



Editorial: Building and Delivering Real-World, Integrated Sustainability Solutions: Insights, Methods and Case-Study Applications

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Editorial on the Research Topic

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Sustaining ecosystems to deliver what people need and value, while mitigating and adapting to global climate change and extreme event impacts, presents a complex set of environmental, economic, and social challenges in ensuring resilient and sustainable food production (Fuhrer, 2007; Newlands, 2016; Whitfield et al., 2018). Regional climate trends drive variability in land productivity, soil water and nutrient availability, crop calendars, and the prevalence of pests and pathogens. Abrupt extreme events that defy clear prediction and attribution to climate trends cause catastrophic crop damage through water-logging, soil erosion, nutrient leaching, heat waves and drought. Sayer et al. (2013) proposed 10 core principles for an integrated landscape approach for reconciling agriculture, conservation, and other competing land uses. Building on these principles, the Climate Smart Landscape (CSL) approach has emerged as an integrated management strategy to address the increasing pressures on agricultural production, ecosystem conservation, rural livelihoods, and climate change mitigation/adaptation (Scheer et al., 2012; Salvini et al., 2018). The CSL approach is strengthened by a broad array of different science-based indicators, metrics, frameworks and modeling systems that enhance its capability to make more informed, integrated decisions. This approach, however, needs to incorporate big data, statistical, and artificial intelligence (AI) methodological improvements, new sensors, and remote-sensing technological advancements (Lee et al., 2010; Wolfert et al., 2017; Willcock et al., 2018). Such improvements offer more flexible monitoring, newer and/or higher-resolution data, better prediction methods, and tools for decision support.

This Research Topic aims to showcase research, development and technology (RDT) work toward devising and delivering integrated solutions that support and enhance the CSL-based approach. This Research Topic comprises 13 articles, including 10 Original Research articles, 1 Review, 1 Hypothesis and Theory article, and 1 Technology Report. State-of-the-art modeling approaches and sampling technologies are showcased. Contributed papers present new methodological/technological innovation, findings, and/or insights across four themes: (1) landscape productivity and crop suitability, (2) variable crop requirements for water and nutrients,

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(3) crop health status, phenology and phenotyping, (4) crop disease assessment and prediction under integrated pest management (IPM) and the CSL approach.

LANDSCAPE PRODUCTIVITY AND CROP SUITABILITY

Bock et al. provide a technology report on a Canadian Land Suitability Rating System (LSRS) is a rule-based algorithm integrating soil, climate, and landscape factors from accessible databases, calculating a classed suitability rating for a given landscape. It is used to support commercial field crop production, and as a spatial research tool for assessing climate change impacts. Subramanian and Crowley present a spatial-based reinforcement learning approach that uses satellite imagery to increase the predictive power of spatial dynamic models that predict, and learn better policies to manage and control spatially spreading processes. They apply this methodology in wildfire event prediction using Canadian data. Exploring landscape gradients, Xu et al. assess how measuring plant community assemblies along habitat severity gradients may improve our ability to understand and monitor community dynamics and species responses under future climate change.

VARIABLE CROP REQUIREMENTS FOR WATER AND NUTRIENTS

Neilsen et al. showcase a landscape-based water demand model for agricultural water use that regional water managers can use to better manage water demand and supply in response to climate change. This model considers high-resolution land use, soil, elevation, historical/future climate scenario data, a digital elevation model, sub-basins, aquifers, and socio-political jurisdictional boundaries. They use this model to explore future scenarios of climate change, and historical effects of crop production systems on irrigation water demand. From water to nutrient requirements, Guo et al. investigate aerially estimating nitrogen uptake from multi-angular hyperspectral data on winter wheat to improve the efficiency of remotely-based techniques for non-destructive, rapid detection of wheat nitrogen (N) nutrient status. A novel, modified right-side peak area index (mRPA) is benchmarked against other widely used indices, and shown to have the highest predictive power. Using this index can increase accuracy in assessing crop N status and management. Martins et al. propose a novel methodology for tracking crop micronutrient composition over time and demonstrate it for predicting maize/corn maximum requirements under variation in nutrient uptake rates, potential evapotranspiration, and micronutrient partitioning over crop growth stages.

CROP HEALTH STATUS, PHENOLOGY, AND PHENOTYPING

Watson et al. use time-lapsed “phenocam” cameras to track the phenology and identify phenological variability of native and exotic grasses across grassland areas in Australia. Their

findings indicate C3/C4 species dominance to be the primary driver of phenological differences among grassland types, with the proportion of non-photosynthetic vegetation, grazing pressure, and species-dependent responses to rainfall and temperature being important biophysical drivers of grassland phenology. MODIS/Landsat satellite and field-based phenocam data were found to be in good agreement. A primary benefit of phenocam data is its higher temporal fidelity in capturing vegetation changes (i.e., increases/decreases in greenness) over periods of only 5 days, compared to coarser satellite or field measurement techniques. Using high-resolution images captured by unmanned aerial vehicles (UAVs), Guo et al. propose a two-step machine-learning based image processing method that can provide more reliable estimates of yield by detecting and counting the number of heads, than manual measurements in sorghum breeding trials, with potential for broader application in field experiments, and field production scouting operations. To better assess adaptation traits in large small-plot breeding trials, Potgieter et al. evaluate the use of a narrowband multi-spectral camera deployed on a UAV. Leaf Area Index (LAI), Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), and Normalized Difference Red Edge (NDRE) were evaluated. Despite variable emergence, these indices tracked canopy cover and LAI well over a large range of plant densities, with NDVI and EVI strongly correlated with plant number per plot, canopy cover, and LAI. NDRE (i.e., leaf chlorophyll content) was found to be most useful in characterizing the leaf area dynamics and senescence patterns in contrasting genotypes. In further addressing practical constraints in genomics-assisted breeding, Watanabe et al. demonstrate UAV remote sensing (with a RGB or near-infrared green and blue (NIR-GB) camera) for measuring sorghum plant height and nitrogen availability for faster and more cost-effective throughput phenotyping. For phenotyping based on root depth distributions, Wasson et al. propose a state-of-the-art Bayesian hierarchical nonlinear mixed statistical modeling approach to estimate root depth distributions for wheat genotypes to enable breeders to select for whole root system distributions appropriate for sustainable intensification. This approach produces de-noised profiles that exhibit rigorously discernible phenotypic traits.

CROP DISEASE ASSESSMENT, PREDICTION UNDER IPM AND CSL APPROACH

Pandey et al. provide a review of soil-borne and foliar fungal diseases of mungbean (*Vigna radiata* var. *radiata*), an important legume crop in South/Southeast Asia. They review pathogen characterization, economic impacts, and integrated management practices including host resistance, fungicides, biocontrol agents, natural plant products, and cultural practices. They highlight the need for longer-term studies to validate biological methods for commercial application. For wheat (yellow) stripe rust (*Puccinia striiformis* f.sp. *tritici*) fungal disease, the greatest global pathogen threat to wheat

production worldwide, Newlands explores the feasibility of an integrated model-based framework for predicting and controlling across large agricultural regions, using a novel spatially-explicit complex model, climate reanalysis and weather station network data.

Deploying cheaper, more accurate, and efficient technology enables the harnessing big data for use in solving sustainability challenges. With improved integrated analytical frameworks, statistical approaches, spatially-explicit models and indices, the CSL approach can be further developed and applied for more resilient, productive, and sustainable ecosystems. Smarter models will however require sufficient training data and operational frameworks assimilating data across a broad range of sampling platforms and data types. Agri-business will likely play an increasing role in sustainable landscape management by involving stakeholders and monitoring progress and outcomes (Salvini et al., 2018). Collectively, we can move faster to confront such complex interplay involved in translating scientific

evidence into real-world operational or actionable solutions (Lamontagne et al., 2019).

AUTHOR CONTRIBUTIONS

NN and TP co-wrote this editorial based on contributions to the Research Topic, incorporating editorial feedback provided by AP, LK, AH, and WG.

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