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REMOTE SENSING OF AGRICULTURAL DISASTERS MONITORING: RECENT ADVANCES

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Abstract

Agricultural disasters are the adverse reaction of crop to environmental conditions that are unfavorable to their growth, such as drought, flooding, extreme temperatures, disease and insect infestation. With the advancement of the agricultural information technology, remote sensing system, and advances in data analysis techniques, these drivers have inspired new thinking and impetus to the agricultural disasters monitoring. Aiming to generalize the knowledge and provide perspectives for remote sensing of agricultural disasters, this paper had summarized data functionalities, data processing methodologies and recent advances of agricultural remote sensing. Literatures on remote sensing of agricultural disasters monitoring were then reviewed. Judging from the development trend, agricultural remote sensing had been significantly benefit from rapid development of information technologies, availability of multi-source data, Precision Agriculture equipment, and the integration with physical model. These advances suggested many opportunities and challenges for remote sensing in agricultural disasters monitoring. The development for remote sensing of agricultural disasters should be paid more attention to the following aspects: (1) fully understanding the merit of remote sensing; (2) quantifying and validating of disasters monitoring; (3) strengthening early warning capability; (4) fusing multi-sources data; (5) bridging the gaps between experimental studies and practical applications.
Keywords: agricultural disasters, remote sensing, monitoring

1 Introduction

With the theoretical breakthroughs in plant spectroscopy, plant biology and ecology had been given quantitative description by spectral responses of pigment variation, physiology or morphology changes (Usha and Singh 2013, Jackson 1986). A variety of biophysical/biochemical characteristics of vegetation can be quantified by electromagnetic spectrum information from detecting sensor (Wallach *et al.* 2006, Mulla 2013, Liang 2008, Dorigo *et al.* 2007, Schaepman *et al.* 2009). Therefore, the cognition based on the correlation between plant physiology and spectral response indicated that detection and prediction models can be established for monitoring crop growth, stress status and yield forecasting (Jackson 1986, Schaepman *et al.* 2009, Ullah *et al.* 2014, Thenkabail *et al.* 2000, Sankaran *et al.* 2010, Martinelli *et al.* 2014).

Large scale remote sensing monitoring on agriculture was proved beneficial for policy making and economic development half a century ago. From the end of 20th century, remote sensing had been widely adopted for agricultural resources investigation, crop yield estimation, and agrometeorological disasters monitoring (Liang 2008, Sivakumar *et al.* 2005, Sivakumar *et al.* 2003, Tralli *et al.* 2005). At present, satellite remote sensing has provided adequate spectral coverage spanning visible (VIS), near infrared (NIR), thermal infrared (TIR) and microwave (e.g., Synthetic Aperture Radar, SAR) bands. Although the existing satellites had not been solely designed for observing natural disasters, global satellite-materials for earth observation had been already adopted for disasters management (Sivakumar *et al.* 2005, Sivakumar *et al.* 2003, Sandau *et al.* 2010). Currently, the on-orbit satellite platforms (geostationary and polar-orbiting) have provided remote sensing data for earth system parameters acquisition, evaluation, and integration. They can be applied in retrieval of meteorological parameters (e.g., radiation, precipitation, temperature), vegetation parameters (e.g., leaf area index (LAI)), and soil moisture(Sivakumar *et al.* 2005, Sivakumar *et al.* 2003), which dedicated to timely detection of droughts, frost, forest fires and other extreme events. Timely monitoring, early warning and forecasting of agricultural disasters are critical for effective crop failures assessment and decision making; enhancing the forecasting capability and establishing emergency response system for agriculture will be of benefit for stability of civil economy and society development (Sankaran *et al.* 2010, Sivakumar *et al.* 2003, Tapia-Silva *et al.* 2011).

Agricultural disasters are generally a dynamic process that requires frequent observation; temporally continuous remote sensing data allow assessment of regional vegetation condition. However, most of agricultural disasters cannot be viewed as physical phenomenon via intuitive remote sensing observation; crop growth monitoring and yield formation have strong relationship with climate condition. For instance, low temperature climate would affect crop development and sterility; high temperature and humidity would induce diseases and pests (Liang 2008, Sivakumar *et al.* 2003, Marques da Silva *et al.* 2015). Therefore, continuous remote sensing observations are required for monitoring those unfavorable weather event.

Due to their frequent occurrences, timely and accurate prediction for agricultural disasters is of great significance for reducing losses; and ensuring sustainable development for agricultural production (Sivakumar *et al.* 2005, Brown *et al.* 2012). However, the occurrences and extent of agricultural disasters depend not only on weather elements, but also on geographical background (e.g., altitude), crop growth status, and local crop management practice. Geographical information system (GIS) had been recognized as a powerful tool for integrating remote sensing data and the auxiliary data. It can manipulate information from different sources, like agro-meteorological databases, remote sensing or digital maps; and visualize the behavior in geo-spatial disasters model (Sivakumar *et al.* 2005, Phillip 2009). The perception of disasters risk is critical for precautions and preventions then indicate rational solutions. Researchers utilize remote sensing and GIS model to perform disasters risk assessment, spatially characterizing potential cautious areas (Sivakumar *et al.* 2005, Sivakumar *et al.* 2003, Tralli *et al.* 2005, Tapia-Silva *et al.* 2011, Phillip 2009, Belal *et al.* 2014). Research cases such as identifying crop-producing area that is potentially experiencing severe disease (Zhang *et al.* 2014); identifying the geographical factors that cause low temperature injury; and social-economic driving forces that cause flood occurrence risk (Sivakumar *et al.* 2003, Tran *et al.* 2010, Cheng *et al.* 2013a), etc. More often than not, for a large scale observation, remote sensing is used as a crucial data source for disaster risk management, combined with GIS and physical models (e.g., meteorological model, crop growth model, or hydrological model) (e.g., meteorological model, crop growth model, or hydrological model) (Wallach *et al.* 2006, Liang 2008, Dorigo *et al.* 2007, Yu *et al.* 2014, Launay and Guerif 2005, Ines *et al.* 2013, Han *et al.* 2010, Chormanski *et al.* 2011).

In recent years, remote sensing techniques had advanced including radiometric/geometric correction, detection methodologies, and especially computational facilities which generated great benefit in remote sensing of agricultural application (Mulla 2013, Liang 2008, Sivakumar *et al.* 2003, Mountrakis *et al.* 2011, Manakos and Braun 2014, Salamí *et al.* 2014, Wang *et al.* 2013). In addition, remote sensing of agriculture had been developed as a multi-sources, multi-scales, and multi-disciplinary reference that spans fields of geography, meteorology, biology, and somewhat related to information sciences. Nowadays, remote sensing data can be used to acquire crop growth status, characterize cropping system (Wardlow and Egbert 2008), monitor crop phenology (Pan et al. 2015), retrieve air temperature (Zhang *et al.* 2013a, Vancutsem *et al.* 2010), measure precipitation (Qin et al. 2014); those measurements are environmental indicators for agricultural disasters in agro-meteorology. Besides, by integrating multi-sources observation and physical modeling it is helpful for understanding the complex consequences from hypothesized disaster scenarios (Tralli et al. 2005). Current agricultural disaster management is primarily meant to assess physical damage to crop area; however, disaster management cannot be solved solely by remote sensing; the susceptibility of other critical elements, such as social structures, economic activities, should be introduced in conceptual risk management frameworks (Wheeler and Braun 2013).

As briefly introduced above, the motivation of writing this review paper is to address an important topic on remote sensing in disaster reduction and mitigation. Even though a lot of problems related to the entitled topic remained unsolved, previous studies had made a lot of contribution for understanding problem. This paper was not aiming to address a specific methodology or focus on a specific type of disaster; neither to provide critical analysis on study cases. Instead, bridging the knowledge gaps in remote sensing of agriculture disasters is the scope of this paper. It also tried to provide an insightful perspective on how to cope with the challenges and take full advantage of the emerging advances. At last, hopefully this review paper is suggestive and supportive for the readers, and proposed future direction for the remote sensing of agricultural applications.

2 Data functionalities and methodologies

2.1 Remote sensing data overview

Remote sensing of agriculture is generally classified by the platform for mounting remote sensors, including satellite, aerial, and ground based platforms (see Fig.1). Three basic questions should be answered before choosing remote sensing data or starting a research project: (1) How much spatial coverage is needed? (2) What spectral coverage makes sense? (3) What spatial resolution of remote sensing data is necessary? The key to the successful application of remotely sensed data for detecting plant stress is to match the appropriate sensor and analysis methods to the information requirements (Zhang et al. 2002). Robust, low-cost, and real-time sensing systems are preferably needed for implementing various agricultural disasters monitoring (Wulder *et al.* 2006).

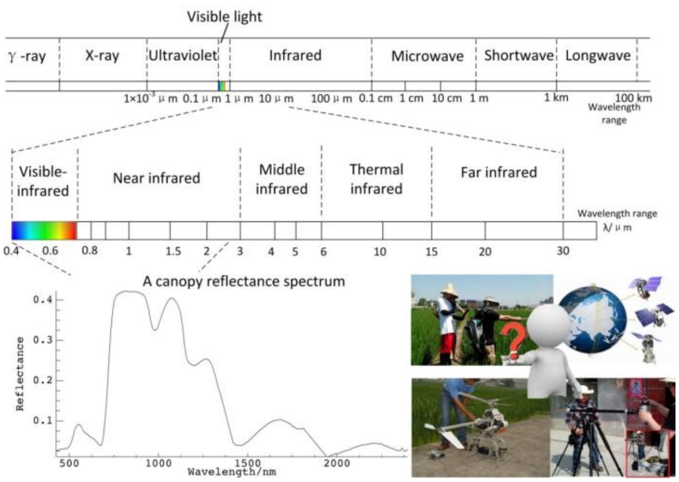

Fig.1 Illustration of electromagnetic spectral range, associated with sensors and platforms

Multispectral optical remote sensing data play a crucial role in agricultural applications. The development of high spatial resolution is appealing at these days (e.g., WorldView, RapidEye). Compared to multispectral remote sensing, hyperspectral sensing is a relatively new technology that is capable of collecting narrow electromagnetic spectrum information to reconstruct a contiguous spectrum; it is capable of discriminating very fine ground features (van der Meer et al. 2012, Goetz 2009). Spectroscopic image acquired from hyperspectral sensors have been used for many aspects in agriculture: estimating crop vigor and yield; discrimination between crops, weeds, residue, and soil; quantitative measurements of crop water content and leaf area index (Zhang et al. 2002, Clevers et al. 2010); diagnosis of low temperature stresses in crop (Wu et al. 2012).

The thermal infrared wavelength usually ranges from 8 to 14 µm; thermal emission radiometer had been implemented on crop leaf and canopy levels to detect thermal-based spectral characteristics which indicate water deficiency and crop health status (Jackson 1986, Pinter et al. 2003). Thermal infrared Satellite data appear as valuable tool for vegetation growth and conditions assessment via retrieval of land surface temperature and estimation of evapotranspiration (ET) by various modeling approaches. Landsat, ASTER, and MODIS are well-known thermal infrared data. Land surface temperature (LST) can be used for agro-meteorological applications such as mapping of extreme high/low temperature weather events, and regional heat resources assessment (Zhang et al. 2013a, Hassan et al. 2007), etc. Herein, the conversion of satellite-observed land surface temperature to air temperature is of interest to the agricultural management community (Kilibarda et al. 2014, Jang et al. 2014).

The distinctive advantage of microwave remote sensing data lies in its capability to penetrate cloud cover to monitor ground surface. On the basis of the contrast in dielectric constant values of dry and wet soils, passive microwave and synthetic aperture radar data are good option for monitoring water content in soils and vegetation (Jackson 1986, Liang 2008, Schmugge 1983). As soil moisture is crucial variable that related to evaporation, occurrence of landslide and flood; recent advances in microwave technology has demonstrated its ability to measure soil moisture under a variety of topographic and vegetative cover (Liang 2008, Sivakumar et al. 2003, Phillip 2009, Schmugge 1983, Zhang and Jia 2013, Owe et al. 2008). The AMSR-E and the SMOS provides global maps of soil moisture with specified accuracy, sensitivity, and spatial coverage (Phillip 2009). Passive microwave is an ideal data source for rainfall monitoring, e.g., the microwave imager Tropical Rainfall Measuring Mission (TRMM) provides global precipitation measurement (Qin et al. 2014). Additionally, owing to the advantage of passive microwave data, a number of researches had attempted to retrieve temperature (Jang et al. 2014, Chen et al. 2011). Besides, active microwave response data had been demonstrated a high correlation with crop chlorophyll that can be used to detect crop diseases and pests damage (Singh et al. 2007).

The development of unmanned aerial vehicles (UAV), has received substantial attention. UAV appears to provide a good complement to the current remote sensing platforms for rapid remote sensing monitoring mission (see Fig.2) attributing to their promising in low-cost and very high resolutions (Sankaran et al. 2010, Martinelli et al. 2014, Jones 2014). The miniaturization of electronics, computers and sensors has created new opportunities for low altitude remote sensing applications (Salamí et al. 2014). Indeed, the Precision Agriculture does gain great benefit from the UAV application, such as crop growth monitoring and fertilizer application. It is a general technology that can be applied on almost any cropping situation, e.g., horticulture (Usha and Singh 2013).

Fig. 2 Unmanned aerial vehicles provide real-time and in-situ crop monitoring

2.2 Spectroscopy and spectral analysis

Spectroscopy and spectral analysis are capable of identifying crop stress because most plants have leaf pigmentation change and water content reduction when suffering from stresses (Usha and Singh 2013, Jackson 1986, Ullah et al. 2014, Clevers et al. 2010, Wu et al. 2012, Gitelson et al. 2001, Blackburn 2006). Consequently, changes in the absorptive chemical concentrations provide a knowledge basis for changes in plant absorbance, transmittance, and reflectance (Schaepman et al. 2009, Blackburn 2006). As leaves expand, mature, senesce, their spectral properties can be affected owing to physiological and morphological changes. Comprehensive explanation on the spectral response of plant at leaf/canopy level and the characteristics of reflectance had been carried out for decades (Usha and Singh 2013, Jackson 1986, Sankaran et al. 2010, Blackburn 2006), which demonstrating that it is feasible to detect specific stress status of crop by means of imaging spectroscopy.

Usually, the wavelength range of spectral analysis covers from: visible-infrared (VIR), 0.4-0.7 μm; near infrared (NIR), 0.720-2.5 μm; middle infrared (MIR), 3.0-5.7 μm; and thermal infrared (TIR), 8.0-15 μm (see Fig.1). Spectral analysis had been employed to verify the capability of spectra detail to represent the crop stress or diseases. There are several commonly used methods to work with spectrum data: (1) Identifying those sensitive wavelengths by establishing spectral indices, or taking derivative in spectral range; (2) Principal Component Analysis (PCA); (3) Using selected bands combination to establish regression model (Mulla 2013, Ullah et al. 2014, Jin et al. 2013, Luedeling et al. 2009). Imaging spectroscopy is feasible to provide a characteristic of spectrum as well as intuitive observation of the area. Based on spectral analysis and vegetation indices calculation, crop stresses under circumstances can be identified, such as freeze injury (Wu et al. 2012), diseases and pests damage (Sankaran et al. 2010). Machine-learning methodology had been adopted in spectral analysis such as Artificial Neural Networks (ANN), support vector machine (SVM) (Behmann et al. 2014a, Behmann et al. 2014b, Liu et al. 2010). Signal-processing methodology such as continuous wavelet analysis for the detection of crop disease and pest damage had been recognized (Cheng et al. 2010). Indeed, the amount and quality of the available reference samples play an important role to obtain accurate prediction model (Huang and Apan 2006).

Vegetation Indices (VIs) are combinations of surface reflectance at two or more wavelengths designed to highlight a particular property of vegetation (Mulla 2013, Thenkabail et al. 2000, Gitelson et al. 2001). VIs are used to detect the presence and relative abundance of pigments, water content, or nutrition as expressed in the solar-reflected optical spectrum (400 nm to 2500 nm). By comparing the results of multi/hyperspectral-derived VIs and field conditions measured on site, researchers can assess which indices particularly representing crop properties, and then map out their variability in image, which can then be interpreted in terms of large scale vegetation growth conditions. Regarding for these, researchers commonly perform VIs value thresholding based on their knowledge and data characteristic (Usha and Singh 2013, Sivakumar et al. 2003, Wardlow and Egbert 2008, Pan et al. 2015, Zhang et al. 2002, Zhang et al. 2013b, She et al. 2015, Huete et al. 2002). In particular, the Normalized Difference Vegetation Index (NDVI) had been employed for various research fields.

However, spectroscopy and spectral analysis are still facing an unsolved obstacle from monitoring scale. The spectral response properties of crop canopy have been found to depend on atmospheric (e.g., illumination, cloudy shadow), edaphic (e.g., soil type, soil moisture), and biotic conditions (e.g., crop variety, leaf area index), as well as field management strategies (Liu et al. 2010, Liu et al. 2008). Even though the present studies indicate that it is possible to accurately identify crop stress with spectral features under laboratory conditions, but in most cases, it is still unpractical to do so when performing field-scale even aerial monitoring. Additionally, different disasters might have the same characteristics of spectral response, which can lead to difficulty in discriminating different stresses. The in-deep theory basis of fluorescence remote sensing in plant were still undiscovered; and their potentiality and application are still lacking research gaps (Usha and Singh 2013, Valentini et al. 1994).

2.3 Mapping, classification and detection with imagery

Remote sensing image interpretation usually involves identification methods to map out target. Undoubtedly, the advancing classification methodologies in remote sensing data are pushing agricultural applications forward.

Basically, the image classification methods can be categorized as: statistical-based and machine learning-based. Most of methodologies can be universally implemented in multi-spectral and hyperspectral image. The frequently adopted classification methods for crop area mapping include unsupervised/supervised classification, and decision tree classification. Using unsupervised classification to cluster pixels in a dataset is only based on data statistics, which includes ISODATA and K-Means. On the other hand, the use of supervised classification requires user-defined training classes which include Parallelepiped, Minimum Distance, Mahalanobis Distance, Maximum Likelihood, Spectral Information Divergence (SID), and Binary Encoding. Indeed, the amount and quality of the available training samples play an important role to obtain accurate land classifications.

Hyperspectral imaging can discriminate classes with very fine spectral signatures. There are many commonly used analysis techniques for hyperspectral remote sensing image: spectrum matching method, such as Spectral Angle Mapping (SAM) and Spectral Feature Fitting (SFF); sub-pixel method, such as Spectral Mixture Analysis (SMA), and Mixture Tuned Matched Filtering (MTMF) (Usha and Singh 2013, Martinelli et al. 2014, van der Meer et al. 2012, Plaza et al. 2009), etc. As spectra reflectance of plant will be change when suffering from stresses, by compared to healthy crop, the severity of spectral features is determined by separability between classes. Before performing image classification, the spectral features are measured using ground-based imaging spectrometers by sampling the training data from identified area.

In recent years, the kernel-based machine-learning image classification techniques have been recognized, e.g., Radial Basis Function Neural Networks (RBFNN), Support Vector Machine (SVM) (Behmann et al. 2014a); These approaches are robust to the Hughes phenomenon and can provide reasonably high classification accuracy (Mountrakis et al. 2011, Manakos and Braun 2014, Plaza et al. 2009). Data mining approaches had been adopted in risk assessment of flood using multi-temporal remote sensing images (Tapia-Silva et al. 2011). Besides, classification methods could be flexibly integrated together to generate higher accuracy (e.g., Hierarchical classification scheme (Wardlow and Egbert 2008); integrated with linear mixture model or neural network (Verbeiren et al. 2008)). Object-oriented classification strategy is superior to pixel-based classification especially for high spatial resolution image (Blaschke 2010, Kurtz et al. 2012). Likewise, hierarchical segmentation of hyperspectral images should be further developed as it greatly enhances the classification capability (Plaza et al. 2009). Nevertheless, there are still numerous kinds of hyperspectral image processing techniques concerning feature extraction, endmember extraction, anomaly target detection, etc. Nevertheless numerous methods were mentioned, they are more or less useful for agricultural disasters detection.

Additionally, knowledge-based classification methods are commonly used in large scale agricultural mapping. Approaches such as a combination with remote sensing imagery and geo-information data to distinguish crop area and types (Liang 2008). In general, evidences suggested that frequent remote sensing imagery and ancillary information such as climate-zoning, local cropping rotation system, phenological calendars, and topography would improve crop area classification (Ozdogan et al. 2010, Peng et al. 2011).

Natural disasters will probably result in land cover change before and after occurrence. According to Manakos and Braun (2014)(Manakos and Braun 2014), several methods were introduced to tackle with change extraction: (1) Image algebra, which leads to change extraction based on spectral values, backscatter values, spectral indices, texture features and related properties; (2) Transformation-based change extraction uses transformed images properties such as principal components analysis (PCA); (3) Classification based approaches; (4) Time series analysis, seasonal and abrupt changes are easily identified due to the variation in time series profile (see Fig.3). The idea of implementing time-series remote sensing data provide a new perspective for classification and land use change detection (Wardlow and Egbert 2008, Verbeiren et al. 2008, Small 2012). Spatiotemporal analysis with time-series data, researchers can monitor vegetation growth cycles and timings over large areas; and recognize the spatial distribution of potential agricultural disasters.

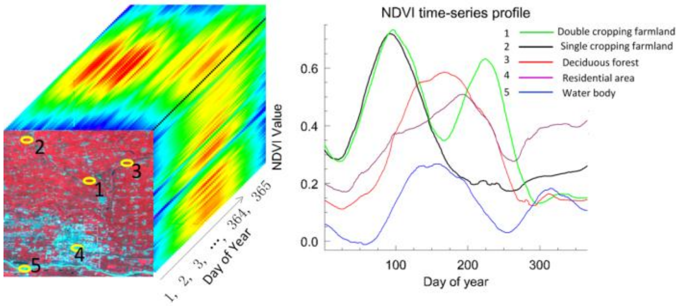

Fig. 3 Time-series remote sensing data represents spatiotemporal characteristics of ground features

Image classification plays a crucial role in remote sensing of agriculture; no argument should be made because agricultural disasters are related to so much knowledge that is beyond the technologies themselves. The performance of classification is quite objective-oriented that is depends on researcher's spatial scale and spectral signatures of land-cover classes (Manakos and Braun 2014).

3 Remote sensing of agriculture disasters

The remote sensing application in disasters monitoring including drought, flooding, low temperature, and crop diseases and pests damage were briefly reviewed.

3.1 Drought

Drought is one of most important weather-related natural disasters. Drought is a slow process which influences vegetation growth. It begins with precipitation/watering deficit, followed by soil moisture deficit, and then leads to crop failures (Belal et al. 2014, Pinter et al. 2003, Du et al. 2013). Remote sensing can measure rainfall, temperature, vegetation growth condition, soil water content which are necessary parameters when concerning drought monitoring and forecast.

Monitoring drought with remote sensing is based on two basic principles. First, changes in soil water content can lead to spectral reflectance variations in soil; second, soil water content can cause physiological changes in plant, and then change the spectral characteristics. Most commonly used crop canopy-level and satellite-level remote sensing involve vegetation indices-based and thermal infrared-based methods to obtain a quantitative description of crop water status (Sivakumar et al. 2003, Han et al. 2010, Du et al. 2013, Cheng et al. 2013b); such as Crop Water Stress Index (CWSI). Thermal infrared and microwave band data can get good indicators in crop water status (Jackson 1986). There are numerous drought monitoring methods using remote sensing; different approaches have their own advantages and limits; the applicability of remote sensing-based drought monitoring should be considered both arid and humid regions as well as multi-sensor data (Rhee et al. 2010).

Typically, NDVI has been employed to assess vegetation growth conditions by inspecting the variations of year-to-year NDVI value to identify drought occurrences (Phillip 2009, Wang et al. 2010). Zhang et al. (2013) modified NDVI time series data to construct a time-integrated vegetation condition index to identify real-time drought (Zhang et al. 2013b). Zhang and Jia (2013) developed a multi-sensor microwave remote sensing drought index, by integrating three remote sensing observations: TRMM-derived precipitation, AMSR-E-derived soil moisture, and AMSR-E-derived land surface temperature (Zhang and Jia 2013). Similarly, Du et al. (2013) suggested a comprehensive drought monitoring using synthesized remote sensing spectral indices: precipitation, soil water content and vegetation. They used TRMM, LST and NDVI to forecast drought occurrences (Du et al. 2013). Besides, as drought is usually related to local water supply and crop phenology stages, extracting such background with remote sensing is implicitly preferable for drought early warning and assessment (Zhang et al. 2008, Rojas et al. 2011).

Several case studies had used agricultural physical model, which allows the scenario-based analysis of drought-induced yield losses and evaluate the large-scale grain production(Yu et al. 2014). To identify drought, Zhong et al. (2014) used a physical model to obtain drought condition, whose model-required land surface parameters, such as temperature, surface albedo, NDVI, and emissivity, had been derived from AVHRR and MODIS data (Zhong et al. 2014).

3.2 Flood and waterlogging

Flood is a temporary inundation of normally dry land with water, suspended by overflowing of rivers, precipitation, storm surge, tsunami, waves, mudflow, lahar, failure of water retaining structures, groundwater seepage and water backup in sewer systems.

Frequent, long time-series remote sensing data allow monitoring perennial flooded area that provides a regional flood risk assessment (Tapia-Silva et al. 2011, Huang et al. 2014). Hydrological or meteorological data provide only point-based information; remotely sensed data is able to map out the characteristics of flood inundation across large river basins (Tapia-Silva et al. 2011, Chormanski et al. 2011, Huang et al. 2014). Frequent occurrences indicates that actual induce of floods is related to the forest cover change and meteorological forcing (Tran et al. 2010). More importantly, enhancing prediction for flood occurrence and crop losses assessment is crucial; by integrating remotely sensed parameters with hydrological models for flood forecast (Chormanski et al. 2011) and by integrating with socioeconomics strategies to estimate agricultural crops losses using remote sensing (Tapia-Silva et al. 2011).

Compared to flood, waterlogging is saturation by groundwater which is sufficient to prevent or hinder crop growth, but not as devastating as flooding; excessively wet condition is capable of depressing grain yield (Sivakumar et al. 2005, Xiao et al. 2014, Mandal and Sharma 2011). It is difficult to identify waterlogging damage to plant. Mandal and Sharma (2011) had adopted multi-temporal satellite images to extract waterlogged area based on spectral properties using visual interpretation with field-survey (Mandal and Sharma 2011). Based on the time-variation in multi-temporal MODIS data (VIs, LST, and albedo), the ecological and thermodynamic characteristics of the waterlogged croplands were analyzed and identified (Xiao et al. 2014).

3.3 Low temperature

Low temperature hazards are usually regarded as chilling, frost and freeze injury. Chilling injury to plant is caused by low temperatures above the freezing point; while frost injury and freeze injury probably occur when temperature is below the freezing point when plants are damaged by ice crystal forming within their tissues.

Satellite remote sensing estimations have been used to delineate areas of chilling injury. As the crop growing season from sowing to maturity requires a certain growing degree days (GDD) which represents accumulation of heat units, low temperature injury assessment can be achieved using land surface temperature derived from remote sensing observation (Zhang et al. 2013a, Vancutsem et al. 2010). Based on the considerable high correlation between satellite-derived LST and air temperature record from meteorological station, the GDD estimated from time series MODIS-LST data could be used to evaluate the chilling injury throughout the growing season (Zhang et al. 2013a, Hassan et al. 2007). Besides, risk of chilling injury will also be affected by geographical background, such as local cropping system (i.e., double cropping would probably be more risky to suffer) and agricultural activities arrangement (i.e., planting and harvesting) (Cheng et al. 2013a, Pan et al. 2015).

In early 2008, freezing rain and snow suddenly hit the South China which lasted for a long time and caused enormous losses. The AMSR-E passive microwave-retrieval of land surface temperature allowed dynamic monitoring the disaster progress (Chen et al. 2011). Freezing damage had jeopardized the vegetation's growth, and even caused physical death. Ground-based and satellite-based remote sensing monitoring could indicate the fluctuation of vegetation due to extreme weather conditions according to plant spectral reflectance (Gu et al. 2008, Chen et al. 2012), such as tremendous drop in vegetation index. In She et al.'s research (2015), the NDVI variation was chosen as an indicator for crop damage; the geographical factors that may affect the susceptibility of freeze injury were mapped out (She et al. 2015). In Feng et al.'s research (2009), winter wheat freeze injury was monitored using MODIS data, combined with ground meteorological data and field survey data (Feng et al. 2009). In Liu et al.'s case (2014), they explored cold damage severity level of mangroves forest by associating the damage with weather factors (wind direction and velocity) and landscape factors (elevation, surface slope, and aspect) (Liu et al. 2014).

3.4 Crop diseases and pests damage

Plant diseases and insect pests are responsible for major economic losses in agricultural industry worldwide. Monitoring plant health and detecting pathogen in an early manner are essential to reduce disease spread and facilitate effective management practices (Sankaran et al. 2010, Martinelli et al. 2014, Singh et al. 2007).

Crop diseases and pests damage would cause plant change in morphology and biochemistry, such as leaf pigment change and water content lost. Through laboratory/field-based observation, spectral features of crop act intuitive response via spectroscopy (Sankaran et al. 2010, Martinelli et al. 2014, Sivakumar et al. 2003, Yuan et al. 2014). Literatures have summarized spectroscopic and imaging techniques including fluorescence, visible-infrared, thermal infrared and microwave wavelengths, various types of spectral analysis methods, as well as various scales spanning from single leaf to a large region (Mulla 2013, Sankaran et al. 2010, Reynolds and Riley 2002).

To identify crop pests and diseases damage, the symptom can be quantified by spectral reflectance using sensitive band selection, principal component analysis, partial least squares regression and vegetation indices (Usha and Singh 2013, Mulla 2013, Sankaran et al. 2010, Luedeling et al. 2009, Liu et al. 2010). Cheng et al. (2010) used continuous wavelet analysis for the detection of water deficit in infested and girdled tree (Cheng et al. 2010). The limitation in large scale remote sensing monitoring for crop pests/disease is explicit;

the anomalism is quite subtle making visual interpretation difficult. Even so, it was reported that utilizing the multi-temporal/spectral data is capable of mapping out severe plant diseases; by incorporating with field investigation, high spatial resolution satellite image with proper classification techniques can be used to detect plant diseases/pests damage in cropping area (Zhang et al. 2014, Yuan et al. 2014). At present, the increasing availability of small, inexpensive sensors has enhanced the operational remote sensing through UAV for crop disease/pests monitoring at the farm scale (Usha and Singh 2013, Salamí et al. 2014). It is still unable to detecting all the types of crop diseases/pests damage as remote sensing detection is 'disease specific' and 'site-specific' (Zhang et al. 2014).

As a matter of fact, the risk of crop pests/disease occurrence would probably relate to their ecological factors (temperature, precipitation, cropping area and phenology, etc.)(see Fig.4); the satellite earth observations are useful in monitoring ecological conditions favorable for crop pests and diseases(Marques da Silva et al. 2015). Ecological conditions such as temperature, humidity, sunshine hours and wind play major influence on the crop pests' population; through remote sensing and GIS spatial analysis, researcher can simulate scenarios of diseases spreading, to identify potential infected area (Reynolds and Riley 2002). For the purpose of crop protection, it is more practicable to assess the damage at an earlier stage than detecting the insects themselves (Behmann et al. 2014a).

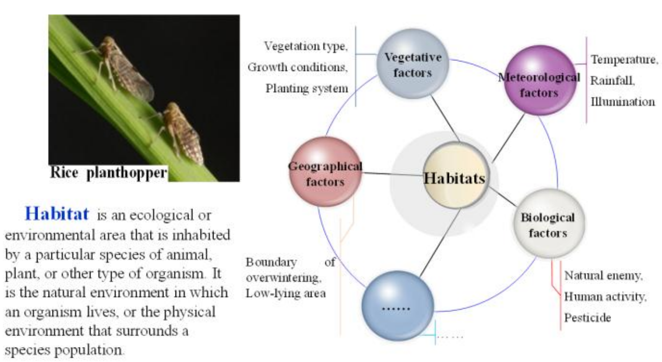

Fig.4 Identifying insect pests' habitat is helpful for early warning and prevention

3.5 Others

Besides those common disasters mentioned above, natural disasters include heavy rain, landslide, hail storms and typhoon which can lead to substantial crop failures by physical damage in crop canopies (Sivakumar et al. 2005); However, these devastative disasters and their impacts on coastal fisheries are not considered in this review due to limited literature for reference.

4 Recent advances, opportunities and challenges

Remote sensing of agriculture had already benefited from agricultural sciences, advanced remote sensors and GIS application. Additionally, wireless sensors network, UAV platform, physiology-based crop yield modeling, high-performance computational capacity, etc.; these technological breakthroughs create tremendous opportunities. Consequently, it is our firm belief that bridging the gaps between remote sensing observation and current advancing technologies will propel remote sensing into practical applications. Herein, this review paper suggested several frontiers for agricultural disasters monitoring based on the recent advances in remote sensing.

4.1 Multi-sources data fusion

Traditionally, good examples for fusion of remote sensing images are to merge the visible/infrared multispectral images with higher resolution panchromatic image, known as 'pan-sharpening'(Liang 2008, Pohl and Van Genderen 1998). To this day, data fusion had been developed diversely and image fusion for agriculture has many aspects to be looked at. In Shi et al.'s perspective (2014), a strong demand of information integration from multi-sources, multi-sensors, and multi-scales is urging in comprehensive agricultural monitoring, modeling, and management (Shi et al. 2014). Ozdogan et al. (2010) had pointed out the opportunity and challenge of agriculture-related remote sensing information are currently being captured by a number of satellite-based sensors with different spatial, spectral, temporal, and radiometric characteristics. By taking advantage of characteristics from different data sources, researchers can better understand the dynamic process of disasters and perform dynamic monitoring (Ozdogan et al. 2010) (see Fig.5).

Originally, the concept of downscaling of satellite image was proposed suggesting that SPOT VEGETATION (1 km resolution) is to be merged with multispectral HRV at 20m resolution (Pohl and Van Genderen 1998). The development of data fusion techniques help to hatch a unified framework that can potentially generate synthetic satellite images with high spatial, temporal and spectral resolution (Hilker et al. 2009, Huang et al. 2013). Several research cases could be found: the coarse-resolution land surface temperature from geostationary satellite had been downscaled to higher spatial resolution for urban heat island monitoring (Zakšek and Oštir 2012); downscaling MODIS VI/LAI products to Landsat TM/ETM+ resolution level, aiming to build a high spatial-temporal resolution time-series data set (Hilker et al. 2009, Roy et al. 2008). In the field of hydrology, the image downscaling method has been used to improve spatiotemporal resolution of remote sensing-based ET maps for irrigation scheduling purposes (Ha et al. 2012, Anderson et al. 2012, Cammalleri et al. 2014). To this end, we had confidence that such technique will be eventually implemented for agricultural disasters monitoring.

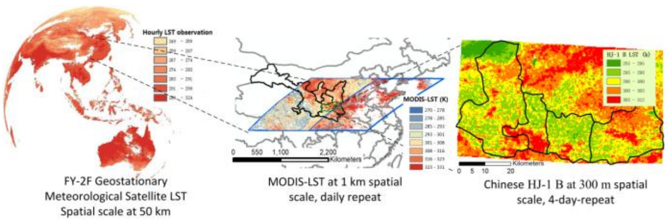

Fig.5 Remote sensing data play different roles in application according to their spatial and temporal difference. Data fusion suggests taking advantage of scale and repeat cycle

Most of the synthesis methods would have a common trait is that ancillary data (e.g., DEM, albedo, etc.) are required. As we had reviewed the research cases above, remote sensing data would not work solely to cope with disasters. Apparently, satellite in-orbit had provided various types of data sources for synthesis. Terra/Aqua MODIS data had already provided more than 20 remote sensing products globally. Zhang et al. (2013) used MODIS-LST, EVI, together with DEM value to establish multi-variable regression function for estimating air temperature (Zhang et al. 2013a), to map the heat accumulation for crop growing season. Agricultural disasters may somewhat related to their natural environment (e.g., low-temperature injury, waterlogging, drought); therefore remotely sensed-derived land surface parameters are useful for spatially modeling to extract interesting area (Cheng et al. 2013a, Zhang and Jia 2013, She et al. 2015, Xiao et al. 2014). These examples will be ideal add-on strategies for regional disasters zoning.

There is a significant potential of utilizing archived remote sensing data to assess the data continuity and complementariness (Fensholt and Proud 2012). The various sensors have different technical specifications, including primary wavelength, spatial resolution, and temporal frequency. Vegetation monitoring for global/regional ecosystems is critical to gain a better understanding of processes related to agricultural change over long periods (Fensholt and Proud 2012, Yin et al. 2012). Therefore, it is crucial to better understand the differences in time series products acquired from different satellite data archives (e.g., NOAA-AVHRR, SPOT-VGT and MODIS), for the purpose of continuously mapping crop phenology, soil moisture, et al. Integration of multi-sources satellite data with different spectral, spatial, temporal resolutions is now an important research frontier and maybe of great benefit.

Here, the term 'data assimilation', is an analysis technique which integrates not only remotely sensed data, but also the observed information accumulated into the model state by taking advantage of consistency constraints with laws of time evolution and physical properties; it also serves as an innovative parameter estimation method for agroecosystem dynamic models (Liang 2008, Dorigo et al. 2007). On one hand, there are many different assimilation algorithms available in the literatures from meteorology, hydrology that may useful for agriculture.

4.2 Integration of model with remote sensing data

Unexpected climate factors indicate risk evaluation is critical for agricultural disasters management; early-warning efforts in agriculture appear particularly important. However, due to the lack of effective forecast capacity by using remote sensing solely, the agriculture relevant models have the capabilities to quantify crop biophysical/biochemical parameters (Wallach et al. 2006, Liang 2008, Dorigo et al. 2007, Pinter et al. 2003). Generally, there are three categories of models related to agricultural remote sensing: empirical models, physiological models and crop growth models (Liang 2008, Dorigo et al. 2007, Verstraete et al. 1996). Models are served as crucial tools for early warning and prediction of agrometeorological disasters, e.g., hydrological and meteorological model are commonly used for the disasters forecast; crop growth model is a very effective tool for predicting possible impacts of climatic change on crop growth and yield (Sivakumar et al. 2005). As numerous agroecosystem-related models exist, in this review we would mainly discuss radiative transfer model and crop growth simulation model.

The radiative transfer models (RTM) is capable of explaining the nature of the measured plants biophysical or chemical parameters, and inversing such parameters for characterizing the growth state of the crop under observation (Dorigo et al. 2007, Verstraete et al. 1996). Most radiative transfer models are usually linked with optical remote sensing reflectance through numerical inversion methods with the purpose of inferring leaf or canopy properties (Liang 2008, Dorigo et al. 2007, Martinelli et al. 2014, Clevers et al. 2010, Blackburn

2006), such as LAI, FPAR, chlorophyll, water content, etc. Remote sensing images acquired from satellites or airplanes provide large scale information on crop characteristics (e.g., growth, nitrogen status); thus inversing crop parameters through radiative transfer models can reflect disasters impact on crop condition.

Crop growth model simulates crop production potentials dictated by environmental conditions (e.g., soils, climate), crop characteristics and crop management (e.g., irrigation, fertilizer application) (Wallach et al. 2006, Liang 2008). The significant advantage of combination of crop growth model and remote sensing is to dynamically evaluate the large-scale yield production (Wallach et al. 2006). In some European countries, crop growth models such as WOFOST (WOrld FOod STudies) and DSSAT (Decision Support System for Agrotechnology Transfer) have been used at the Institute of Meteorology, Faculty of Agronomy etc. They are used not only to assess the crop yield at a regional scale, but also for climate impact assessment and adaptation practice improvement (Sivakumar et al. 2005). In recent years, substantial efforts had been made to improve the use of crop model for observing, mapping, and modeling crop yield.

The use of remotely sensed information to improve crop model simulation was proposed as early as three decades ago. There are different ways to combine a crop model with remote sensing observation: (1) direct use of a driving variable estimated from remote sensing data into the model; (2) updating a state variable of the model (e.g., LAI, ET) derived from remote sensing; (3) re-initialization of the model, i.e., the adjustments of an initial condition to obtain a simulation in agreements with the remote sensing-derived observations (Dorigo et al. 2007, Sivakumar et al. 2003, Li et al. 2014). More often, the crop growth model can simulate a variety of outputs, such as biomass, phenology, soil water content, evapotranspiration, etc.; those simulations are already remotely sensed obtainable. By assimilating the passive microwave remote sensing-derived soil moisture into crop growth model can help to assess yield loss due to drought (van der Velde et al. 2011, de Wit and van Diepen 2007).

A lot of case studies illustrate the potential interest of data assimilation for working with crop model to perform regional yield simulation (see Fig.6); they had presented how the data provided by remote sensing observation are used to adjust the model parameters to improve simulation accuracy. Uncertainties in spatial temporal distribution of rainfall, soil properties, and regional management levels comprise the error in crop model simulation results. For this purpose, there are research cases addressing this demand. De Wit and van Diepen (2007) used the Ensemble Kalman Filter (EnKF) to assimilate microwave-derived soil moisture estimates into model for correcting errors in the water balance of WOFOST crop model (de Wit and van Diepen 2007); Li et al. (2014) used EnKF algorithm to integrate LAI data into a fully coupled hydrology-crop growth model to obtain the spatial distribution and regional variation in maize yield (Li et al. 2014); Ines et al. (2013) had developed the EnKF-DSSAT-CSM-Maize data assimilation framework that incorporates remote sensing-derived soil moisture and LAI into a crop model (Ines et al. 2013).

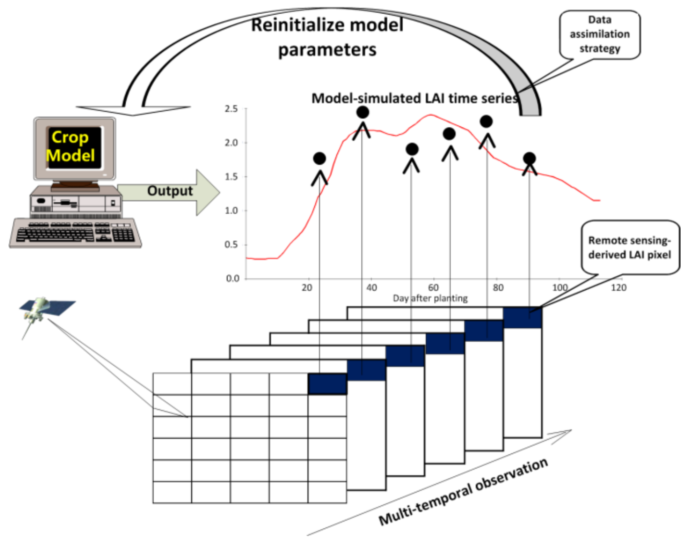

Fig.6 A simple schematic for assimilation of remote sensing data into crop models (the parameters optimization method)

4.3 Information technologies

There is a significant potentiality in Precision Agriculture combined with remote sensing data for improving agricultural management (Mulla 2013). Agricultural disasters managements and Precision Agriculture share the same technical benefit involving data collection/analysis and information management; as well as technological advances in computer processing, field positioning, yield forecast, remote detecting instruments, and pattern recognition on field-based crop biotic stress detection (e.g., weeds, diseases and pests damage) (Mulla 2013, Jones 2014, Behmann et al. 2014a).

The Internet of Things (IoT) is a new information systems paradigm that comprises physical objects and electronic devices (Borgia 2014). Relying on wireless-sensors network, researchers can obtain field-based monitoring data such as soil water content or crop growth condition from a long distance (Phillips et al. 2014). The 3G/4G mobile telecommunications are supporting the wireless-sensors network and multi-media transmission. The sophistication and availability of the Internet systems allow rapid real-time multi-media transmission for farmland condition data and assembling data of field-based crop growth situations (Jones 2014). Herein, observation and expert decision making from a long distance allow taking measures in time to tackle with agricultural disasters and avoid the spread of contagious disease. With various sources of sensors (wireless sensors, satellites/airborne image, real-time weather station, etc.), a novel opportunity of agricultural monitoring is to integrate multi sources data together via data assimilation, e.g., assimilating the observed data into agroecosytem models for simulating evapotranspiration, crop growth and potential yields (Shi et al. 2014, Phillips et al. 2014).

4.4 High-performance computing

With the explosive increase of available data, the rapid processing of remote sensing data is essential in large-scale, real-time monitoring; the data storage, processing and distribution are facing obstacles (Wang et al. 2013, Shi et al. 2014, Ma et al. 2014); timely retrieval of agricultural disasters information is very crucial for policy makers, which requires fast processing of remote sensing production. Specifically for hyperspectral remote sensing images, there is a need to develop cost-effective strategy that is able to speed up processing and to satisfy the extremely high computational requirements (Plaza et al. 2009). Besides, when remote sensing is to be coupled with complex physical model (i.e., crop growth simulation model), the regional assessment and prediction require considerable high computing capacity (Ma et al. 2013). That was why many well-established agroecosystems prompted practitioners and developers to be familiar with issues of parallel and distributed computing systems (Dorigo et al. 2007).

To satisfy with the needs of real time, fast transmission and processing with remote sensing massive data, Grid Computing and Cloud Computing architecture can provide higher efficiency and velocity for processing (Wang et al. 2013, Zhu et al. 2009). Grid is a collaborative computing environment based on multi-machine (i.e., WLAN network); Parallel Computing uses many computer nodes (i.e., CPU core); computation tasks are the significant features of Grid/Parallel computing (Zhu et al. 2009, Zhao et al. 2013). Cloud Computing is a supercomputing paradigm based on the Internet, which makes use of computer nodes in the Cloud cluster through Internet to complete a computing task in parallel (Wang et al. 2013). Zhao et al. (2012, 2013) developed hybrid high-performance computing techniques (i.e., combine Parallel and Grid Computing) to handle and accelerate the performance of large scale, complicated agricultural systems modeling (Zhao et al. 2013, Zhao et al. 2012).

With the development of open-source software and programming languages, it becomes possible to develop customized analysis algorithms and provide a friendly user interface for applications. Herein, Cloud Computing can automatically organize resources that are transparent to users in the Cloud. The continuous-evolving Internet is a powerful tool in facilitating the exchange of remote sensing data for rapid disasters monitoring online. Data storage in the Cloud provides a safe and convenient way for big-data management; hence, the Big-data analysis in remote sensing of agricultural disasters will be in the near future (Ma et al. 2014).

5 Discussion

For a long time period, people's knowledge on remote sensing in agricultural disasters is intuitive observation; research cases had demonstrated that agricultural remote sensing is far beyond mapping; with the knowledge deepened, monitoring and modeling disasters will definitely and continually play an important role. Challenges still require further investigation and consolidation in agricultural remote sensing: (1) selection and optimization of the techniques for a specific disaster; and (2) applying the techniques for practical monitoring of disaster under real-world field conditions.

For instance, the review above indicates that we need to know which sensors, spectral bands or analysis techniques should be suitable for detecting a disease, but there are great differences in conducting an effective and solid research among so many candidates. Specifically, as crop yield formation will be a result from various ecological factors, yield loss may be related to drought, heavy rain, or insect's damage. Question is that how to discriminate plant disease from several conventional stresses (e.g., nitrogen, water deficiency) by spectroscopic analysis? Another commonly discussed question is the 'scale' problem. Even though the present studies indicate that it is possible to accurately identify crop stress with spectral features under laboratory conditions, but in most cases, it is still unpractical to do so when performing field-scale even aerial monitoring. How to bridge the gaps between remote sensing data from different scale? Besides, yield prediction and loss modeling are still quite uncertain. These questions above are still unaddressed. Lacking of reliable loss record from disasters events also hinders loss assessment using remote sensing while validations is considered critical.

Planning, early warning and well-prepared measures are major tactics for mitigating the agricultural disasters losses, researchers should deepen and broaden the study of the disasters occurrence mechanism, improve the ability of detecting agricultural disasters from remote sensing, as well as the ability of comprehensive analysis and scientific judgment. The induced-factors for disasters (e.g., temperature, precipitation, etc.) are crucial for early warning, as remote sensing data could provide such environmental indicators in large scale. Although the theories behind had not been fully established, at least, remote sensing had been proved a vigorous research topic by combining with other data (e.g., field surveys, GIS databases). As remote sensing science had been gradually evolved from theoretical to practical, by taking advantage of the recent advances, it will definitely play an important role in agricultural disasters mapping, monitoring, and modeling.

Particular efforts are needed to develop and consolidate remote sensing approaches for different disasters, integrate different data sources and perform practical losses estimation. Last but not least, the consequence from disasters requires that remote sensing is not only aiming to map out affected target, but also provide information for the government to carry out disasters management practice, such as assessing losses and making rational decisions for agricultural insurance payment.

6 Conclusion

A series of literatures on disaster reduction and mitigation had been collected to support the motivation for writing this review paper. Above all, based on the recent advances in remote sensing community and research cases reviewed above, to the best of our knowledge, here we add several indicators for the future direction.

6.1 Fully understanding the merit of remote sensing

In the public's point of view, remote sensing in agricultural disasters is viewed as an intuitive phenomenon of physical damage; while the process and occurrence of disasters may be invisible. Hence, at present the awareness of the benefit has not received much attention to remote sensing technology. Remote sensing technology should play its critical role in disasters mitigation, by acquiring environmental and ecological parameters. Conventionally, the integration of remote sensing data with GIS spatial-analysis for risk assessment is an essential component of disaster preparedness and mitigation; meanwhile, as agrometeorological disasters are quite weather condition-driven, remote sensing-derived parameters such as temperature, rainfall, and soil moisture will be invaluable data for disasters monitoring and modeling. There are strong evidences and significant trends indicating that multi-sources remote sensing data will support agrometeorological disasters risk zoning and modeling. For instance, spatial modeling of crop pest's habitats area has been proved its potentials in insect pest ecology and management.

6.2 Quantitative assessment of remote sensing-based disaster monitoring

Damage assessment is an essential part of disasters management; at present, remote sensing data are basically used for obtaining crop spatial information, or used as ancillary data source in disasters management. However, when facing complex disasters situation, few substantial research article had been reported to execute the observing, mapping, and modeling disaster processes which leads to agricultural losses. Hence, the assessment of loss will still need to integrate with physical model or socioeconomics methods for quantification.

6.3 Strengthening early warning capability

Damage from catastrophic events is both social and economic relevant. Further studies should aim to bring more awareness of the occurrence and consequence of agricultural disasters that will eventually drive people's attention towards taking measures for prevention. Herein, the cooperation among agrometeorologists, institutes and government agencies is important. For instance, remote sensing can allow early diagnosis or forecast the disease symptoms before occurrence; through priori control strategies such as pesticide applications, and disease-specific chemical applications, famers can avoid dissemination and yield loss. Besides, remote sensing provides government agencies and insurance companies a rapid damage assessment for disasters impacts. Therefore, researchers are encouraged to take advantage of both remote sensing and agroecosystem model in simulation of climate change scenarios beforehand.

6.4 Synergy of multi-sources data for disasters monitoring

Agricultural disasters monitoring will probably involve cropland mapping, crop type identification, and change detection; the accuracy has been improved by integrating various classification methods, multi-source remote sensing data fusion, incorporating with auxiliary geoinformatics data and expert knowledge. Synergy relates to the utilization of two or more data sources together in order to extract more information than the utilization of each individually. Research cases indicate a conceptual framework that multi-sources data work corporately in earth observation: all-weather LST mapping using gap-filling by merging MODIS and AMSR-E data; spatio-temporal interpolation of daily observation in time series remote sensing data (Kilibarda et al. 2014, Jang et al. 2014, Neteler 2010); for drought detection, considering the remotely sensed factors including phenology, meteorology, hydrology and land surface parameters makes the result more convincible (Du et al. 2013, Rhee et al. 2010). Special attention should be given to the potentiality of synthesis of spatial, spectral, and temporal resolution of satellite data, by taking their respective advantages. For instance, NASA's Earth Observation System, ESA-Sentinel series, and China's Gaofen series remote sensing satellite will definitely enhance the capability of agricultural disasters observation.

6.5 Emerging advanced technologies for improving disaster monitoring

A rapid, cost-effective and reliable sensor system is critical for monitoring crop status under field conditions. Implementing the Precision Agriculture technologies makes the field-scale disasters monitoring more intelligent and automatic. The spectroscopic or imaging-based sensors could be integrated with an agricultural vehicle or UAV-based applications for field-based plant disease detection to achieve superior control and management. Newly development of Precision Agriculture includes computation sciences, the Internet of Things-based wireless transmission, mechanical engineering, etc.; by taking full advantage of the ongoing technology, human being were able to effectively tackle with field-based natural disasters. Monitoring and modeling agricultural disasters with remote sensing data requires not only computational capacity, but also advanced technology. Fortunately, the computer sciences are continually supporting this trend.

6.6 Bridging the gaps between experimental study and practical application

As remote sensing techniques have been operationally used in agricultural monitoring, they should actively play a role in agro-advisory service for the policy-maker to tackle with disasters. Farmers do have a considerable interest in knowing climate stresses, pests and diseases that would cause yield reduction; making valuable advisories for field managements will be truly beneficial for the farmers.

As literature reviewed above, remote sensing have evolved as no more a untouchable technique for the public today; researchers are undertaking the mission which makes civilian acceptable and accessible to such techniques, making it low cost, customizing solutions in different scales; these efforts will be truly benefit for the end-user in agricultural production. There is an urgent need for developing standards for data processing flow and analysis system, which would allow fast data processing to generate reliable remote sensing product; and an urgent need for establishing criteria in agricultural disasters monitoring and evaluation. To achieve these goals, the construction of telecommunications facilities, practical application of cases and well-trained personnel are crucial.

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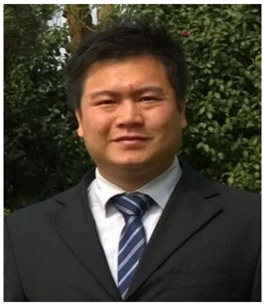

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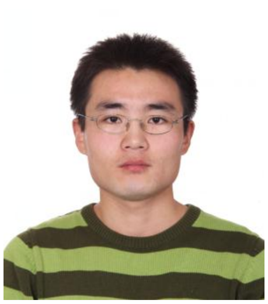

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