Integrating Agronomic Models and Big-Data into Decision Support Systems

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Abstract

Site-specific and data-driven decision support systems in agriculture are evolving fast with the rapid advancements in cutting-edge technologies such as Agricultural Artificial Intelligence (AgAI), machine learning models (ML) and big data integration. Data driven decision support systems have the potential to revolutionize various aspects of farming, from crop monitoring and precision management decisions to the way growers interact with complex technologies. The AgAI-based decision support systems excel at real-time analysis of large datasets, granting farmers the ability to make informed decisions based on accurate and up-to-date information. However, the development of reliable AgAI requires more than just these technologies in isolation. To effectively harness their potential, derive maximum value and promote adoption, a robust framework should be in place to enable these technologies. This framework should encompass several fundamental pillars, including a deep understanding of growers' cropping systems and challenges, expertise in environmental and data sciences, robust agronomic algorithms, a reliable and unified data infrastructure, and an orchestrating system enabling seamless integration of data, algorithms, and agricultural technologies. This approach has been exemplified through two data-driven support systems: a remote sensing-based model for in-field detection of nematode damage and a product and site-specific seeding placement and seed rate decision support system. The Computational Agronomy Team at Syngenta has implemented this framework and will emphasize the learning outcomes and best practices. Through our efforts, we aim to contribute to the advancement of scalable data-driven solutions for growers.

Keywords.

data-driven, decision support systems, artificial intelligence, nematode detection, variable rate seeding

Background

The seamless integration of various agricultural technologies is essential to effectively tackle the diverse and complex challenges encountered by growers in practical farming scenarios. The evolution of site-specific, data-driven decision support systems in agriculture is rapidly progressing alongside advancements in cutting-edge technologies like Agricultural Artificial Intelligence (AgAI), machine learning models (ML), and the integration of big data (Junior et al., 2024). These systems hold the potential to revolutionize multiple facets of farming, ranging from crop monitoring and precise management decisions to transforming the way growers engage with sophisticated technologies (Javaid et al., 2022; Sharma et al., 2022)

Nevertheless, to effectively leverage technology potential, extract maximum value, and encourage widespread adoption, a robust framework should be in place. This framework should encompass several fundamental pillars, including a deep understanding of growers' cropping systems and challenges, expertise in environmental and data sciences, robust agronomic algorithms, a reliable and unified data infrastructure, and an orchestrating system enabling seamless integration of data, algorithms, and agricultural technologies. By incorporating these elements, this framework empowers the comprehensive resolution of complex agricultural challenges.

Agronomic models and big data are integrated in Cropwise® digital tools to offer growers comprehensive solutions. Growers require precise information to enhance yields, streamline operations, and efficiently manage resources. Effective decision-making in agriculture necessitates a blend of knowledge, proficiency, and the optimal utilization of available resources and technology. This paper showcases two data-driven solutions within the Cropwise® digital environment to demonstrate the application of the proposed framework. The first solution (Precise *Seed and Nutrient Placement*) delineates productive environments at the field scale by merging locally calibrated crop models with climate, soil, and growers' management data. This approach is agreed to variations in climate, soil, and essential management practices, allowing tailored agronomic solutions for specific production conditions. To ensure accuracy, automation, and reliability in delivering productivity zones for variable rate application, we integrate data layers and algorithms guided by agronomic principles. Furthermore, we devise plant density recommendations tailored to specific hybrids to maximize productivity at both the field and subfield level. In an additional step, nutrient recommendation and other related management decisions could be implemented.

The second solution (*Nema Digital*) focuses on detecting nematode damage. This model relies on assessing anomalies occurring on the soybean canopy (visible damage). By utilizing historical time series of satellite images, the model filters out field events or anomalies unrelated to nematodes and highlights sites where there is a high likelihood that nematodes are causing stress on the canopy (Santos et al., 2022). Initially the model was developed for Brazil, in which soybean contributes to approximately 35% of the global soybean production, the model addresses the significant issue of plant-parasitic nematodes, which results in estimated annual losses of over USD 5.4 billion in the country. In highly infested areas, yield losses can reach up to 30% (Lima et al., 2017; Allen et al., 2017). The threat from nematodes has been largely imperceptible and inadequately understood due to the abundant presence of nematodes, non-specific symptoms, and the limited feasibility of laboratory analyses on soil samples (Blevins et al., 1995; Franchini et al., 2018; Martins et al., 2017). Consequently, there is a pressing need for a large-scale solution that can offer field-level insights into nematode damage, aiding growers and agronomists in prioritizing fields and selecting optimal countermeasures. In response to this challenge, we have developed a large-scale solution that can assist farmers in comprehending the scope of the nematode problem in their fields.

The data-driven decision systems elucidated in this work represent a sophisticated integration of data, data infrastructure, agronomic models, and grower insights, yet the resulting solution is simple and readily accessible to growers. This accessibility underscores the transformative potential of data-driven solutions, which will play an increasingly pivotal role in shaping the future of agriculture. Looking ahead, the trajectory of these solutions is undeniably promising, with robust AgAI expected to be a defining force. AgAI holds the key to unlocking unprecedented levels of precision, efficiency, and insight in agricultural decision-making, ultimately empowering growers with advanced tools and capabilities to navigate the complexities of modern farming (Akkem et al., 2023). As AgAI continues to evolve, its integration with existing data-driven systems is anticipated to further streamline and enhance the accessibility, usability, and impact of these transformative solutions, steering in a new era of innovation and efficiency in agriculture.

Materials and Methods

The following sections aimed to describe the individual components of Seed placement and Nema Digital.

Precise seed and nutrient placement

The seed and nutrient placement solution available in Cropwise® equips growers with field-level yield estimations tailored to various weather, soil, and management scenarios, enabling informed input decisions such as variety selection, planting density, and nutrients. Additionally, growers with variable rate application technologies receive site-specific management prescriptions to enhance input efficiency through variable planting density and nutrient application customized to specific environmental conditions (Figure 1)

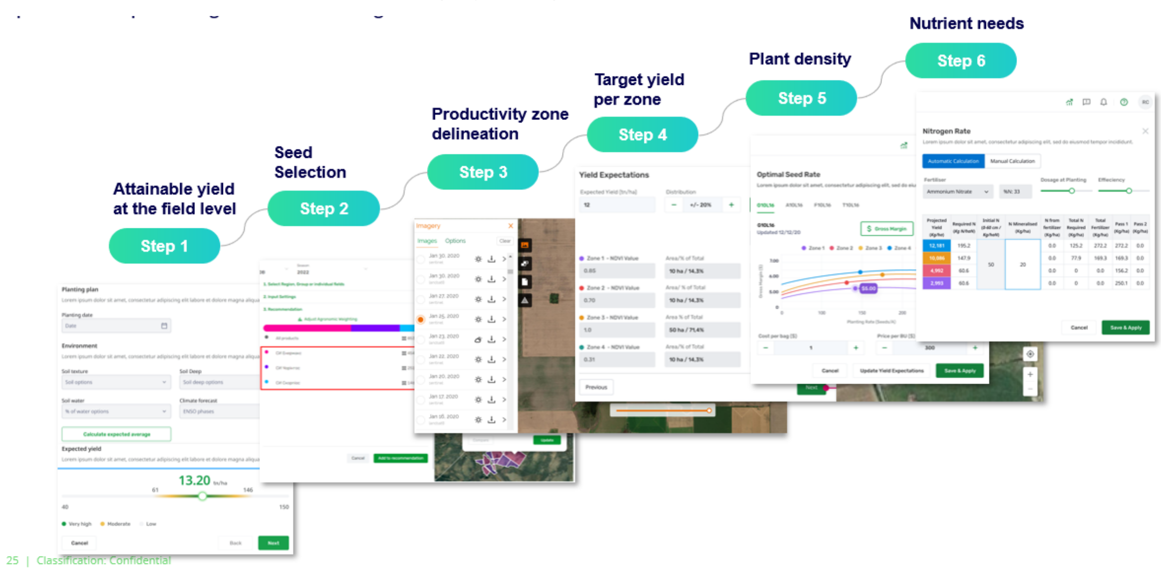

Figure 1 Example of the Precise Seed and Nutrient Placement Solution available through Cropwise using agronomy algorithms developed by Computational Agronomy and Regional Agronomy teams. The data-driven solution involves six major steps: Attainable yield estimation for diverse scenarios of weather, soil, and management practices (Step 1), variety selection (Step 2), site-specific productivity and management zone delineation (Step 3-4), variable plant density recommendation (Step 5), and variable rate prescription creation (Step 6).

Attainable yield estimation

We characterize productive environments at the field scale through an approach that combines local calibrated crop models, and data on climate, soil, and growers' management practices (Figure 2). Our team leverages an extensive network of trials and collaborates closely with local experts to develop and calibrate models, ensuring the reliability of our yield estimations. This approach considers variations in climate, soil, cultivar, and key management practices, providing tailored agronomic solutions specific to each production condition. It is important to note that these yield estimations are specifically relevant for pre-planting decision-making, helping growers define their production yield target. To fully unlock this potential, growers must undertake the necessary management and crop protection practices throughout the growth season.

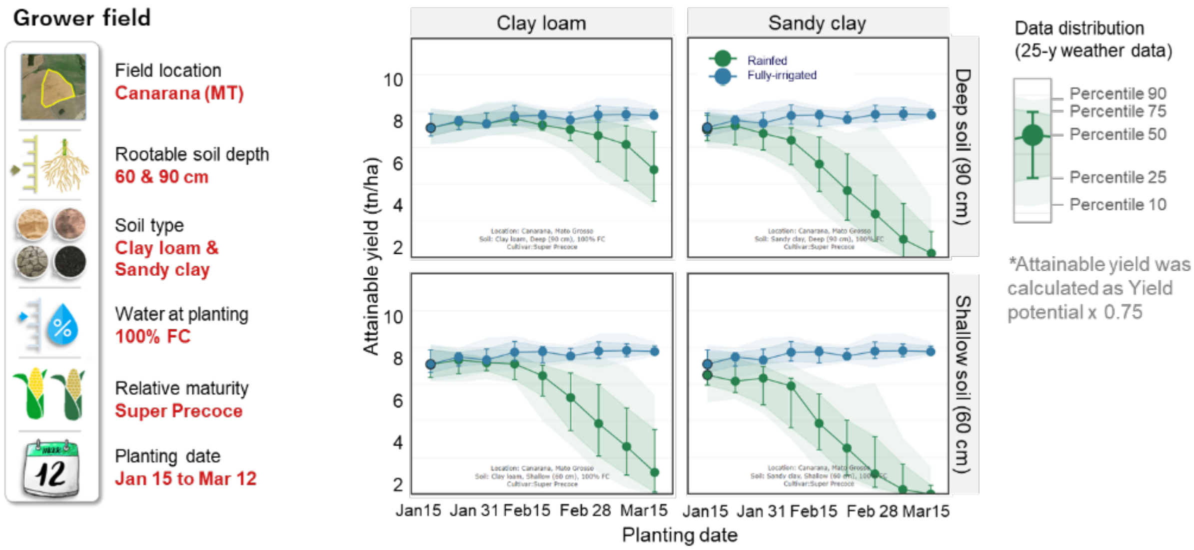

Figure 2 Example of the data set used in Europe to develop Seed Selector model for grain corn.

Seed Selection

The Seed Selector model utilizes a set of rules that integrate environmental model classification and experimental data to deliver product (seed) recommendations. By leveraging a matrix structure, it can derive an unbiased ranking of seed products, drawing on extensive data sets and local expertise for model calibration through side-by-side comparisons (Figure 3). This approach offers a more robust alternative to standard analyses, allowing for the appropriate ranking of products using non-orthogonal data. Following calibration and validation by local and regional crop experts, growers can effectively apply this model to their own fields and specific requirements.

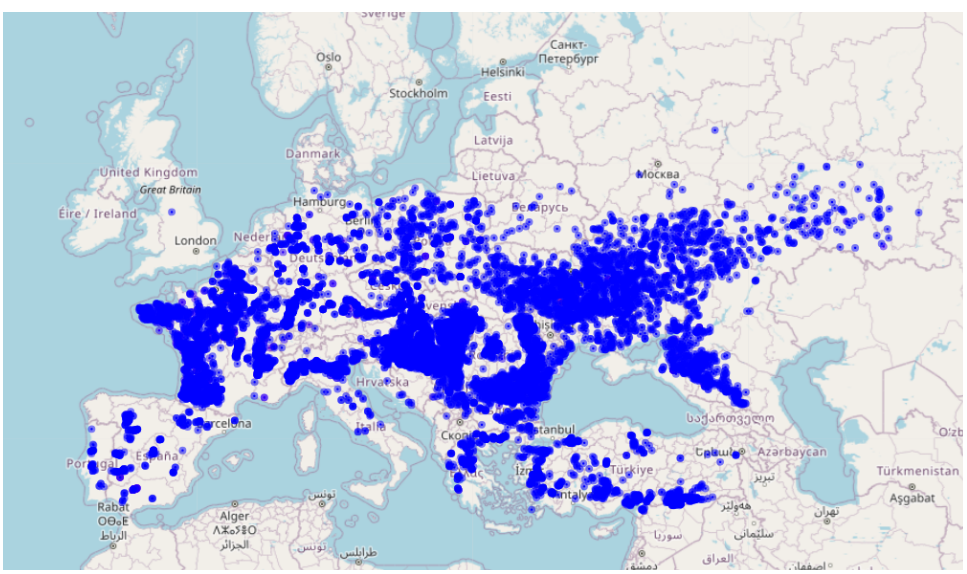

Figure 3 Example of the data set used in Europe to develop Seed Selector model for grain corn.

Productivity and Management zone delineation

Addressing field heterogeneity is a major opportunity for optimizing yield and productivity by enabling producers to adapt resource use to a sub-field level to increase the profitability of farm inputs. The productivity zones model aims at delineating, within one field, contrasting zones in terms of crop productivity (Figure 4). It was trained with minimum user input, but it is possible to adjust as needed. The model algorithm combines multi-season remote sensing data to categorize field zones into different productivity levels. These zones can then support variable seeds, fertilizer, or product rate application (Figure 1 and Figure 4).

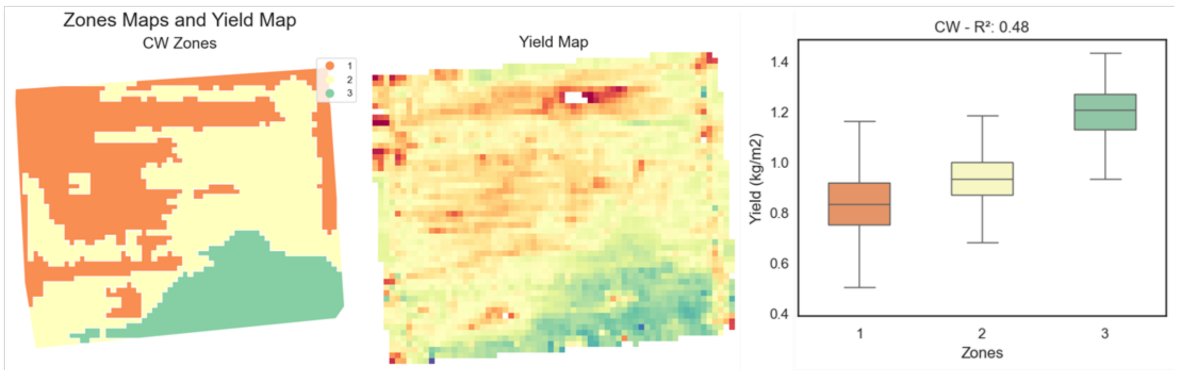

Figure 4 Productivity zones (left), yield map (center) and box plot showing yield variation within productivity zones for a field in Illinois. A higher R^2 indicates a stronger correlation between the productivity zones and yield.

Seed Rate recommendation

To provide precise recommendations, the Computational Agronomy team and regional agronomists calibrate hybrid-specific response curves to plant density across different target environments. For example, in Europe, a total of 141 trials were used to calibrate these models during 2023 (Figure 5). These trials have a multifactorial design with hybrids and densities as factors.

With these trials we fit continuous models that enable the optimization of seed usage in response to changes in the target environment. Environmental Index (EI) is used to characterize the environment and is calculated as the average yield of all plots inside a trial. Then, the density that results in the maximum yield for each EI is used as a recommended seed rate.

Once the grower defines their target environments, whether at the field level (Figure 1, step 1) or within the field (Figure 1, Step 3), and subsequently selects the best product for those environments (Figure 1, Step 3), the next step is to determine the planting density and nutrient needs per environment (Figure 6). In the case of a field with three zones (Figure 6), the user will provide an EI for each zone. Then, these EI are used to extract the density value that maximizes the yield and create a planting prescription with those values.

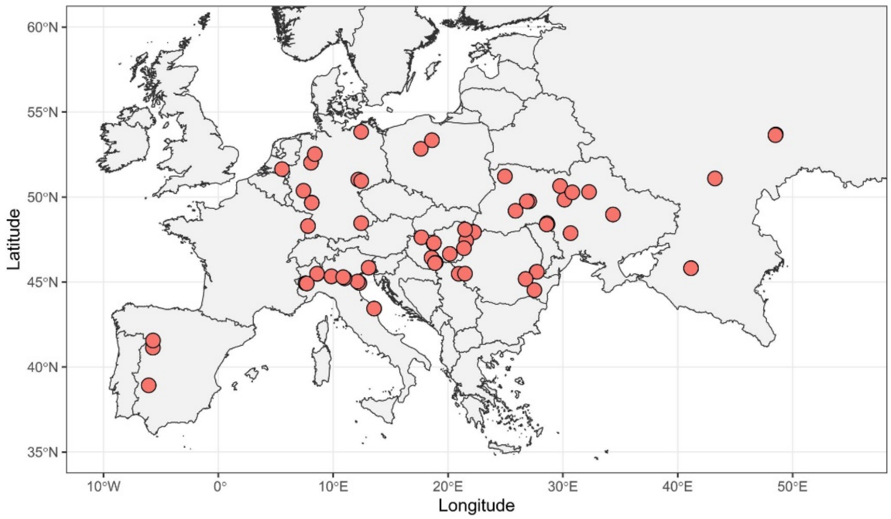

Figure 5. Seed rate trial location for corn in Europe.

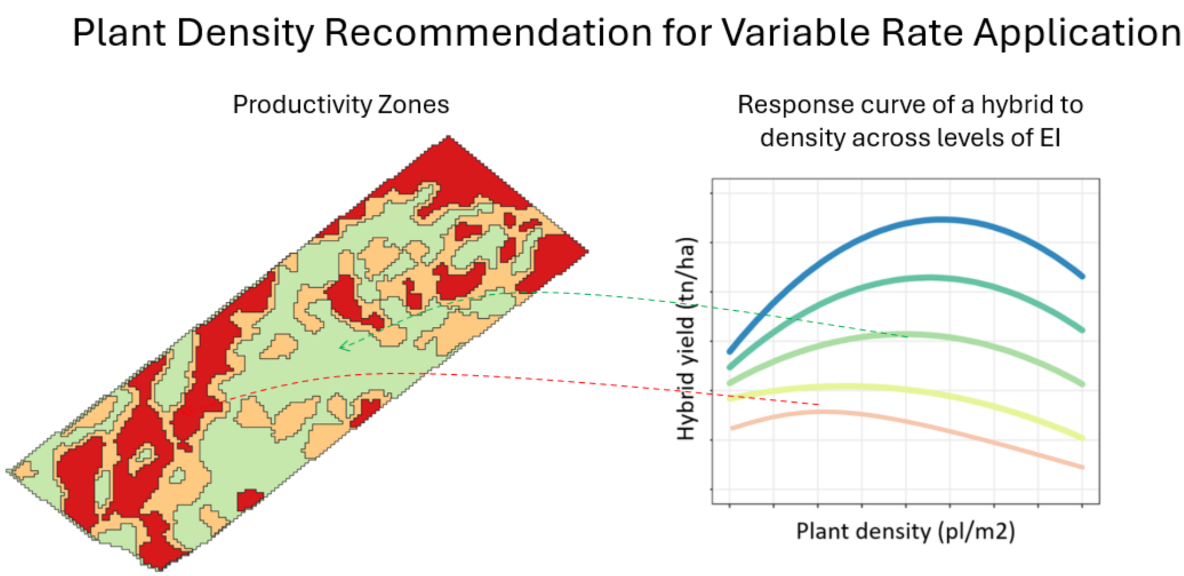

Figure 6. Productivity zones (left) and plant density curves of the recommended hybrid (right). The colors in the plant density curves represent different levels of Environmental Index (EI).

Nema Digital

The Nema Digital solution aimed at highlighting locations that have been damaged by nematodes in a soybean field. The tool helps growers to identify fields with the highest percentage of visible nematode damage and select the best countermeasures that include the use of the appropriate tolerant cultivars and/or crop protection technologies.
The tool also supports growers in their soil sampling activities by providing recommendations on the best locations for soil sampling.

Detecting and identifying nematode damage is not an easy task. There is no specific spectral signature of the nematode damage on the soybean canopy in the field. From a satellite perspective, nematode symptoms can be similar to nitrogen deficiency or fungal infections for example.

The specificity of nematode damage relies on its temporal signature. Nematodes don't impact crops the same way. Species such as soybean cyst nematodes only impacts soybean and not corn that is usually part of the same cropping system in Brazil and US.
Thus, combining knowledge of cropping systems and pathogenicity of nematodes, we designed a model that uses satellite images from multiple seasons to isolate nematode damage in the field.

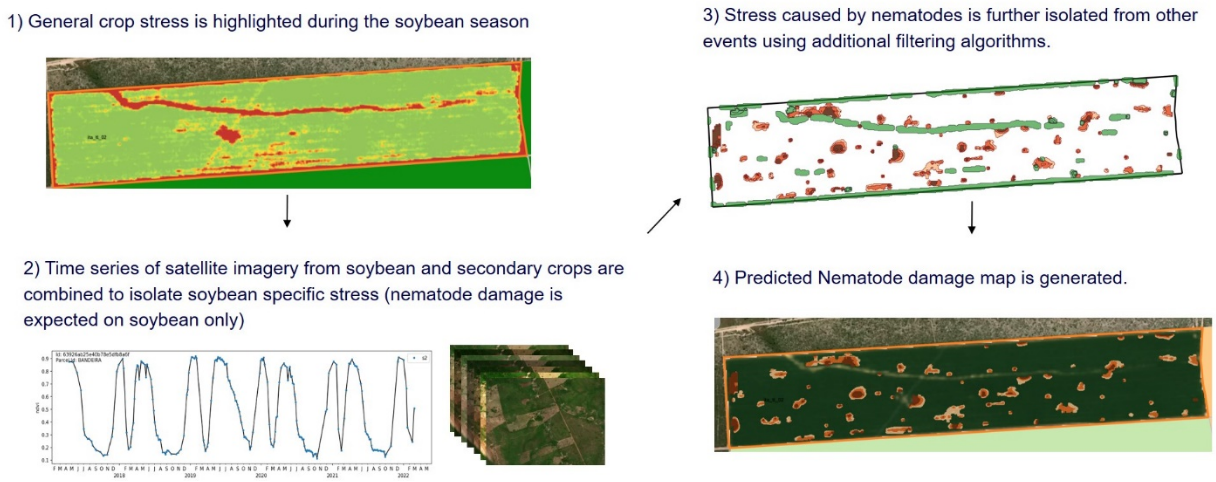

Figure 5 Description of Nema Digital solution. The model uses five years of satellite imagery, a field boundary, and five years of crop rotation history as inputs. The model predicts a nematode damage map.

The model was initially developed for Brazil where the soybean season occurs during the rainy season (November to March). This period is extremely challenging in terms of cloud free satellite images availability. To capture stress on the soybean canopy, images should be collected during the entire soybean season. The model, thus, leverages two sources of images (Sentinel2 and PlanetScope imagery) to make sure the number of images used by the model is sufficient. Using Sentinel2 as a primary source of satellite imagery, the model detects periods without any cloud free images and automatically requests cloud free PlanetScope imagery to fill the gap.

Results & Discussion

Seed placement adoption and usage

In the dynamic landscape of modern agriculture, there is a need for a robust solution to enhance the positioning of seed products. The Seed Selector model plays a pivotal role in driving sales growth, improving customer retention, and optimizing the performance of Syngenta seed products. By leveraging a data-driven approach, the model can analyze environmental factors to identify the most suitable seed product for specific regions and farmer segments. This targeted approach not only enhances the precision of marketing and sales efforts but also ensures that farmers receive tailored solutions that align with their unique needs. Additionally, a well-optimized positioning model can lead to increased customer satisfaction, loyalty, and higher sales volumes. Furthermore, by aligning the seed products with specific environmental conditions and farmer's demands, the model can significantly enhance the overall performance and effectiveness of these agricultural products, benefiting both the company and farmers. The current model reaches 36 combinations of crops (hybrid-barley, grain corn, silage corn, sunflower, and soybean) and countries and will be extended to more countries and new crops (wheat and winter oilseed rape) in Europe.

Nema Digital adoption and usage

The Nema Digital solution has been commercially released in Brazil in 2023 and will be available in the US in 2025. The model has a high precision higher than 90%. The model identifies locations where the probability of finding nematodes is very high. It identifies locations with the expected largest nematode population in the field (since it has visible damage). This assumption has been further tested in 2024. The model only detects location showing vegetation anomalies which ensure consistency in the output (no damage "hallucinations"). If there are nematodes in the soil, but no damage, there will be no detection by the model. The model will fail to identify nematode damage in locations where the damage from nematode stress is associated with another source of stress that is consistently present across the seasons (corn and soybean seasons). In addition, small areas (less than 5 x 5 meters) would not be detected.

Learning lessons and best practices

The integration of agronomic models and big data into decision support systems such as Precise Seeds and Nutrient Placement and Nema Digital has yielded several key lessons:

- Data Quality is Paramount: The success of integrating agronomic models and big data hinges on the quality, accuracy, and reliability of the data. Ensuring data quality through rigorous validation and calibration processes is essential for generating trustworthy insights and recommendations.

- Model Calibration and Validation: Agronomic models must be continuously calibrated and validated using real-world data to ensure their accuracy and relevance in diverse agricultural settings. This iterative process helps refine the models and enhance their predictive capabilities.

- Interdisciplinary Collaboration is Crucial: Effective integration of agronomic models and big data requires collaboration between agronomists, data scientists, software engineers, and domain experts. Interdisciplinary teams can leverage diverse perspectives to develop comprehensive and effective decision support systems.

- Scalability and Adaptability: Decision support systems must be designed to accommodate diverse farming operations, crop types, and geographical variations. Scalability and adaptability are crucial to ensure that the integrated models and data can be effectively applied across different agricultural contexts.

- User-Centric Design: User experience and usability are critical factors in the successful adoption of decision support systems. Systems should be designed with input from end-users to ensure that the insights and recommendations are presented in a clear, actionable, and user-friendly manner.

- Continuous Improvement and Feedback Loops: Establishing feedback loops from users and real-world outcomes is essential for continuously improving decision support systems. This iterative approach allows for the refinement of models, data inputs, and recommendations based on practical experiences and user feedback.

- Ethical Use of Data: The integration of big data into decision support systems requires a commitment to ethical data use, privacy, and security. Clear guidelines and protocols for data collection, storage, and usage are essential to maintain trust and compliance with relevant regulations.

- Education and Training: Providing training and support for users is crucial for the effective utilization of integrated agronomic models and big data. Users need to understand the underlying principles, limitations, and potential applications of the decision support systems to maximize their benefits.

By internalizing these key lessons, stakeholders can navigate the complexities of integrating agronomic models and big data into decision support systems more effectively, leading to improved agricultural decision-making, resource optimization, and sustainable farming practices.

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