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REVIEW

Progress in the use of geospatial and remote sensing technologies in the assessment and monitoring of tomato crop diseases

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ABSTRACT

With a growing global population and accelerating climate change, systematic assessment and monitoring of crop diseases is urgently required to ensure food security and production. However, current dietary transitions inclined towards vegetables such as tomatoes are expected to increase while effective crop disease monitoring and assessment methods are still limited. Therefore, a state-of-the-art review of progress in the assessment and monitoring of tomato crop diseases using geospatial technologies is presented. Results show that tomato crop diseases and their severity could be detected and discriminated from healthy ones more effectively using various remote sensing systems. Furthermore, the recent advances in RS technologies have greatly facilitated its integration with climatic and topo-edaphic factors to determine the possible drivers of disease infection. Although the use of remotely sensed variables and their integration with bioclimatic factors in understanding tomato crop diseases is still at its infancy, it is one of the most promising technologies.

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Bioclimatic; crop health; earth observations; food security; multisource data

1. Introduction

Globally, tomatoes (*Solanum lycopersicum*) are ranked second, after potatoes (FAOSTAT 2019), as the most important vegetable crops for both subsistence and commercial purposes (Kimura and Sinha 2008; Kusano and Fukushima 2013). Both crops have high nutritional value, which includes lycopene, α-tocopherol, flavonoids, ascorbic acid, potassium, folate (vitamin B9), vitamin c and k (Willcox et al. 2003). Several epidemiological studies have indicated that lycopene is an effective antioxidant for thwarting human illness such as cancer, heart attack and stroke (Agarwal and Rao 2000). Statistics from the Food and Agriculture Organization (FAO) of the United Nations (UN) indicates that the area under tomato crop farming accounts for over 4.8 million hectares (ha) globally with

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a total production of about 376 tons/ha and yielding approximately $59.1 billion (FAOSTAT 2019). Currently, the United States of America (USA), China, and India are the major tomato producers (FAOSTAT 2019). In Africa, tomato production was estimated at 21.5 million tonnes, with Egypt being the largest producer followed by Nigeria, Morocco, Tunisia, Algeria and Cameroon (FAOSTAT 2019). Despite the economic importance of this valuable crop, its production is vulnerable to some physiological, biotic and abiotic stressors.

In general, the harmful organisms such as pathogens, parasites, insects, and weeds, and other invasive plants like Prosopis (*Prosopis spicigera* L) remain the principal threats to crop production with considerable implications on the entire crop value chain (Stukenbrock and McDonald 2008). Every year, the agricultural sector loses about 20% to 30% of crops from pathogens, animals, and weeds (Oerke and Dehne 2004; Flood 2010). Pathogens alone, account for approximately 12.5% of crop losses, worldwide (Oerke 2006). Farmers in developing countries experience higher production losses as opposed to their counterparts in developed countries (Hughes and Salathé 2015). Further, scientific predictions have indicated that abiotic factors such as climate change exacerbate disease incidence leading to changes in suitable production areas (FAO. 2018). In fact, warmer temperatures and/or prolonged wet seasons, in particular, may create favourable conditions for certain pathogens, which could lead to larger-scale food crop damages (FAO. 2018). This will, subsequently, result in increased yield losses and consequently, food and nutrition insecurities.

Although various studies have been conducted to review the utility of earth observation in crop diseases (e.g., Sankaran et al. 2010; Mahlein et al. 2012; Zhang et al. 2012; Martinelli et al. 2015; Lowe et al. 2017; Mutanga et al. 2017; Gogoi et al. 2018; Zhang et al. 2019), there is paucity in the literature that focuses on applications of remote sensing (RS) on tomato crop diseases detection and forecasting despite the significant nutritional value and demand of tomatoes globally. This article, therefore, reviews the existing literature on the application of geospatial and remote sensing (RS) tools for modelling and monitoring tomato crop disease, with a special focus on (i) diseases and their impacts on tomato production, (ii) possible causes and drivers of tomato diseases, (iii) impact of climate change on tomato crop diseases, (iv) tomato crop disease detection methods, (v) RS of crop disease, (vi) multisource data application in modelling crop diseases, (vii) the use of RS techniques for detecting tomato crop disease, and (viii) challenges and prospects of tomato disease detection.

2. Diseases and their impacts on tomato production

Tomato plants are susceptible to over 200 diseases, primarily due to pathogenic agents such as viruses, bacteria and fungi, and nematodes (Singh et al. 2017). These diseases affect the plant bio-physiological processes resulting in reduced crop quality and productivity, which negatively impacts the crop value chain. Like in the other plants, tomato diseases can manifest in different parts of the plant such as roots, stems, branches, buds, leaves, flowers and fruits causing morphological, physiological and biochemical modifications (Carter and Knapp 2001). These modifications alter the plant tissue and cause symptoms like blackening of fibre vascular bundles, black spotting of leaves and fruits, rotting of fruit, stem stunting, leaf lesions, leaf or fruit discoloration, dark streaks, premature defoliation and spots, wilting and die-off of seedlings, mainly due to the retarded photosynthetic activities (Horst 2008; Nagendran et al. 2019). For example, tomato fusarium and bacteria wilt multiply rapidly inside the plant water-conducting tissues and fill them with slime. This results in a rapid plant wilting, while the leaves may remain green (Gleason and Edmunds 2005).

Much research efforts have been exerted in determining the prevalence, incidence and severity of tomato diseases (e.g., Xu et al. 2017; Kokaeva et al. 2018; Koshale and Khare 2018; Moodley et al. 2019a, 2019b). For example, Xu et al. (2017) collected 170 samples from tomato fields across China and reported tomato mosaic virus (ToMV) and tomato yellow leaf curl virus (TYLCV) as the two top-most prevalent and destructive viruses among 120 diseases found on tomato leaves and fruits. Meanwhile, Koshale and Khare (2018) investigated tomato diseases in Raipur, India under field conditions and they concluded that leaf curl, mosaic, tomato spotted wilt, early blight and collar rot were the most prevalent diseases in tomato crop fields. Similarly, Moodley et al. (2019b) surveyed the main South African tomato growing regions and noted that multiple tomato diseases such as chlorosis crinivirus (ToCV), tomato torrado virus (ToTV), and tomato curly stunt begomovirus (ToCSV) were caused by whiteflies. Their results indicated that the most widespread leaf diseases were ToSCV, ToTV and ToCV, in order of prevalence. ToCSV was identified in three provinces namely; Mpumalanga, Kwa-Zulu Natal and North West, with an overall incidence of 9.4%. Farmers in KwaZulu-Natal province experiencing over 90% of incidence. These suggest that prevalence varies from one disease to another and from one location to the other.

Several studies have further attributed yield losses to tomato disease incidence and severity. Singh and Kamal (2012), for example, reported 10% to 90% loss in tomato yields in the temperate region due to fusarial wilt disease. Meanwhile, the reduction in yield from spotted tomato wilt virus (TSWV) in Samsun, Turkey, was valued at about $0.9 million (Sevik and Arli-Sokmen 2012). The Tomato leaf curl virus was responsible for approximately 70% of yield losses in tomato crops grown between February and May in Pakistan (Tahir et al. 2012). These losses were noted to be severe when the infection occurs before flowering as it often affected the fruit size and quality. In another study, Jones et al. (1986) reported up to 52% loss of tomato fruit weight due to bacterial spots. Nonetheless, yield losses tend to be greatest where conditions are particularly favourable.

The long-range spread of these infectious crop diseases is often linked to the international trade of fruits, seeds and seedlings. For instance, in South Africa, the ToCV and its vector were introduced from the Mediterranean, Spain and Sudan through international trade relations (Moodley et al. 2019a). This, amongst other factors, compelled the World Trade Organization (WTO) to restrict imports of agricultural products. Meanwhile, pesticides and fungicides are used to protect crops from infectious organisms in agriculture. However, these pose a detrimental impact on the environment (Kumar 2017), hence there is a need for early detection of tomato diseases at a leaf, farm and regional scales.

3. Possible causes and drivers of tomato crop diseases

The occurrences of crop diseases depend on specific climatic conditions, epidemiological characteristics, and general agricultural practices (Zhang et al. 2013). Climatic parameters such as higher temperatures, changes in precipitation and carbon dioxide (CO_2), poor soil aeration and wind foster the development and propagation of tomato diseases while altering pathogen behaviour and distribution (Agrios 2005). Lu et al. (2018) argued that mild temperatures and/or extended wetness periods influence the proliferation of most of the tomato foliar diseases such as late blight, target and bacterial spots. Further, Terna et al. (2016) observed that the occurrence of tomato diseases in major growing areas of Benue

State, Nigeria reached 100% between July 2012 and 2013, when the rainfall was very high. During the wettest month, high relative humidity increases the prevalence of fungal, bacterial and several other plant pathogens. Similarly, the pathogen causing tomato late blight develops when relative humidity is over 90% and the mean temperature is between 16 °C and 26 °C (Zhang et al. 2002). On the other hand, tomato disease can be influenced by topographic and edaphic conditions like slope, aspect and soil properties (i.e., type, structure, moisture content, organic matter, pH and salt) among others.

General farming practices such as tillage, monocultural vegetable crop production, culturing, fertilization, irrigation and use of contaminated equipment have been implicated in the spread of tomato diseases. Hummel et al. (2002) observed that conventional tillage practices significantly reduce the overall activity of pathogens responsible for tomato diseases when compared with conservation tillage. This is because debris from diseased tomato plants can spread diseases such as bacterial speck and leaf mold (Tsitsigiannis et al. 2008; Shenge et al. 2010; Shankar et al. 2014). Generally, these pathogens spread through the roots and infection leads to reduced water and nutrient transportation to other parts of the plant. Secondary transmission of the diseases may be caused by splashing water, contaminated equipment and clothing, clipping, cultivation, or vine training operations among other horticultural operations (Shankar et al. 2014). In certain instances, tomato diseases may develop and spread among plants when bacteria gain entry and rapidly multiplies in the roots of healthy plants from the roots of nearby infected plants, often through irrigation practices (Vidaver and Lambrecht 2004). Bacterial wilt infection may also occur as a result of stem injuries caused by cultural practices (Tsitsigiannis et al. 2008). Exposure to excessive fertilizers such as ammonium nitrate puts tomatoes at risk for diseases like blight and wilt (Hassanein et al. 2010). Tomato bacterial spot survives on contaminated seeds or seedlings with only a few bacterial cells that may consequently result in a relatively large number of infected crops (Giovanardi et al. 2018).

4. Impact of climate change on tomato crop diseases

Major greenhouse gases like carbon dioxide (CO_2) have increased by 30%, with other climatic variables such as average global temperature also increasing by 0.3 °C to 0.6 °C over the last century (Committee on Science, Engineering, and Public Policy 1992; Chakraborty et al. 2000). Likewise, global warming is estimated to increase with an average range of 1.5 °C and 5.8 °C before the year 2101 as a result of high accumulated greenhouse gasses in the atmosphere (IPCC 2013). Future climatic trends further indicate that the nature, extent and intensity of climatic variables will spatially and temporally vary (Biratu 2018). This will, directly and indirectly, alter the biology and life cycle of pathogens and the interaction with their host plants (Johkan et al. 2011; Biratu 2018). There is evidence that climate change could immensely affect tomato pathogens (Juroszek and von Tiedemann 2015; Biratu 2018). However, limited research has been undertaken to understand the effects of current and future climatic conditions on the spread of tomato crop diseases (see Juroszek and von Tiedemann 2015), as compared with studies on the impact of climate change on crop insect pests and nematodes. Despite its infancy, a few studies demonstrated that climate change modelling approaches have been useful in investigating the potential distribution of key diseases that affect tomato crops (e.g., Ramos et al. 2018, 2019). These studies explored the use of bioclimatic and ecological niche models such as species distribution models (SDMs), general circulation models (GCMs), regional circulation model (RCMs), CLIMEX and MaxENT (maximum entropy) for predicting the current and future tomato pathogens distribution. Bioclimatic models, for example, predict and project a pathogen's likelihood of occurrence based on its response to either climate variables (e.g., wind speed, sunshine duration, leaf wetness duration, humidity/moisture) and/or non-climatic covariables (e.g., landuse/landcover, soil properties, topography, biogeographical distribution of the disease, and their hosts) at a broader spatial scale using statistical and mechanistic approach (Juroszek and von Tiedemann 2015). For instance, to determine whether climate change would increase the risk of tomato yellow leaf curl virus (TYLCV) to the open field tomato production, Ramos et al. (2019) used 19 temperature and precipitation variables under four emission scenarios (RCPs 2.6, 4.5, 6.0, and 8.5) for the years 2050 to 2070 extracted from WorldClim database (https://www.worldclim.org/) in MaxTEnt and the GCMs. Their results showed that large areas would be suitable for TYLCV in future. This finding provided insights for designing strategies that control the incidence of TYLCV where it has not yet fully established.

Though climate-based models have proved to be useful in modelling the influence of climate on tomato diseases, there are prominent limitations associated with them. Some of these models are associated with spatial biases in the occurrence observations and lack spatial reference that could completely reflect the ecological niche of the pathogens (He et al. 2015). Satellite-based climate data such as precipitation and radiation measurements are continuously acquired at a higher spatial resolution without interpolation and geographical biases. Subsequently, their inclusion in the pathogen climate-based ecological niche models could circumvent the challenges of spatial biases and improve the accuracy and performance of these models at landscape scales.

5. Tomato crop disease detection methods

Researchers have developed various methods and technologies to detect crop diseases. Conventionally, disease incidence assessment has been conducted primarily through visual inspection which is solely based on looking at leaf colour patterns and crown structures as well as the modification of plant/organ shape and distribution of affected plants (Sankaran et al. 2010; Lowe et al. 2017). Although symptoms of plant diseases are visible at the end of incubation and can be diagnosed through visual inspection, this approach is often labour-intensive, time-consuming, limited to local scales and more often subjective (Zhang, Pu, Yuan, Wang, et al. 2014; Martinelli et al. 2015; Lowe et al. 2017; Ray et al. 2017). Visual assessment of plant symptoms has further been aided by advances in technology and the introduction of laboratory-based analysis. These laboratory analyses include methods such as flow cytometry (FCM), loop-mediated isothermal amplification (LAMP), enzyme-linked immunosorbent assay (ELISA), and polymerase chain reaction (PCR) (Fang and Ramasamy 2015). These analytical methods are destructive, expensive and require expertise to conduct and interpret the derived findings (Martinelli et al. 2015). Furthermore, these methods lack the spatial component and they are limited to the plot or field-level applications. Therefore, it becomes imperative to complement these methods with techniques that offer timely and accurate information suitable for local and regional scale monitoring while focusing on crop-specific diseases in a spatially explicit manner.

Geospatial and remote sensing (RS) tools, unlike traditional approaches, have emerged as the most robust technologies for the detection and continuous monitoring of vegetable crop diseases with a great potential of being utilized as an efficient future assessment tool in a spatially explicit manner (Mutanga et al. 2017; Neuwirthová et al. 2017). Specifically, RS provides spectral and spatio-temporal data useful in quantifying stress related to crop diseases from local to regional scales. Its application in plant health and condition assessment is compounded by the notion that pathogens-induced stresses interfere with plant biochemical properties and the physiological structure making the spectral reflectance of such plants to be different from healthy ones (Lu et al. 2018). A typical healthy green plant is characterised by high absorption of blue and red wavelengths and a reflection of green visible light, near infrared (NIR) and shortwave infrared (SWIR) (Jacquemoud and Ustin 2001; Li et al. 2014; Xie et al. 2017). Depending on the symptoms of a disease, stage of infection and their primary effects, their spectral signature in specific spectral bands will differ from that of a healthy plant. (Carter and Knapp 2001; Mutanga et al. 2017). For example, Lu et al. (2018) observed that the spectral reflectance of tomatoes infected with late blight and at the asymptomatic stage could be detected by reflectance changes in the blue, green (480 nm and 680 nm) and infrared (1400–2500 nm) wavebands. On the other hand, Gazala et al. (2013) established that the red-infrared slopes (red edge) for healthy soybeans showed a drift to the longer wavelengths and increased in amplitude in the red edge peak while yellow mosaic infected bean plants exhibited a shift towards shorter wavelengths with a decline in red edge wavelengths. Their results concurred with those of Jones et al. (2010) who associated the severity of tomato bacterial leaf spot with high peaks in the red edge and (Zhang and Qin 2004) who identified it as the best spectral range for the remote sensing of late blight tomato disease.

Since reflectance data is useful in separating healthy plants from stressed ones, studies have further combined specific bands and transformed them into spectral vegetation indices (SVIs) such as normalized difference vegetation index (NDVI) and ratio vegetation index (RVI) to detect crop diseases. Mahlein et al. (2010) noted that the use of narrow band SVI was promising in detecting diseases. They also noted that narrow band SVI can further be tailored to specific disease applications since each crop disease has a unique characteristic effect on the spectral signature. In that regard, disease-specific wavelengths can be extracted to develop spectral disease indices (SDI) which are aimed at detecting specific diseases as well identifying and differentiating one specific disease from another (Mahlein et al. 2010; Ashourloo et al. 2014a, 2014b, 2016). Mahlein et al. (2010), for instance, developed Cersopora Leaf Spot Index (CLSI), Sugar Beet Rust Index (SBRI) and Powdery Mildew Index (PMI) to characterise Cersopora Leaf Spot (CLS), Sugar Beet Rust(SBR) and Powdery Mildew diseases affecting sugar beet. Nonetheless, indices just provide insight into the level of stress being induced by specific plant pathogens at different stages of infection (Golhani et al. 2018) or assist to discriminate different diseases affecting the same type of crop (see Rumpf et al. 2010).

Meanwhile, the recent shift towards precision agriculture and Integrated Pest Management (IPM) has prompted for the accurate, timely and reliable detection of vegetable crop diseases. Spectral response technologies have eventually broadened the scope of disease assessment (i.e., detection, identification and quantification) and monitoring. Currently, there are numerous crop disease detection techniques that operate under the principle of wide electromagnetic energy. These include thermal, chlorophyll fluorescence, hyperspectral, multispectral, and radar sensors. Specifically, the use of RS datasets, its derivatives and algorithms have proven to be useful for crop disease detection, identification and quantification. Besides, such technology has been used as a proximal sensing tool to create disease incidence maps (Barbedo 2013; Lowe et al. 2017).

6. Multisource data application in modelling crop diseases

Generally, the use of remotely sensed datasets alone for mapping areas at risk or predicting the spatial distribution of crop diseases has been confronted with challenges. In particular, remotely sensed dataset only provides information on crop condition (e.g., health or anomalies), but fall short on providing critical information on the possible drivers that threaten the health of crops. Hence, some studies (e.g., Bhattacharya and Chattopadhyay 2013; Dutta, Singh, Khullar 2014; Zhang, Pu, Yuan, Huang, et al. 2014; Ma et al. 2016; Wakie et al. 2016; Yuan, Bao, et al. 2017; Zhao et al. 2018; Ma et al. 2019) have integrated remotely sensed data with bioclimatic variables to model and predict the spatial distribution of crop diseases.

Considering the complexity of the pathogen-environment interaction, ancillary information such solar radiation, bioclimatic (e.g., temperature, humidity, rainfall), and topo-edaphic (e.g., soil moisture and terrain attributes) variables should be integrated with remotely sensed features (e.g., spectral reflectance, SVIs, land surface temperature LST) for monitoring distribution and propagation of crop diseases. Integration of some of these variables has been successfully executed to obtain more accurate disease distribution estimates for key crops like wheat (Zhang et al. 2014; Yuan, Bao, et al. 2017) and potato (Dutta, Singh, Khullar 2014). To the best of our knowledge, no research has been conducted on the integration of datasets from multiple sources in determining areas susceptible to tomato diseases. Therefore, it is anticipated that such integrative modelling approaches could be useful for monitoring tomato diseases. For example, Zhang, Pu, Yuan, Huang, et al. (2014) constructed a wheat powdery mildew forecasting model by integrating remotely sensed and bioclimatic parameters (precipitation, temperature, solar radiation, humidity). Their findings showed that the integration of the remotely sensed data variables improved the model accuracy from 69% to 78%. In another study, Yuan, Bao, et al. (2017) utilized SVIs, tasseled cap transformation (TCT) parameters and LST derived from WorldView-2 and Landsat 8 for predicting habitat suitability for wheat powdery mildew. Their results showed that using VIs alone the accuracy of the model was 69%, whilst integrating all variables (i.e., VIs, TCT and LST) the model accuracy improved to 78%. Furthermore, Dutta, Singh, Khullar (2014) attempted an early detection and identification of the occurrence of potato late blight using climatic variables (rainfall and temperature) and multi-date normalized difference vegetation indices (NDVI) as well as Land Surface Water Index (LSWI) generated from IRS AWiFS dataset. They found that disease infection, during the early growth stage of wheat is high when minimum temperature and relative humidity are below 5 °C and 40% respectively. The above-mentioned studies proved that the use of multisource datasets yields more accurate results when compared to using remotely sensed datasets only. These, therefore, underscore the potential and strength of multisource data integration in monitoring tomato crop diseases.

7. The use of remote sensing techniques for detecting tomato crop diseases

The use of remotely sensed data in tomato disease detection has received little attention in the remote sensing (RS) literature as compared to other crops (e.g., wheat and maize). Despite its infancy in tomato disease detection, several studies have tested the potential of hyperspectral data at a leaf/canopy level as well as airborne multispectral datasets such as imageries, at a field level. Spectroradiometers and hyperspectral imaging systems, in particular, demonstrated great potential in early detection of tomato diseases such as late blight (Zhang and Qin 2004; Wang et al. 2008; Xie et al. 2015), gray mold (Xie et al. 2017), bacterial leaf spot (Jones et al. 2010), tomato yellow leaf curl virus (Jinzhu et al. 2013), late blight, target and bacterial spots (Lu et al. 2018). For example, Apan et al. (2005) showed that the incidence of early blight tomato disease could be assessed with 82% accuracy using hyperspectral insitu data. Similar successful applications of ground hyperspectral data in tomato disease detection have been conducted by Lu et al. (2018). They investigated the feasibility of detecting, at different stages, multiple tomato leaf diseases (i.e., late blight, target, and bacterial spots), using the high-resolution portable spectral sensor. Their results show that the severe stage of infection yielded the highest classification accuracy (77.1%). The above-mentioned examples demonstrated that hyperspectral technologies have the potential to be used for early detection of tomato diseases, however in situ measurements are not applicable for timely detection of diseases at large-scale farming systems.

Hyperspectral aerial imageries (e.g., AVIRIS: Airborne Visible and Infrared Imaging Spectrometer) have also been utilized to study tomato crop diseases (see Zhang et al. 2003; Zhang and Qin 2004). AVIRIS, for instance, has been significantly used in crop studies since its introduction in the mid to late 1980s to date. AVIRIS was also the first airborne hyperspectral sensor to cover the spectrum from 400 nm to 2500 nm at 10 nm intervals with 224 contiguous spectral channels (bands) (Mulla 2013). Furthermore, the AVIRIS image has a contiguous and narrow spectral resolution of ∼10nm per pixel suitable for detecting crop diseases (Zhang and Qin 2004). Using average mean reflectance values derived from AVIRIS image, Zhang and Qin (2004) successfully discriminated healthy plants from diseased plants at different stages of infection (i.e., lightly, moderately and severely diseased plants). Their results show that the mean reflectance values of healthy plants were highly correlated with lightly and moderately diseased plants, thereby, demonstrating the difficulty of separating early stages of infection categories. Despite the potential demonstrated by airborne hyperspectral, its uses for large-scale tomato disease distribution and mapping is still greatly under-developed.

Although hyperspectral instruments and datasets have proven to be useful in the detection of tomato diseases, they are associated with numerous practical challenges. Firstly, the high cost associated with the acquisition of spectrometers hinders its application in less developed and developing countries (Xie et al. 2008). Secondly, field and low airborne hyperspectral sensors are only limited to leaf, canopy and field-level applications, whereas disease distribution and mapping could be required at a regional scale. Thirdly, environmental conditions such as weather can also play a role in image acquisition, thus hindering the adoption of airborne or satellite image applications. Finally, huge data-volumes are associated with exorbitant acquisition and computational costs, while being limited to small spatial extents (Yadav et al. 2019). Furthermore, data processing is complex and requires robust procedures to deal with the high dimensionality and redundancy associated with these datasets (David 2002; Manolakis and Shaw 2002; Yadav et al. 2019). Subsequently, freely available multispectral sensors have become a panacea to the dearth of spatial datasets in developing regions such as Southern Africa with limited financial resources.

Multispectral data have emerged as the robust and most accurate datasets in detecting and mapping crop diseases at relatively larger scales as compared to field hyperspectral datasets. Multispectral sensors collect synoptic spectral data in a few broad and non-contiguous spectral ranges of the EMS, with a single band representing the average of a wide spectral region (Shoko et al. 2016). Multispectral sensors, conversely, offer an added advantage in monitoring and mapping the distribution of crop diseases. This is due to their synoptic overview as well as a relatively large area and repetitive coverage (Kruse and Perry 2009). Although the use of multispectral satellite sensors in detecting tomato diseases is not well documented, "new generation" multispectral sensors such as Landsat 8, WorldView-2, Sentinel-2, RapidEye, and IKONOS with higher spatial resolution and traditional sensors (e.g., Quickbird, MODIS, Landsat 5 and SPOT) have been applied in detecting various other crop diseases (Franke and Menz 2007; Santoso et al. 2011; Chemura et al. 2017; Dhau et al. 2018; Odindi et al. 2018; Ma et al. 2019) at a field level.

Multispectral sensors have also been applied at a relatively large area to study tomato crop diseases (e.g., Zhang et al. 2005). Broadband multispectral sensors, notably Airborne Data Acquisition and Registration (ADAR) has been explored as a spatial data source for the detection of tomato diseases (e.g., Zhang et al. 2005). Its use in crop disease detection owes to its availability and free -accessibility at large geographic coverages. Successful application of ADAR multispectral sensor at a field scale was also conducted by Zhang et al. (2005) in detecting late blight in tomato crops at a field scale. Their results showed that pathogens could be diagnosed when the disease has advanced to the mild infection stage. Multispectral reflectance data have been successfully used in detecting and mapping tomato diseases at a larger scale. For example, the study by Xu et al. (2006) reported the potential ($R = 0.59$) of derived discriminant partial least squares in the discrimination between healthy and tobacco mosaic virus infected tomato plants using multispectral reflectance measurements.

Researchers have been faced with emerging challenges in the use of multispectral datasets in crop disease mapping. For example, the use of data from coarse spatial resolution sensors results in poor vegetation detection and quantification due to the occurrence of mixed pixel information caused by the spectral aggregation of radiance (Rocchini 2007). Subsequently, this results in the loss of critical information and inaccurate quantification of important vegetation structural attributes (Ponzoni et al. 2002). Furthermore, broadband width associated with multispectral datasets limits its application at a local scale. This limitation prompts the use of relatively high spectral resolution satellite data (e.g., RapidEye, WorldView,) that are very costly. These constraints incite the need to move towards the utilization of new and forthcoming multispectral sensors such as Sentinel 2 Multispectral Instrument (MSI) and Landsat 9.

Table 1 presents a summary of RS studies on tomato disease detection. The applications of RS in tomato disease detection is generally at its infancy. Literature reveals that those few were conducted mostly in North America and Asia to detect tomato diseases using ground-based hyperspectral and airborne platforms and none have been conducted using satellite imageries to the best of our knowledge. This could be attributed to image acquisition costs associated with commercial sensors (Xie et al. 2008) for developing regions such as Africa. The results of the aforementioned studies illustrate the significance of the hyperspectral imaging and non-imaging sensors in providing data required for detecting tomato diseases. These studies further provide a new perspective on the utilization of the readily available multispectral broadband systems like Sentinel-2 multispectral imager with high and/or medium spatial resolution that can be acquired at low cost or no cost for detecting tomato diseases at field or landscape scales.

8. Conventional and machine learning empirical approaches for detecting tomato crop diseases using remote sensing

To date, a variety of empirical analytical algorithms have been employed to detect and monitor the severity of tomato crop diseases using various types of remotely sensed datasets. These approaches can be classified into conventional algorithms (parametric) like principal component analysis (PCA), cluster analysis (CA), ordinary least square regression (OLSR) stepwise multiple linear regression (SMLR), k-means clustering and nonconventional (non-parametric) machine learning techniques such as extreme learning machine (ELM), artificial neural network (ANN), spectral angle mapper (SAM), support

Table 1. The state-of-the-art: Application of remotely sensed data on detecting tomato diseases.

Platform	Sensor used	Disease	Major findings (optimum spectral range)	References
Laboratory	Hyperspectral imaging system	Early and late blight	The significant wavelengths were in the visible (442, 508, 573, 696) and near infrared (715 nm) wavelengths.	Xie et al. (2015)
Laboratory	Hyperspectral imaging system	Gray Mold	Gray mold could be detected in the visible (400) and near infrared region (780 nm).	Xie et al. (2017)
Laboratory	Hyperspectral imaging system	Tomato Yellow Leaf Curl Virus	The significant wavelengths were 586 – 720 nm and 690 – 840 nm	Lu et al. (2018)
Insitu	Spectroradiometer -SVC HR-1024	Late blight, target, and bacterial spot	Healthy and severely infected leaves were discriminated at visible (450-700nm), infrared region (780-980nm, 1100-1950nm and 1950 to 2400).	Lu et al. (2018)
Laboratory	Hyperspectral imaging	Tomato Yellow Leaf Curl Virus	Healthy and stressed tomato leaves were discriminated near infrared (710-730 nm) range.	Lu et al. (2013)
Laboratory	Hyperspectral imaging system	Peroxidase activity in tomato leaves with Botrytis cinerea	Visible (576, 578, 579, 600, 601, 603, 618, 619, 620, 621) and near infrared (741, 742, 746, 747, 748, 752, 753, 777, 893, 895 and 896 nm) regions were the most optimal wavelength for predicting peroxidase activity in tomato leaves.	Kong et al. (2014)
Insitu Airborne	Spectrometer GER-2600. AVIRIS	Late blight	The optimal spectral channels for classifying stressed leaves from healthy ones were in the near infrared range using insitu data (750 and 1350 nm) and the image (700 to 1105 nm).	Wang et al. (2008)
Insitu	Spectrometer (Analytical Spectral Devices 2002).	Early blight	Visible (400-700nm), red edge (690-720nm) and near infrared (730 nm-800nm) regions were useful in separating infected leaves from the healthy ones.	Apan et al. (2005)
Laboratory	Hyperspectral imaging system.	Late blight	Reflectance at visible (442, 508, 573 nm) and red edge (696 and 715 nm) were significant in identifying tomato early and late blight disease.	Zhang et al. (2005)
Insitu Airborne	Spectrometer GER-2600 ADAR	Late blight	Visible region (600-690 and 500-600 nm) and near infrared narrow spectra range (1450-1850 nm and 2000-2400nm) optimally discriminated healthy and diseased plants.	Zhang and Qin (2004)
Insitu Airborne	Spectrometer GER-2600 AVIRIS	Late blight	The Near infrared sections (700–750, 750–930, 950–1030	Zhang et al. (2003)

(*continued*)

Table 1. Continued.

Platform	Sensor used	Disease	Major findings (optimum spectral range)	References
			and 1040–1130 nm) were statistically significant.	
Insitu	Spectroradiometer-GER2600	Late blight	The visible wavelengths (543 nm, 663 nm) and near infrared (761 nm, 761–1300 nm, 1993) sections were important in detecting late blight disease.	Zhang et al. (2002)
Laboratory	Spectrophotometer - Cary 500	Bacterial spot	The significant wavelengths for detecting the bacterial spot were visible to near infrared (367–726 nm, 742–867 nm, 872–877 nm, 884–885 nm, 887–891 nm, 900 nm, 1906–1911 nm, 1913–1962 nm, 1964 nm, 1968 nm, and 1970–1971 nm) wavebands.	Jones et al. (2010)
Insitu	Spectroradiometer (EG&G Model 5801585)	Early blight	The reflectance within the visible spectral regions (380 to 510 and 600 to 690 nm) was significantly correlated with the severity of tomato early blight disease.	Lathrop and Pennypacker (1980)

vector machines (SVM) and random forest (RF; Table 2). The algorithms mentioned in Table (2) have been used in singular and in conjunction with others to discriminate tomato crop diseases. Although these analytical algorithms have their advantages and disadvantages (Jones and Vaughan 2010), none of the approaches is optimal for all remote sensing (RS) applications including tomato crop disease detection (Lu et al. 2018). Instead, several approaches have been assessed to identify those performing well under specific conditions of the disease system and available data.

Image segmentation (classification) is the basis for image processing and analysis (Yuheng and Hao 2017). Common segmentation algorithms like threshold techniques and k-means clustering are not new in the identification and classification of biological features of tomato crops (e.g., Arakeri et al. 2015). The threshold algorithm, for example, automatically determines the optimal threshold according to a certain criterion and uses these threshold values (e.g., image pixel grey level or reflectance) to discriminate phenomenal clusters of different tomato disease scores (Yuheng and Hao 2017). Arakeri et al. (2015) deployed a thresholding algorithm and leaf image processing techniques to classify tomato leaves as diseased or healthy. The algorithm further used the k-means clustering method to analyze and detect tomato leaves infected by late blight disease to an accuracy of 84%.

Since crop pathogens alter the biochemical and physical makeup of the plant which in turn alters the plant reflectance, most of the previously mentioned empirical techniques together with remotely sensed datasets proved to be useful in spectral and spatio-temporal disease detection. Wang et al. (2008), for example, used ANN to spectrally and spatio-temporally diagnose late blight disease in tomato crops. In their study, two late tomato blight severity scores, *viz*., diseased and healthy were discriminated using insitu and remotely sensed image datasets. Zhang et al. (2003) on the other hand, used minimum

Table 2. The state-of-the-art: the conventional and machine learning empirical methods utilized for tomato disease detection using remotely sensed data.

Approach	Remote sensing dataset	Type of disease	Performance	References
PLSR	Hyperspectral (insitu)	Early blight	$R = 0.98$	Apan et al. (2005)
SAM	Hyperspectral imaging	Late blight	$R^2 = 0.9638$, between the healthy and stage 2 infected plant $R = 0.2483$ and 0.1836 for stage 3 and stage 4	Zhang et al. (2003)
PCA	Hyperspectral	Late blight	The first principal component (positive correlation with 100%) was associated with spectral of healthy tomato and the second principal component was associated with those of late blight infected tomato.	Zhang et al. (2002)
CA			Discrimination was reasonable when the clusters 'centroid distance is greater than 0.5	
SR			Sensitive spectral wavelengths were observed at 534 nm, 663 nm, 761 nm, 1993 nm wavelength.	
5 Indices	AVIRIS	Late blight	Tomato diseases were successfully classified with an accuracy of 86.93%	Zhang and Qin (2004)
Indices	Hyperspectral (insitu) ADAR	Late blight	Simple ratio (SR) and the normalized difference vegetation index (NDVI) improved discrimination between healthy and diseased tomato plants.	Zhang et al. (2005)
PLSR	Hyperspectral imaging	Botrytis cinerea	$R = 0.7440$ and RMSEP $= 715.4119$	Kong et al. (2014)
ELM			$R = 0.8297$ and RMSEP $= 983.7830$.	
k-means clustering	Hyperspectral imaging	Late Blight	Accuracy of 84%	Arakeri et al. (2015)
ELM	Hyperspectral imaging	Early and late blight	Overall accuracy ranging from 97.1% to 100%	Xie et al. (2015)
KNN	Hyperspectral imaging	Gray Mold	Accuracy of 94.44%	Xie et al. (2017)
FR-KNN			Accuracy of 97.22%	
C5.0			Accuracy of 94.44%	
SVIs (57) PCA	Hyperspectral (insitu)	Bacterial spot late blight, and target	Principal components with eigenvalues greater than 1 and SVIs characterized by coefficient ranks ranging between 1 and 30 were considered and used in KNN modelling.	Lu et al. (2018)
KNN			The late stage of infection showed the highest (77.1%) classification accuracy	
PLSR	Hyperspectral (insitu)	Bacterial spot	R^2 of 0.77 and RMSD of 5.6%	Jones et al. (2010)

(*continued*)

Table 2. Continued.

Approach	Remote sensing dataset	Type of disease	Performance	References
SMLR			R^2 of 0.79 and RMSD of 5.4%.	
ANN	Hyperspectral (insitu)	Late blight	$R = 0.99$ and 0.82 for in-situ and imagery data, respectively with R^2 of 0.62 and 0.66, respectively.	Wang et al. (2008)
OLSR	Hyperspectral (insitu)	Early blight	F values for the 43-10 nm wavebands correlated with early blight disease severity at the 5 percent significance level.	Lathrop and Pennypacker (1980)

*R^2; the coefficient of determination, R; the correlation between the predicted values and the observed values, RMSEP; Root Mean Square Error of Prediction, RMSD; Root Mean Square Deviation, **PLSR**; Partial Least Square Regression, **ELM**; Extreme learning machine, **CA**; Cluster Analysis, **SAM**; Spectral Angle Mapping, **PCA**; Principal Component Analysis, **ANN**; Artificial Neural Network; **SR**; Spectral Ratio, **KNN**; K-Nearest Neighbour, **FR-KNN**; Feature Ranking K-Nearest Neighbour, **SVIs**; Spectral Vegetation Indices, **ANN**; Artificial Neural Networks, **OLSR**; Ordinary Least-Squares Regression, **SMLR**; Stepwise Multiple Linear Regression

noise fraction (MNF) transformation, SAM and an AVIRIS image to quantify different stages of the tomato late blight disease severity. Their findings showed that the most valuable wavelengths for detecting the disease were between 700 nm and 900 nm. Furthermore, the SAM algorithm easily discriminated leaves that were severely infected with late blight than from those that were healthy. Another study by Xie et al. (2017) showed that tomato gray mold can be detected with a classification accuracy of 94.4% and 97.2% using K-Nearest Neighbour (KNN) and Feature Ranking K-Nearest Neighbour (FR-KNN), respectively. Their model accuracy results indicate that the FR-KNN, which is based on the selected wavelengths produced better results than KNN, which is built upon full wavelengths. These studies indicated the importance of reducing the dimensionality of the data and selecting fewer bands that are yet relevant to detecting a particular disease. Methods such as features ranking (FR) (Xie et al. 2017) and MNF (Zhang et al. 2003) have been shown to be feasible for data dimensionality reduction and effective disease detection.

Various studies have also explored the utilization of conventional and empirical parametric methods to analyze remotely sensed data for tomato crop disease detection (e.g., Zhang et al. 2002; Jones et al. 2010; Abu-Khalaf 2015). The study by Zhang et al. (2002), for example, successfully demonstrated the capability of using PCA and CA in the identification and discrimination of spectral characteristics of the tomato late blight disease infection. Their study showed that both PCA and CA were consistent in successfully detecting the tomato late blight when its infection severity reached the middle to late stages. Similar successful examples have been conducted by Jones et al. (2010) who applied partial least squares regression (PLSR) and simple multiple linear regression (SMLR) procedures to identify the most significant wavelengths to develop spectral-based prediction models for tomato leaves infected with bacterial leaf spot under field conditions. The best model predicted the disease severity to a root mean square difference of 4.9% and a coefficient of determination (R^2) of 0.82. Other studies have employed both conventional and machine learning methods to analyze remotely sensed data to detect crop diseases. For example, Abu-Khalaf (2015) used VIS/NIR spectroscopic dataset with an aid of two empirical classification techniques; namely, PCA and SVM to study artificially inoculated fungi (*Fusarium oxysporum f. sp. Lycopersici* and *Rhizoctonia solani)* and two bacteria (*Bacillus atrophaeus* and *Pseudomonas aeruginosa*) in tomato plants. They obtained high classification accuracies ranging between 74 and 95%.

As far as remotely sensed variables are concerned, studies either used reflectance data or SVIs for the detection of tomato diseases (e.g., Zhang and Qin 2004; Lu et al. 2018). Fifty (50) adopted and 7 newly developed hyperspectral VIs derived from visible and near-infrared portions of the EMS were used by Lu et al. (2018) to detect tomato leaves infected by late blight, target and bacterial spots at four different stages (i.e., healthy, asymptomatic, early and late). Their results showed that SVIs have a relatively better potential for the detection of tomato diseases. However, disease-specific variables, data analysis methods and algorithms are therefore required, especially for tomato disease.

9. Challenges and future prospects of tomato crop diseases detection and monitoring

Although progress has been made in the applications of geospatial and RS tools in tomato disease detection, there are still unprecedented challenges associated with their utility. For example, discriminating between healthy and early infected tomato crops resulted in low predictive accuracies when compared to the spectral differences between healthy and severely diseased crops (see Zhang and Qin 2004). This is mainly due to the low level of symptom manifestation, and most importantly the challenges in choosing the most suitable RS system and the analytical algorithm. Although spectral variables such as SVIs proved to be more useful in tomato disease detection, they are not disease context-specific (Mahlein et al. 2010; Ashourloo et al. 2014b, 2016). Therefore, there is a need for more studies to derive disease-specific variables, particularly for detecting tomato crop disease incidence. Also, the integration of remotely sensed and bioclimatic datasets, and the utilization of advanced geostatistical analysis techniques have not been fully explored despite their possible contribution in improving tomato crop disease monitoring (Yuan, Zhang, et al. 2017). This could be attributed to the lack of availability of such data at finer spatial resolutions and wider spatial coverage (i.e., to cover the farm size). In tomato production systems, sometimes the farms are too small for RS application in relation to the pixel sizes. Finally, operational challenges such as pre-processing and high costs involved in the procurement of ground-based hyperspectral instruments limit its accessibility and usage, especially in resource-constrained regions (Yadav et al. 2019). Its usage, however, contrary to multispectral systems that cover larger farm sizes, is limited to small spatial extents, while crop disease data may be required at a field and/or landscape scales.

The robustness of RS in the detection of tomato diseases has not been fully explored. Its application was only limited to in-situ hyperspectral and airborne imaging data, with late blight being the most studied tomato crop disease. Most studies were biased towards the use of hyperspectral data which lacks the spatial footprint. So far, studies have not incorporated the possibility of satellite multispectral data, multisource data integration in disease detection, monitoring, and mapping despite the promising results that are demonstrated in other crops.

In addition, the impacts of climate change and variability on the development and spread of tomato crop diseases can be fully understood when numerous sensors are infused and further integrated with bioclimatic data. Besides disease detection and monitoring, bioclimatic data can also be used to predict and project areas at risk of infection by certain pathogens and to estimate their shift to suitable environments under specific future climate change scenarios at a broader spatial scale. The use of multisource data can yield better results when compared to using these variables as stand-alone model parameters. For instance, the new generation sensors (e.g., Landsat 8 Operation Land Imager (OLI), WorldView-2, Sentinel-2 MSI, Planetscope and RapidEye) present an opportunity for advanced crops disease assessment and monitoring. However, these remote sensing systems have not yet been extensively applied in tomato disease studies.

Contrary to conventional broadband multispectral data, the new generation of sensors are characterised by a relatively high revisit time, improved signal to noise ratios as well as coverage of the red edged section of the EMS (i.e., Sentinel-2, WorldView-2 and RapidEye). Specifically, the strategically-positioned bands (i.e., red edge) of sensors such as Sentinel-2 MSI can be used to generate significant spectral differences in the biophysical and biochemical properties of crops, at a more refined resolution (Richter et al. 2012; El-Hendawy et al. 2019) which proved to be a setback, when using the old generation of broadband multispectral sensors for crop disease detection. For instance, Laurin et al. (2018) demonstrated the applicability of Sentinel-2 MSI in the mapping of commercial tomato farms in Central and Southern Italy. These characteristics make these remote sensing systems to be more suitable for detecting and mapping crop disease and pests at the field to landscape scales. Furthermore, Landsat 8-OLI and Sentinel-2 are free and readily available, a criterion that makes them easily accessible.

Similar to the newly launched sensors, fourth coming sensors (i.e., EnMapper, HyspIRI) will be associated with high temporal, spatial and spectral resolutions. However, their spectral resolution has numerous narrow bands in the red edge and SWIR portion of the spectrum, which will presumably permit a more accurate estimation of tomato disease variables (Teke et al. 2013). SWIR bands are sensitive to plant and leaf moisture and the reduced absorption in the SWIR bands could be related to disease incidence (Ceccato et al. 2001; Dutta, Singh, Panigrahy 2014). Furthermore, these systems will provide important and better alternative remotely sensed data with the potential of monitoring and mapping diseases at larger scales and a relatively low cost. The anticipated spatial data with narrow bands at relatively large scales may address the sensors' saturation issues. HysIRI sensors, for instance, cover part of the EMS such as the red edge region that has demonstrated sensitivity to variations in plant biophysical properties (see Gazala et al. 2013; Sibanda et al. 2019), which could contribute noticeably to disease detection at high vegetation density (Bajwa et al. 2017; Lowe et al. 2017). Therefore, it is assumed that new generation remote sensing systems could be suitable for tomato and other crop disease monitoring at a regional scale and highlight specific infected optical physical and biochemical plant parameters before the onset of visual symptoms and at several stages of disease infection. These are possible avenues that should be explored in the future if crop diseases are to be explored further and properly understood.

Lastly, the newly emerging analytical algorithms like artificial intelligence (AI), big-data and the development of mobile applications (apps) are being explored for precision agriculture (see Bannerjee et al. 2018; Jha et al. 2019) and they would, therefore, present transformative opportunities for detecting tomato or crop diseases. AI-assists in the processing of a vast amount of hyperspectral data, allowing us to use this data to detect, quantify and predict crop disease more efficiently for making more effective and timeous recommendations. Also, the use of the drones (i.e., UAV: unmanned aerial vehicles) at field or landscape scales to survey, detect and monitor tomato and other crops diseases could complement the progress in the use of geospatial and RS tools for tomato crop disease detection.

10. Conclusions

This present review has shown that the use of RS and ecological niche modelling tools to study the distribution of tomato diseases under present and future climatic conditions is still at its infancy. With regards to the application of RS techniques to study tomato crop diseases, most of the available studies focused on the detection and quantification of tomato disease severity using imaging and non-imaging hyperspectral data at the laboratory level with little emphasis on field hyperspectral imaging, satellite-based sensors and multisource dataset integration. This review has further shown that there is a wide range of empirical conventional and machine learning algorithms that have proven useful in analyzing in situ and imaging hyperspectral data for tomato disease detection and severity quantification. These include segmentation, feature extraction and classification, logistic regression, partial least squares, artificial neural network (ANN), K-Nearest Neighbour (KNN) and support vector machines (SVM), among others. We, therefore, conclude that there is an implicit need for future studies to investigate the use of multispectral datasets with frequent revisit intervals, wider spatial coverage capability and finer spatial, spectral and radiometric resolutions in mapping the spatio-temporal distribution of tomato crop diseases. Furthermore, the need for integration of remotely sensed datasets with bioclimatic and topo-edaphic variables, geostatistical analysis techniques in assessing current tomato disease risk areas and forecasting their future shifts is readily apparent.

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