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Thermal index-based phenology models for maize: A review

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Abstract

Phenology models are critical in understanding and predicting plant development stages, especially in crops like maize (*Zea mays L.*). This review examines thermal index-based phenology models, focusing on their principles, applications, and the latest advancements. Thermal time, commonly known as growing degree days (GDD), is the cornerstone of these models. We discuss various models, their calibration and validation methods, and their effectiveness in different climatic regions. Furthermore, the impact of climate change on these models and the integration of remote sensing technologies are explored. The review aims to provide a comprehensive understanding of how thermal index-based models contribute to maize phenology and agricultural planning.

Keywords: Phenology models, thermal index, growing degree days (GDD)

Introduction

Maize (*Zea mays L.*) is one of the most important staple crops globally, serving as a vital source of food, feed, and industrial raw materials. The ability to accurately predict the phenological stages of maize is crucial for effective agricultural management, optimizing planting schedules, improving yield predictions, and mitigating the impacts of environmental stressors. Phenology, the study of periodic plant life cycle events, is essential in understanding how maize growth and development respond to environmental variables, particularly temperature. Thermal time, commonly measured in Growing Degree Days (GDD), is a fundamental concept in phenology. GDD represents the accumulation of heat units over time, which drives the developmental processes of plants. Unlike calendar days, which do not account for variations in temperature, GDD provides a more accurate and dynamic measure of the thermal environment experienced by a plant. This measure allows for a more precise prediction of developmental stages such as germination, leaf emergence, tasseling, silking, and maturity. The principle behind GDD is relatively straightforward: plant growth is largely temperature-dependent, proceeding faster at higher temperatures and slower at lower temperatures. GDD is calculated by summing the average daily temperatures that exceed a base temperature, below which plant growth is minimal or negligible. For maize, this base temperature is typically set at 10 °C (50°F). In recent years, a variety of phenology models based on GDD have been developed to predict maize growth stages. These models range from simple, empirical models to complex, mechanistic models that incorporate additional environmental factors such as photoperiod, soil moisture, and genetic variability. Each model has its own strengths and limitations, and the choice of model often depends on the specific requirements of the application and the availability of data. Simple GDD models are widely used due to their ease of implementation and minimal data requirements. These models rely solely on thermal time to predict phenological stages and are particularly useful for straightforward applications where high precision is not critical. However, their simplicity can also be a limitation, as they may not adequately capture the influence of other environmental variables on plant development. Complex phenology models, such as the CERES-Maize model and the APSIM (Agricultural Production Systems sIMulator), incorporate a broader range of factors affecting plant growth. These models provide more detailed and accurate predictions but require more comprehensive data inputs and sophisticated calibration and validation processes. They are particularly valuable in research and advanced agricultural management, where understanding the interactions between multiple environmental factors is crucial. Calibration and validation are critical steps in the development and application of phenology models. Calibration involves adjusting the model parameters to fit observed data, while validation tests the model's accuracy with independent data sets. Effective calibration and validation ensure that the models provide reliable predictions across different environments and conditions. The applications of thermal index-based phenology models in maize cultivation are numerous and varied. These models help farmers optimize planting dates, predict yields, manage pests and diseases, and assess the impacts of climate change. By providing timely and accurate predictions of developmental stages, these models enable more efficient use of resources and better planning of agricultural operations. Despite their utility, thermal index-based phenology models face several challenges. Temperature extremes, spatial variability, and climate change can all affect the accuracy of these models. High and low-temperature extremes can skew GDD calculations, leading to inaccurate predictions. Variations in local climate conditions necessitate region-specific calibration. Additionally, rising temperatures and altered precipitation patterns due to climate change demand continuous adjustments to the models. Recent advancements in phenology modeling include the integration of remote sensing technologies and machine learning algorithms. Remote sensing provides real-time data on crop growth and environmental conditions, enhancing the accuracy and applicability of phenology models. Machine learning algorithms can analyze large datasets and identify complex patterns, improving model predictions and adapting to changing conditions.

Objective of paper

The objective of this review paper is to provide a comprehensive analysis of thermal index-based phenology models for maize.

Thermal Time and Growing Degree Days (GDD)

Thermal time, often measured in growing degree days (GDD), is a critical concept in phenology, particularly for understanding and predicting the development stages of plants such as maize. GDD is based on the accumulation of heat units over time, which directly influences plant growth and development.

Growing Degree Days (GDD) is a measure of heat accumulation used to predict the growth stages of plants and insects during the growing season. It is calculated using the following formula:

$$GDD = \Sigma[(Tmax + Tmin)/2 - Tbase]$$

where Tmax is the daily maximum temperature, Tmin is the daily minimum temperature, and Tbase is the base temperature below which plant growth is assumed to stop. This base temperature varies depending on the plant species; for maize, it is typically set at 10 °C (50°F).

GDD is an essential tool in maize phenology because it helps in predicting key phenological stages such as germination, leaf emergence, tasseling, silking, and maturity. It also aids in determining the best planting dates to avoid late-season frosts and ensure timely maturation, scheduling irrigation, fertilization, and pest control measures by predicting the timing of critical growth stages, and improving yield forecasts and harvest planning.

The calculation of GDD involves recording daily maximum and minimum temperatures, calculating the daily mean temperature, subtracting the base temperature from the daily mean temperature, and summing these values over the growing season. For example, if the daily maximum temperature is 30 °C and the minimum temperature is 15 °C, with a base temperature of 10 °C, the GDD for that day would be:

$$GDD = [(30 + 15)/2 - 10] = [22.5 - 10] = 12.5$$

Several factors can influence the accuracy of GDD calculations, including temperature extremes, diurnal temperature variation, base temperature selection, and local environmental conditions such as soil type, humidity, and altitude. Accurate selection of the base temperature is crucial for precise modeling.

Modern agriculture benefits significantly from GDD-based models through precision agriculture, utilizing GDD data to optimize input applications and improve crop management practices. It helps farmers adapt to changing climatic conditions by adjusting planting schedules and management practices based on GDD predictions. The integration of GDD models into decision support systems provides real-time guidance on agricultural practices.

Recent advances in GDD models include the use of satellite and drone-based remote sensing to gather temperature data and monitor crop development in real time, application of machine learning algorithms to refine GDD models and enhance prediction accuracy by analyzing large datasets, and the development of models that account for climate variability and provide more robust predictions under changing climatic conditions.

Growing Degree Days (GDD) is a fundamental concept in thermal index-based phenology models for maize. It provides a reliable measure of heat accumulation, essential for predicting growth stages, optimizing planting dates, and improving overall crop management. As agricultural practices advance, the integration of remote sensing and machine learning technologies continues to enhance the accuracy and applicability of GDD models.

Phenology Models in Maize

Phenology models for maize are crucial for understanding and predicting the various development stages of the crop. These models can be broadly categorized into simple GDD models and more complex models incorporating additional environmental factors.

Simple GDD models rely solely on thermal time to predict key phenological stages such as germination, leaf emergence, flowering, and maturity. These models are easy to implement and require minimal data inputs. By using the accumulated GDD, farmers and researchers can estimate the timing of these stages and make informed decisions about planting and crop management.

Complex models integrate additional variables such as photoperiod, soil moisture, and genetic factors to improve prediction accuracy. Examples of these models include the CERES-Maize model and APSIM (Agricultural Production Systems sIMulator), which provide more comprehensive simulations. These models take into account a wider range of environmental conditions and can offer more precise predictions, which are particularly useful in regions with variable climates.

Calibration and validation of these models are essential to ensure their accuracy and reliability. Calibration involves adjusting model parameters to fit observed data, while validation tests the model's accuracy with independent data sets. Techniques such as cross-validation and split-sample methods are commonly used to assess the performance of phenology models.

Applications of thermal index-based phenology models in maize cultivation are numerous. These models help optimize planting dates, enhance yield predictions, assist in pest and disease management, and evaluate the impact of climate change on maize growth. By predicting the timing of critical growth stages, farmers can schedule irrigation, fertilization, and pest control measures more effectively, leading to better crop management and higher yields.

Despite their utility, thermal index-based models face several challenges. Temperature extremes, spatial variability, and the impact of climate change can affect model accuracy. High and low-temperature extremes can skew GDD calculations, leading to inaccurate predictions. Variations in local climate conditions necessitate region-specific calibration. Rising temperatures and altered precipitation patterns due to climate change demand continuous model adjustments to maintain accuracy. Recent advancements in phenology modeling include the integration of remote sensing technologies and machine learning algorithms. Remote sensing provides real-time data on crop growth, while machine learning enhances model precision by analyzing large data sets. These advancements offer the potential to improve the accuracy and applicability of phenology models in maize cultivation.

In conclusion, phenology models play a vital role in maize cultivation, offering practical tools for predicting growth stages and optimizing agricultural practices. As climate change continues to impact global agriculture, these models must evolve to remain relevant. Future research should focus on improving model accuracy, integrating new technologies, and addressing environmental variability.

Calibration and Validation

Calibration and validation are critical processes in the development and application of phenology models for maize. These processes ensure that the models accurately reflect real-world conditions and can reliably predict the growth stages of maize under varying environmental conditions. Calibration involves adjusting the model parameters to fit observed data from field experiments or historical records. This process helps to fine-tune the model so that its predictions align closely with actual observations. Calibration typically requires a detailed dataset that includes environmental variables such as temperature, precipitation, and photoperiod, as well as phenological observations of maize at different growth stages. By systematically varying the model parameters and comparing the outputs to the observed data, researchers can identify the optimal parameter values that provide the best fit. Validation, on the other hand, tests the calibrated model's accuracy using independent data sets that were not used during the calibration process. This step is crucial for assessing the model's predictive power and generalizability. Validation involves applying the model to new data and comparing its predictions with actual observations. Common validation techniques include split-sample validation, where the dataset is divided into calibration and validation subsets, and cross-validation, which involves partitioning the data into multiple subsets and performing multiple rounds of calibration and validation. Several statistical metrics are used to evaluate the performance of phenology models during calibration and validation. These metrics include the coefficient of determination (R^2), root mean square error (RMSE), and mean absolute error (MAE). A high R^2 value indicates that the model explains a large proportion of the variability in the observed data, while low RMSE and MAE values suggest that the model's predictions are close to the actual values. The calibration and validation of phenology models also involve sensitivity analysis, which examines how changes in model parameters affect the model's outputs. Sensitivity analysis helps to identify the most influential parameters and provides insights into the model's behavior under different scenarios. This information is valuable for refining the model and improving its robustness. In summary, calibration and validation are essential steps in ensuring the accuracy and reliability of phenology models for maize. These processes involve adjusting model parameters to fit observed data, testing the model's performance with independent datasets, and using statistical metrics to evaluate model accuracy. Sensitivity analysis further enhances model understanding and robustness. Effective calibration and validation contribute to the development of reliable phenology models that can support agricultural decision-making and improve crop management practices.

Conclusion

Thermal index-based phenology models play a vital role in maize cultivation by providing practical tools for predicting growth stages and optimizing agricultural practices. These models, based on growing degree days (GDD), are essential for understanding the impact of temperature on maize development and for making informed decisions about planting, irrigation, pest control, and yield predictions.

The accuracy and reliability of these models depend on careful calibration and validation using observed data. By adjusting model parameters and testing with independent datasets, researchers can ensure that the models provide accurate predictions under various environmental conditions. Sensitivity analysis further enhances the robustness of these models by identifying the most influential parameters.

Despite their utility, thermal index-based models face challenges such as temperature extremes, spatial variability, and the effects of climate change. Continuous advancements in remote sensing and machine learning technologies are helping to address these challenges, providing more precise and adaptable models.

Applications of thermal index-based models in maize cultivation are diverse. They assist in optimizing planting dates, enhancing yield predictions, managing pests and diseases, assessing climate change impacts, and improving irrigation scheduling. These applications contribute to sustainable farming practices, resource efficiency, and food security.

As climate change continues to affect global agriculture, the importance of thermal index-based models will grow. Future research should focus on improving model accuracy, integrating new technologies, and addressing environmental variability to ensure these models remain relevant and effective. By doing so, thermal index-based phenology models will continue to be invaluable tools for maize farmers, researchers, and agricultural planners.

In conclusion, thermal index-based phenology models are crucial for the effective management of maize cultivation. Their ability to predict key growth stages and optimize agricultural practices makes them indispensable in modern agriculture. Continued innovation and research will ensure these models evolve to meet the challenges of a changing climate and contribute to sustainable and productive farming systems.

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