1.0 day) and rice flowering (MAE = 2.0 days). Conversely, the largest errors were detected in maize maturity (MAE = 15.0 days) and tomato flowering (MAE = 6.0 days), which were likely due to differences in long-range temperature prediction and physiological responses under different environments. These crop-specific findings illustrate how the GDD-based prediction model outcompetes other crop types consistently, with an overall higher degree of accuracy during the early phenological stages. This reliability enables more targeted on-farm decision-making, especially regarding the optimal allocation of resources at critical growth phases such as flowering. The approach provides valuable input for both short-term and seasonal crop planning, despite the existence of minor differences for longer-term stages such as maturity.

Table 3: Crop-specific prediction accuracy (Mean Absolute Error in days).

S/N	Crop	Stage	MAE (Days)
1	Maize	Flowering	3.5
2	Maize	Maturity	15.0
3	Rice	Flowering	2.0
4	Rice	Maturity	13.5
5	Tomato	Flowering	6.0
6	Tomato	Maturity	11.5
7	Beans	Flowering	5.0
8	Beans	Maturity	2.0

9	Millet	Flowering	7.5
10	Millet	Maturity	1.0

4.4 Statistical Validation of Temperature Data

To evaluate the reliability of temperature data sourced from the Open-Meteo API, a comparative statistical analysis was conducted against temperature records from the Nigerian Meteorological Agency (NiMet). Descriptive statistics for both datasets are presented in Table 4, while Table 5 presents the results of a one-way Analysis of Variance (ANOVA) conducted to test for significant differences between the two sources.

Table 4: Descriptive statistics of minimum and maximum temperatures from NiMet and API sources.

Metric	Tmax-NiMet	Tmax-API	Tmin-NiMet	Tmin-API
Mean (°C)	32.69	32.68	21.74	22.18
Std Deviation	2.33	3.19	1.41	1.31
Variance	5.43	10.14	2.00	1.72
Range	8.92	11.36	6.15	5.35
Minimum (°C)	28.37	27.42	18.66	19.00
Maximum (°C)	37.29	38.78	24.81	24.35
Sum	1111.33	1111.15	739.24	754.18
Count (n)	34	34	34	34

Table 5: ANOVA results comparing NiMet and API temperature datasets.

Variable	F-Statistic	P-Value	F-Critical (α = 0.05)
Tmin-NiMet/API	1.76	0.19	3.99
Tmax-NiMet/API	0. 0000627	0.99	3.99

df1 = 1; df2 = 66

For the Tmax and Tmin data, there are no differences between the NiMet and the API datasets as per the ANOVA output. For the two p-values of 0.19(Tmin) and 0.99(Tmax), respectively, both of which are more than the level of significance of 0.05, we have the conclusion that the differences are not significant. In estimating the Growing Degree Days (GDD) and giving predictions on the stages of growth of the crop, the temperature data obtained using the Open-Meteo API can form a good substitute for NiMet data, according to this statistical similarity. With its affordability as well as user-friendliness it offers, the API does make the CDSS more practical for wider implementation, especially where data is minimal.

4.4 System Scalability and Resource Optimisation

The system was found to be highly scalable, demonstrating effective performance on various crops and under diverse climatic conditions as well. GDD in real-time made it possible to adjust to different temperature patterns, making water usage and fertiliser use more efficient. The predictive model yielded some practical information that made decision-making at the farm level improve when resources were scarce.

4.5 Comparative Evaluation Using Modern CDSS Tools

Numerous Crop Decision Support Systems (CDSS) have emerged worldwide to support agronomists and farmers to maximise the yield of crops through suggestions based on phenological data as well as weather conditions. Examples are AquaCrop created by the Food and Agriculture Organisation (FAO), the Decision Support System for Agrotechnology Transfer (DSSAT), and the Midwestern-specific U2U Corn Growing Degree Days (GDD) Tool based on the United States' Midwestern region. Such systems are best suited to commercial-scale farming activities where sophisticated data inputs are often necessary and steady internet connectivity is provided.

The system developed for this research was particularly set up to meet the conditions of the West African and Nigerian farming communities. It best applies to smallholder farmers with its emphasis on accessibility due to the minimal data requirements and openness to open weather application programming interfaces APIs. What is more, our platform is optimised for real-world use where resources are limited as opposed to other systems such as DSSAT that need to be calibrated with the help of high-resolution field data and expert knowledge. It includes characteristics not normally found on more extensive global platforms, such as mobile-friendly interfaces and the possibility of SMS-based output for the purposes of greater accessibility.

5. Conclusion

This paper elaborates on a web-based Crop Decision Support System (CDSS) that utilises Growing Degree Days (GDD) and ridge regression to predict crop growth stages and water requirements. It has shown high predictive precision in all 5 crops examined, as shown in the statistical analysis of NiMet and Open-Meteo API temperatures. Its implementation in a scalable design offers localised recommendations in real-time to assist with climate-based farming. This work contributes a practical, data-driven tool for enhancing agricultural decision-making in tropical regions.

To promote greater accessibility, future versions will utilize low-technology options, such as SMS or USSD-based applications, to broadcast critical information, requiring minimal Internet connectivity or sophisticated devices. The integration of voice support with regional language support is projected to help overcome usability through the intensification of extension services to farmers

Declaration of Generative AI in Scientific Writing

During the preparation of this manuscript, the author used Grammarly, ChatGPT and Grok to correct language and grammatical errors. After using this tool, the author reviewed and edited the content as needed and take full responsibility for the content of the publication.

Author Contributions: All contributors have reviewed and approved the final version of the manuscript for publication.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data will be made available upon request.

Conflicts of Interest: The authors declare no conflict of interest.

Acknowledgement

The authors acknowledge the Nigerian Meteorological Agency (NiMet) and the Open-Meteo API for providing access to the weather data utilised in this study. No institutional, technical, or financial support was received while conducting this research.

References

Alagesan, A., Vaishnavi, P., & Karthikeyan, R. (2020). Development of computational decision-making tool for predicting the growth and development of rice crop using location-specific diurnal air temperature data. In S.M. Ramasamy, A.K. Soman, & R.V. Thampi (Eds.), *Proceedings of the International Conference on Computational Intelligence and Sustainable Technologies* (pp. 439–444). Springer. https://doi.org/10.1007/978-981-15-3746-2_41

Alipour, H., Abdi, H., & Hamta, M. (2020). Assessment of growing degree-days values of phenological stages in Iranian bread wheat cultivars and landraces. *Journal of Computational Biology*, 12, 71–82. https://doi.org/10.29252/JCB.12.34.71

Anju, V.S., Kaur, S., & Dhaliwal, S.S. (2018). Agro-meteorological indices and phenology of rice cultivars under varied nitrogen and planting dates in Odisha. *Pharma Innovation Journal*, 11(10S), 373–548.

Angel, J.R., Widhalm, M., Todey, D., Massey, R., & Biehl, L. (2017). The U2U Corn Growing Degree Day tool: Tracking corn growth across the US Corn Belt. *Climate Risk Management*, 15, 73–81. https://doi.org/10.1016/j.crm.2016.10.002

Aslam, M.A., Ahmed, M., Stöckle, C.O., Higgins, S.S., Hassan, F.U., & Hayat, R. (2017). Can growing degree days and photoperiod predict spring wheat phenology? *Frontiers in Environmental Science*, 5, Article 57. https://doi.org/10.3389/fenvs.2017.00057

Bonea, D., & Dunăreanu, I.C. (2021). Impact of thermal requirement on growth and grain yield of maize hybrids under rain-fed conditions. *Scientific Papers. Series A. Agronomy*, LXIV(1), 131–142.

Bonhomme, R. (2000). Bases and limits to using 'degree-day' units. *European Journal of Agronomy*, 13(1), 1–10. https://doi.org/10.1016/S1161-0301(00)00058-7

Bullock, D.S., Boerngen, M., Tao, H., Maxwell, B., Luck, J.D., Shiratsuchi, L., Puntel, L., & Martin, N.F. (2019). The data-intensive farm management project: Changing agronomic research through on-farm precision experimentation. *Agronomy Journal*, 111(6), 2736–2746. https://doi.org/10.2134/agronj2019.03.0165

Cao, W., & Tibbitts, T. (1995). Leaf emergence on potato stems in relation to thermal time. *Agronomy Journal*, 87(3), 474–477. https://doi.org/10.2134/agronj1995.00021962008700030013x

Charalampopoulos, I., Polychroni, I., Droulia, F., & Nastos, P.T. (2024). The spatiotemporal evolution of the growing degree days agroclimatic index for viticulture over the northern Mediterranean basin. *Atmosphere*, 15(4), Article 485. https://doi.org/10.3390/atmos15040485

Dong, X., Ling, G., Zhang, P., et al. (2021). Responses of maize with different growth periods to heat stress around flowering and early grain filling. *Agricultural and Forest Meteorology*, 298, 108378. https://doi.org/10.1016/j.agrformet.2020.108378

FAO (2025). *Crop Water Requirement Tool (CROPWAT-online)*. Aquastat Database. Rome: Food and Agriculture Organization. Retrieved July 2025, from https://www.fao.org/aquastat/cropwat

Food and Agriculture Organization (2020). *Manual on Integrated Fall Armyworm Management*. Rome: FAO. Retrieved July 2025, from https://www.fao.org/publications/card/en/c/CA7729EN/

Fraisse, C., Bellow, J., & Brown, C. (2007). Degree days: Heating, cooling, and growing. *EDIS*, 2007(1). https://doi.org/10.32473/edis-ae428-2007

Gu, S. (2016). Growing degree hours – A simple, accurate, and precise protocol to approximate growing heat summation for grapevines. *International Journal of Biometeorology*, 60(7), 1123–1134. https://doi.org/10.1007/s00484-015-1105-8

Jones, J.W., Hoogenboom, G., Porter, C.H., Boote, K.J., Batchelor, W.D., Hunt, L.A., … & Ritchie, J.T. (2003). The DSSAT cropping system model. *European Journal of Agronomy*, 18(3–4), 235–265. https://doi.org/10.1016/S1161-0301(02)00107-7

Kalaisekar, A. (2016). *Insect Pests of Millets: Systematics, Bionomics, and Management*. Academic Press. ISBN 9780128042434

Keramitsoglou, I., Sismanidis, P., Sykioti, O., Pisinaras, V., Tsakmakis, I., Panagopoulos, A., Argyriou, A., & Kiranoudis, C.T. (2023). SENSE-GDD: A satellite-derived temperature monitoring service to provide growing degree days. *Agriculture*, 13(5), 1108. https://doi.org/10.3390/agriculture13051108

Liu, L.-W., Lu, C.-T., Wang, Y.-M., Lin, K.-H., Ma, X., & Lin, W.-S. (2022). Rice (Oryza sativa L.) growth modeling based on growth degree day (GDD) and artificial intelligence algorithms. *Agriculture*, 12(1), 59. https://doi.org/10.3390/agriculture12010059

Mathews, J., Kruger, L., & Wentink, G. (2018). Climate-smart agriculture for sustainable agricultural sectors: The case of Mooifontein. *Jàmbá: Journal of Disaster Risk Studies*, 10(1), a492. https://doi.org/10.4102/jamba.v10i1.492

McMaster, G.S., & Wilhelm, W.W. (1997). Growing degree-days: One equation, two interpretations. *Agricultural and Forest Meteorology*, 87(4), 291–300. https://doi.org/10.1016/S0168-1923(97)00027-0

Oliveira, M. (1998). Calculation of budbreak and flowering base temperatures for *Vitis vinifera* cv. Touriga Francesa in the Douro region of Portugal. *American Journal of Enology and Viticulture*, 49(1), 74–78. https://doi.org/10.5344/ajev.1998.49.1.74

Pacheco, R., Álvarez, E., Ferrer, J., Bonilla, H., Gómez-Correa, J., Hernández, M., & Artiles, L.R. (2019). Accumulation of degree days and their effect on the potential yield of 15 eggplant (*Solanum melongena* L.) accessions in the Colombian Caribbean. *Revista Facultad Nacional de Agronomía Medellín*, 72(3), 8895–8902. https://doi.org/10.15446/rfnam.v72n3.77112

Parthasarathi, T., Velu, G., & Jeyakumar, P. (2013). Impact of crop heat units on growth and developmental physiology of future crop production: A review. Journal of Crop Science and Technology, 2(1), 2319-3395.

Russell, M.P., Wilhelm, W.W., Olson, R.A., & Power, J.F. (1984). Growth analysis based on degree days. *Crop Science*, 24(1), 28–32. https://doi.org/10.2135/cropsci1984.0011183x002400010007x

Sanon, M., Hoogenboom, G., Traoré, S., Sarr, B., García, A., Some, L., … & Roncoli, C. (2014). Photoperiod sensitivity of local millet and sorghum varieties in West Africa. *NJAS - Wageningen Journal of Life Sciences*, 68, 29–39. https://doi.org/10.1016/j.njas.2013.11.004

Sha, Z., & Zhang, M. (2007). Development of web-based decision support system for field-based crop management. In *Proceedings of the 1st International Conference on Digital Ecosystems and Technologies* (pp. 52–57). IEEE. https://doi.org/10.1145/1341012.1341076

Steduto, P., Hsiao, T.C., Raes, D., & Fereres, E. (2009). AquaCrop — The FAO crop model to simulate yield response to water: I. Concepts and underlying principles. *Agronomy Journal*, 101(3), 426–437. https://doi.org/10.2134/agronj2008.0139s

Undersander, D.J., & Christiansen, S. (1986). Interactions of water variables and growing degree days on heading phase of winter wheat. *Agricultural and Forest Meteorology*, 38(3–4), 169–176. https://doi.org/10.1016/0168-1923(86)90056-0

Villordon, A., Clark, C.A., Ferrin, D.M., & LaBonte, D.R. (2009). Using growing degree days, agrometeorological variables, linear regression, and data mining methods to help improve prediction of sweetpotato harvest date in Louisiana. *HortTechnology*, 19(1), 133–144. https://doi.org/10.21273/HORTSCI.19.1.133

Zhou, G., & Wang, Q. (2018). A new nonlinear method for calculating growing degree days. *Scientific Reports*, 8, Article 10149. https://doi.org/10.1038/s41598-018-28392-z