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Short-term Forecasting Tools for Agricultural Nutrient Management

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Abstract

The advent of real-time, short-term farm management tools is motivated by the need to protect water quality above and beyond the general guidance offered by existing nutrient management plans. Advances in high-performance computing and hydrologic or climate modeling have enabled rapid dissemination of real-time information that can assist landowners and conservation personnel with short-term management planning. This paper reviews short-term decision support tools for agriculture that are under various stages of development and implementation in the United States: (i) Wisconsin's Runoff Risk Advisory Forecast (RRAF) System, (ii) New York's Hydrologically Sensitive Area Prediction Tool, (iii) Virginia's Saturated Area Forecast Model, (iv) Pennsylvania's Fertilizer Forecaster, (v) Washington's Application Risk Management (ARM) System, and (vi) Missouri's Design Storm Notification System. Although these decision support tools differ in their underlying model structure, the resolution at which they are applied, and the hydroclimates to which they are relevant, all provide forecasts (range 24–120 h) of runoff risk or soil moisture saturation derived from National Weather Service Forecast models. Although this review highlights the need for further development of robust and well-supported short-term nutrient management tools, their potential for adoption and ultimate utility requires an understanding of the appropriate context of application, the strategic and operational needs of managers, access to weather forecasts, scales of application (e.g., regional vs. field level), data requirements, and outreach communication structure.

Core Ideas

- Advances in weather forecasting, data management, and modeling improve nutrient management.
- New tools facilitate improved farm decisions in response to real-time weather.
- Nutrient management can be performed operationally and strategically with real-time tools.

The widespread adoption of site assessment in agricultural nutrient management planning has centered on decision support tools, notably the Phosphorus (P) Index, to balance agricultural production and water quality objectives (Sharpley et al., 2012). These tools are codified in US state and federal nutrient management laws and applied to individual farm fields on a periodic basis (typically a 2- to 5-yr period corresponding with many crop rotations) to evaluate the interactive effects of crop, tillage, fertilizer, and manure management on the potential for nutrient loss to the environment (USDA-NRCS, 2012). It has been argued that new assessment tools should provide flexibility in management that is not achieved with narrow site assessment approaches, such as agronomic soil-test thresholds, and in doing so, promote a more comprehensive, real-time approach to fertilizer and manure management: what is now referred to as the "4 Rs" of nutrient stewardship (right rate, right placement, right timing, right form of nutrient application). Although state nutrient management planning approaches vary widely (Nelson and Shober, 2012), there is a general consensus that opportunities exist for nutrient management planning to better reflect on-farm realities and to better protect water quality (Sharpley et al., 2012). Indeed, recent surveys highlight concerns by farmers, nutrient management planners, and conservationists related to the static nature of current planning tools, which are often unhelpful when operational decisions must be made over short timeframes (Osmond et al., 2012).

At the core of modern nutrient management planning is the concept of critical source area management (i.e., minimizing the availability of nutrients in areas that are hydrologically active and

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Abbreviations: ARM, Application Risk Management; DSAS, Design Storm Alert System; FAR, false alarm ratio; HRRR, High-Resolution Rapid Refresh; NSE, Nash–Sutcliffe Efficiency; POD, probability of detection; RRAF, Runoff Risk Advisory Forecast; SAC-HT, Sacramento Soil Moisture Accounting–Heat Transfer; SAC-HTET, Sacramento Heat Transfer and Enhanced Evapotranspiration; SAC-SMA, Sacramento Soil Moisture Accounting Model; SWAT-VSA, Soil Water Assessment Tool–Variable Source Area; U2U, Useful to Usable.

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connected with stream networks) (Walter and Walter, 1999; Sharpley et al., 2011). For both P and nitrogen (N), research has shown that an effective strategy for preventing losses in runoff is to disassociate potentially polluting activities, like livestock-manure spreading, in space and time from hydrologically active areas (Walter et al., 2000; Easton et al., 2007). Over the long term, critical source area management must prevent soil nutrient accumulation in hydrologically active areas; this is particularly critical to prevent P losses associated with erosion and soil P desorption to soil water (Kleinman et al., 2011; Sharpley et al., 2013). Over the short term, critical source area management must prevent so-called "incidental transfer" or "wash-off" of recently applied P, the contribution of applied nutrients to runoff immediately after application of manure or fertilizer (Preedy et al., 2001; Buda et al., 2013). The duration of the incidental transfer risk is typically quite short, diminishing exponentially over a period of days to weeks during the growing season as applied nutrients on the soil surface are translocated into the soil by leaching and biological cycling or by sorption to soil (Kleinman and Sharpley, 2003; Vadas et al., 2007). However, it is the incidental transfer of nutrients after fertilizer or manure application that has proven to be particularly difficult to target with existing nutrient management planning approaches, placing a priority on forecasting site-specific potential for nutrient wash-off over the short term using guidance derived from weather prediction models.

Over the past decade, there have been significant advances in the accuracy and precision of numerical weather prediction (Hoskins, 2013; Bauer et al., 2015). For instance, short-range forecasts (12–72 h) of daily accumulated precipitation and medium-range forecasts (3–10 d) of temperature and precipitation have demonstrated marked improvement in lead time, accuracy, and skill, increasing their useful range by about 1 d decade^{-1} (American Meteorological Society, 2015). These advancements have clear benefits to short-term runoff prediction. Additionally, medium-range temperature forecasts have improved greatly in recent years and represent a boon to snowmelt runoff forecasting in the winter. The spatial resolution of most weather models also has also gotten finer, with global models now offering medium-range forecasts of precipitation and temperature at nominal horizontal resolutions of 9 to 17 km. Increasingly finer resolution is being made available in the very short range (12–18 h), with a prime example being the High-Resolution Rapid Refresh (HRRR) model developed by NOAA's National Center for Environmental Prediction (Alexander et al., 2016). The HRRR provides hourly rainfall forecasts at 3-km horizontal resolution out to 18 h, thereby improving the representation of localized rainfall distributions and intensities driven by convective storms. The latter benefit cannot be understated, as peak hourly rainfall intensity is a key determinant of the runoff-generating potential of a storm (Buda et al., 2009). With the exception of very short-range models like the HRRR, which operates only in North America, the global scope of most short- to medium-range weather models enables widespread access to state-of-the-art weather predictions.

With greater availability of high-resolution weather forecasts, great strides have been made in short-term decision support tools in agriculture (Mase and Prokopy, 2014). For instance, the Fusarium Risk Assessment Tool uses local climatic modeling to predict conditions favorable to wheat blight over a 1- to 3-d period (http://www.wheatscab.psu.edu/). Credited with major reductions in fungicide use in wheat production, corresponding to millions of dollars in savings, the wheat blight tool also uses input from local weather and pest monitoring stations to update conditions and improve forecast predictions. In addition to crop disease forecasting, short-range weather forecasts also play an important role in irrigation scheduling, crop growth modeling, and predicting the risk of frost and freeze in fruit production. Many of these tools can be found on the Useful to Usable (U2U) website (https://mygeohub.org/groups/u2u), which serves as a clearinghouse for agricultural decision support tools throughout the North-Central United States. Along the same lines as U2U, the Northeast Climate Center's Climate Smart Farming website (http://climatesmartfarming.org/) offers an array of decision support tools that leverage short-range meteorological forecasts for agricultural decision making, including a grape (*Vitus vinifera* L.) hardiness and freeze risk calculator that is specific to the wine industry in the Northeast United States.

Although this is but a small snapshot of the budding decision support tool landscape in agriculture, the inherent value of short-range weather forecasts to farmers (Haigh et al., 2015) suggests great potential for new tools to address underserved areas of the agricultural decision-making process, such as nutrient application management.

Given the limitations of existing nutrient management planning approaches that often focus on tactical (i.e., weekly to monthly planning horizons) and strategic (i.e., seasonal or yearly timeframes) decision making (Hollinger, 1991), and given the greater availability of high-resolution forecasting data, a spate of operational (i.e., daily) nutrient management decision support tools have been proposed and even tested for short-term P site assessment and other related uses. In this paper, we review six nutrient management decision support tools developed in the United States that span multiple regions and intended uses. Because implementation of these tools has been limited, we first review their individual characteristics (data sources, modeling approaches, outputs, and anticipated uses), then examine them by comparing scales, predictive horizons, practical advantages, and uncertainty. In doing so, we seek to establish the current state-of-the-science and to elucidate the benefits and limitations of forecast-driven nutrient management decision making.

Forecast-Driven Decision Support Systems

The six decision support systems reviewed in this paper share the common goal of leveraging weather forecasts to support operational decision making in nutrient management. Nevertheless, the systems employ a variety of approaches to infer the risk of incidental nutrient losses from agriculture, with four tools running watershed simulation models to forecast runoff amounts and saturated area extents, and two others relying exclusively on regional precipitation forecasts to convey runoff risk (Table 1). Of the tools using watershed models, the Wisconsin Runoff Risk Advisory System and the Pennsylvania Fertilizer Forecaster apply models supported by NOAA to predict runoff and soil moisture conditions that determine the nutrient wash-off potential of a watershed or field. Watershed modeling also underpins New York's Hydrologically Sensitive Area Tool and Virginia's Saturated Area Forecast Tool, although instead of forecasting

Table 1. Characteristics of the six short-term forecasting tools, including forecast information, weather data inputs, and runoff modeling outputs.

State	Tool	Short-term forecasting tool characteristics						Weather input datasets				Runoff modeling and outputs		
								Precipitation		Temperature				
		Forecast type	Forecast display	Risk thresholds†	Forecast issuance	Runoff lead time	Snowmelt lead time	Source	Horizontal resolution	Source	Horizontal resolution	Model(s)‡	Scale(s)	Downscaling to subfield levels
						h	h		km		km		km^2	
Wisconsin	Runoff Risk Advisory Forecast	Runoff risk	Watershed risk map	Based on runoff depth (H, M, L)	Twice per day	24–72 (short range)	72–240 (medium range)	Blended mean QPF§ from NOAA's Weather Prediction Center	5	Blended mean temperature from NOAA's National Digital Forecast Database	5	SAC-SMA lumped model and SAC-HTET distributed model	Watershed (~700) and grid (16)	None
Pennsylvania	Fertilizer Forecaster	Runoff risk	Watershed and subfield risk map	Based on soil moisture and runoff contributing area (H, M, L)	Once per day in the morning	24–72 (short range)	N/A	Blended mean QPF from NOAA's Weather Prediction Center	5	Blended mean temperature from NOAA's National Digital Forecast Database	5	SAC-SMA lumped model and SAC-HT distributed model	Watershed (~300) and grid (4–16)	Runoff-contributing areas mapped with topographic wetness and depth-to-water indices
Virginia	Saturated Area Forecast Tool	Saturated area extent	Subfield risk map	Based on soil saturation (H, L)	Four times per day	24–96 (short range)	72–240 (medium range)	Ensemble mean QPF from Global Forecast System Model Output Statistics	13	Ensemble mean temperature from Global Forecast System Model Output Statistics	13	SWAT-VSA model	Subfield scale	Saturated area extent mapped with topographic wetness index
New York	Hydrologically Sensitive Area Tool	Saturated area extent	Subfield risk map	Based on soil saturation (H, L)	Four times per day	24–72 (short range)	72–240 (medium range)	Ensemble mean QPF from Global Forecast System Model Output Statistics	13	Ensemble mean temperature from Global Forecast System Model Output Statistics	13	STOPMODEL and Thornthwaite–Mather Water Balance	Subfield scale	Saturated area extent mapped with topographic wetness index
Washington	Application Risk Management Tool	Precipitation risk and voluntary field assessment worksheet	Precipitation zone risk map	Based on precipitation depth (H, M-H, M, L)	Once per day in the morning	24–72 (short range)	N/A	Blended mean QPF from NOAA's Weather Prediction Center	5	N/A	N/A	N/A	N/A	N/A
Missouri	Design Storm Alert System	Precipitation risk	County level maps of precipitation risk and email to farmer	Based on design storm precipitation depths (clear, watch, alert)	Once per day	N/A¶	N/A	Multisensor QPE# from NOAA's Advanced Hydrologic Prediction Service	4	N/A	N/A	N/A	N/A	N/A

† H, high; M-H, medium-high; M, medium; L, low.

‡ SAC-SMA, Sacramento Soil Moisture Accounting Model; SAC-HTET, Sacramento Heat Transfer and Enhanced Evapotranspiration; SAC-HT,; SWAT-VSA, Soil Water Assessment Tool–Variable Source Area; STOPMODEL, Soil Topographic Index Model.

§ QPF, quantitative precipitation forecast.

¶ N/A, not applicable.

QPE, quantitative precipitation estimate.

specific runoff amounts, the tools provide subfield maps of saturated areas showing regions of the landscape prone to nutrient wash-off. Unlike the tools from Wisconsin, Pennsylvania, New York, and Virginia, the Washington Application Risk Management Tool and Missouri Design Storm Alert System rely solely on precipitation totals to infer the risk of nutrient loss in runoff, with Missouri's system further distinguished by its use of radar to warn farmers of rainfall events that may have exceeded design criteria for manure storage. The tools described below are in various stages of implementation, ranging from prototype versions that are currently undergoing research and development, such as those operating in Pennsylvania and Virginia (although both are functional and online), to more fully developed and implemented tools like the ones in Wisconsin, New York, Washington, and Missouri. With these basic distinctions in mind, the sections below are intended to provide further insight into each of the six decision support systems, including their key features and uses, input data sources, modeling methods, and forecast outputs.

Wisconsin's Manure Management Advisory System's Runoff Risk Advisory Forecast

The Wisconsin Runoff Risk Advisory Forecast (RRAF) is a web-based application (mobile or desktop) instituted by the state's Manure Advisory System "to identify suitable cropland areas for spreading" and prevent nutrient application during periods of high runoff potential (http://www.manureadvisorysystem.wi.gov). Daily forecasts of low, medium, and high runoff risk are generated for 216 watersheds using 72-h lead times, or "risk windows," over 3-d forecasting periods in the summer and 10-d periods in the winter, when snowmelt runoff is of prime concern (Fig. 1). Currently, runoff risk forecasts are intended for voluntary use by manure applicators and are distinguished, in part, from other forecast-driven decision support tools in the broad scale, at which forecasts are issued (average basin size of ~750 km^2). As such, Wisconsin's tool functions similarly to more familiar fire danger systems (Bradshaw et al., 1984; Burgan, 1988) in that it conveys generalized runoff risks that can then be interpreted by end users at finer, local scales for action. Moreover, Wisconsin's forecast is linked to a variety of online resources, including guidance on selecting fields for spreading manure during times of high runoff risk. County-specific, field-scale manure spreading guidelines can be located through these links, but they do not interface with the dynamic forecasts. Given that it is the longest-running runoff risk system in the United States, end users have had ample time to become familiar with the tool and its forecasts and generally give it high ratings on forecast quality and usability through online feedback and surveys.

Wisconsin's RRAFs are based on output from NOAA's Sacramento Soil Moisture Accounting Model (SAC-SMA) (Burnash, 1995), a lumped hydrological simulation model primarily used in operational flood forecasting by National Weather Service River Forecast Centers across the United States. Principal inputs to the SAC-SMA model include quantitative precipitation forecasts from NOAA's Weather Prediction Center (5-km resolution) and temperature forecasts from the National Digital Forecast Database (5-km resolution). Runoff events in the SAC-SMA environment are predicted when three specific criteria are met, including when rain + snowmelt > 0 (to account for runoff induced by rainfall and snowmelt), upper zone tension water deficit = 0 (i.e., saturated soils), and interflow runoff depths > 0 mm. In winter mode, rain + snowmelt runoff is predicted by SNOW-17, a snow accumulation and ablation model (Anderson, 2006), which is then input into SAC-SMA to determine if runoff is due to rainfall, snowmelt, or their combination. Runoff Risk Advisory Forecasts feature three stages of risk that are based on forecast runoff depths, with forecasts indicating low-, medium-, and high-risk events discerned using runoff depth thresholds that are specific to each forecast basin (see Goering [2014] for more details on how basin-specific runoff thresholds were set). Although the operational version of Wisconsin's tool is watershed based, newer versions are in development, with plans to migrate from the lumped SAC-SMA model to NOAA's Sacramento Heat Transfer and Enhanced Evapotranspiration (SAC-HTET) model (Koren et al., 2010), which possesses finer spatial resolution (16 vs. ~750 km^2). In addition, the success of Wisconsin's tool has spurred plans to extend its general runoff forecasting approach to other states in the Great Lakes region, including Minnesota, Michigan, Indiana, Illinois, Ohio, and Great Lakes drainages of New York.

The operational version of Wisconsin's Risk Advisory Forecast system has largely been corroborated with historical runoff datasets from edge-of-field (0.06–0.16 km^2) and small watershed (25–65 km^2) monitoring programs in Wisconsin. Using the Critical Success Index, a skill score based on a two-by-two contingency table of true positives (hits), true negatives (correct forecasts of no runoff), false positives (runoff forecasts that did not occur), and false negatives (misses), Goering (2014) showed that the Runoff Risk Advisory System could skillfully predict runoff events at edge-of-field and small watershed scales (~5 ha) (Critical Success Index ~ 0.35). A primary emphasis of ongoing model testing and development has been to accurately predict large runoff events considered most important to water quality impacts while minimizing incorrect prediction of small events (false positives). Even so, the model tends to overpredict the occurrence of small runoff events, requiring statistical algorithms to filter these events. Although the Wisconsin system is applicable year round, it tends to be more aggressive in restricting application during winter due to the known elevated risks of manure wash-off during that time period and serves as a key component of the state's winter spreading guidelines. Consequently, it is no surprise that user activity tends to peak in the winter months, in line with the increased risk of snowmelt runoff.

New York's Hydrologically Sensitive Area Tool

New York's Hydrologically Sensitive Area Tool is a web-based system that uses real-time measured data and 24- to 48-h weather forecasts to predict present-day and future soil moisture saturation conditions at a subfield level (Fig. 2). This approach does not estimate the occurrence of runoff but rather predicts antecedent soil moisture saturation, which has been documented to be the most important factor determining runoff occurrence for soils of this area. The tool has been applied to two watersheds in central New York, where it was intended to help guide nutrient management planners and farmers in identifying areas of the landscape prone to nutrient loss in runoff up to 48 h into the future. The tool leverages additional geospatial datasets to help users locate areas of interest (e.g., property and field boundaries via tax parcel code) and other

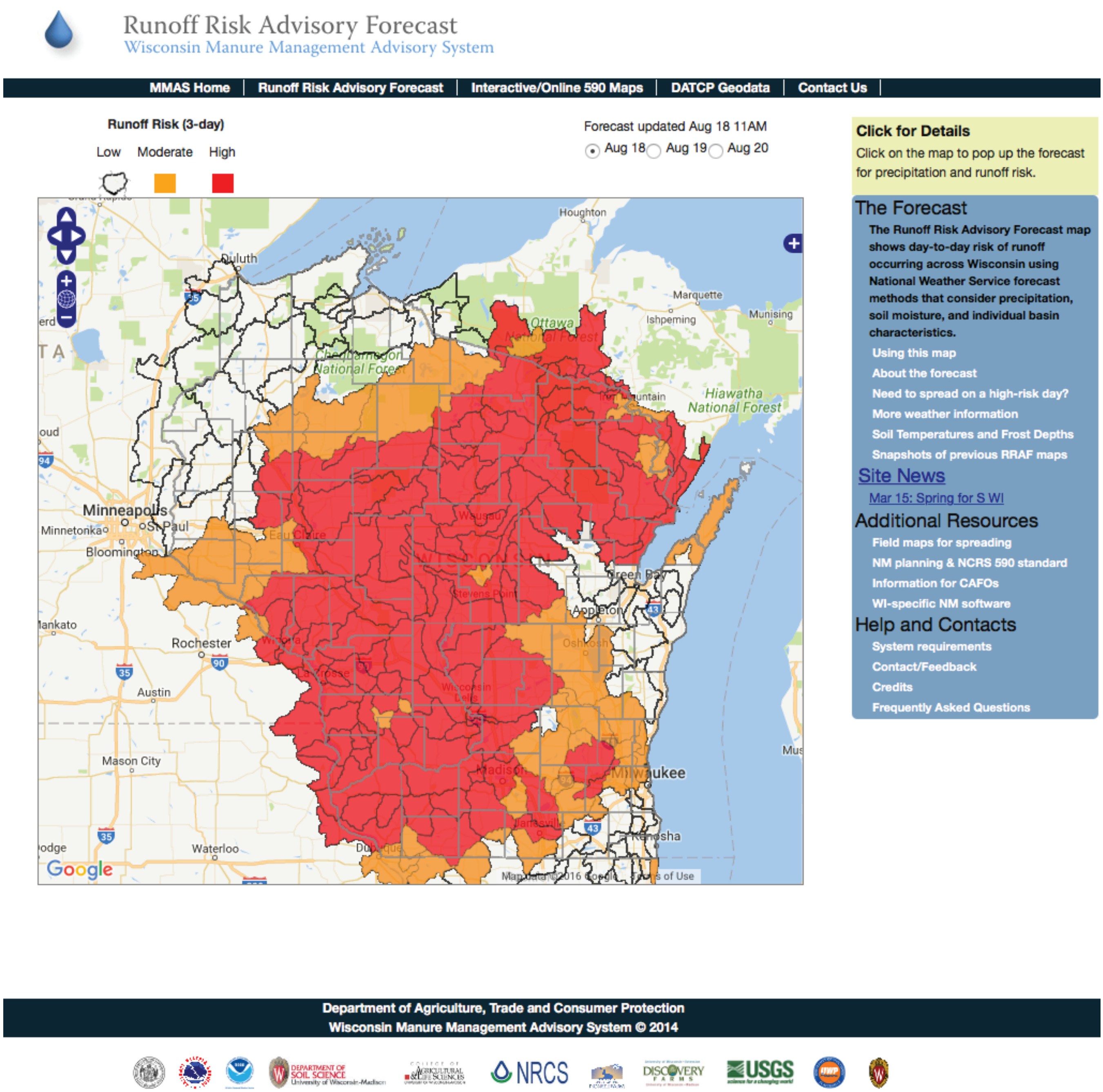


Fig. 1. Screen capture of Wisconsin's Runoff Risk Advisory Forecast. Watersheds depicted in red and orange show areas of high and medium runoff risk, respectively (1-, 2-, and 3-d forecasts are also available).

useful information for nutrient and conservation planning (e.g., flood frequency and soil drainage information).

The model underpinning New York's tool incorporates daily water balance simulation using the Thorthwaite–Mather method (McCabe and Markstrom, 2007) to predict daily streamflow (Dahlke et al., 2013). Results from the daily water balance model are used to estimate the fraction of the watershed that is likely to generate surface runoff. According to this output, the location of saturated zones is distributed throughout the watershed using a soil topographic index (Easton et al., 2008; Dahlke et al., 2013). The New York Hydrologically Sensitive Area Tool has been rigorously evaluated from the standpoint of soil moisture saturation forecasts. Analysis of soil moisture saturation predictions in the Salmon Creek Watershed of New York indicated that 71% of the largest storm events between 2006 and 2009 were correctly predicted on the basis of 48-h forecasted weather data (Dahlke et al., 2013).

Virginia's SWAT-VSA Saturated Area Forecast Model

Virginia's Saturated Area Forecast Model relies on a watershed fate-and-transport model (the Soil Water Assessment Tool–Variable Source Area model, SWAT-VSA; Easton et al., 2008) to provide simple and accessible forecasts designed to inform field-level management decisions that affect water quality (Sommerlot et al., 2016). In addition to serving as a decision support tool for nutrient management, the Saturated Area Forecast Model is spatially and temporally scalable and can forecast a wide variety of variables, including water quality (N, P, and sediment loading to streams), water budget (percolation, runoff volume,

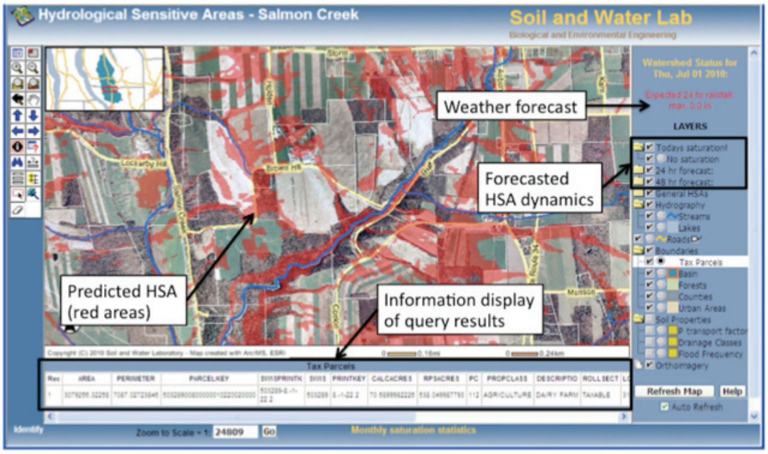


Fig. 2. User interface of New York's Hydrologically Sensitive Area Tool. Red areas show hydrologically sensitive areas (HAS) predicted with the semidistributed water balance model. A daily update of forecasted weather conditions and HSA dynamics in Salmon Creek Watershed is given in the top-right frame.

precipitation, and evapotranspiration), and crop production (plant biomass, plant growth, and harvest yields). These predictions can inform decision making over a range of landscapes (although regions where terrain largely controls the movement of water are most appropriate) and provide management benefit by connecting managers and planners with estimates of water resource impact and even crop yields. The operational version of the Saturated Area Forecast Model is accessible via web-based and mobile applications and provides 24- to 96-h forecasts updated four times per day of watershed-scale stream flow and subfield-level soil moisture status (Fig. 3).

To produce distributed hydrologic predictions of runoff probability and soil moisture, the Saturated Area Forecast Model uses dynamic meteorological forecasts to run the hydrologic model within SWAT-VSA (Sommerlot et al., 2016). Meteorological data from NOAA's Global Forecast System-Model Output Statistics are downloaded every 6 h, producing forecasts four times daily (GFS, 2015). Maps of surface runoff area risk and soil moisture risk are produced using the soil topographic wetness index (Walter et al., 2002; Easton et al., 2008), as is done with New York's Hydrologically Sensitive Area Tool. Soil saturation is determined through a binary classification with a spatially variable threshold soil water depth determined as a function of land use and topography.

Corroboration of Virginia's Saturated Area Forecast Model Tool has primarily focused on hydrologic predictions. For instance, Sommerlot et al. (2016) evaluated model performance in predicting streamflow and the extent of saturated areas within the South Fork of the Shenandoah River, a 2600-km^2 mixed-land-use watershed in North-Central Virginia. Field-level hydrologic forecasts of saturated area extent (3-m resolution) were compared with observed saturated areas mapped on two occasions in December 2015, with results demonstrating a true positive rate of 0.86 and a false positive rate of 0.25. Both metrics

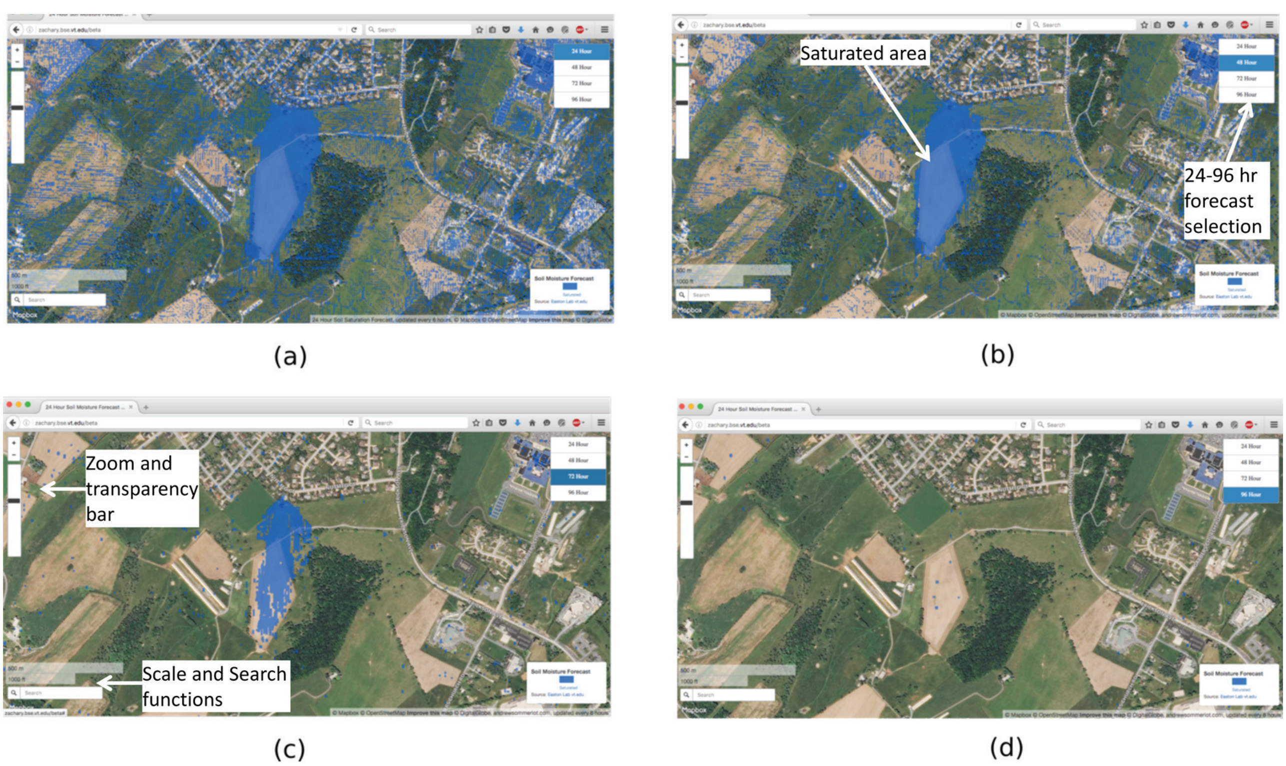


Fig. 3. Interface screen shot of Virginia's Saturated Area Forecast Model showing distributed soil saturation forecasts for (a) 24-, (b) 48-, (c) 72-, and (d) 96-h lead times that depict the drying of a variably saturated area in an agricultural field over multiple days.

range from 0 to 1 though need not add to 1, and high true positive values complimented by low true negative values describe better performance. Although the corroboration was limited to a number of measured areas around the watershed, the classifications generally fit expected distributions of unsaturated and saturated soil extents across the watershed, lending confidence to the saturated area mapping approach.

Pennsylvania's Fertilizer Forecaster

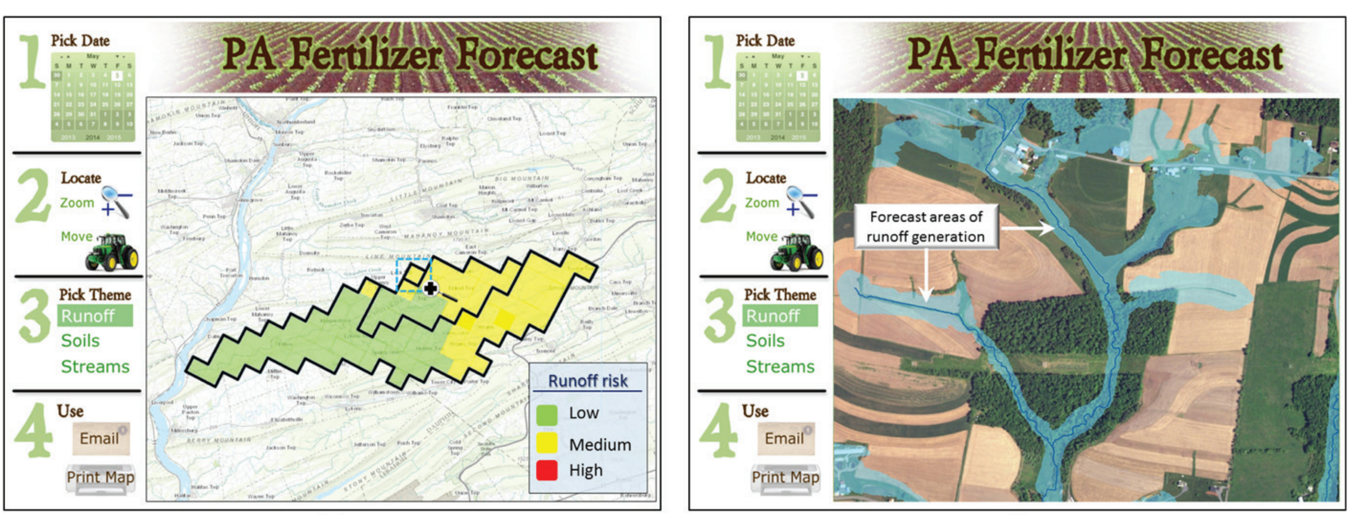
The Pennsylvania Fertilizer Forecaster is a web-based runoff forecasting tool that seeks to enable field-specific decisions by farmers as to when and where to apply fertilizers and manures over the short term. Like the other short-range forecasting tools, Pennsylvania's Fertilizer Forecaster is intended for voluntary use by farmers, with the primary goal being to assist end users in distinguishing high-risk rainfall-runoff events that lead to manure and fertilizer "wash-off" from lighter precipitation events that promote nutrient "wash-in" via infiltration. The tool provides output at two scales, including watershed-level views of low, medium, and high runoff risk, as well as field-scale (e.g., <5 ha) maps showing the likely extent of runoff contributing areas (Fig. 4). All forecasts are provided daily at 24-, 48-, and 72-h lead times, with the main focus being the prediction of rainfall-generated runoff events during the growing season. Future iterations of the tool will strive to address snowmelt runoff events during the winter months, which represent an issue of emerging importance to nutrient managers in Pennsylvania (Pennsylvania DEP, 2011).

Similar to Wisconsin, Pennsylvania's tool leverages quantitative precipitation forecasts from the Weather Prediction Center (5-km resolution) to drive NOAA's Sacramento Soil Moisture Accounting–Heat Transfer (SAC-HT) model (Koren et al., 2010), a fully distributed (2-km resolution) hydrologic simulation model with improved prediction of soil moisture and frozen ground processes. Interflow and surface runoff predictions from SAC-HT are used in conjunction with soil moisture and precipitation forecasts to derive three tiers of runoff risk, with low risk signified by runoff events occurring during dry periods (soil saturation ratio < 0.6), medium risk indicated by runoff events on saturated soils (soil saturation ratio > 0.6) with contributing areas occupying <20% of the watershed, and high risk associated with exceptionally wet conditions (soil saturation ratio > 0.6) and runoff contributions from $\geq$20% of the basin. Daily forecasts of the percentage of the basin expected to generate surface runoff (i.e., the runoff coefficient) are then disaggregated and mapped at the field level using either the topographic wetness index (Beven and Kirkby, 1979) or the depth-to-water index (Murphy et al., 2009). These field-scale maps of likely runoff-contributing zones allow farmers to discern hydrologically active areas from other parts of the basin less likely to be hydrologically connected to streams.

To date, efforts to corroborate the Fertilizer Forecaster include historical simulations of model predictions versus observed runoff data from small watersheds and edge-of-field monitoring. The main emphasis has been on assessing the suitability of runoff risk thresholds and confirming the accuracy of predicted runoff-contributing areas. For instance, the three runoff risk thresholds were recently tested with the Gerrity skill score (Wilks, 2011), which assesses the accuracy of a forecast in predicting the correct risk category relative to that of random chance. Preliminary results using 3 yr of runoff data (2010–2012) from the WE-38 watershed in central Pennsylvania yielded a Gerrity skill score of 0.6, which indicated that the SAC-HT model could adequately categorize runoff risk using the three-tiered system. In addition, field-scale runoff-contributing area maps have also been evaluated by comparing the predictions against "wet-boot" maps of observed saturated areas using various measures of spatial agreement, including Cohen's kappa (Grabs et al., 2009), as well as spatial statistics based on quantity disagreement and allocation disagreement (Pontius and Millones, 2011).

Washington's Application Risk Management System

The Application Risk Management (ARM) System was developed for use in western Washington State to help farmers avoid nutrient runoff and leaching events after manure application. Washington's system works by addressing the timing of application using precipitation forecasts (Manure Spreading Advisory),



(a) (b)

Fig. 4. Images of Pennsylvania's Fertilizer Forecaster showing (a) forecasted runoff risk levels (low, medium, high) for 88 2-km × 2-km grid cells that constitute the Mahantango Creek Watershed and (b) a field-scale view of predicted runoff contributing areas for a moderate risk event (runoff coefficient = 0.3).

assessing current field conditions via a user-input worksheet (ARM Worksheet), and recommending manure spreading setbacks of variable width from waterways (Whatcom Conservation District, 2015). The system provides a web-based 3- and 5-d Manure Spreading Advisory that displays daily regional runoff risk projections according to forecast precipitation. The Manure Spreading Advisory map was created by dividing the Western Washington region into 103 regions (i.e., polygons) of similar precipitation, physiographic, and management conditions. The risk of manure wash-off is then predicted for each region using 72-h cumulative precipitation forecasts from NOAA (>12.7 mm [0.50 in.] = high, 12.7–6.4 mm [0.50–0.25 in.] = medium-high, 6.4–2.5 mm [0.25–0.10 in.] = medium, <2.5 mm [0.10 in.] = low). Initial evaluation of the system determined that precipitation forecasts were most reliable over short lead times of 0 to 72 h as compared with longer lead times.

The ARM System provides a combination of regional and field-level manure spreading advisories. When a region is under the high risk category, no manure application is recommended due to the nature of the forecasted storm (Fig. 5). For lesser risk categories (low, medium, and medium-high), users are encouraged to complete a field-scale assessment to differentiate manure wash-off potential between individual fields. The follow-up assessment relies on a web-based ARM worksheet to guide users through a list of relevant field observations, including soil moisture, water table depth, presence of tiles, crop cover condition, presence of frozen soils, manure application method, and proximity to water body. The completed worksheet also provides farmers with a means for recordkeeping that allows them to assess the effectiveness of past manure application decisions, as well as the forecast guidance that led to each decision.

Missouri's Design Storm Alert System

The Design Storm Alert System (DSAS; Guinan et al., unpublished data, 2016) provides Missouri farmers, regulators, agency personnel, and other interested parties with daily information on precipitation events that may have exceeded design criteria for open manure and wastewater storage facilities. Chronic and catastrophic design storm events are defined in the Missouri Code of State Regulations (Carnahan, 2012) and include the 25-yr/24-h, 10-yr/10-d, 10-yr/90-d, 10-yr/180-d, and 10-yr/365-d storm events. Precipitation events exceeding these defined depths can lead to overflow of storages unless there is a concerted effort to land apply effluent, a possible challenge under wet conditions within the requirements of a nutrient management plan. The notification system has two objectives: (i) to notify farmers when extreme precipitation events may have affected their farm, providing them guidance on how to monitor and manage effluent levels and manure applications under wet weather conditions; and (ii) to notify regulators, agencies, and extension and industry representatives where in the state there is a risk of excessive precipitation and/or documented excessive rainfall to promote active outreach to affected areas, minimizing the potential for mismanagement of storage levels.

Missouri's DSAS tracks daily accumulation of precipitation for ~11,000 4-km × 4-km quadrants using data from NOAA's gridded radar precipitation analysis (AHPS, 2016). Design storm amounts were derived from county averages from the

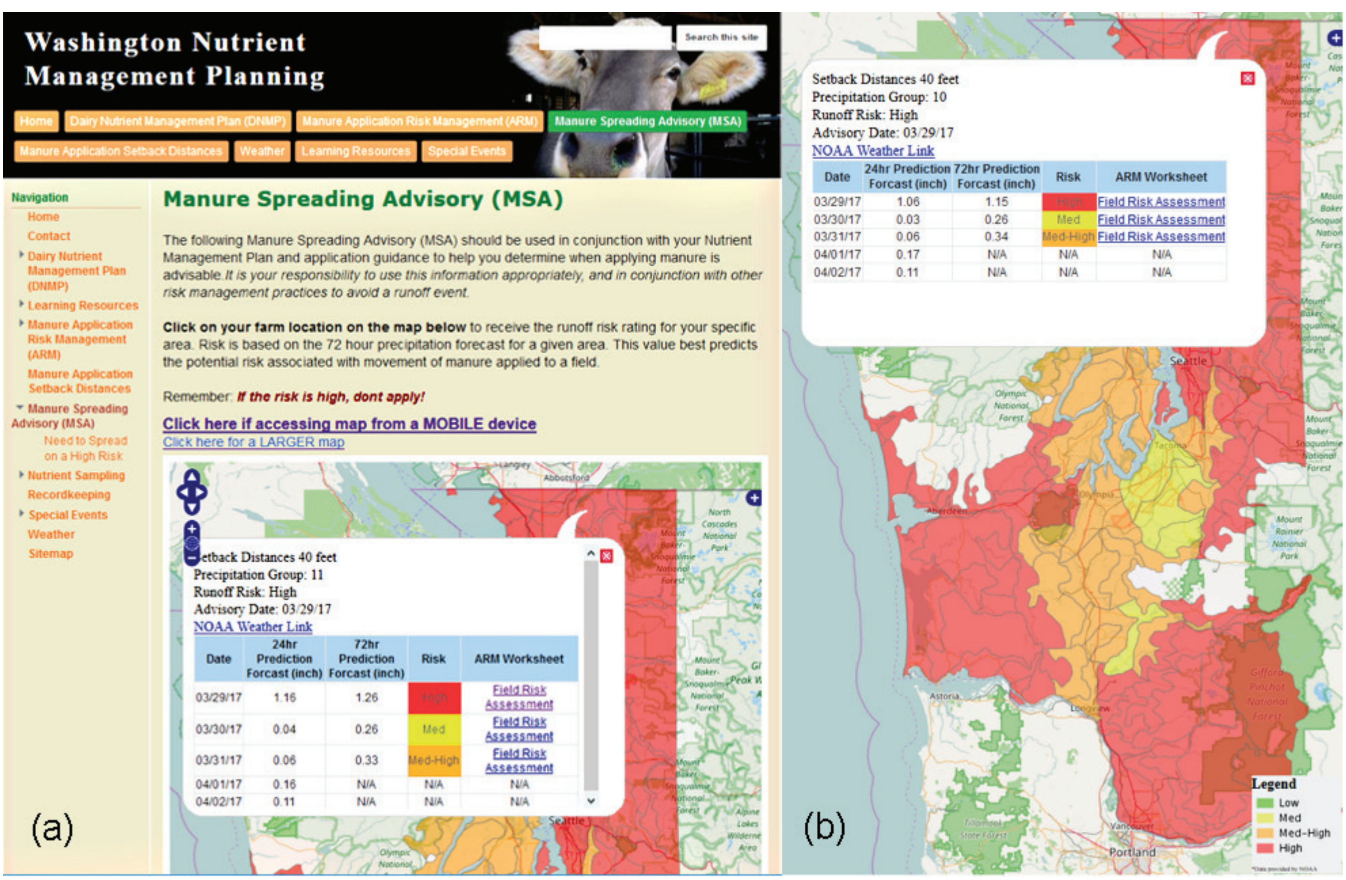


Fig. 5. (a) Washington's Manure Spreading Advisory, part of the Whatcom Conservation District's Application Risk Management system. (b) Example of Manure Spreading Advisory map showing 24- and 72-h precipitation forecasts (in inches) and accompanying risk ratings for each precipitation region.

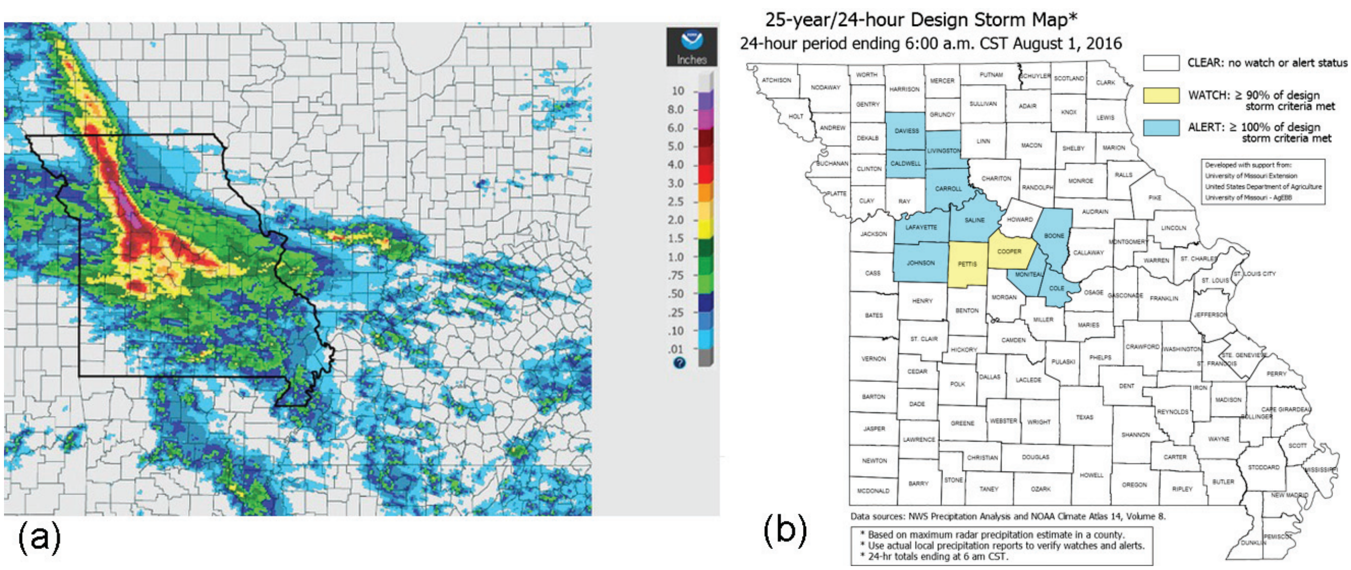


Fig. 6. (a) Daily radar analysis for the 24-h period ending 6:00 AM CST, 1 Aug. 2016, and (b) the resulting 25-yr/24-h Design Storm Alert System map for that day.

NOAA Climate Atlas 14, Volume 8 (Perica et al., 2013). A county is designated in "watch" status if any quadrant in the county fits $\geq$90% of the design storm criteria and in "alert" status if any quadrant fits $\geq$100% of the design criteria. A webpage reports the daily status of each county (http://ag3.agebb.missouri.edu/design_storm/; e.g., Fig. 6). Additionally, farmers can register to receive an email that couples their county alert status with precipitation totals and predictions for their farm. The tool has been tested by comparing outputs with measured data from NOAA and other daily precipitation networks, with generally good correspondence.

Underlying Factors and Tradeoffs of Short-Term Forecasting Tools

Intended Use

There is no doubt that demand exists for short-term forecasting tools, as evidenced by farmer surveys on conservation and nutrient management (Osmond et al., 2012) and by reports of daily use of weather forecasts by farmers and other agricultural services (Haigh et al., 2015). All tools described here are intended to be used by farmers, custom operators, and conservation and extension personnel to protect water quality and improve nutrient use efficiency. Developers clearly envision an immediate audience of farmers and other nutrient applicators who would use daily decision support information to adjust broader, strategic nutrient management planning that constrains fertilizer and manure spreading options over longer planning horizons (e.g., the P Index; Sharpley et al., 2003). Early adopters would include conservationists and those using precision farm management, especially those with modern equipment who are technically savvy (Zhang et al., 2016). Experience with other agricultural decision support systems has demonstrated that, over time, conscientious end users internalize recommendations and eventually make their own predictions on the basis of experience with the decision support tool (McCown, 2002). This potential outcome is obvious with a tool like the Washington ARM, which is precipitation based (with no hydrologic algorithms to adjust forecasts). Moreover, Washington's ARM System features an intensive field assessment component that educates applicators on appropriate site conditions for spreading with continuous use of the tool.

In addition to use by nutrient applicators, there are other potential end uses of these tools, intended and unintended. It is important to recognize that concern exists over the potential that spatially explicit forecasting tools will be used to devise and enforce manure spreading regulations or to report noncompliant applicators. Each of the short-term forecasting systems described above includes uncertainty related to the weather forecast, hydrologic forecast (if given), and other algorithms (Xuan et al., 2009) that will occasionally yield erroneous predictions of runoff risk potential (positive or negative). The tools do, however, represent the best available science and can serve as a backstop to support prudent nutrient management. The short-term forecast tools in Wisconsin and Washington are seen as a means of protecting compliant applicators against enforcement actions, following the logic that their use is a form of best management practice (Wisconsin DNR, 2013). Elsewhere, the Virginia Saturated Area Forecast Tool and the Pennsylvania Fertilizer Forecaster have been billed as guidelines to inform watershed managers and others of the potential benefits and liabilities of alternative nutrient management actions on water quality. This is seen as particularly relevant to ongoing watershed activities in the Chesapeake Bay Region, including as a means of educating a more general audience of the extent to which agricultural nutrient management can contribute to Chesapeake Bay mitigation.

Input Data, Models, and Scaling Considerations

All decision support systems described here are dependent on input from NOAA-derived weather forecast products, with varying spatial resolutions and lead times (Table 1). For instance, the Virginia Soil Saturated Area Forecast Model and the New York Hydrologically Sensitive Area Tool use precipitation and temperature inputs from the Global Forecasting System–Model Output Statistics, which possesses a nominal horizontal resolution of 13 km for lead times out to 10 d. In comparison, short-term runoff forecasting tools from Pennsylvania and Wisconsin, as well as Washington's precipitation-based risk system, rely on NOAA-generated multimodel blends (which include the Global Forecasting System) of forecast weather variables that are mapped at 5-km resolution for lead times of 7 d. Missouri's system offers a stark contrast to the other tools in that it looks backward instead of forward, enabling it to leverage fine-scale, 4-km radar data from NOAA to provide farmers with estimates of accumulated precipitation from storm events occurring over the past 24 h.

Of the six forecasting tools reviewed herein, four rely on hydrologic models that differ in structure and output scale (Table 1). For example, developmental versions of the Wisconsin and Pennsylvania systems use SAC-HTET, a fully distributed model that provides hydrologic forecasts in the range of a 4- to 16-km^2 grid. In comparison, the tools from New York and Virginia both predict watershed-scale (300–1200 km^2) runoff, with New York's tool using Thorthwaite–Mather daily water balance routines and Virginia's tool relying on SWAT-VSA, both of which possesses the added benefit of viewing outputs at the scale of individual hydrological response units or fields (<1 ha) within each basin. Of greater contrast are the routines used to represent winter runoff risk, with New York and Virginia using a landscape energy budget (Fuka et al., 2012) to predict snow accumulation and snowmelt, and Wisconsin and Pennsylvania applying SNOW-17, a temperature index model that predicts snow accumulation and ablation (Anderson, 2006). Neither the Missouri nor Washington tools include specific forecasts of snowmelt, but Washington's Application Risk Management prohibits manure application to frozen and saturated ground.

The spatial and temporal scales of short-term forecast systems have clear implications to the uncertainty of their predictions, as well as their interpretation and use. Indeed, there exist benefits and drawbacks to projecting short-term advisory forecasts at regional and field scales. For instance, precipitation forecasts tend not to vary below the coarse output scales of numerical weather prediction models (~9–13 km), even though hydrologic forecasts may be characterized at scales of meters. Regional projections, such as those offered by the operational tools from Washington and Wisconsin, produce output at scales roughly similar to their input data, avoiding the potential for spurious precision in downscaling. For those forecasting tools that project results at scales finer than the weather forecasts, output data from hydrologic models must be downscaled using various algorithms. Examples include the tools from New York, Pennsylvania, and Virginia, which use variations of the topographic wetness index as a means for downscaling and mapping subfield areas of saturation and runoff generation. Although field specificity is often an expressed desire of farmers and other potential end users of short-range forecasts (Mase and Prokopy, 2014), additional sources of uncertainty stemming from the choice of downscaling method and the source of digital elevation data (Wechsler, 2007) must be acknowledged and reported.

A motivation of the finer-scale forecasts is to elucidate options to end users in deciding which fields or area of a field to apply nutrients on a particular day. However, at field and subfield scales, the complexity of processes limits of downscaling, and potential for compounding error increases greatly. Although regional forecasts such as those issued by Wisconsin and Washington do not visually delineate options to end users on maps, they do have the advantage of being simpler to understand and easier to act on. The regional tools tend to be more computationally efficient than fine-scale tools, even though data needs are approximately the same between scales. Because all tools (subfield and regional scale) produce specific outcomes, uncertainty or probability of error are not currently communicated in their forecasts, something that should be explored in future iterations. Indeed, "imperfect forecasts" using ensembles of models to portray predictive uncertainty may be more valuable to farmer decision making than those that imply confidence through deterministic modeling approaches (Kusunose and Mahmood, 2016).

Forecast Corroboration

Forecast quality (i.e., the accuracy and skill of predicted outcomes by a forecast; Murphy, 1993; Wilks, 2011) is key to the utility of the tools reviewed here. Overall, the accuracy and skill of weather forecasts that drive these tools has consistently improved, especially in predicting large, frontal events typical of fall through spring periods (Siddique et al., 2015; Sharma et al., 2017) that, coincidentally, are also the major manure application windows in many regions. However, sensitivity analysis is needed for all tools to separate errors inherent to weather forecasts from errors derived from the hydrologic models for which they provide input data. Ultimately, this level of understanding of forecast quality will drive solutions such as ensemble modeling, currently at the core of weather forecasting (Regonda et al., 2013).

To some extent, all of the short-term forecasting tools have been evaluated for accuracy and skill, albeit using a variety of approaches focused on a range of output variables.

Assessing the basin-scale-based Wisconsin RRAF tool for success at the field scale highlights inherent challenges with this type of validation. In an effort to address this, Goering (2014) compared the tool against both edge-of-field-scale observations and small USGS watersheds <38 km^2. The results produced measures such as Critical Success Index, which ranged from 0.34 to 0.42 when the two observational scales were combined and thresholds were introduced. The spatial scale difference between observations and model output lead Goering (2014) to rely more on a holistic view and not entirely on statistical assessment measures. Indicators such as probability of detection (POD), false alarm ratio (FAR), and relative magnitudes between events correctly forecast versus events that were missed or false alarms were the primary tools for validation. Values of POD ranged from 0.62 to 0.80 (small USGS watersheds and edge-of-field sites), whereas FAR values ranged from 0.45 to 0.71. Goering (2014) concluded that the POD scores of the Wisconsin RRAF were sufficient to apply to smaller scales and also noted that median event hit-miss and hit-false alarm ratios of ~8 were a good reason to pursue the application of thresholds to stratify the risk based on event magnitudes. Incorporating risk thresholds allowed the RRAF to focus users of the tool on the larger events, where there was more confidence in occurrence, while allowing the presence of smaller events to be indicated, yet with the understanding there was less certainty in those forecasts.

The New York tool was evaluated against several years of daily historical discharge and spatially distributed predictions of field-level soil moisture. The daily model predictions evaluated against the historic discharge data showed an Nash–Sutcliffe Efficiency (NSE; Nash and Sutcliffe, 1970) > 0.6, although convective summer storms tended to be mischaracterized, due in part to missed precipitation forecasts. The spatially distributed predictions of soil moisture were evaluated by comparison against measured saturated areas and agreed in >50% of the days overall and in >67% of the days when large storm events occurred (Dahlke et al., 2013).

The Virginia Saturated Area Forecast Model was evaluated by considering both the streamflow forecasts and the spatially distributed forecast predictions. Evaluation of the streamflow forecast is critical, because the distributed predictions are a function of the overall watershed discharge (Easton et al., 2008). Streamflow predictions were evaluated using the NSE metric and were shown to provide adequate forecast power 4 d into the future (NSE > 0.5). Spatially distributed soil moisture forecasts were evaluated using a confusion matrix approach described above. Of the 49 areas measured, two were incorrectly classified as saturated when they were unsaturated (false positives), and seven were incorrectly classified as unsaturated when they were saturated (false negatives). Thirty true positives (areas correctly classified as saturated) and 10 true negatives (areas correctly classified as unsaturated) were predicted (Sommerlot et al., 2016).

The Pennsylvania Fertilizer Forecaster is mainly evaluated by comparing streamflow predictions against observed discharge data from stream gauging stations. In the WE-38 watershed, a 7.3-km^2 tributary basin to Mahantango Creek, the NSE of streamflow simulations by SAC-HT generally exceeded 0.6, indicating the reliability of forecasts at small basin scales. As mentioned elsewhere, spatial agreement between predicted runoff-contributing areas and saturated zones monitored by wet-boot mapping is being assessed with Cohen's kappa (Grabs et al., 2009) and spatial statistical measures according to quantity disagreement and allocation disagreement (Pontius and Millones, 2011).

The Washington Manure Spreading Advisory was validated by comparing the NOAA forecast data used to create the runoff risk ratings with actual precipitation data. This correlation was assessed using linear regression to determine the degree to which the forecasted precipitation values predicted the actual precipitation amount, as well as how that correlated with other conditions such as soil moisture and frozen ground to predict risk. The general finding was that the forecast tended to predict the short-term risk (cumulative precipitation for 24 h, $r^2 = 0.59$) better than the long-term risk (72-h cumulative precipitation, $r^2 = 49$). The trend was for the greatest error when the forecast prediction was low (<12.7 mm) but the actual amount was high (>12.7 mm).

The Missouri tool relies on repackaged radar data and thus has been evaluated by NOAA during the gridded radar precipitation analysis product development and deployment.

Understanding model accuracy and skill is also fundamental to the establishment of risk thresholds or categories in short-term forecasting tools. Both the spatial extent and intensity of risk are portrayed by the different tools. For instance, the Missouri, Pennsylvania, Washington, and Wisconsin tools all display categorical representations of risk (e.g., low, medium, high), whereas the New York and Virginia tools display areal extent of saturated area risk without gradation in saturation potential. In all cases, the models employ thresholds to determine whether a particular category or spatial extent of risk is displayed. The criteria used to determine these thresholds are different in every case, from forecasts or summations of rainfall amount (Missouri and Washington), to watershed runoff depths (Wisconsin), to soil moisture and runoff-contributing area (Pennsylvania), to extent of saturated area (Virginia and New York). Developing these thresholds can be much more complex than what is belied by the risk forecasts. For instance, empirical knowledge of runoff generation was used to identify soil moisture and runoff-contributing area thresholds in Pennsylvania's Fertilizer Forecaster, whereas the Wisconsin RRAF System developed thresholds from a statistical optimization routine that maximizes true positive estimates of runoff depth over false alarms (Goering, 2014). Regardless of approach, it is incumbent on developers of forecasting systems to assure end users that risk thresholds are sufficiently stringent to protect against nutrient wash-off events without unnecessarily restricting one's ability to apply manures and fertilizers due to erroneous forecasts of runoff risk.

Communication and Adoption

The wide use of devices with direct links to the internet is a 21st century advancement, both technological and behavioral, that has tremendous potential for delivering information. Surveys have shown that >70% of US farms have computer access and 43% use computers for farm business of some kind, as of 2015 (USDA, 2007, 2015). This, coupled with increasing internet access on farms, especially larger farms with wealthier owners (Frisvold and Murugesan, 2013), has increased the use of weather forecasts in daily decisions (Mase and Prokopy, 2014). Equally important is the near-ubiquitous access to online weather forecasts by farm advisory services, including public and private sector consultants, which have been shown to be one of the most trusted sources of information by farmers (Haigh et al., 2014). The rapid adoption of smartphones and similar technologies by agricultural industries provides even richer opportunities for linking hydrological and biogeochemical sciences with land management, although these opportunities currently appear to lie mostly with younger farmers (<45 yr old) who are more technologically savvy than their older peers (Semler, 2015).

Although both the capability of modern technology and farm internet access are increasing, the adoption of decision support technologies by farmers for their intended use is a separate question and depends on a wide variety of social factors, regulatory requirements, and economic incentives that may differ across regions (Baumgart-Getz et al., 2012). For example, the adoption of new technology aimed at water quality protection in the eastern United States (i.e., various best management practices, soil testing) is mainly driven by education through extension efforts and government incentive programs (Baumgart-Getz et al., 2012; Leisnham et al., 2013), whereas agriculture in the western United States has seen a great increase in technology adoption, including wireless internet use, areal imagery, and computer-based automation, driven by water shortages (Hanak and Lund, 2012; Wardlow et al., 2012; Suprem et al., 2013). In the case of decision support tools like those reviewed here, segmentation of potential groups of adopters by social drivers, historical actions, and current needs can inform the design and marketing of future tools to be tailor-made for particular adopters and uses. Indeed, each of the tools described here was developed in response to specific users' needs, and it is the size of this end user pool that ultimately determines the degree to which tools are adopted and used. If tools are made for a more general audience, they should focus on simple, accessible design and flexibility to minimize potential implementation barriers and allow for future adjustments on the basis of new information. Extension-based efforts will continue to be an important driver in technology adoption on farms, and researchers developing tools like those reviewed here should consider the information and opportunities for collaboration provided by these programs. In addition, nontraditional partnerships with entities such as industry or university startup incubators may play a major role in spurring future adoption (Reimer, 2015).

The short-term forecasting tools reviewed herein reside within a much larger landscape of agricultural decision support tools (McCown, 2002; McIntosh et al., 2011). While there is no shortage of agricultural decision support systems, most of these tools neither make it past the development phase nor gain the institutional support needed for public reliance on their output. Ultimately, institutional support is fundamental to ensuring that an end user has confidence in the availability of forecasts, which must be reliably updated over time periods in which operational decisions are made. Key to development, therefore, are participatory approaches that engage a wide array of possible end users and consider factors such as trust and attitude (Lynch and Gregor, 2004). A body of experience reveals that the likelihood of use of decision support tools by farmers hinges on the transparency of their recommendations, ability to reduce uncertainty and, ultimately, their utility (Armstrong and Stedman, 2009). Mase and Prokopy (2014), in reviewing farmer use of weather and climate data, found that a key to gaining farmer trust is convincing them of the improved accuracy and skill in weather forecasts. If farmers distrust a source of these weather data, then acceptance of outputs derived from weather forecasts (e.g., hydrologic models) will be correspondingly poor. Indeed, farmers also tend to distrust divergent forecasts, placing a premium on approaches that can satisfactorily convey uncertainty. Again, running models in ensemble mode can help with perceptions of transparency, enabling farmers to assess forecast uncertainty in making decisions.

The Future

It is unclear whether the utility of short-term decision support tools will be realized, as a plethora of unused or discarded decisions support systems have been developed for agriculture over the past several decades (McCown, 2002). Nevertheless, computer ownership, internet access, and the use of mobile devices (phones, tablets) by farmers have expanded greatly in the United States in recent years, increasing the prospect that farmers will integrate short-term forecasting information into their operational decisions. A valuable short-term forecasting tool for nutrient management should assist producers and planners in making daily decisions by quickly identifying high-risk environmental conditions, be they fields or portions of fields, at high risk of generating storm runoff or times when nutrient transport risk is high. This ensures that those areas and times can be protected from potentially polluting activities (e.g., manure or fertilizer applications) that adversely affect water resources. Ultimately, short-term forecasting tools must enhance and complement existing conservation and nutrient management programs, such as the site assessment and guidance provided by USDA-NRCS's 590 Nutrient Management standard. Inherent to this outcome is the expectation that the tools offer unambiguous, actionable, and scientifically defensible information on when and where to apply nutrients.

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References

AHPS. 2016. Advanced Hydrologic Prediction Service. NWS precipitation analysis. NOAA. http://water.weather.gov/precip/ (accessed 20 Sept. 2016).

Alexander, C., D. Dowell, S. Benjamin, S. Weygandt, J. Olson, J. Kenyon et al. 2016. The hourly updated US High-Resolution Rapid Refresh (HRRR) storm-scale forecast model. Geophys. Res. Abstr. 18:EGU2016–EGU11044.

American Meteorological Society. 2015. Weather analysis and forecasting: An information statement of the American Meteorological Society. Am. Meteorol. Soc. https://www.ametsoc.org/ams/index.cfm/about-ams/ams-statements/statements-of-the-ams-in-force/weather-analysis-and-forecasting/ (accessed 11 July 2016).

Anderson, E.A. 2006. Snow accumulation and ablation model: SNOW-17. National Weather Service Hydrology Laboratory. http://www.nws.noaa.gov/oh/hrl/nwsrfs/users_manual/part2/_pdf/22snow17.pdf (accessed 24 May 2016).

Armstrong, A., and R.C. Stedman. 2009. An assessment of the Trees for Tribs initiative and buffers in the Hudson River Estuary Program. Final Rep. Hudson River Estuary Program, New Paltz, NY.

Bauer, P., A. Thorpe, and G. Brunet. 2015. The quiet revolution of numerical weather prediction. Nature 525:47–55. doi:10.1038/nature14956

Baumgart-Getz, A., L.S. Prokopy, and K. Floress. 2012. Why farmers adopt best management practice in the United States: A meta-analysis of the adoption literature. J. Environ. Manage. 96:17–25. doi:10.1016/j.jenvman.2011.10.006

Beven, K.J., and M.J. Kirkby. 1979. A physically based, variable contributing area model of basin hydrology. Hydrol. Sci. Bull. 24:43–69. doi:10.1080/02626667909491834

Bradshaw, L.S., J.E. Deeming, R.E. Burgan, and J.D. Cohen. 1984. The 1978 National Fire-Danger Rating System: Technical documentation. Gen. Tech. Rep. INT-169. USDA, Forest Serv., Intermountain Forest and Range Exp. Stn., Ogden, UT.

Buda, A.R., P.J.A. Kleinman, R.B. Bryant, G.W. Feyereisen, D.A. Miller, P.G. Knight, and P.J. Drohan. 2013. Forecasting runoff from Pennsylvania landscapes. J. Soil Water Conserv. 68:185–198. doi:10.2489/jswc.68.3.185

Buda, A.R., P.J.A. Kleinman, M.S. Srinivasan, R.B. Bryant, and G.W. Feyereisen. 2009. Factors influencing surface runoff generation from two agricultural hillslopes in central Pennsylvania. Hydrol. Processes 23:1295–1312. doi:10.1002/hyp.7237

Burgan, R.E. 1988. 1988 revisions to the 1978 National Fire-Danger Rating System. Res. Pap. SE-273. USDA, Forest Serv., Southeastern Forest Exp. Stn, Asheville, NC.

Burnash, R.J.C. 1995 The NWS river forecast system-catchment modeling. In: Singh, V.J., editor, Computer models of watershed hydrology. Water Res. Publ., Highlands Ranch, CO. p. 311–366.

Carnahan, R. 2012. Code of State Regulations 10 CSR 20-6.300. In: Rules of Department of Natural Resources Division 20: Clean Water Commission, Chapter 6: Permits. p. 56–57. http://s1.sos.mo.gov/cmsimages/adrules/csr/current/10csr/10c20-6.pdf (accessed 20 Sept. 2016).

Dahlke, H., Z.M. Easton, D.R. Fuka, M.T. Walter, and T.S. Steenhuis. 2013. Real-time forecast of hydrologically sensitive areas in the Salmon Creek Watershed, New York State, using an online prediction tool. Water 5:917–944. doi:10.3390/w5030917

Easton, Z.M., D. Fuka, M.T. Walter, D. Cowan, E. Schneiderman, and T.S. Steenhuis. 2008. Re-conceptualizing the soil and water assessment tool (SWAT) model to predict runoff from variable source areas. J. Hydrol. 348:279–291. doi:10.1016/j.jhydrol.2007.10.008

Easton, Z.M., P. Gérard-Marchant, M.T. Walter, A.M. Petrovic, and T.S. Steenhuis. 2007. Hydrologic assessment of an urban variable source watershed in the Northeast United States. Water Resour. Res. 43:W03413 doi:10.1029/2006WR005076

Frisvold, G.B., and A. Murugesan. 2013. Use of weather information for agricultural decision making. Weather Clim. Soc. 5:55–69. doi:10.1175/WCAS-D-12-00022.1

Fuka, D.R., Z.M. Easton, E.S. Brook, J. Boll, T.S. Steenhuis, and M.T. Walter. 2012. Process-based snowmelt modeling: Integration into the SWAT model. J. Am. Water Resour. Assoc. 48:1151–1161. doi:10.1111/j.1752-1688.2012.00680.x

GFS. 2015. Global Forecast System (GFS). National Centers for Environmental Information (NCEI), formerly the National Climatic Data Center (NCDC). https://www.ncdc.noaa.gov/data-access/model-data/model-datasets/global-forcast-system-gfs (accessed 11 Apr. 2016).

Goering, D.C. 2014. Decision support focused on improving water quality: Development of the Runoff Risk Advisory Forecast for Wisconsin farmers. Tech. Rep. NWS 55. NOAA. http://docs.lib.noaa.gov/noaa_documents/NWS/TR_NWS/TR_NWS_55.pdf (accessed 9 July 2016).

Grabs, T., J. Seibert, K. Bishop, and H. Laudon. 2009. Modeling spatial patterns of saturated areas: A comparison of the topographic wetness index and a dynamic distributed model. J. Hydrol. 373:15–23. doi:10.1016/j.jhydrol.2009.03.031

Haigh, T., L.W. Morton, M.C. Carmen, C. Knutson, L.S. Prokopy, Y.J. Lo, and J. Angel. 2014. Agricultural advisors as climate information intermediaries: Exploring differences in capacity to communicate climate. Weather Clim. Soc. 7:83–93. doi:10.1175/WCAS-D-14-00015.1

Haigh, T., E. Takle, J. Andresen, M. Widhalm, J.S. Carlton, and J. Angel. 2015. Mapping the decision points and climate information use of agricultural producers across the U.S. Corn Belt. Climate Risk Manage. 7:20–30. doi:10.1016/j.crm.2015.01.004

Hanak, E., and J.R. Lund. 2012. Adapting California's water management to climate change. Clim. Change 111:17–44. doi:10.1007/s10584-011-0241-3

Hollinger, S.E. 1991. Incorporating weather and climate data into integrated crop management systems. In: Climate, agriculture, and drought: Miscellaneous papers. Res. Rep. 91-01. Midwestern Climate Center, Champaign, IL. p. 1–24.

Hoskins, B. 2013. The potential for skill across the range of the seamless weather-climate prediction problem: A stimulus for our science. Q. J. R. Meteorol. Soc. 139:573–584. doi:10.1002/qj.1991

Kleinman, P.J.A., and A.N. Sharpley. 2003. Effect of broadcast manure on runoff phosphorus concentrations over successive rainfall events. J. Environ. Qual. 32:1072–1081. doi:10.2134/jeq2003.1072

Kleinman, P.J.A., A.N. Sharpley, R.W. McDowell, D. Flaten, A.R. Buda, L. Tao et al. 2011. Managing agricultural phosphorus for water quality protection: Principles for progress. Plant Soil 349:169–182. doi:10.1007/s11104-011-0832-9

Koren, V., M. Smith, Z. Cui, B. Cosgrove, K. Werner, and R. Zamora. 2010. Modification of Sacramento Soil Moisture Accounting Heat Transfer component (SAC-HT) for enhanced evapotranspiration. Tech. Rep. NWS 53. US Dep. of Commerce, NOAA, Nat. Weather Serv., Washington, DC.

Kusunose, Y., and R. Mahmood. 2016. Imperfect forecasts and decision making in agriculture. Agric. Syst. 146:103–110. doi:10.1016/j.agsy.2016.04.006

Leisnham, P.T., H. Montas, A. Shirmohammadi, V. Chanse, D. Lansing, A. Rockler, and T. Hutson. 2013. Watershed diagnostics for improved adoption of management practices: Integrating biophysical and social factors across urban and agricultural landscapes. In: Proceedings of the 2013 ASABE International Meeting, Kansas City, MO. 21–24 July 2013. ASABE, St. Joseph, MI. doi:10.13031/aim.20131668614

Lynch, T., and S. Gregor. 2004. User participation in decision support systems development: Influencing system outcomes. Eur. J. Inf. Syst. 13:286–301. doi:10.1057/palgrave.ejis.3000512

Mase, A.S., and L.S. Prokopy. 2014. Unrealized potential: A review of perceptions and use of weather and climate information in agricultural decision making. Weather Clim. Soc. 6:47–61. doi:10.1175/WCAS-D-12-00062.1

McCabe, G.J., and S.L. Markstrom. 2007. A monthly water-balance model driven by a graphical user interface. Open File Rep. 2007-1088. USGS, Reston, VA.

McCown, R.L. 2002. Changing systems for supporting farmers' decisions: Problems, paradigms, and prospects. Agric. Syst. 74:179–220. doi:10.1016/S0308-521X(02)00026-4

McIntosh, B.S., J.C. Ascough, II, M. Twery, J. Chew, A. Elmahdi, D. Haase et al. 2011. Environmental decision support systems (EDSS) development: Challenges and best practices. Environ. Model. Softw. 26:1389–1402. doi:10.1016/j.envsoft.2011.09.009

Murphy, A.H. 1993. What is a good forecast? An essay on the nature of goodness in weather forecasting. Weather Forecast. 8:281–293. doi:10.1175/1520-0434(1993)008<0281:WIAGFA>2.0.CO;2

Murphy, P.N.C., J. Ogilvie, and P. Arp. 2009. Topographic modeling of soil moisture conditions: A comparison and verification of two models. Eur. J. Soil Sci. 60:94–109. doi:10.1111/j.1365-2389.2008.01094.x

Nash, J.E., and J.V. Sutcliffe. 1970. River flow forecasting through conceptual models part I: A discussion of principles. J. Hydrol. 10:282–290. doi:10.1016/0022-1694(70)90255-6

Nelson, N.O., and A.L. Shober. 2012. Evaluation of phosphorus indices after twenty years of science and development. J. Environ. Qual. 41:1703–1710. doi:10.2134/jeq2012.0342

Osmond, D., D. Meals, D. Hoag, M. Arabi, A. Luloff, G. Jennings et al. 2012. Improving conservation practices programming to protect water quality in agricultural watersheds: Lessons learned from the National Institute of Food and Agriculture–Conservation Effects Assessment Project. J. Soil Water Conserv. 67:122A–127A. doi:10.2489/jswc.67.5.122A

Pennsylvania DEP. 2011. Land application of manure: A supplement to manure management for environmental protection. Pennsylvania Dep. of Environ. Prot. http://extension.psu.edu/plants/nutrient-management/manure/overview-of-deps-manure-management-manual/land-application-of-manure-manure-management-plan-guidance (accessed 21 July 2016).

Perica, S., D. Martin, S. Pavlovic, I. Roy, M. St. Laurent, C. Trypaluk et al. 2013. NOAA Atlas 14. Precipitation-frequency atlas of the United States. Vol. 8, Ver. 2.0: Midwestern states. US Dep. of Commerce, NOAA, Nat. Weather Serv., Silver Spring, MD.

Pontius, R.G., Jr., and M. Millones. 2011. Death to kappa: Birth of quantity disagreement and allocation disagreement for accuracy assessment. Int. J. Remote Sens. 32:4407–4429. doi:10.1080/01431161.2011.552923

Preedy, N., K. McTiernan, R. Matthews, L. Heathwaite, and P. Haygarth. 2001. Rapid incidental phosphorus transfers from grassland. J. Environ. Qual. 30:2105–2112. doi:10.2134/jeq2001.2105

Regonda, S., D. Seo, B. Lawrence, J. Brown, and J. Demargne. 2013. Short-term ensemble streamflow forecasting using operationally-produced single-valued streamflow forecasts: A Hydrologic Model Output Statistics (HMOS) approach. J. Hydrol. 497:80–96. doi:10.1016/j.jhydrol.2013.05.028

Reimer, A. 2015. Ecological modernization in US agri-environmental programs: Trends in the 2014 Farm Bill. Land Use Policy 47:209–217. doi:10.1016/j.landusepol.2015.04.013

Semler, J. 2015. 2014 Media channel study. American Business Media, Agri Media Council survey research. Readex Research. http://www.siia.net/Portals/0/pdf/ABM/TobeDistributed%20-%20AgriMediaCouncil2014Reportv2.pdf (accessed 1 June 2016).

Sharma, S., R. Siddique, N. Balderas, J.D. Fuentes, S. Reed, P. Ahnert et al. 2017. Eastern U.S. verification of ensemble precipitation forecasts. Weather and Forecasting 32:117–139. doi:10.1175/WAF-D-16-0094.1

Sharpley, A., D. Beegle, C. Bolster, L. Good, B. Joern, Q. Ketterings et al. 2012. Phosphorus Indices: Why we need to take stock of how we are doing. J. Environ. Qual. 41:1711–1719 doi:10.2134/jeq2012.0040

Sharpley, A., H.P. Jarvie, A. Buda, L. May, and P. Kleinman. 2013. Phosphorus legacy: Overcoming the effects of past management practices to mitigate future water quality impairment. J. Environ. Qual. 42:1308–1326. doi:10.2134/jeq2013.03.0098

Sharpley, A.N., P.J.A. Kleinman, D.N. Flaten, and A.R. Buda. 2011. Critical source area management of agricultural phosphorus: Experiences, challenges and opportunities. Water Sci. Technol. 64:945–952. doi:10.2166/wst.2011.712

Sharpley, A.N., J.L. Weld, D.B. Beegle, P.J.A. Kleinman, W.J. Gburek, P.A. Moore, and G. Mullins. 2003. Development of phosphorus indices for nutrient management planning strategies in the United States. J. Soil Water Conserv. 58:137–152.

Siddique, R., A. Mejia, J. Brown, S. Reed, and P. Ahnert. 2015. Verification of precipitation forecasts from two numerical weather prediction models in the Middle Atlantic Region of the USA: A precursory analysis to hydrologic forecasting. J. Hydrol. 529:1390–1406. doi:10.1016/j.jhydrol.2015.08.042

Sommerlot, A.R., M. Berbero, D.R. Fuka, and Z.M. Easton. 2016. Coupling the short-term global forecast system weather data with a variable source area hydrologic model. Environ. Model. Software 86:68–80. doi:10.1016/j.envsoft.2016.09.008

Suprem, A., N. Mahalik, and K. Kim. 2013. A review on application of technology systems, standards and interfaces for agriculture and food sector. Comput. Stand. Interfaces 35:355–364. doi:10.1016/j.csi.2012.09.002

USDA. 2007. Farm computer usage and ownership. USDA. https://www.nass.usda.gov/Statistics_by_State/Arizona/Publications/Annual_Statistical_Bulletin/09bul/pdfs/65-Farm%20Computer%20Usage%20and%20Ownership_repeat.pdf (accessed 27 Sept. 2015).

USDA. 2015. Farm computer usage and ownership: August 2015. http://usda.mannlib.cornell.edu/usda/current/FarmComp/FarmComp-08-19-2015.pdf (accessed 27 Sept. 2015).

USDA-NRCS. 2012. Conservation practice standard: Nutrient management. Code 590. http://www.nrcs.usda.gov/Internet/FSE_DOCUMENTS/stelprdb1046433.pdf (accessed 16 Aug. 2016).

Vadas, P.A., R.D. Harmel, and P.J.A. Kleinman. 2007. Transformations of soil and manure phosphorus after surface application of manure to field plots. Nutr. Cycl. Agroecosyst. 77:83–99. doi:10.1007/s10705-006-9047-5

Walter, M.T., T.S. Steenhuis, V.K. Mehta, D. Thongs, M. Zion, and E. Schneiderman. 2002. Refined conceptualization of TOPMODEL for shallow subsurface flows. Hydrol. Processes 16:2041–2046. doi:10.1002/hyp.5030

Walter, M.T., and M.F. Walter. 1999. The New York City Watershed Agricultural Program (WAP): A model for comprehensive planning for water quality and agricultural economic viability. Water Res. Impact 1:5–8.

Walter, M.T., M.F. Walter, E.S. Brooks, T.S. Steenhuis, J. Boll, and K.R. Weiler. 2000. Hydrologically sensitive areas: Variable source area hydrology implications for water quality risk assessment. J. Soil Water Conserv. 55:277–284.

Wardlow, B.D., M.C. Anderson, and J.P. Verdin, editors. 2012. Remote sensing of drought: Innovative monitoring approaches. CRC Press, Boca Raton, FL.

Wechsler, S.P. 2007. Uncertainties associated with digital elevation models for hydrologic applications: A review. Hydrol. Earth Syst. Sci. 11:1481–1500. doi:10.5194/hess-11-1481-2007

Whatcom Conservation District. 2015. Manure spreading advisory. Whatcom Conserv. District. http://whatcomcd.org/msa (accessed 31 Aug. 2016).

Wilks, D.S. 2011. Statistical methods in the atmospheric sciences. 3rd ed. Academic Press, Cambridge, MA.

Wisconsin DNR. 2013. Wisconsin's nutrient reduction strategy. Wisconsin Dep. Natural Res. http://dnr.wi.gov/topic/surfacewater/nutrient/combined_draft.pdf (accessed 20 Sept. 2016).

Xuan, Y., I.D. Cluckie, and Y. Wang. 2009. Uncertainty analysis of hydrological ensemble forecasts in a distributed model utilizing short-range rainfall prediction. Hydrol. Earth Syst. Sci. 13:293–303. doi:10.5194/hess-13-293-2009

Zhang, W., R.S. Wilson, E. Burnett, E.G. Irwin, and J.F. Martin. 2016. What motivates farmers to apply phosphorus at the "right" time? Survey evidence from the Western Lake Erie Basin. J. Great Lakes Res. 42:1343–1356. doi:10.1016/j.jglr.2016.08.007