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Eco-smart pest management in rice farming: prospects and challenges

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ABSTRACT

The insect pests and diseases problems are accentuated in intensive rice cropping where tthey occur throughout the year. Over 800 insect species damaging rice in one way or another, although the majority of them do very little damage. In India, about a dozen of insect pests and dozen of diseases are of major importance but the economic damage caused by these species varies greatly from field to field and from year to year. Insect pests cause about 10-15 per cent yield losses. Farmers lose an estimated average of 37% of their rice crop to insect pests and diseases every year. This review focuses on precision farming tools being used in rice pest and diseases management viz., forecasting model for real-time pest-advisory services, hyper-spectral remote sensing in pest damage assessment, computer-based decision support system, disruptive technologies (mobile apps).

Key words: *Rice, insect pests, diseases, biotic stress, forecasting, GIS, remote sensing, UAV, mobile app, ricexpert*

INTRODUCTION

Increasing global population and potential impacts of climate change have reinvigorated interest in global food security, which is defined by the United Nations Food and Agriculture Organization as "existing when all people, at all times, have physical, social and economic access to sufficient, safe and nutritious food which meets their dietary needs and food preferences for an active and healthy life". Increases in yields through plant breeding, increases in cropping intensity and expansion of arable land are fundamental to ensuring sufficient food supply in developing economies such as those in many African nations. However, sustaining yields through vigilance in biosecurity remains a key challenge globally.

The reliable detection and identification of pest, diseases and abiotic stress are a current challenge in agriculture. Standard existing methods of detection often rely on crop protection scientists manually checking the crop for indicator signs that are already visible. Depending on the type of crop and the size of the crop area-which for many commercial crops is often very large-this method of monitoring plant health is both time consuming and demanding. Manual detection also relies on the pest, disease or stress exhibiting clearly visible symptoms, which frequently manifest at middle to late stages of infection.

Crop protection is a key issue in farm management. It involves dealing with important risks and expensive pesticides. In crop production precision agriculture methodologies are applied for the site-specific application of fertilizer or pesticides, automatic guidance of agricultural vehicles, product traceability, on-farm research and management of production systems. Precision pest management is a demanding challenge within precision agriculture and offers great potential to reduce the costs of plant protectionand environmental impact of pesticide use.

Pest and disease scenario

The insect pest and disease problems are prominent in intensive rice cropping where they occur throughout the year. Over 800 insect species were found to damage rice crop in one way or other, although the majority of them inflict very little damage. In India, about a dozen of insect species are of major importance but the economic damage caused by these species varies greatly from field to field, and from year to year. These species include stem borers [Yellow stem borer (*Scriphophaga incertulas*), White stem borer (*Scirphophaga innotata*), pink stem borer (*Sesamia inferens*), stripped stem borer (*Chilo polychrysus*), dark-headed stem borer (*Chilo suppressalis*)], leaf folder (*Cnaphalocrocis medinalis* (Guenee), brown planthopper (*Nilaparvata lugens* Stal.). In addition, species distribution and abundance vary among rice ecosystems within a given location. For example, some species are primarily upland rice feeders while others are more numerous and damaging under lowland conditions. Some species may be abundant in all rice-growing environments. Among the biotic stresses, insect pests cause about 10-15 per cent yield losses. The average yield losses in rice have been estimated to vary between 21-51 per cent. At national level, stem borers accounted for 30% of the losses while planthoppers (20%), gall midge (15%), leaf folder (10%) and other pests (25%) (Krishnaiah and Varma, 2018).

Of the various rice diseases reported, blast, bacterial leaf blight, sheath blight, stem rot, brown leaf spot and false smut were recorded to be the significant ones. Of these, the sheath blight, bakane and the false smut became important only after the green revolution. Although, false smut disease of rice was considered as the sign of good harvest is now regarded as a serious disease. Some of the diseases appeared in few pockets would become major constraints in future are fungal sheath rot, bacterial sheath rot, seedling mortality by *Sclerotium rolfsi*. Primary source of inoculum are internally seed borne, bacterial blight (BB), blast, brown spot, sheath rot (fungal and bacterial), seedling elongation, foot rot, seedling rot by *Fusarium moniliforme*; externally seed borne or as admixture in seed are Sheath blight, False smut, seedling blight by *Sclerotium rolfsi*. Some of the soil borne diseases are Seedling elongation, foot rot and Seedling rot by *F. moniliforme*; sheath blight, false smut, seedling blight by *Sclerotium rolfsi*. Besides the above, all the diseases may spread through collateral host / stubbles of infected plant / diseased plant parts left in field. Collectively, rice diseases result in yield reductions of 10-15% in tropical Asia.

Crop losses due to arthropods, diseases and weeds across the world have increased from about 34.9% in 1965 to about 42.1% in the late 1990s and the trend is very alarming. Indian farmers face many biotic constraints in their mission to increase rice production. The yield losses in India due to pests ranges from 15-25%, which is approximately 15-23.3 billion US$ in annual monetary value. India can meet their domestic needs of 2030 even with the present levels of crop productivity as well keeping in view the stagnation in yields for certain crops, if losses due to pest damage in terms of quantity are can be saved. This manuscript focuses on literature generated on various aspects of rice insect pests, diseases *viz*., pest status and their distribution, bio-ecology, diversity, use of hyper-spectral remote sensing in pest damage assessment, impact of climate change on insect biology, population structure and epidemiology of different rice diseases (Mohapatra et al. 2018).

Pest forecasting

The timing and severity of infestation by insect pests and diseases vary greatly among regions, seasons, and individual crops within a region. In absence of stable, desirable, and diverse sources of resistance to insect pests and diseases, pesticides remain the only effective means to manage them. Detecting an impending disease outbreak or pest attack early enough serves as a strong management tool. This can be enabled by development of region, crop, and pest-specific prediction models to forewarn these menaces. Forecast models provide an alternative to calendar spray schedules to bring need-based precision. Since insect pest and disease menaces are weather dependent, weather-based prediction models enable management of these pests. Weather variables including temperature, rainfall, and relative humidity, have been tested and reported extensively in many insect pests and disease studies. In most cases, favourable temperature is critical for insect pest growth, development, pest epidemics, the extent of damage caused to crops, and the overall crop yield. Insects are sensitive to temperature, and therefore insects typically respond to higher temperature, which increases the rate of development and reduces the time between generations.

Pest forecasting are maily two types based on period of forecasting. (i) Short term forecasting - based on one or two seasons (ii) long term forecasting - Based on effect of weather parameters on pest. Diverse modelling approaches viz. Generalized regression neural networks (GRNN) and multiple regression (REG), back-propagation neural network (BPNN), support Vector machine (SVM) have been followed to date for disease prediction in plant populations.

In pest forecasting, several intrinsic attributes of the insects and the determining environmental and host factors need to be considered. Most pest forecast models take into account the phenology of the herbivore and its host. Near real-time pest incidence data coupled with remote sensing and GIS tools facilitate early warning of impending pest build-up in a temporal and spatial perspective. In addition, collection and analysis of weather data from pest-affected areas is an essential input for models. The practical application of model outputs is aided by decision support systems. Weather-based forecasting systems reduce the cost of production by optimizing the timing and frequency of application of control measures for minimizing crop loss and reducing cost of plant protection. Devising forecast model consumes a lot of resources *viz*., manpower, time, etc. Hence, it is important that such resources are provided only to an important crop. The candidate pest (both insect-pest and disease) should be sporadic and its occurrence, severity, progression should be influenced by weather factors and hence should vary accordingly, should cause economically significant yield losses over large area and availability of timely and quality forecast could enable to mitigate the risks due to the occurrence of the same by application of effective economic prophylactic measure. Forecast models provide an alternative to calendar spray schedule to bring need-based precision, *e.g*., instead of sprays at 7-14 day intervals to spray at precise time just when and where the pest is likely to appear or has just initiated to reduce input costs. Thus, precision pest management may bring down number of chemical pesticide sprays to provide economic and environmental benefits. Finally, the system of forecast should enable take economically acceptable action as an integral part of IPM package while growers should be capable and flexible enough to take due advantage of a pest forewarning. Forecasting model is a set of formulae, rule or algorithm patterned after the biology of the specific pathogen or insect-pest keeping in view the host and standard crop management practices.

Insect pests

DYMEX model used to analyze the relationship between climatic parameters and organism population changes in a certain region (Maywald et al., 2007). DYMEX consists of two parts, namely builder (consists of various modules that are integrated for building models) and Simulator (to run the model that has been built in the builder). The model DYMEX was able to predict the influence of climate on the dynamics of YSB population and produce a monthly or seasonal trend pattern, with the value of R^2 of 0.74 (calibration) and 0.88 (validation) (Nurhayati et al., 2017).

Several workers have analyzed influence of weather factors on Brown Plant Hopper (BPH) population and observed temperature, humidity and rainfall to be important ones (Yadav et al., 2010; Win et al., 2011). In general, pest weather relations have been analyzed through empirical models, which behave in location- specific manner (Chander, 2010).

A forewarning model for rice leaf folder was developed based on peaks of its light trap catches weather parameters such as maximum temperature, morning relative humidity, evening relative humidity and SSH, wherein these four weather factors together could explain 99 % variability in leaf folder light trap peaks in Punjab. Weather analysis suggested that besides other factors, hotter and drier conditions during June and July in 2012 might have played a role in the leaf folder outbreak (Singh et al., 2015).

Diseases

A number of simulation models have been developed for rice diseases to understand, predict, and manage rice diseases (Hashimoto et al., 1984; Kobayashi et al., 2001). To predict disease incidence more precisely, the models generally try to incorporate all major environmental and cultural factors into the model simulation. Thus, a successfully developed model may not be widely adaptable to other areas where cultivars, cultural practices, and environments are quite different. In addition, due to structural complexities and temporal and spatial restrictions of their input requirements, it is difficult to link these models to other applications such as GIS and global climate model (GCM)-generated climate data at various temporal and spatial resolutions.

To consider as many factors affecting disease development as possible, many rice disease models need cultivation-related information such as the rice cultivar, transplanting date, and even daily trapped airborne fungal spore numbers as input variables. A broad range of weather variables is also used for the modeling, including air temperature, relative humidity, rainfall, solar radiation, wind speed and others. Furthermore, some of the models were validated for only one or a few field-level sites, limiting their application to specific regions.

Rice blast is the most destructive rice disease causing enormous losses every year. The most frequent climatic variables used are air temperature, followed by relative humidity and rainfall. The key pathogenesis factors, for instance leaf wetness, nitrogen fertilization and varietal resistance showed restricted incorporation for the development of these models. Currently, five forecasting systems are operational in Japan, Korea and India. Manibhushanrao and Krishnan (1991) developed EPIBLA (EPIdemiology of BLAst) model using multiple regression equations based on maximum temperature and maximum RH for simulation of leaf blast incidence. Kaundal et al. (2006) introduced a machine learning techniques model for forecasting rice blast in India. Six weather variables were selected *viz*; temperature, RH, rainfall and rainy days per week. Blast is mostly preferred by particular air and soil temperatures, relative humidity (RH), hours of continuous leaf wetness (LW), degree of light intensity and duration and timing of dark periods, all of which have been considered as very crucial for development of the disease. Yoshino (1979) in Japan developed a model that determined *P.oryzae* (Blast) infection periods, evaluating weather conditions every hour, producing hourly results that indicated if the conditions would result in successful infections. The model consisted of two parts of which the first comprised three favourable conditions for successful conidium penetration and hence successful infections:

1. The moving average of air temperature during past 5 day is 20-25°C

2. The rainfall to be below 4 mm h^{-1}

3. The continuous wet period >4 h than the base wet hours, calculated by the equation below:

Base wet hours = $60.09 - 4.216 \times temp_{wet} + 0.08858 \times temp_{wet}2$

(Where $temp_{wet}$ is the air temperature when the leaves are wet)

The second part estimated the number of "infection hours", the hours where the three conditions of the first part are hold true. The infection hours for each day determined by the model were accumulated for 1 day, in order to calculate the daily infection warning hours (DIWH). The DIWH was categorized into four risk levels: 1) zero risk, DIWH = 0 h; 2), low risk, 1 h ≤ DIWH < 3 h; 3), intermediate risk, 3 h ≤ DIWH < 6 h; and 4) and high risk, DIWH < 6 h. The Yoshino model is still used as part of three forecasting systems: a commercial system developed in Austria and in the models published by Kang et al. (2010). In India EPIBLA (EPIdemiology of BLAst) a simulated model on incidence of blast has been developed and made 7-day forecasts of disease progression in many parts of India. Calvero and Teng (1992) in the Philippines developed BLASTSIM.2 model for blast. Kang et al. (2010) developed a forecasting model describing an online information system for plant diseases based on weather data.Savary et al. (2012) in Korea developed EPIRICE, a generic model for plant diseases which was coupled with GIS.

Computer based decision support system

Decision support systems (DSS) is a computer programme that contains expert knowledge about a particular problem domain, that is able to solve the problems at a Level equivalent to or greater than human expert. DSSs include knowledge-based systems and acts as an interactive software-based system to help decision makers compile useful information from a combination of raw data, documents and personal knowledge or business models to identify and solve problems and make decisions (Goodell et al., 1990). Computer-based DSSs have the potential to be important tools in the decision-making process for farmers in pest management and their advisers. Several DSS were developed for agricultural management, but majority of them addressed issues like scheduling irrigation and water requirements. There has been limited research on decision support systems for real-time estimation of damage inflicted by insect pests and diseases in rice. Decision support system for insect pests of rice and cotton based cropping systems has been developed by Central Research Institute for Dryland Agriculture, India (Coughlan and Huda, 2008; Patel and Kadam, 2016 and Prasad et al., 2006). National Institute of Agricultural Extension Management (MANAGE), India developed an expert system to diagnose insect pests of rice crop and suggest preventive/curative measures. The rice crop doctor illustrates the use of expert systems broadly in the area of agriculture and more specifically in the area of rice production through development of a prototype, taking into consideration a few major pests and some deficiency problems limiting rice yield.

Machine learning for crop protection

Effective crop protection requires early and accurate detection of weeds, plant diseases and insect pests in crops. These are related both to the development of non-invasive, high resolution optical sensors and data analysis methods that are able to cope with the resolution, size and complexity of the signals from these sensors. The main aim of using machine learning methods in precision crop protection is to detect variability or heterogeneity within crop stands caused by biotic stresses (such as diseases or weeds) from sensor data. Machine learning methods are able to analyze high dimensional data with unknown statistical characteristics for precision crop protection by learning the model structure directly from training data. Remote and near-sensed optical data has been widely explored as a possible data source for the detection and mapping of weeds and plant diseases in agricultural crops (Behmann et al., 2014; Mahlein et al., 2012b).

Several methods of machine learning have been utilized for precision crop protection such as support vector machines and neural networks for classification (supervised learning); k-means and self-organizing maps for clustering (unsupervised learning). These methods are able to calculate both linear and non-linear models, require few statistical assumptions and adapt flexibly to a wide range of data characteristics. Successful applications include the early detection of plant diseases based on spectral features and weed detection based on shape descriptors with supervised or unsupervised learning methods. Machine learning methods like artificial neural networks (ANN) or support vector machines (SVM) are the most common methods used for data analysis (Zhang et al., 2003; Moshou et al., 2004; Rumpf et al., 2010). Moshou et al. (2004) used ANNs to differentiate healthy plants from diseased wheat plants. Rumpf et al. (2010) using SVMs identified foliar diseases sugar beet in a pre-symptomatic stage. Quin et al. (2009) differentiated healthy citrus fruits, canker diseased and damaged fruits using hyperspectral imaging sensors. Mahlein et al. (2010) identified different significant regions of difference spectra from healthy plants and plants diseased with *Cercospora* leaf spot, powdery mildew and sugar beet rust. Delalieux et al. (2007) detected apple scab at different stages of disease development due to *V. inaequalis*, by using SVIs (Steddom et al., 2005) calculated different indices of sugar beet by using SVIs and compared to disease severity visually rated by plant pathologists.

In recent years, remarkable results have been achieved in crop protection and pest management through sensor systems, such as multi-spectral, hyperspectral and chlorophyll fluorescence, can provide high resolution data concerning precision agriculture (Behmann et al., 2014; Mahlein et al., 2012a; Mahlein et al., 2013). Progress in sensor technology along with advances in computer science and geographic information system offers new opportunities for precision agriculture, and constitutes the basis for early detection and identification of weeds and plant diseases (Behmann et al., 2014; Chaerle et al., 2004; Lee et al., 2010; Moshou et al., 2004; Rumpf et al., 2010). Advanced methods of machine learning, such as k-means, support vector machines (SVMs) and neural networks (NNs), require less prior information and are applicable to a wider range of tasks as they derive the underlying distributions and model assumptions implicitly from training data (Mitchell, 1997). A brief literature overview on the application of machine learning methods for the detection of pest and disease within the current process of digital innovations are given below,

Detection of plant diseases

Detecting and forecasting plant diseases in the field provides a basis for sustainable and effective plant protection. In this context, machine learning is applied to different kinds of sensor data.To differentiate biotic stress of plants using machine learning was revealed by Moshou et al. (2004). They automatically detected yellow rust in wheat on the basis of reflectance measurements using Neural Network (NNs). Wang et al. (2008) were able to predict *Phytophthora infestans* infections on tomato plants by relevant regions of hyperspectral signatures using NNs. They identified diseased tomato plants when first symptoms were visible. Wu et al. (2008) showed that early detection of *Botryis cinerea* on eggplant leaves is possible by applying Principal Component Aanalysis (PCA) before NN classification using hyperspectral signatures as features. In their study, first small symptoms of grey mold on eggplant leaves were accurately detectable. Liu et al. (2010) detected rice glume blight disease in rice panicles combining PCA and subsequent NN classification, differentiating between healthy, light, moderate and serious infection levels. However, this study was performed under controlled conditions and they stated that it is probably not applicable for monitoring the health status of rice under field conditions. Rumpf et al. (2010) published one of the first studies demonstrating early detection of plant diseases before visible symptoms appeared by using SVMs. Nine spectral vegetation indices, related to physiological parameters, were used as features for automatic classification of relevant sugar beet diseases.

Geographic Information System and Remote Sensing technology

Geographic information systems (GIS) are computer hardware and software that use feature attributes and location data to produce maps. An important function of an agricultural GIS is to store layers of information, such as yields, soil survey maps, remotely sensed data, crop scouting reports and soil nutrient levels. Geographically referenced data can be displayed in the GIS, adding a visual perspective for interpretation. In addition to data storage and display, the GIS can be used to evaluate present and alternative management by combining and manipulating data layers to produce an analysis of management scenarios. GIS and global positioning systems are currently being used for variable rate application of pesticides, herbicide and fertilizers in precision agriculture applications, but the comparatively lesser-used tools of remote sensing and spatial analyses can be of additional value in integrated pest management practices.

Remote sensing is collection of data from a distance. Data sensors can simply be hand-held devices, mounted on aircraft or satellite based. Remotely-sensed data provide a tool for evaluating crop health. Plant stress related to moisture, nutrients, compaction, crop diseases and other plant health concerns are often easily detected in overhead images. Electronic cameras can also record near infrared images that are highly correlated with healthy plant tissue. New image sensors with high spectral resolution are increasing the information collected from satellites. Remote sensing can reveal in-season variability that affects crop yield, and can be timely enough to make management decisions that improve profitability for the current crop. Remote sensing technologies may provide an alternative to visual disease assessment (Nutter et al., 2010).

Thermography can be applied in terms of near or remote sensing, from microscope application over ground-based equipment to airborne sensors. The major advantage of infrared thermal imaging is the non-invasive, non-contact, and non-destructive nature of the technique to determine the temperature distribution of any object in a short period of time (Vadivambal and Jayas, 2011).Insect pests and diseases are usually unevenly distributed throughout an area in nature. Despite this knowledge, analytical methods and technology have limited insect pest and disease management to uniform management decisions in the field. Recently, the methods and technology to map and analyze insects and diseases spatial distribution and have been developed to a level where the uneven nature of insect populations and disease severity can be considered for application of management tactics. This new approach to pest management is termed site-specific pest management. Site-specific pest management utilizes spatial information about pest distribution to apply control tactics only where pest density is economically high within a field (Park et al., 2007). Early detection of insect pest infestation is an essential step to take up timely management measure. The real time pest and disease detection in large-scale farming of rice crop for pest management is a difficult task; to overcome this hyper spectral remote sensing is a powerful for detecting stresses caused due to insect pests and diseases in green vegetation at the leaf and canopy levels (Kobayashi et al., 2001).

The interaction of electromagnetic radiation and plants varies with the wavelength of the radiation. The same plant leaves may exhibit significant different reflectance depending on the level of health and or vigor (West et al. 2003; Luo et al., 2010). Healthy and vigorously growing plant leaves will generally have (i) Low reflectance at visible wavelengths owing to strong absorption by photoactive pigments (chlorophylls, anthocyanins, carotenoids) (ii) High reflectance in the near infrared because of multiple scattering at the air-cell interfaces in the leaf's internal tissue (iii) Low reflectance in wide wave bands in the short-wave infrared because of absorption by water, proteins, and other carbon constituents. The incidence and severity of pest and diseases can be monitored according to the differences of spectral characteristics between healthy and stressed plants.

Infestation of rice insect pests such as yellow stem borer (YSB) (*Scirpophaga incertulas*), brown planthopper (BPH) (*Nilaparvata lugens*), leaf folder (*Cnaphalocrocis medinalis*) and diseases like blast, bacterial blight, sheath blight, false smut are the most notable risks in rice yield in tropical areas especially in Asia. In order to use visible and infrared images to detect stress in rice production caused by these biotic stress, several remote sensing techniques have been developed (Table 1). High spectral resolution remote sensing imagery with more bands and narrower bandwidth is required to diagnose crop stress. The crop affected by insect gives different tonal variation in imageries than normal crop. Normal crops give red, bright red and dark red with smooth texture but pest affected areas give pink, yellow and yellow pinkish red colour with irregular shape and rough texture.

Hyperspectral techniques

The evolution of spectral sensors started with multispectral sensors, to hyperspectral sensors, and to forthcoming ultra spectral sensors. These technical complex devices provide a multiplicity of information over the covered spectral range (350-2500 nm). Spectral resolution of modern instruments may be <1 nm. Non-imaging sensors average the reflectance over an area depending on the sensor's field of view; the mixed information from different objects hardly allows significant inferences on the reflectance sources/objects (Mahlein et al., 2010). Quin et al. (2009) developed a hyperspectral imaging approach to detect canker lesions on citrus fruits. Zhao et al. (2012) used hyperspectral imaging data to quantify infestation of oilseed rape by cabbage caterpillar. Mewes et al. (2011) stated that the entire spectrum from 350 to 2500 nm is not needed to detect crop stress due to fungal infections. Since non-imaging hyperspectroscopy has been used in most of the studies published up to now, the application of hyperspectral imaging focusing on spectral information of disease symptoms is limited. Bravo et al. (2003) used in field spectral images for an early detection of yellow rust infecting wheat, Hillnhütter et al. (2011) successfully discriminated symptoms caused by *Heterodera schachtii* and *Rhizoctonia solani* on sugar beet. At the present time, hyperspectral imaging is more widespread in the field of monitoring fruit security and quality.

Table 1. Sensitive bands and spectral indices for different kinds of biotic stresses in rice.

Insect pests/ Diseases	Platform	Spectral resolution	Optimum bands (in nm)/ indices/ technique used	Reference
Panicle blast	Ground based and air borne	Hyperspectral	485,675 nm; (R470/R570);(R520/R675);(R570/R675);(R550/R970); (R725/R900)	Kobayashi et al. (2001)
Leaf blast	Ground based	Multispectral	(R550/R675), (R570/R675)	Kobayashi et al. (2003)
Sheath blight	Air borne	Multispectral (ADAR)	RI, SDI	Qin and Zhang (2005)
Bacterial leaf blight	Ground based	Hyperspectral	943 and1039 nm, MLR	Yang (2010)
Brown spot	Ground based	Hyperspectral	(R702/R718), (R692/R530), (R692/R732)	Liu et al. (2008)
Brown plant hopper	Ground based	Hyperspectral	426, 1450 nm, linear	Yang et al. (2007)
Leaf folder	Ground based	Hyperspectral	757, 445nm correlation intensity analysis	Yang et al. (2007)
Rice stem borer	Ground based	Hyperspectral	570-700nm, BPNN	Fan et al. (2017)

Unmanned aerial vehicle

Recently, the growing use of unmanned aerial vehicles (UAV) for pesticide application has been reported against a wide range of crops with promising results in East Asian countries such as Japan, South Korea and China. This UAV-based application technology for agrochemicals is considered as a high efficiency alternative to the conventional manual spray operations and a low-cost choice as compared to the classical manned aerial application. Medium or small unmanned aerial vehicles (UAV), also known as drones or remotely piloted aircraft (RPA) systems are increasingly investigated and used now-a-days for pesticide applications.The rapid development of Asian agricultural UAV is mainly due to its advantages including: (1) UAV does not require any dedicated airport and navigation station, and may land on the edge of cultivated land, the highway and the top of a truck, reducing the expenditure of airline and for agriculture and forestry; (2) the short turning radius of UAV could help it hover and turn round flexibly in the air; (3) the high rate of climb of UAV could help it fly vertically and have good performance of super low flight; (4) low rate of no-load flight of UAV and filling fuel and liquid on the ground of working area could reduce invalid working time; (5) UAV is suitable for working in rough terrain and small plots with high efficiency; (6) high automaticity, less flight crew, low labor intensity and simple to use and maintain as compared to traditional manned aircraf (Xiongkui et al., 2017).

In terms of spray effect: (1) UAV's high working efficiency and good spray performance is as great as helicopter; (2) UAV can change velocity flexibly, accelerate from 0 to the normal speed directly, and get better droplets coverage at low speed, also especially its downwash flow generated by rotors may reduce the droplets drift and the upflow generated by thedownwash flow let droplets crash into the reverse side of plant leaves.

Mobile application in pest management

The need for timely access to information for taking appropriate decision in pest management needs no emphasis. Keeping this in view, various options have been explored for transferring information to farmers in a timely and cost-effective manner. The potential of information and communication technologies (ICTs) in enabling access to and exchange of information for farmers is evident. Among ICTs, there has been increasing use of mobile phones which is changing the agricultural communication process. The introduction of mobile phones has resulted in new services and applications. In the crop protection sector, these include proper identification of insect pests, diseases and other biotic stresses etc.

As on 31st July 2017 the number of telephone subscribers was 1210.71 million (1186.79 million wireless and 23.92 million fixed land line telephones) as estimated by the Telecom Regulatory Authority of India (TRAI, 2017). The tele-density has reached 93.88 per cent as of July 2017. However, there is huge gap between urban and rural tele-density, 173.21 and 57.45, respectively. According to International Data Corporation (IDC), India has the fastest-growing smartphone market in the world, accounting for 27.5 million devices sold in the second quarter of 2016, up 17 percent from the previous quarter. Mobile subscriptions are expected to reach1.4 billion by 2021, according to the Ericsson Mobility Report of June 2016.

The introduction of mobile phones has led to the development of new services and applications in agriculture for the benefit of farmers and other stakeholders. Services that started with occasional messages have evolved to multimodal and multimedia delivery of advisory and to mobile-agriculture applications for smartphones. These services are addressing the information and communication gap between farmers and extension personnel and giving a bargaining position to farmers (Saravanan, 2014). Access to information on new varieties, inputs such as seed, fertilizers, machinery,price information, weather, pests and diseases, nutrient management at the right time can help farmers get access to crucial information to support activities from production to marketing.

riceXpert app: A case study

Mobile applications or apps are popular and resourceful media of mass communication these days. Since agriculture is the socio-economic backbone of India and many developing countries, agriculture-related mobile apps hold many possibilities to empower the farmers and other stakeholders alike for sustainable agriculture (Deobhanj, 2018, ICAR, 2018; Mohapatra et al, 2018a).

Keeping in view the multifold benefits of mobile app and with the aim of building inexpensive tools and user-friendly technologies to bridge some of the information gaps in farmer's field, the ICAR-National Rice Research Institute (NRRI), Cuttack has developed a mobile App 'riceXpert' in tri-lingual (English, Hindi and Odia) to reach the latest rice technologies to the farmers in real time basis.

The riceXpert app is designed and developed in Android platform which is compatible with the Android version 4.0.3 and above smartphones which will operate in online system. This app provides real time diagnosis of insect pests, diseases, nematodes, weeds, nutrient deficiencies and toxicities to farmers. The App has other features like rice varieties, agricultural implements, news, expert consultation through e-advisory services module, weather information and customized Pest Solution and Fertilizer Calculator etc. Farmers and farm women can use this App as a diagnostic tool in their rice fields and also make customized queries through text, photo or voice and that would be addressed by panel of experts on real time basis and get quick solution along with recommendations of their problem through Short Message Service (SMS). This app also provides platform for the farmers who have no organized way to sell their produce and rice related products and by-products. Farmers can post their rice or rice related products for interested buyer. The buyer can access the detailed information about the products through the app and get the products at the best prices through direct interaction. The App is also very useful tool for the researchers, Scientists, Students and village level workers working on rice crop. From pest management prospective, a detailed information has been provided in the following headings (Mohapatra et al., 2017a; 2017b; 2018b; 2018c; 2018d; 2018e).

Insect pests

Under this menu, there are list of rice insect pests based on their mode of feeding viz., stem borer, foliage feeder, sap feeder, leaf feeder, panicle feeder is provided. Besides, the potential natural enemies of rice insect pests, Economic threshold level (ETL) of the major insect pests of rice at different crop stages and recommended insecticides by the experts are clearly mentioned. Control measures of the insect pests through Integrated Pest Management (IPM) are also given.

Diseases

Rice crop is generally affected by three types of diseases fungal disease, bacterial disease, viral and mycoplasma disease. All these diseases included under these three categories are described in easy to understand language. Photos, identification symptoms and management of the disease will be shown from primary stage to severe stage if any one disease option will be choosen. Under integrated disease management (IDM) option, control of the disease by cultural and bio-control methods which are not harmful to environment are described. Also under another option the name of the fungicides and bactericides with recommended doses are also given.

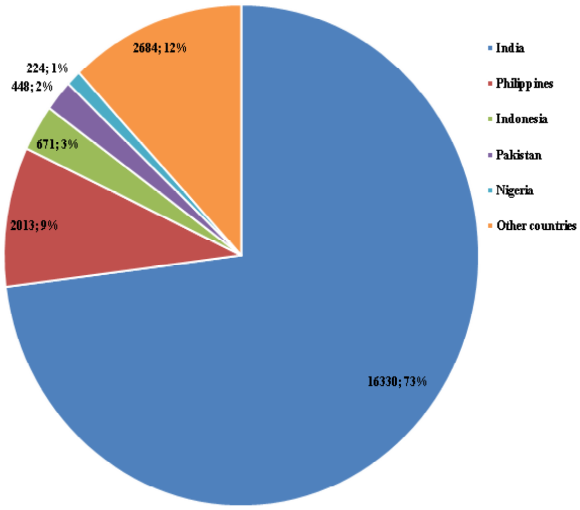
Nematodes

There are three major nematodes which are described under this option. These are root knot nematode, white tip nematode and root nematode. By selecting any of these three nematodes photos of infected plant parts, identification symptoms and management methods will be shown immediately.

Pest Solution

By using this module, farmers can calculate the required quantity of recommended pesticide for their affected area based on their pest (insect pest, disease, weed) problems through this module. Automatically a prescription will be generated as per their selected pest problem which can be downloaded and printed.

riceXpert, currently having more than 23,000 users covering India (73%), Philippines (9%), Indonesia (3%), Pakistan (2%), Nigeria (1%) and other counties (12%). More than 1500 queries relating to rice insect pest, disease, weed, variety, farm implement, nutrient toxicity/deficiency and other aspects of rice have been received from the Indian users through e-rice advisory module of the app covering almost all rice growing states of India and the queries are being addressed by the panel of experts from and the solutions are being sent to them through SMS. Perusal of the month-wise statistics on the year 2018 downloads of riceXpert app revealed that August (1583) month recorded the highest users of the riceXpert app followed by September (1236) and October (1110).



Country-wise NRRI riceXpert app users as on August 2018

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