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Article

Predictive modelling of wheat yield under waterflooding stress: a Chaid algorithm approach

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Abstract

Our research aims to examine the impact of waterflooding on durum wheat yield using a predictive modelling approach based on CHAID analysis. Randomized complete block trials were conducted in two locations, with and without waterflooding, using four durum wheat cultivars (GTA dur, Citra, Simeto, and Boussalem). The assessment of yield loss highlighted significant sensitivity of cultivars to waterflooding, with Simeto showing the highest yield loss (64.33%). The CHAID analysis enabled the identification and prioritization of factors influencing yield, revealing that waterflooding is the most important predictor (71.14%), followed by the average number of tillers per plant (16.74%), cultivar (6.32%), and plant emergence density (5.8%). Beyond merely observing the negative impact, our model allows for predicting yield losses based on various agronomic parameters. The results showed that waterflooding significantly reduces yield (16.89 q ha^{-1}) but tillering and cultivar also play an important role in wheat response to waterflooding. The study highlights the importance of predictive modelling to anticipate yield losses and guide crop management decisions in flood-prone areas.

Palabras clave:

precision agriculture, risk management, water stress, *Triticum durum* L.

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Introduction

Durum wheat (*Triticum durum* L.) is an essential cereal crop, playing a crucial role in global food security (Dadrasi *et al*., 2023). However, its production is increasingly threatened by extreme climatic events, particularly waterflooding (Lesk *et al*., 2016). Waterflooding can lead to substantial yield losses due to hypoxic and anoxic stress experienced by plants, disruption of nutrient absorption, and the development of diseases (Trought *et al*., 1980; Voesenek *et al*., 2006). Yield prediction models are valuable tools for anticipating crop losses and guiding crop management decisions (Basso *et al*., 2019; Elbasi *et al*., 2023).

Among various modeling approaches, Chi-squared automatic interaction detection (Chaid) analysis stands out for its ability to identify complex interactions between environmental and agronomic factors (Kass, 1980). This method enables data segmentation into homogeneous groups based on variables that most influence the target variable, thereby providing a better understanding of yield-determining factors (Rokach *et al*., 2014).

The aim of this study is to develop a predictive model of durum wheat yield under waterflooding stress using Chaid analysis to prioritize the influence of agronomic factors such as tillering, cultivar and plant density, in order to anticipate yield losses and guide effective crop management decisions in flood-prone areas. We examined the influence of waterflooding, tillering, cultivar and emergence density on yield to identify key factors and their interactions. The findings of this study will contribute to a better understanding of wheat response mechanisms to waterflooding and the development of adaptation strategies to minimize yield losses.

Material and methods

Experimental design and study sites

The study was conducted at two distinct sites: Annaba, Algeria (no waterflooding observed) and Constantine, Algeria (characterized by waterflooding episodes). The waterflooding event at Constantine was a natural occurrence that took place during the tillering stage. The duration of this continuous soil saturation event was seven days. This event was characterized as waterlogging. The crops at the non-flooded Annaba site were rainfed to maintain optimal conditions.

At each site, an experimental plot of 2 500 m^2 was established. This total area was divided into 12 experimental plots (four cultivars x three replicates) for the randomized complete block design (RCBD), resulting in a gross area of approximately 208.33 m^2 per replicate of each cultivar. The trials were conducted using a randomized complete block design (RCBD) (Steel *et al*., 1997) with three replicates per cultivar to minimize spatial variability (Slafer *et al*., 2007). The four durum wheat cultivars selected for this study were GTA Dur, Citra, Simeto, and Boussalem.

Agronomic practices

To ensure optimal growth conditions for the cultivars, various agronomic practices were implemented. Sowing was performed at a rate of 2 q ha^{-1} to establish adequate planting density and uniform emergence. A base fertilization consisting of monoammonium phosphate (MAP) was applied at a rate of 1.5 q ha^{-1} to meet the initial nutritional requirements of the plants. Additionally, fungicidal treatments using Celest Top and Acil were applied to protect crops from diseases and promote their development.

Measured parameters

Several parameters were measured to evaluate the impact of waterflooding on durum wheat yield. Time-sensitive growth parameters, namely emergence density (plants m^{-2}) and average number of tillers per plant, were assessed during the tillering stage. Final yield components were determined at physiological maturity and included: number of grains per spike; number of spikes per m^2; thousand-

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kernel weight (TKW); theoretical yield (q ha^{-1}); and practical yield (q ha^{-1}). These measurements allowed for assessing the response of the different cultivars under contrasting water conditions at the two sites and quantifying the impact of waterflooding on yield components.

Wheat yield loss rate

The wheat yield loss rate (YLR %) was calculated to assess the impact of waterflooding on the yield of different wheat cultivars. This calculation was based on the practical yield obtained under non-waterflooding conditions (Y_{NWF}) and under waterflooding conditions (Y_{WF}). The yield loss rate (YLR) was determined using the formula proposed by Berry *et al*. (2012):

$$YLR\% = \frac{Y_{NWF} - Y_{WF}}{Y_{WF}} \times 100$$

Data analysis

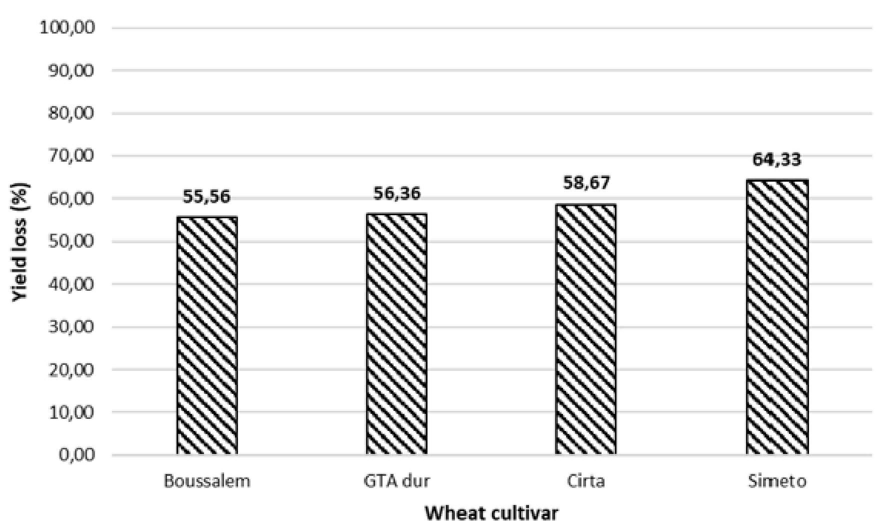
Data analysis was performed using IBM SPSS Modeler 18.0. The Chi-squared Automatic Interaction Detection (Chaid) modeling method was used to identify relationships between a dependent variable (practical yield) and multiple independent variables (predictors). This method segments data into homogeneous groups based on the variables most influencing the target variable (Kass, 1980).

Results

Wheat yield loss rate

The yield loss rates presented in Figure 1 clearly illustrate the substantial impact of waterflooding on the productivity of the four wheat cultivars evaluated. The magnitude of these losses highlights pronounced genotypic variability in tolerance to excess soil moisture, with certain cultivars exhibiting severe reductions in yield while others maintain comparatively higher performance.

Figure 1. Wheat yield loss rates caused by waterflooding.



The comparison of the four wheat cultivars under flooded and non-flooded conditions revealed clear differences in yield reduction intensity. Across all measured parameters, Simeto showed the highest decline in performance, registering a yield loss rate of 64.33%, which represents the

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largest discrepancy between practical yields obtained under normal and flooded conditions. This substantial reduction reflects a marked contrast between its theoretical productivity and the values recorded following exposure to flooding.

Cirta also exhibited a considerable decline in productivity, with a yield loss rate of 58.67%. The reduction in practical yield under flooded conditions was consistently greater than that observed under normal conditions, placing Cirta among the most impacted cultivars in the dataset. The difference between theoretical and practical yield values was similarly pronounced.

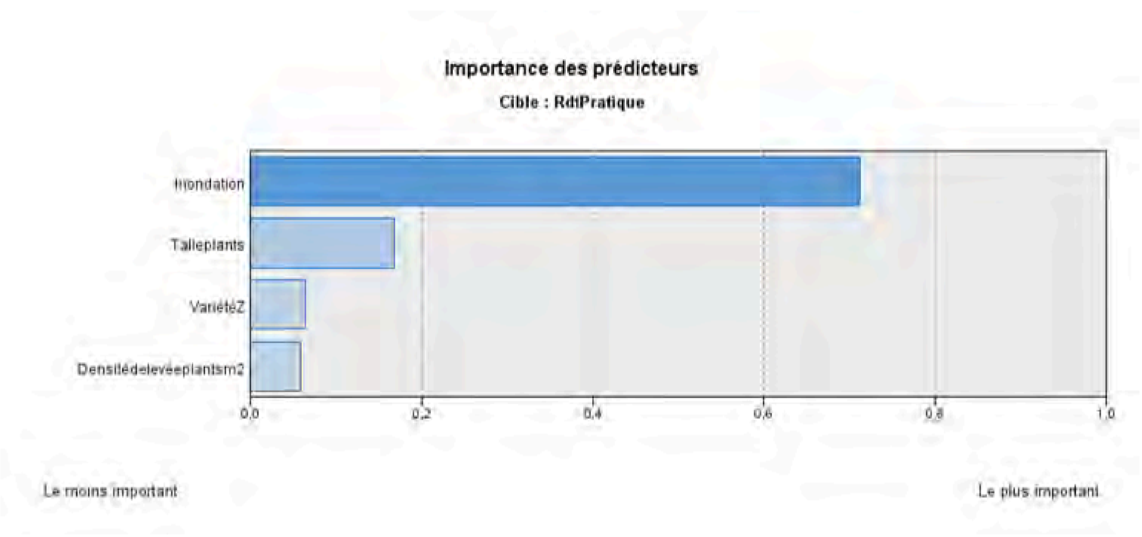
GTA dur recorded a yield loss rate of 56.36%, positioning it in an intermediate range among the tested cultivars. The reduction observed between normal and flooded conditions was consistent across yield components, with a noticeable drop in practical yield values relative to those recorded in non-flooded plots.

Boussalem registered the lowest yield loss rate at 55.56%, showing the smallest gap between practical yields obtained under normal and flooded conditions. Although a decline in performance was still present, the extent of reduction was less marked compared to the other cultivars. Overall, the dataset shows a progressive gradient in the magnitude of yield loss across cultivars: Simeto demonstrated the largest decline, followed by Cirta, GTA dur, and finally Boussalem, which presented the most moderate reduction in yield under flooded conditions.

Predictors' importance

The Chaid analysis enabled the identification and ranking of various predictors contributing to wheat yield modelling, highlighting the most influential factors and their relative importance (Figure 2).

Figure 2. Importance of the studied predictor.



The results from the Chaid analysis show that the most important predictor is waterflooding, with an importance of 71.14% (Figure 2). This result highlights the major impact of the presence or absence of waterflooding on wheat yield.

The second most important predictor is the average number of tillers per plant, with an importance of 16.74%. Tillering, which represents the plant's ability to produce secondary stems, plays a crucial role in determining yield. Adequate tillering can compensate for losses due to other stress factors, but its effect is significantly modulated by the presence or absence of waterflooding, as demonstrated by the Chaid decision tree.

Wheat cultivar ranks third, with an importance of 6.32%. Although less influential than waterflooding and tillering, cultivar significantly contributes to yield variation. Finally, plant emergence density per

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square meter is the least important predictor, with an importance of 5.8%. Although planting density is a fundamental agronomic practice, its influence on yield is relatively weak compared to other factors considered, especially under water stress conditions. This suggests that, within the studied limits, emergence density has a limited impact on final yield, particularly when waterflooding is the primary limiting factor.

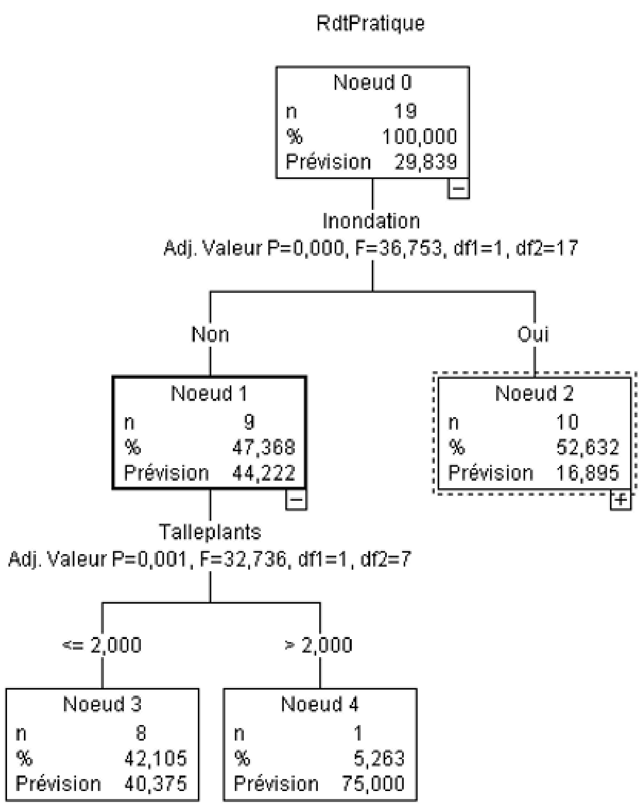
Modeling of yield-influencing factors

Under non-flooded conditions, the dataset shows a clear increase in overall productivity, with an average yield of 44.222 q ha^{-1}. Within this subset, the number of tillers per plant emerges as the key discriminating parameter, structuring the division of observations and associated yield values.

When the average number of tillers per plant exceeds 2, the corresponding group exhibits a markedly elevated yield, reaching 75 q ha^{-1}, which represents the highest yield level recorded in the non-flooded category. This subgroup forms a distinct node characterized by consistently high productivity values. In contrast, observations with an average number of tillers per plant equal to or below 2 form a separate cluster in the decision tree, associated with substantially lower yield values relative to the >2 tiller group.

The segmentation captured in Figure 3 highlights the sharp differentiation between these two classes, illustrating the strong association between tiller number and yield levels under non-flooded conditions. Overall, the non-flooded branch of the model displays a structured progression of yield values, where the subgroup with more than two tillers per plant consistently aligns with the maximum yield values observed in the dataset.

Figure 3. Segmentation of wheat yield by Chaid analysis in non-waterflooding area.



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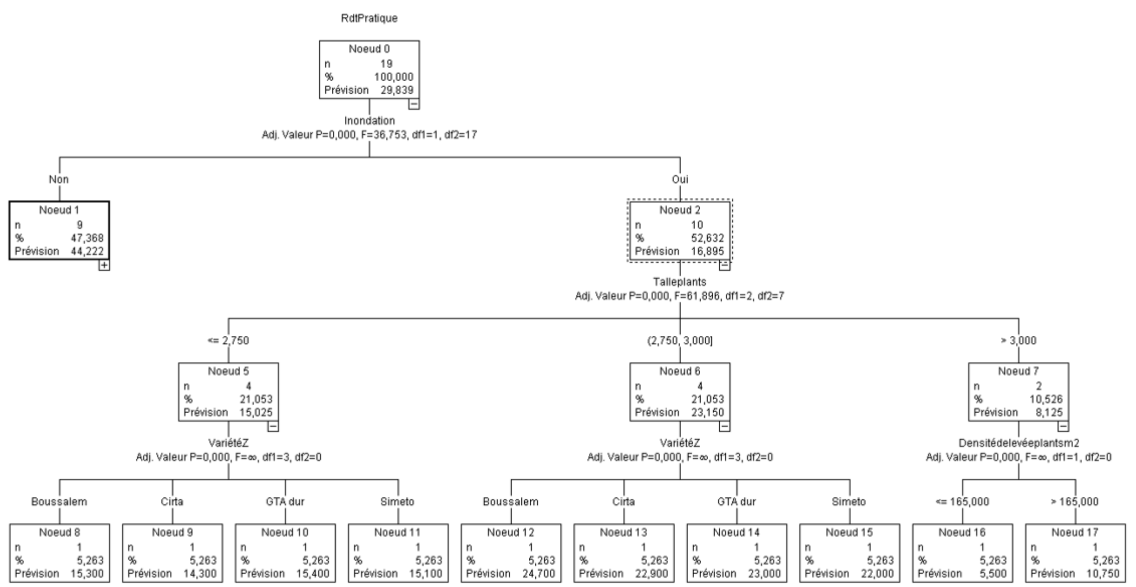
Under waterflooding conditions, the dataset shows a substantial reduction in productivity, with the average yield decreasing to 16.895 q ha^{-1}. Within this flooded branch, the number of tillers per plant remains a structuring variable in the decision tree, although the differences between classes become less pronounced compared to the non-flooded scenario.

Observations characterized by an average tiller number less than or equal to 2.75 form a distinct group associated with low yield values, reaching 15.025 q ha^{-1}. This cluster represents the majority of cases within the flooded condition and displays limited internal variability. Minor differences between cultivars appear within this node, but the overall yield remains consistently low across the varieties included in this subgroup.

The segmentation illustrated in Figure 4 highlights the concentration of low-yield observations within the ≤2.75 tiller category under flooding, forming a homogeneous group with narrow yield dispersion. In contrast, cases exceeding this tiller threshold occupy a separate terminal node, characterized by slightly higher yield values but still falling within the lower range recorded under waterflooding. Overall, the flooded portion of the model is defined by uniformly low yield outputs, with the ≤2.75 tiller group representing the dominant low-yield profile identified in the decision tree.

Figure 4. Segmentation of wheat yield by Chaid analysis in waterflooding area.



Within the subgroup characterized by an average number of tillers per plant less than or equal to 2.75, the decision tree further differentiates observations based on cultivar. In this segment, Boussalem, GTA Dur, and Simeto display closely aligned yield values, all situated around 15 q ha^{-1}, forming a compact cluster with minimal dispersion. The Cirta cultivar falls within the same structural branch but exhibits a slightly lower yield of 14.3 q ha^{-1}, positioning it at the lower end of this group. Although the numerical differences remain narrow, the decision tree delineates these varieties into distinct terminal nodes, reflecting measurable but limited separation in yield performance under waterflooding.

A subsequent branch of the model groups observations with an average number of tillers per plant between 2.75 and 3, generating a distinct yield level of 23.15 q ha^{-1}. This subgroup constitutes a separate node within the flooded condition and marks a notable shift from the uniformly low yields observed in the ≤2.75 tiller category. The yield values within this interval show a moderate increase, forming a discrete cluster characterized by consistently higher outputs relative to the preceding nodes.

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The structure of the tree captures this yield elevation clearly, with the transition between classes represented by a marked segmentation in Figure 4. Beyond this intermediate tillering range, the model isolates observations with an average number of tillers per plant greater than 3, generating a corresponding terminal node with markedly lower yield, reaching 8.125 q ha^{-1}. This group represents the lowest yield category identified under waterflooding. The associated observations form a compact and homogeneous cluster, distinguished by a sharp decrease in yield relative to the 2.75-3 tiller class. This distinct separation is clearly represented in the model's hierarchical structure, emphasizing the pronounced contrast between the yield values of these successive nodes.

Within this final branch, emergence density is introduced as an additional discriminating variable, producing two subordinate nodes. Cases with emergence densities exceeding 165 plants m^{-2} exhibit a slightly higher yield level of 10.75 q ha^{-1}, positioned above the main cluster of the >3 tiller category. Conversely, observations with emergence densities of 165 plants m^{-2} or less remain associated with the lower value of 8.125 q ha^{-1}, forming the smallest yield subset under flooded conditions. Although the numerical difference between these two groups remains modest, the model captures this bifurcation, documenting a secondary structural effect attributable to plant density.

Overall, the flooded portion of the decision tree presents a stratified organization of yield values, with cultivars forming tightly grouped low-yield classes, intermediate tillering generating a distinct yield increase, and higher tillering combined with density effects defining the lowest-yielding terminal nodes in the model.

Discussion

Yield losses due to flooding can vary widely among different wheat cultivars (Berry *et al*., 2012). A study by Collaku *et al*. (2002) reported yield reductions ranging from 20% to 60%, depending on the cultivar and duration of flooding. The higher yield loss observed in the Simeto cultivar aligns with findings from studies that have identified certain wheat genotypes as particularly susceptible to waterlogging (Bassu *et al*., 2009).

Wheat yield losses due to flooding can vary among different cultivars, influenced by factors such as stress duration, growth stage, agricultural management, and soil characteristics (Berry *et al*., 2012). For instance, studies have reported yield reductions ranging from 20% to over 60% under waterlogging conditions (Collaku *et al*., 2002). The higher yield loss observed in the Simeto cultivar aligns with findings from studies that have identified certain wheat genotypes as particularly susceptible to waterlogging. For example, some cultivars have shown yield losses ranging from 10% to 70%, depending on their susceptibility and environmental conditions (Bassu *et al*., 2009).

In addition to genetic factors, environmental conditions such as soil type and climatic factors play a role in determining the extent of yield loss due to waterflooding. A previous study examining the impact of waterlogging at different growth stages (tillering, stem elongation, booting) and confirming that the severity of yield loss is highly dependent on the timing and duration of the stress, often showing the greatest reduction when waterlogging occurs early in the life cycle (Shao *et al*., 2013). Therefore, understanding the interaction between cultivar characteristics and environmental factors is essential for developing effective management strategies to mitigate yield losses due to flooding (Liliane *et al*., 2020).

The results confirm the devastating impact of waterflooding on wheat yield, aligning with the findings of previous research (Herzog *et al*., 2016). However, the Chaid modeling approach allowed us to go beyond the mere observation of this negative impact by quantifying the relative importance of this factor (71.14%) and integrating it into a robust predictive model. The underlying physiological mechanisms contributing to yield reduction, such as decreased photosynthesis and ethanol accumulation, are well documented (Bailey-Serres *et al*., 2008). Recent studies have also highlighted the importance of hormonal signaling, particularly abscisic acid (ABA) and ethylene, in wheat's response to water stress (Aslam *et al*., 2023).

The significance of tillering, highlighted by our analysis (16.74%), confirms its crucial role in wheat's response to water stress. As noted by Miralles *et al*. (2000), tillering can enhance plant

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recovery after waterflooding. However, our findings nuance this view, showing that excessive tillering can be counterproductive under severe stress conditions. This observation underscores the need for fine-tuned tillering management, adapted to the specific conditions of each environment. Recent research has also explored the impact of sowing density on tillering and flood tolerance, emphasizing the importance of appropriate cultural practices (Kaur *et al*., 2020).

Our modeling approach enabled us to quantify the impact of cultivar on yield and incorporate it into a predictive model. Recent studies have also identified genes involved in flood tolerance in wheat, paving the way for marker-assisted selection (MAS) to develop more resilient cultivars (Shen *et al*., 2021).

Integrating the concepts of prediction and modeling in our study allows us to go beyond the simple description of waterflooding effects. The Chaid modeling enabled us to build a predictive yield model based on the main influencing factors. This model can be used to anticipate yield losses in case of waterflooding and guide crop management decisions.

The use of predictive models in agriculture is rapidly expanding, driven by advances in machine learning and artificial intelligence (AI) (Liakos *et al*., 2018). These technologies are increasingly integrated into modern crop production systems, where they enable the analysis of large and complex datasets to forecast crop performance, optimize resource allocation and support evidence-based decision-making. The capacity of AI-based models to learn from empirical data and to detect non-linear interactions among climatic, genetic, and agronomic variables offers significant advantages over traditional statistical approaches (Githui *et al*., 2022).

Recent research has also underscored the central role of precision agriculture in enhancing productivity and resilience in cropping systems. Precision agriculture technologies-including multispectral sensors, soil moisture probes, UAV-based imaging and GPS-guided machinery-provide high-resolution, real-time information on crop status and environmental conditions (Gebbers *et al*., 2010). This continuous flow of spatial and temporal data enables early detection of stress, precise input management, and timely intervention, thereby reducing yield losses associated with climatic hazards such as drought, heat stress or waterflooding (Zhang *et al*., 2023).

A comprehensive approach to modeling the effects of waterlogging in wheat must extend beyond direct physiological damage to include the resulting soil-plant interactions. While models often quantify the yield losses due to root anoxia and nutrient deficiencies, they frequently overlook the biological feedback loops exacerbated by stress (Degaïchia *et al*., 2019). The comprehensive nature of modeling waterlogging stress in wheat necessitates integrating insights from both physiological tolerance mechanisms and advanced data science (Setter *et al*., 2003).

Furthermore, the integration of predictive modeling with precision agriculture platforms is emerging as a transformative approach in crop management. By combining sensor-derived data with machine learning algorithms, predictive systems can forecast crop growth stages, estimate yield potential, and identify risk zones within fields. Such tools contribute to improved decision-support systems, allowing farmers and researchers to anticipate stress events and adjust management practices proactively. This convergence of AI, big data and precision agriculture thus opens new pathways for enhancing environmental sustainability, productivity and climate resilience in wheat-based agroecosystems.

Conclusions

The assessment of yield loss revealed clear and substantial differences in susceptibility among the cultivars evaluated. The Simeto cultivar exhibited the highest yield loss rate, confirming its pronounced sensitivity to waterflooding. Cirta followed closely, also showing a marked decline in productivity under stress, while GTA dur displayed moderate susceptibility. Boussalem, with the lowest yield loss rate, emerged as the most tolerant cultivar within the experimental conditions. These distinctions underline the strong genotypic variability in wheat responses to waterflooding, demonstrating the importance of cultivar selection in environments prone to excess soil moisture.

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This study demonstrated the effectiveness of the Chaid modeling approach for predicting wheat yield under waterflooding conditions. The model provided a clear classification structure and robust insights into the relationships among agronomic and environmental variables. The analysis established a consistent hierarchy in the importance of predictors, with waterflooding identified as the predominant factor shaping yield outcomes, followed by tillering, cultivar and emergence density. This ranking reflects the overwhelming influence of flooding stress on plant development and yield formation, while also highlighting the continued relevance of physiological traits and genetic factors.

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