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Dynamic Water Stress Threshold Determination for Precision Deficit Irrigation Control using Progressive Clustering Approach ⋆

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Abstract: Precision deficit irrigation offers a solution to the increasing global pressure on freshwater resources occasioned by a rising demand for agricultural outputs to support a growing human population. Plant physiological responses to water deficit are describe in terms defining severity of water stress. Implementation of deficit irrigation control strategies capable of achieving the twin goals of maximizing potential yield and minimizing cumulative water consumption requires the identification of water deficit levels corresponding to significant stress thresholds to ensure memory initiation and prevent permanent damage to the crop. In this contribution machine learning approaches are implemented for dynamic identification of water stress thresholds during deficit irrigation of potted maize plants. K-means clustering is initally applied to delineate three zones of water stress described as "no stress", "mild stress" and "high stress" for chronologically segmented data points. Least squares-based polynomial curve fitting is employed to mathematically represent the dynamic progression of stress cluster centroids, with accuracy values ranging between 90 % and 98 %.

Keywords: Machine learning, Clustering, K-means, Deficit irrigation control.

1. INTRODUCTION

Sustainability of irrigation-based agriculture depends on continued availability of freshwater resources. A growing human population has resulted in rising demand for agricultural outputs, placing increasing pressure on global freshwater availability. Modern approaches to irrigation water management are based on the paradigm "more crop per drop" (Giordano et al., 2006), which seeks to achieve an acceptable compromise between crop yield and water consumption.

Deficit irrigation approaches involve supplying irrigated crops with quantities of water lower than evapotranspiration-based demand, resulting in physiological responses described as water stresss or drought stress. Commonly measured indicators of plant stress include leaf surface temperature, turgidity, growth rate and visual indicators. Successful implementation of deficit irrigation requires achievement of two goals- initiation of stress memory to ensure triggering of a recovery response upon withdrawal of water stress, and prevention of damage, which requires a knowledge of quantitative and chronological water stress thresholds.

Various approaches have been applied for definition of quantitative and chronological thresholds used to describe deficit irrigation treatments. A common approach is an expression of applied water as a ratio of full water holding capacity of the growth substrate, with well watered conditions corresponding to a replenishment of soil status to 100 % of the water holding capacity during each irrigation event (Álvarez et al., 2012; Mohawesh and Karajeh, 2015; Wasonga et al., 2020). Deficit is induced by application of lower quantities of water during common irrigation events (Ismail and Phizackerl, 2008). An alternative strategy involves implementation of varied water application frequency, with irrigation events triggered by specific water availability thresholds (Halli et al., 2021). In this approach, the severity of water deficit is described by the maximum allowable depletion of substrate water availability, with greater severity of deficit corresponding to higher maximum allowable depletion values (Barker et al., 2019). The severity of water deficit in crops with known irrigation requirements at specific stages of growth can also been defined by determining the ratio of applied water to documented requirements. This approach is implemented in (Jia et al., 2017) in field grown maize under semi arid conditions. Quantification of water deficit severity has additionally been approached by comparing the quantity of supplied water to plant demand, quantified in terms of evapotranspiration (Cea et al., 2022) or stomatal conductance (Puértolas et al., 2017).

Existing definitions of water deficit severity as applied to deficit irrigation in potted plants assume a static

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relationship between plant response to stress and water deficit level as compared to well watered crops. This neglects the effect of root growth on actual water availability, as root expansion increases the ability of the plant to access a greater proportion of supplied water (Turner, 2018), thereby resulting in dynamic stress thresholds despite constant watering conditions.

In this contribution, dynamic stress thresholds for pot-grown maize plants are evaluated. The evolution of the stress thresholds over time are mathematically defined.

2. PLANT STRESS RESPONSE TO WATER DEFICIT

Exposure to water deficit elicits a physiological response in plants, with measurable indicators including leaf surface temperature, growth rate and turgidity. Severity and duration of stress episodes govern the nature and permanence of plant response. In (Kögler and Söffker, 2020), the level and duration of stress is mapped out with regard to the initiation of a memory response in the plant and/or occurrence of damage, described as a permanent retardation of growth rate in comparison to a well watered control group, even after subsequent reirrigation. In this contribution, a similar evaluation of stress characterization is adopted, with a focus on deficit levels. Plant stresses are categorized under "no stress", representing well watered conditions, "mild stress", representing observable reduction in growth rate with a recovery to pre-stress levels upon reirrigation, and "high stress", representing observable permanent reduction in growth rate, with occurrence of damage. The growth rate in this work is described based on daily leaf elongation rate, which is calculated from manually obtained measurements of maize leaf length.

Characterization of stress levels in existing literature adopts a one-on-one static relationship to water deficit levels, with preset boundaries used to characterize mild and severe deficit/stress, both in field and pot-based research. A key limitation of this approach arises due to the expansion of plant roots within growing pots, which results in greater availability of water to the plant even at relatively lower values of water content. This is observed in leaf surface temperature readings taken from plant groups subjected to mild stress with a static boundary (Figure 1). During initial water stress events, the test plants are easily discernible by the elevated leaf surface temperatures in comparison to the control group. In a subsequent stress event, the differences in surface temperature are less visible, which could be attributed either to a higher stress tolerance exhibited by the plant, or to a dynamic stress threshold as the plant roots expand to allow access to more water within the pot.

3. MACHINE LEARNING-BASED DYNAMIC STRESS THRESHOLDING

The generation of dynamic stress thresholds was achieved through a three-step process involving data pre-processing, k-means clustering and regression analysis of obtained centroids. Evaluation of clustering accuracy was based on the R^2 value of the generated regression equations.

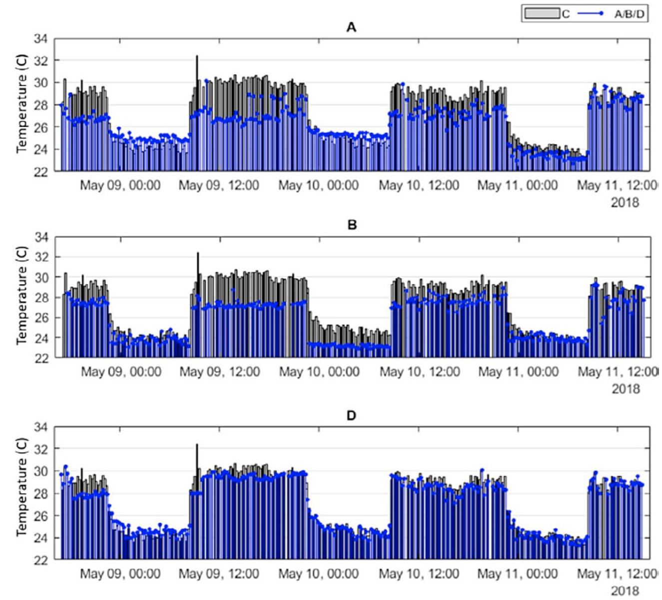

Fig. 1. Leaf surface temperature measured in water-stressed and unstressed maize plants, with test groups A, B, and C (subjected to mild to severe water stresses, displayed individually as blue markers) compared to the control group C (no stress / full irrigation, displayed as outlined grey bars in each graph)

3.1 Pre-processing of data

Experimental data was obtained from growth experiments conducted in an indoor greenhouse located in the Chair of Dynamics and Control at the University of Duisburg-Essen. Maize plants (SWS Ronaldinio variety) were grown in a granular loamy-clay substrate (Seramis© clay granulate) under artificial lighting (9500K, 14 hour day length). Temperatures were maintained at 25 ° C during the day and 17 ° C in the night (± 2 ° C). Data referenced in this work was obtained in May and June of 2019.

Plants were grown in individual 500 ml PET containers each filled with 175 g of substrate. A single maize seed was planted in each container, and all plants maintained at a water content equivalent to the pot capacity, which had previously been experimentally determined to be 145 g of water (0.8286 g/g gravimetric water content) until the first three leaves were visible. High stress was induced by withholding irrigation until the water content in the pot had reduced to zero through evapotranspiration, upon which reirrigation was performed to full pot capacity. Mild stress was induced based on thresholds surmised from previous experiments, with a water content of 100 g presumed to represent the mild stress threshold. Plants under no stress received full irrigation throughout the test period. An upper limit of three consecutive days of mild stress was set to avoid damage due to prolonged exposure to mild stress. The key experimental goals involved determination of the mild stress and high stress thresholds/boundaries.

Pre-processing of the experimental data involved segmentation of the growth data by total number of appeared

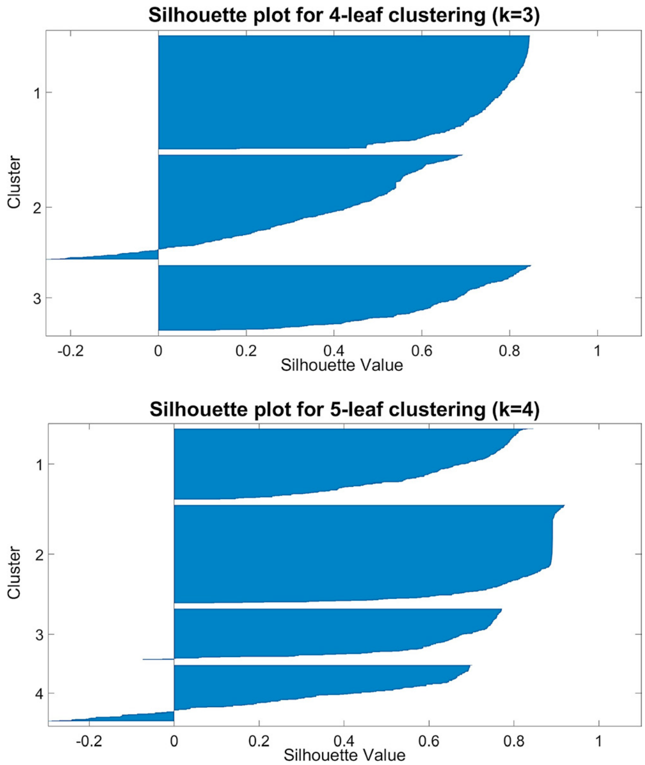

Fig. 2. Silhouette plots for 4-leaf stress clustering (with $k = 3$) and 5-leaf stress clustering (with $k = 4$) showing negative silhouette values indicative of overlapping datapoints in neighboring clusters

leaves, followed by an additional chronological segmentation. This article focuses on the data obtained at the 4-leaf and 5-leaf stages, with chronological segmentation done on a day to day basis. Thermal time is used to evaluate the progression of stress boundaries, with a base temperature of 10 ° C used for the calculation of growing degree days. Measurement of leaf length was done manually using a flexible rule, with daily elongation rate calculated from consecutive total leaf length measurements.

3.2 Clustering into stress levels

The pre-processed data was grouped based on water stress levels using k-means clustering. The determination of the number of clusters was based on evaluation of silhouette plots generated in MATLAB® for different numbers of clusters for each set of data. Mean and median silhouette values produced relatively high values (above 0.75) for up to 4 clusters. Silhouette plots for k=3 for the 4-leaf stage and k=4 for the 5-leaf stage however produced multiple negative values, indicating overlap between neighbouring clusters, as shown in Figure 2. For simplicity, it was decided to implement $k = 2$ and $k = 3$ for the 4-leaf and 5-leaf stages respectively, representing no stress, mild stress and high stress levels, where the 4-leaf stage was considered to have no plants expressing a high stress response.

3.3 Generation of stress clusters

The normalized total leaf elongation rates during the 4-leaf and 5-leaf growth stages were grouped into clusters using

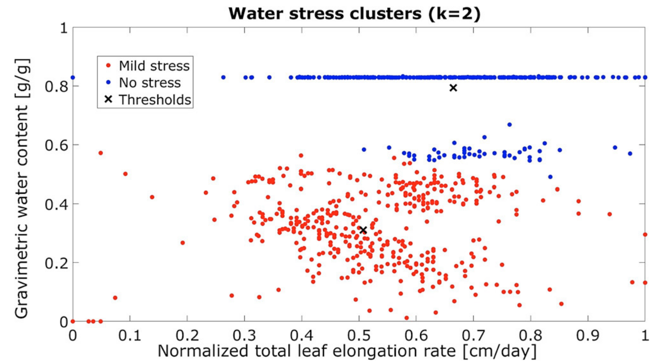

Fig. 3. Static clustering for 4-leaf growth stage using all growth data

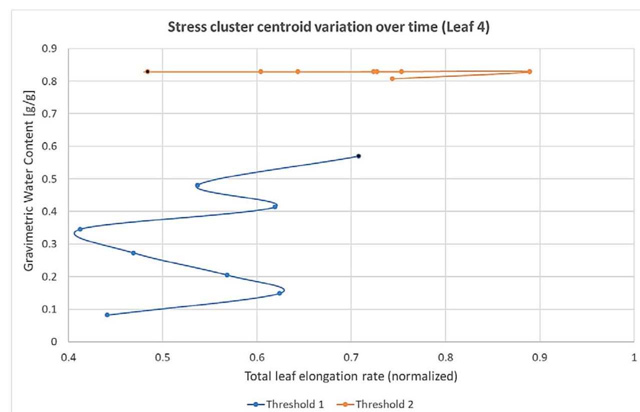

Fig. 4. Dynamic behavior of stress cluster centroids partitioned chronologically. The black spot indicates the initial location of the centroid.

k-means clustering, with k values of 2 and 3 respectively. Five replications were performed, with squared Euclidean and city block distance options (which calculate the centroid as the mean and median of individual cluster points respectively) producing similar outcomes. The clustering was initially performed for all the recorded observations, then individually repeated for groups consisting of daily observations. The coordinates of the cluster centroids were stored for each iteration. Regression curves for the mild stress and high stress centroids observed over time (expressed as thermal time) were then defined for both sets of data using basic curve fitting.

4. RESULTS AND DISCUSSION

Results for an initial clustering for the 4-leaf stage with $k = 2$ are shown in Figure 3. The cluster containing "no stress" data shows a clear distinction from the stressed data points. The cluster representing stressed plants exhibits large variations both in terms of gravimetric water content represented and physiological response as expressed in the normalized leaf elongation rate.

Partitioning of the data chronologically and extraction of the centroids from the different data clusters allowed a visualization of the dynamic behavior of the stress thresholds, as presented in Figure 4.

The 4-leaf stage shows relatively constant values for the "no stress" region. The "mild stress" centroid curve

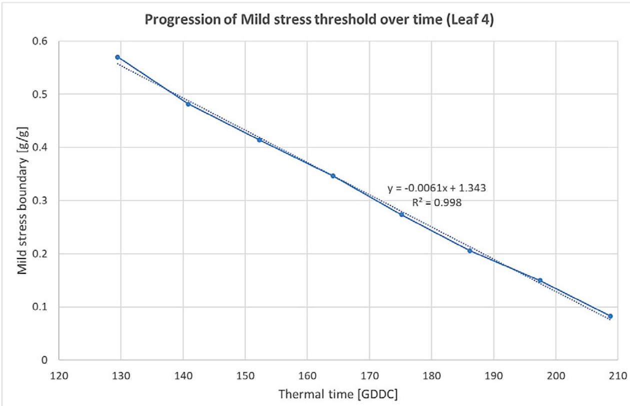

Fig. 5. Dynamic behavior of mild stress threshold for the 4-leaf growth stage

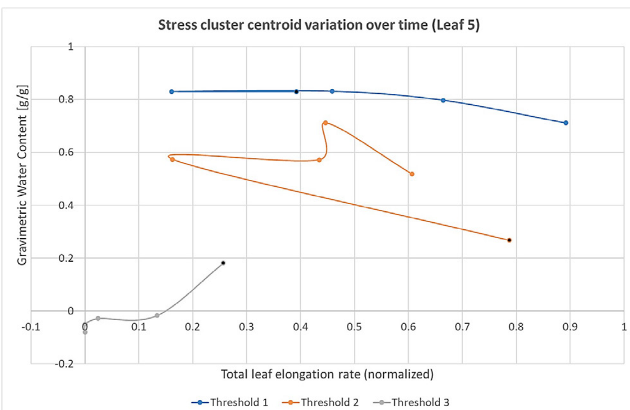

Fig. 6. Dynamic behavior of stress cluster centroids for the 5-leaf stage partitioned chronologically. The black spot indicates the initial location of the centroid.

exhibits significant variations both in terms of gravimetric water content values and normalized total leaf elongation rates. Extraction of the water content values and comparison with values of thermal time allow an evaluation of the dynamic variation in mild stress threshold. This is presented in Figure 5.

A linear relationship with an R^2 value of 0.998 is observed between the mild stress threshold and thermal time, with the boundary decreasing with increase in thermal time. This matches the hypothesized behavior, with an expansion of plant roots within the pot over time allowing access to reduced quantities of water, thereby shifting the stress threshold gradually downwards.

The observed centroids obtained from clustering of the 5-leaf stage observations are presented in Figure 6. In this case, the "no stress" cluster centroids display a downward trend (with respect to gravimetric water content), indicating an expansion of the range within which the plant displays no physiological response, even with water content below pot capacity. The "mild stress" region similarly occupies a greater range than observed for the 4-leaf stage, and the "high stress" cluster covers the bottom left section, representing lowest observed values both for water content and elongation rate.

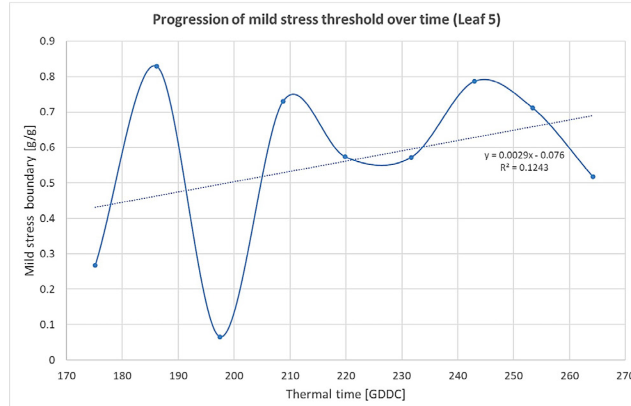

Fig. 7. Dynamic behavior of mild stress threshold for the 5-leaf growth stage

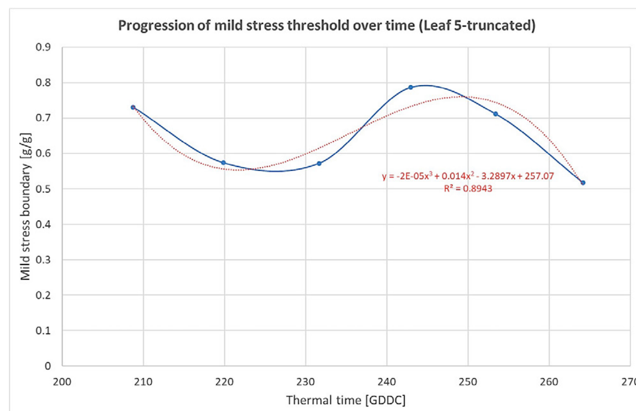

Fig. 8. Adjusted curve representing dynamic behavior of mild stress thresholds for the 5-leaf growth stage (excluding outlier values from first three days)

Assessment of the dynamic behavior of the stress thresholds follows based on the chronologically recorded variation of cluster centroids over thermal time. The progression of mild stress is presented in Figure 7.

The first three data points represent outliers, with observations representing less than 10 % of test plants (3 plants out of 35, which all displayed leaf 5 two to three days before all other plants) thus showing the strongest individuals. Filtering out of the outliers allows a more accurate projection of the trend, as presented in Figure 8. With the elimination of outliers, it is possible to represent the dynamic behavior of mild stress thresholds for the 5-leaf stage using a third order polynomial to an accuracy of 89 %. Despite the high accuracy, the need to exclude initial elongation rate values introduces a reduction in reliability, signifying a need for further data analysis to confirm obtained results.

The demarcation of the high stress cluster from the mild stress and no stress clusters was observed to be markedly distinct, as can be seen in Figure 6. The water content component of the centroids for all generated clusters showed zero overlap with any of the other clusters. An evaluation of the dynamic behavior "high stress" cluster for the 5-leaf stage is based on the results presented in Figure 9.

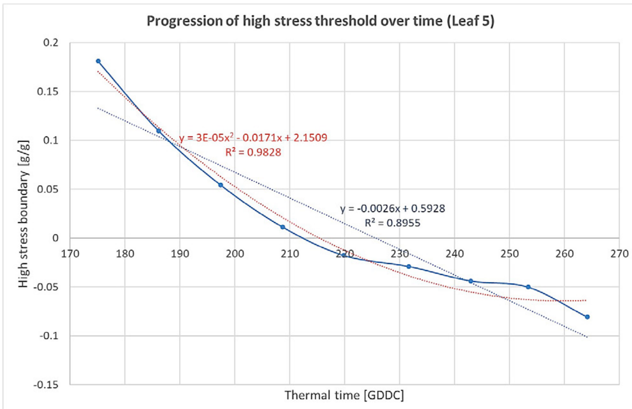

Fig. 9. Dynamic behavior of high stress thresholds for the 5-leaf growth stage

The dynamic behavior of the high stress threshold can be approximated linearly to an accuracy of 89 %, and using a second order polynomial to an accuracy of 98 %. A downward trend is observed over time, with negative water content values appearing as a result of utilization of the residual moisture present in the substrate during initial use.

5. APPLICATION IN MODEL-BASED PLANT GROWTH CONTROL

A model predictive deficit irrigation-based plant growth controller as described in (Owino and Söffker, 2022) has been developed based on a state machine description of plant growth. The elongation rate (representative of growth), appearance of new leaves (described in (Owino and Söffker, 2019)), and state-specific evapotranspiration rate (based on a multiple linear regression model) are required for determination of the required irrigation sequence to achieve targeted growth and/or water consumption. Previous experimental work has relied on static, user-determined stress thresholds based on expert knowledge, limiting the performance of the controller. The dynamic stress thresholding approach described in this contribution would allow a dynamic adaptation of the state machine-based plant growth and evapotranspiration models. The updated model-based predictive controller is represented in the block diagram shown in Figure 10.

Implementation requires the calculation of elapsed thermal time (since sowing), which can be generated from the temperature inputs integrated in the evapotranspiration prediction model. Fully automated growth control throughout the vegetative phase within desired limits of yield loss and cumulative water consumption additionally requires automated measurement of growth (in this work represented by total leaf length), evapotranspiration (or substrate water content), and number of plant leaves (representing specific growth stage within the vegetative phase).

6. SUMMARY AND OUTLOOK

A clustering-based approach for evaluation of dynamic behavior of stress thresholds for deficit irrigation implementation in potted maize plants is presented. Stress onset and level is characterized using total leaf elongation rate as an indicator to represent physiological response of the plant to water deficit. It is hypothesized that the effect of root expansion and increase in root density with growth in potted plants should result in a gradual lowering of stress thresholds as the plant gains access to more moisture within the growth substrate. The hypothesis is tested by chronological segmentation of growth data and clustering into stress levels. The hypothesis is validated for growth at both the 4-leaf and 5-leaf stage, with trajectories of both stress thresholds observed to trend downwards over time. Outliers are observed in the initial days of the 5-leaf stage (which overlap with the final days of the 4-leaf stage). The dynamic progression of stress thresholds is represented using polynomials of between first and third order.

While this work focuses on the dynamic nature of the stress boundaries as the maize plant progresses through the vegetative stage, underlying reasons for the differences in trajectories observed for the mild and high stress boundaries have not been investigated. It is theorized that the physiological response of the plant is determined by the main goal during different stress events. It is assumed that during mild stress events the focus is on conservation of resources by growth limitation during the periods of water withdrawal, and acceleration of growth during recovery stages to prepare the plant to handle future stresses. During periods of high stress, the focus would be on mitigating damage to prevent plant death. Evaluation of these underlying reasons could be a potential area for future research.

Further investigation of additional growth stages as well as an experimental evaluation of generated stress thresholds would be useful next steps in the further definition of dynamic stress thresholds for deficit irrigation. Automatic determination of optimal number of clusters could also be integrated by calculation of silhouette values during clustering, with the maximum number of clusters limited to the number of stress states integrated in the growth model (the implemented state machine model allows up to seven states based on deficit levels and previously encountered states). Future work could include additional validation of the results using classification approaches. Implementation of the described approach in other maize cultivars or other crops exhibiting similar physiological responses to water stress would require similar training data in order to adequately parametrize the growth model.

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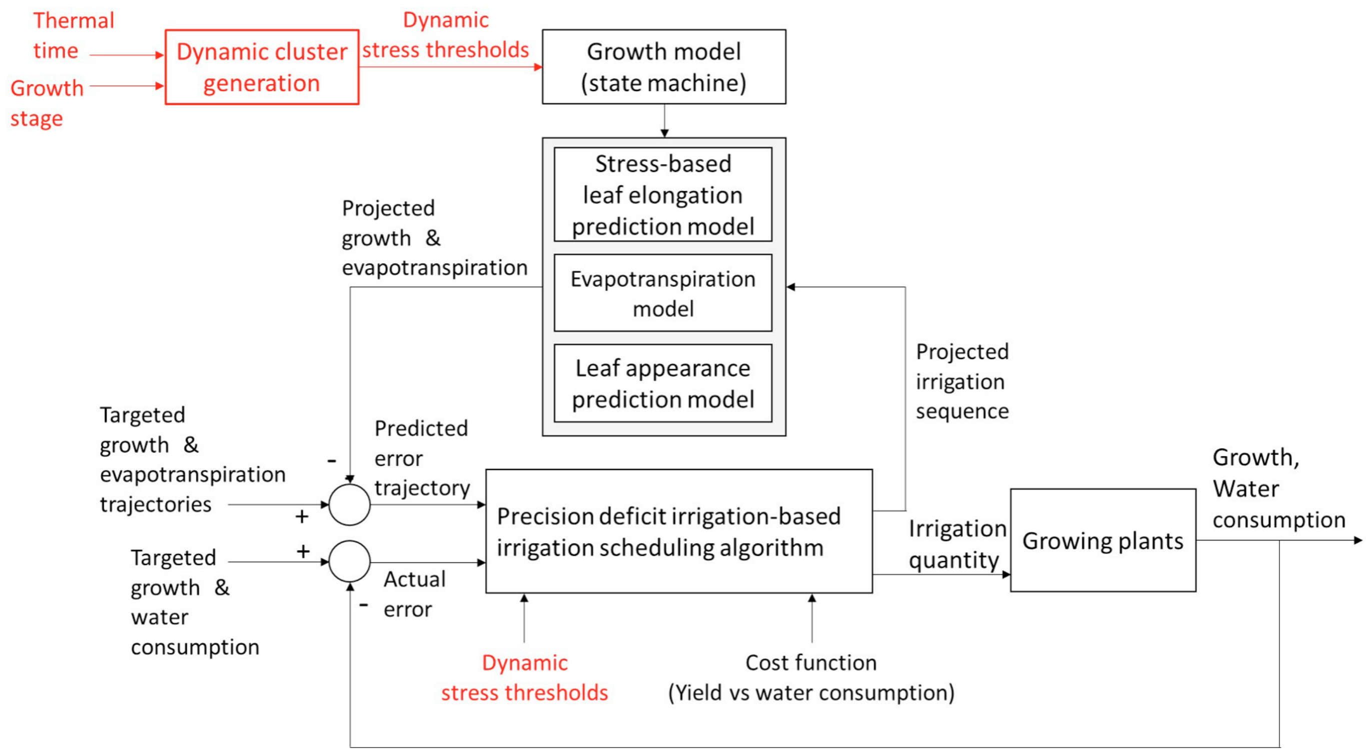

Fig. 10. Updated block diagram of model predictive deficit irrigation-based plant growth controller integrating dynamic stress thresholding approach

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