

Chapter III

Geoinformatic Applications in Management of Pests and Diseases

Chandrashekhar Biradar, Layal Atassi, Khalid Omer, Khaled El-Shamaa, Mustapha El-Bouhssini, Claudia Toscano, Arash Nejatian, and Azaiez Belgacem

International Center for Agricultural Research in Dry Areas (ICARDA)

Email: c.biradar@cgiar.org

1. Introduction

Global climate variability and change (and farming system) pose a serious threat to food and to nutritional security, with increased concerns of agricultural risks and vulnerability to pests and diseases. The nature and magnitude of the risks and threats to the vulnerability of crops to insect pests and diseases are not yet well-defined and uncertain in terms of spatio-temporal distributions under ever changing bio-physical and plant physiological conditions. This hinders the effective implementation of the pest management strategies and planning of integrated pest management (IPM). One of the foremost preventive measures is to map the vulnerability of crops to specific pests and diseases. The spatial and temporal hotspots are used to curb and to mitigate the risks in advance and/or to take action on already prevailing outbreaks in order to prevent further spread. At the larger scales, fundamental ecological concepts that address factors governing species distribution were often the foundation for the

development of pest risk and vulnerability maps at regional and global scales (Biradar et al., 2014). However, at local scales, such as farm level management of pests, the use of the regular and in-situ monitoring protocols is required to better understand the risks for the proper management at field scales. The spatial model combined geo-spatial climate data, crop and host phenology, persistence of pests and similarity conditions in conjunction with in-situ observations. This type of risk analysis helps to measure the persistence of the pests at a given time and location and the potential risks, vulnerability, and subsequent epidemic outbreaks in a given location.

Geoinformatics tools and technology (GIS, RS, GPS, modeling, web apps) can be used to collect, archive, analyze, and visualize pests and diseases efficiently and economically for the integrated pest and disease management practices. In this chapter, we outline the geoinformatics technology and its potential application in mapping, monitoring, and management of the pest risks to help with the effective implementation of the IPM. Managers/decision makers at farm level need to understand the variability of the risks at spatio-temporal scales and decide when and where to use IPM practices and relevant control measures to reduce the risk and economic damages.

2. Geoinformatics

Geospatial science, technology, and applications have become indispensable tools for modern day research, especially in studies on natural resources and sustainable agro-ecosystems. The recent proliferation of spatial data in agricultural research is due to: a) recent advances in satellite sensor technology, b) guaranteed availability of quality time-series data, c) open (free) access to high quality satellite sensor images, d) advances in processing and handling of large amounts of data, e) rapid increases in computational power, processing chain, and storage/archiving mechanisms, f) decreases in cost of proprietary software, and g) ease and increasing expertise in handling these complex datasets.

Over the last five years, there has also been an increase in the releases of high quality datasets into the public domain, resulting in greater use of spatial data and the development of machine learning algorithms for thematic research. This trend is likely to increase in the coming years and has ushered in a new era of ‘open access.’

2.1. Increased resolution

The recent development of advanced sensor technology (e.g., specific bands, red-edge, yellow bands), platforms (e.g., spaceborne, airborne, UAVs), satellite constellation, (e.g., increased orbital speed (WorldView2), multiple-clone satellites (RapidEye)), onboard capacity and grounding stations, etc. has opened a new era of remote sensing applications. Just three years ago, it was a dream to get detailed high-resolution images on a daily basis. Today, one can get satellite imagery on a near-real time basis at sub-meter level (<60cm) each day for any given location. The quality and details of the imagery and therefore of the inherent information has increased dramatically (Biradar et al., 2013). Simultaneously, software companies and open-access platforms are developing the necessary calibration and processing tools to make such information easily available to a range of end users.

2.2. Improved processing

Armed with increased computational power for faster image processing, better GIS infrastructure, and a host of tools, including new algorithms for modeling, the geoinformatics community can now study and characterize agricultural production systems at scales ranging from the field to global levels. One of the primary objectives of the system research is to develop detailed, baseline databases for different “action sites” in order to characterize and understand the current status and the extent of different production systems, in terms of land use and land cover types, as well as various processes such as land degradation, water use, etc. These databases will allow researchers and stakeholders to track the progress and assess the impact of various program interventions. For example, the capability to identify different land management units or production systems through their associated spectral properties is a major step forward in our ability to classify and monitor dryland systems.

Ameliorated computational storage, processing power, and automated machine learning algorithms have been playing a greater role in enhancing pixel-based image analysis of high resolution data acquired over complex and highly variable agro-ecosystems. Of course, there are still certain limitations associated with time-variant identical spectral characteristics among different land use and land cover types. However, the combined use of higher spatial, spectral, and temporal resolution images has enabled us to produce better thematic maps with higher classification accuracy.



Fig. 1. Schematic representation of the geoinformatic application in pest management (Biradar et al., 2017).

2.3. Decreased cost of operations

In the past, the operational cost of Geoinformatics was one of the major bottle necks in adopting the technology for a wide array of applications. A major portion of the cost used to be associated with the acquisition of satellite images, followed by the cyber infrastructure for processing and handling the satellite data, and the high prices of major software packages and expertise. However, such overhead costs have been declining in the last few years due to increased open access to data, open source programs and algorithms, decreasing costs of mass storage and increased computational efficiency.

This drastic reduction in the operational costs has led researchers to use geoinformatics tools and technology across wide areas of applications in agricultural research, starting from molecular level research to landscape level assessments, ensuring food and environmental security.

3. Approaches

There are several ways and approaches to map and monitor pest risk at field to landscape and regional level (Low et al., 2016). Here, we discuss geoinformatic approaches to mapping pest risks and associated parameters in order to better manage insect pests and diseases.

Farm managers, extension workers, and often farmers need to know the precise locations of insect pests or disease infestation/infection in their fields, how abundant they are, their direction and magnitude over time, etc. in order to make good timely decisions about control measures, use of chemicals, and deployment of the work force. Without timely and localized treatment, the insect populations can grow and cause substantial yield reduction and economic damage. Alternatively, if an excessive amount of chemicals and/or IPM practices is needlessly applied to areas that pose little to no threat of insect damage, then unnecessary spray costs and other disruptions can occur and, vice versa, failing to locate real risks in the control application. This could happen without knowledge of the location of the pests on the spatio-temporal scales. Taking these points into consideration, as well as size of the farm holdings, crop types, management network, and extension systems in place, one has to select a monitoring tool, which is cost effective and easy to use from data collection to visualization and decision making.

Evaluating the risk of a particular pest or disease can be done using the source of the information (point-based) or modelling of the ecological niche for a broader scale. The information intensive hotspot approach is one of the best and accurate methods to track and to quantify the risk hotspot at spatio-temporal scales. The following assumptions were used to identify these hotspots:

Risk is directly proportional to the presence of the vulnerable host (e.g., crop, date plum);

Risk associated with the presence of the virulent agent or pests (e.g., insects, viruses);

Risk is associated with climate and biophysical conditions (temperature and precipitation patterns) being similar to the area in which the pest/disease has been epidemic.

3.1. Ground truthing

Geo-tagging field data is essential for the risk assessment of several associated variables. The simple approach is to identify areas at higher risk than others. Certain factors need to be taken into consideration for risk analysis and management. One of the easy and economical options is to use smart phones or tablets, with GPS sensors, and/or to use a smart extension diary enabled with Google APIs. Google Earth high-resolution images as background images with GPS-enabled devices can be used to mark individual trees with decent position accuracy. Another approach is to use existing or already collected field survey data and to geo-tag those data with farm coordinates to GIS field boundary to assess at farm level.

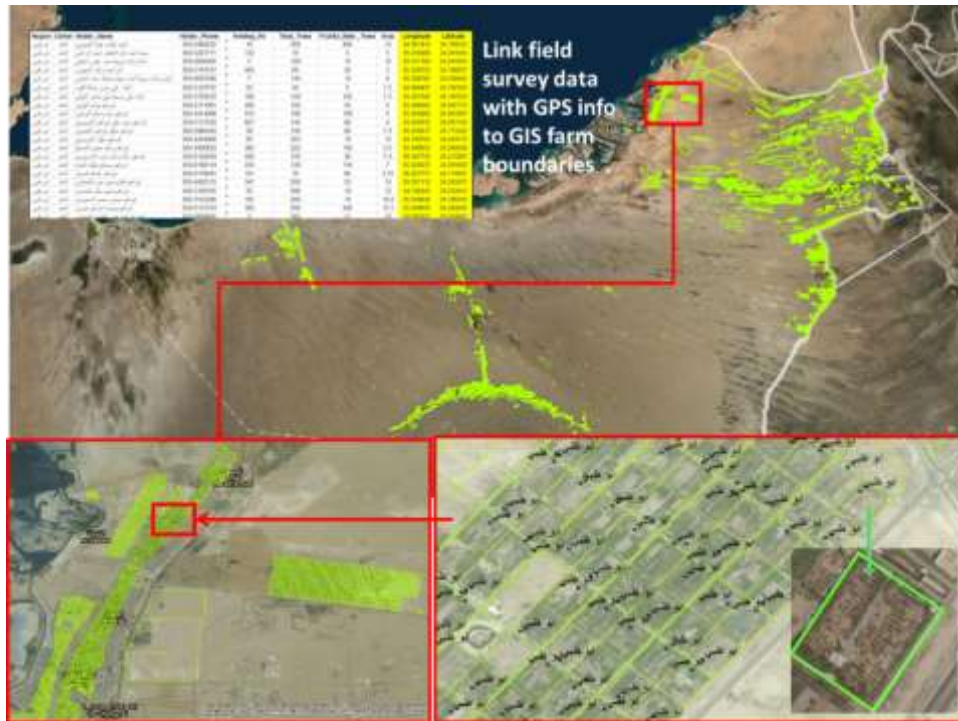


Fig. 2. Geotagging of the field data to GIS field boundary.



Fig.3. Geo-tagging individual trees using mobile devices and apps.

3.2. Spatial modeling

3.2.1. In-situ Observations and Geo-tagging

A lack of geo-referenced information (GPS readings) in field surveys is one of the major limitations for developing risk models and potential risk analysis at spatio-temporal scales. In many instances, the conventionally collected field data will not have GPS coordinates. Sometimes, even if they are collected, they are collected as separate information with no common fields to be able to link to the main database. Furthermore, the collected data could have missing information or some error while entering the data in the field or after the survey, such as data entry errors, wrong GPS coordinates or format which lead to several errors such as displaced points, missing points, double entries, etc. Secondly null values are entered as zeros, which results in misleading information, such as either a particular field is visited or visited but with no records, or records are entered as zeros as parameters with no incident, etc.

Such errors affect the result of spatial statistics and data analysis. Thus, these errors should be detected and eliminated before further analysis in the GIS platform. Preventing such errors can be done by using developed applications and apps on smart phone and tablets with general or tailor-made survey forms or questionnaires to minimize the errors and also data collection efforts, which often saves over 80% of the data collection and post survey curation and analysis.

When all field observations either at point level (tree level) or farm level are tied to their location, their actual position on the ground with the help of GPS coordinates or auto-geotagging can bring a 3rd dimension to the data. This additional position info will help understand the spatial and temporal patterns and arrangements of the data. These geo-tagged data will help in developing GIS layers for spatial matrix analysis using various geo-statistical methods, the use of spatial-based methods allows us to consider issues of spatial error, relative location and proximity in the data, which may give us an insight into the problems and needs of investigation.

Measure of distribution

The simplest measure of the center of a distribution is the mean to the center, which is the direct spatial equivalent of the mean. The calculation of the mean center is similar to the calculation of the mean and involves estimating the average position of the data points with their positional information (geographic coordinates). The resulting means are the coordinates of the mean center of the distribution. In certain cases, there may be a need to consider more than just the average distribution of the data points. We might also want to take the other relative observation made at that location into account. For example, if we want to know the mean center of the infested date palm trees with a specific pest, we can use the weighted mean center of the given pest or all pests. The weighted mean center is where we weigh the calculation of the mean center using the observation at each point.

Basically, the x and y coordinates are weighted by the observations at each point. Such analysis will help in deploying appropriate IPM practices at the right place and time. For example, questions, such as where to place the pheromone traps and how many units are required etc., can be addressed by mapping hotspots of concentration (mean of the distribution) to place the traps.

Measuring dispersion

Another important measure is data dispersion, which measures how the data points in the datasets are spread around the center. Standard distance is a convenient measure of point dispersion. However, the spread about the mean center may vary in different directions. Thus, a standard deviational ellipse could be used to investigate whether there is an uneven spread in the data. This measure uses an ellipse to characterize the spread in the data, rather than the circle used in standard distance, so that it can account better for uneven directional variation. The ellipse used is centered on the mean center and is orientated such that its long axis is in the maximum direction of dispersal and the short axis (which is orthogonal to the long axis) is orientated in the minimum direction of dispersal. This parametric analysis will help to identify if there is a temporal pattern in the pest distribution. This temporal pattern will help design better IPM management practices in response to several environmental factors.

3.2.2. Hotspot analysis and risk mapping

Field data points or field boundary polygons create a map of statistically significant hotspots using GIS based hotspot matrix using Getis Gi statistics (ArcGIS; ESRI 2016). It evaluates the characteristics of the input feature class to produce optimal results. The analysis generates a spatial matrix using parameters derived from characteristics of field survey and input data. The optimized hotspot analysis in the GIS domain interrogates the data to obtain the settings that will yield optimal hotspot maps. Using the distribution of the weighted features, the tool will identify an appropriate scale of analysis.

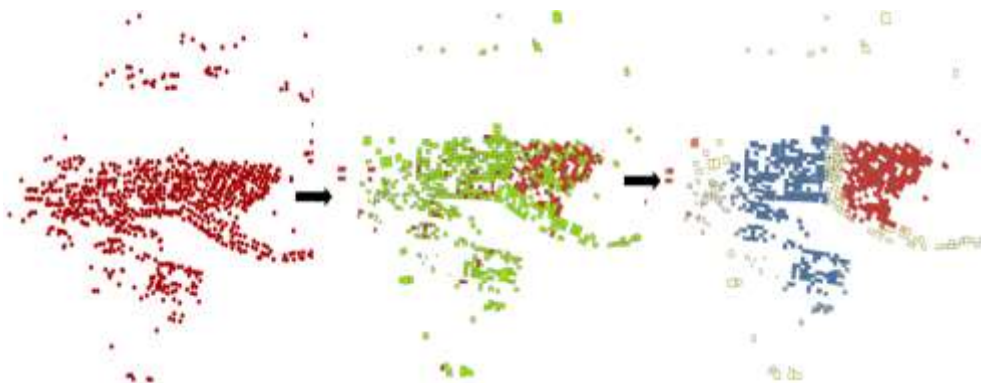


Fig. 4. Hotspot spatial analysis in GIS domain

The corrected shapefile of the date palm data needs to be projected to any metric coordinate systems, such as transverse mercator or polyconic. This is because chordal distances are based on a sphere rather than the true oblate ellipsoid shape of the earth. Given any two points on the earth's surface, the chordal distance between them is the length of a line, passing through the three dimensional earth, to connect those two points. Then, the spatial analysis is run to identify statistically significant spatial clusters of high values (more risk) and low values (low risk). It automatically aggregates incident data, identifies an appropriate scale of analysis, and corrects for both multiple testing and spatial dependence. This tool interrogates your data in order to determine settings that will produce optimal hot spot analysis results.

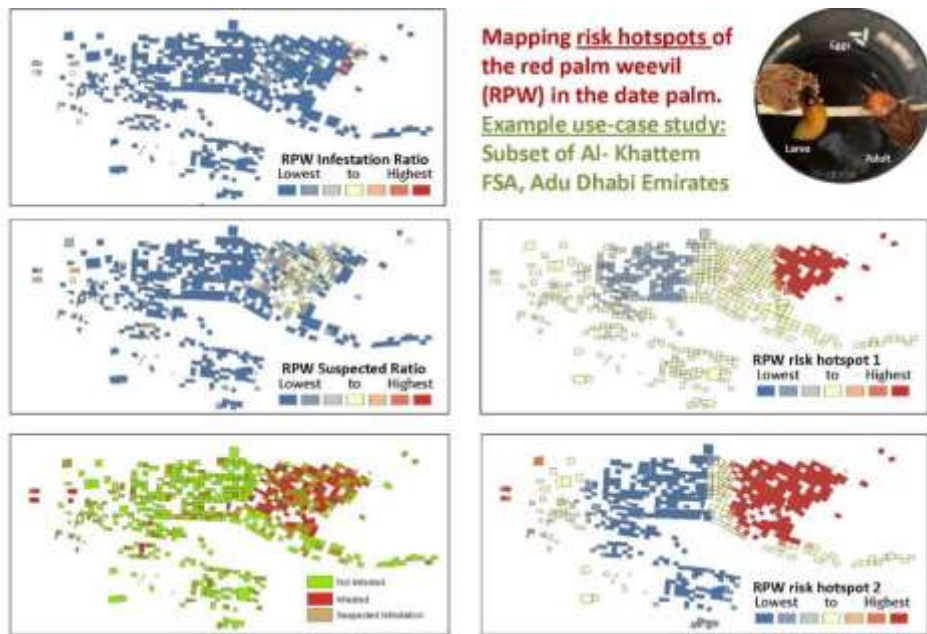


Fig. 5. Pilot case study of the Al Khattem Farmers Service Center area, Abu Dhabi showing the maps of the infested, suspected and hotspot risk maps of the red palm weevil

4. Conclusion

Recent advances in geoinformatics tools with improved processing power and algorithms have opened a new era for mapping and managing agricultural production systems and associated resources. Today, it is possible to map and characterize the date palm production systems more precisely through enhanced availability of high resolution remotely sensed data, increased use of the location analytics, GPS, mobile gadgets with institutional adoption of open-access data policies, and improved big-data analytics and web-GIS tools. These will allow better access to the knowledge needed by researchers, policy makers, and other stakeholders at the right time for a better integration of the several management

practices and IPM packages. These tools will enrich an enormous amount of the field data collected over the years for designing better management practices while minimizing economic losses and ecological damages (ICARDA, 2017). The mapping of the potential risks, current and future trends and patterns will help to draw a quantitative description of the various components needed to improve overall system sustainability and productivity. It will also lead to the development and monitoring of the key indicators across a range of cross-cutting activities needed for improved pest and diseasemanagement, agronomic, and cultural practices. The resulting outcomes will lead to improved and more efficient production systems.

References

- Biradar, C.M., Thenkabail, P.S., Noojipady, P., Yuanjie, L., Dheeravath, V., Velpuri, M., Turrall, H., Gumma, M.K., Reddy, O.G.P., Xueliang, L. C., Xiao, X., Schull, M.A., Alankara, R.D., Gunasinghe, S., and Mohideen, S. 2009. A global map of rainfed cropland areas (GMRCA) at the end of last millennium using remote sensing. *International Journal of Applied Earth Observation and Geoinformation*, 11: 114–129.
- Biradar, C., Tulaymat, M., Kumari, S., Damte, T., Andaloussi, F., Moussadek, R., Lhaloui, S., Ramdani, M., Bencheqroun, S., Ziyaev, Z., Abraham, A., Bekele, B., Denbel, W., Seid, A., El-Bouhssini, M., and Aw-Hassan, A. 2014. Mapping vulnerability of agriculture to pests and disease risks under changing climate in dry areas. *Arab Journal of Plant Protection*, 32:142-143.
- Biradar, C., Payne, Xiao, X., and Gowda, P. H., 2013. Role of Geoinformatics in ensuing global food security with special reference to dryland agro-ecosystems. In proceedings of 2nd International Conference on Agro-Geoinformatics 2013. August 12-16, 2013. Fairfax, VA, USA.
- Biradar, C., Atassi, L., Omer, K., El-Shama, K., El-Bouhssini, M., Toscano, C., Nejatian, A. and Belgacem, A. 2017. Geo-ICTs for mapping and managing of pests and diseases risks in date palm. GFIA, 2017. March 20, 2017, Abu Dhabi, UAE.
- ESRI, 2016. ArcGIS Desktop: Release 10. Redlands, CA: Environmental Systems Research Institute.
- FAO, 2016. The State of Food and Agriculture 2016, Climate Change, Agriculture and Food Security. Rome.
- ICARDA 2017. Mapping and Monitoring Insect Pests and Disease Risks in Date Palms. <http://geoagro.icarda.org/datepalm/index.html>
- Low, F., Waldner, F., Latchinsky, A., Biradar, C., Bolkart, M. and Colditz, R.R. 2016. Timely monitoring of Asian Migratory locust habitats in the Amudarya delta, Uzbekistan, using time series of satellite remote sensing vegetation index. *Journal of Environmental Management*, 183, pp. 562-575.