**Testimony before the**
**US House Conservation and Forestry Subcommittee**
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**Topic: Conservation Benefits of Precision Agriculture**

Chairperson Spanberger and distinguished members of the Committee, thank you for this opportunity to discuss the conservation benefits of precision agriculture, some examples of precision agriculture, barriers to adoption and the role of the Land-grant Universities. Precision agriculture technologies are and their potential applications for conservation benefits are diverse and significant. Precision agriculture technologies utilize spatial and temporal agroecosystem and hydrologic data in geographic information systems (GIS) software that can be linked to automate equipment navigation of agricultural operations such as planting and spraying operations via robotic technologies. In addition, real-time data from sensing technologies such as in-field sensors, remote sensing or thermal imaging can be integrated with the GIS data and historical management data in decision support tools (DST) and decision support systems (DSS) (Drohan et al., 2019). Agroecological and hydrologic computer simulation models are of utilized in decision support systems along with other factors such as weather forecasts and/or economic data to provide farmers and land managers with site-specific management options that can result in reduced environmental impact and economic costs of agricultural activities. For instance, integrating maps of soil characteristics such as fertility, slope and drainage; crop yields, and pest infestations along with weather forecasts can enable managers identify zones for specific application rates of seeds, nutrients, pesticides and irrigation water at the optimal time with variable rate technologies (VRT). Similarly, livestock managers can utilize precision feeding to develop nutritionally balanced cost-effective rations that meet the metabolic needs of livestock at various life stages without excess nutrients.

*Adoption Barriers*
A recent analysis of multiple US survey data on the adoption precision agriculture since 2000, suggested some rapid adoption as well as barriers to adoption. Adoption of global navigation satellite systems (GNSS) with auto guidance and technologies such as sprayer control and planter row or section automatic shutoffs has been relatively rapid for agronomic crops (see Figure 3 from Lowenberg-DeBoer and Erickson, 2019), while adoption of variable rate technology (VRT) has been relatively slow and “rarely exceeds 20% of farms” (see Fig. 4 from Lowenberg-DeBoer and Erickson, 2019). The study’s authors summarized three hypotheses for the slow rate of adoption that were frequently described in the surveys cited: i. the cost of VRT was too high, ii. “more reliable VRT decision rules” were needed, particularly for nitrogen, and iii. farmers weren’t convinced VRT would increase their profits (Lowenberg-DeBoer and Erickson, 2019).

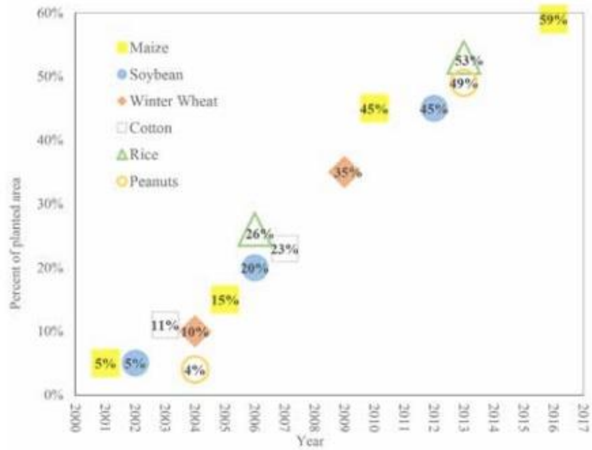



Fig. 3. Planted area by crop in the United States where Global Navigation Satellite Systems (GNSS) auto guidance was used, 2000 to 2016.

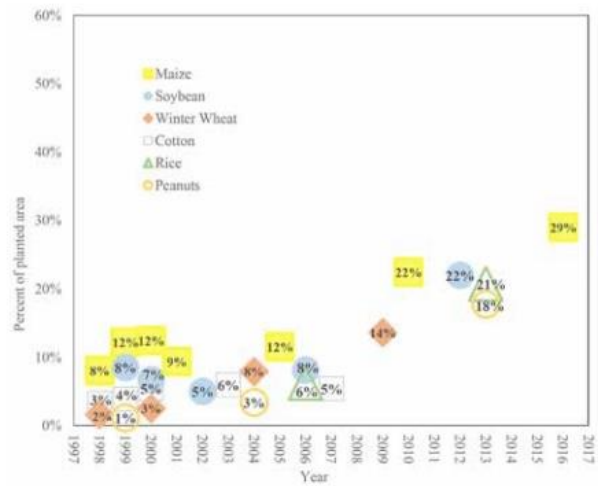



Fig. 4. Planted area by crop in the United States where variable rate technology (VRT) was used for any purpose, 1998 to 2016.

Figures 3 and 4 from Lowenberg-DeBoer J. and B. Erickson. 2019. Setting the Record Straight on Precision Agriculture Adoption. Agronomy Journal 2019 111:1535-1551, doi:10.2134/agronj2018.08.0535

Additional adoption barriers that others describe include the need for and technical expertise needed to install and operate precision technologies, and the fact that new equipment is needed to be compatible with the new technologies, as well as additional factors that are summarized and shown below in Table 1 from Wolfe and Richard (2017).

**Table 1**

**Overview of barriers to the adoption of pro-environmental technological innovations (general and agriculture specific) based on literature review (from Long *et al.* [31]). Sources are listed in [31] and not repeated here**

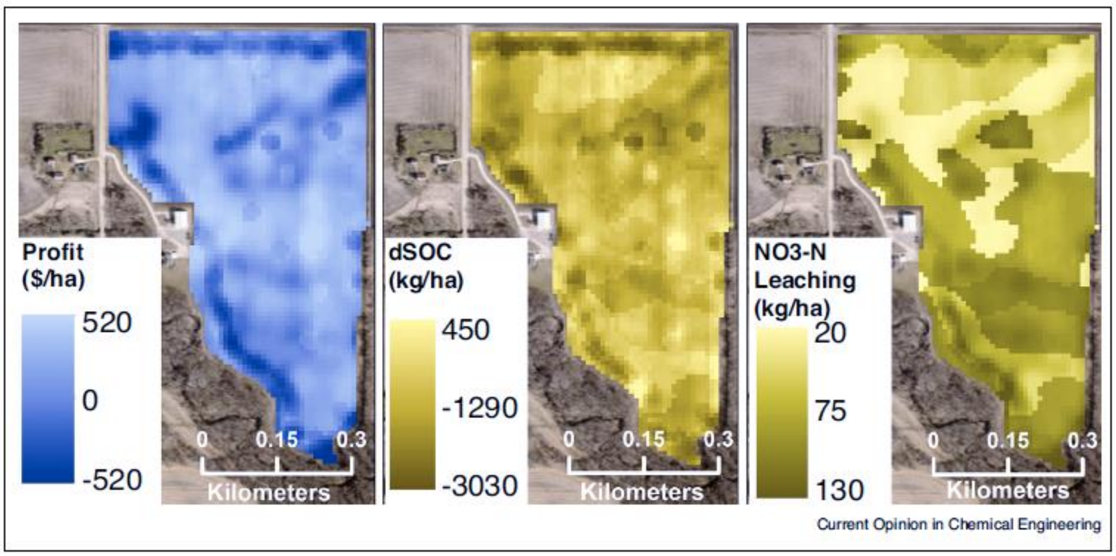
| Barrier | | Sources |
|---|---|---|
| Economic | High initial investments<br>Poor access to capital<br>Hidden costs<br>Competing financial priorities<br>Long pay-back periods (ROI)<br>Switching costs/existence of installed base<br>High implementation costs (actual and perceived)<br>Uncertain returns and results<br>Temporal asymmetry between costs and benefits<br>Over discounting the future | (Bogdanski, 2012; Brunke *et al.*, 2014; Cullen *et al.*, 2013; del Río Gonzalez, 2005; Faber and Hoppe, 2013; Hoffman and Henn, 2008; Luken and Van Rompaey, 2008; Luthra *et al.*, 2014; McCarthy *et al.*, 2011; Montalvo, 2008) |
| Institutional/regulatory | Low institutional support<br>Use of overly scientific language (Jargon)<br>Farmer's knowledge not considered in R&D<br>Lack of regulatory framework<br>Prohibitively prescriptive standards | (Bogdanski, 2012; Eidt *et al.*, 2012; Luthra *et al.*, 2014; Montalvo, 2008) |
| Behavioral/psychological | Lack of management support/awareness<br>Conflict with traditional methods<br>Overly complex technologies<br>Results/effects of technology difficult to observe<br>Farmer's beliefs and opinions<br>Low trust of advisers or consultants/lack of acceptance<br>Irrational behavior<br>Negative presumed assumptions | (Brunke *et al.*, 2014; Eidt *et al.*, 2012; Hoffman and Henn, 2008; Johnson, 2010; Ratten and Ratten, 2007; Sneddon *et al.*, 2011; Vishwanath, 2009; Wheeler, 2008) |
| Organizational | Lack required competencies/skills<br>Poor readiness<br>Poor information<br>Inability to assess technologies<br>Overly short-term/perverse rewards<br>Organizational inertia/habitual routines | (Brunke *et al.*, 2014; Faber and Hoppe, 2013; Johnson, 2010; Luken and Van Rompaey, 2008; Luthra *et al.*, 2014; Montalvo, 2008) |
| Consumers/market | Poor information<br>Lack market attractiveness/do not align to preferences<br>Uncertainty<br>Consumers/farmers level of motivation<br>Market uncertainty | (Bogdanski, 2012; Bohnsack *et al.*, 2014; Brunke *et al.*, 2014; del Río Gonzalez, 2005; Johnson, 2010; Luthra *et al.*, 2014) |
| Social | Social/peer pressures | (Montalvo, 2008) |

For farmers with limited capital facing small profit margins, the capital investment required for new precision agriculture technologies and the technical expertise required can be significant barriers. Land-grant university researchers and educators such as my colleagues at Penn State are currently working with farmers, the national laboratories and government agencies (ex. NRCS), as well as private sector partners to develop low cost new technologies and open-source or free software and decision support tools and systems that can be operated on smartphones or personnel computers. Land grants are also well-positioned to conduct objective, trusty-worthy assessments of precision technologies, while training students, educators and the workforce to develop, improve and assist in the use of precision technologies.

Decision support systems can empower farmers and producers to fine-tune their management practices when coupled with economic incentive policies that promote adoption (Drohan et al., 2019). Support for on-farm assessment and peer-to-peer learning also appear facilitate adoption of precision conservation technologies. A final report from a Penn State interdisciplinary research and extension projected provides an example of what DSS can provide. "There is no one production practice that will make or break a herd's profitability…. Combining financial metrics with decision-making on cropping and feeding practices is still a challenge for both producers and consultants. …. The bottleneck is how cropping strategies and animal performance influence the whole farm system and the impact to the bottom line. Unless nutritionists and crop consultants work with financials on a routine basis, it is unlikely they will embrace this aspect when working with their clientele." (Ishler et al., 2019).

Some examples of precision conservation technologies and DSS that offer promise of adoption are briefly described. Decision support systems (DSS) that produce farm profit maps can enable farmers and land managers to identify opportunities to increase their profits while reducing their environmental impact. Agroecosystem DSS can identify field zones that are consistently low profit or unprofitable enabling land-managers to consider alternative managements. Low profit or very unprofitable zones also are often zones of significant soil and/or nutrient losses associated with soil and landscape factors (Delgado and Bausch, 2005; Muth, 2014) as illustrated in Figure 1 from Wolfe and Richard, 2017 that may also make them particularly vulnerable to extreme weather events such as drought or flooding. For instance, a 2017 NRCS funded study of over 200,000 acres from nearly 3800 fields on 136 farms in a dozen states found that a) more than 90% of fields included zones that were losing money due to some combination of risks, and b) over 50% of the unprofitable acres were also acres with substantial environmental concerns (Wolfe and Richard, 2017).

**Figure 1**




Subfield economic analysis demonstrates high variability in profitability, with a significant fraction of currently farmed acres highly unprofitable for annual crops. Left panel: profit in $ ha$^{-1}$; center panel: change in Soil Organic Carbon in kg ha$^{-1}$, and right panel, nitrate ($NO_3$–N) leaching in kg ha$^{-1}$.

Figure 1 from Wolfe, M.L. and T. L. Richard. 2017. 21st Century Engineering for On-Farm Food-Energy-Water Systems. Current Opinion in Chemical Engineering https://doi.org/10.1016/j.coche.2017.10.005

Decision support tools that integrate landscape characteristics, with crop management history and yields agroecosystem models and economic analyses and sensor data can help farmers to identify practices for low profit zones to reduce their production costs and/or increase their cropping system resilience (Fig. 2. Wolfe and Richard, 2017).

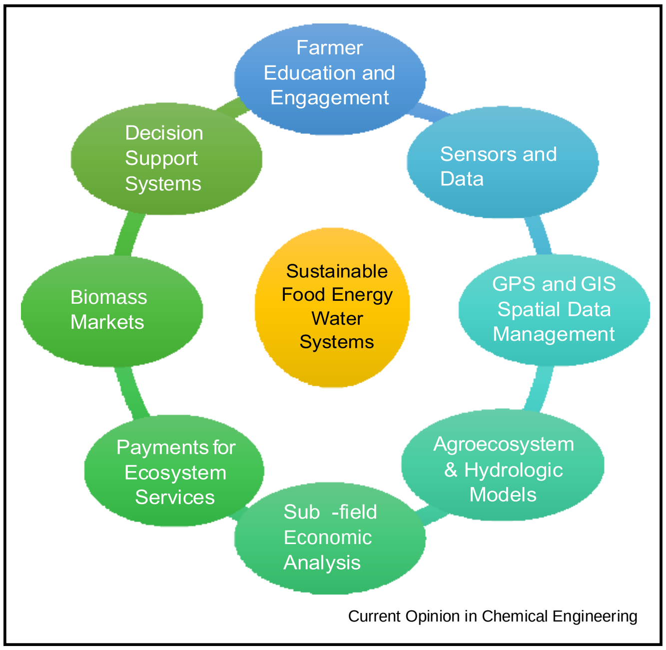



Figure 2 from Wolfe and Richard, 2017. Sustainable food–energy–water systems are enabled by an expanded precision agriculture toolset that includes economic analysis,payments for ecosystem services, and biomass markets, all managed through decision support systems that go beyond inputs and single crop management to innovative cropping system and landscape design.

Alternative management scenarios may include reducing fertilizer inputs and adopting conservation farming practices (Delgado and Bausch, 2005, Muth, 2014, Capmourteres et al., 2018). In zones where annual cropping is unprofitable, the establishment of perennial plants for bioenergy offers a viable economic alternative (Wolfe and Richard, 2017) such as shown below in Figure 6 from Brandes et al. 2018.

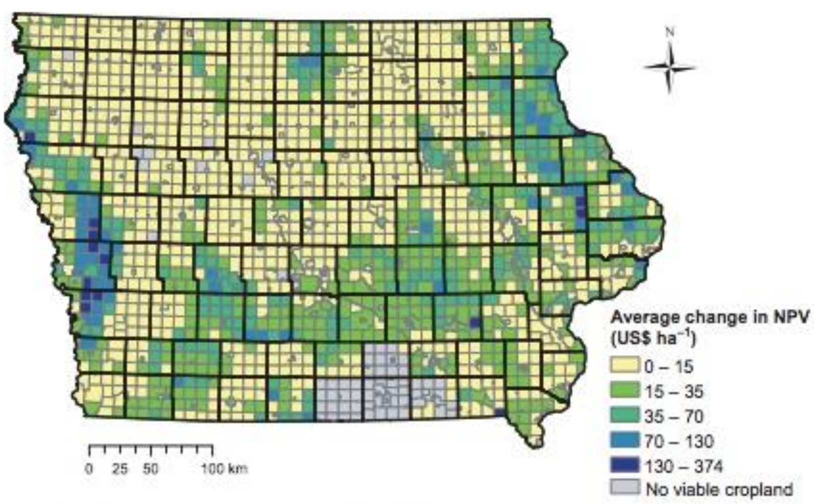



**Fig. 6** Average annualized changes in net present value (ΔNPV) when economically underperforming cropland is converted from corn/soybean to switchgrass. Values (in US$ ha$^{-1}$) are calculated by dividing the sum of annualized ΔNPV by the total corn/soybean cropland area per township. Gray areas represent townships without any cropland economically viable in switchgrass. The results assume USDA projected (medium) grain prices, medium switchgrass price, medium switchgrass yield, and that all land is owned by the farm operator.

Figure 6 from Brandes, E, A, Plastina, and E. Heaton.2018. Where can switchgrass production be more profitable than corn and soybean? An integrated, sub-field assessment in Iowa, USA. Global Change Biology Bioenergy. 10, 473–488, doi: 10.1111/gcbb.12516

Planting perennials (Capmourteres et al., 2018) and removing zones from production can also provide multiple conservation benefits for a relatively low cost. In Iowa, compared to similar watersheds that were 100% row-cropped, planting only 10% of a corn-soybean field to prairie strips reduced sediment loss by 95%, phosphorus and nitrogen losses by 90% and 85%, while also providing habitat for biodiversity, such as grassland birds and pollinators (Liebman and Schulte, 2015).

Decision support systems (DSS) such as CropSyst (Stockle et al. 2014) that integrate agroecosystem and hydrological models or climate projections have also been employed to evaluate various management scenarios such as nutrient management or projected climate change impacts and mitigation approaches. Land-grants researchers working with USDA ARS, other national laboratories, and "big-data" have developed multiple DST and DSS to provide growers with information to strategically reduce soil phosphorus and comply with nutrient regulations (Drohan et al., 2019); and to reduce production costs, pesticide applications, and crop damage from insect pests and disease infestation through free online real-time pest monitoring websites. Some examples of these free online precision technologies and additional precision DST and DSS that were developed or are under development at Penn State are described below.

In conclusion, the strength of Land-grants and Penn State is in our ability to bring together diverse faculty and extension educators to work with farmers, USDA partners, national laboratories, and the private sector. With evidence of multiple opportunities for precision agriculture and conservation technologies to provide environmental and economic benefits, we are advancing the development, application, and educational activities to support farmers and land managers in the conservation of our agricultural and natural resources.

A brief description of some additional precision agriculture technologies that were developed or are under development at Penn State are described below.

- PestWatch is a long-term monitoring program developed at Penn State that has expanded from 200+ stations in the East Coast, to 700+ stations nationwide (mostly MS river and east). PestWatch provides guidance for individual producers on the extent and location of various corn pests in the agricultural regions of the eastern United States. The unique use of climate and weather data within Pestwatch has led to additional tools for battling brown-marmorated stinkbugs, slugs, and the newly critical insect pest, Spotted Lantern Fly. The core tool is located at: http://www.pestwatch.psu.edu/
- Wheat Fusarium Headblight is the leading plant pathogen of wheat in the United States and abroad. Penn State, along with collaborators at Kansas State and across the Wheat Belt, has developed the Wheat Fusarium Head Blight Prediction Center to provide farmers with actionable information on this crop pathogen. The Prediction Center, and it's associated map tool, has been in continuous use and supported by the USDA Wheat and Barley Scab initiative for more than 19 years. This tool provides daily guidance for farmers across the entire US Wheat growing region. The tool is located at: http://www.wheatscab.psu.edu/

- Reducing the risk of crop damage by using drones, to monitor air temperatures on nights when there is frost and sending commands to ground robots with heaters mounted on them so growers can target only those areas most at risk are protected, while minimizing energy use.
- Precision, automated irrigation systems (drip irrigation) for tree fruit and vegetable crops that operate on soil moisture sensors and IoT (internet of things) system. The use of precision and automated irrigation systems can maximum the water use efficiency (apply water at right time and right amount), reduce the impact to the environment caused by the nutrient leaking, and save energy and costs.

**Predictive Models**

- Every winter, 30-40% of managed honey bee colonies in the US die. This is an enormous economic cost to beekeepers, and threatens our food security since 75% of our major food crops benefit from the pollination services of honey bees and other insects. Using data provided by Pennsylvania beekeepers, a team at Penn State and the USDA-ARS has developed models which can predict winter survival rates with 70% accuracy. These complex models integrate data on climate, landscape quality, and beekeeper management practices. We have developed an online portal, called Beescape, which allows individuals to evaluate the quality of their landscapes for supporting bee health. We are current integrating our predictive models into Beescape so that beekeepers can understand the risk to their honey bees in their locations, and take steps to improve bee survival. Beescape can easily be adapted to provide information on other measures of honey bee and wild bee health, including honey production and biodiversity. This program is funded by USDA NIFA and the Foundation for Food and Agricultural Research.
- In soybeans, we have been working from an extensive dataset (10 states, three years, just under 5,400 responses) to determine under what conditions foliar fungicides would be warranted. We have built a global models for (1) management factors, and (2) management in combination with environmental and physiological parameters, all with the goal to understand under which environmental domains might a foliar fungicide show a positive weight (i.e., influence positively the observed yield).

## Remote Sensing and Decision Support Technologies

- We are actively engaged in applied research to use a combination of sUAS-based (drone-based) sensors, including multispectral cameras and Lidar sensors in both airborne and terrestrial modes, to develop, test, and apply new techniques to measure forest ecosystem attributes at scales ranging from individual trees to forest stands. We combine emerging low-cost reality capture sensors with a seamless user interface, through custom software applications, to foster automation in the forest industry. We aim to transform the current rudimentary and labor-intensive mensuration methodology employed by foresters through the what we've named the "RealForests" system. RealForests fuses low-cost remote sensing hardware and intuitive software design to allow for rapid data collection of key forest attributes for forest appraisal and to support management decisions. Easy data collection integrated into existing field procedures is critical to market entry. Existing algorithms have allowed our team to locate individual tree objects and estimate critical measurements. RealForests will allow the user to add information, such as species identification, that can be linked to objects in the 3D model of the forest created by the system.

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