UNIVERSITY OF SOUTHERN QUEENSLAND

REMOTE SENSING OF PEANUT CROPPING AREAS AND MODELLING OF THEIR FUTURE GEOGRAPHIC DISTRIBUTION AND DISEASE RISKS

A Thesis submitted by

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Abstract

Peanut or groundnut (*Arachis hypogaea* L), one of the most important oil seed crops, faces several challenges due to climate change. The unfavourable climate in Australia, as a result of high climate variability, could easily affect peanut production. For example, the incidence of drought stress will increase the likelihood of one of the major problems in the peanut industry, i.e. aflatoxin. In addition, if the climate changes as projected, shifts in geographic distribution of peanut crops and the associated diseases are inevitable. In view of these concerns, this study set the following objectives: 1) to assess the effectiveness of PROBA-V imagery in mapping peanut crops; 2) to study the effects of climate change on the future geographic distribution of peanut crops in Australia; and 3) to examine the effects of climate change on the future distribution of aflatoxin in peanut crops, and to locate high risk areas of aflatoxin in the future areas of peanut crop production. In this study, the area of peanut crop mapping was the South Burnett region in Queensland, while the area of future geographic distribution of peanut crops and aflatoxin covered the entire continent of Australia.

To address the first objective, the peanut crop areas were mapped using time-series PROBA-V NDVI by stacking time-series imagery and generating the phenological parameter imagery. Three classification algorithms were used: maximum likelihood classification (MLC), spectral angle mapper (SAM), and minimum distance classification (Min). The results reveal that the overall accuracy of mapping using time-series imagery outweighed phenological parameter imagery, although both datasets performed very well in mapping peanut crops. MLC application in the time-series imagery dataset produced the best result, i.e. overall accuracy of 92.75%, with producer and user accuracy of each class ≥ 78.79%. Specifically for peanut crops, all the algorithms tested produced satisfactory results (≥75.95% of producer and user accuracy), except for the producer accuracy of Min algorithm. Overall, PROBA-V imagery can provide satisfactory results in mapping peanut crops in the study area.

For the second objective, the effects of climate change in the potential future geographic distribution of peanut crops in Australia for 2030, 2050, 2070, and 2100 were studied using the CLIMEX program (a Species Distribution Model) under

Global Climate Models (GCMs) of CSIRO-Mk3.0 and MIROC-H. The results show an increase in unsuitable areas for peanut cultivation in Australia throughout the projection years for the two GCMs. However, the CSIRO-Mk3 projection of unsuitable areas for 2100 was higher (76% of Australian land) than MIROC-H projection (48% of Australian land). Both GCMs agreed that some current peanut cultivation areas will become unsuitable in the future, while only limited areas will still remain suitable for peanut cultivation. The present study confirms the effects of climate change on the suitability of peanut growing areas in the future.

In the third objective, the impacts of climate change on future aflatoxin distribution in Australia and the high risk areas of aflatoxin incidence in the projected future distribution of peanut crops were examined. The projected future distribution of aflatoxin for 2030, 2050, 2070, and 2100 was also modelled using CLIMEX under CSIRO-Mk3.0 and MIROC-H GCMs. The results demonstrated that only a small portion of the Australian continent will be optimal/suitable for aflatoxin persistence, due to the incidence of heat and dry stresses. The map overlay results between the future projections of aflatoxin and peanut crops resulted in small areas of low aflatoxin risk in the future projected areas of peanut crops. It is projected that most of the current peanut cultivation areas will have a high aflatoxin risk, while others will no longer be favourable for peanut cultivation in the future.

This study has clearly demonstrated the ability of PROBA-V satellite imagery in mapping peanut crops. It has also demonstrated that climate change incidence will affect the suitability areas of future geographical distribution of peanut crops and the associated aflatoxin disease. This study provides strategic information on current peanut growing areas, future suitable areas for peanut crops in Australia, and future high risk areas of aflatoxin incidence. This information will provide valuable contributions to the long-term planning of peanut cultivation in the country.

Certification of thesis

This Thesis is entirely the work of Haerani except where otherwise acknowledge. The work is original and has not previously been submitted for any other award, except where acknowledge.

Prof. Armando A. Apan
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Student and supervisors signatures of endorsement are held at USQ.

Statement of Contribution

The agreed shares of contribution for the student and co-authors in the presented publications in this thesis are the following:

- **Article 1: Haerani**, Armando Apan, and Badri Basnet. 'Mapping of peanut crops in Queensland, Australia, using time-series PROBA-V 100-m Normalized Difference Vegetation Index imagery'. *Journal of Applied Remote Sensing*, vol. 12, no. 3, p. 036005. [IF: 1.391, SNIP: 0.701]. DOI: http://dx.doi.org/10.1117/1.JRS.12.036005.

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Abbreviations

ABS	Australian Bureau of Statistics
ABARES	Australian Bureau of Agricultural and Resource Economics
ALA	Atlas of Living Australia
AR5	The Fifth Assessment Report of IPCC
AR4	The Fourth Assessment Report of IPCC
BoM	Bureau of Meteorology
CBR	Cylindrocladium Black Rot
CLIMEX	Climatic index
CMIP 5	Coupled Model Intercomparison Project Phase 5
CRU	Climate Research Unit
CS	Cold Stress
CSIRO	Commonwealth Scientific and Industrial Research Organisation
DAF	Department of Agriculture and Fisheries
DERM	Department of Environment and Resources Management
DPIF	Department of Primary Industries and Fisheries
DS	Dry Stress
DHCS	Cold stress degree-day rate
DTCS	Day-degree temperature threshold of cold stress
EC	European Commission
EI	Ecoclimatic Index
ENSO	El Nino – Southern Oscillation
EVI	Enhanced Vegetation Index
FAO	Food and Agriculture Organization
FAS	Foreign Agricultural Service
GBIF	Global Biodiversity Information Facility
GCMs	Global Climate Models
GHG	Greenhouse gasses
GI	Growth Index
GIEWS	Global Information and Early Warning System
GPS	Global Positioning System

GSD	Ground Sampling Distance
GRDC	Grain Research and Development Corporation
HANTS	Harmonic Analysis of Time-series
HDS	Dry stress rate
HS	Heat Stress
HWS	Wet stress rate
IARC	International Agency for Research on Cancer
IOD	the Indian Ocean Dipole
IPCC	Intergovernmental Panel on Climate Change
JM	Jeffries-Matusita
JRC	Joint Research Centre
LULC	Land use and land cover
MARS	Monitoring Agricultural Resources
MI	Moisture Index
Min	Minimum distance classification
MJO	Madden-Jullian Oscillation
MLC	Maximum likelihood classification
MODIS	Moderate Resolution Imaging Spectroradiometer
NDVI	Normalized difference vegetation index
AVHRR	Advanced Very High Resolution Radimeter
PA	Producer accuracy
PCA	Principal Component Analysis
PROBA-V	Project for On-Board Autonomy - Vegetation
QGSO	Queensland Government Statistician's Office
RCPs	Representative Concentration Pathways
RF	Random Forest
RH	Relative Humidity
ROI	Regions of interest
SAM	Spectral angle mapper
SAM	Southern Annual Mode
SDMs	Species Distribution Models
SI	Stress Index
SMDS	dry stress threshold
SMWS	Wet stress threshold

SRES	Special Report on Emission Scenarios
SVM	Support Vector Machine
TAR	The Third Assessment Report of IPCC
THHS	Heat weekly accumulation rate
TI	Temperature Index
TOA	Top-of-atmosphere
TOC	Top-of-canopy
TTHS	Heat stress temperature threshold
UA	User accuracy
USA	United States of America
USDA	The U.S. Department of Agriculture
UTM	Universal Transverse Mercator
VIs	Vegetation Indices
WS	Wet Stress

Chapter 1

INTRODUCTION

1.1 Background of the study

Peanut or groundnut (*Arachis hypogaea* L.) crops play an important part in the agricultural domain. The crops rank sixth among the most important oil-seed crops, and rank thirteenth among the food crops in the world (Waliyar et al. 2013). High quality edible oil (48-50%) can be retrieved from peanut seeds (Waliyar et al. 2013). In addition, peanut crops contain a high number of nutrients, i.e. nearly half of the thirteen essential vitamins and seven of the essential minerals for human growth (Waliyar et al. 2013). Moreover, peanut crop residue is a source of high quality fodder for livestock (Waliyar et al. 2013). Therefore, taking into account these benefits, it can be presumed that peanut plays an important role as a source of livelihood, as well as a source of nutrients for poor farmers (Waliyar et al. 2013). This condition occurs in several peanut growing countries, such as Mali and Malawi (Waliyar et al. 2013; Waliyar et al. 2015).

Originating from South America, peanut crops are now cultivated around the world and have contributed to the economies of many countries. These legume crops have dispersed to the tropical, sub-tropical, and warm climate regions in the world (Stalker 1997), including Australia. Geographically, peanut-growing countries can be grouped into America (Northern, Southern, and Latin), Africa (Eastern, Southern, and Western), and Asia (Eastern, South Eastern, and South Western). The regions of Eastern Asia and West Africa play an important role in the peanut market by contributing around two-thirds of the world annual peanut production (Fletcher & Shi 2016). The average world peanut production from 2010 to 2013 was 39,526,000 MT (Fletcher & Shi 2016). This production is higher 136% than the world peanut production in the 1970s, due to the application of technology-driven gains in yield (Fletcher & Shi 2016), such as fertilizer and high yield seeds. In general, peanut-growing countries use their production output to meet their domestic market (DPIF 2007). Outside the peanut-growing countries, Europe (Eastern, European Union-28, and Western) and Oceania are also among the peanut-consuming countries (Fletcher & Shi 2016). In Australia, the majority of peanut crops are produced in Queensland, with a gross production value of 18.2 million dollars in 2017/2018 (QGSO 2019). Around 40,000 tonnes of peanut are produced annually in Australia and are used to meet the domestic market (Wright et al. 2017).

Considering the role of peanut crops as agricultural commodities and as important oilseed and food crops in the world, projecting the production of peanut crops is essential. This projection is crucial in planning agricultural production and monitoring food supply (Srivastava 2015). Two components of crop production are crop area (to be) harvested and (anticipated) yield per unit area (Gallego et al. 2008; Craig & Atkinson 2013). Accurate predictions of both components are equally important in confirming crop production accuracy (Craig & Atkinson 2013). However, compared to crop area estimation, more studies have been conducted in crop yield estimation (Craig & Atkinson 2013; Iizumi & Ramankutty 2015). In terms of mapping peanut crops, not many studies have been conducted.

The agricultural sector depends significantly on climate, thus any change in climate will affect this sector significantly. Unfortunately, evidence confirms the occurrence of climate change; and it is projected to continue in the future (Howden et al. 2007). Climate change has led to changes in the long-term mean climate, changes in the year-to-year climate variability and extreme weather events, such as extreme temperature, drought, heavy rainfall, and flooding (Gornall et al. 2010). All of these impact agricultural practices directly (Gornall et al. 2010). In addition, climate change also affects this sector indirectly, such as the incidence of pests and diseases due to the changes in climate, changes in water availability which is critical for dry-land farming, and the increase of mean sea-level which threatens the agricultural lands and increases the salinity of groundwater (Gornall et al. 2010). The increase of the mean temperature in the northern latitude has contributed to the changes of agricultural practices and occurrences of pests and disease (Gregory et al. 2009), such as aflatoxin (Giorni et al. 2007). In addition, climate change will also influence the geographical distribution of planted areas of agricultural crops (Steffen et al. 2012), including peanut crops.

The application of technologies is one of the solutions in solving problems related to lack of peanut crop mapping and the impacts of climate change in peanut crops. For example, the use of remote sensing technologies will offer great benefits in estimating the peanut crop areas to provide the projection of peanut crop production. It could increase the coverage and accuracy of crop area estimation due to its rapid objective assessment and the ability to capture changes over time (BeyerJarmer, et al. 2015; Srivastava 2015). The accessibility and availability of time-series imagery have provided opportunities to easily differentiate crop types (BeyerJarmer, et al. 2015), which are essential in crop mapping. In terms of managing the impacts of climate change in shifting geographical distribution of peanut crops and aflatoxin incidence, modelling techniques such as Species Distribution Models (SDMs) can be used.

The peanut industry in Australia faces a challenging situation to increase its production for the domestic and international market, especially with the occurrence of climate change. This situation becomes more difficult with the reduction in the available peanut cropping areas, due to the conversion to other land uses, which could lead to a decrease in peanut production (QGSO 2019). Since Australia has a high climate variability (Head et al. 2014), unfavourable weather conditions, such as drought and excessive rainfall, can easily affect peanut production in Australia (Meinke et al. 1996). In addition, Australia has experienced a temperature increase, which is on average higher than other countries (Cleugh et al. 2011). Therefore, it is projected that the future geographic distribution of peanut crops and associated diseases will be affected. Considering these situations, reasonable steps should be taken to overcome the challenges of Australian peanut industry. One important step is to provide information about area estimation of peanut crops, the future geographic distribution of peanut crops (in light of changing climate), and the future high risk areas of associated peanut diseases, such as aflatoxin. Such information will promote strategic decisions to optimise production and reduce climate change risks to the peanut industry in Australia.

1.2 Statement of the problem

Climate change is projected to continue in the future, and as the agricultural sector depends on the climate, the impacts of climate change threatens global food production and food security. The projected increase of world population has escalated the challenge, especially with the depletion of natural resources (Anwar et al. 2013). As one of the main important sources of protein, peanut crops also encounter this challenge. Climate influences the productivity level of agricultural productivity through its four factors, namely: temperature and precipitation, atmospheric CO_2 concentration, water availability, and climate variability and extreme events (Anwar et al. 2013). Unfortunately, climate change will lead to an increase in temperature and CO_2 concentration, as well as a varied effect on moisture (Gautam et al. 2013). On average, the global temperature increased by 0.74°C in the last 100 years, and similarly, the atmospheric CO_2 concentration rose from 280 ppm in 1750 to 400 ppm in 2013 (Gautam et al. 2013). The increase in the occurrence of extreme events, such as droughts, floods, and forest fires, and shifts in precipitation patterns, were also observed (Gautam et al. 2013). As a result, agricultural practices, including those in peanut crops, need to adapt with climate change in order to maintain and probably increase its productivity (Anwar et al. 2013).

Climate change also affects the distribution of agricultural crops and their pathogens, including peanut crops and their aflatoxin disease. It is known that climate holds an important role in determining crop planting suitability (Anwar et al. 2013). Global warming is projected to provide positive impact for crop production in northern latitude above 55°, while in tropical and sub-tropical countries, it will lead to negative impact (Newton et al. 2011). For example, as an impact of temperature increase and lower average rainfall, the traditional peanut growing areas in Queensland, Australia have experienced a production decrease of around 30% over the past 25 years (Marshall et al. 2014). As a result, the peanut industry expanded its peanut growing region to Katherine in the Northern Territory, which has suitable condition and readily available irrigation water (Marshall et al. 2014). In addition, climate also determines the limited range of many pathogens, which could result in their geographic expansion (Gautam et al. 2013). One example is the first occurrence of aflatoxin disease in peanut crops due to *Aspergillus flavus* pathogen in an area known as free aflatoxin infection in the northern part of Italy (Perrone et al. 2014). As one of most important legume crops, investigating the impacts of climate change in peanut crops and its associated aflatoxin disease will provide useful knowledge in anticipating climate change effect in this commodity.

The Australian climate has been changing, and if this trend continues in the future as expected, the agricultural sector will be considerably affected. Over the last 50 years, Australia has become hotter, the rainfall geographic distribution has changed substantially with some areas becoming drier while others becoming wetter, and severe weather incidence has increased (Steffen et al. 2012). As a result, agricultural industries are exposed to some risks, such as heat stress, waterlogging, salinity, production reduction, and unsuitability of current planting area (Steffen et al. 2012). Peanut industry in Australia has suffered due to the effect of climate change; results in a decision to relocate its peanut growing areas (Marshall et al. 2014). If the climate changes as projected, there will be a reduction in the seed yield of peanut (Vara Prasad et al. 2003), and shifts in distribution areas of agricultural crops and agricultural pests and diseases (Chakraborty et al. 2000). These could lead to economic impacts from crop loss (Chakraborty et al. 2000).

In order to secure the production level of agricultural crops, an accurate prediction of crop production is a paramount important. Accurate data of crop production components, namely crop area and yield estimate, will be essential to diminish the uncertainty of future climate change effects on crop production and to develop appropriate adaptation responses (Iizumi & Ramankutty 2015). Remote sensing offers great help in crop area estimation, including estimating peanut crop area. However, not many studies have been done in estimating peanut crop area. Knudby (2004) used NOAA AVHRR satellite imagery data to study the groundnut yield variation in the peanut growing region (peanut basin) of Senegal, but did not map the peanut crops. In Australia, peanut crops were accurately mapped over four consecutive years (2004 – 2007) using a single date multi-spectral imagery of 2.4m high resolution commercial satellite of QuickBird (Robson et al. 2007). However, this study was applied in a small area of the peanut growing region of the South Burnett (64 km^2), and was quite costly due to the high-resolution commercial satellite imagery used.

The use of time-series imagery provides great benefits in crop mapping, especially with the increasingly available types of satellite imagery, such as medium and low spatial resolutions of time-series imagery. Technology and methodology advancements in time-series satellite imagery enable the easy separation of different types of crops (BeyerJarmer, et al. 2015). Some studies in estimating crop area by using time-series imagery have been conducted in a number of crops, such as winter crops (barley, chickpea, and wheat) (Potgieter et al. 2007; Sun et al. 2012), summer crops (sorghum, corn, and soybeans) (Wardlow & Egbert 2008), sugarcane (Xavier et al. 2006), and rice paddy (Yang et al. 2011; Zhang et al. 2015). In terms of peanut crops, Schultz et al. (2015) mapped the crops, together with other agricultural crops in South-eastern Brazil, by using time-series Landsat imagery. However, the study encountered difficulties in separating peanut and cassava crops due to the similarity in spectral behaviours and the high variabilities within the classes. Therefore, the challenge in carrying out this specific aspect of the study is to determine the most appropriate techniques in analysing time-series imagery for mapping the peanut crops in a particular growing season.

Modelling the impacts of climate change in the geographic distribution of peanut crops and their associated aflatoxin disease in Australia is a significant aspect of managing the peanut industry. As the Australian climate is becoming warmer (Steffen et al. 2012), some regions could become more favourable for future peanut cultivation and aflatoxin invasion, while others could become less favourable/unfavourable. Therefore, it is important to identify and map those favourable and less favourable/unfavourable regions. CLIMEX (Sutherst & Maywald 1985) is a tool that can be used to model species geographic distribution in the future in relation to climate change incidence. The CLIMEX model has been applied in several studies to predict future geographic distribution of a wide range of taxa including plants, pathogens, mammals, and insects (Kriticos & Leriche 2010). These studies include the future distribution of date palm (Shabani, Kumar & Taylor 2014; Shabani, Kumar, et al. 2015), oil palm (Paterson et al. 2015), cotton and wheat (Shabani & Kotey 2015), common bean (Ramirez-Cabral et al. 2016), tomato (Silva et al. 2017), *Fusarium oxysporum* f. spp. pathogen (Shabani, Kumar & Esmaeili 2014), and wheat curl mite, *Aceria tosichella*, (Schiffer et al. 2009). However, studies about projected suitable peanut planting areas and aflatoxin invasion areas in the future have not been undertaken in any part of the world, including Australia. Vellidis et al. (2007) studied the spatial distribution of aflatoxin, but this was a pilot study and did not model the future distribution.

1.3 Significance of the study

It is obvious that climate change will affect the agricultural sector, including the peanut crop industry in Australia. This study investigated the use of remote sensing and modelling techniques in providing vital information in the current estimation of peanut crop areas and the future geographic distribution of peanut crops and the associated aflatoxin incidence in Australia. The information resulting from this study can be used to improve the yield of peanut crops, minimise crop losses, and enhance food security. In addition, the results of this study will provide strategic information on current peanut growing areas in Queensland, future suitable areas for peanut crops in Australia, and future high risk areas of aflatoxin incidence. Thus, governments and the peanut industry in Australia can take reasonable steps to anticipate the level of peanut production and the possible future condition of peanut crops in Australia.

Accurate assessments of two components of crop production (crop area and yield estimation) are needed to achieve accurate production estimation. For years, crop area estimation, including peanut crops, has been collected by censuses, which are accurate but expensive and time-consuming, or by samples, which are cheap but not always accurate (Craig & Atkinson 2013). The ability to estimate peanut crop areas planted using time-series imagery provides an opportunity to increase the accuracy and reduce the associated time and costs. Thus, it will lead to more effective and efficient management of peanut crops. In addition, using remote sensing makes the mapping of peanut crops both easier and more objective. It also provides an opportunity to retrieve near real-time data collection due to satellite frequent revisit time, especially since real-time objective estimations of end-season cropping areas is not often available (Potgieter et al. 2007). Utilising remote sensing may allow crop area mapping several months before harvest, such as in the early season (Robson et al. 2007). This will be beneficial in making decisions such as supply, staff requirements, and import needs (Robson et al. 2007), which are important for the peanut industry in Australia; especially since the peanut market is supplied from the production of domestic peanut cultivation.

This study examines the use of time-series imagery from a relatively new vegetation satellite, PROBA-V, in mapping the peanut crops in a peanut growing region of the South Burnett in Queensland, Australia. The peanut crop map generated from this study will provide important information to estimate peanut production in Australia. In addition, apart from achieving the benefits as detailed in the previous paragraph, mapping peanut crops will also be beneficial in formulating policies for minimising the impacts of climate change. As is widely known, legume crops, such as peanut crops, are the second highest sources of nitrogen gas emissions (Monfreda et al. 2008). Therefore, mapping legume crops will provide an understanding of the global distribution of nitrogen cycling (Monfreda et al. 2008), which can be used in determining climate change policies.

Knowledge of suitable areas of peanut crops and high risk areas of aflatoxin incidence in the future retrieved from this study will help to plan and develop management decisions and policies to anticipate the impacts of climate change. Due to its devastating health impacts, the maximum level of aflatoxin was regulated in more than 120 countries (Bui-Klimke et al. 2014). Aflatoxin could lead to symptoms of carcinogenicity and acute toxicity, especially in fish, birds, and mammals (Newberne & Butler 1969). The most affected organ is liver, although signs of damage were also obvious in other organs, especially kidney (Newberne & Butler 1969). The occurrence of liver cancer in humans and animals is associated with aflatoxicosis (Turner et al. 2002). This study is the first to evaluate the impacts of climate change on future distribution of peanuts crops and the associated aflatoxin incidence. This study will fill the gap of mapping potential future areas of peanut crops and potential hotspot (high risk) areas of aflatoxin incidence. Locating the high and low risks of aflatoxin areas will be useful in determining the appropriate location of peanut cultivation areas. This information is valuable in securing food and increasing crop production, especially since crop disease is among the key constraints in increasing crop production and quality (Chakraborty & Newton 2011).

1.4 Research aim and objectives

The general aim of this study is to investigate the potential of time-series imagery data and spatial modelling techniques in mapping current peanut cropping areas, the future geographic distribution of peanut crops and the associated aflatoxin incidence in Australia under climate change scenarios. Specifically, the study has the following objectives:

1. To assess the effectiveness of time-series PROBA-V 100m NDVI imagery for peanut crop mapping in the South Burnett region of Queensland, Australia by using crop phenology and traditional approaches.
2. To study the effects of climate change on the future geographic distribution of peanut crops in Australia by using the Species Distribution Models (SDMs) of CLIMEX under two different climate models.
3. To examine the effects of climate change on the future geographic distribution of aflatoxin in peanut crops in Australia by using the Species Distribution Models (SDMs) of CLIMEX under two different climate models, and to locate high risk areas of aflatoxin in the future peanut growing areas of peanut crop production.

1.5 Scope and limitation of the study

This study used a relatively new vegetation satellite, PROBA-V (100m spatial resolution), which is an intermediate satellite resolution between traditional 250m MODIS and 30m LANDSAT satellites. In addition, with its daily revisit frequency, PROBA-V has a high temporal resolution. To the best of our knowledge, this study is the first that has used PROBA-V imagery in crop mapping in Australia. The time-series of PROBA-V NDVI 100m was used to map peanut crops due to its ability to capture changes over the crops' growth period. In mapping the peanut crops, this study analysed the use of phenology imagery derived from PROBA-V 100m NDVI imagery, along with the use of PROBA-V NDVI imagery itself. Since Queensland is the main peanut growing areas in Australia, the peanut crop mapping was carried out in this state. More specifically, the peanut crop mapping was focused in one peanut growing region in Queensland, namely the South Burnett region, since the extent of peanut cropping areas in this region is adequate for that particular part of the study.

The spatial modelling of future distribution of peanut crops and the associated aflatoxin incidence in Australia was carried out using the Species Distribution Models (SDMs) of CLIMEX (Sutherst & Maywald 1985). CLIMEX is a computer model which has been developed based on species' or other biological entities' response to climate (Beddow et al. 2010). The fundamental approach of CLIMEX is that climate eventually limits species distribution (Beaumont et al. 2008). Consequently, CLIMEX only considers climatic factors in modelling the current and future distribution of species. Climate is also one of the major factors in determining the geographic boundary in planting crops (Anwar et al. 2013), including peanut. Similarly, among several driving factors of aflatoxin synthesis, climate is the main factor. Therefore, as CLIMEX was developed based on climatic factors, this program was used in this study to model the future distribution of peanut crops and aflatoxin in relation to climate change incident. It should be noted that the results of future peanut distribution could be improved further by including non-climatic factors, such as economic aspects, social factors, topography, soil type, and land use. In addition, the results of future aflatoxin distribution could also be enhanced by considering other factors which affect the distribution. These include host availability, susceptibility and abundance, historical contingency (e.g. evolutionary change), and interacting factors such as crop and pest management, crop rotation, and crop acreage.

1.6 Conceptual framework

Climate change is likely to continue in the future (Steffen et al. 2012). It can generate adverse impacts in agriculture, such as reduction in crop production (Xie et al. 2008), changes in crop area planted (Steffen et al. 2012), and shifting in areas that are favourable for pest infestation (Luck et al. 2011). Like other crops, peanut crops could also be affected by this climate change incidence. In Australia, peanut crops are usually grown under dryland conditions (Meinke & Hammer 1995). Unfortunately, unfavourable weather conditions, for instance drought and excessive rainfall can adversely affect peanut production in Australia (Meinke et al. 1996), and they could trigger aflatoxin contamination (Cotty & Jaime-Garcia 2007).

This study used remote sensing methods and modelling techniques to address the potential impacts of climate change in peanut crop production. Firstly, it examined the use of time-series imagery in mapping peanut crop areas, thus peanut production assessment could be done accurately and effectively. Secondly, in order to manage climate change impacts in the future, this study projected the potential future geographic distribution of peanut crops and future potential high risk areas of aflatoxin incidence using the Species Distribution Models (SDMs) of CLIMEX. Finally, the high and low risks of aflatoxin areas were used to determine the appropriate location of peanut cultivation areas in the future. The conceptual framework of this study is presented in Figure 1.1.

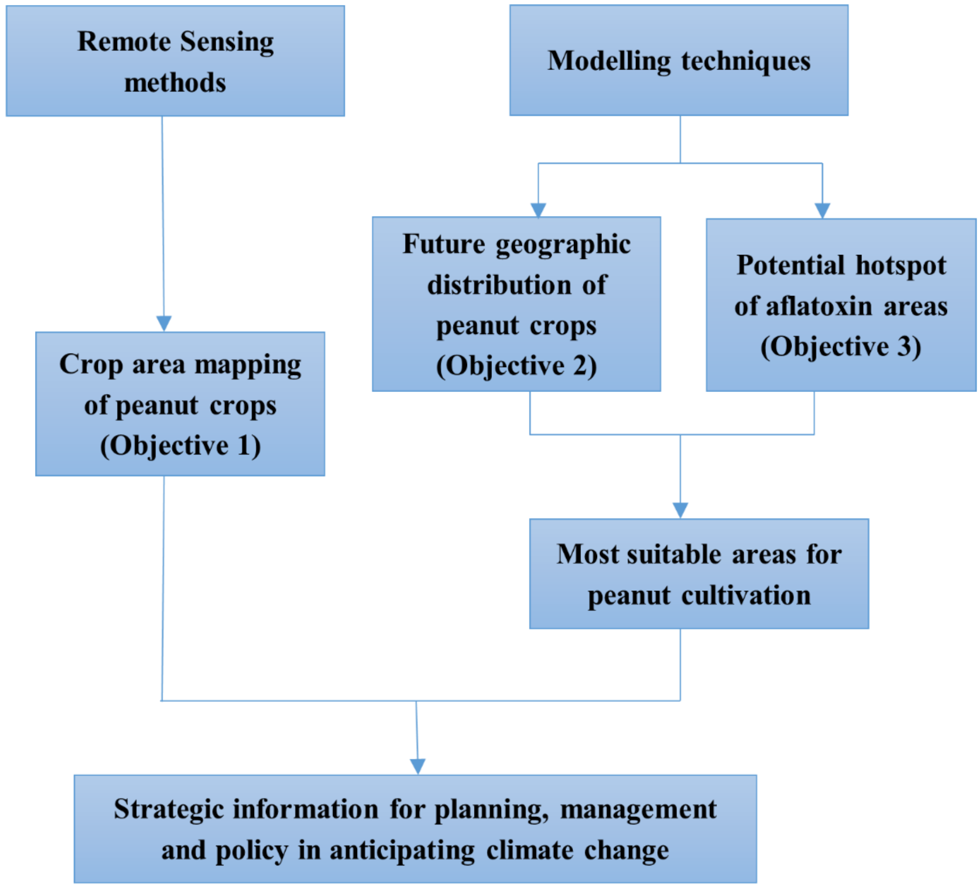

Figure 1.1 Conceptual framework of the study.

1.7 Organisation of the thesis

This thesis is organised into seven chapters. **Chapter 1**, Introduction, provides the background of the study, identifies the research gaps, explains the significance of the study, enumerates the aim and specific objectives of the research study, defines the scope and limitations, and describes the conceptual framework of the study. **Chapter 2**, Literature Review, provides a review of the current knowledge and gaps relevant to the study. This includes explanations of peanut crops and aflatoxin, the importance of crop mapping, the use of time-series imagery in crop mapping, the incidence of climate change and its impacts, and the use of Species Distribution Models (SDMs) in modelling the future distribution of a species in relation to climate change incidence. **Chapter 3**, Research Methods, explains the research methods adopted by the study. It presents the study area, as well as the acquisition, pre-processing, and analysis of the data.

Chapter 4 addresses the first objective of this study. It presents the use of PROBA-V 100m NDVI imagery in mapping the peanut crops in the South Burnett, Queensland, Australia using time-series NDVI imagery and phenology imagery derived from the time-series NDVI imagery. **Chapter 5** addresses the second objective of the study. Using the CLIMEX model, the projection of future geographic distribution of peanut crops in Australia by taking into account climate change incidence is presented. The last objective is addressed in **Chapter 6**. This chapter discusses the projection of future geographic distribution of aflatoxin incidence in peanut crops using the computer model of CLIMEX under climate change scenarios. In addition, an analysis of aflatoxin risk areas in the projections of future geographic distribution of peanut crops is also presented in this chapter. Finally, **Chapter 7**, Conclusion, explains the overall summary, findings, research contributions, and recommendations for future studies.

Chapter 2

LITERATURE REVIEW

2.1 Introduction

The previous chapter presented the overall framework of the study, highlighting the need to investigate peanut crop mapping, the projected future peanut crop distribution, and the projected future aflatoxin incidence distribution in order to provide strategic information for planning, management, and policy, especially in anticipating climate change. This second chapter presents the reviews of current literature regarding the explanations of peanut crops and aflatoxin, the importance of crop mapping, the use of remote sensing technology in peanut crop mapping, the impact of climate change on peanut crops, and the computer model used in modelling the future distribution of peanut crops and aflatoxin. The specific and detailed reviews of literature for each objective are presented in Chapters 4 to 6.

Chapter 2 is divided into nine sections. Sections 2.2 and 2.3 provide information regarding peanut crops and aflatoxin. Section 2.4 reviews the utilisation of remote sensing technologies in crop mapping. Section 2.5 elaborates the nature, application, and analysis techniques of time-series imagery data. Section 2.6 evaluates the impact of climate change. Section 2.7 reviews the Global Climate Models (GCMs) and the scenarios of future anthropogenic GHG emissions. Section 2.8 explains species distribution models (SDMs) and CLIMEX, the model specifically used in this study. Then, lastly, the chapter ends with a summary in Section 2.9.

2.2 Peanut crops

Groundnut or peanut (Figure 2.1) is one of the most important oilseed crops (Fletcher & Shi 2016) and has 26% more protein than eggs, dairy products, meat, and fish (DPIF 2007). The peanut species (*Arachis hypogaea* L.) is a member of the genus *Arachis* which belongs to the family Fabaceae or leguminosae, in the subtribe Stylosanthinae of the tribe Aeschynomeneae (Pattee & Stalker 1995). The species is divided into two subspecies, namely ssp. *hypogaea* (the Virginia group) and ssp. *fastigiata* (the Spanish-Valencia group) (Gibbons et al. 1972), with several botanical varieties (Stalker 1997). The two subspecies are differentiated based on the branching patterns of reproductive to vegetative nodes on the lateral branches (Stalker 1997). Peanut crops are unique since the flowers are above ground, but once pollinated, their fruits are produced below the surface of the soil (Wright et al. 2017). An embryo embedded between two cotyledons develops into a bush of 50 cm height and spreads up to 100 cm wide. The flowers which are small, yellow, and pea-shaped, emerged from the axils of the leaves, 30-40 days after planting. After self-pollination, the fertilised ovary starts to elongate and enter the soil, then develops a pod containing 1-3 kernels (DAF 2011; Wright et al. 2017).

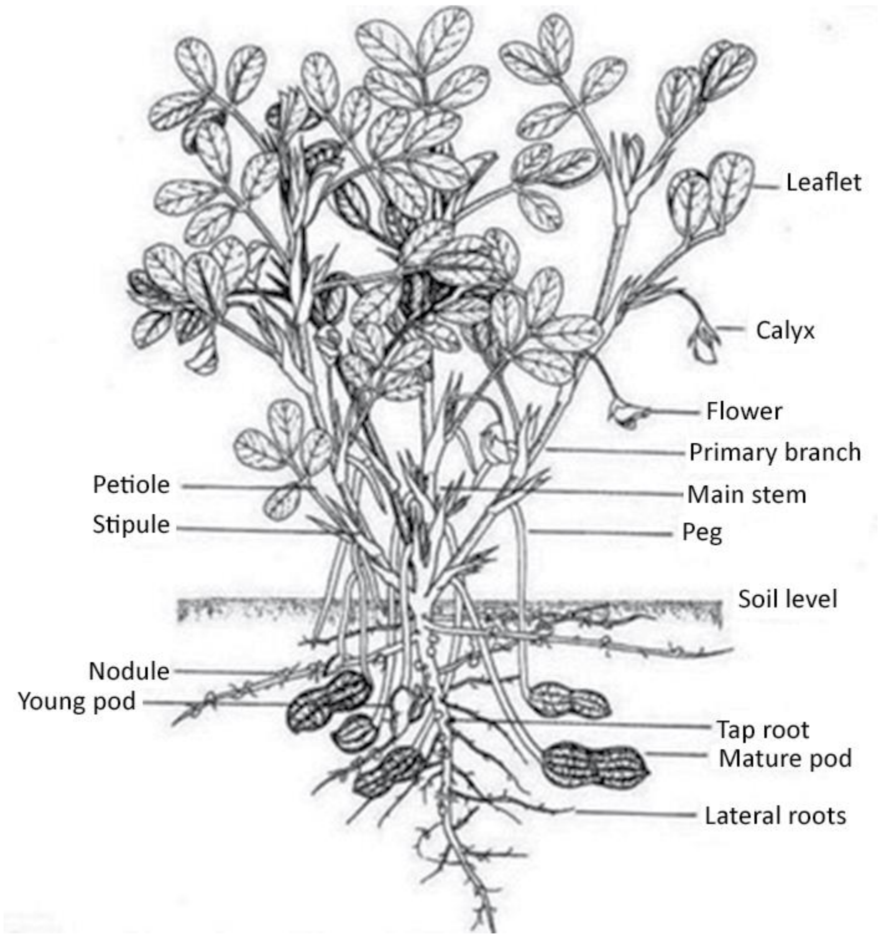

Figure 2.1 Arachis hypogaea L plant. (Madhan & Nigam 2013)

Peanut crops require relatively warm conditions, 500 – 600 mm well distributed rainfall annually, and stored soil water to harvest a high-yielding crop (Crosthwaite 1994). In order to germinate, the soil temperature at the planting depth should be at least 18°C (20°C is better) at 9 am measured over three days. Vegetative growth requires a warm temperature, 25-30°C, while temperature for reproductive growth is 22-24°C. In Australia, it is important to schedule planting time carefully, since peanut crops require a warm temperature at the early stage of crop development, then experience a cooler temperature at the flowering stage, and finally they should mature before the temperature reached freezing. Consequently, in inland southern Queensland, crops should be harvested before the end of April. Growth stage length depends on temperature and the peanut variety, and results in the variation of the peanut growing season, from 110 to 170 days (16 to 24 weeks). An example of growth stages is revealed in Table 2.1 (DPIF 2007) and Figure 2.2 (Torres et al. 2014). Although known as moderately drought tolerant crops (Stalker 1997), inadequate water at the flowering stage will reduce pod yield; while at the pod filling stage, drought stress will result in severe yield reduction (Wright et al. 1991). In addition, inadequate water supply during the late season will also increase the possibility of aflatoxin infection (Kambiranda et al. 2011).

Table 2.1 Growth stages of a Virginia peanut variety in south and north Queensland.

Growth stages	**Days after planting**	
	South Queensland	**North Queensland**
Planting	6-14	6-12
Emergence to first flower	20-40	28-38
Flowering	35-65	28-65
Pegging	45-75	36-75
Pod filling	60-130	55-130
Harvest maturity	140-150	125-150

Source: (DPIF 2007)

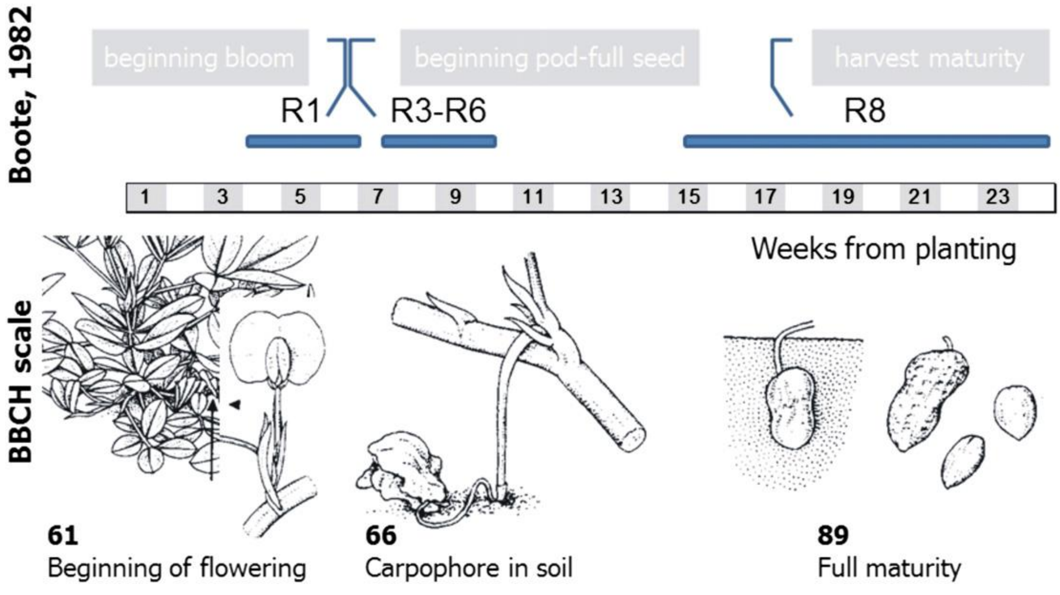

Figure 2.2 Peanut crop phenology (adopted from Boote 1982) and BBCH scale (edited by the Federal Biological Research Centre for Agriculture and Forestry) (Torres et al. 2014).

Originally, peanut crops come from South America, and nowadays, they are planted around the world, in the tropical, sub-tropical, and warm climate zones (Stalker 1997). Geographically, peanut planting areas can be grouped into three major regions, namely: the Americas (Northern, Southern, and Latin), Africa (Eastern, Southern, and Western), and Asia (Eastern, South Eastern, and South Western) (Fletcher & Shi 2016). In Australia, peanut crops were first grown in North Queensland in 1880s by Chinese gold-miners (Wright et al. 2017), and adapted successfully to the conditions. Conventionally, peanuts were grown in red basaltic soil which has good water holding capacity and is friable. Therefore, the initial peanut growing areas were in the red soils of the Burnett and the Atherton Tableland regions. However, in 1990, the common belief that red soils were the only soils where peanut could be grown has changed, as soil texture is an important consideration (Crosthwaite 1994). Subsequently, the cropping areas have expanded to other Queensland regions, such as Bundaberg, Mackay, and Emerald (Crosthwaite 1994). Currently, the cropping areas have expanded further to Katherine in the Northern Territory, and to other Queensland regions: Texas, Inglewood, St. George, Childers, Chinchilla, and Georgetown (Chauhan et al. 2013). Annually, around 15,000 hectares in Australia are planted with peanut crops (Wright et al. 2017) to meet the domestic market (DPIF 2007). More than 90% of peanut cropping areas is located in Queensland (Wright et al. 2017). Around 40,000 tonnes of peanut are produced annually, although in order to meet the domestic market, Australia would need 50,000 tonnes of peanut (Wright et al. 2017). Therefore, it is important to be aware of the need to increase peanut production capacity in Australia to maintain profitability and secure production demands.

Unlike insects, diseases are considered to be a major problem in growing the peanut crops (Wright et al. 2017), as they can affect peanut crops' yield and quality. The disease can be defined as the presence of an abnormality in the foliage, roots, pods, and seeds of peanut crops (Kokalis-Burelle et al. 1997). In general, peanut crops are categorised into three types: seedling diseases, foliar diseases, and soil-borne diseases (Wright et al. 2017). Seedling diseases can be caused by several fungi. The popular one is crown rot, which is caused by *Aspergillus niger* (GRDC 2014). The impacts of seedling diseases vary from preventing the seeds to germinate (seed rot), germinating the seeds but failed to grow (pre-emergence damping off), or the incident of dying seeds soon after emerge (post-emergence damping off) (Jordan et al. 2010). For soil borne diseases, the common diseases are sclerotinia, white mould, and CBR (Cylindrocladium Black Rot); while common foliar diseases are leafspot, rust and net blotch (Wright et al. 2017). Based on the sources, peanut diseases are divided into two groups: (1) diseases due to biotic (infectious) factor and (2) diseases due to abiotic (non-infectious) factor. Among the biotic factors are fungi, bacteria, nematodes, viruses and viroids, and phytoplasmas (mycoplasma like organism) (Kokalis-Burelle et al. 1997). One of the examples of peanut disease caused by fungi is aflatoxin. In general, peanut diseases spread through wind and equipment, particularly diggers and threshers which can potentially spread soil borne diseases (Crosthwaite 1994). The development and severity of peanut diseases are determined by the complex interaction between host plant, pathogen, and environment (Figure 2.3) (Kokalis-Burelle et al. 1997; Huber & Haneklaus 2007).

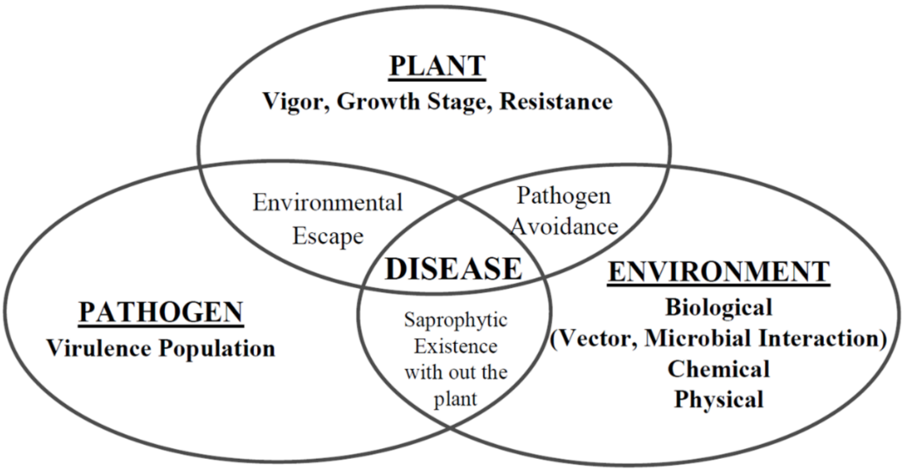

Figure 2.3 The interaction factors associated with plant disease (Huber &Haneklaus 2007).

2.3 Aflatoxin

2.3.1 Aflatoxin and Aspergillus species

Aflatoxin is one of the major mycotoxin problems which occurs in several crops, including peanut crops, and generates several negative impacts. Mycotoxin is a secondary metabolite synthesized by certain fungi; its consumption can cause symptoms of toxicity and in some cases, it can be fatal (Diener et al. 1987). In addition, it also generates economic impacts, originating from loss of human and animal life, escalation of health care and veterinary care costs, decline in livestock production, production of waste from contaminated foods and feeds, and financial costs relating to the generation of research and other programs to reduce the severity of the impact of mycotoxin (Hussein & Brasel 2001). Considering its significant effect on health and agro-economic, one of the most studied mycotoxins is aflatoxin (Hussein & Brasel 2001). Aflatoxin is a secondary metabolite produced by common soil fungi namely *aspergillus* (Perrone et al. 2014). The first aflatoxicosis, an exposure of aflatoxin, incident occurred in 1961 when more than 100,000 young turkeys in England died due to aflatoxin infection in their groundnut feed (Blount 1961). The latest notable incident was an outbreak of aflatoxicosis in Kenya from 2004 to 2006 which claimed more than 150 lives (Mutegi et al. 2012). In general, aflatoxicosis can be grouped into two categories: first, acute aflatoxicosis resulting in fatality, and second, chronic aflatoxicosis resulting in cancer (especially liver cancer), immune suppression, teratogenicity, and other symptoms (Bennett & Klich 2003).

In a similar way to other fungal species, the primary reservoir of *Aspergillus* (Figure 2.4) is the soil (Zorzete et al. 2011). *Aspergillus* section flavi includes the major aflatoxin producing fungi in agricultural crops, namely *aspergillus flavus* (*A. flavus*) and *aspergillus parasiticus* (*A. parasiticus*) (Klich 2007; Perrone et al. 2014). *A. parasiticus* is more frequently found in peanut crops than other crops (Diener et al. 1987). Nevertheless, *A. flavus* is the major vector for aflatoxin contamination (Guo et al. 2003; Torres et al. 2014) and produces a high number of toxins (Schroeder & Boller 1973). When both species are present in the soil, *A. flavus* is more aggressive in invading the host crops (Perrone et al. 2014). In addition to these two species, there are other *aspergillus* section flavi which produce aflatoxin, although less frequently, namely *A. nomius*, *A. pseudotamarii*, *A. bombysis*, and *A. parvisclerotigenus* (Klich 2007). Moreover, apart from section flavi, species that produce aflatoxin are *A. ochraceoroseus*, *A. rambellii*, *Emericella venezuelensis*, and *E. astellata* (Frisvad et al. 2005). All of these fungi spread across soil, organic matter, and crop hosts (Kachapulula et al. 2017a), and commonly invade high nutrient media of oilseed crops, which are grown in similar latitude with the fungi, such as peanut, corn, cottonseeds, and tree nuts (Klich 2002; Guo et al. 2003; Klich 2007). As a result, these crops have a high risk of aflatoxin contamination.

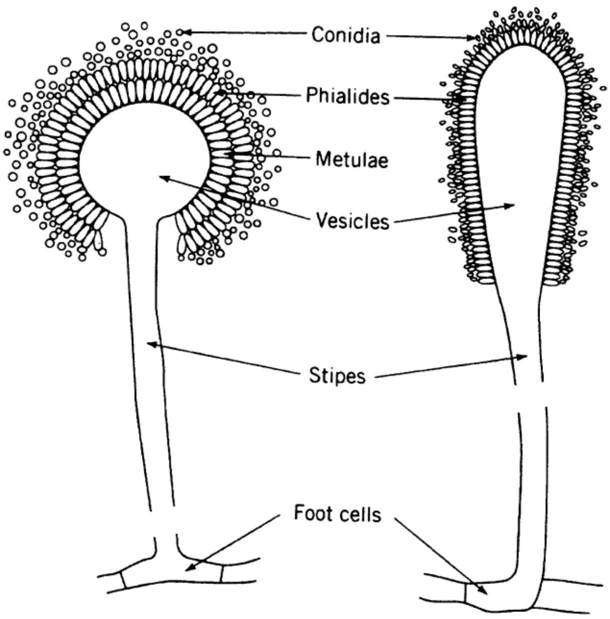

Figure 2.4 Characteristic conidiophores of Aspergillus (Klich 2007).

Although it may be found in all climatic zones (Klich 2007), *aspergillus flavus* persists most frequently in tropical latitudes (below 25 degrees of south and north), and more frequently in the warm temperate zones of 26-35 degrees (Klich 2002). These climatic zones provide the most suitable climate for *aspergillus* development. The species' optimum temperature is between 25 and 40°C, while its minimum temperature is 10°C (Klich et al. 1992). However, the presence of *aspergillus* in a crop's seeds does not necessarily mean the occurrence of aflatoxin (Hill et al. 1983; Atayde et al. 2012). Environmental stresses, such as prolonged drought and heat, are needed for aflatoxin infection (Cole et al. 1989; Cotty & Jaime-Garcia 2007; Smartt 2012). A natural protective mechanism of the crops against aflatoxin incidence (Smartt 2012), known as phytoalexins, antimicrobial compounds produced by the crops (Klich 2007). However, drought stress leads to a reduction of phytoalexins production (Wotton & Strange 1987), and put crops at a high risk of aflatoxin invasion. In addition, proline, an amino acid, is known to stimulate aflatoxin production (Payne & Hagler 1983). Unfortunately, drought stress incidence increases proline production in crops (Barnett & Naylor 1966) and thus increase the probability of aflatoxin infection.

More than 20 aflatoxins have been isolated from several fungal species (Hussein & Brasel 2001). However, only four aflatoxins occur frequently (Abbas et al. 2004) with a devastating effect on agricultural commodities, i.e. aflatoxins B_1

(AFB$_1$), G$_1$ (AFG$_1$), B$_2$ (AFB$_2$), and G$_2$ (AFG$_2$) (Figure 2.5). Aflatoxin type B is produced by *A. flavus* and *A. parasiticus*, while aflatoxin type G is only produced by *A. parasiticus* (IARC 2012; Kachapulula et al. 2017a). The most potent and carcinogenic aflatoxin is aflatoxin B$_1$ (AFB$_1$), followed by aflatoxins G$_1$ (AFG$_1$), B$_2$ (AFB$_2$), and G$_2$ (AFG$_2$) (Zorzete et al. 2011). Aflatoxins B$_1$ and G$_1$ showed sufficient evidence for carcinogenic potential, thus were categorised as a group 1 human carcinogen (IARC 2012), i.e. a group of agents with sufficient evidence of causing cancer in human (IARC 2006). Meanwhile, aflatoxin B$_2$ showed limited evidence and aflatoxin G$_2$ showed inadequate evidence (IARC 2012).

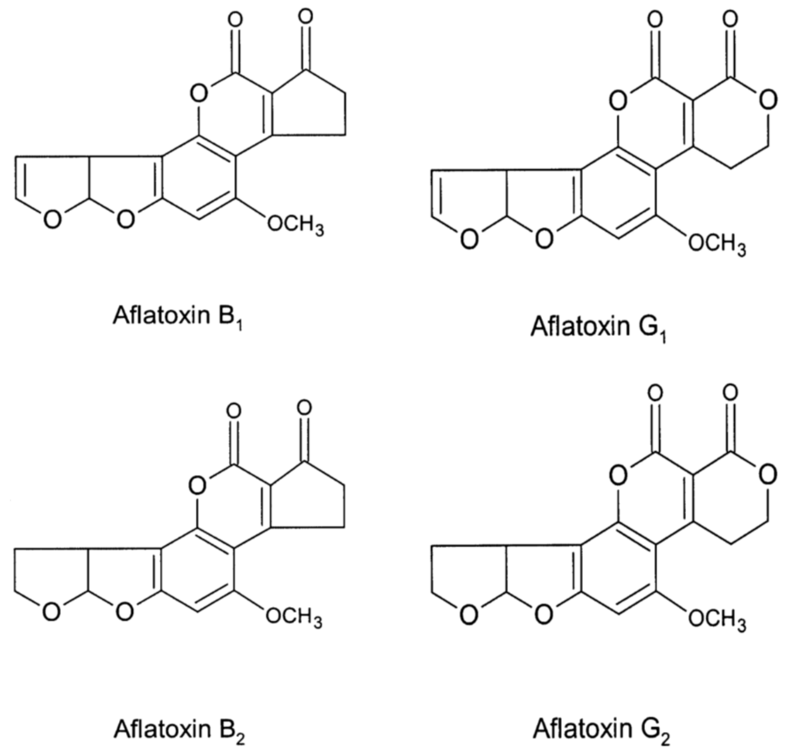

Figure 2.5 Chemical structure of aflatoxin B (AFB$_1$ and AFB$_2$) and G (AFG1 and AFG2) (Hussein & Brasel 2001).

Because of its carcinogenic potential, more than 120 countries have regulated the maximum content of aflatoxins in agricultural products (Bui-Klimke et al. 2014). The European Union, as one of the major peanut importing areas (Fletcher & Shi 2016), has determined the maximum level for aflatoxin B$_1$ and other aflatoxins in peanut commodities as 2 and 4 µg/kg, respectively (EC-European Commission 2010). A possible significant economic loss could be sustained if the standard level is not achieved, especially since two-thirds of annual peanut production is supplied from Eastern Asian and West African regions (Fletcher & Shi 2016), which are known as aflatoxin epidemic areas. It is predicted that around $450 million will be loss annually from the peanut industry in the USA, China, Argentina, and the African continent if the European standard of aflatoxin maximum limit is applied (Wu 2004).

2.3.2 Aflatoxin occurrence in peanut crops

The presence of *aspergillus* in peanut seeds does not necessarily indicate the infection of aflatoxin (Hill et al. 1983). Prolonged heat and drought stress during the last 3 to 6 weeks of the peanut growing period are required for the synthesis of aflatoxin in peanut seeds (Figure 2.6) (Kokalis-Burelle et al. 1997). Although many factors are responsible for aflatoxin infection in agricultural crops, climate is the dominant factor (Paterson & Lima 2010). Climate stresses, i.e. drought, extreme temperature, and rain at the end stages of crop production, will induce aflatoxin contamination and determine its severity (Cotty et al. 2008). Cole et al. (1989) suggested that a drought and heat stress period of 20 days is insufficient for aflatoxin synthesis in groundnut, while 30 days of stress is sufficient, and the most conducive period for aflatoxin synthesis is between 40 and 50 days of stress. Blankenship et al. (1984) also revealed that drought and heat stresses in the last 50 days of peanut growing time will induce aflatoxin synthesis in peanut crops. Some experiments have shown that the optimum geocarposphere temperatures for aflatoxin contamination in peanut crops are in the range of 27 – 30°C (Kokalis-Burelle et al. 1997), 26.3 – 29.6°C (Cole et al. 1985), 28 – 30.5°C (Sanders et al. 1985), and 25 - 28°C (Hill et al. 1983). Therefore, severe aflatoxin incidence commonly occurs in tropical and subtropical climate regions, and also in temperate regions, like temperate areas of the USA (Perrone et al. 2014). However, climate alteration of hot and dry climate in free-aflatoxin areas of the northern part of Italy in 2003-2004 had stimulated the synthesis of aflatoxin in corn crops (Perrone et al. 2014). This incident provides a warning of shifting aflatoxin areas due to climate change. As a result, further studies of future aflatoxin areas in relation to climate change occurrence will be beneficial and necessary in providing information to manage aflatoxin incidence in the future. Chapter 6 (**Objective 3**) of the thesis addressed this research gap.

Figure 2.6 Aflatoxin contamination in peanut pod (DAF 2018).

Peanut crops have a high risk of aflatoxin contamination. In a study of aflatoxin contamination in peanut and corn crops in Zambia, Kachapulula et al. (2017b) discovered that aflatoxin contamination in peanut crops was more severe and frequent than contamination in corn crops. In addition, in a survey of the *Aspergillus* population in the agricultural fields of the southern regions of the USA, peanut fields contain more *aspergillus* species than other fields, such as corn, cotton, and soybean (Horn & Dorner 1998). Schroeder and Boller (1973) revealed that the majority of aflatoxin-producing strains of *A. flavus* are found in peanut crops. In addition, although peanut crops flower above the ground, once they are pollinated, the fruits are below the ground (Wright et al. 2017). As a result, peanut fruits have direct contact with soil microorganisms, such as *Aspergillus* species, which increase the probability of fungi contamination and aflatoxin infection. Apart from climatic and environmental factors, it has been suggested that peanut seeds might provide some factors which enable the synthesis of aflatoxin, thus making the seeds very favourable substrates for infection (Schroeder & Boller 1973).

In view of the significant impact of climate stress on aflatoxin development in agricultural crops, climate change may stimulate an increase of aflatoxin incidence and severity. Climate models have projected simultaneous drought stress episodes in the future due to the increase of temperature and the decrease in summer rainfall (Medina et al. 2014). As an impact of the climate change, it is projected that Australia will experience a temperature increase, uncertainty in summer tropical rainfall in the northern areas, a rainfall reduction in the southern and western areas, and an increase of extreme climate events (Cleugh et al. 2011; Head et al. 2014).

Moreover, the arid climate zones which dominate the Australian continent, put the broad-acre crops mostly mature under hot and dry conditions (Pitt & Hocking 2006). As a result, it is suggested that Australia will experience an increase of aflatoxin incidence and severity, especially since the majority of peanut crops are grown under dry-land practice and are imposed with drought stress risks at the final stage of their growing period (Pitt & Hocking 2006). Therefore, modelling the effect of climate change in aflatoxin incidence in Australia will be significant in anticipating the adverse effect in the future. This gap will be addressed in Chapter 6 (**Objective 3**) of the Thesis.

2.4 Crop mapping utilizing remote sensing

Crop mapping plays a critical role in securing and managing agricultural crops to meet the food demands of an increasing world population. The agricultural sector faces challenges in increasing its production and productivity to feed the projection of nine-billion people by mid-century, and at the same time, reducing the environmental impacts of agricultural activities (Atzberger 2013). Therefore, estimating crop production is exceptionally important in order to plan agricultural production and monitor food supplies (Srivastava 2015). Two components of crop production are crop area (to be) harvested and (anticipated) yield per unit area (Gallego et al. 2008; Craig & Atkinson 2013). Accurate predictions of both components are equally important in confirming crop production accuracy (Craig & Atkinson 2013). However, compared to crop area estimation, more studies have been conducted on crop yield estimation (Craig & Atkinson 2013; Iizumi & Ramankutty 2015). In addition, classifying and mapping crops are crucial elements in managing natural resources (Xie et al. 2008), since crops hold an important role in climate change occurrence through the emission of CO_2 (Xiao et al. 2004) and other greenhouse gasses (GHG).

Traditionally, crop area mapping is carried out periodically by censuses, i.e. data enumeration of the total population of the object, or by samples, i.e. data enumeration of a small part of the population (Craig & Atkinson 2013). The former method typically requires enormous amount of time and budget, but with a high accuracy of results. Meanwhile, the latter method is cheap and quick, but with a less accuracy of results (Craig & Atkinson 2013). Sample survey system can be carried out through farmer reported data, large point samples with observed data, conventional area frame systems, and the use of administrative data. Generally, this method involved expert opinion in analysing the data (Craig & Atkinson 2013). Traditional methods have been established for a long period, and still being employed. One example is the National Resources Inventory (NRI) conducted by the USDA's Natural Resource Conservation Service (NRCS) which employed an extremely large point sample and survey (Craig & Atkinson 2013).

The application of remote sensing technology in observing agricultural crops, including crop mapping, has provided great advantages. The technology overcomes the shortcoming of traditional methods, especially in terms of time, budget, and accuracy (Atzberger 2013; Craig & Atkinson 2013; Srivastava 2015). In addition, it has distinct benefits, i.e. large coverage areas, rapid objective assessment and longitudinal assessment (capturing changes over a period of a particular area) (Atzberger 2013; Srivastava 2015). Considering these benefits, remote sensing could support traditional methods in estimating crop area and forecasting crop yield (Srivastava 2015). The utilisation of remote sensing technology in crop area mapping has been done since 1970s, but the popularity of its adoption and use has just increased over the past few decades (Craig & Atkinson 2013). The advancement of Geographic Information System (GIS) and the invention of new devices, such as Global Positioning System (GPS) and various types of handheld computer tablets, has enhanced the performance of remote sensing technology (Craig & Atkinson 2013).

Fundamental knowledge of spectral reflectance and thermal emittance properties of crops and soils have enabled the advance and usage of numerous remote sensing methods (Pinter et al. 2003). Various imagery with different spectral, spatial, and temporal characteristics have provided an exceptional opportunity for monitoring and managing agriculture at every level, from field to global scales (Pinter et al. 2003; Xie et al. 2008). Currently, there are numerous earth observation data available, supported with novel image compositing approaches and an improved computing and storage capacity (Gómez et al. 2016). Table 2.2 presents some commonly used land observation sensors.

Table 2.2 Commonly used land observation sensors (adopted from Sun et al. (2012))

Sensor	Satellites	Spatial resolution (m)	Temporal resolution (days)	Coverage (km)
Enhanced Thematic Mapper Plus (ETM+)	Landsat 7	30, 15 (pan)	16	185
Operational Land Imager (OLI)	Landsat 8	30, 15 (pan)	16	185
High Resolution Visible and Infrared (HRVIR)	SPOT 4	20, 10 (pan)	26	60
High Resolution Geometric (HRG)	SPOT 5	10, 2.5-5 (pan)	26	60
Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER)	Terra	15, 30, 90	16	60
Multi-spectral instrument (MSI)	Sentinel-2	10, 20, 60	5	290
Advanced Very High Resolution Radiometer (AVHRR)	NOAA-Series	1100	1	2399
Moderate-Resolution Imaging Spectroradiometer (MODIS)	Terra, Aqua	250, 500, 1000	1-2	2330
VEGETATION (VGT)	SPOT 4, 5	1000	1	2250
Vegetation	PROBA-V	100	1	2285

*. *) pan = panchromatic*

The application of remote sensing studies in peanut crops are limited (Rajan et al. 2014), despite the crops' position as important source of protein and as contributing agents in nitrogen gas emission. Using high spatial resolution of satellite imagery, Robson et al. (2007) explored the inherent spatial variability on specific peanut paddocks. They also found correlation between the NDVI dataset with yield and pod maturity of peanut crops to be highly significant (r=0.91) and moderately significant (r=0.67), respectively. Ground cover of peanut crops can be estimated accurately based on perpendicular vegetation index (PVI) by using an airborne remote sensing technology (Rajan et al. 2014). In Senegal, (Knudby 2004) carried out a study of crop yield estimation in a peanut-growing region (Peanut Basin).

Only few remote sensing studies have focused on peanut crop mapping. For example, Schultz et al. (2015) mapped several crops in Brazil including peanut crops, but found difficult to differentiate between peanut and cassava crops. Meanwhile, Robson et al. (2007) also mapped peanut crops in the South Burnett, Australia, but the study only covered small areas and utilised high spatial resolution of satellite imagery, which is usually costly. It is well known that legume crops, such as peanut crops, are the second most important source of nitrogen gas emission (Monfreda et al. 2008). As a result, mapping these crops will provide more understanding regarding the global spatial distribution of nitrogen cycling (Monfreda et al. 2008). Therefore, mapping peanut crops will be essential, not only in terms of securing peanut market, but also in determining policy for climate change impact. Chapter 4 (**Objective 1**) of this Thesis will address this peanut crop mapping gap.

2.5 Time-series imagery

2.5.1 The nature and application of time-series imagery

The ability of earth observation satellites to repetitively capture imagery of a particular location has enabled the emergence of time-series or multi-temporal imagery data, which provides some advantages for crop mapping. It is acknowledged that the use of remote sensing data in determining land use of agricultural areas is still very challenging (BeyerJarmer, et al. 2015). Different vegetation types frequently demonstrate very similar spectral behaviour. As a result, it is difficult to classify crops using one multispectral data alone (BeyerJarmer, et al. 2015). However, different physiological growth (phenological) stages of each crop reflect different spectral behaviours (BeyerJarmer, et al. 2015), which lead to frequent changes of a crop’s reflectance at different times (Sun et al. 2012). As a result, the use of time-series data can provide an opportunity to capture these differences, and at the end, crops with similar spectral behaviour can be classified easily (BeyerJarmer, et al. 2015). In addition, time-series data also offer the benefits of providing near real-time information on large areas (Eerens et al. 2014).

Several issues to consider in mapping land use of agriculture are the spatial resolution, temporal resolution, coverage, ability/quality (such as cloud cover), imagery costs, and classification methods (Sun et al. 2012). Basically, land observation sensors can be grouped into two types: first, sensors with high spatial resolution but small in coverage area and low in temporal resolution; and second, sensors with high temporal resolution and large coverage area but low in spatial resolution. The former is appropriate for attaining detailed local information, while the latter is appropriate for gaining time-series data and have more possible opportunity to retrieve cloud-free imagery (Sun et al. 2012). A relatively new earth observation satellite, Project for On-Board Autonomy - Vegetation (PROBA-V), was employed in this study **(Objective 1)**. PROBA-V offers an intermediary spatial resolution between medium spatial resolution imagery, such as Landsat (30m) and Sentinel-2 (10m), and low spatial resolution imagery, such as MODIS (250m). Thus, it has higher temporal resolution and large coverage areas than the medium spatial resolution satellite, with a fairly good spatial resolution. In order to map agricultural crops accurately, a medium to high spatial resolution, with a pixel size of 5 to 100m, is required (Liu et al. 2014). PROBA-V has a spatial resolution of 100m (Wolters et al. 2017), thus it fulfils the requirements of crop mapping. In addition, with a swath width of 2,285 km (Wolters et al. 2017), PROBA-V has superiority compared to Landsat 8 and Sentinel-2, which have a coverage of 185 and 290 km, respectively. The satellite also has a daily temporal resolution. As a result, PROBA-V is ideal for future crop mapping and agricultural monitoring (Zhang et al. 2016), especially since it was designed specifically for vegetation monitoring (Wolters et al. 2017).

In classifying crops, utilizing the single-date reflectance bands with low spatial resolution is frequently difficult; consequently Vegetation Indices (VIs) are generally used to extract green plant properties in multi-spectral remote sensed data (Sun et al. 2012). VIs measure the basic difference among soil and crop spectra (Pinter et al. 2003), and primarily derive from the transformation of red and near infra-red (NIR) reflectance (Xavier et al. 2006). One example of VIs is the normalized difference vegetation index (NDVI), which is the most popular satellite-derived VIs used in agricultural studies (Foerster et al. 2012). Some satellites have readily available derived NDVI products; one example of these satellites is PROBA-V earth observation satellite. Considering its benefits in terms of resolution and coverage area, PROBA-V NDVI imagery will be used in mapping peanut crops in this study (Chapter 4 - **Objective 1** of the Thesis). Moreover, none of studies have been undertaken in mapping peanut crops using PROBA-V, a relatively new vegetation monitoring satellite.

2.5.2 Time-series analysis technique

Mapping vegetation and crops using remote sensing often comprises of image pre-processing and image classification. The former involves all preparatory steps, including bad line replacement, radiometric correction, geometric correction, and image enhancement and masking; while the latter refers to the process of extracting the discriminated classes (Xie et al. 2008). Before classifying multi-temporal imagery, an analytical approach is employed to enhance image quality. For example, BeyerJarmer, et al. (2015) used the Jeffries-Matusita (JM) separability test to acquire a time-series data set with best spectral separability, thus preventing the run of a huge number of classification classes. Sun et al. (2012) used curve shape matching in mapping winter wheat and removing time-series noise using Savitzky Golay filter and Fast Fourier Transform (FFT) to smooth the raw data. Xavier et al. (2006) employed cluster analysis which grouped the sample data. Yang et al. (2011) used TIMESAT software to smooth enhanced vegetation index (EVI) imagery and acquire the seasonal development by employing the three processing methods available in TIMESAT software.

TIMESAT is a software package for estimating the growing season of time-series imagery by extracting the seasonality parameters, such as the beginning and end of the growing season, its length, and integrated values (Eklundh & Jönsson 2015a). It iteratively fits mathematical functions to smooth the time-series of noisy satellite data, and extract the seasonality parameters from each imagery pixel (Jönsson & Eklundh 2015). The process involves two steps: first defining the number of seasons and their approximate time, and second, filtering or smoothing the data by using the available mathematical functions, i.e. Savitzky-Golay filter, asymmetric Gaussians function, and double logistic function (Jönsson & Eklundh 2004). Originally, TIMESAT was used to smooth noisy time-series of AVHRR NDVI data (Jönsson & Eklundh 2015), but currently, it has been used in numerous time-series data.

TIMESAT has been applied in several studies involving several earth observation satellites. The software has been used successfully in extracting phenological parameters from PROBA-V data in mapping crops in China (Zhang et al. 2016). Li et al. (2014) also used TIMESAT software to filter MODIS EVI data and successfully mapping crop cycles in China using the filtered data. The resulting phenological parameters generated from MODIS EVI data using TIMESAT software also successfully mapped paddy rice in China (Yang et al. 2011). Gao et al. (2017) used TIMESAT software to generate a crop phenology map of LANDSAT-MODIS data fusion, and found a strong correlation between the remotely sensed phenological stages with the observed crop physiological growth stages. In addition, Bendini et al. (2016) concluded that phenological parameters derived from LANDSAT 8 EVI using TIMESAT has the potential for agricultural land use map. However, Hentze et al. (2016) suggested careful use of the phenological data retrieved from the TIMESAT program in discriminating rainfed agriculture with grassland in semi-humid tropical regions, as it may incorrectly classify the classes. In addition, crop calendars of each crop influenced the classification accuracy of crop mapping, although TIMESAT software was employed in filtering the time-series data (Muhammad et al. 2016). It has been discovered that crops with near similar crop calendars had lower classification accuracy than crops with different crop calendars. (Muhammad et al. 2016).

2.6 Climate change and its impacts

The earth has experienced an increase of average combined land and ocean surface temperature of 0.85°C since 1880; and the consecutive last three decades are becoming warmer than any earlier decade since 1850 (Figure 2.7) (IPCC 2014). In addition, there is a reduction of glaciers and ice sheets, an increase in sea level, and a change in precipitation Figure 2.7 (IPCC 2014). The increase of anthropogenic greenhouse gas emissions since the pre-industrial era has contributed predominantly to climate change (Figure 2.8). As can be seen in Table 2.3, it is projected that if the trends continue, the increases in temperature and sea levels are inevitable.

Table 2.3 Projected change in global mean surface temperature and global mean sea level rise for the mid and late 21st century, relative to 1986-2005 period (IPCC 2014).

		2046-2065		2081-2100	
	Scenario	**Mean**	***Likely* range**	**Mean**	***Likely* range**
Global mean surface temperature change (°C)	RCP2.6	1.0	0.4 to 1.6	1.0	0.3 to 1.7
	RCP4.5	1.4	0.9 to 2.0	1.8	1.1 to 2.6
	RCP6.0	1.3	0.8 to 1.8	2.2	1.4 to 3.1
	RCP8.5	2.0	1.4 to 2.6	3.7	2.6 to 4.8
	Scenario	**Mean**	***Likely* range**	**Mean**	***Likely* range**
Global mean sea level rise (m)	RCP2.6	0.24	0.17 to 0.32	0.40	0.26 to 0.55
	RCP4.5	0.26	0.19 to 0.33	0.47	0.32 to 0.63
	RCP6.0	0.25	0.18 to 0.32	0.48	0.33 to 0.63
	RCP8.5	0.30	0.22 to 0.38	0.63	0.45 to 0.82

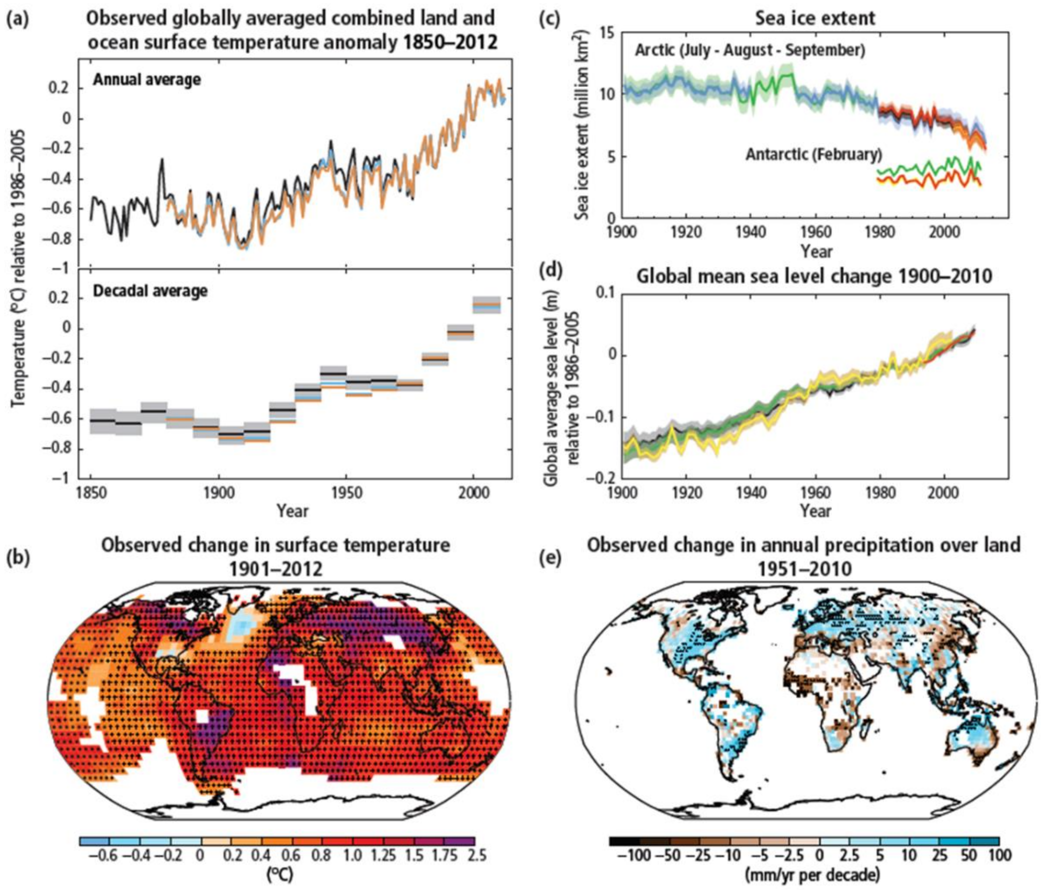

Figure 2.7 The increase of average global temperature (a), changing in surface temperature (b), extent of sea ice (c), increase of sea level (d), and change in annual precipitation (e) (IPCC 2014).

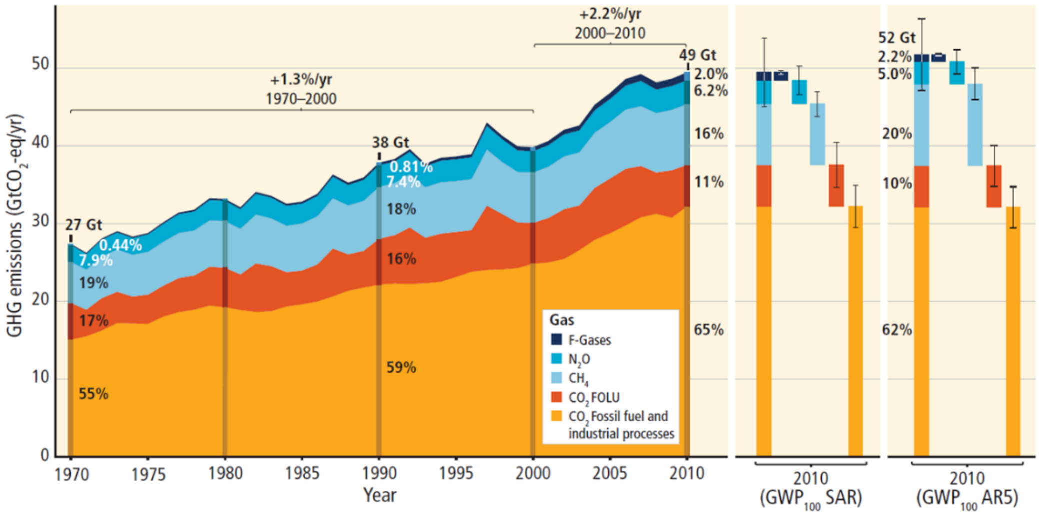

Figure 2.8 Total annual anthropogenic GHG by gases 1970-2010 (IPCC 2014).

Data in the previous paragraph shows the evidence of climate change incidence. Climate change results in mean temperature alteration, climate variability, and extreme weather incidence, including drought, very high or very low temperatures, heavy rain, and floods (Gornall et al. 2010). Since weather and climate have a significant effect on agricultural production (Gornall et al. 2010), agriculture will become a susceptible sector (Anwar et al. 2013). Temperature and precipitation alterations will affect land and water regimes, which will in turn, affect agricultural productivity (Anwar et al. 2013). Many agricultural regions will experience negative impacts due to the increase in temperature, which will result in a reduction of crop yields (Rosenzweig et al. 2014). The growing rate becomes faster, thus the crops become incapable of acquiring sufficient sunlight and resulting in biomass reduction (Stokes & Howden 2010).

In addition the agricultural sector also faces other challenges, such as pests and diseases, water supply, waterlogging, salinity, soil degradation, heat stress, drought, and unsuitability of current planting areas (Gornall et al. 2010; Steffen et al. 2012; Rosenzweig et al. 2014). The increase in the sea level may also result in the loss of agricultural land (Gornall et al. 2010). Geographical distribution and growth of plant species will be affected by climate change, even though the scale will depend on the species type (annual or perennials) and their growth patterns (agricultural crops or natural vegetation) (Coakley et al. 1999). For example, the change in the climate of some high-latitude regions will enable the cultivation of some crops in these regions, although viability assessment is needed to ensure the suitability of their soil quality (Rosenzweig et al. 2014). Similar with crops, pathogen distribution will also be influenced by climate change. Warming temperatures will limit some pathogen life-cycles, such as *Puccinia striifromis* f.sp. *triciti*, while CO_2 increase could establish favourable conditions for *Fusarium pseudograminearum* (Luck et al. 2011).

Australia has one of the most variable climates in the world (DERM 2010), due to the influences of El Nino – Southern Oscillation (ENSO), the Indian Ocean Dipole (IOD), the Madden-Jullian Oscillation (MJO), and the Southern Annular Mode (SAM) (King et al. 2014; CSIRO & BoM 2015). It is acknowledged that agricultural practices in Australia are sensitive to long-term climatic conditions and year-to-year climate variability (Stokes & Howden 2010). As a result, the incidence of climate change puts the agricultural sector in Australia in a more susceptible position. Compared to other countries, Australia has experienced a higher temperature increase since 1910, i.e. 0.9°C (Stokes & Howden 2010; Garnaut 2011; CSIRO & BoM 2015). Moreover, the geographic distribution, averages, seasonality, and intensity of rainfall are changing (DERM 2010; Stokes & Howden 2010). Considering the role of climate in peanut crops and aflatoxin development, the adverse climate change in Australia could shift the geographical distribution of these peanut crops and aflatoxin in the future. These gaps are addressed in Chapter 5 **(Objective 2)** and Chapter 6 (**Objective 3**) of the Thesis.

2.7 Climate models and scenarios

Information about future changes in climate average and variability is needed by decision makers and resource managers to improve the management of climate change effects (Santoso et al. 2008). One of the best instruments for projecting climate change is Global Climate Models (GCMs) (Suppiah et al. 2007; CSIRO & BoM 2015). The models are developed using mathematical representations of the climate systems, based on the laws of physics, such as mass, energy, and momentum (CSIRO & BoM 2015), and comprehensively verified against historical observations (IPCC 2014). GCMs simulate various climate aspects, such as the temperatures of the oceans and atmosphere, precipitation, winds, clouds, ocean currents, and sea-ice extent (IPCC 2014). Currently, 48 GCMs are available from the Coupled Model Intercomparison Project Phase 5 (CMIP5) (CSIRO & BoM 2015).

GCMs project future climate using scenarios of greenhouse gasses (GHG) and air pollutant emissions and land use patterns. The scenarios are based on the key factors determining anthropogenic GHG emissions, i.e. economic and population growth, lifestyle and behavioural changes, energy use and land use changes, technology, and climate policy (IPCC 2014). The Fifth Assessment Report (AR5) of the Intergovernmental Panel on Climate Change (IPCC) provides the standard set of scenarios, namely Representative Concentration Pathways (RCPs). RCPs consists of rigorous mitigation scenario (RCP2.6), intermediate scenarios (RCP4.5 and RCP6.0), and very high GHG emission scenario (RCP8.5) (IPCC 2014). The previous third (TAR) and fourth (AR4) of IPCC assessments used emission scenarios of Special Report on Emission Scenarios (SRES), consisting of the A1, A2, B1, and B2 scenario family (Nakicenovic et al. 2000). Generally speaking, the resemble of RCP to SRES scenario are RCP8.5 to SRES A2 or A1F1, RCP6.0 to SRES B2, and RCP4.5 to SRES B1. Meanwhile, RCP2.6 is not comparable to any SRES scenarios (IPCC 2014).

2.8 Species Distribution Models (SDMs) and CLIMEX

Species Distribution Models (SDMs) are models which are developed based on the relation between species distribution data (occurrence or abundance) at known locations and environmental and/or spatial characteristics of the locations (Barry & Elith 2006; Elith & Leathwick 2009). The fundamental approach of SDMs is that climate ultimately limits species distributions (Beaumont et al. 2008). Therefore, the resulting data can be used to project future species distribution using particular climate models and climate change scenarios (Heikkinen et al. 2006). Different terminology with occasionally different emphases and meanings are being used to refer to SDMs, i.e. bioclimatic models, climate envelopes, habitat models, and Ecological Niche Models (ENMs) (Elith & Leathwick 2009). Many SDMs have been developed, among them are ANUCLIM/BIOCLIM, CLIMATE, CLIMATE ENVELOPE, DOMAIN, GARP, HABITAT, and CLIMEX (Kriticos & Randall 2001).

CLIMatic indEX (CLIMEX) (Sutherst & Maywald 1985) is a mechanistic or process-oriented computer model that infers species' response to climate, using species' geographical distribution and species' seasonal growth and mortality patterns in different areas (Beddow et al. 2010; Kriticos et al. 2015). CLIMEX uses the assumption that is also used by other SDMs, i.e. it is possible to deduce tolerant climatic requirements of a species based on their persistence areas (Kriticos et al. 2015). However, unlike other SDMs which characterise species' occupied environments, CLIMEX mimics the mechanism that limits species' geographical distribution, defines species' seasonal phenology, and to a lesser extent species' relative abundance (Kriticos et al. 2015). In addition, most of the models emphasise defining the relationship between species occurrences with respect to static environmental covariates, while CLIMEX describes the species response to climatic variable at suitable temporal measures (daily or weekly) (Kriticos et al. 2015).

CLIMEX has been used broadly in a wide range of taxa, such as plants pathogens, mammals, and insects (Kriticos & Leriche 2010). The model was employed in the future projections of the geographic distribution of several crops in relation to climate change occurrence. This includes common bean (Ramirez-Cabral et al. 2016), corn (He & Zhou 2012), wheat and cotton (Shabani & Kotey 2015), oil palms (Paterson et al. 2015), tomato (Silva et al. 2017), and date palms (Shabani, Kumar & Taylor 2014; Shabani, Kumar, et al. 2015). However, a study regarding the projected suitable areas for peanut cultivation in the future has not been carried out in any part of the world, including Australia. Therefore, Chapter 5 (**Objective 2**) of this Dissertation addressed this gap. Similarly, CLIMEX also has been used in the projected future geographic distribution of several pests and diseases, such as *Fusarium oxysporum* f. spp. (Shabani, Kumar & Esmaeili 2014), *Leptinotarsa decemlineata* (potato pest) and *Ostrinia nubilalis* (corn pest) (Kocmánková et al. 2011), *Sitodiplosis mosellana* (wheat pest) (Olfert et al. 2016), and *Aceria tosichella* (cereal pest) (Schiffer et al. 2009). It is acknowledged that the main driving factor of aflatoxin synthesis is climate (Paterson & Lima 2010). Therefore, since CLIMEX is based on species' climatic preference, the use of this model in projecting future aflatoxin distribution is appropriate. Unfortunately, despite the significant negative impact of aflatoxin, the projection of its future geographic distribution has not been undertaken. As a result, this study addressed the gap in Chapter 6 (**Objective 3**) of the Thesis.

2.9 Concluding remarks

Based on the preceding reviews of the potential use of remote sensing technologies and spatial modelling techniques in mapping peanut cropping areas and projecting the future geographic distributions of peanut crops and aflatoxin, the following research gaps are summarised:

- Crop mapping holds an essential role in managing the market and distribution of agriculture crops. However, only limited studies have been carried out in mapping peanut crops, despite their essential role as important sources of protein and as contributing agents in the emission of nitrogen gas.
- As a relatively new vegetation monitoring satellite, PROBA-V offers an advantage in terms of resolution and coverage area, which could provide benefits for mapping peanut crops. Nevertheless, as of the time of writing this Dissertation, none of studies have been undertaken in mapping peanut crops using this satellite.
- Time-series imagery data offers an opportunity to differentiate crops with very similar growing seasons by capturing different physiological growth (phenological) stages of the crops over their growing period. One of the examples of software to analyse time-series data is TIMESAT, which has been used widely and successfully in several studies, although some encounter challenging results. Therefore, using TIMESAT in generating phenological parameters to map peanut crops could provide an opportunity for mapping these crops.
- As geographical distribution and growth of crops will be affected by climate change, investigating the future geographical distribution of peanut crops will be beneficial in managing this commodity to anticipate the impact of climate change. This is particularly so since none of studies have been carried out in modelling future geographic of peanut crops in relation to climate change.
- In particular, the effect of climate change in Australia will further put the agricultural sector in a susceptible position, due to its sensitivity with long-term climatic conditions and year-to-year climate variability. Therefore, there is a need to study the impact of climate change on the geographical distribution of peanut crops in Australia.

- Considering its risk of fatality, aflatoxin has become one of the major mycotoxin problems with a high risk of occurrence in peanut crops. Since climate is the main driving factor in aflatoxin incidence, climate change might influence the synthesis and distribution of aflatoxin. Unfortunately, no study has been carried out to investigate this issue, although it will be beneficial in managing aflatoxin incidence in the future.
- Climatic stresses, i.e. drought and heat stresses, are the triggers for aflatoxin synthesis in peanut crops. It is projected that Australia will experience an increase of incidence and severity of aflatoxin due to the projected increase of temperature and projected variability and reduction of rainfall in the future. It is found that there is limited knowledge regarding the favourable areas for aflatoxin invasion in Australia.
- Having knowledge of suitable areas for peanut cultivation and favourable areas for aflatoxin infection will provide an opportunity to locate suitable peanut cultivation areas with a low risk of aflatoxin infection. Unfortunately, none of the studies have related peanut cultivation areas with aflatoxin favourable areas, including in Australia.

Chapter 3

RESEARCH METHODS

3.1 Introduction

The previous two chapters provided an overview of the key problems and issues in the peanut crop industries, especially in overcoming the challenges of climate change. The chapters explained the overall framework of the study and identified the current research gaps on the topic that need to be addressed. These knowledge gaps were then used as basis for developing the aim and objectives of this study. The present chapter discusses the methods adopted by the study in achieving the objectives enumerated in Chapter 1. Specific methods are detailed in the ensuing chapters corresponding to the specific objectives of this study (**Chapters 4**, **5**, and **6**). The contents of this chapter are presented in the following sections: description of the study area (Section 3.2), data acquisition, processing, and analysis (Section 3.3), and summary (Section 3.4).

3.2 The study area

The study area for peanut crop mapping using remote sensing (**Objective 1**) was located in the South Burnett region, Queensland, Australia, while the study area for projecting the future geographic distribution of peanut crops and their associated aflatoxin incidence (**Objective 2** and **Objective 3**) covered the entire Australian continent (Figure 3.1). The South Burnett region is situated in the southern catchment of the Burnett River, approximately 200 km north-west of Brisbane, the capital city of Queensland, Australia. The proximity with Brisbane has put the South Burnett region in a strategic location for domestic and international markets, and has enabled the region to be an important food producing area (Sorby & Reid 2001). The main town in the South Burnett region is Kingaroy, which is well known as the 'peanut capital of Australia'. Historically, the peanut industry in Australia began in the Burnett region in 1924, with the establishment of the *Peanut Marketing Board* (Wright et al. 2017). Currently, the board has been transformed into the largest peanut company in Australia and is still located in Kingaroy (Wright et al. 2017).

The climate of the South Burnett region is subtropical (Sorby & Reid 2001). The region has a seasonal rainfall of wet summer and low winter rainfall (BoM 2016), with a mean annual rainfall of 662.6 mm (South Burnett Regional Council 2014). The wettest month (108.1 mm) is recorded in December (South Burnett Regional Council 2014). The temperature/humidity zones are characterised by warm summers and cold winters (BoM 2016). The average mean maximum temperature ranges from 19.4°C in July to 30.8°C in January, while the average minimum temperature ranges from 3.4°C in July to 18.0°C in January (South Burnett Regional Council 2014). The region covers an area of 8,381 km^2, with a total population of 32,575 (around 0.14% of the Australian population) (ABS 2018). The land use is dominated by grazing native vegetation, and the majority of agricultural land is dryland cropping (Figure 3.1) (ABARES 2019). The region has a soil dominated by red ferrosol which is historically suitable for cropping activities, and has made the South Burnett region an important summer crop producer, especially of peanut, navy beans, and maize (Sorby & Reid 2001). The summer crops are typically sowed in September to early January, and usually harvested in February to May (DAF 2014).

The study area of future geographic distribution of peanut crops and the associated aflatoxin (**Objective 2** and **Objective 3**) covered the Australian continent, with a total area of 7.692 million km^2 (Geoscience Australia 2018) and a total population of 25.18 million people (ABS 2019). The country has an expanse of land with great variability in climate, water, and soil conditions (Tapsell et al. 2011). The climate in Australia comprises five major climate groups: tropical, subtropical, desert, grassland, and temperate (Figure 3.1) (Kriticos et al. 2012). These classifications are based on the Koppen-Geiger classification following the application of the rules of Kriticos et al. (2012) applied to the 5’ resolution of WorldClim – Global Climate Data (Hijmans et al. 2005).

The agricultural sector has become one of the important components in the economy of Australia (Tapsell et al. 2011). Although the majority of the Australian land is desert and the agricultural sector frequently encounters problems of drought and water shortage, the country has a substantial agricultural production and a relatively self-sustaining food supply (Tapsell et al. 2011). Agricultural production areas in Australia are concentrated in the eastern parts of Queensland and New South Wales, the majority of Victoria, the southern part of South Australia, and the south-western part of Western Australia (ABARES 2019). These agricultural areas comprise subtropical, grassland, and temperate climatic regions. Summer crops planted in Australia are mostly sorghum, cotton, rice, corns, mung beans, peanuts, soybeans, and sunflowers; while winter crops planted are mostly wheat, barley, canola, chickpeas, faba beans, field peas, lentils, lupin, oats, safflowers, and triticale (ABARES 2016). In general, peanut crops are grown under dry-land practices (Pitt & Hocking 2006) and are cultivated across the eastern part of Queensland and northern part of the Northern Territory (Crosthwaite 1994; Chauhan et al. 2013). Aflatoxin incidence, which commonly occurs in peanut crops, is one of the major problems of the peanut industry in Australia (Pitt & Hocking 2006).

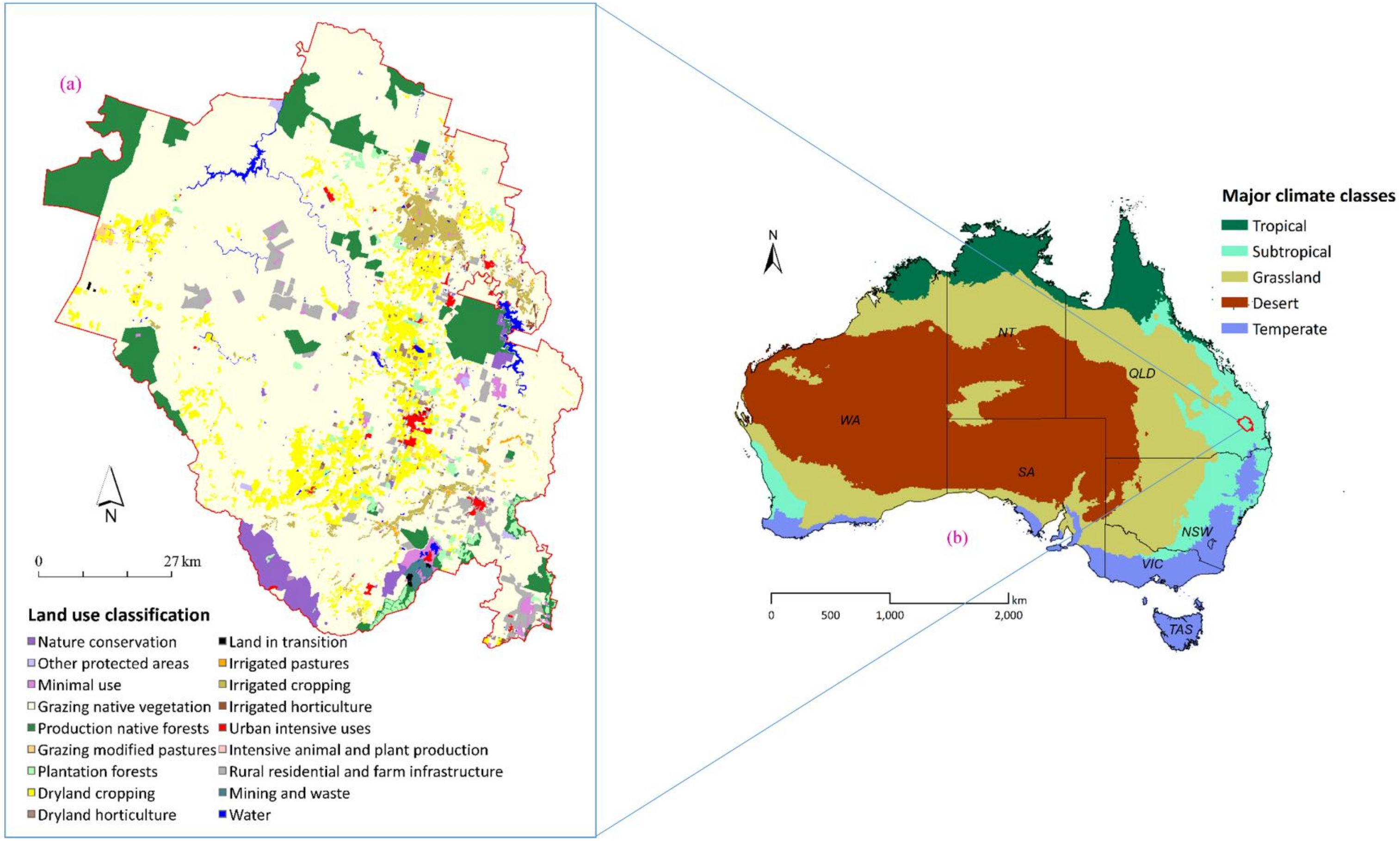

Figure 3.1 Study area for Objective 1 in the South Burnett region, Queensland, Australia (a), and study area for Objectives 2 and 3 covering the entire Australian continent (b).

3.3 Data acquisition, processing, and analysis

An overview of the data inputs, processes, and the outputs of this study is shown in Figure 3.3, while the summary of datasets used is presented in Table 3.1. This section only describes the general overview of the data acquisition, processing, and analysis, since the details are explained further in the succeeding chapters of this Thesis.

Briefly, the data acquisition for Objective 1 (i.e. peanut crop mapping) consists of field survey data and satellite imagery datasets, namely time-series PROBA-V NDVI imagery, Landsat 8 imagery, and Google Earth data. The field survey (Figure 3.4) was used to determine regions of interest (ROI) with the guidance of higher resolution satellite imagery from Google Earth and Landsat 8. Meanwhile, the time-series PROBA-V NDVI imagery was pre-processed, was then analysed using the separability test of Jeffries-Matusita (JM) distance, the traditional approach (stacking the NDVI dataset), and the phenology approach of the TIMESAT time-series analysis program. Afterwards, the imagery was classified using supervised classification algorithms, namely maximum likelihood classification (MLC), minimum distance classification (Min), and spectral angle mapper (SAM). The accuracy of the classified imagery/map was then assessed using an error matrix which was used to calculate the overall accuracy, producer accuracy (PA), user accuracy (UA), and kappa coefficient (KP).

Accuracy assessment of classified results was based on the number of pixels matches between classified image/data and reference data in the error matrix (Figure 3.2). Around 28% of the reference data collected from field work in this study was used. The error matrix consists of rows and columns of corresponding feature classes, which fill in with the number of observed pixels in each cell. The feature classes in the rows represent the classified data, while feature classes in the columns represent the reference data (Story & Congalton 1986; ITC 2010). The overall accuracy is the accuracy for the whole class classification which is calculated by dividing the number of correctly classified pixels (i.e. the sum of the diagonal cells in the error matrix) to the total number of all samples in the matrix, and multiplying with 100%. To assess the classified map in detail, the accuracies of individual feature classes were investigated using the producer accuracy (PA) and user accuracy (UA) metrics. PA is defined as the probability of a reference data to be correctly classified in the classification map. This accuracy is related to omission error, i.e. the omission of a reference data from its actual feature class in the classified map. PA is calculated by dividing the number of correctly classified samples of a specific feature class with the total number of reference data of that class (column total). The other individual feature class accuracy, UA, is defined as the probability of a classified data from a specific feature class, indeed actually represent the feature class on the ground. This accuracy is related to commission error, i.e. the inclusion of classified data into incorrect feature class in the classified map. UA is calculated by dividing the number of correctly classified samples of a specific feature class with the number of classified data of that class (row total) (Story & Congalton 1986; ITC 2010). In order to observe the differences between actual agreement and agreement expected by chance in the classification result, Kappa coefficient (KC) was used. The coefficient is calculated as follows (Stefman 1996):

$$KC = \frac{N\sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r}(x_{i+} \times x_{+i})}{N^2 - \sum_{i=1}^{r}(x_{i+} \times x_{+1})} \qquad (1)$$

where

r = number of row in the error matrix

x_{ii} = number of observation in row *i* and column *i* (on the major diagonal)

x_{i+} = total observation in row *i*

x_{+i} = total observation in column *i*

N = total number of observations included in matrix

Classified Data	Reference Data F	Reference Data W	Reference Data U	Row Total
F	28	14	15	57
W	1	15	5	21
U	1	1	20	22
Column Total	30	30	40	100

Sum of the major diagonal = 63

Overall Accuracy = 63/100 = 63%

Producer's Accuracy

F = 28/30 = 93%
W = 15/30 = 50%
U = 20/40 = 50%

User's Accuracy

F = 28/57 = 49%
W = 15/21 = 71%
U = 20/22 = 91%

Figure 3.2 Accuracy assessment of an error matrix (Story & Congalton 1986)

In Objective 2 (i.e. the projection of future geographic distribution of peanut crops), the data acquisition consists of three datasets: (1) the peanut developmental threshold on temperature and soil moisture from various academic articles; (2) the global geographical distribution data of peanut crops from the Global Biodiversity Information Facility (GBIF) and the Atlas of Living Australia (ALA); and (3) the historical and Global Climate Models (GCMs) of CSIRO-Mk3.0 and MIROC-H climate data from CliMond database. One of Species Distribution Models (SDMs), CLIMEX, was used in modelling the future geographic distribution of peanut crops in Australia for 2030, 2050, 2070, and 2100. The modelling process started by iteratively fitting the CLIMEX parameters for peanut crops using the developmental threshold and global geographical distribution data. The resulting model was then validated against independent data of the global geographic distribution of peanut crops. Once the model was validated, it was used to project the future geographic distribution of peanut crops in Australia.

Initially, 23 GCMs were analysed based on three selection criteria (Kriticos et al. 2012): (1) the ability to provide climate data needed in calculating the input data for CLIMEX, as well as the extended list of 35 Bioclim variables. The climate data consists of monthly averages of daily maximum and minimum temperatures, precipitation, mean sea level pressure, and specific humidity; (2) having a relatively smaller-horizontal grid spacing; and (3) the ability to perform well compared to other GCMs in representing basic aspects of the observed climate at a regional scale. Three GCMs fulfilled this criteria, namely CSIRO-Mk3.0 (CSIRO, Australia), NCAR-CCSM (National Centre for Atmospheric Research, USA), and MIROC-H (Centre for Climate Research, Japan). However, NCAR-CCSM produced some concerning errors in arid regions; thus it was eliminated. Widely recognised and more popular GCMs should be used in employing Species Distribution Models (SDMs) (Olfert et al. 2016). CSIRO-Mk3.0 and MIROC-H GCMs have been used widely in modelling variety of species distributions, including those using CLIMEX model. Both GCMs were used in the distribution studies of tomato (Silva et al. 2017), date palm (ShabaniKumar, et al. 2015), oil palm (Paterson et al. 2015), cotton and wheat (Shabani & Kotey 2015), common bean (Ramirez-Cabral et al. 2016), *Melanoplus sanguinipes* (Fabricius) (Olfert et al. 2011), and *Fusarium oxysporum* f. spp. (Shabani, Kumar & Esmaeili 2014).

The data acquisition for Objective 3 (i.e. the projection of future geographic distribution of aflatoxin and the identification of high risk areas of aflatoxin in the future geographic distribution of peanut crops) is similar with Objective 2. It consists of the aflatoxin developmental threshold on temperature and soil moisture, and the global geographic distribution data of aflatoxin incidence. These two datasets were retrieved from various academic articles. It also included the historical and GCMs of CSIRO-Mk3.0 and MIROC-H climate data from the CliMond database. The CLIMEX model was also used in modelling the future distribution of aflatoxin in Australia for 2030, 2050, 2070, and 2100. The processes in developing the model followed similar steps to those described in modelling the future geographic distribution of peanut crops. It started with fitting the CLIMEX parameter values, and was then validated against independent data. Once the model was developed, it was used to project future geographic distribution of aflatoxin. The projection results of future aflatoxin distribution were then overlaid with the projection results of future peanut crop distribution (Objective 2) to identify the high risk areas of aflatoxin incidence in the future peanut crop distribution.

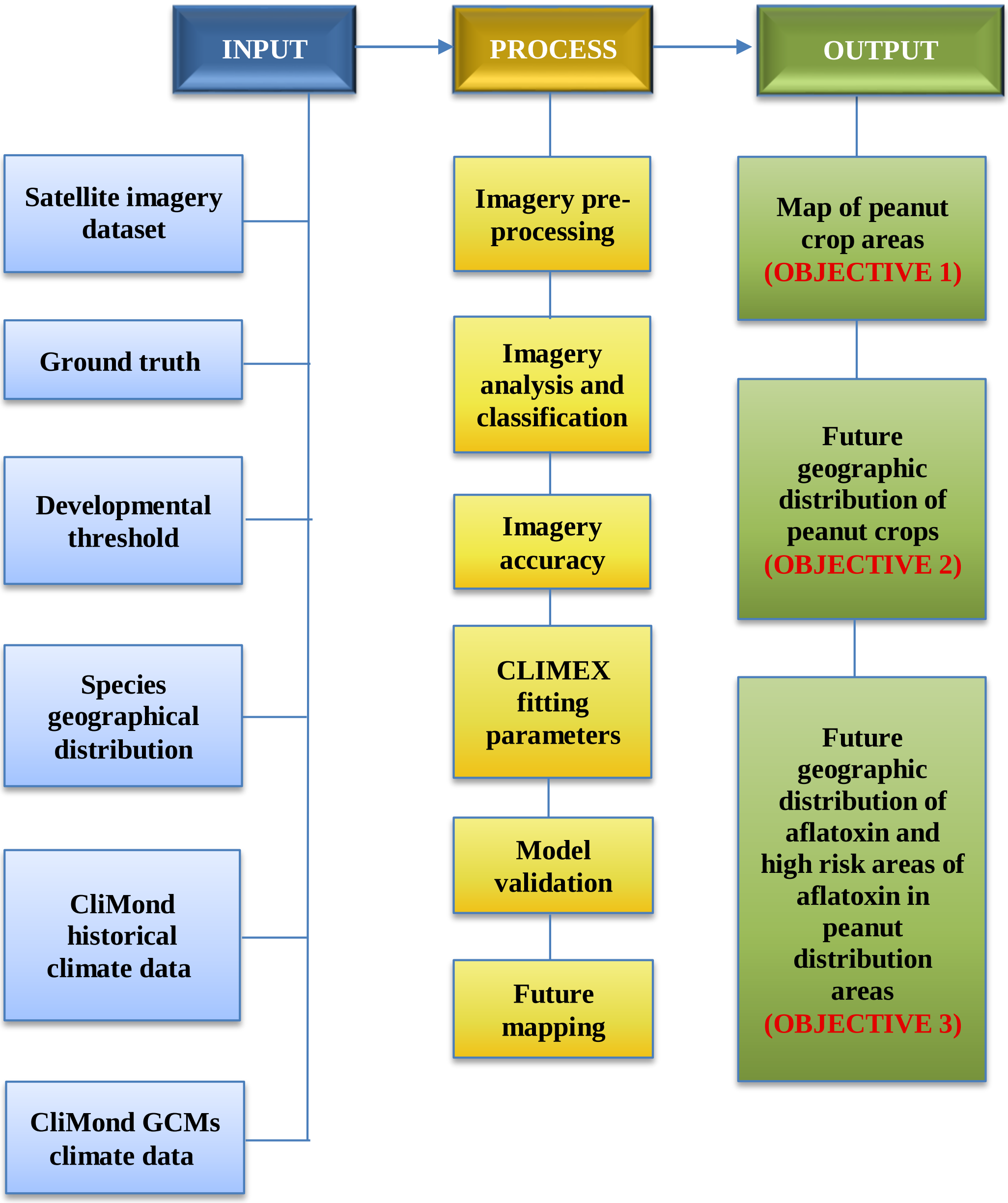

Figure 3.3 The input-process-output model of the study.

Table 3.1 Types of data collected for the study.

Dataset	Description	Acquisition year/period
1. PROBA-V imagery	End-user product (Level 3) of S1TOC NDVI with spatial resolution of 100 m.	3 June 2015 to 28 June 2016
2. Landsat 8 imagery	It is used as a guidance in determining region of interest (ROI) with a spatial resolution of 30 m.	25 March 2016
3. Google Earth	It is used as a guidance in determining region of interest (ROI) with a spatial resolution of 15 m.	March 2015
4. Ground truth	A field survey of various locations throughout the study area to collect training areas or ROI	March 2016
5. Developmental threshold of peanut crops	Developmental threshold on temperature and soil moisture from various academic articles.	July 2017
6. Developmental threshold of aflatoxin	Developmental threshold on temperature and soil moisture from various academic articles.	May - June 2018
7. Global geographical distribution of peanut crops	Dataset retrieved from the Global Biodiversity Information Facility (GBIF) and the Atlas of Living Australia (ALA).	August 2017
8. Global geographical distribution of aflatoxin	Dataset retrieved from various academic articles.	May – June 2018
9. Historical climate data	Dataset retrieved from the CliMond gridded data at 10’ resolution. It comprises of: ➢ Average maximum monthly temperature ➢ Average minimum monthly temperature ➢ Average monthly precipitation ➢ Relative Humidity (RH) measured at 9am ➢ Relative Humidity (RH) measured at 3pm	August 2017 (for running peanut model) July 2018 (for running aflatoxin model)
10. Future climate data of Global Climate Models (GCMs) of CSIRO-Mk3.0 and MIROC-H	Dataset retrieved from the CliMond gridded data at 10’ resolution for 2030, 2050, 2070, and 2100. It comprises of: ➢ Average maximum monthly temperature ➢ Average minimum monthly temperature ➢ Average monthly precipitation ➢ Relative Humidity (RH) measured at 9am ➢ Relative Humidity (RH) measured at 3pm	August 2017 (for running peanut model) July 2018 (for running aflatoxin model)

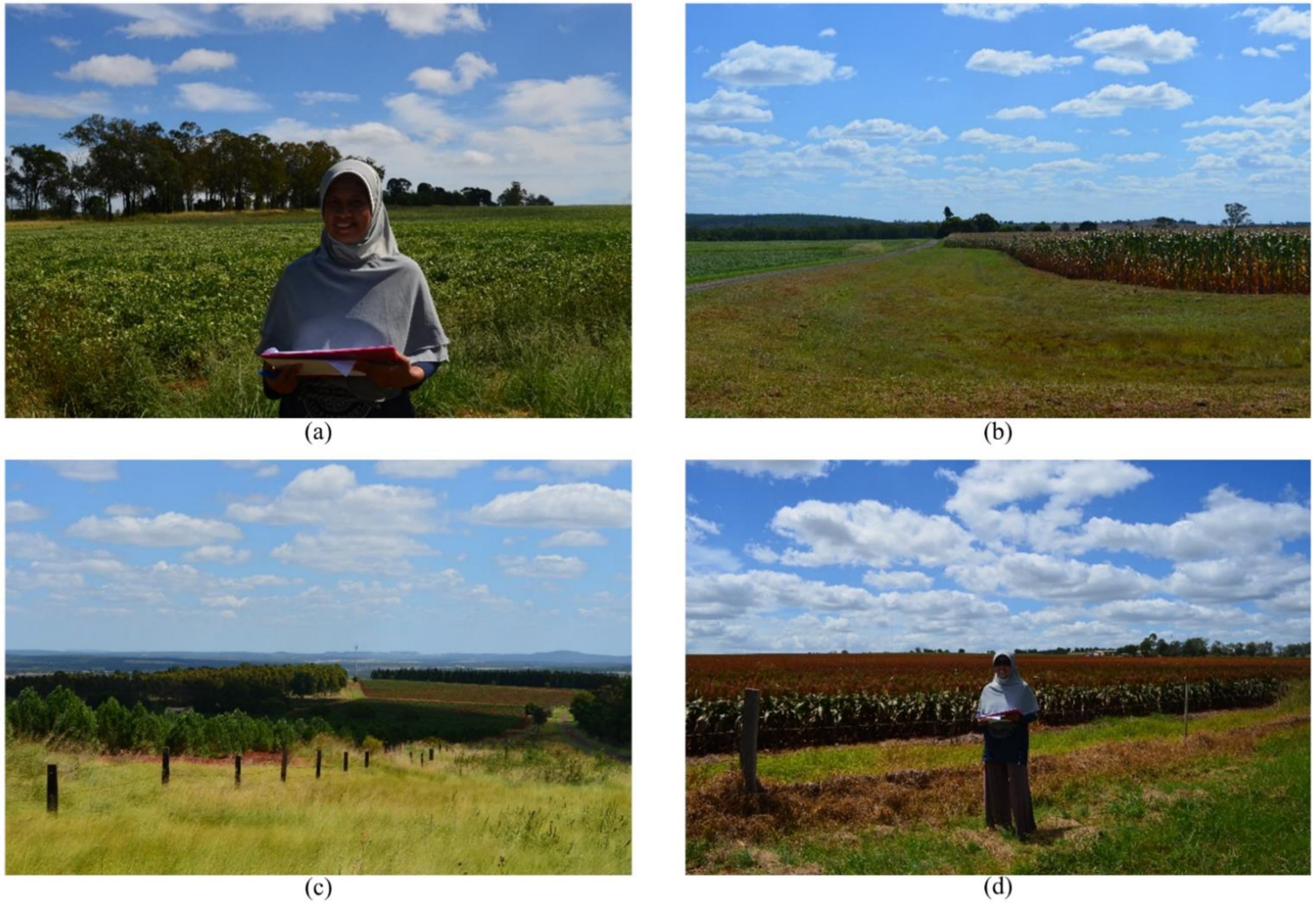

Figure 3.4 Field work documentation for Objective 1 in the South Burnett region: fields of (a) peanut crops, (b) corn and peanut crops, (c) duboisia or corkwood trees, and (d) sorghum.

3.4 Summary

This chapter presents the overall approach and general methods used to achieve the objectives of the study. As the detailed methods are discussed in each of the technical chapters (i.e. **Chapters 4**, **5**, and **6**), this chapter only discusses the methods briefly. In summary, the peanut crop mapping was undertaken by using time-series PROBA-V 100m NDVI imagery in two different analytical approaches: stacking the NDVI dataset; and the phenology dataset of TIMESAT time-series analysis program. The projected future geographic distribution of peanut crops in Australia was carried out by using Species Distribution Models (SDMs) of CLIMEX based on the developmental threshold and global geographic distribution of peanut crops. Similarly, the projected future geographic distribution of aflatoxin in Australia was determined using the CLIMEX model based on the developmental threshold and global geographic distribution of aflatoxin. The identification of high risks of aflatoxin incidence in the distribution of peanut crops was carried out by overlaying the results of future geographic distribution of peanut crops and aflatoxin.

Chapter 4

MAPPING OF PEANUT CROPS USING TIME-SERIES PROBA-V 100M NDVI IMAGERY

4.1 Introduction

As Australia has a high climate variability (Head et al. 2014), the peanut industry in this country has encountered a number of challenges in increasing its productivity and meeting the market demand. Therefore, forecasting peanut production is essential in securing and managing peanut crop's logistics and marketing. One of the key components of the forecasting crop production is crop area mapping (Gallego et al. 2008; Craig & Atkinson 2013). However, limited studies are to be found in the literature about mapping areas of peanut crops, including Australia.

Utilising satellite imagery in crop area mapping offers great benefits in terms of providing objective results and reducing time and cost. The advancement and diversity in remote sensing systems have provided opportunities to obtain the maximum benefits of using these technologies. One of the recent earth observation satellite systems, namely Project for On-Board Autonomy Vegetation (PROBA-V) (Wolters et al. 2017), has the advantage of increased spatial and temporal resolutions relative to other systems like MODIS. This satellite specialised in monitoring global vegetation (Dierckx et al. 2014), and has been applied successfully in several studies around the world. Therefore, examining the use of time-series PROBA-V imagery in mapping peanut crops over regional areas in Australia will be important in providing information about the area estimation of peanut crops.

This chapter addressed the issue of using time-series satellite imagery in mapping peanut crops. The primary aim of this study was to assess the effectiveness of time-series PROBA-V 100m NDVI imagery for peanut crop mapping in the South Burnett region of Queensland, Australia. The following are the specific objectives: 1) to map peanut crops using PROBA-V 100m NDVI images and test the value of crop phenology as an alternative to traditional approach; and 2) to determine the most appropriate classification method(s) in mapping peanut crops in the study area.

This chapter addressed this issue by using time-series PROBA-V NDVI imagery in mapping peanut crops. The primary aim of this study was to assess the effectiveness of time-series PROBA-V 100m NDVI imagery for peanut crop mapping in the South Burnett region of Queensland, Australia. The following are the specific objectives: 1) to map peanut crops using PROBA-V 100m NDVI images and test the value of crop phenology as an alternative to traditional approach; and 2) to determine the most appropriate classification method(s) in mapping peanut crops in the study area.

This chapter is organised into six sections. Section 1 explains the objectives of the chapter. Section 2 presents the literature review on the benefits of peanut crop mapping, the utilisation and benefits of using satellite imagery in crop mapping, the analysis techniques of time-series imagery, and the research gap of the study. Section 3 describes the methods that were used to achieve the objectives of this study. Section 4 presents the results of this study in mapping peanut crops and Section 5 provides the discussion and interpretation of the results. Lastly, the chapter ends with Section 6 which concludes the new knowledge achieved in this study. This chapter has been published in the *Journal of Applied Remote Sensing* (Haerani et al. 2018) with some reformatting done to suit the format of the Thesis.

This study contributes novel knowledge on the application of a relatively finer (100m) remote sensing data product, including the assessment of multi-temporal data analysis techniques, to peanut crop mapping and monitoring. This is particularly true for mapping crops during the summer season where cloud cover is a major issue.

4.2 The benefit of peanut crop mapping by using satellite imagery

Peanut or groundnut (*Arachis hypogaea L.*) is one of the most important legume crops, as it is an important source of protein and oil (Adomou et al. 2005), and it has 26% protein higher than eggs, dairy products, meat, and fish (DPIF 2007). Generally, peanut-growing countries use their production output to meet their domestic market (DPIF 2007). In Australia, peanut production is about 40,000 tonnes per year, which is less than 0.2% of the world's peanut production. The crop area planted in Australia is about 15,000 hectares, and more than 90% is located in Queensland (Wright et al. 2017). In Queensland, the peanut industry contributed to gross value production of 15.2 million dollars in 2014/2015 (QGSO 2016). In general, Australian peanut production can meet domestic demand, except when a severe drought occurs. However, efforts have been made to develop and supply an export market (DPIF 2007). Therefore, there is a need to increase the industry's capabilities in producing peanut using more effective and efficient methods to meet production demands and profitability.

Crop area estimation and crop yield estimation are the two main components of crop production (Gallego et al. 2008; Craig & Atkinson 2013). Compared to crop area estimation, more studies have been conducted on crop yield estimation (Craig & Atkinson 2013; Iizumi & Ramankutty 2015). For years, crop area estimation has been collected by censuses which is accurate but expensive and time consuming, or by samples which is cheap but not always accurate (Craig & Atkinson 2013). Remote sensing offers great help in crop area estimation by providing opportunities to increase the accuracy of the estimate and to reduce associated time and cost of mapping. It has distinct benefits pertaining to rapid objective assessment and longitudinal assessment, i.e. capturing changes over time at the same area (Srivastava 2015). Utilising remote sensing may allow crop area estimates to be conducted several months before harvest, including in the early season. This will be beneficial in making decisions such as supply, staff requirements, and import needs (Robson et al. 2007). However, studies on peanut crop mapping using satellite imagery are limited.

Schultz et al. (2015) studied crop mapping of several crops, including peanut, in a sub-tropical region, Brazil, by using Landsat imagery and employing a combination of segmentation and Random Forest classification algorithm. It was found that using Landsat imagery is not enough to separate peanut and cassava due to similarity in spectral behaviour and the high variabilities within the class. In Australia, Robson et al. (2007) employed a single-date high resolution QuickBird imagery in one area of the South Burnett to identify spatial variability in peanut fields. This study also mapped peanut crops within the area with accurate results. However, this study was conducted in small areas (64 km^2) and used a high spatial resolution satellite imagery. In Senegal, a study on peanut crop yield estimation has been done in a peanut growing region (Peanut Basin) (Knudby 2004), but peanut crop area mapping has not been conducted.

Crop mapping using satellite imagery can be done by using multispectral, Radar, and hyperspectral sensors. Having many narrow spectral bands, hyperspectral satellite data provides the opportunity to collect more detailed spectral information than the few broad spectral bands of multispectral sensors (Im & Jensen 2008). Therefore, hyperspectral data can adequately discriminate crops' properties and can perform well in crop mapping (Whiting et al. 2006). Nevertheless, fewer hyperspectral sensors are mounted in satellites (i.e. Hyperion EO-1) (Vorovencii 2009) which results in limited data availability. In regard to multispectral sensors, it is often difficult to classify different crop types using a single image (Alganci et al. 2013), since crops frequently demonstrate very similar spectral behaviour (BeyerJarmer, et al. 2015). However, different physiological growth phases of each crop exhibit different spectral behaviour, thus the use of multispectral time-series imagery provides an opportunity to capture these temporal differences (BeyerJarmer, et al. 2015). This intra-annual multispectral time-series imagery can produce average phenology of individual land cover types (Gómez et al. 2016), which is an indirect estimation of physiological crop growth phases (Gao et al. 2017). As a result, crops with similar spectral behaviour can be classified easily using this time-series data (BeyerJarmer, et al. 2015). In a study of crop classification in Kansas, USA, the VI time-series profile of a crop was found to be similar with its phenology attributes, such as timing of green-up, peak greenness, and senescence (Wardlow et al. 2007).

Several mathematical functions have been used to smooth time-series vegetation indices from various satellite sensors (Atkinson et al. 2012; Atzberger 2013). These include principal component analysis (PCA) (Hirosawa et al. 1996), harmonic analysis (Jakubauskas et al. 2001), Harmonic Analysis of Time-series (HANTS) (Potgieter et al. 2007), Savitzky-Golay filter (Chen et al. 2004), double logistic function fitting (Zhang et al. 2003), and asymmetric Gaussian function fitting (Jönsson & Eklundh 2002). Some tools have been developed to analyse time-series data, such as TIMESAT, TIMESTATS, TiSeG, BFAST, and STARFM (Foerster et al. 2014). TIMESAT is a free software program that uses a curve fitting approach to smooth noisy time-series imagery to generate phenological parameters and map them (Jönsson & Eklundh 2002, 2004; Eklundh & Jönsson 2015b). Using phenological parameters of MODIS Enhanced Vegetation Index (EVI) imagery produced from the TIMESAT program, Yang et al. (2011) successfully mapped paddy rice in China. However, the use of a TIMESAT program in mapping land use and land cover (LULC) in a semi-humid tropical region of Zimbabwe using time-series MODIS has failed to distinguish rainfed agriculture from grassland (Hentze et al. 2016).

Mapping agricultural land use requires the consideration of spatial resolution, temporal resolution, coverage, availability/quality (such as cloud cover), imagery costs, and classification methods (Sun et al. 2012). The definition of spatial resolution of satellite imagery can be divided into four (Navulur 2006): (1) coarse or low resolution imagery (ground sampling distance (GSD) ≥ 30m); (2) medium resolution (GSD between 2 – 30m); (3) high resolution imagery (GSD in the range of 0.5 – 2.0m); and (4) very high resolution (GSD < 0.5m). Fundamentally, the trade-off in mapping crops is focused on temporal versus spatial resolutions (Khan et al. 2016).

Higher resolution (high spatial) data provides an opportunity to capture in-depth local information (Sun et al. 2012; Petitjean et al. 2014), which is appropriate to map cropping areas on a small scale (Xie et al. 2008). The use of decametric sensors such as Landsat (30m), ASTER (15m), Sentinel-2 (10m), and Resourcesat-2 (5.8m), will be useful in mapping crop areas with paddocks of a few hectares (Schultz et al. 2015). However, most of these sensors usually have insufficient temporal resolution to generate crop phenology stages (Pan et al. 2015), e.g. Landsat and ASTER have a temporal resolution of 16 days. Another disadvantage of using these sensors is the possibility of having noise, due to cloud cover (Zhang et al. 2016). Coarse resolution (low spatial) sensors, e.g. MODIS (250m), AVHRR (1km), and SPOT VEGETATION (1km), have become the main sources of data for mapping large areas, for example in the United States (Ozdogan & Woodcock 2006). These sensors typically have wider swaths which lead to high temporal resolution data (Khan et al. 2016); for example, MODIS and AVHRR have a resolution of 1-2 days and <1 day, respectively. Nevertheless, in mapping small paddock sizes, inaccurate estimates may result from these sensors due to their coarse spatial resolution (Khan et al. 2016). To compensate for the trade-off, some studies composite imagery data using different sensors; for example Liu et al. (2014) incorporated high and low spatial resolution image in their crop mapping study. Nevertheless, with their frequent temporal resolution, coarse resolution sensors are more feasible to get cloud-free imagery and are suitable for gaining time-series data (Sun et al. 2012; Petitjean et al. 2014), which can facilitate the derivation of phenology phases (Pan et al. 2015).

Many agricultural fields are characterised by small farm size (i.e. less than 1 ha). Thus, to accurately map crops, a medium to high spatial resolution imagery, with a pixel size of 5 to 100m, is required (Liu et al. 2014). A recent earth observation satellite, namely Project for On-Board Autonomy Vegetation (PROBA-V), could satisfy this requirement, since it has a spatial resolution of 100m. Moreover, derived Normalized Difference Vegetation Index (NDVI) products are also available from PROBA-V (Wolters et al. 2017) which could be very useful in mapping crops. This satellite has finer spatial resolution than the commonly used coarse resolution satellite data, i.e. MODIS, which has 250m resolution, although both satellites have similar temporal resolution, i.e. daily (PROBA-V) and 1-2 days (MODIS).

The increasing resolution of PROBA-V can potentially generate better accuracy, since the number of spectral mixtures can be eliminated (Mingwei et al. 2008). For instance, Zhang et al. (2016) compared the use of MODIS and PROBA-V to map crops in complex cropping systems in Hongxing, China, and revealed that PROBA-V generated better accuracy (73.29%), compared to MODIS (46.81%). In addition, crop mapping studies using PROBA-V imagery are limited since this remote sensing satellite was launched in recent years (Durgun et al. 2016). For instance, Lambert et al. (2016) have recently mapped cropland in Sahelian and Sudanian regions using 100m PROBA-V time-series. Moreover, the successful study of crop area mapping with PROBA-V in Belgium, Russia, Ukraine, and Brazil provides the possibility of using this remote sensing system to map crop areas around different regions in the world (Durgun et al. 2016). Thus, the use of time-series PROBA-V satellite imagery in mapping peanut crops over regional areas in Australia has been examined in this study.

4.3 Materials and methods

4.3.1 Study area

The region selected for this study is located in the South Burnett region, Queensland, Australia, covering an area of 8,381.70 km^2 (Figure 4.1) (ABS 2018).

The climate in the study site is temperate (BoM 2016), with the average mean maximum temperature between 19.4°C in July and 30.8°C in January, while the average minimum temperature is between 3.4°C in July and 18.0°C in January (South Burnett Regional Council 2014). It falls within the summer rainfall zones (BoM 2016), with mean annual rainfall of 662.6 mm, while the wettest month (108.1 mm) is recorded in December (South Burnett Regional Council 2014). These temperature and rainfall ranges are suited for peanut crops, i.e. 25-30°C during vegetative growth and 22-24°C during generative growth, with 500-600 mm well distributed rainfall (DPIF 2007). The region has a soil dominated by red ferrosols, which is suitable for growing peanut crops (Sorby & Reid 2001). Summer and winter crops, such as peanuts, navy bean, wheat, and sorghum, are often planted in this region (South Burnett Regional Council 2016). These summer crops are typically sowed in September to early January, and usually harvested in February to May (DAF 2014).

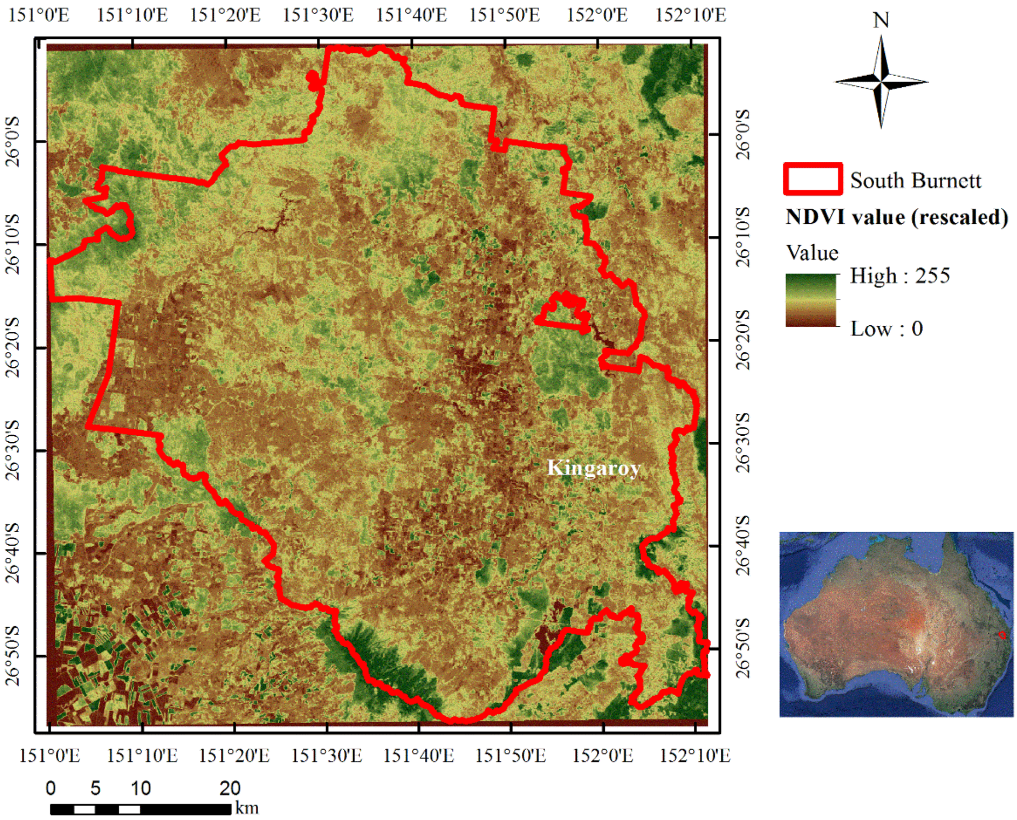

Figure 4.1 Study area in the South Burnett region, Queensland.

4.3.2 Image data acquisition and pre-processing

PROBA-V offers an intermediary spatial resolution between medium spatial resolution imagery, such as Landsat and HJ-1 A/B (30 m resolution), and low spatial resolution datasets, such as MODIS, SPOT-Vegetation, and AVHRR (250 m – 1 km resolution) (Zhang et al. 2016). It was specifically designed as a 'gap-filler mission' between SPOT-VEGETATION which was terminated in 2014 and ESA Sentinel-3 satellite, to ensure the continuation of vegetation time-series data (Francois et al. 2014; VITO 2016). The end-user products include daily synthesis (S1) collections which are available for 100m, 300m, and 1km resolution, and 5-day synthesis (S5) with 100m resolution top-of-atmosphere (TOA) reflectance. In addition, top-of-canopy (TOC) (atmospherically corrected) products are also available, including a 10-day synthesis (S10) with 300m and 1 km resolution. NDVI collections are available for S1 and S5 products with 100m resolution, as well as S10 datasets with 300m and 1km resolution TOC.

In this study, PROBA-V S1TOC (daily synthesis atmospherically corrected) 100m NDVI products were selected in mapping peanut crops (Table 4.1). Since the growing season of peanut crops in this region is between October and June, images were collected during the period of June 2015 to June 2016 to adequately cover the entire season. A total of 163 images covering the study area from X33Y10 PROBA-V tile were available. However, only cloud free images were selected and processed for this study, which resulted in 24 images. Out of these 24 images, a total of 15 images were within the peanut growing season. A coverage of one year time-series data was used, since multiple years' data can generate inaccurate phenological features (Jia et al. 2014) and may cause confusion due to land cover changes (Gao et al. 2017). Afterwards, the 24 images were subset into a study area and re-projected into a Universal Transverse Mercator (UTM) projection. Lastly, the original NDVI values for each image were rescaled (0-255) using a linear function to enable software compatibility, better data handling, and data standardisation.

Table 4.1 Summary of imagery used in this study.

Imagery	Characteristics
Product	End-user product (Level 3) of S1TOC NDVI
Spatial Resolution	100m
Swath	2285 km
Global coverage	5 days
Date/Period	22 June 2015; 1, 19, and 28 July 2015; 15 August 2015; 2, 16, 20, and 25 September 2015; 4 and 13 October 2015; 18, 23, and 27 November 2015; 6, 11, and 15 December 2015; 7 January 2016; 26 February 2016; 20 April 2016; 13, 17, and 26 May 2016; and 9 June 2016.
Number of imagery	24 cloud free imagery
Tile	X33Y10
File format	HDF5

4.3.3 Field data gathering

In March 2016, a field survey of various locations throughout the study area was conducted to collect training areas or Region of Interest (ROI) for classification and accuracy assessment. Using a Global Positioning System (GPS), the reference data collection was conducted by capturing crops or land feature types (i.e. peanut, corn, sorghum, mung bean, woody vegetation, pasture, and water.) on the main, secondary and farm roads. It was done by randomly selecting large paddocks, water bodies, pasture lands, and forest vegetation areas to avoid mixed pixels; and ensuring geographical representativeness of the reference data. In addition, high resolution image from Landsat 8 satellite captured on 25 March 2016 and from Google Earth captured in March 2015 were also used to determine ROIs by using visual interpretation techniques (de Souza et al. 2015). Typical appearances of crop classes examined in this study taken from TIMESAT output of crop phenology, a Landsat image, and field work photos were illustrated in Figure 4.2. Based on study area observation during the field work, there were eight (8) classes selected for this study with a total number of reference data of 1,690 pixels (Table 4.2). The original pixel size of 100 × 100m was retained for the training samples.

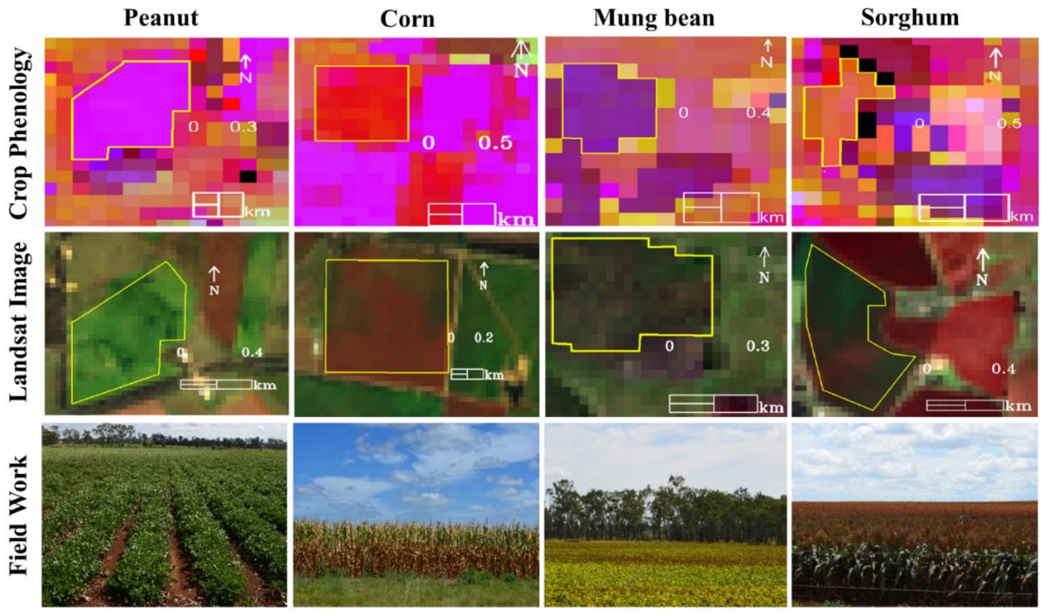

Figure 4.2 Example image of peanut, corn, mung bean, and sorghum classes were taken from crop phenology layers of TIMESAT program, a Landsat image, and field work photos. The yellow lines indicate the boundary of paddocks for each class. The Landsat image, particularly corn, may not represent the actual cover due to the date of data captured (i.e. during harvesting time).

Table 4.2 Total number of reference data for each class.

Class	Training Data
Peanut	263
Mung bean	63
Corn	198
Sorghum	63
Pasture	368
Bare soil	161
Woody vegetation	412
Water	162
Total	1,690

4.3.4 Extracting time-series profiles and separability test

The time-series profiles of NDVI datasets were generated and displayed by extracting the average spectral value of selected sample pixels from each date/layer of 24 NDVI image data for each class. Field data and high-resolution image from Google Earth were used as references in determining pixel samples, where only 'pure pixels' were selected. Pure pixels ensure that the chosen pixels were indeed the pixels of the representative class. In this case, pixels in the middle of paddock or class area were chosen. Spectral profiles were used to observe the reflectance pattern and differences between classes, including the examination of temporal separability. Especially for crop classes, such profiles were also used to examine the ability of PROBA-V NDVI imagery in presenting crop phenology cycles and ageing (Arvor et al. 2011). In addition, a separability test, namely Jeffries-Matusita (JM) distance, was performed in order to avoid or reduce potential misclassification due to using similar classes in classification (Richards 2006). BeyerJarmer, et al. (2015) have demonstrated the effectiveness of JM as a pre-testing method in finding the best layer stack combination for spectral separation of different land cover classes. This test can be used to determine the spectral distance between any pair of layers before conducting classification. If the distance is insignificant, the layers can be eliminated from the classification to ensure the best result (Gambarova et al. 2010). JM distance measures the separability between a pair of two classes based on the average distance between their spectral means. Its output value ranges from 0 to 2, where a good separability is indicated by a larger value (Wardlow et al. 2007). The JM distance between a pair of probability distributions is calculated as

$$J_{ij} = \int_x \left[\sqrt{p(x/\omega_i)} - \sqrt{p\left(x/\omega_j\right)}\right]^2 dx \quad (1)$$

In this study, x represents the span of NDVI time-series values, while i and j represent crop and/or other land cover classes under consideration. In a normally distributed assumption, equation (1) becomes

$$J_{ij} = 2(1 - e^{-B}) \quad (2)$$

where

$$B = 1/8\, D^2 + 1/2\, ln\left[(|\sum i + \sum j|2)/\left(|\sum i|^{1/2}|\sum j|^{1/2}\right)\right] \quad (3)$$

and $D^2 = \left(m_i - m_j\right)^t [(\sum i + \sum j)/2]^{-1}\left(m_i - m_j\right)$ (4)

4.3.5 Time-series image analysis

PROBA-V NDVI time-series imagery was used to map peanut crops, other crops, and additional land cover classes. Two datasets were analysed in this study, i.e. stack of 24 PROBA-V NDVI time-series imagery and stack of phenological parameters imagery generated from the time-series using a TIMESAT software program (Jönsson & Eklundh 2002, 2004). TIMESAT analyses time-series data in relation to its seasonality, such as phenology and temporal development (Eklundh & Jönsson 2015b). It is a user friendly software with advanced algorithms (Jayawardhana & Chathurange 2015). The program generates eleven phenological parameters of a growing season, such as start and end seasons (Table 4.3 and Figure 4.4) (Eklundh & Jönsson 2015b). Figure 4.3 presented the entire workflow to map these land features.

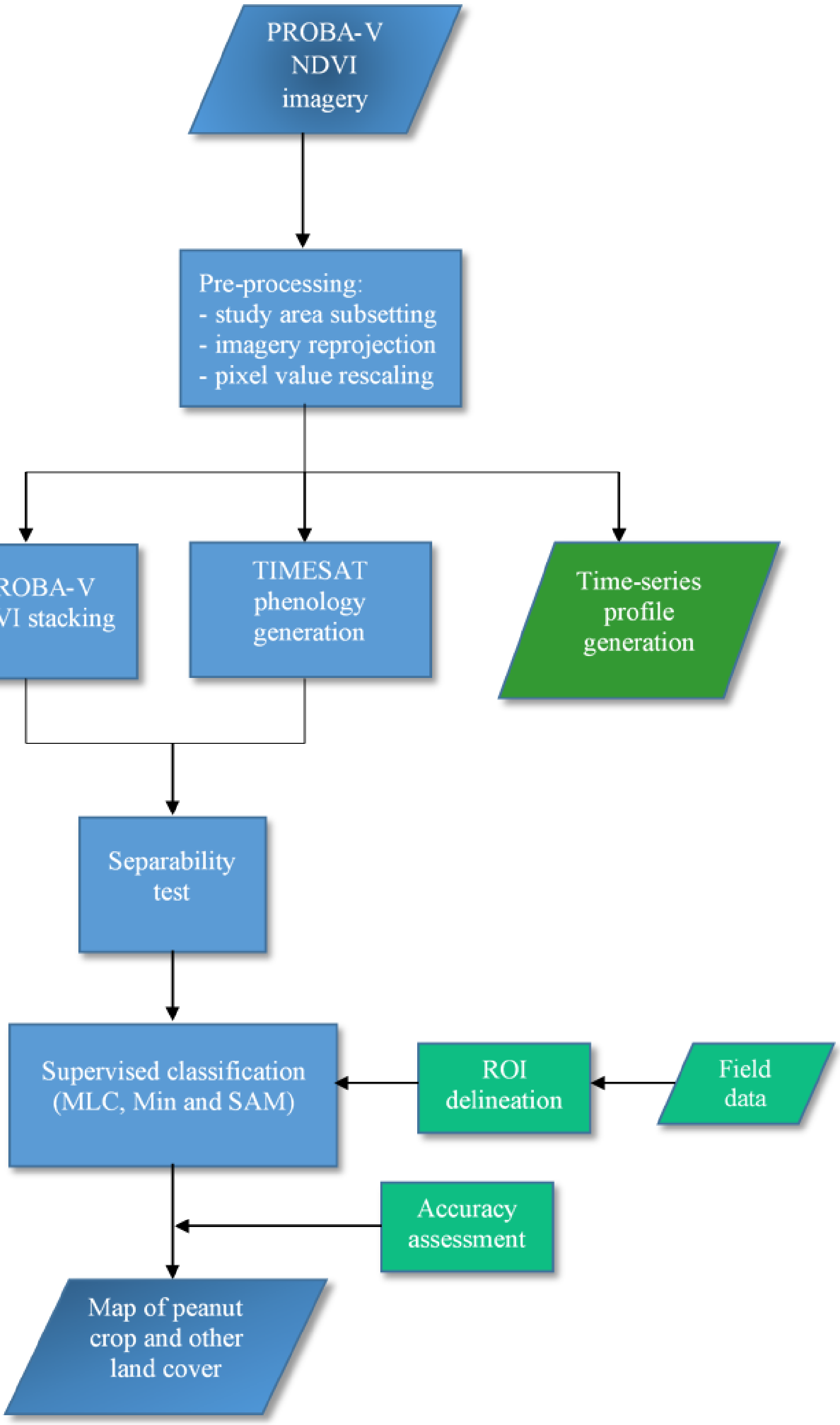

Figure 4.3 Flow chart of data and key processing tasks employed in the study.

Table 4.3 Eleven phenological parameters of the TIMESAT software program.

Phenological parameters	Label	Description
Start of the season	a	Similar to green-up period
End of the season	b	Harvesting period
Length of the season	c	Growing period
Base value	d	The average of minimum value of left and right of the season
Middle season	e	The mean value of the times, where the left edge has increased to the 80% level and the right edge has decreased to the 80% level
Maximum value	f	Phenology peak where time-series hit its highest data value
Seasonal amplitude	g	The difference between the maximum value and the base level
Left derivative (i.e. rate of increase at the beginning of the season)	-	The ratio of the difference between the left 20% and 80% levels of the fitted function
Right derivative (i.e. rate of decrease at the end of the season)	-	The absolute value of the ratio of the difference between the right 20% and 80% levels of the fitted function
Small integral	h	The area between start and end of the season, and between base value and maximum value
Large integral	h+i	The area under fitting curve, between start and end of the season

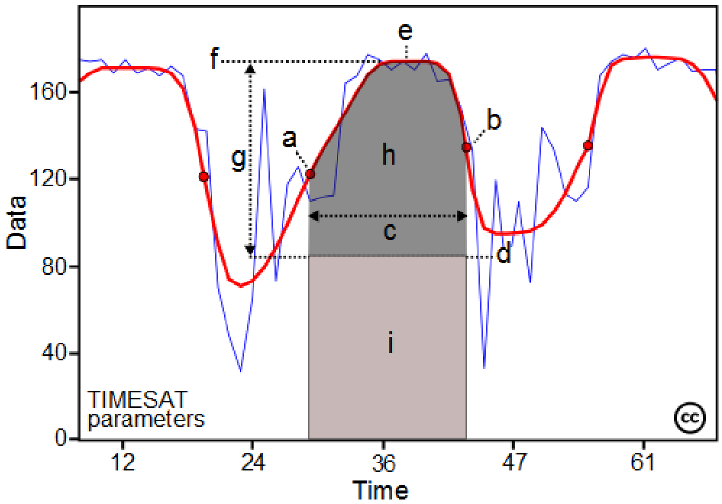

Figure 4.4 Some of the phenological parameters generated from the TIMESAT program: (a) beginning of season, (b) end of season, (c) length of season, (d) base value, (e) time of middle of season, (f) maximum value, (g) amplitude, (h) small integrated value, (h+i) large integrated value. The blue line represents the original time-series data, while the red line represents filtered data (Eklundh & Jönsson 2015b).

The TIMESAT program iteratively fits mathematical functions to smooth noisy time-series data, in which the phenological parameters are extracted from each imagery pixel (Jönsson & Eklundh 2015). Theoretically, as long as the growing season peaks in the middle of a year, the phenological parameters could be generated from each year of time-series data. However, TIMESAT is not based on this. In TIMESAT, for a time-series spanning n years, the number of years of phenological parameters produced will be $n - 1$ center-most seasons (Eklundh & Jönsson 2015b). Therefore, for one year time-series data, i.e. the case for our study, Eklundh and Jönsson (2015b) recommend the creation of artificial time-series data for the dataset of first and third years, since the phenological parameters will be calculated from the centre of time-series data, i.e. our original year data. The artificial time-series data were created by duplicating our one year time-series data.

Three fitting methods to the upper envelope of time-series data are available in the TIMESAT program, i.e. Savitzky-Golay filter, asymmetric Gaussian, and double logistic (Jönsson & Eklundh 2004). In this study, the asymmetric Gaussian (local polynomial function) was used, since this method is less sensitive to time-series noise and provides better results for the season start and season end parameters (Jönsson & Eklundh 2004). The TIMESAT program comprises various processing aspects, such as choosing the best fitting method and fine-tuning the program parameter settings. The parameter settings for running the program in this study were summarised in Table 4.4.

Table 4.4 TIMESAT parameter settings used in this study.

Parameters	Value	Description
Amplitude value	0	0 = include all pixels in the processing.
Spike method	1	To detect and remove outliners and spike. 1 = median filter method.
Spike value	2	To determine the removing degree. Low value will remove more spike and outliners.
Seasonal parameter	0.5	To determine the number of season. Value is between 0 and 1, where 0 = dual seasons and 1 = single season.
Envelope iterations	3	3 = two additional fits. Function fits to approach the upper envelope of time-series imagery.
Adaptation strength	2	To indicate the strength of upper envelope adaptation. Value is a number between 1 and 10.
Start of season method	1	To determine start/end of the season. 1 = amplitude (start/end where the fitted curve reaches a proportion of seasonal amplitude).
Season start	0.2	The proportion of left minimum value.
Season stop	0.2	The proportion of right minimum value.

4.3.6 Image classification and accuracy assessment

Image classification techniques were performed for two data sets used in this study, i.e. stack of PROBA-V NDVI imagery and stack of phenological parameters of PROBA-V NDVI imagery derived from the TIMESAT program. To achieve higher classification accuracy, imagery layers with small discrimination information for class separability were avoided by carrying out data set dimensionality reduction (Arvor et al. 2011). Thus, only parameters which had most useful information to separate eight classified classes were selected in this study. Based on this criteria, only eight phenological layers derived from TIMESAT program were used in this study, namely amplitude, position middle, base value, large integral, left derivative, right derivative, season end, and season length.

In this study, a supervised classification algorithm, i.e. Maximum Likelihood Classification (MLC), was used to map peanut crops, other crops and additional land cover classes using ENVI 5.0 software (Exelis Visual Information Solutions). In previous studies, the classification accuracy produced from MLC was found to be comparable with machine learning algorithms such as Support Vector Machine (SVM) and Random Forest (RF) (Otukei & Blaschke 2010; Beyer, Jarmer, et al. 2015; BeyerJarmer, et al. 2015). To compare the results gained by MLC, this study also used other supervised classification algorithms, namely Minimum Distance Classification (Min) and Spectral Angle Mapper (SAM). In MLC, inadequate training pixel number can produce poor classification results, while the Minimum Distance Classification method can handle limited pixel counts. The reference data of 1,690 pixels were divided into two groups, i.e. training and test samples (Table 4.5). The accuracy assessment of classification results was conducted by using an error matrix to calculate the overall accuracy, Kappa coefficient, producer accuracy (PA) and user accuracy (UA) (Congalton 1991).

Table 4.5 Reference data division into training and test samples.

Samples	The number of pixels	Percentage (%)
Training	1,221	72.25
Test	469	27.75
Total	1,690	100

4.4 Results

4.4.1 Time-series profiles and separability test

Time-series profiles characterised the reflectance pattern of each classified class, which then can be used to observe their differences. The mean value of PROBA-V NDVI time-series during the period 22 June 2015 to 9 June 2016 (Figure 4.5) for each feature class showed distinct profiles, especially between crop and non-crop classes. Non-crop classes, i.e. woody vegetation, bare soil, water, and pasture, showed more even profiles, since these objects tend to be static throughout time. On the other hand, crop classes experienced a dynamic life-cycle growth, starting from planting, peak season, and senescence, which was then reflected in their time-series profiles. The crop profiles for a curved shape which started from a planting season, then increased until reaching a maximum reflectance value (peak), and finally decreased to a period of senescence where the crops were harvested. In addition, each crop grows in a specific period depending on its characteristics, climate and water availability.

As a result, different crops may have different or similar time-series profiles. Among all crops, sorghum showed a distinct time-series profile, although it has similar start of the season (planting time) and end of the season (harvesting time) with corn. The other three crops, namely peanut, corn, and mung bean, showed almost similar profiles, especially in the peak of the season. However, their start of the season is slightly different; peanut, corn, and mung bean started at November 2015, December 2015, and January 2016, respectively. In addition, due to its longer growing period, i.e. 110 to 170 days (16 to 24 weeks) (DPIF 2007), peanut harvesting time was in May 2016. Meanwhile, the harvesting time for corn and mung bean was around April 2016, which is similar with sorghum. Compared to corn and sorghum, the NDVI value of mung bean at the harvesting time is the highest. Meanwhile, among these crops, sorghum produced the lowest NDVI value at the harvesting time. The figure also illustrated that during crop growing seasons, there was a limited number of NDVI imagery. It was also observed that spectral responses outside of the crop growth period, i.e. June to October 2015, tend to be static, indicating that crops were not planted during this time.

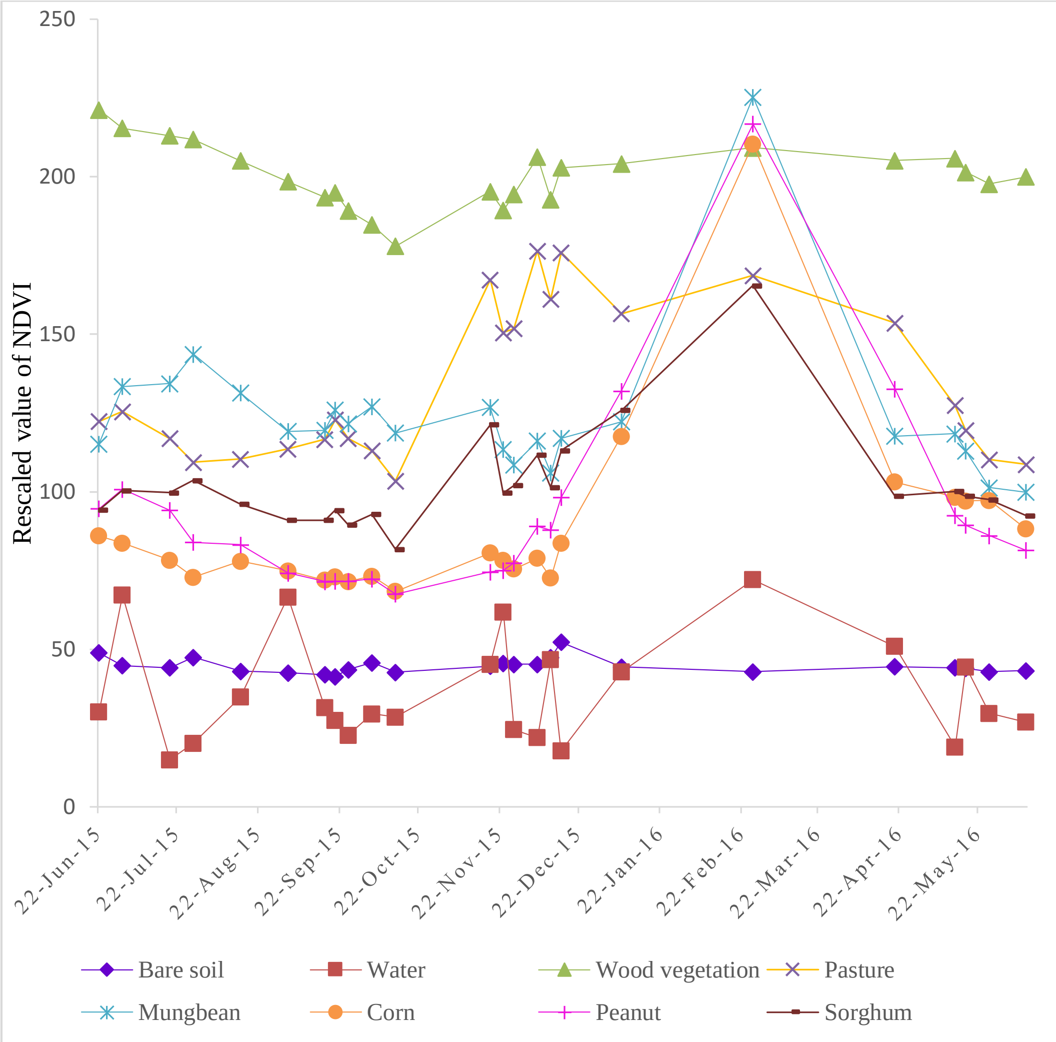

Figure 4.5 Mean NDVI profiles of different crops and land cover classes extracted from PROBA-V NDVI time-series imagery.

Good separability of values among all classes was found for both the 24-layer PROBA-V NDVI imagery and the corresponding phenological parameters. The results of Jeffries-Matusita (JM) distance calculations between class pairs in PROBA-V NDVI imagery were dominated by 2.00 (Table 4.6), which is the highest measure of class separation. This is slightly better than JM distance in phenological parameters in which two class pairs resulted in 1.88 JM (sorghum and pasture) and 1.92 JM (water and bare soil). The dominant JM distance for phenological parameters was 1.99 (Table 4.7).

Table 4.6 Separability of time-series PROBA-V NDVI imagery.

Classes	Peanut	Corn	Mung bean	Sorghum	Woody veg	Pasture	Water	Bare soil
Peanut		1.99	2.00	1.99	2.00	1.99	2.00	2.00
Corn	1.99		2.00	1.99	2.00	1.99	2.00	2.00
Mung bean	2.00	2.00		2.00	2.00	1.99	2.00	2.00
Sorghum	1.99	1.99	2.00		2.00	1.99	2.00	2.00
Woody veg	2.00	2.00	2.00	2.00		1.99	2.00	2.00
Pasture	1.99	1.99	1.99	1.99	1.99		2.00	2.00
Water	2.00	2.00	2.00	2.00	2.00	2.00		2.00
Bare soil	2.00	2.00	2.00	2.00	2.00	2.00	2.00	

Table 4.7 Separability of phenological parameters of PROBA-V NDVI.

Classes	Peanut	Corn	Mung bean	Sorghum	Woody veg	Pasture	Water	Bare soil
Peanut		1.99	1.99	1.99	2.00	1.99	1.99	2.00
Corn	1.99		1.99	1.99	1.99	1.99	1.98	1.99
Mung bean	1.99	1.99		1.98	1.99	1.99	1.99	1.99
Sorghum	1.99	1.99	1.98		1.99	1.88	1.98	1.99
Woody veg	2.00	1.99	1.99	1.99		1.99	1.99	1.99
Pasture	1.99	1.99	1.99	1.88	1.99		1.99	2.00
Water	1.99	1.98	1.99	1.98	1.99	1.99		1.92
Bare soil	2.00	1.99	1.99	1.99	1.99	2.00	1.92	

4.4.2 TIMESAT features

Time-series profiles resulting from image data processing using the TIMESAT program also showed distinctive profiles between crop and non-crop classes (Figure 4.6). The profiles were selected from a sample pixel of each class, which in general represent the group pixel values. Since TIMESAT requires at least three years of time-series data (as previously indicated), one year time-series data of 24 imagery employed in this study were replicated into 72 imagery (the axis in the profiles) as recommended by the software. However, the analysis in this study only focussed on the original time-series data, i.e. the centre data, from 25 to 48.

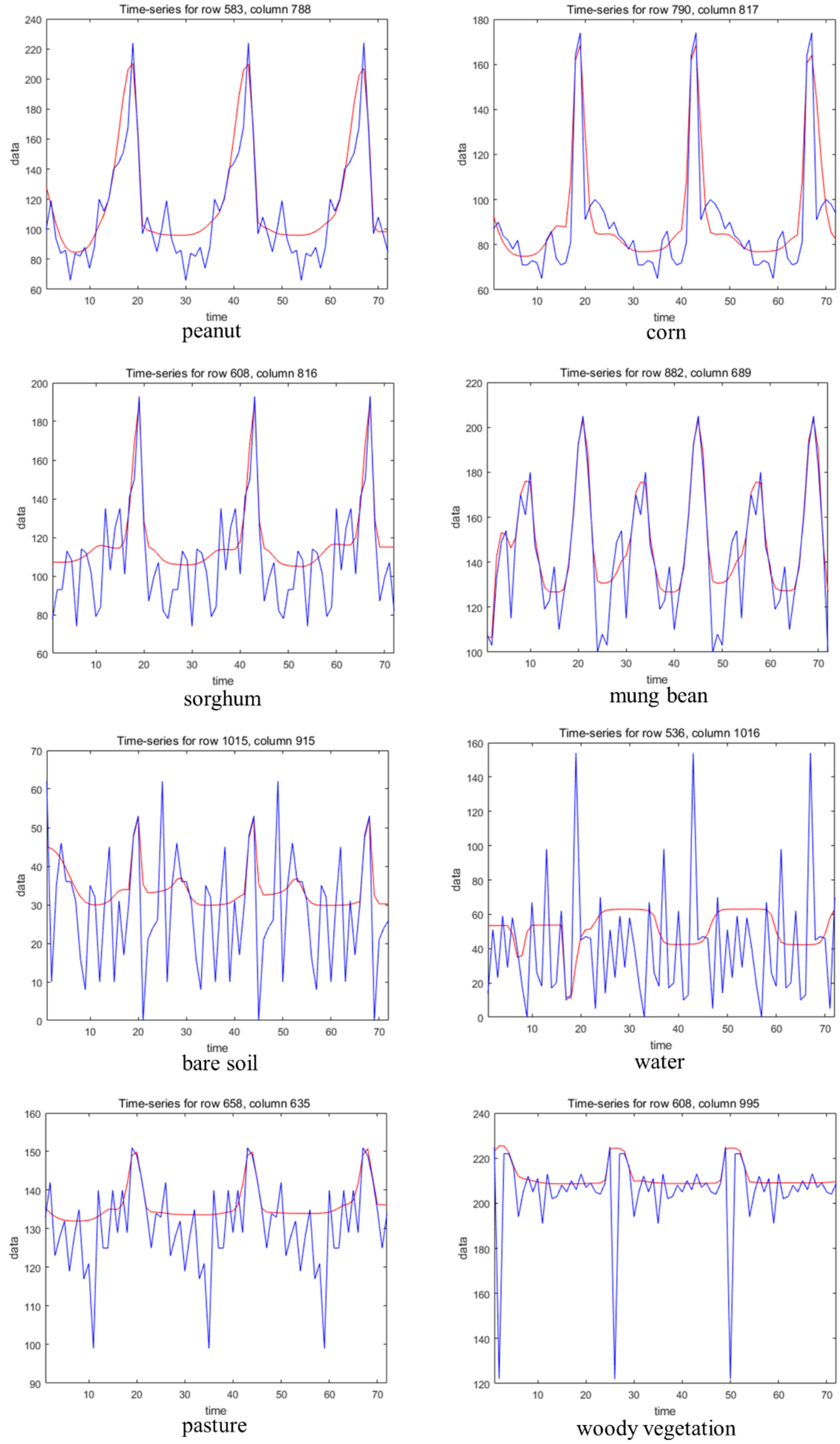

Figure 4.6 Time-series profiles from the TIMESAT program: blue line represents original time-series data, while the red line represents fitted time-series data using asymmetric Gaussian method.

In the time-series profiles from TIMESAT, non-crop classes showed generally constant NDVI values. Bare soil and water had low NDVI values (around 35 and 50, respectively), while pasture and woody vegetation had high NDVI value (around 135 and 210, respectively). Profiles of four crop classes (i.e. peanut, corn, sorghum, and mung bean) represent its phenological phases, which depict the start, peak, and end of seasons. Among all crop classes, peanut showed the longest growing period, while the other three crops presented almost similar length of growing period. The results agree with the crops' growing period. The peanut crop growing period is between 110 to 170 days (DPIF 2007). Meanwhile, the other three crops, i.e. corn, mung bean, and sorghum, are grown in a period of 72 – 100 days (DPI NSW 2007), 90 – 120 days (DFF 2010), and 115 – 140 days (GRDC 2017), respectively.

In the second phase of analysis, the phenological parameters output of PROBA-V NDVI imagery resulted from the TIMESAT program were used to map peanut crops. Two out of eleven phenological parameters, i.e. 'maximum value' and 'season start' failed in performing the separability test, while including the 'small integral' parameter has reduced the classification accuracy. Therefore, only eight phenological parameters were used in the classification process, namely amplitude, position middle, base value, large integral, left derivative, right derivative, season end, and season length (Figure 4.7).

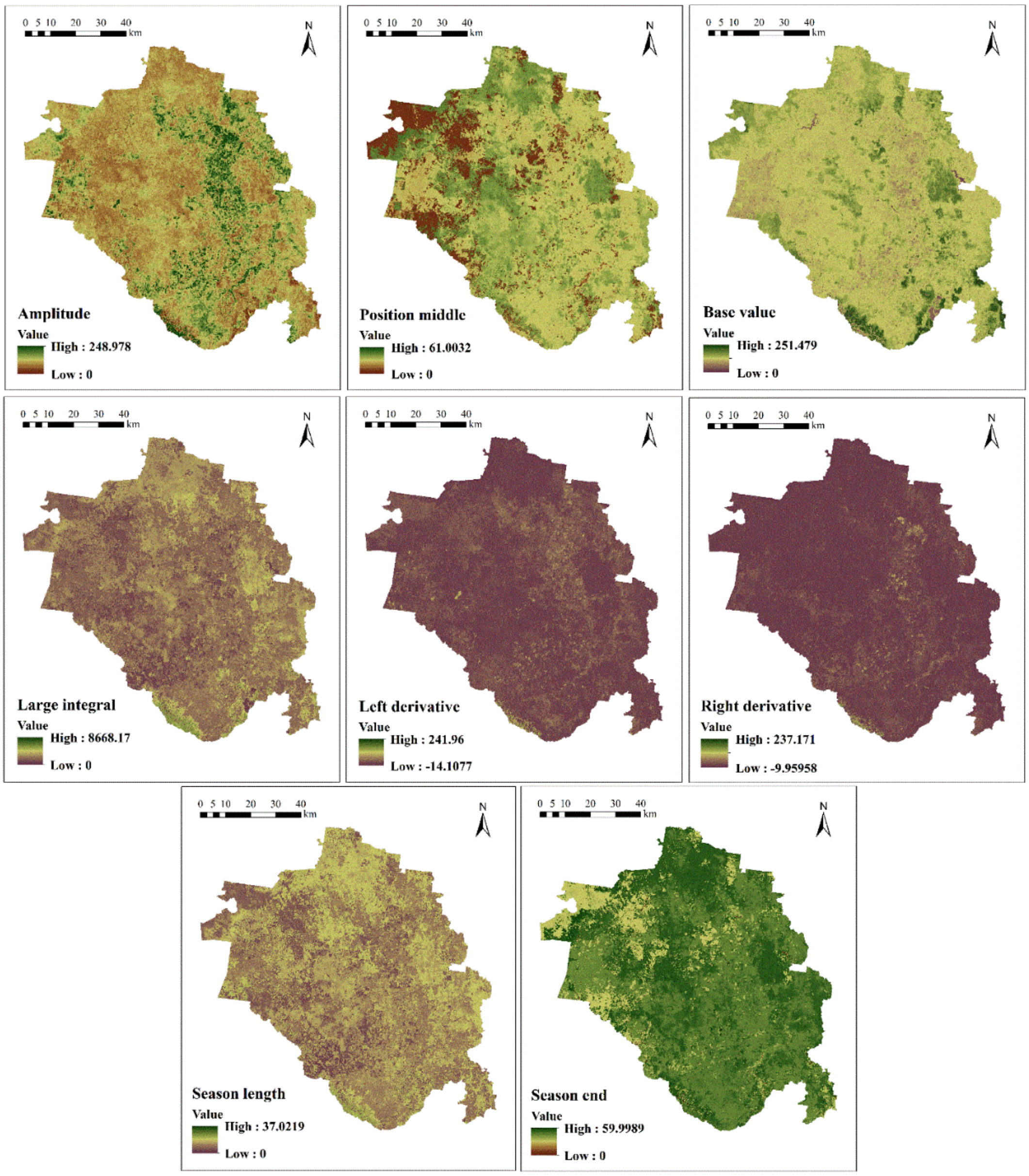

Figure 4.7 Phenological parameters used in mapping peanut crops and other crop/land cover classes.

4.4.3 Classification results

The classification results of Maximum Likelihood Classification (MLC), Minimum Distance Classification (Min), and Spectral Angle Mapper (SAM) for both PROBA-V NDVI imagery and its phenological parameters derived from the TIMESAT program are presented in Figure 4.8. In conducting classifications, the process involved choosing the most suitable parameter for each classification algorithm to achieve the best and the most appropriate classified imagery. Visual analysis through comparison of different land cover classes, i.e. woody vegetation, water, bare soil, and pasture, in classified imagery and Landsat 8 imagery showed similar distribution. Classification results of the MLC algorithm for both NDVI and phenological parameters showed better outcomes than Min and SAM classifier, even though parameter adjustment of these two latter classifiers had been repeatedly tested several times.

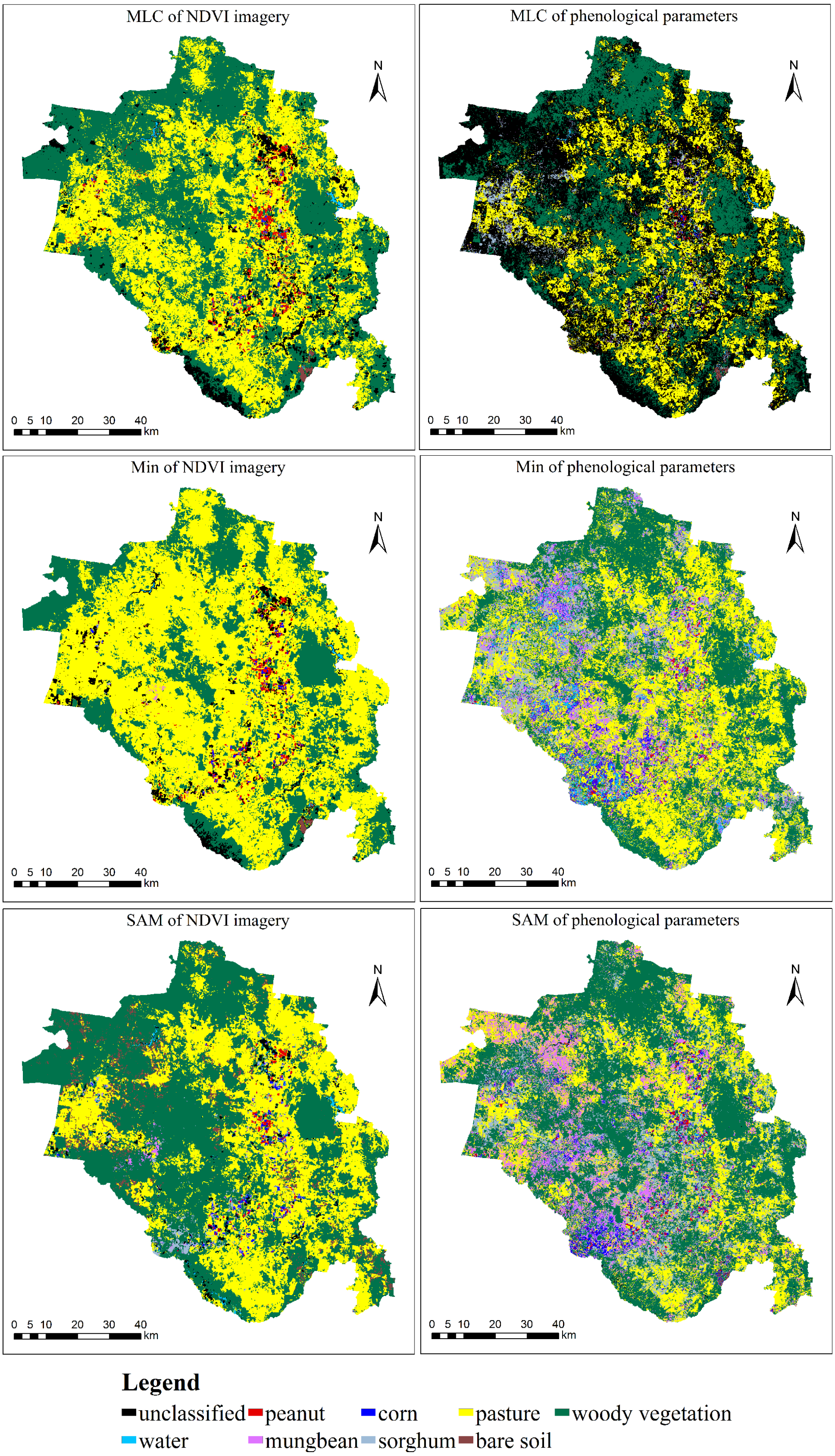

Figure 4.8 Classified image outputs from Maximum Likelihood Classification (MLC), Minimum Distance Classification (Min) and Spectral Angle Mapper (SAM) classifiers (the unclassified pixels occurred due to the threshold values applied in MLC).

4.4.4 Accuracy assessment

The classification performance of phenological parameters and NDVI imagery was analysed based on error matrix and kappa coefficient (k) value for the three classification methods, i.e. MLC, Min, and SAM. In general, NDVI imagery provided better classification performance than phenological parameters for all the classification methods (Table 4.8). Comparing the three classification methods, MLC was the best classification method in this study, for both phenological parameters and NDVI imagery. Looking in closer detail, the overall accuracy of MLC classifier for the NDVI imagery was the highest, i.e. 92.75%, compared to 79.53% of MLC classifier for the phenological parameters. The lowest overall accuracy was 62.26%, which resulted from the Min classifier of phenological parameters. The Kappa coefficients (k) for NDVI imagery classification varied between 0.73 to 0.9, which is considered to be very good ($0.61 < k \leq 0.80$) and excellent ($k > 0.81$) (Landis & Koch 1977). On the other hand, the k values for phenological parameters classification were 0.55 to 0.76, which can be considered as moderate ($0.41 < k \leq 0.60$) and very good (Landis & Koch 1977).

Table 4.8 Overall accuracy and Kappa coefficient of classified images.

Classification	NDVI imagery		Phenological parameters	
	Overall accuracy (%)	Kappa coefficient	Overall accuracy (%)	Kappa coefficient
MLC	92.75	0.91	79.53	0.76
Min	85.29	0.82	62.26	0.55
SAM	77.83	0.73	66.74	0.60

The producer accuracy (PA) and user accuracy (UA) of the image classified using maximum likelihood classification (MLC) of NDVI imagery presented the best result, i.e. ≥ 78% (Table 4.9), which indicated a good classification performance. The maximum likelihood classification of phenological parameters also gave a good result for the producer and user accuracy, except for the mung bean class which had producer accuracy of 52%, indicating that many pixels belonging to this class were omitted. Compared to phenological parameters, the Spectral Angle Mapper (SAM) of NDVI imagery provided better results, where the user accuracy was slightly better than producer accuracy. On the other hand, the application of Minimum Distance Classification (Min) in phenological parameters resulted in low producer and user accuracy, which indicated the high inclusion (omission error) and exclusion (commission error) of pixels to the targeted class. In relation to the peanut class, all classification methods gave good results in producer and user accuracy for both the NDVI imagery and the phenological parameters, i.e. > 75%, except for producer accuracy of the Minimum Distance Classification (Min) algorithm which accounted for 59%. Interestingly, the SAM algorithm provided the best result in the peanut class for user accuracy (UA) of NDVI imagery and producer accuracy (PA) of phenological parameters, i.e. 100% and 90%, respectively. However, the MLC algorithm still presented the best results for producer accuracy (PA) of NDVI imagery and user accuracy (UA) of phenological parameters, i.e. 79% and 88%, respectively.

Table 4.9 Classic contingency matrix of NDVI imagery dataset.

MLC of NDVI										
	Reference test data (number of pixels)									
	Peanut	Corn	Mung-bean	Sorghum	Woody veg	Pasture	Water	Bare soil	**Total**	**UA (%)**
Peanut	52	10	0	0	0	0	0	0	62	83.87
Corn	0	41	0	0	0	0	0	0	41	100
Mung-bean	0	0	16	0	0	0	0	0	16	100
Sorghum	0	0	0	12	0	2	0	0	14	85.71
Woody veg	0	0	0	1	129	0	0	0	130	99.23
Pasture	0	0	0	0	0	95	0	0	95	100
Water	0	0	0	0	0	0	48	0	48	100
Bare soil	0	0	0	0	0	0	0	42	42	100
Unclassified	14	0	1	0	6	0	0	0	21	
Total	66	51	17	13	135	97	48	42	469	
PA (%)	78.79	80.39	94.12	92.31	95.56	97.94	100	100		
Overall Accuracy = 92.75%, Kappa Coefficient = 0.91										
MLC of crop phenology										
	Reference test data (number of pixels)									
	Peanut	Corn	Mung-bean	Sorghum	Woody veg	Pasture	Water	Bare soil	**Total**	**UA (%)**
Peanut	51	7	0	0	0	0	0	0	58	87.93
Corn	0	38	0	0	0	0	0	0	38	100
Mung-bean	0	0	9	0	0	0	0	0	9	100
Sorghum	0	0	0	9	0	3	0	0	12	75
Woody veg	0	0	0	0	105	0	0	0	105	100
Pasture	0	0	0	3	0	86	0	0	89	96.63
Water	0	0	0	0	0	0	45	3	48	93.75
Bare soil	0	0	0	0	0	0	1	30	31	96.77
Unclassified	15	6	8	1	30	8	2	9	79	
Total	66	51	17	13	135	97	48	42	469	
PA (%)	77.27	74.51	52.94	69.23	77.78	88.66	93.75	71.43		
Overall Accuracy = 79.53%, Kappa Coefficient = 0.76										
Min of NDVI										
	Reference test data (number of pixels)									
	Peanut	Corn	Mung-bean	Sorghum	Woody veg	Pasture	Water	Bare soil	**Total**	**UA (%)**
Peanut	39	1	0	2	0	0	0	0	42	92.86
Corn	13	50	0	1	0	0	0	0	64	78.13
Mung-bean	0	0	1	0	0	0	0	0	1	100
Sorghum	0	0	0	3	0	0	0	0	3	100
Woody veg	0	0	3	0	121	0	0	0	124	97.58
Pasture	0	0	4	3	8	97	0	0	112	86.61
Water	0	0	0	0	0	0	48	1	49	97.96
Bare soil	0	0	0	0	0	0	0	41	41	100
Unclassified	14	0	9	4	6	0	0	0	33	
Total	66	51	17	13	135	97	48	42	469	
PA (%)	59.09	98.04	5.88	23.08	89.63	100	100	97.62		
Overall Accuracy = 85.29%, Kappa Coefficient = 0.82										

Min of crop phenology										
Reference test data (number of pixels)										
	Peanut	Corn	Mung-bean	Sorghum	Woody veg	Pasture	Water	Bare soil	**Total**	**UA (%)**
Peanut	50	11	0	0	0	2	0	0	63	79.37
Corn	5	21	4	3	0	12	4	6	55	38.18
Mung-bean	11	6	12	6	2	1	12	3	53	22.64
Sorghum	0	0	1	2	4	10	5	4	26	7.69
Woody veg	0	0	0	0	117	0	0	0	117	100
Pasture	0	0	0	2	12	60	0	0	74	81.08
Water	0	10	0	0	0	12	26	25	73	35.62
Bare soil	0	3	0	0	0	0	1	4	8	50
Unclassified	0	0	0	0	0	0	0	0	0	
Total	66	51	17	13	135	97	48	42	469	
PA (%)	75.76	41.18	70.59	15.38	86.67	61.86	54.17	9.52		
Overall Accuracy = 62.26%, Kappa Coefficient = 0.55										

SAM of NDVI										
Reference test data (number of pixels)										
	Peanut	Corn	Mung-bean	Sorghum	Woody veg	Pasture	Water	Bare soil	**Total**	**UA (%)**
Peanut	51	0	0	0	0	0	0	0	51	100
Corn	1	51	3	5	0	0	0	0	60	85
Mung-bean	0	0	8	0	0	0	0	0	8	100
Sorghum	0	0	2	5	0	8	0	0	15	33.33
Woody veg	0	0	1	0	128	19	0	30	178	71.91
Pasture	0	0	0	3	1	70	0	0	74	94.59
Water	4	0	1	0	0	0	41	0	46	89.13
Bare soil	0	0	0	0	6	0	0	11	17	64.71
Unclassified	10	0	2	0	0	0	7	1	20	
Total	66	51	17	13	135	97	48	42	469	
PA (%)	77.27	100	47.06	38.46	94.81	72.16	85.42	26.19		
Overall Accuracy = 77.83%, Kappa Coefficient = 0.73										

SAM of crop phenology										
Reference test data (number of pixels)										
	Peanut	Corn	Mung-bean	Sorghum	Woody veg	Pasture	Water	Bare soil	**Total**	**UA (%)**
Peanut	60	11	0	0	0	0	8	0	79	75.95
Corn	5	18	0	0	0	11	9	12	55	32.73
Mung-bean	1	0	16	2	7	16	0	0	42	38.1
Sorghum	0	0	0	2	0	20	5	0	27	7.41
Woody veg	0	0	0	1	123	5	0	2	131	93.89
Pasture	0	0	1	8	5	45	0	0	59	76.27
Water	0	1	0	0	0	0	22	1	24	91.67
Bare soil	0	21	0	0	0	0	4	27	52	51.92
Unclassified	0	0	0	0	0	0	0	0	0	
Total	66	51	17	13	135	97	48	42	469	
PA (%)	90.91	35.29	94.12	15.38	91.11	46.39	45.83	64.29		
Overall Accuracy = 66.74%, Kappa Coefficient = 0.60										

4.5 Discussion

Our study demonstrates the ability of using imagery from a recent satellite mission, PROBA-V, in mapping the peanut cropping area in the South Burnett region of Queensland, Australia. It successfully differentiated and mapped eight classes of crops and other land cover features using time-series PROBA-V NDVI 100m imagery and its phenological parameters. The good performance of PROBA-V data could be attributed to its improvement in spatial resolution compared to traditional time-series data, such as the commonly used MODIS 250m data. The choice of 100m spatial resolution contributed to desirable outcomes of this study, as Roumenina et al. (2015) found that PROBA-V 100m achieved better results than PROBA-V 300m in mapping crops in Bulgaria. In addition, the compact design of PROBA-V platform and payload, which is equipped with vegetation sensors, enables the application of high-performance operation to achieve its specific objective in providing time-series vegetation data (Francois et al. 2014).

The PROBA-V NDVI mean time-series profiles in this study indicated that this satellite sensor has successfully captured temporal separability between eight crops and other land cover classes examined. In addition, it showed the ability of PROBA-V NDVI time-series in presenting phenological stages of crop classes included in this study. This time-series imagery was also analysed further by using the TIMESAT program which smoothed the time-series data and generated phenological parameter maps. It was found that the phenology profiles from the TIMESAT program (Figure 4.6) closely resemble the mean NDVI time-series profiles (Figure 4.5).

Comparing two data sets, i.e. PROBA-V NDVI imagery and its phenological parameters derived from the TIMESAT program, the former produced better overall accuracy in all classification methods. However, not all phenological parameters were included in the classification efforts. Phenological parameters of ‘maximum value’ and ‘season start’ failed in the separability test, while including the ‘small integral’ parameter in the classification has decreased the classification accuracy. It was suggested that the limited number of NDVI imagery during the crop growth period, especially in the peak of the season, has contributed to the exclusion of these three parameters. Moreover, the better outcomes from the separability test of Jeffries-Matusita (JM) distance in NDVI imagery (dominated by 2.00) than the phenological parameters (dominated by 1.99) have predicted the better accuracy results of NDVI imagery. Additionally, in a study of crop mapping in Bulgaria, it was sufficient to utilize only three to four PROBA-V imagery distributed along the crop growth period, to acquire good classification accuracy (Roumenina et al. 2015). Since this study used 24 stacked imagery of the PROBA-

V NDVI dataset, it would be expected that this number was more than enough to achieve good classification results. It should be noted that the Region of Interest (ROI) development for classification and accuracy assessment was performed in the phenological parameters stack. This study recognises that the distinct spectral differences between classes in the phenological parameters stack, compared to NDVI imagery, were useful in guiding and locating ROIs. Different results could be generated from this study if the phenological parameters stack was not used in determining ROI. In this case, it would be expected that if NDVI imagery was used to locate ROI, different ROI datasets would take place.

The Maximum Likelihood Classification (MLC) algorithm performed better than the Spectral Angle Mapper (SAM) and the Minimum Distance Classification (Min), with an accuracy of 92.75%. This result agrees with BeyerJarmer, et al. (2015) study in evaluating eight classification algorithms (including MLC, SAM, and Min) to map agricultural crops in Israel, which resulted in the superior performance of MLC compared to most of the classification algorithms. A comparison of the three classification algorithms (i.e. MLC, SAM, and Min) was also carried out by Fontanelli et al. (2014) in mapping crops in Italy, which found MLC to be the best algorithm.

The classification accuracy achieved in this work was comparable to the accuracy results of previous crop mapping studies using PROBA-V imagery. Lambert et al. (2016) mapped cropland into four classes of crop proportions in the Sahelian and Sudan regions using PROBA-V 100m and attained an accuracy of 84%. High accuracy between 65% and 86% was also achieved in using this satellite data to map crops globally in Flanders (Belgium), Sria (Russia), Kyiv (Ukraine), and Sao Paulo (Brazil) (Durgun et al. 2016). The crops mapped in these studies were maize, potato, sugar beet, winter barley, winter wheat, flax, peas, soybean, spring barley, sunflower, winter rape, spring wheat, and sugarcane (Durgun et al. 2016). Furthermore, PROBA-V data has been successfully used to map crops with similar phenology profiles (i.e. corn and soybean) in China with accuracy of 73.29% (Zhang et al. 2016). It is important to realise that even though the number of classes used in our study was relatively large, i.e. eight classes in total, the application of Maximum Likelihood Classification (MLC) in NDVI imagery produced very good overall accuracy with producer and user accuracy of each class ≥ 78%. Interestingly, this result was achieved without masking out non-cropping areas (e.g. using land use maps), which could further improve the accuracy, as achieved by Potgieter et al. (2007). Conversely, masking out land use cover could also generate some problems related to the currency of data and accuracy of land use map employed.

Peanut crop maps resulting from this study will be valuable in supporting peanut production, yield prediction, and commodity forecasting, especially as focused work on peanut crop mapping is limited. Combining with yield per unit area, an estimation of peanut production can be calculated, which then can be used to support decisions for planning and management purposes. Moreover, this study utilised remote sensing technology which could overcome significant shortcomings of traditional survey methods. The use of multi-band data, such as Vegetation Indices, and time-series imagery as employed in this study has offered great benefits in peanut crop mapping.

4.6 Conclusion

The use of imagery from a recently launched satellite, PROBA-V, was successful in mapping peanut crops in the South Burnett region in Queensland, Australia, using two datasets, i.e. PROBA-V 100m NDVI imagery and its derived phenological parameters. In general, the overall accuracy of NDVI imagery outweighed phenological parameters, but specifically for peanut crops, both datasets have performed very well. The best classification method for both datasets involving all classes was the Maximum Likelihood Classification (MLC) approach, i.e. 92.75% for NDVI imagery and 79.53% for phenological parameters. However, in classifying peanut crops, all classification methods performed well for producer and user accuracy, with the best results provided by MLC and Spectral Angle Mapper (SAM) classifiers.

It is recommended that sufficient number of imagery during the crop growth period is available to enable modelling of phenological parameters. Furthermore, the use of machine learning algorithms has not been considered in this study, but can be explored in further work. To the best of our knowledge, this is the first study which used PROBA-V imagery in crop mapping in Australia. Our study confirmed that the PROBA-V satellite has great potential in crop area mapping and can fulfil its mission to support vegetation user communities. The findings in this study reinforce the necessity to continue the PROBA-V mission, which was originally designed as a ‘gap-filler mission’, by launching its second-generation satellite.

Chapter 5

MODELLING FUTURE DISTRIBUTION OF PEANUT CROPS UNDER CLIMATE CHANGE SCENARIOS

5.1 Introduction

The agricultural sector faces an increasing number of challenges. Gornall et al. (2010) point out that the agricultural sector is strongly dependent on having a suitable climate; as a result, the impacts of climate change in this sector are inevitable. Unfortunately, an observation of the recorded data indicates that climate change is likely to continue in the future (Steffen et al. 2012); therefore, together with an increase in the global population, food security is potentially at risk. One of the impacts of climate change in agriculture is the changes in suitability that are occurring in crop planting areas. Areas that are currently suitable could become unsuitable in the future, or vice versa. Australia is particularly significant as a country where extensive changes are taking place. Some studies have been carried out in assessing future suitable crop planting areas but unfortunately, none of these studies has assessed suitable areas for peanut crops in the future, including areas in Australia.

This chapter fills in this gap by identifying and mapping areas which will be favourable for peanut production in the future, and areas which will be adversely affected by the impact of climate change. The primary aim of this study was to study the effects of climate change on the future geographic distribution of peanut crops in Australia. The following are the specific objectives: 1) to develop CLIMEX model parameters on geographic distribution of peanut crops by using current crop distribution and climate data; and 2) to project and analyse the potential future geographic distribution of peanut crops in Australia under two different climate models. The knowledge of suitable future peanut crop planting areas obtained from this study will assist government and policy makers to plan and develop programs and policies to anticipate climate change impacts in the future.

This chapter is organised into six sections. Section 1 enumerates the objectives of the chapter, while Section 2 discusses the background literature on the effects of climate change on crops' geographic distribution, the species distribution model and previous studies conducted in this field. Section 3 describes the methods that were used to achieve the objectives of this study. Section 4 presents the study results of CLIMEX model development in peanut crops, model validation, and projections of future peanut crop planting areas in Australia. Section 5 discusses and interprets the results in light of the objectives and research. Finally, the chapter concludes with Section 6 with implications and recommendation of the results.

The novelty and significant contributions of this chapter are: 1) the development of CLIMEX model parameters for peanut crops; and 2) the first study on projecting the future distribution of peanut crops in Australia in relation to climate change.

5.2 The need for projecting future peanut distribution

Climate change is ongoing and inevitable. As weather and climate have a significant influence on agricultural production (Gornall et al. 2010), future climate change and climate variability place agriculture as a susceptible sector (Anwar et al. 2013). Research indicates that the increase in anthropogenic gas emissions is the dominant cause of climate change (IPCC 2014). The increase in emissions leads to alterations in mean temperature, climate variability, and increasing extreme weather events, such as very high or very low temperatures, drought, heavy rainfall, flooding, and tropical storms (Gornall et al. 2010). Global mean temperature has risen by 0.76 +/- 0.19°C since the mid-1800s. In 2010, there was a temperature increase of 0.53°C above the temperature mean of the 1961-1990 period (Garnaut 2011). It is recorded that the temperature of the three last decades has consecutively increased compared to any decades since 1850 (IPCC 2014).

Australia's climate is influenced by El Nino – Southern Oscillation (ENSO), the Indian Ocean Dipole (IOD), the Madden-Jullian Oscillation (MJO), and the Southern Annular Mode (SAM) (King et al. 2014; CSIRO & BoM 2015), all of which lead to Australia having one of the most variable climates in the world (DERM 2010; Potgieter et al. 2013). Over the last 50 years, Australia has become hotter with substantial changes in the geographic distribution of rainfall (DERM 2010). The country experienced a mean temperature increase of 0.9°C since 1910

(Stokes & Howden 2010; Garnaut 2011; CSIRO & BoM 2015). As a result of the variability, climate change will continue to significantly influence the agricultural sector in Australia.

The climate in the future will be different to the climate at present and in the past (DERM 2010; Steffen et al. 2012). Global Climate Models (GCMs) are among the best instruments for projecting climate change; these are developed using mathematical representations of the climate systems, based on the laws of physics, including conservation of mass, energy, and momentum (Suppiah et al. 2007; CSIRO & BoM 2015). The projections are built based on various greenhouse gas and aerosol emission scenarios (Suppiah et al. 2007), which are determined by using historical data and plausible assumptions on future socio-economic factors such as economic activity, energy sources, and population growth (Nakicenovic et al. 2000). It is predicted that continuing greenhouse gas emissions will result in further temperature increases and long-term changes in climate system components (IPCC 2014).

Because of the impacts of climate change, agricultural industries are exposed to a number of risks like heat stress, drought, water availability, waterlogging, salinity, the occurrence of pests and diseases, reduction in production, and unsuitability of current planting areas (Gornall et al. 2010; Steffen et al. 2012). Major factors determining the geographic boundary in planting crops include soil quality, availability of nutrients, and climate (Anwar et al. 2013). Therefore, geographical distribution and growth of plant species will be affected by climate change, although the scale will depend on the species type (annuals or perennials) and their growth patterns (agricultural crops or natural vegetation) (Coakley et al. 1999). Unfortunately, in most landscapes, plant species are unable to cope with the projected climate change which results in a natural shift in their geographical range (IPCC 2014). If the climate changes as projected, there will be shifts in crop areas planted and the occurrence of pests and diseases, which could lead to economic impacts from crop loss (Chakraborty et al. 2000).

Shifting geographic distribution of crops due to climate change can be mapped using modelling techniques such as Species Distribution Models (SDMs). A fundamental approach of SDMs is that climate ultimately limits distributions of species (Beaumont et al. 2008). These models establish the relationship of known species distribution data and environmental variables and/or spatial characteristics of those locations to determine appropriate environmental conditions for a species to survive (Elith & Leathwick 2009). The resulting data can be then used to predict species potential distribution under a particular climate change scenario (Heikkinen et al. 2006). Some examples of SDMs are Bioclimatic Prediction and Modelling System (BIOCLIM/ANUCLIM), Climatic Index (CLIMEX), Climate Profile (CLIMATE), and Genetic Algorithm for Rule-set Production (GARP) (Kriticos & Randall 2001).

CLIMatic indEX (CLIMEX) (Sutherst & Maywald 1985) is a computer model that deduces species' or other biological entities' responses to climate, based on their geographical distribution and their seasonal growth and mortality patterns in different areas (Beddow et al. 2010). It is based on the key assumption that if it is known where a species lives, it will be possible to deduce tolerant climatic conditions for the species, an assumption also used by other models. However, while other models try to characterise species' occupied environments, CLIMEX attempts to mimic mechanisms that limit geographical distribution of the species, determine species' seasonal phenology, and to some extent determine species' relative abundance (Kriticos et al. 2015). CLIMEX has been used widely to predict future geographic distributions of several crops, such as the common bean (Ramirez-Cabral et al. 2016), wheat and cotton (Shabani & Kotey 2015), oil palms (Paterson et al. 2015), tomato (Silva et al. 2017), and date palms (Shabani, Kumar & Taylor 2014; Shabani, Kumar, et al. 2015).

Peanut (*Arachis hypogaea* L.) is one of the most important sources of protein and has 26% more protein than eggs, dairy products, meat, or fish (DPIF 2007). Peanut crops are subtropical crops which require relatively warm conditions, 500-600 mm well distributed rainfall, and stored soil water to harvest a high-yielding crop (Crosthwaite 1994). Peanut crops originated in South America and have adapted without problems to warmer regions of Australia (DPIF 2007). Queensland is the main peanut cropping area in Australia, producing more than 90% of Australia's peanuts (GRDC 2014). Originally, peanut crops were grown in the Burnett and the Atherton Tableland regions in Queensland, but in 1990s, the cropping areas expanded into other Queensland areas, namely Bundaberg, Mackay, Emerald, and southern Queensland (Crosthwaite 1994; DPIF 2007). Currently, the peanut planting areas further expand into Katherine in the Northern Territory and other Queensland areas, i.e. Texas, Inglewood, St. George, Childers, Chinchilla, and Georgetown (Chauhan et al. 2013).

In the same way as other crops, peanut crops can also be affected by climate change. In Australia, peanuts are usually grown under dryland conditions (Meinke & Hammer 1995). Unfortunately, since Australia's climate is highly variable due to the impact of El Nino-Southern Oscillation (ENSO) (Nicholls et al. 1997), unfavourable weather conditions, for instance drought and excessive rainfall, can easily affect peanut production in the country (Meinke et al. 1996). Recently, Australia's climate has been becoming warmer (DERM 2010). Consequently, some regions could turn out to be more suitable for future peanut planting, while others could turn out to be less favourable. Therefore, it is important to identify and map which areas will be favourable for peanut production in the future, and which areas will be adversely affected by climate change impacts.

5.3 Materials and methods

5.3.1 Study area

This study covered the entire Australian continent (Figure 5.1), with a total area of 7.692 million km^2 (Geoscience Australia 2018). Australia has a variety of climates comprising five major climate groups, i.e. tropical, subtropical, grassland, desert, and temperate (Kriticos et al. 2012). The climate classifications are based on Koppen-Geiger classifications, which developed by applying the rules of Kriticos et al. (2012) to the 5'resolution WorldClim global climatology (Hijmans et al. 2005). Agricultural lands in Australia are located in the eastern parts of Queensland and New South Wales, the majority of Victoria, the southern part of South Australia, and the south-western part of Western Australia (ABARES 2019). These agricultural lands are dominated by subtropical, grassland, and temperate climates. Summer crops planted in Australia are sorghum, cotton, rice, corns, mung beans, peanuts, soybeans, and sunflowers; while winter crops planted are wheat, barley, canola, chickpeas, faba beans, field peas, lentils, lupin, oats, safflower, and triticale (ABARES 2016).

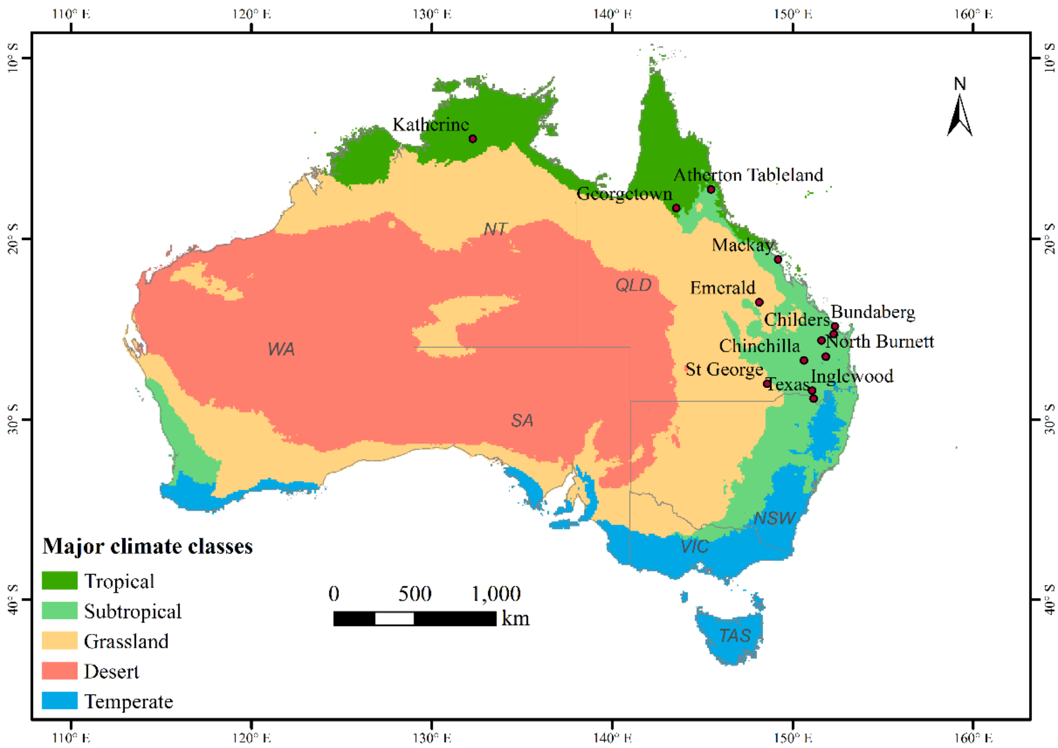

Figure 5.1 Map of the study area (Australia) with the current geographical distribution of peanut crops throughout different climate zones adapted from Kriticos et al. (2012).

5.3.2 Data acquisition

5.3.2.1 Peanut crop geographic distribution

Data representing the current distribution of peanut (*Arachis hypogaea* L.) (Figure 5.2) was obtained from the Global Biodiversity Information Facility (GBIF) (GBIF 2017) and the Atlas of Living Australia (ALA) (ALA 2017). A total of 9,011 records was obtained from these databases. However, only 1,912 records were used in this study, since the other 7,099 records were identified as records without geographic coordinates, preserved specimens, duplicate records, and data outliners. During the CLIMEX model parameter development, these geographic distribution records were divided into two: one area was used for parameter fitting, while the other area was used for model validation. The geographic distribution data used in model parameter development was South America, North America, South Asia, South-East Asia, and East Asia. Meanwhile, the geographic distribution data acquired for model validation includes Africa, Central America, and Australia. The division of peanut distribution data was based on the representation of the heterogeneous range of climate in training and validation dataset. This division is important to ensure data independency of model validation, thus affirms the reliability of the model.

In developing CLIMEX models, it is important to acquire the global geographic distribution of modelled species as real as possible. As with other CLIMEX studies (Taylor et al. 2012; Ramirez-Cabral et al. 2016), this study also used native and exotic distribution data with a heterogeneous environment to develop and validate peanut CLIMEX parameters. A heterogeneous environment with variable climates is recommended in fitting CLIMEX parameters (Sutherst 2003; Kriticos et al. 2015), since it facilitates the required range of possible temperature and moisture values for species' permanent occupations (Sutherst 2003). Furthermore, Sutherst (2003) and Kriticos and Leriche (2010) have suggested the use of both native and exotic (agricultural worldwide) distribution data of the species. After being released from the effects of natural enemies, a species might occupy exotic distribution areas which have totally different climate ranges from the native distribution areas. Therefore, the inclusion of these climate ranges will enhance the model's ability to approximate the species' potential distribution (Sutherst 2003; Kriticos & Leriche 2010; Kriticos et al. 2015).

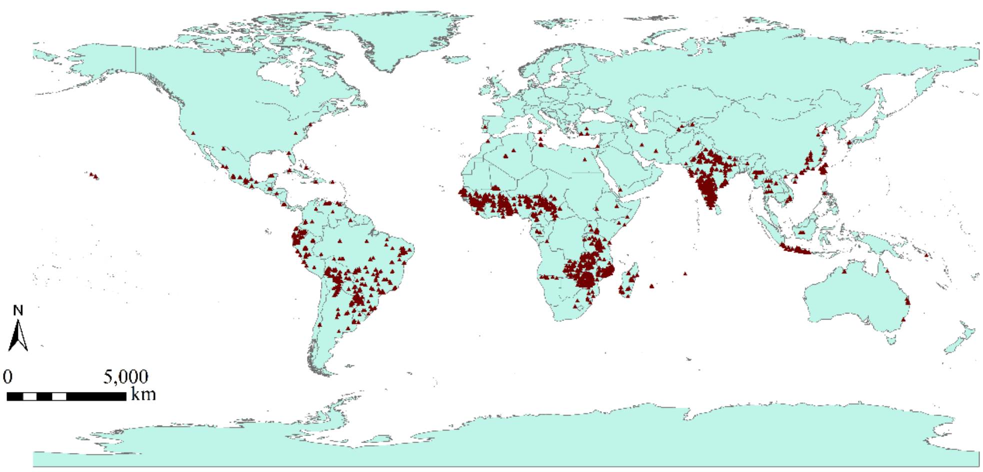

Figure 5.2 The current distribution of peanut crops taken from GBIF 2017 and ALA 2017. Red triangles represent the distribution data.

5.3.2.2 Climate data and climate change models and scenarios

The CliMond gridded climate data at 10' resolution (Kriticos et al. 2012) was employed in modelling geographical distribution of peanut crops. The climate variables used to run CLIMEX model are average maximum monthly temperature (T_{max}), average minimum monthly temperature (T_{min}), average monthly precipitation (P_{total}) and Relative Humidity recorded at 9am ($RH_{09:00}$) and 3pm ($RH_{15:00}$) (Kriticos et al. 2012). Historical climate data of these five climate variables for a period of 1950-2000 (centred at 1975) was retrieved from CliMond database to develop peanut CLIMEX parameters. The same climate variables were also used to model future peanut distribution in Australia by employing Global Climate Models (GCMs) and the climate change scenarios.

Two GCMs, i.e. CSIRO-Mk3.0 (developed by CSIRO, Australia) and MIROC-H (developed by the Centre for Climate Research, Japan) were used in this study and downloaded from the CliMond database. The choice of these GCMs was based on three criteria (Kriticos et al. 2012): 1) their availability of monthly average of minimum and maximum daily temperature, precipitation, mean sea level pressure, and specific humidity; 2) their relatively small horizontal grid spacing; and 3) their superior performance relative to other GCMs. These two climate models have been used widely in CLIMEX studies of crop distributions, including oil palms (Paterson et al. 2015), date palms (Shabani, Kumar, et al. 2015), tomato (Silva et al. 2017), and common bean (Ramirez-Cabral et al. 2016). The SRES (Special Report on Emissions Scenarios) A2 family (Nakicenovic et al. 2000) was used as emission scenarios for both GCMs. The 'A' family of SRES emission scenarios is the most extreme SRES scenario family; it was chosen in this study based on its consistency with the emission of carbon dioxide since 2000 (Manning et al. 2010). The A2 emission scenario family depicts the world as very heterogeneous with high population growth, but slow economic growth, largely due to slow changes in technology (Bernstein et al. 2008). This scenario family's theme is self-reliance and local identities preservation, which leads to regional orientation of economic development (Nakicenovic et al. 2000).

5.3.3 Species Distribution Models (SDMs)

5.3.3.1 CLIMEX model

CLIMEX is a dynamic model based on a mechanistic (process-oriented) approach of species population processes. It enables the determination of a species' relative abundance, potential geographic distribution, and seasonal variations based on climate related processes (Kriticos et al. 2015). There are three options in running the model: compare locations, compare years, and compare locations/years (Kriticos et al. 2015), and this study has employed the compare locations option. The model can utilise minimum field data by extracting maximum information of species' responses to climate (Sutherst 2003). It works on the assumption that most species experienced both favourable season(s) for population growth, which is known as the growth season and unfavourable season(s) for population growth, which is known as the survival or stress season (Sutherst 2003; Kriticos et al. 2015).

The CLIMEX model develops a Growth Index (GI_A) to describe the potential species' growth during favourable season(s), and a Stress Index (SI) to describe the survival ability of species during unfavourable season(s). The philosophy of the model is that a range of climatic parameters defined by Growth Indices (i.e. Temperature Index (TI_W) and Moisture Index (MI_W)) will determine species' population growth. Values outside these ranges will stimulate stress and lead to a negative population growth, which is described by Stress Indices: Cold Stress (CS), Heat Stress (HS), Dry Stress (DS), and Wet Stress (WS). Growth and Stress Indices define species' responses to temperature, soil moisture, and if applicable, light. The CLIMEX program calculated these indices every week, then combined them into an annual value. The model's purpose is to combine the GI and SI indices into an Ecoclimatic Index (EI) value, which describes the climatic favourability of a location for a species' permanent occupation (Sutherst & Maywald 1985; Kriticos et al. 2015). The EI can be calculated as follows:

$EI = GI_A \times SI$ (1)

where:

GI_A, the annual Growth Index, $= 100 \sum_{i=1}^{52} GI_w / 52$ (2)

GI_W, the weekly Growth Index = $TI_W \times MI_W$ (3)

TI_W is weekly Temperature Index and MI_W is weekly Moisture Index

SI, the annual Stress Index, $= \left[\left(1-\frac{CS}{100}\right) \times \left(1-\frac{DS}{100}\right) \times \left(1-\frac{HS}{100}\right) \times \left(1-\frac{WS}{100}\right)\right]$ (4)

CS, DS, HS, WS, respectively are the annual cold, dry, heat, and wet stress indices.

The Ecoclimatic Index (EI) value ranges from 1 to 100 which denotes unsuitable to optimal conditions for a species to survive in one location. If the climate of a location is ideal for a species to persist throughout the year, the EI value will be 100. However, this rarely occurs since GI seldom reaches its maximum value (Kriticos & Leriche 2010; Kriticos et al. 2015). In areas with distinct wet and dry seasons, it would be expected that the maximum EI value would be around 50 (Sutherst 2003; Kriticos et al. 2015). It has been found that EI values of more than 20 have been adequate to support substantial population densities, while EI values less than 10 indicate that the location is likely to experience large annual climate fluctuation and is therefore marginal for species' permanent occupation (Sutherst 2003). The EI classification used in this study was defined as follows: unsuitable (EI = 0), marginal (0<EI<10), suitable (10<EI<20), and optimal (EI>20).

5.3.3.2 Fitting CLIMEX parameters

The most challenging task in CLIMEX modelling is fitting species' CLIMEX parameters. It requires an understanding of global geography and climatic patterns and the sensitivity of Stress and Growth indices (Kriticos et al. 2015). The underlying philosophy is that Stress Indices limit the geographical distribution of the species, while Growth Indices indicate the seasonal population growth (Kriticos et al. 2015; Ramirez-Cabral et al. 2016). In addition, the resulting parameters should be biologically reasonable, based on theoretical and practical species' knowledge from experimental domains (Kriticos et al. 2015).

In this study, peanut geographical distribution data, which provides general pictures of peanut climatic preferences, was used as a guideline in fitting CLIMEX parameters. The peanut distributions in South America, North America, South Asia, South-East Asia, and East Asia were used as training data in developing/fitting CLIMEX parameters. Comparing the peanut distribution data with the available CLIMEX template, this study chose the CLIMEX wet tropical template, which showed the best fit with overall peanut geographical distribution, as a starting point to develop peanut CLIMEX parameters.

In the first place, an intensive study to understand the biology and growth requirements of peanut was carried out to retrieve field and laboratory data on the peanut developmental threshold of temperature and moisture levels. These field and laboratory data were then used as initial CLIMEX parameter values to start fitting the CLIMEX parameters. Fitting CLIMEX parameters involved a manual iterative procedure (Ramirez-Cabral et al. 2016). The initial CLIMEX parameter values were adjusted, by visually comparing various CLIMEX indices with the peanut geographic distribution data. Each of CLIMEX indices were adjusted by running the CLIMEX model. The output map of this model was then compared visually with the peanut geographic distribution data. This process was conducted until a satisfactory level of agreement between model output and the peanut geographic distribution data was achieved; here the best visual fit was accomplished between the CLIMEX output and peanut distribution maps. Afterwards, parameter values for future reference could be justified (Kriticos et al. 2015). Initially, Stress Indices were iteratively fitted, since they pointed to areas without stress conditions for peanut growth, and hence established the peanut geographical boundaries. Then, Growth Indices were established using the same iterative procedure. The determination of peanut CLIMEX parameter values are explained in detail below, and the value of CLIMEX parameters are presented in Table 5.1.

Cold stress: The day-degree temperature threshold of cold stress (DTCS) of 8°C and the accumulation rate derived from it (DHCS) of -0.00025 week^{-1} denoted cold stress of peanut species. The stress parameters were iteratively adjusted to fit areas in the coldest peanut distributions, i.e. Shandong-China (GBIF 2017), Hebei-China (WMO 2010), Virginia-USA and Kalama (Washington)-USA (GBIF 2017).

Heat stress: Craufurd et al. (2003) found that many peanut genotypes showed consistently high temperature tolerance, which enabled them to persist in arid and semi-arid environments. In order to enable peanut persistence in known distribution areas of Rajasthan, India (GBIF 2017), the heat stress temperature threshold (TTHS) was set to 45°C with the weekly accumulation rate (THHS) of 0.0002 week^{-1}. Setting heat stress at these value has eliminated heat stress in peanut distribution areas.

Dry stress: To include peanut persistence in the arid climate of Rajasthan, India, the dry stress threshold (SMDS) was set to be similar to the permanent wilting point of a crop, where peanut growth diminished, i.e. 0.1. Peanut crops started to accumulate dry stress when they stopped growing, with accumulation rate (HDS) of -0.0001 week^{-1}.

Wet stress: The wet stress threshold (SMWS) was set at the same level as the highest CLIMEX soil moisture threshold (SM3), i.e. 2, and the wet stress accumulation rate (HWS) was chosen at 0.001 week^{-1}. These parameters values prevented wet stress occurring in peanut distribution areas.

Temperature index: The CLIMEX Temperature Index consists of lower temperature threshold (DV0), lower optimum temperature (DV1), upper optimal temperature (DV2), and upper temperature threshold (DV3) parameters, which define the suitable temperature range for species' growth and development (Kriticos et al. 2015). Peanuts require relatively warm conditions (Crosthwaite 1994), with different temperature requirements for its growing stages. The base temperature where peanuts start to grow and develop is widely considered between 9°C to 11°C (Williams & Boote 1995). Other scientists, Leong and Ong (1983), considered a range of 10-11°C as peanut base temperature, while Bell et al. (1991) discovered Virginia and Spanish cultivar of peanut crops have a base temperature of 8.2°C and 12.4°C, respectively. Based on this, DV0 was set at 10°C to accommodate the above mentioned values.

The optimum temperatures at which peanuts grow and develop maximally are at a range of 25°C and 30°C for different crop stages (WMO 2010). Williams and Boote (1995) found the optimum temperature is 27-33°C, whereas Vara Prasad et al. (2003) and DPIF (2007) suggested that peanut vegetative growth requires a temperature of 25-30°C, and generative growth requires a temperature of 22-24°C. As a result, DV1 and DV2 were established at 24°C and 30°C, respectively. Although peanut crops were grown with sufficient water supply, their development started to decrease when the crops were exposed to 35°C temperature (Ketring 1984). Furthermore, if peanut crops were exposed to a temperature of 38°C from flowering to maturity stages, there was a significant reduction in peanut pod yield (Vara Prasad et al. 2000). Based on this, DV3 was set at 38°C. In general, setting the DV0, DV1, DV2, and DV3 at these values has enabled the coverage of peanut distribution areas in China and the United States.

Moisture index: The CLIMEX Moisture Index works on the assumption that soil moisture significantly determines a crop's moisture content. The index provides a species' responses to the soil moisture values, which consists of four parameters: lower soil moisture threshold (SM0); lower optimal soil moisture (SM1); upper optimal soil moisture (SM2); and upper soil moisture threshold (SM3) (Kriticos et al. 2015). Peanuts are considered to be drought tolerant crops at two specific development stages: at the beginning of the vegetative phase and at the maturation stage (DPIF 2007; Wright et al. 2009), where peanut water requirement can be as much as 40% of soil moisture level (Wright et al. 2009; Lindsay

Corporation 2010). Based on this information, the SM1 value in this study was set to 0.4.

However, to achieve a yield that is high in quantity and quality, adequate soil moisture is needed (DPIF 2007), especially in the developmental stages of flowering/pegging and pod formation when peanut crops use the greatest amount of water (Wright et al. 2009). In general, soil moisture levels should be maintained at around 85-90% of the plant's available water holding capacity (Lindsay Corporation 2010). In fact, by setting SM2 at 0.85, the model produced in this study had the ability to include peanut cropping areas in the arid region of Rajasthan, India. SMO was established using a permanent wilting point value of 0.1 (Kriticos et al. 2015), whereas SM3 was set at 2, since excessive soil moisture can stimulate leaf disease (DPIF 2007).

Table 5.1 CLIMEX parameter values generated from this study and used in modelling peanut distribution.

Index	Parameter	Values
Temperature	DV0	10°C
	DV1	24°C
	DV2	30°C
	DV3	38°C
Moisture	SM0	0.1
	SM1	0.4
	SM2	0.85
	SM3	2
Cold stress	DTCS	8°C
	DHCS	-0.00025 week^{-1}
Heat stress	TTHS	45°C
	THHS	0.0002 week^{-1}
Dry stress	SMDS	0.1
	HDS	-0.0001 week^{-1}
Wet stress	SMWS	2
	HWS	0.001 week^{-1}

5.3.3.3 Model validation

Validating the CLIMEX parameters is important to ensure model consistency and reliability. The model is indicated as reliable if the model parameters built in one distribution area can predict distribution in other areas successfully (Shabani & Kotey 2015). In this study, the CLIMEX parameters which showed the best visual fit for the peanut distribution data in South America, North America, South Asia, South-East Asia, and East Asia were validated against independent distribution data in Africa, Central America, and Australia. To validate the model, the percentage of peanut distribution data which categorised as unsuitable areas for peanut cultivation in the model was calculated.

5.3.3.4 Future distribution model

The final CLIMEX parameters were used to project peanut distribution in Australia for 2030, 2050, 2070, and 2100. The projections were conducted by using climate data derived from two Global Climate Models (GCMs), namely CSIRO-Mk3.0 and MIROC-H, with the SRES A2 climate change scenarios. Model output from these two GCMs was analysed further by overlaying the results, thus making it possible to acquire the common areas of future peanut distribution.

5.3.4 Research flowchart

The entire workflow employed in this study is presented in Figure 5.3.

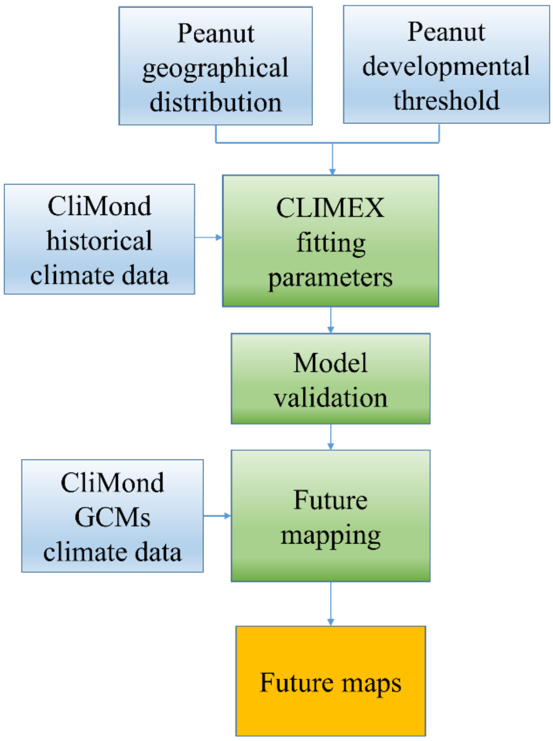

Figure 5.3 Flow chart of data and key processing tasks employed in the study.

5.4 Results

5.4.1 Model evaluation and current climate

The peanut distribution model produced from the CLIMEX model (Figure 5.4) shows a consistent distribution with the current peanut distribution data retrieved from GBIF (2017) and ALA (2017) (Figure 5.2), with approximately 2.3% of peanut distribution data falling outside the model. Peanut distribution data in its native range in South America countries, i.e. Bolivia, Brazil, Peru, Paraguay, and Uruguay, can be well-presented in the model. Only data in the Andes mountain region in Peru was not included in the model, due to the persistence of cold stress (Figure 5.5). The model also successfully captured peanut distribution data in exotic locations, where the species is cultivated, including China, The United States, India, Indonesia, Myanmar, Thailand, Vietnam, and the Philippines. Only small amount of distribution data in the arid region of Rajasthan, India was not included in the model, due to lack of rainfall and dry stress persistence (Figure 5.5). It was found in this study that peanut crop distribution were affected by cold stress, where low temperature limited peanut crop distribution, and dry stress, where low moisture limited peanut crop distribution.

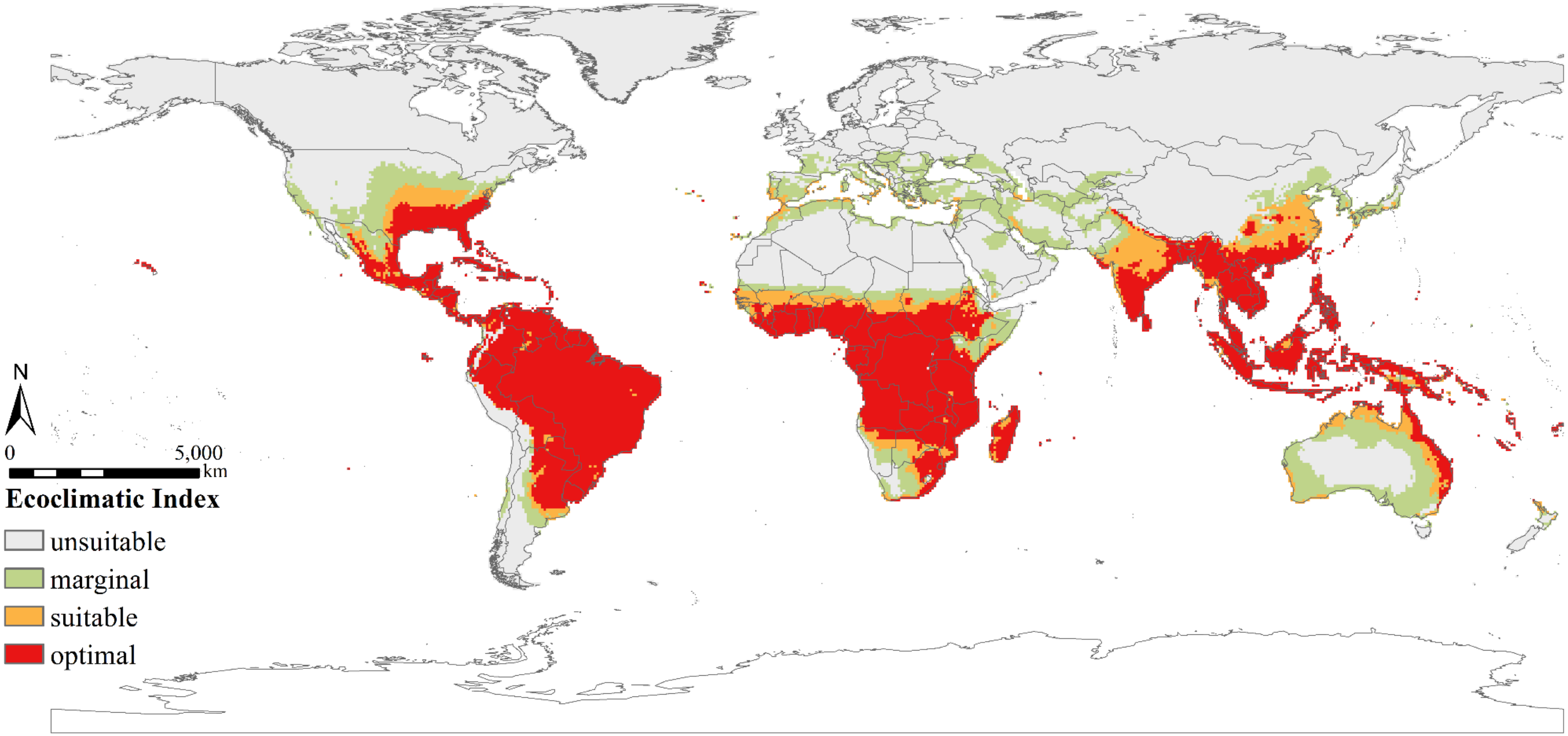

Figure 5.4 The Ecoclimatic Index (EI) of current peanut distribution using current climate data.

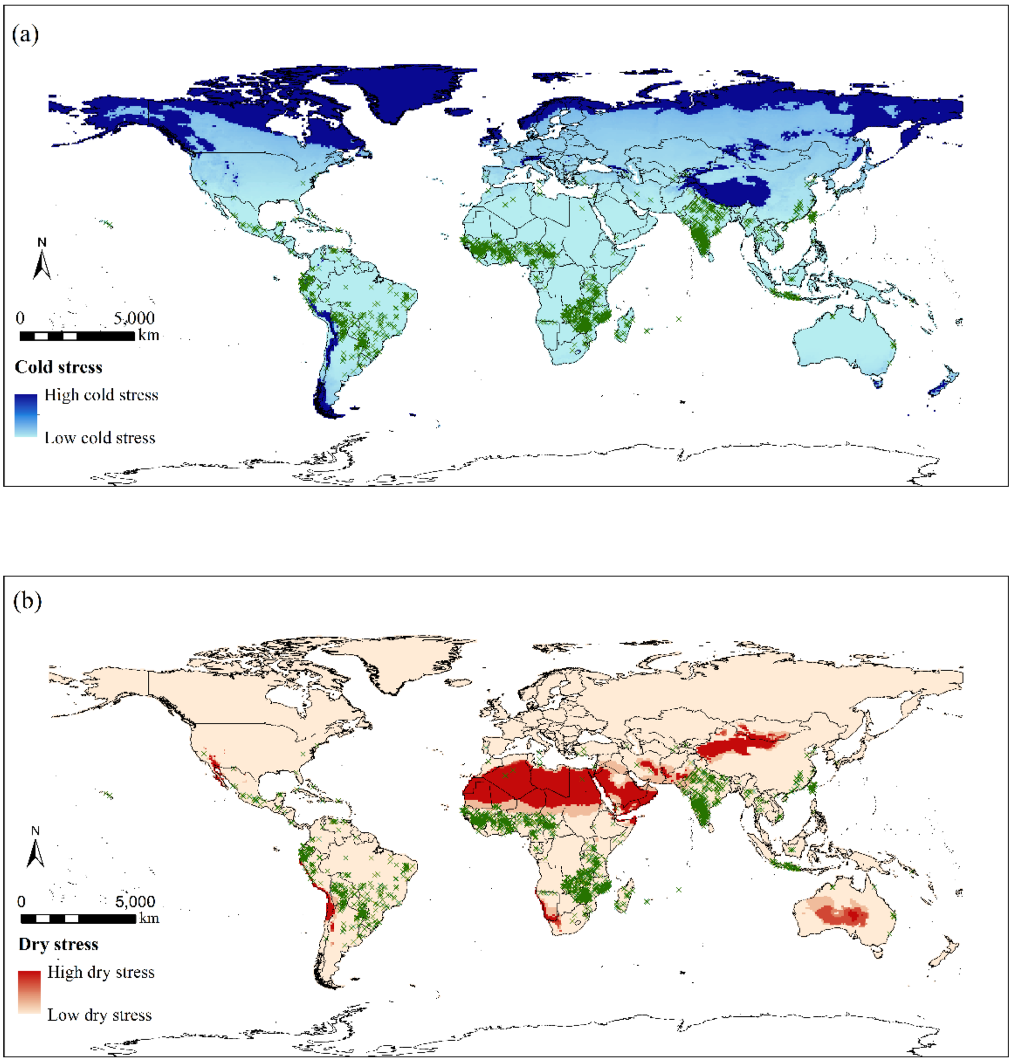

Figure 5.5 (a) Cold stress map and (b) dry stress map of peanut crops generated from the CLIMEX model. Green cross represents the peanut distribution data taken from GBIF (2017) and ALA (2017).

The majority of peanut distribution data in Africa, Central America, and Australia, which was retained for model validation, shows general agreement with the CLIMEX model output (Figure 5.6). All distribution data in Australia were included in the CLIMEX model and only one outliner data found in Central America. Closer detail of the African region reveals that 99.3% of peanut records was incorporated in the model. In addition, the majority of distribution data of these validation areas fell within optimal and suitable areas for peanut planting.

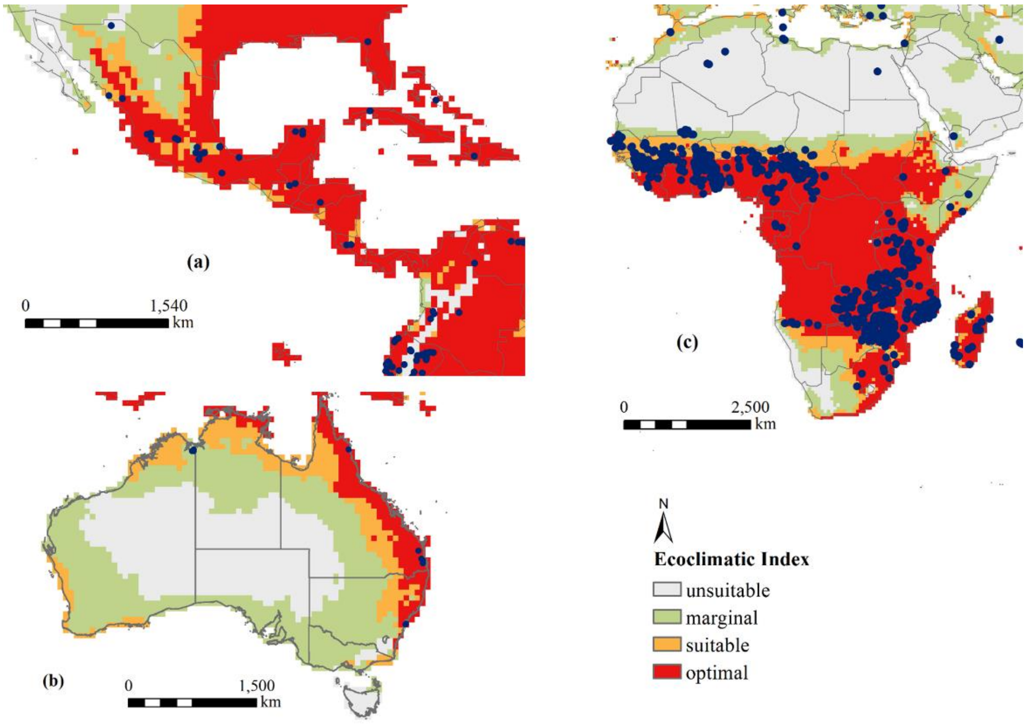

Figure 5.6 The distribution of peanut crops in validation areas of (a) Central America, (b) Africa, and (c) Australia. Blue dots represent current peanut distribution data.

Most of the areas with optimal suitability for growing peanut crops are found in tropical regions, i.e. South East Asia, East India, Central Africa, the northern part of South America, and Central America. However, it has been found that some subtropical and arid regions, including the southern part of China, the eastern part of Australia, the north-eastern part of Argentina, Uruguay, the south-eastern part of the United States, and the eastern parts of South Africa, Zambia, and South Angola, also show optimal suitability. In addition, areas which are categorized as suitable for peanut cultivation are found in subtropical regions, such as the middle-eastern part of The United States and the eastern part of China, and arid regions, such as the northern parts of India and Central Africa (Figure 5.4). In Australia, current suitable areas for peanut growing are located in the eastern parts of Queensland and New South Wales; the northern parts of Queensland, the Northern Territory, and Western Australia; and the eastern part of Western Australia, which are characterised as tropical and subtropical climate regions (Figure 5.6).

5.4.2 Future projections

The results of projections of future peanut cropping areas in Australia using CSIRO-Mk3.0 are shown in Figure 5.7. A comparison of the projection years shows that there is a significant increase in unsuitable peanut cropping areas, which is marked by approximately 76% of Australia continent in 2100. In 2030, the projected unsuitable areas only covers the arid region in the middle of Australia, but these unsuitable areas will be expanded throughout the projection years, until in 2100, they are projected to reach the current peanut growing areas in subtropical regions of the eastern part of Queensland and tropical regions of northern Queensland and the Northern Territory. Current peanut planting areas which will not be suitable in 2100 are Katherine in the Northern Territory and Georgetown, Emerald, St. George, Chinchilla, Inglewood, and Texas in Queensland. These areas are the expansion of peanut growing regions in Australia, due to decreasing productivity in the traditional dryland peanut regions in the South and North Burnett (Chauhan et al. 2013).

Moreover, the traditional dryland peanut regions, i.e. the South Burnett and the North Burnett, have been projected as marginal peanut growing areas in 2100. In terms of projection for optimal and suitable areas which are mainly located in the eastern coast of Australia and known as peanut main production regions, there is a significant reduction under the CSIRO-Mk3.0 model. Interestingly, small areas in the south-western part of West Australia and south-eastern parts of New South Wales and Victoria, which are marked as marginal areas in current peanut distribution, are projected to become suitable areas in 2100.

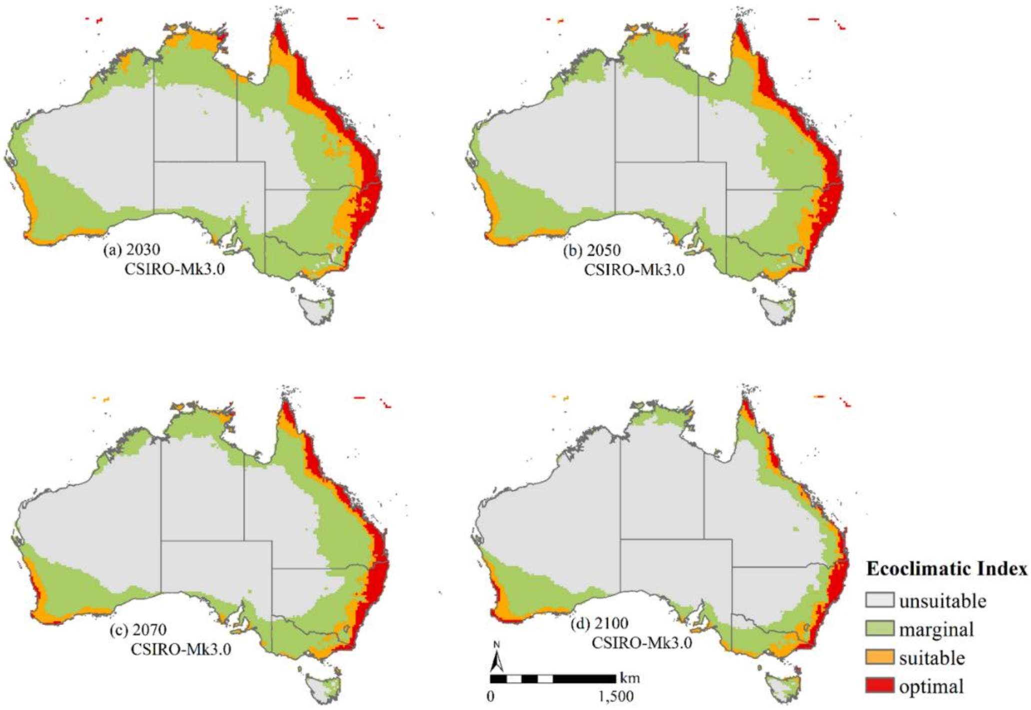

Figure 5.7 The future distribution of peanut crops in Australia using CSIRO-Mk3.0 Global Climate Model, with climate scenarios of the SRES A2.

The results of MIROC-H projections in areas of peanut crop suitability in Australia (Figure 5.8), especially for optimal and suitable areas, are not as dramatic as CSIRO-Mk3.0 projections. Although there is a significant increase for unsuitable peanut areas in 2100, it only accounts for approximately 48% of Australia continent. In addition, unlike CSIRO-Mk3.0 projections, MIROC-H projections of unsuitable areas are mainly concentrated in the middle of Australia, with a smaller effect for tropical regions in the northern part of Australia. The number of current peanut production areas which will become unsuitable in 2100, according to the MIROC-H projection, is considerably smaller than the number CSIRO-Mk3.0 number. Only two current peanut production areas will be affected: Georgetown in northern Queensland and Katherine in the Northern Territory.

Interestingly, the subtropical regions in the eastern part of Australia where peanuts are mainly produced, i.e. South Burnett, North Burnett, Chinchilla, Inglewood, and Texas, are still categorised as optimal and suitable areas in 2100. There is little change in these regions throughout the projection years. Meanwhile, other current peanut production areas, i.e. Emerald and St. George, are projected to be marginal areas in 2100. Moreover, similar to the CSIRO-Mk3.0 projections, some areas in the south-western part of West Australia and south-eastern parts of New South Wales and Victoria will become suitable for peanut cultivation in 2100 according to the MIROC-H projection. However, MIROC-H projection coverages for these regions are bigger than the CSIRO-Mk3.0 projection coverage.

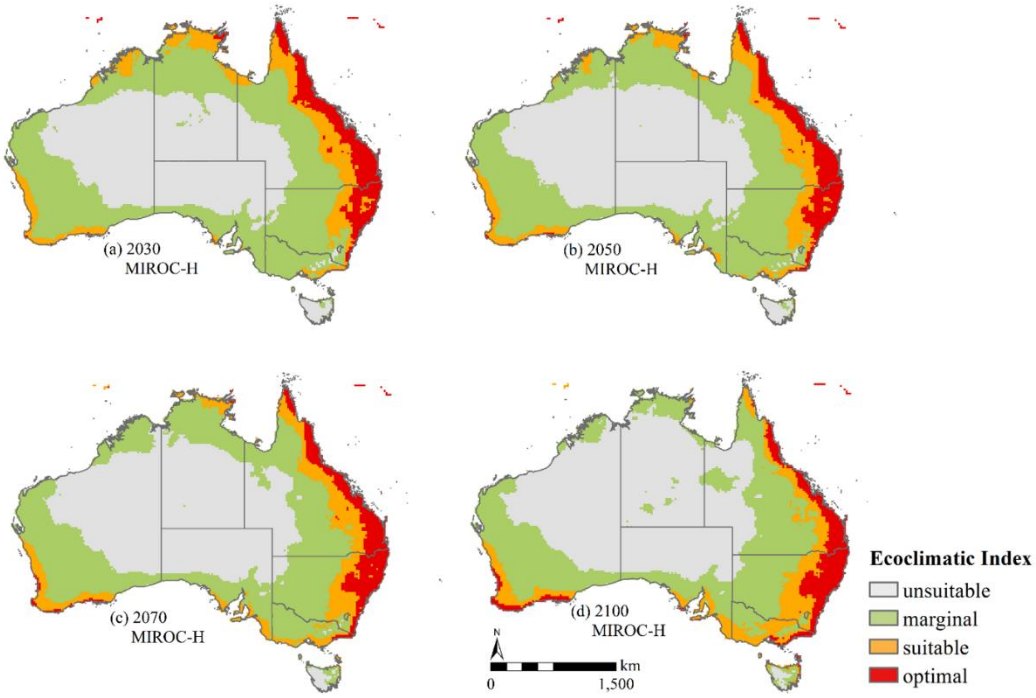

Figure 5.8 The future distribution of peanut crops in Australia using MIROC-H Global Climate Model, with climate scenarios of the SRES A2.

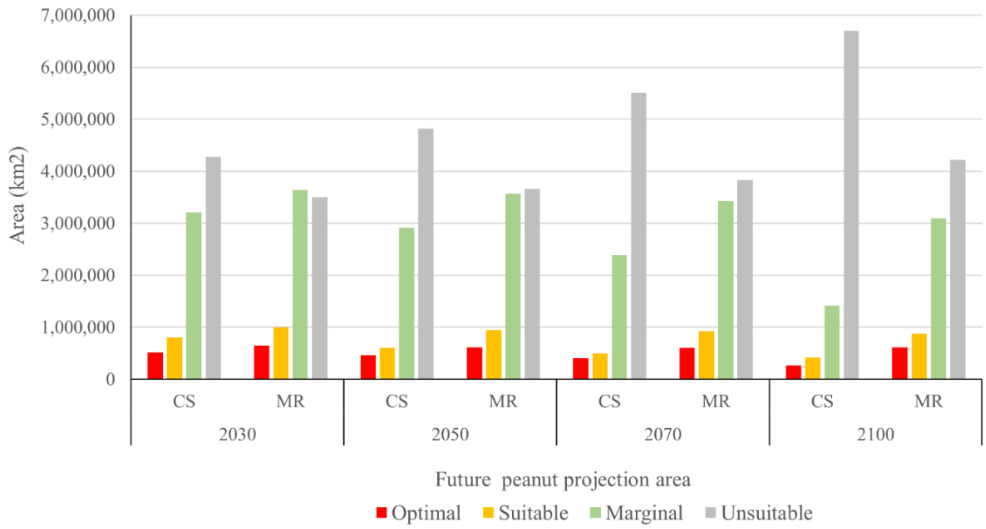

Figure 5.9 The total areas of future peanut crops using the CSIRO-Mk3.0 (CS) and MIROC-H (MR) projections for 2030, 2050, 2070, and 2100.

In general, the results show a projected reduction in suitable areas for peanut crop planting in Australia under the SRES (Special Report on Emissions Scenarios) A2 using two Global Climate Models (GCMs), CSIRO-Mk3.0 and MIROC-H; although a few areas will experience increasing suitability for peanut planting (Figure 5.7 and Figure 5.8). Both models, CSIRO-Mk3.0 and MIROC-H, show a decreased trend in optimal, suitable, and marginal areas throughout the projection years (Figure 5.9). However, CSIRO-Mk3.0 projected a significant reduction from year to year, which could be seen from the decrease of 56% of marginal areas and almost 50% of optimal and suitable areas in 2100, compared to 2030. Meanwhile, MIROC-H predicted a small reduction in 2100 compared to 2030 for optimal, suitable, and marginal peanut planting areas, i.e. 5, 13, and 15%, respectively. Comparing the two models, MIROC-H projections for optimal, suitable, and marginal areas are higher than CSIRO-Mk3.0 projections. It should also be noticed that, for the MIROC-H projection, marginal areas for peanut cultivation in 2030 are slightly higher than unsuitable areas. Nevertheless, from 2050, unsuitable areas of MIROC-H projection exceed marginal areas, and the trend continues until 2100.

In contrast, there is an increased trend for unsuitable projection areas for both models. However, similar to the trends for other category areas, the increase for MIROC-H in 2100 compared to 2030 is lower than for CSIRO-Mk3.0, which accounted for 20 and 57%, respectively. In general, the CSIRO-Mk3.0 projection for future unsuitable peanut crop areas shows a higher number than the MIROC-H projection, with a trend of an increasing gap between the two models throughout the projection years. As a result, there is a significant difference between projections of unsuitable peanut cropping areas for both models in 2100.

Examining cold stress projections for peanut planting areas, both the CSIRO-Mk3.0 and MIROC-H models forecast almost similar cold stress areas for peanut cultivation. These are located in temperate regions in the south-eastern part of Australia. In detail, the models predicted a reduction in cold stress areas throughout the projection years. Comparing the two models, the MIROC-H model projected a slightly higher cold stress severity and coverage area than the CSIRO-Mk3.0 model, especially in 2070 and 2100. In terms of dry stress projections, which are mainly located in the arid region of central Australia, the areas affected by dry stress are larger for the CSIRO-Mk3.0 model than the MIROC-H model. Moreover, the CSIRO-Mk3.0 model predicted an increase in dry stress areas throughout the projection years. It is projected that by 2100, dry stress areas will expand to central Queensland, majority of Western Australia, and tropical regions in the Northern Territory. Meanwhile, the MIROC-H projected a reduction in dry stress in central Australia and a small dry stress increase in the northern part of Western Australia. Analysing the heat stress, both models projected that Australia will not experience heat stress until 2100. However, compare the two models, more areas are significantly affected by heat stress in the CSIRO-Mk3.0 projection than MIROC-H projection, i.e. areas in the northern and middle parts of Australia.

The results of overlaid maps between the two models, CSIRO-Mk3.0 and MIROC-H, shows an agreement in the reduction of peanut planting areas in the tropical regions in the northern part of Australia, and an increase in the peanut suitability in the temperate regions in the south-eastern part of Australia (Figure 5.10). While the percentage of unsuitable/marginal agreement areas between two models moderately constant from 81.09% of Australia continent in 2030 to around 82.87% of Australia continent in 2100, the percentage of optimal/suitable areas decreased from 14.65% of Australia continent in 2030 to 7.51% of Australia continent in 2100. In addition, the overlaid maps also show a disagreement between two models. For example in 2100, Chinchilla is categorised as an unsuitable area in the CSIRO-Mk3.0 projection, while the MIROC-H projection included Chinchilla as suitable area. The disagreement areas increased from 4.26% of Australia continent in 2030 to 9.62% of Australia continent in 2100.

The overlaid maps show that some current peanut cropping areas, i.e. Katherine in the Northern Territory, Georgetown in northern Queensland, St. George in southern Queensland, and Emerald in central Queensland, will be not be suitable for peanut planting in 2100. Meanwhile, two models, i.e. CSIRO-Mk3.0 and MIROC-H, disagreed with the projections in 2100 of other current peanut planting areas in Queensland such as South Burnett, North Burnett, Chinchilla, Inglewood, and Texas.

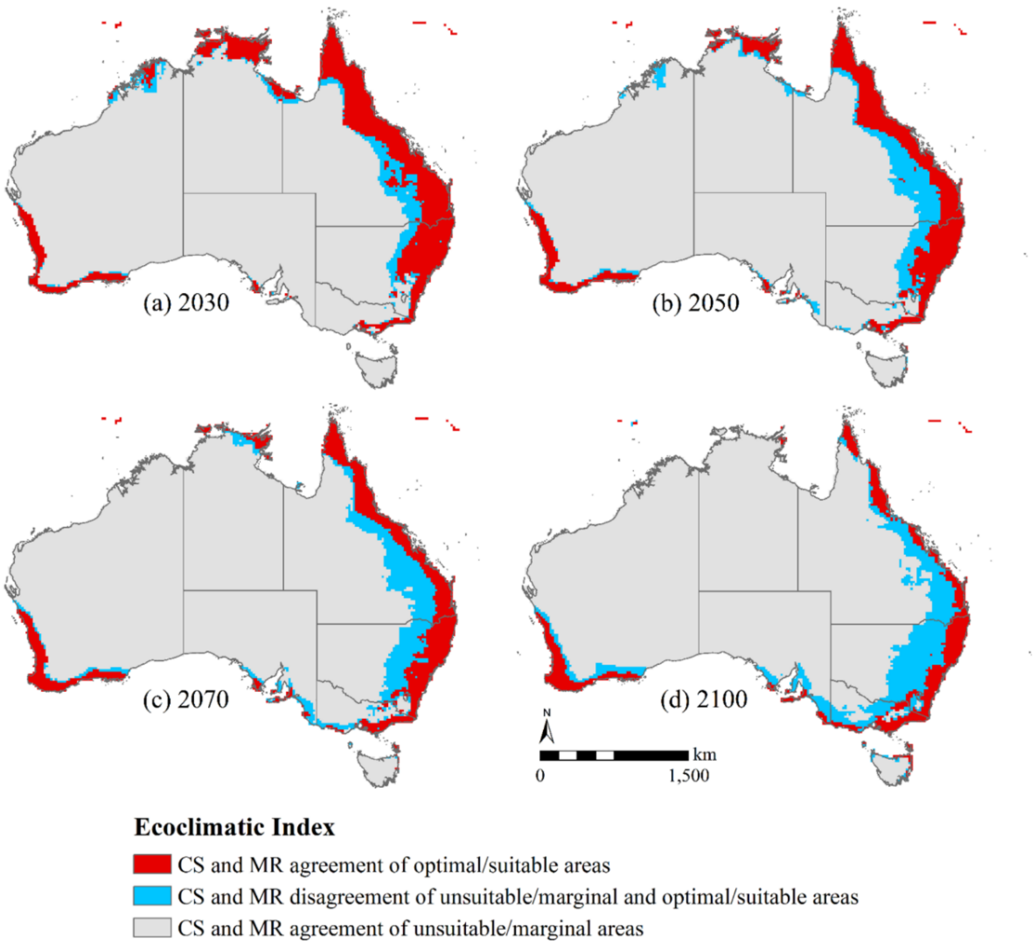

Figure 5.10 CSIRO-Mk3.0 (CS) and MIROC-H (MR) overlaid map of future distribution of peanut crops in Australia under climate scenarios of the SRES A2.

5.5 Discussion

5.5.1 Peanut distribution under the current climate

The CLIMEX model for peanut crops was developed by examining peanut distribution in the native and exotic ranges. The model showed agreement with the majority of distribution data in both native and exotic ranges, which confirmed the correctness of selected peanut CLIMEX parameter values. Only a small amount of peanut distribution data, i.e. 2.3%, were not included in the CLIMEX model, which could be peanut herbarium records or errors in GBIF or ALA databases. In addition, the fact that majority of peanut distribution data was categorised as optimal and suitable peanut planting areas, together with the inclusion of majority peanut distribution data in model validation, has strengthened the validity of the model.

Although known as moderately drought tolerant crops, peanut crops require at least 600 mm of well-distributed water throughout the growing season for achieving optimal yields. In addition, the crops typically require warm temperatures, i.e. around 25-30°C for vegetative growth and around 22-24°C for generative growth (DPIF 2007). Therefore, as can be seen in the peanut CLIMEX model, tropical regions are the most suitable areas to cultivate peanut crops, although the model also includes some subtropical regions. In fact, the starting point to develop peanut CLIMEX parameters in this study was the CLIMEX wet tropical template parameters, which are provided in the CLIMEX program. In addition, due to the temperature and water requirements as mentioned before, peanut crop distribution was limited by cold and dry stress. As a result, peanut distribution cannot be found in extremely arid regions, such as northern Africa, or in extremely cold regions, such as northern Europe and northern America.

5.5.2 Peanut distribution under future climate scenarios

The results of this study and other crop distribution studies, such as wheat and cotton (Shabani & Kotey 2015), common bean (Ramirez-Cabral et al. 2016), tomato (Silva et al. 2017), oil palm (Paterson et al. 2015), and date palm (Shabani, Kumar, et al. 2015), confirm the effects of climate change on crop distribution. Climate is one of the significant factors in determining crop planting suitability (Anwar et al. 2013). Currently, regions with low temperature constraints, such as high mid-latitude countries, may increase their agricultural productivity, while current productive areas in mid-latitude continental countries may experience productivity decrease due to moisture stress increase. In addition, countries in lower middle and low latitudes, which have limited production capacity, will experience further crop stress as a result of climate change (Parry et al. 1990).

CLIMEX model projections on future peanut cropping areas in Australia showed a decrease in suitable peanut planting areas and the emergence of new suitable peanut planting areas for two climate models used in this study, i.e. CSIRO-Mk3.0 and MIROC-H. In the future, it is predicted that dry stress will limit peanut distribution in Australia, since the results of this study have shown that the increase in unsuitable areas is in line with the increase in projected dry stress. This study also found that dry stress projection coverage for CSIRO-Mk3.0 was larger than MIROC-H coverage, which explains the larger coverage of unsuitable areas for CSIRO-Mk3.0 than MIROC-H coverage. In addition, the influence of heat stress occurrence in 2100, also contribute for the decrease of suitable areas for peanut planting in Australia. Interestingly, some areas in the south-western part of West Australia and south-eastern parts of New South Wales and Victoria which are currently not suitable for peanut planting due to cold stress occurrence, are predicted to be suitable in the future. It is predicted that cold stress limitation in these areas will be reduced in the future, since the areas will become warmer due to climate change.

The results in this study were consistent with the results of future distribution study of another legume crop, the common bean (*Phaseolus vulgaris* L.), which also originated in South America. In their study, Ramirez-Cabral et al. (2016) used two climate models, CSIRO-Mk3.0 and MIROC-H, in projecting future common bean distribution. Their findings produced similar results to our study, i.e. CSIRO-Mk3.0 (rather than MIROC-H) projected a less suitable area for common bean cultivation in Australia in 2100. It should be noted that CSIRO-Mk3.0 was developed by Australian researcher under the CSIRO Climate Change Research Program (Gordon et al. 2002), which could include more specific information about Australia. Ramirez-Cabral et al. (2016) also projected a slight increase in suitable common bean planting area in the New South Wales coast and the southern coast of Western Australia.

Analogous to other CLIMEX studies used to project future cotton and wheat distribution in Australia (Shabani & Kotey 2015), the projection of peanut planting areas produced from CSIRO-Mk3.0 and MIROC-H were overlaid to identify common areas between the two models. This method will enhance the likelihood of projections in the future, and thus possible errors can be minimised. Traditionally, in Australia, peanut crops are planted in the South Burnett and North Burnett regions under dryland conditions. However, due to recurring droughts in those regions, peanut areas have been expanded into Katherine in the Northern Territory and areas in the central and northern parts of Queensland, such as Georgetown, the Atherton Tablelands, Emerald, Chinchilla, St. George, Childers, Inglewood, Texas, and Bundaberg (Chauhan et al. 2013). Unfortunately, based on the overlaid projections of future suitable peanut planting areas using CLIMEX model, some of these expansion regions will experience unsuitable climatic condition for peanut growing.

The overlaid CLIMEX model maps from CSIRO-Mk3.0 and MIROC-H climate models indicate that Katherine in the Northern Territory and Georgetown, Emerald, and St. George in Queensland will have low suitability or will not be suitable for peanut planting areas. Only Bundaberg, Mackay, the Atherton Tableland, and Childers in Queensland can be reserved as suitable or optimal areas in 2100. Meanwhile, both CSIRO-Mk3.0 and MIROC-H models disagreed on climate suitability in 2100 for other peanut regions, including the traditional peanut planting areas of South Burnett and North Burnett, where one model included a region as an optimal/suitable area, while other model included it as an unsuitable/marginal area. Indeed, this fact gives a warning of the potential negative impacts of climate change in the current peanut growing regions in Australia. Currently, more than 90% of peanut growing regions in Australia, which supply the majority of the peanut domestic market, are located in Queensland (Wright et al. 2017). Therefore, it is important to develop strategic measures to overcome and manage the economic impacts of the projected shifting climate suitability of the majority of current peanut growing regions.

Based on the projections, future peanut distribution in Australia will be limited by the occurrence of dry stress, which could have unfavourable effects for peanut crops. Although known as moderately drought tolerant, peanut crops require readily available moisture throughout their development stages, especially in flowering and pod formation stages (DPIF 2007). Inadequate water supply during flowering will reduce pod yield, while severe drought stress during the pod filling stage will lead to more severe yield reduction (Wright et al. 1991). Reoccurrence of water deficit during the late season decreases yield, reduces peanut quality, and increases the possibility of aflatoxin disease contamination (Kambiranda et al. 2011). Peanut seed physiological activity is reduced with the occurrence of drought stress, thus it becomes more susceptible to fungal invasion, such as aspergillus invasion which leads to aflatoxin disease (Kambiranda et al. 2011).

As a result of frequent water deficit, crops experience anatomical changes, i.e. reduction in size of cell and intercellular spaces, cell walls thickening, and larger development of epidermal tissue. In addition, severe water deficits could also influence a crop's metabolic process, i.e. reduction in enzymatic activity (Kambiranda et al. 2011). Shahenshah and Isoda (2010) found that drought stress in peanut caused an increase of leaf temperature and non-photochemical quenching. Moreover, it leads to a reduction in water content per unit leaf area, chlorophyll content, and maximum quantum yield of photosystem. Furthermore, peanut crops also experience an increase of root dry weight with small reduction of leaf area when they are suffering drought stress (Shahenshah & Isoda 2010).

Therefore, it is important to take strategic measures to anticipate the future shifting suitable areas of peanut crops in Australia, especially since the majority of current peanut planting areas will be affected negatively. One measure that has been taken and is still in progress is the development of drought tolerant varieties. Currently, drought tolerant peanut genotypes were screened by using advanced molecular tools, which involved studies on the peanut at the molecular and cellular level (Kambiranda et al. 2011). Although an improved peanut genotype that can tolerate drought stress has been developed, the process still needs to continue to develop advanced genotypes (Kambiranda et al. 2011). Another measure that can be considered is to apply and improve irrigation and greenhouse technologies, although economic constraints must also be taken into account.

It should be noted that careful considerations should be taken in interpreting this study result, since the CLIMEX model only considers climatic factors in determining the current and future distribution of species. Non-climatic factors that could limit species distribution, such as biotic interactions (e.g. competition and predator), habitats (e.g. presence of suitable host, soil type and humans), and topographic elements (Kriticos et al. 2015), were not considered. In addition, the model development of this study did not consider the application of irrigation in peanut crops which could increase the suitable areas of peanut crop planting.

5.6 Conclusion

This study has successfully developed CLIMEX model parameters for peanut crops which are found consistent with current peanut geographic distribution. In addition, using CSIRO-Mk3.0 and MIROC-H Global Climate Models under the climate scenarios of the SRES A2, CLIMEX model projections for future peanut distribution in Australia shows an increase of unsuitable areas for peanut cultivation. In detail, the projections of unsuitable peanut cultivation areas in 2100 is higher for CSIRO-Mk3.0 than MIROC-H, i.e. 76% of Australia continent compared to 48% of Australia continent. In the future, dry stress is projected to increase and cause limitations of suitable peanut areas. The overlaid maps of CSIRO-Mk3.0 and MIROC-H models projected that in 2100, some existing peanut cultivation areas, namely, Katherine (the Northern Territory) and Georgetown, Emerald, and St. George (Queensland), will become unsuitable for peanut cultivation. Only peanut cropping areas of Bundaberg, Mackay, the Atherton Tableland, and Childers in Queensland are projected to be suitable or optimal for peanut cultivation in 2100. Meanwhile, CSIRO-Mk3.0 and MIROC-H models disagreed on climatic suitability in 2100 for other peanut cropping areas, such as the traditional peanut planting areas in South and North Burnett, Chinchilla, Inglewood, and Texas.

The future peanut distribution maps resulting from this study will provide valuable contributions in long term planning of peanut cultivation in Australia, especially with regard to projected unsuitable areas for the majority of current peanut cultivation regions. However, further work is needed to include non-climatic factors, such as topography, soil type, and biotic interactions, to further increase the accuracy and robustness of the projected future distribution of peanut cropping areas.

Chapter 6

THE IMPACT OF CLIMATE CHANGE ON FUTURE DISTRIBUTION OF AFLATOXIN IN PEANUT CROPS

6.1 Introduction

Aflatoxin attracts significant attention because of its negative effects on human and animal health. Approximately 90,000 cases of liver cancer occur every year due to aflatoxin, some of which may be fatal (Grace et al. 2015). Moreover, aflatoxin is also known to be responsible for stunted growth and immune suppression in children (Grace et al. 2015). As a result of these health problems, over 100 countries have set up special regulations for monitoring aflatoxin limits and have arranged specific guidelines for mycotoxins in food (Van Egmond et al. 2007; Wu & Guclu 2012).

Although incidence of aflatoxin is influenced by many factors, climate is the most significant consideration (Paterson & Lima 2010). Consequently, climate change could affect aflatoxin incidence, including a shift in its potential geographical distribution (Van der Fels-Klerx et al. 2016). Unfortunately, although it is crucial, research in modelling the effects of climate change on aflatoxin incidence are still limited (Battilani 2016). Peanut crops are at a high-risk of aflatoxin infection (Klich 2007). In Australia, the major mycotoxin problem is aflatoxin invasion in peanut crops (Pitt & Hocking 2006). Therefore, with the projection of climate change occurrence in the future, it will be important to identify areas in Australia which are suitable for growing peanut crops but have a low aflatoxin risk.

This chapter focuses on the third specific objectives of the study. It examines the impact of climate change on future aflatoxin distribution in Australia and identifies potential future peanut growing areas with a lower risk of aflatoxin incidence. The primary aim of this study was to examine the effects of climate change on the potential geographic distribution of aflatoxin in peanut crops in

Australia and its high risk spots on the future projected distribution of peanut cropping areas. The specific objectives of the study were: 1) to develop CLIMEX model parameters of aflatoxin in peanut crops; 2) to identify the projected geographic distribution of aflatoxin in Australia under climate models; and 3) to identify the projected peanut planting areas in Australia which could be affected by aflatoxin.

The chapter is organised into six sections. Section 1 details the objectives of this chapter. Section 2 reviews literature on aflatoxin incidence in peanut crops, including the cause, effect, and current knowledge deficiency. Section 3 describes the methods of the study used in achieving the chapter's objective. Sections 4 and 5 respectively present the results and discussions on the development and validation of the aflatoxin CLIMEX model, the future aflatoxin distribution in Australia, and the future distribution of peanut crop growing areas in Australia in comparison with future aflatoxin distribution. The chapter concludes by highlighting the new knowledge gained from this study.

The novelty and significant contributions of this chapter include the followings: 1) it describes the development of CLIMEX model parameters for aflatoxin; 2) it is the first study on projecting the effects of climate change on future aflatoxin distribution in Australia; and 3) it is the first study on investigated projected suitable areas for future peanut distribution in conjunction with projected suitable areas for future aflatoxin distribution, in order to identify aflatoxin low-risk areas for peanut cultivation.

6.2 Aflatoxin problems in peanut crops

One of the major problems in peanut consumption is the presence of aflatoxin in peanuts which could lead to cancer and even fatality due to aflatoxicosis. The latest major outbreak of aflatoxicosis occurred in Kenya between 2004 and 2006, and claimed the lives of more than 150 people (Mutegi et al. 2012). The first aflatoxicosis outbreak, known as Turkey X disease epidemic, occurred in 1961 in England due to the imported groundnut ingredients in bird feed. The hepatotoxic product of *aspergillus* species found in the feed was concluded to be the responsible agent for the disease (Blount 1961). This toxin was subsequently named aflatoxin (Blount 1961), which is a secondary metabolite produced by common soil fungi, namely *aspergillus* (Perrone et al. 2014). There are four major aflatoxins: aflatoxins

B_1, B_2, G_1, and G_2, which occur naturally in agro-products (Klich 2007), and the most toxic is aflatoxin B_1 (Zorzete et al. 2011). Evidence indicates that aflatoxins B_1 and G_1 have carcinogenic potential and have been categorised by the International Agency for Research on Cancer (IARC) as a group 1 human carcinogen (IARC 2012), that is, a group of agents with sufficient evidence of causing cancer in humans (IARC 2006).

Two *aspergillus* species, *aspergillus flavus* and *aspergillus paraciticus*, are associated with aflatoxin infection in agricultural crops (Perrone et al. 2014). *Aspergillus flavus* has been identified as the major vector for aflatoxin infection (Torres et al. 2014). Aflatoxin commonly infects crops such as peanut, corn, cottonseeds, and tree nuts which are grown in the latitude where *aspergillus* species is commonly found (Klich 2007). Klich (2002) revealed that while *aspergillus* species persists at projected frequencies in tropical latitude, i.e. below 25 degrees of south and north, and is found more frequently in the subtropical or warm temperate zones of 26-35 degrees, it hardly persists in higher latitudes. It is suggested that differences in the latitude temperature might be the factor for these differences in persistence (Klich 2002). The optimal temperatures for *aspergillus* development are between 25 and 40°C, while the minimum temperature for its growth is 10°C (Klich et al. 1992). The optimal temperature range continues in the subtropical or warm temperate zone for a relatively long period which explains the persistence of *aspergillus* species in this zone (Klich 2002).

Fortunately, the presence of *aspergillus* in the crops does not necessarily indicate the occurrence of aflatoxin (Hill et al. 1983). Certain environmental stresses, e.g. temperature increase and prolonged drought, are required for the infection to occur (Cole et al. 1989; Cotty & Jaime-Garcia 2007). The longer the crops are exposed to environmental stress and other risk factors (e.g. high soil insect incidence), the greater the probability of aflatoxin infection (Rachaputi et al. 2002). In addition, agricultural practices, such as adapted cultivars, seed density, fertilization (especially nitrogen), irrigation, and harvesting time (Klich 2007), also determine the infection rate of aflatoxin (Horn & Dorner 1999). In spite of these, climate is the main driving factor for aflatoxin contamination (Paterson & Lima 2010).

Peanut crops are one of the legume crops. They are unique because the flowers are above ground, but once pollinated, they produce fruits below the surface of the soil (Wright et al. 2017). As a result, throughout their growth and development period, peanut fruits have direct contact with soil microorganisms, including *aspergillus* fungus which prefer to grow in high nutrient media, such as seeds (Guo et al. 2003). Consequently, peanut fruits have a high-risk of aflatoxin contamination (Zorzete et al. 2011). Schroeder and Boller (1973) found that peanut is one of the most suitable substrates for high aflatoxin production. Aflatoxin infection in peanut crops is determined significantly by climate. In particular, prolonged heat and drought stress during the last 3 to 6 weeks of the peanut growing season facilitates the synthesis of aflatoxin in peanut seeds (Kokalis-Burelle et al. 1997), resulting in pre-harvest contamination. In a recent study, Kachapulula et al. (2017b) found that climate is the main factor responsible for high aflatoxin concentration in groundnut in Zambia. Environmental stresses also induce subsequent post-harvest aflatoxin contamination in peanut crops during harvest, handling, or storage (Diener 1960). However, in general, pre-harvest contamination is still the dominant factor in aflatoxin infection in peanut crops (Cole et al. 1989).

Due to the adverse effects of aflatoxin contamination in human health, the maximum acceptable level of aflatoxin in agricultural products have been regulated, in more than 120 countries (Bui-Klimke et al. 2014). For example, the European Union, where some of its member countries are major peanut importers (Fletcher & Shi 2016), regulated the maximum level of aflatoxin B_1 and other aflatoxin types in groundnuts at 2 and 4 µg/kg, respectively (EC-European Commission 2010). The regulations of aflatoxin content would induce significant economic losses if the maximum acceptable level could not be achieved. Wu (2004) found that the peanut industries in USA, China, Argentina, and Africa will suffer around $450 million annual losses if the European standard of aflatoxin maximum limit is applied.

As aflatoxin occurrence and severity depend on climate stresses, such as drought, extreme temperature, and rain at the end stages of crop production (Cotty & Jaime-Garcia 2007), changes in climate could affect aflatoxin contamination in agricultural crops, including peanut. Climate change leads to alteration in mean temperature, climate variability, and occurrence of extreme weather events, such as drought, very high or very low temperature, heavy rain, and floods (Gornall et al. 2010). These changes may affect agricultural systems, including plant disease epidemiology and severity (Chakraborty et al. 2000; Luck et al. 2011). A latitude bias in the range shifts of crop pests and pathogens indicates the impact of global warming (Bebber 2015). For example, a shift in the dry and hot summer climate in 2003 resulted in the occurrence of aflatoxin for the first time in Italy (Giorni et al. 2007). It is expected that if climate and atmospheric composition continue to change as projected, the distribution of crops and diseases will be affected, which could lead to adverse economic impacts (Chakraborty et al. 2000). Therefore, there is a need to differentiate future disease trends on a geographic and future time scale (Juroszek & von Tiedemann 2013).

One of the methods to evaluate the impact of climate change in the geographic distribution of aflatoxin is the use of Species Distribution Models (SDMs), such as CLIMatic indEX or CLIMEX (Sutherst & Maywald 1985). Since the availability of plant disease historical data for fingerprint analysis is limited, plant pathologists rely primarily on mathematical or statistical models for the purpose of impact assessment (Scherm 2004). Furthermore, there is an increase in model capability in taking into account the complex interaction between a pathogen, its host, and the environment (Luck et al. 2011), which enables a more accurate prediction of the impact of climate change on the distribution of the pathogen.

As discussed in previous chapter, CLIMEX is a mechanistic or process-oriented computer model which is designed to explore the effects of climate on species (Kriticos & Leriche 2010). A set of species growth and stress functions is used in assessing the response of species to climate variables and the ability of species to persist in a location. The growth and stress functions are fit based on experimental laboratory data or geographic distribution data using inductive and deductive approaches (Kriticos & Leriche 2010; Kriticos et al. 2013). The model has been used successfully in a wide range of taxa, including plants, pathogens, mammals, and insects (Kriticos & Leriche 2010). It is also well suited to model invasive species (Kriticos et al. 2013). Some examples of successful applications of CLIMEX model include the study of future distribution of another legume crop, the common bean (*Phaseolus vulgaris* L.) (Ramirez-Cabral et al. 2016) and the study of *Fusarium oxysporum* f. spp. pathogen (Shabani, Kumar & Esmaeili 2014).

Climate change projection in Australia has placed peanut crops in a vulnerable position for aflatoxin contamination. The Australian average temperature increased by 0.9°C from 1910 to 2009, which is 0.2°C higher than the global average (Cleugh et al. 2011). The warming trend continues with a projection of an average temperature increase of 1.0°C by 2030 (Cleugh et al. 2011). There is also a projection of summer rainfall uncertainty in northern Australia (Cleugh et al. 2011), where the majority of peanut crops is grown. In addition, it is projected that Australia is likely to suffer more frequent extreme events, such as drought, heat-waves, and floods (Head et al. 2014). These factors could result in the occurrence of drought and heat stresses that stimulate the synthesis of aflatoxin in peanut crops. This is especially true because the majority of peanut crops in Australia are cultivated under dryland practice with a high climatic risk (Meinke & Hammer 1995), and the Australian climate is dominated by an arid climate regime and is well known for its high variability (Head et al. 2014).

In the last 40 years, the management of pests and diseases has contributed to the doubling of food production, but pathogens are still responsible for a reduction of 10-16% in the global harvest (Chakraborty & Newton 2011). In particular, despite their limited host range, fungal pathogens have the most widely dispersed distribution, which marks them as being the leaders of invasive species of agricultural crops (Bebber et al. 2014). Taking this into account climate change could affect the geographical distribution of aflatoxin in peanut crops. Therefore, further investigation in this area is undoubtedly important. Specifically, aflatoxin distribution may further limit the area of peanut planting in the future.

6.3 Materials and methods

6.3.1 Study area

The study was carried out in the Australian continent covering a total of 7.692 million km^2 (Geoscience Australia 2018) (Figure 6.1). Major climate types in Australia include: tropical, subtropical, desert, grassland/semi-arid, and temperate (Kriticos et al. 2012). These classes are based on the Koppen-Geiger classification, following the application of the rules of Kriticos et al. (2012) applied to the 5’ resolution of WorldClim – Global Climate Data (Hijmans et al. 2005). Agricultural activities are performed in areas of Australia that are suitable for cultivation, including the eastern parts of Queensland and New South Wales, most part of Victoria, the southern part of South Australia, and the south-western part of Western Australia (ABARES 2019). In general, peanut crops are grown under dry culture practice in large scale farms with fully mechanized systems (Pitt & Hocking 2006). These peanut areas spread across the eastern part of Queensland and the northern part of the Northern Territory (Crosthwaite 1994; Chauhan et al. 2013). Unfortunately, aflatoxin contamination in peanut is the dominant mycotoxin problem in Australia (Pitt & Hocking 2006). In a study, Hansen and Norman (1999) revealed the historical level of aflatoxin contamination in dryland South and Central Burnett, Atherton Tableland, and Northern Territory as 42%, 11%, and 17%, respectively, which generated economic loss. In fact, for some extreme climate conditions, almost 100% of peanut from dryland South and Central Burnett may be contaminated with aflatoxin (Hansen & Norman 1999).

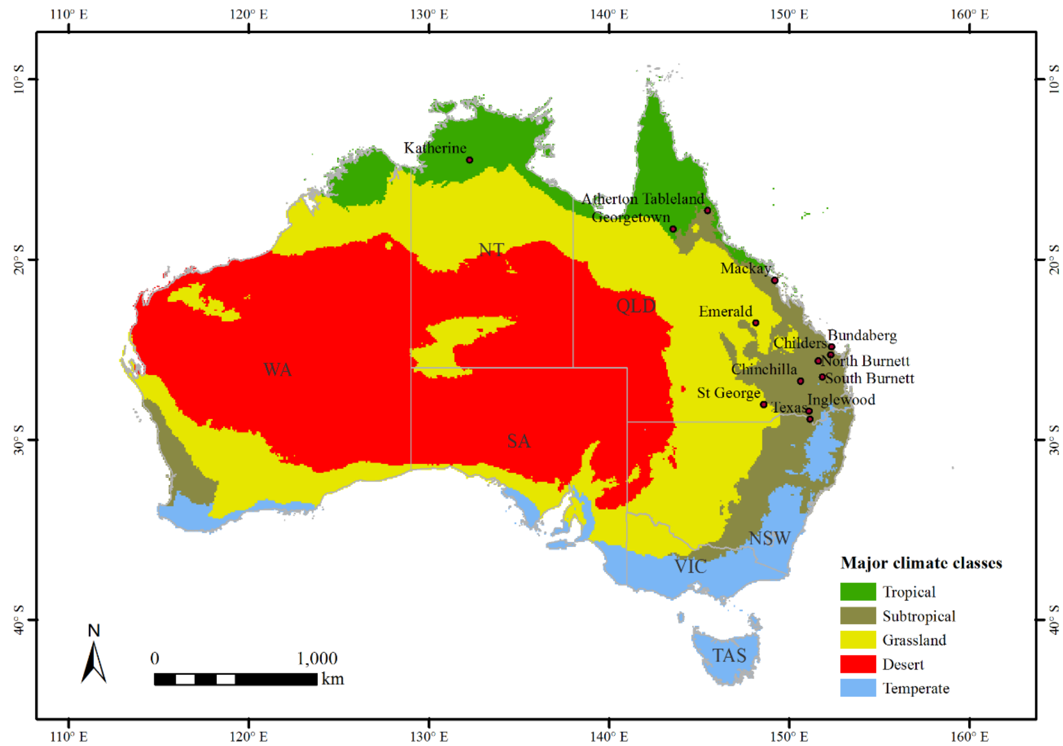

Figure 6.1 Study area of Australia and current cultivation areas of peanut crops throughout different climate classes based on Kriticos et al. (2012) rule.

6.3.2 Global geographic distribution of aflatoxin

Evidence concerning the global distribution of aflatoxin incidence was retrieved from various academic articles. In general, aflatoxin incidence spread across tropical, sub-tropical and semi-arid climates in America, Africa, Asia, Europe and Australia. In total, there were 405 recorded locations of aflatoxin outbreaks, with 151 locations in Asia, 150 locations in Africa, 87 locations in America, 12 locations in Italy, Europe, and 5 locations in Australia. In detail, the locations of aflatoxin data were retrieved from the following academic articles: Kenya (Lewis et al. 2005; Collins et al. 2010; Mutegi et al. 2012); Zambia (Kachapulula et al. 2017b); Ghana (Agbetiameh et al. 2018); Ethiopia (Chala et al. 2013; Chauhan et al. 2016); Mali (Waliyar et al. 2015); Democratic Republic of Congo (Kamika & Takoy 2011; Kamika & Tekere 2016); Malawi (Waliyar et al. 2013); Nigeria (Bankole & Mabekoje 2004); Tanzania (Seetha et al. 2017); Benin (Setamou et al. 1997); Uganda (Kaaya et al. 2006); the Philippines (Quitco 1991; Yamashita et al. 1995; Arim 2000; Arim 2003); Indonesia (Yamashita et al. 1995; Ali et al. 1998; Rahayu et al. 2003); Thailand (Siriacha et al. 1988; Yamashita et al. 1995); India (Sinha 1990; Kishore et al. 2002; Vijayasamundeeswari et al. 2009; Navya et al. 2013; Sharma & Parisi 2017); China (Daren 1989; Li et al. 2001; Zhang et al. 2011; Wu et al. 2016); the USA (Pettit et al. 1971; Lillehoj et al. 1975; Horn et al. 1995; Robens & Cardwell 2003); Brazil (Gonçalez et al. 2008; Moreno et al. 2009; Rocha et al. 2009; Atayde et al. 2012); Argentina (Resnik et al. 1996; Barros et al. 2003); Costa Rica (Mora & Lacey 1997); Mexico (García & Heredia 2006); Italy (Battilani et al. 2013); Australia (Chauhan et al. 2010). This global distribution of aflatoxin outbreaks is presented in Figure 6.2. The global distribution data were divided into two groups, one for parameter fitting and the other one for model validation.

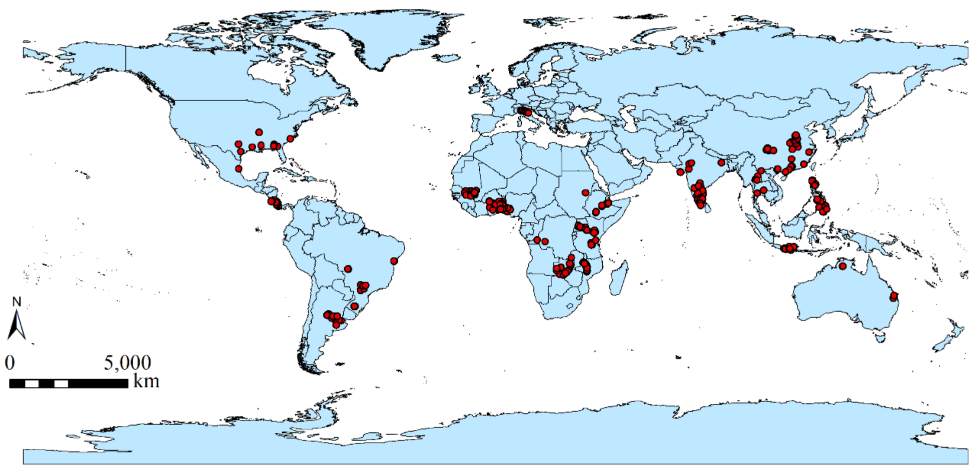

Figure 6.2 The distribution of aflatoxin outbreaks throughout the world from various academic articles. Red circles represent the distribution data.

6.3.3 Meteorological database and climate change models

CliMond 10’ (18.55km) resolution climate database (Kriticos et al. 2012) was used in this study to provide historical and future climatic variables required for CLIMEX modelling of aflatoxin distribution. The historical climate data were retrieved from 1950 to 2000, centred at 1975 (Kriticos et al. 2012). The CliMond database is a hybrid of WorldClim and Climate Research Unit (CRU) (CL1.0 and CL2.0) datasets which provide humidity data and additional 16 Bioclim variables (Kriticos et al. 2012). The climate variables for CLIMEX model consist of average maximum monthly temperature (T_{max}), average minimum monthly temperature (T_{min}), average monthly precipitation (P_{total}) and Relative Humidity recorded at 9am ($RH_{09:00}$) and 3pm ($RH_{15:00}$) (Kriticos et al. 2015).

The future climate was modelled using two Global Climate Models (GCMs), namely CSIRO-Mk3.0 (developed by CSIRO, Australia) and MIROC-H (developed by the Centre for Climate Research, Japan). They were obtained from the CliMond database. Twenty three GCMs were initially analysed based on three selection criteria: (1) the ability to provide monthly averages of daily maximum and minimum temperatures, precipitation, mean sea level pressure, and specific humidity; (2) having a relatively smaller-horizontal grid spacing (e.g. less than 2×2° over Australia); and (3) providing relatively good performance at a regional scale compared to other GCMs in representing basic aspects of the observed climates (Kriticos et al. 2012). As a result, CSIRO-Mk3.0, MIROC-H, and another GCM, NCAR-CCSM (developed by National Centre for Atmospheric Research, USA) were selected. However, in the next stage, NCAR-CCSM was eliminated due to the occurrence of some concerning errors in arid regions. The use of two GCMs, i.e. CSIRO-Mk3.0 and MIROC-H, is widely recognised in CLIMEX studies over a variety range of taxa. Some examples of these studies are cotton and wheat (Shabani & Kotey 2015), tomato (Silva et al. 2017), common bean (Ramirez-Cabral et al. 2016), fruit flies (Hill et al. 2016), and wheat midge (a major wheat pest) (Olfert et al. 2016).

The future aflatoxin distributions were modelled using the SRES (Special Report on Emission Scenarios) A2 scenario family (Nakicenovic et al. 2000), which was found to be consistent with the carbon dioxide emissions since 2000 (Manning et al. 2010). This is also available from the CliMond database. The latest IPCC report of the AR5 Synthesis Report disclosed the new climate scenarios, namely the Representative Concentration Pathways (RCPs), which consist of RCP8.5, RCP6, RCP4.5, and RCP2.6. The closest similar RCP scenario to SRES A2 is RCP8.5, which is the revised version of SRES A2 (Van Vuuren et al. 2011; Van Vuuren & Carter 2014). The temperature increase of SRES A2 at the end of the 21st century (relative to 1980-1999) is projected to be 3.4°C with a likelihood ranging from 2.0°C to 5.4°C (Bernstein et al. 2008). Meanwhile, the temperature increase of RCP8.5 at the end the of 21st century (relative to the 1986-2005 period) is projected to be 3.7°C with a range of 2.6 – 4.8°C (IPCC 2014).

6.3.4 CLIMEX model

The CLIMEX program is a simplified dynamic model that infers species response to climatic conditions, based on their geographical distribution and their growth and mortality patterns (Beddow et al. 2010; Kriticos et al. 2015). There are several modes of CLIMEX program, and this study used the 'compare locations' mode. The program is run by determining a set of parameter values that reveals species response to temperature, soil moisture, and if applicable, light (Kriticos et al. 2015). These values reflect the climatic conditions that favour species growth and limit species survival (Sutherst & Bourne 2009); and is calculated weekly in the form of Growth Index (GI) and Stress Index (SI) indices. The Growth Index determines species' population growth, and consists of two parameters: Temperature Index (TI_W) and Moisture Index (MI_W). The Stress Index leads to species' negative population growth, and is calculated from Cold Stress (CS), Heat Stress (HS), Dry Stress (DS), and Wet Stress (WS) parameters (Sutherst & Maywald 1985; Kriticos et al. 2015). The weekly indices of GI and SI are then combined into annual value, i.e. GI_A and SI_A, which are used to calculate Ecoclimatic Index (EI) value.

The EI value shows favourable conditions for a species to persist in a location, with a range from 1 (indicates unsuitable conditions for species persistence) to 100 (indicates optimal conditions for species persistence) (Sutherst & Maywald 1985; Kriticos et al. 2015). As with most of the CLIMEX studies, this study classifies EI values into four categories: unsuitable (EI = 0), marginal (0<EI<10), suitable

(10<EI<20), and optimal (EI>20). The CLIMEX functions are calculated as follows (Kriticos et al. 2015):

$EI = GI_A \times SI$ (1)

where:

GI_A, the annual Growth Index, $= 100 \sum_{i=1}^{52} GI_w / 52$ (2)

GI_W, the weekly Growth Index = $TI_W \times MI_W$ (3)

TI_W is weekly Temperature Index and MI_W is weekly Moisture Index

SI, the annual Stress Index, $= \left[\left(1 - \frac{CS}{100}\right) \times \left(1 - \frac{DS}{100}\right) \times \left(1 - \frac{HS}{100}\right) \times \left(1 - \frac{WS}{100}\right)\right]$ (4)

CS, DS, HS, WS, respectively are the annual cold, dry, heat, and wet stress indices.

6.3.5 Adjustment of CLIMEX parameters

The CLIMEX parameters have to fit the geographical distribution and they have to be biologically reasonable, based on the theoretical and experimental domains of the species (Kriticos et al. 2015). As a result, the parameter fitting in this study was developed based on: (1) aflatoxin developmental threshold of temperature and moisture level from various academic literature, and (2) the global geographical distribution of aflatoxin as provided in section 3.2. In this study, the aflatoxin distribution data in the African and American continents were used in the parameter fitting process.

The CLIMEX program provided several parameter templates which represent different geographical distributions. These templates can be used as a starting point to develop CLIMEX parameters (Kriticos et al. 2015). The determination of CLIMEX parameter template used in this study was based on the comparison between aflatoxin distribution map and the distribution map retrieved from all templates. The CLIMEX parameter template which showed the closest distribution with aflatoxin distribution was ‘wet tropical template’. As a result, this template was used as a basis in developing the CLIMEX parameters of aflatoxin.

The starting point to fit the CLIMEX parameters was the adjustment of Stress Indices rather than Growth Indices. The purpose of this step was to recognise the unsuitable areas of aflatoxin persistence in the wet tropical template; thus the boundary of aflatoxin distribution could be set. The process of these adjustment was carried out iteratively. Afterwards, Growth Indices were developed using the same iterative fitting procedures. The developmental threshold acquired from the academic literature was used to fit the CLIMEX parameters iteratively, i.e. by adjusting them according to the aflatoxin distribution data. The parameter adjustment process was carried out until an agreement between the CLIMEX model output and aflatoxin geographical distribution was achieved (Kriticos et al. 2015). The final parameters (Table 6.1) were then used to develop future aflatoxin models in Australia in relation to climate change occurrences.

Based on the analysis of wet tropical template and aflatoxin distribution maps, it can be resolved that most aflatoxin distribution which was not included in the wet tropical template was due to the presence of cold or dry stresses. Therefore, the fitting process for CLIMEX aflatoxin parameters was started by adjusting cold and dry stress parameters. Below is the detailed explanation on the process of CLIMEX parameters determination.

Cold stress: In order to incorporate the aflatoxin occupation areas in the USA, China, and Argentina into the CLIMEX aflatoxin model, the day-degree temperature threshold of cold stress (DTCS) and the cold stress degree-day rate (DHCS), were set at 15°C and -0.00012 week^{-1}, respectively.

Dry stress: The determination of dry stress threshold (SMDS) was based on the value of permanent wilting point of crops, i.e. 0.1. Meanwhile, in order to include the aflatoxin occupation areas in Mali, Sudan, and Zambia, dry stress rate (HDS) was set to -0.00008 week^{-1}.

Heat stress: Heat stress temperature threshold (TTHS) and heat weekly accumulation rate (THHS) were determined at 40°C and 0.00009 week^{-1}, respectively, to allow the inclusion of aflatoxin incidence in Mali and Sudan.

Wet stress: In order to eliminate wet stress incidents in aflatoxin geographic distribution, wet stress threshold (SMWS) and wet stress rate (HWS) were set at 2 and 0.0009, respectively.

Temperature index: The temperature range which supports aflatoxin growth and development were parameterised in the CLIMEX model as a lower temperature threshold (DV0), a lower optimal temperature (DV1), a lower optimal temperature (DV2), and an upper temperature threshold (DV3). Since peanut fruits are underground, the aflatoxin temperature range for peanut crops is mostly measured at the fruiting zone, known as geocarposphere (Smartt 2012), 5 cm below the soil surface. On average, air temperature is lower (4 to 6°C), compared to geocarposphere temperature (Smartt 2012).

Unfavourable geocarposphere temperature for aflatoxin development in peanut was found to be at 23.6°C or lower (Blankenship et al. 1984) and at 24.6°C (Cole et al. 1985), which are around air temperature of 17.6°C to 20.6°C. Therefore, after iteratively fitting CLIMEX parameters, DV0 was determined at 17.5°C. In regard to optimum temperature for aflatoxin incidence in peanut crops, favourable geocarposphere temperatures are 26.3 - 29.6°C (Cole et al. 1985), 28 – 30.5°C (Sanders et al. 1985), and 25 - 28°C (Hill et al. 1983). Based on these data and iteratively fitting parameter process, DV1 and DV2 were set at geocarposphere temperature of 26°C and 30.5°C or 20°C and 24.5°C air temperature. In terms of maximum temperature for aflatoxin occupation, Chauhan et al. (2008) set the temperature at 35°C, while Gallo et al. (2016) found aflatoxin contamination at almonds was halted at 37°C. Therefore, in order to include the aflatoxin areas in Mali and Sudan, DV3 was set to be 38°C.

Moisture index: The lower soil moisture threshold (SM0) of CLIMEX parameter of aflatoxin was set according to permanent wilting point, i.e. 0.1 or 10% of soil moisture. In a study, Chauhan et al. (2008) identified that aflatoxin accumulated at less than 20% of soil moisture, while Sanders et al. (1985) indicated that moisture tension bars of 2.9 (around 84% of soil moisture) did not stimulate aflatoxin contamination in peanut crops. Therefore, after being iteratively adjusted, the lower and upper optimal soil moisture (SM1 and SM2) were set at 0.2 and 0.8, respectively. Meanwhile, in order to prevent wet stress occurrence in aflatoxin distribution areas, the upper soil moisture threshold (SM3) was set to be similar to the wet stress threshold (SMWS), i.e. 2.

Table 6.1 CLIMEX parameter values generated from this study and used in modelling aflatoxin distribution.

Index	Parameter	Values
Temperature	DV0	17.5°C
	DV1	20°C
	DV2	24.5°C
	DV3	38°C
Moisture	SM0	0.1
	SM1	0.2
	SM2	0.8
	SM3	2
Cold stress	DTCS	15°C
	DHCS	-0.00012 week^{-1}
Heat stress	TTHS	40°C
	THHS	0.00009 week^{-1}
Dry stress	SMDS	0.1
	HDS	-0.00008 week^{-1}
Wet stress	SMWS	2
	HWS	0.0009 week^{-1}

6.3.6 Model validation

Geographic distribution data of aflatoxin incidence in India, China, the Philippines, Thailand, Indonesia, Italy, and Australia were not used in model development, but were reserved for model validation purposes. The developed CLIMEX model in the America and Africa continents was validated against these independent data to ensure model performance and reliability. The model validation was carried out by calculating the percentage of aflatoxin geographical distribution which categorised as unsuitable areas for aflatoxin invasion in the CLIMEX model.

6.3.7 Future aflatoxin distribution and it comparison with peanut crop distribution

Using the developed aflatoxin CLIMEX parameters, this study modelled the future geographic distribution of aflatoxin incidence in Australia under predicted climate change incidence for 2030, 2050, 2070, and 2100. To enhance the accuracy of the output, results from the two GCMs, i.e. CSIRO-Mk3.0 and MIROC-H, were overlaid to determine the common aflatoxin contamination areas in Australia in the future. Since aflatoxin became one of the major problems in the peanut industry, the future distributions of aflatoxin in Australia resulting from CSIRO-Mk3.0 and MIROC-H GCMs were overlaid with the Australian future distributions of peanut crops (Chapter 5) which were also modelled under CSIRO-Mk3.0 and MIROC-H GCMs. It is expected that the overlaid result between peanut crops and aflatoxin incidence will provide information regarding the most suitable areas for planting of peanut crops in Australia, i.e. those areas which are suitable for peanut crops but not suitable for aflatoxin persistence.

6.3.8 Research flowchart

The workflow for this study is presented in Figure 6.3.

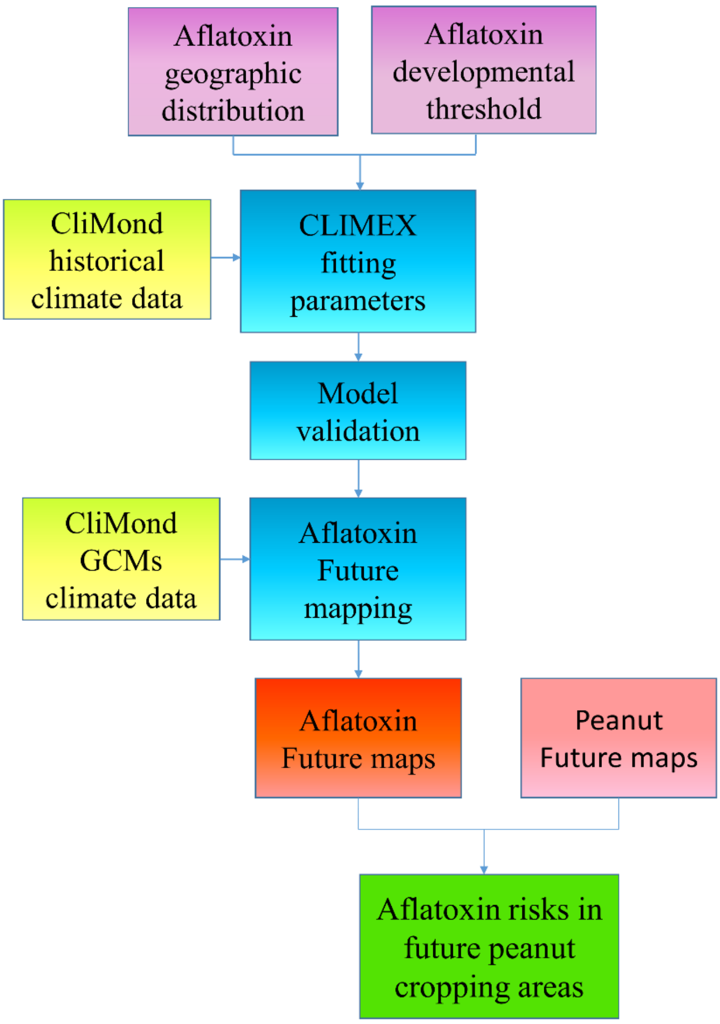

Figure 6.3 The study flowchart and key processing tasks.

6.4 Results

6.4.1 Model evaluation and current climate

The CLIMEX aflatoxin model result shows a consistency with the global distribution data of aflatoxin (Figure 6.4). In general, none of the aflatoxin geographic distribution data was categorised as unsuitable areas for aflatoxin occurrence. It means that 0% of aflatoxin distribution data falls outside the optimal/suitable/marginal areas in the model. Indeed, most of the distribution data were included in optimal areas of the model. For example, most aflatoxin data in the American continent were categorised in optimal areas, while only small amounts were incorporated in suitable areas, and none of them were included in marginal or unsuitable areas. Cold stress is found to be the major obstacle for further aflatoxin occupation in the northern and southern part of the continent (Figure 6.5). In the case of the African continent, the majority of distribution data were included in optimal areas for aflatoxin persistence. Meanwhile, some of the distribution data were fitted to suitable areas of the CLIMEX aflatoxin model, i.e. distribution data in the northern part of Ghana, northern part of Benin, and the major part of Mali. Only a small portion of aflatoxin incidence in Mali and Sudan were incorporated in marginal areas, merely due to their closeness with areas which suffered dry and heat stresses in the northern part of Africa (Figure 6.5).

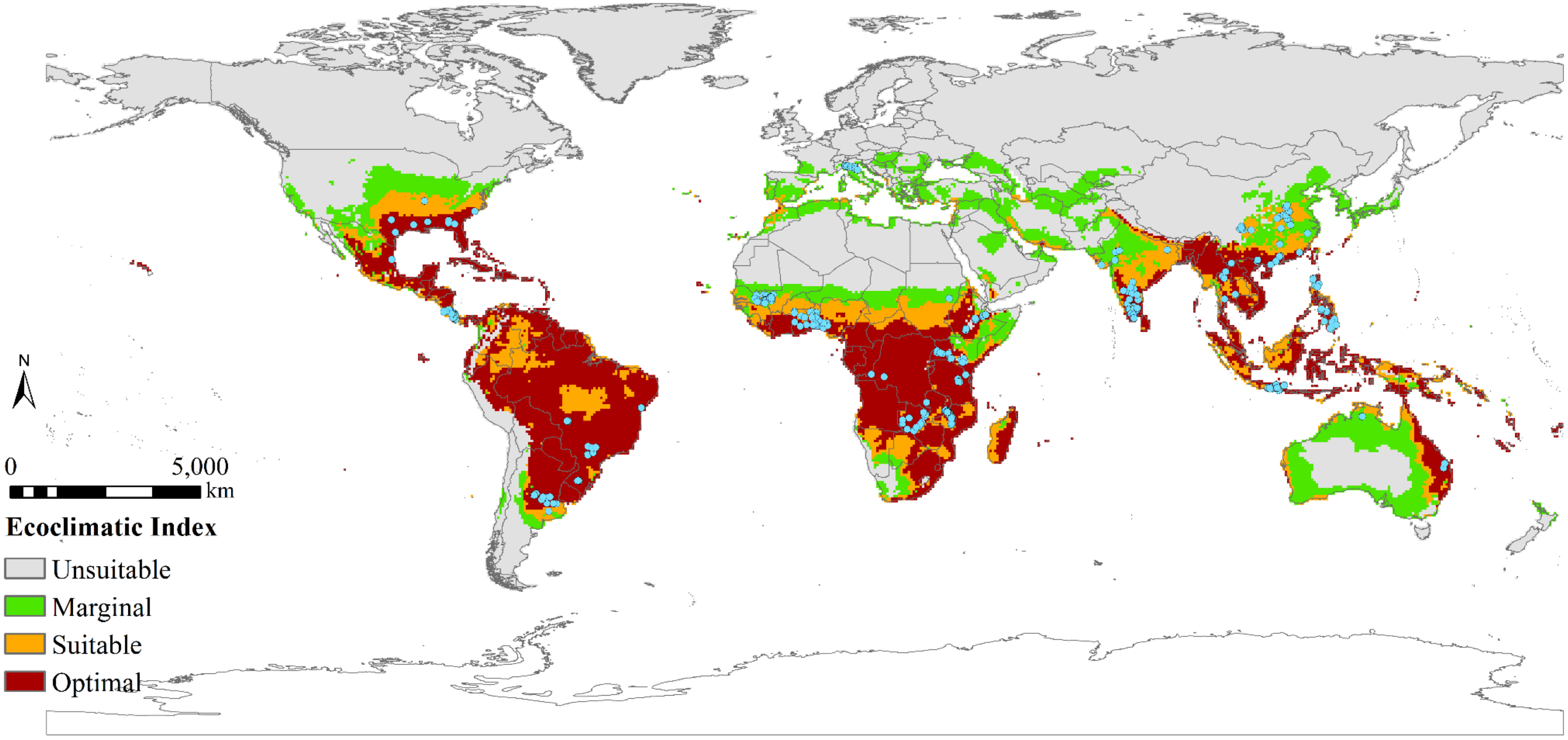

Figure 6.4 CIMEX model output of Ecoclimatic Index (EI) of aflatoxin using current climate data. Blue circles represent the current distribution of aflatoxin.

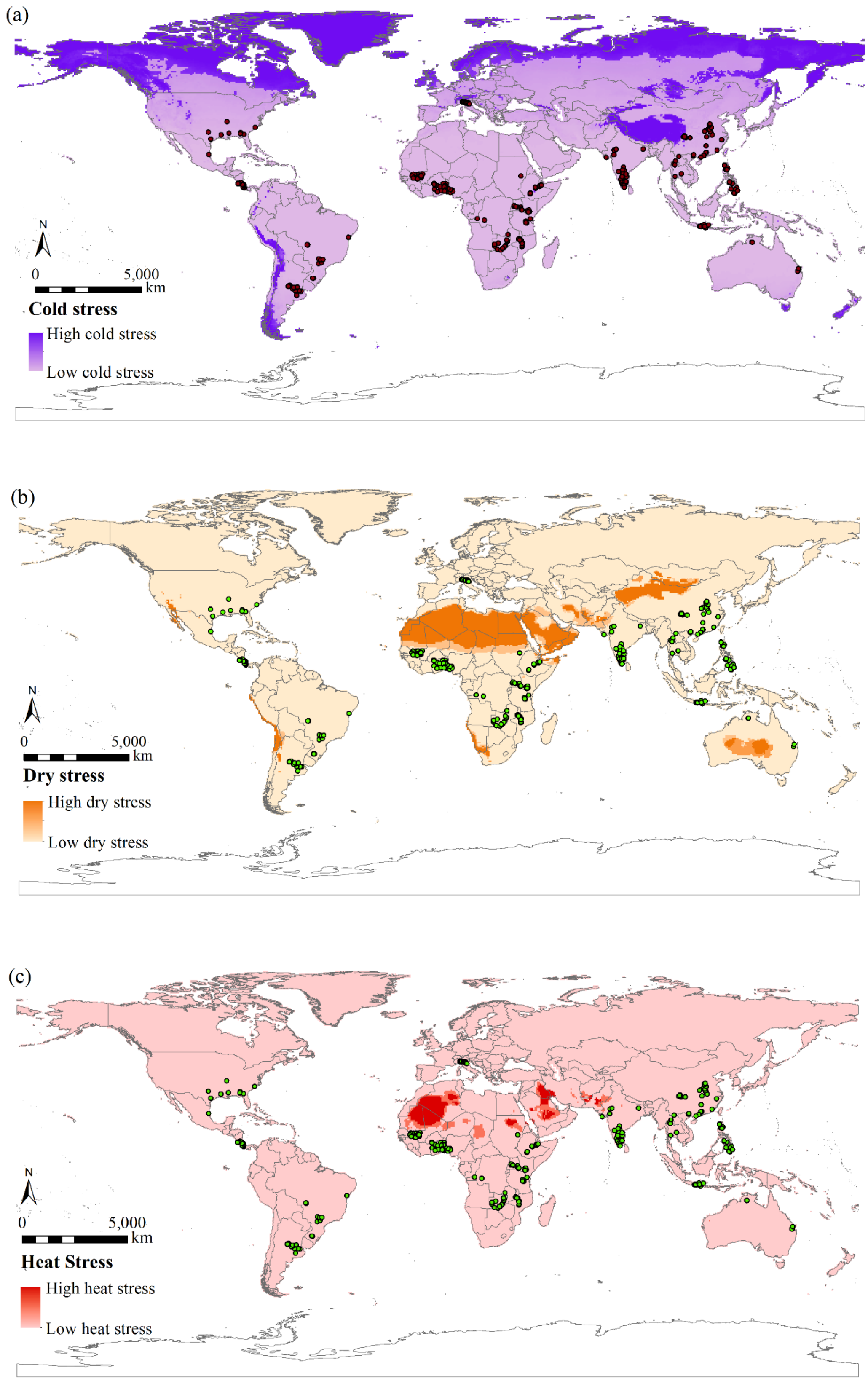

Figure 6.5 Map of cold stress (a), dry stress (b), and heat stress (c) of aflatoxin CLIMEX model. Green and red circles represent global geographical distribution of aflatoxin.

Aflatoxin distribution in model validation areas (India, China, the Philippines, Thailand, Indonesia, Italy, and Australia) showed agreement with the distribution in the model development areas (the American and African continents). Figure 6.6 showed that most of the distribution data in the validation areas were categorised as optimal in the aflatoxin model, especially those in tropical climate regions, such as Indonesia, Thailand, and the Philippines. Some of the subtropical and semi-arid distribution areas in China, India, Australia, and Italy fell in suitable and marginal categories. None of distribution data were categorised as unsuitable areas for aflatoxin occupation. Adjusting cold stress parameters to include the northern and southern distribution point of the American continent in the subtropical climate into the aflatoxin CLIMEX model, had also enabled the inclusion of validation area of northern distribution point in China, which has a similar climate type. Similarly, the inclusion of northern point distribution of the African continent was carried out by adjusting heat and dry stress parameters, which automatically resulted in the inclusion of aflatoxin distribution in validation area of India, i.e. Rajasthan, Bihar, and Gujarat. Both of the areas in Africa and India have grassland or semi-arid climates.

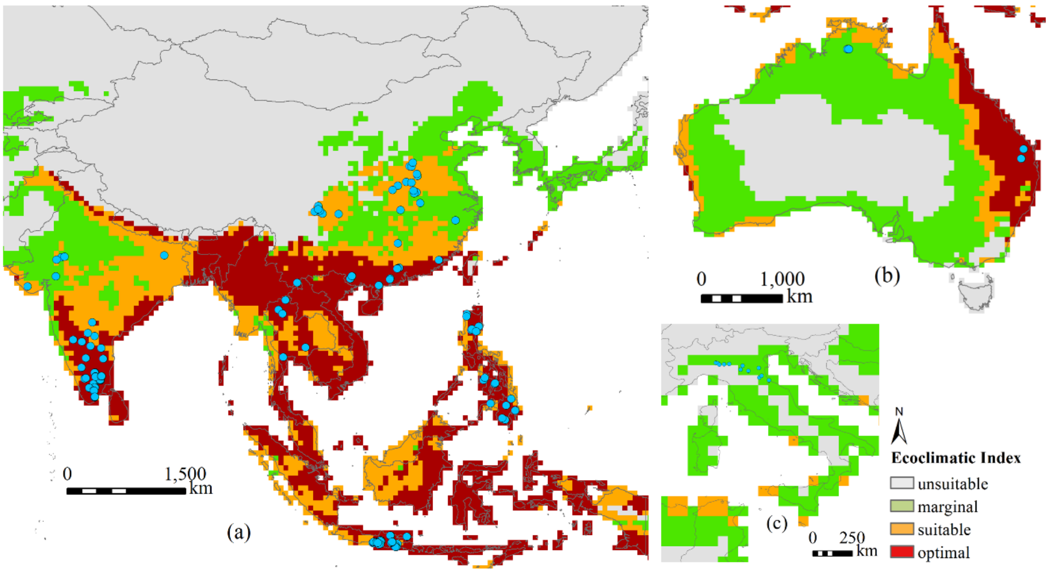

Figure 6.6 CLIMEX model output of Ecoclimatic Index (EI) of aflatoxin in validation areas of Asia (a), Australia (b), and Italy (c). Blue circles represent the current distribution of aflatoxin.

Based on the global distribution of aflatoxin (Figure 2), it can be seen that aflatoxin occurs between 40° North latitude and 40° South latitude. The majority of aflatoxin incidence occurred in tropical and subtropical climate zones, although some incidence were also found in the semi-arid grassland climate zone. Interestingly, the majority of aflatoxin distribution in tropical regions, such as the central part of the African continent, Brazil, India, Thailand, Indonesia, and the Philippines were categorised as optimal areas in the CLIMEX model. Similarly, most of the aflatoxin distribution in subtropical regions was also included as optimal areas for aflatoxin incidence, i.e. the USA, Argentina, Zambia, and Australia. However, some of the distributions in this subtropical zone were also categorised in suitable areas of the CLIMEX model, such as most of the aflatoxin distribution in China. Only a small number of distributions in the subtropical region were included in marginal areas for aflatoxin persistence, for example aflatoxin distribution in Italy. In terms of aflatoxin distribution in semi-arid climate regions, only a small proportion occurred, with the majority categorised as suitable and marginal areas in the CLIMEX model, except small distributions in India which were categorised as optimal areas.

6.4.2 Future projections

Projected aflatoxin areas in Australia under the CSIRO-Mk3.0 climate model using the CLIMEX model are presented in Figure 6.7. In general, the majority of the Australian continent is categorised as unsuitable areas for aflatoxin contamination, i.e. areas in the middle, north, and north-western part of Australia, which are known as regions of arid climate type. In addition, under CSIRO-Mk3.0 projections, the number of unsuitable areas will increase significantly throughout the projection years of 2030 to 2100, due to the conversion of marginal areas into unsuitable areas. Similar to unsuitable areas, most of the marginal areas are characterised by the arid climate type.

Meanwhile, only small areas of Australia are categorised as optimal and suitable for aflatoxin infection. The majority of these categories are located in the eastern part of Australia, while small amounts are located in the south-western part of Western Australia. Both of these areas are included as subtropical and temperate climate regions. In contrast to unsuitable areas, the projections of optimal and suitable areas show a remarkable reduction trend from 2030 to 2100. Although the number of optimal and suitable areas in the subtropical region of north-eastern part of Australia are reduced at the latter period of projection years, the areas of optimal and suitable in the temperate region of south-eastern and south-western part of Australia have increased.

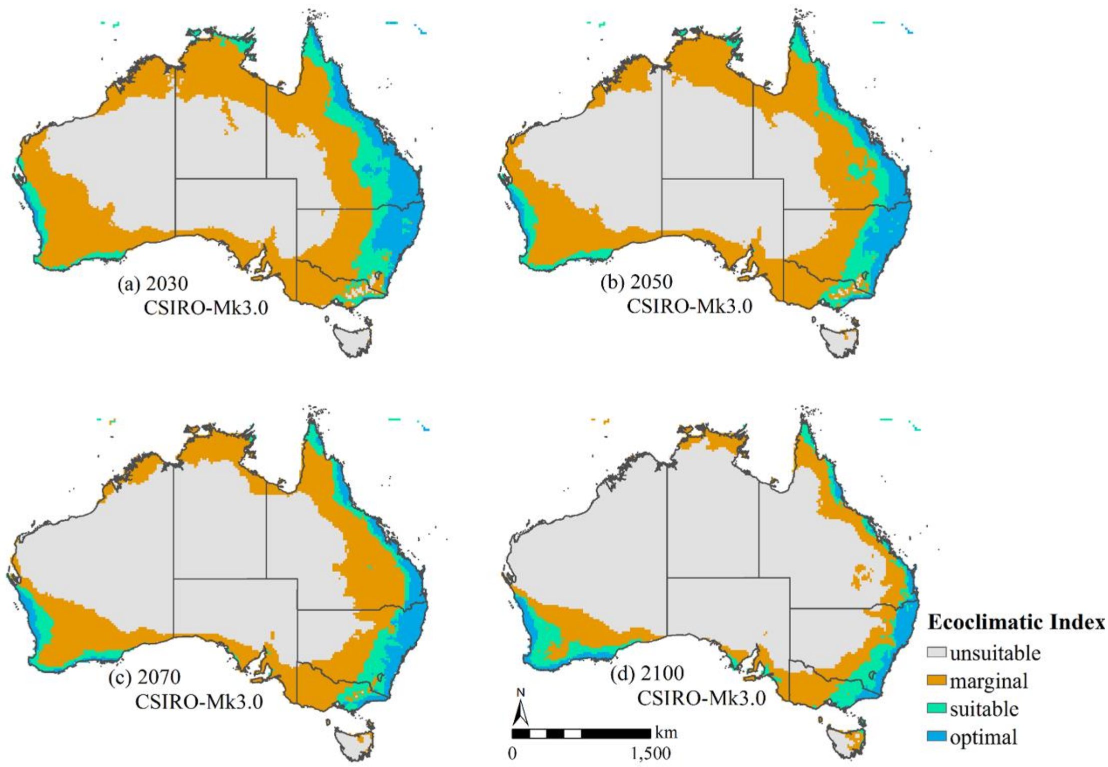

Figure 6.7 The future aflatoxin distribution in Australia using CLIMEX model under CSIRO-Mk3.0 Global Climate Model with SRES A2 climate scenario.

The results of MIROC-H climate model projections of aflatoxin using the CLIMEX model are shown in Figure 6.8. In similar way to CSIRO-Mk3.0, the projection of unsuitable areas under the MIROC-H climate model are dominated by unsuitable areas for aflatoxin occupation, but with a smaller area compared to CSIRO-Mk3.0 projection. In addition, unlike CSIRO-Mk3.0, the increase of unsuitable areas of MIROC-H throughout projection years is slight. The results show that unsuitable and marginal areas are mainly located in arid climate zones (grassland/semi-arid and desert) of Australia, i.e. in the middle, north, and north-western areas. Although some marginal areas in the northern part of Australia are converted into unsuitable areas in the latter period of the projection years, some parts of the unsuitable areas in the semi-arid regions of middle Australia are converted into marginal areas. However, in overall there is a decrease in the marginal areas.

In similar way to CSIRO-Mk3.0, the majority of optimal and suitable areas for aflatoxin contamination under the MIROC-H model are located in the eastern part of Australia. Some of these areas can also be found along the coast of Western Australia. Although the optimal and suitable areas for CSIRO-MK3.0 and MIROC-H models are not really different in 2030, the areas difference at the following projection years are significant. Throughout the projection years, MIROC-H projected an increase in optimal and suitable areas, while CSIRO-Mk3.0 projected a decrease. The significant difference can be seen in 2100 projection, where the total optimal areas of CSIRO-Mk3.0 accounted for 34% of the total optimal areas of MIROC-H, and the total suitable areas of CSIRO-Mk3.0 accounted for 39% of the total suitable areas of MIROC-H. In addition, MIROC-H projected an increase of optimal and suitable areas in the south-eastern, south-western, and southern part of Australia, which are mainly categorised as temperate regions.

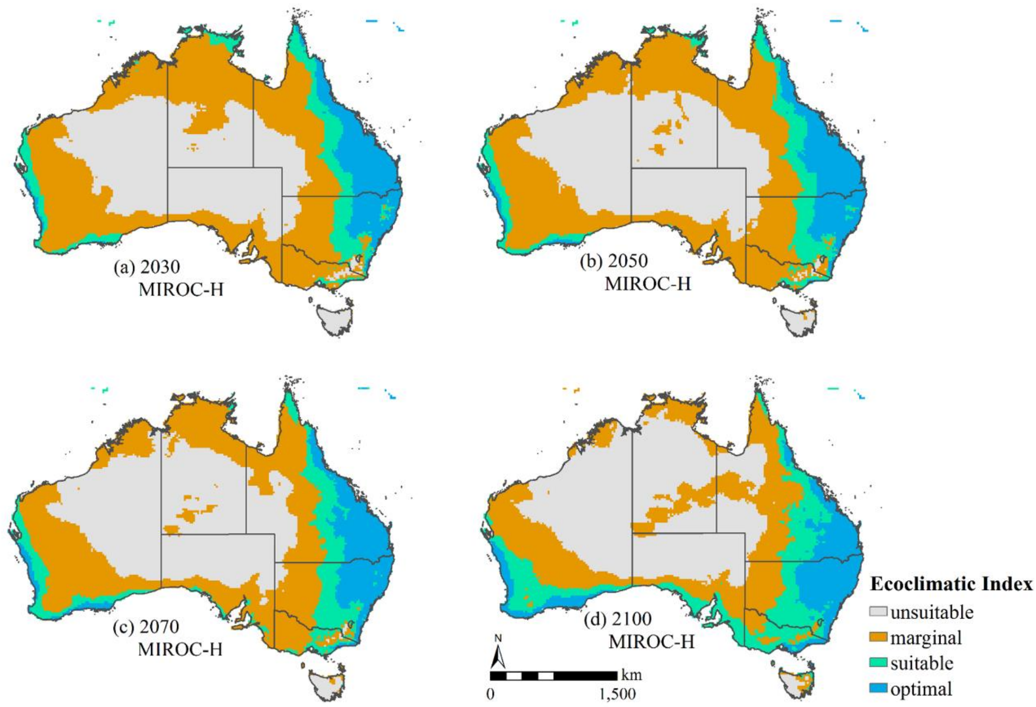

Figure 6.8 The future aflatoxin distribution in Australia using CLIMEX model under MIROC-H Global Climate Model with SRES A2 climate scenario.

Table 6.2 The percentage of projected optimal, suitable, marginal, and unsuitable areas for aflatoxin contamination in Australian continent under CSIRO-Mk3.0 (CS) and MIROC-H (MR).

CLIMEX output	2030		2050		2070		2100	
	CS (%)	MR (%)	CS (%)	MR (%)	CS (%)	MR (%)	CS (%)	MR (%)
Optimal	7	10	6	10	5	11	4	12
Suitable	9	9	7	10	6	11	6	15
Marginal	38	43	34	41	28	37	16	30
Unsuitable	46	37	52	39	61	41	74	43

Table 6.2 shows the percentage of projected optimal, suitable, marginal, and unsuitable areas for aflatoxin contamination in Australia. Looking at the difference between the projection results of CSIRO-Mk3.0 and MIROC-H, it can be said that optimal, suitable, and marginal areas for aflatoxin contamination of MIROC-H model are higher than CSIRO-Mk3.0 model, with an increase in difference gaps throughout the projection years. On the contrary, unsuitable area percentages of

CSIRO-Mk3.0 are higher than MIROC-H throughout the projection years, also with an increase in difference gap.

It can be seen that the majority of the Australian continent is projected to be unsuitable for aflatoxin contamination under the CSIRO-Mk3.0 and MIROC-H climate models. CSIRO-Mk3.0 shows a significant increase (up to 62%) of unsuitable areas, from 46% of the Australian continent in 2030 to 74% of the Australian continent in 2100. Meanwhile, MIROC-H only shows a slight increase (up to 16%) of unsuitable areas from 2030 to 2100, i.e. 37% to 43% of the Australian continent, respectively.

Marginal areas become the second majority group in aflatoxin projections of CSIRO-Mk3.0 and MIROC-H models. Respectively, both models projected a decrease in these areas from 38 and 43% of the Australian continent in 2030, to 16 and 30% of the Australian continent in 2100. Resulting in a decrease of 58 and 31% of marginal areas throughout the projection years for CSIRO-MK3.0 and MIROC-H, respectively.

Only a small portion of the Australian continent will be optimal and suitable for aflatoxin persistence under two climate model projections. CSIRO-Mk3.0 suggests that less than 10% of the continent will be in these categories, with a decrease throughout the projection years. Comparing the optimal and suitable areas of CSIRO-Mk3.0 projection between 2030 and 2100, respectively, there are 45 and 33% reductions. On the other hand, MIROC-H projection shows an increase of optimal and suitable areas throughout the projection years, i.e. up to 17 and 61% increase, respectively. In 2030, only 10 and 9% of the Australian continent are projected to be optimal and suitable areas under MIROC-H projection; while in 2100, they are projected to be 12 and 15% of the Australian continent.

The projections of future cold, dry, and heat stress for aflatoxin are presented in Figure 6.9, Figure 6.10, and Figure 6.11. Both CSIRO-Mk3.0 and MIROC-H projected that some of the temperate climate regions of Australia, i.e. the south-eastern areas, will experience cold stress for aflatoxin persistence in the future. However, MIROC-H predicted more coverage area and severity of cold stress than CSIRO-Mk3.0. Nevertheless, both models predicted a reduction in areas of cold stress throughout the projection years. In terms of dry stress, the projections of two climate models are different. MIROC-H projections remain relatively unchanged in terms of dry stress areas and severity from 2030 to 2100. Meanwhile, CSIRO-

Mk3.0 projected an increase of dry stress areas and severity throughout the projection years. Dry stress projections of the CSIRO-Mk3.0 model cover almost all of the arid climate zone of Australia, while MIROC-H projections only cover some parts of Australia's arid zone. Looking into heat stress projections, both climate model projections are significantly increased at the end of the projection years. At the beginning of the projection years, only small areas in the north-western part of Australia experience dry stress. However, at the end of the projection years, dry stress areas have expanded to most of the areas in the northern and central parts of Australia. Comparing the two models, dry stress areas of CSIRO-Mk3.0 are larger than those of MIROC-H.

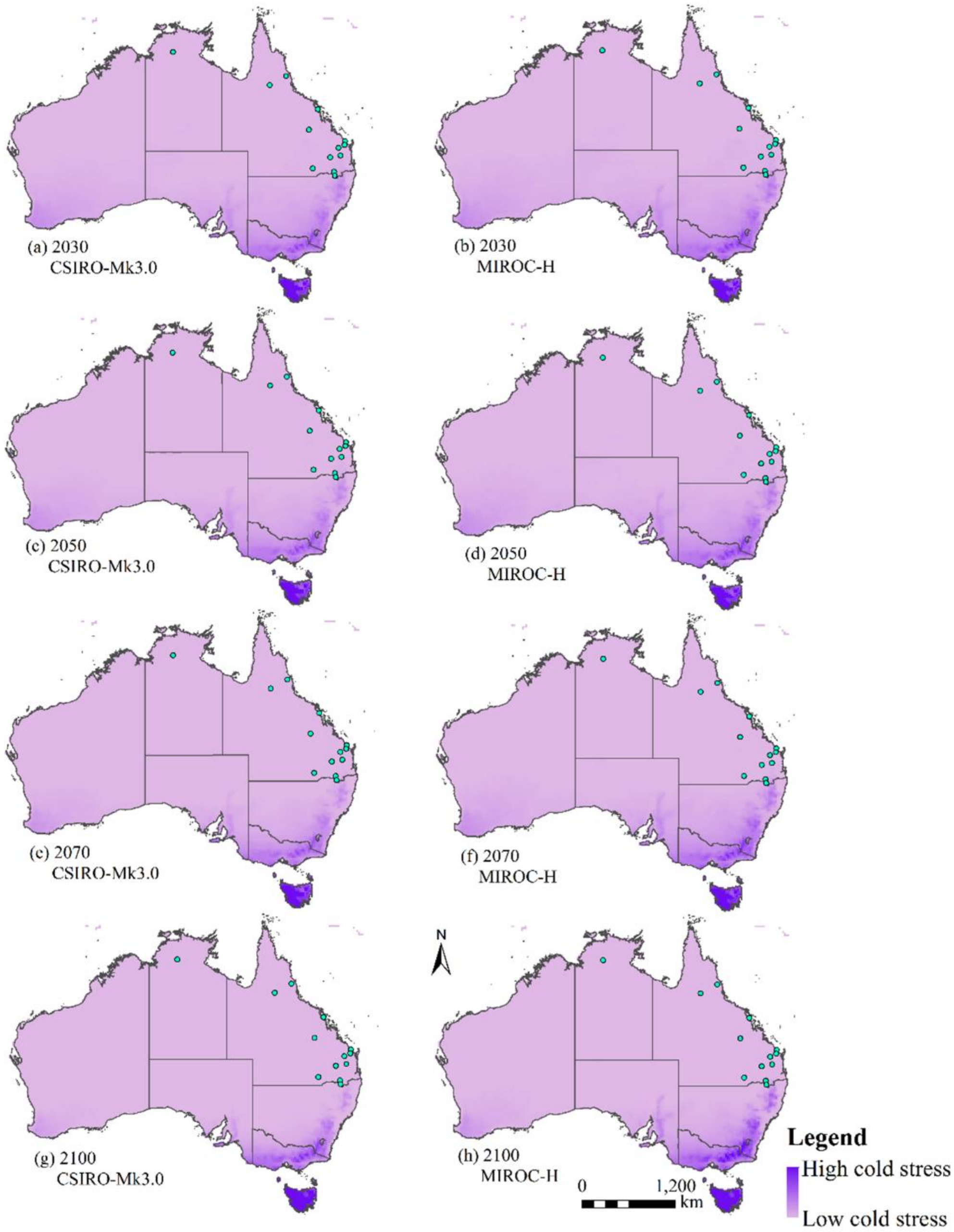

Figure 6.9 Cold stress projection of aflatoxin model in 2030, 2050, 2070, and 2100 under CSIRO-Mk3.0 and MIROC-H Global Climate Models. Green dots are the current peanut planting areas in Australia.

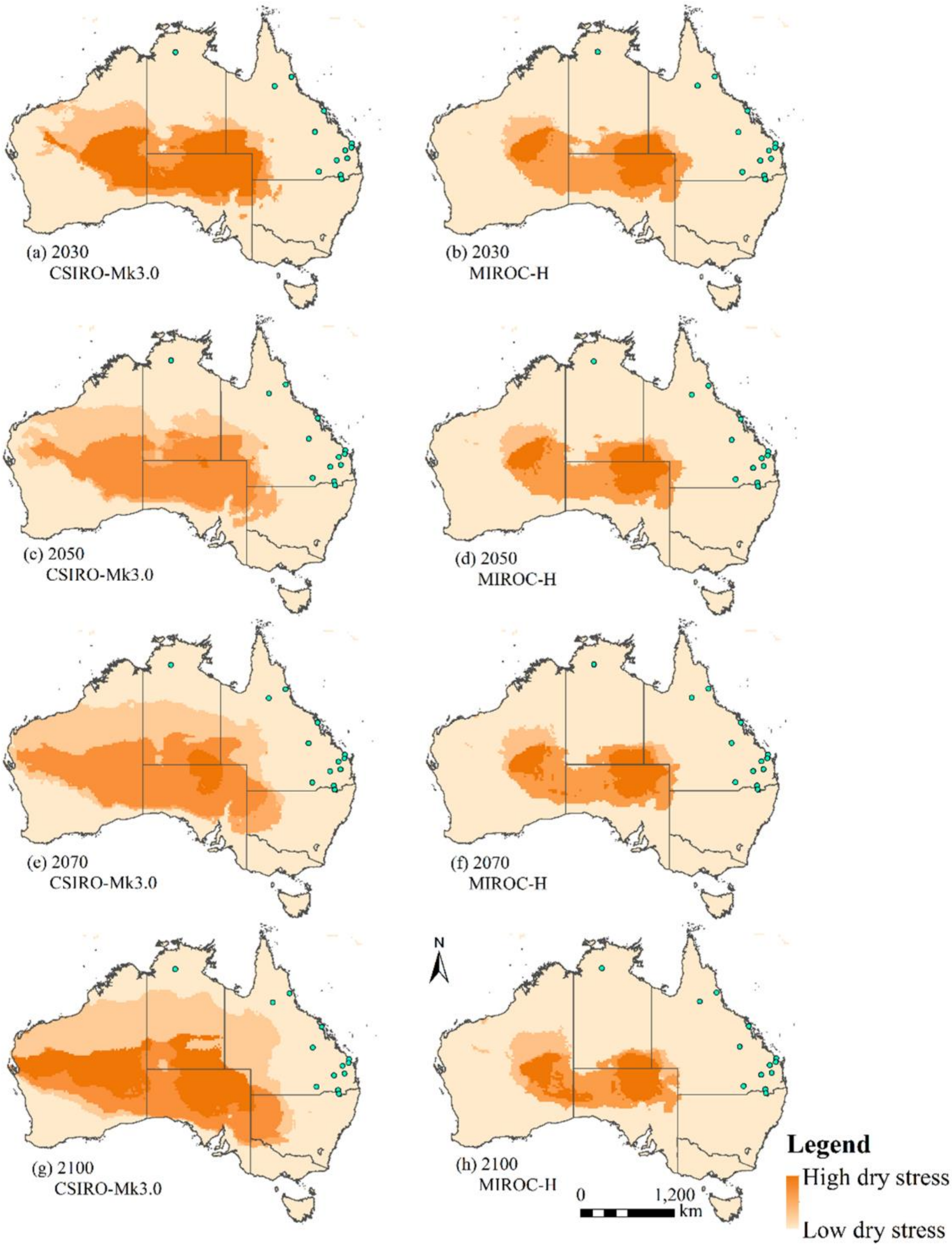

Figure 6.10 Dry stress projection of aflatoxin model in 2030, 2050, 2070, and 2100 under CSIRO-Mk3.0 and MIROC-H Global Climate Models. Green dots are the current peanut planting areas in Australia.

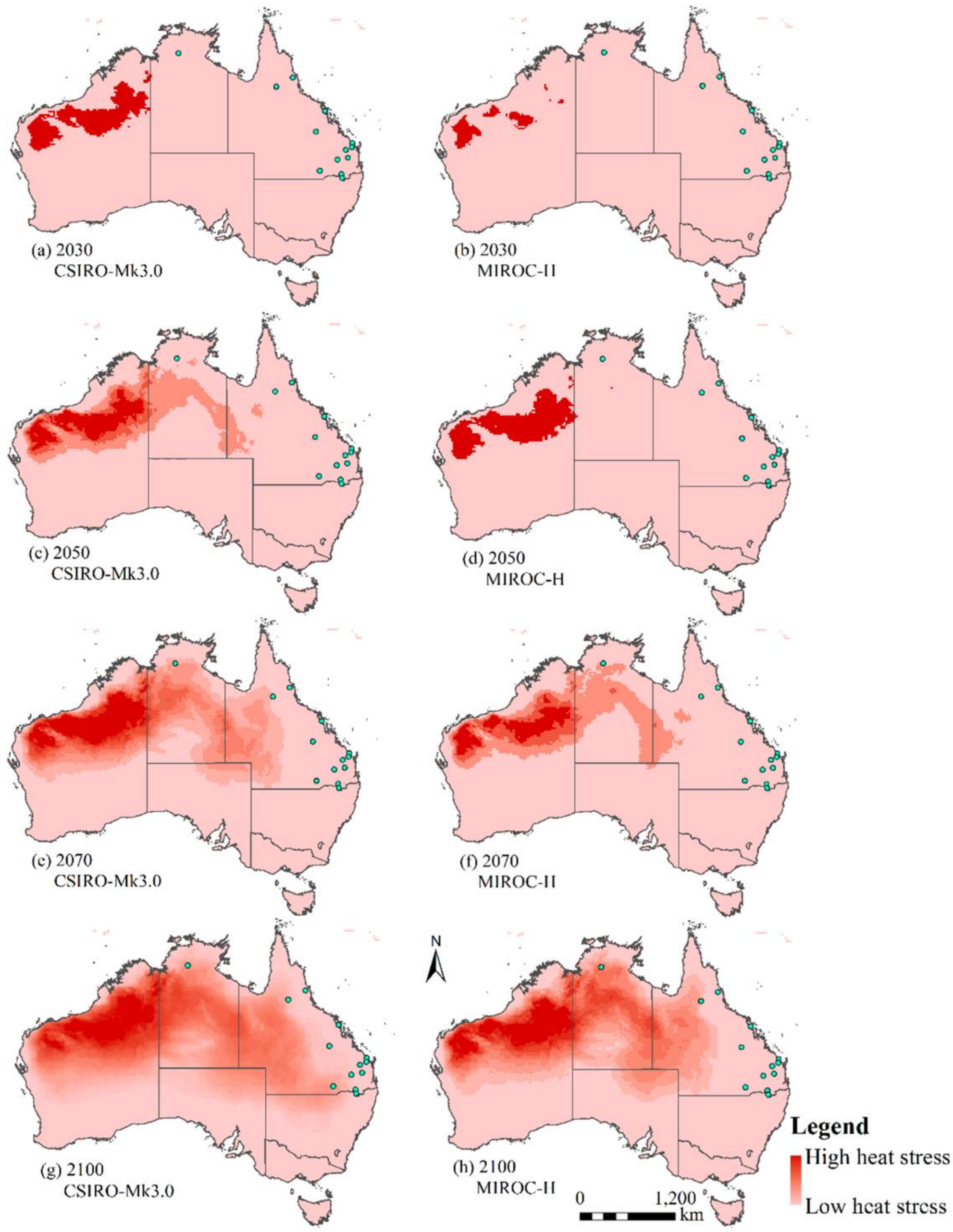

Figure 6.11 Heat stress projection of aflatoxin model in 2030, 2050, 2070, and 2100 under CSIRO-Mk3.0 and MIROC-H Global Climate Models. Green dots are the current peanut planting areas in Australia.

The overlaid results of future aflatoxin models between CSIRO-Mk3.0 and MIROC-H projections are presented in Figure 6.12. In general, both projections show a decrease of agreement relating to optimal/suitable areas for aflatoxin persistence throughout the projection years. As a result, there is an increase of disagreement in determine the suitability areas for aflatoxin occupation between the two projections. In 2030, both climate models projected that around 15.66% of the Australian continent will be optimal/suitable for aflatoxin contamination, while in 2100, this percentage will be reduced to 9.54%. In earlier projection years (2030 and 2050), the optimal/suitable areas are mainly located in tropical and subtropical climate zones of the eastern part of Australia. At the end of projection years (2100), the majority of optimal/suitable areas are mainly located in temperate climate zones of the south-eastern and south-western parts of Australia. In terms of unsuitable/marginal areas for aflatoxin contamination, the agreement areas of both climate models show a relatively constant percentage, i.e. 79.95% and 72.62% in 2030 and 2100, respectively. Meanwhile, the disagreement between two projections in determine the suitability areas for aflatoxin infection increase from 4.40% in 2030 to 17.84% in 2100. In 2030, both climate models agree that most of the subtropical region in the eastern part of Australia is predicted to be optimal/suitable, while in 2100, both climate models disagree regarding the suitability of aflatoxin infection in this region.

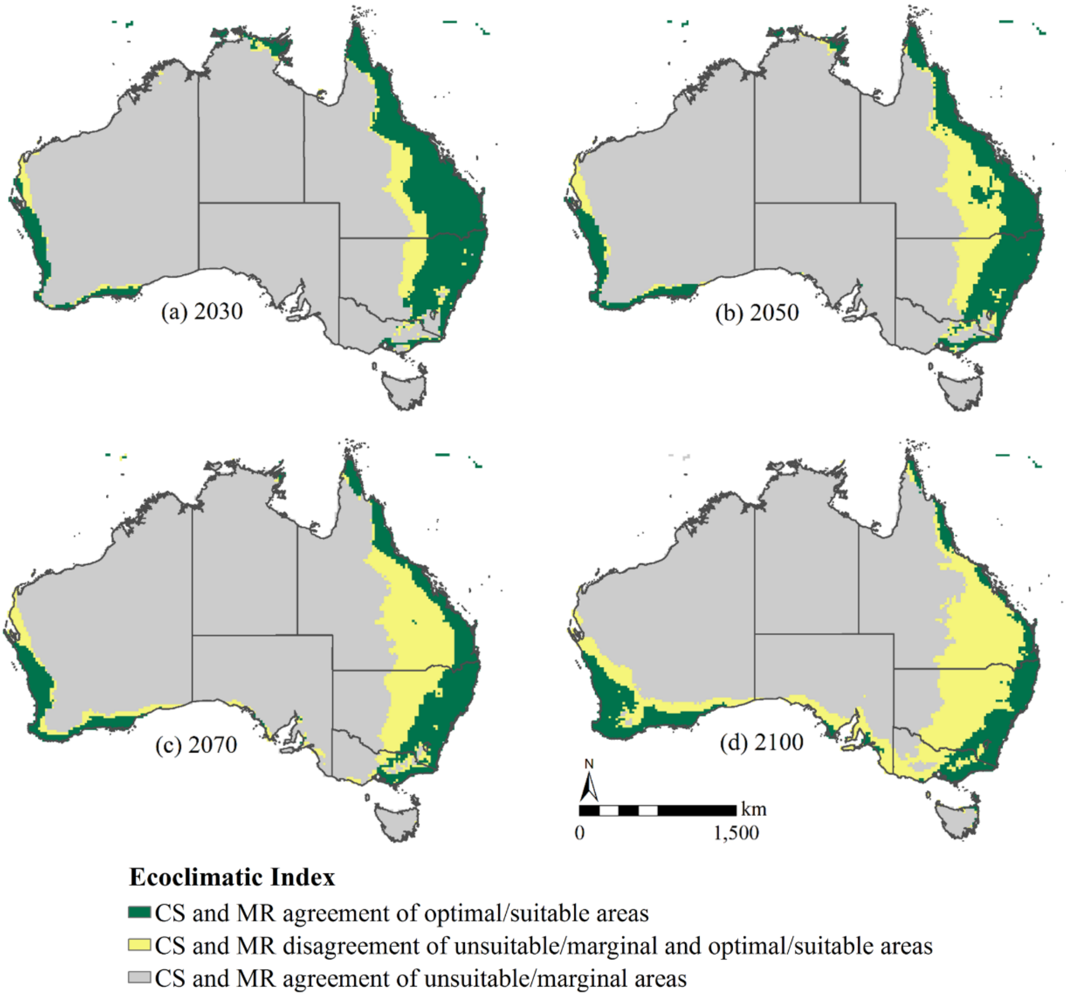

Figure 6.12 CSIRO-MK3.0 and MIROC-H overlaid map of aflatoxin projection in Australia using CLIMEX model.

6.4.3 Future distribution of peanut crops in comparison with aflatoxin distribution

The overlaid results between future projections of aflatoxin and peanut crops in Australia under the CSIRO-Mk3.0 climate model are presented in Figure 6.13. In general, the overlaid maps show a reduction in suitable areas for peanut crops and aflatoxin persistence throughout the projection years. Unfortunately, the dominant suitable areas for peanut crops, which are mainly located in the eastern part of Australia, are also going to be susceptible to aflatoxin contamination. However, throughout the projection years, the suitability of these areas is reduced. On the other hand, there is an increase in peanut and aflatoxin suitability areas in the south-eastern part of Western Australia at the end of the projection years. In addition, the overlaid maps also reveal that some areas in the northern, eastern, and western parts of Australia, which are projected to be marginal in 2030, 2050, and 2070, will become unsuitable in 2100.

Ideal areas for peanut cultivation are those which are optimal/suitable/marginal for peanut crops but are unsuitable/marginal for aflatoxin infection. In this study, one of the ideal combinations for peanut cultivation is the combination of suitable areas for peanut crops and marginal areas for aflatoxin invasion. In 2030, dominant areas for this combination are found in the northern part of Australia, such as Etheridge, Mareeba, and Cook in Queensland, while there are relatively small areas within this combination in the southern part of Western Australia, South Australia, and Victoria. However, throughout the projection years, areas in the northern part of Australia and the southern part of Western Australia show a reduction; meanwhile, areas in the southern part of South Australia and Victoria show an increase and are projected to become larger areas by 2100. Overall, there is a reduction in this combination from 250,819 km^2 (2.85% of the Australian continent) in 2030 to 84,763 km^2 (0.96% of the Australian continent) in 2100. However, the size of this combination is small compared to areas which are suitable/optimal/marginal for peanut crops and aflatoxin infection.

Other ideal areas for peanut cultivation will be those that are unsuitable for aflatoxin contamination but marginal for peanut cultivation. Unfortunately, these areas are relatively small compared to other categories, and are estimated to be reduced throughout the projection years. This combination will account for 48,082 km^2 (0.55% of the Australian continent) in 2030, before it is reduced to 46,595 km^2 (0.53% of the Australian continent) in 2100. It is projected that by 2070, Tasmania will be the dominant area for this combination. Yet, as the suitable areas for peanut and aflatoxin persistence reduces, the northern part of Australia will become dominant for this combination by 2100.

An examination of the current peanut cultivation areas shows that in 2030, most of the areas will be optimal/suitable for peanut crops and aflatoxin, including South Burnett, Chinchilla, Bundaberg, the Atherton Tableland, Childers, Inglewood, Mackay, Emerald, St. George, and Texas. Meanwhile, Katherine and Georgetown are projected to be marginal for both, peanut crops and aflatoxin. In 2050, Emerald and St. George are predicted to be included in the marginal group, while other peanut planting areas will remain in the optimal/suitable group. In 2070, it is predicted that Texas and Chinchilla will also become marginal for peanut cultivation and aflatoxin infection. Finally, at the end of the projection years, Katherine, Georgetown, Emerald, and St. George will become unsuitable for peanut crops and aflatoxin persistence, while Texas, Inglewood, and Chinchilla are projected to be marginal for both, peanut crops and aflatoxin. Only the Atherton Tableland, Bundaberg, and Childers are projected to remain optimal/suitable for peanut cultivation and aflatoxin infection.

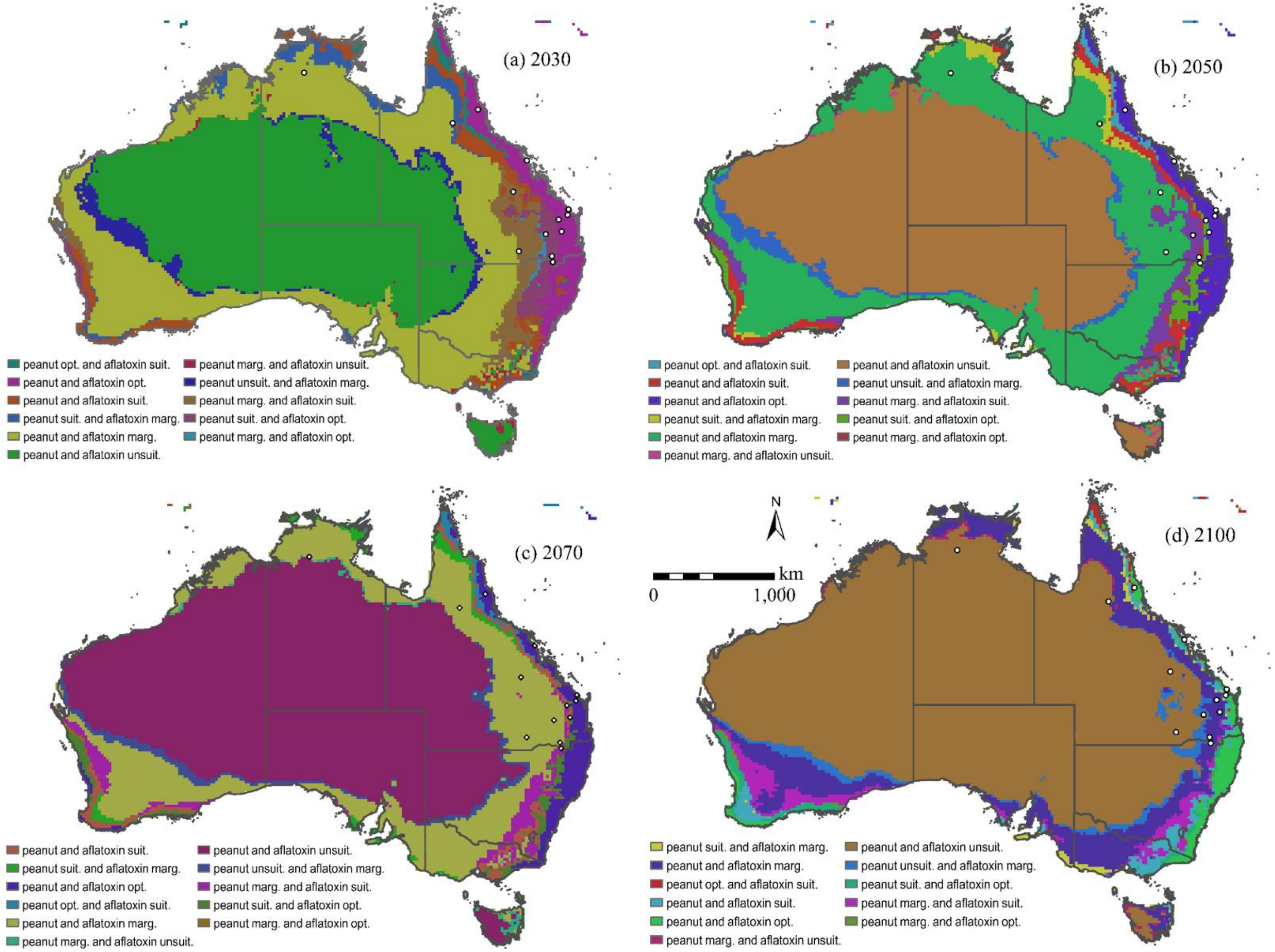

Figure 6.13 The overlaid map of aflatoxin and peanut crop projections in Australia using CLIMEX model under CSIRO-Mk3.0 Global Climate Model. White dots are current peanut planting areas.

Figure 6.14 shows the overlaid maps of peanut crop and aflatoxin future projections using the MIROC-H climate model under SRES A2 scenario. Overall, the overlaid maps show relatively small changes in suitability areas of peanut crop and aflatoxin from 2030 to 2100 projections. In a similar way to CSIRO-Mk3.0 projections, the dominant suitability areas for peanut crops and aflatoxin occupation are in the eastern part of Australia. However, the suitability areas for peanut crops and aflatoxin will increase in the south-western part of Western Australia throughout the projected years, owing to the occurrence of climate change. Interestingly, some areas in the central part of Australia will become marginal for peanut crops and aflatoxin persistence by 2100.

Ideally, peanut cultivation is conducted in areas which are free from aflatoxin contamination. However, it is predicted that only small areas will be accounted for in this category in Australia. The majority of the projected areas which are favourable for peanut cultivation, are also predicted to be favourable for aflatoxin contamination. In a similar way to CSIRO-Mk3.0, the MIROC-H overlaid maps in 2030 demonstrate areas which are suitable for peanut cultivation but marginal for aflatoxin infection are located mostly in the northern part of Australia, such as Queensland (Georgetown, Etheridge, Cook, Carpentaria, and Mareeba) and the Northern Territory (Gulf of Carpentaria). In addition, small areas in the southern parts of Western Australia, South Australia, and Victoria are also included in this combination. However, there is a reduction in the combination of suitable peanut and marginal aflatoxin areas throughout the projection years. In 2070, the areas in the northern part of Australia and southern part of Western Australia are expected to be reduced dramatically, resulting in the elimination of Wyndham-East Kimberly shire in the northern part of Western Australia. Remarkably, there are additional areas for this combination in the southern part of Victoria and South Australia. Nevertheless, in 2100, only small areas will be left for this combination, i.e. northern part of Cook shire in the lower latitude of northern part of Queensland. In 2030, around 329,138 km^2 (3.74% of the Australian continent) is projected for this combination, while in 2100, only 50,065 km^{2-} (0.57% of the Australian continent) will remain.

The other combination which is ideal for the peanut industry refers to those areas which are unsuitable for aflatoxin contamination but marginal for peanut crops. However, as with CSIRO-Mk3.0, the size of this combination for MIROC-

H is very small and predicted to be reduced throughout the projection years. In 2030, this combination should occur in Tasmania, Victoria, South Australia, and Western Australia, which accounted for 94,181 km^2 (1.07% of the Australian continent). Meanwhile, in 2070, small areas in the northern part of Australia will be included in this combination, and by 2100, only Tasmania and the northern part of Australia will be left with an area of 42,134 km^2 (0.48% of the Australian continent).

The only current peanut growing area which is projected to have a low aflatoxin invasion risk in 2030 is Georgetown. The other peanut areas, namely Atherton Tableland, Mackay, Emerald, Childers, Bundaberg, Chinchilla, South Burnett, Texas, and Inglewood, are projected to be optimal/suitable for peanut cultivation and aflatoxin occupation, whereas Katherine is projected to be marginal for peanut crops and aflatoxin. However, from 2070 to 2100, Georgetown will become a marginal area for peanut and aflatoxin persistence. The projection for St. George remains unchanged throughout the projection years, i.e. marginal for peanut planting and optimal for aflatoxin persistence. In 2100, Katherine is projected to become unsuitable, while Emerald is likely to become marginal for peanut crops and suitable for aflatoxin. In addition, other peanut growing regions will be optimal/suitable for peanut crops and aflatoxin in 2100, including the Atherton Tableland, Mackay, Childers, Bundaberg, South Burnett, Inglewood, and Texas.

The overall results of CSIRO-Mk3.0 and MIROC-H overlaid projections show similar trends. However, the CSIRO-Mk3.0 projection demonstrates more severe climate change effects and a reduction in suitable areas for peanut crops and aflatoxin persistence. In addition, the areas which are suitable for peanut crops but marginal for aflatoxin are larger in the MIROC-H projection, compared to the CSIRO-Mk3.0 projection. Another significant difference is in terms of marginal areas for peanut crops and aflatoxin persistence, where MIROC-H has projected larger marginal areas than CSIRO-Mk3.0 throughout the projection years. These marginal areas are located in the inland arid climate region of Australia.

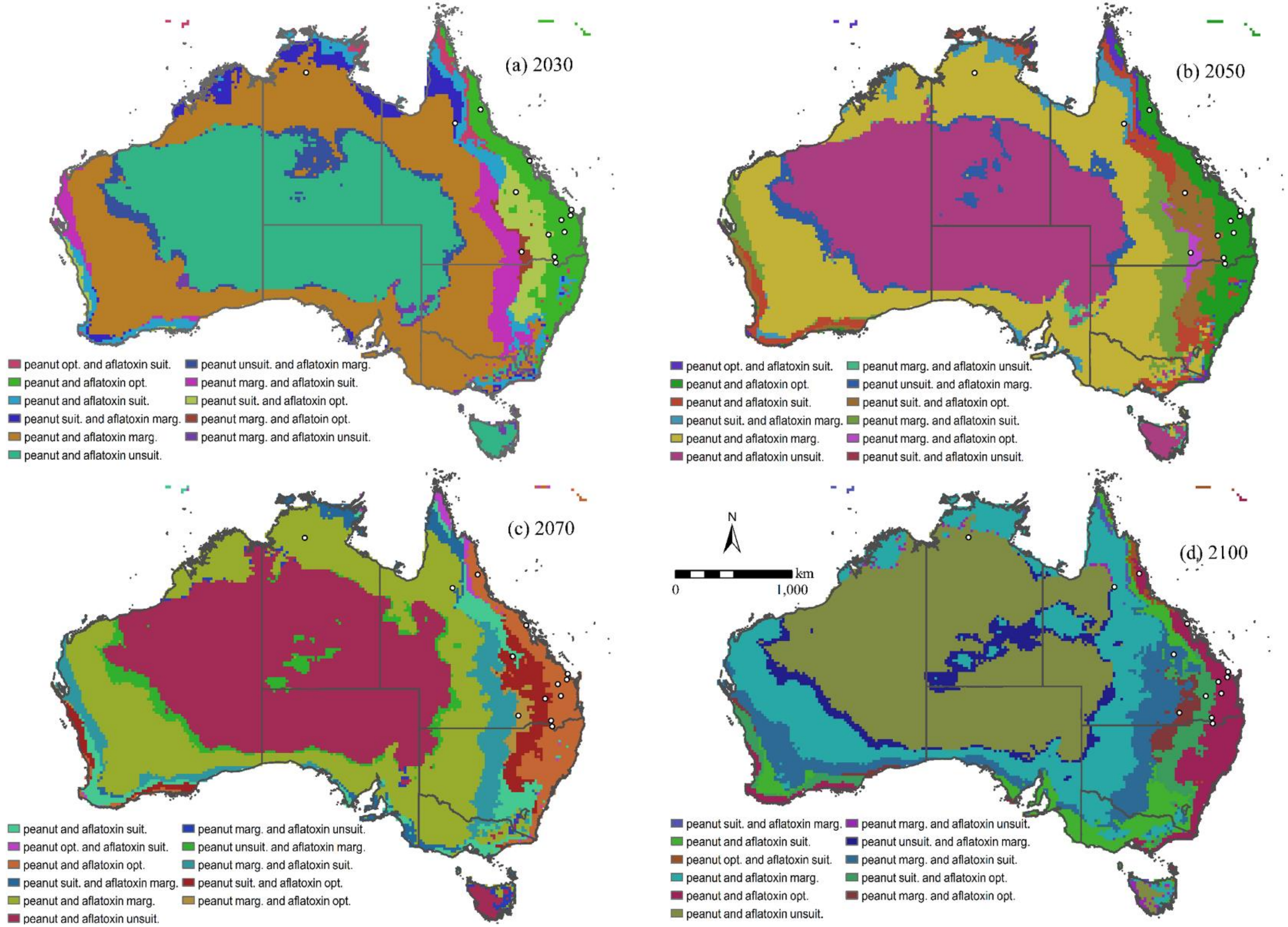

Figure 6.14 The overlaid map of aflatoxin and peanut crop projections in Australia using CLIMEX model under MIROC-H Global Climate Model. White dots are current peanut planting areas

6.5 Discussion

6.5.1 Aflatoxin distribution under the current climate

The CLIMEX model of aflatoxin developed in this study has a high reliability of result, since it shows a strong agreement (100%) between distribution areas used for the CLIMEX fitting process, i.e. the African and American continents, and distribution areas used for model validation, i.e. India, China, the Philippines, Thailand, Indonesia, Italy, and Australia. In addition, the inclusion of all aflatoxin distribution data into the CLIMEX model and the fact that most of the distribution data were categorised as optimal areas for aflatoxin infection, confirms the model's reliability.

The model shows that majority of optimal areas for aflatoxin contamination are located in the tropical and subtropical climate regions, such as South East Asia, Central America, the central part of Africa, India, the USA, Brazil, and Argentina. Only a small number of aflatoxin distribution from these climate regions was categorised as suitable and marginal areas for aflatoxin contamination. Therefore, these results confirmed the susceptibility of tropical and subtropical climate zones for aflatoxin contamination, as previously cited by other researcher such as Pettit and Taber (1968) and Souza et al. (2014). The tropical climate is characterised with minimum temperature of ≥18°C and minimum precipitation of around 60mm. Meanwhile, subtropical climate zones of warm temperate humid and winter dry are characterised with minimum temperatures between 3°C and 18°C, and maximum temperatures of ≥ 22°C during summer time (Kottek et al. 2006). As a result, these climate zones provide environmental factors favourable for aflatoxin persistence.

Aflatoxin production in peanut is determined by environmental factors, namely temperature, relative humidity, and moisture content of the peanut substrate (Pettit & Taber 1968). Extreme heat and elongated drought stress in the final three to six weeks of the peanut growth period will stimulate pre-harvest aflatoxin contamination in peanut crops (Kokalis-Burelle et al. 1997). Heat and drought stresses can affect plant physiology, which in turn can increase crop susceptibility for aflatoxin infection (Klich 2007). For example, the formation of phytoalexins, antimicrobial compounds used to prevent aflatoxin infection, is repressed during drought stress (Klich 2007). In addition, drought stress incidence increases the production of proline in crops (Barnett & Naylor 1966), which is known to stimulate aflatoxin production (Payne & Hagler 1983). Another factor that supports aflatoxin contamination is the ability of *Aspergillus* species, especially *A. flavus* to persist in high temperature conditions (i.e. up to 40°C) where other fungi cannot persist, providing a competitive advantage for *Aspergillus* species (Klich 2007).

6.5.2 Aflatoxin distribution under future climate scenarios

The results of this study indicate a geographical distribution shift of aflatoxin occupation areas in Australia in the future, due to climate change impact. Climate change influences the components of complex biological interactions differently (Newton et al. 2011). Although many factors, such as biological issues (susceptible crop and compatible toxigenic fungus) and harvesting conditions (crop maturity, temperature, moisture, and detection/diversion) can generate aflatoxin contamination, climate factors remain the most important (Paterson & Lima 2010). Climatic conditions alters the complex communities of aflatoxin producing fungi (*aspergillus*), for example modifying the fungi number and fungal community structure (Cotty & Jaime-Garcia 2007). The shifting of aflatoxin areas as indicated in this study is consistent with the first outbreak of aflatoxin occurrence in areas known as free aflatoxin infection, i.e. the northern part of Italy, in 2003-2004 due to climate alteration of hot and dry climate (Perrone et al. 2014). There is a risk of shifting in traditional aflatoxin areas due to the increase of average temperature, particularly shifting the aflatoxin areas into cool and temperate climate regions, such as South East Europe (Paterson & Lima 2010; Perrone et al. 2014).

The increase of unsuitable areas for aflatoxin persistence, as projected by two climate models used in this study, CSIRO-Mk3.0 and MIROC-H, is due to the increase of areas suffering from severity of dry and heat stresses in Australia. Comparing these two models, CSIRO-Mk3.0 shows a significant increase of unsuitable areas throughout the projection years. This significant increase can be explained by the larger dry stress coverage of CSIRO-Mk3.0 which consists of almost all arid climate regions, compared to MIROC-H coverage, which covers only some part of the arid region. Similarly, the heat stress coverage of CSIRO-Mk3.0 projection is also larger than the MIROC-H projection. The significant increase of unsuitable areas under CSIRO-Mk3.0 has decreased the optimal, suitable, and marginal areas. Meanwhile, the increase of optimal and suitable areas of MIROC-H projection is due to the decrease of marginal areas. The relatively steady dry stress projection under MIROC-H model has contributed to a small increase of unsuitable areas, although heat stress projection is increased significantly throughout the projection years. The projection of Australia’s warmer temperature in the future years can also be seen on the decrease of cold stress projections from both climate models. As a result, the temperate region of the south-eastern part of Australia will become more tolerant for aflatoxin contamination in the future. This study reveals that only a small percentage of the Australian continent will be suitable for aflatoxin contamination in the future. Understanding these issues will help to improve the aflatoxin management in Australia. It is suggested that arid climate region, the dominant climate in Australia, has encouraged the heat and dry stress limitation for aflatoxin invasion.

The overlaid aflatoxin maps resulting from CSIRO-Mk3.0 and MIROC-H climate models were produced to observe the common areas for aflatoxin suitability areas, as shown by Shabani and Kotey (2015) in projecting the future distribution of cotton and wheat in Australia. This method will confirm the reliability of suitable areas of aflatoxin occurrence in Australia, and thus minimise possible errors in using the results of this study. The differences in the results between these two climate models are expected, since each model employed different methods in quantifying the effects of climate change in the future. The climate parameterization in CSIRO-Mk3.0 consists of a comprehensive representation of the four major components of the climate systems, namely atmosphere, land surface, oceans and sea-ice (Gordon et al. 2002). Meanwhile, MIROC-H contains parameterization in five components: atmosphere, land, river, sea ice, and ocean (Hasumi & Emori 2004). The CSIRO-Mk3.0 model however was developed by an Australian research institute, the CSIRO (Gordon et al. 2002), and therefore could include more specific information about Australia. The disagreement regarding aflatoxin suitability areas between CSIRO-Mk3.0 and MIROC-H increases throughout the projection years, especially in the agricultural areas of the eastern part of Australia. Considering the negative impacts of aflatoxin infection in agricultural commodities, careful analysis of these disagreements is essential. The results of this study will be useful in supporting the management of aflatoxin outbreaks in Australia. Knowledge of projected aflatoxin outbreaks will enable the preparation and implementation of countermeasures to mitigate the negative effects of aflatoxin.

6.5.3 Future peanut crop distribution in comparison with aflatoxin distribution

In general, the overlaid maps between peanut and aflatoxin projection models reveal that the most of optimal/suitable areas for peanut crops are also optimal/suitable areas for aflatoxin. Similarly, most of the unsuitable areas for peanut crops are also unsuitable areas for aflatoxin. These results confirmed the similar climatic requirements for peanut crops and aflatoxin, since both are distributed in generally identical locations. Klich (2007) stated that aflatoxin producing fungus are isolated more in the latitude between 26-35°, therefore chronic aflatoxin problems frequently associated with crops growing under 35° latitude.

The results of this study show that most of the Australian continent will be unsuitable for aflatoxin and peanut persistence, since the continent is dominated by arid climate regions. In addition, most of the optimal and suitable areas for peanut crops are located in the eastern part of Australia and the south-western part of Western Australia, which have subtropical and temperate climate types and are suitable agricultural areas. Unfortunately, the optimal and suitable areas for aflatoxin contamination are also located in these parts of the continent, because it has similar climatic requirements to peanut crops. The ideal areas for peanut cultivation are those which are optimal/suitable to cultivate peanut crops, but have low risk of aflatoxin incidence, i.e. unsuitable/marginal for aflatoxin. However, in the future only a small percentage of the Australian continent will be projected as ideal areas for peanut cultivation, and this is reduced throughout the projection years. CSIRO-Mk3.0 projected only 3.40% of the continent will be ideal for peanut cultivation, before it is reduced to 1.49% in 2100. Meanwhile, MIROC-H projected the ideal areas will be 4.82% of the Australian continent in 2030, and reducing to 1.05% in 2100. These percentages are very small, compared to the total area of land use under primary production (livestock grazing, dryland, irrigated agriculture, and intensive agriculture) which is nearly 4.5 million km^2 (around 58% of the continent) (ABARES 2019).

The overlaid maps indicate that none of the current peanut growing regions are included as low aflatoxin risk regions, except for Georgetown in 2030. Overall, most of the current peanut growing regions will still be optimal/suitable for peanut cultivation and aflatoxin invasion in 2030. However, while none of the regions is unsuitable for peanut crops and aflatoxin in 2030, by the end of the projection years, most of the regions are projected to become unsuitable and marginal for peanut and aflatoxin persistence. Only a small number of regions will still be optimal/suitable in 2100. This study has projected that current peanut growing areas will always have a high-risk of aflatoxin invasion. The projection areas of peanut crops always coincide with the projection areas of aflatoxin. In addition, some current peanut growing regions are projected to be unsuitable in the future, resulting in the need to shift peanut growing areas. There will be an opportunity to consider the low-risk aflatoxin areas for peanut cultivation. However, careful considerations should be taken, since the percentage of the low-risk areas is small, compared to other primary production land use. Moreover, most of the low-risk areas are projected to be in the northern part of Australia, which are dominated by land use relating to nature conservation, protected areas, and minimal use (ABARES 2019). The opportunity will be to shift peanut growing areas to the low-risk areas in the south-eastern part of Australia, but this will be limited considering its small acreage.

Considering the risk of aflatoxin infection, determining cultivation areas for peanut crops in Australia will be challenging in the future. Utilising the low risk aflatoxin areas will be limited, since it has small percentage compared to the high risk areas suitable for peanut crops. In addition, there is a reduction in suitable areas for peanut crops in the future. Countermeasures to manage aflatoxin incidence in peanut growing areas should be taken, for example continuity of genetic resistance development, proper crop management systems (crop rotation, tillage, planting date, and management of irrigation and fertilization), and the use of chemical and/or biological control (Torres et al. 2014).

6.6 Conclusion

This study has successfully developed CLIMEX model parameters for aflatoxin. The consistency of the results between aflatoxin map produced from the CLIMEX model and the aflatoxin geographical distribution map has assured model reliability. The results support the outcomes of other studies which confirmed the climatic zone preferences of aflatoxin incidence. The future projections of aflatoxin distribution in Australia under CSIRO-Mk3.0 and MIROC-H GCMs indicated that only a small portion of the Australian continent will be optimal/suitable for aflatoxin persistence, due to heat and dry stress incidence. Comparing the projections of the two GCMs, CSIRO-Mk3.0 projected larger unsuitable areas and more severe heat and dry stresses in the future. The shifts in aflatoxin invasion areas from the tropical and subtropical climate zones of the eastern part of Australia to the temperate climate zones of the south-eastern and the south-western parts of Australia by 2100 indicate the effect of climate change in aflatoxin distribution. The overlaid results between the future projections of aflatoxin and peanut crops indicated the similar suitability areas for both. Only a small part of Australia will have low aflatoxin risks for peanut cultivation. In addition, it is projected that most of the current peanut growing regions have a high aflatoxin risk. Some of the existing peanut growing regions will not continue to be favourable for peanut cultivation in the future. As a result, a shift in peanut growing regions in Australia should be deliberated. Considering the significant negative effects of aflatoxin incidence in peanut crops, the results of this study will provide valuable information regarding favourable areas for aflatoxin persistence in Australia. The overlaid results between CLIMEX models of aflatoxin and peanut will assist in locating the high and low risk aflatoxin areas which will be useful in determining the appropriate location of peanut cultivation areas. This study is based on the suitability of climatic conditions, thus further analysis is needed to include other factors of aflatoxin invasion, such as host availability, susceptibility and abundance, historical contingency (e.g. evolutionary change) and interacting factors, such as crop and pest management, crop rotation, and crop acreage.

Chapter 7

CONCLUSION

7.1 Introduction

Since agricultural sector depends heavily on climate, climate change will affect this sector significantly, including peanut crop commodity. The peanut production and the future geographic distribution of peanut crops and the associated aflatoxin incidence could be affected. Although quantifying area planting of peanut crops will be essential in determining the production level, few studies have investigated this issue; a similar case arises with the studies of future geographic distribution of peanut crops and aflatoxin.

This study aimed at investigating the potential of time-series imagery data and spatial modelling techniques in mapping current peanut crop areas, the future geographic distribution of peanut crops and the associated aflatoxin incidence in Australia. This study is one of the first studies to use PROBA-V imagery, a specialised vegetation monitoring satellite, in crop mapping in Australia. This is also one of the first studies to project the future geographic distribution of peanut crops and the associated aflatoxin incidence in relation to the occurrence of climate change.

This chapter summarises the findings of the study and provides recommendations for future research. This chapter is organised into four sections. Section 7.2 describes the summary of findings resulting from the three objectives, while Section 7.3 provides the conclusions. Lastly, the chapter ends with Section 7.4 which presents the recommendations for future work.

7.2 Summary of findings

This study has provided new knowledge on peanut crop mapping, projected future suitability areas for peanut cultivation, and projected high risk areas of aflatoxin invasion. This was achieved by using time-series analysis applied to

PROBA-V NDVI imagery, while one of Species Distribution Models (SDMs), CLIMEX, was applied in modelling future geographic distribution of peanut crops and the associated aflatoxin disease. The PROBA-V imagery has not been used in mapping crops in Australia, while CLIMEX has not been applied in modelling peanut crops and aflatoxin.

7.2.1 Peanut crop mapping

Chapter 4 reveals the success of PROBA-V imagery in mapping peanut crops in the South Burnett region, Queensland, Australia using two datasets, namely PROBA-V 100m NDVI imagery and its derived phenological parameters. The overall accuracy of NDVI imagery outweighed the overall accuracy of phenological parameter dataset. However, both datasets performed very well in classifying peanut crops. Compared with the other two algorithms, namely the spectral angle mapper (SAM) and minimum distance classification (Min), the use of maximum likelihood classification (MLC) provided the best accuracy, i.e. 92.75% for NDVI imagery and 79.53% for phenological parameters. On examining details of peanut crop classification, all algorithms produced satisfactory results with producer and user accuracy, i.e. ≥75.95%, except for the producer accuracy of Min algorithm which accounted for 59%. The excellent performance of PROBA-V data could be attributed to its specific vegetation sensors and its improvement in spatial resolution (100 m) compared to the commonly used MODIS 250 m data.

7.2.2 Future geographic distribution of peanut crops

The study of future geographic distribution of peanut crops using the CLIMEX model under Global Climate Models (GCMs) of CSIRO-Mk3.0 and MIROC-H is presented in Chapter 5. The results reveal the effects of climate change incidence in the shifting of geographic distribution of peanut crops in Australia for 2030, 2050, 2070, and 2100. The study projected an increase of unsuitable areas for peanut cultivation throughout the projection years. CSIRO-Mk3.0 has projected that by 2100, 76% of Australian land will be unsuitable for peanut cultivation, which is much higher than the MIROC-H projection of 48%. Compared to the projection in 2030, there is likelihood of significant reduction for

CSIRO-Mk3.0 projection on optimal, suitable, and marginal areas in 2100. However, MIROC-H has only projected a small reduction in these suitability areas.

Unfortunately, the study reveals that some existing peanut cultivation areas, namely, Katherine (the Northern Territory) and Georgetown, Emerald, and St. George (Queensland), will become unsuitable in the future. Only a limited number of the current peanut areas will be maintained as being suitable, including Bundaberg, Mackay, Atherton Tableland, and Childers in Queensland. However, the projection results of other peanut cultivation areas, i.e. South and North Burnett, Chinchilla, Inglewood, and Texas, showed differences between the two GCMs. It is likely that the increase of dry stress in the future could cause limitations in the areas that are currently suitable.

7.2.3 Future geographic distribution of aflatoxin and its high risk areas

Chapter 6 demonstrates the effects of climate change on geographical distribution of aflatoxin incidence and presents a map of high risk areas for aflatoxin incidence in future geographical distribution of peanut crops. The study revealed that only small portion of the Australian continent will be optimal/suitable for aflatoxin occupation in the future. The majority of the continent will be unsuitable for aflatoxin incidence, with an increase of the areas throughout the projection years of 2030, 2050, 2070, and 2100. The increase of heat stress areas and the incidence of dry stress are suggested to be responsible for the increase of unsuitable areas for aflatoxin invasion. CSIRO-Mk3.0 projected an increase and more severe dry stress incidence throughout the projection years, resulting in larger unsuitable areas for aflatoxin invasion in 2100 (74% of the Australian continent), compared to MIROC-H (43% of the Australian continent).

The study also projected a shift in aflatoxin invasion areas from the tropical and subtropical zones of the eastern part of Australia in 2030, to the temperate zones of the south-eastern and south-western parts of Australia by 2100. The identification of aflatoxin risk areas in the future distribution of peanut crops revealed that most of the optimal/suitable areas for peanut crops are also optimal/suitable areas for aflatoxin. Only a small part of Australia will have a low risk of aflatoxin in peanut cultivation. The study also projected that most of the current peanut growing areas will have a high risk of aflatoxin, while others will no longer to be favourable for peanut cultivation.

7.3 Conclusions

The successful application of a specialised vegetation monitoring satellite, PROBA-V, in this study has confirmed the great potential of the satellite in crop area mapping and in fulfilling its mission to support the vegetation-user community. It provides a significant contribution of new knowledge on the potential application of PROBA-V imagery in mapping crops in Australia. This study confirmed that the use of finer resolution 100m of PROBA-V imagery (i.e. relative to MODIS 250m resolution) has contributed to the success of mapping peanut and other crops in the study area. Apart from the accuracy of this study, the large coverage (517 km) and frequent revisit period (5 days) of the PROBA-V satellite has provided an opportunity for a near real time data collection. These accurate, objective, and near real time crop area estimations will be useful in determining peanut crop logistics and marketing, such as supply, staff requirements, and import needs. Compared to the traditional methods of crop area estimation, such as censuses and samples, the use of satellite imagery can reduce the associated time and costs, and can make the mapping of peanut crops both easier and more objective. In addition, the peanut map produced from this study provides important information to estimate peanut production in Australia, which will be very useful in securing the domestic market of peanut commodity.

One of the major contributions of this study is the new knowledge generated on the effects of climate change on the future geographic distribution of peanut crops in Australia. This is an issue which has not yet been explored in any other studies in any part of the world. Understanding the future geographic distribution of peanut crops in Australia will provide knowledge regarding suitable areas for peanut cultivation. This knowledge is important in determining the long-term planning of peanut cultivation in Australia. The results of this study have confirmed the effects of climate change on the suitability of peanut cropping areas. Unfortunately, some of the current peanut growing areas will become unsuitable in the future, due to the projected increase of unsuitable areas for peanut cultivation in Australia. Therefore, this result can be used as a guide in anticipating the possibility of shifting the peanut cropping areas in the future.

In addition, this study also contributes significantly to the knowledge of the effects of climate change on the future geographic distribution of aflatoxin, a major issue in the peanut industry in Australia. It also provides a major contribution in new knowledge on locating the high risk areas of aflatoxin incidence in the future distribution of peanut crops in the country. Due to its negative effects on human and animal health, aflatoxin attracts significant attention. This study supports the outcomes of other studies which confirmed the climatic zone preferences of aflatoxin incidence. Looking into the projection of the incidence of aflatoxin in Australia, this study has projected a shift in aflatoxin invasion areas. Having this knowledge will provide valuable resources in anticipating the incidence of aflatoxin in the future. Comparing the future distribution of peanut crops and aflatoxin disease, the study reveals that peanut crops have similar climatic requirements to aflatoxin, resulting in small areas of low aflatoxin risks for peanut cultivation. Since the study found that most of the current peanut growing regions have a high aflatoxin risk, shifting the peanut growing regions in Australia should be considered. The high and low risk aflatoxin areas resulted from this study will be useful in determining the location of peanut cultivation areas.

Overall, this study has contributed to generate new knowledge on the application of time-series PROBA-V 100m NDVI imagery in mapping peanut crops in the South Burnett region of Queensland, Australia. It has also contributed to the new knowledge of the future geographic distribution of peanut crops and aflatoxin in relation to the incidence of climate change. This study provides strategic information on estimating current peanut planting areas, future suitable areas for peanut crops, and future high risk areas of aflatoxin incidence in Australia. This information provides valuable contributions in the planning, management, and policy formulation of the peanut industry in Australia to anticipate the impact of climate change.

7.4 Recommendations

Studies on peanut crop mapping using multi-temporal satellite imagery and predicting the future distribution of peanut crops and aflatoxin in Australia are still at an early stage. Further investigations could contribute to the need. Based on the findings of this study, the following recommendations for future investigations are made:

1. The use of other classification algorithms, such as machine learning, can be explored in further work of peanut crop mapping using PROBA-V imagery. In addition, comparing the results of this study with those that used other satellite imagery, such as higher or lower spatial resolution satellites, will provide some knowledge of the options to use in mapping.
2. Based on the successful use of PROBA-V imagery in this study and from other studies, the continuity of the PROBA-V satellite should be investigated by launching its successor mission. Initially, the PROBA-V satellite was designed as a ‘gap-filler mission’ between SPOT-Vegetation and ESA Sentinel 3 satellites.
3. The future distribution of peanut crops and the associated aflatoxin incidence resulting from this study were carried out using the CLIMEX model. The model was developed based on species’ or other biological entities’ response to climate. Non-climatic factors, such as economic, social, topography, soil type, and land use, were not considered in this study. However, the future distribution map resulting from this study could be enhanced by incorporating these non-climatic factors.
4. In order to further enhance the results of mapping future geographic distribution of aflatoxin, other factors which specifically affect the distribution of aflatoxin can also be incorporated. Some of these factors include host availability, susceptibility and abundance, historical contingency (such as evolutionary change), and interacting factors (such as crop and pest management, crop rotation, and crop acreage).

REFERENCES

ABARES 2016, *Australian crop report*, Australian Bureau of Agricultural and Resource Economics and Sciences, Canberra.

ABARES 2019, *National scale land use of Australia 2010-11*, ABARES, viewed 13 March 2019, <http://www.agriculture.gov.au/abares/aclump>.

Abbas, H, Zablotowicz, R & Locke, M 2004, 'Spatial variability of Aspergillus flavus soil populations under different crops and corn grain colonization and aflatoxins', *Canadian Journal of Botany*, vol. 82, no. 12, pp. 1768-75.

ABS 2018, *National Regional Profile (NRP): South Burnett*, ABS, viewed 26 June 2019, <http://stat.abs.gov.au/itt/r.jsp?RegionSummary&region=36630&dataset=ABS_REGIONAL_LGA&geoconcept=REGION&datasetASGS=ABS_REGIONAL_ASGS&datasetLGA=ABS_REGIONAL_LGA&regionLGA=REGION&regionASGS=REGION>.

ABS 2019, *Australian demographic statistics*, ABS, viewed 30 June 2019, <https://www.abs.gov.au/AUSSTATS/abs@.nsf/mf/3101.0>.

Adomou, M, Prasad, P, Boote, K & Detongnon, J 2005, 'Disease assessment methods and their use in simulating growth and yield of peanut crops affected by leafspot disease', *Annals of Applied Biology*, vol. 146, no. 4, pp. 469 - 79.

Agbetiameh, D, Ortega-Beltran, A, Awuah, RT, Atehnkeng, J, Cotty, P & Bandyopadhyay, R 2018, 'Prevalence of aflatoxin contamination in maize and groundnut in Ghana: population structure, distribution, and toxigenicity of the causal agents', *Plant Disease*, vol. 102, no. 4, pp. 764-72.

ALA 2017, *Atlas of Living Australia*, viewed 17 August 2017, <http://www.ala.org.au/>.

Alganci, U, Sertel, E, Ozdogan, M & Ormeci, C 2013, 'Parcel-level identification of crop types using different classification algorithms and multi-resolution imagery in southeastern Turkey', *Photogrammetric Engineering & Remote Sensing*, vol. 79, no. 11, pp. 1053-65.

Ali, N, Sardjono, Yamashita, A & Yoshizawa, T 1998, 'Natural co-occurrence of aflatoxins and Fusavium mycotoxins (fumonisins, deoxynivalenol, nivalenol and zearalenone) in corn from Indonesia', *Food Additives & Contaminants*, vol. 15, no. 4, pp. 377-84.

Anwar, MR, Li Liu, D, Macadam, I & Kelly, G 2013, 'Adapting agriculture to climate change: a review', *Theoretical and Applied Climatology*, vol. 113, no. 1-2, pp. 225-45.

Arim, RH 2000, 'Recent status of mycotoxin research in the Philippines', *JSM Mycotoxins*, vol. 50, no. 1, pp. 23-6.

Arim, RH 2003, 'Mycotoxin contamination of food and feeds in the Philippines', *International Symposium of Mycotoxicology*, Japanese Association of Mycotoxicology, Kagawa, pp. 167-73.

Arvor, D, Jonathan, M, Meirelles, MSP, Dubreuil, V & Durieux, L 2011, 'Classification of MODIS EVI time series for crop mapping in the state of Mato Grosso, Brazil', *International Journal of Remote Sensing*, vol. 32, no. 22, pp. 7847-71.

Atayde, DD, Reis, TA, Godoy, IJ, Zorzete, P, Reis, GM & Corrêa, B 2012, 'Mycobiota and aflatoxins in a peanut variety grown in different regions in the state of São Paulo, Brazil', *Crop Protection*, vol. 33, pp. 7-12.

Atkinson, PM, Jeganathan, C, Dash, J & Atzberger, C 2012, 'Inter-comparison of four models for smoothing satellite sensor time-series data to estimate vegetation phenology', *Remote Sensing of Environment*, vol. 123, pp. 400-17.

Atzberger, C 2013, 'Advances in remote sensing of agriculture: context description, existing operational monitoring systems and major information needs', *Remote Sensing*, vol. 5, no. 2, pp. 949-81.

Bankole, S & Mabekoje, O 2004, 'Occurrence of aflatoxins and fumonisins in preharvest maize from south-western Nigeria', *Food Additives and Contaminants*, vol. 21, no. 3, pp. 251-5.

Barnett, NM & Naylor, A 1966, 'Amino acid and protein metabolism in Bermuda grass during water stress', *Plant Physiology*, vol. 41, no. 7, pp. 1222-30.

Barros, G, Torres, A, Palacio, G & Chulze, S 2003, 'Aspergillus species from section Flavi isolated from soil at planting and harvest time in peanut-growing regions of Argentina', *Journal of the Science of Food and Agriculture*, vol. 83, no. 13, pp. 1303-7.

Barry, S & Elith, J 2006, 'Error and uncertainty in habitat models', *Journal of Applied Ecology*, vol. 43, no. 3, pp. 413-23.

Battilani, P 2016, 'Recent advances in modeling the risk of mycotoxin contamination in crops', *Current Opinion in Food Science*, vol. 11, pp. 10-5.

Battilani, P, Leggieri, MC, Rossi, V & Giorni, P 2013, 'AFLA-maize, a mechanistic model for Aspergillus flavus infection and aflatoxin B1 contamination in maize', *Computers and Electronics in Agriculture*, vol. 94, pp. 38-46.

Beaumont, LJ, Hughes, L & Pitman, A 2008, 'Why is the choice of future climate scenarios for species distribution modelling important?', *Ecology Letters*, vol. 11, pp. 1135-46.

Bebber, DP 2015, 'Range-expanding pests and pathogens in a warming world', *Annual Review of Phytopathology*, vol. 53, pp. 335-56.

Bebber, DP, Holmes, T & Gurr, SJ 2014, 'The global spread of crop pests and pathogens', *Global Ecology and Biogeography*, vol. 23, no. 12, pp. 1398-407.

Beddow, JM, Kriticos, D, Pardey, PG & Sutherst, RW 2010, *Potential global crop pest distributions using CLIMEX: HarvestChoice Applications*, Harvest Choice.

Bell, M, Shorter, R & Mayer, R 1991, 'Cultivar and environmental effects on growth and development of peanuts (Arachis hypogaea L.). I. Emergence and flowering', *Field Crops Research*, vol. 27, no. 1-2, pp. 17-33.

Bendini, HdN, Sanches, I, Körting, T, Fonseca, L, Luiz, A & Formaggio, A 2016, 'Using Landsat 8 Image Time Series for Crop Mapping in a Region of Cerrado, Brazil', *ISPRS-International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, pp. 845-50.

Bennett, JW & Klich, M 2003, 'Mycotoxins', *Clinical Microbiology Reviews*, vol. 16, no. 3, pp. 497-516.

Bernstein, L, Bosch, P, Canziani, O, Chen, Z, Christ, R, Davidson, O, Hare, W, Huq, S, Karoly, D & Kattsov, V 2008, *Climate change 2007: Synthesis* *report: An assessment of the Intergovernmental Panel on Climate Change*, IPCC.

Beyer, F, Jarmer, T & Siegmann, B 2015, 'Identification of agricultural crop types in Northern Israel using multitemporal RapidEye data', *Photogrammetrie-Fernerkundung-Geoinformation*, vol. 2015, no. 1, pp. 21-32.

Beyer, F, Jarmer, T, Siegmann, B & Fischer, P 2015, 'Improved crop classification using multitemporal RapidEye data', *8th International Workshop on the Analysis of Multitemporal Remote Sensing Images (Multi-Temp 2015).* IEEE.

Blankenship, PD, Cole, RJ, Sanders, TH & Hill, RA 1984, 'Effect of geocarposphere temperature on pre-harvest colonization of drought-stressed peanuts by Aspergillus flavus and subsequent aflatoxin contamination', *Mycopathologia*, vol. 85, no. 1-2, pp. 69-74.

Blount, W 1961, 'Turkey “X” disease', *Turkeys*, vol. 9, no. 7, pp. 52-61.

BoM 2016, *Climate classifications*, BoM, viewed 26 June 2019, <http://www.bom.gov.au/jsp/ncc/climate_averages/climate-classifications/index.jsp?maptype=seasgrpb#maps>.

Bui-Klimke, TR, Guclu, H, Kensler, TW, Yuan, J-M & Wu, F 2014, 'Aflatoxin regulations and global pistachio trade: insights from social network analysis', *PloS One*, vol. 9, no. 3, p. e92149.

Chakraborty, S & Newton, AC 2011, 'Climate change, plant diseases and food security: an overview', *Plant Pathology*, vol. 60, no. 1, pp. 2-14.

Chakraborty, S, Tiedemann, A & Teng, P 2000, 'Climate change: potential impact on plant diseases', *Environmental Pollution*, vol. 108, no. 3, pp. 317-26.

Chala, A, Mohammed, A, Ayalew, A & Skinnes, H 2013, 'Natural occurrence of aflatoxins in groundnut (Arachis hypogaea L.) from eastern Ethiopia', *Food Control*, vol. 30, no. 2, pp. 602-5.

Chauhan, NM, Washe, AP & Minota, T 2016, 'Fungal infection and aflatoxin contamination in maize collected from Gedeo zone, Ethiopia', *SpringerPlus*, vol. 5, no. 1, p. 753.

Chauhan, Y, Wright, G & Rachaputi, N 2008, 'Modelling climatic risks of aflatoxin contamination in maize', *Australian Journal of Experimental Agriculture*, vol. 48, no. 3, pp. 358-66.

Chauhan, Y, Wright, G, Rachaputi, R, Holzworth, D, Broome, A, Krosch, S & Robertson, M 2010, 'Application of a model to assess aflatoxin risk in peanuts', *The Journal of Agricultural Science*, vol. 148, no. 03, pp. 341-51.

Chauhan, YS, Wright, GC, Holzworth, D, Rachaputi, RC & Payero, JO 2013, 'AQUAMAN: a web-based decision support system for irrigation scheduling in peanuts', *Irrigation Science*, vol. 31, no. 3, pp. 271-83.

Chen, J, Jönsson, P, Tamura, M, Gu, Z, Matsushita, B & Eklundh, L 2004, 'A simple method for reconstructing a high-quality NDVI time-series data set based on the Savitzky–Golay filter', *Remote Sensing of Environment*, vol. 91, no. 3, pp. 332-44.

Cleugh, H, Smith, MS, Battaglia, M & Graham, P 2011, *Climate change: science and solutions for Australia*, CSIRO, Collingwood - Australia.

Coakley, SM, Scherm, H & Chakraborty, S 1999, 'Climate change and plant disease management', *Annual Review of Phytopathology*, vol. 37, no. 1, pp. 399-426.

Cole, R, Sanders, T, Dorner, J & Blankenship, P 1989, 'Environmental conditions required to induce preharvest aflatoxin contamination of groundnuts:

summary of six years' research', *International Workshop on Aflatoxin Contamination of Groundnut, Patancheru, AP (India), 6-9 Oct 1987*, ICRISAT.
Cole, RJ, Sanders, TH, Hill, RA & Blankenship, PD 1985, 'Mean geocarposphere temperatures that induce preharvest aflatoxin contamination of peanuts under drought stress', *Mycopathologia*, vol. 91, no. 1, pp. 41-6.
Collins, S, Mahuku, G, Nzioki, HS, Narrod, C & Trench, P 2010, *Prevalence of aflatoxin in Kenya: summary of findings January - June 2010*, Aflacontrol Project Note 3, International Food Policy Research Institute, Washington.
Congalton, RG 1991, 'A review of assessing the accuracy of classifications of remotely sensed data', *Remote Sensing of Environment*, vol. 37, no. 1, pp. 35-46.
Cotty, PJ & Jaime-Garcia, R 2007, 'Influences of climate on aflatoxin producing fungi and aflatoxin contamination', *International Journal of Food Microbiology*, vol. 119, no. 1, pp. 109-15.
Cotty, PJ, Probst, C & Jaime-Garcia, R 2008, 'Etiology and management of aflatoxin contamination', in JF Leslie, et al. (eds), *Mycotoxins: detection methods, management, public health, and agricultural trade.*, Cromwell Press, Towbridge, pp. 287-99.
Craig, M & Atkinson, D 2013, *A literature review of crop area estimation*, FAO, viewed 25 March 2017, <http://www.fao.org/search/en/?cx=018170620143701104933%3Aqq82jsfba7w&q=www.fao.org%2F...%2FCrop_Area_Estimation_Lit_review&cof=FORID%3A9>.
Craufurd, P, Prasad, PV, Kakani, V, Wheeler, T & Nigam, S 2003, 'Heat tolerance in groundnut', *Field Crops Research*, vol. 80, no. 1, pp. 63-77.
Crosthwaite, I 1994, *Peanut growing in Australia*, Department of Primary Industries, Brisbane.
CSIRO & BoM 2015, *Climate change in Australia information for Australia's Natural Resource Management Regions: Technical Report*, CSIRO and BoM, Australia.
DAF 2011, *Growing Peanuts*, viewed 2 February 2016, <https://www.daf.qld.gov.au/plants/field-crops-and-pastures/broadacre-field-crops/peanuts/growing-peanuts>.
DAF 2014, *Broadacre field crops*, DAF, viewed 6 March 2017, <https://www.daf.qld.gov.au/plants/field-crops-and-pastures/broadacre-field-crops>.
Daren, X 1989, 'Research on aflatoxin contamination of groundnut in the People's Republic of China', *International Workshop on Aflatoxin Contamination of Groundnuts*: *Proceedings of the International Workshop on Aflatoxin Contamination of Groundnuts* ICRISAT, Patancheru, India.
de Souza, CHW, Mercante, E, Johann, JA, Lamparelli, RAC & Uribe-Opazo, MA 2015, 'Mapping and discrimination of soya bean and corn crops using spectro-temporal profiles of vegetation indices', *International journal of remote sensing*, vol. 36, no. 7, pp. 1809-24.
DERM 2010, *Climate change in Queensland* - *what the science is telling us*, DERM - State of Queensland, Brisbane.
DFF 2010, *Mung bean production guide*, F Department Agriculture, and Fisheries South Africa, Department Agriculture, Forestry, and Fisheries South Africa, Pretoria.

Diener, UL 1960, 'The mycoflora of peanuts in storage', *Phytopathology*, vol. 50, no. 3, pp. 220-3.
Diener, UL, Cole, RJ, Sanders, T, Payne, GA, Lee, LS & Klich, MA 1987, 'Epidemiology of aflatoxin formation by Aspergillus flavus', *Annual Review of Phytopathology*, vol. 25, no. 1, pp. 249-70.
Dierckx, W, Sterckx, S, Benhadj, I, Livens, S, Duhoux, G, Van Achteren, T, Francois, M, Mellab, K & Saint, G 2014, 'PROBA-V mission for global vegetation monitoring: standard products and image quality', *International Journal of Remote Sensing*, vol. 35, no. 7, pp. 2589-614.
DPI NSW 2007, *Sweet corn growing*, viewed 10 Desember 2019, <https://www.dpi.nsw.gov.au/agriculture/horticulture/vegetables/commodity-growing-guides/sweet-corn>.
DPIF 2007, *Best management practices for peanuts*, Department of Primary Industries and Fisheries - The State of Queensland, Brisbane.
Durgun, YÖ, Gobin, A, Van De Kerchove, R & Tychon, B 2016, 'Crop Area Mapping Using 100-m Proba-V Time Series', *Remote Sensing*, vol. 8, no. 7, p. 585.
EC-European Commission 2010, 'Commission Regulation (EU) No 165/2010 of 26 February 2010 amending Regulation (EC) No 1881/2006 setting maximum levels for certain contaminants in foodstuffs as regards aflatoxins', *Official Journal of the European Union*, vol. 50, pp. 8-12.
Eerens, H, Haesen, D, Rembold, F, Urbano, F, Tote, C & Bydekerke, L 2014, 'Image time series processing for agriculture monitoring', *Environmental Modelling & Software*, vol. 53, pp. 154-62.
Eklundh, L & Jönsson, P 2015a, 'TIMESAT: a software package for time-series processing and assessment of vegetation dynamics', in C Kuenzer, et al. (eds), *Remote sensing time series - revealing land surface dynamics*, Springer International Publishing, Switzerland, pp. 141-58.
Eklundh, L & Jönsson, P 2015b, *TIMESAT 3.2 with parallel processing - Software manual*, Lund University and Malmo University.
Elith, J & Leathwick, JR 2009, 'Species distribution models: ecological explanation and prediction across space and time', *Annual Review of Ecology, Evolution, and Systematics*, vol. 40, no. 1, pp. 677-97.
Exelis Visual Information Solutions 2012, *ENVI Version 5.0*, Boulder, Colorado.
Fletcher, SM & Shi, Z 2016, 'An overview of world peanut markets', in HT Stalker & RF Wilson (eds), *Peanuts: Genetics, Processing, and Utilization*, Elsevier, pp. 267-87.
Foerster, M, Welle, BA, Schmidt, T, Nieland, S & Kleinschmit, B 2014, 'TimeSpec—A software tool for analyzing time-series of spectral data', *IEEE International Geoscience and Remote Sensing Symposium (IGARSS) 2014*, IEEE, pp. 3941-4.
Foerster, S, Kaden, K, Foerster, M & Itzerott, S 2012, 'Crop type mapping using spectral–temporal profiles and phenological information', *Computers and Electronics in Agriculture*, vol. 89, pp. 30-40.
Fontanelli, G, Crema, A, Azar, R, Stroppiana, D, Villa, P & Boschetti, M 2014, 'Agricultural crop mapping using optical and SAR multi-temporal seasonal data: A case study in Lombardy region, Italy', *IEEE International Geoscience and Remote Sensing Symposium (IGARSS) 2014*, IEEE, pp. 1489-92.

Francois, M, Santandrea, S, Mellab, K, Vrancken, D & Versluys, J 2014, 'The PROBA-V mission: the space segment', *International Journal of Remote Sensing*, vol. 35, no. 7, pp. 2548-64.

Frisvad, JC, Skouboe, P & Samson, RA 2005, 'Taxonomic comparison of three different groups of aflatoxin producers and a new efficient producer of aflatoxin B1, sterigmatocystin and 3-O-methylsterigmatocystin, Aspergillus rambellii sp. nov', *Systematic and Applied Microbiology*, vol. 28, no. 5, pp. 442-53.

Gallego, J, Craig, M, Michaelsen, J, Bossyns, B & Fritz, S 2008, *Best practices for crop area estimation with remote sensing*, Joint Research Centre - European Comission, Ispra.

Gallo, A, Solfrizzo, M, Epifani, F, Panzarini, G & Perrone, G 2016, 'Effect of temperature and water activity on gene expression and aflatoxin biosynthesis in Aspergillus flavus on almond medium', *International Journal of Food Microbiology*, vol. 217, pp. 162-9.

Gambarova, YM, Gambarov, AY, Rustamov, RB & Zeynalova, MH 2010, 'Remote Sensing and GIS as an Advance Space Technologies for Rare Vegetation Monitoring in Gobustan State National Park, Azerbaijan', *Journal of Geographic Information System*, vol. 2, no. 02, pp. 93-9.

Gao, F, Anderson, MC, Zhang, X, Yang, Z, Alfieri, JG, Kustas, WP, Mueller, R, Johnson, DM & Prueger, JH 2017, 'Toward mapping crop progress at field scales through fusion of Landsat and MODIS imagery', *Remote Sensing of Environment*, vol. 188, pp. 9-25.

García, S & Heredia, N 2006, 'Mycotoxins in Mexico: Epidemiology, management, and control strategies', *Mycopathologia*, vol. 162, no. 3, pp. 255-64.

Garnaut, R 2011, *The Garnaut review 2011: Australia in the global response to climate change*, Cambridge University Press.

Gautam, H, Bhardwaj, M & Kumar, R 2013, 'Climate change and its impact on plant diseases', *Current Science*, vol. 105, no. 12, pp. 1685-91.

GBIF 2017, *Global Biodiversity Information Facility*, Copenhagen, viewed 5 August 2017, <http://www.gbif.org/species>.

Geoscience Australia 2018, *Area of Australia - State and Territories*, Geoscience Australia, viewed 3 April 2018, <http://www.ga.gov.au/scientific-topics/national-location-information/dimensions/area-of-australia-states-and-territories>.

Gibbons, R, Bunting, A & Smartt, J 1972, 'The classification of varieties of groundnut (Arachis hypogaea L.)', *Euphytica*, vol. 21, no. 1, pp. 78-85.

Giorni, P, Magan, N, Pietri, A, Bertuzzi, T & Battilani, P 2007, 'Studies on Aspergillus section Flavi isolated from maize in northern Italy', *International Journal of Food Microbiology*, vol. 113, no. 3, pp. 330-8.

Gómez, C, White, JC & Wulder, MA 2016, 'Optical remotely sensed time series data for land cover classification: A review', *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 116, pp. 55-72.

Gonçalez, E, Nogueira, JH, Fonseca, H, Felicio, JD, Pino, FA & Corrêa, B 2008, 'Mycobiota and mycotoxins in Brazilian peanut kernels from sowing to harvest', *International Journal of Food Microbiology*, vol. 123, no. 3, pp. 184-90.

Gordon, H, Rotstayn, L, McGregor, J, Dix, M, Kowalczyk, E, O'Farrell, S, Waterman, L, Hirst, A, Wilson, S, Collier, M, Watterson, I & Elliot, T 2002,

The CSIRO Mk3 climate system model, CSIRO Atmospheric Research Technical Paper.
Gornall, J, Betts, R, Burke, E, Clark, R, Camp, J, Willett, K & Wiltshire, A 2010, 'Implications of climate change for agricultural productivity in the early twenty-first century', *Philosophical Transactions of the Royal Society B: Biological Sciences*, vol. 365, no. 1554, pp. 2973-89.
Grace, D, Mahuku, G, Hoffmann, V, Atherstone, C, Upadhyaya, HD & Bandyopadhyay, R 2015, 'International agricultural research to reduce food risks: case studies on aflatoxins', *Food Security*, vol. 7, no. 3, pp. 569-82.
GRDC 2014, *GRDC Grownotes: Peanuts*, GRDC - Grains Research and Development Corporation.
GRDC 2017, *GRDC Grownotes: Sorghum*, GRDC - Grains Research and Development Corporation.
Gregory, PJ, Johnson, SN, Newton, AC & Ingram, JS 2009, 'Integrating pests and pathogens into the climate change/food security debate', *Journal of Experimental Botany*, vol. 60, no. 10, pp. 2827-38.
Guo, B, Yu, J, Holbrook, C, Lee, R & Lynch, R 2003, 'Application of differential display RT-PCR and EST/Microarray technologies to the analysis of gene expression in response to drought stress and elimination of aflatoxin contamination in corn and peanut', *Journal of Toxicology: Toxin Reviews*, vol. 22, no. 2-3, pp. 287-312.
Haerani, H, Apan, A & Basnet, B 2018, 'Mapping of peanut crops in Queensland, Australia, using time-series PROBA-V 100-m normalized difference vegetation index imagery', *Journal of Applied Remote Sensing*, vol. 12, no. 3, p. 036005.
Hansen, R & Norman, K 1999, 'Economic importance of aflatoxin to the Australian peanut industry', *ACIAR Proceedings*, Australian Centre for International Agricultural Research, pp. 7-9.
Hasumi, H & Emori, S 2004, 'K-1 coupled model (MIROC) description (K-1 Technical Report 1)', Center for Climate System Research, University of Tokyo.
He, Q & Zhou, G 2012, 'The climatic suitability for maize cultivation in China', *Chinese Science Bulletin*, vol. 57, no. 4, pp. 395-403.
Head, L, Adams, M, McGregor, HV & Toole, S 2014, 'Climate change and Australia', *Wiley Interdisciplinary Reviews: Climate Change*, vol. 5, no. 2, pp. 175-97.
Heikkinen, RK, Luoto, M, Araújo, MB, Virkkala, R, Thuiller, W & Sykes, MT 2006, 'Methods and uncertainties in bioclimatic envelope modelling under climate change', *Progress in Physical Geography*, vol. 30, no. 6, pp. 751-77.
Hentze, K, Thonfeld, F & Menz, G 2016, 'Evaluating crop area mapping from MODIS time-series as an assessment tool for Zimbabwe's "Fast track land reform programme"', *PloS One*, vol. 11, no. 6, p. e0156630.
Hijmans, RJ, Cameron, SE, Parra, JL, Jones, PG & Jarvis, A 2005, 'Very high resolution interpolated climate surfaces for global land areas', *International Journal of Climatology*, vol. 25, no. 15, pp. 1965-78.
Hill, M, Bertelsmeier, C, Clusella-Trullas, S, Garnas, J, Robertson, M & Terblanche, J 2016, 'Predicted decrease in global climate suitability masks regional complexity of invasive fruit fly species response to climate change', *Biological Invasions*, vol. 18, no. 4, pp. 1105-19.

Hill, RA, Blankenship, PD, Cole, RJ & Sanders, TH 1983, 'Effects of soil moisture and temperature on preharvest invasion of peanuts by the Aspergillus flavus group and subsequent aflatoxin development', *Applied and Environmental Microbiology*, vol. 45, no. 2, pp. 628-33.

Hirosawa, Y, Marsh, SE & Kliman, DH 1996, 'Application of standardized principal component analysis to land-cover characterization using multitemporal AVHRR data', *Remote Sensing of Environment*, vol. 58, no. 3, pp. 267-81.

Horn, B & Dorner, J 1998, 'Soil populations of Aspergillus species from section Flavi along a transect through peanut-growing regions of the United States', *Mycologia*, vol. 90, no. 5, pp. 767-76.

Horn, B & Dorner, J 1999, 'Regional differences in production of aflatoxin B1 and cyclopiazonic acid by soil isolates of Aspergillus flavus along a transect within the United States', *Applied and Environmental Microbiology*, vol. 65, no. 4, pp. 1444-9.

Horn, B, Greene, R & Dorner, J 1995, 'Effect of corn and peanut cultivation on soil populations of Aspergillus flavus and A. parasiticus in southwestern Georgia', *Applied and Environmental Microbiology*, vol. 61, no. 7, pp. 2472-5.

Howden, SM, Soussana, J-F, Tubiello, FN, Chhetri, N, Dunlop, M & Meinke, H 2007, 'Adapting agriculture to climate change', *Proceedings of the National Academy of Sciences*, vol. 104, no. 50, pp. 19691-6.

Huber, DM & Haneklaus, S 2007, 'Managing nutrition to control plant disease', *Landbauforschung Volkenrode*, vol. 57, no. 4, pp. 313 - 22.

Hussein, HS & Brasel, JM 2001, 'Toxicity, metabolism, and impact of mycotoxins on humans and animals', *Toxicology*, vol. 167, no. 2, pp. 101-34.

IARC 2006, *Preamble IARC monographs on the evaluation of carcinogenic risks to humans*, International Agency for Research on Cancer, Lyon, France.

IARC 2012, *Monographs on the evaluation of carcinogenic risks to humans: chemical agents and related occupations*, A review of human carcinogens, International Agency for Reseacrh on Cancer, Lyon, France.

Iizumi, T & Ramankutty, N 2015, 'How do weather and climate influence cropping area and intensity?', *Global Food Security*, vol. 4, pp. 46-50.

Im, J & Jensen, JR 2008, 'Hyperspectral remote sensing of vegetation', *Geography Compass*, vol. 2, no. 6, pp. 1943-61.

IPCC 2014, *Climate change 2014: synthesis report - Contribution of working groups I, II and III to the fifth assessment report of the Intergovernmental Panel on Climate Change*, IPCC, Geneva.

ITC 2010, *GI science and earth observation: a process based approach*, The International Institute for Geo-information Science and Earth Observation (ITC), Enschede.

Jakubauskas, ME, Legates, DR & Kastens, JH 2001, 'Harmonic analysis of time-series AVHRR NDVI data', *Photogrammetric Engineering and Remote Sensing*, vol. 67, no. 4, pp. 461-70.

Jayawardhana, W & Chathurange, V 2015, 'Extraction of Agricultural Phenological Parameters of Sri Lanka Using MODIS, NDVI Time Series Data', *International Conference of Sabaragamuwa University of Sri Lanka 2015 (ICSUSL 2015)*, Procedia Food Science, Colombo, Sri Lanka, pp. 235-41.

Jia, K, Liang, S, Wei, X, Yao, Y, Su, Y, Jiang, B & Wang, X 2014, 'Land cover classification of Landsat data with phenological features extracted from time series MODIS NDVI data', *Remote Sensing*, vol. 6, no. 11, pp. 11518-32.

Jönsson, P & Eklundh, L 2002, 'Seasonality extraction by function fitting to time-series of satellite sensor data', *IEEE Transactions on Geoscience and Remote Sensing*, vol. 40, no. 8, pp. 1824-32.

Jönsson, P & Eklundh, L 2004, 'TIMESAT—a program for analyzing time-series of satellite sensor data', *Computers & Geosciences*, vol. 30, no. 8, pp. 833-45.

Jönsson, P & Eklundh, L 2015, *Timesat: a software package to analyse time-series of satellite sensor data*, viewed 16 Maret 2017, <http://web.nateko.lu.se/timesat/timesat.asp?cat=0>.

Jordan, DL, Brandenburg, RL, Brown, AB, Bullen, SG, Roberson, GT, Shew, B & Spears, JF 2010, *Peanut information 2010*, North Carolina Cooperative Extension Service and North Carolina State University.

Juroszek, P & von Tiedemann, A 2013, 'Climate change and potential future risks through wheat diseases: a review', *European Journal of Plant Pathology*, vol. 136, no. 1, pp. 21-33.

Kaaya, A, Harris, C & Eigel, W 2006, 'Peanut aflatoxin levels on farms and in markets of Uganda', *Peanut Science*, vol. 33, no. 1, pp. 68-75.

Kachapulula, P, Akello, J, Bandyopadhyay, R & Cotty, PJ 2017a, 'Aspergillus section Flavi community structure in Zambia influences aflatoxin contamination of maize and groundnut', *International Journal of Food Microbiology*, vol. 261, pp. 49-56.

Kachapulula, P, Akello, J, Bandyopadhyay, R & Cotty, P 2017b, 'Aflatoxin contamination of groundnut and maize in Zambia: observed and potential concentrations', *Journal of Applied Microbiology*, vol. 122, no. 6, pp. 1471-82.

Kambiranda, DM, Vasanthaiah, HK, Katam, R, Ananga, A, Basha, SM & Naik, K 2011, 'Impact of drought stress on peanut (Arachis hypogaea L.) productivity and food safety', in H Vasanthaiah (ed.), *Plants and environment*, InTech, Rijeka, Croatia, pp. 249 -72.

Kamika, I & Takoy, LL 2011, 'Natural occurrence of Aflatoxin B1 in peanut collected from Kinshasa, Democratic Republic of Congo', *Food Control*, vol. 22, no. 11, pp. 1760-4.

Kamika, I & Tekere, M 2016, 'Occurrence of aflatoxin contamination in maize throughout the supply chain in the Democratic Republic of Congo', *Food Control*, vol. 69, pp. 292-6.

Ketring, D 1984, 'Temperature effects on vegetative and reproductive development of peanut', *Crop Science*, vol. 24, no. 5, pp. 877-82.

Khan, A, Hansen, MC, Potapov, P, Stehman, SV & Chatta, AA 2016, 'Landsat-based wheat mapping in the heterogeneous cropping system of Punjab, Pakistan', *International Journal of Remote Sensing*, vol. 37, no. 6, pp. 1391-410.

King, AD, Klingaman, NP, Alexander, LV, Donat, MG, Jourdain, NC & Maher, P 2014, 'Extreme rainfall variability in Australia: patterns, drivers, and predictability', *Journal of Climate*, vol. 27, no. 15, pp. 6035-50.

Kishore, GK, Pande, S, Manjula, K, Rao, JN & Thomas, D 2002, 'Occurrence of mycotoxins and toxigenic fungi in groundnut (Arachis hypogaea L.) seeds in

Andhra Pradesh, India', *The Plant Pathology Journal*, vol. 18, no. 4, pp. 204-9.
Klich, MA 2002, 'Biogeography of Aspergillus species in soil and litter', *Mycologia*, vol. 94, no. 1, pp. 21-7.
Klich, MA 2007, 'Aspergillus flavus: the major producer of aflatoxin', *Molecular Plant Pathology*, vol. 8, no. 6, pp. 713-22.
Klich, MA, Tiffany, LH & Knaphus, G 1992, 'Ecology of the aspergilli of soils and litter', in JW Bennett & MA Klich (eds), *Aspergillus: Biology and Industrial Applications*, Butterworth-Heinemann, Boston.
Knudby, A 2004, 'An AVHRR-based model of groundnut yields in the peanut basin of Senegal', *International Journal of Remote Sensing*, vol. 25, no. 16, pp. 3161-75.
Kocmánková, E, Trnka, M, Eitzinger, J, Dubrovský, M, Štěpánek, P, Semerádová, D, Balek, J, Skalak, P, Farda, A & Juroch, J 2011, 'Estimating the impact of climate change on the occurrence of selected pests at a high spatial resolution: a novel approach', *The Journal of Agricultural Science*, vol. 149, no. 02, pp. 185-95.
Kokalis-Burelle, N, Porter, D, Rodriguez-Kabana, R, Smith, D & Subrahmanyam, P 1997, *Compendium of Peanut Diseases*, vol. 2, American Phytopathological Society.
Kottek, M, Grieser, J, Beck, C, Rudolf, B & Rubel, F 2006, 'World map of the Köppen-Geiger climate classification updated', *Meteorologische Zeitschrift*, vol. 15, no. 3, pp. 259-63.
Kriticos, DJ & Randall, RP 2001, 'A comparison of systems to analyse potential weed distributions', in RH Groves, et al. (eds), *Weed risk assessment*, CSIRO Publishing, Melbourne, pp. 61-79.
Kriticos, DJ & Leriche, A 2010, 'The effects of climate data precision on fitting and projecting species niche models', *Ecography*, vol. 33, no. 1, pp. 115-27.
Kriticos, DJ, Morin, L, Leriche, A, Anderson, RC & Caley, P 2013, 'Combining a climatic niche model of an invasive fungus with its host species distributions to identify risks to natural assets: Puccinia psidii sensu lato in Australia', *PloS One*, vol. 8, no. 5, p. e64479.
Kriticos, DJ, Maywald, GF, Yonow, T, Zurcher, EJ, Herrmann, NI & Sutherst, RW 2015, *Climex version 4: Exploring the effects of climate on plants, animals and diseases*, CSIRO, Canberra.
Kriticos, DJ, Webber, BL, Leriche, A, Ota, N, Macadam, I, Bathols, J & Scott, JK 2012, 'CliMond: global high-resolution historical and future scenario climate surfaces for bioclimatic modelling', *Methods in Ecology and Evolution*, vol. 3, no. 1, pp. 53-64.
Lambert, M-J, Waldner, F & Defourny, P 2016, 'Cropland mapping over Sahelian and Sudanian agrosystems: A knowledge-based approach using PROBA-V time series at 100-m', *Remote Sensing*, vol. 8, no. 3, p. 232.
Landis, JR & Koch, GG 1977, 'The measurement of observer agreement for categorical data', *Biometrics*, vol. 33, no. 1, pp. 159-74.
Leong, S & Ong, C 1983, 'The influence of temperature and soil water deficit on the development and morphology of groundnut (Arachis hypogaea L.)', *Journal of Experimental Botany*, vol. 34, no. 11, pp. 1551-61.
Lewis, L, Onsongo, M, Njapau, H, Schurz-Rogers, H, Luber, G, Kieszak, S, Nyamongo, J, Backer, L, Dahiye, AM & Misore, A 2005, 'Aflatoxin contamination of commercial maize products during an outbreak of acute

aflatoxicosis in eastern and central Kenya', *Environmental Health Perspectives*, vol. 113, no. 12, pp. 1763 - 7.
Li, F-Q, Yoshizawa, T, Kawamura, O, Luo, X-Y & Li, Y-W 2001, 'Aflatoxins and fumonisins in corn from the high-incidence area for human hepatocellular carcinoma in Guangxi, China', *Journal of Agricultural and Food Chemistry*, vol. 49, no. 8, pp. 4122-6.
Li, L, Friedl, MA, Xin, Q, Gray, J, Pan, Y & Frolking, S 2014, 'Mapping crop cycles in China using MODIS-EVI time series', *Remote Sensing*, vol. 6, no. 3, pp. 2473-93.
Lillehoj, E, Kwolek, W, Fennell, D & Milburn, M 1975, 'Aflatoxin incidence and association with bright greenish-yellow fluorescence and insect damage in a limited survey of freshly harvested high-moisture corn', *Cereal Chemistry*, vol. 52, pp. 403-12.
Lindsay Corporation 2010, 'Increasing peanut yields through efficicent irrigation solutions - higher yields, lower costs, precision application', Lindsay Corporation, Omaha, Nebraska, The USA.
Liu, MW, Ozdogan, M & Zhu, X 2014, 'Crop type classification by simultaneous use of satellite images of different resolutions', *IEEE Transactions on Geoscience and Remote Sensing*, vol. 52, no. 6, pp. 3637-49.
Luck, J, Spackman, M, Freeman, A, Griffiths, W, Finlay, K & Chakraborty, S 2011, 'Climate change and diseases of food crops', *Plant Pathology*, vol. 60, no. 1, pp. 113-21.
Madhan, M & Nigam, S 2013, *Principles and Practices for Groundnut Seed Production in India.*, ICRISAT, Patancheru, Andhra Pradesh
Manning, MR, Edmonds, J, Emori, S, Grubler, A, Hibbard, K, Joos, F, Kainuma, M, Keeling, RF, Kram, T, Manning, AC, Meinshausen, M, Moss, R, Nakicenovic, N, Riahi, K, Rose, S, Smith, S, Swart, R & van Vuuren, D 2010, 'Misrepresentation of the IPCC CO_2 emission scenarios', *Nature Geoscience*, vol. 3, no. 6, pp. 376-7.
Marshall, NA, Dowd, A-M, Fleming, A, Gambley, C, Howden, M, Jakku, E, Larsen, C, Marshall, PA, Moon, K, Park, S & Thorburn, PJ 2014, 'Transformational capacity in Australian peanut farmers for better climate adaptation', *Agronomy for Sustainable Development*, vol. 34, no. 3, pp. 583-91.
Medina, A, Rodriguez, A & Magan, N 2014, 'Effect of climate change on Aspergillus flavus and aflatoxin B1 production', *Frontiers in Microbiology*, vol. 5, p. 348.
Meinke, H & Hammer, G 1995, 'Climatic risk to peanut production: a simulation study for Northern Australia', *Australian Journal of Experimental Agriculture*, vol. 35, no. 6, pp. 777-80.
Meinke, H, Stone, R & Hammer, G 1996, 'SOI phases and climatic risk to peanut production: a case study for northern Australia', *International Journal of Climatology*, vol. 16, no. 7, pp. 783-9.
Mingwei, Z, Qingbo, Z, Zhongxin, C, Jia, L, Yong, Z & Chongfa, C 2008, 'Crop discrimination in Northern China with double cropping systems using Fourier analysis of time-series MODIS data', *International Journal of Applied Earth Observation and Geoinformation*, vol. 10, no. 4, pp. 476-85.
Monfreda, C, Ramankutty, N & Foley, JA 2008, 'Farming the planet: 2. Geographic distribution of crop areas, yields, physiological types, and net

primary production in the year 2000', *Global Biogeochemical Cycles*, vol. 22, no. 1.
Mora, M & Lacey, J 1997, 'Handling and aflatoxin contamination of white maize in Costa Rica', *Mycopathologia*, vol. 138, no. 2, pp. 77-89.
Moreno, EC, Garcia, GT, Ono, MA, Vizoni, É, Kawamura, O, Hirooka, EY & Ono, EYS 2009, 'Co-occurrence of mycotoxins in corn samples from the Northern region of Paraná State, Brazil', *Food Chemistry*, vol. 116, no. 1, pp. 220-6.
Muhammad, S, Zhan, Y, Wang, L, Hao, P & Niu, Z 2016, 'Major crops classification using time series MODIS EVI with adjacent years of ground reference data in the US state of Kansas', *Optik-International Journal for Light and Electron Optics*, vol. 127, no. 3, pp. 1071-7.
Mutegi, C, Ngugi, H, Hendriks, S & Jones, R 2012, 'Factors associated with the incidence of Aspergillus section Flavi and aflatoxin contamination of peanuts in the Busia and Homa bay districts of western Kenya', *Plant Pathology*, vol. 61, no. 6, pp. 1143-53.
Nakicenovic, N, Davidson, O, Davis, G, Grubler, A, Kram, T, La Rovere, EL, Metz, B, Morita, T, Pepper, W, Pitcher, H, Sankovski, A, Shukla, P, Swart, R, Watson, R & Dadi, Z 2000, *Special report on emissions scenarios (SRES), a special report of Working Group III of the Intergovernmental Panel on Climate Change*, Intergovernmental Panel on Climate Change.
Navulur, K 2006, *Multispectral image analysis using the object-oriented paradigm*, CRC Press Taylor & Francis Group, Boca Raton, Florida.
Navya, H, Hariprasad, P, Naveen, J, Chandranayaka, S & Niranjana, S 2013, 'Natural occurrence of aflatoxin, aflatoxigenic and nonaflatoxigenic Aspergillus flavus in groundnut seeds across India', *African Journal of Biotechnology*, vol. 12, no. 19, pp. 2587 - 97.
Newberne, PM & Butler, WH 1969, 'Acute and chronic effects of aflatoxin on the liver of domestic and laboratory animals: a review', *Cancer Research*, vol. 29, no. 1, pp. 236-50.
Newton, AC, Johnson, SN & Gregory, PJ 2011, 'Implications of climate change for diseases, crop yields and food security', *Euphytica*, vol. 179, no. 1, pp. 3-18.
Nicholls, N, Drosdowsky, W & Lavery, B 1997, 'Australian rainfall variability and change', *Weather*, vol. 52, no. 3, pp. 66-72.
Olfert, O, Weiss, R & Kriticos, D 2011, 'Application of general circulation models to assess the potential impact of climate change on potential distribution and relative abundance of Melanoplus sanguinipes (Fabricius)(Orthoptera: Acrididae) in North America', *Psyche*, vol. 2011, p. 980372.
Olfert, O, Weiss, R & Elliott, R 2016, 'Bioclimatic approach to assessing the potential impact of climate change on wheat midge (Diptera: Cecidomyiidae) in North America', *The Canadian Entomologist*, vol. 148, no. 01, pp. 52-67.
Otukei, JR & Blaschke, T 2010, 'Land cover change assessment using decision trees, support vector machines and maximum likelihood classification algorithms', *International Journal of Applied Earth Observation and Geoinformation*, vol. 12, pp. S27-S31.
Ozdogan, M & Woodcock, CE 2006, 'Resolution dependent errors in remote sensing of cultivated areas', *Remote Sensing of Environment*, vol. 103, no. 2, pp. 203-17.

Pan, Z, Huang, J, Zhou, Q, Wang, L, Cheng, Y, Zhang, H, Blackburn, GA, Yan, J & Liu, J 2015, 'Mapping crop phenology using NDVI time-series derived from HJ-1 A/B data', *International Journal of Applied Earth Observation and Geoinformation*, vol. 34, pp. 188-97.

Parry, M, Porter, J & Carter, T 1990, 'Agriculture: climatic change and its implications', *Trends in Ecology & Evolution*, vol. 5, no. 9, pp. 318-22.

Paterson, RRM & Lima, N 2010, 'How will climate change affect mycotoxins in food?', *Food Research International*, vol. 43, no. 7, pp. 1902-14.

Paterson, RRM, Kumar, L, Taylor, S & Lima, N 2015, 'Future climate effects on suitability for growth of oil palms in Malaysia and Indonesia', *Scientific Reports*, vol. 5, p. 14457.

Pattee, HE & Stalker, HT 1995, *Advances in peanut science*, American Peanut Research and Education Society Inc., Stillwater, Oklahoma.

Payne, GA & Hagler, W 1983, 'Effect of specific amino acids on growth and aflatoxin production by Aspergillus parasiticus and Aspergillus flavus in defined media', *Applied Environmental Microbiology*, vol. 46, no. 4, pp. 805-12.

Perrone, G, Gallo, A & Logrieco, AF 2014, 'Biodiversity of Aspergillus section Flavi in Europe in relation to the management of aflatoxin risk', *Frontiers in Microbiology*, vol. 5, p. 377.

Petitjean, F, Inglada, J & Gancarski, P 2014, 'Assessing the quality of temporal high-resolution classifications with low-resolution satellite image time series', *International Journal of Remote Sensing*, vol. 35, no. 7, pp. 2693-712.

Pettit, RE & Taber, RA 1968, 'Factors influencing aflatoxin accumulation in peanut kernels and the associated mycoflora', *Applied Microbiology*, vol. 16, no. 8, pp. 1230-4.

Pettit, RE, Taber, RA, Schroeder, HW & Harrison, AL 1971, 'Influence of fungicides and irrigation practice on aflatoxin in peanuts before digging', *Applied Microbiology*, vol. 22, no. 4, pp. 629-34.

Pinter, PJ, Hatfield, JL, Schepers, JS, Barnes, EM, Moran, MS, Daughtry, CS & Upchurch, DR 2003, 'Remote sensing for crop management', *Photogrammetric Engineering & Remote Sensing*, vol. 69, no. 6, pp. 647-64.

Pitt, J & Hocking, AD 2006, 'Mycotoxins in Australia: biocontrol of aflatoxin in peanuts', *Mycopathologia*, vol. 162, no. 3, pp. 233-43.

Potgieter, A, Meinke, H, Doherty, A, Sadras, V, Hammer, G, Crimp, S & Rodriguez, D 2013, 'Spatial impact of projected changes in rainfall and temperature on wheat yields in Australia', *Climatic Change*, vol. 117, no. 1-2, pp. 163-79.

Potgieter, AB, Apan, A, Dunn, P & Hammer, G 2007, 'Estimating crop area using seasonal time series of Enhanced Vegetation Index from MODIS satellite imagery', *Crop and Pasture Science*, vol. 58, no. 4, pp. 316-25.

QGSO 2016, *Queensland Statistics*, Queensland Government Statistician's Office, viewed 25 May 2017, <http://www.qgso.qld.gov.au/products/tables/agriculture-gross-value-production/index.php>.

QGSO 2019, *Queensland Statistics*, Queensland Government Statistician's Office, viewed 11 June 2019, <http://www.qgso.qld.gov.au/products/tables/agriculture-gross-value-production/index.php>.

Quitco, RT 1991, 'Aflatoxin studies in the Philippines', *Fungi and mycotoxins in stored products*, ACIAR Proceedings, Bangkok, Thailand, pp. 180-86.
Rachaputi, N, Krosch, S & Wright, G 2002, 'Management practices to minimise pre-harvest aflatoxin contamination in Australian peanuts', *Australian Journal of Experimental Agriculture*, vol. 42, no. 5, pp. 595-605.
Rahayu, ES, Raharjo, S & Rahmianna, AA 2003, 'Cemaran aflatoksin pada produksi jagung di daerah Jawa Timur', *Agritech*, vol. 23, no. 4, pp. 174-83.
Rajan, N, Puppala, N, Maas, S, Payton, P & Nuti, R 2014, 'Aerial remote sensing of peanut ground cover', *Agronomy journal*, vol. 106, no. 4, pp. 1358-64.
Ramirez-Cabral, NYZ, Kumar, L & Taylor, S 2016, 'Crop niche modeling projects major shifts in common bean growing areas', *Agricultural and Forest Meteorology*, vol. 218, pp. 102-13.
Resnik, S, Neira, S, Pacin, A, Martinez, E, Apro, N & Latreite, S 1996, 'A survey of the natural occurrence of aflatoxins and zearalenone in Argentine field maize: 1983–1994', *Food Additives & Contaminants*, vol. 13, no. 1, pp. 115-20.
Richards, JA 2006, *Remote sensing digital image analysis : an introduction*, 4th edn, Springer, New York.
Robens, J & Cardwell, K 2003, 'The costs of mycotoxin management to the USA: management of aflatoxins in the United States', *Journal of Toxicology: Toxin Reviews*, vol. 22, no. 2-3, pp. 139-52.
Robson, A, Wright, G & Phinn, S 2007, 'Remote sensing applications in peanuts: the assessment of crop maturity, yield, disease, irrigation efficiencey and best management practices using temporal images', *5th Australian Controlled Traffic Farming & Precision Agriculture Conference*: *Proceedings of the 5th Australian Controlled Traffic Farming & Precision Agriculture Conference* Australian controlled Traffic Farming Association Inc. (ACTFA), Perth.
Rocha, LO, Nakai, VK, Braghini, R, Reis, TA, Kobashigawa, E & Corrêa, B 2009, 'Mycoflora and co-occurrence of fumonisins and aflatoxins in freshly harvested corn in different regions of Brazil', *International Journal of Molecular Sciences*, vol. 10, no. 11, pp. 5090-103.
Rosenzweig, C, Elliott, J, Deryng, D, Ruane, AC, Mueller, C, Arneth, A, Boote, KJ, Folberth, C, Glotter, M, Khabarov, N, Neumann, K, Piontek, F, Pugh, TAM, Schmid, E, Stehfest, E, Yang, H & Jones, JW 2014, 'Assessing agricultural risks of climate change in the 21st century in a global gridded crop model intercomparison', *Proceedings of the National Academy of Sciences of the United States of America*, vol. 111, no. 9, pp. 3268 - 73.
Roumenina, E, Atzberger, C, Vassilev, V, Dimitrov, P, Kamenova, I, Banov, M, Filchev, L & Jelev, G 2015, 'Single-and multi-date crop identification using PROBA-V 100 and 300 m S1 products on Zlatia test site, Bulgaria', *Remote Sensing*, vol. 7, no. 10, pp. 13843-62.
Sanders, TH, Cole, RJ, Blankenship, PD & Hill, RA 1985, 'Relation of environmental stress duration to Aspergillus flavus invasion and aflatoxin production in preharvest peanuts', *Peanut science*, vol. 12, no. 2, pp. 90-3.
Santoso, H, Idinoba, M & Imbach, P 2008, *Climate scenarios: what we need to know and how to generate them*, Center for International Forestry Research (CIFOR), Bogor.

Scherm, H 2004, 'Climate change: can we predict the impacts on plant pathology and pest management?', *Canadian Journal of Plant Pathology*, vol. 26, no. 3, pp. 267-73.
Schiffer, M, Umina, P, Carew, M, Hoffmann, A, Rodoni, B & Miller, A 2009, 'The distribution of wheat curl mite (Aceria tosichella) lineages in Australia and their potential to transmit wheat streak mosaic virus', *Annals of Applied Biology*, vol. 155, no. 3, pp. 371-9.
Schroeder, H & Boller, R 1973, 'Aflatoxin production of species and strains of the Aspergillus flavus group isolated from field crops', *Applied Microbiology*, vol. 25, no. 6, pp. 885-9.
Schultz, B, Immitzer, M, Formaggio, AR, Sanches, IDA, Luiz, AJB & Atzberger, C 2015, 'Self-guided segmentation and classification of multi-temporal Landsat 8 images for crop type mapping in southeastern Brazil', *Remote Sensing*, vol. 7, no. 11, pp. 14482-508.
Seetha, A, Munthali, W, Msere, HW, Swai, E, Muzanila, Y, Sichone, E, Tsusaka, TW, Rathore, A & Okori, P 2017, 'Occurrence of aflatoxins and its management in diverse cropping systems of central Tanzania', *Mycotoxin Research*, vol. 33, no. 4, pp. 323-31.
Setamou, M, CardwelL, KF, Schulthess, F & Hell, K 1997, 'Aspergillus flavus infection and aflatoxin contamination of preharvest maize in Benin', *Plant Disease*, vol. 81, no. 11, pp. 1323-7.
Shabani, F & Kotey, B 2015, 'Future distribution of cotton and wheat in Australia under potential climate change', *Journal of Agricultural Science*, vol. 154, no. 2, pp. 175-85.
Shabani, F, Kumar, L & Esmaeili, A 2014, 'Future distributions of Fusarium oxysporum f. spp. in European, Middle Eastern and North African agricultural regions under climate change', *Agriculture, Ecosystems & Environment*, vol. 197, pp. 96-105.
Shabani, F, Kumar, L & Taylor, S 2014, 'Projecting date palm distribution in Iran under climate change using topography, physicochemical soil properties, soil taxonomy, land use, and climate data', *Theoretical and Applied Climatology*, vol. 118, no. 3, pp. 553-67.
Shabani, F, Kumar, L & Taylor, S 2015, 'Distribution of date palms in the Middle East based on future climate scenarios', *Experimental Agriculture*, vol. 51, no. 02, pp. 244-63.
Shabani, F, Kumar, L, Nojoumian, AH, Esmaeili, A & Toghyani, M 2015, 'Projected future distribution of date palm and its potential use in alleviating micronutrient deficiency', *Journal of the Science of Food and Agriculture*.
Shahenshah & Isoda, A 2010, 'Effects of water stress on leaf temperature and chlorophyll fluorescence parameters in cotton and peanut', *Plant Production Science*, vol. 13, no. 3, pp. 269-78.
Sharma, RK & Parisi, S 2017, 'Aflatoxins in Indian food products', in *Toxins and Contaminants in Indian Food Products*, Springer, pp. 13-24.
Silva, R, Kumar, L, Shabani, F & Picanço, M 2017, 'Assessing the impact of global warming on worldwide open field tomato cultivation through CSIRO-Mk3.0 Global Climate Model', *Journal of Agricultural Science*, vol. 155, no. 3, pp. 407-20.
Sinha, KK 1990, 'Incidence of mycotoxins in maize grains in Bihar State, India', *Food Additives & Contaminants*, vol. 7, no. 1, pp. 55-61.

Siriacha, P, Kawashima, K, Okazaki, H, Saito, M, Kawasugi, S & Tonboon-ek, P 1988, 'Aspergillus flavus and aflatoxin contaminations of maize ears and kernels in Thailand', *JSM Mycotoxins*, vol. 1988, no. 28, pp. 23-8.
Smartt, J 2012, *The groundnut crop: a scientific basis for improvement*, Springer Science & Business Media.
Sorby, P & Reid, R 2001, *Soils and agricultural suitability of the South Burnett agricultural lands, Queensland*, Land resources bulletin, Department of Natural Resources and Mines, Brisbane.
South Burnett Regional Council 2014, *South Burnett economic brief*, SBR Council.
South Burnett Regional Council 2016, *South Burnett Regional Council 2014-15 Annual Report*, SBR Council.
Souza, GFd, Mossini, SAG, Arrotéia, CC, Kemmelmeier, C & Machinski Junior, M 2014, 'Evaluation of the mycoflora and aflatoxins from the pre-harvest to storage of peanuts: a case study', *Acta Scientiarum. Agronomy*, vol. 36, no. 1, pp. 27-33.
Srivastava, MK 2015, *Crop monitoring for improved food security*, FAO and ADB, Bangkok.
Stalker, H 1997, 'Peanut (Arachis hypogaea L.)', *Field Crops Research*, vol. 53, no. 1-3, pp. 205-17.
Steffen, W, Hughes, L, Sahajwalla, V & Hueston, G 2012, *The critical decade: Queensland climate impacts and opportunities*, Climate Comission Secretariat (Department of Climate Change and Energy Efficiency), Canberra.
Stefman, SV 1996, 'Estimating the Kappa Coefficient and its variance under stratified random sampling', *Photogrammetric Engineering & Remote Sensing*, vol. 62, no. 4, pp. 401-2.
Stokes, C & Howden, M 2010, *Adapting agriculture to climate change: preparing Australian agriculture, forestry and fisheries for the future*, CSIRO Publishing, Collingwood, Victoria.
Story, M & Congalton, RG 1986, 'Accuracy assessment: A user's perspective', *Photogrammetric Engineering and Remote Sensing*, vol. 52, no. 3, pp. 397-9.
Sun, H, Xu, A, Lin, H, Zhang, L & Mei, Y 2012, 'Winter wheat mapping using temporal signatures of MODIS vegetation index data', *International Journal of Remote Sensing*, vol. 33, no. 16, pp. 5026-42.
Suppiah, R, Hennessy, K, Whetton, P, McInnes, K, Macadam, I, Bathols, J, Ricketts, J & Page, C 2007, 'Australian climate change projections derived from simulations performed for the IPCC 4th Assessment Report', *Australian Meteorological Magazine*, vol. 56, no. 3, pp. 131-52.
Sutherst, R & Maywald, G 1985, 'A computerised system for matching climates in ecology', *Agriculture, Ecosystems & Environment*, vol. 13, no. 3-4, pp. 281-99.
Sutherst, R & Bourne, A 2009, 'Modelling non-equilibrium distributions of invasive species: a tale of two modelling paradigms', *Biological Invasions*, vol. 11, no. 6, pp. 1231-7.
Sutherst, RW 2003, 'Prediction of species geographical ranges', *Journal of Biogeography*, vol. 30, no. 6, pp. 805-16.
Tapsell, LC, Probst, Y, Lawrence, M, Friel, S, Flood, V, McMahon, A & Butler, R 2011, 'Food and nutrition security in the Australia-New Zealand region:

impact of climate change', in *World Review of Nutrition and Dietetics*, Karger Publishers, pp. 192-200.
Taylor, S, Kumar, L, Reid, N & Kriticos, DJ 2012, 'Climate change and the potential distribution of an invasive shrub, Lantana camara L', *PloS One*, vol. 7, no. 4, p. e35565.
Torres, A, Barros, G, Palacios, S, Chulze, S & Battilani, P 2014, 'Review on pre- and post-harvest management of peanuts to minimize aflatoxin contamination', *Food Research International*, vol. 62, pp. 11-9.
Turner, PC, Sylla, A, Diallo, MS, Castegnaro, JJ, Hall, AJ & Wild, CP 2002, 'The role of aflatoxins and hepatitis viruses in the etiopathogenesis of hepatocellular carcinoma: A basis for primary prevention in Guinea–Conakry, West Africa', *Journal of Gastroenterrology and Hepatology*, vol. 17, pp. S441-S8.
Van der Fels-Klerx, H, Liu, C & Battilani, P 2016, 'Modelling climate change impacts on mycotoxin contamination', *World Mycotoxin Journal*, vol. 9, no. 5, pp. 717-26.
Van Egmond, HP, Schothorst, RC & Jonker, MA 2007, 'Regulations relating to mycotoxins in food', *Analytical and Bioanalytical Chemistry*, vol. 389, no. 1, pp. 147-57.
Van Vuuren, DP & Carter, TR 2014, 'Climate and socio-economic scenarios for climate change research and assessment: reconciling the new with the old', *Climatic Change*, vol. 122, no. 3, pp. 415-29.
Van Vuuren, DP, Edmonds, J, Kainuma, M, Riahi, K, Thomson, A, Hibbard, K, Hurtt, GC, Kram, T, Krey, V & Lamarque, J-F 2011, 'The representative concentration pathways: an overview', *Climatic Change*, vol. 109, no. 1-2, pp. 5 - 31.
Vara Prasad, P, Craufurd, P & Summerfield, R 2000, 'Effect of high air and soil temperature on dry matter production, pod yield and yield components of groundnut', *Plant and Soil*, vol. 222, no. 1-2, pp. 231-9.
Vara Prasad, P, Boote, KJ, Hartwell Allen, L & Thomas, JM 2003, 'Super-optimal temperatures are detrimental to peanut (Arachis hypogaea L.) reproductive processes and yield at both ambient and elevated carbon dioxide', *Global Change Biology*, vol. 9, no. 12, pp. 1775-87.
Vellidis, G, Ortiz, B, Renga, M, Perry, C, Rucker, K & Morari, F 2007, 'Spatial distribution of aflatoxin in growing peanut', *Poster Proceedings of the Sixth European Conference on Precision Agriculture (6ECPA),* Skiathos, Greece.
Vijayasamundeeswari, A, Mohankumar, M, Karthikeyan, M, Vijayanandraj, S, Paranidharan, V & Velazhahan, R 2009, 'Prevalence of aflatoxin B1 contamination in pre-and post-harvest maize kernels, food products, poultry and livestock feeds in Tamil Nadu, India', *Journal of Plant Protection research*, vol. 49, no. 2, pp. 221-4.
VITO 2016, *Proba Vegetation the small satellite for global vegetation monitoring*, VITO, Belgium, viewed 24 April 2017, <http://proba-v.vgt.vito.be/>.
Vorovencii, I 2009, 'The hyperspectral sensors used in satellite and aerial remote sensing', *Bulletin of the Transilvania University of Brasov, Series II: Forestry, Wood Industry, Agricultural and Food Engineering*, vol. 2, pp. 51-6.
Waliyar, F, Osiru, M, Siambi, M & Chinyamunyamu, B 2013, 'Assessing occurrence and distribution of aflatoxins in Malawi', Lilongwe, Malawi.

Waliyar, F, Umeh, V, Traore, A, Osiru, M, Ntare, B, Diarra, B, Kodio, O, Kumar, KVK & Sudini, H 2015, 'Prevalence and distribution of aflatoxin contamination in groundnut (Arachis hypogaea L.) in Mali, West Africa', *Crop Protection*, vol. 70, pp. 1-7.

Wardlow, BD & Egbert, SL 2008, 'Large-area crop mapping using time-series MODIS 250 m NDVI data: An assessment for the US Central Great Plains', *Remote Sensing of Environment*, vol. 112, no. 3, pp. 1096-116.

Wardlow, BD, Egbert, SL & Kastens, JH 2007, 'Analysis of time-series MODIS 250 m Vegetation Index data for crop classification in the US Central Great Plains', *Remote Sensing of Environment*, vol. 108, no. 3, pp. 290-310.

Whiting, ML, Ustin, SL, Zarco-Tejada, P, Palacios-Orueta, A & Vanderbilt, VC 2006, 'Hyperspectral mapping of crop and soils for precision agriculture', *SPIE Optics + Photonics Conference*, SPIE, San Diego, California, USA.

Williams, JH & Boote, KJ 1995, 'Physiology and modeling - predicting the unpredictable legume', in HE Patee & HT Stalker (eds), *Advances in peanut science*, American Peanut Research and Education Society, Stillwater, Oklahoma, pp. 301-53.

WMO 2010, *Guide to Agricultural Meteorological Practices (GAMP) WMO - No. 134*, World Meteorological Organization, Geneva.

Wolters, E, Dierckx, W, Iordache, M-D & Swinnen, E 2017, 'PROBA-V Product User Manual Version: 2.1', VITO, 6 June 2017.

Wotton, H & Strange, R 1987, 'Increased susceptibility and reduced phytoalexin accumulation in drought-stressed peanut kernels challenged with Aspergillus flavus', *Applied and Environmental Microbiology*, vol. 53, no. 2, pp. 270-3.

Wright, D, Tillman, B, Jowers, E, Marois, J, Ferrell, J, Katsvairo, T & Whitty, E 2009, *Management and cultural practices for peanuts*, SS-AGR-74 UF/IFAS Extension University of Florida, Gainesville, Florida.

Wright, G, Hubick, K & Farquhar, G 1991, 'Physiological analysis of peanut cultivar response to timing and duration of drought stress', *Australian Journal of Agricultural Research*, vol. 42, no. 3, pp. 453-70.

Wright, G, Wieck, L & O'Connor, D 2017, 'Peanut Production Guide', Peanut Company of Australia, viewed 9 May 2018, <http://www.pca.com.au/wp-content/uploads/2017/12/Peanut-Production-Guide-2017.pdf>.

Wu, F 2004, 'Mycotoxin risk assessment for the purpose of setting international regulatory standards', *Environmental Science & Technology*, vol. 38, no. 15, pp. 4049 - 55.

Wu, F & Guclu, H 2012, 'Aflatoxin regulations in a network of global maize trade', *PloS One*, vol. 7, no. 9, p. e45151.

Wu, L, Ding, X, Li, P, Du, X, Zhou, H, Bai, YZ & Zhang, L 2016, 'Aflatoxin contamination of peanuts at harvest in China from 2010 to 2013 and its relationship with climatic conditions', *Food Control*, vol. 60, pp. 117-23.

Xavier, AC, Rudorff, BF, Shimabukuro, YE, Berka, LMS & Moreira, MA 2006, 'Multi-temporal analysis of MODIS data to classify sugarcane crop', *International Journal of Remote Sensing*, vol. 27, no. 4, pp. 755-68.

Xiao, X, Zhang, Q, Braswell, B, Urbanski, S, Boles, S, Wofsy, S, Moore III, B & Ojima, D 2004, 'Modeling gross primary production of temperate deciduous broadleaf forest using satellite images and climate data', *Remote Sensing of Environment*, vol. 91, no. 2, pp. 256-70.

Xie, Y, Sha, Z & Yu, M 2008, 'Remote sensing imagery in vegetation mapping: a review', *Journal of Plant Ecology*, vol. 1, no. 1, pp. 9-23.

Yamashita, A, Yoshizawa, T, Aiura, Y, Sanchez, PC, Dizon, EI, Arim, RH & Sardjono 1995, 'Fusarium mycotoxins (fumonisins, nivalenol, and zearalenone) and aflatoxins in corn from Southeast Asia', *Bioscience, Biotechnology, and Biochemistry*, vol. 59, no. 9, pp. 1804-7.

Yang, S, Zhao, X, Li, Y & Liu, R 2011, 'Mapping rice paddy in Henan Province using multi-temporal MODIS images', *2011 International Conference on Remote Sensing, Environmnet and Transportation Engineering (RSETE).* IEEE, pp. 454-6.

Zhang, G, Xiao, X, Dong, J, Kou, W, Jin, C, Qin, Y, Zhou, Y, Wang, J, Menarguez, MA & Biradar, C 2015, 'Mapping paddy rice planting areas through time series analysis of MODIS land surface temperature and vegetation index data', *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 106, pp. 157-71.

Zhang, H, He, J, Li, B, Xiong, H, Xu, W & Meng, X 2011, 'Aflatoxin contamination and research in China', in *Aflatoxins-Detection, Measurement and Control*, InTech.

Zhang, X, Zhang, M, Zheng, Y & Wu, B 2016, 'Crop Mapping Using PROBA-V Time Series Data at the Yucheng and Hongxing Farm in China', *Remote Sensing*, vol. 8, no. 11, p. 915.

Zhang, X, Friedl, MA, Schaaf, CB, Strahler, AH, Hodges, JC, Gao, F, Reed, BC & Huete, A 2003, 'Monitoring vegetation phenology using MODIS', *Remote Sensing of Environment*, vol. 84, no. 3, pp. 471-5.

Zorzete, P, Reis, TA, Felício, JD, Baquião, AC, Makimoto, P & Corrêa, B 2011, 'Fungi, mycotoxins and phytoalexin in peanut varieties, during plant growth in the field', *Food Chemistry*, vol. 129, no. 3, pp. 957-64.

APPENDICES

Appendix 1 Field work documentation for peanut crop mapping (**Objective 1**) in the South Burnett region, Queensland, Australia. (a) street direction, (b) pine trees, (c) mung bean, (d) corn, and (e) and (f) peanut crops.

(a)

(b)

(c)

(d)

(e)

(f)

Appendix 2 Coordinates of reference data for peanut crop mapping (**Objective 1**), which collected during the field survey in the South Burnett region, Queensland, Australia.

Easting	Northing	Land Cover
351616.97	7041619.38	pasture (grass and trees), pasture, trees
369291.06	7051552.36	Peanut, pasture with trees, small farm, farm + pasture
369639.25	7051679.05	Mungbean (big paddock), tress (north mungbean), pasture (opposite mungbean)
373420.60	7052782.37	Peanut paddock, pasture + tress
374594.18	7053841.03	Corn paddock, pasture
375741.16	7054511.39	Peanut (big field/paddock), pasture
382879.74	7060638.27	Corn paddock (big area, i.e. > 1 km), house + trees, cropping
379376.20	7071760.73	Peanut (not big enough), pasture
377054.37	7071481.35	Forest
378920.22	7071652.44	Corn (bigger area), pasture/patch of trees, crop have been harvested
382526.12	7078821.25	Sorghum (bigger area, > 1 km), sports ground, trees, lake
385053.32	7075755.32	Duboisia/Corkwood tree (bigger area), corn, forest
383825.57	7075693.69	Pine trees, corn (bigger area), Duboisia
383918.05	7076592.17	Peanut (bigger area, peanut until the end of the road), corn (bigger area, > 1 km)
383996.98	7077213.87	Peanut (very big area, almost along the road)

381984.48	7082551.65	Forest trees, pasture
379355.93	7082914.53	Peanut (about 5 km), trees (opposite peanut)
378782.88	7082993.09	Corn
377377.04	7083612.71	Peanut (about 3 km), Duboisia
377589.04	7085221.24	Peanut (about 1 km)
375979.26	7085831.00	Duboisia (about 5 km), houses
375778.07	7084256.35	Corn (about 2-3 km), peanut (about 1 km), Duboisia
383124.09	7083953.16	Mungbean (several paddocks, very big area), house + tree, forest
385060.49	7074191.84	Corn
387236.05	7068262.24	Duboisia, pasture

Appendix 3 The global distribution of peanut crops for develop CLIMEX parameters (**Objective 2**) retrieved from GBIF and ALA database.

No.	Country	Decimal Latitude	Decimal Longitude
1	Uzbekistan	40.5	70.917
2	The USA	40.338	-74.492
3	The USA	40.338	-74.448
4	Azerbaijan	40.152	47.690
5	Uzbekistan	39.667	66.950
6	China	38.912	121.602
7	Turkey	38.75	30.67
8	Uzbekistan	38.568	65.714
9	China	37.591	120.874
10	Italy	37.522	13.0418
11	The USA	37	-119
12	The USA	37	-80
13	Turkey	36.95	28.667
14	Turkey	36.858	30.950
15	China	36.428	118.804
16	Libya	34.9	13.183
17	Morocco	34.033	-6.85
18	Morocco	34.019	-6.841
19	Morocco	33.972	-6.842
20	Pakistan	33.667	73.133
21	Japan	33.625	130.611
22	Pakistan	33.285	72.804
23	Libya	32.881	13.192
24	Iran	32.683	51.683
25	Iran	32.650	51.68
26	Libya	32.623	13.519
27	Israel	32.002	24.829
28	Mexico	31.216	-107.450
29	China	31.009	121.226
30	India	30.85	75.866
31	India	30.85	76.18

No.	Country	Decimal Latitude	Decimal Longitude
32	Algeria	30.57	2.88
33	India	30.316	78.05
34	India	30.309	78.080
35	Iran	30.3	57.083
36	Iran	30.299	57.080
37	India	29.966	77.583
38	India	29.67	78.330
39	The USA	29.65	-82.610
40	China	29.583	115.966
41	China	29.367	120.780
42	India	29.32	77.259
43	India	29.27	74.400
44	India	29.18	74.760
45	India	28.93	79.690
46	India	28.92	73.93
47	India	28.92	78.25
48	China	28.7	115.916
49	India	28.5	79
50	India	28.48	73.75
51	Algeria	28.441	-0.283
52	Algeria	28.3	0.033
53	India	28.200	73.389
54	China	28.2	115.766
55	India	28.17	80.5
56	India	28.15	80.370
57	India	28.08	75.25
58	India	27.93	81.580
59	India	27.92	85.5
60	Nepal	27.91	85.150
61	Nepal	27.9	85.169
62	Nepal	27.860	84.910
63	India	27.83	80.919
64	Nepal	27.82	85.25
65	Nepal	27.77	85.080

No.	Country	Decimal Latitude	Decimal Longitude
66	India	27.690	74.470
67	India	27.67	80.830
68	India	27.67	80.919
69	India	27.51	71.709
70	India	27.5	81.330
71	India	27.469	75.580
72	China	27.426	116.074
73	China	27.383	114.616
74	India	27.33	79.580
75	India	27.280	71.239
76	India	27.25	80.830
77	India	27.17	79.300
78	India	27.17	81.599
79	Nepal	27.17	87.050
80	China	27.066	119.616
81	Nepal	27.030	87.220
82	Egypt	27	30
83	India	26.93	80.169
84	India	26.92	71.25
85	India	26.92	73.830
86	India	26.85	73.779
87	China	26.833	116.266
88	China	26.780	114.816
89	India	26.780	77.129
90	India	26.73	77.019
91	India	26.530	76.330
92	India	26.49	73.690
93	India	26.469	73.790
94	India	26.469	76.709
95	India	26.469	80.349
96	India	26.45	80.233
97	India	26.3	73.133
98	India	26.299	76
99	India	26.23	78.169

No.	Country	Decimal Latitude	Decimal Longitude
100	India	26.17	76.080
101	India	26	74
102	India	26	81.330
103	India	25.883	81.853
104	India	25.83	79.419
105	China	25.816	114.533
106	China	25.7	114.316
107	India	25.57	83.790
108	India	25.566	91.883
109	India	25.48	82.580
110	Pakistan	25.433	68.533
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1861	Argentina	-27.25	-55.533
1862	Paraguay	-27.283	-55.907
1863	Argentina	-27.316	-58.583
1864	Argentina	-27.32	-58.580
1865	Paraguay	-27.333	-55.9
1866	Argentina	-27.380	-55.910
1867	Argentina	-27.383	-55.885
1868	Argentina	-27.389	-58.507
1869	Argentina	-27.45	-55.833
1870	South Africa	-27.462	32.066
1871	Argentina	-27.467	-58.833
1872	Argentina	-27.483	-55.483
1873	Australia	-27.5	153

No.	Country	Decimal Latitude	Decimal Longitude
1874	Argentina	-27.516	-58.566
1875	Argentina	-27.516	-58.566
1876	Argentina	-27.55	-58.716
1877	Argentina	-27.668	-58.252
1878	Argentina	-27.909	-58.680
1879	Argentina	-28.104	-56.280
1880	Brazil	-28.133	-54.466
1881	Argentina	-28.494	-58.911
1882	South Africa	-28.916	26.316
1883	Brazil	-28.95	-51.616
1884	Brazil	-29.35	-49.8
1885	Brazil	-29.6	-50.066
1886	Brazil	-30.030	-51.209
1887	Brazil	-30.033	-51.216
1888	Brazil	-30.05	-51.166
1889	Argentina	-30.1	-63.933
1890	Brazil	-30.101	-51.159
1891	Argentina	-30.25	-57.683
1892	Brazil	-30.4	-54.333
1893	Brazil	-30.414	-53.652
1894	Argentina	-30.766	-57.983
1895	Argentina	-31.181	-60.166
1896	Argentina	-31.666	-60.766
1897	Brazil	-31.75	-52.333
1898	Argentina	-31.63	-63.75
1899	Argentina	-32	-64
1900	Uruguay	-32.026	-55.670
1901	Argentina	-33.133	-64.35
1902	Australia	-33.871	151.207
1903	Australia	-33.916	151.166
1904	Uruguay	-34.3	-57.733
1905	Uruguay	-34.333	-57.716
1906	Argentina	-34.866	-57.916
1907	Uruguay	-34.916	-56.166

No.	Country	Decimal Latitude	Decimal Longitude
1908	Argentina	-34.922	-57.950
1909	Argentina	-35.033	-58.024
1910	Chile	-35.815	-70.890
1911	Argentina	-37.147	-60.031
1912	Argentina	-38.421	-63.584