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Modelling of Dubas Bug (*Ommatissus lybicus*) Habitat and Population Density in Oman Based on Association with Environmental, Climatological and Human Practices Factors

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Abstract

The Dubas bug (*Ommatissus lybicus* de Bergevin) is a type of pest that spends its entire life cycle on date palms (*Phoenix dactylifera* L), thereby causing serious damage and reducing both the growth and the yield of the date palms. The overall aims of this study were (1) to develop and model the habitat, population density and presence or absence of Dubas bug (DB) in Oman based on the associations of those factors with various environmental, climatological and human variables and (2) to predict the potential geographical distribution of parasitic natural enemies of the DB using spatial techniques. The investigations conducted in order to achieve these aims focused on four key research areas, namely (a) the spatial patterns of DBs on the date palms in the study area, (b) the impact of environmental variables on the DB infestation rate (i.e. the impact of human-related practices on DB infestations of date palms), (c) the potential effects of climate-related factors on the absence/presence of DBs and their infestation rate, and (d) the potential of parasitic natural enemies of the DB. These key research areas were studied by means of extensive field investigations, sampling and laboratory testing, as well as detailed analyses.

The results of the first investigation, which took place over the ten-year period from 2006–2015, showed varying degrees of DB infestation, with some regions or conditions having more or fewer hotspots and coldspots than others. The hotspots indicated the sites of potential outbreaks and also revealed the underlying causes of infestation. The distribution patterns of the hotspots varied considerably over time.

In the second investigation, the results of modelling the spatial relationships based on the environmental determinants of DB infestation indicated that three environmental variables, namely elevation, geology and distance from drainage pathways, all had a significant positive effect on the level of DB infestation. In contrast, significant negative relationships were found between the hillshade and aspect variables and the level of DB infestation.

During the third investigation, the analysis of the impact of human-related practices on the degree of DB infestation of date palms indicated strong correlation between the level of DB infestation and several human-related parameters (R^2 = 0.70). We found that palm density, flood irrigation and greater use of pesticides increased the number of DB populations on the studied date palms; however, the row spacing, farm maintenance, offshoot removal, education level of

employees and use of fertilisers all had significant negative relationships with the number of DB populations.

In the first part of the fourth investigation, a logistic regression (LR) analysis was used to model the relationships between the presence and absence of DBs and the annual averages for various weather and microclimate data in both short-term (spring and autumn of 2017) and long-term (2005–2015) scenarios. In the second part of this investigation, the ordinary least squares (OLS) and geographically weighted regression (GWR) techniques were used to explore the relationships between the DB infestation levels (hotspots and coldspots) and various climate-related variables. The results of three model analyses showed that certain variables positively (e.g. elevation, wind direction, temperature and humidity) or negatively (e.g. wind speed) impacted on the rate of DB survival and the density of the DB populations. It was further found that spatial analytical techniques are useful for detecting and modelling correlations between the presence, absence and density of DBs in response to climatological, environmental and human factors.

During the fifth investigation, the results of the spatial pattern analysis indicated the presence of clustered distributions of parasitic natural enemies of the DB in the study area. The results derived via the spatial regression method revealed models that confidently predicted the influence of DB infestation levels, as well as climatological and environmental variables, on the presence of *P. babylonica, A.* nr. *Beatus* and *B. hyalinus* with a 63%, 89% and 94% confidence level, respectively. The distribution of each species was found to be influenced by distinct and geographically associated climatological features, environmental factors and habitat characteristics.

Overall, this study reveals that spatial analysis and modelling can prove highly useful in terms of studying the distribution and the presence/absence of DBs, as well as their natural enemies. The results are anticipated to contribute to a reduction in both the extent and the cost of the aerial and ground spraying of insecticide required by date palm plantations. Furthermore, this study makes recommendations for future studies, and it offers suggestions concerning monitoring and surveillance methods in relation to the design of both local- and regional-level integrated pest management strategies for palm trees and other affected cultivated crops.

Certification of Thesis

I certify that the substance of this thesis has not been submitted for any degree and is not currently submitted for any other degree or qualification.

I certify that, to the best of my knowledge, any assistance received in preparing this thesis, and all sources used, have been acknowledged.

Khalifa Mohamed Al-Kindi

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Note to Examiners

This thesis has been written in journal-article format. I have attempted to minimize the duplication of material between chapters. However, some repetition remains, particularly in the methodology section of certain articles. This is due to the requirements of the journals and the need for each of the papers to stand alone.

Although an effort has been made to ensure consistency in the format for the purposes of this thesis, I acknowledge that some inconsistencies remain due to the requirements of each of the journals to which the separate papers were submitted.

Publications from this Thesis during Candidature

Al-Kindi, KM., Kwan, P., Andrew, N. R., & Welch, M. (2017). Modelling spatiotemporal patterns of dubas bug infestations on date palms in northern Oman: A geographical information system case study. *Crop protection, 93*, 113-121. https://doi.org/10.1016/j. cropro.2016.11.033.

Al-Kindi, KM., Kwan, P., Andrew, N. R., & Welch, M. (2017). Remote sensing and spatial statistical techniques for modelling Ommatissus lybicus (Hemiptera: Tropiduchidae) habitat and population densities. *PeerJ*, 5, e3752. https://doi.org/10.7717/peerj.3752.

Al-Kindi, KM., Kwan, P., Andrew, N. R., & Welch, M. (2017). Impacts of human-related practices on Ommatissus lybicus infestations of date palm in Oman. *PloS one*, *12*(2), e0171103. https://doi.org/10.1371/ journal. pone.0171103.

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Chapters 4 and 7 have been redacted in accordance with publisher post-print embargo periods. Published versions of these chapters can be accessed here:

Chapter 4

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Chapter 7

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List of Abbreviations

AFRI aerosol free vegetation index
ANN artificial neural network
AI artificial intelligence
ASTER advanced space thermal emission and reflection radiometer
AVHRR advanced very high resolution radiometer
AVIRIS airborne visible/infrared imaging spectrometer
ALOS advanced land observing satellite
AC atmospheric correction
ARVI atmospherically resistant vegetation index
BIO bare soil index
CA cellular automata
CART classification and regression tree
CIR colour-infrared
DEM digital elevation model
DB Dubas bug
DVI different vegetation index
ER exploratory regression
FS fluorescence spectroscopy
GIS geographical information systems
GEMI global environmental monitoring index
GR geometrical rectification
GWR geographically weighted regression
HTR humid-thermal ratio
IDW inverse distance weighted
IPM integrated pest management
IR image registration
KDE kernel density estimation
KI kriging interpolation
LAI leaf area index
LISA local indicators of spatial association
LIDAR light detection and ranging
LR logistic regression
LWC I leaf water content index

MAF Ministry of Agricultural and Fisheries

MGD measuring geographic distribution

MIR mid-infrared

MODIS moderate resolution imaging spectroradiometer

MORMEWR Ministry of Regional Municipalities, Environmental and Water Resources

MAS multi-agent system

MNF minimum noise fraction

MSS multi-spectral scanner

NAIP national agricultural imagery programme

NDMI normalisation different moisture index

NDV normalised different vegetation

NIR near-infrared

NNS nearest neighbour statistical

OBIA object-based image analysis

OLS ordinary least square

PCA principal components analysis

PVI perpendicular vegetation index

RBF radial basis function

REPD red-edge position determination

RS remote sensing

RVI ratio vegetation Index

SAVI soil adjusted vegetation

SCI shadow canopy index

SKD simple kernel density

SPOT Satellite Probatoire l'Observation de la Terre

SDE standard deviational ellipse

SVM support vector machines

TM thematic mapper

TC topographic correction

UAV unmanned aerial vehicle

VIS Visible

VI vegetation indices

Chapter 1. General Introduction

1.1. Statement of the problem

Date palm, *Phoenix dactylifera* L., is an economically important crop, cultivated in the Middle East and North Africa. It is an ideal choice for agriculture in arid environments (Al-Dous et al. 2011; Chao & Krueger 2007). Dates are the main fruit product in Oman. The total area allocated to cultivating date palms in Oman is about 35.5 thousand hectares, which occupies more than 82% of the total fruit areas and about 42% of the total agricultural lands. There are about 8 million date palms in Oman, of which 6 million are productive. Oman is home to a wide variety of date palms (i.e. about 250), with a total production of about 281 thousand tons per year (Al-Farsi et al. 2005). Of the productive date palms, 64% are for fresh consumption, whereas 36% are used for commercial consumption (Al-Yahyai & Al-Khanjari 2008).

Insect pests are a major problem impacting on date palm cultivation and production. Some pests attack fronds, some destroy fruits, and some others damage trunks. The Dubas bug (DB), *Ommatissus lybicus*, is considered the most destructive sucking pest in Oman (Al-Kindi et al. 2017d; Al-Yahyai & Khan 2015; Al Sarai 2015b) and many countries in the Middle East and North Africa; sucking pests cause serious damage to the growth and yield of date palms (Al-Kindi et al. 2018b; Bagheri et al. 2017; Bagheri et al. 2018b; Ehsani et al. 2017).

Although chemical control is still an integral part of the integrated pest management (IPM) programme, environmental preservation and human health safety have become major concerns when applying insecticides in agriculture (Al-Kindi et al. 2017c; Mamoon et al. 2016; Wakil et al. 2015). Thus, the use of chemicals against DB is a very risky operation, not least because plantations of date palm are found in all regions where date palms naturally occur. Despite many efforts to control DB, it is still a serious problem, necessitating the promotion of DB management strategy to integrate several techniques and tactics (Hassan 2014; Leeuwen 2007). To achieve DB control, rigorous research is required to create comprehensive databases and develop advanced tactics to manage DB and preserve the agricultural environment (Al-Kindi et al. 2017d).

1.2. Project goals

To understand the distribution and prevalence of DB, highly detailed and sophisticated information about the environment, climate, and human practices are needed to distinguish the complex gene-environmental interactions. This research intends to use data relating to the climate, environment, and human practices to develop and model the spatial links and correlations concerning DB presence/absence and densities. These goals can be summarised as follows:

1. Review the remote sensing (RS) literature, geographical information system (GIS), spatial statistical techniques (SSTs), and spatial modelling applications that can be used to study DB absence, presence, and density in northern Oman;
2. Identify and visualise the hot and cold spots, and analyse DB spatial patterns of infestation stress levels in northern Oman;
3. Model and analyse the relationship between the environmental variables and DB infestation levels;
4. Model and analyse the associations between the human practices and DB infestation levels;
5. Develop regression models for investigating the correlation between climate variables and DB infestations levels; and
6. Predict areas that might be susceptible to natural enemies of DB based on the conditions at sites.

1.3. The significance of the thesis

This study highlights the technological advances in the field of RS and SSTs that can be used to enhance our ability to detect and characterise the physical and biological effects on several plant species (Al-Kindi et al. 2017d). In particular, more advanced RS and SSTs need to be developed and implemented for the surveillance and control of DB adults and nymphs on large spatial scales. In turn, this will greatly assist farmers, plant protection service (PPS) projects, and integrated pest management technology (IPMT) programmes in protecting their palm tree orchards by adopting timely preventative measures.

Most ecological and entomological research has been conducted on local or field-level scales. This study, however, is the most extensive investigation that has hitherto taken place in

Oman. In this research, spatial technologies will be used to extract inventive details about the spatial patterns, spatial correlations, and other factors about DB and different environmental, climatic, and cultural variables. These variables can help us understand, control, and manage the impact of DB on palm trees across Oman. An extensive literature review revealed that there is a paucity of information about links between location-based infestation levels of pests (e.g., DB) and climatic, environmental, and human practice-related variables (Al-Kindi et al. 2017d).

A key issue in ecology and conservation is the mapping of pest species distribution; this information can help devise more effective management strategies for their control. Thus, mapping DB infestations is important for developing predictive models, which provide information about the probability of occurrence, spatial distribution, and densities under different environmental, meteorological, anthropogenic, and resources availability conditions. Maps such as the DB hazard map can be used to develop IPM programmes to educate and empower farmers to control insect pests. Mapping DBs can also enhance the design and management of farms, including what cultivars to plant, how to space the rows, etc. Mapping also helps minimise costs, especially given that the remote sensing- based methods developed as part of this study will promise more efficient and cost-effective solutions (Cheng et al. 2016; Mumby et al. 1999; Westoby et al. 2012).

The findings of this research can inform future DB research concerning the impact of climate change on (a) the distribution and productivity of date palms in the Middle East and Oman, and (b) DB population and distribution patterns. Although a few studies have discussed the natural enemies of DB (Al-Khatri 2011b; Hassan et al. 2004; Hubaishan & Bagwaigo 2010), none has applied GIS and spatial analyses to model these species in Oman (Al-Kindi et al. 2018a). This study is also the first to investigate how environmental, climatological, and DB infestation variables can impact the population of *Pseudoligosita. Babylonica* Viggiani, *Aprostocetus.* nr. *Beatus,* and *Bocchus. Hyalinus* Olmi (parasitic natural enemies) in Oman (Al-Khatri 2011a; El-Shafie 2012; Hassan et al. 2004; Hubaishan & Bagwaigo 2010; Kosheleva & Kostjukov 2014; Oliveira et al. 2014). Moreover, this study intends to illustrate the benefits of spatial analysis and modelling concerning the distribution, presence/absence of DB, and their natural enemies (e.g., predators, parasitoids, parasites, and pathogens). The other benefits of this research include minimising the costs and scope of aerial and ground insecticidal spraying in date palm plantations as well as reducing the impact of the pesticides on DBs' natural enemies on the environment and humans.

This study will help Omani entomologists, biologists, and agriculturists, among others, to become leaders in advanced analytical methods. The statistical modelling system developed during this project will promote advanced research among biologists in Oman and across the Middle East. This study will concentrate on the farmers and other stakeholders whose date palms have been affected by DB; levels of risk and infestation will be appraised, and the most appropriate precautionary methods will be offered.

Date palms play a vital role in Oman's economy and attract considerable investments from the government and local people (AbdulRazak 2010). This accounts for the high employment of many Omanis in farms or date-processing factories—what we call 'the value adding chain'. It is hoped that the results of this study will help increase the production of quality dates and promise farmers improved returns on their crops and substantial revenue for the country.

1.4. Content and structure of the thesis

This thesis has been divided into nine chapters, comprising an introduction, seven research articles, and a conclusion. Chapters 2 and 3 are literature reviews. Chapter 2, published in *PeerJ* (citations), focuses on the use of remote sensing and GIS techniques to detect the DB infestation levels. Chapter 3 concentrates on the advanced geospatial and statistical analyses, linked to GIS techniques; these techniques can help develop and model spatial links and correlations between DB presence, absence, and densities, considering the climatological, environmental, and human factors and conditions.

The review chapters elaborate the strengths and weaknesses of each technique and stress the importance of assessment accuracy of palm plantations and DB infestation detection. Moreover, these chapters provide an overview and background regarding the importance of palm fruits, DB biology and life history, the study area, RS and GIS techniques, and data requirements for studying DB infestation levels in Oman.

The remaining five chapters discuss how GIS and spatial modelling can be applied in the study of DB prevalence and spread. Five of these chapters have been published in leading journals (citations). There is an inevitable degree of repetitiveness in the manuscripts' introduction sections and methodology chapters, mainly because each manuscript was designed to stand alone. Details of these chapters are as follows:

Chapter 4: Modelling spatiotemporal patterns of Dubas bug infestations on date palms in northern Oman: A geographical information system case study.

This chapter identifies and visualises the geographic distributions, hot and cold spots, and outliers; it presents longitudinal analyses of the change patterns of DB infestation levels. Spatial analytic methods (e.g., measuring the geographic distribution and mapping hot spot methods) were chosen mainly because temporal dynamics of DB infestations have hitherto been largely ignored, leading to difficulties in assessing infestation levels of DB out cracks and decision-making. Understanding the historical and spatiotemporal patterns of occurrence of DB infestations at the landscape level promises valuable insights into how out cracks develop, persist and subside. This chapter has been published in *Crop Protection* (Al-Kindi et al. 2017c).

Chapter 5: The impact of environmental variables on Dubas bug infestation rate: A case study from Sultanate of Oman.

This chapter investigates the environmental variables, impacting DB infestations in northern Oman. In this study, we considered the contribution of elevation, slope, aspect, soil type, water type, geology, hillshade, and distance to the sea and drainage pathways. This chapter investigates the correlations of infestation with every single variable to develop a correlation model. Next, this correlation model will be used to construct a more complex predictive model for assessing the relative impacts of the candidate environmental variables. This chapter has been published in *PLoS One* (Al-Kindi et al. 2017a).

Chapter 6: The impact of human-related practices on *Ommatissus lybicus* infestation of date palms in Oman.

This chapter applies spatial analytic and modelling techniques to understand the correlations between various human factors related to date palm farming as well as the distribution and density of DBs. This chapter addresses this question: What are the relationships between the observed patterns of DB infestation and human-related activities? These activities include irrigation type, planting (row spacing), pruning, removing/keeping suckers, insecticides, fertilising, tree density, removing unproductive palms, weeds, field crops, cultivation interfaces, and educated and non-educated issues. This chapter has been published in *PLoS One* (Al-Kindi et al. 2017b).

Chapter 7: Modelling the potential effects of climate factors on Dubas bugs' (*Ommatissus lybicus*) absence/presence and their infestation rate: A case study from Oman.

This chapter investigates the potential relationships, in the form of absence/presence and density that might exist between BD and associated climate factors. This chapter explores the impact of climate factors on determining DB distribution and assesses the usefulness of spatial predictions generated from spatial relationships models. This chapter proposes a method for modelling correlated prorations, such as the proportion of each year in the study period that had experienced an outbreak, based on both annual and seasonal outbreak presence or absence data and the density data over a period of 10 years. This paper has been published in *Pest Management Science* (Al-Kindi el al 2019e).

Chapter 8: Predicting the potential geographic distribution of parasitic natural enemies of Dubas bug (*Ommatissus lybicus* de Bergevin) using geographic information systems.

This chapter probes how the environmental, climatological, and DB infestation level variables impact the population of *Pseudoligosita babylonica* Viggiani, *Aprostocetus nr. Beatus* and *Bocchus hyalinus* Olmi in northern Oman. This chapter illustrates the benefits of spatial analysis and modelling for studying DB distribution, presence/absence, and their natural enemies. It is hoped that the findings can help reduce the extent and cost of aerial and ground insecticidal spraying in date palm plantations. This chapter has been published in *Ecology and Evolution* (Al-Kindi et al. 2018a).

In the concluding chapter, I synthesise the research findings of this study and discusses its limitations. This chapter also discusses how the results of this research can inform planners and developers manage growth and plan a sustainable development programme in this area of research.

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Chapter 2. Remote Sensing and Spatial Statistical Techniques for Modelling *Ommatissus Lybicus* (Hemiptera: Tropiduchidae) Habitat and Population Densities

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Abstract
In order to understand the distribution and prevalence of *Ommatissus lybicus* (Hemiptera: Tropiduchidae) as well as analyse their current biographical patterns and predict their future spread, comprehensive and detailed information on the environmental, climatic, and agricultural practices are essential. The spatial analytical techniques such as Remote Sensing and Spatial Statistics Tools can help detect and model spatial links and correlations between the presence, absence and density of *O. lybicus* in response to climatic, environmental, and human factors. The main objective of this paper is to review remote sensing and relevant analytical techniques that can be applied in mapping and modelling the habitat and population density of *O. lybicus*. An exhaustive search of related literature revealed that there are very limited studies linking location-based infestation levels of pests like the *O. lybicus* with climatic, environmental, and human practice related variables. This review also highlights the accumulated knowledge and addresses the gaps in this area of research. Furthermore, it makes recommendations for future studies, and gives suggestions on monitoring and surveillance methods in designing both local and regional level integrated pest management strategies of palm tree and other affected cultivated crops.

Subjects: Agricultural Science, Entomology, Environmental Sciences, Plant Science, Coupled Natural and Human Systems.

Keywords: Remote sensing, Dubas bug, *Ommatissus lybicus*, Spatial statistics.

2.1. Introduction

Remote sensing (RS) is a powerful technology that has been applied in precision agriculture applications (Liaghat & Balasundram 2010). Remotely sensed data can be used in mapping tools to classify crops and examine their health and viability. They can also be used for monitoring farming practices and to measure soil moisture across a wide area instead of at discrete point locations that are inherent to ground measurement (Atzberger, 2013). Based on these spatial differences, variable rate application of chemicals such as fertilisers or pesticides can be made. Remote sensing information can further be used to establish sub-field management zones, providing a less expensive yet finer resolution option than grid sampling.

Although RS technologies are more widely used in other industries, their potential for profitable use by farmers is less frequently studied. As examples in agriculture, RS technologies have been used successfully for monitoring and mapping water stress, crop quality and growth, wetland, water quality, phosphorus and nitrogen deficiencies in vegetation, as well as detecting and predicting insect infestations (*e.g., O. lybicus*) (Al-Kindi et al., 2017a; Gooshbor et al., 2016; Lamb & Brown, 2001; Riley, 1989) and plant diseases (Neteler et al., 2011).

2.1.1. Background

The date palm, *Phoenix dactylifera* Linnaeus, is an important economic resource in the Sultanate of Oman. Plant-parasitic nematodes, associated with date palm trees in Oman and in most other Arab countries, can reduce their economic yields (El-Juhany, 2010). A variety of insect pests can cause major damages to this crop through production losses and plant death (Abdullah, Lorca & Jansson, 2010; Al-Khatri, 2004; Blumberg, 2008; El-Shafie, 2012; Howard, 2001). One such species, *Ommatissus lybicus* de Bergevin 1930 (Hemiptera: Tropiduchidae), which is known more commonly as the Dubas bug (DB), has been identified as a major economic threat, and is presently affecting palm growth yield in Oman (Al-Yahyai, 2006). Indeed, the DB has been identified as one of the primary reasons for the decline in date production in Oman (Al-Yahyai & Al-Khanjari, 2008; Al- Zadjali, Abd-Allah & El-Haidari, 2006; Mamoon, Wright & Dobson, 2016). It is also a principal pest of date palms in many locations throughout the Middle East, East and North Africa, (Klein & Venezian, 1985; Mifsud et al., 2010). The DB is believed to have been introduced into the Tigris-Euphrates River Valley, from there it has spread to other zones in recent decades (Blumberg, 2008; El-Haidari, Mohammed & Daoud, 1968).

The DB is a sap feeding insect; both adults and nymphs suck the sap from date palms, thereby causing chlorosis (removal of photosynthetic cells and yellowing of fronds). Prolonged high infestation level will result in the flagging and destruction of palm plantations (Al-Khatri, 2004; Howard, 2001; Hussain, 1963; Mahmoudi et al., 2015; Mokhtar & Al Nabhani, 2010; Shah et al., 2013). There is also an indirect effect whereby honeydew secretions produced by the DB can promote the growth of black sooty mould on the foliage and consequently a reduction in the photosynthetic rates of date palms (Blumberg, 2008; Mokhtar & Al-Mjeini, 1999; Shah et al., 2012). Nymphs pass through five growth instars (Hussain, 1963; Shah et al., 2012), with adult female DB reaching 5–6 mm and the males 3–3.5 mm in length (Aldryhim, 2004; Mokhtar & Al Nabhani, 2010). Their colour is yellowish green while the main distinguishing feature between males and females is the presence of spots on females; males have a more tapered abdomen and larger wings relative to the abdomen (Al-Azawi, 1986; Al-Mahmooli, Deadman & Al-Wahabi, 2005; Elwan & Al-Tamimi, 1999; Hussein & Ali, 1996;

Jasim & Al-Zubaidy, 2010; Kaszab, Wittmer & Buttiker, 1979; Khalaf et al., 2012; Mokhtar & Al Nabhani, 2010; Thacker, Al-Mahmooli & Deadman, 2003).

2.1.2. Study area

The Sultanate of Oman, which covers an area of 309,500 km^2, extends from 16°40'N to 26°20'N, and 51°50'E to 59° 40'E. It occupies the south-eastern corner of the Arabian Peninsula (Fig. 2-1). It has 3,165 km of coastline, extending from the Strait of Hormuz in the north to the border with the Republic of Yemen in the South. The coastline faces onto three different water bodies, namely the Arabian Sea, the Persian Gulf (also known as Arabian Gulf), and the Gulf of Oman.

To the west, Oman is bordered by the United Arab Emirates and the Kingdom of Saudi Arabia. Mountainous areas account for 15% of the land area, while desert plains and sandy areas cover 74%, agro-biodiversity areas cover 8%, and the coastal zone covers 3%, respectively (Luedeling & Buerkert, 2008). The location of Oman provides favourable conditions for agriculture, with land under agricultural use accounting for 8% of the territory and the economic output accounting for 14.6% of the GDP in 2008. According to the 2004–2005 soil survey conducted by the Ministry of Food and Agricultural (MFA), 22,230 km^2 (equivalent 2.223 million ha) is optimal for agricultural activity, which represents ∼7.5% of the country's land area. Approximately 728.2 km^2 (∼72,820 ha) of the country is irrigated using the Falaj irrigation system, where local springs or wadis (streams) underflow areas are cultivated with palm trees, banana, limes, alfalfa, and vegetables (Gebauer et al., 2007).

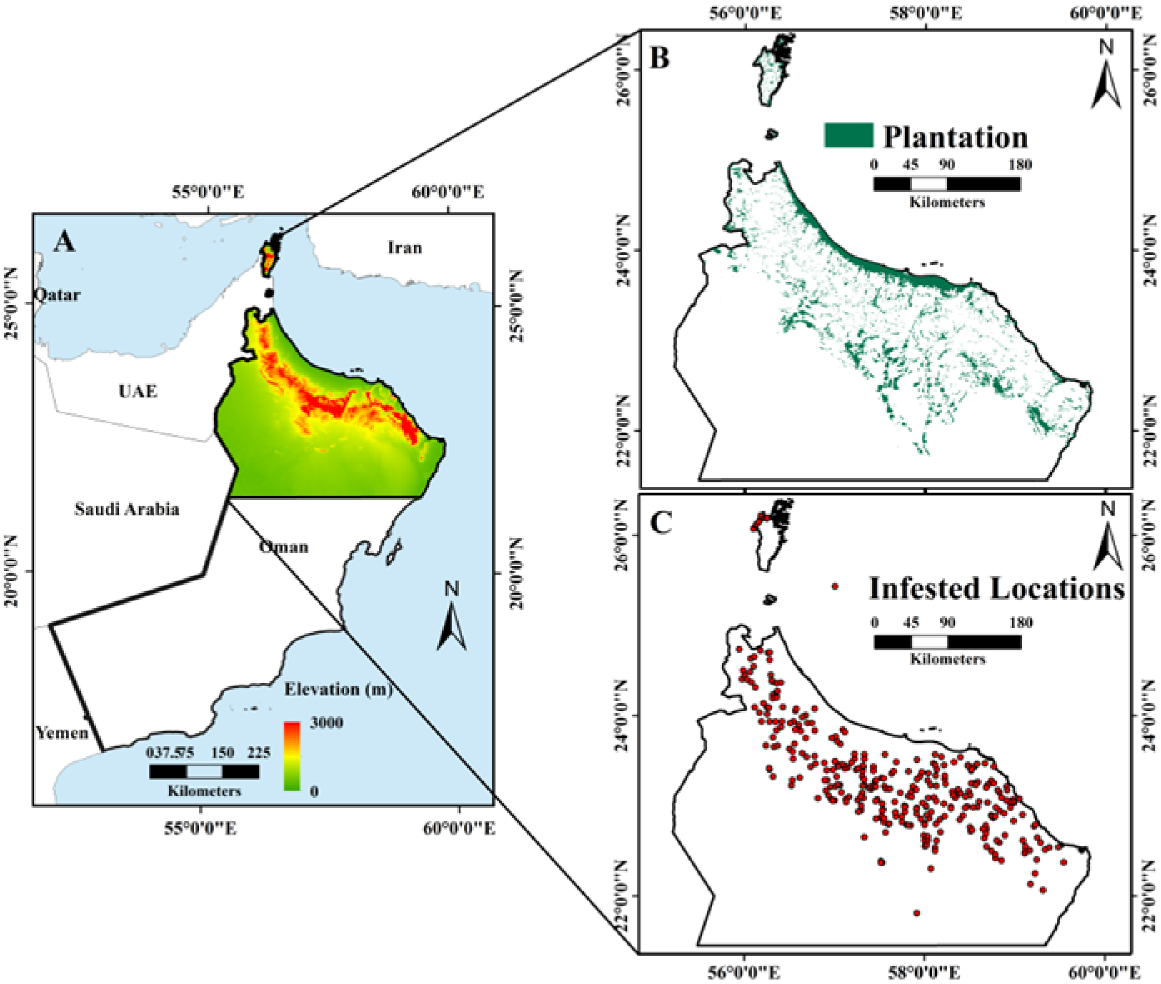

Figure 2-1 Maps of the study area, including: (A) topography and location of Oman, with the study area outlined by the black rectangle; (B) elevation change within the study area; and (C) distribution of date palm plantations in the study area (Esri ArcGIS 10.3)

Oman has an arid climate, receiving less than 100 mm of rainfall per year; however, the mountainous parts of the country receive higher precipitation levels (Kwarteng, Dorvlo & Vijaya Kumar, 2009). As the dependent variable, DB infestations occur where palm trees are concentrated; therefore, in this study we focused on northern Oman (26° 50'N to 22° 26'N, and 55° 50'E to 59° 50'E) which experiences high infestations (Fig. 2-1) (Al-Kindi et al., 2017b).

Dubas bugs are active on leaflets, rachis, fruiting bunches, and spines during different stages of growth of date palm trees. These infestations are capable of causing up to 50% crop loss during a heavy infestation (Shah et al., 2013). Studies of insect pests of the date tree palm indicated more than 54 arthropod species connected with date plantations. Nevertheless, DB and red weevil (RPW) *Rhynchophorus ferrugineus* Oliver, and lesser moth, are considered major economically significant pests affecting growth and yield of date palm trees (Al-Zadjali, Abd-Allah & El-Haidari, 2006).

2.1.3. Biology and life history

The biology of this species has been investigated in a number of studies (Al-Azawi, 1986; Arbabtafti et al., 2014; Hussain, 1963; Jasim & Al-Zubaidy, 2010; Klein & Venezian, 1985; Payandeh & Dehghan, 2011; Shah et al., 2012). The DB produces two generations annually, including the spring and autumn generations (Blumberg, 2008; Hussain, 1963). In the spring generation, eggs start hatching from February to April, after which nymphs pass through five instars to become adults in approximately 6–7 weeks. The eggs aestivate during the hot season (i.e., summer) until the autumn generation, when they start hatching from late August to the last week of October. A nymph takes about 6 weeks to develop into an adult, which then lives for about 12 weeks. Females lay between 100 and 130 eggs (Elwan & Al-Tamimi, 1999; Mokhtar & Al Nabhani, 2010). The female DB lays her eggs by inserting them into holes in the tissue of the date palm frond at the end of each generation. The eggs remain dormant for about three months. When they hatch, the resulting nymphs remain on the fronds of the same tree, feeding on the sap, and defecating large amounts of honeydew, which eventually covers the palm fronds and promotes the growth of black sooty mould (Zamani, Aminaee & Khaniki, 2013).

In extreme cases, the sooty mould that develops from the honeydew secretions can block the stomata of the leaves, causing partial or complete suffocation of the date palm, which in turn reduces its yield. The honeydew secretion also makes the dates unpalatable (Aminaee, Zare & Assari, 2010; El-Juhany, 2010; Gassouma, 2004; Mamoon, Wright & Dobson, 2016). The eggs of DB are sensitive to temperature. In summer, the eggs can hatch within 18–21 days, but in winter they may take up to 170 days to hatch (Blumberg, 2008). The developmental time of DBs eggs has been studied at three different temperatures, 17.6, 27.5, and 32.4 ^{o}C in Oman (Al-Khatri, 2011). The results showed that a temperature of 27.5 ^{o}C appeared to be the optimal temperature for the biological activities of this species (Al-Khatri, 2011). At 35 ^{o}C, the biological processes of the pest are disrupted, thus leading to high mortality, particularly in females (Bagheri et al., 2016; Bedford et al., 2015).

Investigations into the population and the fluctuation in spatial distribution (Khalaf & Khudhair, 2015) of the two DB generations in the Bam region of Iran showed that this pest has an aggregated spatial distribution pattern (Payandeh, Kamali & Fathipour, 2010). Seasonal activities effected by climate change showed that nymphs were dynamic from April to May in the first generation and August to October in the second generation. In the first and second generations, the adults are active from May to June and from September to November, respectively. Earlier work (Blumberg, 2008) reported that temperature exposure below 0 ^{o}C adversely affects the ability of adults to survive. The DB avoids direct sunlight (Klein & Venezian, 1985; Shah et al., 2013), and it is spread via the transfer of infested offshoots as well as by wind or wind dust (Hassan, 2014; Jasim & Al-Zubaidy, 2010).

2.1.4. Biological control

Some research has also been conducted on the natural biological control of the DB, such as using predators and parasites. Early results showed a variety of natural predators that could be used as biological control agents, among these being *Aprostocetus* sp., *Oligosita* sp., and *Runcinia* sp. (Cammell & Knight, 1992). Furthermore, Hussain, 1963 reported that the eggs of the DB could be parasitised by a small Chalcidoid, while the nymphs and adults were preyed upon by the larvae of the lace wing (*Chrysopa carnea Steph*.). Hussain also stated that three adult species of Coccinellids prey on nymphs and adults of the DB. However, further study is needed to determine the distributions of these natural enemies in Oman and their effectiveness in controlling DB populations. Some measure of success was also achieved with pathogenic bacteria as microbiological control agents (Khudhair, Alrubeai & Khalaf, 2016), although their toxicological aspects require further research in order to assess the safety of their implementation at a large scale (Cannon, 1998).

2.1.5. Chemical control

Given the significant economic impact of this pest, research into effective management strategies demands high priority. Several insecticides have been evaluated for DB control in Oman since 1962 (Table 2-1) with Sumi-Alpha-5 EC® being effective as a ground spray and Karate® 2 ULV, Trebon® 30 ULV, and Sumicombi 50® ULV achieving some measure of success as aerial sprays. Karate-Zeon® was also found to be very effective as it gave 100% reduction in numbers of DB instars and adults, between three and seven days after application. However, the use of this particular pesticide is restricted due to its side effects such as irritation (Al-Yahyai & Khan, 2015). In Israel, systemic carbamates such as aldicarb and butocarboxim have been successful, while in Iraq dichlorvos (DDVP) injected directly into the infected palms were also successful in suppressing the pest population (Blumberg, 2008). Nonetheless, this method of control is expensive with negative environmental impacts on non-target species (particularly natural enemies of DB) as well as on human health (Al-Yahyai & Khan, 2015).

Research has shown that some pesticide residues persist in the fruit up to 60 days after application (Al-Samarrie & Akela, 2011). In addition, chemical control has achieved limited successes and DB continues to pose a major challenge to Omani agriculture. More information about the biological and chemical control and their impacts can be found in literature (Shifley et al., 2014; Thacker, Al-Mahmooli & Deadman, 2003).

Table 2-1 Major pesticides used in Dubas bug management in Oman.

Brand names	Active ingredients	Chemical group
Dubaklin	Dintefurn 10% ULV	Neonicotinoid
DECIS	Deltamethrin 12.5% ULV	Synthetic pyrethroid
Sumicombi-Alpha	Fenitothion %24.5 + esfenvalerate %0.5 ULV	Organophosphate + pyrethorid
Trebon	Etofenprox %20 EC	Non-ester pyrethroid
Sumi-Alpha	Esfenvalerate %0.5% EC	Synthetic pyrethroid
Kingbo	Oxymstrin %0.2 & 0.6 SL	Botanical
Actellic	Pirimiphos-methy1 %50 EC	Organophosphate
Pyrethrum	Pyrethrums %50 EC	Botanical
Sumi-Mix	Fenitrothion 25% + fenpropathrin %2.5 EC	Organophosphate + pyrethorid
1-Green	Angulation A: %1 W/V	Botanical
Karate-Zeon	Lambda-cyhalothrin %10 CS	Synthetic pyrethyroids
Fytomax	Azadirachtin %1 ULV	Botanical

2.1.6. Research opportunities

A number of opportunities exist for research into the biology and ecology of this species in order to gain a thorough understanding of its life cycle and its distribution. The climatic factors that influence its survival and distribution also merit study because such information may be useful in determining current and future potential distributions, particularly in light of climate change.

In a review of the effects of climate change on pest populations, an earlier report (Cammell & Knight, 1992) suggested that increases in mean global temperatures, as well as changes in rainfall and wind patterns, could have profound impacts on the population dynamics, abundance, and distribution of insect pests of agricultural crops. More recent research has supported this finding (Bale et al., 2002; Cannon, 1998; Cook, 2008; Shifley et al., 2014; Tobin, Parry & Aukema, 2014). A key issue in ecology and conservation is the mapping of pest species distributions as this information can be used to devise more effective management strategies for their control.

Mapping of DB infestations is important for developing predictive models that give the probability of occurrence, spatial distributions and densities under different environmental, meteorological, anthropogenic and resource availability conditions. Maps such as the DB hazard map can be used to devise an integrated palm management (IPM) plan, thus enhancing capacity and educating farmers on how to apply IPM for the control of this pest.

Mapping DBs are also beneficial in terms of better planning of date palm orchard locations, better design and management of farms, what cultivars to plant, distance between palms, irrigations, pesticides, fertilisations, etc. (Bouyer et al., 2010). There will also be savings in the cost of monitoring since RS based techniques developed as part of this study can provide a more efficient and cost-effective means for large scale monitoring of infestations and observation of stress levels on date palm trees.

The aim of this review is to highlight technological advances in the fields of RS (i.e., by aircraft or a satellite platform) and spatial statistical techniques that can be used to significantly enhance our ability to detect and characterise physical and biological stresses on several plant species. In particular, advanced RS and spatial statistical techniques need to be developed and implemented for the surveillance and control of DB adults and nymphs over large spatial scales. In turn, this will greatly assist plant protection service (PPS) projects, integrated pest management technology (IPMT) programs and farmers in protecting their palm tree orchards by adopting timely preventative actions.

2.2. Remote Sensing Data

2.2.1. Data requirements for crop management

It is important to collect data regarding crops and soil and to identify the changes that occur in the field to achieve precise crop management in the agricultural sector Pinter et al. (2003). Data are needed on the conditions that are stable across seasons (e.g., crop type, soil fertility), differing during the seasons (e.g., pest attacks, water quality and quantity, nutrient contents, moisture, temperature), and on factors that contribute to crop yield variability (Hall, Skakun & Arsenault, 2006; Jadhav & Patil, 2014). This data is valuable for determining the unique phenological cycles of agricultural crops in different geographic regions (Jensen, 2000; Abdullah & Umer, 2004; Acharya & Thapa, 2015).

A good example of this are date palms. Typically, date palm trees are 7–10 m tall with crowns 2–4 m in diameter, and the trees are normally spaced 3–5 m apart. The understory of date palm plantations might include banana palms, mango trees, acacia bushes, vegetable crops, grain crops, forage crops. The reflectance characteristics of a date palm area are often driven by the density and health of the understory vegetation (Harris, 2003). It can be difficult to use small pixel data to study date palm areas with little or no understory vegetation because the small pixel effects may make it difficult to identify infestations (e.g., where date palms are infested between mountains and dry rivers) given the tree spacing and density of leaves and branches. Studies like Hussain (1963) and Mahmoudi et al. (2015) have revealed that heavy infestations occur mostly along valleys. Additionally, the characteristics of the understory vegetation may dominate the contribution of spectral responses rather than the tree vegetation themselves.

2.2.2. Optical remote sensing data

The vital feature of RS is the detection of radiant energy emitted by various objects. The energy detected might be in the form of acoustic energy (sound) or electromagnetic energy (visible light, infrared heat, ultraviolet, and microwaves). Remote sensing technology deployed from ground, air, or space-based platforms is capable of providing detailed spectral, spatial, and temporal information on vegetation health and is particularly useful for crop yield estimation applications (Justice et al., 2002).

2.2.2.1. Temporal resolution of remotely sensed data

The temporal resolution of remote sensing data is important for commercial monitoring or management projects. The commercial Landsat and SPOT have revisit intervals of 16 and 26 days, respectively. The IKONOS revisit times range from 1 to 3 days. On the other hand, airborne (aircraft-mounted) sensors are more amenable to user defined re-visitation. The capacity of high temporal resolution RS technology has been exploited for monitoring seasonal vegetation variations, over wide areas is the estimation of net primary production and deciding time boundary conditions for crop yield modelling (Hatfield & Pinter, 1993; Marx et al., 2010; Reynolds, Reynolds & Riley, 2009; Reynolds & Riley, 1997). We believe temporal RS data can be used to study seasonal DB infestations because there are two generations, namely spring and autumn.

Longer term temporal images (e.g., covering a 15-year period) can be used to classify and to determine the directions and speed of spread of DB infestations. This approach can also be applied to historical images to obtain as much information as possible on selected areas. Change detection can also be performed to quantify the degree of variation in the infestation levels that is needed to occur before the change can be detected by satellite technology. This is important for the development of a management and surveillance strategy for DB.

2.2.2.2. Spatial resolution of remote sensing data

Spatial resolution is measured in terms of the smallest target on the ground. The number of available image-forming pixels in the sensor and its distance from the ground contribute to determining the pixel-size on the ground and the overall image footprint allowing low and high spatial resolution data on damaged caused by insect pests like DB, as RS will pick up the damage, not the actually insect (Kerr & Ostrovsky, 2003). Depending on the goals of a study, technology with an appropriate spatial resolution should be chosen. For example, certain Landsat data sets have spatial resolution of 30 m while certain SPOT data sets have spatial resolution of 20 m in each dimension. If it is a large-scale study (e.g., large orchard), Landsat imagery at a 30 m resolution may be sufficient (White & Roy, 2015).

However, if the study is for small orchards surrounding the mountains where several types of plantations are present, high resolution data would be needed. High resolution imagery products are available, such as SPOT's panchromatic 10 m resolution data sets and Landsat's multispectral scanner 20 m resolution imagery, Wolter, Townsend & Sturtevant (2009). Furthermore, very high-resolution imagery are available, including QuickBird's 2.15 m resolution images or the National Agricultural Imagery Programme's (NAIP's) 1m resolution orthophotographs (Boryan et al., 2011).

More recently, high resolution satellite imagery from IKONOS, which consists of 4 m resolution multispectral imagery, have become available; but the costs for obtaining such data remain a significant impediment to their widespread use. These high resolution images can be used to classify and map the spatial distribution and infestation levels of DB. Very high resolution data collected with unmanned aerial vehicle (UAV)-based remote sensing technology can be used for detecting and mapping of plant diseases and infestations such as those due to

DB (Colomina & Molina, 2014; Kattenborn et al., 2014; Loper, 1992; Nebiker et al., 2008; Sperlich et al., 2014; Zhang & Kovacs, 2012).

2.2.2.3. Spectral resolution of remotely sensed data

Spectral resolution is typically defined as the number of bands of the electromagnetic spectrum that are sensed by the RS device. A very important aspect of spectral resolution is the width of the bands. Different band-widths have been employed extensively in multispectral imagery applications (Zwiggelaar, 1998), and these data often cover an entire colour or colours such as, the red and blue bands of the spectrum. Multispectral systems commonly obtain data for 3–7 bands in a single observation such as in the visible and near-infrared (NIR) regions of the electromagnetic spectrum (dos Santos et al., 2016). Multispectral imagery, however, lacks the sensitivity to detect subtle changes in tree canopy reflectance that are caused by physiologic stress from insects or pathogens (Lawrence & Labus, 2003).

Dakshinamurti et al. (1971) found that multispectral photography is useful for clearly differentiating between coconut plantations and other crops such as jack fruit, mangoes, and bananas in India. Another relevant study, Leckie et al. (2004), used multispectral data for detecting and assessing trees infested with Phellinus weirii which causes *Laminated* root rot disease. Other work (Stephens, Havlicek & Dakshinamurti, 1971) has shown that multispectral photography can be used to clearly distinguish between many types of fruit orchards and crops.

Hyperspectral imagery tends to have much narrower band widths, with several to many bands within a single colour of the spectrum (Jadhav & Patil, 2014). These might include the visible (VIS), NIR, mid-infrared (MIR), and thermal infrared portions. In the visible portion of the electromagnetic spectrum (400–700 nm), the reflectance of healthy green vegetation is relatively low because of the strong absorption of light by the pigments in plant leaves (Apan, Datt & Kelly, 2005; Shafri & Hamdan, 2009; Teke et al., 2013). If there is a reduction in pigments (e.g., chlorophyll) due to pests, the reflectance in the affected spectral region will increase (Carter & Knapp, 2001; Prabhakar et al., 2011). A past study (Vigier et al., 2004) reported that reflectance in the red wavelengths (e.g., 675–685 nm) dominated most of detection data for Sclerotinia spp. stem rot infections in soybeans. Over approximately 700–1,300 nm (the NIR portion), the reflectance of healthy vegetation is very high. Damages caused by DB infestations in the form of black sooty mould on palm tree leaves and understory vegetation that is promoted by bug excrement causes overall reflectance in the NIR region to be lower than expected. The new hyperspectral RS technology could be used to develop early (pre-visual) detection methods for DB infestations.

Colour-infrared technology with supporting hyperspectral reflectance data could be used to identify specific trees and fronds of date palm trees that have been infested with DB. These methods can be used to monitor changes in infestation levels according to honeydew, which is converted to sooty mould on the fronds during high levels of infestation. Honeydew secretion is a good indicator of DB feeding activity (Al-Abbasi, 1988). The indirect assessments of the insect populations can be carried out by measuring the amounts of honeydew caused by the insects (Southwood, 1978). Additionally, airborne visible/infrared imaging spectrometer (AVIRIS) can be used to determine the extent and severity of DB infestation damage in different areas (see Table 2-2).

Table 2-2 Example applications of the use of remote sensing technologies to detect change in vegetation.

Satellite and aircraft sensor	Spatial resolution	Biophysical variables for vegetation
Landsat 7 (ETM+)	15 m Panchromatic (Pan) bands; 30 m in the sex VIS, NIR, IR, and shortwave (SWIR) infrared bands; and 60 m in the thermal infrared bands	Designed to monitor seasonal and small-scale processes on a global scale such as cycles of vegetation and agriculture
Landsat 8 (OLI)	15 m pan bands; 30 m in the sex VIS, NIR, SWIR1, SWIR2; and 30 m in the cirrus bands	
ASTER	15 m in the VIS and NIR range, 30 m in the shortwave infrared band	Land cover classification and change detection
NOAA (AVHRR)	1.1 km spatial resolution	Large-area land cover and vegetation mapping
SPOT	5 and 2.5 m in single-band, and 10 m in multiband	Land cover and agricultural
GeoEye/IKONOS	Panchromatic at 1 m resolution and multispectral at 4 m resolution and colour images at 1 m	Pigments Canopy structure
Digital Globe's/QuickBird **RADAR (SAR)**	Panchromatic with 61 cm resolution and multispectral images with 2.44 m resolution and colour images with 70 cm 3 m resolution	Biomass derive from vegetation indices Leaf index Vegetation stress Absorbed photosynthetically active radiation Evaporations
LIDAR	0.5–2 m resolution and vertical accuracy of less than 15 cm	

2.2.3. Radar data

For many years, airborne technology has been employed in agricultural operations. Nevertheless, space-borne synthetic aperture radar (SAR) technology such as those of the Advanced Land Observing satellite; TerraSAR-X and Phased Array L-band have become available since the 2000s (Ortiz, Breidenbach & Ka¨ndler, 2013). Multiple radar sensors can work autonomously to detect solar radiation variation, but dissimilar optical sensors from which spectral reflectance measurements are taken are affected differently by variation in the solar emission. Radar technology has found limited applications in regional studies because of its high costs, the narrow swath widths, and limited extent of coverage (Feng et al., 2003).

The data can be extracted routinely by using the existing network of weather radars, and it can be used to alert growers that local crops are at heightened risk (Westbrook & Isard, 1999; Drake, 2002). Such information can then be used for fine tuning pest management practices such as pesticide applications, and could potentially reduce pesticide use by nearly 50% and lessen the overall impact of toxic chemicals on the environment (Dupont, Campanella & Seal, 2000), as well as on the natural enemies of these insect pests. Table 2-2 shows example applications of different remote sensing technologies used to detect change in vegetation.

2.2.4. Spectroscopic analysis

Fluorescence spectroscopy (FS) is a type of spectroscopic method by which fluorescence is measured of an object of interest following excitation by rays of light. Fluorescence has been used for vegetation research to monitor stress levels and physiological states in plants. There are two types of fluorescence. The first is blue green fluorescence in the ∼400–600 nm range and the second type is chlorophyll fluorescence in the ∼650–800 nm range. Fluorescence spectroscopy can be used to monitor nutrient deficiencies, environmental conditions based on stress levels, infestations, and plant diseases. In fact, it can be used to monitor fruit quality, photosynthetic activity, tissue stress, and infestations in many types of crops (Karoui & Blecker, 2011; Tremblay, Wang & Cerovic, 2012).

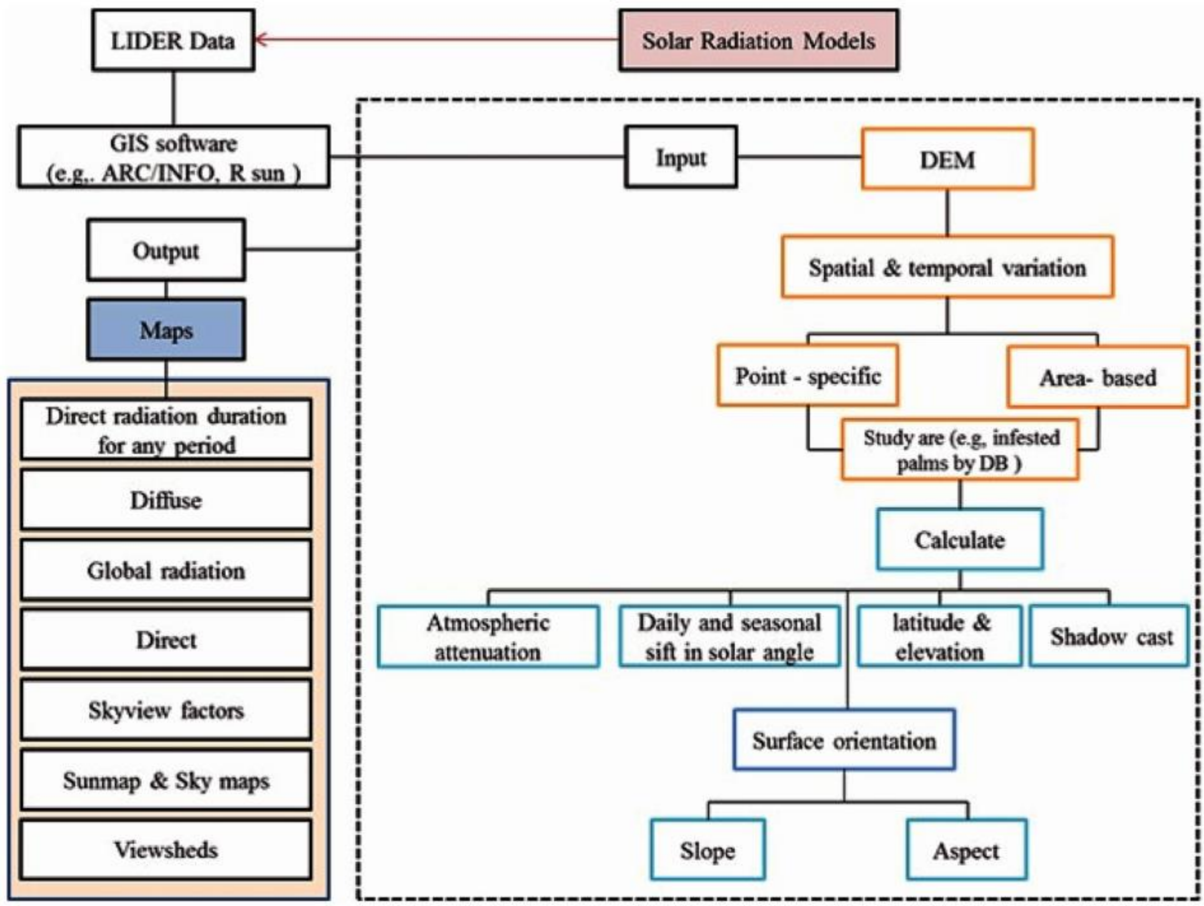

Figure 2-2 A diagram showing the design and use of solar radiation models to analyse the relationship between Dubas bug infestation levels and positional solar radiation.

Remote Sensing is a powerful technique for visualising, diagnosing, and quantifying plant responses to stress like temperature, drought, salinity, flooding, and mineral toxicity. Approaches can range from the use of simple combinations of thermal and reflectance sensor data to visible reflectance and fluorescence data. In particular, combined fluorescence reflectance and thermal imaging sensor data can be used for quick investigations of vegetation stress (Lenk et al., 2007).

2.2.5. Solar radiation and the humid-thermal ratio

Biological systems are highly dependent on two most important climatic factors, namely temperature and precipitation. Temperature is influenced by solar radiation and thermal emissions, while precipitation controls the dry or wet conditions (humidity) associated with plant growth. These factors are especially important in regions where extreme temperatures and humidity conditions are prevalent and large fluctuations exist throughout the seasons as such conditions can predispose plants to insect pests and diseases. In this regard, solar radiation models can be used to investigate insect infestations. Solar radiation models can be applied to calculate the potential solar radiation at a chosen location over a 12-month period.

The results from solar radiation studies can then be used to find correlations with different infestation levels to examine if solar radiation plays a determinant role in different infestation levels (see Fig. 2-2). Solar radiation can also be used to study the presence/absence and density of animals, plants diseases and infestations such as those caused by DB. More information on the theory and technical aspects of solar radiation models can be found in Bonan (1989), Dubayah & Rich (1995), Flint & Childs (1987), Geiger et al. (2002), Hetrick et al. (1993), Kumar, Skidmore & Knowles (1997), Kirkpatrick & Nunez (1980), Mazza et al. (2000), and Swift (1976).

The humid-thermal ratio (HTR) has successfully been used to develop and test relationships between different plant infestations levels in varied climate conditions in areas such as Australia, India, Europe, and North America. An HTR prototype has been developed to simulate ecological conditions appropriate for the establishment and spread of plant diseases in India (Jhorar et al., 1997). The HTR method has also been used to evaluate the risk of the establishment and spread of Karnal in wheat, grown under a variety of climatic conditions and in different areas (Mavi et al., 1992; Stansbury & Pretorius, 2001; Workneh et al., 2008). This method has potential value in researching insect pests and their associated diseases, which may allow for the prediction of occurrence and non-occurrence under specific combinations of climate and weather conditions.

2.3. Vegetation

2.3.1. Image processing for vegetation

In order to detect changes, important information must be provided including spatial distributions of change, change rates, change trajectories for different vegetation types, and assessment of the accuracy of the change detection results. The three main steps in implementing change detection are (1) image pre-processing, e.g., geometrical rectification (GR), image registration (IR), minimum noise fraction (MNF) analysis, radiometric, automorphic, and topographic correction (the latter is needed if the study area is close to mountains) (Bagheri et al., 2016; Bishop & Colby, 2002; Civco, 1989; Teillet, Guindon &

Goodenough, 1982); (2) selection of optimal techniques to conduct the change detection analysis; and (3) accuracy assessments (Datt et al., 2003; Lu et al., 2004; Lunetta et al., 2006; Lyon et al., 1998; Song et al., 2001) (see Fig. 2-3).

Although the selection of appropriate change detection techniques is important for the accuracy of change results, in practice, it might not be easy to select a suitable algorithm for a specific change detection application. Some simple techniques can be used to provide change and non-change information (e.g., image differencing). Other techniques may be used to provide a complex matrix of change direction data such as that used for post-classification comparisons (Lu et al., 2004). This review provides examples of change detection methods that can be used to address DB infestations and their impacts on date palm trees.

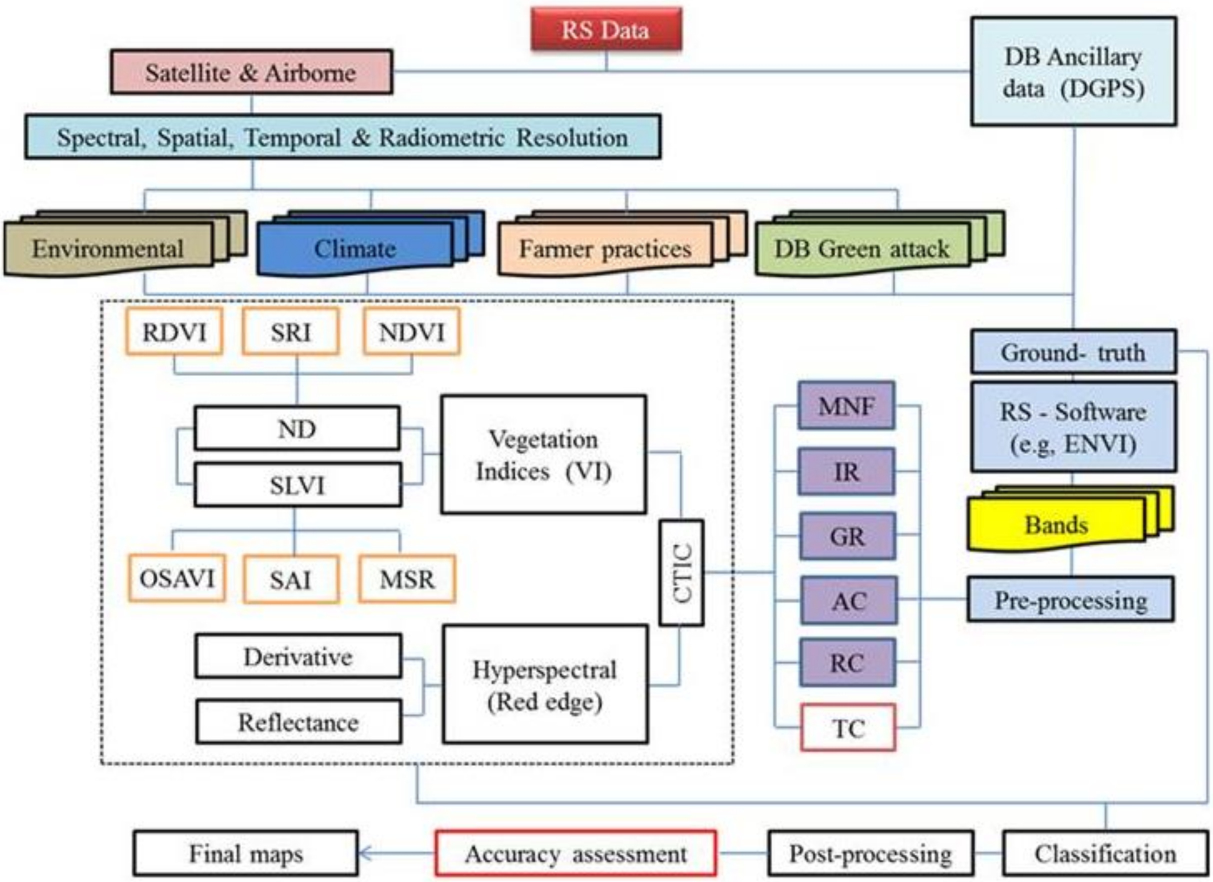

Figure 2-3 Flowchart of an image processing methodology, which include three main steps for implementing change detection research, namely: (1) image pre-processing work: geometrical replication (GR), image registration (IR), minimum nose fraction (MNF) analysis, radiometric correction (RC), atmospheric correction (AC), and topographic correction (TC); (2) selection of optimal techniques to conduct the change detection; and (3) accuracy assessments to obtain final maps.

2.3.2. Techniques and methods

2.3.2.1. Vegetation indices

Vegetation indexes (VIs) are used to compile data into a single number that quantifies vegetation biomass and/or plant vigour for each pixel in a RS image. An index is computed by using several spectral bands that are sensitive to plant biomass and vigour (McFeeters, 1996). Such indices can be used to (1) specify the amount of vegetation (e.g., biomass, SAVI, the percentage of vegetation cover); (2) discriminate between soil and vegetation; and (3) reduce atmospheric and topographic effects. However, variability in VI data can arise from atmospheric effects, viewing and illumination angles, sensor calibrations, errors in geometric registration, subpixel water and clouds, snow cover, background materials, image compositing, and landscape topography (e.g., slope and relief). For example, in sparsely vegetated areas, the reflectance of soil and sand are much higher than the reflection of vegetation; so the detection of reflection from the vegetation cover is difficult.

Difference vegetation index

The difference vegetation index (DVI) is the simplest vegetation index (DVI = NIR–Red). DVI is sensitive to the amount of vegetation, and it can be used to distinguish between soil and vegetation. However, it does consider the difference between reflectance and radiance caused by the atmosphere and shadows (Jiang et al., 2006). Previous research (Glenn et al., 2008) that used the utility of image differencing, image rationing, and the vegetation index for detecting gypsy moth defoliation found that a difference of the MSS7/MSS5 ratio was more useful for delineating defoliated areas than any single band pair difference.

Ratio-based vegetation indices

Ratio-based vegetation indices are also called the simple ratio (SR) or RVI (SR = NIR/Red). The SR provides valuable information about vegetation biomass or leaf area index (LAI) variations in high-biomass vegetation areas such as forests. It is also useful in low-biomass situations, such as those containing soil, water, ice, etc., where the SR indicates the amount of vegetation present. The SR is capable of reducing the effects of the atmosphere and topography on the analysis results.

Normalised difference vegetation index

Normalised difference vegetation index (NDVI) are generally well-documented, quality-controlled data sources that have been re-processed for many applications and problems. It is possible to use the NDVI values to discriminate between dense forests, non-forested areas, agricultural fields, and savannahs; however, distinguishing between forests with different dominant species is not possible by using this type of RS data because several assemblages of plant species can produce similar NDVI values or similar NDVI temporal trends. Atmospheric conditions are another aspect that must be considered when using the NDVI (Willers et al., 2012).

One study, Nageswara Rao et al. (2004), reported that bananas and coconuts have close greenness profiles in mid-April, but have rather distinct greenness profiles in mid- March. Another study Chavez & MacKinnon (1994) reported that red band image differencing provided better change detection results for vegetation than red data when using the NDVI in arid and semi-arid environments of south-western United States. The NDVI may not be appropriate to use in dry areas, and caution is warranted for such applications. Date palms trees are often planted in a regular grid pattern, as are olive trees and such trees may be able to be easily distinguished with NDVI data.

Normalisation difference moisture index

The normalisation difference moisture index (NDMI) data can be used to determine the threshold presence of pest infestations (green attack). Such data can also be potentially used for deriving regional estimates of the year of stand death, for example, by using Landsat data and decision tree analysis. However, there are limitations associated with using the NDMI, which include difficulties in detecting low rates of infestation and the need to add images from other dates (to achieve a higher temporal frequency) to quantify the spectral response to insects such as the DB.

The application of a VI such as the NDVI and SAVI to multispectral satellite imagery (blue, red, and NIR) has been shown to be useful to quantify variations in plant vigour, make relative biomass predictions, assess yields and investigate the occurrences of pests and disease attacks outbreaks (Plant, 2001). Landsat TM data can be used to assess both plant age and LAI values by applying a number of indices such as the shadow index (SI), bare soil index (BI), NDVI, and advanced vegetation index (AVI).

2.3.2.2. Transformation

Feature space transformation, which relates to band space, involves processing data that are n-dimensions. It may be difficult to visualise these data because the feature space (where n is roughly the number of bands). However, several mathematical techniques are readily available to analyse the feature space; they include principal components analysis (PCA), Kauth's Tasseled Cap (KTC), perpendicular vegetation index (PVI), leaf water content index (LWCI), SAVI, NDMI, atmospherically resistant vegetation index (ARVI), aerosol free vegetation index (AFRI), global environmental monitoring index (GEMI), and red-edge position (REP) determination (Eitel et al., 2011). These techniques and many more can be used to find areas that contain plentiful spectral information.

The PCA and the KTC transformations can be used for land cover change detection via NIR reflectance or greenness data that can detect crop type changes between vegetation and non-vegetation features (Gorczyca, Gong & Darzynkiewicz, 1993; Lu et al., 2004). An earlier study (Rondeaux, Steven & Baret, 1996) found that SAVI, where the value X was tuned to 0.16, easily out-performed all other indices when applied to agricultural surfaces. Others (Kaufman & Tanre, 1992; Leprieur, Kerr & Pichon, 1996) have concluded that the GEMI and ARVI are less sensitive to atmosphere but may be incapable of dealing with variation in soil reflectance. More information about feature space transformation can be found in Gebauer et al. (2007) and Luedeling & Buerkert (2008). According to Darvishzadeh et al. (2008), REP is the most studied feature on vegetation spectral curve because it is strongly correlated with foliar chlorophyll content and can be a sensitive indicator of stress in vegetation.

2.3.2.3. Classification

The objective of image classification is to categorise all pixels in the imagery into one of several land cover classes or themes. The categorised data can then be used to produce thematic maps of land cover (e.g., vegetation type) based on remotely sensed data. Most image processing techniques offers several methods to test hypotheses. The best-known methods include supervised and unsupervised classification; however, these techniques require ground reference data.

Maximum likelihood classification, for example, requires samples of pixels obtained by field observations or aerial photography interpretations that are deemed to be representative of specific land cover types. The maximum likelihood method relies on the assumption that the populations from which these training samples are drawn are multivariate–normal in their distributions. The traditional methods employ classical image classification algorithms (e.g., *k*-means and ISODATA) for unsupervised classification, and maximum likelihood classification for supervised classification.

Maximum likelihood classification algorithm

The maximum likelihood classification algorithm (or parametric information extraction) is the most widely adopted parametric classification algorithm. However, it requires normally distributed training data, especially for n (rarely the case) to compute the class variance and covariance matrices. Another limitation is that it is difficult to integrate non- image categorical data into a maximum likelihood classification. However, fuzzy maximum likelihood classification algorithms are also available (Zhang & Foody, 2001).

Classification techniques

Supervised classification. The supervised classification methods can be used to select representative samples for each land cover class in a digital image. Sample land classes are more commonly called training sites. The image classification software uses the training sites to identify the land cover classes in the entire image. The classification of land cover is based on spectral signatures defined in the training set. The digital image classification software determines the class based on what it resembles most in the training set. The limitation on the use of supervised classification is that analysis is required to identify areas on an image of known informational types and to create a training area (group of pixels) from which the computer generates a statistics file (Mountrakis, Im & Ogole, 2011).

Unsupervised classification. The advantage of the use of unsupervised classification is that all spectral variation in the image are captured and used to group the imagery data into clusters. The major disadvantage is that it is difficult to completely label all the clusters to produce the thematic map.

Combined and advanced methods. Many examples exist whereby the supervised and unsupervised techniques were combined together in analyses. The associated advantages and disadvantages can be found in Castellana, D'Addabbo & Pasquariello (2007) and Pao & Sobajic (1992). However, the combined approach only slightly improves the ability to create thematic maps when compared to using each technique separately. Moreover, a large amount of effort has been devoted to developing advanced classification approaches to improve our ability to create thematic maps from digital remotely sensed imagery. One of the most recent advances has been the adoption of artificial neural networks (ANNs) in the place of maximum likelihood classification (standard in most RS software). This review only covers a few of the non-parametric techniques.

Artificial neural network. Fortunately, the ANN methods (non-parametric information extraction) do not require normally distributed training data and may be used to integrate with virtually any type of spatially distributed data in classification. The disadvantage of using ANN is that occasionally it is difficult to determine exactly how the ANN came up with a certain assumption because such information is locked within weights in a hidden layer or layers. The method has been used successfully for classifying infestations, diseases/conditions of plants and the associated damage based on spectral data (Cox, 2002; Liu, Wu & Huang, 2010; Pydipati, Burks & Lee, 2005). In recent years, spectral mixture analysis, ANNs, GISs, and RS data have become important tools for change detection applications.

Artificial intelligence. Use of nonmetric information extraction or AI methods allows the computer to analyse data perhaps better than people. The benefits of using AI for image analysis involve the use of expert systems that place all the information contained within an image in its proper context with ancillary data and then to extract valuable information (Duda, Hart & Stork, 2001).

Classification and regression tree. Classification and regression tree is a non-parametric algorithm that uses a set of training data to develop a hierarchical decision tree. The decision tree is created by using a binary partitioning algorithm that selects the best variable by which to split the data into separate categories at each level of the hierarchy. Once the final tree is generated, it can be used to label all unknown pixels in the image. This method is extremely robust and provides significantly better map accuracies than those that have been achieved by using more basic approaches (Lawrence &Wright, 2001).

Support vector machines. Support vector machines are derived from the field of statistical learning theory and have been used in the machine vision field for the last 10 years. These methods have been developed for use in creating thematic maps from remotely sensed imagery. The SVM performs by projecting the training data using a kernel function and this results in a data set that can then be linearly separated. The capability to separate out the various informational classes in the imagery is a powerful advantage. The use of SVM is relatively new, but it offers great potential for creating thematic maps from digital imagery.

Several advanced techniques for classifying digital remotely sensed data involve the extensive development and adoption of object-based image analysis (OBIA). Moreover, advanced image classification techniques such as k-means, ISODATA, fuzzy ARTMP, fuzzy multivariate cluster analysis, the WARD minimum variance technique, SOM, the artificial neural classification algorithm (i.e., for the propagation of neural networks and self-organising maps) and Bayesian analysis can be used (1) for the classification of remotely sensed data; and (2) to delineate horticultural crops in satellite maps. The major advantage of these techniques is their ability to generate a matrix of change information and to reduce external impacts from the atmospheric and environmental differences among the multi-temporal images. However, it may be difficult to select high quality and sufficiently numerous training sets for image classification, in particular for important historical image data classifications due to the lack of data (Lu, Moran & Batistella, 2003; Lu & Weng, 2007; Lunetta et al., 2006; Monteiro, Souza & Barreto, 2003; Rogan, Franklin & Roberts, 2002).

All these classifications are performed on a pixel-by-pixel basis. Therefore, given that a pixel maps an arbitrary delineation of an area on the ground, any selected pixel may or may not be representative of the vegetation/land cover of that area. In OBIA, unlabelled pixels are grouped into meaningful polygons that are then classified as polygon pixels (Blaschke, 2010; Dey, Zhang & Zhong, 2010; Haralick & Shapiro, 1985; Stafford, 2000).

Classified satellite imagery can also be used to extract palm crown data. The centre of crowns can be isolated because they often remain green and are not as severely impacted by the DB as the palm fronds. Densities of the DB tend to be highest outside of the crown region. The removal of the centre and concentration on the outer parts of the vegetation can then lead to a higher probability of detecting the impacts of DB and categorising the infestation levels accurately. The images can also be used by classification techniques (e.g., unsupervised) to detect stages for which users do not have ground truth data.

Image segmentation techniques

Image segmentation techniques can be used to extract information on palm canopies. The crown information can be used to calculate the density of palms per unit. This information can then be applied as part of a GIS-based spatial analysis to answer questions about whether infestation levels are linked to the density of palms or not. The crown information could also be used to determine the random or systematic nature of farms.

This information can be further used in GIS-based analyses to answer questions about whether or not randomly situated plants have a higher risk of infestation than non-randomly situated plants. Such information would be useful for determining the optimal row spacing. Research published in the literature suggests that those plantations that have wide row spacing have a lesser likelihood of DB infestations (Ali & Hama, 2016). The row spacing data extracted from satellite imagery could thus be used to confirm the relationship between row spacing and infestation levels.

Image fusion

Image fusion is a technology that merges two or more images of the same area collected by different sensors or at different wavelengths. For example, merging a 2.5 m multispectral image with a 0.7 m panchromatic image can be done to capitalise on the advantages of both image sets. The panchromatic images have very good spatial resolution but lack the multiband information that the 2.3 m multispectral image provides. Thus, the advantage of using image fusion for change detection is that fusion can allow for both high spatial and spectral resolutions, which will enable users to extract high quality land cover/vegetation information (Boryan et al., 2011; Simone et al., 2002). Image fusion techniques such as the HSV (hue, saturation, value), Brovey, Gram-Schmidt, and principle components methods can be used to compare the accuracy and distortion levels of images (e.g., 8-band Worldview images).

2.4. Accuracy Assessment

Accuracy assessment is an important part of any classification algorithm process, and it should be undertaken for every project because it is difficult to know how accurate a classification is without an accuracy assessment. The accuracy of a classification is usually assessed by comparing the classification with some reference data that is believed to accurately reflect the true land-cover. Reference data may include ground truth data, higher resolution satellite images and maps derived from aerial photographic interpretations. However, in the case for all reference data, even ground truth data, these data sets may also contain some inaccuracies. More information about accuracy assessments can be found in Congalton (2001), Foody (2002), Gibbs et al. (2010), Hirano, Welch & Lang (2003), Huang et al. (2007), and Hughes, McDowell & Marcus (2006).

Positional accuracy methods can be used to provide an assessment of the differences in distance among a sample of locations on the map and those same locations on a reference data set. This same basic process can be used in assessing the thematic accuracy of a map, and it involves a number of initial considerations such as taking into account the sources of errors and the proper selection of classification systems (Congalton & Green, 2008). Determination of the thematic accuracy is more complicated than that of the positional accuracy.

This is due to the size requirements for sampling thematic accuracy assessments, which are larger than those for positional accuracy assessments. An error matrix technique can be used to compute the thematic accuracy, and the error matrix can be generated by using reference data and correct or incorrect designations; one can also use qualifiers such as good, acceptable and poor to produce a fuzzy error matrix. Additionally, there are a number of analysis techniques that can be performed using the error matrix, such as the Kappa analysis. The Kappa analysis can be used to test statistically whether or not one error matrix is significantly different than another (Goodchild, 1994).

2.5. Modelling the spatial relationships between insect infestations and the environmental and climate factors

While RS techniques focus on visual and pre-visual detection and mapping, spatial analytical techniques can be used to evaluate correlations, identify important variables, and develop predictive models. Spatial statistics functions and tools have made it possible to implement state-of-the-art spatial autoregressive techniques to investigate many research problems (e.g., insect pest) (Carrie`re et al., 2006; Carruthers, 2003; Wulder et al., 2006). Advances in spatial analytical techniques software, such as ArcInfo®, have greatly reduced the time for estimating spatial parameters. For example, regression analysis allows users to examine, model, and explore spatial relationships in order to better understand the factors behind the observed spatial patterns. It also allows users to predict hypotheses based on understanding of these factors. There are three main types of regressions, namely, linear regression, local regression, and logistic regression (Liebhold, Rossi & Kemp, 1993; Wichmann & Ravn, 2001). Linear regression can be used to predict the values of y from values of x_i as follows:

$$y = a + b_1x_1 + b_2x_2 + ... + b_nx_n \qquad (1)$$

where y is the dependent variable, x_i represents the independent variables i, and b_i… b_n are the regression coefficients. However, this requires several assumptions about the error, or residuals, between the predicted values and the actual values (Miles & Shevlin, 2001). Some errors are related to a normal distribution for a set of independent variables, while others are related to the expected mean value of zero. Linear regression has been used to model wildlife home ranges (Anderson et al., 2005) and soil moisture (Lookingbill & Urban, 2004; Lema, Mendez & Blazquez, 1988). According to Harris et al. (2010), local regression or geographically weighted regression (GWR) analysis can be used to predict information for every known point in order to derive a local model. Moreover, parameters for this method can include variations in space, thereby providing a basis for exploring non-stationary spatial relationships. The logistic regression method can be applied to model spatial relationships between features, such as when the dependent variable is categorical (e.g., presence or absence data) and when the independent variables are categorical, numeric, or both (Menard, 2002). The advantage of using the logistic regression is that it does not require the same set of rigid assumptions as required by linear regression.

Various studies have involved the use of autoregressive models to investigate the relationships between insect infestations and factors that are based on environmental information. Munar-Vivas, Morales-Osorio & Castan˜eda-Sa´nchez (2010) combined environmental information, spatial data, and attribute data in GIS-based maps to assess the impact of *Moko* disease on banana yields in Colombia. Specifically, they used a regression model to investigate the relationship between infested areas and distances from the Moko foci to cable-ways and drainage channels. Coops et al. (2006) studied the associations among the likelihood of occurrence, forest structure and forest predisposition variables using regression tree models. They found through modelling that location and slope were the major factors driving variations in the probability of red tree outbreaks. The GWR model has been used to detect high-risk infestations caused by mountain pine beetle invasions of lodge-pole pine forests over large areas (Robertson et al., 2008).

It is important to start by using single variables to develop correlations before moving to more complicated predictive models and regression analyses, where all factors are incorporated to investigate which combination of factors is most conducive to the survival and spread of insects or diseases. In our study, for instance, GWR could be used to model the correlation between DB infestation and meteorological variables such as humidity, rainfall, temperature, wind direction, and wind speed; GWR could also be applied to model the correlations between DB infestations and environmental variables including soil type, slope, aspect ratio, ecology, soil salinity, and solar radiation. Additionally, autoregressive models could be used to investigate the relationships between DB infestations and human practices such as irrigation, plantation systems, insecticide use, and methods of spraying (Al-Kindi et al., 2017a).

2.5.1. Suitability model for detecting and investigating insect infestations

All of the methods used to study the relationships between dependent and independent variables discussed previously are traditional statistical methods, which sometimes might not reflect the complicated relationships between infestations and environmental factors. In particular, ecological and geographical environments represent complex systems in which individual elements interact to create complex behaviour, and consequently, complex methods such as ANN, Cellular Automata (CA), and multi-agent systems (MAS) may be better suited to study the relationships and conduct factor analyses in insect infestation or disease detection research and to perform spread simulations (De Smith, Goodchild & Longley, 2007).

Numerous suitability models have been proposed to identify locations that have a particular set of characteristics. In Hernandez et al. (2006), the authors compared four different models (BIOCLIM, GAPP, DOMIN, and MAXENT) and found that MAXENT was most capable for producing useful results with small sample sizes and minimum species occurrences. These models can also be used to identify areas that are susceptible to risks such as insect infestations, based on conditions favoured by the species. For example, a relevant study (Drees et al., 2010) used the habitat suitability selection method to model potential conservation areas for a rare ground beetle species (using barcode index number or BIN). Specifically, they used five different data sets to identify several key habitat factors for *Carabus variolosus* stress levels. A model was developed in Bone, Dragicevic & Roberts (2005) by using fuzzy theory to identify areas of susceptibility to *Dendroctonus ponderosae* Hopkins in Canada. However, spatial data have unique characteristics that can impact the results of the model (Crooks & Castle, 2012).

Raster data models are often used for finding and rating suitable locations. The raster overlay results are formatted in a single layer of suitable versus unsuitable cells, rather than in a vector layer with many polygons and an attribute table, which contains the attribute values for each of the polygons. There are two ways to create raster suitability layers. The first approach is to query the individual sources to create the suitability layer. The query can be used to create a suitability layer with two values, '1' for cells meeting all criteria of a suitable habitat, and '0' for the others. Because the layer consists of only two values, one indicating suitable and the other unsuitable cells, they are called binary suitability layers. Binary processing however is not always necessary. Combined with other evaluation models, suitability mapping can be achieved by overlaying directly or by post processing the overlay results. Figure 2-4 shows a process that could be used to find suitable location conditions (habitat) for insects such as DB by using a raster method overlay.

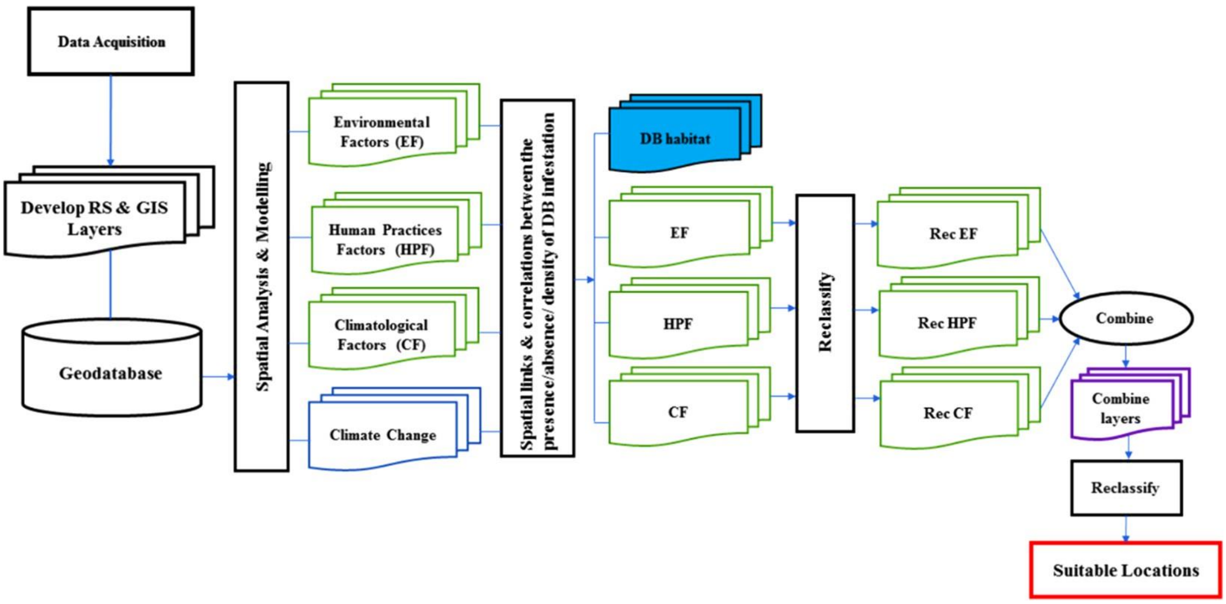

Figure 2-4 Schematic of the process that can be used to model the suitable location for Dubas bug infestations.

The uncertainty that results from geo-processing operations, demonstrates that sophisticated spatial analysis cannot be achieved using traditional, deterministic geoprocessing methods alone (Goodchild & Glennon, 2010; Zhang & Goodchild, 2002). Fuzzy logic is a superset of Boolean logic and has the ability to handle uncertainty in data that arises from vagueness instead of randomness alone (Li et al., 2010).

Fuzzy logic can be utilised to extract information from high resolution RS data and combined with a raster-based spatial data to produce maps representing the spatial variation of vulnerability to pests across a landscape (Zhang & Foody, 2001). This method also allows for partial association with one or more classes, meaning that objects may be represented by a value based on a membership function between '0' and '1' (Li & Zhao, 2007). The membership function of an element *x* belonging to a fuzzy set A is computed by:

$$\mu_A : U \rightarrow [0,1] \quad (2)$$

where *U* is the universal set of *x*. The concept of fuzzy sets has also been employed for defining the spatial and attributes characteristics of geographic objects (Burrough & Frank, 1996; Wang & Hall, 1996). The results of such analysis can be rendered directly into a decision framework via maps, tables, and charts. The results can also be used in further analyses or to provide additional understanding of the problem.

The challenge in any particular area of study is the geographical extent and the resolution of analysis, which is determined by the phenomenon being modelled. To achieve validity, researchers must ensure that they are using accurate and current data whenever possible. If the data are from one's own organisation, one can rely on data quality controls that are in place. Data quality should be checked against alternate sources if possible, in order to ensure it meets the requirements of the analysis. Assessing the quality of data will provide guidance to predicting what level of confidence can be attributed to the result of the modelling work.

2.6. Proof-of-Concept Cases

The first proof-of-concept case is published in Al-Kindi et al. (2017a). In this paper, we analysed a set of IKONOS satellite images collected in 2015 on our study area (5 m spatial resolution) by processing them using chosen image segmentation functions and extracted density information of the palm canopies. The techniques used can be found in 'Image Segmentation Techniques.'

Next, sample locations (i.e., GPS points) were identified in the satellite images by examining their normalised different vegetation index (NDVI) values. NDVI served as a surrogate measure of palm plantation density and homogeneity in the neighbourhood surrounding an image pixel. The relevant techniques can be found in 'Normalised Difference Vegetation Index.'

In addition, spatial statistical techniques including GWR, Ordinary Least Squares and Exploratory Regression (corresponding implementations included in ArcGIS^{TM}) were applied to study the correlations between various human factors related to date palm farming and the distribution density of the DB. These techniques have been reviewed in 'Modelling the Spatial Relationships between Insect Infestations and the Environmental and Climate Factors.'

The second proof-of-concept case is published in Al-Kindi et al. (2017b). In that paper, we applied spatial statistical techniques to model spatiotemporal patterns of DB on date palm in north of Oman. Data on the DB infestations and their impact were collected through observations of palm trees from 2006 to 2015 by the Ministry of Agriculture and Fisheries of the Sultanate of Oman. The techniques used can be found in 'Modelling the Spatial Relationships between Insect Infestations and the Environmental and Climate Factors' and 'Data Requirements for Crop Management.'

2.7. Conclusion

In this review, a variety of spatial information technologies, including remote sensing and spatial statistical methods, have been shown to be useful in areas of research involving insect infestations worldwide. Environmental and climatic conditions are very important in determining the distribution and survival of any species, including the DB, which is a problematic pest in date palm plantations. We argue that most of the current research on DB has focused on its ecology, biology, or control mechanisms only. There has been very limited research linking the presence/absence, density, spatial, and temporal distributions of DB with environmental, meteorological, and human practices that promote its development, prevalence, and spread. Understanding the distribution and affinity of the DB in terms of these variables and mapping of the data can play a key role in its control and management, as well as resource allocation.

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Chapter 3. Geospatial and Statistical Techniques for Modelling Ommatissus lybicus (Hemiptera: Tropiduchidae) Habitat and Population Densities

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Abstract

This paper reviews the advanced geospatial and statistical techniques available in geographical information system (GIS) software that can be used to identify, visualise and model insect pests, such as *Ommatissus lybicus* (Hemiptera: Tropiduchidae), which has caused the widespread infestation of date palms. Hypothesis testing using geospatial and statistical techniques is a very important step in confirming the validity of predictive models of any set of features and investigating why they are clustered in certain regions or under particular conditions. Spatial statistical analysis methods can be used to model and develop spatial links and correlations between *O. lybicus* habitat and population densities by analysing environmental, climatological and human-practice factors. These techniques can be useful for identifying the most important variables that enable *O. lybicus* to develop, prosper and spread. Studying the relationships between insect pests (i.e., *O. lybicus*) and various spatial and temporal factors can begin with a single variable in order to develop correlations, followed by more advanced predictive models and regression analysis in which all features and their combinations that are most conducive to the survival and spread of *O. lybicus* are analysed. Understanding the distribution and affinity of *O. lybicus* to these factors is expected to play a key role in its mapping, control and management, including resource allocations.

Keywords: *Ommatissus lybicus*; Dubas bug; date palm; GIS; spatial information; population densities

3.1. Introduction

Ommatissus lybicus de Bergevin 1930 (Hemiptera: Tropiduchidae) is a principal pest of date palms in many locations throughout the Middle East and North African countries (Klein & Venezian 1985; Mifsud et al. 2010). More commonly known as the Dubas bug (DB), *O. lybicus* is of major economic importance, affecting date palm tree growth yield both quantitatively and qualitatively (Al Sarai Al Alawi 2015; Ali 2010; El-Shafie et al. 2015). It has spread to other zones in recent decades (Blumberg 2008; El-Haidari et al. 1968) Figure 3-1).

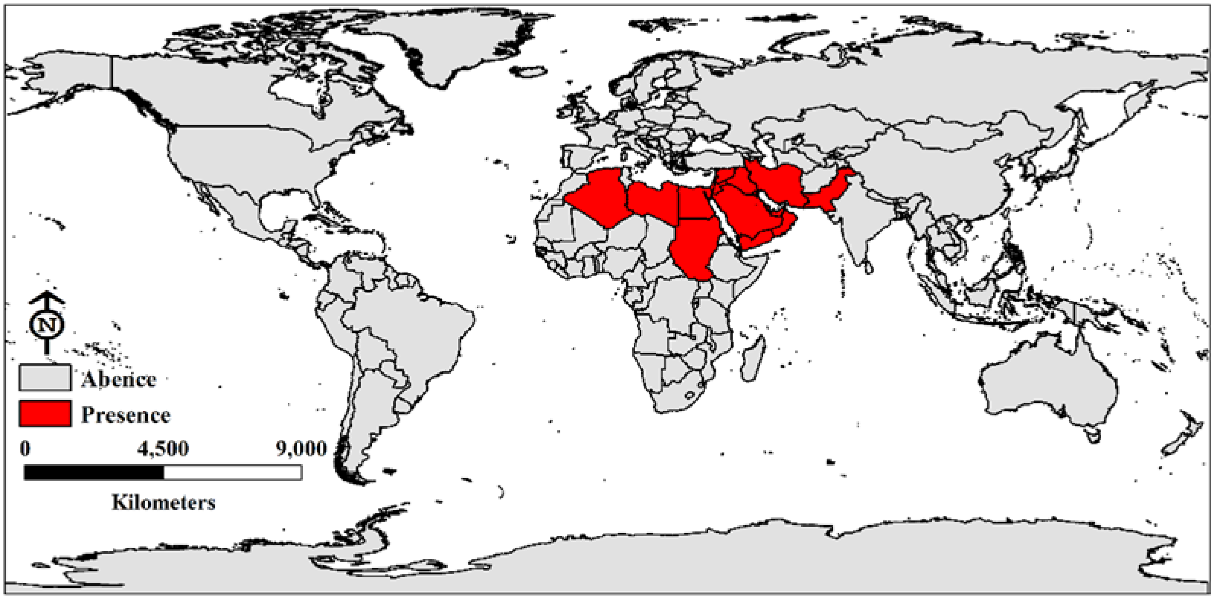

Figure 3-1 Current global observed absence and presence of the DB (*O. lybicus*).

The DB is a sap-feeding insect; both adults and nymphs suck the sap from date palms, thereby causing chlorosis (the removal of photosynthetic cells and yellowing of fronds). Prolonged high infestation levels will result in the flagging and destruction of palm plantations (Al-Khatri 2004; Howard 2001; Hussain 1963; Mahmoudi et al. 2015; Mokhtar & Al Nabhani 2010; Shah et al. 2013). Infestation also exerts an indirect effect whereby honeydew secretions produced by the DB can promote the growth of black, sooty mould on the foliage and consequently a reduction in the photosynthetic rates of date palms (Blumberg 2008; Mokhtar & Al-Mjeini 1999; Shah et al. 2012).

Remote sensing (RS) technologies are used to gather information about the surface of the earth from a distant platform, usually a satellite or airborne sensor. Most remotely sensed data used for mapping and spatial analysis is collected as reflected electromagnetic radiation, which is processed into a digital image that can be overlaid with other spatial data. Geographical information systems (GISs) are computer-based tools for mapping and analysing feature events on earth. GIS techniques integrate common database operations, such as query and statistical analysis, with maps. GISs allow users to link databases and maps in order to create dynamic displays (Maguire 1991). The topics of this review are organised according to a systematic framework in order to provide the reader with a clear understanding of the state of the art in GISs, such as spatial analysis and the modelling of tree-crop pests in general. Thus, a wide range of techniques are reviewed, and some useful technical information is provided regarding methods that can be used to examine and model the relationships between DB infestation levels and environmental, climatological and human-practice factors (Al-Kindi et al. 2017a; Al-Kindi et al. 2017b; Al Shidi et al. 2018).

Spatial analysis and modelling techniques for climatological, environmental and human-practice factors are essential for understanding current biogeographical patterns associated with the DB and for predicting future ones. Therefore, the application of GIS-based techniques can play a significant role in the mapping, control and management of the DB and its impact on ecosystems. Thus, it is important to conduct research that links the presence, absence, density and spatial and temporal distribution of the DB with environmental, climatological and human-practice factors that could promote the development and prevalence of this insect pest (Al-Kindi et al. 2017c).

GISs have been used successfully to detect insect pests and plant diseases in agriculture (Cahill et al. 1996; De Luigi et al. 2011; Dminić et al. 2010; Everitt et al. 1996; Everitt et al. 1994; Liebhold et al. 1993; Zhou et al. 2010). Examples include the study of patterns of plant infestations, the causal understanding of these patterns and the investigation of the geographical aspects of infestation and disease control. One such study (Heesterbeek & Zadoks 1987) provided a detailed report on the use of maps to highlight the spread of plant infestations at both the regional and continental scale and classified the types of maps that can be used effectively for these analyses.

At present, GIS techniques represent one of the less studied areas in Oman and many countries in the Middle East and North Africa, but such techniques need to be explored in order to predict and forecast outbreaks (i.e., of the DB) (Al-Kindi et al. 2017d). Relevant personnel should be trained to effectively utilise GIS techniques to control DB infestations, which compromise the developing palm tree plantations.

The aim of this review is to highlight advanced geospatial and statistical techniques that can be used to develop and model spatial links and correlations between the presence, absence and densities of insect pests, such as the DB, with climatological, environmental and human-practice factors and conditions. In particular, these advanced GIS techniques can facilitate both the surveillance and control of the DB at a large scale. In turn, this will greatly assist plant protection service (PPS) projects, integrated pest management technology (IPMT) programs and farmers in adopting timely preventative actions to protect their palm tree orchards.

3.2. Spatial analyses

3.2.1. Spatial interpolation

Spatial analyst, one the most important GIS features, has the ability to apply spatial operators of GIS data to derive new information, such as terrain analysis, spatial relationships, suitable locations and the accumulated cost of travelling from one point to another. However, to provide data for populations of insect pests at given sites, many processes are required, including data collection, the use of traps, the identification of longitude and latitude (coordinate systems) and the subsequent analysis (Arbogast et al. 2000; Liebhold et al. 1993). Spatial density and interpolation methods can be used to predict unknown values within the site by using known georeferenced point locations and the associated table of population data. However, the number and distribution of certain points can affect the accuracy of spatial interpolation (Nansen et al. 2003). To play an effective role in estimation, control points should be well distributed within the study area. Nonetheless, this ideal situation is rare in real-world applications, because a study area frequently contains some data-poor areas. This review illustrates the types of spatial interpolation and which elements can be used to attain a valid result.

3.2.1.1. Density estimation

Kernel density estimation (KDE) and simple kernel estimation (SKE) methods have been used to measure cell densities in a raster map by using a sample of known points. Whereas the KDE technique is based on likelihood functions and offers options depending on how density estimation is made, SKE is a counting technique. Furthermore, to use the simple density method, it is necessary to place a raster on a point distribution, tabulate points that fall within this site, total the point value and estimate the cell's density by dividing the total point value by the cell size (Wallner et al. 2014).

KDE, by contrast, associates each known point with a kernel function for the purpose of estimation (Bailey & Gatrell 1995; Scott 2015; Silverman 1986). The KDE method typically produces a smoother surface than the simple density estimation method. KDE has been applied to a wide variety of field management, such as forest and agricultural resources. It has also been used study large-scale insect population distributions (Al-Kindi et al. 2017a; Duque-Lazo & Navarro-Cerrillo 2017; Tini et al. 2018).

Through spatial interpolation, an estimation of the precipitation values at a location can be made with no recorded data by using known precipitation readings at nearby weather stations. Thus, spatial interpolation works with rasters to create surface data that can be used for analysis and modelling. The density surface method can be used to identify DB infestations such as damaged palm trees, hot spots and cold spots and direction (e.g., north Oman) (Al-Kindi et al. 2017c). Therefore, KDE has been used to develop GIS layers, such as DB density and distribution, and it may be possible to link these layers with environmental, meteorological and human-practice factors in more advanced analyses (Al-Kindi et al. 2017e).

3.2.1.2. Inverse distance weighted, radial basis function and kriging interpolation methods

Currently, several GIS software packages (i.e., QGIS, GVSIG, SAGA, ArcGIS, R spatial packages, GRASS, and MATLAB) can be used to import the georeferences of insect infestation locations, capture data and perform spatial distribution analysis. For example, the average nearest neighbour analysis tool in ArcGIS can be used to determine whether the pattern of distribution of insect infestation locations at each site can potentially be clustered, because they are distributed in an irregular fashion (Vinatier et al. 2011).

Inverse distance weighted (IDW), radial basis function (RBF) and kriging interpolation methods have been used to produce contour maps of pest insect infestations and diseases (Al-Kindi et al. 2017a; Beckler et al. 2005; Karami et al. 2018; Reay-Jones 2010; Roberts et al. 1993; Semeao et al. 2012; Tillman et al. 2009; Weisz et al. 1995). IDW is an exact method that imposes the condition that the estimated values of a point are influenced more by nearby known points than by those at a greater distance. The most important characteristic of the IDW method is that all predicted values are within the range of maximum and minimum values of the known points (Lu & Wong 2008).

The five RBF methods are thin-plate spline, spline with tension, completely regularised spline, multiquadratic function and inverse multiquadratic function. Each RBF interpolation has a parameter that controls the smoothness of the generated surface. The difference between the surfaces is usually small, and each combination of the RDF method and a parameter value can create a new surface. RDF is considered informative only when working with large datasets and attributes of little variation. Splines have been used for interpolating mean rainfall surface (Hutchinson 1995) and land demand surface (Wickham et al. 2000).

Kriging differs from other local interpolation methods, because it can be used to evaluate the quality of prediction and estimated prediction errors (Oliver & Webster 1990). For GIS approaches, environmental kriging has become a popular method and has been adopted in a wide variety of disciplines (e.g., DEM). The semivariance technique has been used in the kriging method to measure the spatially correlated component, a component known as spatial autocorrelation or spatial dependence. It can also be used to estimate the degree of variance between multiple pairs of measurements and provide information on the scale and pattern of the spatial variance (Curran 1988; Journel & Huijbregts 1978). According to Krige (1976), the most common form of kriging is ordinary kriging, a spatial modelling technique that provides optimal and unbiased estimates of unknown values from sample data (Curran & Atkinson 1998).

Another method, the semivariogram cloud of kriging can be used to investigate the spatial variability of the phenomena under investigation (Gringarten & Deutsch 2001). However, semivariogram clouds are too difficult to use and manage, because they have pairs of known points. In this case, a method called binning is typically used in kriging to average semivariance data according to distance and direction. Geostatistics interpolation is widely used to identify the spatial association of insects (Duque-Lazo & Navarro-Cerrillo 2017; Kemp 1987; Liebhold et al. 1990; Martins et al. 2018; Park & Obrycki 2004; Pearce & Zalucki 2006; Wang et al. 2001; Zhou et al. 2012).

Comparative studies have used geostatistics interpolation with kriging to analyse the spatial pattern of insects. Indeed, this method can facilitate the analysis of the spatial structural dynamics of insects' habitats under different environmental conditions (Zhang et al. 2007). For example, Zhou et al. (2012) used semivariogram kriging to analyse the spatial patterns of grasshoppers in vegetation in China. All these examples represent valuable methods for ecological, entomological and geographical studies in the monitoring and management of insect pests (Figure 3-2).

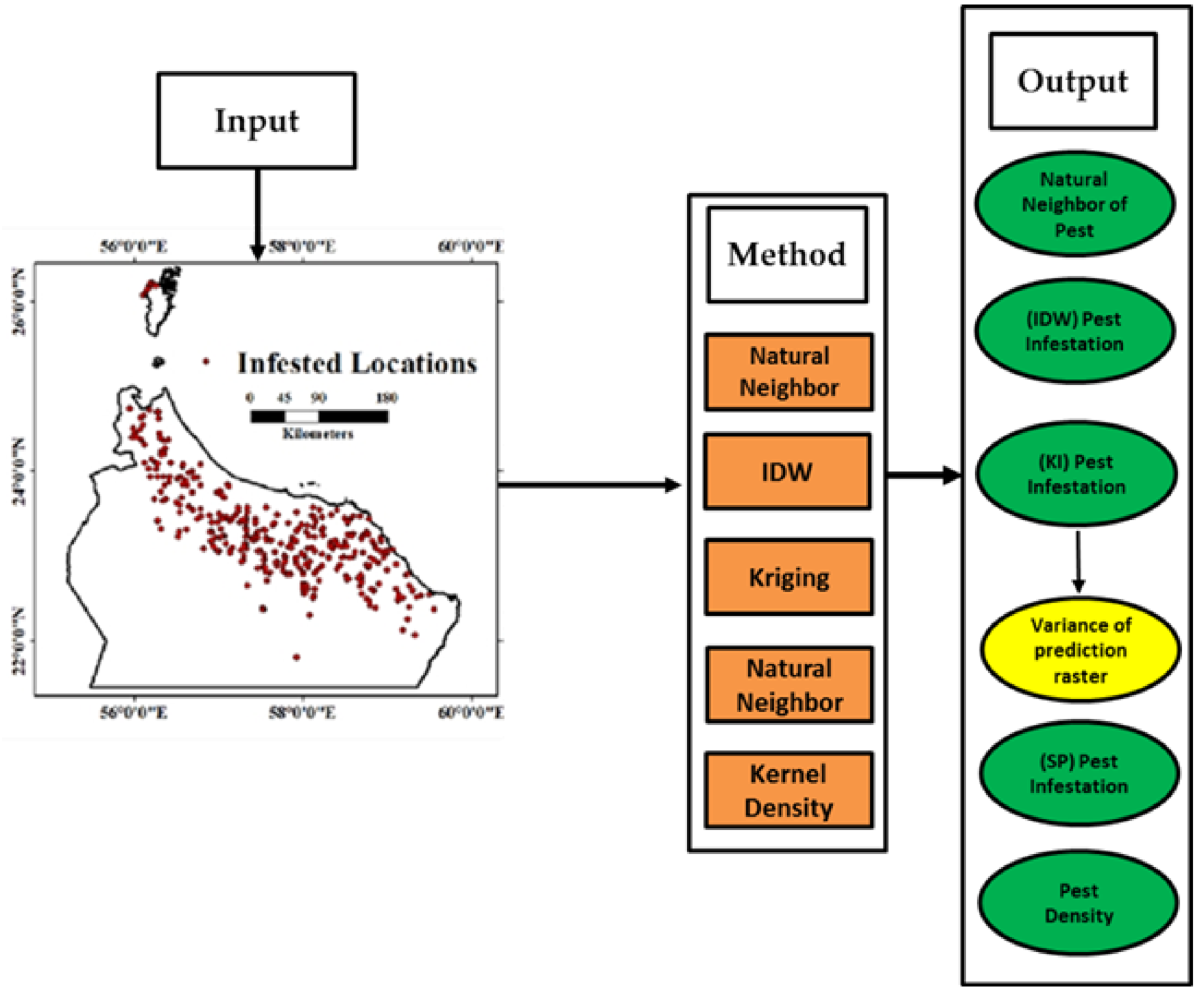

Figure 3-2 Flowchart showing the use of spatial estimation and interpolation methods for creating output surface data from sample points that can be used for the analysis and modelling of insect infestation levels i.e., *O. lybicus*;(Al-Kindi et al. 2017a)

3.2.1.3. Surface analysis

Based on the digital elevation model (DEM), spatial analyst integrates real-world features such as elevation into the geospatial environment to help solve complicated problems (e.g., DB infestation levels). Spatial analyst can be used to derive useful information such as slope, aspect map, hillshade, viewshed, contour and visibility. This topographic information enables the user to relate the study data (e.g., DB infestation levels) to real-world elevations and determine how these varied surface features might affect the data in question. Amalgamating surface maps with vector data (e.g., GPS data of the DB infestations) creates a more pragmatic depiction of the area (Al-Kindi et al. 2017a).

3.3. Spatial statistics for investigating the distribution of insect infestations

3.3.1. Data exploration

The first and most simple type of geographic analysis is visual analysis (data visualisation) Visual analysis is very helpful in presenting information, but it shows only where certain things are located (Buja et al. 1996). However, mapping where things (such as insect pests) are located can be used to help researchers determine where they need to take action or identify areas that meet their criteria (Worner & Gevrey 2006). For example, authorities in the agricultural sector can use spatial statistics methods to map where DB infestations occur each year, and to determine whether similar infestations have occurred in the same place or moved to another part of the study region (Al-Kindi et al. 2017c). For instance, an entomologist might look at the distribution of insect-pest infestation levels to determine whether the infestation patterns are related to elevation, rainfall, soil type, water type or other variables (Al-Kindi et al. 2017a).

3.3.2. Identifying nearby features

Although identifying features inside a region is a powerful form of analysis, not every significant geographic relationship is based on overlapping or adjacent features. Numerous relationships are based on the close proximity of features. What constitutes close proximity, however, is rather subjective; what is nearby to some researchers may not be to others (Zalucki et al. 2012). Thus, a near value should be related with the type of data and the situation in which the data exists. Identifying what lies within a given distance enables users to monitor activity in the area.

3.3.3. Mapping change

Temporal analysis deals with mapping change, such as changes in location, in magnitude, or in the associated values of data. It may be possible to show the change on a single map, but the results of the change may nevertheless require a map series. Features or phenomena that change in more than one characteristic present an especially difficult challenge for cartographers (e.g., absence or presence and density of the DB; (Al-Kindi et al. 2017c). Carefully controlling the symbology and the amount of data being shown, as well as the number of maps used in a map series, can improve the presentation of the results. Mapping change methods have been used to map where things move or how conditions such as infestation and diseases change in a given location over time (Southwood & Henderson 2009; Thomson & Connor 2000). Hence, knowing what has changed can help users understand how things behave over time, anticipate feature conditions or evaluate the results of an action policy. Mapping changes, for example, could be used to compare historical DB infestation-level patterns and determine how current conditions developed (Al-Kindi et al. 2017c).

3.3.4. Measuring geographic distribution methods

These methods, such as measuring the distance between features within a dataset, helps users identify potential pattern clustering in the data. Thus, measuring the compactness of the data and applying statistical methods to the measurements can reveal otherwise unseen characteristics (Gray et al. 2009; Kitron & Kazmierczak 1997; Nicholson & Mather 2014).

3.3.4.1. Mean centre method

The mean centre method has been used to identify the geographic centre of the concentration of a set of features (Kelly et al. 2008). For example, entomologists interested in determining where a species is spreading could calculate and map the centre of infestations week by week during seasonal generations (e.g., DB spring and autumn generations). They could also calculate the mean centre of DB infestation stress observations within farms over several years to determine where the DB congregates in spring and autumn generations in order to inform authorities about the highest places to view areas exposed to DB infestation. This method is valuable for tracking changes or comparing distributions of different types of features (i.e. DB infestation levels; (Al-Kindi et al. 2017c).

3.3.4.2. Median centre method

The median centre is usually use to identify the location that minimise overall Euclidean distance (straight-line distance) to the features in a dataset. Straight-line distance is an appropriate method for modelling continuous data such as temperature variations (Gardner et al. 2003). This method is useful for identifying the most accessible location. However, calculating the central feature is more straightforward than calculating the median centre (De Smith et al. 2007). This method can be used to find the most accessible location for a species.

3.3.4.3. Central feature method

The central feature method is used to identify the feature that lies at the shortest total distance from all other features. This method is also helpful for finding the most accessible location. There are two ways to calculate the central feature: the unweighted centre and weighted centre method. Both weighted and unweighted centre techniques are often used for incidents or events that occur at a specific place and time, such as DB infestation. However, the unweighted centre of stationary features may be not very meaningful. Therefore, finding the centre influenced by an attribute could yield useful information. The weighted centre is useful when analysing the distribution of values associated with areas (whether contiguous or discrete). The weighted centre technique, for example, could be used to analyse the potential habitat areas for species (Araujo & Guisan 2006).

3.3.4.4. Standard distances

The standard distance is a useful statistic as it provides a single summary measure of feature distribution around their centre (Bebber et al. 2014; Freeman 1977). The value is a distance, so the compactness can be represented on a map by drawing a circle with a radius equal to the value. To calculate the compactness of a distribution, the GIS measures the average distance of the features from the mean centre. This method is called standard distance or standard distance deviation. It can be used to compare two or more distributions of insect species (e.g., natural enemies of DB infestation). A comparison of DB distribution and DB concentration over different time periods—spring and autumn generation—can be mapped to show whether DBs are more concentrated in the spring than in the autumn generation. Nevertheless, distance calculation works best when there is no strong directional trend. If there is a directional trend, the standard deviational ellipse (SDE), which can be used to measure both compactness and orientation, is recommended.

3.3.4.5. Standard deviational ellipse

The SDEs can be used to investigate and illustrate the direction and orientation of any given distribution. The SDE allows researchers to determine whether the distribution of features is elongated and hence has a particular orientation (Al-Kindi et al. 2017c; Baker et al. 1986; Chen 2014; de Queiroz et al. 2013). Although researchers can get a sense of the orientation by drawing features on a map, calculating the SDE makes the trend clear. It also gives researchers confidence in their analysis, because the result is based on a statistical calculation and not just on visual interpretation of the map. Therefore, the SDE gives a more accurate picture than using the SD circle. The SDE measures the standard deviation of the feature from the mean centre separately for the x- and the y-coordinates.

3.4. Analysis pattern

There are two methods of identifying patterns in the geographic data. The first method is to display the features or values on a map, and the second is to use statistics to measure the extent to which features, or values are clustered, uniform or regular and random. However, using statistics to measure patterns is more accurate than identifying such patterns by looking at a map (Scott & Janikas 2010; Stinner et al. 1983). Generally, pattern analysis is used to gain an understanding of the distribution of features, monitor conditions, compare different features and track changes (e.g., of a pest insect; (Garcia et al. 2005; Zhang et al. 2013). Numerous methods can be used to measure the patterns of feature locations, such as quadratic analysis, nearest neighbour index, counting the number of features within defined distances (K-function, Overlapping areas of equal size). On the other hand, various methods can be used to measure the spatial patterns of feature values, such as identifying patterns for areas with categories, identifying patterns for features having continuous values, measuring the similarity of nearby features and measuring the concentration of high or low values. In this review, we discuss a few of the most relevant methods that can be used to study DB infestation levels.

3.4.1. Moran's I autocorrelation analysis

Spatial autocorrelation analysis can be used to describe these mapped populations in spatial terms. The procedure determines the spatial distribution pattern (i.e., random, uniform and clustered) of the subject by measuring the relationship population density (attributes of objectives) (i.e., infestation and disease sites) and spatial factors with distance between objectives (Al-Kindi et al. 2017a; Griffith 1987). The most common measure of spatial autocorrelation is Moran's I. It can be used to measure the spatial autocorrelation of insect infestations based simultaneously on the infestation locations and values (Kremen et al. 2004; Nestel et al. 2004; Rochester et al. 2002).

The values tracked by Moran's I are anchored at the expected value *E(I)* for a random pattern: *E(I)* approaches when the number of points *n* is large. Moran's I is close to *E(I)* if the pattern is random. It is greater than *E(I)* if adjacent points tend to have similar values. Moran's method is similar to nearest neighbour analysis and can be used to compute the Z score associated with Moran's I. The Z score indicates the likelihood that the point pattern is a result of random chance. However, the drawback of Moran's I autocorrelation is that its ability to detect spatial patterns depends on the data collection unit size used in the analysis (Getis & Griffith 2002).

Moran's I can also be applied to polygons and remains the same for computing the index value, but the coefficient is based on the relationship between polygons. However, recent developments in spatial statistics have included the local indicator of spatial association (LISA; (Anselin 1995).

3.4.2. A local version of Moran's I

A local version of Moran's I, LISA calculates an index value and a Z score for each feature (point or polygon). A high negative Z score suggests that the feature is adjacent to features of similar values, either above or below the value. This method allows for the detection of spatial clusters and outliers.

Numerous studies have used Moran's I to model insect pests. For example, Beckler et al. (2005) used Moran's I coefficient to measure corn rootworm spatial distribution and determine the degree of autocorrelation for the interpolated species abundance map. In British Columbia, Canada, (Bone et al. 2013) used local Moran's I to estimate the risk of mountain pin beetle attacks on pines. Kitron (1998) also employed it to identify the degree of spatial cluster of Lyme disease cases, ticks and forest disease. However, Moran's I, whether general or local, can only detect the presence of the clustering of similar values (Al-Kindi et al. 2017e). It cannot tell whether the clustering consists of high or low values. Such methods require more knowledge of how spatial patterns will change from the past to the future.

3.4.3. Geary's index

Geary's index statistical method was developed by economist and statistician Robert Geary in the 1950s and is termed Geary's contiguity ratio. He first used it to identify agricultural and demographic patterns in his native Ireland. Geary's index can be used to measure the similarity of nearby features or similar values occurring together (Chessel 1981; da Silva et al. 2008). However, as with Moran's I function, one cannot discern from the statistics whether clusters are composed of high or low values of distribution. There is a great deal of information in the literature about Geary's index statistical method and its applications in the agricultural and forest sectors (Liebhold & Gurevitch 2002; Prasetyo et al. 2013; Vinatier et al. 2011). This method can be used to model two or more species that occur in the same time and place (e.g, the DB and its natural enemies).

3.4.4. G-statistic

The G-statistic can be used to separate clusters of high values from those of low values (Getis & Ord 1992). The overall G-statistic method is based on a stated distance *d*. The weight can be based on some *G(d)* to evaluate its statistical significance. However, it is similar to Moran's I, and a local version of the G-statistic is also available (Anselin & Getis 2010; Ord & Getis 1995). The local G-statistic, denoted by $G_i(d)$, is often described as a tool for hot-spot analysis. Moreover, a cluster of high positive Z scores suggests the presence of a cluster of hot-spot values.

On the other hand, a cluster of low positive Z scores suggests the presence of a cluster of cold-spot values. The G-statistic allows for the use of a distance, but no discernible increase in clustering of high or low values exists (Al-Kindi et al. 2017e).

3.4.5. Multi-distance spatial cluster analysis using Ripley's K-function

Ripley's K-function, or the multi-distance spatial cluster analysis, can be used to identify clustering of features over a distance. Moreover, it is a standard technique that can be used to analyse the spatial distribution and structure of plant species (Hao et al. 2007; Wiegand & A Moloney 2004).

Thus, modern geostatistical and statistic techniques, such as Grey's index, Moran's I, Ripley's K-function, spatial autocorrelation, local G-statistical and Getis Ord Gi*, can be used to examine the hot spots and clustering of pests such as the DB and investigate why they cluster in certain regions or conditions (Figure 3-3). Table 3-1 shows techniques that can be used to identify the most important combinations of variables that help the DB develop, prosper and migrate.

Table 3-1 Comparison of methods for measuring the patterns of features' values.

Displays	Statistic	Advantages	Limitations
Similarity of nearby features	Moran's I & Geary's index	Deliver a single statistic to summarise the pattern (da Silva et al. 2008; Pavoine et al. 2008)	Does not indicate whether clustering is for high or low values
Concentration of high/low values	General G	Determine whether high or low values are clustered (Scott & Janikas 2010)	No visible rise in clusters of low or high values occurs
Counting the number of features within defined distances	K-function	Calculate the concentration of features at a range of scales or distances simultaneously (Haase 1995; Lynch & Moorcroft 2008)	Patterns are less accurate at a distance because of edge effects (Yamada & Rogerson 2003)

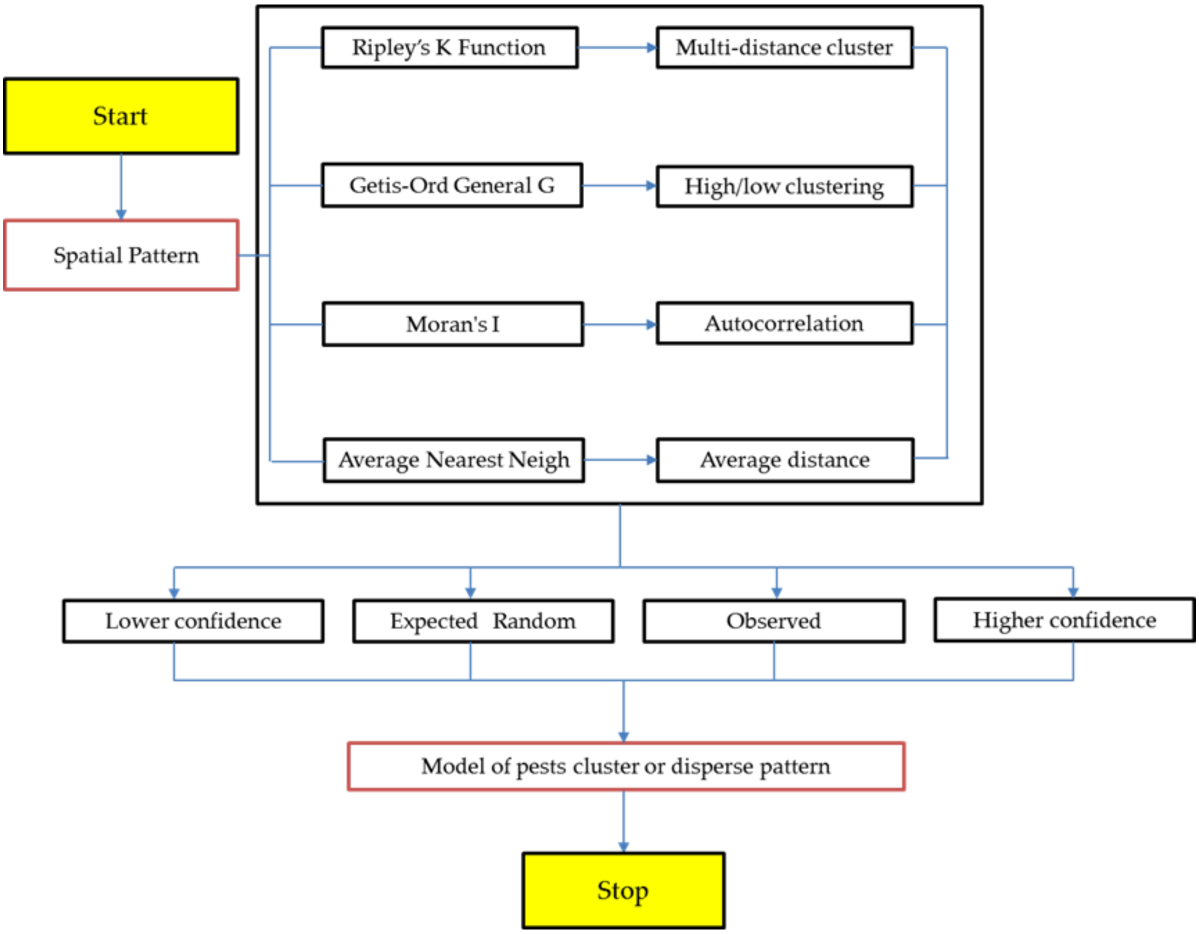

Figure 3-3 Flowchart of different spatial statistical tools for analysing patterns of phenomena.

3.5. Mapping clusters

3.5.1. Hot-spot analysis using Gi*

Another variant of Gi, called Gi*, is the value of the target feature. Gi* can be used to identify either hot spots or cold spots of diseases, insect infestations and the migration of the target (Al-Kindi et al. 2017c; Greig et al. 2018; JP et al. 2014; Liang et al. 2014; Manne et al. 2012). Gi* uses a neighbourhood that is based either on adjacent features or on a set distance. When using a distance-based neighbourhood, the distance specified is based on the knowledge of the feature and its behaviour.

To calculate Gi*, the GIS software sums up the values of the neighbours and divides this sum by the sum of the values of all features in the study area. Studies with different applications have used Gi* hotspots in various countries (Kounatidis et al. 2008; Pinault & Hunter 2011; Schools et al. 2012). A Gi* value close to 0 indicates that there is no concentration of either low or high values in the neighbourhood of the target feature. This happens when the surrounding values are close to the mean, or when the target feature is surrounded by a mixture of low and high values.

To analyse DB hot spots, DB locations and infestation levels must be identified. This information can be extracted from the classified satellite image. All infested levels, as detected by the satellite image, can be used to extract and code for different levels of infestation. The raster data could be polygonised to give polygon data as an input to the cluster analysis algorithms. In a recent study, (Al-Kindi et al. 2017c) used the Gi* method to model spatial and temporal patterns of DB infestations in northern Oman (Figure 3-4).

Thus, spatial statistics tools, such as mapping clusters, can be used to find hot spots and outliers and analyse changes in patterns overtime, such as a loss of palm plantations. This can help us to anticipate future conditions and implement policies that will positively impact our nation. There are many methods of spatial statistics for mapping clusters such as grouping analysis, optimised hot-spot analysis, similarity search; however, these methods are not mentioned in this paper.

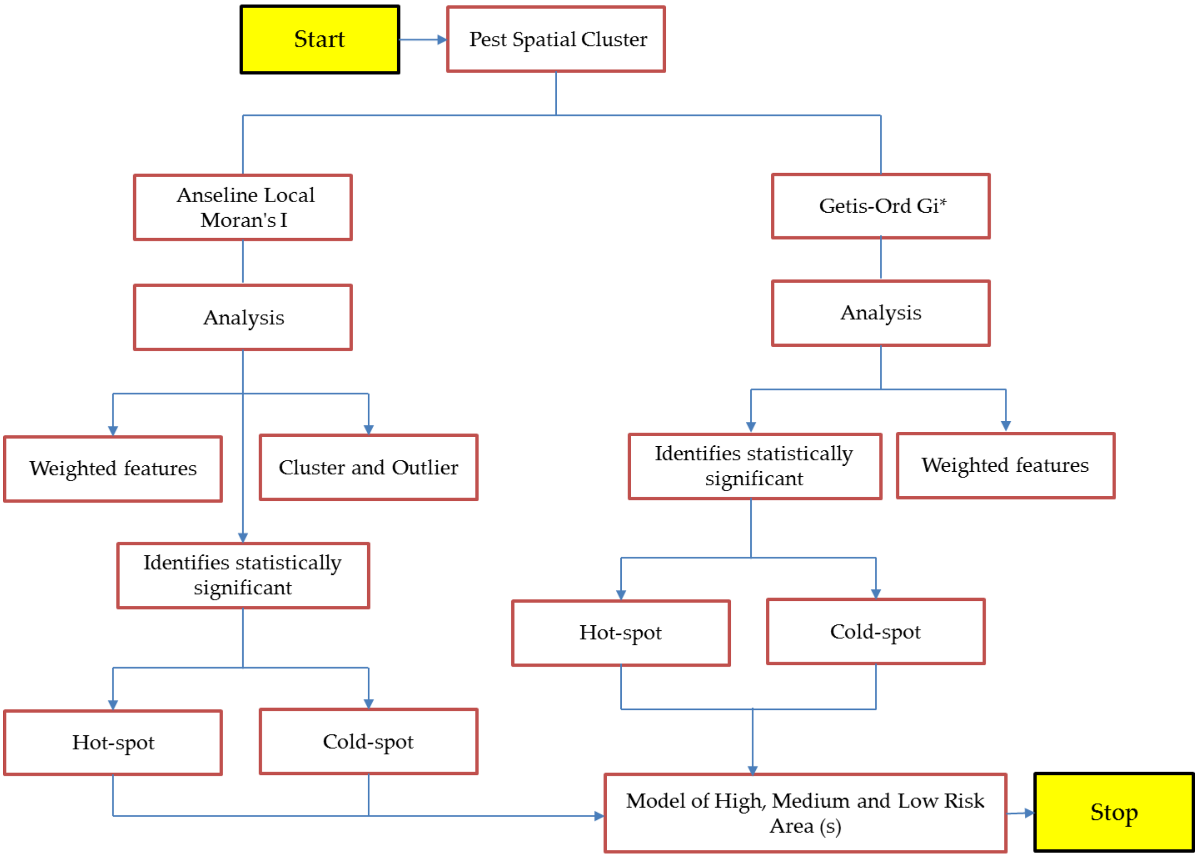

Figure 3-4 Flowchart of the analysis of cluster hot spots and outliers of insect pests.

3.6. Spatial relationships techniques

IDW and RBF, with the exception of kriging, are techniques that do not sufficiently address the problem of spatial dependence and spatial heterogeneity. However, kriging with its own assumptions might be an effective method in an area in which there is a richness of available data for analysing the placement of new rain gauges. Therefore, spatial patterns and clusters methods mentioned above this section, the focus was the abundance and arrangement of single set features can be calculated or displayed on a map. Also, spatial patterns can be used to compare two or more sets of features in the same area to determine their degree of spatial associations. To determine where and how environmental variables change together across landscape, then users may be better able to explain why spatial association occurs. Describing how environmental variables vary together within a geographic area, will help to predict association in other areas.

The integration of these methods into GIS environmental models makes it comparatively easy to apply them to a variety of spatial phenomena. GIS functions and tools have made it possible to implement state-of-the-art spatial autoregressive techniques to investigate many research problems, such as insect outbreaks (Carriere et al. 2003; Meigs et al. 2015; Wermelinger 2004; Wu et al. 2008). Advances in GIS environments, such as ArcInfo, have greatly reduced the time for estimating spatial parameters. For example, regression analysis allows users to model, examine and explore spatial relationship to better understand the factors behind observed spatial patterns. It further allows users to predict where infestation or diseases may occur based on the understanding of these factors. There are many types of regression, such as linear, local and logistic regression models. However, it requires several assumptions about error, or residual, between the predicted values and the actual values (Miles & Shevlin 2001). Some errors are related to the normal distribution for a set of independent variables, whereas others concern the expected mean value of zero. Linear regression has been widely used to model insect infestations (Bautista et al. 1984; Evans & Gregoire 2007; Hagstrum 1989).

3.6.1. Ordinary least squares vs geographically weighted regression

Ordinary least squares (OLS), a global linear regression, is commonly used to globally estimate the influence of independent variables on the dependent variable (relationships are fixed across the study area). The goal is to identify the set of variables that best describes the response to another variable and predicts the response with the same variables in a similar population. However, if there is spatial non-stationarity, then the global prediction of spatial relationships using OLS will mispresent the relationships between dependent and independent variables.

Geographically weighted regression (GWR), a local linear regression model, is commonly used to locally estimate how independent variables influence the response variable (relationships can vary across the study area). GWR has been used in many projects and publications, and those in favour of using GWR have found significant improvements in their local model compared to global models like OLS. However, both OLS and GWR should be examined to determine which method would better fit the observations. More information about the difference between OLS and GWR regressions can be found in Zhang et al. (2005), Jetz et al. (2005), Koutsias et al. (2010) and Oliveira et al. (2014). OLS and GWR methods have been widely used to investigate infestations and diseases (Al-Kindi et al. 2018b; de Gasper et al. 2015; Hu et al. 2016; Ramezankhani et al. 2017).

3.6.2. Logistic regression and geographically weighted logistic regression

Logistic regression (LR) and geographically weighted logistic regression (GWLR) methods can be used to model spatial relationships between features when the dependent variable is categorical (e.g., presence or absence) and the independent variables are categorical, numeric or both (Berg et al. 2006; Lippitt et al. 2008; MacKenzie et al. 2017). They should be used for binary data. The advantage of using the LR and GWLR methods is that they do not require the set of assumptions required by linear regression.

It is important to begin by using single variables to develop correlations before moving to more complicated predictive models and regression analysis, in which all factors are incorporated in order to investigate which combination of factors is most conducive to the survival and spread of insects or diseases. In our study, for instance, OLS, GWR, LR and GWLR could be used to model the correlation between DB absence, presence and population density and meteorological variables, such as humidity, rainfall, temperature, wind direction and wind speed. These methods can also be used to model the correlations between DB infestations and environmental variables, including soil type, slope, aspect, geology, soil salinity and solar radiation.

Additionally, autoregressive models can be used to investigate the relationships between DB infestations and human practices, such as irrigation, plantation systems, insecticides and methods of spraying. Any study can be initiated using single variables to develop correlations; it can then progress to more complicated predictive models and regression analysis where possible, incorporating all the factors to investigate what combinations of factors are most conductive to the survival and spread of the DB and its natural enemies (see Figure 3-5; (Al-Kindi et al. 2017a; Al-Kindi et al. 2017b; Al-Kindi et al. 2017d).

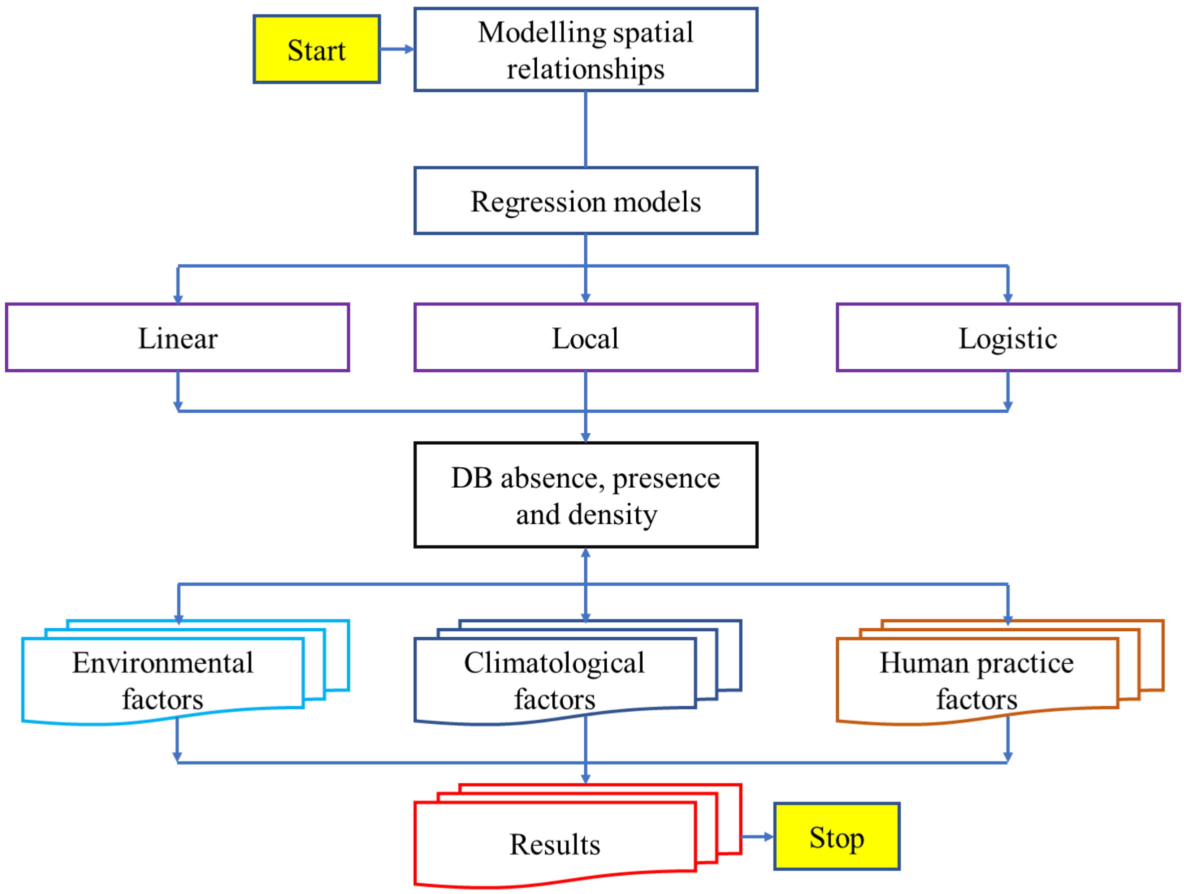

Figure 3-5 Flowchart of the modelling of the spatial correlation between pests and environmental, climatic and human-practice factors.

3.7. Data integration systems

Survey and land-records maps are important sources for creating the row data for spatial digital databases (spatial data). Data analysis (of both spatial and nonspatial data) and integration systems have been used to investigate (indicator parameter) to authenticate databases (e.g., insect-pests-sighting databases) and ultimately to estimate a tangible total population of species in a particular period (short or long term) (Fraser et al. 2018; Raab et al. 2016; Vicent & Blasco 2017; Villela et al. 2015; Watson et al. 2017).

3.7.1. Bayesian method

Through the Bayesian method, which involves weights of evidence modelling (e.g Fuzzy membership), all the data can be analysed and, ultimately, indicator parameters can be identified automatically as significant for species population and for further qualitative analysis. Information (indicator parameters) extracted from a database can be combined by Bay's theorem, in which conditional probabilities of mutually independent patterns or parameters are considered. The result is predictor data or a predictor map showing distribution of the species (e.g., DB infestation levels) across the entire study area. The intended data integration system is a decision-level data fusion system. All the decision-level fusion and the results of the individual source interpretations should be combined to create a new interpretation (Figure 3-6).

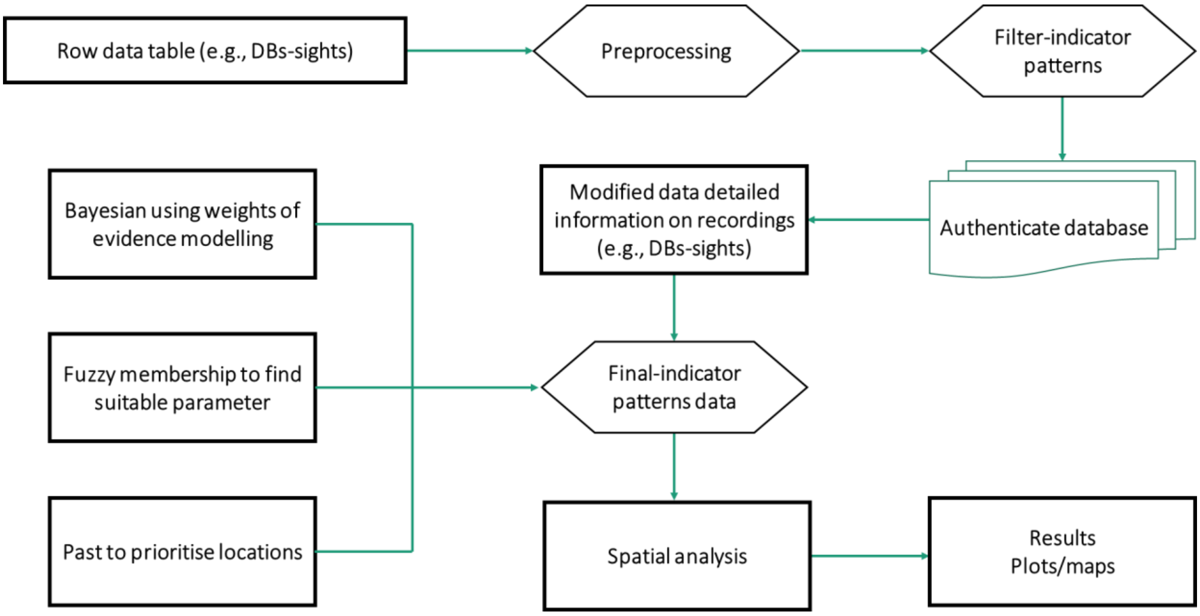

Figure 3-6 Data modelling inference flow.

The results can be tested to determine whether layers are correlated using a statistical tool such as the Pearson's correlation or the Spearman's rank correlation, or by using regression analysis (Mitchell 2005). The Spearman's rank correlation can be computed as follows:

$$p = 1.0 - \frac{6 \times D^2}{(n^3 - n)} \tag{1}$$

A *p*-value ranges from -1 to +1. The closer *p* is to +1 or -1, the stronger the positive or negative spatial correlation between the two categories of features. The following guidelines are used to interpret the value *p*:

- P = +1 implies total positive spatial dependency
- P = -1 implies total negative spatial dependency
- P = 0 implies no spatial dependency

The results of any model can be used to generate summary information that will be useful for decision-makers or researchers. For example, we might calculate statistics such as the total amount of suitable habitat in the study area or the amount of suitable habitat in each land-ownership category. The challenge in any particular area of study is the geographical extent and the resolution of analysis, which is determined by the phenomenon being modelled. To achieve validity, researchers must ensure that they are using accurate, current data whenever possible. If the data is from one's own organisation, one can rely on the data controls that are in place. Data quality should be checked against alternate sources if possible in order to ensure that the data meets the requirements of the analysis. Assessing the quality of the data will provide a guideline for predicting what level of confidence can be attributed to the result of the modelling.

3.8. Conclusions

Date palms are important in several arid and semiarid regions of the world, including Oman, because considerable money has been invested in the area by the government and local people. Climatological and environmental conditions are critical to determining the distribution and survival of any species, whether plant or animal, and the same applies to the DB. Understanding the DB's distribution and its affinity to variables can play a significant role in mapping, control and management, including the allocation of resources such as spray teams and field personnel.

Spatial information technologies such as remote sensing and GIS can be used to extract intensive details about spatial patterns, spatial correlations and other factors related to pest infestations and to various environmental, climatic and cultural variables that might facilitate the understanding, control and management of the impact of the DB on palm trees.

Clustering techniques, such as Gi*, Moran's I and Ripley's K-function, can be used to identify and visualise the hot and cold spots of the DB. Hot-spot analysis has been used to provide information about the regions that have a higher risk of infestation (Crespo-Pérez et al. 2013). As a result, different layers can be created for each level of infestation. Moreover, hot-spot analysis can be used to determine the spatial direction for each risk level (see Figures 3-3 and 3-4).

Regression models, such as linear regression, local regression and logistic regression, can be used to model correlations between pest infestations (dependent variable) and meteorological factors (independent variables) including temperature (max, min), relative humidity (max, min) and rainfall. This can be done in two ways. The first is to correlate each infestation level with each individual meteorological variable to identify the meteorological variables and range that promote the development of the DB. The second is to create an overall model including variables with the highest correlations with infestation levels.

Regression models can be also used to model the correlation between the DB and the environmental variables, such as soil type, soil salinity, water type, elevation, slope, aspect, geology and solar radiation. These models can also be used to model the correlation between pest-infestation-related practices, including irrigation, row spacing, density and management in terms of undercover vegetation (see Figure 3-5). In particular, advanced GIS techniques need to be developed and implemented for the large-scale surveillance and control of the DB. This will greatly assist PPS projects, IPMT programs and farmers in the adoption of timely preventative actions to protect their palm tree orchards.

Suitability models available in GIS environments can be used to map the distribution of any entity, including insect pests. These models can also be used to predict areas susceptible to risks such as DB infestations based on the condition of the species (see Figure 3-6).

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Chapter 4. Modelling Spatiotemporal Patterns of Dubas Bug Information on Date Palm in Northern Oman: A Geographical Information System Case Study

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Chapter 5. Impact of environmental variables on Dubas bug infestation rate: A case study from the Sultanate of Oman

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Abstract
Date palm cultivation is economically important in the Sultanate of Oman, with significant financial investment coming from both the government and from private individuals. However, a global infestation of Dubas bug (*Ommatissus lybicus Bergevin*) has impacted the Middle East region, and infestations of date palms have been widespread. In this study, spatial analysis and geostatistical techniques were used to model the spatial distribution of Dubas bug infestations to (a) identify correlations between Dubas bug densities and different environmental variables, and (b) predict the locations of future Dubas bug infestations in Oman. Firstly, we considered individual environmental variables and their correlations with infestation locations. Then, we applied more complex predictive models and regression analysis techniques to investigate the combinations of environmental factors most conducive to the survival and spread of the Dubas bug. Environmental variables including elevation, geology, and distance to drainage pathways were found to significantly affect Dubas bug infestations. In contrast, aspect and hillshade did not significantly impact on Dubas bug infestations. Understanding their distribution and therefore applying targeted controls on their spread is important for effective mapping, control and management (e.g., resource allocation) of Dubas bug infestations.

5.1. Introduction

Date palm is one of oldest crop fruits in the world and has played a particularly important role in the economic yield of most Arab countries, which are arid and semi-arid [1], including the Sultanate of Oman (hereafter referred to as Oman) [2]. Palm fruits have a high nutritional value and many people in the Middle East depend on them for their livelihood [3].

Oman has a comparatively long growing season that normally extends from early May to November. However, date fruits production in Oman is being threatened by a variety of pests that can cause major damages including plant death, reduced yield, and falling production [4,5]. The Dubas bug (*Ommatissus lybicus* Bergevin, Homoptera: Tropiduchidae) represents one of the major pests responsible for the decline of date fruits production in the Middle East and North Africa [6–11]. Blumberg [7] identified the Tigris-Euphrates River Valley as the primary origin of the Dubas bug, which subsequently spread to other regions.

The Dubas bug (DB) is a sap feeding insect; both adults and nymphs suck the sap from date palms, thereby causing chlorosis [12–17]. There is also an indirect effect whereby honeydew secretions produced by the DB can promote the growth of black sooty mould on the foliage and consequently a reduction in the photosynthetic rates of date palms [7,18,19]. Prolonged high infestation level will result in the flagging and destruction of palm plantations [6,20–23]. Nymphs pass through five growth instars [13,19], with adult female DB reaching 5–6 mm and the males 3–3.5 mm in length [14,24]. Their colour is yellowish-green while the main distinguishing feature between males and females is the presence of spots on females; males have a more tapered abdomen and larger wings relative to the abdomen.

Two populations of DB are generated each year. The summer generation of nymphs hatch in mid-late April. After two months, they mature and lay eggs for the second generation, which lay dormant for approximately three months before hatching in late September. Blumberg [7] showed that eggs can hatch within 18–21 days in the summer, but can take up to 170 days in winter. Each female can produce more than 120 eggs, which are laid by insertion into holes in the tissue of date palm fronds at the end of each season. The eggs of DB are sensitive to temperature. The developmental time of a Dubas bug's eggs has been studied at three different temperatures, 17.6, 27.5 and 32.4°C in Oman [25]. The results showed that a temperature of 27.5°C appeared to be the optimal temperature for the biological activities of this [25]. At 35°C, the biological processes of the pest are disrupted, thus leading to high mortality, particularly in females [6,26].

In Oman, vector control activities aim to exterminate or reduce DBs infestations have concentrated on the use of insecticides, including both ground and aerial sprays. However, use of the most effective pesticide is restricted owing to its side effects (e.g., irritation) [5]. In Israel, systemic carbamates (e.g., aldicarb and butocarboxim) have been used successful, while in Iraq dichlorvos (DDVP) injected directly into infected palms has been successful in suppressing the pest population [7]. However, these methods are expensive and can have negative environmental impacts on both non-target species, particularly the natural enemies of the DB (e.g., *Aprostocetus sp*. (Hymenoptera: Eulophidae), *Oligosita sp*. (Hymenoptera: Trichogammidae, and *Runcinia sp*. (Aranae: Thomsidae)), and on human health [27]. Research has shown that some pesticide residues can persist on the date fruits for up to sixty days after application [28–30]. Furthermore, chemical control measures have met with limited success in Oman, while Dubas bug continues to pose a major challenge to the agricultural industry.

To gain a thorough understanding of the life cycle and distribution of this pest, new research into the biology and ecology of the species is needed. To date, no published studies have focused on the spatial distribution of DB infestations, or the environmental variables associated with their distribution at the stress level. Furthermore, no previous studies have developed risk maps of DB distribution on a large scale, or have systematically analysed patterns of infestations at either a large-scale or orchard level. Understanding the distribution and affinity of DB to different environmental variables will play a key role in the mapping; control and management of DB infestations, including resource allocation (e.g., spray teams and field personnel).

The main objective of this study is to investigate the environmental variables impacting DB infestations in northern Oman. We considered the contributions of elevation, slope, aspect, soil type, water type, geology, hillshade, distance to the sea, and distance to drainage pathways in our study. Firstly, we investigate the correlations of infestation with each single variable in order to develop a correlation model. Next, based on this correlation model, we construct a more complex predictive model for assessing the relative impacts of the candidate environmental variables. The results of this study show that the presence and spread of DB are most conducive to a combination of variables rather than individual ones.

5.2. Materials and methods

5.2.1. Study area

The Sultanate of Oman, which covers an area of 309,500 km^2, extends from 16 40'N to 26 20'N, and 51 50'E to 59 40'E. It occupies the south-eastern corner of the Arabian Peninsula (Fig 5-1). It has 3,165 km of coastline, extending from the Strait of Hormuz in the north to the border with the Republic of Yemen in the South. The coastline faces on to three different water bodies, namely the Arabian Sea, the Persian Gulf (also known as *Arabian Gulf*), and the Gulf of Oman [31].

To the west, Oman is bordered by the United Arab Emirates and the Kingdom of Saudi Arabia. Mountainous areas account for 15% of the land area, while desert plains and sandy areas cover 74%, agro-biodiversity areas cover 8%, and the coastal zone covers 3%, respectively.

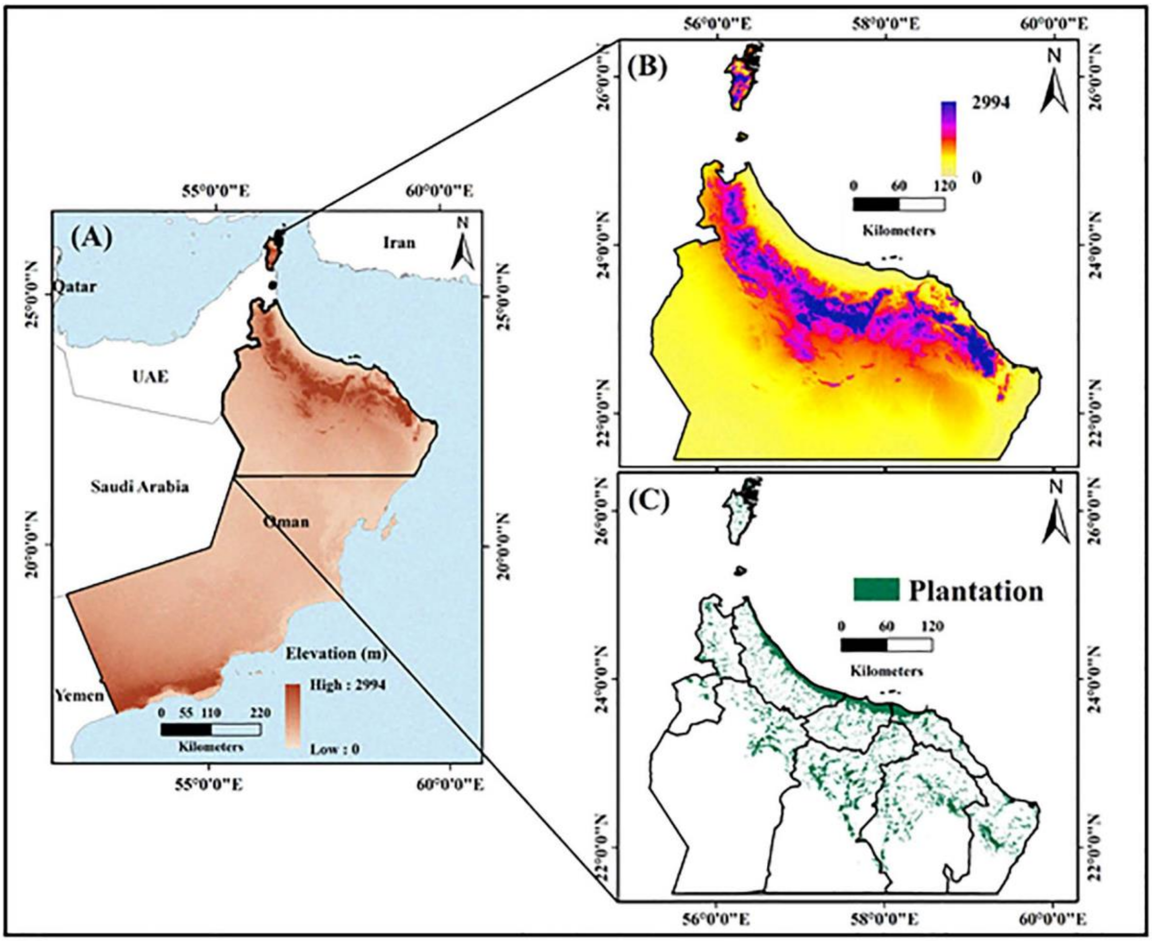

Figure 5-1 Maps of the study area, including: (A) topography and location of Oman, with the study area outlined by the black rectangle; (B) elevation change within the study area; and (C) distribution of date palm plantations in the study area (Esri ArcGIS 10.3).

The location of Oman provides favourable conditions for agriculture, with land under agricultural use accounting for 8% of the territory and the economic output accounting for 14.6% of the GDP in 2008. According to the 2004–2005 soil survey conducted by the Ministry of Food and Agricultural (MFA), 22,230 km^2 (equivalent 2.223 million ha) is optimal for agricultural activity, which represents ~7.5% of the country's land area. Approximately 728.2 km^2 (~72,820 ha) of the country is irrigated using the falaj irrigation system, where local springs or wadis (streams) underflow areas are cultivated with palm trees, banana, limes, alfalfa, and vegetables [32].

Oman has an arid climate, receiving less than 100 mm of rainfall per year; however, the mountainous parts of the country receive higher precipitation levels. As the dependent variable, DB infestations occur where palm trees are concentrated; therefore, in this study we focused on northern Oman (26 50'N to 22 26'N, and 55 50'E to 59 50'E) which experiences high infestations.

5.2.2. Data collection

We used historical data from the Ministry of Agriculture and Fisheries (MFA) to identify regions or areas that have been infested by the DBs. In total, 840 sites were identified, and for each we used the MFA's resource to collect data on their geographical locations (see Appendix A, S1 File), time of the survey, infestation levels, and the trapping procedure. The original data were not in a digital format and more than 400 hours were spent cleaning as well as modifying the data to create a geo-database that would be suitable for GIS analysis. Additional data (e.g., DBs population data) were collected from selected sampling points/stations, which were chosen based on distance to the sea and to streams, elevation, slope, hillshade, water type, soil type, and geology.

Insect trapping was performed at 80 sites (i.e., 10% of the total sites considered) in mid-March 2015 in order to collect both adult and nymph DB from the summer generation. Trapping was necessary because population dynamics played an important role and an absolute population estimate was needed. We used emergence traps (sticky yellow traps of 0.2 x 0.3 m in size) placed on palm fronds in maize fields. At each site, four date palms were selected, and two traps apiece were attached to 6 fronds per palm. Traps were distributed at different levels in the crop row in order to capture both adult bugs and nymphs as they emerged from the fronds. These emergence traps were used to monitor the DB population throughout the growing season (spring-fall). Based on data from 2–3 sampling sites in each district (wilayat), We classified the DB infestation levels into 4 groups (very low, low, moderate and high) in ArcGIS 10.3 as follows: very low infestation (0–4 nymphs per leaflet); low (5–7 nymphs per leaflet); moderate (8–9 nymphs per leaflet); and high infestation 10 or more nymphs per leaflet.

A 30-m resolution Digital Elevation Model (DEM) was provided by the National Survey Authority, MOD. Soil and water data were provided by the Ministry of Regional Municipalities, Environment and Water Resources (MORMEWR). All data and GIS layers collected from the Sultanate of Omani Ministries and Departments were projected to WGS 1984 UTM zone 40.

5.2.3. Spatial analysis

5.2.3.1. Interpolation

We used the `interpolate to raster tool' in ArcGIS software package (version 10.3, ESRI, Redlands, CA) to combine the MFA data with our sampling data to create species population maps. This process was used to estimate DB abundance from geo-referenced infestation locations [33]. We used the Inverse Distance Weighted (IDW) interpolation method to create the abundance or surface maps. The IDW method imposes the condition that estimated values of a point are influenced more by nearby points than they are by points by at a greater distance [34]. Most importantly, all predicted values are within the range of maximum and minimum values of the known points. The general equation for the IDW method is expressed as:

$$Z_0 = \frac{\sum_{i=1}^{s} z_i \frac{1}{d_i^k}}{\sum_{i=1}^{s} \frac{1}{d_i^k}} \qquad (1)$$

where Z_0 is the estimated value at point 0, z_i is the z value at known point i, d_i is the distance between point 0 and point i, s is the number of known points used in the estimation, and k is the specified point. The IDW technique is particularly appropriate in the case of irregularly distributed DB infestations because it can use an interpolated surface occurring only at the data points. Furthermore, IDW does not include outlier data values (e.g., negative numbers and exceptional values) that do not match the observed data values at each location.

5.2.3.2. Spatial and surface analyses

A clip function was used to extract the study variables for each region of the study area, including water type, soil type, palm date plantations, and the 30-m resolution (DEM). The DEM was used to analyse elevation, slope, aspect, and hillshade, which represent the basic elements used when analysing and visualising ecological problems (e.g., forest and wildlife habitat suitability site analyses). Euclidean spatial analysis was used to calculate and create a Euclidean raster for each site (e.g., the distance to the sea and to streams). Vector datasets (e.g., soil type, water type, geology) were converted to raster datasets; thus allowing cell values to be extracted for locations specified in point features classes (e.g., DB sampling sites).

5.2.4. Statistical analysis

5.2.4.1. Nearest neighbour statistics

We used nearest neighbour statistical (NNS) analysis to predict if DBs absent, or if their distribution was random, regular, or clustered. This method measures the spacing by finding the distance between each point feature and its nearest neighbour [35]. NNS compares the mean spacing with the expected mean spacing calculated assuming a random distribution of point features. This spatial statistic can be computed by:

$$r = \frac{\sum_{i=1}^{n} \delta_i}{n} \tag{2}$$

The average spacing r is computed by summing the nearest neighbour distance and divided the total by the number of points n. If r is less than 1, the points pattern is more clustered than random and greater than 1 if the points pattern is more clustered or regular than random.

5.2.4.2. Spatial autocorrelation

We used the Moran's I autocorrelation method to measure the relationships between DB infestations and the environmental variables. Spatial autocorrelation considers the degree to which variables on the Earth's surface are both spatially and numerically similar to other variables located nearby [36,37]. Moran's I method helped us to determine if values and their associated features were clustered, randomly distributed, or uniform. This method measures correlation in terms of proximity between adjacent features of the same phenomenon and is commonly used to detect the spatial order feature of points. Moran's I can be expressed as:

$$I = \frac{\sum_{i=1}^{n}\sum_{i=1}^{m} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{S^2 \sum_{i=1}^{n}\sum_{i=1}^{m} w_{ij}} \tag{1}$$

where x_i is the value at point i, x is the value at neighbouring point j, w_{ij} is a coefficient, n is the number of points, and s^2 is the variance of x values. The values of the Moran's I are anchored at the expected value $E(I)$ for a random pattern, with $E(I)$ methods 0 when the number of points n is large. Moran's I is close to $E(I)$ if the pattern is random but is greater than $E(I)$ if adjacent points tend to have similar values. The z-score associated with Moran's I shows the likelihood that a point pattern could be the result of random chance. Moran's I can also be applied to polygons and remains the same for computing the index value, but the coefficient is based on the relationships between polygons. Recent developments in spatial statistics have included the Local Indicator of Spatial Association (LISA), which is a local version of Moran's

I [38]. For each feature (point or polygon), LISA calculates for each feature an index value and a *z*-score. A high negative *z*-score suggests that the feature is adjacent to features of similar values.

5.2.4.3. G-statistic for measuring clustering

We used the G-statistic to separate clusters of high and low values for different environmental features. The G-statistic method is based on a stated distance *d*. Weight can be based on some value of *G(d)*, which is used to evaluate statistical significance. This approach is similar to Moran's *I* and a local version of the G-statistic is also available. The local G-statistic, denoted by $G_i^*(d)$, is often described as a tool for “hotspot” analysis [39]. Moreover, a cluster of high positive *z*-scores suggests the presence of a cluster of hotspot values. In contrast, a cluster of low positive *z*-scores suggests the presence of a cluster of cold spot values. G-statistic based on a specified distance *d* is defined as:

$$G(d) = \frac{\sum\sum w_{ij}(d) x_i x_j}{\sum\sum x_i x_j} i \neq j \tag{4}$$

where x_i is the value at location *i*, x_j is the value at location *j*, plus if *j* is within distance *d* of *I* and w_{ij} *(d)* is the spatial weight based on some weighted distance between 1 and 0. The expected value of *E(G)* is:

$$E(G) = \frac{\sum\sum w_{ij}(d)}{n(n-1)} \tag{5}$$

where *E(G(d))* is typically a very small value when *n* is huge. A high *G*(*d*) value proposes a clustering of high values, and a low *G*(*d*) value proposes a clustering of low values.

We applied the Local Moran's *I* statistic to detect the accurate locations of `hotspot' clusters of DB infestations. We used a surface analysis function to create a continuous map from the z-scores to present a generalised view of hotspots and cold spots. This approach allowed us to identify features with high values that might represent a statistically significant hotspot.

To be a statistically significant hotspot, a feature should have a high value and be enclosed or surrounded by other features with similarly high values [6]. We used the output of hotspot values as the input for incremental spatial autocorrelation analysis in order to measure a series of distances and to create a line chart of those distances and their corresponding *z*-scores. This method provides a good conceptualization of the relationships between hotspot infestation and distance (i.e. distance to sea, streams, and water type) [40–42]. Since *z*-scores mirror the intensity of spatial clustering, statistically significant peak *z* scores indicate distances where spatial processes that promote clustering are most pronounced. These peak distances are often appropriate values for use in tools with a distance band.

5.2.4.4. Exploratory regression

We used exploratory regression tools to model relationships by using all possible combinations for a given list of candidate explanatory variables to select the appropriate dependent (DB infestation) and independent variables (elevation, slope, aspect, hillshade, soil type, geological features, water type, distance to the sea, and distance to streams). We evaluated all possible combinations of variables in order to construct the most robust model for solving DB problems and to answer questions on DB infestations. The exploratory regression (ER) can be calculated by the following equation:

$$\gamma = \beta_0 + \beta_1\chi_1 + \beta_2\chi_2 + \beta_3\chi_3 + ... + \beta_n\chi_n + \varepsilon \qquad (6)$$

where γ is the dependent variable, β are coefficient values, χ are explanatory variables, and ε are residuals. Geographically weighted regression (GWR) was used to produce maps of the coefficients, r^2 values, standard residuals, and predictions [43], detailing a good sense of the relationships between DB infestations (dependent) and environmental variables (independent) across the study area.

5.3. Results and discussion

5.3.1. Spatial and surface analysis

The elevation raster map produced in this study contains five elevation classes of equal interval (Fig 5-2a), which indicate the percentage occupation of the landscape:-112–234 m (40%), 235–484 m (25%), 485–838 m (15%), 839–1408 m (12%), and 1409–2994 m (8%).

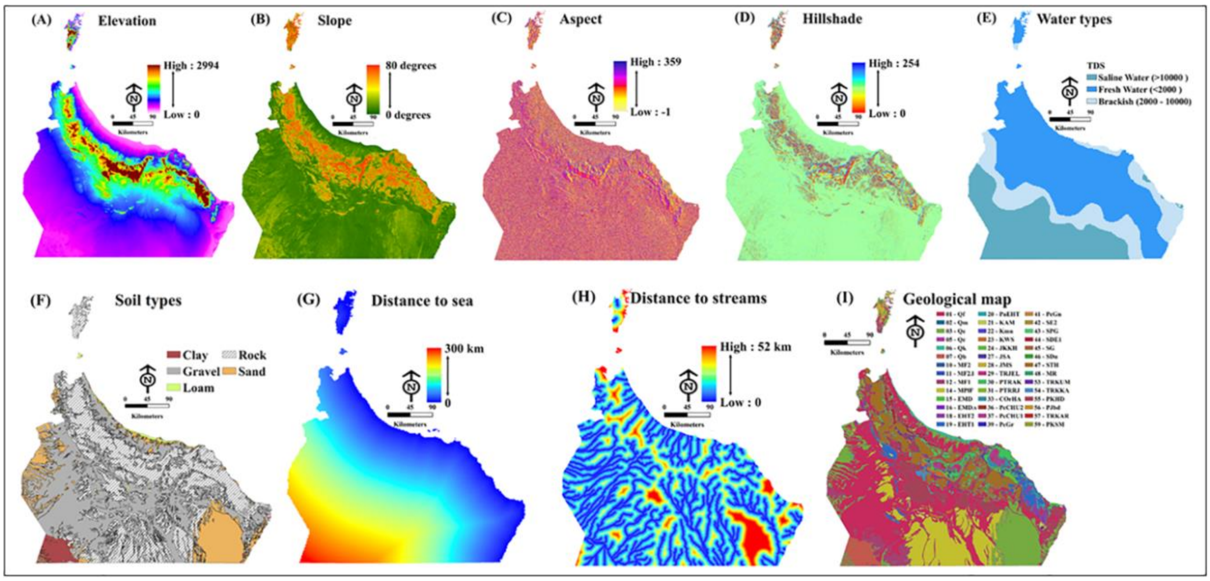

Figure 5-2 Surface analysis maps of the study area for: (A) elevation, (B) slope, (C) aspect, (D), hillshade, (E) water type, (F) soil type, (G) Euclidean distance to the sea, (H) Euclidean distance to streams, and (I) geology (Esri GISTM 10.3).

The slope raster map contains five equally spaced slope classes between 80 (the steepest slope class) and 0 (Fig 5-2b). The aspect raster map contains ten aspect classes of equal interval, ranging from 359°N for the highest aspect to -1° for flat zones, or zones with no data (Fig 5-2c). The water vector map contains three categories of water class, classified based on total dissolved solid (TDS) content (Fig 5-2e): brackish water (2000–10,000 TDS), fresh water (< 2000 TDS), and saline water (>1000 TDS). The soil vector map contains five soil type categories: clay, gravel, loam, rock, and sandy soils (Fig 5-2f).

The map of Euclidean raster distance to the sea contains six distance classes, where 0 km is closest to the sea distance, and 300 km is furthest from the sea (Fig 5-2g). The map of Euclidean raster distance to streams contains six distance classes, where 0 km is closest to a stream and 30 km is furthest from a stream buffer line (Fig 5-2h). The geological vector map contains 59 geological classes (Fig 5-2i).

5.3.2. Spatial statistics

5.3.2.1. Nearest neighbour statistics

The results of NNS analysis, in which the nearest neighbour ratio was 0.328347, showed that the expected mean distance or spacing of DB infestations distribution was greater than the observed mean, and that the difference was less than zero (i.e., a negative number; Table 5-1). These results indicate clustered distribution of DBs infestations.

5.3.2.2. Autocorrelation analysis

We used the interpolated IDW raster map layers to conduct autocorrelation analysis in order to determine cell values, cell statistics, and types of spatial distribution exhibited by the DBs (Fig 5-3). Autocorrelation found between DB infestations and some environmental features (i.e., water type, elevation, slope, soil type, geology, distance to the sea and distance to stream) were observed (Table 5-2). For example, *p*-values (probability) for elevation and geology were ($p < 0.01$), while the *z*-scores (standard deviation) were < 2.58, indicating a confidence level of more than 99%. In contrast, there was a weaker relationship between DB infestations and other variables (e.g., aspect and hillshade). However, autocorrelation cannot identify environmental variables with high or low cluster values, and for this a G-statistic was used.

5.3.2.3. G-statistic for measuring clustering

Elevation, geology ($p < 0.1$) and distance to the sea ($p < 0.5$) were found in high value significant clusters, while water type, slope, soil type and distance to the streams were found in low value significant clusters (Table 5-3). Dubas bug populations occurred with high frequency in the 251–500 m, and 501–750 m elevation classes, but occurred only occasionally in the 8–250 m (the smallest class), 751–1000 m, and 1001– 1250 m (Fig 5-4). Dubas bug populations were shown to occur most frequently in areas of gravel and loam soils. Dubas bug infestations also occurred in areas of rocky soil, but in smaller numbers.

Table 5-1 Mean nearest neighbour distribution of Dubas bug infestations.

Observed mean distance	1791.949 meter
Expected mean distance	5457.4916 meter
p-value	< 0.01
z-score	- 40

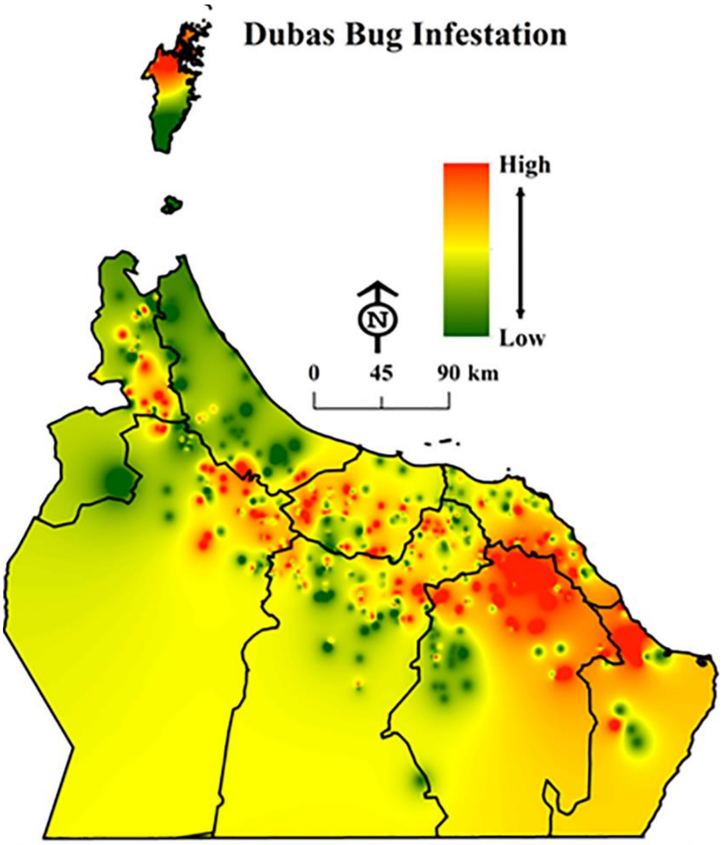

Figure 5-3 Raster map layer illustrating interpolated values of Dubas bug infestations in northern Oman (Esri ArcGIS 10.3).

Of the 59 geological categories, we found that DB infestations occur most frequently on the Samail Ophiolites and the East Oman Ophiolite Complex (47-STH), which are unique to the Sultanate of Oman [44]. Infestations on shelf facies, volcanic rocks (Al-Akhdar mountain group; PTRAK) and alluvial deposits were also observed but were less numerous.

Table 5-2 Moran's I correlation coefficients between Dubas bugs and environmental features.

Variables	Moran's I	Variance	p-value	z-score	Sign
TDS (water)	0.1559	0.00007	0.03*	61.061	Cluster
Elevation	0.2946	0.00007	0.01*	114.220	Cluster
Slope	0.0076	0.00007	0.07*	3.388	Cluster
Aspect	- 00003	0.00007	0.79	0.266	Random
Soil Types	0.0342	0.00007	0.01*	13.657	Cluster
Geology	0.0370	0.00007	0.01*	14.740	Cluster
Distance to Sea	0.4241	0.00007	0.01*	164.519	Cluster
Distance to stream	0.1438	0.00007	0.01*	56.552	Cluster
Hillshade	- 0.0103	0.00007	0.33	- 0.972	Random

*An asterisk next to number indicates a statically significant p-value ($p < 0.01$)

Table 5-3 G-statistic for Dubas bug infestations.

Variables	OGG	EGG	p-value	z-score	Sign
Water type	0.194605	0.215308	0.000000	-10.363497	Low-Cluster
Elevation	0.281037	0.215308	0.000000	18.368917	High-Cluster
Slope	0.225077	0.215308	0.186305	1.321590	Low-Cluster
Aspect	0.17328	0.000018	0.731915	-0.342579	Random
Soil type	0.187690	0.215308	0.000549	-3.455668	Low- Cluster
Geology	0.237637	0.215308	0.000007	4.496675	High-Cluster
Distance to Sea	0.292797	0.215308	0.000000	18.954813	High-Cluster
Distance to Streams	0.189344	0.215308	0.023924	-2.258354	Low-Cluster
Hillshade	0.215760	0.215308	0.586149	0.544425	Random

Although the Moran's *I* and G-statistic identified strong spatial patterns in the relationships between environmental variables and DB infestations, they only considered the distribution of a single variable in a single layer at a time. It is difficult to determine whether strong or weak relationships are becoming more or less spatially segregated. To fully model the environmental controls on DB infestations, multivariate statistical techniques were needed to integrate the correlations.

5.3.2.4. Local Moran's I statistics

By identifying hotspot and cold spot clusters for each variable, we were able to compare cluster locations in order to gain a better understanding of cluster control. Accurate "hotspot and cold spot" locations of DB infestations calculated from the statistic Local Moran's I were mapped based on their *z*-score. The *z*-score values (> 2.58) indicated that the DB hotspots observed were statistically significant (Fig 5-5). Thus, these data were suitable for use in multivariate regression analysis to investigate the dependence of DB infestations on environmental variables (see Appendix A, S2 and S3 Files).

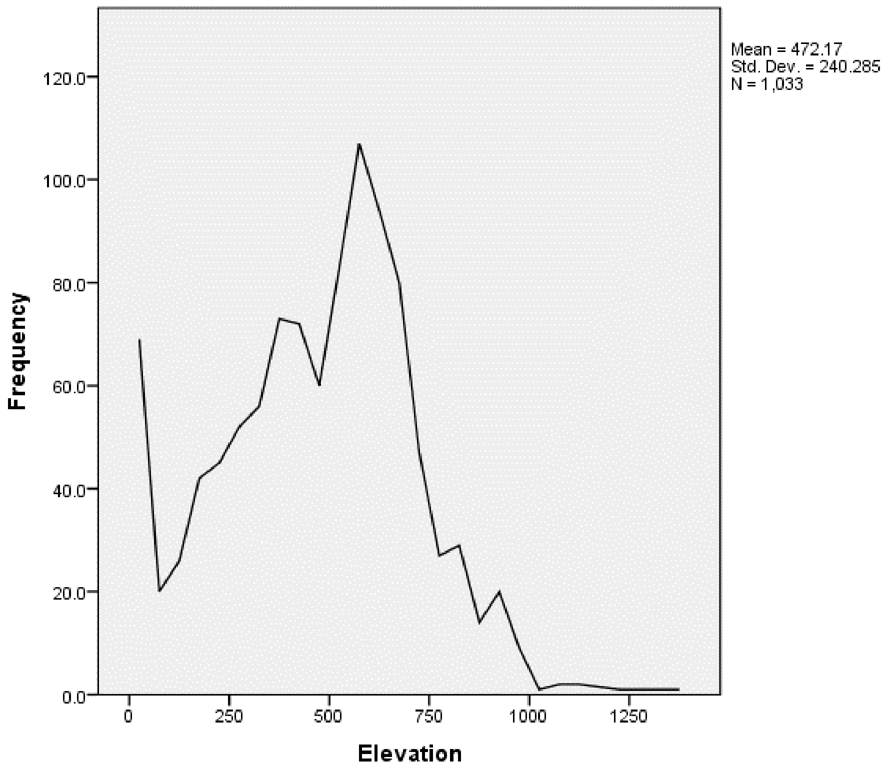

Figure 5-4 Frequency of Dubas bug infestations and elevation (Esri ArcGIS 10.3).

5.3.3. Modelling spatial relationships

Exploratory regression. A global linear regression was used to build a model relationships between the dependent variable (DB hotspot and cold spot infestations) and candidate environmental variables (Table 5-4). Positive significant relationships were found between DB infestations and elevation, geology, distance to streams (Table 5-5). In contrast, negative significant relationships were found between the hillshade and aspect factors of the DB infestations.

We created surface analysis maps of predictive values, r^2 values, and standard residuals from GWR. These allowed us to investigate the combination of factors most conducive to the survival and spread of DBs. The coefficient surface maps created through GWR showed where the variable had the biggest impact of the regression across the study area, with strong relationship mapped with warm colours (orange to dark red) and relationship mapped weak with cold colours (yellow to dark green) (Fig 5-6).

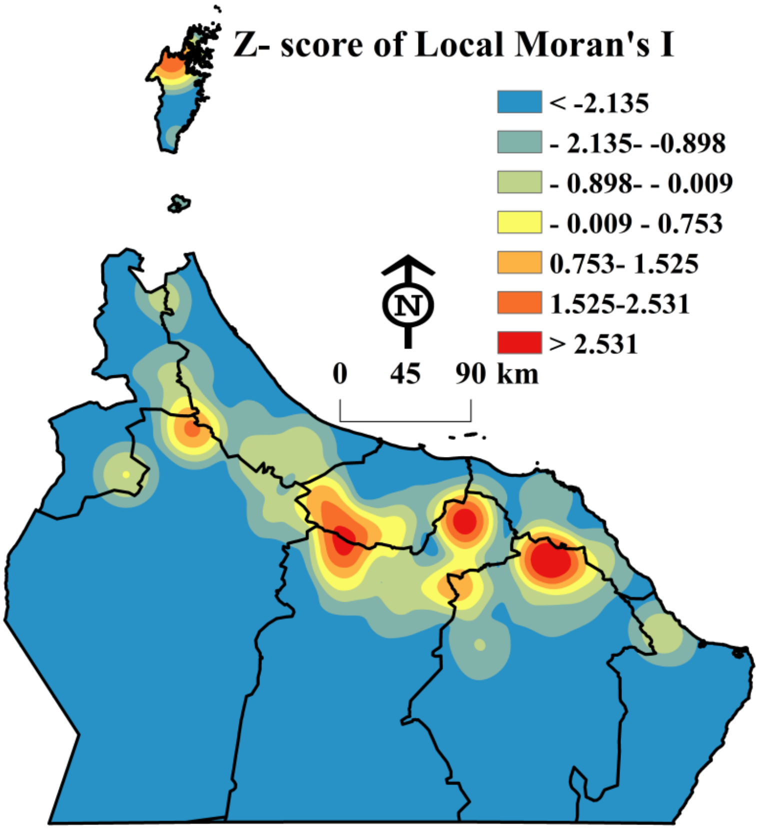

Figure 5-5 Surface map created from z-scores to present a generalized view of Dubas bug infestation hot and cold spots. Dark red areas denote a high infestation of the bugs that is significantly similar to its neighbours (at a confidence level of 0.01) Esri ArcGIS 10.3).

Table 5-4 Summary of residual normality (JB) and residual spatial autocorrelation (SA).

Variables	AdjR2 [a]	SA [b]	[c] AICc	JB [d]	VIF [e]	Model [f]
Elevation	0.012286	0.00	7501.396	0.00	1.98	+***
Slope	0.000426	0.00	7512.998	0.00	1.29	+*
Aspect	-0.000244	0.00	7513.649	0.00	1.13	–
Hillshade	0.001550	0.00	7511.904	0.00	1.17	–
Soil	0.008685	0.00	7504.934	0.00	1.19	+*
Geology	0.005026	0.00	7508.514	0.00	1.13	+**
Distance to streams	0.040466	0.00	7473.261	0.00	1.07	+***
Water	-0.000615	0.00	7514.010	0.00	1.25	+*
Distance to sea	-0.001012	0.00	7514.395	0.00	1.80	+*

a. Min Adjusted $r^2 > 0.50$
b. Min spatial autocorrelation *p*-value > 0.10
c. Akaike's Information Criterion
d. Min Jarque-Bera *p*-value 0.10
e. Max VIF Value < 7.50
f. Model variable signs are denoted by + and _; model variable significance is denoted by * = 0.10, ** = 0.05, *** = 0.01.

The standardized residuals and distribution of locally weighed coefficients of determination (r^2) between observed and fitted values showed which model had a higher proportion of dependent variable variance accounted for by the regression model (Fig 5-7).

The results of our analyses showed that certain variables impact more on DB survival (e.g., elevation, geology, and distance to streams). The infestations seem more severe in the mountains wadi biomes and less in the open plains (e.g. desert), and coastal areas away from mountains [33]. Furthermore, we observed that heavy infestations occur mostly along wadi where there is intensive and fresh water in Oman [45]. Wadi plains might also produce the quantity and quality of juices favoured by nymphs and adults of Dubas bug. Soil type and water type have had less impact of DB infestations. This is possible because soil permeability is related to the degree of water holding of soil and assuming that DB may have relationship with water in soil.

Table 5-5 Summary of variables significance.

Variables	Significant[a]	Positive[b]	Negative[c]
Elevation	100.00	100.00	0.00
Slope	0.00	76.07	23.93
Aspect	0.00	0.00	100.00
Hillshade	0.61	0.00	100.00
Soil	86	100.00	0.00
Geology	51.53	100.00	0.00
Distance to streams	100.00	100.00	0.00
Water	0.00	39.26	60.74
Distance to sea	31.90	45.40	31.90

[a] Percentage with a significant correlation
[b] Percentage with a positive correlation
[c] Percentage with a positive correlation

Hillshade and aspect are linked because both factors impact on the level of direct sunlight, which in turn impact on DB infestation rate. In particular, Dubas bugs avoid extreme temperature (high and low) and direct sunlight [16,46] as well as dry areas with disturbing wind [47,48]. Observations by the Sultan Qaboos University (SQU) in 2008 and 2009 indicated a mass migration of Dubas bugs from low elevation like date fruit gardens around Al-Jabal Al-Khader to high elevation [49]. Migration from wadies (dry rivers) to mountains (or vice versa), could reflect migration towards more suitable temperature, and the mechanism of transportation may be provided by the daytime rising convectional air currents [33].

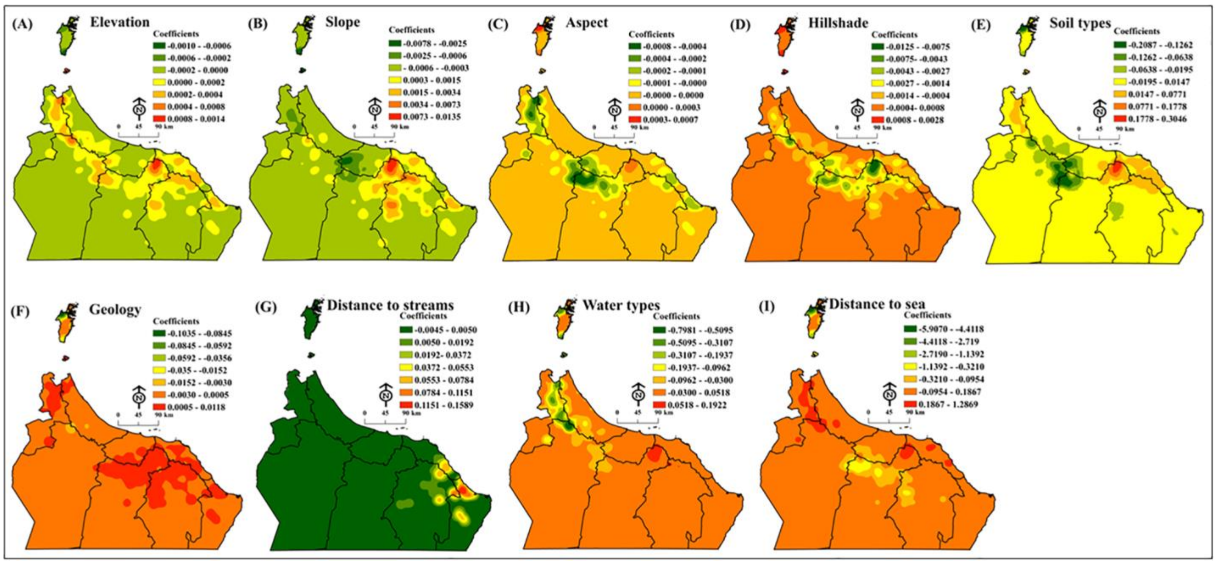

Figure 5-6 Geographically weighted regression (GWR) GWR optionally creates coefficient surface maps for each model explanatory variable reflecting variations in the modelled correlation, including: (A) elevation, (B) slope, (C) aspect, (D) hillshade, (E) soil types, (F) geology, (G) distance to streams, (H) water type, and (I) distance to the sea (Esri ArcGIS 10.3).

The optimal temperature for the biological activities of DB is 30 C, while temperature below 0 C could affect their ability to survive [50]. We believe that other factors play a more significant role in determining the distribution and survival on DBs, and future studies will continue to focus on identifying these variables.

Based on our results, we applied GWR to construct predictive surface maps to identify potential areas for future Dubas bug infestations (Fig 5-7c). The areas of highest risk included Al-Dakhliyah North, Al-Sharqiyah North, Al-Batinah South, Al-Dhahirah to the north-east and north-west, respectively, and a small island in Musandam Governorate.

5.4. Summary and conclusions

Environmental variables are important for determining the distribution and survival of any species, whether plants or animals, and this includes the DB. Understanding the distribution and affinity of DBs to different environmental variables can play a significant role in the mapping, control, and management of infestations that will involve resource allocation (e.g., spray teams, field personnel).

Novel spatial analysis and geostatistical technologies have the ability to replace the use of insecticides in controlling DB population and maintaining the required environmental balance. Elevation, slope, geology, soil type, water type and distance to streams were all found to be associated with increased DB infestations in northern Oman. By incorporating the spatial influences into the analysis of our results, we were able to better reflect real-world relationships and to build predictive models of future infestations. Furthermore, we believe that additional variables such as climatological conditions and human practices might contribute to influencing the distribution and survival of the DB in the north of Oman. These variables will be the subjects of our study in the immediate future.

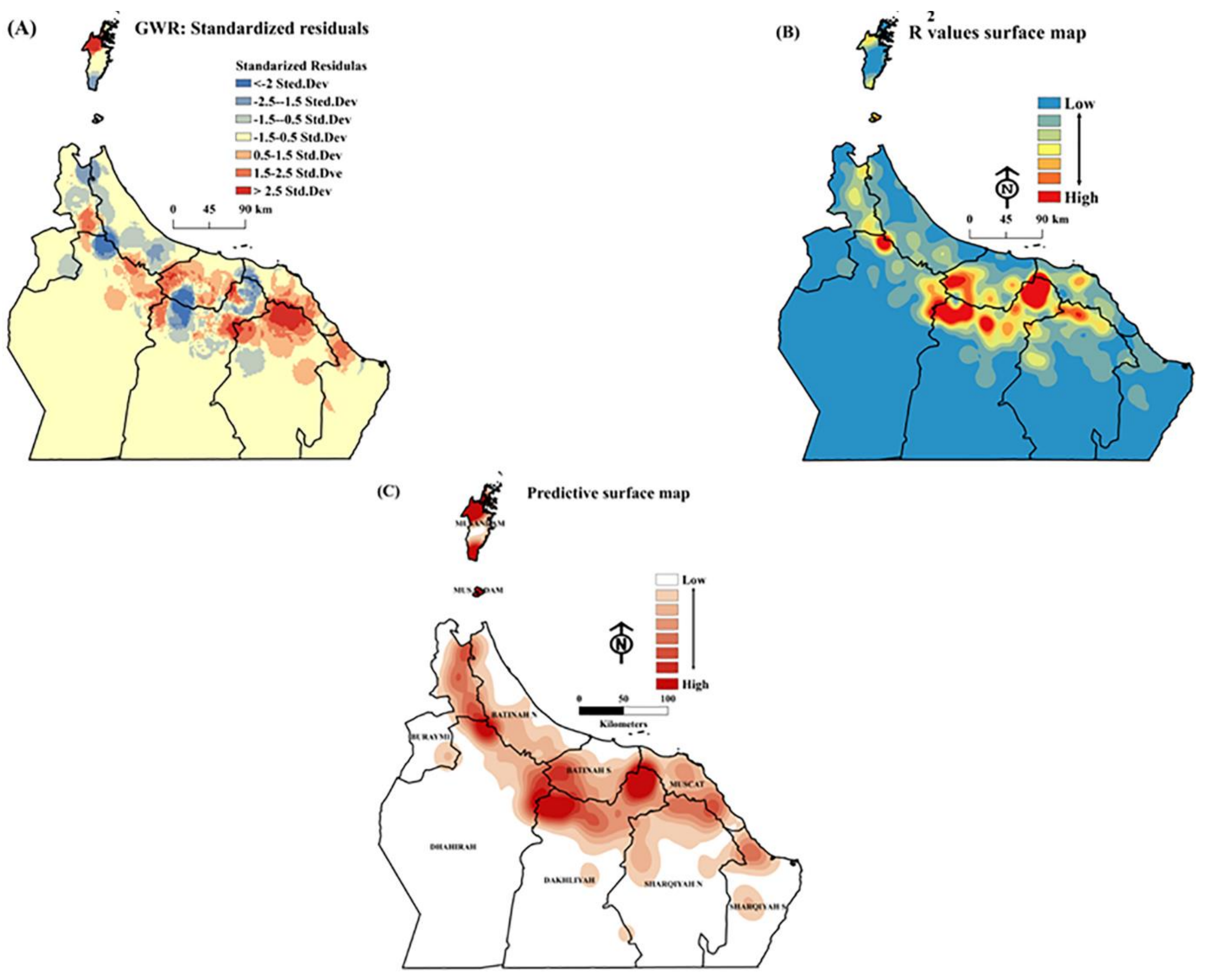

Figure 5-7 Geographically weighted regression (GWR) surface map of : (A) standardized residuals, (B) locally weighted coefficients of determination (r^2) between observed and fitted values, and (C) predictive data on possible future infestation areas (ESRI 10.3).

Moreover, we believe the results of our study will provide guidance and ideas to policy makers on how to adopt more appropriate and more specific control and prevention strategies of DBs in specific areas. We propose a simple and inexpensive technique, based on case notification data, for early warning, categorization and identifications of at-risk area that can be incorporated into routine monitoring by the agriculture authorities. The method prevents DB prevalence, helps mentoring and identifying DB adults and nymphs shelters for the elimination of DB breeding sites such as farms close to mountains and streams. In addition, reducing the cultivation of palm crop nearby mountains zone and finding open plains exposed the sunlight and air between palm trees. Dubas bug detected in relatively unpopulated area that should also be occasionally monitored for the presence or absence of the bugs.

Supporting Information

S1 File. Name of locations and geographic coordinates for the data set.
https://doi.org/10.1371/journal.pone.0178109.s001
S 2 File. Local Moran's / statictic, A spatial analyset results.
https://doi.org/10.1371/journal.pone.0178109.s002
S3 File. Hotspot analysis (Getis-Ord Gi*
https://doi.org/10.1371/journal.pone.0178109.s003

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Chapter 6. Impacts of human-related practices on *Ommatissus lybicus* infestations of date palm in Oman

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Abstract

Date palm cultivation is economically important in the Sultanate of Oman, with significant financial investments coming from both the government and private individuals. However, a widespread Dubas bug (DB) (*Ommatissus lybicus* Bergevin) infestation has impacted regions including the Middle East, North Africa, Southeast Russia, and Spain, resulting in widespread damages to date palms. In this study, techniques in spatial statistics including ordinary least squares (OLS), geographically weighted regression (GRW), and exploratory regression (ER) were applied to (a) model the correlation between DB infestations and human-related practices that include irrigation methods, row spacing, palm tree density, and management of undercover and intercropped vegetation, and (b) predict the locations of future DB infestations in northern Oman. Firstly, we extracted row spacing and palm tree density information from remote sensed satellite images. Secondly, we collected data on irrigation practices and management by using a simple questionnaire, augmented with spatial data. Thirdly, we conducted our statistical analyses using all possible combinations of values over a given set of candidate variables using the chosen predictive modelling and regression techniques. Lastly, we identified the combination of human-related practices that are most conducive to the survival and spread of DB. Our results show that there was a strong correlation between DB infestations and several human-related practices parameters (R^2 = 0.70). Variables including palm tree density, spacing between trees (less than 5 x 5 m), insecticide application, date palm and farm service (pruning, dethroning, remove weeds, and thinning), irrigation systems, offshoots removal, fertilisation and labour (non-educated) issues, were all found to significantly influence the degree of DB infestations. This study is expected to help reduce the extent and cost of aerial and ground sprayings, while facilitating the allocation of date palm plantations. An integrated pest management (IPM) system monitoring DB infestations, driven by GIS and remote sensed data collections and spatial statistical models, will allow for an effective DB management program in Oman. This will in turn ensure the competitiveness of Oman in the global date fruits market and help preserve national yields.

6.1. **Introduction**

Date palm (*Phoenix dactylifera* L) cultivation is economically important in the Sultanate of Oman, with significant financial investments coming from both the government and private individuals. However, a widespread Dubas bug (*Ommatissus lybicus* Bergevin) infestation has impacted regions including the Middle East, North Africa, Southeast Russia and Spain, resulting in substantial damage to date palms [1–6]. Dubas bugs are yellowish green in colour; females range in length from 5 to 6 mm, and males range from 3 to 3.5 mm. Male and female bugs are primarily distinguished by a spot on the females. Moreover, male bugs have a tapered abdomen and larger wings relative to the females. Nymphs have five instars and each instar has waxy filaments. However, the nature and level of DB infestation vary with location, conditions and human-related practices.

Two generations of Dubas bugs appear yearly in Oman, one in spring and another in autumn [7]. In the spring generation, eggs start hatching from February to April where nymphs pass through 5 instars to become adults in approximately 6–7 weeks. The eggs aestivate during the hot season (i.e., summer) until the autumn generation where they start hatching from late August to the last week of October. A nymph takes about 6 weeks to develop into an adult, which lives for about 12 weeks. Each female can produce more than 120 eggs, which are laid by insertion into holes in the tissue of date palm fronds at the end of each season [8].

DBs are dynamic on leaflets, rachis, fruiting bunches and spines during different stages of the date palm lifecycle. They cause direct and indirect damage to palm trees. The direct damage arises once the nymphs and adults feed by sucking sap from leaflets and rachis in the spring and autumn generations. The indirect damage comes from the deterioration of palm fruits and other crops that are cultivated underneath the palm trees through honeydew, which attracts dust, dry leaflets and rot fungi. The copious feeding of DBs weakens the tree, whereas the honeydew pollutes the vegetation and provides a substrate for the growth of black sooty mould that reduces photosynthesis of the frond surface, which then becomes chlorotic after several months [7,9,10].

DBs require much effort and money for control in several countries in the world, including the Sultanate of Oman [11]. The impacts of DBs are more severe than other insect pests, like red palm weevil [12,13]. It is the primary cause of infestation that leads to death of palm trees. In Oman, the control activities that aim to exterminate or reduce DB infestations have concentrated on the use of insecticides that include both ground and aerial sprays. Given the significant economic impact of this pest, research into effective management strategies demands high priority. Several insecticides have been evaluated for DB control in Oman; SUMI-ALPHA 5 EC® is effective as a ground spray and KARATE 2 ULV®, TREBON 30 ULV® and SUMICOMBI 50 ULV® have achieved some measure of success as aerial sprays [14,15].

KARATE-ZEON® was also found to be very effective because it gave a 100% reduction in the numbers of DB instars and adults between three and seven days after application.

However, the use of the most effective pesticides is restricted because of their side effects such as irritation [14]. In Israel, systemic carbamates (e.g., aldicarb and butocarboxim) have been used successfully, whereas in Iraq, dichlorvos (DDVP) injected directly into infected palms has been successful in suppressing the pest population [3]. However, these methods are expensive and can have negative environmental impacts on both non-target species, particularly the natural enemies of the DB *(e.g., Aprostocetus sp., Oligosita sp., and Runcinia sp.)*, and on human health [16,17]. Research has shown that some pesticide residues can persist on date fruits for up to 60 days after application [18–20]. Moreover, chemical control measures have met with limited success in Oman, where DBs continue to pose a major challenge to the agricultural industry.

Although there are a number of studies on the biology and ecology of DBs, applications of geographic information systems (GIS), remote sensing (RS) and spatial analysis of DB infestations in the Sultanate of Oman are limited [21]. In fact, there is no focused research on the spatial distribution and modelling of the DB and its relationships with human-related factors. Therefore, it became necessary to conduct a survey on DBs in different regions and conditions within the Sultanate to enable development of an applied research program that aims to decrease losses caused by DBs as well as to suggest an effective IPM program [22]. We highlighted the importance of understanding and regulating date palm human-related practices for successful DB management. This study was conducted in date cultivations in the nine governorates of northern Sultanate of Oman to ascertain the impact and to quantify the influence of human-related practices adopted by farmers on the infestation levels of DB on date palms.

The main objective of this study is to apply spatial analytic and modelling techniques to gain an understanding of the correlations between various human factors related to date palm farming as well as the distribution and density of DBs. To achieve this, we considered the contributions of factors including irrigation type, planting (row spacing), pruning, removing or keeping suckers, insecticides, fertilising, tree density per hectare, removing unproductive palms, weeds, field crops, cultivation interfaces, educated and non-educated issues. The study addressed this question: “What are the relationships between the observed patterns of DB infestation and human-related practices (i.e. variables)”.

6.2. Materials and methods

6.2.1. Study area

Significant numbers of palm trees are primarily grown in the northern part of Oman, where agriculture and climate conditions satisfy the requirements of production [23]. The date palm has the ability to survive under the adverse conditions found there [24]. Although the study area covered 9 governorates in northern Oman, analysis of our data revealed that most commercially managed and high-quality data palm plantations are located in 6 of these governorates: Al-Dakhliyah (Samail), Al-Dhahirah (Ibri), Al-Batinah (North and South), and Al-Sharqiyah (North and South) (see Fig 6-1). In addition, Northern Oman (26 50'N to 22 26'N, and 55 50'E to 59 50'E) has also experienced high infestations [25] (Fig 6-1).

6.2.2. Dependent and independent variables

The spatial correlations between DB infestation (dependent variable) and human-related or cultural practices (candidate/independent variables) such as irrigation type, row spacing (distance between trees), palm density per hectare, palm and farm services (pruning, old tree removal, remove weeds), offshoots removal from mother palm, cultivation interfaces, fertilisation, educated and non-educated employees are critical. There are a number of methods that can be used to determine the spatial correlations. Four commonly used spatial regression techniques include exploratory regression analysis (ERA), geographically weighted regression (GWR), ordinary least squares (OLS) and logistic regression (LR). However, finding a good spatial regression model can be complicated, particularly when researchers or users have an extended list of potential explanatory factors that support their analyses [26].

In this study, ERA was chosen to investigate the spatial correlation between DB infestation and the human-related practice variables mentioned earlier. ERA is a statistical data mining tool that can be used to determine properly specified OLS models. ERA builds OLS models using all possible combinations of a given list of candidate explanatory variables and assesses which, if any, satisfy the essential OLS criteria. The regression analysis applies the OLS method to perform diagnostic tests based on the joint Wald statistic, Koenker (BP) statistic, and Jarque-Bera statistic [27,28].

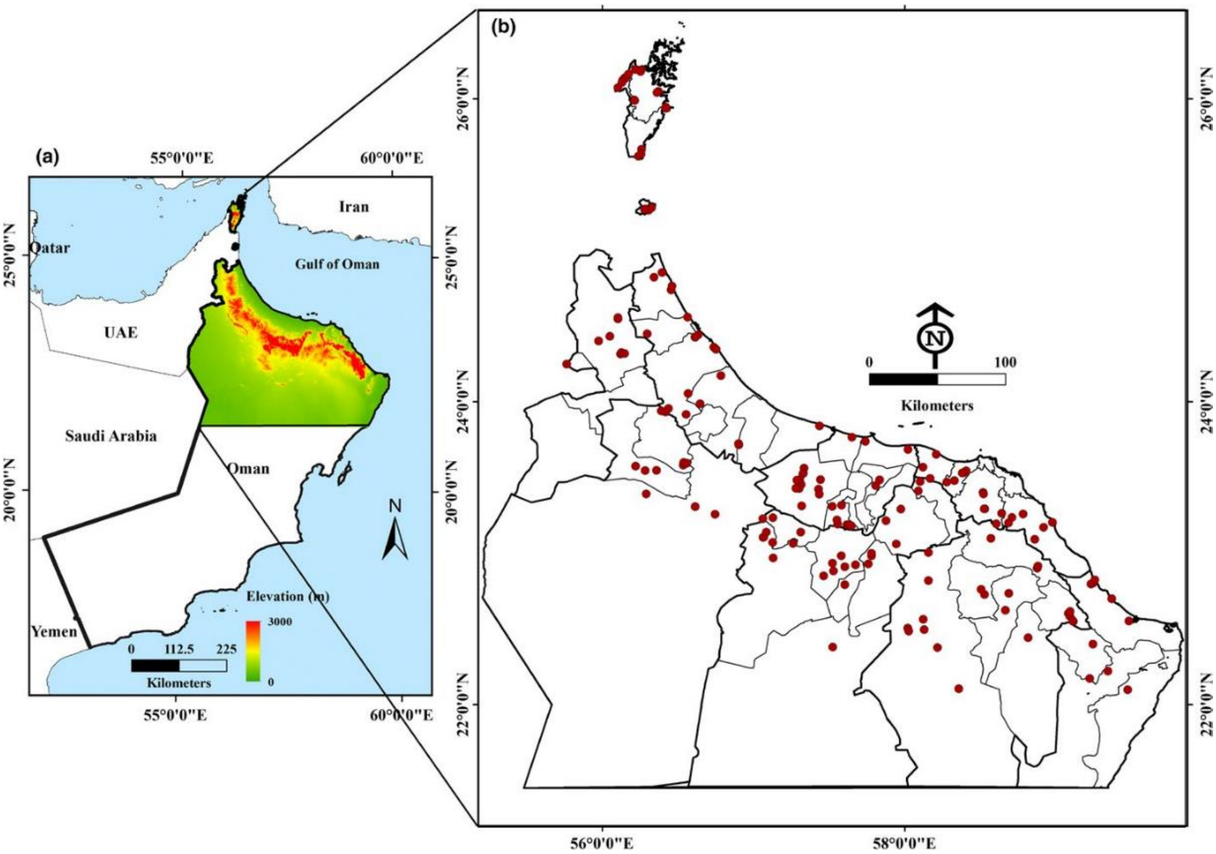

Figure 6-1 The study areas (nine governorates in the northern Sultanate of Oman) with sampled date palm plantations highlighted in red (Esri ArcGISTM 10.3).

Exploratory spatial data analysis (ESDA) tools create a report summary comparing all the satisfied models, which helps users identify models that do not pass and thus provides useful information to determine the problem areas. The significance of each variable is given as the percentage of all models tested for which the candidate explanatory variable was statistically significant [26]. OLS can be computed by:

$$Y = \beta_0 + \beta_1 \times X_1 + \beta_2 X_2 + ...\beta_n X_n + \varepsilon \qquad (1)$$

where Y is the dependent variable (number of nymph per leaflets), $X_1 + X_2. . ., X_n$ represent the independent variables (explanatory variables), $\beta_1 + \beta_2. . ., \beta n$ are regression coefficient, and ε is residual.

6.2.3. Geographically weighted regression

Geographically weighted regression (GWR) was used to create coefficient maps, residuals, local R-squared values, condition numbers and predictions. GWR performs a local form of linear regression that can be used to model spatially varying relationships [29]. A GWR model has been used to detect high-risk infestations caused by mountain pine beetle invasions of lodgepole pine forests over large areas [30]. However, GWR has not consistently differentiated between stationary and nonstationary data generating processes. Moreover, multicollinearity-estimated coefficients may bias the results, and it is unclear which tests can reliably diagnose model problems [31].

6.2.4. Data collection process

There are two methods that have been commonly used to identify the economic threshold of DB infestation during the autumn and spring generations. The first method involves counting the number of nymphs on each leaflet. The Ministry of Agricultural and Fisheries (MAF) in Oman considered a scale from low, moderate to heavy infestation. Low infestations are cases where five or less nymphs (instars) are found on the leaflet; moderate infestations are cases where 5 to 10 nymphs are found per leaflet; heavy infestations are cases where there are 10 or more nymphs per leaflet [11]. The second method involves determining the infestation level by counting the number of honeydew droplets from palm trees [7].

In this study, we have selected the counting of nymphs method. We modified the MAF's suggestion slightly and classified the DB infestation levels into 4 groups (no infestation, low, moderate and high) in ArcGIS 10.3 as follows: no infestation (no nymphs per leaflet); low infestation (1 to 5 nymphs per leaflet); medium infestation (6 to 9 nymphs per leaflet); and high infestation (10 or more nymphs per leaflet). The number of nymphs per leaflet at each potentially infested site was collected in only the autumn generation in 2015.

This survey covered two levels of palm, small and medium trees, respectively. We selected 3–5 point locations (Easting and Northing) in each district and different locations were considered, such as farms close to sea, desert or mountain plain that covers the nine governorate of northern Oman.

The irrigation type and the spatial data were obtained from the Ministry of Regional Municipalities and Water Resources (MRMAWR) of the Sultanate of Oman in December 2015 and combined with questionnaires to gain more accurate details (see Table 6-1). After measuring the distance between trees, we decided on three categories to indicate the amount of row spacing between trees: low if the distance is between 1 to 3 m, medium from 4 to 7 m, and high from 8 to 10 m. The density of palm trees in each farm was determined by calculating the number of palm trees per hectare. The IKONOS satellite images for 2015 (5 m spatial resolution) for the study area, used with permission from the National Survey Authority (NSA) of the Sultanate of Oman, were processed by the image segmentation (IS) functions available in the software ENVI 5.1 to extract the density information of palm canopies. The crown of palm canopies was used as the proxy indicator to calculate the real tree density. Sample locations were identified from the satellite image by examining the Normalised Difference Vegetation Index (NDVI).

In this study, NDVI served a surrogate measure of palm plantation density and homogeneity in the neighbourhood surrounding an image pixel. The degree of palm plantation density is expressed in the image information in percentages: high palm plantation canopy density (more than 100 palms per hectare), medium palm plantation canopy density (palms from 50 to 100 per hectare) and low palm plantation canopy density (palms from 0 to 49 per hectare). Large area would be expected to result from high density palm (deciduous tree canopy) or more than 100 palm trees per /hectare. Thus, areas containing a higher biomass and more reflectance leaf area will have a higher NDVI value. NDVI can be computed as NDVI = (NIR-RED) / (NIR+RED) [32], where NIR is the recorded radiance in the near infrared, and RED is recorded value in the red portion of the spectrum for a particular image pixel. The NDVI for non-vegetation area are negative values, while vegetated areas have values between 0.1 and 1.0.

The questionnaire data on number of trees/hectare are used as ground truth data to link satellite image information to the quality of tree plantations. In the absence of available detailed information for measuring the palm density for the study areas, we believe that the approach would best approximate the reality on the ground at local scales. This analysis was used for broad scale application and was conducted much cheaper and more effective using remotely sensed imagery than with extensive field based surveys. We determined the criteria used for classification of palm density per hectare for each sampling.

Table 6-1 Independent variables and the dependent variable and their classification index levels.

Independent variables	Index values			
	0/No	1/Yes	2	3
Row spacing (distance between trees)	-	1–3 m	4–7 m	8–10 m
Palm density (trees per /hectare)	-	>100	50–100	1–49
Group 1: Farm service (indicates 5 elements)	-	< 2	3 out of 5	5 out of 5
Pruning regime Remove weeds Debris regime Thinning regime Remove old tree (non-economic palms)				
Group 2: Removal offshoots	No	Yes	-	-
Group 3: Pesticides	No	Yes	-	-
Irrigation system		Flood [24]	Borehole	Drip
Fertilisation	No	Manure	Urea	-
Field crop	No	Maize	Alfalfa	-
Cultivation interface (grass)	No	Yes		
Educated	No	Yes	-	-
Dependent variable	Index values			
DB infestation levels (Number of nymphs per/leaflets)	0	< 5	6-9	2:10
	No	Low	Medium	High

We divided the services (i.e., palm and farm services) to prevent DB infestation into three groups (or factors). The first group includes measures such as pruning, removing unproductive palms, removing weeds under trees, debris removal and thinning regime. If these services are performed regularly, this factor are given the number 3, which means that the palms and farm are in a high service condition; similarly, the number 2 means medium service, and the number 1 means low service. The second group of services includes removing the offshoots from the mother palm. The third group is pesticide application; we collected insecticide data from the MFA in 2015 and then combined them with our field survey for a more detailed investigation and more accurate results (see Table 6-1). The survey covered 185 fields (observations and questionnaire) collected in the autumn DB generation in 2015.

The fertilisation factor was also surveyed; the questionnaire investigated the type of fertilisation used regularly on the farm, the employees hired (educated and non-educated), the cultivation interface (grass), and field crops (alfalfa and maize) as explanatory variables (see Table 6-1).

The kernel was specified as a fixed distance to solve each regression analysis. The bandwidth was specified using the AIC (ESRI, 2015) to determine the extent of the kernel. This was the bandwidth or number of neighbours used for each sample's number of estimation and was perhaps the most important parameter for ERA because it controlled the degree of smoothing in the model.

Table 6-2 The best fit model variables from OLS exploratory regression and their related VIF values.

Variables	VIF
Flood (*Falaj*) irrigation	4.12
Borehole irrigation	3.44
Row spacing	2.23
Fertilisation (manure)	2.08
Fertilisation (urea)	2.04
Group 2: Offshoots removal	2.02
Group 1: (pruning, remove weeds, remove unproductive palm, thinning and debris regime)	1.98
Maize grown in the same farm	1.78
Group 3: % Pest control (pesticides)	1.71
Grass under trees	1.56
Alfalfa	1.46
Density palm (trees per hectare)	1.31
% Educated employees	1.28
% Non-educated employees	1.23
Drip irrigation	1.18

6.3. Results

6.3.1. Exploratory regression tools, OLS and GWR findings

The model variables that best explain the occurrence of DB in the study area, along with their variance inflation factors (VIF) are shown in Table 6-2. Variance Inflation Factors (VIF) is a test designed to measure if two or more variables are telling the same story (i.e. collinearity) [33–35]. The idea is that any variable that has a value of greater than 7.5 should be removed from consideration. As the initial steps in the OLS regression analysis, multicollinearity testing by variance (VIF) was run on the pool of 15 independent variables, selected to correspond to the conceptual model. For the 49 regressions, the average VIF value is 1.96, with the minimum value of 1.18. The VIF values are all well under the ESRI-defined threshold of 7.5, which confirmed that these variables are not redundant. The maximum was (flood irrigation) with 4.12, which stabilizes model multicollinearity.

The significance values were also valuable in removing variables from subsequent modelling attempts. Although the visible clustering indicated that the amount of impervious surface may have been a predicting feature (see Fig 6-2), with respect to model importance it was among the least likely predictors. Instead, distance between trees, palm tree density, pesticides and date palm and farm services (pruning, thinning, remove weed, remove unproductive trees, debris removal regime) were the four most significant explanatory variables and thus appeared in the majority of passed models (see Table 6-3).

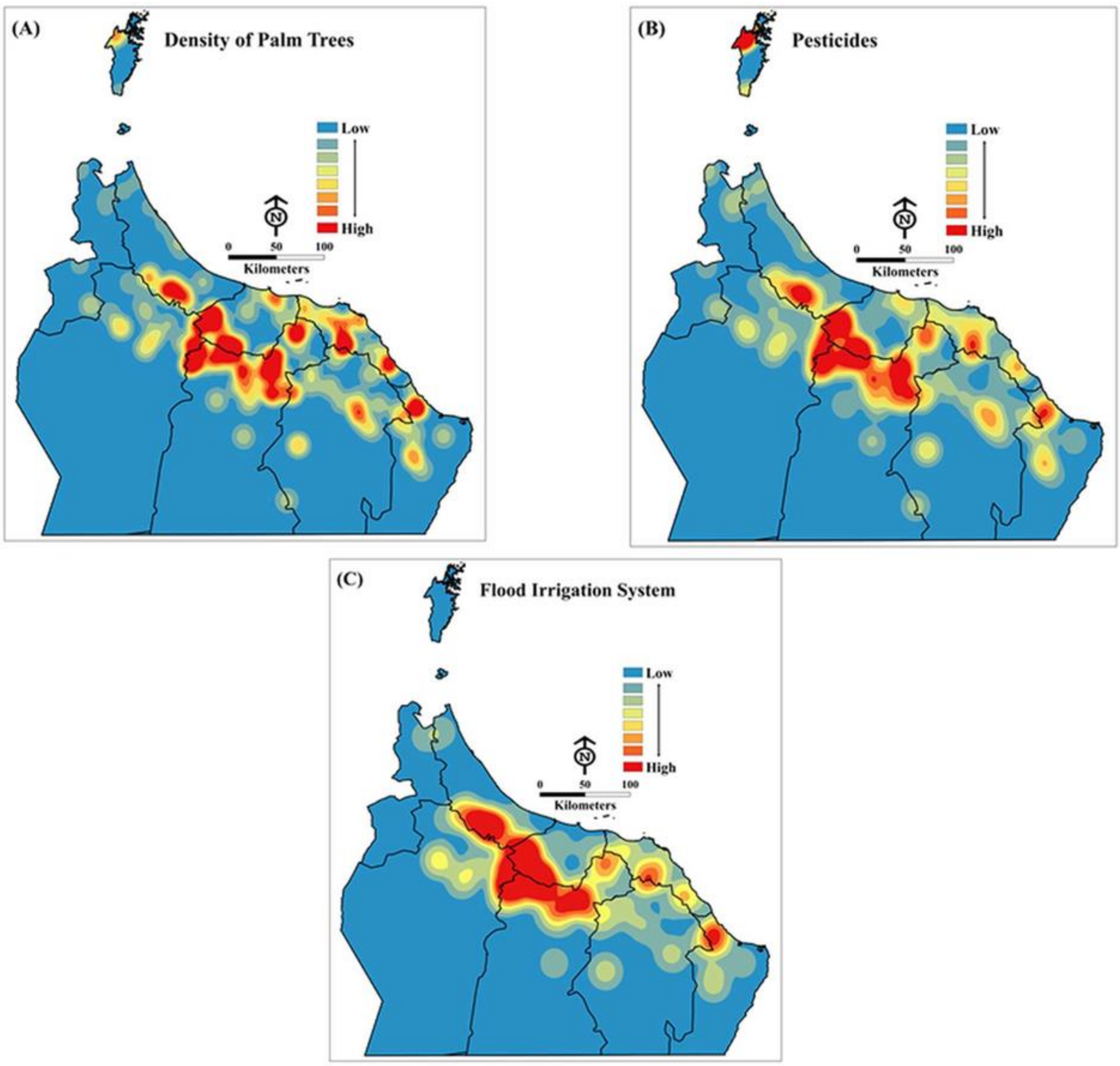

Figure 6-2 Example of GWR parameters (βs) for (A) density of palm trees per acre, (B) pesticides and (C) flood irrigation system. The examples show how modelled relationships vary across the study area. All maps are of the same scale (Esri ArcGISTM 10.3)

Eight of the fifteen variables in Table 6-4 above had significant p-values of less than 0.05, which indicates strong relationships between the individual explanatory variables and the dependent variable (see Table 6-4). It should also be noted that whereas these eight variables provide the highest adjusted R^2 value, the pesticides factor alone met all OLS assumptions with an R^2 value of 61% and a higher AIC value (732). Each variable added into the model improved the R^2 percentage by approximately 2% and reduced the AIC number by 2. The coefficient values displayed in Table 6-4 and Fig 6-3 show that the percentage of row spacing between palm trees, density of palm trees per acre, pesticides, date palm and farm services, and flood (*falaj*) irrigation system have the strongest correlations with DB infestation levels and that other variables still proved to predict a strong correlation with DB infestation levels in the study area. The maps of local R^2 in Fig 6-3 show where the model performs best.

Table 6-3 Explanatory regression model variables and the percentage of prototypes in which were found significant.

Variable	% Significant
Row spacing (distance between trees)	100
Density tree per hectare	99.88
Pesticides	99.58
Date palm and farm services (pruning, thinning, remove weed, remove unproductive trees, debris removal regime).	99.5
Flood (falaj) irrigation system	84.11
Fertilisation (manure)	82.43
Offshoots not removed from the mother palm tree.	81.31
Non-educated	43
Borehole irrigation system	23.74
Fertilisation (Urea)	21.43
Educated	19.02
Planting maize crop	11.93
Drip irrigation	10.50
Grass	6.18
Planting alfalfa crop	0.09

A significant result of model predictions is evident in the mapping of residual standard deviation. The model produced under predictions; it is likely that other variables still proved to predict a strong correlation with DB infestation levels in the study area shown in Fig 6-4.

The model explained 70% of the impacts of human-related practices on DB infestation levels. The Koenker (BP) statistic returned a p-value of 0.0029, which was highly statistically significant; this means that the model showed consistent relationships across the geographic areas of the study. The Jarque-Bera statistic of 0.3798 was not significant, which indicated a normal distribution of residuals (see Fig 6-5). The Akaike's Information Criterion (AIC) was 959.47. Similar to the adjusted R-square value, the AIC is an indicator of good model presentation.

We ran the spatial autocorrelation tool on the residual standard deviations (RSD) of each area in order to investigate where the model predictors were greater or less than (over/under predictions) reality (see Fig 6-5). It should be noted that even the same orchards (locations) that were predicted high or low remained less than 2.5 standard deviations (SD) from the mean. For the under predictions, the largest SD was 0.9 and for the over predictions a single orchard had a 2.72 deviation, whereas the next largest was 2.06.

Table 6-4 P-values showing statistically significant variables.

Variable	Coefficient [a]	StdError	T-Statistics	Probability [b]	Robust_t	Robust_SE	Robust_Pr [b]
Intercept	15.093	5.697	2.649	0.009*	2.671	5.650	0.009*
Palm density	8.445	2.089	4.043	0.000*	4.376	1.683	0.005*
Flood (falaj) irrigation	2.961	1.163	2.546	0.013*	2.905	1.019	0.009*
Row spacing	-2.968	1.046	-2.836	0.006*	-2.666	1.113	0.001*
Group [1]	-5.367	1.164	-4.611	0.000*	-4.381	1.224	0.000*
Removal offshoots	-5.936	1.589	-3.734	0.000*	-3.068	1.934	0.003*
Pesticides	3.151	0.689	4.571	0.000*	4.395	0.717	0.000*
Non-educated	-3.569	1.492	-2.392	0.018*	-2.615	1.365	0.010*
Fertilisation (manure)	-9.784	2.682	-3.648	0.000*	-4.453	2.197	0.000*

*An asterisk next to a number indicates a statistically significant p-value ($p < 0.01$).
[a] Coefficient: represents the strength and type of relationships between each exploratory variable and the dependent variable.
[b] Probability and Robust Probability (Robust_ Pr): Asterisk (*) indicates a coefficient is statistically significant ($p < 0.01$); if Koenker
(BP) Statistic [f] is statistically significant, use the Robust Probability column (Robust_Pr) to determine coefficient significance.
Group [1]: incudes pruning, remove weed, remove non-economic palm, thinning and debris regime.

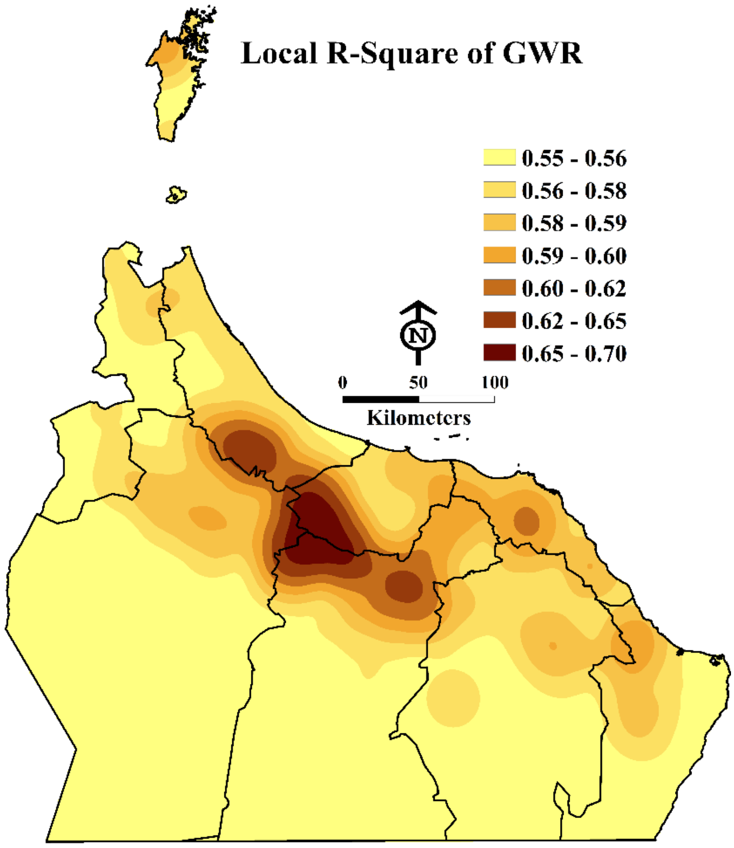

Figure 6-3 Local R² of GWR shows where the model performed best (Esri ArcGISTM 10.3).

The final hypothesis of the OLS model requires a minimum of 0.10 for the spatial autocorrelation p-value. Given the result value of 0.56, the selected model is shown to be neither excessively clustered nor random. The GWR tool was also used but did not improve the model in our study. However, according to the best practices for model spatial correlation, it is important to consider the use of GWR when using the OLS Exploratory Regression method [26]. The GWR model had an AIC value of over 732 and the adjusted R-square value of 0.70. However, the only difference between the OLS and GWR model was a higher AIC, which confirmed that GWR would not improve the model.

6.4. **Discussion**

The results of the OLS exploratory method revealed a model that confidently predicts 70% of the impact of DB infestation on the date palms in the study area. Realistically, a higher R^2 value would have predicted even higher confidence in the model; however, OLS specifies a minimum of 50.13% in order to pass. This model is well above that goal. The selection model represents the best of 6,884 trials and resulted in a combination of factors that include row spacing (the distance between palm trees), palm density (palms per hectare), insecticide application, irrigation type (flood, borehole and drip), fertilisation (manure and urea), offshoots removal, intercropping (alfalfa, grass and maize) and date palm farm services (pruning, thinning, removing weeds, removing unproductive trees and clean farm practices).

Within each of these variables, it should be noted that whereas the final model reflects one variable within each category, the significance of other variables may have been more prevalent in the other models; for example, the percentage of insecticide may have been more significant than distance between trees. However, in combination with other explanatory variables, the inclusion of row spacing (distance between trees) percentage yielded the better model (see Table 6-3).

Our results recorded in Table 6-4 highlights how each significant human practice variable included in this study promotes an increase or decrease of DB population as follows. We found the palm density, the type of flood irrigation and impact of pesticides are positively significant in increasing the DB populations; however, row spacing, farm service (group 1), offshoots removal, education level of employees and the fertilisation used are negatively significant.

The highest number of DB infestation levels was recorded in the farms where palms were planted at a distance of 3 to 5 m, which is a common palm spacing in many farms surveyed in the study area. This may be because a closer spacing with high palm density is likely to retain in-grove humidity. We recommend that commercial date plantations be planted at a spacing of 10 x 10 m, accommodating 80 palms per acre. Some human-related cultural practices help infestation was negatively correlated with the row spacing. An early study [36] reported that well-spaced palms never become infested with DB. Properly spaced palms allow for wind movement and sunlight between trees [3,37,38].

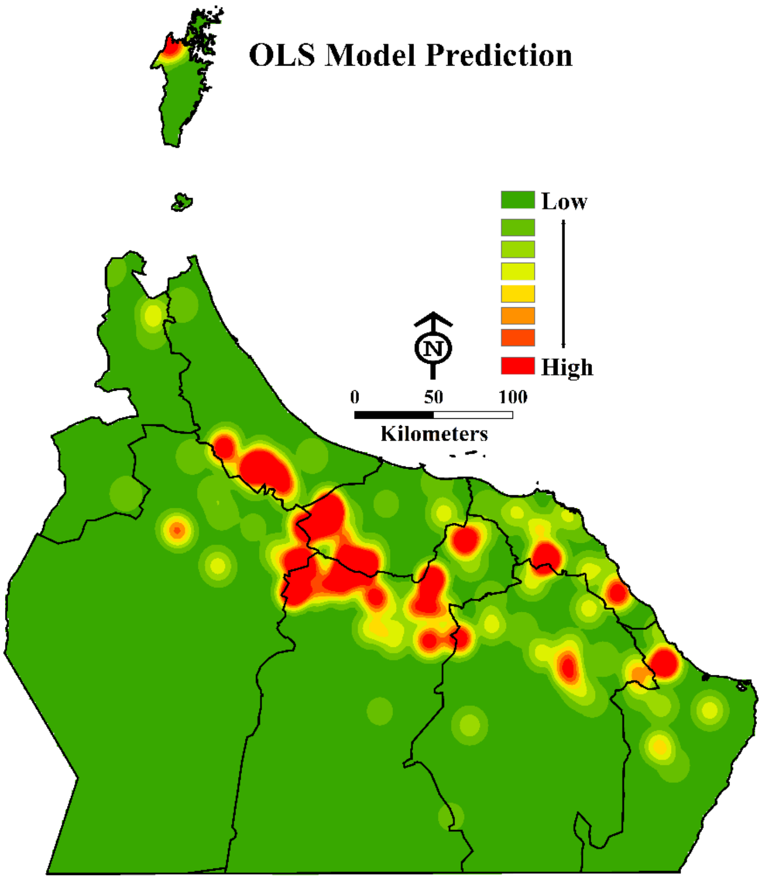

Figure 6-4 The OLS model predictions of impacts of all human-related practice variables on DB infestation on date palm plantations in the study area. The prediction model shows the areas at risk of DB based on different human-related practice parameter (Esri ArcGISTM 10.3).

Our results also found that offshoots not removed from the mother palm tree and farm services (unremoved unproductive palms, non-pruning, non-thinning and cleanliness) increased DB infestation levels in many areas of the study [39,40]. Moreover, unremoved offshoots mean that mother palms must compete to obtain enough of the important elements nitrogen, magnesium, potassium, sulphur and calcium. Iron, manganese, zinc, copper and molybdenum are also needed in small amounts. All of these elements serve as medicine for date palms for protection from diseases and infestations. In view of the severity of DB infestation on date palms in the region, we propose that human-related cultural practices that cause damage to the date palm tissue, such as shaving of fronds and removal of offshoots, be performed when DB activity is the lowest, not during the peak of the spring and autumn generations. Human-related practice controls can also be accomplished by removing old and infested fronds and by burning them, taking good care of the date palm and fronds and giving attention to agricultural cleaning.

We also found that 84.11% of the infestations in the study areas were recorded in plantations that were irrigated with flood irrigation systems, compared with 10.89 % and 5 % infestation in plantations that were irrigated through open basins or boreholes and drip lines, respectively. Open flood irrigation and high soil moisture is known to favour in-grove habitats for DB. Consequently, using a drip irrigation system with appropriate use of water is better than irrigation with bubblers because the farmer increases the efficiency of water use with minimal losses.

In view of our findings, we propose to reduce excess moisture levels in date plantations in the study area by adapting the recommended spacing at planting and using drip lines for irrigation, which would not generate excess in-grove humidity and soil moisture and would conserve the precious irrigation water resource. To date, palm trees have the capacity to survive under relatively harsh climatic and soil conditions [14] while maintaining those farms without irrigation from four to seven weeks or more before Dubas females begin to insert eggs into the fronds of the palm trees. This process diversity helps to reduce the humidity in the farms and the juice that DB is likely to sap from palm fronds and leaves [41]. Moreover, the reduced amount of irrigation may be useful to reduce the high pressure due to rich water, which assists DBs in sucking water from fronds for survival.

In Oman, although socio-economic changes have had negative effects on traditional date plantations, they have not led to the disappearance of the date palm crop. Date palm dominates agricultural production in Oman [42]. It is the traditional national staple and was Oman's main source of income before oil, and the same applies to most Arab countries [43]. However, Oman has undergone some drastic changes that have impacted consumption patterns. For example, socio-economic changes include improvement in living standards, continuous urban drift and the introduction of technology. Al-Farsi et al. [44], reported that human-related cultural practices and post-harvest handling had a great impact on palm fruit nutritional quality.

These changes might also result from introducing non-educated labourers who lacked experience in working on farms of date palms, especially in dealing with traditional crops such as palm trees. They should also be able to take part in the training of farmers in the different components of DB control, including the knowledge of the life cycles of serious pests such as DB. This can be resolved through certain economic incentives to farming communities to preserve traditional agriculture practices such as providing jobs with satisfactory compensation for Omanis to work in palm plantations.

Successful control of DB infestations of date palms depends to a great extent on the standards of the agricultural extension services. It is the responsibility of the extension officers, who should be well-trained themselves, to train farmers and steer them away from the continuous use of chemical insecticides towards safer and more efficient alternative agents of control. Moreover, in different countries such as those of the Middle East, there could be a cadre of plant protection officers whose main duty is to carry out surveys to assess DB infestations of date palm, forward unidentified arthropod pests such as DB to identification centres, and access to identification laboratories for the isolation of fungi.

Pesticides should rarely be used for the control of DB or any pests because they also kill the natural enemies of the pests, whereas this pest is protected by its scales. Enhancements in human-related practices, such as the correct use of pheromone and light traps, proper handling of organic manures in the farms and farm hygiene, are all important measures in the reduction, elimination and control of DB infestations. Insecticide application (i.e., aerial spraying), which has been used in Oman since 1997, is different in the study region than in other areas because reduction in the amount of DB infestations on palm trees in the open plains is relatively easy, whereas this process (i.e., aerial spraying using helicopters) faces many difficulties in farms located between mountains due to elevation, slope and aspect factors.

Although presently under chemical control, DBs are a threat to date palm production in the Sultanate of Oman. In Oman, there is increasing interest in biopesticides and safe natural enemies of DB. For example, the egg parasitoids *Pseudoligosita babylnoica* (Hymenoptera: Trichogrammatidae) have been recorded in some locations and can be considered as a potential biological control agent for DBs [36]. Generally, such natural products may be highly effective but require extensive knowledge of target DB infestation and well-timed and thorough application techniques. Additionally, selection of insecticides to control DB in the date palm agroecosystem should be carefully done to avoid the harmful effects of these chemicals on predators and parasitoids. We believe that lack of efficient integrates pest management (IPM) and lack of efficient communications within the frame of integrates crop management (ICM) have resulted in spread of pests and diseases in different regions worldwide, including Oman.

GIS and remote sensing (RS) can be used to study the distribution and density of DB and the locations of its natural enemies. For example, remote sensing technology such as ancillary data (DGPS) can be used to collect spatial densities of the natural enemies against Dubas bug infestations. The DGPS data then can be applied to identify and visualise the hot-spot, cold spot, spatial patterns of these natural enemies [45].

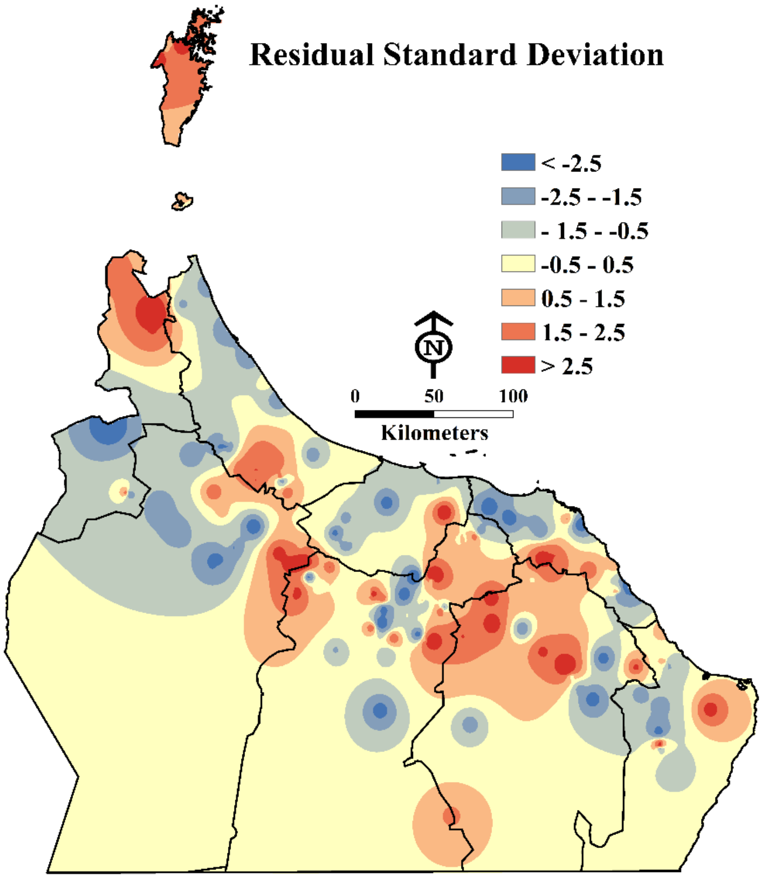

Figure 6-5 A map showing the spatial pattern of under or over predictions (in other words, lower or higher than actual infestation level) based on the calculated residual standard deviations from the model (Esri ArcGISTM 10.3).

RS tools can also be used to develop early detection for DB and study the health of date plantations. Early detection can play a crucial role in the management of DB infestation, and further research into techniques for early detection merits urgent attention. For example, Quick-bird remotely sensed images (panchromatic, hyperspectral and multispectral) and the new band World- View (Red-Edge ~705–745 nm) images can be used to map the spatial distribution of the honeydew resulting from DB infestation [22]. This approach suggests using RS to calculate the honeydew produced by DB as an indicator to estimate a threshold. The idea is based on considering the number of nymphs that can produce honeydew that cover the upper surfaces of leaflets at the critical level of infestation. Passive remote sensing methods, based on collecting and counting honeydew droplets produced by the DB, can also be used to detect and determine the effectiveness of control measures for DB. This method is effective, rapid and less hazardous and saves labour and time. Therefore, field efficacy has to be demonstrated and appropriate support and guidance transferred to the farming community.

In Oman, date palm growers manually apply fertilisers, specifically animal manure, two times per year, whereas chemicals are not commonly used in date groves. Moreover, date palms are intercropped with legumes that are used as fodder. This may make adequate nitrogen available to date palms. Al-Kharusi et al. [46] reported that the mineral fertilisers have been a significant influence on date palm quality. Ploughing the soil around the palm trunk and inspecting offshoots before planting in new groves is considered one of the best methods to restrict the spread and outbreak of DB. We propose the use of GIS tools to improve the distribution of manure at the local and field scales as a means to minimise environmental contaminations.

6.5. Conclusion

This study has determined that many human-related cultural practices adopted in date plantations significantly impact infestation levels of DB on date palms, which should be suitably modified in order to reduce critical infestation levels. DB inhabits certain areas because those areas have suitable breeding and survival conditions. For every single plant and animal species, organisms inhabit sites that are most suitable for their needs, including DB.

A list of recommended IPM strategies resulting from this study is as follows:

1. The row spacing (or distance between the date palms) should not be less than 10 × 10 meters in order to allow sunlight penetration and wind movements between the palms.
2. The offshoots should be separated from the mother palms at the proper age because their presence around the parent palm increases the level of infestation.
3. Reduce or stop irrigation of the date palms for at least 4 to 7 weeks before DB generation (spring and autumn) each year. This is vital to reduce the juices on the frond which most likely contribute to DB survival.
4. Insecticides should be used with precise scientific implementation based on other measure such as GIS and remote sensing.

5. Establish a GIS database to improve the main processes for date palm cultivation such as propagation, irrigation, pruning, pollination, fruit thinning, fertilisation, and pest control.
6. Educating farmers and offering refresher courses for extension service personnel and crop protection officers.

Supporting Information

S1 File. Blank survey**.**

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Chapter 8. Predicting the potential geographical distribution of parasitic natural enemies of the Dubas bug (*Ommatissus lybicus* de Bergevin) using geographic information systems

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Abstract

The Dubas bug (*Ommatissus lybicus* de Bergevin) is a pest species whose entire life cycle occurs on date palms, *Phoenix dactylifera* L, causing serious damage and reducing date palm growth and yield. *Pseudoligosita babylonica* Viggiani, *Aprostocetus* nr. *Beatus*, and *Bocchus hyalinus* Olmi are very important parasitic natural enemies of *Ommatissus lybicus* in northern Oman. In this study, random farms were selected to (a) model the link between occurrences of the *Pseudoligosita babylonica*, *Aprostocetus* nr *beatus*, and *Bocchus hyalinus* (dependent variables) with environmental, climatological, and Dubas bug infestation levels (the independent variables), and (b) produce distribution and predictive maps of these natural enemies in northern Oman. The multiple R^2 values showed the model explained 63%, 89%, and 94% of the presence of *P. babylonica, A.* nr *beatus,* and *Bocchus hyalinus,* respectively. However, the distribution of each species appears to be influenced by distinct and geographically associated climatological and environmental factors, as well as habitat characteristics. This study reveals that spatial analysis and modeling can be highly useful for studying the distribution, the presence or absence of Dubas bugs, and their natural enemies. It is anticipated to help contribute to the reduction in the extent and costs of aerial and ground insecticidal spraying needed in date palm plantations.

Keywords: *Aprostocetus* nr. *beatus, Bocchus hyalinus,* Dubas bug, GIS, natural enemies, *Pseudoligosita babylonica*, spatial statistical analysis

8.1. **Introduction**

Widespread Dubas bug (*Ommatissus lybicus* de Bergevin) infestations affect several Middle Eastern and North African countries, resulting in substantial damage to date palms (*Phoenix dactylifera* L) in some of these countries (El-Haidari, 1982; Waller & Bridge, 1978). Dubas bugs (DBs) have been considered a major economic threat and presently affect palm growth and yields in Oman, Iraq, Iran, Pakistan, and the United Arab Emirates. Indeed, DBs have been identified as a primary reason for the decline in date production in Oman, on account of the total area infested and the large-scale crop losses that resulted (Al-Yahyai & Khan, 2015).

DBs are found on leaflets, spines, rachis, and fruit bunches of the date palms and cause direct and indirect damages to palm trees (Figure 8-1). The direct damage arises when the nymphs and adults feed by sucking sap from leaflets and rachis during the spring and autumn generations (Aldryhim, 2008; El-Shafie, Peña, & Khalaf, 2015). Direct damage also results from injury to tissue due to egg laying activity (Bagheri, Fathipour, Askari-Seyahooei, & Zeinolabedini, 2016; Fathipour, Bagheri, Askari-Seyahooei, & Zeinolabedini, 2018; Khalaf & Khudhair, 2015). Indirect damage comes from the presence of honeydew (sticky liquid excretion), which allows dust accumulation and sooty mould growth, causing the possible deterioration of the palm fruits and other crops that are cultivated underneath the palm trees. The copious feeding of DBs weakens the tree, and the honeydew's accumulation of dust and mould reduces photosynthesis and other physiological processes on the fronds' surfaces, which then become chlorotic after several months (Bagheri, Fathipour, Askari-Seyahooei, & Zeinalabedini, 2017; Klein & Venezian, 1985; Mokhtar & Al Nabhani, 2010). A high DB population can cause a date palm tree to lose its vitality, leading to a decline in its productivity (Thacker, Al-Mahmooli, & Deadman, 2003).

Controlling DBs requires the effort and money of several countries worldwide, including the Sultanate of Oman (Thacker et al., 2003). Since DBs were first recorded in Oman in 1962, activities aiming to control DB infestations have focused on the use of insecticides via annual ground and aerial sprayings. However, the control of DBs using insecticides has led to many problems. The authorities have mainly and increasingly relied on them to manage this pest, a process that costs the government large sums of money every year (Al-Zadjali, Abd-Allah, & El-Haidari, 2006). From 1993 to 2011, about 523 tonnes of insecticides were used in aerial applications to control DB infestations, at an estimated cost of $18.5 million (Al-Khatri, 2011). In 2016, the Omani government spent $1,550,000 and $395,630 for the spring and autumn generations, respectively, to control DB infestations (direct communication with the Plant Protection Department, Ministry of Agriculture and Fisheries, Oman).

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Figure 8-1 Dubas bug, *Ommatissus lybicus* life cycle (Al-Khatri, 2011).

Insecticides have been banned in many countries including Oman because of their perceived negative environmental effects, such as the pollution of water resources; deterioration of human health; and the resulting reductions in populations of nontarget species, particularly the natural enemies of DB and because of the relatively high application cost (Ansari, Moraiet, & Ahmad, 2014). Studies have shown that some insecticide residues can persist on date palm fruit for up to 2 months after application (Khan, Azam, & Razvi, 2001), which poses a high risk to both humans and animals. Moreover, aerial spraying is difficult to conduct on farms located within mountains, owing to high elevations and valley features (Al-Kindi, Kwan, Andrew, & Welch, 2017a). Thus, chemical control measures have resulted in limited success in Oman, where DBs continue to pose a major challenge to the date palm industry.

The natural enemies of DB consist of a range of predatory, parasitic, and pathogenic species (Howard, 2001). Of the parasitic species, there are three relatively specific parasitoid wasp species that are present in Oman. Due to their specificity, they may be highly important factors for regulating the population of the DB. Two of these species attack the egg stage, while the third attacks the nymphal and adult stages. Relatively few studies exist on these species, and most of these have focused on the internal egg parasitoid *Pseudoligosita babylonica* Viggiani (Hymenoptera: Trichogrammatidae). This species has been recorded in Iraq, Oman, Iran, Saudi Arabia, and Yemen (Al-Khatri, 2011; El-Shafie, 2012; Hassan, Al Rubeai, Al-Jboory, & Viggiani, 2004; Hubaishan & Bagwaigo, 2010). It may also be present in other countries where the DB exists. It is a small, stout, yellowish wasp measuring 0.7 mm in length that parasitises and kills DB eggs (Hubaishan & Bagwaigo, 2010). Each parasitoid wasp develops inside a single DB egg. A significantly higher proportion of date palm leaflets, compared to interleaflet areas (the frond parts between leaflets) showed signs of egg parasitism by this wasp (AKA, unpublished data). According to Al-Khatri (2011), *P. babylonica* has three generations during each of the spring and autumn generations of the DB: a pre-DB egg hatching generation, a generation coinciding with DB egg hatching, and a post-DB egg hatching generation. Al-Khatri (2011) studied the biology and ecology of *P. babylonica* in Oman and stated that this egg parasitoid could be considered a potential biological control agent of DB.

The second parasitoid associated with the eggs of DB is *Aprostocetus* nr. *beatus* (Eulophidae: Hymenoptera) (Kinawi, 2005). The mature larva of this wasp has been observed to be an external feeder on one or more eggs of the DB within the midrib area of date palm leaflets (AKA, unpublished data), but younger larvae could act as internal egg parasitoids, as demonstrated in the case of *A. beatus* attacking eggs of other planthoppers and leafhoppers in other parts of the world (Carnegie, 1975, 1980; Kosheleva & Kostjukov, 2014).

The nymph-adult parasitoid *Bocchus hyalinus* Olmi (Hymenoptera: Dryinidae) has been recorded as present in Oman, the United Arab Emirates (UAE), and Kenya (Olmi, Copeland, & Guglielmino, 2015). Olmi (1998) described this wasp more than a decade ago, based on a female specimen collected in Oman. This small wasp species develops in the nymphs and adults of the DB, producing a dark pouch or sac that protrudes from the abdomen of its host. Although both sexes are winged, the female's body is generally yellowish-orange, measuring 2.8–3.8 mm in length, whereas the male is black to brown and measures 1.5–2.25 mm (Olmi, 2008, 2009).

Although a few studies exist on the above parasitic natural enemies of DB (e.g., *P. babylonica, A.* nr. *beatus* and *B. hyalinus*) (Al-Khatri, 2011; Hassan et al., 2004; Hubaishan & Bagwaigo, 2010), none have applied geographic information system (GIS) and spatial analyses to these species in the Sultanate of Oman. In addition, the effective biological control of a pest requires biological and ecological knowledge: host plant(s), host insects, biological control agent(s), and the locations (areas) where the biological control agent is going to be used. No focused research exists on the spatial and temporal distributions of these natural enemies and their relationships with environmental, climatological, and resource availability conditions. Practical tools and approaches are needed for mapping, analyzing and, more importantly, predicting the distribution of these important DB natural enemies and for understanding the interactions between these enemies and environmental and climatological factors, so that decision makers may improve the management of DB infestations on a large scale.

The main objective of this study was to investigate how the environmental, climatological, and DB infestation level variables impact populations of *P. babylonica, A.* nr. *Beatus,* and *B. hyalinus* in northern Oman. We considered environmental (e.g., elevation, slope, aspect or direction of slope, soil, water type and distance to streams), climatological (e.g., temperature, humidity, rainfall, and wind direction), and DB infestation level variables and incorporated them into a GIS platform to evaluate which combinations of variables are associated with these natural enemies of DBs. This study will also allow for the prediction of the future distribution of populations of these three potential biological control agents of DB in Oman.

8.2. **Materials and Methods**

8.2.1. Study area

Oman covers an area of 309,500 square kilometers and extends from 16°40′N to 26°20′N, and 51°50′E to 59°40′E. It occupies the south-eastern corner of the Arabian Peninsula. It has 3,165 km of coastline, extending from the Strait of Hormuz in the north to its border with the Republic of Yemen in the south. The coastline faces three bodies of water, namely the Arabian Sea, the Persian Gulf (also known as Arabian Gulf), and the Gulf of Oman (Figure 8-2).

To the west, Oman is bordered by the UAE and the Kingdom of Saudi Arabia. Mountainous areas account for 15% of all land area, while desert plains, sandy areas, and coastal zones cover 77% of the land area. The remaining land area is covered by agricultural land. According to the 2004–2005 soil survey conducted by the Ministry of Agriculture and Fisheries (MAF), in the Sultanate of Oman, 22,230 km^2 (equivalent 2.223 million ha) are optimal for agricultural activity, which represents roughly 7.5% of the country's total land area. Oman's location provides favorable conditions for agriculture development. Land devoted to agriculture uses accounted for an economic output equal to 14.6% of the GDP in 2008 (Al-Kindi, Kwan, Andrew, & Welch, 2017d).

The elevation ranges in the study zone from 0 to 2,994 m above sea level, and the soil contains five soil-type categories: clay, gravel, loam, rock, and sand. The water in the area can be categorized into three classes based on total dissolved content: brackish water, freshwater, and saltwater (Al-Kindi et al. 2017a). Oman has an arid climate, receiving <100 mm of rain per year; however, the mountainous parts of the country enjoy higher precipitation levels. As one of the independent variables, DB infestations occur where palm trees are concentrated; therefore, in the present study, we focused on northern Oman, the area from latitude 26°50′N to 22°26′N and from longitude 55°50′E to 59°50′E (see Figure 8-2). The study region is approximately 114,336 km^2 in area. The date palm plantations are denser in the coastal plains and many interior places in the study area (Al-Busaidi & Jukes, 2015). The area covered by this study contains different levels of DB infestation. Higher levels of DB populations have resulted in direct and indirect damage to infested palm trees and nearby trees (Al-Kindi, Kwan, Andrew, & Welch, 2017c).

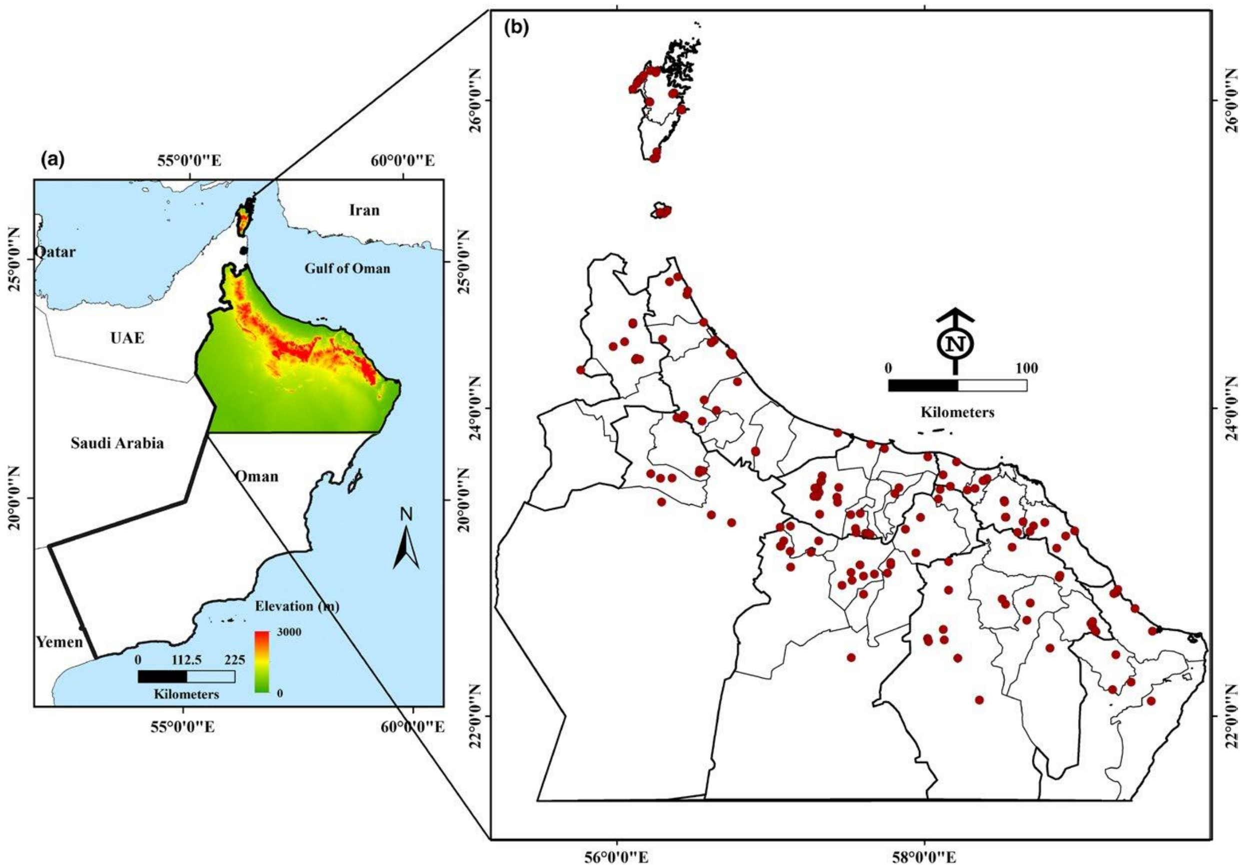

Figure 8-2 The study areas: (a) location and topography, (b) nine governorates in the Sultanate of Oman, with date palm plantations sampled for DB and its natural enemies highlighted in red.

8.2.2. Data collection and analysis of DBs

8.2.2.1. Sampling periods and sites

Date palm materials and insect specimens were obtained during four periods: summer (June–August) 2009, spring (March–June) 2010, spring (March–April) 2011, and spring (April) 2015. The first round of sampling, in summer 2009, targeted the DB's egg stage, so no nymphs or adults were present in the samples. The spring of 2010, 2011, and 2015 rounds of sampling targeted the nymphal and adult stages, which tended to be higher in number during the spring generation than during the fall generation. Sites visited during the first round of sampling included all Oman governorates (Muscat, Al-Batinah North, Al-Batinah South, Musandam, Al-Buraymi, Al-Dhahirah, Al-Dakhiliyah, Al-Sharqiyah North, Al-Sharqiyah South, Al-Wusta and Dhofar).

The second round of sampling included all governorates except Al-Wusta and Dhofar. The third included sites in Muscat, Al-Sharqiyah South, and Dhofar, while the fourth round involved only one site in Al-Dakhiliyah. Al-Wusta was not visited during the second, third or fourth rounds because the first round of sampling revealed no records of DB there. All sites visited in each governorate were chosen at random. They included, for the most part, farm sites (cultivated or neglected) in villages and towns or, more rarely, aggregations of wildly growing date palms in wadis. Sites were marked geographically using GPS device (Garmin) to give positional and elevation data, and site names were recorded.

8.2.2.2. Sampling of DB eggs

Three to five trees were selected randomly at each site. In most cases, samples were taken from shorter trees, those up to 2 m in height (growing point height). Fronds of these trees were reachable from the ground, making them easy to examine and cut. One middle-aged green frond was cut from each tree. All fronds were examined for the presence of new DB eggs. At farm sites with tall trees, a farm attendant/laborer was asked to climb each tree to collect one green frond. Each collected frond was then cut into 3–6 pieces, which were placed in large trash bags. In some cases, leaflets were excised from the frond (using pruning scissors) and then placed in bags. Trash bags with frond material were placed in a shaded area in the field and then moved inside a large cool box. Finally, they were transported to the entomology laboratory at College of Agricultural and Marine Sciences, Sultan Qaboos University.

8.2.2.3. Sampling of DB nymphs and adults

Sampling was performed on relatively short date palms of up to 2 m in height. At least five trees were sampled at each site, but when the DB populations were low, up to ten trees were examined. Nymphs and adult DBs were sampled using three methods. When populations were relatively large, suction was applied using handheld vacuum machines (Black & Decker car vacuum, and Bio-quip custom-made vacuum). DBs collected via a vacuum machine from a particular site were pooled inside a large jar. When populations were relatively low, one of the two following methods was used: Removal of leaflets infested with nymphs and adults using pruning scissors, and then, leaflets were placed inside a large jar; or shaking of the leaflets to dislodge the insects into a large jar. The field samples were taken roughly between 8 a.m. and 11 a.m. as this is when the insects are feeding and not moving off the leaflets due to excessive heat exposure.

8.2.2.4. Processing egg samples in the laboratory

If not already performed in the field, leaflets were separated from the rest of the fronds in the lab. All leaflets and frond pieces were then checked for new eggs. Leaflets and frond pieces with new eggs were retained, and the rest were discarded. The apical parts of leaflets were cutoff, and the leaflets were placed into large, 5-litre jars with a small amount of water at the bottom. Some space was left in the jar between leaflets, jar to allow for sufficient aeration. Leaflets from each farm site were combined together, but in cases with a large number of leaflets, they were distributed in more than one jar. Frond pieces were placed in 5-litre jars in a similar manner to that described above for leaflets. All jars were labeled with site information and the collection date. Frond material was incubated for2 months at an average, minimum, and maximum temperatures of 22.29, 19.42, and 27.52°C respectively. The average, minimum, and maximum humidity were 49.94%, 27.1%, and 66.1%, respectively.

Frond pieces and leaflets from each site were checked twice weekly for insects, including potential emerging parasitoids. Interleaflet frond areas and leaflets with observed adult parasitoids were marked with red ink and kept separate from the rest of the frond material, to make it easier to follow up on the progress of parasitism of eggs. The material was also checked for the emergence holes of parasitoids in or around DB eggs. Emerged or observed stages of parasitoids were photographed.

8.2.2.5. Processing of nymph-adult samples in the laboratory

For a particular site, all collected nymphs and adults were combined in small plastic vials containing 80% ethanol as a preservative. These vials were labeled to indicate each sample's site and date and were stored at room temperature for later assessment. The presence of nymphal-adult parasitism was determined in a particular site by examining sampled nymphs and adults and checking for the presence of a characteristic dark (brown-black) sac, indicative of parasitism, on the side of the abdomen of each DB.

8.2.3. Data collection and spatial analysis of natural enemies Parasitoid data

Although the study samples came from many governorates, data used in GIS analysis are based only on samples from nine governorates in northern Oman: Al-Dakhiliyah, Al Dhahirah, Al-Batinah (North and South), Al-Sharqiyah (North and South), Al-Buraymi, Musandam, and

Muscat. The natural enemies' data of parasitoids *P. babylonica, A. beatus,* and *B. hyalinus* were based on collections made at 168 locations. All collected data were then converted to a GIS shapefile using ArcGIS 10.4 (ESRI, Redlands, CA) for mapping and spatial analyses. The shapefile data were used to map the absence and presence of *P. babylonica, A. beatus,* and *B. hyalinus* in the study area.

Data on DB infestations and their impact were determined by observations of their prevalence in palm trees from 2009 through 2015 based on data obtained from the Ministry of Agricultural and Fisheries (MAF), Oman. These data comprised spatial coordinates (sites' longitudes and latitudes), governorates and DB infestation levels. First, we classified the DB infestation levels into four groups (very low, low, moderate, and high) in ArcGIS as follows: very low infestation, 0–4 nymphs per leaflet; low, 5–7 nymphs per leaflet; moderate, 8–9 nymphs per leaflet; and high infestation, 10 or more nymphs per leaflet (Al-Kindi et al., 2017c). In addition, we calculated the average levels of DB infestation over two seasons (spring and autumn generations) from 2009 to 2015. By linking attribute identifications of the pixels with continuous datasets (environmental, climatological, and DB infestation levels), we displayed the presence of the natural enemy species in the GIS rasters.

8.2.3.1. Environmental and climatological data

To examine the environmental and climatological variables associated with the distribution of *P. babylonica, A. beatus,* and *B. hyalinus*, data on elevation, slope, aspect, hillshade, soil types, water type, distance to streams (wadis), precipitation, temperature, humidity, wind direction, and wind speed were obtained for each collection location of natural enemies and compiled into a database. First, we obtained elevation and derived slope, aspect, hillshade, and rivers (dry valleys) for each site by importing a 30-m resolution of digital elevation model (DEM) map into ArcGIS 10.4 and extracting the underlying value (in meters). Second, the Euclidean distance method (i.e., surface analysis) was used to calculate the distance from the observation points using the "wides" feature (Al-Kindi et al., 2017d).

The vector GIS dataset, including governorate boundaries and shapefiles, was obtained from the National Centre for Statistics & Information, Oman. The water type dataset (e.g., freshwater, saltwater, and brackish water) was obtained from the Ministry of Regional Municipalities and Water Resources (MRMWR), Oman. The climate data, such as temperature, humidity, wind speed, and wind direction, were obtained from the Directorate General of

Meteorology, Oman. The averages of temperature, humidity, wind speed, and wind direction were calculated for 22 weather stations in the study area over the period 2009–2015. The average rainfall from 2009 to 2015 was calculated for 120 weather stations in the study area, using data obtained from MRMWR. Interpolation techniques, in combination with GIS, were used to interpolate the weather spatially. The climate in each parasitoid sampling location was estimated by interpolating the data from all enrolled weather stations, using the inverse distance weighting and spline methods (Abatzoglou, 2013). Finally, we linked climatological, environmental, and DB infestation levels data with the presence/absence of *P. babylonica*, *Aprostocetus* nr. *Beatus*, and *B. hyalinus*.

8.2.4. Data and spatial analysis

To understand the factors behind observed spatial patterns or to predict spatial distributions, regression analysis methods are useful for modeling, examining, and exploring these relationships. In this study, ordinary least square (OLS) and geographically weighted regression (GWR) for multiple predictions in ArcGIS 10.4® (Wooldridge, 2003) were used to generate prediction maps and modeled the relationships (Braun & Oswald, 2011) between the dependent (*P. babylonica, Aprostocetus nr. Beatus, and B. hyalinus*) and independent variables (environmental, climatological, and DB infestation levels) . The independent variables included DB infestation levels, elevation, slope, aspect, hillshade, soil type, water type, distance to streams (wadis), precipitation, temperature, humidity, wind speed, and wind direction.

First, the OLS model was used to compute a single coefficient to represent both positive and negative relationships between the dependent and independent variables. This tool automatically checks for multicollinearity and computes standard errors and model significance indices that are robust to heteroscedasticity. In addition, the output attribute data from the OLS and GWR for multiple regression analysis, including residual, coefficients, and *p*-values, were used to create maps, tables, and figures showing the model's predictions of *P. babylonica, A.* nr *beatus,* and *B. hyalinus*, including predictions of area of overproduction and underproduction of these parasitic species.

8.3. Results

8.3.1. Natural enemies mapping

The most prevalent parasitoid species was *P. babylonica*, which was found at 66 sites, followed by *Aprostocetus* nr. *beatus* at 35 sites and *B. hyalinus* at 33 sites (see Figure 8-3). Of the *P. babylonica*, *Aprostocetus,* and *B. hyalinus* data, a total of 168 collection sites returned information. The collection sites were located predominately in nine geographical governorates in northern Oman. The distribution of *P. babylonica* occurred in all nine governorates but varied across the study area. *Aprostocetus* nr. *beatus* distributions were found primarily in seven governorates, being absent in Al-Dhahirah and Ash-Sharqiyah South. By contrast, *B. hyalinus* distributions were found in seven governorates, but not in Musandam or Ash-Sharqiyah North (Figure 8-3).

8.3.2. Nearest neighbour statistical analysis

The results of our nearest neighbour statistical analysis, in which the nearest neighbour ratios were 0.520, 0.636, and 0.689, respectively, showed that the expected mean (EM) distance (or spacing) of *Aprostocetus* nr. *beatus*, *B. hyalinus*, and *P. babylonica* distributions were, respectively, higher than the observed mean (OM), with the difference less than zero (a negative number). These results indicated that the distributions of *Aprostocetus* nr. *beatus*, *B. hyalinus,* and *P. babylonica* were largely clustered (see Table 8-1).

Table 8-1 Mean nearest neighbour distribution of *A. nr. beatus, B. hyalinus, and P. babylonica*.

	Observed mean distance (km)	Expected mean distance (km)	Nearest mean ratio	*Z*-score	*p*-Value
Aprostocetus* nr.*beatus	12.14	23.33	0.520	−5.344533	0.00001
B. hyalinus	12.75	20.04	0.636	−3.263810	0.00109
P. babylonica	14.26	20.67	0.689	−4.326245	0.00015

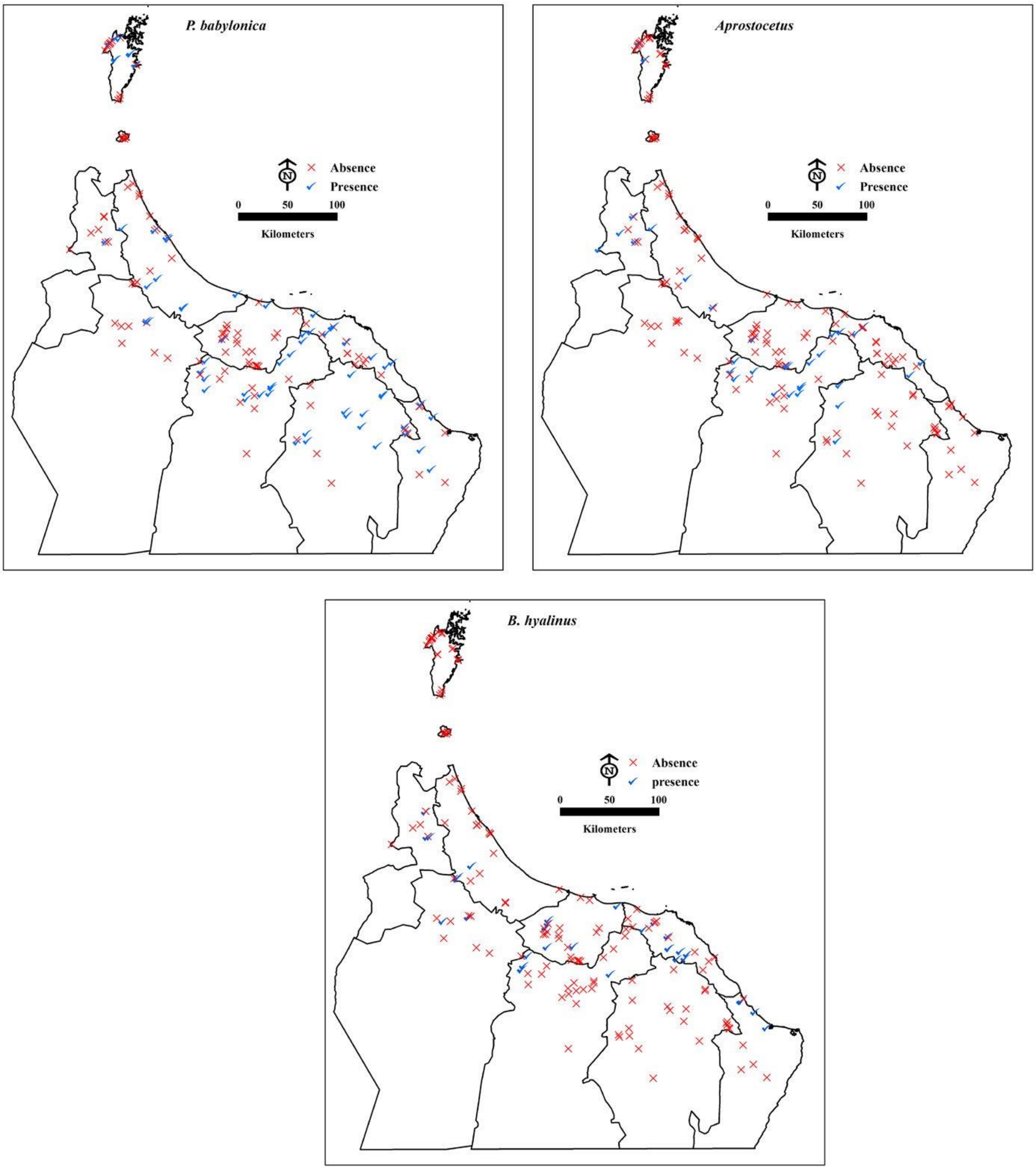

Figure 8-3 Point showing observed the presence (red) and absence (blue) of *P. babylonica, A. nr. Beatus, and B. hyalinus* in the area.

8.3.3. Spatial relationships modeling analysis

The model variables that best explain the occurrence of *P. babylonica*, *A.* nr. *Beatus*, and *B. hyalinus* in the study area, along with their variance inflection factors (VIF), are shown in Table 3. VIFs are based on tests designed to measure whether two or more factors are telling the same story (O'brien, 2007). The idea is that any factor that has a value of higher than 7.5 should be removed from consideration. The preliminary steps in the OLS analysis, multicollinearity testing by mean square deviation and VIF were run separately (once per species) on the pool of 13 independent factors, which were selected to correspond to the conceptual model (see Table 8-2). The average VIF value in Model 1 was 1.49, followed by Model 2, at 2.11 and 1.96 in Model 3 (see Table 8-3). The VIF values in the three models are all well under the ESRI-defined threshold of 7.5, confirming that these factors are not redundant (see Table 8-2).

Table 8-2 Best fit variables from OLS exploratory regression and their related VIF values

	Dependent variables		
	***P. babylonica* (model 1)**	***A. nr. beatus* (model 2)**	***B. hyalinus* (model 3)**
Independent variables	VIF	VIF	VIF
DB infestation levels	1.97	1.91	1.93
Elevation	1.25	3.87	2.96
Slope	1.47	1.81	2.37
Aspect	1.39	1.64	1.52
Hillshade	1.31	1.94	1.99
Water type	1.63	2.37	2.67
Soil type	1.23	1.58	1.30
Temperature	1.70	2.46	1.24
Humidity	1.86	1.96	2.72
Wind direction	1.85	2.37	1.82
Wind speed	1.34	2.40	1.47
Rainfall	1.23	2.06	2.14
Distance to (wadis)	1.56	2.16	1.91

OLS and multiple regression revealed that the *P. babylonica* distribution had significant positive relationships *p*-value ($p < 0.01$) with DB infestation level ($R^2 = 0.80$), elevation ($R^2 = 0.83$), wind direction ($R^2 = 0.64$), humidity ($R^2 = 0.45$), and water type ($R^2 = 0.48$); however, significant negative correlations were found between temperature ($R^2 = 0.53$) and *P. babylonica* presence (Table 8-3).

Table 8-3 shows significant positive association *p*-values ($p < 0.01$) were found between *A.* nr. *beatus* and elevation ($R^2 = 0.90$), DB population ($R^2 = 0.88$), and wind direction ($R^2 = 0.71$); nevertheless, significant negative associations were found between the temperature ($R^2 = 0.93$), humidity ($R^2 = 0.94$), and wind speed ($R^2 = 0.60$) factors and *A.* nr. *beatus* presence. In addition, significant positive relationships were found between *B. hyalinus* and DB population (R^2 = 0.81), elevation (R^2 = 0.72), humidity (R^2 = 0.46), rainfall (R^2 = 0.74), and water type (R^2 0.39); but significant negative relationships were found between temperature (R^2 = 0.94) and wind speed (R^2 = 0.37) on the one hand and *B. hyalinus* presence on the other hand (see Table 8-3).

Several factors in Table 8-3 were significant at a confidence level of >95%, which indicates strong relationships between individual exploratory factors and the dependent variable. The coefficient values displayed in Figure 8-4 shows the impact of each of the variable that has the strongest correlation with *P. babylonica, A.* nr, and *B. hyalinus*, and that other variables still predicted a strong correlation with *P. babylonica, A.* nr. *Beatus,* and *B. hyalinus* distributions in the study area.

The significance of the models' predictions is evident in the mapping of residual standard deviations. The models produced under predictions, although it is likely that other variables could also predict strong correlation with *P. babylonica, A.* nr, and *B. hyalinus* in the study area as shown in (Figure 8-5). The three parasitoid models explained 63%, 89%, and 94% of the impact of environmental, climatological and DB infestation levels on *P. babylonica, A.* nr. *Beatus,* and *B. hyalinus*, respectively.

Table 8-3 p-Values showing statistically significant variables.

	P. babylonica	*A. nr. beatus*	*B. hyalinus*
DB infestation	+0.0001*	+0.0001*	+0.0002*
Elevation	+0.0001*	+0.0006*	+0.0001*
Slope	0.7357	0.0528	0.9168
Aspect	0.4197	0.3121	0.8772
Hillshade	0.0824	0.8771	0.5245
Water type	+0.0006*	0.3803	+0.0026*
Soil type	0.0824	0.0202	0.2538
Temperature	−0.0003*	−0.0013*	−0.0019*
Humidity	+0.0044*	−0.0001*	+0.0001*
Wind direction	+0.0025*	+0.0001*	0.0715
Wind speed	0.1500	−0.0001*	−0.0005*
Rainfall	0.0374	0.2055	+0.0001*
Wadis	0.6904	0.3144	0.0599

Notes. An asterisk next to a number indicates a statistically significant *p*- value ($p < 0.01$).

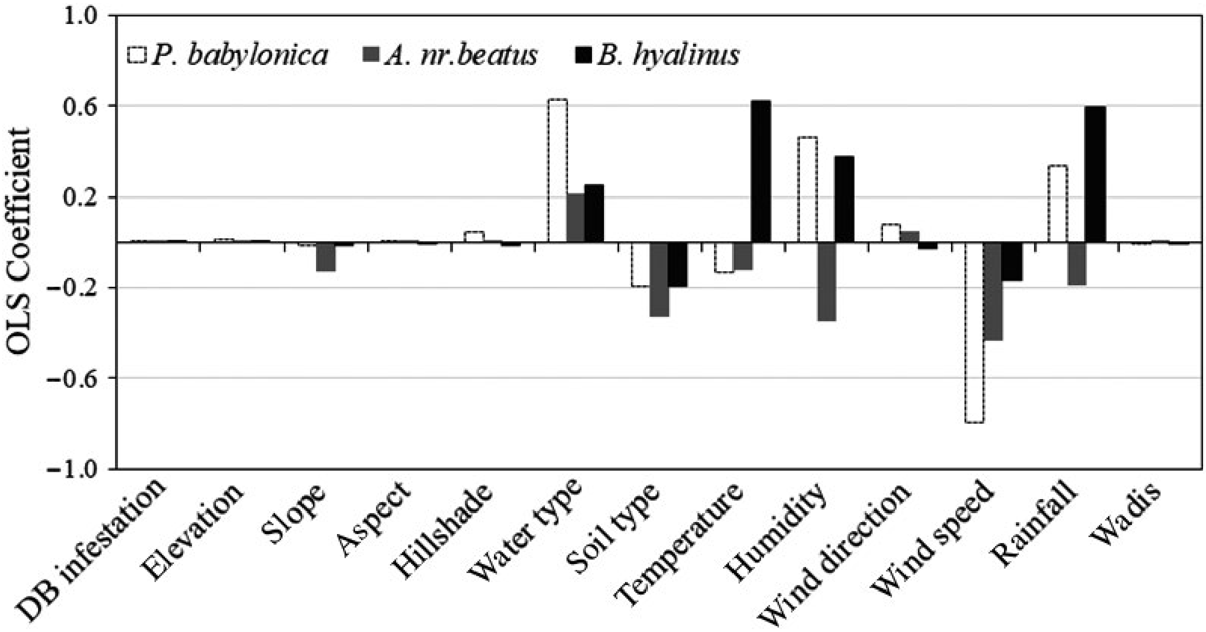

Figure 8-4 Coefficients among environmental, climatological, and DB infestation variables (independent variables) and *P. babylonica, A. nr. Beatus, and B. hyalinus* (dependent variable).

8.4. Discussion

Results shown in Table 8-1 indicated that the expected mean distances of the species' distributions were greater than the observed mean distance. These results indicated the presence of clustered distributions of *P. babylonica, A.* nr. *Beatus,* and *B. hyalinus* in the study area. The results of the OLS regression method revealed models that confidently predict 63%, 89%, and 94% of the influence of DB infestation levels, and climatological and environmental variables on the *P. babylonica, Aprostocetus* nr. *beatus* and *B. hyalinus* presence in the study area, respectively.

Although *P. babylonica* is by far the most important natural enemy of DB, the result shows that the ability of the studied independent variables to predict the distribution of this natural enemy is relatively low (63%) compared with the two other parasites. One possible explanation for this contrast between *P. babylonica* and the other two parasitoids involves differences in life history between the three species. *P. babylonica* is an internal egg parasitoid of DB eggs which are mostly hidden (expected for operculum or egg cap) within date palm leaf tissues. *A.* nr.*beatus* is an external egg feeder as a mature larva and possibly an internal egg feeder as a younger larva, and *B. hyalinus* feeds on nymphs and adults. A 63% explanation by the model is still quite strong, but as it is purely an internal egg parasite, the low R^2 value could be due to other biological variables that we did not take into account when developing the model.

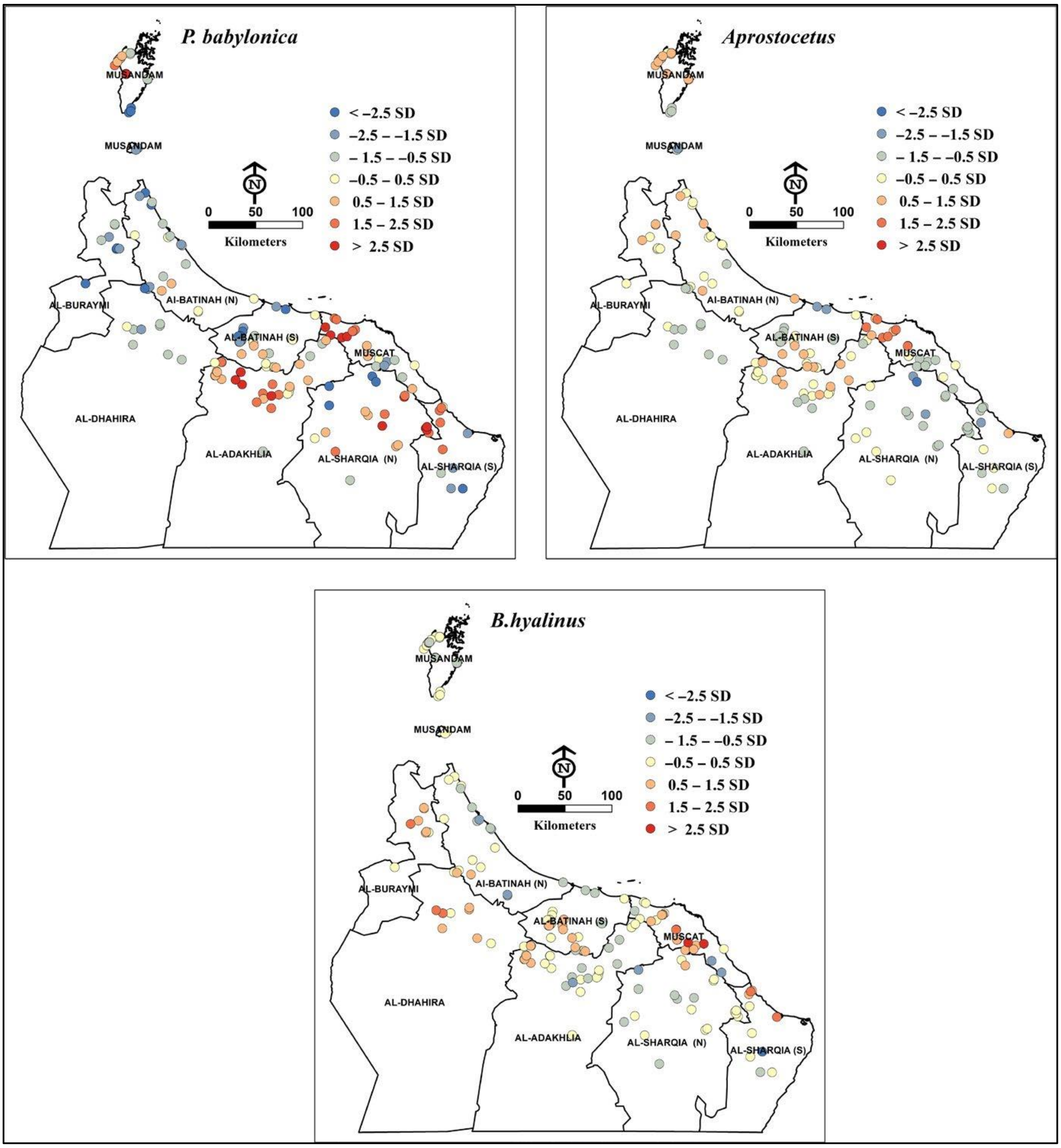

Figure 8-5 Ordinary Least Square (OLS) maps of standardized residuals showing the spatial patterns of under-or over-production of the natural enemies.

Our environmental and climatological analyses suggested that DB infestation levels, elevation, water type, temperature, humidity, rainfall, wind speed, and wind direction drive the spatial distribution of each natural enemy, as well as differences between them. The distribution of each species is influenced by distinct and geographically associated climatological, environmental factors, and habitat characteristics. In particular, high suitability was predicted in the Al-Dakhiliyah North, Al-Batinah South, Ash-Sharqiyah South (north-west), Muscat, and Musandam (north-west) governorates for *P. babylonica*. DB population, elevation, temperature, humidity, wind direction, and water type were important predictors for calculating the probability of occurrence of *P. babylonica*. Likewise, we found high suitability in Al-Dakhiliyah North, Al-Batinah South, and Musandam governorates for *A.* nr. *beatus*, where factors such as DB infestation, elevation, temperature, humidity, wind direction, and wind speed are significant predictors for calculating the probability of its occurrence. Similarly, we found high suitability in Al-Dakhiliyah North, Al-Batinah South, Muscat, and Ash-Sharqiyah (north-west), where factors such as DB infestation, temperature, humidity, rainfall, and water type were important predictors in calculating the probability of occurrence for *B. hyalinus* (see Figure 8-6).

Pseudoligosita babylonica occurred most frequently in elevation classes of 7–619 m and 898–918 m. It also occurred between 1,000 and 1,047 m, but in smaller proportion (mean ± *SD* = 411 ± 323 m). *A.* nr. *beatus* occurred at a high rate of frequency in the 7–600, 826–850 and 1,099–1,192 m elevations (519 ± 343 m). *Bocchus hyalinus* occurred most frequently in elevation classes of 10 –1,114 m (428 ± 309 m) (see Figure 8-7). The influence of elevation and DB infestation variables on the presence of *P. babylonica*, *A.* nr. *beatus* and *B. hyalinus* was concentrated in farms located between mountains and less concentrated in desert and coastal areas away from the mountains. In particular, higher infestations were more severe in mountain wadi biomes and less in the open areas.

Wind direction has a positive impact on the presence of *P. babylonica* and *A.* nr.*beatus*. Both species were found most frequently among wind direction classes between 148–180° SW and 212–277° SE. The southwest wind, which is commonly known as the “kous” in the Gulf countries, is warm and moist. This wind may bring with it viable conditions for these two species to survive in northern Oman. In contrast, we found no influence of wind direction on the *B. hyalinus*.

Temperature, relative humidity, and rainfall are critically important abiotic factors that can influence insect development and the presence of insect pests and their natural enemies (Feeley, Malhi, Zelazowski, & Silman, 2012). The present study’s regression analyses indicated that humidity was an important factor for *B. hyalinus, A.* nr. *Beatus,* and *P. babylonica*. We found that, as the mean daily humidity increased, so did the occurrence of *B. hyalinus* and *P.*

babylonica in the study area. *P. babylonica* and *B. hyalinus* were found to be present where mean daily humidity ranged between 38% and 63%, with means of 48% and 49%, respectively. In contrast, negative significant relationships were found between temperature and *A.* nr. *beatus* and *P. babylonica* occurrence. Our results also showed negative significant relationships between wind speed and *A.* nr. *beatus* and *B. hyalinus* species. This is possible because DBs avoid extreme temperatures (both high and low), direct sunlight, and dry areas with disturbing winds (Al-Kindi et al., 2017d).

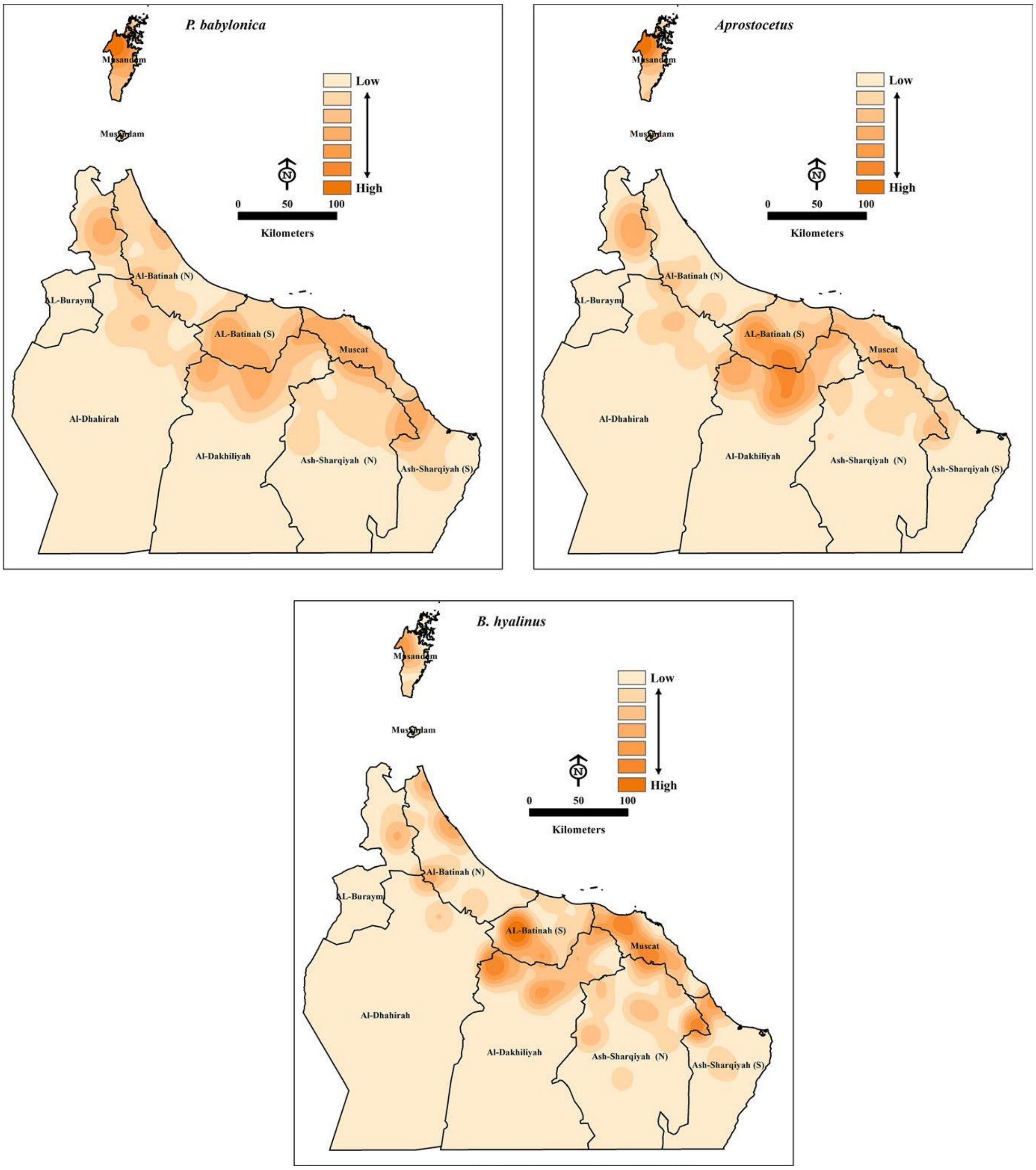

Figure 8-6 OLS models' predictions of influences of all independent variables (climatological, environmental, and DB infestations) on the presence or absence of *P. babylonica, A. nr. Beatus, and B. hyalinus* in the study area.

Our results also found that higher mean rainfall increases the occurrence of *B. hyalinus*, but no correlation was found between rainfall and *A.* nr. *beatus* and *P. babylonica* in the study area. Observations on the distributions and predominance of *P. babylonica,* in a larger portion of the palm plantation in Oman, as found in this study, confirmed the suggestions that *P. babylonica* has a broad environmental range and that it is found in more locations than *Aprostocetus* nr and *B. hyalinus*.

In this study, we have analyzed the distribution patterns of the presence or absence of *P. babylonica, Aprostocetus* nr and *B.* hyalinus, which are natural enemies of the DB, in northern Oman. Identifying patterns for different sets of features is crucial for understanding the ecological processes (Al-Kindi, Kwan, Andrew, & Welch, 2017b; Haslett, 1990) of DBs and their enemies. In general, there are two approaches of identifying patterns in geographical data. The first is to display features on a map without conducting any statistical analyses, as showing the data in a spatial format can be valuable endeavor, even without detailed analysis (see Figure 8-3).

The second approach is to use spatial statistics to measure the extent to which features are clustered, regular, or random (Getis & Ord, 1992). Each of these measures is important when comparing the patterns for different sets of features or when comparing patterns across a given area (Kozak, Graham, & Wiens, 2008). Geostatistical analyses allow us to generate optimal surfaces from sample data and to evaluate predictions, leading to better decision-making. GIS techniques are helpful in many data analysis models, such as environmental, precision agricultural, wildlife, and ecological studies (Al-Kindi et al., 2017d). However, the results of the present study are in the form of first approximation models. More data and ecological information on *P. babylonica, A.* nr. *Beatus,* and *B. hyalinus* could produce better results in the future. Hence, more surveys are needed to determine the distribution and density of these natural enemies for controlling DBs and for recording other enemies that can be used successfully against DBs throughout Oman. With this in mind, the relationship between natural enemies and DB infestation should be investigated prior to any planning for chemical control application. Farmers and the responsible authorities in Oman should take care of these natural enemies of DBs using alternative methods of insecticide application, to minimize impact on nontarget insects including beneficial ones such as honeybees and other pollinating insects as well as natural enemies of pest insects.

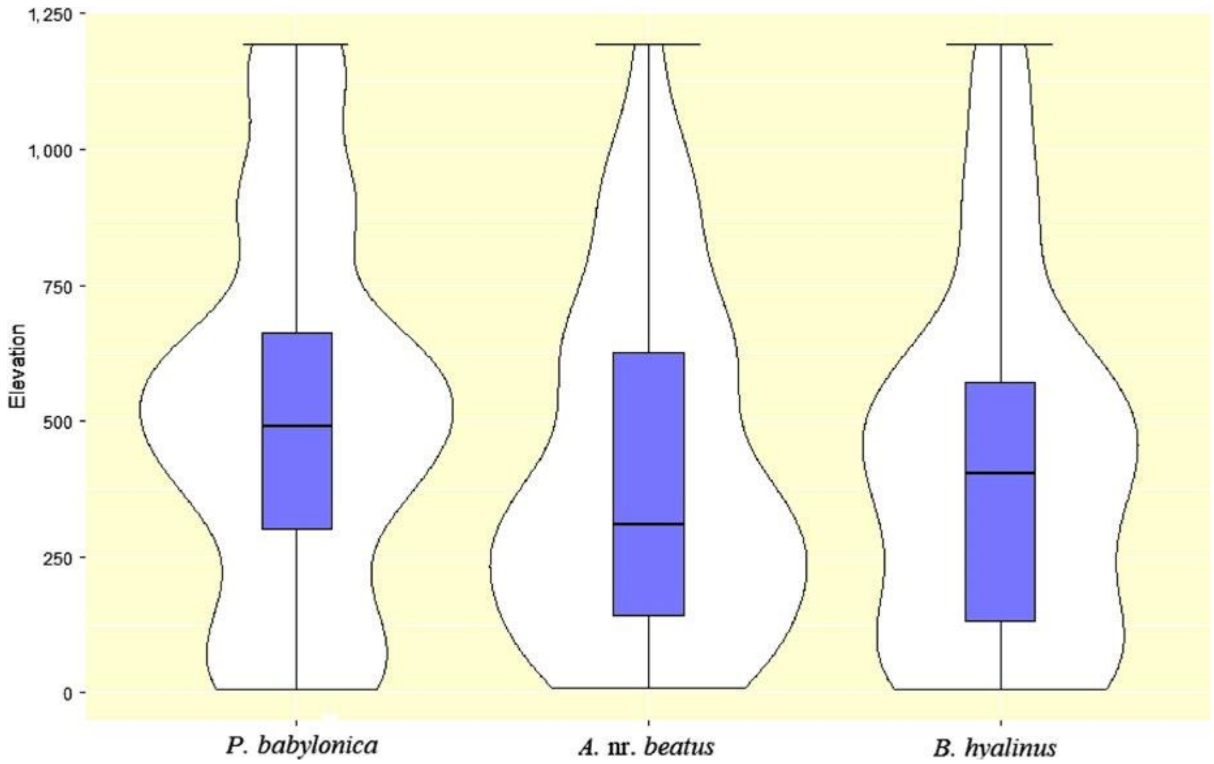

Figure 8-7 Frequency distributions of *Pseudoligosita. babylonica, A. nr. Beatus, and B. hyalinus* with respect to elevation in the study area.

8.5. Conclusion

Pseudoligosita. babylonica, A. nr. *Beatus,* and *B. hyalinus*, along with other natural enemies, may provide effective control of DB infestations throughout Oman if their populations are not disturbed by human activities, such as the use of pesticide sprays. A greater understanding of the ways in which environmental and climatological factors determine the distribution of DBs and their natural enemies is expected to lead to new methods of predicting which areas of a palm plantation are most at risk for infestation. The targeted application of insecticides in date palm plantations to areas of high DB infestation and low occurrence of its natural enemies would control the DB infestation better than a blanket application to all plantations without regard to DB infestation level or occurrence of associated natural enemies. Advancing our knowledge of environmental and climatological factors and behavioral responses determining the spatial and temporal distribution of DBs and their parasitoids may also lead to the development of more effective IPM strategies for DBs based on treatments which are more precise, both spatially and temporally.

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	Author's Name (please print clearly)	**% of contribution**
Candidate	Khalifa Al-Kindi	70%
Other Authors	Ali Al-Wahaibi	5%
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Chapter 9. Conclusion and Recommendations

9.1. Conclusion

In order to model Dubas bug (DB) risk, it is important to understand the distribution and prevalence of DBs as well as analyse their current biographical patterns and predict their spread. Comprehensive and detailed information on environmental, climatic and agricultural practice variables are essential (Al-Kindi et al. 2017d). The overall aims of this research were to 1) develop and model DB habitat, population density and presence or absence in Oman based on association with environmental, climatological and human variables and 2) predict the potential geographical distribution of parasitic natural enemies of DB using spatial techniques. These were achieved through the scientific investigations detailed in *Chapters 4–8*. The investigations conducted focused on four key research areas; (a) spatial patterns of DB in data palms in the study area; (b) impact of environmental variables on DB infestation rate; (impact of human-related practices on DB infestations of date palms; (c) potential effects of climate factors on DB absence/presence and their infestation rate; (d) predicting the potential of parasitic natural enemies of the DB. These studies involved extensive field investigations, sampling and laboratory testing and detailed and analysis. Here I summarise the findings and provides general recommendations.

9.1.1. Spatiotemporal patterns of the DBs in data palms

Determining their spatial patterns was the first step in understanding the phenomenon of DB infestation (Chapter 4). Based on the 10-year period from 2006–2015, my results showed varying degrees of infestation, with some regions or conditions having more or fewer hotspots and cold spots than others. By applying procedures such as hotspot detection and kernel density estimation, I was able to identify which spatial regions showed a higher likelihood of infestation events. The hotspots indicated potential outbreaks and revealed the underlying causes of infestation. The annual hotspots over the study period were mainly concentrated in the mountains plains, particularly where farms are located between gradient elevations (the infestations seemed to be more severe in the mountains of the wadi biome and less severe in the open plains and coastal areas away from the mountain plains). The distribution patterns of hotspots varied considerably over time (Al-Kindi et al. 2017c). The average annual risk maps for the 10-year period also showed that most of the hotspots occurred in the nine central governorates of Northern Oman. Based on the average DB density for the 10-year period, I was able to classify northwest Musandam, Ash-Sharqiyah North, northern Al-Dakhliah and Al-Batinah South as high-risk areas during this period, while Al-Batinah North was classified as a very low-risk area.

The results indicated that entomologists can identify infestation clusters by factoring in temporal properties such as the number of adults and nymphs present within a specific time frame. Analyses presented in this study confirmed that the use of temporal risk and geographical analysis models based on the annual infestation level could produce data to understand these changes better. Analysing hotspots, cold spots, outliers and pattern changes of DB infestation levels provide policymakers with valuable insight; additionally, knowing how hotspots grow over time provides further information that can help guide decision making (Al-Kindi et al. 2017c). The variations in both spatial and temporal distribution of DBs indicate a complex biology that is likely attributable to different environmental, climatological and farming methods throughout factors.

Determining spatiotemporal risk by modelling DBs based on seasonal and annual data is a useful tool for interpreting and applying surveillance data (Al-Kindi et al. 2017c; Al-Kindi et al. 2018a). It can also potentially be used as a decision support tool for DB infestation. However, such models may require daily data collection. The logic for using such a technique is that it increases the precision of the estimates. The spatiotemporal risk model, based on the case notification data, is a simple and inexpensive technique. Its use is proposed for early warning, categorisation and identification of areas at risk, which can be incorporated into routine monitoring by authorities (Fagan et al. 2002; Koch & Smith 2008).

9.1.2. Impact of environmental variables on Dubas bug infestation rates

In this study, spatial analysis and geospatial techniques were used to model the spatial distribution of DB infestations to 1) identify correlations between DB densities and different environmental variables and 2) predict the locations of future DB infestations (Chapter 5). Firstly, I considered individual environmental variables and their correlations with infestation locations. Then, I applied more complex predictive models and regression analysis techniques to investigate the combination of environmental factors most conducive to the survival and spread of DBs. The results of nearest neighbour statistics indicated a clustered distribution of

DB infestations. Autocorrelation analysis results found a correlation between DB infestations and environmental features such as water type, elevation, slope, soil type, geology, distance to the sea and distance to streams. A high correlation was found between density and both elevation and geology variables. In contrast, the relationships between DB infestations and other variables such as aspect and hillshade were weaker. However, autocorrelation cannot identify environmental variables with high or low values, thus a G-statistic was used. The results of the G-statistic for measuring clustering indicated that elevation, geology and distance to sea were found in high-value significant clusters, while water type, slope, soil type and distance to streams were found in low-value significant clusters.

Although the autocorrelation and G-statistic identified strong spatial patterns in the relationships between environmental variables and DB infestations, these approaches only considered the distribution of a single layer at a time. It was difficult to determine whether strong or weak relationships were more or less spatially segregated. To fully model the environmental controls on DB infestations, multivariate statistical techniques were needed to integrate the correlations. By identifying hotspots and cold spots (Local Moran's I statistics) clusters for each variable, I was able to compare cluster location in order to gain an understanding of cluster control. Thus, these data were suitable for use in multivariate regression analyses to investigate the dependence of DB infestations on environmental variables.

The results of modelling spatial relationships on environmental determinants of DB infestation levels indicated that the environmental variables of elevation, geology and distance of drainage pathways were found to have a significant positive effect on DB infestations. In contrast, significant negative relationships were found between hillshade and aspect factors of DB infestations. Hillshade and aspect factors are linked because both factors impact the level of direct sunlight, which in turn impacts DB infestation rates. The coefficient surface maps created through geographically weighted regression (GWR) showed where variables had the biggest impact on the regression across the study area (Al-Kindi et al. 2017a; Fotheringham et al. 1998). The areas of high risk included northern Al-Dakhliyah, Al-Sharqiyah North, Al-Batinah South, all of northern Al-Dhahirah and a small island in the Musandam Governorate. Therefore, by incorporating the spatial influence into the analysis of our results, I was able to reflect real-world relationships better and build predictive models of future infestations (Al-Kindi et al. 2017a).

Novel spatial analysis and geostatistical technologies have the ability to replace the use of insecticides in controlling the DB population and maintaining a necessary environmental balance. I believe the results of this analysis will provide guidance and ideas to policymakers on how to adopt more appropriate and specific control and prevention strategies for DBs in specific areas. I propose a simple and inexpensive technique based on case notification data for early warning by agricultural authorities. This method prevents DB prevalence and helps with monitoring and identifying DB adult and nymph shelters for the elimination of DB breeding sites, such as farms close to mountains and streams. In addition, reducing the cultivation of palm crops near mountains and locating them in open plains will lead to more exposure to sunlight and air between palm trees. Relatively unpopulated areas should also be occasionally monitored for the presence or absence of the bugs.

9.1.3. Impact of human-related practices on Dubas bug infestations of date palms

The analysis of the impact of human-related practices on DB infestations of date palms showed that there was a strong correlation between DB infestations and several human-related parameters ($R^2 = 0.70$) (Chapter 6). Variables including palm density, the spacing between trees, insecticide application, date palm maintenance (pruning, dethroning, remove weeds and thinning), irrigation systems, removal of offshoots, fertilisation and labour (uneducated labourers) issues were all found to influence the degree of DB infestations significantly. We found that palm density, flood irrigation and using more pesticides increased DB populations; however, row spacing, farm maintenance, offshoot removal, education level of employees and use of fertilisers had a significant negative relationship with DB populations.

The highest level of DB infestation was recorded in the farms where palms were planted at a distance of 3 to 5 m apart, which is common for palm spacing in many farms surveyed in the study area. This may because a closer spacing with high palm density is likely to retain in-grove humidity. Our results found that the highest level of DB infestation was negatively correlated with row spacing. Well-spaced palms rarely become infested with DB because proper spacing allows for wind movement and sunlight between trees (Al-Kindi et al. 2017b; Blumberg 2008; El-Askary & Baraka 2015; Klein & Venezian 1985). My results also found that not removing unproductive palms or offshoots from the mother palm tree, failure to thin palms and a lack of cleanliness increased DB infestation levels (Thacker et al. 2003).

Open flood irrigation and high soil moisture are known to be favourable grove and habitats for DBs. I propose reducing excess moisture levels in date plantations by adapting the recommended spacing at planting and using drip lines for irrigation, which will not generate excessive in-grove humidity and soil moisture while also conserving precious irrigation water resources. To date, palm trees have the capacity to survive under relatively harsh climates and soil conditions; thus, farms should be maintained without irrigation from four to seven weeks prior to DB egg laying season. This will help to reduce the humidity in the farms and thus the juice that DBs eat from palm fronds and leaves. Therefore, the reduced amount of irrigation may be useful for reducing pressure in the palms, which will prevent DBs from sucking water from the fronds to survive.

Although socioeconomic changes have had negative effects on traditional date plantations in Oman, they have not resulted in the disappearance of the date palm crop. The date palm dominates agricultural production in Oman (Al-Yahyai & Manickavasagan 2012). It is a traditional national staple and was Oman's main source of income before oil, as was the case for most Arab countries. Nevertheless, Oman has undergone some drastic changes that have impacted consumption patterns. For instance, socioeconomic changes include new living standards, continuous urban drift and the introduction of technology. Human-related cultural practices and post-harvest handling have had a tremendous impact on the nutritional quality of palm fruits (Al-Farsi et al. 2007). These changes have also resulted from introducing uneducated labourers who lack experience working on date palm farms, especially in dealing with traditional crops such as palm trees. Farmers should be trained in different components of DB control, including the DB life cycles. This can be accomplished by providing economic incentives to farming communities to preserve traditional agricultural practices, such as providing jobs with satisfactory compensation for Omanis to work in palm plantations.

9.1.4. Potential effects of climate factors on Dubas bug absence/presence and their infestation rate

In this chapter, methods for modelling spatial relationships were applied to model the potential relationships, in the form of absence/presence and density that might exist between DBs and associated climate variables based on seasonal and annual spatial data (Chapter 7). In the first part, a logistic regression analysis was used to model relationships between DB presence and absence and annual averages for various weather and microclimate data in short-term (spring and autumn of 2017) and long-term (2005–2015) scenarios. In the second part of this study, OLS and GWR techniques were used to explore the relationships between DB infestation levels (hotspots and cold spots) and climate variables. The results of three model analyses showed that certain variables positively (e.g., elevation, wind direction, temperature and humidity) or negatively (e.g., wind speed) impacted DB survival and density. Spatial analytical techniques are useful for detecting and modelling correlations between the presence, absence and density of DBs in response to climatic, environmental and human factors.

Based on seasonal data, the results showed that the population density varied in space and time. Al-Kindi et al. (2017c) stated that the DB infestation level varied from year to year and from one location to another during the 10-year period of 2006–2015. Based on the interpolation analysis of climate data among nine governorates, the results showed that the annual mean temperature ranged from 25–29ºC, whereas the mean temperature ranged from 22–33ºC in spring and 16–35ºC in fall based on the microclimate (spatial data loggers). The results showed that the mean annual daily relative humidity ranged from 29–78%, whereas it ranged from 25–75.5% during spring and 25.1–63% during the autumn of 2017.

An understanding of DB infestation risk based on DB abundance and meteorological variables can be developed, applied sustainably and measured prospectively. Our future study will use more complicated predictive, suitability and simulation models that incorporate all of the climatological, environmental and human-related variables to investigate which combinations of variables are the most conducive to the survival and spread of DBs.

Additionally, these models will be used to forecast the spatial distribution and density of DBs under prevailing conditions at the beginning of each season. These results, in turn, could be used for management purposes and for decision making regarding where resources should be directed for preventive action. Another future study will focus on the relationships between DB density and microclimate based on the mean hourly temperature and relative humidity.

9.1.5. Predicting the potential geographic distribution of parasitic natural enemies of the DB

The results of the spatial patterns analysis indicated the presence of clustered distributions of natural enemies in the study area. The results of the OLS regression method revealed models that confidently predicted the influence of DB infestation levels and climatological and environmental variables on the presence of *P. babylonica*, *A.* nr. *beatus* and *B. hyalinus* with 63%, 89% and 94% confidence, respectively (chapter 8).

Although *P. babylonica* is by far the most important natural enemy of DBs, the results showed that the significance of the studied independent variables to predict the distribution of this natural enemy is relatively low (63%) compared with the other two parasites. One possible explanation for this contrast between *P. babylonica* and the other two parasitoids involves differences in the life cycles between the three species. *P. babylonica* is an internal egg parasitoid of DB eggs, which are mostly hidden (expected for operculum or egg cap species) within date palm leaf tissues. *A.* nr. *beatus* is an external egg feeder as a mature larva and possibly an internal egg feeder as a younger larva, and *B. hyalinus* feeds on nymphs and adults. A 63% confidence level is still quite strong, but as it is purely an internal egg parasite, the low R^2 value could be due to other biological variables that I did not take into account when developing the model.

Our environmental and climatological analyses suggested that DB infestation levels, elevation, water type, temperature, humidity, rainfall, wind speed and wind direction drive the spatial distribution of each natural enemy, as do the biological differences between these species. The distribution of each species is influenced by distinct and geographically associated climatological features, environmental factors and habitat characteristics. In particular, high suitability was predicted for *P. babylonica* in northern Al-Dakhiliyah, Al-Batinah South, the northwest part of Ash-Sharqiyah South, Muscat and northwest Musandam governorates. DB population, elevation, temperature, humidity, wind direction and water type were important predictors for calculating the probability of *P. babylonica* occurrence. Likewise, I found high suitability for *A.* nr. *beatus* in northern Al-Dakhiliyah, Al-Batinah South and Musandam governorates, where factors such as DB infestation, elevation, temperature, humidity, wind direction and wind speed were significant predictors for calculating the probability of its occurrence. Similarly, I found high suitability in northern Al-Dakhiliyah, Al-Batinah South, Muscat and northwest Ash-Sharqiyah North, where factors such as DB infestation, temperature, humidity, rainfall and water type were important predictors in calculating the probability of *B. hyalinus* occurrence.

Geostatistical analyses allowed us to generate optimal surfaces from sample data and to evaluate predictions, leading to better decision-making. GIS techniques are helpful in many data analysis models, such as environmental, precision agricultural, wildlife and ecological studies

(Al-Kindi et al. 2017d). However, the results of the present study are first approximation models. More data and ecological information on *P. babylonica*, *A.* nr. *Beatus* and *B. hyalinus* could produce better results in the future. Hence, more surveys are needed to determine the distribution and density of these natural enemies for controlling DBs and for recording other predators that can be used successfully against DBs throughout Oman. With this in mind, the relationship between natural predators and DB infestation should be investigated before any planning for chemical control application. Farmers and the responsible authorities in Oman should take care of these natural enemies of DBs using alternative methods of insecticide application to minimise the impact on non-target insects, including beneficial ones like honeybees and other pollinating insects as well as natural predators of pest insects.

The models developed in this research can be used for different control management purposes in Oman. The hotspots model (Al-Kindi et al. 2017c), based on seasonally and yearly data, can be used to give an overview of high-impact areas (in terms of DB populations) during spring and autumn. In order to model DB risk, it is important to assess and use an extensive range of variables, such as DB population (annual and seasonal data) based on inhabited areas, total DB population per area and neighbourhood quality (palm tree health). The resulting model can identify the changes that occur in the field to achieve precise crop management in the agricultural sector in the future due to the prevalence of relevant environmental, climatological and human practices conditions. It is important to have a study that shows different models for surveillance systems that can be used for DBs with appropriate temporal and spatial scale. Models can be categorised in different ways. The focus for modelling the risk of DB can be based on seasonal data (spring and autumn) or yearly data; however, the question here is whether these two types of models are optimally scaled and sufficient for effective management programmes. In light of these considerations, this research was designed to illustrate the impact of different temporal and spatial scales on DB management decisions.

9.2. Recommendations

Remote sensing (RS) and GIS have not been widely used to model, analyse and identify DB infestations and its natural enemies. This study shows a variety of GIS implications in the planning of healthy vegetation (palm trees) that can be used to enhance the surveillance system. The spatial techniques used in this study allow decision-makers to consider changes in the environmental, climatological and human practices variables, which are the key determinants of DB infestations levels.

The surveillance system can be integrated into RS, GIS and spatial modelling environments with agricultural, biological, entomological, farming, economic, integrated pest management, environmental and climatological factors. This integration may contribute to greater accuracy in the development of infestation forecasting models. Additionally, it may have significant implications for DB management, monitoring, decision-making and practices, which may help the Ministry of Agricultural and Fisheries in Oman prioritise and use resources more effectively and efficiently.

The findings of my research suggest that determinates of DB infestation levels differed in space and time in the study areas. Therefore, different palm tree strategies may need to be developed in the infestation control and risk management programmes. The control programmes should focus on governorates or areas with a high population density during spring and autumn. The vector control programming should focus on communities in districts and sub-districts with a high density during the infestation arrival month or season. Systemic and integrated training may be necessary for agricultural practitioners to achieve some spatial knowledge of DB infestation outbreak. Computer models need to be developed based on my findings to predict possible entomologic activities under different conditions and as a means of predicting future consequences of changes in these conditions. The development of the entomological forecasting system is important in the control and prevention of DB outbreaks. Early detection based on forecasts from the model can assist in improving population control and protecting date palm plantations.

This research shows how various spatial models can be incorporated into a DB management and monitoring system in Sultanate Oman to improve the current system. The same methodology can be used in other parts of the world as well.

9.2.1. Data collection

We must continue to improve the effectiveness of the current DB surveillance regime to deliver more accurate, detailed surveillance data. Therefore, to examine the likelihood of infestation under-reporting and over-reporting, a rigorous assessment is required. This will provide forewarning of DB outbreaks. In addition, valuable information needs to be made available about palm tree health, DB surveillance and monitoring programmes. It is important to collect data about crops and soil to identify changes that occur in the field and to achieve precise crop management in the agricultural sector. Data are needed on the conditions that are stable across seasons (e.g., different types of palm trees, soil type and soil fertility) and that differ across seasons (e.g., DB attacks, water quality, nutrient contents, moisture and temperature) as well as the factors that contribute to crop yield variability. Therefore, it is advised that optical RS, radar and lidar investigations with more consistent palm samplings continue in order to identify specific vegetation and to better describe the stress conditions associated with damage to infested palms. The temporal resolution of RS data is important for commercial monitoring or management of seasonal vegetation variations over wide areas and for estimating net primary production and detection time boundary conditions for yield modelling. I suggest that temporal RS can be used to study seasonal DB infestations because there are two generations, one in spring and one in autumn. High-resolution data sets, such as SPOT's panchromatic 10 m resolution and Landsat's multispectral scanner 20 m resolution, or very high-resolution imagery-based RS (including QuickBird's 2.5, IKONOS 4 m multispectral resolution and those collected with unmanned aerial vehicles) are recommended to detect and map DB populations. While these satellite images are available, the cost for obtaining such data remains a significant impediment to their widespread use. Therefore, hyperspectral RS technology should also be used to develop early (pre-visual) detection methods for DB infestations.

Colour-infrared technology with hyperspectral reflectance data could be used to identify specific date palm trees and fronds that have been infested with DBs. These methods can be used to monitor changes in infestation levels according to honeydew secretion, which is converted to sooty mould on the fronds during high levels of infestation. Honeydew secretion is a good indicator of DB feeding activity. Indirect assessments of the insect populations can be carried out by measuring the amount of honeydew caused by the insects. The Airborne Visible/Infrared Image Spectrometer can be used to determine the extent and severity of DB infestation damage in different areas. The outputs, especially the spatial distribution and spread images, can be used as future inputs for GIS-based predictive models.

9.2.2. Geospatial database

A prototype webserver should be developed to help decision makers at different management levels in Oman to make more informed decisions. A prototype web GIS information system can be developed incorporating all spatial and non-spatial details pertaining to DB issues. The clearinghouse is a proposed physical repository structure that will collect, store and disseminate information, data and metadata. Using this application, GIS layers can be dynamically added and/or removed during runtime, and it will have basic functionalities like zooming in and out and panning in order to view the map. It will have options for displaying attributes like area, type of species, population and other relevant information. The query window options will help the user to select the theme, attribute table and attribute values. When the query is executed, the features in the themes (e.g., wadi) that satisfy the condition will be highlighted in the map window. The saved queries can be used to access the classified output based on the client's requirements.

An administrator in each zone can help to maintain the server and data. Spatial data in the GIS and non-spatial data in the RDBMS can be retrieved from the GIS environments through open database connectivity. Care should be taken to ensure that the linkage of maps to the attribute database remains dynamic so that whenever there is a change to the attribute in the attribute database, it is reflected in the GIS. Another aim is to enable precise deployment of resources and insecticide spraying schedules. This can lead to less insecticide use, which is better for the environment and reduces resource costs. A comprehensive ongoing database and scheme for recording DB infestations (locations, date, intensity, etc.) should be established. This web-based reporting and management system can help all of the stakeholders in the date palm industry. This will also enable researchers to see what research has been conducted, where it was conducted and what GIS data are available.

9.2.3. Spatial techniques and analysis

Analyses can be carried out on a broad scale much more cheaply and effectively using RS imagery instead of extensive field-based surveys. Early detection can play a crucial role in the management and control of the infestations and further research into techniques for early detection merits urgent attention.

For a better understanding of DB infestations, more geographical and entomological analysis is needed. Oman is home to a wide variety of date palms (about 250); however, the four major cultivars are Khalas, Fardh, Khasab and Naghal. Intensive spatio-temporal models can be used to investigate which of these types is the most attractive to DBs. Infestation levels on these major cultivars in Oman can be determined by direct assessment. The most convenient way to do this is by collecting frond samples and distinguishing between newly laid eggs (e.g., spring and autumn generations) from those of previous seasons which did not hatch. Pre-season (June and January) samples should be taken from three fronds facing different compass directions at three different heights (bottom, middle and top) to represent different frond ages. Three fronds should be cut from four different palms of each of the four major cultivars on the farms mentioned above. This will result in a maximum of 48 frond samples per farm. Unhatched, unparasitised new eggs (white with greenish tissues) will be counted to determine the current season's density (which will predict the next season's infestation) in a subsample of 10 randomly selected leaflets and 10 inter-leaflets from the base, middle and apex of each frond. Old eggs (hatched, unhatched and parasitised) on the bottom frond can also be counted (based on the same subsamples indicted above) once at the beginning of the sampling program to get an idea of past infestations (accumulated over the past 5–10 years).

Models for predicting egg hatching and the size of populations will lead to better preparation and less costly mistakes in future studies, resulting in a reduction in overall costs. Based on classification technologies, a number of different areas can be selected for more intensive spatiotemporal risk studies; as many historical data images should be obtained as possible for these areas and should be supplemented by the next two years of data. The goal of this future study is to build a picture of which of the four cultivars is the most infested by DBs over a 10-year period. The change detection will tell us the degree of change in the infestation levels in each of these types that needs to occur before they are detected by satellites. This is important for further development of a management and surveillance system for DB monitoring.

Several advanced techniques for classifying digital RS data involve the extensive development and adoption of object-based image analysis. Moreover, advanced image classification techniques such as k-means, ISODATA, fuzzy ARTMP, fuzzy multivariate cluster analysis, the WARD minimum variance technique, SOM, the artificial neural classification algorithm (for the propagation of neural networks and self-organising maps) and Bayesian analysis can be used 1) for the classification of remotely sensed data and 2) to delineate horticultural crops in satellite maps. The major advantages of these techniques are their abilities to generate a matrix of change information and to reduce external impacts of the atmospheric and environmental differences among the multi-temporal images. However, it may be difficult to select high quality and sufficiently numerous training sets for image classification, particularly for important historical image data classifications, due to a lack of data.

Links between DB hotspots, cold spots, density and presence or absence of the four major palm tree cultivars in Oman can be useful in future studies to investigate their correlation with environmental factors such as elevation, slope, water type, soil type, soil salinity, geology, hillshade and solar radiation. The results can also be used in future studies to investigate the relationships between DB infestations and climatological factors such as relative humidity, rainfall, temperature, wind speed and wind direction. Furthermore, farming practices factors such as row spacing, traditional irrigation, fertilisers and so forth may also play key roles in enhancing the development, survival and spread of DBs. In addition, human-related factors such as aerial spraying might be of value to gather aerial and ground insecticide spraying data from the past 20 years and correlate these with current DB densities and the densities of its key natural enemies.

Further studies can utilise more complicated predictive, suitability and simulation models (based on current and future data and results) and an overall model that incorporates all climatological, environmental and human-related variables to investigate which combinations of variables are the most conducive to the survival and spread of DBs. Additionally, these models can be used to forecast the spatial distribution and density of DBs under prevailing conditions at the beginning of each season. The results, in turn, could be used for management purposes and for decision making regarding where to direct resources for preventive action.

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