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Review Paper

Application of big data analytics and artificial intelligence in agronomic research

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ABSTRACT

Agronomic research involves study of crop-soil-environment interactions validated by field experiments. Modern statistical tools complemented in designing field experiments and immensely contributed in drawing useful inferences for developing good agronomic practices for increased crop production, input-use efficiencies and environmental sustainability. However, timely analyses of huge agronomic data sets having huge spatio-temporal variations are important in translation of research to real field situations. In order to enhance the reach of agronomic research, use of emerging tools of big data analytics, geo-referenced satellite information Unmanned aerial vehicle (UAV) based imaging and artificial intelligence (AI)-based techniques which can process large data sets are described which could be validated by agronomic field experiments. Some areas of data science for use in agronomy include: satellite and UAV based data acquisition, Internet of Things (IoT), AI (machine and deep learning) and big data analytics. Recent studies demonstrated that using AI-based algorithms the accuracy in yield prediction and image classification is enhanced up to 85%. Our study using all India wheat (*Triticum aestivm* L.) production data for a period of 58 years showed that Bi-directional Long Short-Term Memory (LSTM) model reduced error in time-series prediction to the order of 50% in comparison with conventional statistical models. Since agronomists aim for holistic understanding of agro-ecosystems, System Dynamic Model (SDM) of specific agricultural systems wherein the topography, climate, hydrology, natural resources and societal requirements are coupled along with their feedback impacts on agronomic systems has been introduced and discussed. Agronomists could collaborate with experts in other fields such as data science to bring about a new paradigm agronomic research.

Key words : Big data, Agronomic research, Artificial intelligence, Deep learning, Internet of Things, Multi spectral images, Unmanned aerial vehicle, Image analytics

Agronomic research integrates all fields of agricultural sciences interfacing crop, soil and environment to arrive at field advisories. Hitherto, agronomic research in India has largely been conducted in research farms and farmers' fields and the available statistical methods have helped to analyze and interpret the agronomic data. The need for acquisition and analysis of large and heterogeneous data sets at higher spatial and temporal resolutions for meaningful utilization of research results has necessitated the need for looking beyond conventional data analytical tools. Agriculture in India is facing multi-dimensional challenges and agronomists have to address more complex issues (Ghosh *et al.,* 2020), for example, use of chemicals, machinery in conservation agriculture systems (Nath *et al*., 2015) which deal with huge data sets. The first 3 paradigms of agriculture, viz. farm mechanization, use of chemicals and genetic and biotechnological interventions, are seen to be followed by the fourth paradigm of big data and data analytics in agriculture (Turner *et al.,* 2017). Big data analytics, digital methods, climate and weather informatics are seen to enhance agronomic capabilities (Rakesh and Goswami, 2016; Himesh *et al.,* 2018; Rakesh and Ramesh, 2019). Modelling of soil-environment interactions is possible for land-use planning and sustainable agriculture (Prakasa Rao *et al*., 2012).Participatory research involving all stake-holders holds key to agriculture where agronomists work with digital designers, human-computer interaction researchers, and collaborate with a wider community of scientists (Jeske *et al.*, 2020). Role of data analytics in agronomy of crops is in infancy now and agronomists have to capture the emerging areas to their advantage to lead a new paradigm in agronomic research (Turner *et al.,* 2017). Current research across the world involves expertize in diverse science disciplines; for example space and medical sciences.

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Agronomists also need to collaborate with other science disciplines and there is also a need to upgrade agronomy syllabus in the universities to meet the emerging demands. Around 25% of the world's food is produced by small farmers having less than 2 ha (Ricciardi *et al.,* 2018). There is a danger of small farmers being left out of such advances due to lack of capital and infrastructure and there is a need to make accessible big-data based agronomy to help small farmers and publicly funded research organizations have to formulate compatible agronomic research (Mehrabi *et al*., 2018). Publicly funded research organizations may restrict to create knowledge on digital agriculture applications, models and algorithms and commercial organizations may focus on digital agriculture platforms for use by service providers (Keogh and Henry, 2016). At the Purdue University in West Lafayette, USA, the Agronomy Center for Research and Education (ACRE) is constantly assessing better ways for farm to enhance yields and improve efficiency, with sensors collecting 1.4 petabytes of data daily (*www.techrepublic.com*). In India too, agronomists have not yet explored big data and AI-based technologies and there is a scope to utilize such advances (Rao, 2018; Ramesh, 2019). In order to closing yield gaps to attain potential crop yields, location-based agricultural intensification is necessary (Pradhan *et al.,* 2015) which needs support of big data analytics. Agronomic models and data analytics are as good as quality of data; agronomists have a major role in quality data acquisition and interpretation. As agronomic research addresses holistic farm situations, it is proposed that System Dynamics Models (SDM) as a combination of computational and simulation models integrated with predictive data analytics could help in overcoming several limitations of classical sector-oriented models, which help in better communication with non-academic stakeholders and policy-makers (Monasterolo *et al.,* 2015; Ramesh and Rakesh, 2019). The purpose of the paper is to bring to the attention of agronomists the importance and possibilities of big data analytics and artificial Intelligence in agronomic research.

Observations for agronomic applications

Multispectral data from remote sensing: The frequency and surface resolution of remotely sensed multispectral images have grown and established as useful tools in crop management. The applications of remote sensing data in crop field management are crop identification, crop acreage estimation, identification of planting and harvesting dates, identification of pests and disease infestation, crop-condition assessment and stress detection, soil-moisture estimation, irrigation monitoring and management, land cover and land-degradation mapping etc. Use of remote sensing data also aids in forecasting yields, monitoring plant stresses, optimizing agronomic practices and thereby ensuring cultivation of healthy crops that guarantees farmer's optimum harvests over a given period of time. In addition, the historical availability of these images will provide a spatio-temporal data for better understanding of phenological cycles of different crops and their interactions with environment. The free accessibility to most of these data is another advantage for effective and timely utilization. The popular satellite-based remotely sensed data used in agronomic research are Moderate Resolution Imaging Spectroradiometer (MODIS), Landsat and Sentinel missions. Terra's orbit around the Earth is timed, so that it passes from north to south across the equator in the morning, while Aqua passes south to north over the equator in the afternoon. The most important derived parameters from MODIS for crop-related studies are Land surface temperature, Land use Land cover, Vegetation Indices (NDVI and EVI), Fraction of Photosynthetically Active Radiation (FPAR), Leaf Area Index (LAI), Evapotranspiration, and Gross Primary Productivity. Landsat mission time period extends from 1972 to 2020 with 9 completed missions and this provides a continuous observation for 40 years. While Landsat operates with 11 spectral bands, the Sentinel 2A and 2C sensors are on board from 2015 onwards with 13 multispectral bands. Nonhomogeneity in data availability and cloud cover-related issues are crucial for the success, credibility, interpretation and validation of these satellite data for local or field-level analysis. In the context of increased applications using free and open data at regional scale, field-level agronomic data are essential for validation, successful analysis and interpretation. Rule-based approaches are validated for crop identification using multi-temporal and multi-sensor phenological metrics using remote sensing data for cereal crops with an accuracy of 80% (Ghazaryan *et al.,* 2018). Sadeh *et al.* (2019) demonstrated the use of satellite images for detecting actual sowing dates of individual fields and got an accuracy of 85% for the total sown fields with an average RMSE of 0.9 days. It is shown that remote sensing can provide fast and accurate forecasting of targeted insect-pests and subsequently minimize management costs (Abd *et al.,* 2020). High resolution (1 km) soil moisture data were generated (Park *et al.,* 2017) using downscaling approach with the help of machine learning using different remote-sensing products, including soil moisture from AMSR2 and ASCAT, NDVI, LST, and land cover from MODIS, and a digital elevation model from Shuttle Radar Topography Mission (SRTM). The temporal evolution of the *in-situ* leaf-area measurement were compared with estimates based on multiple satellite data and found that satellite product showed good agreement with *in-situ* measurements with a root-mean-square-error (RMSE) of 0.39–0.47

m^2/m^2 for Landsat and SPOT5, respectively, and a strong correlation ($R^2 > 0.92$) for both the cases (Campos-Taberner *et al.,* 2016).

Unmanned aerial vehicle (UAV)-based high-resolution multispectral imaging for agronomic applications: Aerial mapping of agricultural land provides information to estimate crop and environmental states that can be used to monitor progress over time in site-specific farming to tailor specific crop and soil management for each field (Rudd *et al.,* 2017). The spatial resolution of satellite and aircraft sensory data are much coarse compared to that of UAV, which flies at a much lower altitude. Coarse spatial resolution sensory data may not accurately estimate productivity and environmental factors, and result in insufficient inferences. The UAVs have been used in agriculture to get high spatial resolution images to detect individual crops and weeds at sub-millimeter scale. For example, Fig. 1 shows the image collected over a cotton (*Gossypium* sp.) field, with a camera operating in 5 bands (red, green, blue, red edge and NIR) at 1.87 m ground resolution, placed on a UAV at 30 m height from the field. The NDVI (Fig. 1b) was derived from the multispectral image bands, as described earlier. The zoomed version of Red-Green-Blue (RGB) composite image clearly discriminates the individual crops and bare soil (Fig. 1c). In another example, the rice blast [*Magnaporthe grisea* (Herbert Barr)] disease was clearly captured by UAV-based multispectral image of 5-mm ground resolution, placing UAV at 10 m height (Fig. 2).

Light Detection and Ranging (LiDAR) sensors have mainly been used in agriculture in ground-based systems for mapping soils (Jensen *et al.,* 2014) and crops (Andujar *et al.,* 2013; Reiser *et al.,* 2016). The LiDAR mapping data can also be used to evaluate the impact of crop production methods on yields (Jensen *et al.,* 2017). Orchards also tend to be an area of research where LiDAR have been used for mapping and monitoring (Jaeger-Hansen *et al.,* 2012; Eitel *et al.,* 2014; Uderwood *et al.,* 2015). Currently methods are available to estimate biomass based on volume estimate from LiDAR on board UAV and crop nitrogen concentration can be measured from multi-spectral imaging recorded from a UAV (Schirrmann *et al.,* 2016). Of late, remote sensing imagery has become an effective way to estimate biomass and carbon, providing a viable alternative to indicate the carbon sink without destructive protocols (Englhart *et al.,* 2012; Ramesh and Prakasa Rao, 2016).

Integration of unmanned aerial vehicle with satellite-based remote sensing images: Precision agriculture is moving towards precision planting, efficient crop management, intelligent decision making, and quantitative implementation at field or even subfield levels (Huang and Song, 2012; Cai *et al.,* 2018; Yang *et al.,* 2018). Subfield-level (within field) crop monitoring is essential to precision farming, which requires frequent crop-growth information at high-spatial resolution for mid-season crop management (Campos-Taberner, 2016). Satellite sensors such as MODIS, VEGETATION, PROBA-V, VIIRS, and Sentinel-3 provide daily observations of the globe, but their kilometric resolution is far from the requirement of subfield-level crop monitoring (Gao *et al.,* 2017; Li *et al.,* 2017). The mid-

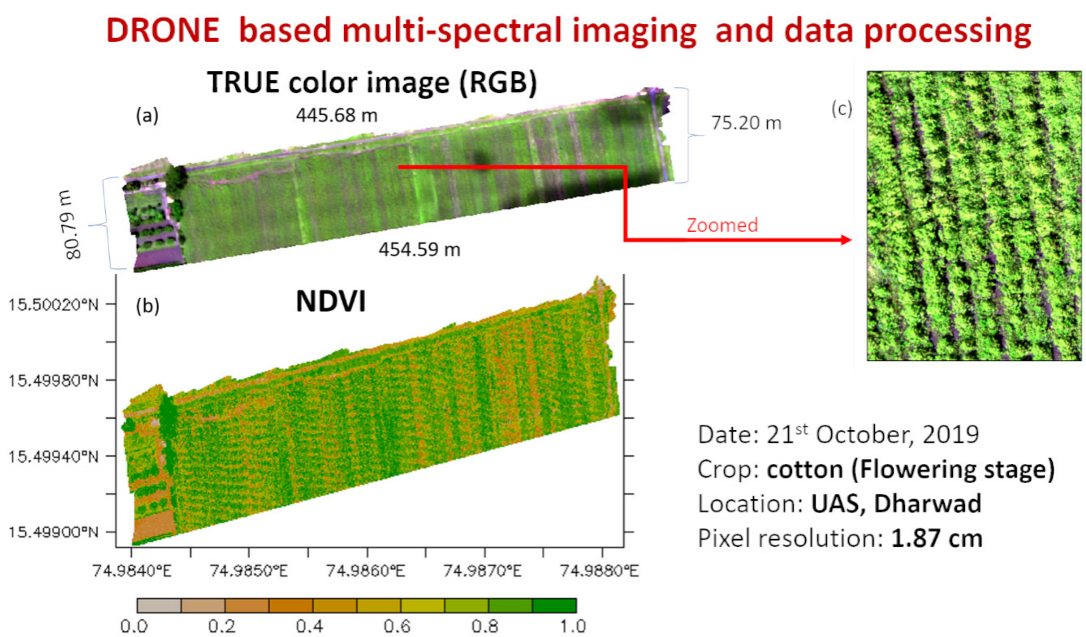

Fig. 1. Unmanned aerial vehicle-based multispectral image of cotton field (a), derived NDVI values from the image (b) enhanced image of the area of interest (c)

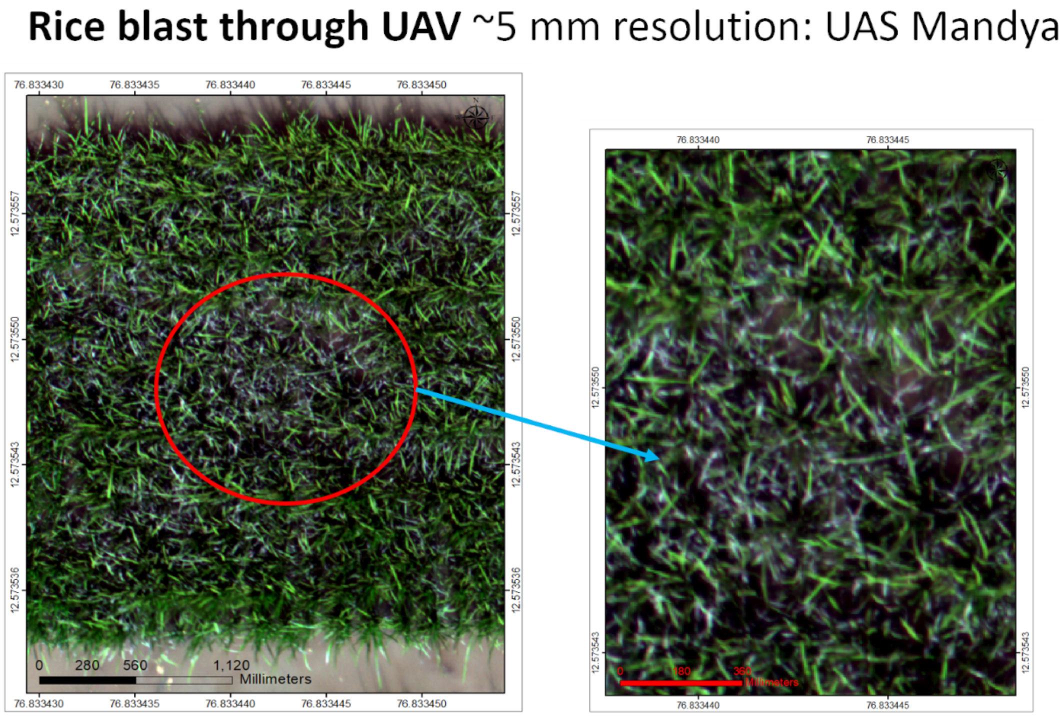

Fig. 2. Unmanned aerial vehicle-based multispectral imaging of rice field; 5 mm resolution image taken from multi-spectral camera (*left*), rice blast disease is clearly visible in the enhanced image (*right*).

resolution satellite imagery with weekly or bi-weekly revisit frequency, such as Sentinel-2, Landsat, and ASTER, has the potential in monitoring crop-growth status over critical growth stages (Jimenez-Munoz *et al.,* 2006; Gao *et al.,* 2017, Delloye *et al.,* 2018), but it is typically difficult to use the imagery for mapping smallholder farms. Those are the main crop-management units in many Asian and African countries such as India, China, and Ethiopia, where the size of a typical field (<1 ha) is often smaller than the pixels of the mid-resolution images (Jain *et al.,* 2016; McCarty *et al.,* 2017; Burke and Lobell, 2017). To this end, high-spatial resolution images (<1 m) are derived to overcome the issue of mixed pixels. To achieve the desired fine spatial resolution, it is necessary to collect UAV based very high-resolution multispectral field imageries. Existing spatio-temporal image fusion techniques can be helpful, but they were often proposed to generate medium-resolution images. Spatio-temporal fusion approaches represent a feasible alternative for generating high spatial and temporal resolution images by blending temporally frequent but spatially coarse imagery and spatially fine but temporally less frequent imagery. An approach of spatio-temporal fusion of various imageries is shown in Fig. 3. It involves integration of coarse and fine resolution satellite-based multispectral images along with UAV-based images through image co-registration and spatio-temporal fusion methods. The rationale of co-registration is to ensure that the images become spatially aligned, so that any feature in one image overlaps as well as possible relation with its footprint in any other image in the series. An exact match of footprints is, however, seldom possible. In agronomic applications, certainly in smallholder contexts, accurate image co-registration is a prerequisite for the accurate extraction of temporal profiles of crop fields. Misalignment between images may result in the extraction of incorrect temporal profiles (or crop signatures) and may subsequently give incorrect crop mapping results. Fusion of high-resolution UAV-based spatio-temporal multispectral image at field level with large-scale satellite images can resolve this issue to some extent with desired accuracy. The collection of filed data at farm level by agronomists is crucial in validating such merged products before using such products for field implementation. Thus, agronomists have tools and technology to collect large data sets which will greatly help in further data analysis and validation of viable agro-technologies for field advisories.

Internet of things-based field data collection and organization for data analytics

The basic building block for developing a data analytics platform in agriculture is organizing the past data in a time-tagged geo-referenced format. To achieve this, it is necessary to have a cropland data layer product, which is a multi-layer geo-referenced crop-specific land cover data set (crop-specific parameters). This will help us to identify the data gap and allows us to design future data collection programme. It will also help to bridge the data gap in a structured way and will provide a standard protocol for data collection and its organization. The basic cropping data are broadly classified as weather, soil, crop phenology (root, stem, leaf, flowering, grain formation, biomass, yield etc), biotic and abiotic stresses, hydrology, vegetation indices, crop height, LAI, etc. This field data are necessary to validate and standardize various satellite products as well as model simulations.

The huge wealth of historical field data already available with different sources needs to be organized in a time-tagged geo-referenced format. A large amount of field experimental data, soil and crop information are available with Indian Council of Agricultural Research (ICAR) institutions and agricultural universities in digital and print formats and a good amount of data is in the form of reports in krishikosh (*https://krishikosh.egranth.ac.in*) and is in document form which needs to be converted in digital format. For comprehensive data analytics in agronomic research, these data from various sources need to be integrated in a user-friendly platform and in independent common format. Another important information is regarding the traditional knowledge like land preparation, organic manures and crop rotation over different parts in India which also needs to be documented. Real-time surveillance of field in conventional way over large areas is difficult and time-consuming.

Precision farming at small-farm holdings needs solutions which work at sub-field level. Hence, it is necessary to adopt new technologies in field data collection; this will improve data frequency as well as minimize manual errors. Advances in Internet of Things (IoT)-based sensing systems have improved capabilities to precisely monitor crop parameters, thermal imaging and environmental conditions. These sensing systems are connected to wireless sensor network (WSN) refers to a group of spatially dispersed and dedicated sensors for monitoring and recording the physical conditions of the environment and organizing the collected data at a central location. These are similar to wireless *adhoc* networks in the sense that they rely on wireless connectivity and spontaneous formation of networks, so that sensor data can be transported wirelessly. The WSNs are spatially distributed autonomous sensors to monitor physical or environmental conditions, and to cooperatively pass their data through the network to a main location. The modern networks are bi-directional, both collecting data from distributed sensors and enabling control

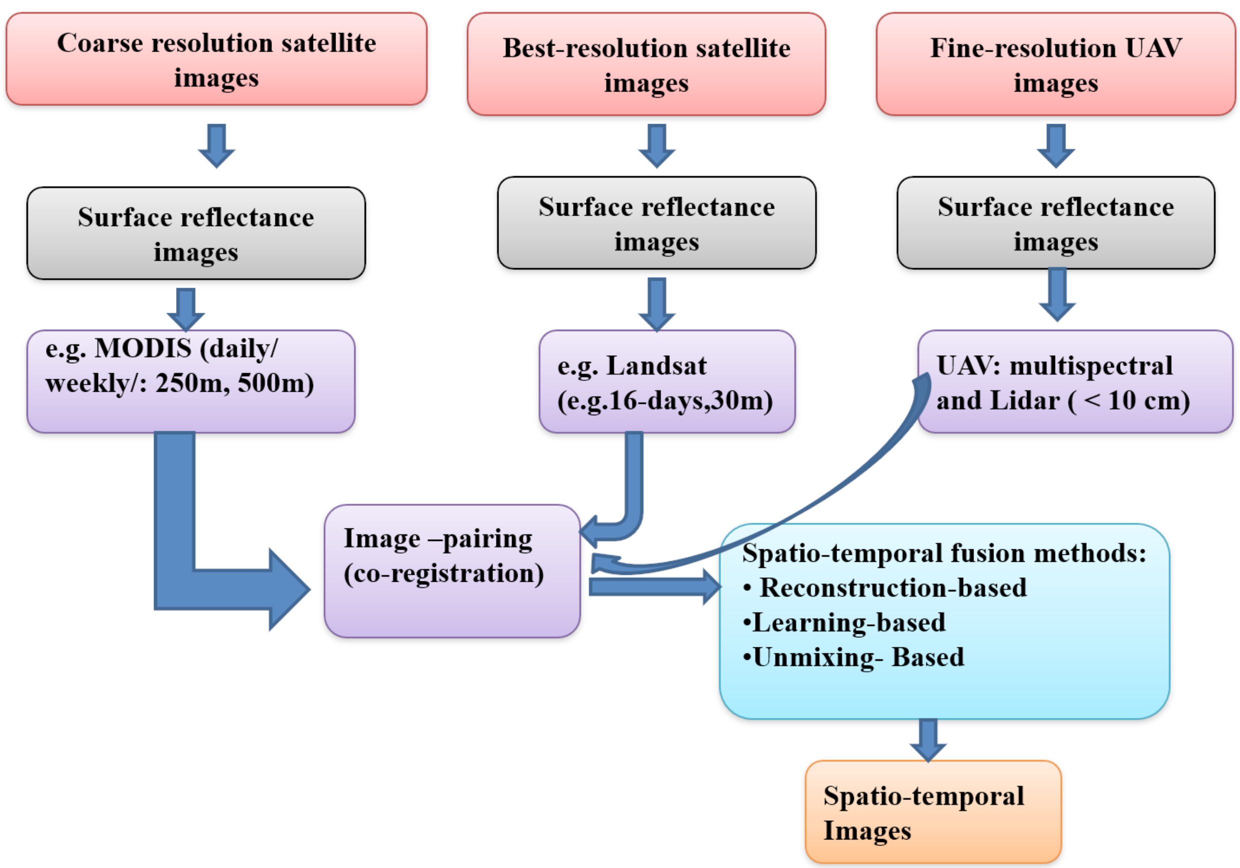

Fig. 3. Framework for spatio-temporal multispectral image through fusion from multisource multispectral images

of sensor activity. The IoT connected with WSNs will provide a basic framework for high-density data collection, for example, microclimate (temperature, relative humidity, rainfall, wind speed, solar radiation etc), soil temperature and moisture etc. High-resolution sensing of agro-meteorological parameters help to solve critical issues about the crop-weather-soil continuum; for example, early identification or prediction of biotic and abiotic stresses in the crops. In addition to fixed field measurements it is necessary to collect regular field measurements with instruments like plant canopy analyser (LAI), porometer (leaf properties), chlorophyll meter, GreenSeeker (NDVI) etc. This leads to an integrated data structure that will enable us to perform modelling and data analytics. Global metadata use is driven by technical or working teams and groups in industry, at universities, research bodies and institutes etc. Agriculture is a good example of application development and integration of the systems requiring structured data (Santos and Riyuiti, 2012). The reviews of the literature summarize available research, systematic quantitative reviews with synthesis go a step further to collate and summarize studies and capture all available information in a repeatable manner (Higgins and Green, 2011). Meta-analysis broadens the potential impact of primary research studies by placing them as substantial contributions within the larger picture of a research topic (Gerstner *et al.,* 2017; Li *et al.,* 2019; Lili *et al.,* 2020).

Integrated modeling and data analytics

Image analytics: The AI-based systems are already helping farmers with soil analysis, planting, animal husbandry, water conservation and more. Image analytics is the intelligence inbuilt digital image-processing system, which has automatic algorithmic extraction and logical analysis of information found in image. As the growing nature of image (RGB, Infrared, multi-spectral, hyperspectral, etc.) data through multiple sources, there is a growing need of analytical systems to interpret images, which are unstructured data to machine readable format, for example detecting species of animals or plants. The basic building blocks of the image analytic platform is explained in 4 steps. The initial step is to check the image quality and develop a spatio-temporal data through image fusion to bring the available data in machine readable uniform format. In next step, images are segmented into structured elements and prepped up for feature extraction-identification of low-level features in the image. During the third transformation step, the application detects the relationships between the features, variables and time. The final transformation step is the extraction of variables with time-stamped values. In the image processing application, a variable is represented by a series of values related to an entity (for example, evolution of a biotic or abiotic stress). Each value is time stamped which makes it possible to treat a variable as a time series. Essentially, image analytics transforms the image-input, adds value and creates a rich set of time series as analytically prepared data output. Image segmentation or classification is the process of partitioning an image into a collection of connected sets of pixels. Image segmentation helps to identify certain features in the image.

More recent development is accurate and real-time visual pattern recognition and extraction of features of a farmland which has enormous economic value. Aerial image semantic segmentation for detecting field conditions can help farmers to avoid losses and enhance yields throughout the growing season. Progress on visual-pattern recognition in agriculture, however, has been slow, hindered in particular by a dearth of relevant datasets. One of the challenges in developing aerial image datasets for agricultural pattern analysis is image size. Semantic segmentation for detecting field conditions over aerial farmland images requires inference over extremely large-size images with extreme annotation sparsity (Chiu *et al.,* 2020). Although the extremely large aerial farmland images created unique challenges, the Agriculture-Vision dataset (Chiu *et al.,* 2020) offers the research community an opportunity to explore the field with abundant data resources. The research team plans to expand the dataset with more images and additional modalities such as thermal images, soil maps, and topographic maps (Chiu *et al.,* 2020).

Identification of crop phenology and yield estimation: Biophysical crop models are mathematical algorithms that simulate the quantitative information of agronomy and physiology experiments in a way that can explain and predict crop growth and yield. They help in exploring the dynamics between weather, crop, and soil, assist in crop agronomy, pest and natural resource management, and assess the impact of climate change on crop yield. Crop models, such as the Decision Support System for Agrotechnology Transfer-Cropping System Model (DSSAT-CSM) (Jones *et al.*, 2003) and Agricultural Production Systems sIMulator (APSIM) (Keating *et al.*, 2003), are extensively used in the analysis, evaluation, and prediction of crop growth and production at in-field scale up to regional levels using field level weather, soil and field experimental data. Experimental studies have shown that incorporating phenology dynamics in such models can help to improve the accuracy of yield estimation (Fang *et al.,* 2011; Bolton and Friedl, 2013; Zhu *et al.,* 2018). Satellite-based remote sensing enables large-scale monitoring of crop-growth with increasing spatial and temporal resolutions of observations in the past decades (Luo *et al.,* 2013; Chen *et al.,* 2018). The crop phenology dynamics is very important for understanding yield variations because the crop sensitivities towards different weather events vary during each growth phase (Challinor *et al.,* 2009; Sánchez *et al.,* 2014). There are many ways to incorporate remote-sensing information in yield estimation, such as detecting crop dynamics, deriving unique growth parameters, and developing phenology-based predictors (Li *et al.,* 2019). Many crop models simplify the representation of the crop-progress dynamics based on integrated remote sensing and meteorological indices into a fixed timescale, such as monthly (Prasad *et al.,* 2006). Crop modelling has been a useful tool to assess climate change effects on crop production. However, their limitations require extensive engagement of stakeholders (Campbell *et al.,* 2016), which indicates the need of handling big data. Studies combining accurate phenology information are limited due to the lack of large-scale and high-resolution crop phenology information. As an example, estimated green-up date for rice (*Oryza sativa* L.) growing regions of Koppal district, Karnataka, from MODIS 8-day NDVI 250 m resolution using Timesat software is shown in Fig. 4. Such estimation can help in prediction of crop yield well in advance and timely modulation of farm-management practices. However, how to better integrate the experimental field data with remote sensing-derived information and other environmental factors for yield estimation requires further research.

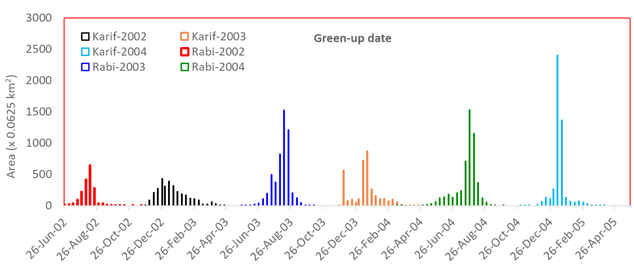

Fig. 4. Estimation of green-up date for paddy growing regions of Koppal district, Karnataka, from MODIS 8-day NDVI 250m resolution using Timesat software

Recent studies have leveraged data driven models to derive nonlinear relationship between crop and environmental variables using multi-scale remote sensing data which accommodates the changes in location, year, and timing of observations (Prasad *et al.,* 2006; Huang and Singh, 2012; Van *et al.,* 2020). However, these data-driven models were mostly built based on knowledge of single domain, and many times, the crop phenology dynamics, soil and meteorology variations were ignored. For better understanding on how crop yields respond to daily changes of environmental factors throughout the growing season, an approach which integrates knowledge of crop phenology with deep learning techniques is highly recommended. Emerging deep learning techniques such as the Long Short-Term Memory (LSTM) model addressed many problems with multi-dimensional data in recent years (You *et al.,* 2017). The LSTM model implements a Recurrent Neural Network (RNN) structure, representing a deep network structure for incorporating the crop-growth processes. The LSTM model has been proved to accommodate different types and representations of data, recognize sequential patterns over long-time spans, and capture complex nonlinear relationships (Thornton *et al.,* 2014). It has been applied to solve real world problems such as in protein simulations (Hanson *et al.,* 2017), yield prediction (You *et al.,* 2017), and plant-disease detection (Pryzant *et al.,* 2017). Identifying and understanding the cumulative and nonlinear relationships between the different components of the cropping ecosystem is critical in learning how any one component of the system interacts with crop production. However, taking full advantage of multi-dimensional and heterogeneous geospatial data for yield estimation requires an advanced and robust modelling approach. A schematic of approach to integrate multiple components of the natural cropping system in an interactive predictive analytic platform to predict yield through better understanding of the system is shown Fig. 5. It is clear from Fig. 5 that region/field-specific crop-phenology information and deep learning-based time series structure can reveal cumulative and nonlinear effects, through the integration of (all natural) systems associated in the cropping system with field observation, remote sensing, modelling and machine learning. The most critical stage is to validate each component as well as assess performance and effectiveness of the analytics system. In agriculture, data-driven decisions can enable a sustainable use of water, land utilization, and chemicals control through optimized analytics (McBratney *et al.,* 2005)

Crop health monitoring and prediction: Traditional crop-stress/disease-forecasting models are mostly based on statistical or dynamical models, which mainly depend on weather variables (Ramesh and Goswami, 2007; Goswami *et al.,* 2014; Saharan *et al.,* 2019). Conventional methods of identification of particular crop stress or stage monitoring are based on only one spectral pixel information which lacks dynamic features and limits their application for crop discrimination, mainly in heterogeneous parcels with high spectral variability and mixed pixels. Another source of error is due to the high spectral similarity among different crops with common development patterns and growth calendars, e.g. herbaceous ones such as tomato [(*Solanum lycopersium* (L.)], corn (*Zea mays* L.), safflower (*Carthamus tinctorius* L.) or sunflower (*Helianthus annuus* L.) (Ham *et al.,* 2005). Hyperspectral images are able to convey much more spectral information than RGB or other multispectral data: each pixel is in fact a high-dimensional vector typically containing reflectance measurements from hundreds of contiguous narrow-band spectral channels. Traditional learning-based approaches to hyperspectral image data interpretation rely on the extraction of hand-crafted features on which to hinge a classifier. Starting early on with simple and interpretable low-level features followed by a linear classifier, subsequently both the feature set and the classifiers started becoming more complex. This is the case, for instance, of Scale-Invariant Feature Transform (SIFT), Histogram of Oriented Gradients (HOG) (Dalal and Triggs, 2005) or Local Binary Patterns (Li *et al.,* 2015), in conjunction with kernel-based Support Vector Machines (SVM) (Camps-Valls and Bruzzone, 2005), Random Forests (Ham *et al.,* 2005) or statistical learning methods (Camps-Valls, 2014). The advantages introduced with deep learning solutions lie in the automatic and hierarchical learning process from data itself (or spatial–spectral portions of it) which is able to build a model with increasingly higher semantic layers until a representation suitable to the task at hand (e.g. classification, regression, segmentation, detection etc.) is reached.

Deep-learning-based semantic segmentation can yield a precise measurement of vegetation cover from high-resolution aerial photographs. One challenge is differentiating classes with similar visual characteristics, such as trying to classify a green pixel as grass, shrubbery or tree. To increase classification accuracy, some data sets contain multispectral images that provide additional information about each pixel. For example, the Hamlin Beach State Park data set, New York supplements the colour images with near-infrared channels that provide a clearer separation of the classes. Crop segmentation, an application of image segmentation, plays a fundamental role in agricultural information automation. Many issues, such as crop-growth stage prediction, crop-line detection (Vidovie and Scitovski, 2014), density estimation (Sheather, 2004), crop-cover identification (Cruz-Ramirez, 2012), leaf-disease detection (Meunkaewjinda, 2008; Rastogi *et al.,* 2015) and crop-biomass monitoring (Bending *et al.,* 2015; Ramesh and Prakasa Rao, 2016) are highly dependent on the performance of crop-segmentation algorithms. Deep convolutional neural network (DCNN) is in the spotlight in agricultural vision problems such as land-cover classification (Lu *et al.,* 2017) and weed detection (Milioto *et al.,* 2017). Rebetez *et al.* (2016) applied DCNN on aerial images collected using an EOS 5D camera at 650 m and 500 m above ground in Penzhou and Guanghan County, Sichuan, China and labeled cultivated land vs background with high accuracy. In another recent work (Chiu *et al.,* 2020), an experi-

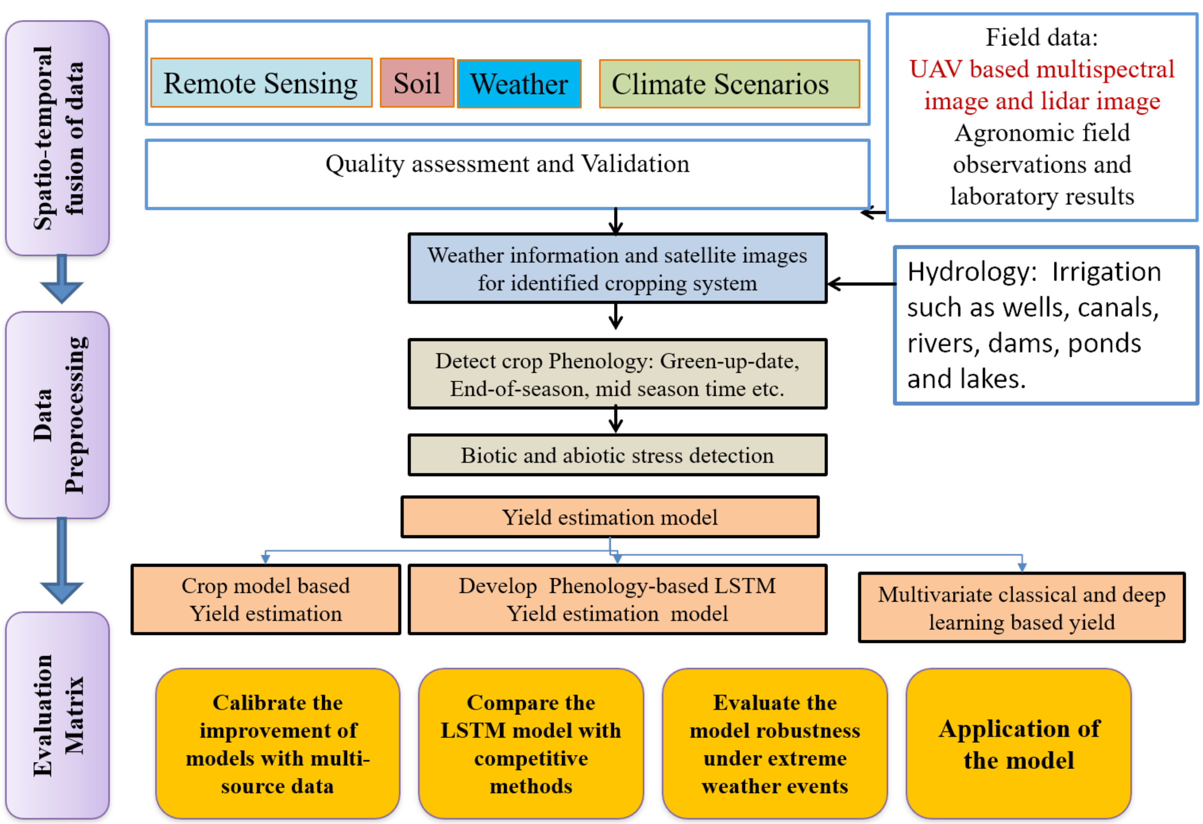

Fig. 5. The basic structure of predictive analytics system for crop yield prediction

mental farmland dataset collected by the Swiss Confederation's Agroscope Research Centre is deployed in a DCNN-Hist NN hybrid model to categorize plant species on a pixel-level.

Time series forecasting: classical and deep-learning methods

One of the most popular and well-known methods to predict future values is Box-Jenkins method that is based on a linear combination of weighted past values. There are studies in the past showing improvements in Box-Jenkins method and its variants (support vector regression (SVR), Auto Regressive Integrated Moving Average (ARIMA), Vector Autoregressive Models (VAR)) by adding Artificial Neural Networks (ANN) layer to capture the non-linearity in the target system. Similarly, ANN are widely used in time-series forecasting in agriculture such as crop yield forecasting from satellite images (Sakamoto, 2014; Bose *et al.,* 2016), agrometeorology (Gerrit, 2000; Edwin *et al.*, 2019, 2020), farm data (Patrick *et al.,* 2019), climate projections (Lobell and Burke, 2010), crop price (Jha and Sinha, 2014), cropping systems (Prasad *et al.,* 2006). As an example, time-series forecasting of all India wheat production using various multivariate data models and their comparison with deep-learning (LSTM)-based model is shown in Fig. 6. All the models were trained for a 40-year period (1961–2000) and test simulations were carried out for the period 2001–18. It is clear from the average error statistics for different models that LSTM has distinct advantage over other conventional data models in time series prediction (Fig. 6).

Agronomy being a holistic science of crop production, needs to absorb emerging trends of research. As agronomy needs to analyze and interpret large volumes of data sets, it is imperative to derive from the recent advances in big data analytics. In this paper, we have attempted to bring to the attention of agronomists the possibilities of new methods of data acquisition, analysis and interpretation and the need of collaboration among experts of multi-disciplinary areas. The various techniques discussed were satellite and unmanned aerial vehicle (UAV)-based data acquisition, internet of things (IoT), AI (machine and deep learning) and big data analytics. Systems dynamical model (SDM) concept has been introduced to integrate various systems to enhance the agronomic research.

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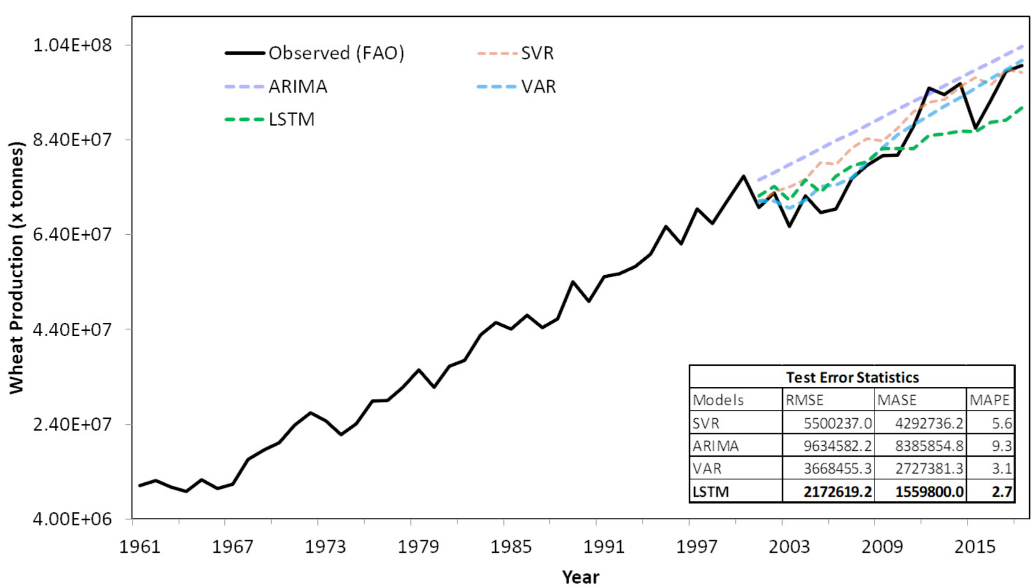

Fig. 6. Comparison of performance in all India wheat production prediction simulation by various multivariate data models with deep learning technique. Models are trained for a 40-year period (1961–2000) and test simulations are carried out for rest of the period (2001–18; the dotted line with different colors)

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