

DAWN

Dashboard for Agricultural Water Use and Nutrient Management—A Predictive Decision Support System to Improve Crop Production in a Changing Climate

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ABSTRACT: Climate change presents huge challenges to the already-complex decisions faced by U.S. agricultural producers, as seasonal weather patterns increasingly deviate from historical tendencies. Under USDA funding, a transdisciplinary team of researchers, extension experts, educators, and stakeholders is developing a climate decision support Dashboard for Agricultural Water use and Nutrient management (DAWN) to provide Corn Belt farmers with better predictive information. DAWN's goal is to provide credible, usable information to support decisions by creating infrastructure to make subseasonal-to-seasonal forecasts accessible. DAWN uses an integrated approach to 1) engage stakeholders to coproduce a decision support and information delivery system; 2) build a coupled modeling system to represent and transfer holistic systems knowledge into effective tools; 3) produce reliable forecasts to help stakeholders optimize crop productivity and environmental quality; and 4) integrate research and extension into experiential, transdisciplinary education. This article presents DAWN's framework for integrating climate–agriculture research, extension, and education to bridge science and service. We also present key challenges to the creation and delivery of decision support, specifically in infrastructure development, coproduction and trust building with stakeholders, product design, effective communication, and moving tools toward use.

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Climate variability, economic uncertainty, and changes to agricultural policy all impact farmers' ability to sustainably manage their farms and crop production. In response, the USDA has supported several large interdisciplinary projects with coordinated research, extension, and education focused on assessing climate impacts and agricultural sustainability (Eigenbrode et al. 2014). Technological and agronomic advances toward digital agriculture are providing farmers with opportunities to improve productivity and efficiency, while reducing environmental impact (Morton et al. 2011; McFadden et al. 2023). Advances in weather and climate modeling have produced increasingly accurate and fine-resolution forecasts, particularly at the subseasonal-to-seasonal (S2S) scales (Mariotti et al. 2020; Zhu et al. 2023). Predictions at the S2S scale, ranging from 2 weeks to 9 months, have great potential value to improve agricultural decision-making regarding crop choices, planting dates, water and nutrient management, and field practices (Shafiee-Jood et al. 2014). Nevertheless, large gaps persist between climate research and agricultural applications (White et al. 2022). Researchers are often unaware of the capabilities and adoption of existing agricultural technology, while advancements in S2S-scale prediction often remain siloed in academic journals or are distributed in formats not relevant to local decision-making (Merryfield et al. 2020). Even after forecast information becomes available, it may not be immediately used until after farmers perceive it as reliable and potentially valuable (Shafiee-Jood et al. 2021).

Giving farmers easy access to high-quality S2S climate forecasts will help to close the gap between research and farming operations. To be readily usable, such information must be presented in forms already familiar to and used by *farmers*, at relevant time scales and resolutions, and with easily interpretable measures of accuracy and uncertainty (Janssen et al. 2017). Furthermore, predictive information must fit into existing farmer workflows without significantly increasing data collection and data transfer requirements. Discussions with agricultural stakeholders and DAWN's internal extension team have revealed that farmers want to be able to evaluate the impact of predicted seasonal climate

on their operations and to explore hypothetical decision pathways to exploit new opportunities or mitigate risk.

Developing predictive decision support capabilities requires a coproduction approach that brings together scientists, software developers, extension experts, and stakeholders (Meadow et al. 2015; Prokopy et al. 2017). Such an approach prioritizes intersectoral conversations at an early stage, allowing stakeholders to share their information needs and comfort with uncertainty and helping scientists to identify potentially overlooked model outputs (Prost 2021). Effective coproduction is challenging, in part because it requires clear communication among communities with separate knowledge bases and expectations about accuracy and uncertainty (Norström et al. 2020). Researchers must therefore think creatively about model capabilities and explore model outputs different from those originally envisioned. Additionally, developers should build tools based on a shared vision with users to avoid logistical hurdles around incommensurate time scales and data requirements. Finally, developing long-term capacities requires educational infrastructure to share the generated knowledge and train the next-generation of leaders (Malayil et al. 2021).

In response to these challenges, an interdisciplinary team of researchers, extension specialists, and stakeholders are collaborating, under funding from the USDA, to create a predictive decision support Dashboard for Agricultural Water use and Nutrient management (DAWN; <https://dawn.umd.edu/>), to improve food and energy crop production in the Corn Belt (Fig. 1). DAWN is building infrastructure to translate complex system science into predictive information that assists with agricultural decision-making and to make that information available to users through a web-based dashboard where they can visualize the impact of climate on agricultural productivity and profitability and explore options to increase water and nutrient use efficiency.

Coproduction approach

DAWN's extension team includes faculty from several land grant universities, as well as staff from UnCommon Farms, a farm business and consulting organization that works with farmers across the Corn Belt. These project members engage stakeholders in an iterative, three-stage coproduction process of 1) an initial assessment of needs and capabilities (Clark et al. 2023), 2) coupled model and tool development, and 3) postrelease engagement and evaluation. The first step in the coproduction process involves deep engagement of model developers with extension and industry specialists who have extensive background on user needs to determine which existing agricultural workflows and informational needs align with predictive model abilities. DAWN model developers, tool designers, and extension specialists work together in an Agile framework to create user stories: descriptions of the identities, objectives, and workflows of expected users (Amna and Poels 2022). These follow a semistructured format of "I am... I want... so that..." Through these stories, DAWN extension experts and early-adopter users draw on their deep knowledge of stakeholder needs, timelines, and level of comfort with technology to profile potential users and sketch out specific model and interface requirements for the software development team. Model developers and interface designers work iteratively with extension personnel to align the desired information needs with the capabilities of the modeling system and development environment. Importantly, results of each iteration are documented, as they often generate ideas for new model uses.

The coproduction process and user stories have led to insights into stakeholder needs and have formed the basis for the development of the dashboard's infrastructure and products. In particular, they help address potential mismatches between current modeling capabilities and existing user needs. DAWN's modeling platform consists of multiple components, all with different development cycles, data requirements, flexibility to respond to user needs, and application readiness, a combination that creates significant coproduction challenges.

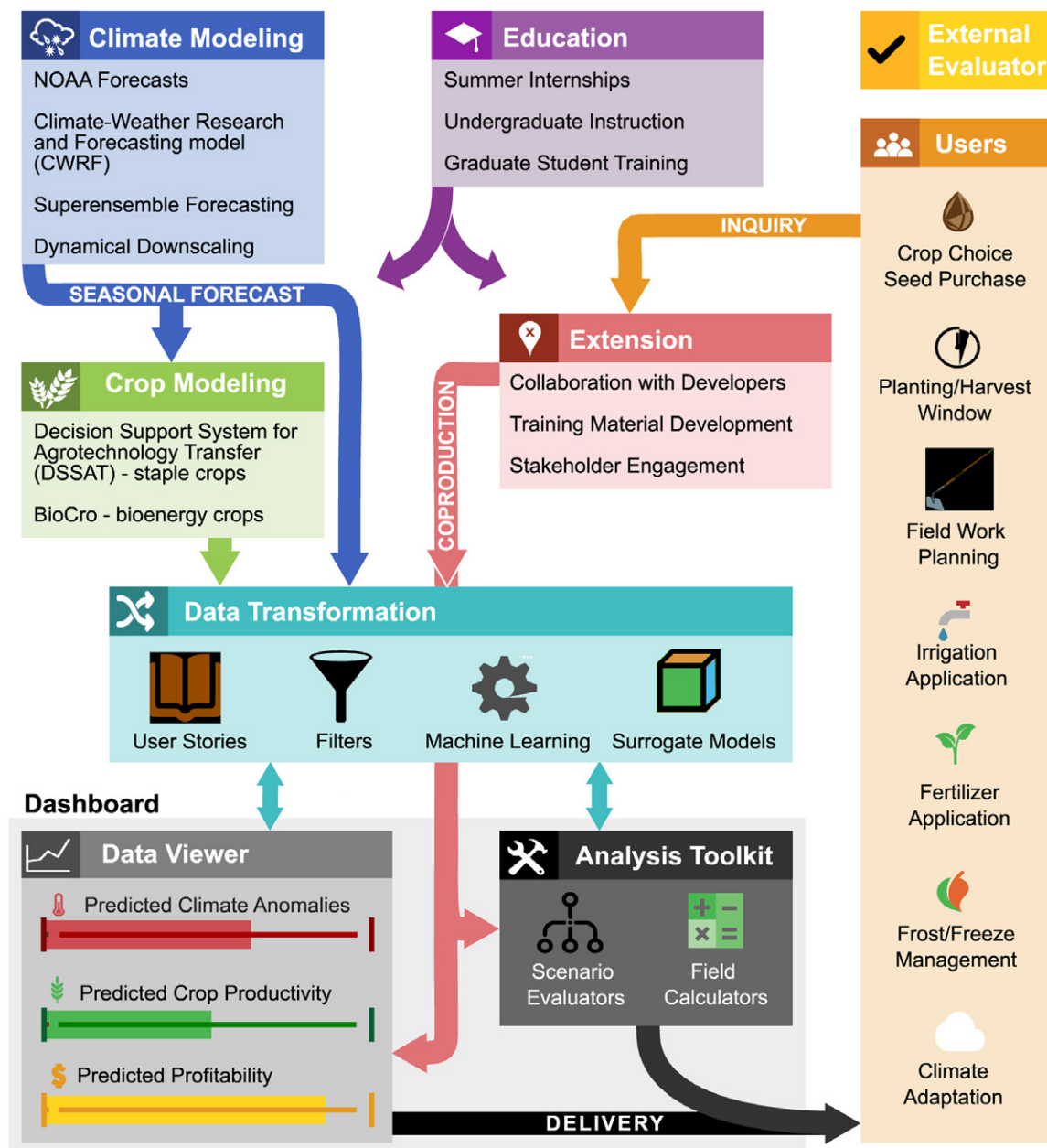


Fig. 1. DAWN schematic overview. Arrows depict information flows among DAWN's major research and extension activities. The education component engages student training across all these system development activities. The external evaluator assesses intrateam and transdisciplinary partnerships to support project effectiveness.

For example, the climate prediction and crop growth models are currently production-ready at the S2S time scale and require only easily accessible user data (such as crop type and planting date); however, they are relatively inflexible and are largely limited to preset input and output data. User story conversations for these models therefore often center around the data transformations necessary to develop user-relevant metrics at appropriate spatiotemporal scales using the potential existing outputs. Other models, such as irrigation scheduling and fertilizer application, require more extensive modifications in order to meet S2S user needs; they may need extensive input data that farmers are unable to easily provide, or generate outputs at scales less relevant to farm-level decision-making. Here, user stories help determine necessary model modifications. This allows greater flexibility in responding to identified user needs, but also is a longer process that carries the risk of working toward functionality that may prove to be infeasible.

Once tools have been developed and released, DAWN's extension specialists meet with stakeholders, which include farmers, farm managers, and consultants, to gather feedback on the public's use and perception of these tools. These meetings typically take the form of trainings or think-aloud interviews with farmer groups (Krahmer and Ummelen 2004; McDonald et al. 2012). This allows for continual engagement and evidence-based improvements to existing DAWN tools. Throughout the development, deployment, and adaptive improvement process, DAWN has also consulted a Stakeholder Working Group composed of growers and representatives from agricultural research, service, and commodity organizations who meet periodically to identify development priorities, barriers to use, and incentives to adopt DAWN by a wide range of practitioners.

Use-inspired predictive modeling platform

Current decision support systems (e.g., Rose et al. 2016; Zhai et al. 2020) tend to assume a stationary crop response to climate without feedback, but incorporating seasonal forecasts with interactions into planning is critical as climate anomalies covary with underlying soil and canopy conditions, increasing system variability and extremes. DAWN translates S2S coupled climate and crop forecasts into metrics and formats compatible with existing agricultural planning workflows. The current DAWN system launched uses baseline climate forecasts from NOAA, transforming them for increased accessibility and relevance to farming practices. The upcoming system will be supplemented with dynamically downscaled forecasts from CWRf, a regional climate model that incorporates advanced physics representations at finer resolution (Liang et al. 2012) and has improved prediction of regional temperature and precipitation anomalies and extremes in the United States (Yuan and Liang 2011; Liu et al. 2015; Sun and Liang 2020, 2023).

CWRf currently produces national forecasts at 30-km resolution, with plans to nest a 3-km grid over the Corn Belt pending computing resource availability. To improve accuracy and reliability, DAWN modelers are testing the use of both machine learning to correct systemic biases due to inevitably incomplete representations of climate physics (Carter et al. 2021; Golian and Murphy 2022) and superensemble forecasting from all available global operational S2S forecasts and NOAA-driven CWRf multiphysics downscaling results (Liang et al. 2012; Roy et al. 2020). This bias-corrected superensemble prediction better captures regional climate anomalies and will become the primary forecast driving the dashboard.

DAWN's modeling platform feeds NOAA operational, CWRf-downscaled, and superensemble-optimized climate–hydrology forecasts into crop models to predict the timing of development stages and the magnitude of end-of-season yields for crops in the Corn Belt. Decision Support System for Agrotechnology Transfer (DSSAT) is widely used to simulate crops such as corn and soybeans (Hoogenboom et al. 2021), while BioCro focuses primarily on bioenergy crops like miscanthus (Lochocki et al. 2022). Together, these models generate crop-specific growth predictions based on current and predicted seasonal climate conditions and management decisions. While current crop prediction research has been primarily based on standalone simulations using statistical or dynamical crop models driven by climate predictions (Peng et al. 2018), DAWN is developing coupled forecasting capability with crop–climate feedbacks. Incorporating such feedbacks can improve prediction of both crop production and climate variation (He et al. 2022).

The seasonal climate and crop forecasts, incorporating all aforementioned prediction enhancements, are then transformed into agriculturally relevant metrics or outcomes through a pipeline of domain-specific algorithms (Fig. 1). These include growing degree days, crop progress, days suitable for field work, recommendations for optimizing irrigation and fertilizer application, and estimates of return on investment for various inputs. The transformed data

supplement the forecasts by allowing users to explore climate implications and evaluation decisions in the context of specific seasonal forecasts.

A user-centric dashboard

DAWN's dashboard includes both a comprehensive data viewer and a scenario analysis toolkit. The data viewer delivers S2S predictions as a coherent, customizable selection of data metrics and visualizations, which are updated weekly with increasing accuracy to allow users to monitor the evolution of conditions throughout the growing season and make adjustments accordingly. The scenario analysis toolkit allows users to explore predicted outcomes from choices related to crop type, planting dates, and irrigation and fertilizer applications, allowing easy comparison (Fig. 2). Both components were designed to be:

Easy to use. Digital decision tools have been available in the agricultural sector for over a decade (Rose et al. 2016; Angel et al. 2017), and many users have existing workflows using other software, often which already monitor large amounts of data. Additionally, farmers have busy schedules and often wish to access data while on the field. Consequently, the dashboard is built to be easy to access on both PC and mobile devices, to require little overhead setup, and to integrate easily with other programs. To lower data entry burdens, the tools require as little user information as possible, and are populated with default values. Algorithms in the scenario analysis toolkit require user input to constrain the range of predictions that are generated; however, the options are limited to easily specified metrics

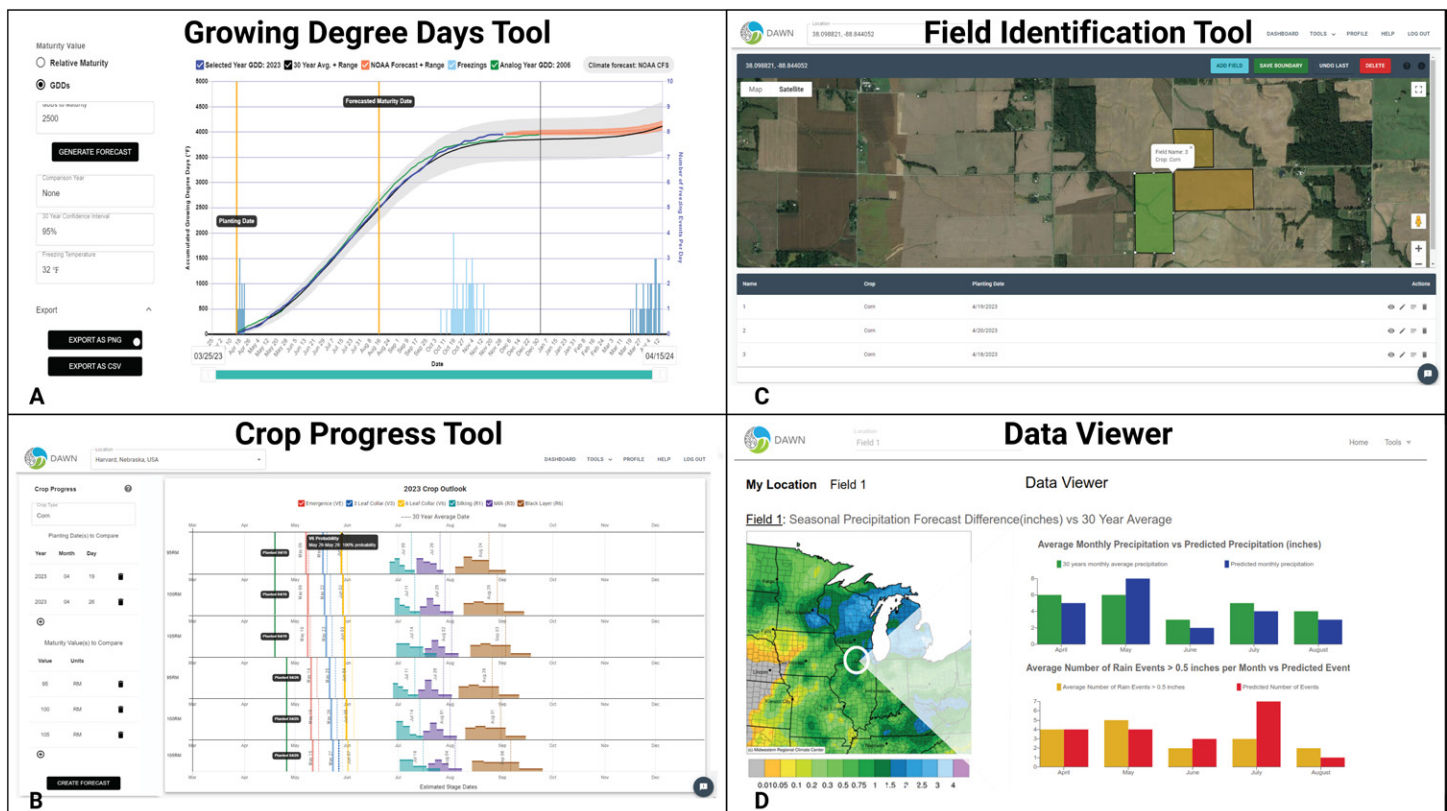


Fig. 2. DAWN dashboard examples. (a) The *growing degree days* tool allows users to view a 9-month forecast of growing degree-days and freezing occurrences, with optional comparisons to historical means/ranges and analog years; users can also view a crop's maturity outlook by adjusting planting date and relative maturity. (b) The *crop progress* tool displays a probabilistic distribution of the time window at which a specified crop is projected to reach each maturity stage, and allows users to compare among different planting dates and maturities. (c) The *field identification* tool allows users to manually select and name one or multiple farm fields or upload a shapefile of fields, which can then be used as the location or area for other predictive tools. (d) The *data viewer* allows users to visualize temporal and spatial data in a variety of customizable graphics, including maps, comparative bar charts, and cumulative line graphs, to support agricultural decision-making.

like location, crop type, and planting date. To streamline workflows, data and results can be downloaded or directly accessed by other software via application programming interfaces (APIs). The dashboard is not intended to replicate existing farm management software such as Field IQ or Conservis, but instead focus on S2S forecasts that complement tools developed for tracking and near-term optimization.

Personalized. Rather than a collection of individual agricultural calculators, the dashboard provides a coherent, synchronized interface through which users can create a curated environment of relevant forecasts and data streams specific to their fields. Additionally, they may customize their displays so that data appear in easily understood maps and figures that automatically update with new forecasts. Account settings, including preferences and records, persist between logins, so that users can return to previous analyses. Currently, the dashboard tools are built around corn; since most of the Corn Belt grows corn and soybeans in rotation, soybean-focused tools are a high priority for future development, along with perennial grasses.

Context driven. The dashboard not only delivers forecasts, but situates them in contexts necessary for interpretation, providing comparative historical data and measures of prediction accuracy and uncertainty. Forecasts are presented alongside a range of observational data from previous years and are linked to analog years predicted to be similar to the current year, facilitating comparisons to past experiences. For example, a simple forecast of the number of days suitable for fieldwork during the planting period will be supplemented by the probability that it exceeds the decadal average. The dashboard will also include accuracy and uncertainty measures based on both ensemble statistics and on expected bias generated from hindcast analyses for farmers to evaluate risks.

Community engagement and education

Wider uptake of the dashboard's predictive climate/crop information requires outreach and community engagement to introduce the dashboard to key stakeholders (e.g., farmers, extension agents), provide training in its use and applications, and collect feedback on possible improvements. As of 2023, DAWN extension specialists have engaged around 1,340 participants across 33 conferences and events, ranging from broad informational seminars to intensive small group or one-on-one training and feedback sessions. Phase 1 of the dashboard was publicly released at the UnCommon Farms Annual Meeting in 2023, opening the doors to a wider group of potential users. These events served both to increase awareness of the dashboard's existence and capabilities and to engage in conversations about user needs and interests. Parallel with the dashboard's development, DAWN is creating a series of extension materials including fact sheets and video tutorials exploring how to use and interpret the new resources.

DAWN also strives to involve students in each stage of its development through experiential education. Leveraging infrastructure from the USDA-funded CONSERVE and NSF-funded UMD Global STEWARDS projects, DAWN provides interdisciplinary graduate and undergraduate courses focused on the food–energy–water nexus, as well as an undergraduate summer internship program (Malayil et al. 2021). The DAWN summer internship program provides students, many from traditionally underrepresented groups, with 10 weeks of paid research training and career development opportunities in fields relevant to DAWN focus areas. Of the 33 interns trained so far, 73% are women and 21% are black, indigenous, and people of color (BIPOC). In addition, graduate students and early-career scientists are participating in professional development workshops covering topics including media communication, grant writing, and entering the job market.

Early challenges and evolving priorities

Transitioning from research to operations through a coproduction process creates unique challenges for grant-funded projects, partly because it requires that priorities and structures be allowed to evolve in response to stakeholder feedback. DAWN's first year of operations revealed the importance of nonresearch roles, particularly web development and communications. Additionally, the process of aligning user needs and expectations with scientific and computing capabilities led to an increased focus on S2S prediction, as well as a strong emphasis on user experience design. DAWN's continual evolution to meet user needs has motivated structural changes and reprioritization of funding, highlighting the importance of adaptive management strategies.

Communications. Development of both internal and external communications strategies quickly became a key priority. DAWN is a large team spanning multiple institutions and disciplines, and the parallel workflows typical of interdisciplinary academic research do not necessarily translate easily to interactions with stakeholders. Development delays or changes in priority affected the work of other project members, particularly extension experts directly communicating with stakeholders about the timing and features of new releases. In responding to this need the project leadership developed workflows, timelines, and intergroup collaboration strategies and reprioritized funding to support a communications specialist. This specialist developed an internal newsletter to keep project members informed of progress as well as stakeholder-focused resources such as news updates, FAQs, and dashboard tutorials.

Model applicability. The most scientifically advanced model framework may not always translate into effective tools that can be used in agricultural decisions. DAWN started with an initial set of advanced models chosen to capture key components of Earth's climate–agro–hydro–economic system. As the project progressed, conversations among extension experts and stakeholders revealed that some of the component models require extensive site information and user input that could prove difficult to acquire or do not operate at the spatiotemporal scales needed for on-farm decision-making. In response, DAWN has adapted its modeling priorities, such as shifting focus from weather-scale operations to S2S planning.

Operationalizing tools. Building and maintaining an operational decision support dashboard requires more computing resources than were included in the original proposal. Fortunately, DAWN was able to acquire more resources through the generous support of NSF's XSEDE and ACCESS programs and DOE's Oak Ridge Leadership Computing Facility. Additional financial support, however, will be needed to sustain DAWN's operations after USDA funding ends in September 2025. The project leadership had also originally hired undergraduate student web developers to build the dashboard interface. Although the students performed well, their academic commitments, limited availability, and eventual graduation meant that progress was slower and less regular than anticipated. The leadership eventually hired a part-time professional developer and implemented an Agile software development framework to coordinate the undergraduate team.

Conclusions

Increasing agricultural resilience to climate variability requires unified efforts across agricultural and scientific communities to build decision support systems that allow farmers access to subseasonal-to-seasonal (S2S) predictive information that can be applied in critical farm planning choices. Accurate seasonal forecasts can allow farmers to choose and time crop

planting and management to better synergize with climate conditions, thus reducing risk, minimizing waste, and taking advantage of potential opportunities. Through collaboration across research, extension, and stakeholder communities, DAWN is building an S2S-focused dashboard that transforms climate forecasts into farm-relevant predictions using crop, hydrology, and economic models. DAWN aims to allow users to quickly understand the impacts of current forecasts for their specific locations, crops, and fields, by presenting forecasts in terms of user-selected metrics. Additionally, DAWN's scenario analysis capabilities allow users to explore the impacts or risks of different choices or climate conditions. All products are being coproduced by a team of researchers, programmers, and extension experts, with continuous feedback from stakeholders. DAWN's approach is evolving based on both stakeholder feedback and a growing understanding of research and operational challenges. Alongside the process of dashboard construction, DAWN is working to engage students in interdisciplinary learning and to promote the sustained development and use of predictive climate information in agricultural operations.

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