CROP SUITABILITY MAPPING FOR UNDERUTILIZED CROPS IN SOUTH AFRICA

by

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PREFACE

The candidate completed the research in this thesis while based in the Discipline of Crop Science, School of Agricultural, Earth and Environmental Sciences of the College of Agriculture, Engineering and Science, University of KwaZulu-Natal Pietermaritzburg, South Africa. The Water Research Commission of South Africa and the University of KwaZulu-Natal financially supported the research.

The contents of this work have not been submitted to another university, and, except where the work of others is acknowledged in the text, the results reported are due to investigations by the candidate.

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DECLARATION 1: PLAGIARISM

I, **Hillary Mugiyo**, declare that:

(i) the research reported in this thesis, except where otherwise indicated or acknowledged, is my original work;

(ii) this thesis has not been submitted in full or in part for any degree or examination to any other university;

(iii) this thesis does not contain other persons' data, pictures, graphs, or other information unless expressly acknowledged as being sourced from other persons;

(iv) this thesis does not contain other persons' writing unless expressly acknowledged as being sourced from other researchers. Where other written sources have been quoted, then:

a) their words have been re-written, but the general information attributed to them has been referenced;

b) where their exact words have been used, their writing has been placed inside quotation marks, and referenced;

(v) where I have used material for which publications followed, I have indicated in detail my role in the work;

(vi) this thesis primarily collects material prepared by myself, published as journal articles, or presented as a poster and oral presentations at conferences. In some cases, additional material has been included;

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DECLARATION 2: PUBLICATIONS

Chapter 2

Mugiyo.H, Vimbayi Grace Petrova Chimonyo, Sibanda.M, Kunz.R, Masemola.C. R, Modi.A. T and Mabhaudhi. T., (2021) **Evaluation of Land Suitability Methods with Reference to Neglected and Underutilised Crop Species**: A Scoping Review. Published in MDPI land, https://doi.org/10.3390/land10020125

Chapter 3

Hillary Mugiyo, Vimbayi Grace Petrova Chimonyo, Cecilia Ramakgahlele Masemola, Mbulisi Sibanda, Richard Kunz, Luxon Nhamo, Albert Thembinkosi Modi and Tafadzwanashe Mabhaudhi. **A non-parametric machine learning algorithm is applied to delineate bioclimatic regions with high rainfall variability for water-scarce environments.** Submitted on 29 June 2022 to Scientific Reports.

Chapter 4

Hillary Mugiyo, Vimbayi Grace Petrova Chimonyo, Mbulisi Sibanda, Richard Kunz, Luxon Nhamo, Cecelia R. Masemola, Carole Dalin, Albert T. Modi and Tafadzwa Mabhaudhi (2021). **Multi-criteria suitability analysis for neglected and underutilised crop species in South Africa.** The article was published in Plos One, https://doi.org/10.1371/journal.pone.0244734.

Chapter 5

Hillary Mugiyo, Vimbayi Grace Petrova Chimonyo, Mbulisi Sibanda, Richard Kunz, Luxon Nhamo, Cecelia R. Masemola, Carole Dalin, Albert T. Modi, and Tafadzwa Mabhaudhi, **Mapping the spatial distribution of underutilised crop species using the maxent model: a case of Kwazulu-Natal, South Africa.** The article was published in Climate Services.

Chapter 6

Hillary Mugiyo, Vimbayi Grace Petrova Chimonyo, Richard Kunz, Albert T. Modi and Tafadzwa Mabhaudhi, Sorghum management practices in rain-fed production: A crop modelling approach. It was submitted on 01 July 2022 to the International Journal of Plant Production

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ABSTRACT

Several neglected and underutilised species (NUS) provide solutions to climate change and create a Zero Hunger world, the Sustainable Development Goal 2. However, limited information describing their agronomy, water use, and evaluation of potential growing zones to improve sustainable production has previously been cited as the bottlenecks to their promotion in South Africa's (SA) marginal areas. Therefore, the thesis outlines a series of assessments aimed at fitting NUS in the dryland farming systems of SA. The study successfully mapped current and possible future suitable zones for NUS in South Africa. Initially, the study conducted a scoping review of land suitability methods. After that, South African bioclimatic zones with high rainfall variability and water scarcity were mapped. Using the analytic hierarchy process (AHP), the suitability for selected NUS sorghum (*Sorghum bicolor*), cowpea (*Vigna unguiculata*), amaranth and taro (*Colocasia esculenta*) was mapped. The future growing zones were used using the MaxEnt model. This was only done for KwaZulu Natal. Lastly, the study assessed management strategies such as optimum planting date, plant density, row spacing, and fertiliser inputs for sorghum. The review classified LSA methods reported in articles as traditional (26.6%) and modern (63.4%). Modern approaches, including multi-criteria decision-making (MCDM) methods such as AHP (14.9%) and fuzzy methods (12.9%), crop simulation models (9.9%) and machine-learning-related methods (25.7%), are gaining popularity over traditional methods. The review provided the basis and justification for land suitability analysis (LSA) methods to map potential growing zones of NUS. The review concluded that there is no consensus on the most robust method for assessing NUS's current and future suitability. South Africa is a water-scarce country, and rainfall is undoubtedly the dominating factor determining crop production, especially in marginal areas where irrigation facilities are limited for smallholder farmers. Based on these challenges, there is a need to characterise bioclimatic zones in SA that can be qualified under water stress and with high rainfall variation. Mapping high-risk agricultural drought areas were achieved by using the Vegetation Drought Response Index (VegDRI), a hybrid drought index that integrates the Standardized Precipitation Index (SPI), Temperature Condition Index (TCI), and the Vegetation Condition Index (VCI). In NUS production, land use and land classification address questions such as “where”, “why”, and “when” a particular crop is grown within particular agroecology. The study mapped the current and future suitable zones for NUS. The current land suitability assessment was done using Analytic Hierarchy Process (AHP) using multidisciplinary factors, and the future was done through a machine learning model Maxent. The maps developed can contribute to evidence-based and site-specific recommendations for NUS and their mainstreaming. Several NUS are hypothesised to be suitable in dry regions, but the future suitability remains unknown. The future distribution of NUS was modelled based on three representative concentration pathways (RCPs 2.6, 4.5 and 8.5) for the years between 2030 and 2070 using the maximum entropy (MaxEnt) model. The analysis showed a 4.2-25% increase under S1-S3 for sorghum, cowpea, and amaranth growing areas from 2030 to 2070. Across all RCPs, taro is predicted to decrease by 0.3-18 % under S3 from 2050 to 2070 for all three RCPs. Finally, the crop model was used to integrate genotype, environment and management to develop one of the NUS-sorghum production guidelines in KwaZulu-Natal, South Africa. Best sorghum management practices were identified using the Sensitivity Analysis and generalised likelihood uncertainty estimation (GLUE) tools in DSSAT. The best sorghum management is identified by an optimisation procedure that selects the optimum sowing time and planting density-targeting 51,100, 68,200, 102,500, 205,000 and 300 000 plants ha^{-1} and fertiliser application rate (75 and 100 kg ha^{-1}) with maximum long-term mean yield. The NUS are suitable for drought-prone areas, making them ideal for marginalised farming systems to enhance food and nutrition security.

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DEDICATION

This work is dedicated to the Almighty.

CHAPTER 1: INTRODUCTION

1.1 Background, justification and motivation

The world's population is projected to reach approximately 9.9 billion by 2050, and about two-thirds of the predicted growth will occur in Africa (James, 2019). It is within the African region where several countries struggle to adequately feed the current population (UN DESA, 2017). In South Africa, for instance, food security is dichotomous, characterised by a distinct, dominant agro-industrial and alternative, informal food system (Mabhaudhi et al., 2018). Within the informal food system, smallholder farmers are the predominant actors, and more than 85% rely on rainfed crop production (Archer et al., 2007; Nchanji et al., 2021), and food insecurity is high (Reynolds et al., 2015; van Dijk et al., 2021). Crop production in these informal systems is affected by several challenges, including weather variability, the uncertainty of climate change, lack of resources to adapt to weather extremes, poor infrastructure, worsening land degradation, especially declining soil fertility~~,~~ and dwindling arable land (Goldblatt and von Bormann, 2010; Jones et al., 2015). To improve the contribution of crop production to rural food security, (Mabhaudhi et al., 2017a) have suggested using context-specific farming practices. A plausible pathway could be mainstreaming technologies such as neglected and underutilised crop species adaptable to prevailing socio-economic and environmental conditions.

Neglected and underutilised crops are defined as “crop species that are parts of more substantial biodiversity, were once popular (in and out of their centres of diversity) and are neglected by users and research but remain relevant in the regions of their diversity” (Mabhaudhi et al., 2017c). These crops are also called orphan, underutilised, indigenous, and traditional. These crops are regarded as indigenous because they have been independently selected by farmers over several generations and have developed into varieties specifically adapted to local conditions. These crop species are said to be nutrient-dense, climate-resilient, profitable, and locally available or adaptable are fundamental to improving dietary and production diversity (Massawe et al., 2016). They are parts of solutions to food and nutrition security, environmental degradation and poverty reduction, mainly in marginal land (Massawe et al., 2016; Mpandeli et al., 2018; Mabhaudhi et al., 2019; Akinola et al., 2020). Mabhaudhi et al. (2018) hypothesised that promoting neglected and underutilised crops (NUS) in marginal lands can offer climate-proof solutions. This is because many of these crops thrive in drought-prone areas and require little to no agrochemicals, making them ideal for low-input farming systems in semi-arid regions (Massawe et al., 2016). However, while NUS generally adapt to marginal production systems, knowledge of their suitability is mainly anecdotal (Mkuhlani et al., 2020; Mabhaudhi et al., 2017, 2019). This has often resulted in challenges to appraising crops as part of climate change strategy and motivates investments in new value chains.

Understanding “where”, “when”, and “how" NUS are suitable can provide a road map for mainstreaming these crops into existing cropping systems (Chivenge et al., 2015; Mabhaudhi et al., 2017, 2019). However, limited information is available showcasing the suitability of NUS in current and future environments (Chivenge et al., 2015; Mabhaudhi et al., 2017, 2019). Therefore, it is essential to establish whether NUS are suitable across marginal agroecosystems and if improved agronomy can optimise their suitability (Adhikari et al., 2017). Furthermore, this will aid in fitting "into" or "within" current smallholder production systems (Mkuhlani et al., 2020) while complementing existing efforts to improve resilience to climate variability and change as well as intensifying productivity for sustainable food and nutrition security (Mabhaudhi et al., 2019). Such assessments will contribute to the needed information on where, when and why NUS can be included as crop choices in farming systems for resource-poor farmers who need to adapt to risks related to climate especially false start of the season, mid-season dry spells, wet spells and drought (Mkuhlani et al., 2020).

There is significant spatial and temporal heterogeneity in existing climate, physical, social and economic datasets, each with a firm footing in its discipline (Nhamo et al., 2018). However, these various datasets offer great opportunities to study the suitability of NUS. Among the available datasets, such as Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) (Funk et al., 2015) and WorldClim have provided meaningful, acceptable results for land suitability analysis (Hijimans et al., 2005). This study uses such available datasets to create a land suitability analysis of NUS in South African agroecology. Overly, the study hypothesises that NUS are suitable for the current and future agroecology of South Africa. It is reasonable to assume that NUS displays some natural selection and climatic adaptability traits on specified agroecology (Nyadanu and Lowor, 2014; Chivenge et al., 2015; Baldermann et al., 2016; Mabhaudhi et al., 2017b). To suit NUS in the South African environment, the specific objectives of the study were:

- to evaluate suitable methods for assessing land suitability for neglected and underutilised crops,

- to identify bioclimatic zones with high rainfall variability and water scarcity that may be suitable for the production of NUS in South Africa,
- to assess the suitability of NUS in current and projected agroecology in South Africa,
- to develop best management practices for rain-fed production of NUS in KwaZulu-Natal, South Africa.

1.2 Outline of the thesis

This thesis is written in paper format. The thesis consists of seven interlinked chapters, excluding the present chapter. The experimental chapters (3 to 6) comprise stand-alone manuscripts published, submitted or prepared for submission to a journal. Where manuscripts have already been published, it is stated so, and where such manuscripts are under review, information is provided stating the journal name and submission date. For completeness, each chapter has its list of references.

Chapter 2 presents a literature review that provides the basis and justification for land suitability analysis (LSA) methods to map potential growing zones of neglected and underutilised crop species (NUS). There is no consensus on the most robust method for assessing NUS's current and future suitability. The thesis reviewed 64 articles worldwide from 1993 to 2019 to identify major methodological strategies for developing appropriate approaches for LSA of neglected and underutilised crop species (NUS). Therefore, the review synthesises the existing methods and tools that can be used to create land suitability maps that can be applied to NUS. The review results could improve insights into NUS's land evaluation and provide the researchers and decision-makers with the most robust methods for developing LSA for NUS. The literature review helped conceptualise the possible LSA method used in suitable areas for NUS in South Africa.

Chapter 3 addresses the second objective and identifies regions with high rainfall variability and water-scarce environments in South Africa. South Africa is a water-scarce country, and rainfall is undoubtedly the dominating factor determining crop production, especially in marginal areas where irrigation facilities are limited for smallholder farmers (Ziervogel et al., 2014). Based on these challenges, there is a need to characterise bioclimatic zones in SA that can be qualified under water stress and with high rainfall variation. This will give credence to whether the areas to be identified as suitable (Chapters 4 and 5) deemed to be suitable are indeed falling within the marginal regions.

Chapter 4 addresses the third objective and seeks to develop land suitability maps for selected NUS: sorghum, cowpea, amaranth, and taro. The land suitability assessment was done using Analytic Hierarchy Process (AHP). Multidisciplinary factors from climatic, soil and landscape, socio-economic and technical indicators were overlaid using Weighted Overlay Analysis. Validation was done through field visits, and the area under the curve (AUC) was used to measure AHP model performance. The maps developed can contribute to evidence-based and site-specific recommendations for NUS and their mainstreaming. Several NUS are hypothesised to be suitable in dry regions, but the future suitability remains unknown. Chapter 5 addresses whether NUS are suitable in future, and crop scientists and planners can design strategies that aim to mainstream NUS in marginal lands to achieve food and nutrition security.

Chapter 5 assesses the application of presence-only data for current and future crop suitability modelling using the MaxEnt model. In this chapter, the application of a machine-learning, algorithm-based model designed to estimate the likelihood of occurrence based on presence-only data allowed for mapping future NUS production zones in KwaZulu Natal, SA. After mapping cropping land suitable to NUS, site-specific cropping guidelines were developed using crop simulation models in Chapter 6.

Chapter 6 aims to develop a framework to assess best management practices for rain-fed production of the selected NUS. Using sorghum as an example, the model Decision Support System for Agrotechnology Transfer (DSSAT) (Jones et al., 1998, 2003) was used to assess optimum planting date, plant density, row spacing, and fertiliser inputs. In DSSAT, the Sensitivity Analysis tool allows for developing the best crop management without going through entire field experiments (Liu et al., 2017). This confirmed the feasibility of applying crop models to develop the best management guidelines for optimising sorghum yields under smallholder systems. Access to climate information, services and products remains a crucial aspect of building the resilience of smallholder farmers to climate change.

Chapter 7: This chapter was divided into Discussion, Recommendations and Conclusion. It highlights the major findings and implications and the conclusion of the thesis. Lastly, it also provides future direction and a way forward.

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CHAPTER 2: EVALUATION OF LAND SUITABILITY METHODS WITH REFERENCE TO NEGLECTED AND UNDERUTILISED CROP SPECIES: A SCOPING REVIEW

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Abstract: In agriculture, land use and classification address questions such as "where" and "why" a particular crop is grown within agroecology. There are several land suitability analysis (LSA) methods, but there is no consensus on the best method for crop suitability analysis. We conducted a scoping review to evaluate methodological strategies for LSA. Secondary to this, we assessed which would suit neglected and underutilised crop species (NUS). The review classified LSA methods reported in articles as traditional (26.6%) and modern (63.4%). Modern approaches, including Multi-Criteria Decision Making (MCDM) methods such as Analytical Hierarchy Process (AHP) (14.9%) and Fuzzy methods (12.9%); crop simulation models (9.9%), and machine learning-related methods (25.7%), are gaining popularity over traditional methods. The MCDM methods, namely AHP and fuzzy, are commonly applied to LSA, while crop models and machine learning-related methods are gaining popularity. 67 climatic, hydrology, soil, socio-economic, and landscape parameters are essential in LSA. The unavailability and inclusion of categorical datasets from social sources is a challenge. Using big data and the Internet of Things (IoT) improves the accuracy and reliability of LSA methods. The review expects researchers and decision-makers to provide the most robust methods and common parameters required in developing LSA for NUS. Qualitative and quantitative approaches must be integrated into a unique hybrid land evaluation system to improve LSA.

Keywords: hybrid land evaluation systems; land management; machine learning; MCDM; NUS

2.1. Introduction

Neglected and underutilised crop species are crops that have not been previously classified as major crops, are under-researched, occupy low utilisation levels and are mainly confined to smallholder farming areas (Chivenge et al., 2015). NUS are important in rural food systems, and their recognition as part of a solution to improve food and nutrition security in marginal areas has been recognised. However, mainstreaming of NUS into rural production systems remains low, and information regarding their suitability across diverse agricultural landscapes remains mainly anecdotal, with limited information detailing "where" they can grow and "why" they grow (Ceballos-Silva and López-Blanco, 2003; Sekiyama and Nagashima, 2019). Such information is essential if NUS are to be incorporated into existing cropping systems, increase the productivity of marginal landscapes, and reclaim degraded agricultural land.

Cropland identification and classification exercises address questions such as "where" and "why" a particular crop is grown for a specific area (Hopkins, 1977; Kazemi and Akinci, 2018). There are many different land suitability analysis (LSA) methods (Malczewski, 2006); this suggests there is no universal and exhaustive process. Land suitability analysis is a process applied to determine the suitability of a specific area for considered use; it reveals the suitability of a site regarding its intrinsic characteristics (suitable or unsuitable) (Malczewski, 2004). After that, land suitability mapping can address the question of "where" in terms of land and resource use, hence establishing favourable conditions for the sustainable production of a particular crop (Bera et al., 2017). Due to many factors considered during LSA, the process is often identified as Multi-Criteria Evaluation (MCE) (Akpoti et al., 2019).

A Geographical Information System (GIS) has become central to LSA as it allows the investigation of multiple geospatial data (Akinci et al., 2013; AbdelRahman et al., 2016). The integration of remote sensing (RS), machine learning tools and techniques, use of big data, Internet of Things (IoT), blockchain and cloud computing to form hybrid land evaluation systems can improve the accuracy and reliability of land suitability methods (Singha and Swain, 2016). In hybrid land evaluation systems, the linkages between two models simulate qualitative reasoning and quantitative modelling (McDowell et al., 2018). In recent years, mechanistic crop simulation models have proven helpful in optimising and developing hybrid land evaluation systems (Phillips et al., 2006; Araújo and Peterson, 2012). Nevertheless, LSA has often focused on commercially essential field crops and methods for analysing suitability, and their application within NUS is yet to be established. Due to the limited scientific knowledge of NUS, it is imperative to develop appropriate methods and tools that can be used.

Decision-makers must know the current spatial occurrence of NUS and the interaction of biophysical and socio-economic factors to detect both threatened areas and potential growing zones, especially in semi-arid and arid regions (Olayinka Atoyebi et al., 2017). Mapping the potential spatial distribution of NUS is a transformative agenda for achieving food and nutrition security goals in marginal environments (Olayinka Atoyebi et al., 2017). Given the need to mainstream NUS into existing agricultural landscapes, there is a need to identify reliable land suitability approaches and methods. Therefore, the review synthesises the existing techniques, methods and tools that can be used to develop land suitability maps that can be applied to NUS. The review will address the following research questions: which methods have been used to assess land suitability for crop production, and which parameters have been used in developing land suitability? Perspectives for future research will be provided that recognise the land cover aspect without further characterising land use in terms of NUS suitability and management interventions. This review also identifies parameters and common LSA methods that can help researchers, practitioners, and policymakers to develop guidelines on the successful crop suitability mapping process for improved crop productivity. Therefore, the optimum method for land suitability should consider the tools' cost, the procedure's complexity, and the benefits of handling a specific land evaluation.

2.2. Methodology

Literature Search

A scoping review approach was used to acquire and synthesise information on land suitability for crops. Previously, there were 11 review studies related to land evaluation in agriculture and environmental studies; however, few focused on land suitability analysis for crops (Malczewski, 2004; Byeon et al., 2018; Akpoti et al., 2019). The literature review sourced information from 1993 to 2019 using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA, 2009). Literature was sourced from Scopus and Web of Science using a Boolean search approach. The following search syntax was used (("land suitability" OR "land suitability analysis" OR "land evaluation methods" OR "species distribution models" OR "habitat suitability" OR "bio-climatic models") AND (crop* OR plant* OR yield OR agriculture). The search was limited to titles, abstracts and keywords. This search identified 786 and 737 articles in Scopus and Web of Science. Identified articles were exported to Mendeley® as BibTex files, removing duplicates and leaving 974 articles (Appendix page 225). Articles assessing the land suitability of various crops, including annual food crops, shrubs and trees, non-food crops, animals, and invertebrates, were retained for further analysis. The articles were screened to assess whether land suitability analysis was done for food crops. Those not focusing on food crops and did not mention any were excluded. After screening, only 113 relevant abstracts were identified. Where available, full-length articles were downloaded. We had access to 101 articles. For the sourced articles, research study details were extracted, such as the country where the study was carried out, the study's objective, methods or model used, crop(s) studied, and whether it was an NUS (Yes/No) as presented by the priority list for SSA (see Williams and Haq 2015 and Mabhaudhi et al. 2017 for complete list). The thematic factors used in assessing suitability were extracted. We developed a Microsoft Excel spreadsheet to enter and later quantitatively assess the extracted data. We assumed no selection bias as the literature search and curatorship was done by two independent researchers.

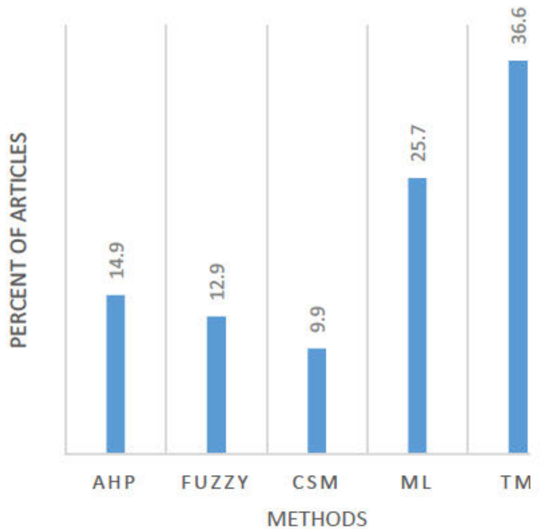
2.3. Results

2.3.1. Results of Literature Search

Following the systematic search, 101 papers were selected for further. From the articles reviewed, only five crops were regarded as NUS. These were sorghum (Ramirez-Villegas et al., 2013; Kahsay et al., 2018; Ohadi et al., 2018), cassava (Olayinka Atoyebi et al., 2017;

Purnamasari et al., 2019), cowpea and pearl millet (Chen et al., 2010), and foxtail millet (Chen et al., 2003) (Tables S2 and S3; Supplementary information 2). Within the southern African context, sorghum, cassava, millet (pearl or foxtail) and cowpea are considered underutilised crops due to the undeveloped nature of their value chains and low production. Mabhaudhi et al. (2017b) have identified these as part of priority underutilised crops based on drought and heat stress tolerance and nutritional value. Other crop species identified include maize, rice and wheat, soybean and the tuber potato (Appendices Tables 1 and 2).

The highest number of articles were from Iran, and the smallest article compilation was from Africa. The identified literature used in this review showed that 36.6% used traditional methods empirically in Figures 2.1a and 2.1b. The results indicated that 25.7% used machine learning-related methods, and 14.9 and 12.9% used AHP and fuzzy approaches, respectively. Notably, 9.9% of the articles used crop simulation models (Figure 2.1a).



(a) **(b)**

Figure 2. 1(a) The percentage distribution of land suitability methods published from 1993 to 2019. (Analytical Hierarchy Process (AHP), Crop Simulation Models (CSM), Machine learning Method (MLM), Traditional Method (TM)). (b) The hybrid land evaluation systems were selected from land suitability methods published from 1993 to 2019. (Analytical Hierarchy Process (AHP), Crop Simulation Models (CSM), Machine learning Method (MLM), Traditional Method (TM)).

The hybrid methods that used more than one technique to assess suitability were the ones that integrated AHP with Machine Learning methods (MLM) (e.g., Habibie et al. (2019) and Raza et al. (2018a) (Table 2.1). The least common hybrid method was that between Fuzzy and Crop Simulation Models (CSM) methods. Based on the reviewed literature MLM was the most versatile and could be integrated with other LSA methods (Figure 2.2b). No articles from the identified literature showcased the integration of AHP and CSM or TM with either CSM or FUZZY. The distribution of methods discussed is indicated in Figure 2.1, and a complete list of articles is provided in (appendices tables S1–S6).

Across the identified articles, the terms land capability and land suitability were often used interchangeably, although they refer to different types of appraisals in a stricter sense. According to Neitsch et al.1997, land capability is the inherent capacity of the land to perform at a given level for general use. Neitsch et al. (1997) defined land capability as a classification of land primarily based on degradation hazards. The results might suggest that the search strategy was not entirely exhaustive. However, a good number of articles were identified to support the synthesis of suitable methods for LSA for NUS

Table 2. 1. Description of hybrid land evaluation systems used in cropland suitability assessments.

Author	Methods	Crops
(Bagherzadeh and Gholizadeh, 2016)	ANN, TOPSIS	Alfalfa
(Bagherzadeh et al., 2016)	ANN, Fuzzy	Soybean
(Danvi et al., 2016)	ML_BL	Rice
(Deng et al., 2014)	AHP, Fuzzy	Alfalfa
(Estes et al., 2013)	MaxEnt, GAM, DSSAT	Maize
(Jiao and Liu, 2007)	ANN, GA	Rice
(Manna et al., 2009)	Micro LEIS, WAP, CropSyst	Maize
(Pilehforooshha et al., 2014)	CA, Fuzzy, GP	Multiple crops
(van Lanen et al., 1992)	ALES, WOFOST	Multiple crops
(Jafarzadeh et al., 2008)	Simple Limitation Method (SLM), Limitation Method regarding Number and Intensity (LMNI) square root and storie	Maize, Potato, alfalfa, onion
(Habibie et al., 2019)	ML, AHP	Maize
(López-Blanco et al., 2018)	ML, GAEZ	Maize
(Raza et al., 2018b)	ML, AHP	Rice

(Seyedmohammadi et al., 2018)	SAW, TOPSIS, Fuzzy	maize, rapeseed, soybean

According to Teixeira et al. (2013), land capability is based on assessing soil conditions that support cultivated crops. Such systems include the Canada Land Inventory and the USDA land classification system (Slough and Sadleir, 1977). Since the issue that we are trying to address with NUS goes beyond the bio-physical attributes within agriculture and speaks to the socio-ecological characteristics of an area, land suitability is most appropriate. Table 2.1 provides an overview of cropland suitability assessment hybrid land evaluation systems.

2.3.2. Approaches to Land Suitability Analysis

Land suitability analysis depends on several factors: data availability (quality and quantity), expert skills, and suitability assessments' end-use. Therefore, having a universal technique is not always feasible. In the context of NUS, a vital source of agro-biodiversity is socially and culturally significant for marginalised communities. It can address pertinent challenges, such as building resilience to climate change (Mabhaudhi et al., 2017). The assessed literature includes a wide range of approaches, differing in level of complexity and data requirement. According to Akpoti et al. (2019), these LSA methods can be categorised as traditional or modern methods discussed in section 3.2.1.

2.3.2.1. Traditional land suitability methods

In traditional LSA methods, biophysical factors are mainly used to assess crop options using qualitative, quantitative and parametric methods (Appendix Table 1.1). According to Manna et al. (2009) and Akpoti et al. (2019), qualitative approaches assess land potential in terms of the degree of suitability, such as highly, moderately, or not suitable (Bodaghabadi et al., 2015). On the other hand, quantitative assessment methods give numeric indicators and use mathematical models to describe the physical conditions of geo-biophysical scenarios (Demirtas and Nordgren, 2017). Qualitative approaches evaluate land on a broader scale depending mainly on land uses, while quantitative approaches comprise more detailed technical procedures (Mendoza and Martins, 2006; Kaim et al., 2018). Within these procedures, arithmetical or parametric methods consisting of statistical analysis are applied (Mendoza and Martins, 2006; Kaim et al., 2018). The difference between the two approaches lies in the technical procedures adopted for land evaluation (Hopkins, 2007; Ghansah et al., 2018). In promoting NUS in the marginal cropping system, LSA methods selected to delineate homogenous zones should accommodate minimum multidisciplinary data to map land units with homogenous zones. The low requirement of input data is because NUS has poorly developed knowledge systems and lacks empirical data to map where it was not included before and how it can be cultivated. In this regard, parametric methods, integrating qualitative and quantitative approaches to form hybrid land evaluation systems, have been used to improve the accuracy, reliability, and applicability of land suitability analyses to real-world challenges (Gibbs and Salmon, 2015).

Parametric methods are derived from the numerical inferred effects of various land characteristics on a land use system (Malczewski, 2006). These methods allocate a numerical value to the most significant land characteristics. They account for interactions between factors expressed through simple multiplication or single-factor indices (Liebig, 2002). The main weakness of parametric methods is that the scores can be very small or very large, affecting the overall suitability (El Baroudy, 2016). Another bottleneck of the parametric method is the absence of any uncertainty or vagueness associated with factors determining land use suitability for crops (Danvi et al., 2016). Then again, within the context of promoting NUS, a socially and economically relevant subset of agrobiodiversity, it is vital to consider using a hybrid land evaluation system to capture NUS's qualitative and quantitative properties.

Several methods that have been coined "traditional" but are still widely used include Boolean logic (Hoseini and Kamrani, 2018), weighted linear combination (WLC) (Silva-Gallegos et al., 2017), weighted overlay (WO) (Hassan et al., 2020), storie and square root (Ghanbarie et al., 2016), multiple linear regression models (Leroux et al., 2019) and multivariate statistics (Akpoti et al., 2019) (Table 2.2). Among the traditional methods, categorical data for social-economic is limited except for the WLC and qualitative approaches (Table 2.2) (Munene et al., 2017). According to the literature, the Food and Agriculture Organisation approach has been used as a major LSA framework for assessing crop suitability (Kurukulasuriya and Mendelsohn, 2008; FAO, 2012). Across most of the identified traditional methods, socio-economic data is minimal, yet socio-economic data is critical when assessing crops such as NUS. Also, Hopkins (2007) pointed out limitations associated with using ordinal, linear combination methods, which can be addressed using a combination of non-linear methods. Manna et al. (2009) concluded that changing land use and management practices must be based on land evaluation results on suitability and vulnerability, thus transcending the reductionistic approaches of qualitative and quantitative methods. Table 2.2 provides an overview of selected traditional methods used in land suitability assessments.

The FAO Approach

The FAO Land Evaluation Framework was published in 1976 (Kurukulasuriya and Mendelsohn, 2008; FAO, 2012). The Food and Agriculture Organization of the United Nations and the International Institute for Applied Systems Analysis (IIASA) have developed the Agro-Ecological Zones (AEZ) methodology over the past 30 years for assessing agricultural resources and potential (FAO, 2012). The FAO approach evaluates land suitability for specific land use rather than general land use, of which the latter often denotes land capability. The FAO approach seeks to match land utilisation types with the land use requirements across land units (Bodaghabadi et al., 2015). This approach requires a description of the land in terms of its characteristics to the intended use. The method indicates the difference between land suitable for crops (S) and not suitable for crops (N). At the same time, classes show the degree of land suitability, such as (S1) highly suitable, (S2) moderately suitable, (S3) marginally not suitable, (N1) currently not suitable and (N2) permanently not suitable (FAO, 2012).

Table 2. 2 Description of traditional methods used in land suitability assessments.

Methods	Crops	NUS Yes/No	Thematic Factors			
			Climate	Soil and Landscape	Socio-Economic	LULC
Parametric	Wheat	No		[2] N-P-K, Zn, Tex, Dep, Topo, SS, HP, HC, WHC, EC, ESP, $CaCO_4$, pH	No	No
Boolean Logic, Maximum Limiting factor	Rice	No	P, T, RH, Flooding	D, Dep, CEC, BSP, pH, OC	No	No
WLC	Rice and Soybean	No	P, T, LGP, Stream order, discharge	Tex, OC, Phosphorus, pH, Drain, S, H, S, Dep, fertility	Land tenure, roads, markets, credit systems, incentive benefits	Yes
WO	Palm Oil, Rice	No	P, T, SR, PET, AWC	ESP, Tex, S, G, Silt, clay	Land reforms	Yes
Square root mean	Wheat, *Sorghum*[1], Alfalfa, Barley, Maize, Rice, *Cassava*, Groundnut	Yes	P, RH, T, SR,	Dep, Tex, OC, ST, S, $CaSO_4$, EC, CEC, ESP, Drain	No	Yes
Expert Knowledge, FAO method	Chemoriya		P, T, LGP, RH	SG, Tex, Dep, CEC, OM	No	No
Qualitative approach	Maize, *Pearl millet*, *Foxtail millet*, Potato, Apple, Vegetable	Yes		S, As, SG, H	Income	Yes
GAEZ	Wheat, Maize, Rice, Soybean		Min and Max T, P, RH, vapour pressure	SG, H, S	No	Yes
Computer overlay	Canola, Soybean	No	P, T	As, H, S, Tex, pH, EC	No	No

[1] The italicised crop is considered a priority Neglected and Underutilised species within Africa. [2]List of abbreviations: Temperature degree day (TDD), aridity index (AI), Temperature (T), dry month/length of the dry season (DM), Wet month (WM) rainfall (P), potential evapotranspiration (PET), Potential evapotranspiration (PET), solar radiation (SR), Sunshine hours (SH), soil erosion (SE), length of the phenological period (LPP), Gypsum (% $CaSO_4$), Relative humidity, Weighed Overlay (WO) and Weighted Linear Combination (WLC, Length of growing period (LGP), Post-harvest technology (PHT), Growing degree days (GDD), Land use land cover (LULC), Topography (Topo), Slope (S), Aspect (As), Elevation (H), Surface Stoniness (SS), hard pan (HP), hydraulic conductivity (HC), water holding capacity (WHC), Groundwater (GW), Soil moisture (SM), depth to water-table (DTW), soil drainage (Drain), texture (Tex), effective depth (Dep), cation exchange capacity (CEC), base saturation percentage (BSP), soil pH (pH), Organic carbon (OC), (RH), Boron Toxicity (BT), Soil type (ST), Depth (D), Bulk Density (DB), Flood (F), Cation exchange capacity (CEC), Calcium carbonate equivalent (CCE), electrical conductivity or salinity (EC); sodium adsorption ratio (SAR), Sodicity (ESP), surface stoniness/rockiness (SS), Soil groups/Soil, types (SG), Depth to water table (DWT), Irrigation Water Use (IWU).

It uses a Boolean mapping approach that ignores the continuous soil variation and possible uncertainties in measurement (Hoseini and Kamrani, 2018). As such, the implicit assumption in Boolean approaches is the absence of any uncertainty or vagueness associated with the land suitability analysis, measurement, imprecision, and specified concepts (Danvi et al., 2016). These assumptions may be invalid in smallholder farming systems. Many of them could be located on similar land classes but are highly variable in the social and economic landscape and farming activities. Also, the FAO approach can result in areas with variations in soil texture, depth, pH, and landscape being excluded from the set of suitable land because they fail to match strictly defined requirements (Hennebert et al., 1996). Then again, the framework tends to be a top-down approach, ignoring the social constructs of the evaluated land. In reality, NUS are suitable in marginal areas with high climate, soil and landscape variation; there is a need for methods that capture uncertainties and data variation. One of the most significant developments in the FAO approach has been the advent of affordable computer-based (vs mainframe) geographic information systems (GIS) and machine learning skills to address some of these challenges. Integrating FAO and modern methods ensures that an objective LSA can be carried out for NUS.

Geographic Information System tools and machine learning skills ease the storage and analysis of a wide range of spatial data (Sharma et al., 2018). Despite the great development of modern LSA methods, such as crop simulation and machine learning tools, the FAO conceptual land evaluation framework gives the basic guidelines in agriculture to carry out a land evaluation process (Fontes et al., 2009). Land suitability from the FAO method does not necessarily identify a single-use index as best on each land unit; the results become qualitative (Martinez-Casasnovas et al., 2008). Multi-criteria decision-making (MCDM) methodologies, which fall under modern methods, have been proposed for overcoming problems related to vagueness in definition and other uncertainties, especially in the context of NUS suitability analysis (Akpoti et al., 2019).

2.3.2.2. Modern Land Suitability Approaches to mapping crops

Akpoti et al. (2019) classified modern LSA methods as combining GIS and machine learning algorithms (Table 2.3). They are termed modern land suitability approaches because they integrate several variables to map areas with homogenous characteristics. The modern LSA methods are populated by more complex, often time-consuming, and dynamic algorithms (Sharma et al., 2018). The modern methods are often grouped into three major categories: (i) computer-assisted overlay mapping; (ii) soft computing or geo-computation, also known as artificial intelligence (AI); (iii) multi-criteria evaluation (MCE) or multi-criteria decision-making (MCDM) (Malczewski, 2004, 2006; Akpoti et al., 2019).

Combining more than one MCDM forms a hybrid land evaluation system in LSA. The hybrid method allows approximate representations of vague, incomplete and uncertain information because land suitability will be defined as continuous classes rather than "true" or "false" as in the Boolean model (Malczewski, 2006). MCDM methodologies in NUS can provide better land suitability than Boolean approaches because they can accommodate attribute values and properties close to category boundaries. Table 2.3 provides an overview of selected modern land suitability methods used in crops LSA.

Table 2. 3 A description of modern methods used in land suitability assessments. References to the showcased methods can be found in the supplementary information.

Methods	Crops	NUS	Thematic Factors			
			Climate	Soil and Landscape	Socio-Economic	LULC
AHP	Maize, Potato, Saffron, Rice, Grapes, Wheat, Sugarcane,	No	P, PET, Max T, Min T, RH, GDD, Frost, SH	N-P-K, Zn, D, Tex, Dep, Topo, SS, HP, HC, WHC, EC, ESP, $CaCO_4$, pH, OM, sand dune waviness, SE, Drain, DWT, SG, S, As, H	Infrastructure, Population, Literacy, Labour force, distance to road, economics index	Yes
Fuzzy methods	[1] *Cassava*, Groundnut, Maize, *Millet*, Rice, Soybean, *Sorghum*, Barley, Spinach, Wheat, Rye, Oats, Sugar beet, Hybrid Poplar	Yes	P, T, LGP, Stream order, discharge	Tex, Phosphorus, pH, Drain, S, H, S, Dep, fertility, Dep, Ca, Mg, K, CEC, OC, pH, H, Water availability, Gravel, Cobbles, EC, ESP, WHC, Tex, pH, OM	Market land value per acre, roads	Yes
Use of crop models: GIS-based Environmental Policy Integrated Climate (EPIC) model, Almagra, ECOCROP, CROPWAT	Sweet Potato, *Sorghum*, Soybean, Wheat, Maize	Yes	P, T, LGP, RH, SR, WM, AWC, AET, LGP, PET	Dep, Tex, Drain, EC ESP, CEC, pH, OC, BD, OM	GDP, Population, Undernutrition data	No
Machine learning-related methods: Artificial Neural Networks, TOPSIS, Bayesian Networks (BNs), Goal programming Species distribution models, for example, MaxEnt	Wheat, Barley, Maize, Alfalfa, Potato, Wheat, *Cassava*	Yes	P, T, AI, PET, frost days, Chill hours, SR, AEP	Tex, EC, ESP, $CaCO_4$, Gravel, Dep, OC, pH, S, Drain, F, $CaSO_4$, OC, Tex, Thickness of tilth, S, N-P-K, Water conservancy, SG	Income, population, roads	Yes

[1] *The italicised crop is considered a priority Neglected and Underutilised species within Africa.* [2]*List of abbreviations: Temperature degree day (TDD), aridity index (AI), Temperature (T), dry month/length of the dry season (DM), Wet month (WM) rainfall (P), potential evapotranspiration*

(PET), Potential evapotranspiration (PET), solar radiation (SR), Sunshine hours (SH), soil erosion (SE), length of the phenological period (LPP), Gypsum (% $CaSO_4$), Relative humidity, Weighed Overlay (WO) and Weighted Linear Combination (WLC, Length of growing period (LGP), Post-harvest technology (PHT), Growing degree days (GDD), Land use land cover (LULC), Topography (Topo), Slope (S), Aspect (As), Elevation (H), Surface Stoniness (SS), hard pan (HP), hydraulic conductivity (HC), water holding capacity (WHC), Groundwater (GW), Soil moisture (SM), depth to water-table (DTW), soil drainage (Drain), texture (Tex), effective depth (Dep), cation exchange capacity (CEC), base saturation percentage (BSP), soil pH (pH), Organic carbon (OC), (RH), Boron Toxicity (BT), Soil type (ST), Depth (D), Bulk Density (DB), Flood (F), Cation exchange capacity (CEC), Calcium carbonate equivalent (CCE), electrical conductivity or salinity (EC); sodium adsorption ratio (SAR), Sodicity (ESP), surface stoniness/rockiness (SS), Soil groups/soil, types (SG), Available water capacity (AWC), Depth to water table (DWT), Irrigation Water Use (IWU).

Multi-Criteria Decision Analysis

Due to the many attributes and criteria involved in decision-making, land suitability evaluation has been identified as a multi-criteria evaluation problem. To address these challenges, Multi-criteria Decision Analysis (MCDA) was developed in the 1960s to assist decision-makers in incorporating many options into a potential or retrospective framework (Adem Esmail and Geneletti, 2018). Multi-criteria decision analysis involves input data (from socio-economic, bio-physical and geopolitical domains), the decision maker's preferences, and manipulation of both using specified decision rules (Greene et al., 2011). Using GIS tools, the information is combined to form a single index of evaluation (Adem Esmail and Geneletti, 2018). Geographic information system tools are best suited for handling a wide range of criteria data with different spatial and temporal scales from different sources for a time-efficient and cost-effective analysis (Greene et al., 2011). Multi-criteria Decision Analysis approaches that are GIS-based are useful because various production variables can be evaluated. Each is weighted according to its relative importance on crop optimal growth conditions. Then again, its use involves developing an optimisation suitability index derived from heterogeneous data (Adams et al., 1996). This is a challenge because weights given to parameters depend on subjectivity. Malczewski (2004) classified decision support models into multi-objective decision-making (MODM) and multi-attribute decision-making (MADM) (Figure 2.2**Error! Reference source not found.**). In MADM, methods are data-oriented, aiming to design the best alternative (Saaty, 2016). The MODM uses a series of mathematical models where alternative decisions are not predetermined but are a set of objective functions to optimise (Saaty, 2016). Multi-attribute decision-making methods can be classified as:

Weighting methods (linear additive model, AHP and the Multi-Attribute Utility Theory).

Multiple Objective Programming (Multi-Objective Linear Programming).

Outranking approaches (ELECTRE, PROMETHERE).

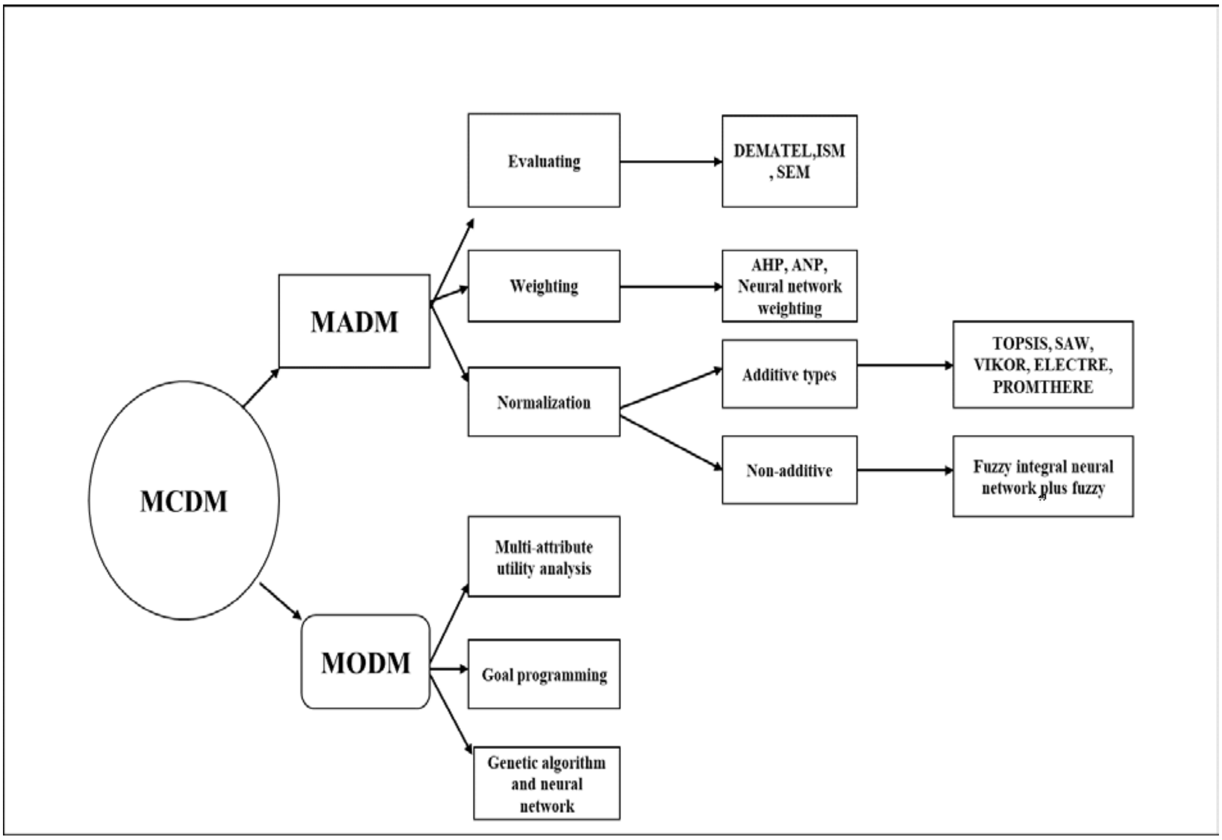


Figure 2.1 MCDM classification is split between MADM and MODM(Castro and Parreiras, 2018).

Spatial MCDM has also become one of the most valuable methods for land use, environmental planning, and agricultural water management. High-resolution spatial data will go a long way to solving land suitability issues, especially in areas where input data is not readily available. Spatial MCDM is more complex and difficult than conventional MCDM, as many factors with strong correlations are needed (Yalew et al., 2016). In this context, fuzzy set theory (FST), which expresses uncertainties in human opinions, can be successfully used together with MCDM methods to get more sensitive, concrete and realistic results (Brisson et al., 1992; Akinci et al., 2013; Hoseini, 2018; Ugbaje et al., 2019). In addition, Kaya et al. (2019) indicated that AHP, when used as an individual tool or integrated with another MCDM method, is the most applied and preferred MCDM method since it is capable of handling a large degree of uncertainty in linguistic terms during decision ranking (Kaya et al., 2019). Such integration is important when mapping the suitability of NUS because it considers many factors affecting crop production.

Analytical Hierarchy Process

Analytic Hierarchy Process (AHP) is a tool for complex decision-making (Saaty, 2016). AHP is the most widely accepted agriculture method and the most reliable MCDM method (Kihoro et al., 2013). It can be used as a consensus-building tool in committee/group decision-making (Saaty, 2016). The AHP helps capture both subjective and objective aspects of a decision by reducing the complexity of pairwise comparisons and synthesising the results into a single index (Romano et al., 2015; Singha and Swain, 2016). The AHP considers a set of evaluation criteria and alternative options from which the best decision is to be made. It generates a weight for each criterion according to the decision maker's pairwise comparisons (Rodcha et al., 2019). The higher the weight, the more critical the corresponding criterion (Akinci et al., 2013). Next, the AHP assigns a score to each option for a fixed criterion according to the decision maker's pairwise comparisons based on that criterion (Akinci et al., 2013). The higher the score, the better the performance of the option concerning the considered criterion. Finally, the AHP combines the criteria weights and the option scores, thus determining a global score for each option and a consequent ranking. A given option's score is a weighted sum of the scores obtained for all the criteria (Akinci et al., 2013). Although the AHP can solve complex spatial scenarios, the method has some limitations in consistency and is subjective (Alkimim et al., 2015). In AHP, weights given to inputs depend on a scientist's expertise, though it can be improved by: deriving a pairwise matrix based on a scientific objective in a non-scarce data situation (Alexander and Benjamin, 2012).

Individual estimation of the relative importance of factors can be done using scientists' opinions through a questionnaire or focus group discussions with key informants. To reduce the subjectivity of human opinion, there is a need to give attention to an upper limit. In this case, the upper limit can be a consistency ratio (CR) that must be less than 0.1 for a pairwise matrix judgment to be accepted (Milad Aburas et al., 2015). To minimise the interrelationship among various factors included in the AHP approach, a data reduction method such as principal component analysis (PCA) can combine fewer new variables. The process is based on three principles: decomposition, comparative judgment, and synthesis of priorities. For example, the synthesis of priorities can be manipulated to evaluate land use opportunity costs, especially when NUS production can complement major crops in semi-arid areas to improve food security.

The AHP uses a 9-point scale measurement (1 = equal importance, 3 = moderate importance of one over another, 5 = strong or essential importance, 7 = very strong or demonstrated importance, 9 = extreme importance, and 2, 4, 6, 8 = intermediate values) to express individual preferences or judgments (Jafari and Zaredar, 2010). It is important to note that, since some of the criteria could be contrasting, it is not true in general that the best option is the one that optimises every single criterion, but rather the one that achieves the most suitable trade-off among the different criteria. The weighting of parameters for AHP suitability can be estimated using a geometric mean method (Leinenkugel et al., 2011). Though AHP can be used as a decision tool, it can be combined with other MDCM methods like fuzzy logic, to create a unique hybrid land evaluation system (Benke and Pelizaro, 2010). The procedure seeks to consider the spatial planning decision context, identifying and arranging the criteria into different groups (Akinci et al., 2013; Chen et al., 2013). The results show that the majority (20.3%) of articles used the AHP method to generate land suitability, mainly for major crops like maize and potatoes (Ceballos-Silva and López-Blanco, 2003). It could be that using AHP in NUS's land suitability will help develop a quantitative index from heterogeneous data to indicate suitable areas. In this regard, AHP applies to NUS suitability because it is used in scenarios where production data is limited and can accommodate categorical datasets such as social-economic factors.

Fuzzy Logic Technique

Fuzzification is the process by which crisp attribute values are mapped into a common suitability scale using membership functions (Dubey et al., 2013). The attributes measured using different scales are converted into a standard range called fuzzy sets (Badr et al., 2018).

Since the approach is based on "degrees of truth", the technique is useful in limited classification data. It cannot be used where actual boundaries are needed (Baja et al., 2002).

The fuzzy method is common in LSA because it can characterise vague and uncertain objects in classification since it does not have definite boundaries (Mbũgwa et al., 2015). Fuzzy logic requires fewer data to run the model; therefore, it can be manipulated to map NUS in agroecologist with limited information about their production (Nhamo et al., 2019). Also, fuzzy logic techniques can be used where the ethnobotany of NUS is poorly documented and patchy. Most available social ecology datasets are categorical and require flexible models such as fuzzy logic (Zabel et al., 2014). The method's flexibility allows it to be combined with other methods, making it suitable for mapping complex systems like NUS might be suitable. Feng et al. (Feng et al., 2017) assessed the suitability of switchgrass using a fuzzy logic technique, a one-step-at-a-time method, and a weighted linear combination. It is also possible to use the Minimum Law to provide a consistent framework to assess crop suitability of crops using a fuzzy logic model. The Law of the Minimum is the outcome of fuzzy intersection using the minimum t-norm between those propositions (Kim et al., 2018). However, NUS are mostly grown in remote rural areas where production information is scarce and not documented. Therefore, the results from fuzzy indices cannot be used where precision agriculture is required to achieve sustainable intensification of NUS (Mabhaudhi et al., 2019).

Crop Simulation Models

Crop simulation models (CSM) are considered one of the most reliable ways to measure land suitability in the context of specific crop requirements within a defined cropping system. A CSM is a mathematical model that describes crop growth and development as a function of weather conditions, soil conditions, and crop management. Ecological drivers simulate biological processes and account for the interactions of weather, soils, and management factors (Ramirez-Villegas et al., 2013). Many of the popular models (e.g., DSSAT (Jones et al., 1998, 2003), CropSyst (Abraha and Savage, 2006), CROPWAT (FAO, 2018), CROPGRO (Boote et al., 1998), and APSIM (Probert et al., 1998; Wang et al., 2018) are process-based; they simulate critical physiological processes such as crop development, net carbon assimilation, biomass partitioning, crop water relations, and grain/fruit growth using point input data (Ramirez-Villegas et al., 2013).

Several crop models have evaluated crop suitability at different scales (Brisson et al., 1992). For instance, the Ecocrop model (Hijmans et al., 2001) is a simple empirical model intended for suitability assessments of crop species. This model has been used on sorghum (Ramirez-Villegas et al., 2013) and various food crop species, including NUS (Lane and Jarvis, 2007). The MicroLEIS, an empirical model, has evolved toward a user-friendly agroecological system for sustainable land management; it has been used to predict agricultural land suitability (Liambila and Kibret, 2016). Also, CSM can validate suitability indices from other LSA methods. For example, Estes et al. (2013) used a mechanistic crop growth model (DSSAT) to validate a maize suitability index for South Africa derived from using MaxEnt in South Africa. Hence, CSMs can be used as a scientific method to validate land suitability indices derived from species distribution models (Liambila and Kibret, 2016).

Then again, CSMs often rely on massive datasets with long time series and high-resolution data, often unavailable at national or continental scales. Following the increased accessibility of remote sensing datasets, CSMs are evolving to process a high volume of data due to platforms like R and Python (Hoogenboom et al., 2019). Another essential criterion is whether the model can be run in "batch mode" or gridded mode. (Kunz et al., 2015) noted that considerable effort was spent on automating the stand-alone version of AquaCrop to enable the model to run non-stop at a regional and national level in South Africa. They noted that over 5000 lines of computer code were written to facilitate this process.

Similarly, the APSIM model can also be run in gridded form from a command-line prompt without the user's need to interact with the model. Hence, model runs can also be automated, as was done for AquaCrop. To date, 9.9% of 101 articles in land suitability mapping used CSMs (Appendices Table 3). Despite efforts to use CSMs in NUS research to develop crop production guidelines (Chimonyo. et al., 2016; Mabhaudhi et al., 2017), the approach depends on the availability of input data like climate data, which may be unavailable in some areas. Furthermore, using CSMs requires high-approach computers and expert skills compared to fuzzy logic and AHP. LSA should use machine learning-related methods to capture complicated scenarios and large datasets.

Machine Learning-Related Methods

Artificial intelligence through machine learning algorithms is gaining popularity in land suitability analysis (Mendoza and Martins, 2006; Senay and Worner, 2019). The technique can handle large time series and categorical datasets for land evaluation obtained from remote sensing, climate models, and direct field data collections. Automating land classification through machine learning algorithms has become a critical modelling tool in land suitability analysis (Mockshell and Kamanda, 2018). The machine learning method (MLM) can be defined as a data analysis method that automates multivariate data using statistical analysis and validated approaches (Bagherzadeh and Gholizadeh, 2016). Commonly used methods are Artificial Neural Networks (ANNs), Logistic Regression, Regression tree, Cellula automata (CA), Markov chain, fuzzy rule-based systems, goal programming, species distribution models like MaxEnt, and Global Environmental Stratification Strata (Appendices Table 1.5).

Machine learning algorithms have several advantages: no human intervention (automation), easy identification of trends and patterns, and the ability to handle multi-dimensional and multi-variety data required in NUS land suitability analyses. However, MLMs are not perfect, as they need massive data sets to train with. These should be inclusive/unbiased, a significant limitation in NUS production in marginal areas. Phillips et al. (2009) noted that high collinearity is less of a problem for MLMs than statistical methods. However, we caution that this is only true if the presence's predictive accuracy is the study goal. Coding ML algorithms require programming skills, which are still challenging in most African regions. Therefore, user interface MLMs such as MaxEnt can help map NUS. The MaxEnt software package can accommodate non-parametric and parametric datasets; however, it uses the machine learning approach by default (Castellanos-Frías et al., 2018; Pecchi et al., 2019).

Species Distribution Models

Understanding species' geographic range has become more critical with concerns over climatic variability and change and the need to fit adaptable crops within a defined construct. In this case, mainstreaming NUS into production systems would benefit smallholder farmers. Species distribution models (SDMs) simulate species' suitability in ecology (Araújo and Peterson, 2012). They can estimate changes in habitat suitability and identify conservation priorities (Byeon et al., 2018). These models match crop phenology and bio-physiological and then calculate the suitable area (Aertsen et al., 2010, 2011). They are also used in climate change studies to quantify species-environment relationships to inform management, assess assemblage changes under different land-use patterns, predict responses to future climate or restoration scenarios, aquatic mapping biodiversity, and identify species conservation priorities (Aertsen et al., 2010, 2011). Species distribution models have been used to predict the potential growing areas for potatoes in Australia (Kidd et al., 2015). This is done by identifying environmental determinants of species suitability by assessing the relative importance of predictor variables (e.g., climate) and examining the crop response curves in partial regions of selected predictor variables (Rose et al., 2016). Species distribution models could be used to examine the climatic suitability of a crop (Senay and Worner, 2019).

Several machine learning-based SDMs are widely used to generate bioclimatic models for predicting the geographic range of organisms as a function of climate (Rose et al., 2016). However, the success of machine learning-based approaches depends on their ability to distinguish heterogeneous zones. Therefore, SDMs require evaluation to measure sensitivity and accuracy through confusion matrices (Lever et al., 2016). Evaluating suitability for a specific purpose requires a comprehensive analysis of natural and socio-economic factors (Mendoza and Martins, 2006; Raza et al., 2018). Despite their applicability, SDMs require many input variables and must be trained with the presence of species data to predict crop suitability zones (Fourcade et al., 2014; Qin et al., 2017). Overfitting is a problem if more variables are used in the land evaluation (Ovalle-Rivera et al., 2015).

The different use of SDM and several studies indicated that climate changes have already affected species' geographical distributions (Austin, 2007). Nevertheless, SDMs have certain advantages and disadvantages, per the Austin (2007) review. They offer a tool for undertaking relatively rapid analysis for numerous individual species and identifying critical relationships between a species and its distribution governing factors. However, the drawback with most land suitability assessment studies using the SDMs is that they tend to be general and assume a linear relationship. However, an environment's suitability for NUS is a function of complex interactions between various factors operating at different scales and magnitudes (Soberon and Nakamura, 2009).

2.3.3. Combining geographic information systems, remote sensing and other artificial intelligence tools

A land suitability analysis should identify innovative ways to derive maximum value from the possible integration of GIS with big data and IoT technologies. The geographic information system and other artificial intelligence tools can handle the volume of data with different structures, especially the socio-economic data, usually in categorical form (Phillips et al., 2006). In Africa, wireless sensor networks with IoT-based applications could measure LULC changes. Still, the return on investment (ROI) is low due to the poor penetration of smartphones and low connectivity. It is understood that the IoT applications in crop suitability will empower most NUS-related industries to extend their value chains to cater to their stakeholders resulting in increased profitability (Rymaszewska et al., 2017). The IoT is one of the highly promising technologies which provides many techniques for modernising land suitability methods. The IoT supports interoperability among various connected devices and helps obtain real-time information on land suitability (Singha and Swain, 2016). Drones use automated control systems and can provide the necessary geospatial data, thus reducing the complexities involved in capturing field data (Tripicchio et al., 2015).

Future research studies should develop an intelligent decision support system for land suitability analyses and a web-based spatial decision support system (Yu et al., 2014). Future studies should integrate GIS, remotely sensed data, computer modelling, and MCDM approaches within a hybrid land evaluation system to better insights into land suitability and improve the strategic, tactical and operational level of decision-making (Nguyen et al., 2019). Tripicchio et al. (2015) suggested using a windows-based GIS application with an artificial neural network (ANN) to delineate land suitable for crops. Similar approaches will need to be adopted in future studies in NUS with a specific focus on land suitability.

For land suitability analysis, remote sensing plays a vital role at different spatial and temporal scales. It also offers an efficient and reliable method of visualising and mapping agricultural lands. Spatial crop suitability information is one of the key input parameters for agroecosystem modelling (Liao et al., 2017). In RS, big data challenges are not limited to analysing high volumes of data but involve big data acquisition, storage, management and analysis. Systems that use cloud computing can overlay multiple data from different sources. The major challenge in remotely sensed data is its ownership and connectivity between the different stakeholders in agriculture. Big data analysis requires modern computing and analytical methods to analyse the unevenly distributed data originating near real-time from different locations. Therefore, future studies should focus on developing new algorithms that can be used to develop land suitability maps that are not static but rather dynamic to factor in climate change and climate variability effects.

2.3.4. Hybrid land evaluation systems

In recent years, NUS studies have gained momentum with a lingering question on how and where they fit in the current agricultural landscape. Land suitability analysis for agriculture is essential in deciding future agricultural cropping patterns, planning and activities. Consequently, land suitability is decided on the merits of each land unit's bio-physical and socio-economic properties. All methods reviewed in this study can be used to assess NUS's suitability in agricultural landscapes; however, each method carries some limitations. For instance, in AHP, the consistency of original datasets, biased weighting and selection criteria may result in uncertainties in final decisions. Akpoti et al. (2019) indicated that the main limitation of the fuzzy logic approach is the lack of a definite method for determining the membership function, which is often based on expert opinion. The integration of RS-GIS, Fuzzy-logic, and multi-Criteria Evaluation using the Analytical Hierarchy Process (AHP) could provide a superior database and guide map for decision-makers considering cropland substitution to achieve better agricultural production.

Interestingly, 14.8% of the articles used hybrid land evaluation systems (HLES) (Table 2.1). The review identified that there is no single method that is supreme. The application of LSA depends on data availability, data types, expertise, available software and the objective of the exercise (Liebig, 2002). Although we recommend HLES, the hybrid method did not come out as the panacea of methods. However, we acknowledge that much research gravitates towards them, especially for planning and monitoring climate change-related issues.

In land evaluation hybrid systems, linking more than two types of models is gaining momentum in LSA (Liebig, 2002). The HLES can combine traditional land evaluation systems and crop models to give land suitability for crops and formulate strategies to promote NUS in marginal lands (Bonfante et al., 2015). Following attempts to combine land evaluation methods with crop modelling, newly developed hybrid methods have captured and handled multidisciplinary data sets. However, this is often not possible due to a lack of data, the most important being climatic data, phenological information, recorded yields, and primary social-economic data such as costs, availability of markets, management and agricultural inputs (Akinola et al., 2020; Mabhaudhi et al., 2017). For example, (Bonfante et al. (2015) developed and tested a hybrid land assessment methodology to demonstrate the impact of climate change on Italy's maize varieties. Applying these methodologies to minor crops and their landraces will require compromise in defining unknown crop growth parameters (Jahanshiri et al., 2020). Jahanshiri et al. (2020) noted that assessing the potential of land for crop diversification involving NUS at a specific location requires a practical approach that takes advantage of available data and knowledge. Hence, GIS and machine learning skills have seen a drastic evolution from traditional practices involving land use planning to new land evaluation methods. The use of big data, cloud computing, Internet of Things (IoT) and other technological advancements improves the accuracy and reliability of land suitability methods (Sharma et al., 2018). The availability of accountable and reliable free online data is expected to play a significant role in shaping up land use planning because local datasets are not readily available in many cases.

2.3.5. Factors Considered in Crop Suitability Mapping

The mapping and the accuracy of land use systems and their associated characteristics depend on the scale and availability of data at an acceptable resolution. Evaluating land suitability for a specific purpose requires a comprehensive analysis of natural and socio-economic factors influencing the land (Mendoza and Martins, 2006; Raza et al., 2018). The elements used can be divided into high and lower factors based on experts' opinion weightings (Zabihi et al., 2015). High-level factors are natural or biophysical factors that directly affect crop growth, such as rainfall, temperature, and soil fertility. Lower-level factors are social and economic factors that affect crop growth and influence the land use degree of appropriateness to a specific purpose. The interactions, dependencies and feedback between higher and lower-level elements form a multi-criteria land evaluation approach for sustainable NUS production. Multidisciplinary factors were ranked to show the most commonly used factors (Appendices Table 1.6). The factors were grouped into climatic indicators, hydrology, soil and landscape attributes, land use land cover, and socio-economic and technical indicators. Many climate data sources are accessible over the internet, like WorldClim and Environmental Raster for Ecology Modelling (Pecchi et al., 2019).

Understanding change patterns of land use and land cover (LULC) is vital for crop suitability analysis and efficient environmental management, including effective water management practice (Sharma et al., 2018). To fit NUS in a farming system, updated LULC maps must be used to understand the proportion of land use patterns to guide planners to make better-informed decisions and achieve a balance between urban growth and preserving the natural environment.

2.4. Discussion and Way Forward

The use of NUS to address food and nutrition insecurity, unemployment and rural development has been advocated for; however, their production continues to be disconnected from the current agricultural production system. NUS is widely believed to offer more options for building temporal and spatial diversity into cropping systems (Akinola et al., 2020; Mabhaudhi et al., 2017). However, this information is mainly anecdotal. The paradox of being widely adapted to diverse agroecologies while having limited information detailing land suitability makes it challenging for policymakers to mainstream NUS into current agricultural programs. Many studies have used MCDM techniques for analysing the complexities involved in land capability and suitability evaluation in crop production. However, all land suitability analysis methods are imperfect and require careful testing and evaluation before application (Liebig, 2002). To improve land use planning and give a real picture of land use, especially in smallholder farming systems, socio-economic factors should be included where available (Kamilaris and Prenafeta-Boldú, 2018; Sharma et al., 2018). Socio-economic factors are required in hybrid land evaluation. Integrating quantitative simulation modelling and qualitative land evaluation techniques leads to excellent scientific and practical results, gradually improving the models' accuracy and applicability (McDowell et al., 2018). Finally, the practical automated application of land evaluation systems is described as a land-use decision support tool that uses information technologies to link integrated databases and various models (Bagherzadeh and Gholizadeh, 2016). Therefore, future research studies should encompass more substantial attributes of NUS LSA's hybrid land evaluation system.

Artificial intelligence (AI) development in LSA accommodates more multidisciplinary datasets (Kurtener et al., 2008; Elsheikh et al., 2013). It includes programming techniques of calculation that may help describe complex inference systems and decision-making (Šporčić et al., 2010). MLMs have recently been popular (Firdaus et al., 2017). There is considerable potential for integrating big GIS analytics (BGA) in agriculture with other technologies, such as LiDAR, to improve land suitability mapping. Integrating analytical techniques (hybrid methods) will improve land suitability mapping, resulting in future climate-related risks based on past and current trends.

It is observed that the majority of the studies in resource allocation utilised primitive GIS techniques. In resource allocation, GIS is a powerful tool for spatial analysis. As land resources are being depleted drastically, effective land use planning must be done to identify new crop production areas. However, the studies by Rey et al. (2016) and (Singh and Rathore, 2017) have used advanced geomatic tools to improve resource allocation. Models for simulating crop production and distribution are gaining attention from the research community (Mockshell and Kamanda, 2018). The use of advanced simulation software helps to remove the redundancy of the other processes and increase accuracy. Hence, researchers should carry out studies involving new and upgraded GIS software. Unmanned aerial vehicles (UAVs) provide high-resolution images (Tripicchio et al., 2015).

2.5. Recommendations

To efficiently identify homogenous zones, especially for NUS, hybrid methods that combine traditional and modern methods (e.g., MCDM, CSM and MLMs) are needed. Suitable hybrid land evaluation systems may be helpful in handling complexities such as the extreme variability, intermittence and socioeconomic factors involved in NUS production.

Future research should consider using data with a finer resolution to improve mapping accuracy. This will help improve land suitability mapping in marginalised agricultural communities known to be highly heterogeneous. Using sensors mounted on unmanned aerial vehicles can validate satellite-derived data and capture high-resolution images (Rosell and Sanz, 2012; Lin, 2015). Using data derived from cloud computing, big data, and IoT technologies can improve the reliability and relevance of land suitability, especially in areas with high ecological risk. Future studies should focus on using new predictive tools to assess spatial distribution and stimulate the production of crops. It is observed that the majority of the studies in resource allocation utilised primitive GIS techniques.

2.6. Conclusions

The review used a scoping method to acquire and synthesise information on land suitability for crop species. Robust land suitability methods are essential to developing land suitability maps to improve current and future planning on crop production guidelines, climate change issues and environmental management. The FAO land evaluation framework provides the basic guidelines for delineating crop suitability. Modern land suitability methods are gaining popularity in cropland suitability analysis. The commonly used MCDM methods are AHP and fuzzy. Using current and future climate change projections in LSA is the way forward for sustainable agriculture and food security. Qualitative and quantitative approaches could be integrated into a unique Hybrid Land Evaluation System to improve the land evaluation approach. The review is expected to improve NUS land evaluation and provide researchers and decision-makers with the most robust methods for developing LSA for NUS.

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CHAPTER 3: APPLICATION OF A NON-PARAMETRIC MACHINE LEARNING ALGORITHM TO MAP BIOCLIMATIC REGIONS WITH HIGH RAINFALL VARIABILITY FOR WATER-SCARCE ENVIRONMENTS

Under review: Scientific Reports

Abstract: Mapping high-risk agricultural drought areas is critical for informing policy and decision-making to formulate drought adaptation strategies. This study used the Vegetation Drought Response Index (VegDRI), a hybrid drought index that integrates the Standardised Precipitation Index (SPI), Temperature Condition Index (TCI), and the Vegetation Condition Index (VCI) to delineate bioclimatic zones with both high rainfall variability and water scarcity for South Africa. Historical satellite climate data (1981-2019) was used with land use/cover maps to generate five scales ranging from very severe to no drought. A machine learning algorithm, the Classification and Regression Tree (CART) in *R* statistic and ArcGIS, was used for analysis and map graphics. Average sorghum yields obtained at the district level were used to validate results obtained from the mapping exercise. This was done using Kappa statistics that gave the relative accuracy of each index. The VegDRI (74.1%), VCI (71.8%), TCI (66.2%), and SPI (59%) showed higher performance in explaining sorghum yield, respectively. The results showed that more than 50% of South Africa's land experienced droughts of different magnitudes. The predictive accuracy of drought risk maps was computed from the cell-by-cell comparison. However, high accuracy values from Kappa of VegDRI with VCI (0.80-0.98) and TCI (0.72-0.90) do not necessarily indicate an accurate mapping of drought risk maps. VegDRI is a helpful index in designing climate-smart practices for improved food and nutrition security under increasing water scarcity.

Keywords: Adaptation; Climate variability; Food security; Underutilised crops; Water scarcity

3.1. Introduction

Drought is one of the most complex natural hazards and substantially impacts water, food, and nutrition security (Mishra and Singh, 2011). Severe dry episodes in sub-Saharan Africa (SSA) have often been linked with the effects of El Niño–Southern Oscillation (ENSO), which often leads to precipitation and temperature anomalies around the globe (Timmermann et al., 2018). Since 1900, 80% of the most severe droughts experienced in the region have been linked to mature El Niño events (Malherbe et al., 2016). The 2015/2016 ENSO-induced drought, one of the strongest events in recorded history, has had unforgettable effects on agriculture, water, food, and nutrition security across SSA (Heino et al., 2018; Nhamo et al., 2019b). Evidence suggests that climate change has increased the frequency and severity of droughts, regardless of the ENSO (AGRA, 2014; Miralles et al., 2014). It is, therefore, necessary to understand drought and, more importantly, assess where it is expected to be severe. Then mapping drought-prone zone can appropriate risk control and mitigation measures (IPCC, 2015).

Drought can exist in different forms: meteorological, agricultural, hydrological, and socio-economic drought (Kogan and Sullivan, 1993; Mishra and Singh, 2010). There is no single technical definition of drought because of the substantial variability in water supply and demand worldwide (Mishra and Singh, 2010). Monitoring the hazard in terms of progression and possible impact is important across various industries, especially agriculture, which is central to livelihoods and human well-being (Zargar et al., 2011). More than 150 drought indices (Zargar et al., 2011) reflect different types and conditions, including intensity and severity (Mishra and Singh, 2011). For example, the rainfall anomaly index (RAI) addresses drought that affects agriculture and water resources (Kosgei, 2009; Foufou et al., 2017), the Palmer Drought Severity Index (PDSI), which is based on water demand (evapotranspiration) and losses (runoff) (Ebrahimpour et al., 2015) and the commonly used Standardised Precipitation Index (SPI), which is a precipitation-based index (McKee, 1993). However, traditional indices methods require multiple observations to determine weights to map drought risk zones. Several data mining methods can be used to overcome this limitation. However, standard data mining methods also have limitations when handling large amounts of data. These problems may be solved using machine learning-related algorithms (Shen et al., 2019a).

Across the region, climate-based drought indices using point-based meteorological observations have been used to help quantify drought impacts on crop production (Botai et al., 2017; Adisa et al., 2019). Given the four physical forms of drought, there is no single unifying approach to quantify drought severity (Algorithm, 1999; Wang et al., 2016). Even within an individual category, the supremacy of a specific index is not immediately clear (Halwatura et al., 2017). However, for any selected drought index, Wang et al. (2016) indicated that the drought index should have certain qualities such as robustness, tractability, transparency, sophistication, extendibility, and dimensionality to improve drought classification bioclimatic zones under water stress. Bioclimatic zones are areas with similar climates, vegetation, and soils, where agricultural activities are closely related to the conditions of each zone (Rivas-Martínez et al., 2011). Regarding bioclimatic zones, consideration should also be given to long-term historic near real-time climatic data from earth observed (EO) data (Brown et al., 2008). Therefore, to capture the complexity of drought in a bioclimatic zone, a hybrid method that integrates historical climate data, satellite-based earth observations and biophysical information is required (Tadesse and Wilhite, 2011).

Remote sensing is essential for assessing climate change and its impact on agricultural production over time, which are necessary for developing context-based adaptation strategies. Remote sensing data instantly offers a synoptic vision covering bioclimatic zones and high repetitiveness adapted to drought monitoring over time (Park et al., 2016). Combining different indices from four physical forms of drought is hypothesised to detect agricultural drought more accurately and be more helpful in informing drought management strategies (Mubiru et al., 2018). The Vegetation Drought Response Index (VegDRI) is a hybrid drought index that integrates traditional climate-based drought indicators and satellite-derived vegetation index metrics with other biophysical information (e.g., land use land cover (LULC) type, soils, elevation, and ecological setting) (Brown et al., 2014). The resultant map produced has a resolution of 5 km showing historical water-stressed zones (Brown et al., 2014). The VegDRI was developed by the National Drought Mitigation Centre (NDMC) and the U.S. Geological Survey (USGS) Earth Resources Observation and Science (EROS) Centre as an operational tool to monitor drought-induced vegetation stress (Brown et al., 2008). It provides drought-specific information that addresses challenges faced by traditional climate and satellite-based indices (Quiring and Ganesh, 2010). However, it cannot be used as an indicator of hydrological drought or low-flow conditions in streams or rivers (Nam et al., 2018). The VegDRI has been used to monitor vegetation drought stress in South Korea (Brown et al., 2008). The VegDRI portrays vegetation conditions as plants respond to solar energy and portrays soil moisture. The VegDRI has not been used under South African conditions, where drought affects agriculture, particularly rainfed crop production. Therefore, it offers new insights into assessing drought impacts from local to regional scales (Otkin et al., 2016; Nam et al., 2018).

Agricultural drought involves complex soil water stress, vegetation growth status, and meteorological precipitation loss (Dai, 2011, 2012). In constructing comprehensive drought models, machine learning algorithms such as classification and regression tree (CART) and artificial neural network (ANN) are considered prediction models widely used for time-series forecasting. As a classification technique, the ANN has also been used to deal with complicated or imprecise data to identify hidden patterns (Nam et al., 2018). The CART and ANN can extract more valuable features from many drought factors beyond the reach of other traditional indices (Park et al., 2016; Shen et al., 2019a). There are several algorithms in this study CART was selected because results are easily interpretable (Higgins et al., 2008). In addition, CART offers automatic handling of variable selection, missing values, outliers, local effect modelling, variable interaction, and nonlinear relationships(Li and Parrott, 2016). Surrogate splits handle missing values in a variable. There is a more accurate algorithm, such as a random forest. Random forest inherits CART properties like variable selection, missing values and outlier handling, nonlinear relationships, and variable interaction detection. Unlike the CART model, Random Forest's rules are not easily interpretable (Nam et al., 2018). The rise of machine learning has introduced nonlinear empirical models such as the classification and regression tree (CART) algorithm to analyse the nonlinear relationship between predictor variables and the response variable (Nam et al., 2018). However, few studies on drought monitoring use machine learning algorithms in SSA (Tadesse et al., 2008; Rojas et al., 2011; Pulwarty and Sivakumar, 2014). Therefore, this study used machine learning methods to construct models by considering various hazard factors and exploring the use of multiple remote sensing data sources for regional, remote sensing comprehensive drought mapping.

South Africa is a water-scarce country (Ziervogel et al., 2014), and about 61% of the country receives less than 500 mm of rainfall annually. The country is characterised by a mild, temperate climate (Aliber and Cousins, 2013), where a small proportion of land (10.3%) is considered arable for agriculture. The amount of rainfall received is considered the minimum for successful dryland farming (Smithers and Schulze, 2000). Drought is a significant threat to crop production, water resources, and, more importantly, food and nutrition security in South Africa (Malherbe et al., 2016). Previous studies on bioclimatic zoning indicated that no single index could describe all aspects of droughts (Unganai and Kogan, 1998; Botai et al., 2019). There is a need to explore meteorological and agricultural factors in tandem to capture the complexity of drought (Hao et al., 2017; Shen et al., 2019b). As such, a multi-index approach is needed for operational drought risk identification. Therefore, a non-parametric machine learning-related algorithm can explore the relationships between meteorological and agricultural factors to delineate drought risk zones.

In South Africa, there is no prior mapping of drought-based bioclimatic zones using machine-related learning algorithms. The methodological approach adopted proposed an improvement of the VCI, TCI, and SPI through the VegDRI to better detect the agricultural drought risk zones without knowing the causal mechanisms of these factors. This study provided a detailed, spatially explicit understanding of the drought risk zone using machine learning algorithms in South Africa, focusing on developing a customized version of the VegDRI, including VCI, TCI, and SPI. The approach allows for mapping agricultural drought-prone areas and bioclimatic map zones with high rainfall variability and water scarcity. Secondary to this, a correlation test between the VegDRI and normalised crop yield data for sorghum was used to test and validate the applicability and usefulness of the VegDRI index.

3.2. Methodology

3.2.1. The Geography of South Africa

South Africa is located on the southernmost tip of Africa between 22°S and 35°S, covering 1 219 912 km^2. The country is characterised by a mild, temperate climate (Aliber and Cousins, 2013), where a small proportion of land (10.3%) is considered arable for agriculture. South Africa is a water-scarce country (Ziervogel et al., 2014), and about 61% of the country receives less than 500 mm of rainfall (**Error! Reference source not found.Error! Reference source not found.Error! Reference source not found.Error! Reference source not found.Error! Reference source not found.Error! Reference source not found.**Figure 3.1**Error! Reference source not found.Error! Reference source not found.Error! Reference source not found.Error! Reference source not found.**). The amount of rainfall received is considered the minimum for successful dryland farming (Smithers and Schulze, 2000). Where rainfall exceeds 500 mm, major crops, including maize (*Zeal mays*), soybean *(Glycine max),* tobacco (*Nicotiana tabacum*), sugar cane (*Saccharum officinarum*), and other high-value horticultural crops are produced. Drought is a significant threat to crop production, water resources, and, more importantly, food and nutrition security in South Africa (Malherbe et al., 2016).

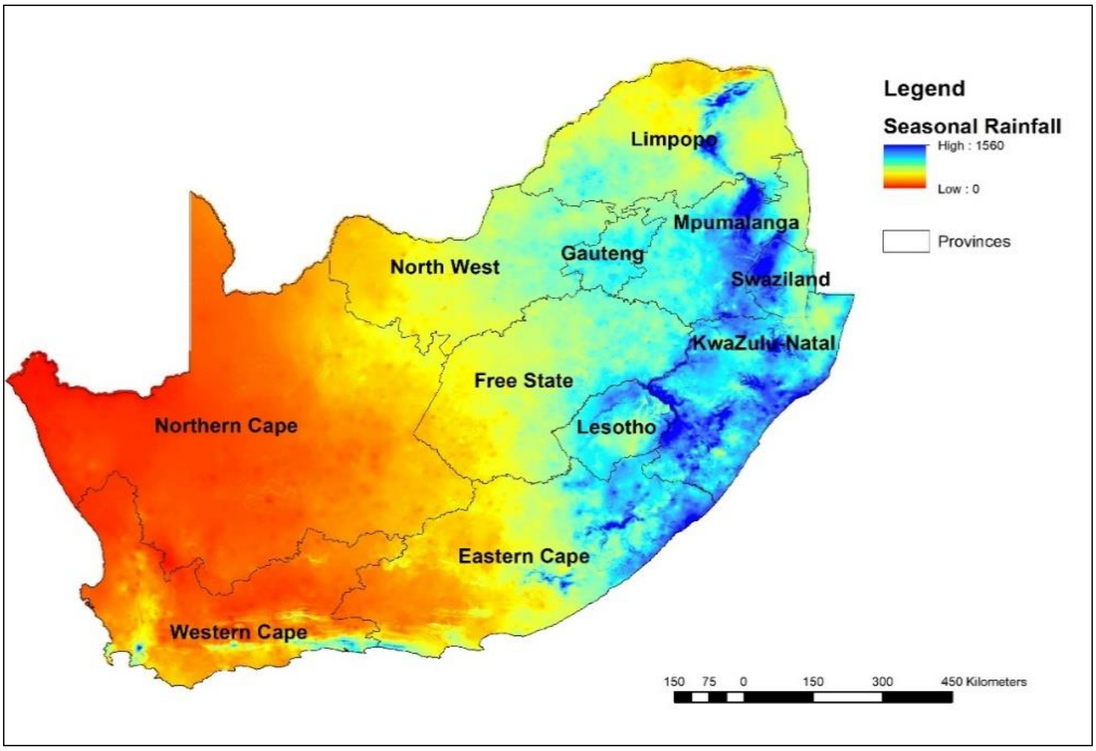

Figure 3. 1 Average Seasonal rainfall distribution from 1981-2019 rainfall data for South Africa (CHIRPS datasets - Funk et al. (2015))

3.2.2. Vegetation drought response index model generation using a CART model

The VegDRI model's development involves a training database of the satellite and climate-based variables for 39 years, from 1981 to 2019. The VegDRI models for each month (from 1981 to 2019) were generated using the CART algorithm, which Breiman (2001) originally developed. The CART is a supervised learning algorithm that creates a training model to predict the class or value of the target variable using simple decision rules inferred from preliminary data. To create a training model that can predict the class or value of the target variable by learning simple decision rules inferred from prior data (training data). During training, the CART algorithm performs repeated binary recursive partitioning that subdivides the training data until the partitioning process is terminated by user-defined criteria (Brown et al., 2013).

For the development of VegDRI, 80% of the dataset was used for training and 20% for validation of the training model. The dataset was randomly sampled and split into calibration and validation datasets. This procedure was implemented 100 times to evaluate the stability of the model. The VegDRI map contains five categories of varying levels of drought-induced vegetation stress based on the PDSI drought classification scheme (Palmer, 1965). The details of some of the processing and analysis methods are given in the subsequent sub-sections.

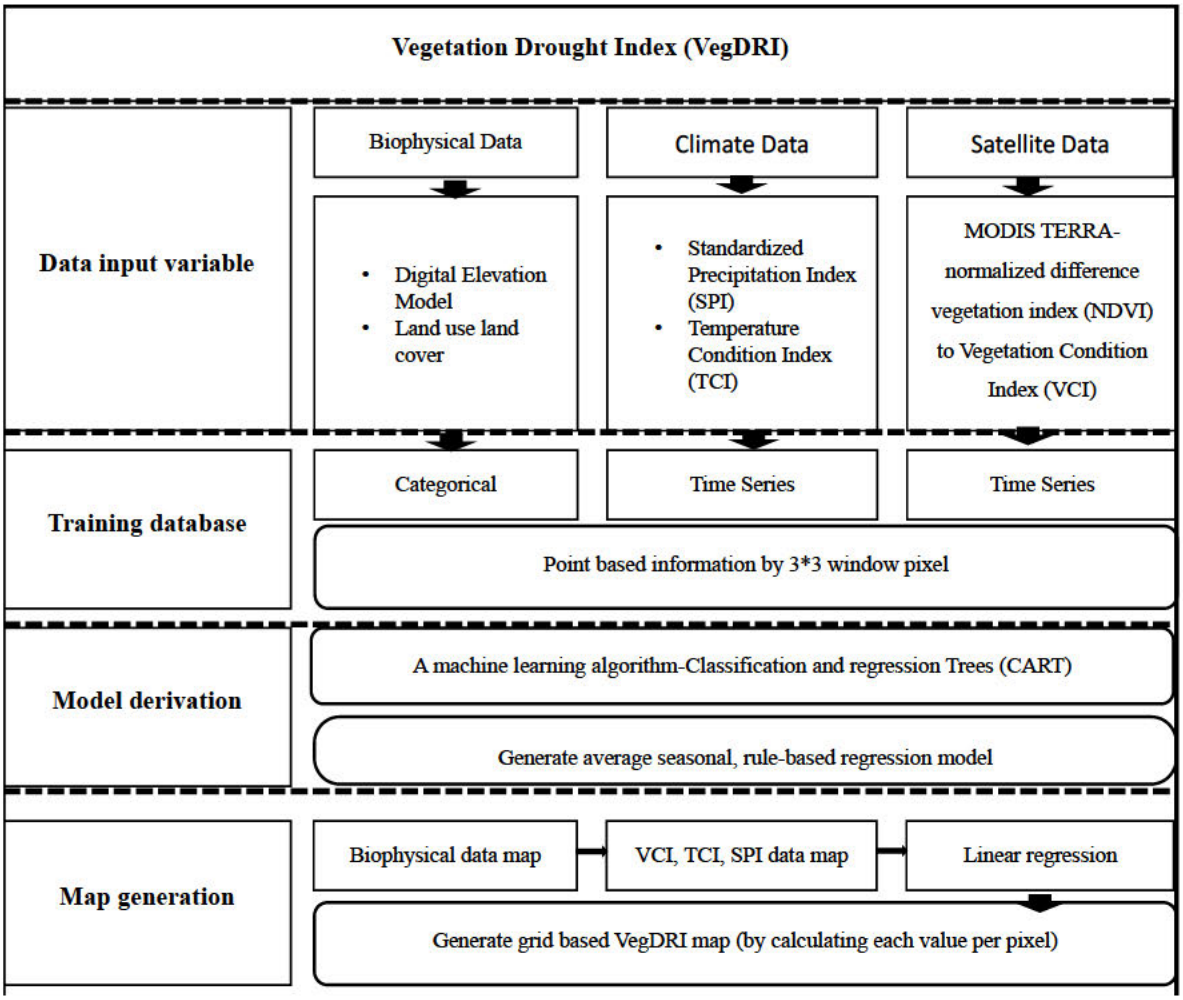

Figure 3. 2 Flow chart of generating vegetation drought index (Nam et al., 2018).

3.2.2.1 VegDRI model implementation

The input data used in VegDRI consists of three major variable categories: satellite, climate, and biophysical data (Brown et al., 2014). A 39-year historical record (1981–2019) of climate-based drought indices and satellite-derived vegetation condition index (VCI) observations were included in the input database (Table 3.1). The vegetation indices, such as the Normalised Difference Vegetation Index (NDVI) and the Enhanced Vegetation Index (EVI), were mined from a big data software called Application for Extracting and Exploring

Analysis Ready Samples (AppEEARS Team, 2019). AρρEEARS enables users to subset geospatial datasets using spatial, temporal, and band/layer parameters. The NDVI and VCI are readily available, and pre-processing stages such as geometric correction, radiometric correction, and image enhancement have already been undertaken (Crespi and de Vendictis, 2009; Richter and Schläpfer, 2011). Amongst the biophysical variables, elevation was unchanged in the VegDRI trend analysis (Table 3.1). A long-term, annual average of satellite and climate indices defined bioclimatic zones. The datasets were resampled to 5 km resolutions by the bilinear interpolation method (Du et al., 2013). The analysis was done in R version 3.5.1 (R Core Team, 2014) and map presentation in the ArcGIS 4.6 environment.

Table 3. 1 Data input variables for the VegDRI model

Data type	Data set name	Format	Resolution	Source
Satellite data	Standardised seasonal greenness using MODIS Terra/Vegetation condition index	Raster	5.0 km	https://lpdaacsvc.cr.usgs.gov
	Temperature Condition Index (TCI)	Raster	5.0 km	https://lpdaacsvc.cr.usgs.gov
Climate data	Precipitation Gridded precipitation	Point Raster	5.0 km	https://sasri.sasa.org.za/pls/sasri https://climateserv.servirglobal.net
	Standardised precipitation index	Raster	5.0 km	https://climateserv.servirglobal.net
Biophysical data	Digital elevation model	Raster	0.25 km	http://www.cgiar-csi.org
	Land use land cover of 2018	Raster	0.016 km	https://egis.environment.gov.za/gis_data_downloads

The VegDRI model uses the classification and regression tree (CART) algorithm to generate bioclimatic zones from satellite, climate, and biophysical datasets (Nam et al., 2018). The CART algorithm analyses the nonlinear relationship between predictor and response variables (Nam et al., 2018). Rule-based linear regression models were applied to the geospatial data to produce a 5 km resolution grid-based VegDRI map by calculating the VegDRI values for the pixel climatic zone. According to Lemma (1996), the probability of drought occurrence in a given area can be classified into high, moderate, and low drought probability zones when drought occurs in >50%, 30-50%, and < 30% of the years, respectively. Based on this criterion, the frequency maps of each drought class were reclassified into five categories based on the frequency of drought occurrence in study periods: ≤2.00 classified as no drought; (-0.99) to1.99 classified as slight drought,

-2.99 to (-1.00) classified as moderate drought; -3.99 to (-3.00) classified as severe drought; 4< classified as very severe drought (Table 3.2).

Table 3. 2 The VegDRI classification (Brown et al., 2014)

Value range	**Bioclimatic class**	**Reclassification***
Greater than 4.00	Extremely wet	No Drought (> 2.00)
3.00 to 3.99	Severely wet	
2.00 to 2.99	Moderately wet	
1.00 to 1.99	Slightly wet	Slight Drought (-0.99 to1.99)
0.99 to (-0.99)	Near normal	
-1.99 to (-1.00)	Mild dry	Moderate Drought (-2.99 to -1.00)
-2.99 to (-2.00)	Moderately dry	
-3.99 to (-3.00)	Severely dry	Severe Drought (-3.99 to -2.00)
Less than (-4.00)	Extremely dry	Very Severe Drought (<-4.00)

* *Indicate that the colour corresponds with the drought classification on the map*

3.2.3. Climate and Satellite data inputs for VegDRI

3.2.3.1. Climate data

Long-term rainfall data is essential in climate analyses and applications. Rainfall data from station observations are sometimes patchy and unavailable in many parts of the world due to sparse or lack of weather station networks and limited reporting of gauge observations (Malherbe et al., 2016). To address this limitation, satellite rainfall estimates have been used as an alternative or a supplement to station observations (Funk et al., 2015). Gridded rainfall data was obtained from https://climateserv.servirglobal.net over 39 years from 1981 to 2019. A detailed description of the Climate Hazards Group Infrared Precipitation (CHIRPS) products have been provided by Funk et al. (2015). The purpose of the CHIRPS dataset was to provide high-resolution data for areas where rainfall data is not readily available. The CHIRPS data were compared with recorded data across KwaZulu-Natal from four automatic weather stations (AWS), namely Wartburg – Byruns Hill, Ulakazi, KwaDukuza, and Tugela Mouth, which were selected based on data available from the South African Sugarcane Research Institute (SASRI) (https://sasri.sasa.org.za/pls/sasri). The coefficient of determination (R^2), bias, and efficiency were applied to evaluate any difference between seasonal climatic data from the automatic weather station and CHIRPS precipitation. The comparison process performed in R-Instat software assumed that both AWS and CHIRPS datasets have similar distributions (Willmott, 1981; Eum et al., 2012) (Table 3.3).

Table 3. 3 Descriptions of validation statistics used in the article

Statistics	Formula		Range	Best value
Bias	$Bias = \frac{\Sigma S}{\Sigma G}$	Equation 1	0 to ∞	1
Efficiency	$Eff = \frac{\Sigma(S-G)^2}{\Sigma(S-\bar{G})^2}$	Equation 2	∞ to1	1
Correlation coefficient	$C = \frac{(G1-\bar{G})(S1-\bar{S})}{\sqrt{\overline{(G1-\overline{G})^2}}\,\overline{(S1-\overline{S})^2}.}$	Equation 3	−1 to 1	-1 or 1

Note. G=gauge rainfall measurements; $\bar{G}$=average of the gauge measurements; S =satellite rainfall estimate

A non-parametric Kolmogorov-Smirnov (K-S) significance test with a 95% confidence level was applied to precipitation between in-situ/observed data, assuming both in-situ and CHIRPS data have similar distributions (Funk et al., 2015; Dinku et al., 2018).

3.2.3.2. Standardised Precipitation Index (SPI)

The Standardised Precipitation Index (SPI) is designed to quantify the precipitation anomaly for a specified time for a location based on the long-term precipitation record over that specific time interval (McKee and Thomas B. McKee, 2012). The SPI quantifies the degree of wetness/dryness by comparing accumulated rainfall over different periods with historical rainfall (McKee, 1993). The SPI is highly related to drought conditions because it reflects energy and water exchanges among vegetation, soil, and atmosphere and considers soil moisture characteristics (Mishra and Singh, 2010). The SPI is useful for distinguishing dry from wet years or deficit from surplus years. The SPI uses a probability distribution function to transform precipitation data into a normal distribution (McKee et al., 1993). It can be calculated for any period of interest, and different timescales are appropriate for monitoring various types of drought (Adisa et al., 2019; Botai et al., 2019). The SPI values represent if precipitation was more or less than the historical mean rainfall (McKee, 1993). The more positive means it is more representative. The magnitude of the drought was classified as very severe dry (≤ -2), severe dry (-1.5 to -1.99), moderate dry (-1.00 to -1.49), light drought

(-0.99 to 0.99), and no drought (≥ 1.00) (McKee and Thomas B. McKee, 2012). However, it is point-based and limited in covering vast areas to show the spatial distribution of drought (McKee and Thomas B. McKee, 2012). It requires spatial interpolation, often producing high uncertainty in interpolated regions (Peters et al., 2002).

3.2.3.3. Vegetation Condition Index (VCI)

Vegetation Condition Index (VCI), the Terra Moderate Resolution Imaging Spectroradiometer (MODIS) Vegetation Indices MOD13Q1 was calculated from remote sensing data obtained from the Moderate Resolution Imaging Spectroradiometer (MODIS) optical satellite imagery (Solano et al., 2010). The index assesses drought severity in areas where episodes are localised and ill-defined (Quiring and Ganesh, 2010). This is achieved by comparing the current state of the vegetation as measured by NDVI to the range of values observed over the same period in previous years in the R environment (UNOOSA, 2019). The VCI is calculated as follows:

$$VCI_{ijk} = \frac{\mathrm{VI}_{ijk} - VI_{i,min}}{VI_{i,max} - VI_{i,min}} * 100 \qquad (4)$$

where VCI_{ijk} is the VCI value for the pixel *i* during week/month/DOY*j* for year *k*, VI_{ijk} is the weekly/monthly/DOYs VI value for pixel *i* in week/month/DOY *j* for year *k,* whereby both the NDVI or EVI can be used as VI, $VI_{i,\,min}$ and $VI_{i,\,max}$ is the multi-year minimum and maximum VI, respectively, for pixel *i*. The state of drought is presented as a percentage; lower and higher values indicate bad and good vegetation state conditions, respectively (Table 3.4).

Table 3. 4 Vegetation condition severity index

Value (%)	Category	Reclassification*
90-100	No Drought	No Drought (80-100%)
80-90	No drought	
70-80	No drought	Slight Drought (70-80%)
50-60	No drought	Moderate Drought (40-50%)
40-50	No drought	
30-40	Light drought	Severe Drought (20-40%)
20-30	Moderate drought	
0-10	Extreme drought	Very Severe Drought (0-10%)

* *Indicate that the colour corresponds with the drought classification on the map*

3.2.3.4. Temperature Condition Index (TCI)

The Temperature Condition Index (TCI) determines stress on vegetation caused by temperature and excessive wetness (Villamarín et al., 2013). In this case, the environment's degree of hotness or coldness determines the crop species' suitability (García-León et al., 2019). Temperature affects biochemical reactions such as photosynthesis, respiration, and crop production (Lobell, 2007). Conditions are estimated relative to the maximum and minimum temperatures and modified to reflect different vegetation responses to the temperature at a specified time and location (Kogan, 1995). The TCI is a practical approach for monitoring drought occurrence after the crops turn green; as a result, the index can indicate zones under water stress and high rainfall variability (Villamarín et al., 2013). Temperature Condition Index values vary from zero, for highly unfavourable conditions, to

100, for optimal conditions. The temperature condition index is given by equation 5.

$$TCI\ 100 * \frac{BT_{max} - BT}{BT_{max} - BT_{min}} \qquad (5)$$

Where BT is the Bio-temperature, $BT_{max,}$ and BT_{min} are the smoothed ten-day radiant temperature and represent the multi-year maximum and multi-year minimum for each pixel in a given area, respectively.

3.2.4. Drought indices evaluation

To assess the relative importance of each drought index, we performed pixel-to-pixel comparisons between VegDRI with VCI, TCI, and SPI and calculated the mean difference in pixel scores. The mean differences were calculated for the period between 2000 and 2019. In addition, a two-sample Student's t-test was used to examine whether the mean difference in corresponding pixel scores from the VegDRI map to either VCI, TCI, or SPI was greater than would be expected by chance alone. The comparison assumed a null hypothesis that both maps were identical regardless of which input parameters were used (van Vliet et al., 2011). The coefficient of determination (R^2) evaluated model performance by comparing it with sorghum yield. Historical sorghum yields were sourced from the Department of Agriculture, Forestry, and Fisheries (DAFF). The DAFF collects sorghum yield data yearly, and this is done across the districts. The DAFF randomly samples 10% of points per district for the data. The sampled data is representative of key agro-climatic zones and farming systems and forms the basis of yield estimates for each district (DAFF, 2020). The Free State produces about 50% of South Africa's sorghum with an average production yield of 2 tonnes ha^{-1}. Sorghum is produced on a wide range of soils in different farming systems and under fluctuating rainfall conditions of approximately 400 mm in the drier western parts of the country to about 800 mm in the wetter eastern parts of South Africa (Chimonyo et al., 2016). A total of 15 of 52 data points were available for analysis and correlated with associated pixels.

We then utilized weighted kappa statistics to compare the relative difference of each map.

When judging a common stimulus, Kappa statistics were used to evaluate the inter-rater reliability and the drought indices. At the same time, the stimulus was the data provided by the variables (each map being compared), and the agreement objective was the pixel score generated by each drought index. A kappa value of 1 indicates perfect agreement between raters, and 0 indicates no more than expected by chance (Hernandez, 2012; Merow et al., 2013; Pecchi et al., 2019).

3.3. Results

3.3.1. Precipitation evaluation

The performance of CHIRPS and in-situ or observed precipitation was assessed based on the empirical distribution function (EDF) of daily scale precipitation at two thresholds (2.5 and 4.95 mm/day) at four weather stations (Table 3.5). The 2.5 mm represents meteorological rainfall per day, and 4.95 mm represents rainfall influencing crop production per day. CHIRPS precipitation data was highly correlated with observed weather data across all weather stations used in South Africa. Based on the results, CHIRPS datasets can be used for agricultural drought analysis.

Table 3. 5 Validation statistics for rainfall products over KwaZulu-Natal using point-to-pixel comparisons

Location	Coordinates	CHIRPS (mm)*	Correlation coefficient	Efficiency	Bias
Wartburg	29^0 55. 0’S	2.5	0.68	0.66	0.78
Bruyns Hill	31^0 46.0’E	4.95	0.78	0.70	0.88
Umlakazi	28^0 55. 0’S	2.5	0.62	0.64	0.72
	31^0 46.0’E	4.95	0.76	0.69	0.85
KwaDukuza	29^0 29.0’S	2.5	0.60	0.63	0.70
	31^0 12.0’ E	4.95	0.78	0.70	0.88
Tugela Mouth	29^0 14.0’S	2.5	0.68	0.66	0.78
	31^0 8.45’E	4.95	0.79	0.73	0.89

*****_2.5 mm represents meteorological rainfall per day, 4.95 mm represent rainfall which_ *influences crop production per day*

3.3.2. Temperature condition index map for South Africa

Figure 3.3 presents the long-term TCI for South Africa based on the long-term averages (1981-2019) data. The spatial degree of hotness varied across the country, translating to different drought severity. The results indicated that about 10% of the arable land is classified as very severe drought, 44% as severe drought, 22% as moderate drought, 22% as slight drought, and 2% as no drought in South Africa. Very high to severe drought conditions were indicated in the Northern Cape and Eastern Cape provinces (Figure 3.3). There is a spatial variation of moderate to slight drought in central provinces, northeast, and south-eastern provinces of South Africa (Figure 3.3).

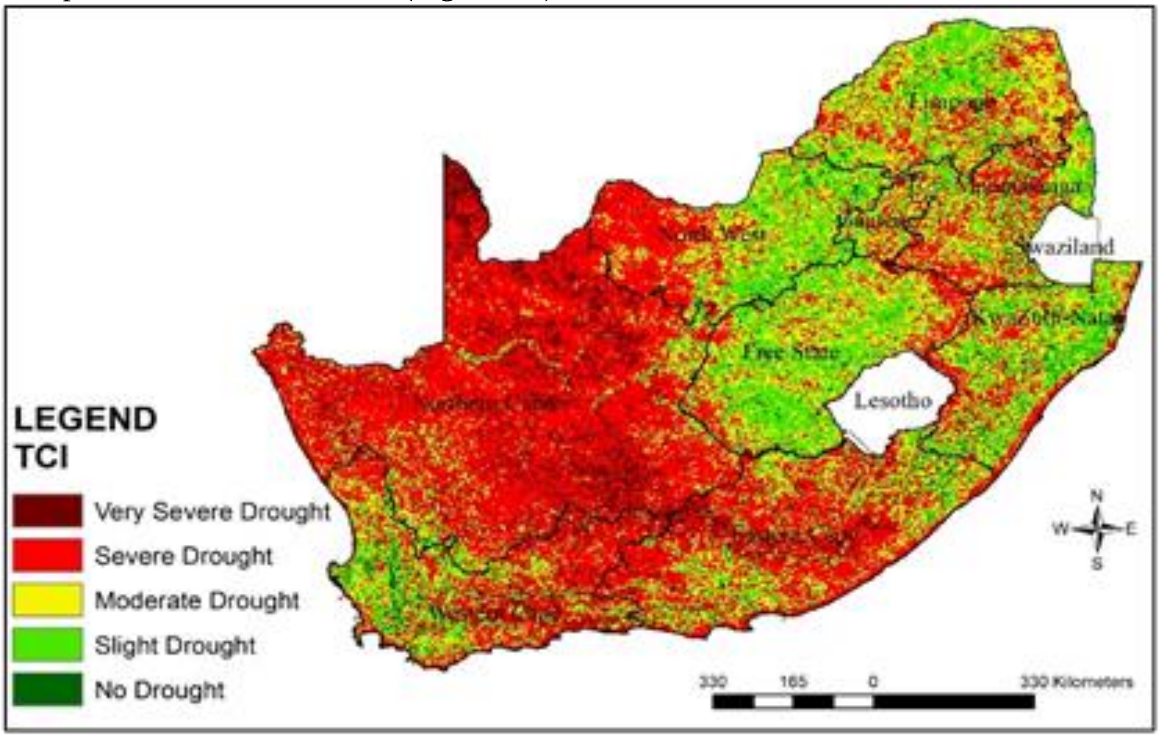

Figure 3.3 Long-term average (2000-2019) Temperature condition index (TCI) for South Africa.

3.3.3. Vegetation condition index

The level of drought severity based on the VCI ranged from very severe drought (26%), severe drought (31%), moderate drought (14%), slight drought (23%), and no drought (6%) of arable land for South Africa. The distribution of VCI was consistent with TCI. The extent of very severe to severe drought covered the northwest to southwest provinces (Northern west, Northern, Western, and Eastern Cape) of South Africa. The central to eastern provinces (Free State and Limpopo) were characterised by moderate and no drought conditions (Figure 3.4).

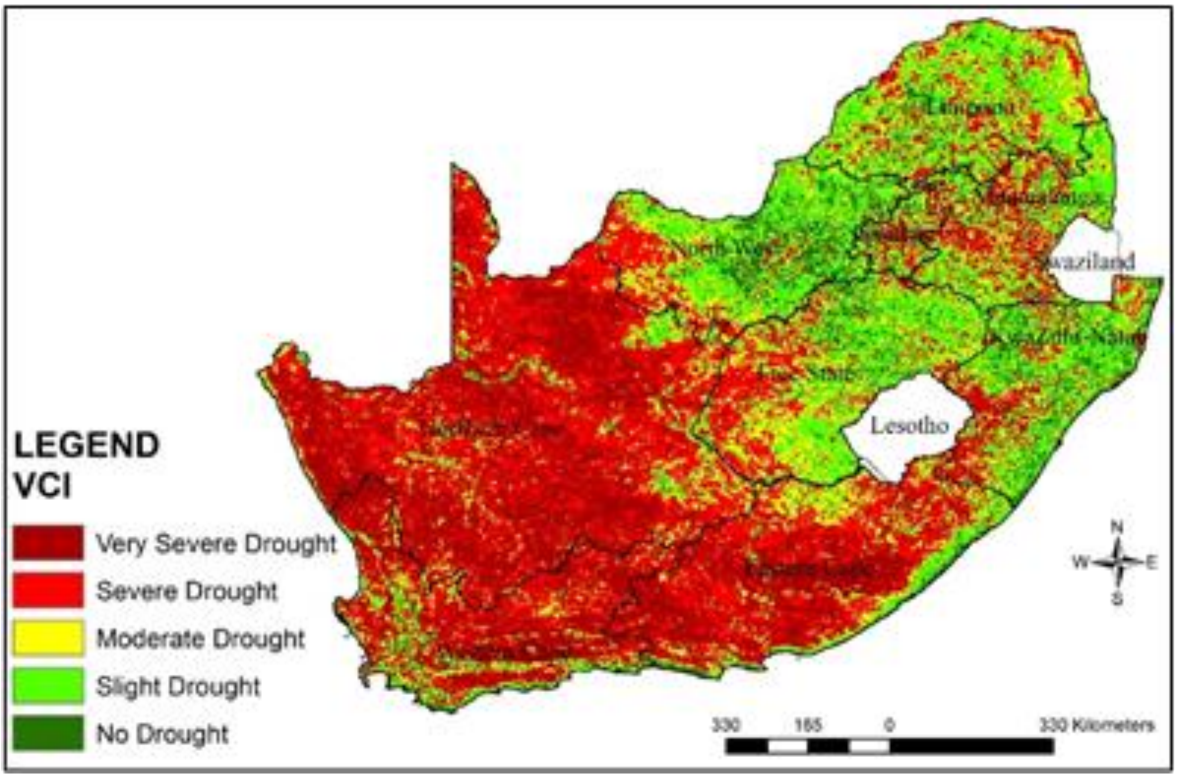

Figure 3. 3 Long-term average (2000-2019) vegetation condition index (VCI) for South Africa.

3.3.4. Standard precipitation index in South Africa

The intensity of precipitation anomaly varies across South Africa, with 25% very severe dry zones, 29% severe drought, 18% moderate drought, 21% slight drought, and 7% experiencing no drought zones (Figure 3.5). The spatial aridity was high in the south-eastern and central provinces of the country. The precipitation anomaly was classified as very severe to severe in western provinces and part of eastern Limpopo province.

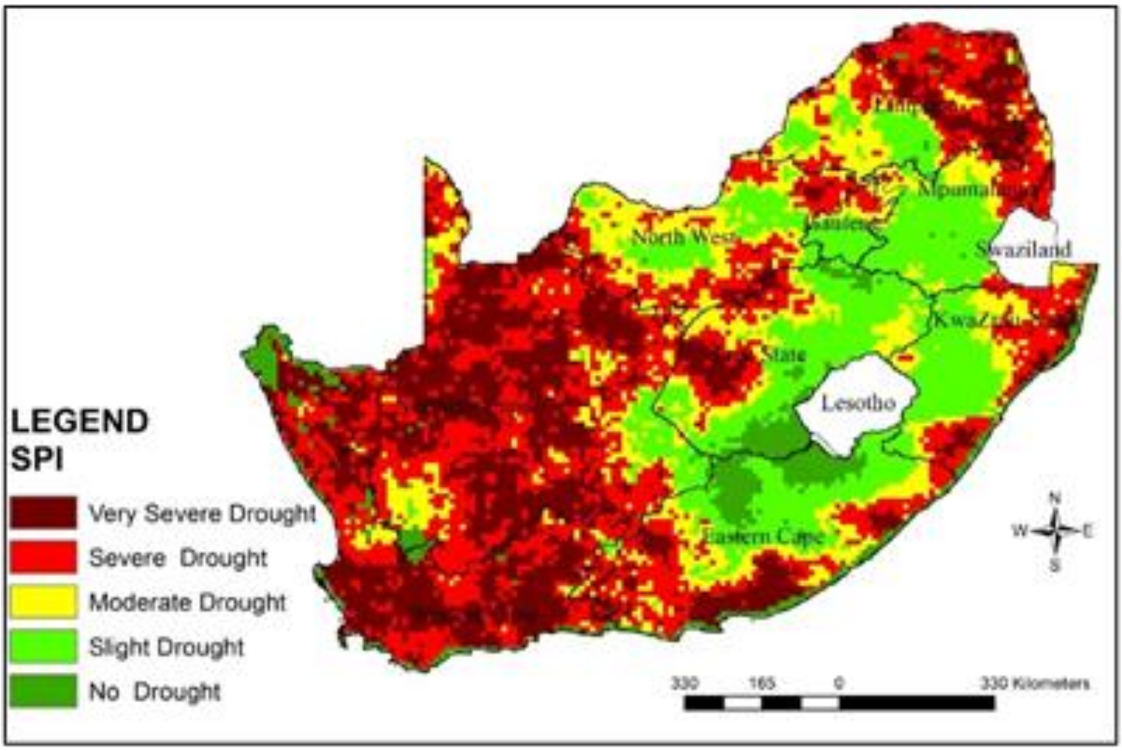

Figure 3. 4 Long term average standard precipitation index (SPI) for 6 months from 1981-2019 from CHIRPS

3.3.5. Vegetation Drought Response Index (VegDRI)

Figure 3.6 shows the long-term seasonal time series of the VegDRI for South Africa. The VegDRI-South Africa map shows a variation of very severe drought (16%), severe drought (34%), moderate drought (38%), slight drought (11%), and no drought conditions (1%) detected over South Africa. Over the Northern Cape and Eastern Cape provinces, drought was very severe to severe, indicating acute water scarcity. Moderate to no drought conditions are reported from the central province to the eastern provinces of South Africa.

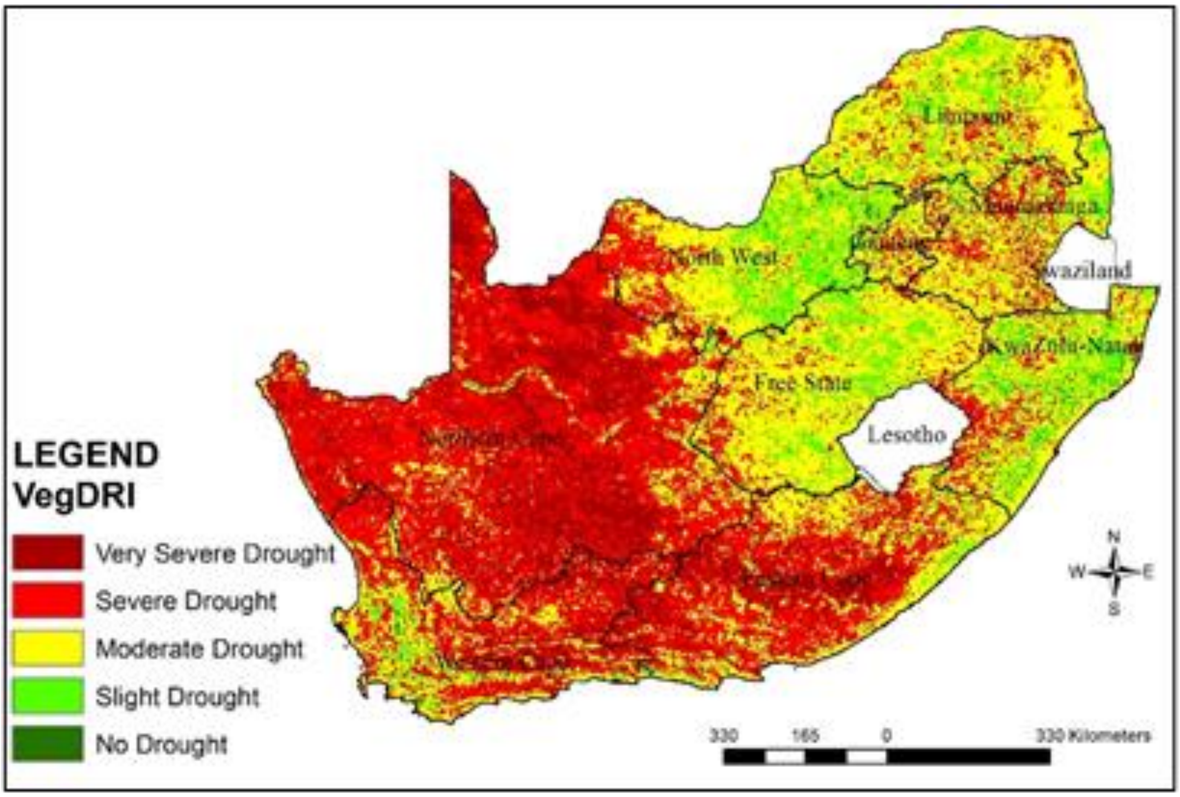

Figure 3. 5 Average seasonal Vegetation Drought Response Index

3.3.6. Drought indices evaluation

The performance of each drought index was evaluated using the coefficient of determination (R^2), measuring the fitness between actual sorghum yield and predicted values (drought indices). Amongst the four indices, VegDRI (74.1%) performed the best in predicting sorghum average district yields for the period 2010 to 2019, followed by VCI (71.8%), TCI (66.2%), and SPI (59%) (Figure 3.7). All indices responded to low rainfall in the 2015/16 agricultural season and recorded the lowest sorghum yield (Figure 3.7). The three indices (VegDRI, VCI, and TCI) performed systematically better than the precipitation-based SPI in explaining sorghum yield.

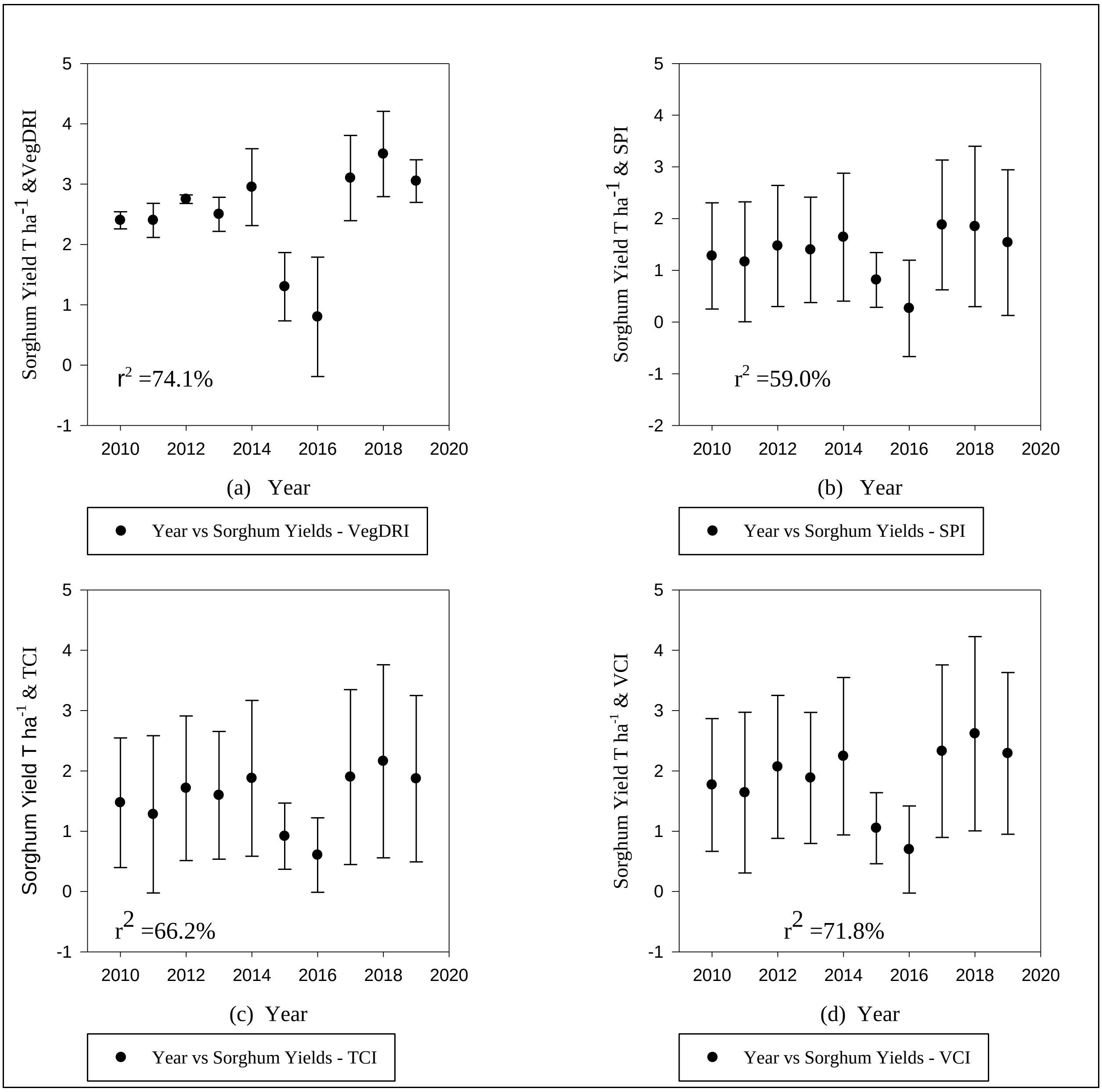

Figure 3. 6 A relationship between district sorghum yields and drought indices (a) VegDRI vs Sorghum yields, (b) standard precipitation index vs sorghum yields, (c) Temperature condition index (TCI) vs sorghum yields, (d) Vegetation condition index (VCI) vs sorghum yields respectively for the period 2010 to 2019. The Y-axis shows the average district sorghum yield computed as a function of drought. The error bars represent the standard deviation of sorghum yields.

Figure 3.8 shows the evolution of the classification accuracy of VegDRI compared to VCI, TCI and SPI maps with 95% confidence intervals. The highest Kappa coefficients were observed between VegDRI vs VCI, followed by TCI, and the lowest inter-rater reliability or agreement was on SPI with a value of 0.70. The highest Kappa coefficients were observed in the agricultural season 2015, VCI (0.98), TCI (0.90), and SPI (0.87).

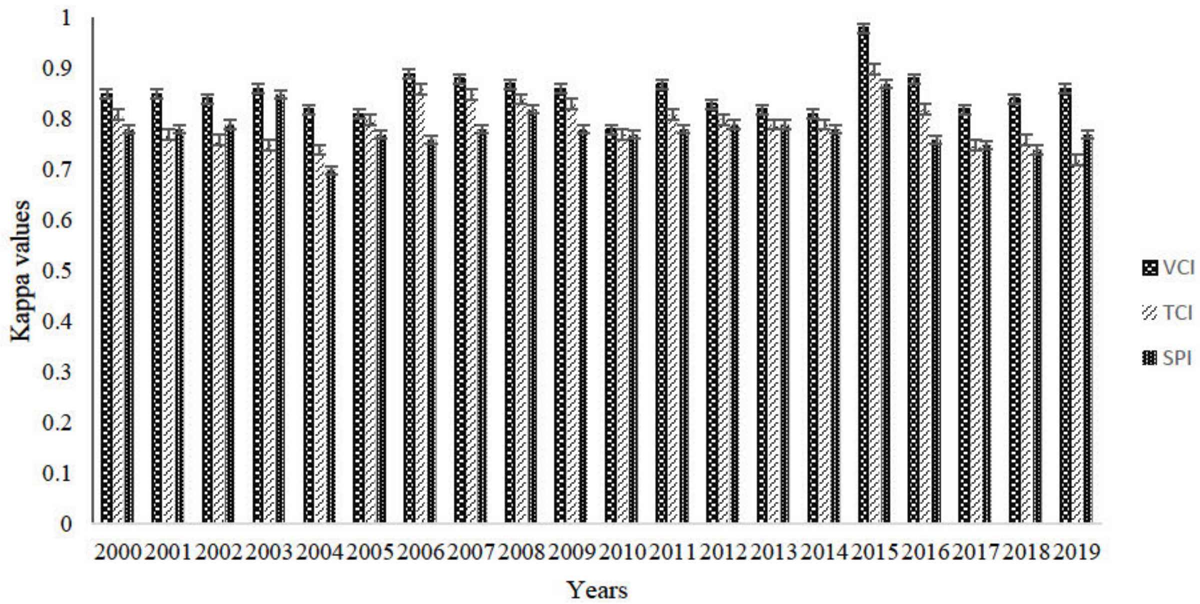

Figure 3. 7 Kappa statistic compares VegDRI vs (VCI, TCI and SPI) from 2000-to 2019. Error bars indicate 95% confidence intervals.

3.4. Discussion

The identification of bioclimatic zones characterised as water-stressed and with high rainfall variability is a pre-requisite to spatial and temporal variation analysis that can inform crop management strategies to improve food security in marginal lands of South Africa (Masih et al., 2014; Shiferaw et al., 2014; Baudoin et al., 2017). The mapped bioclimatic or agricultural risk areas produced by integrating VCI, TCI, and SPI drought indices indicate that South Africa can be classified into slight, moderate, and severe agricultural drought risk zones, respectively (Brown et al., 2013; Nam et al., 2018). The indices evaluated in this study provide options for identifying the severity and location but do not show the duration, onset, and cessation of drought conditions. The combination of VCI, TCI, and SPI allows us to detect drought in the agricultural areas of South Africa, and VegDRI was found to be more effective compared to other indices (Brown et al., 2014).

The relationships between SPI, TCI, VCI, and VegDRI against sorghum yield data evaluated bioclimatic areas under water stress and high rainfall variability. Under rainfed conditions, crop production is primarily a function of rainfall; crop failure is often associated with water deficit or agricultural drought (Consoli and Vanella, 2014). Thus, correlation analysis between VegDRI and average sorghum grain yield anomaly is indispensable for validation (Singh Choudhary et al., 2012; Jiao et al., 2019b; Möllmann et al., 2019). The overall fit of VegDRI (74.1%), VCI (71.8%), and TCI (66.2%) were slightly better than those obtained from SPI (59%) (Figure 3.7). The results were consistent with Estes et al. (2013), where maize yield was predicted using MODIS TCI and NDVI in South Africa.

Precipitation and water-related indices are closely related to meteorological drought, while vegetation-related indices, TCI, and SPI are more related to agricultural drought (Tadesse et al., 2017). The cultivated sorghum in South Africa is grown in the northern provinces' drier areas, which concur with mapped zones, especially in moderate to slight drought classes of generated indices (van der Merwe et al., 2016; Malobane et al., 2018). Therefore, VegDRI-based agricultural drought assessment can better capture agricultural drought conditions or areas under water stress. There was a relationship between sorghum yields and TCI, which implies that the index determines the stress on vegetation caused by temperatures and excessive wetness. The conditions from TCI are estimated relative to the maximum and minimum temperatures and modified to reflect different vegetation responses to heat. The correlation between TCI and sorghum district yields is lower than VegDRI and VCI because TCI has the potential for cloud contamination, especially from mid-January to April, which might reduce the surrogate of the index and sorghum (Suryabhagavan, 2017). Based on the results, the operational drought index for forecasting crop yields should be based on drought indicators at a higher frequency and less contamination by clouds (Park et al., 2016). The TCI and VCI indices have a higher correlation than SPI because VCI is provided at a maximum of 8-day frequency, whereas accumulated SPI is only available monthly, making it less surrogate to sorghum yields (Kogan, 1995; Tsiros et al., 2004). The VCI and TCI related to vegetation health give a better picture of characterising bioclimatic zone under water scarcity and rainfall variability than the drought index that only relies on rainfall SPI, mainly because vegetation-related indices inherently use the water balance to measure water balance crop performance (Jiao et al., 2019a).

The SPI scored the lowest correlation with sorghum yield because SPI was normalised and computed from only precipitation data. Therefore, drier and wetter climates can be represented similarly; thus, wet periods can also be monitored using the SPI (Adisa et al., 2019). SPI is a measure of water supply only and a widely used index to characterise meteorological drought on a range of timescales. Still, it does not account for evapotranspiration and crop water requirement (Mishra and Singh, 2011). This limits its ability to capture the effect of increased temperatures associated with climate change on water demand and the availability of crops. Alternative indices that deal with evapotranspiration, such as the Standardised Precipitation-Evapotranspiration Index (SPIE), can map the bioclimatic zones under water stress (Mishra and Singh, 2011). It must be stressed that the SPI is not suitable for climate change analysis because the temperature is not an input parameter (UNOOSA, 2019). Kappa values presented in figure 3.8 for VegDRI and VCI are very close to 1 compared to TCI and SPI. This indicates a very high agreement between the VegDRI and VCI. Weighted kappa values between 0.8 and 1 are generally accepted as having an excellent agreement between the raters; values falling below 0.8 may be considered less statistically significant (van Vliet et al., 2011; Pecchi et al., 2019). However, this high agreement between VegDRI vs VCI and VegDRI vs TCI does not necessarily indicate an accurate mapping of drought in South Africa (Moeletsi et al., 2013; Botai et al., 2019). The Kappa coefficient of agreement is a statistic for discrete multivariate analysis (van Vliet et al., 2011). It expresses the agreement between two categorical datasets corrected for the agreement as expected by chance, depending on the distribution of class sizes in both datasets. Therefore, the drought indices produced, especially the VegDRI, need to be ground-truthed.

The mapped bioclimatic zones with moderate to severe drought are the most water-stressed zones in South Africa (Aliber and Cousins, 2013). In these zones, compounding factors such as poverty and inappropriate land use increase vulnerability to drought. Also, smallholder farmers in these bioclimatic zones lack irrigation facilities to mitigate water stress effects (Cai et al., 2017). Each drought event's spatial and temporal variability makes preparing and responding effectively. In South Africa, agriculture is the most vulnerable and sensitive sector to climate variability and change, primarily manifest through rainfall variability and recurrent droughts (Nhamo et al., 2019a). Using satellite data as an input parameter for drought indices, spatial-temporal variation of seasonal agricultural drought patterns and severity can be detected and mapped with the help of remote sensing and GIS (Park et al., 2016).

The study used a machine-learning algorithm to analyse and mine higher spatial resolution climatic datasets to fill the gaps where climatic data was unavailable. Comparisons of CHIRPS data with available climatic records were used as a benchmark to determine the strengths and limitations of remotely sensed products. The in-situ data recorded through traditional rain gauges represent point-scale observations, which are not representative of the area-averaged precipitation (Table 3.5). Precipitation from infrared and microwave-based algorithms also has limitations due to terrain and wet and dry regional climates (Dinku et al., 2018). The analysis of climatic data depends on its distribution pattern, especially in marginal areas. Schwarz et al. (2020) higher spatial resolution datasets must be considered to generate drought-related risk maps in agriculture. The choice of a rainfall product can significantly influence the performance of such applications(Le Coz and Van De Giesen, 2020). However, the study used CHIRPS datasets to evaluate or compare rainfall products over different parts of South Africa. In SA, rainfall products from gauge-only, satellite-based, and radar are recommended. In addition, the use of global rainfall products such as the African Rainfall Climatology version 2 (ARC2), the Rainfall Estimate version 2 (RFE2), and the Tropical Applications of Meteorology Using Satellite Data and Ground-Based Observations (TAMSAT) African Rainfall Climatology and Time Series (TARCAT) need to be compared with CHIRPS datasets (Le Coz and Van De Giesen, 2020). The availability of global meteorological products will help advance studies on lesser common research areas where data is still scarce.

The results show that VegDRI can delineate bioclimatic zones under stress and high rainfall variability (Brown et al., 2014). The South Africa VegDRI map can be used with traditional drought indicators (VCI, TCI, and SPI) to inform various management decisions, such as crop selection within bioclimatic zones, justifying disaster management actions, and identifying potential risks zones for livestock production, and assessing fire risk zones. However, the interpretation of our results relative to climate change is limited because we used a historical data set (1981-2019). Future studies should use data from global circulation models (GCMs) to inform climate change scenarios more specifically. However, the current maps remain helpful in informing the areas currently classified as water-stressed and with high rainfall variability for sustainable intensification management strategies. It is essential to ground truth in the mapped bioclimatic zones and validate and operationalize the results. It is important to note that drought impacts can be as varied as their causes. Results from this study highlight the potential for the use of a hybrid index, the VegDRI, in agricultural decision support systems such as drought risk maps for agricultural drought early warning systems, crop yield forecasting models, and water resource management tools

3.5. Limitations

Using biophysical factors, our methodology assessed bioclimatic zones under water stress and high rainfall variability. Such impacts depend on the socio-economic context in which drought occurs, regarding who or what is exposed to the drought and the specific vulnerabilities of the detected entities. Therefore, there is a need to identify innovative ways to derive maximum value from the possible integration of GIS with block-chain and the Internet of Things (IoT) technologies to integrate socio-economic factors. Machine learning and deep learning algorithms can predict and forecast complex local drought conditions. Features of both nonlinearity and unstableness usually characterize drought time series; there is a need to evaluate different deep learning algorithms in mapping drought risk zones in the SSA region. In addition, the drought indices were assessed only against the district sorghum average yields instead of other drought tolerance crops. Input data for calculating the VegDRI and statistics from the sorghum crop are independent and from different sources. However, that did not prevent us from obtaining strong correlations between VegDRI and sorghum district average yields. This makes it possible to say that the VegDRI is a good indicator of agricultural drought and can be used to detect drought-prone zones in South Africa.

The study used Kappa to measure the agreements of dry zones and areas where sorghum is grown in South Africa despite practical applications of the index in remote sensing (Pontius and Millones, 2011). The kappa values represent the level of agreement of two datasets corrected by chance. There is a large difference between Kappa and overall accuracy in that one of the classes (class 1) accounts for the large majority of the map. The kappa statistic controls only those instances that may have been correctly classified by chance (Pecchi et al., 2019). This can be calculated using both the observed (total) and the random accuracy. Kappa can be calculated as Kappa = (total accuracy – random accuracy) / (1- random accuracy) (Pontius and Millones, 2011). As propounded by Pontius and Millones (2011), Kappa indices are misleading and/or flawed for practical applications. According to Pontius & Millones (2011) Kappa index is a ratio that can introduce calculation and interpretation problems, and the indices attempt to compare observed accuracy relative to a baseline of accuracy expected due to randomness. He goes on to say that Kappa indices offer useful information because the Kappa indices attempt to compare accuracy to a baseline of randomness, but randomness is not a reasonable alternative for map construction.

3.6. Implications of the drought risk maps for crop production

The agricultural drought risk maps generated help guide decision-making on drought mitigation and adaptation using the integrated climate risk management approach using the R4 framework; (Risk reduction); insurance (Risk transfer); livelihoods diversification and microcredit (prudent Risk-taking); and savings (Risk reserves) (Andersson-Sköld et al., 2015; Gopichandran et al., 2016). The R4 framework enables vulnerable farmers to adapt to climate risks by adopting appropriate sustainable intensification and climate-smart strategies through its innovative nature. The generated maps are useful to farmers, agronomists in extension, researchers, non-governmental organisations (NGOs), the private sector such as insurance companies, and banks to develop drought resilience strategies (Table 3.6). Additionally, the generated maps can help increase the value and relevance of information available to decision-makers, enhancing and supporting drought response and mitigation activities. The information generated from drought indices in accessible formats such as maps generated and trend analysis increases the value and relevancy of drought to support drought response and mitigation activities in marginal areas (Park et al., 2016). Drought risk mapping is a critical element of drought management. It helps identify the most prone areas to droughts, allowing policy-makers and agriculturists to plan and give guided recommendations to improve agriculture production sustainably (Shiferaw et al., 2014).

Table 3. 6 Resilience strategies and usefulness of maps generated in crop production

Strategy	Key findings	Specific use	Proposed adaptation and mitigation strategies	Recommendations
1. Risk reduction	Identified drought-prone areas and areas with low risk	• To indicate where drought-tolerant crops such as NUS can be promoted as alternative crop choices • To understand the regions within South Africa which are at greater risk of drought hazard	• To inform site-specific crop diversification recommendations as a sustainable intensification strategy • Investing in climate risk assets such as the construction of dams and irrigation facilities • Mainstreaming weather information into agricultural extension support using bulletins to guide preparedness efforts • Crop diversification at a spatial and temporal scale • Ex- and in-situ rainwater harvesting and conservation techniques	• A higher spatial resolution VegDRI would be more applicable for local-scale monitoring and decision • Climate scenarios should be included to allow for more proactive agricultural planning • Researchers need to consider the inclusion of socio-economic parameters in delineating drought risk zones
		• Early warning action	• Maps can be used as a base for monitoring, assessing, and	• Gridded climatic need to be validated with locally generated

			forecasting the likelihood of drought and wet spells in high-risk areas	datasets (South Africa Weather Service)
		Promoting green zones for climate action in agriculture	• Promote tolerance crops such as NUS in dry regions to gain agro-ecosystem services and improve food security in marginal lands	
2. Risk Transfer	Refined maps of where the risk of drought is low or high	• Weather index insurance • Area yield index insurance	• Insuring smallholder farmers from drought	• Maps work as a base map for drought monitoring and initiate weather index claims for insurance companies like Africa Risk Capacity (ARC),
3. Risk Prudence and Reserves		• Sustainable transformation of existing farming systems	• Livelihood diversification, such as livestock production • Access to microcredit to promote alternative productions that are less vulnerable • Saving and lending groups to caution against hazards.	• Diversification of crop-livestock systems to spread the risk (intercropping, rearing small livestock, market gardening, and promotion of NUS to complement major crops to improve food and nutrition in marginal lands
4. Policy	The arable land constitutes	• Evidence-based	• To generate policies that	• Harmonisation of existing

and funding context	16% of extreme/very severe, 34%-severe, 38%- moderate, 11%-slight, and 1%-no drought conditions in South Africa.	policy formulation	support good agricultural practices	policies and institutes that speak to land, environment, agriculture, and health

3.7. Conclusions

This study used CART, a machine learning algorithm. We established drought indices, SPI, TCI, and VCI, to generate a hybrid drought index VegDRI to characterize bioclimatic zones with high rainfall variability and water scarcity in South Africa. VegDRI characterised water-stressed bioclimatic zones with high rainfall variability better than the established drought indices. The VegDRI approach can be adapted for other regions in sub-Saharan Africa using available climate, satellite, and biophysical data. It can be applied to any vegetated area where remote sensing data are accessible even with limited in situ data availability. However, to improve its accuracy and applicability future research can incorporate hydrology, soil water, evapotranspiration, and socio-economic factors to delineate bioclimatic zones with high rainfall variability and water scarcity to improve drought management. The predictive accuracy of drought risk maps is computed from the cell-by-cell comparison. However, the absolute value of the Kappa coefficient depends on input data used to delineate drought indices. However, the high agreement of VegDRI with VCI and TCI does not necessarily indicate an accurate mapping of drought risk maps. Ground truthing is recommended to validate the new VegDRI map in South Africa. The adjusted maps can show homogenous areas with similar water requirements for crop production in marginal areas of South Africa. The results from this study highlight the potential for using a hybrid index, the VegDRI, in agricultural decision support systems such as drought risk maps for agricultural drought early warning systems, crop yield forecasting models, or water resource management tools.

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CHAPTER 4: MULTI-CRITERIA SUITABILITY ANALYSIS FOR NEGLECTED AND UNDERUTILISED CROP SPECIES IN SOUTH AFRICA

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Abstract: Several neglected and underutilised species (NUS) provide solutions to climate change and create a Zero Hunger world, the Sustainable Development Goal 2. Several NUS are drought and heat stress-tolerant, making them ideal for improving marginalised cropping systems in drought-prone areas. However, current crop suitability maps do not include them as crop choices due to their status as NUS. This study aimed to develop land suitability maps for selected NUS [sorghum, (*Sorghum bicolor*), cowpea (*Vigna unguiculata*), amaranth and taro (*Colocasia esculenta*)] using Analytic Hierarchy Process (AHP) in ArcGIS. Weighted Overlay Analysis overlaid multidisciplinary factors from climatic, soil and landscape, socio-economic and technical indicators. Validation was done through field visits, and the area under the curve (AUC) was used to measure AHP model performance. The results indicated that sorghum was highly suitable (S1) = 2%, moderately suitable (S2) = 61%, marginally suitable (S3) = 33%, and unsuitable (N1) = 4%, cowpea S1= 3%, S2 = 56%, S3 = 39%, N1 = 2%, amaranth S1 = 8%, S2 = 81%, S3 = 11%, and taro S1 = 0.4 %, S2 = 28%, S3 = 64%, N1 = 7%, of calculated arable land of SA (12 655 859 ha). Overall, the validation showed that the mapping exercises exhibited a high degree of accuracies (i.e., sorghum AUC = 0.87, cowpea AUC = 0.88, amaranth AUC = 0.95 and taro AUC = 0.82). Rainfall was the most critical variable and criteria with the highest impact on land suitability of the NUS. This study suggests that South Africa has a huge potential for NUS production. The maps developed can contribute to evidence-based and site-specific recommendations for NUS and their mainstreaming. Also, the maps can be used to design appropriate production guidelines and support existing policy frameworks that advocate for sustainable intensification of marginalised cropping systems through increased crop diversity and stress-tolerant food crops.

Keywords: AHP, Food and nutrition security GIS; Land suitability analysis; Marginal areas

4.1. Introduction

The world is challenged by the need to feed a growing population with healthy food while minimising the negative impacts on the environment and adapting to changing climate (de la Hey and Beinart, 2017). Despite the importance of smallholder agriculture to global food production and poverty reduction (Garrity et al., 2010), there has been a decline in the level of agricultural production in the sub-Saharan Africa (SSA) region (Hardy et al., 2011). More so, in South Africa (SA), the contribution of agriculture to household food consumption among smallholder farmers continues to fall (de la Hey and Beinart, 2017). It is understood that inherent water scarcity, exacerbated by climate variability and changes in land use, has contributed to reduced land available for agricultural expansion to produce major crops, especially in resource-poor farming systems (World Bank and Statistics SA, 2018). Agriculture requires innovative approaches that address food and nutrition security and environmental degradation, adapt to climate variability, and plan land use. Sustainable intensification of smallholder food production systems is considered essential to meeting the United Nations Sustainable Development Goals 1 (poverty eradication) and 2 (zero hunger) (Shumsky et al., 2014). There is a need to introduce and promote practices that fit "into" or "with" current smallholder production systems while complementing existing efforts to improve resilience to climate variability and change as well as intensifying productivity for sustainable food and nutrition security (Mabhaudhi et al., 2019).

Neglected and underutilised crop species are an option for redressing food and nutrition challenges faced in marginalised communities (Baldermann et al., 2016). These crops are native to specific areas in geological time (Raihana et al., 2015) and are known to be suitable in marginal areas characterised by severe dry spells and flash floods (Massawe et al., 2016). Across the world, several research initiatives examined the mechanisms that allow for stress adaptation within a range of NUS (Hermann et al., 2013; Mabhaudhi et al., 2014a; Chimonyo et al., 2016a). For instance, in SA, Chibarabada et al. (2020) modelled the productivity of ground nuts under water deficit conditions; in Malaysia, Peter et al. (Gregory et al., 2019) examined the adoption of underutilised crops, while Ebert (2014) from Taiwan, assessed the potential of underutilized traditional vegetables and legume crops in contributing to food and nutritional security. These studies illustrate that, while NUS may be well adapted to multiple stress conditions, they are grown in geographical pockets that are often far from where they could provide the most positive contribution to food and nutrition security (Massawe et al., 2016). The lack of scientific evidence has resulted in the slow promotion of NUS into existing food systems, whether formal or informal (Mabhaudhi et al., 2018). For example, it is known that sorghum is a nutrient-packed grain. It is rich in vitamins and minerals like magnesium, potassium, phosphorus, iron, and zinc compared to maize (Stefoska-Needham et al., 2015). South Africa produced, on average, 225 000 tons of sorghum per annum, only about 3% and 12% of the size of the average domestic maize and wheat crops, respectively (DAFF, 2020). However, it imports an additional 50 000 tons to meet demand. As such, policy frameworks on agriculture, health and environment continue to remain silent on the potential use of NUS in contributing towards increasing adaptation of marginalised agricultural systems to climate risks. In addition, little mentioned about their contribution towards good health as well as nutrition and rehabilitation of degraded agricultural lands. As such, information detailing the suitability of NUS is essential if they are to be recognised as a sustainable and plausible option for contributing towards the sustainable development and improved resilience of marginalised farming communities (Boatemaa et al., 2019).

Land suitability analysis assesses the appropriateness of crops to a specific practice or land use (Ziadat, 2007). Specifically, land suitability evaluates land capability and other factors such as land quality, land ownership, customer demand, economic values, and road proximity (Malczewski, 2006a). Multi-criteria decision making (MCDM), also referred to as, Multi-criteria decision analysis (MCDA), can be used to define land potential to solve complex problems of land-use and land-use changes(Rabia et al., 2013; Zabel et al., 2014; Nguyen et al., 2015). Multi-criteria decision-analysis methodologies can overcome problems related to vagueness in definition and other uncertainties, especially in the context of NUS suitability analysis (Ranjitkar et al., 2016). Land suitability analysis can be done using geographic information system-based MCDM to identify suitable areas for cultivating NUS. To improve the interpretations of MCDA, Saaty (1980) introduced the Analytic Hierarchy Process (AHP) as a method to capture aspects of a decision in both a subjective and objective manner to reduce confounding (Romano et al., 2015; Singha and Swain, 2016). The AHP methodology provides scope for combining expert opinions with numerical predictions from biophysical models to provide an integrated approach to resource management (Chen and Paydar, 2012; Saaty, 2016). Similar agricultural techniques have been used to identify land suitable for agricultural land reform (Musakwa, 2018). Kazemi and Akinci (2018) for rain-fed wheat, Zabihi et al. (2015) for citrus, Kihoro et al. (2013) for rice in Kenya, and Benke and Pelizaro (2010) for wheat and rye-grass production.

Currently, the mapping of South Africa's rain-fed agricultural land use is for a few major cash crops such as maize, sugar cane, and soybean. The few crops reflect the current lack of agro-biodiversity, which culminates in increased sensitivity of agriculture to climate risks (Kepe and Tessaro, 2014). An example is the 2015/16 ENSO drought that caused South Africa to import more than 30% of its annual cereal grain requirements due to poor harvests. In general, NUS are hypothesised to be suitable for marginal agro-ecologies (Mabhaudhi et al., 2019) and can help increase the resilience of rain-fed cropping systems in the wake of climate variability and change. In current and future environments, NUS have the potential to contribute to improving rural livelihoods and maybe a "better bet" technology; however, this potential remains largely untapped due to limited information detailing their genetic, eco-physiological and agronomic performance (Chivenge et al., 2015). In this regard, NUS can offer ecologically viable options for increasing agriculture productivity, especially in marginal areas, as they are locally adapted and would not strain the environment further (Chivenge et al., 2015). Therefore, promoting indigenous crops such as sorghum (*Sorghum bicolor*), cowpea (*Vigna unguiculata*), and taro (*Colocasia esculenta*) is integral to ensuring that households consume more diversely diets (Thow et al., 2018). In Chapter 3 we outlined the drought prone areas it would be interesting to see if NUS are truly suited to these areas. Mapping NUS production potential zones in SA will help inform the decision on where NUS can be promoted as part of the crop choice, assist decision-makers in formulating policies with a sustainable intensification concept and then create markets for NUS, which will enhance food and nutrition security. Therefore, the main objective of the research is to identify potential areas suitable for sorghum-cowpea, taro, and amaranth- using a GIS-based MCDA-AHP.

4.2. Methodology

4.2.1 Multi-criteria decision analysis (MCDA) approach

Crop suitability is a function of crop requirements and land characteristics; therefore, matching the land characteristics with the crop growth requirements gives the suitability (Han and Chen, 2018). Suitability analysis has to be carried out so that farming systems and local needs are reflected well in the final decisions (Reshmidevi et al., 2009). There are several land suitability analysis (LSA) methods, but there is no consensus on the best method for crop suitability analysis. A scoping review from this study evaluated methodological strategies for LSA, which would be suitable for neglected and underutilised crop species (NUS). The review classified LSA methods reported in articles as traditional (26.6%) and modern (63.4%). Modern approaches, including Multi-Criteria Decision Making (MCDM) methods such as Analytical

Hierarchy Process (AHP) (14.9%) and Fuzzy methods (12.9%); crop simulation models (9.9%), and machine learning-related methods (25.7%), are gaining popularity over traditional methods. The MCDM methods, namely AHP and fuzzy, are commonly applied to LSA while crop models and machine learning-related methods are gaining popularity. The MCDA combines qualitative and quantitative criteria while specifying the degree and nature of the relationships between those criteria to support spatial decision-making (Malczewski, 2004).

Evaluating land suitability for a specific purpose requires a comprehensive analysis of natural and socio-economic factors influencing the land (Mendoza and Martins, 2006; Raza et al., 2018). The elements used can be divided into high and lower factors based on experts' opinion weights (Zabihi et al., 2015). High-level factors in crop suitability analysis are natural or biophysical factors that directly affect the growth of crops, for example, rainfall, temperature and soil fertility. The lower level factors are social and economic factors which indirectly affect crop growth but influence land use degree of appropriateness to a purpose (Yi and Wang, 2013). The interactions, dependencies and feedback between higher and lower-level elements form a multi-criteria land evaluation approach for sustainable NUS production. Figure 4.1 presents a conceptual framework for developing NUS Cropland suitability maps using GIS.

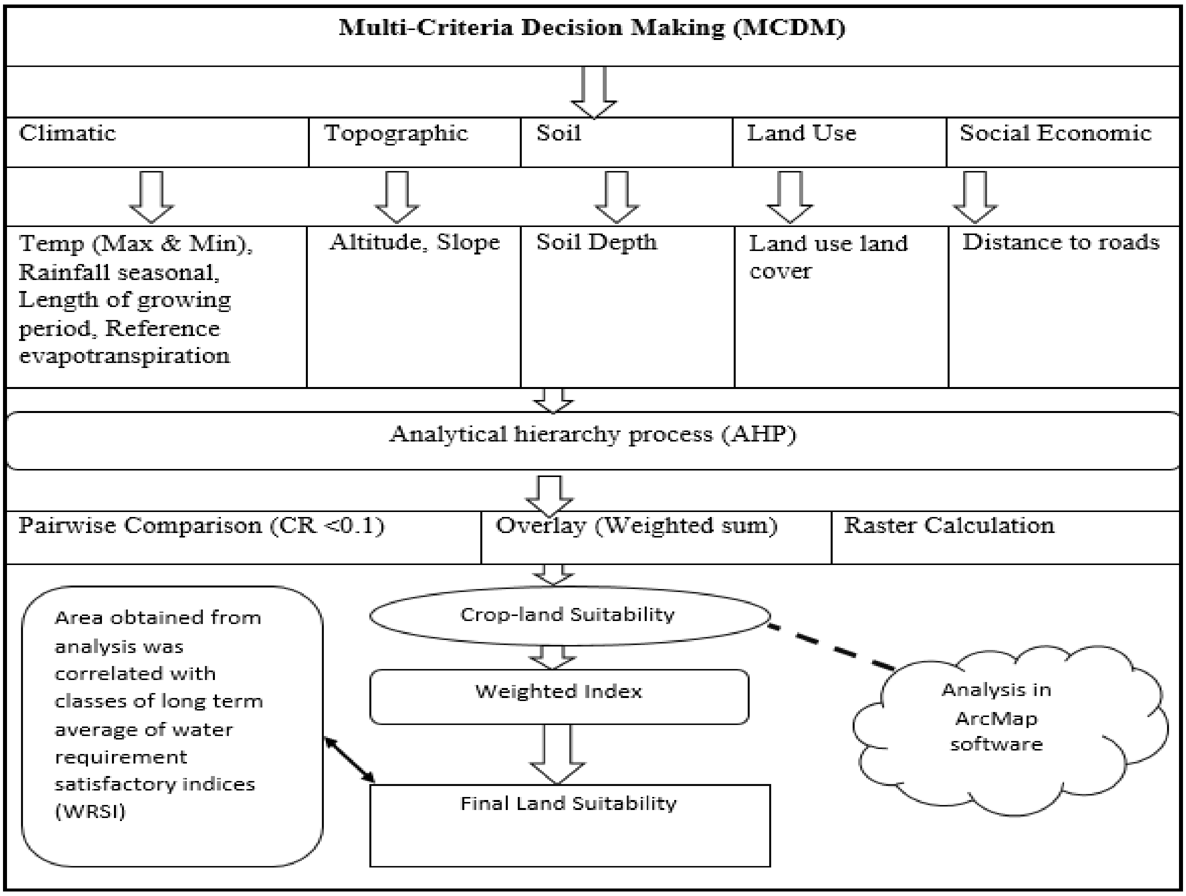

Figure 4. 1 A framework used to compute suitability maps for neglected and underutilised crop species in South Africa.

The general land use suitability model is:

$$S\,(a1\ldots,an) = \sum_{j=1}^{n} wjbj. \qquad Equation\,4.\text{Error! Reference source not found.}$$

where S ($a_{1\ldots,}$ a_n) is the suitability measure, and b_j is the j^{th} largest of the a1 factors affecting the suitability of the sites (Jeong et al., 2014; Romano et al., 2015). A weighted average is an average where each observation in the data set is multiplied by a predetermined weight before calculating equation 1 (Nzeyimana et al., 2014). The ordered weighted averaging (OWA) operator is a non-linear operator due to the process of determining the bj, which was achieved by choosing different weights to implement different aggregation operators' equation 4.1.

4.2.2 Data sources

For this study, data were obtained from the South African Quaternary Catchments database (Table 4.1). The multidisciplinary data was grouped into climatic, soil and landscape attributes, social-economic and technical indicators. Nine parameters were used, including five climatic, three soil, and one social parameters (Table 4.1). High-resolution climatic parameters were derived from 1950 to 2000, a 51-year time series of continuous daily data from selected 1 946 stations in Quaternary Catchments covering South Africa (Schulze, 2002). The Water Research Commission developed the datasets and funded a project titled "Mapping the Mean Annual Precipitation and Other Rainfall Statistics" (Smithers and Schulze, 2000). The spatial resolution of climatic data was one arc minute; this implies that one grid is represented as 1.7 x 1.7 km. Lynch (2004) calculated monthly precipitation using a geographically weighted regression method, and monthly means of daily average temperatures were derived (Lynch, 2004). Abrams (Abrams, 2018) indicated that over 70% of South African food production is rain-fed. In South Africa, only 1,5% of the land is under irrigation, producing approximately 30% of the country's crops. Therefore, all climatic parameters were calculated using the rainy season and not annual data. Wet periods can be calculated from daily precipitation events like the start, dry spells, and end of the season. In SA, precipitation is undoubtedly the dominating factor determining crop production, especially in marginal areas where irrigation facilities are limited for smallholder farmers (Tibesigwa et al., 2017).

Table 4. 1 Factors used to delineate land suitability maps for neglected and nderutilised crop species

Factors	Source
Climate-related factors	
Precipitation (mm) 1.7 km resolution	South African Quaternary Catchments database- Water Research Commission
Temperature 1.7 km resolution	South African Quaternary Catchments database- Water Research Commission
Reference crop evapotranspiration (ETo) millimetres (mm) or (lm^{-2}) 1.7 km resolution	South African Quaternary Catchments database- Water Research Commission
Length of growing period (LGP) 1.7 km resolution	South African Quaternary Catchments database- Water Research Commission
Water Requirement Satisfaction Index (WRSI)-at 10 km resolution	Fewsnet https://earlywarning.usgs.gov/fews
Soil and landscape attributes used to delineate land suitability maps for neglected and underutilised crop species	
Soil depth at 250 m resolution	South African Quaternary Catchments database- Water Research Commission
Elevation (mm) 30 m resolution	http://earthexplorer.usgs.gov
Slope	South African Quaternary Catchments database- Water Research Commission
Social and economic factors are used to delineate land suitability maps for NUS.	
Distance from road/accessibility	South African Quaternary Catchments database- Water Research Commission

A full description of each parameter is explained in the S1_Appendix.docx.

All thematic variables used in this study were converted to raster layers. Before the analysis, all thematic layers were resampled into the World Geodetic System 1984 (WGS84) geo-referencing system (Macomber, 1984). The resolution of finer grid layers was resampled to 1.7km resolution of climatic factors. All the transformations of the GIS layers were done in ArcGIS.

4.2.3 Analytic Hierarchy Process (AHP)

The analytic hierarchy process (AHP) is the most widely accepted method and is considered by many the most robust MCDA (Kaim et al., 2018). The AHP helps capture subjective and objective aspects of a decision by reducing complex decisions to pairwise comparisons and synthesising the results (Nguyen et al., 2015). Since AHP considers a set of evaluation criteria and a set of alternative options among which the best decision is to be made, a 9-point scale measurement was used in this study (Table 4.2). This study used the AHP calculator to calculate weights (Nasrollahi et al., 2017). The assignments of weights were based on information from literature, as well as the team's local knowledge and expert consultation (soil scientist, GIS and remote sensing specialists from the University of KwaZulu Natal) (Table 4.3).

Table 4. 2 The fundamentals for pairwise comparison (Saaty, 1990)

Intensity of importance	Definition	Explanation
1	equal importance	Two activities contribute equally to the objective
3	moderate importance of one over another	Experience and judgment slightly favour one activity over another
5	the strong or essential importance	Experience and judgment strongly favour one activity over another
7	very strong or demonstrated importance	Activity is strongly favoured, and its dominance showed in practice
9	extreme importance	The evidence favouring one activity over another is of the highest possible order of affirmation
2,4,6 and 8	Even numbers represent intermediate values between the two adjacent judgements	When compromise is needed

Factor weights were calculated by comparing two factors together at a time. The AHP weights were calculated using Microsoft Excel. Table 4.3 shows a pairwise comparison matrix for the research

Table 4. 3 Pairwise comparison matrix

Factors	Rainfall	Temp	ET_o	LGP	Elevation	Slope	LULC	Soil Depth	Distance to Road	Weight
Rainfall	1	2	2	2	5	5	3	2	9	0.24
Temp	1/2	1	2	3	3	3	3	2	8	0.18
ET_o	1/2	1/2	1	1/3	5	3	3	2	5	0.13
LGP	1/2	1/3	3	1	5	3	3	3	5	0.17
Elevation	1/5	1/3	1/5	1/5	1	2	1/2	1/2	2	0.04
Slope	1/5	1/3	1/3	1/3	2	1	2	2	5	0.08
LULC	1/3	1/3	1/3	1/3	2	1/2	1	1/2	3	0.06
Soil Depth	1/2	1/2	1/2	1/3	2	1/2	2	1	5	0.08
Distance from road	1/9	1/8	1/5	1/5	1/2	1/5	1/3	1/5	1	0.02

Maximum eigenvalue (λmax) = 9.6082, n=9, Consistency index $(CI) = (\lambda max - n)/(n - 1)$*=0.07602, Random index (RI) = 1.45, Consistency Ratio* $(CR) = CI/RI$*=0.052428*

The pairwise comparisons in the AHP were determined according to the scale introduced by Saaty, (1980). These scales had values from 9 to 1/9. A rating of 9 indicates that concerning the column factor, the row factor is more important. On the other hand, a rating of 1/9 indicates that the row factor is less important relative to the column factor. In cases where the column and row factors are equally important, they have a rating value of 1. Through the pairwise comparison matrix, the AHP calculates the weighting for each criterion by taking the Eigenvector corresponding to the largest Eigenvalue of the matrix and then normalising the sum of the components to unity (Chandio et al., 2013). The ratio scales were derived from the principal Eigenvectors, and the consistency index was derived from the principal Eigenvalue. An eigenvalue is a number which explains how much variance is spread out (Ceballos-Silva and López-Blanco, 2003). According to Brandt et al. (2017) and (Feng et al. (2017), the AHP is subjective; deriving weights depends on human expertise. The inconsistency can be improved by:

- Deriving a pairwise matrix based on a scientific objective in a non-scare data situation (Alexander and Benjamin, 2012),
- Estimating the relative importance of factors individually and based more on scientists' opinions through informal interviews with key informants like a ministry of Agriculture (Akinci et al., 2013) and
- Giving attention to an upper limit, the upper limit is a consistency ratio (CR) that must be less than 0.1 for a pairwise matrix judgment to be accepted (Milad Aburas et al., 2015). To minimise the interrelationship among various factors included in the AHP approach, data reduction method such as Ordered Weighted Averaging (OWA) was used (Jelokhani-Niaraki and Malczewski, 2015). The weighted linear combination allows the variability of continuous and discrete factors to be retained and standardised to a standard numeric range (Romano et al., 2015).

4.2.3.1 Fitting neglected and underutilised crop species in ecophysiology based on drought-tolerance characteristics

Agro-climatic indices were calculated to crop growth requirements to fit NUS in an environment (Table 4.4). The dynamic consideration of crop phenology allows for assessing agro-climate factors' effects on NUS's phenological development. The overall suitability was estimated based on Liebig's law of the minimum (Mesgaran et al., 2017). Liebig's Law of the minimum provides a flexible framework to assess the climate suitability of crops in a situation where the crop suitability is subjected to imprecision and vagueness, or the pairwise comparisons are subjective, especially when fuzzy was used to classify NUS (Kazemi and Akinci, 2018; Ugbaje et al., 2019). It is based on three mathematical functions; the equations transform each variable to a suitability value varying from -1 (unsuitable) to 1 (optimum or highly suitable). Liebig's Law of the minimum is the outcome of AHP using the minimum t-norm between variables (Kim et al., 2018). The mathematical expression for this type of relationship was formulated as follows.

$$S(V) = \begin{matrix} 0 \\ \frac{\{V - Vmin\}}{\{Vol - Vmin\}} \\ 1 \end{matrix} if\ V \leq Vmin;\ if\ Vmin < V < Vol;\ if\ V \geq Vol \quad Equation\ 4.2$$

Where S (V) is the suitability index as a function of the individual variable; V is the parameter; V_{min} indicates the minimum value of V required for crop growth; Vol is the lowest optimum value of V at or beyond the highest suitability can be obtained.

In general, an increase in precipitation increases the suitability of crops in semi-arid regions. Based on the water use of a crop, the lower limit of precipitation was used to delineate an area suitable for a crop; for example, 111 mm per year was used for amaranth (Table 4.4). According to FAO (2004), a minimum of 500 mm of rainfall per year is required to achieve reasonable economic yields; therefore, we used 500 mm as the upper threshold in our stepwise function (Steduto et al., 2012). Some variable like the terrain is inversely correlated with growth suitability (Table 4.4); the following criterion was used to mark the suitability of NUS.

$$S(V) = \begin{matrix} 1 \\ \frac{\{Vmax - V\}}{\{Vmax - Vou\}} \\ 0 \end{matrix} if\ V \leq Vou;\ if\ Vou < V < Vmax;\ if\ V \geq Vmax \qquad Equation\ 3$$

Where V_{max} is the maximum value of variable V beyond which no cropping is possible, Vou is the uppermost optimum value of V for cropping. In all areas with 0 to 5% slope has no limitation about the steepness and above 5%- optimal upper bound (Vou) field tends to have challenges in using have machines.

Table 4. 4 Characteristics of sorghum (Chimonyo et al., 2016b), cowpea(Chimonyo et al., 2016b), taro (Mabhaudhi et al., 2014a) and amaranth (Nyathi et al., 2018)

	Sorghum (*Sorghum bicolor*)	Cowpea (*Vigna unguiculata*)	Taro (*Colocasia esculenta*)	Amaranth- (*Amaranthus*)
Water use (mm)	261 - 415	133 - 265	800– 1 288	111 - 448
Precipitation per agricultural season (mm)	450 - 800	400-700	800– 2000	400-650
Time to maturity (Days)	100 - 120	90 - 150	240 - 300	20 - 45
Temperature range (C) in a growing season.	26-30	25-30	25-32	18-30
Yield (kg ha^{-1})	2 802 - 4 304	776 - 1 120	3 830- 17 330	3 400 -5 200

4.2.4 Qualitative land suitability classification

This study used five different FAO land suitability framework classes to quantify the magnitude of suitability for NUS within South Africa (Table 4.5). It classified the land into five suitability classes: land suitability orders, land suitability classes, land suitability sub-classes and land suitability units (Cools et al., 2003). In FAO, orders indicate lands suitable for crops (S) or not suitable for crops (N) while classes show the degree of land suitability, such as (S1) highly suitable, (S2) moderately suitable, (S3) marginally suitable, (N1) currently not suitable and (N2) permanently not suitable, and then subclass explains limitations. The classification designates a single-use index as best on each land unit (Fontes et al., 2009).

Table 4. 5 Suitability indices for the different suitability classes (FAO, 2012).

Suitability Class	Suitability index (SI)	Description Class
S1	Highly suitable (>80)	Land has no limitations for a given use or constraints that do not reduce the productivity and benefits appreciably, with no need for a high level of input
S2	Moderately suitable (60-80)	Land having minor limitations that could reduce productivity or benefits, additive inputs are required to reach the same yield as that of class S1
S3	Marginally suitable (45-59)	Land having moderate limitations for a particular use, in which the amount of surplus input is only marginally justified
N1	Currently unsuitable (30-44)	Land with severe limitations for land use under consideration. Every sustainable use is precluded, and the costs for correction are unacceptable with the existing

		condition. Only new technologies could improve land productivity
N2	Permanently unsuitable (<30)	Land-use type under analysis is not acceptable at all for the land.

4.2.5 Validation of cropland suitability

The validation data was gathered through field surveys in KwaZulu Natal between the 1st of October and the 21st of November 2019. A total of 60 GPS locations of taro, amaranth, sorghum and cowpea were randomly collected during the survey. The GPS locations were measured at the centre of an identified field. The GPS locations were captured in excel, and GPS locations were converted to a point map in a GIS. The crop presence was captured as one of the attribute tables. Six hundred points were randomly generated in a GIS across South Africa. These points represent the crops' absence (value 0). We used a ratio of 1:10 between known present points to pseudo-absence; hence, 600 pseudo-absence points were generated (Tshabalala et al., 2019). These two-point maps were merged into one layer, overlaid with the MCDM/AHP-derived suitability maps. A new table containing the presence and absence and the crop suitability information was produced and exported as an excel spreadsheet. This data was then used to measure the magnitude of agreement between the generated NUS suitability maps and the field-measured locations of crops using the receiver operating characteristic (ROC), and the area under the curve (AUC) derived based on the logistic regression. Each crop's accuracy assessment using the logistic regression analysis was carried out with R version 3.6.1 (R Core Team 2019, 2019) using the ‘RATTLE’ package (Williams, 2011). The ROC plot has an x-axis indicating the false-positive error rate, which signifies a wrong prediction by the model. The y-axis shows the positive rate, indicating a correct prediction by the model (Williams, 2011). An AUC value that is less than or equal to 0.5 indicates a random prediction, while AUC values higher than 0.5 and closer to 1 indicate a better prediction by the model (Jiménez-Valverde, 2012; Senay and Worner, 2019). The composite operator helps illustrate how well two layers or maps agree regarding how the categories are clustered spatially.

The magnitude of dryness of classes by correlating the NUS land suitability index and the mean average of the Water Requirement Satisfaction Index (WRSI) from 1981 to 2017 from the Famine Early Warning Systems Network (FEWSNET). The spatially explicit water requirement satisfaction index (WRSI*) indicates crop performance based on water availability to the crop during a growing season (Singh Rawat et al., 2019). The water requirement satisfaction index is the ratio of seasonal actual crop evapotranspiration (AET_c) to the seasonal crop water requirement, which is the same as the potential crop evapotranspiration (PET_c) (Singh Rawat et al., 2019). Potential crop evapotranspiration denotes crop-specific potential evapotranspiration after an adjustment is made to the reference crop potential evapotranspiration (PET) using appropriate crop coefficients (K_c). Crop coefficient values define the FAO developed the water use pattern of a crop WRSI, and FEWSNET mostly uses it to monitor and investigate maize production in agricultural drought-prone parts of the world. The WRSI is an indicator of crop performance based on water availability to the crop during a growing season (Singh Rawat et al., 2019). The classes of WRSI are crop failure- less than 49%, Poor-50-79%, average-80-94, and good-95-100%.

4.3. Results

4.3.1 Sorghum land suitability map

Figure 4.2 presents the analysis of the suitability of sorghum-based on MCDA-AHP and OWA operators. These results show the existing distribution of the land suitability classes, excluding areas where present land use is nature conservation, plantation, urban and water. Results indicated that about 2% of the land is highly suitable (S1) to produce sorghum. Moderately suitable (S2) land constitutes the most substantial proportion (61%) of the calculated arable land of South Africa (12 655 859 ha), while marginally suitable (S3) and unsuitable (N1) constitute 33% and 4%, respectively, of calculated arable land (Figure 4.2). Large areas of suitable (S1 and S2) land were concentrated in eastern provinces, and suitability intensity decreased in western provinces (Figure 4.2). A total of 60 GPS locations were used to confirm the presence of sorghum within selected locations in KwaZulu Natal province.

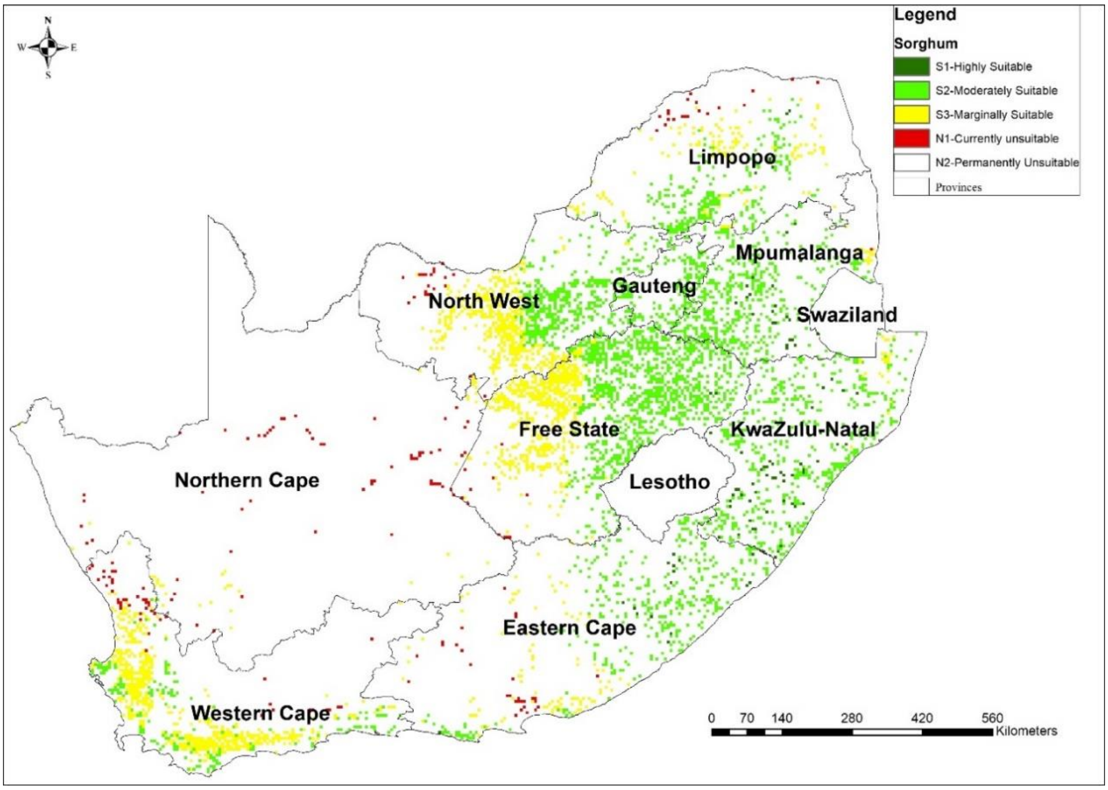

Figure 4. 2 Suitability map for sorghum production in South Africa computed using MCDA-AHP and OWA operators.

4.3.2 Cowpea land suitability map

Cowpea suitability varies across the country. The results indicated that about 3% of the land is highly suitable (S1) for cowpea production. Moderately suitable (S2) land constitutes the most substantial proportion with 56% of the calculated arable land of South Africa (12 655 859 ha), while marginally suitable (S3) and unsuitable (N1) constitute 39% and 2%, respectively, of calculated arable land (Figure 4.3). The spatial suitability is high in the south-eastern and central provinces of South Africa. The intensity of suitability gradually decreases from the central part of the country to the western regions of the country (Figure 4.3). Like sorghum, the suitability distribution was consistent but not in the order of rainfall, slope, soil depth and ET_O distribution.

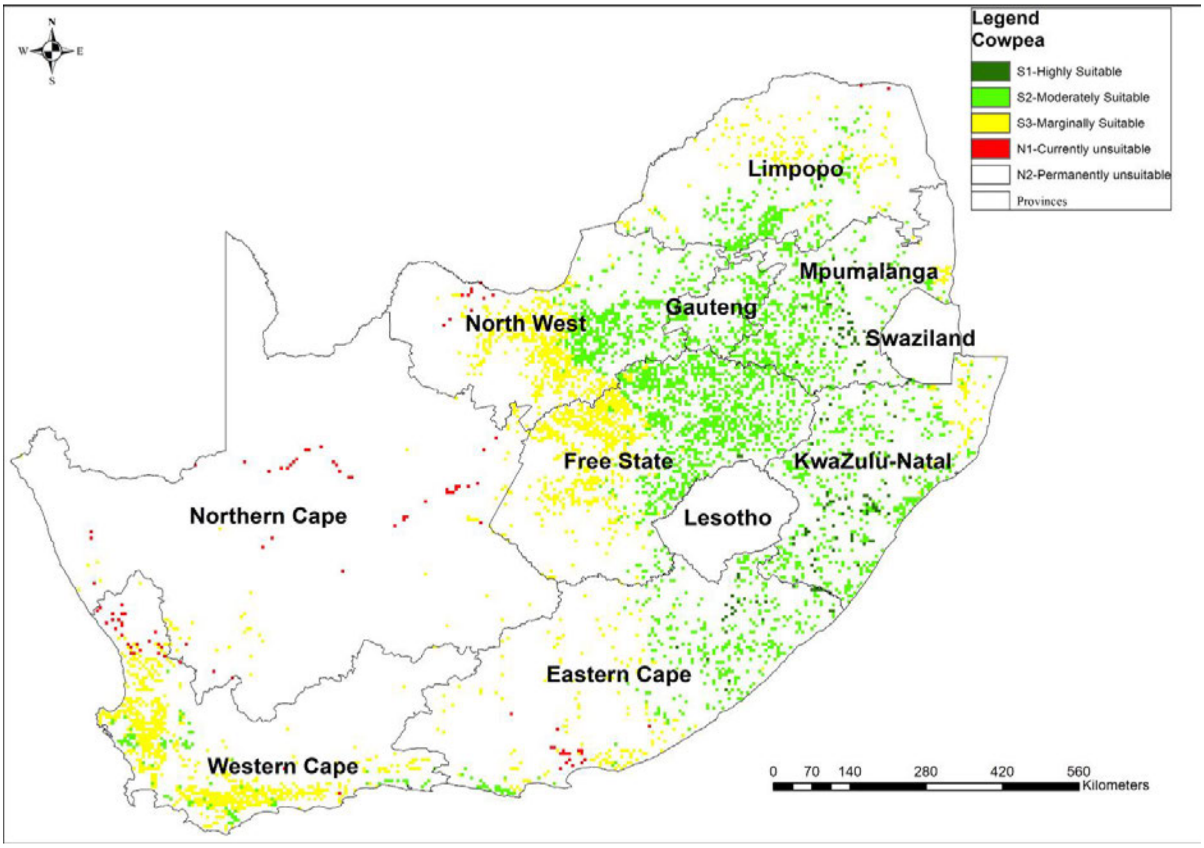

Figure 4. 3 Suitability map for cowpea production in South Africa computed using MCDA-AHP and OWA operators.

4.3.3 Taro land suitability map

Figure 4.4 presents the spatial distribution of the suitability scores for taro based on the MCDA-AHP method. The results indicated that about 0.4% of the land is highly suitable (S1) for taro production. Moderately suitable (S2) land constitutes 28% of the calculated arable land of South Africa (12 655 859 ha), while marginally suitable (S3) constitutes the most substantial proportion, 64%, and (N1) 7% of calculated arable land. Taro's suitability is high in KwaZulu Natal and Mpumalanga provinces. Limpopo, North West, Northern Cape and Western Cape are marginally suitable for taro (Figure 4.4). The distribution of taro suitability was consistent with maximum temperature, length of the growing season, and rainfall distribution.

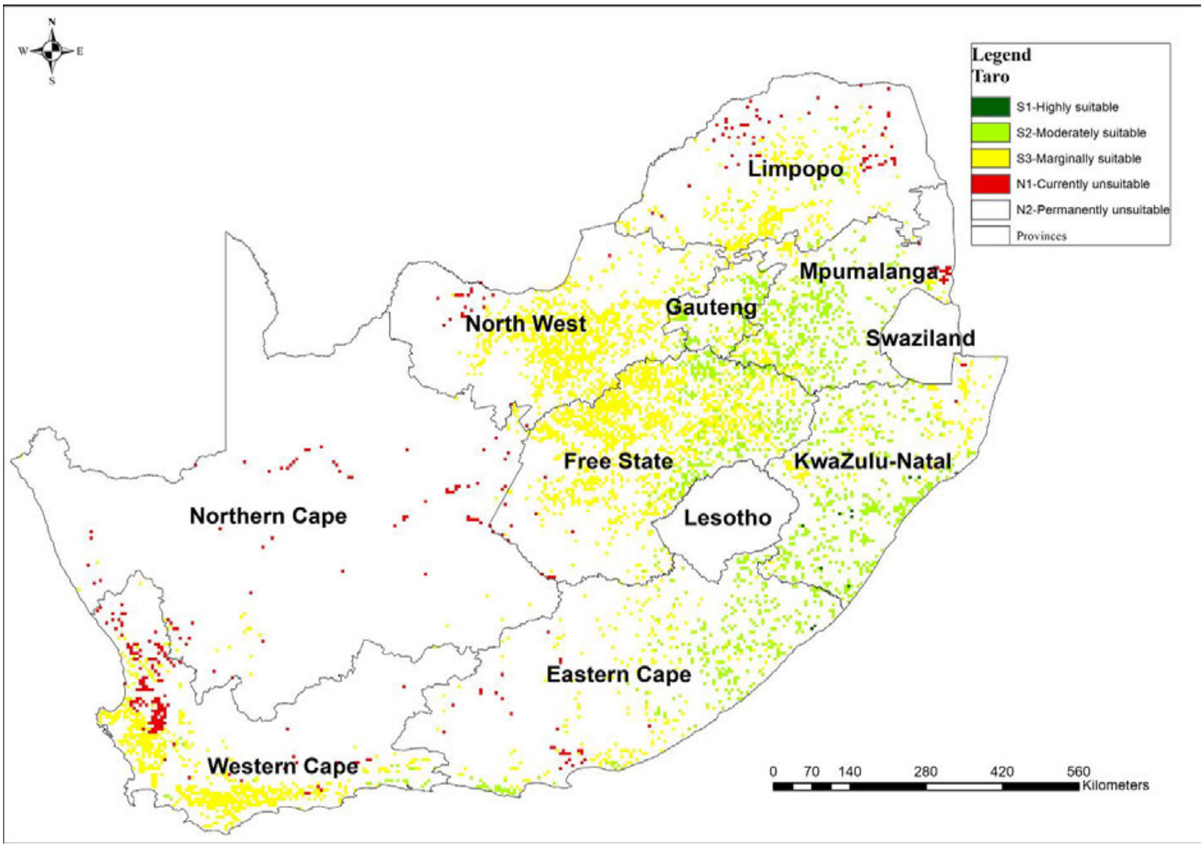

Figure 4. 4 Suitability map for taro production in South Africa computed using MCDA-AHP and OWA operators.

4.3.4 Amaranth land suitability map.

The land suitability analyses indicated that amaranth is highly suitable across South Africa. The results indicated that about 8% of the land is highly suitable (S1) for the production of amaranth. Moderately suitable (S2) land constitutes the most substantial proportion, with 81% of the calculated arable land of South Africa (12 655 859 ha), while marginally suitable (S3) constitutes 11% of calculated arable land (Figure 4.5). Amaranth is high suitable across South Africa in most cropping areas, even in the Western Cape, where the investigated crops had low suitability (Figure 4.5). The observed suitability could be associated with the growth requirements of the crops that allow for its production even under marginal conditions. From field visits, farmers confirmed that amaranth is suitable and grows naturally in KwaZulu Natal environments.

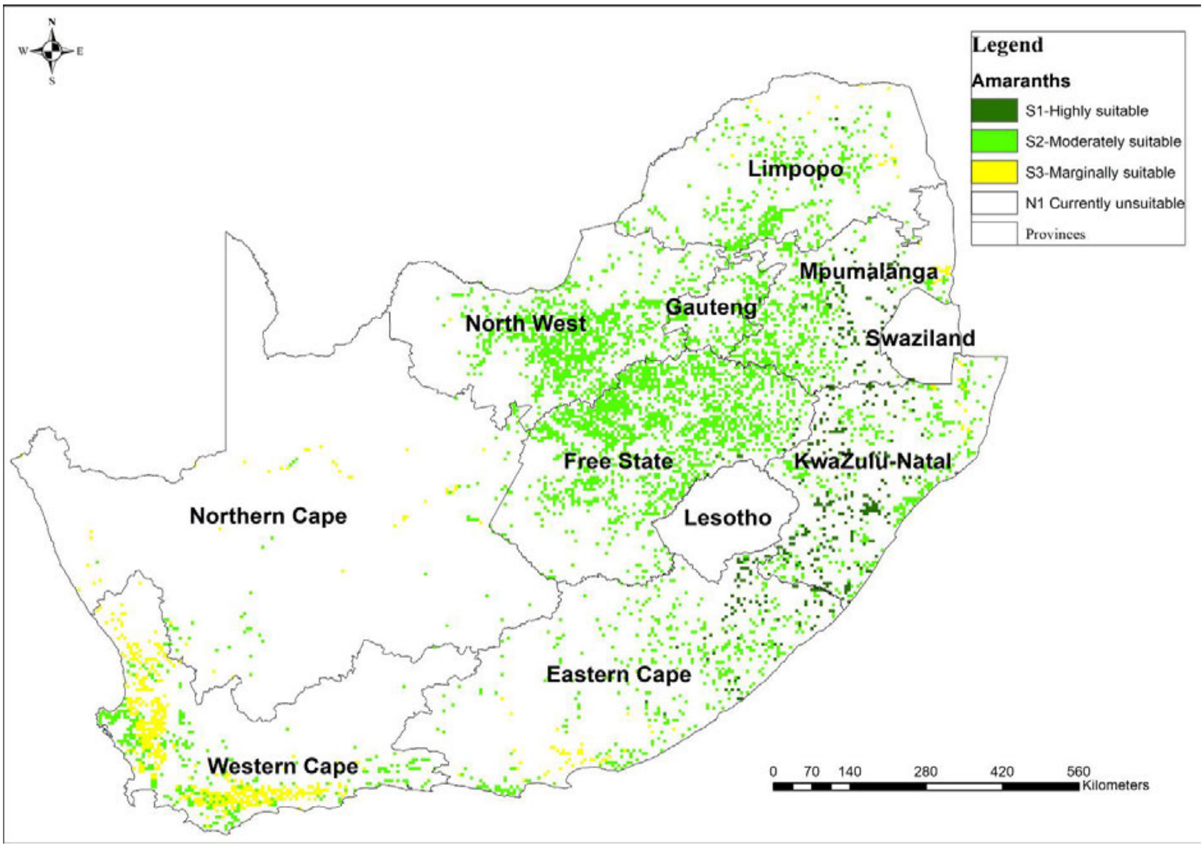

Figure 4. 5 Suitability map for amaranth production in South Africa computed using MCDA-AHP and OWA operators.

4.3.5 Water requirement satisfaction index for the period 1981 to 2017

The WRSI classification in the country's driest areas, mainly the Northern provinces, was not applicable (Figure 4.6).

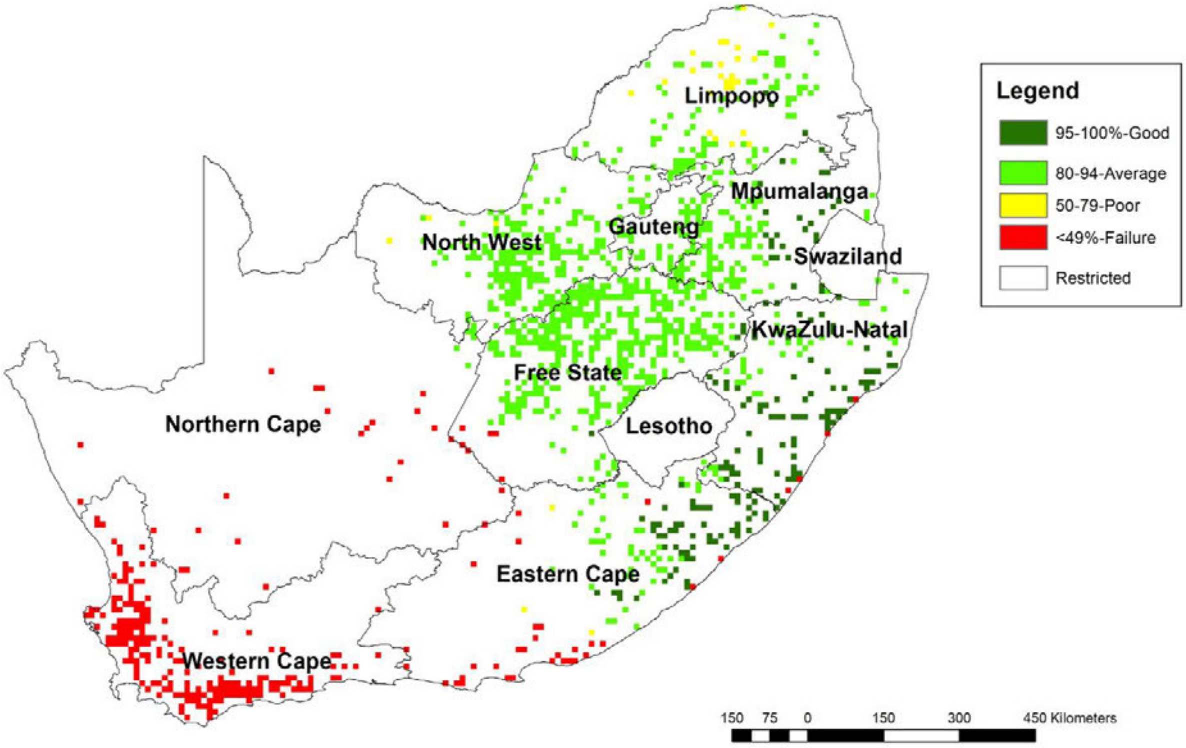

Figure 4. 6 Average water requirement satisfactory indices for 1981 to 2017 in cropping lands in South Africa.

4.3.6 Multi-criteria model accuracy validation

The area under curve (AUC) of sorghum (0.87) cowpea (0.88), amaranth (0.95) and taro (0.82) values were greater than 0.5 (Figure 4.7). Considering that the AUCs of all the crops were above 0.8, all the models in this study accurately estimated the NUS suitability based on sixty GPS points in KwaZulu-Natal.

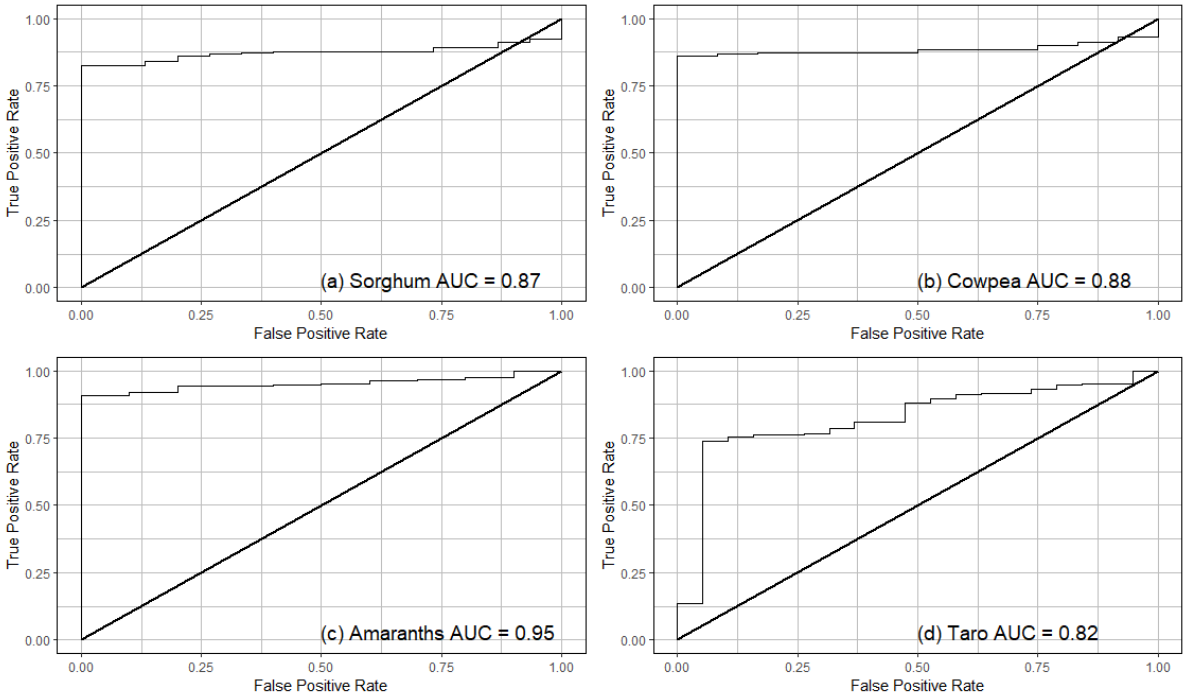

Figure 4. 7 The Receiver Operating Characteristic (ROC), used to generate the Area Under the curve (AUC), which is used for model validation of the logistic regression model for spatial prediction of (a) sorghum, (b) cowpea, (c) amaranth and (d) taro.

4.4. Discussion

In this study, we assessed the land suitability of NUS using climatic, soil-landscape, and socio-economic factors. The use of AHP provides scope for combining expert opinion with measurements in pairwise comparisons between criteria at each level of the hierarchy to come up with relative weights. According to the local experts' judgment, rainfall was the most critical variable, followed by temperature, while soil depth and distance from the road were the least important (Table 4.3). The ranking of the variables is somewhat consistent with what was reported as important crop limiting factors for South Africa (Tshabalala et al., 2019). Malczewski (2006b) noted that the relationship between the objectives and attributes has a hierarchical structure. The consistency ratio was calculated as 0.05 (Table 4.3) and is considered acceptable(Elsheikh et al., 2013; Flynn, 2019).

Nine thematic input layers were used using matrix pairwise comparison to reduce the risk associated with over-fitting or noise modelling. The pairwise matrix comparison was obtained from different experts, and factor weights were calculated using a pairwise comparison matrix (Table 4.3). The accuracy of weights used is subjective as it depends on expert opinion; however, the results of the relative weights were used in land suitability evaluation because the Consistency Ratios were within the established acceptable limits (0.1) (Saaty and Saaty, 1980).

The challenge of a deterministic MCDA-AHP method is that assigning weights may be subjective, the setting of weights represents imprecise point estimates, and the process does not indicate error or confidence (Benke and Pelizaro, 2010). However, the AHP methodology provides scope for combining expert opinion with measurements (Mendoza and Martins, 2006; Mustafa et al., 2011; Bagherzadeh and Gholizadeh, 2016). Expert opinion weighted distance from the road with the lowest weight (Table 4.3) because the social-economic factor does not affect crop growth directly, but it influences the adoption of NUS by farmers. The road network highly influences accessibility to markets because it affects markets. Other socio-economic factors (availability of extension services, access to markets and credit, etc.) can be included in MCDA to develop cropland suitability mapping (Akpoti et al., 2019).

Based on the analyses, there are potential environmental benefits to growing NUS in SA. The introduction of NUS into regions classified as moderately suitable (S3) to highly suitable (S1) could increase the crop choices available and also contribute to biodiversity (SDG 15). The low environmental impacts and increased biodiversity brought about by the introduction of NUS can be viewed as a climate change adaptation strategy (SDG -13) for increasing farmer resilience (Drimie and Pereira, 2016). More so for marginalised farming communities with limited access to improved technologies such as hybrid seeds and fertilisers (Modi, 2003). Introducing NUS into existing cropping systems can be viewed as a sustainable intensification approach (Harvey, 2010). Also, promoting NUS in marginal lands can contribute to food and nutrition security (SDG 2) and poverty alleviation (SDG 1) by creating new value chains and human health and wellbeing (SDG 3).

The area under the curve (AUC) of sorghum, cowpea, amaranth and taro was above 0.8, indicating that the land classification based on the logistic regression was highly accurate (Figure 4.7).-The robustness could explain these high accuracies, holistic nature and optimal performance of the GIS-based MCDA and AHP modelling, which characterise optimal land for the NUS production in this study. Sun et al. (2017) provide an essential guarantee of the AHP model as a decision-support tool for improving water use efficiency. Amongst the four crops, taro had the lowest AUC because the crop generally has a high water requirement compared to the other crops (Mabhaudhi et al., 2014a; b).

The results of the total area suitable for the production of sorghum, taro, and cowpea were consistent with what has been reported to be available arable land (approximately 10.3%) in South Africa (Shackleton et al., 2014). About 70% of South Africa’s land is categorised as unsuitable for rain-fed crop production due to poor rainfall distribution and soils with low fertility, yet NUS are naturally suitable in marginal areas. However, there were variations in the magnitude of suitability for each of the NUS crops investigated. The results indicated that sorghum and cowpea suited South African environments, especially in KwaZulu-Natal, Eastern Cape and Limpopo provinces, where most agricultural households reside (Chivenge et al., 2015). Based on AHP analysis, these crop species are well adapted to high climate risk and can be produced under water-limited and extremely hot (33-38°C) conditions. Amaranth was highly suitable across most cropping lands in South Africa, and this is because the crop has a short growing period and low water requirement (Nyathi et al., 2018).

The suitability of taro is consistent with the observed length of the growing period. Specifically, taro takes up to 300 days to mature and has a high water use rate (651 – 1 701 mm) (Mabhaudhi et al., 2013). In this regard, the areas suitable for taro production in South Africa were low and mostly confined to areas receiving high rainfall. Therefore, our results indicate areas where the investigated crops can be introduced as part of sustainable intensification approaches for climate change adaptation. The results are vital in increasing the options for crop choice for marginalised farmers throughout South Africa. However, the information on suitability needs to be complemented with information on "better bet" agronomic management to realise the full potential of the crops in question (Massawe et al., 2016). Cowpea, sorghum, and amaranths are highly suitable in areas which receive more than 500 mm per season, and most of these areas are highly urbanised (i.e., Gauteng province). Therefore, the opportunity cost of promoting NUS near urban areas might be affected by the land value near urban areas, then high valued horticultural crops and dairy products with higher market demands are more preferred by peri-urban farmers (Massawe et al., 2016).

Our methodology focused on assessing crop suitability using physical and single socio-economic factors. Neglected and underutilised crop species are important within smallholder farming systems and address several socio-economic indicators such as widening food value chains, increasing food and nutrition security and reducing gender inequality (Akinola et al., 2020). Promoting or introducing NUS in mapped zones can be essential to addressing food insecurity, specifically malnutrition, reducing vulnerability to climate variability and change, environmental degradation, and gender inequality. It is argued that holistic land suitability maps, which consider several socio-economic indices, could be more useful to policy-makers and enhance the participation of marginalised farmers in the food system (Mabhaudhi et al., 2019). The exclusion of key socio-economic indicators in developing suitability maps might affect the uptake and adoption of these crop species in areas where they are biophysically suitable. Therefore, to generate information on socioeconomic indicators, there is a need for future studies to identify innovative ways to derive maximum value from the possible integration of GIS with block-chain, big data, and Internet of Things (IoT) technologies to mine updated data, especially on climatic data and social-economic factors (Wolfert et al., 2017; Sharma et al., 2018). To achieve this, farmers, the private sector and the government will need to support further research on NUS value chains.

The results show that NUS are suitable in a wide range of agro-ecological zones, especially in the drought-prone areas identified in the previous chapter (***c.f.*** Chapter 3). Therefore, mainstreaming them into existing systems as alternative crop species to commercially important crops might be a sound adaptation strategy to climate variability and change. However, the interpretation of our results relative to climate change is limited because we used a historical data set (1950-2000). While this spans five years, the most extreme climate hazards have been observed in the last 30 years (1990 – present) (IPCC, 2018). Future studies should use data from global circulation models (GCMs) to inform climate change scenarios more specifically. However, the current maps remain useful in identifying areas currently suitable for NUS production for the first time in South Africa.

The high coefficient of determination between MCDA-AHP and WRSI indicated that the climatic parameters used were sufficient to map marginal areas within South Africa. The FAO developed the WRSI and is mostly used by FEWSNET to monitor and investigate crop production in agricultural drought-prone parts of the world (Consoli and Vanella, 2014). It is used to monitor crop performance during the growing season and to calculate a ratio of actual to potential evapotranspiration based on how much water is available for the crop (Consoli and Vanella, 2014). These ratios are crop-specific based on crop development and known relationships between yields and drought stress (Consoli and Vanella, 2014). Short-duration crops such as amaranth and crops with a low water requirement fit well in all environments of South Africa. While the WRSI uses climate-related stress factors other than soil available water, the relationship between two independent classifications showed that this study's NUS land suitability was satisfactory. The negative coefficient of determination (R=-0.15) observed for taro suitability and WRSI might be due to crop water requirements and the length of the growth period, which overlaps with the dry season.

Taro is predominantly a wetland crop; however, upland varieties exist, and these have been shown to have lower water use levels and drought tolerance through avoidance and escape mechanisms (Mabhaudhi et al., 2013). However, escape mechanisms (i.e., phenological plasticity) negatively correlate taro suitability with WRSI. One of the significant limitations of the WRSI index is that it uses satellite-based rainfall estimates, which are influenced by cold-cloud-duration (CCD), especially from February to March, because of overcasting clouds in subtropics. Therefore, a degree of error could influence WRSI classification, especially on the balance of evapotranspiration in a lean season in South Africa (Duchemin et al., 2006; Liu et al., 2010). To overcome these challenges, future studies could employ unarmed aerial vehicles derived data with very high-spatial-resolution images and LiDAR (Light Detection and Ranging) technology, which can provide 3D models of farmland (Gago et al., 2015). LiDAR technology could provide accurate maps of natural resources and farmlands for sustainable production of NUS in South Africa (Rosell and Sanz, 2012; Lin, 2015).

Sorghum, cowpea and amaranth have characteristics that allow them to grow in water-stressed environments compared to major crops, which agrees with the WRSI classification (Consoli and Vanella, 2014). This means selected NUS could use unsuitable land for growing cash crops, offering a complement crop production scenario rather than a substitution production scenario (Mabhaudhi et al., 2019). This study is a first step towards the reclassification of land in South Africa in the acknowledgement of NUS in national cropping systems.

4.5. Recommendations

The land suitability maps generated in this study indicate where NUS can be promoted as alternative crop choices or complement the current range of crops grown within marginalised cropping systems. The maps can inform site-specific crop diversification recommendations as a sustainable intensification strategy (Schiefer et al., 2016). A transdisciplinary approach is required to mainstream NUS into cropping systems found in the delineated regions of suitability maps developed in this study. Moreover, there is a need to create a conducive environment for all participating stakeholders. This can be achieved if there is a harmonisation of existing policies that speak to land, environment, agriculture and health, and new land-use policies are co-designed based on evidence. Policies such as the National Environmental Management: Biodiversity Act of 2004, National Food and Nutrition Security Policy (Department of Agriculture, 2013) and Draft Policy on Preservation and development of Agricultural Land Bill 2015 could foster co-development of NUS technologies and aid in addressing challenges in the land, environment, agriculture and health domains;

We identified several challenges in defining the suitability of NUS. These included urbanisation, increased food and nutrition insecurity, bush encroachment, and competition between agriculture and protected natural habitats. In this regard, agronomists, climatologists, ecologists and economists need to collaborate in co-designing the suitability indices to inform policy and practice. Such collaborations will ensure that suitability maps for NUS are holistic and relevant in addressing cross-cutting challenges. Researchers must consider including socio-economic parameters to make current land suitability maps more relevant to addressing grand global challenges. The AHP is one of the most relied-on methods in MCDM; however, consistency is difficult to achieve when there are more than nine criteria/indicators under consideration (Saaty, 2016). Nevertheless, its ability to measure consistency is one factor that gives it an edge over other methods. Therefore, parameters considered in MDCM should be context-specific and informed by an outcomes-based approach.

While our results remain applicable, future research should consider using data with a finer resolution to improve mapping accuracy. This will aid in improving land suitability mapping in marginalised agricultural communities known to be highly heterogeneous. The application of unarmed aerial vehicles could be used to validate satellite-derived data and capture high-resolution images. One such sensor is LiDAR (Light Detection and Ranging) technology, which can provide 3D models of farmland (Gago et al., 2015). LiDAR technology can provide accurate maps of natural resources and farmlands for sustainable production of NUS in South Africa (Rosell and Sanz, 2012; Lin, 2015). The use of high-resolution images in developing the land suitability of NUS is of utmost importance in solving land use challenges. However, the process is often difficult, labour intensive and costly. The return on investment (ROI) of LiDAR in delineating areas suitable for NUS may be low as NUS still lacks developed markets and value chains (Escolà et al., 2017). Overall, the cost-benefit of using LiDAR for smallholder farmer settings needs to be evaluated to determine the feasibility of such investments (Escolà et al., 2017).

Climate change is projected to shift current agro-ecological zones and land-use patterns (Mabhaudhi et al., 2013). Land suitability analysis should include climate scenarios in their simulation. The inclusion of climate scenarios in land suitability analysis will allow for more proactive agricultural planning by informing policies such as the National Climate Change and Health Adaptation Plan on the suitability of agricultural land to produce diverse crops in short-, medium- and long-term.

Future studies should focus on using new predictive tools in forecasting. It is observed that the majority of the studies in resource allocation utilised primitive GIS techniques. Future studies should focus on combining the Environmental Policy Integrated Climate (EPIC) models with other methods for assessing the spatial distribution and stimulating the production of crops. The EPIC model is used for predicting crop production levels incorporating the near-real-time changes in crop environment can be integrated with other techniques for improved decision making.

4.6. Conclusion

We investigated the potential spatial suitability distribution for sorghum, cowpea, amaranth and taro in South Africa. This study used the AHP model in GIS to integrate nine multidisciplinary thematic factors from climatic indicators from 1950 to 2000 (seasonal rainfall, seasonal maximum and minimum temperature), soil and landscape attributes (soil depth, slope, elevation), social-economic (road) and technical indicators (LULC). Rainfall was the most critical variable and criteria with the highest impact on the land suitability of the NUS in this study. Neglected and underutilised crop species can be grown on marginal land. They can complement major crops and create greater diversity in cropping systems for building resilient cropping systems. The analysis indicated that sorghum, cowpea, and amaranth suitability mostly occur in S3 zones where land has moderate limitations for agricultural use. The suitability for sorghum, cowpea, and amaranth concurred with the water requirement satisfactory index (WRSI). Matching crop requirements with available resources through land suitability analysis is essential to sustainable agriculture.

Mapping NUS production potential zones in SA is key to promoting NUS production by providing evidence to assist decision- and policy-makers on crop choice. Specifically, the results help inform the Climate Smart Agriculture Strategy, National Policy on Comprehensive Producer Development Support and Indigenous Food Crops Strategy currently under development in South Africa. The suitability maps are also helpful in informing decisions on climate change adaptation (climate-smart agriculture) and sustainable agriculture practices and informing decisions on creating markets for NUS.

The findings are useful in informing land-use classification, especially in marginal environments. The method can be adapted to other SSA countries and regions that share a similar context regarding promoting the cultivation of NUS. Promoting NUS within marginal production areas has the potential to create new and sustainable economic pathways and improve availability and access to nutrient-dense foods. The importance of smallholder farmers to sustainable food systems, and their participation in local food systems, must be emphasised.

Finally, policies such as the National Food and Nutrition Security Policy and National Developmental Plan of South Africa (National Planning Commission, 2012) need to give a clear road map for NUS production, especially by explicitly mentioning NUS and targeting them for production on marginal lands that are currently not suitable commercial crops production as a strategy to improve food and nutrition security within these areas.

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CHAPTER 5: MAPPING THE SPATIAL DISTRIBUTION OF UNDERUTILISED CROP SPECIES UNDER CLIMATE CHANGE USING THE MAXENT MODEL: A CASE OF KWAZULU-NATAL, SOUTH AFRICA.

Published: Climatic Services

Abstract: Knowing the spatial and temporal suitability of neglected and underutilised crop species (NUS) is important for fitting them into marginal production areas and cropping systems under climate change. The current study applies climate change scenarios to map the future distribution of selected NUS, namely, sorghum (*Sorghum bicolor*), cowpea *(Vigna unguiculata*), amaranth (*Amaranthus*) and taro (*Colocasia esculenta*) in the KwaZulu-Natal (KZN) province, South Africa. The future distribution of NUS was simulated using a maximum entropy (MaxEnt) model for the years 2030 to 2070, using future climate scenarios from an ensemble of global circulation models using three Representative Concentration Pathways (RCPs 2.6, 4.5 and 8.5). The analysis projected an increase for sorghum, cowpea, and amaranth growing areas from 2030 to 2070. The study showed an increase of 0.1-11.8% under highly suitable (S1), moderately suitable (S2), and marginally suitable (S3) S1-S3 for sorghum, cowpea, and amaranth growing areas from 2030 to 2070. From 2050 to 2070, the total highly suitable area for taro production will decrease by 0.3-9.78% across all RCPs. The observed results are consistent with the temperature and water requirements of the crops. The jack-knife tests of the MaxEnt model were run for fourteen environmental variables, and the model performed efficiently, with areas under the curve being more significant than 0.8. The study identified annual precipitation, length of the growing period, and minimum and maximum temperature as variables contributing to model predictions. The developed maps show changes in the future suitability of NUS within the KZN province. This information helps delineate sustainable crop, land, and water resources management strategies under climate change. It is recommended to develop regionally differentiated climate-smart agriculture production guidelines matched to spatial and temporal variability in crop suitability.

Keywords: Food and nutrition security, land suitability analysis; machine-learning algorithms, neglected and underutilised crop species

5.1 Introduction

The Intergovernmental Panel on Climate Change (IPCC) projects a global temperature increase by 2050 of 1.2°C and 2.2°C under low and high emissions conditions, respectively (IPCC, 2018). In South Africa, the impacts of climate change have rapidly escalated; by 2080, temperatures in the coastal regions of the country are projected to increase by 1.5 °C and between 3 and 6 °C over the western, central and northern parts of South Africa (Chersich and Wright, 2019). Several consequences, including shifting agroecological zones, weather extremes (drought, floods and temperatures), and significant rainfall variability, affect crop production regardless of adaptability (Akinola et al., 2020). In rural farming communities in marginal areas, climate variability and change are already impacting food and nutrition security, and the extent varies across localities. Moreover, poverty, youth unemployment, and inequality within these communities remain high, with little to no access to climate services and inherently low adaptive capacity. However, African regional governments, including South Africa, continue to promote agriculture as a plausible solution to reduce food and nutrition insecurity, poverty, youth unemployment and inequality (NPC, 2013). There is a need to focus on innovative agricultural technologies adapted to changing climate and create sustainable rural development opportunities. It is within this context that several researchers are advocating for mainstreaming of neglected and underutilised crop species (NUS) into agricultural and food systems under climate change (Mabhaudhi et al., 2017; Chibarabada et al., 2020; Chimonyo et al., 2016a; Hadebe et al., 2017; Nyathi et al., 2018).

Neglected and underutilised crop species (NUS) are defined as crops that were once popular (in and out of their centres of diversity) but have become neglected by users and researchers despite their relevance in diversity (Mabhaudhi et al., 2017). They form an important part of agrobiodiversity and are naturally adapted to marginal areas. Akinola et al. (2020) could contribute to food and nutrition insecurity in marginal communities under climate change (Mabhaudhi et al., 2019). Several researchers have reported the benefits of NUS and highlighted high nutritional value, adaptation to marginal soils, and tolerance to drought and heat stresses (Chimonyo et al., 2016a; Hadebe et al., 2017; Nyathi et al., 2018; Chibarabada et al., 2020). In addition, they have low water use, which means they do not threaten water resources (Mabhaudhi et al., 2019). It is reasonable to assume that NUS display traits from natural selection that make them adaptable to harsh agro-ecologies.

Moreover, NUS have been reported to offer ecologically viable options for increasing agriculture production and productivity at present or in the future (Chivenge et al., 2015). Despite their reported adaptability to marginal environments and climate change, there is a lack of studies in one literature focusing on climate change impacts on NUS' temporal and spatial distribution. This limits the ability of policy and decision-makers to include them in adaptation options for smallholder farmers (Olayinka Atoyebi et al., 2017).

Spatial modelling and analysis techniques can aid in understanding the distribution of NUS (Pecchi et al., 2019). Species distribution models (SDM) involve collating species occurrence data, relating these occurrences to terrain and climate variables, and generating maps that predict past, present, or future species distributions (Shabani and Kotey, 2016; Akpoti et al., 2020). They relate environmental variables to species occurrence records to gain insight into ecological or evolutionary drivers and help predict agro-ecology suitability across large scales (Kramer-Schadt et al., 2013). These models include climatic-envelop models (Heumann et al., 2013), statistical models, such as generalised linear models (GLM), generalised additive models (GAM) (Austin, 2007), and machine-learning algorithms such as a genetic algorithm for rule-set production (GARP) and maximum entropy (MaxEnt) (Phillips et al., 2006). The latter model has become a popular tool for predicting species distributions in environmental research (Su et al., 2021). The model can cope well with sparse, irregularly sampled data and minor location errors (Phillips et al., 2006). The MaxEnt model has been successfully used by Kogo et al. (2019) to identify suitable areas for maize production in Kenya. Similarly, with limited training data, Akpoti et al. (2020) mapped land suitability for rice production in Benin and Togo. Bunn et al. (2019) mapped recommendation domains to scale-out climate change adaptation strategies in cocoa production in Ghana. MaxEnt is among the most preferred methods for niche-based geographic species distribution modelling and performs exceptionally well with small datasets (Phillips et al., 2006; Kramer-Schadt et al., 2013)."

This study applied the MaxEnt model to assess climate change impacts on the geographic distribution of suitable production areas for selected NUS with limited empirical data on occurrence. The study assessed the application of presence-only data to evaluate the current and future crop suitability of sorghum (*Sorghum bicolor),* cowpea (*Vigna unguiculata*), amaranth *(Amaranthus)* and taro (*Colocasia esculenta*). This study considered sorghum as NUS because it plays an important role in African diets, yet the production is low, and utilisation in sub-Saharan Africa is still regarded as low (Taylor, 2003; Macauley, 2015). The application of MaxEnt, a machine-learning algorithm-based model designed to estimate the likelihood of occurrence based on presence-only data, has great potential for use, mainly where extensive land use information is often difficult to obtain. The study is the first step toward understanding the present and future NUS suitability. The evidence-based crop suitability maps produced are useful for informing policy, developing crop production guidelines, and identifying NUS that fit projected environmental conditions.

5.2 Methodology

5.2.1 Study area

This study was carried out in the KwaZulu-Natal (KZN) province in South Africa. The province covers 94 361 km^2, of which 65 000 km^2 is considered suitable for farming. This study classified farming land as either arable (cropland and fallows) or land under permanent crops, pastures, and hayfields. The province has a dual agricultural economy consisting of commercial and subsistence farms (Tibesigwa et al., 2017). KwaZulu-Natal is characterised by summer rainfall, and most of its rain is received in the austral summer period, between October and March (Kruger and Nxumalo, 2017). The mean annual rainfall ranges from 650 mm in the eastern Grasslands to 1400 mm in the east of Coastal Bushveld, and the Central Bushveld receives 900 mm (Walker and Schulze, 2006; Ghile and Schulze, 2008). Across space and time, rainfall in the province is unevenly distributed (Lobell et al., 2008; Dai, 2011; Ziervogel et al., 2014) and is the dominating factor determining crop suitability (Walker and Schulze, 2006).

5.2.2 MaxEnt model description

MaxEnt (Phillips et al., 2006) is a general-purpose machine learning model based on a precise and straightforward mathematical formulation (Reddy et al., 2015; Akpoti et al., 2020). It is also described as a presence-only model that uses predictor datasets to distinguish species occurrence patterns (Merow et al., 2013). The model utilises categorical and continuous datasets (Merow et al., 2013; Heumann et al., 2013). Although a fundamental assumption of MaxEnt is that regions have been systematically sampled across most existing land, the MaxEnt model is usually built from occurrence records that are spatially biased towards better-surveyed areas (Akpoti et al., 2020). The model offers both a user-friendly graphical user interface and command-line functions.

MaxEnt is among the most preferred niche-based geographic species distribution modelling methods and performs exceptionally well with small datasets (Phillips et al., 2006; Kramer-Schadt et al., 2013). The model also provides useful model assessment tools such as i) jack-knife environmental parameter contributions, ii) species-environment curves (with and without other ecological parameters) and iii) Area Under the Curve of the Receiver Operating Characteristic (AUC-ROC) as a metric of model performance (Phillips et al., 2006; Merow et al., 2013). This study used MaxEnt Version 3.4.4 (www.cs.princeton.edu/~schapire/maxent) to model the distribution of the four NUS (sorghum, cowpea, amaranth and taro) in KZN.

5.2.3 Species occurrence data

The species occurrence data points were gathered from field surveys conducted in KZN between October and November 2019. During the survey and for each crop (sorghum, cowpea, taro, amaranth), we collected 60 GPS locations, making 240 data points, and the points were randomly selected in a linear pattern (Figure 5.1). These data points were randomly collected within 20 m of farmer’s fields where the crops were seen to be established.

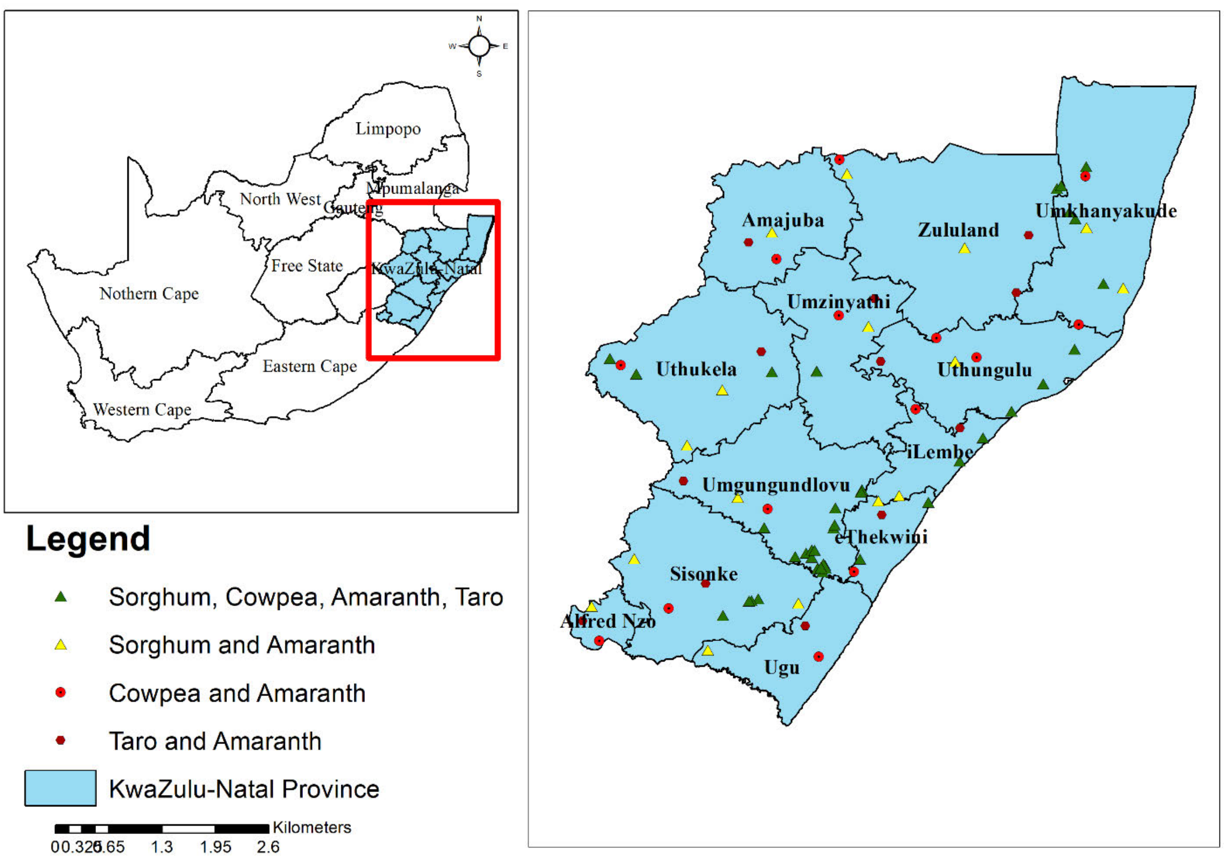

Figure 5. 1 Map of South Africa and the location of KwaZulu Natal province. Also, the presence data for sorghum, cowpea amaranth and taro in KwaZulu-Natal in South Africa is shown.

5.2.4 Predictor variables

In the current study, the MaxEnt model was adopted to simulate the planting area of the selected NUS by combining a set of known geo-coordinates with layers of environmental variables under KZN's current and future environmental conditions. The datasets used in this study were divided into i) continuous surfaces of bioclimatic variables (e.g., climate and topography) and ii) categorical (or discrete) surface variables (e.g., known locations of NUS growing areas). Four climatic, six soil physical and chemical properties, two topographic and two socioeconomic variables were used (Table 5.1). Social and economic factors, such as the distance along with the road network and distance to metro cities, can significantly affect crop profitability, influencing crop choice to be grown on a farm. These social-economic factors affect farmers' crop preference because some crops like taro are heavy to transport to the markets. In this regard, some farmers who reside far away from metro towns where markets are situated might not grow these crops on large hectarages because of the cost of transporting them to the markets.

In this study, historical and future climatic data were mined from high-resolution regional climate projections from the newly performed Coordinated Output for Regional Evaluations (CORE) embedded in the Coordinated Regional Climate Downscaling Experiment (CORDEX) framework (Ciarlo et al., 2020). The CORDEX dataset is provided to conduct climate change impact assessment at the regional and local scales and to understand patterns of projected future climate (Coppola et al., 2020). Three climatic parameters, namely, minimum temperature, maximum air temperature and precipitation with a spatial resolution of 0.25° by 0.25° at the ground level, were selected from the Copernicus Climate Change Service (C3S) (2017). We selected five different Earth System /Regional Climate Model (ESM/RCM) combinations at a spatial resolution of 0.22°. The five climate scenarios where MPI-ESM- LR/REMO2015, HadGEM2-ES/REMO2015, NorESM1-M/REMO2015, HadGEM2-ES/RegCM4-7, and NorESM1-M/RegCM4-7 (Thrasher et al., 2012; Teichmann et al., 2021). Each climate projection includes daily maximum temperature, minimum temperature, and precipitation from 1950 through 2100. Musie et al. (2020) and Vautard et al. (2021) provided more details about the CORDEX method used to generate the datasets.

The elevation and categorical soil type datasets were resampled to 0.25° by 0.25° resolutions using the bilinear interpolation method (Du et al., 2013) (Table 5.1). Social and economic factors, such as the distance between the main road, road network and distance to metro cities, can significantly affect crop profitability, influencing farmer crop choices. For instance, farmers residing far away from a good road network and markets might be less inclined to grow taro, a tuber crop that is bulky and heavy, owing to the high transportation cost. Finally, South Africa's environmental data in GCS-WGS-1984 were obtained from the above global raster data overlaid by the administrative boundary maps of KwaZulu- Natal in ESRI shape format in ArcGIS (Phillips et al., 2006).

A multicollinearity test was undertaken using R- Package 'virtualspecies' (version 4.0.4) Leroy et al. (2016), and Pearson correlation coefficient (r) was selected as an absolute value to filter out correlated variables. The correlation coefficient threshold of 0.7 was chosen to minimise multicollinearity and screen highly correlated environmental predictors. The test was done on both current and future databases.

Table 5. 1 Input variables used to predict land suitability of NUS in KwaZulu-Natal with MaxEnt, including the original data source and native spatial resolution.

Variable	Name	Source	Resolution
Climate			
Seasonal precipitation (mm)	Seasonal precipitation	http://cordex.org/domains/region-5-africa/	25 km
Minimum temperature (°C)	Minimum temperature	http://cordex.org/domains/region-5-africa/	1 km
Maximum temperature (°C)	Maximum temperature	http://cordex.org/domains/region-5-africa/	1 km
Length of the growing period (days)	LGP	Schulze et al. (2008)	1 km
Soil physical and chemical properties			
Available soil water capacity until wilting point (volumetric fraction)	WWP	SoilGrids250m	250 m
Soil pH	PH	AfSoilGrids250m	250 m
Soil depth (mm)	DEPTH	AfSoilGrids250m	250 m
Soil texture fraction: clay (%)	CLAY	AfSoilGrids250m	250 m
Soil texture fraction: silt (%)	SILT	AfSoilGrids250m	250 m
Soil texture fraction: sand (%)	SAND	AfSoilGrids250m	250 m

Topography			
Elevation (m a.s.l)	DEM	earthexplorer.usgs.gov	30 m
Slope (%)	SLOPE	earthexplorer.usgs.gov	30 m
Socioeconomic factors			
The distance along with the road network (km)	EUCDIST	Derived in ArcGIS	2 km
Distance to metro cities (km)	ACCESS	Derived in ArcGIS	1 km

5.2.5. Future scenario

The Representative Concentration Pathways (RCPs), published in the IPCC's Fifth Assessment Report (AR5), represent greenhouse gas concentration trajectories that may determine possible future climates (Wei et al., 2018). Datasets of 21 models under Coupled Model Inter-Comparison Project Phase 5 (CMIP5) were generated by downscaling coarser-resolution GCMs. The future projections of the CORDEX datasets are available for three representative concentration pathways (RCPs2.6, 4.5 and 8.5), covering the entire range in radiative forcing (Haile et al., 2020). RCP 2.6 assumes that global annual greenhouse gas emissions will peak between 2010 and 2020 and substantially decline. This RCP projects a rise in global mean temperature of 0.4 to 1.7°C by the end of the century, relative to 1850 (Thrasher et al., 2012; Teichmann et al., 2021). According to IPCC (2018), the RCP 4.5 is an intermediate scenario, and the emissions are projected to around 2040, then decline. The RCP 4.5 is more likely to result in a global temperature rise between 2-3 degrees C, by 2100, with a mean sea level rise 35% higher than RCP 2.6 (IPCC, 2014). For RCP 8.5, emissions continue to rise throughout the 21st century, and the global mean temperature is projected to rise by 2.6 to 4.8°C (Hijmans et al., 2005; Reddy et al., 2015). In this study, we used all three RCPs to estimate the distribution and suitability of sorghum, cowpea, taro, and amaranth for two the periods (2050 and 2070) across KZN.

5.2.6 Model setting and evaluation

The MaxEnt model partitioned the crop presence data collected from farmer fields using a random 50/50% split for training and calibration. The following default settings were used: random test percentage = 25; regularization multiplier = 1; the maximum number of background points = 10 000 (Phillips et al., 2006). Ten replicates were simulated and used to calculate the mean relative occurrence or suitability probabilities. The MaxEnt model assumes that species are equally likely to be anywhere on the landscape by default. As such, a 10th percentile training presence logistic threshold was used. This then assumes that 10% of occurrence records of NUS in the least suitable habitat occur in KZN agro-ecosystems. In this study, we used the area under the receiver operating characteristic (ROC - AUC), a commonly used threshold independent metric, to evaluate the fit of the MaxEnt model to the true presence and absence data (Heumann et al., 2013; van Proosdij et al., 2016). If AUC $\leq$ 0.5, it indicates a random prediction, while AUC > 0.5 indicate a better model prediction (Jiménez-Valverde, 2012; Senay and Worner, 2019). This study used an AUC threshold of 0.7 (or above) to identify good discriminatory power results (van Proosdij et al., 2016; Somodi et al., 2017). The relative suitability probability of > 0.5 was used, which denotes a 50% chance of NUS being present in suitable production areas of KZN.

5.2.7 Analysis of model outputs

The MaxEnt model outputs a map of occurrence probabilities and tables of model selection (e.g., variable contribution to the model) and the AUC for the training and validation datasets. The mean and the 95th percentile of the 1000 runs conducted for habitat suitability were mapped. Variable contributions and AUC were displayed as jack-knife plots. The contributions for each variable were determined by randomly permuting the values of a variable at each species occurrence point and measuring the resulting decrease in training (AUC). The continuous probability maps were then converted into binary maps (suitable vs unsuitable) based on the probabilities being equal and that the model was correctly classified as i) suitable and ii) unsuitable area (i.e., sensitivity = specificity). The simulated MaxEnt model outputs were then reclassified in ArcGIS using the natural breaks (Jenks) classification method. Change detection was undertaken using an overlay analysis to find spatial shifts from present to projected future suitability. Suitable crop production areas were reclassified as highly suitable (S1), moderately suitable (S2), marginally suitable (S3), and unsuitable (N1), as described in Table 5.2.

Table 5. 2 Suitability assessment for sorghum, cowpea, amaranth and taro cultivation in KwaZulu-Natal (FAO, 2007).

Class of Suitability	Suitability index (SI)	Description of class

Highly suitable (S1)	> 0.8	Optimal conditions for crop cultivation
Moderately suitable (S2)	0.6-0.79	Minor limitations that could reduce crop productivity
Marginally suitable (S3)	0.2-0.59	Land with major limitations that may significantly reduce crop production
Unsuitable (N1)	< 0.19	Lands with severe limitations that are not favourable for crop cultivation

5.3.0 Results

5.3.1 Current vs future crop production areas

The current and future suitability maps of sorghum predicted by the MaxEnt model are shown in Figure 5.2. Under current conditions, land deemed suitable for sorghum production followed the west to east suitability trend, mainly due to rainfall distribution. From Figure 5.2, areas classified as highly suitable (S1) are located in the western and central parts of the province, whilst the north-eastern was considered largely unsuitable (N1). Highly suitable and unsuitable areas occupy approximately 13.4 and 14.5% of the province's total land area.

The cowpea distribution for present conditions had a similar trend to sorghum (Figure 5.3). Areas classified under S1 and S2 were in the western part of the province, whilst the north-eastern region was largely S3 and N1. Currently, highly suitable and unsuitable areas are estimated to occupy approximately 13.1 and 17.5% of the total land in the province, respectively. The current distribution maps for amaranth showed that the crop could be produced throughout the province. Like sorghum and cowpea, suitability followed the west to east trend, with areas in the west being more suitable than the east. The spread in suitability for taro remained sparse across KZN for all scenarios (Figure 5.5). Suitable land was concentrated in the province's southwest, northwest, and central parts.

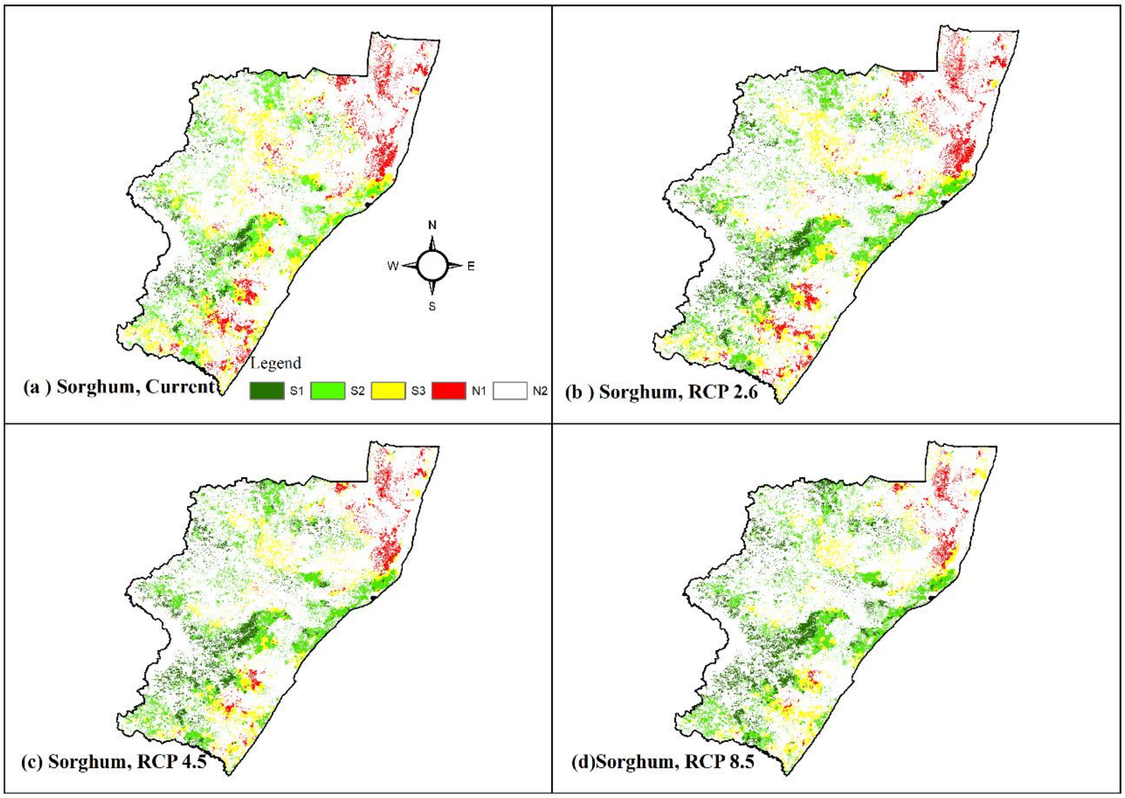

Figure 5. 2 Land areas deemed potentially suitable for sorghum under (a) current and three future environmental conditions for the 2050s, based on Representative Concentration Pathways (RCPs) (b) 2.6, (c) 4.5 and (d) 8.5. The maps were developed from the continuous probability maps based on the threshold optimisation method (sensitivity =specificity). Highly suitable (S1), Moderately Suitable (S2), Marginally suitable (S3) and Unsuitable (N1)

5.2

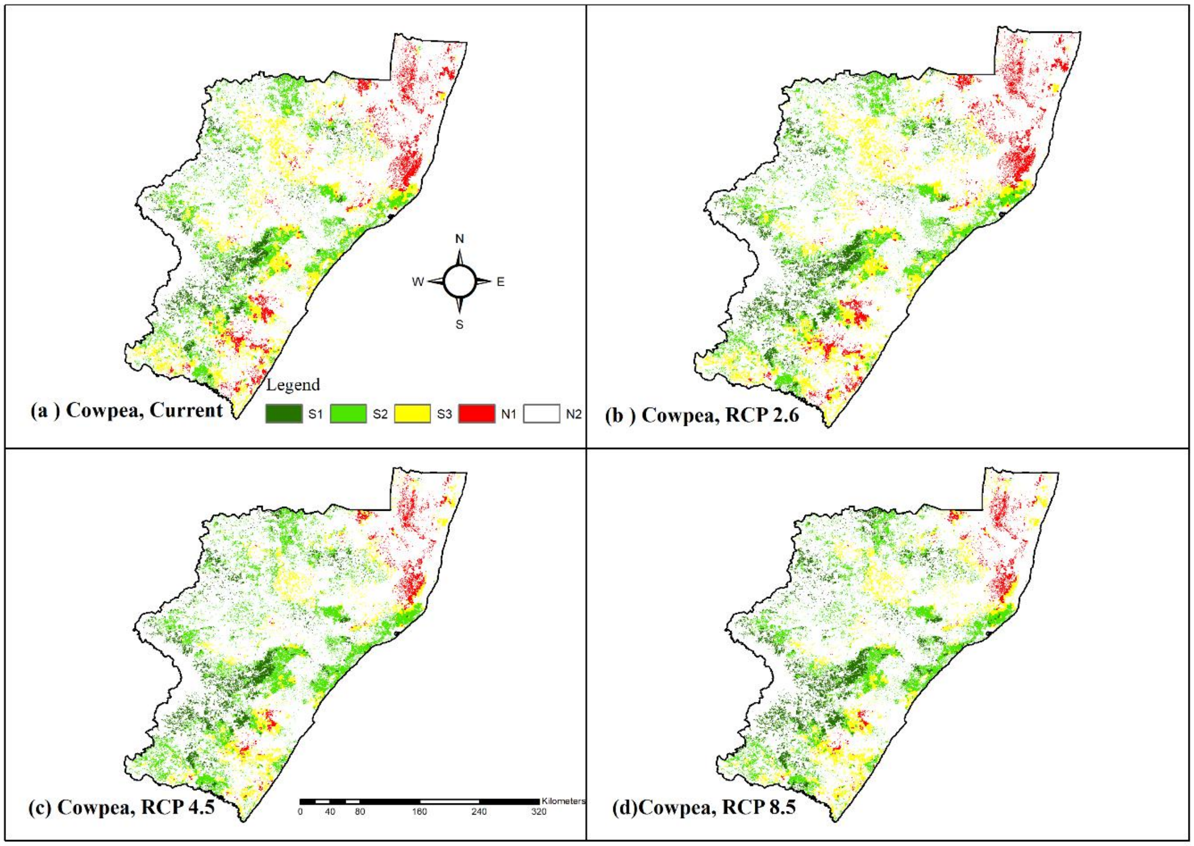

Figure 5. 3 Land deemed potentially suitable for cowpea under (a) current and three future environmental conditions for the 2050s, based on Representative Concentration Pathways (RCPs) (b) 2.6, (c) 4.5 and (d) 8.5. The maps were developed from the continuous probability maps based on the threshold optimisation method (sensitivity =specificity). Highly suitable (S1), Moderately Suitable (S2), Marginally suitable (S3) and Unsuitable (N1)

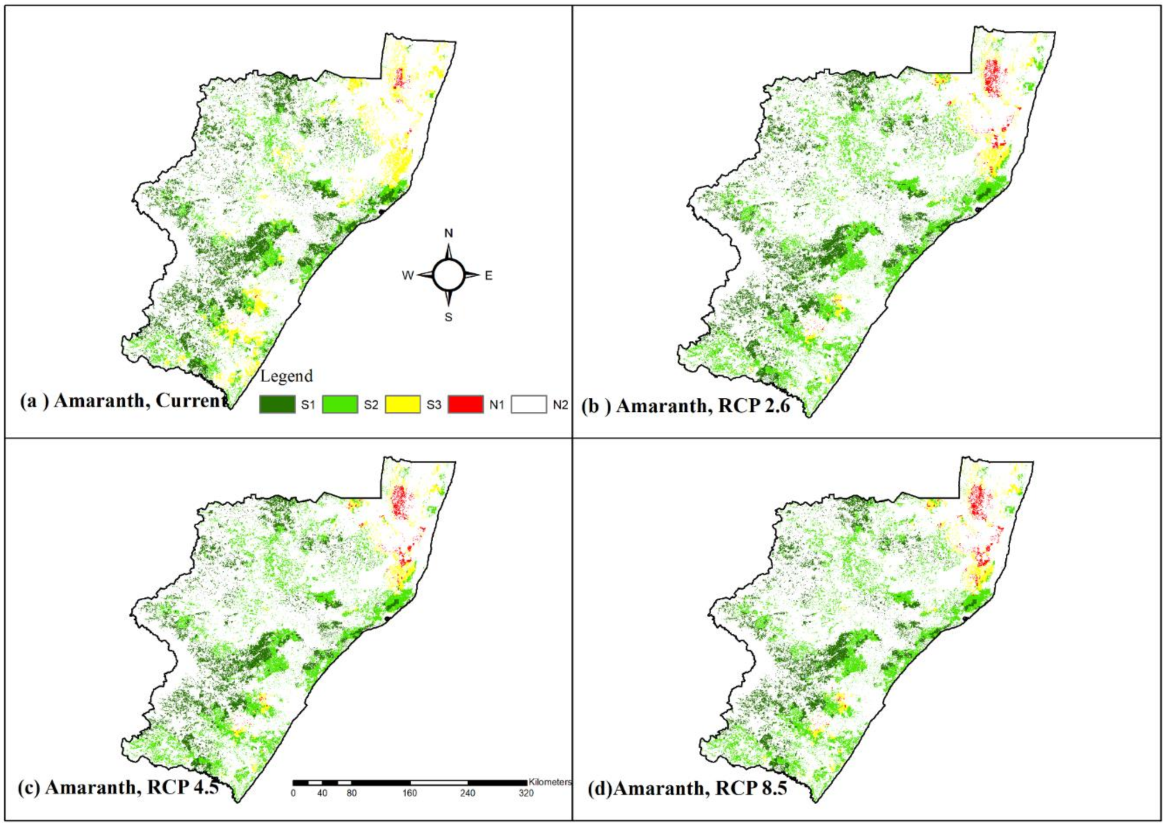

Figure 5. 4 Land deemed potentially suitable for amaranth under (a) current and three future environmental conditions for the 2050s, based on Representative Concentration Pathways (RCPs) (b) 2.6, (c) 4.5 and (d) 8.5. The maps were developed from the continuous probability maps based on the threshold optimisation method (sensitivity =specificity). Highly suitable (S1), Moderately Suitable (S2), Marginally suitable (S3) and Unsuitable (N1)

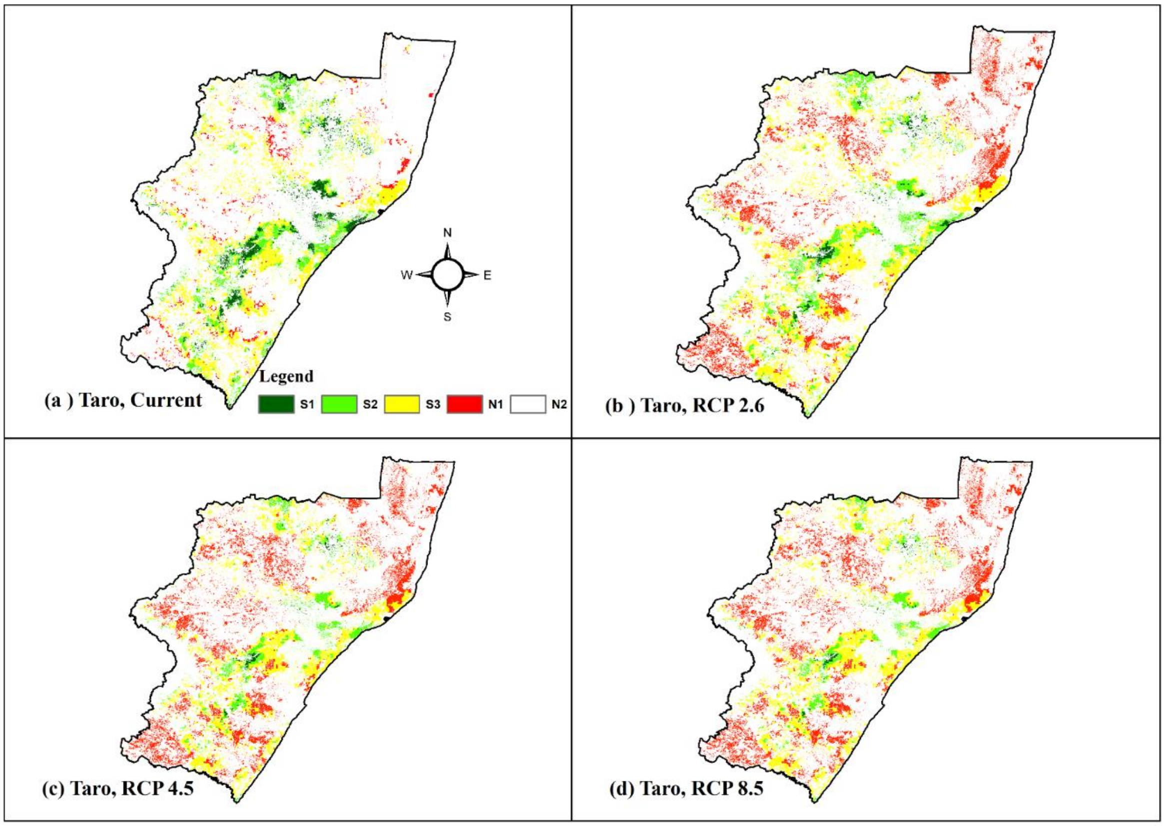

Figure 5. 5 Land deemed potentially suitable for taro under (a) current and three future environmental conditions for the 2050s, based on Representative Concentration Pathways (RCPs) (b) 2.6, (c) 4.5 and (d) 8.5. The maps were developed from the continuous probability maps based on the threshold optimisation method (sensitivity =specificity). Highly suitable (S1), Moderately Suitable (S2), Marginally suitable (S3) and Unsuitable (N1)

5.3.2 Change detection under RCPs 2.6, 4.5 and 8.5

The spatial and quantitative changes in land area for each suitability category under RCPs 2.6, 4.5 and 8.5 relatives to present growing conditions for each crop are shown in Figures 5.2 to 5.5. The results showed a significant difference between the present suitable habitats and those predicted in the 2050s across all RCPs, with substantial changes occurring under RCP 4.5 and 8.5. In particular, the area deemed moderately suitable for production continues to increase insignificantly for sorghum, cowpea and amaranth (Figure 5.2 – 5.4). Simulations indicate a decrease in unsuitable areas (N1) of 35.3 - 39.9%, 46.5 - 47.5% and 10.6 - 15.4% for sorghum, cowpea and amaranth, respectively. Contrary to this, the results showed an increase (15.6 - 18.0%) in unsuitable areas for taro (Table 5.3). The change in highly suitable areas increased by 3.6 - 11.8%, 3.5 - 0.8% and 0.1 - 2.9% for sorghum, cowpea and amaranth, respectively, yet decreased by 15.5 - 8.2% for taro across all scenarios (Table 5.3).

Suitable land for sorghum, cowpea and amaranth production will increase in the 2070s (Figure 5.7). However, in the 2070s and across all RCPs, the highly suitable growing area for taro is projected to decrease by 4.59-9.78% in S1 (Table 5.4). The moderately suitable and unsuitable areas for taro are projected to increase in the 2070s by 13.68-16.69 and 38.86-40.75%, respectively (Table 5.4).

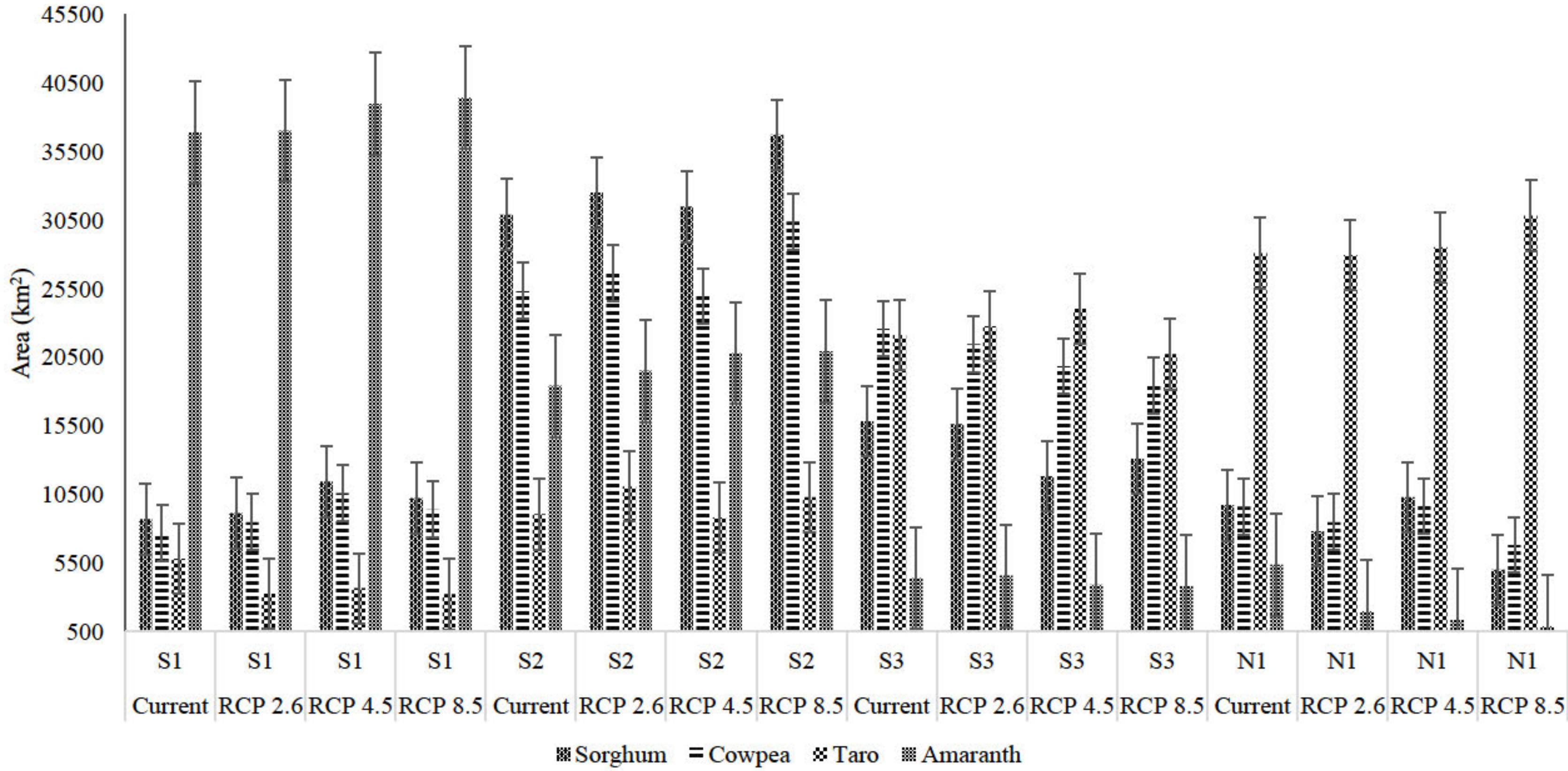

Figure 5. 6 Changes in land suitability for sorghum, cowpea, taro and amaranth under Representative Concentration Pathways (RCPs) 2.6, 4.5 and 8.5 in the 2050s, relative to present conditions. Highly suitable (S1), Moderately Suitable (S2), Marginally suitable (S3) and Unsuitable (N1)

Table 5. 3 Changes in land suitability for sorghum, cowpea, amaranth and taro under Representative Concentration Pathways (RCPs) 2.6, 4.5 and 8.5 in the 2050s, relative to present conditions.

Scenario	Suitability Index	Sorghum	Change of area as a %	Cowpea	Change of area as a %	Taro	Change of area as a %	Amaranth	Change of area as a %
Current	**S1**	**8579**		**7678**		**5789**		**36890**	
RCP 2.6	S1	8884	3.6	7945	3.5	4892	-15.5	36902	0.0
RCP 4.5	S1	9594	11.8	8505	10.8	4326	-25.3	37560	1.8
RCP 8.5	S1	9320	8.6	8469	10.3	3580	-38.2	37946	2.9
Current	**S2**	**27902**		**28250**		**9007**		**18402**	
RCP 2.6	S2	28905	3.5	28882	2.2	8568	-4.9	19800	7.6
RCP 4.5	S2	29002	3.8	29931	6.0	8542	-5.2	20098	9.2
RCP 8.5	S2	30987	10.7	30508	8.0	8023	-10.9	20059	9.0
Current	**S3**	**19003**		**19502**		**22101**		**4338**	
RCP 2.6	S3	18201	-4.2	19045	-2.3	23209	5.0	4206	-3.0
RCP 4.5	S3	17203	-9.5	17525	-10.1	23800	7.7	3841	-11.5
RCP 8.5	S3	14992	-21.1	17064	-12.5	24499	10.9	3699	-14.7
Current	**N1**	**9516**		**9570**		**28103**		**5370**	
RCP 2.6	N1	9010	-39.9	9128	-46.5	28331	15.6	4092	10.6
RCP 4.5	N1	9201	-38.6	9039	-47.0	28332	15.6	3501	-5.4
RCP 8.5	N1	9701	-35.3	8959	-47.5	28898	18.0	3296	-10.9

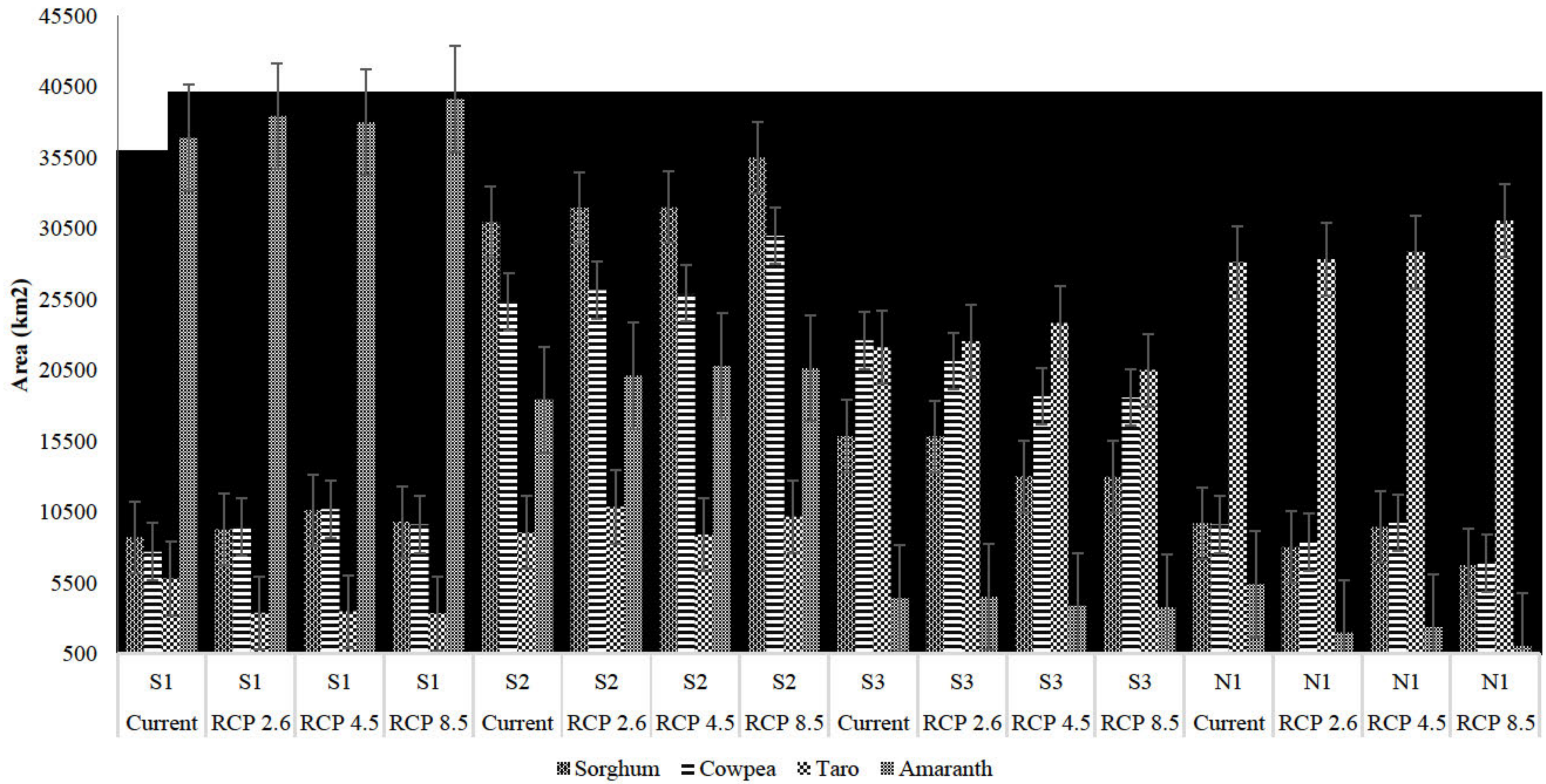

Figure 5. 7 Changes in land suitability for sorghum, cowpea, taro and amaranth under Representative Concentration Pathways (RCPs) 2.6, 4.5 and 8.5 in the 2070s. Highly suitable (S1), Moderately Suitable (S2), Marginally suitable (S3) and Unsuitable (N1).

Table 5. 4 Changes in land suitability for sorghum, cowpea, amaranth and taro suitability under Representative Concentration Pathways (RCPs) 2.6, 4.5 and 8.5 in the 2070s, relative to present conditions. Highly suitable (S1), Moderately Suitable (S2), Marginally suitable (S3) and Unsuitable (N1)

Scenario	Suitability Index	Sorghum Area km^2	Change of area as a %	Cowpea Area km^2	Change of area as a %	Taro Area km^2	% Change for taro	Amaranth Area km^2	Change of area as a %
Current	**S1**	**8579**		**7678**		**5789**		**36890**	
RCP 2.6	S1	8615	0.42	7952	3.57	5396	-6.79	37942	2.85
RCP 4.5	S1	8617	0.44	8081	5.25	5523	-4.59	37890	2.71
RCP 8.5	S1	8622	0.50	8158	6.25	5223	-9.78	37841	2.58
Current	**S2**	**27902**		**28250**		**9007**		**18402**	
RCP 2.6	S2	28206	1.08	28395	0.51	7775	-13.68	19833	7.78
RCP 4.5	S2	28391	1.73	28567	1.12	7628	-15.31	19800	7.60
RCP 8.5	S2	28439	1.90	28745	1.75	7504	-16.69	20044	8.92
Current	**S3**	**19003**		**19502**		**22101**		**4338**	
RCP 2.6	S3	18700	-1.59	18922	-2.97	21028	-4.86	4033	-7.03
RCP 4.5	S3	18416	-3.09	18450	-5.39	21049	-4.76	3901	-10.07
RCP 8.5	S3	18177	-4.35	18167	-6.85	21884	-0.98	3809	-12.19
Current	**N1**	**9516**		**9570**		**28103**		**5370**	
RCP 2.6	N1	9479	-47.85	9730	-46.44	30801	40.75	3192	-16.20
RCP 4.5	N1	9576	-47.32	9902	-45.49	30800	40.74	3409	-10.50
RCP 8.5	N1	9762	-46.29	9930	-45.34	30389	38.86	3306	-13.21

5.3.3 MaxEnt evaluation under current and future growing conditions

The jack-knife plots from the MaxEnt model were used to determine the contribution of all 14 environmental variables (Figures 5.8 and 5.9) to the final maps produced. The AUC varied across all crops; however, the highest contributions were obtained from climatic variables where AUC > 0.8. Different biophysical parameters influenced the suitability of each crop and geographical range. The plots revealed that the climatic variables minimum and maximum air temperature, length of growing period and seasonal precipitation made a relatively higher contribution to sorghum, cowpea and taro (Figures 5.8 and 5.9) suitability. More specifically, rainfall-related factors had the most significant influence on the potential suitability. For edaphic factors, lower AUC values were obtained for soil depth, pH, and slope.

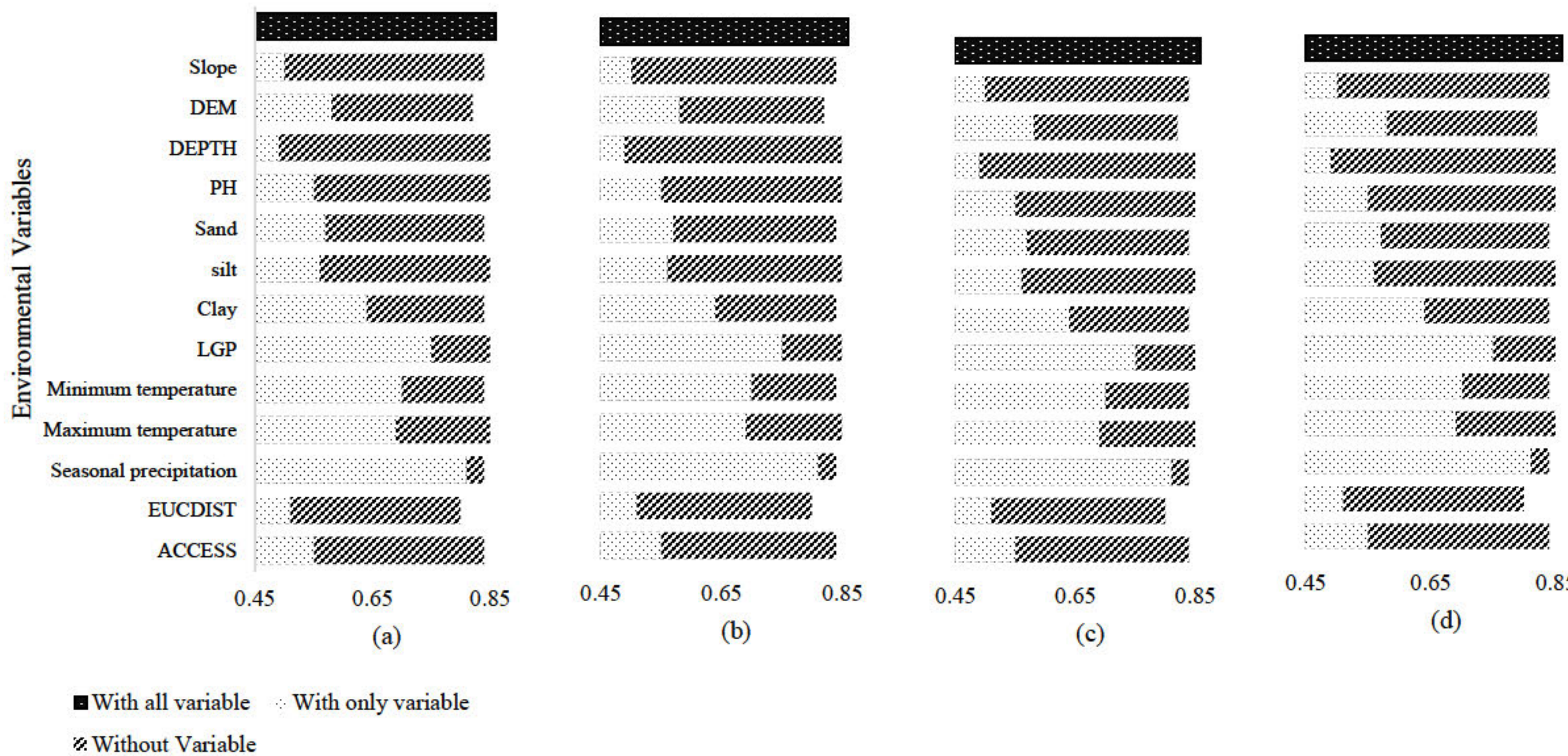

Figure 5. 8 Jack-knife plots evaluating the relative importance in MaxEnt of environmental variables for (a) sorghum, (b) cowpea, (c) taro and (d) amaranth under present growing conditions. The stripped black bars (without variable) show the performance lost when the variable is removed. In contrast, the dotted black bars (with only one variable) indicate the performance when using a variable in isolation. The boxed dark black bar (with all variables) indicates the model performance when using all variables.

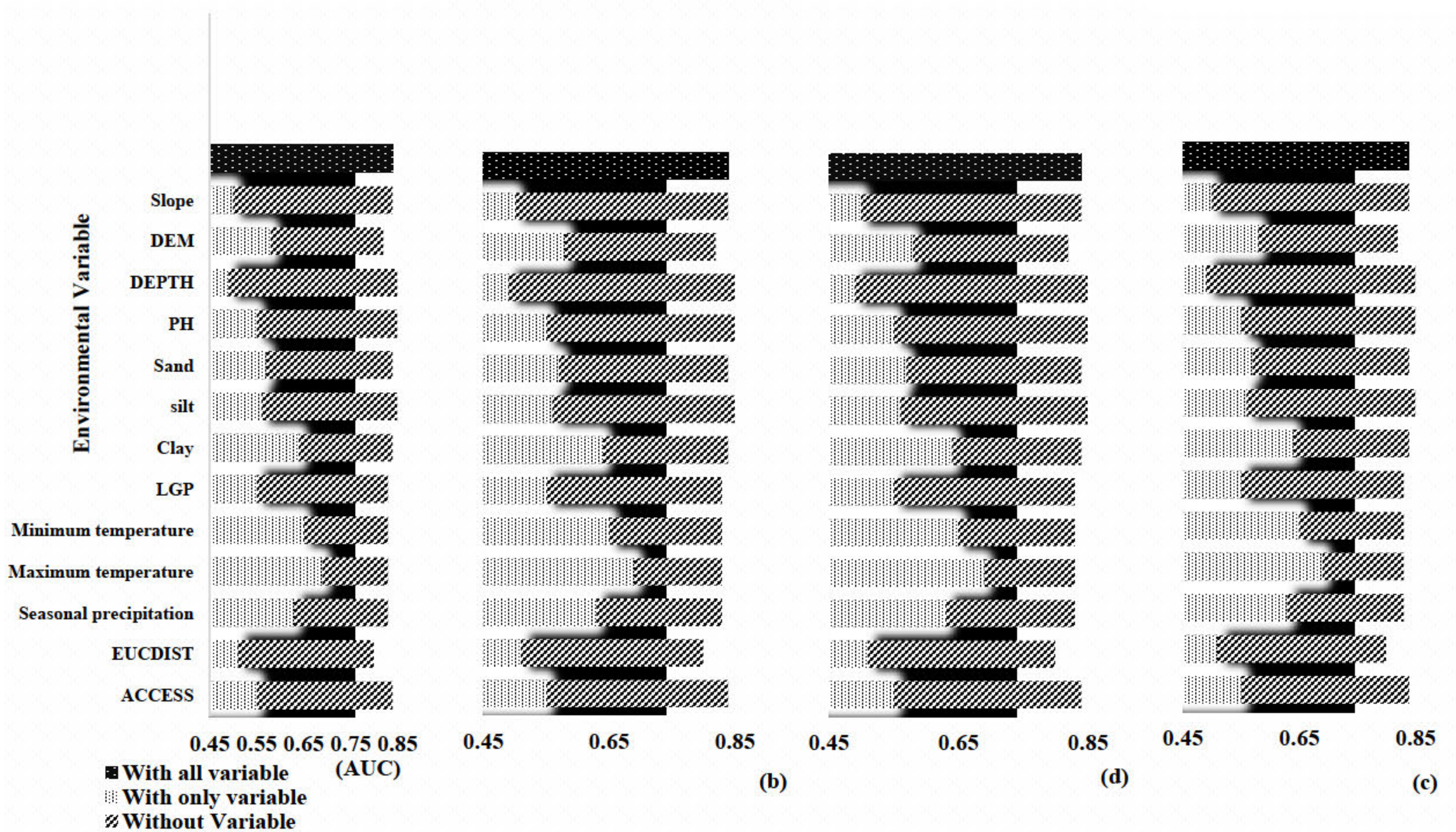

Figure 5. 9 Jack-knife plots evaluating the relative importance in MaxEnt of environmental variables for (a) sorghum, (b) cowpea, (c) taro and (d) amaranth under future (the 2050s) growing conditions. The stripped black bars (without variable) show the performance lost when the variable is removed. In contrast, the dotted black bars (with only one variable) indicate the performance when using a variable in isolation. The boxed dark black bar (with all variables) indicates the model performance when using all variables

The receiver operating characteristic curves (ROCs) are shown in Figure 5.10, together with the final AUCs of 0.93 (sorghum), 0.89 (cowpea), 0.91 (amaranth) and 0.84 (taro). These values represented the average of the replicate runs and were above 0.8, thus indicating that MaxEnt can satisfactorily estimate land suitability for NUS in KZN.

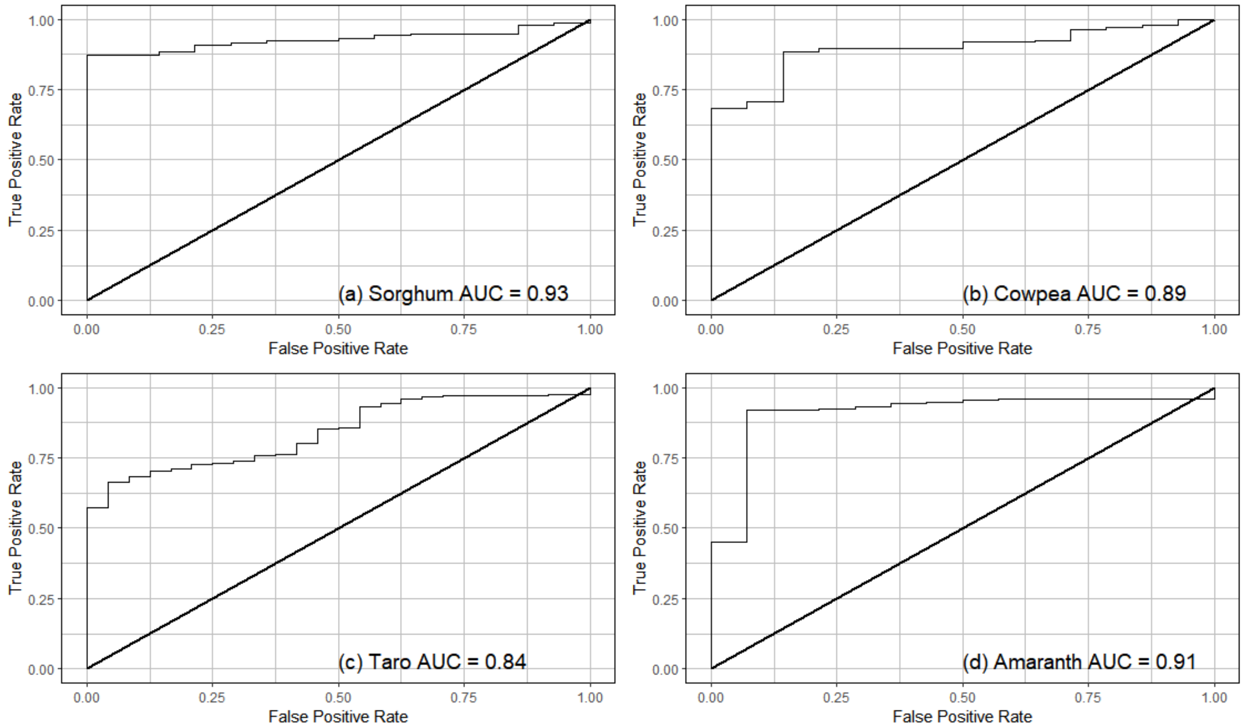

Figure 5. 10 The receiver operating characteristic (ROC) curve for (a) sorghum, (b) cowpea, (c) taro and (d) amaranth for the present period. The area under the curve (AUC)

5.4.0 Discussion

This study was the first to explore the impacts of climate change on areas deemed potentially suitable for sorghum, cowpea, amaranth and taro production in KZN. The MaxEnt model identified the most critical biophysical predictors of suitability for each crop. Our analysis of model parameterisation showed two things: (1) that the accuracy of the suitability models increased when maximum temperature and seasonal precipitation were included in the modelling, and (2) that the suitability of the studied NUS was affected more by maximum temperature and seasonal precipitation, and (3) socioeconomic factors did not increase the accuracy of the models. The observed results suggest that the reliability of models increases with crop growth indices as they are more related to the observed spatial and temporal distribution of the selected NUS, which provides more confidence in the application of the model for climate impact studies. The finding that precipitation-based factors are most important for the suitability of NUS is in line with other studies that identified rainfall as the critical determinant of marginal production systems (Chemura et al., 2020).

Contrary to finding on precipitation and temperature, the low relevance of socioeconomic factors included in the model could be attributed to the sampling structure used in the study. The study adopted a random sampling approach where the sighting of the investigated NUS did not follow the same trend as major roads. In light of our findings, further investigations are needed to identify the effects of socioeconomic variables and land-use changes on NUS cultivation to ensure sustainable production and mitigate future food insecurity. Transport affects farmers' crop produce; NUS must be transported from farms to the market. Usually, poor transportation in rural areas has resulted in low productivity, low income, a fall in the standard of living of smallholder farmers, and a high poverty rate in KZN. Distance to markets and reliable transport systems are essential in distributing agricultural products. It, therefore, helps to facilitate market access for NUS products and reduces spoilage of farm products.

The results indicated suitable land for sorghum and cowpea followed the same pattern, whilst amaranth is a highly suitable area in s KwaZulu-Natal. In contrast, taro's suitability mainly was confined to higher rainfall areas in the province. The similarity in suitable land for sorghum and cowpea could be because these crops have similar water and temperature requirements and length of growing cycle (Neely et al., 2018). Sorghum and cowpea are tropical crops requiring moderately high temperatures and water. Chimonyo et al. (2016) and Neely et al. (2018) noted that sorghum and cowpea need 450-650 mm of rainfall and are often found in the same cropping system (i.e., monocrop or intercrop). The observed similarities in suitability would suggest that these crops could be recommended, in tandem, in areas earmarked for agroecological intensification. The general suitability of amaranth to present and future climatic conditions could be attributed to its short growing cycle and adaptability to broader temperature ranges. It also requires less water over the growing season (Bello and Walker, 2017). Short-duration crops have long been suggested to increase farmers' resilience to drought and/or its mitigation. The observed suitability of sorghum, cowpea and amaranth supports claims on the potential benefits of NUS enhancing climate resilience in marginalised land. However, to further guide sustainable climate resilience in these farming systems, climate services should integrate crop suitability assessments into short (1-5 years), medium (decadal) and long term (30 years) climate impact analysis within agricultural planning.

The study revealed that taro would be most affected by future climate as the crop is less suited to the hotter growing conditions. Nevertheless, results also showed that the tested landrace variety was suitable in dry regions receiving less than 500 mm. Then again, Mabhaudhi et al. (2014) estimated that taro requires 2500 mm of water per year, which explains why the crop is best suited to the province's wetter regions, the western region the province. The studied taro landrace is the upland type, not the swamp or wetland type. Mabhaudhi et al. (2014) indicated that the upland taro landrace grown in the greater KZN region possesses drought avoidance mechanisms. During the dry spell, upland taro regulates water loss through stomatal closure and adjustments in canopy size (Mabhaudhi et al., 2014). Results suggest taro may be out of place for drought adaptation because of its high-water demand, and SA is becoming more water-stressed. Then again, climate projections indicate an increase in floods within the region. In this regard, taro can be grown to mitigate flood losses in other cropping systems. In S1 to S3, it would be necessary to continue supporting and improving climate-smart crop production techniques. However, marginalised smallholder farmers have experienced several challenges when adopting NUS in their farming practices. There is a generation gap among them regarding recipes prepared; to a certain extent, the current generation does not accept NUS. There is a need for concretising end-users about the importance of NUS. In several parts of South Africa, markets of NUS are not well organised (Massawe et al., 2016). Therefore, our results indicate areas where the investigated crops can be introduced as an adaptative management strategy.

There is an increase in suitability for all crops in the Drakensberg area (central region along the western border of KZN). The Drakensberg is a mountain range that experiences relatively high summer rainfall (> 700 mm) and has fertile soil foothills (Egziabher and Edwards, 2013). Lawrence et al. (2012) indicated that for RCP 8.5, the CORDEX projects an increase in minimum and maximum temperature within the central region of South Africa. Based on these projections, the Drakensberg area will become more suitable for producing crops such as sorghum and amaranth (Nyathi et al., 2018). The added suitability for sorghum and amaranth production in this area will increase farmer crop choices. However, this suggests that crops currently occupying these areas will become less suitable. Shifts in crop suitability would suggest a need to re-evaluate the distribution, diversity and suitability of existing crops within areas where the current suitability of crops is projected to increase.

5.4.1 Practical implications of the chapter

Climate change undermines resource-poor farmers' ability to respond to risk timely (Tom et al., 2018). Also, climate change will affect species and ecosystem distribution. Climate-induced shifts in species suitability compound further adaptation efforts by resource-poor farmers. The developed current and future suitability maps for NUS help individuals and organizations improve ex-ante climate-smart decision-making. Under climate projections, the increase in areas where NUS can be produced (i.e., S1-S3) can increase crop choices for farmers. Improving farmer crop choice is particularly beneficial in areas where maize monoculture is dominant, and productivity is projected to reduce under changing climate. Also, the knowledge that more than one crop species (e.g. sorghum, cowpea and amaranth) is suitable in a locality can increase the likelihood of improved agrobiodiversity.

This research proposes a method that can be used to improve the targeting of underutilised crop species crops, ultimately allowing research institutes to develop strategic (long term) and operational (short term) crop forecasting. Therefore, such crop mapping methods increase the ability of key stakeholders to address the risks to local food value chains posed by climate variability and change. Furthermore, the developed maps can provide independent and complementary information for national governments, commercial entities and international organizations to monitor and forecast crop distribution, hence suitability. Mapping the potential impacts of climate change on crop productivity in dryland farming systems is important for predicting appropriate adaptation interventions, including crop switching. However, the information on suitability needs to be complemented with information on "better bet" agronomic management to realise the full potential of the crops in question (Massawe et al., 2016). Notably, the maps developed are useful for informing decisions on transformative agriculture in situations where climate change adaptation requires a shift in crop choice.

Therefore, the suitability maps generated in this study can guide decision-making processes using the integrated climate risk management approach. The approach consists of 4R's: risk reduction; risk transfer that deals with insurance; risk-taking-prudence-live livelihoods diversification; and microcredit and risk reserves that deal with savings (Andersson-Sköld et al., 2015; Gopichandran et al., 2016). The maps can inform which 4Rs can reduce the risk associated with climate variability and change.

However, the information on crop suitability needs to be complemented with regionally differentiated "better bet" policies and agronomic management guidelines to realise the full potential of the crops.

5.4.2 Study limitations

Like most modelling studies on the effects of climate change on crop production, this study also has some limitations. The analysis assumes no improvements in drought and heat tolerance of crops through plant breeding efforts, which would affect their future distribution. Secondly, during data collection, we have not considered the influence of farming systems such as irrigation or dryland farming in KZN because the visual selection of occurrence location points may cause substantial bias in sample selection (Araújo and Peterson, 2012; Merow et al., 2013). A systematic random sampling technique is recommended to capture the dynamics of farming systems in KZN. In addition, this study assumed that future land use and farming systems remain constant, which is an unlikely situation. The approach taken in this study assumes all four crops can grow anywhere, regardless of current land use. Therefore, changes in land use should be considered in future research to improve the results further. In addition, more ground truthing is required to verify the area under NUS in KZN. Despite these limitations, the results of the current study still hold value and significance in terms of informing planning and decision making.

The study managed to downscale the existing climate information to achieve local detail and bridge geographical scales. While the results of our study suggest a good agreement between simulated occurrences and observed occurrences of the crop species, the classification algorithm and the GCM projections introduce some uncertainty to the outputs. Such uncertainty has implications for how the results can be used. In our case, the results are exploratory and can be used for planning purposes. There is significant spatial and temporal heterogeneity in existing climate, physical, social and economic datasets, each with a strong footing in its discipline. CORDEX datasets are a promising input for crop suitability and climate change impact studies in developing countries such as South Africa, where the required bias correction data are scarce (Teichmann et al., 2021). The model may not identify a novel agro-climatic zone emerging under future conditions. It could be worthwhile to use an ensemble of GCMs to reduce the magnitude of uncertainty.

5.5 Conclusion

This study is the first step toward a better understanding present and future suitability for NUS production. The results showed that MaxEnt could predict NUS’s present and future suitability across a heterogeneous province like KZN. These results suggest that the same analytic framework could be adopted across South Africa and the region. The analysis predicted that the potential distribution of the selected NUS's current and future growing areas was based more on environmental variables than socioeconomic factors. Climatic variables related to rainfall (length of growing and seasonal rainfall) and minimum and maximum air temperature significantly contributed to the model performance and crop suitability. The study provided essential insight into the potential of NUS production. The suitability maps developed for NUS can assist decision-makers with improving ex-ante climate-smart agriculture decision-making. In the long term, the maps developed are useful for informing regionally differentiated strategies on transformative agriculture in regions where climate change adaptation will require a shift in crop choice and cropping systems.

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CHAPTER 6: SORGHUM MANAGEMENT PRACTICES IN RAIN-FED PRODUCTION: A CROP MODELLING APPROACH

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Abstract

Sorghum plays a vital role in global food and nutrition security and may contribute to climate change sustainable food systems. However, climate-proof good sorghum production guidelines remain unclear to smallholder farmers on marginal land. Crop simulation models can play a vital role in developing crop production guidelines in a short period compared to field trials. The study aimed to develop crop management guidelines for sorghum produced under marginal conditions. The study used the Sensitivity Analysis and generalised likelihood uncertainty estimation (GLUE) tools in DSSAT. Firstly, the DSSAT model was calibrated and validated using secondary data from the literature. In DSSAT ecosystems, the split-plot design (SPD) was used to optimise planting date, planting density and fertiliser rates. The planting criteria of 25 mm of rainfall in 5 days and 40 mm in 4 days were calculated in R-Instat and used to identify optimum planting dates. Planting density targets were 51 100, 68 200, 102 500, 205000, 300 000 plants ha^{-1} and ammonium nitrate application rates of 75 and 100 kg ha^{-1}. A good agreement was achieved between the simulated and measured data in the calibration and testing season. In the evaluation process, the normalised root mean square error (RMS) for anthesis, grain yield, and biomass was 5.4 % and 5.6% and 4.3%. The best combination of management was when sorghum was planted in the second dekad of November, at a density of 68 200 plants ha^{-1} with 100 kg of nitrogen split applied as basal (50%) and top-dress (50%) 28 days after emergence. Optimum planting dates within a planting window and optimum planting density and fertiliser management practices increased sorghum yields under rain-fed conditions. Crop models can serve as a decision tool for good agricultural practices to enhance food and nutrition security in marginal lands.

Keywords: Agronomy, Crop Simulation Modelling, DSSAT, Neglected and underutilised crop species (NUS), Resilient agriculture

6.1 Introduction

Like many southern African countries, South Africa (SA) is characterised by a dichotomous agricultural system (Pereira, 2013). On the one hand, about 40 000 commercial farmers are responsible for national food security. Then, more than 2 million rural farmers (Goldblatt and von Bormann, 2010) are considered food and nutrition insecure (FNSWG, 2015). This farming community has high poverty levels (Akinyemi and Mushunje, 2019). Current production systems employed by resource-poor farmers are considered unsuitable (Akinola et al., 2020). Maize is the main cereal crop produced in these farming systems and has recurrent low yields attributed to sub-optimum management strategies (Akinnuoye-Adelabu et al., 2017). In addition, due to the increased incidence of extreme weather events such as drought and heatwaves, the yields have been further compromised (Conway et al., 2015). There is, therefore, a need to improve the resilience of resource-poor farmers. It has been suggested that there is a need to adopt more adaptable crop species such as sorghum (Araya et al., 2018; Chimonyo et al., 2016).

Sorghum is the fifth most important grain crop after maize, wheat, rice and barley (Macauley, 2015). The crop is drought-tolerant and has a low water requirement than most cereal crops (Chimonyo et al., 2019). Although sorghum has similar macronutrients, vitamins, and minerals to maize, it has more protein (Slavin and Slavin, 2017). Furthermore, it has more antioxidants than blueberries, strawberries, and plums (Khoddami et al., 2017). Despite these benefits, sorghum is still a neglected and underutilised crop species (NUS) in the southern African region (Chimonyo et al., 2019). The term neglected and underutilised crop species has been defined as crops that have either originated in a geographic location or those that have become ‘indigenised’ over many years (> 10 decades) of cultivation as well as natural and farmer selection (Mabhaudhi et al., 2017). According to Akinola et al. (2020), such crops are often characterised by limited development relative to their potential, which has led to poorly developed and understood value chains. Such is the case of sorghum within SA in particular.

The national production of sorghum in SA varies from 100 000 tonnes (130 00 ha) to 180 000 tonnes (150 000 ha) per annum (Mengistu et al., 2016; Malobane et al., 2018), and this is far below the required 250 000 tonnes by industry and the food sector. Under commercial production systems, and with the advent of hybrid seed and conventional technology, the productivity fluctuates around a mean of 2.4 t/ha, consistent with a global average of 2.2 t/ha (Macauley, 2015).

On the other hand, productivity by rural farmers, who are also characterised as resource-poor, has been observed to be less than 1.0 t/ha (Malobane et al., 2018), suggesting significant yield gaps within rural farming communities. Crop yield gaps can be linked to many factors, including the lack of irrigation (Mabhaudhi et al., 2018), market influence, market accessibility (Wegerif, 2020), agricultural labour (Neumann et al. 2010), climate and land management levels (Licker et al. 2010), and crop genetics or seed technology (Mungai et al., 2016). There is still much potential to increase productivity within rural farming communities (Basso et al., 2013; van Ittersum et al., 2016; Chimonyo et al., 2021).

Within the context of SA, literature has shown that, for sorghum, markets, labour and improved seeds are readily available (Chimonyo et al., 2016a; du Plessis, 2008; Hadebe et al., 2020; Malobane et al., 2018; Mengistu et al., 2016; Taylor, 2003). However, one of the main challenges is bio-physical factors such as weather, edaphic factors, and agronomy (Chimonyo et al., 2016). Most sorghum production is grown under rainfed conditions with suboptimum management strategies. More importantly, available information on when to plant, how much to plant, and how to apply fertiliser to maximise production under uncertain climates within rainfed cropping systems is limited to smallholder farmers in KwaZulu-Natal. Yearly variation at the start of the cropping season has made crop production management difficult for smallholder farmers (Hadebe et al., 2020). Planting too early may lead to crop failure as critical growth stages may coincide with extended mid-season dry spells that have become recurring (Hsiao et al., 2009; Mhizha et al., 2012; Vanuytrecht et al., 2014).

On the other hand, planting too late may reduce the growing season and crop's ability to utilise growth resources, resulting in yield reductions. Furthermore, suboptimum planting dates may confound other management strategies (i.e., fertiliser and plant populations), resulting in significant yield penalties. Therefore, agronomic management of sorghum, which includes optimum planting dates, plant populations and fertiliser, could reduce the yield gaps observed under marginal production systems. In light of this, crop simulation models (CSM) have been used widely as decision support tools (Ewert, 2019) and can optimise sorghum agronomic management.

Crop Simulation Models are mathematical algorithms that describe crop growth and development as a function of weather conditions, soil conditions, and crop management (Keating and Thorburn, 2018). Crop simulation models can reliably determine ‘what if’ and ‘when’ scenarios across a diverse cropping system. Crop Simulation Models are now employed to generate quick and practical cropping guidelines to aid decision-making (Ewert et al., 2019). There is a wide range of crop growth simulation models, DSSAT (Jones et al., 2003), AquaCrop (Steduto, 2009), CROPWAT (Smith, 1992; FAO, 2018), CROPGRO (Boote et al., 1998), or APSIM (Probert et al., 1998). The DSSAT has been used widely within sub-Saharan Africa to simulate the crop yield of a system under different management strategies (Soltani and Hoogenboom, 2007; Anar et al., 2019). More importantly, the model has been used to establish best management practices for optimum resource use and sustainable crop production with minimum effect on the environment and take the right decision based on the economic return of a system and alter management options under rainfed conditions (Ngwira et al., 2014; Alderman et al., 2015; Akinseye et al., 2017; Paff and Asseng, 2019). This has been made possible by the DSSAT ecosystems proven to be useful in simulating different management options under a range of soils and climates; as such, DSSAT can be used to optimise sorghum productivity.

Therefore, the study's objective was to apply a well-calibrated version of DSSAT to develop sorghum management guidelines for optimum planting date, plant population, and fertiliser inputs under rainfed conditions. Secondary to this, the study identified optimum planting windows for sorghum production.

6.2 Materials and methods

6.2.1. Study area

The study was conducted at Ukulinga (29°31′S; 30°41′E; 876 m altitude in KwaZulu-Natal province, South Africa (Mengistu et al., 2016). The climate is subtropical, with relatively wet summers and cold, dry winters (Mabhaudhi and Kunz, 2017). Annual total rainfall for Ukulinga varied between 580-1080 mm, with an average of approximately 850 mm (Mengistu et al., 2016). The long-term mean annual air temperature was 17.9 °C. The monthly average maximum and minimum air temperatures are 24.0 and 11.8 °C, respectively (Mengistu et al., 2016). The area's soils are generally classified as clay loam (Mengistu et al., 2016).

6.2.2 Description of Decision Support System for Agrotechnology Transfer (DSSAT)

The Decision Support System for Agrotechnology Transfer (DSSAT) Version 4.7 is a computer software encompassing crop simulation models for over 42 crops (Hoogenboom et al., 2019). It stimulates the growth, development and yield of a crop growing on a uniform land area under prescribed or simulated management and the changes in soil water, carbon and nitrogen under the cropping system over time (Hoogenboom et al., 2019). DSSAT was selected for its global use and proved crop management and climate impact studies (Hoogenboom et al., 2019). In DSSAT, a sensitivity analysis tool enables the user to evaluate the model sensitivity to changes in cultivars, single genotype-specific parameters (GSPs), soil profiles, weather inputs for different locations or years, and plant and row spacing (Hoogenboom et al., 2019). The sensitivity analysis tool automatically creates a new experimental file ready to run with the selected sensitivity input variation. Following the simulations, the linked GBuild graphics program allows for visual analysis of simulation results and associated statistics (Hoogenboom et al., 2019).

Crop models such as CERES in DSSAT v4.7 can be used as decision support tools for sorghum production (Amaducci et al., 2016; Sannagoudar et al., 2019). The DSSAT family of crop models was used in this study as a sample crop model to illustrate the needs, challenges, and opportunities to simulate dryland farming systems under data limitations in South Africa (Jones et al., 2015; Zinyengere et al., 2015). The DSSAT considers various management practices such as planting dates, tillage, fertilisation, residue and organic matter application, rotation, etc., found in Africa's dryland systems (Ewert et al., 2019). The CERES sorghum model is a predictive, deterministic model designed to simulate sorghum growth based on the soil water supply and crop water demand, a water stress factors (MacCarthy et al., 2010; Singh et al., 2014). The CERES model simulates sorghum yield under limiting water by calculating potential evaporation, soil water evaporation, and plant water transpiration, derived from potential evaporation and leaf area index (Hoogenboom et al., 2019). The CERES sorghum model has been extensively used worldwide to simulate sorghum growth and grain yield and as a tool for farmers' planning and decision-making in several countries (Corbeels et al., 2016).

6.2.3 Model calibration

6.2.3.1 Climate data

Meteorological data for Ukulinga were obtained from an automatic weather station (AWS) (within a 100 m radius), courtesy of the Agricultural Research Council – Institute for Soil, Climate and Water (ARC–ISCW). The data from Ukulinga was used to calibrate the model from 2013 to 2015 and validate the sorghum CERES model in the 2015 agricultural season. Daily weather for the climatic file was maximum (T_{max}) and minimum (T_{min}) air temperature (◦C), solar radiation (Rad, MJ m^{-2}), rainfall (mm) and reference evapotranspiration (ET_o, mm). Reference evapotranspiration was obtained from the weather station and based on the FAO Penman-Monteith equation from full daily weather datasets..

6.2.3.2 Crop data

The DSSAT CERES sorghum model was calibrated and later evaluated for the cultivar PAN8816. The crop coefficients were obtained from Chimonyo et al. (2016), where data from the 2013/14 to 2014/15 cropping season was used to calibrate and validate the model (Table 6.1). If model performance was unsatisfactory, the variety coefficients were optimised using Gencalc, a semi-automated program embedded within DSSAT, followed by a manual method (Araya et al., 2018).

Table 6. 1 Crop parameters of sorghum hybrid (PAN8816) determined from field data (Chimonyo et al., 2016) and literature to calibrate the DSSAT model (Sannagoudar et al., 2019).

Parameter	Description	Sorghum
P1	Thermal time from seedling emergence to the end of the juvenile phase	**280[a]**
P2	Thermal time from the end of the juvenile stage to heading under short days	**90[a]**
P20	Critical photoperiod or the longest day length (in hours) at which development occurs at a maximum rate.	**12.5[a]**
P2R	The extent to which phasic development leading to heading is delayed for each hour increases in photoperiod above P2O.	**90.0[b]**
PANTH	Thermal time from the end of heading to fertilisation	**580.5[b]**
P3	Thermal time from to end of flag leaf expansion to fertilisation	**140.5[b]**
P4	Thermal time from fertilisation to the beginning of grain filling	**81.5[b]**
P5	Thermal time from the beginning of grain filling to physiological maturity	**570.0[b]**
PHINT	Phyllochron interval; the interval in thermal time between successive leaf tips.	**49.0[b]**
G1	The scaler for relative leaf size	**5.0[b]**
G2	The scaler for the partitioning of assimilates to the head.	**6.0[b]**

The superscript [a] stands for parameters adopted from (Chimonyo et al., 2016), and [b] stands for parameters adopted (Sannagoudar et al., 2019).

6.2.3.3 Soil data

The DSSAT requires soil data for different soil profiles of specified depths. For each profile, the data required is the soil profile thickness, soil water content at permanent wilting point (PWP), field capacity (FC), hydraulic conductivity (Ksat), saturation (SAT) and total soil water content (TAW) (Vanuytrecht et al., 2014). For this study, soil data for Ukulinga was obtained from Chimonyo et al. (2016) and Mabhaudhi (2012) based on a soil water content hydraulic properties calculator. The soil textural class was described as clay (USDA Taxonomic System). The model used soil hydraulic and physical properties to develop a soil (.SOL) file. The soil was classified as clay, with 0.6 m soil depth. Other values used to describe the soil file were: PWP = 28.3%, FC = 40.6%, SAT = 48.1%, TAW= 123.0 mm^{-1}, and Ksat = 25.0 $mm \cdot d^{-1}$.

6.2.3.5 Carbon dioxide

Carbon dioxide (CO_2) data were based on the default mean annual atmospheric CO_2 concentration measured at the Mauna Loa Observatory for historical and future years. The CO_2 file is available in the SIMUL subdirectory of DSSAT.

6.2.4 Spatial analysis of the onset of rainfall

Farmers often know the risk associated with early planting in KwaZulu Natal. Planting early with ineffective rains leads to smallholder farmers' replanting and losing seed. Hence, attempts have been made to estimate planting dates to support smallholder farmers with scientifically proven information on planting dates. From an agronomical point of view, suitable planting dates for a specific crop should fulfil at least three crop water requirements.

- The field must be wet enough for sowing, and the water requirements for germination and emergence must be met and support the crop for 14 days. This depends on the specific soil type and crop (Mhizha et al., 2014).
- To reduce the risk associated with a false start of the season, dry spells longer than 14 days during the early stage of crop development should be avoided to reduce the risk of crop failure (Raes et al., 2004; Nyagumbo et al., 2017).
- The length of the growing season must fit with the crop duration period to ensure sufficient water availability (Raes et al., 2004). For instance, late planting by waiting for soils to reach field capacity alleviates the risk of prolonged water stress through the rainy season. However, it increases the risk of a shorter growing season, resulting in a significant loss of production or a total crop failure in the reproductive stage (Raes et al., 2004).

This study used R Instat to define events of interest based on soil water balance (Gallagher and Stern, 2015). The soil water balance calculates the amount of rain or irrigation water in a given soil depth available for plants at a particular time (Steduto et al., 2009). In the R Instat environment, soil water balance was considered suitable for planting crops if an area received effective rain. In this study, effective planting events were based on the following definitions.

1. Either when, any day after the 1st of October, more than 25 mm of rain is received within five days with the condition that there is no 10-day dry spell or longer occurring within the next 20 days was considered (Department of Agriculture Forestry and Fisheries, 2011). This study will be termed the "DAFF criteria", or
2. when any day after the 1st of October, an area receives at least 40 mm of rain within four days (Raes et al., 2004). It considers a cumulative rainfall depth that will bring the top 0.25m of the soil profile to field capacity during a maximum of 4 days. In this study, this will be termed the "DEPTH criterion". The logic in the DEPTH criterion is to allow the rain to percolate deeper soil layers, forming a recognisable wetting front. The DEPTH criterion is for risk-averse farmers (Raes et al., 2004; Fiwa et al., 2014). The corresponding threshold rainfall quantifies the field inspection method by farmers to determine whether conditions are favourable for wet sowing.

6.2.4.1 Climate data for spatial assessment

Temporally and spatially consistent rainfall datasets are essential in climate analyses and applications. However, meteorological stations in many parts of South Africa are sparse or non-existent, especially in marginal lands (Botai et al., 2019). As a result, we used satellite rainfall estimates to estimate effective planting dates. Gridded climate data (rainfall, air temperature, and solar irradiance) for KZN province were obtained from https://climateserv.servirglobal.net for 39 years from 1981 to 2019. A detailed description of the Climate Hazards Group Infrared Precipitation (CHIRPS) products has been provided (Funk et al., 2015). The (CHIRPS) data were compared with measured weather data from four automatic weather stations (AWS), namely Wartburg (Bruyns Hill, Ulakazi, Kwadukuza and Tugela Mouth) that were situated across the KZN province. The AWS data is from the South African Sugarcane Research Institute (SASRI) link (https://sasri.sasa.org.za/pls/sasri). One of the stations, Wartburg-Bruyns Hill, has been installed 43 km from a trial site (Ukulinga). The long-term seasonal climatic daily rainfall and maximum and minimum temperature from SASRI were used for DSSAT simulations.

The performance of CHIRPS and in-situ precipitation products was assessed based on the empirical distribution function (EDF) of daily scale precipitation at two thresholds (2.5 and 4.95 mm/day) at four weather stations. The coefficient of determination (R^2), bias, efficiency and a non-parametric Kolmogorov-Smirnov (K-S) significance test with a 95% confidence level was applied to precipitation between seasonal climatic data from the automatic weather station, assuming that both AWS data and CHIRPS datasets have similar distributions (Willmott, 1981; Eum et al., 2012). The description of CHIRPS was presented in chapter 3, sections 2.31 and 2.41.

In this study, the spatial onset of the growing season was based on DEPTH and DAFF criteria. By manipulating R Instat, spatial planting windows were calculated using the CHIRPS dataset with a temporal resolution of 10-day periods to make a dekad. In R Instat, the DEPTH and DAFF criteria were applied to produce a 5 km resolution grid-based planting windows map by calculating the values for each pixel.

6.2.5 Management and Agronomic Scenarios

Three management factors were used to develop recommendations for best management practices. The scenarios were as follows.

Factor 1: Planting dates

Based on the spatial analysis results of effective planting dates, the most optimum dates under the "DEPTH" and "DAFF" planting criteria were used in the scenario analysis. During scenario analysis, optimum planting dates (OPDs) from the two planting criteria were obtained by finding planting dates with the highest simulated potential sorghum yields and a reduced inter-annual yield variability (lower coefficients of variation (CV) for 39 years. The fitness function for each iteration was evaluated in a sequence of two steps (Equation 6.1); the fitness function (f) has been set as follows:

$$f = {Y_{sim}}^{(1-CV)} \quad \text{equation 6.1}$$

Where CV is the coefficient of variation in crop yield, Y_{sim} is the mean value of the simulated crop yield.

Factor 2: Fertiliser application rates

Under resource-poor farming systems, sorghum productivity can be improved by knowing the right amount of fertiliser. According to Chimonyo et al. (2016), in marginal lands, sorghum requires 72-100 kg N ha^{-1} of fertiliser to achieve a tonnage of 1-1.5 t ha^{-1} in South Africa. To increase the yield to meet and surpass world sorghum averages of 2.2-3.0 t ha^{-1} fertiliser application rates, timing must be optimised. Nitrogen can be applied as basal or top-dressing fertiliser. Generally, in South Africa, the recommended dose of blend fertilisers in sorghum is 100:75:25 kg ha^{-1} of N, P_2PO_5, and K_2O, respectively (Rohrbach, 1998; Walker et al., 2016). The fertiliser levels of 0, 75 and 100% of the recommended N for optimum sorghum production were used for model scenario analyses in the sensitivity analysis tool in DSSAT. The range provided a scenario whereby farmers do not have access to fertilisers (0%), have some fertiliser (50%), or have all (100%) recommended N requirements. In each treatment, 50% of total N and a full dose of P and K were applied as basal during sowing, and the remaining 50% of N was applied as a top dressing 28 days after sowing (DAS). 25 kg ha-1 N was applied at 28 DAS at calibration. This represented practices by smallholder farmers in marginal lands of KwaZulu Natal and served as the 'low' N rate (Chimonyo et al., 2016). In another treatment, 100 kg N ha^{-1} representing a high rate, 50% of N 28 DAS, was applied on the 28th day.

Factor 3: Plant density

Crop density is an important agronomic factor that manipulates the microenvironment of the field (Corbeels et al., 2016; Attia et al., 2021). It affects the growth, development and yield formation of sorghum. The optimum plant density to attain the highest sorghum yield may vary with the genotype and geographical location (Habte et al., 2021). Chimonyo et al. (2016) and Hadebe et al. (2017) recommended 44 444 plants $ha^{-1,}$ but with modern agriculture, which promotes water use efficiency per unit area, the sorghum density may be regarded as low. This study used the sensitivity analysis tool to find the best planting density by targeting population densities of 51 100, 68 200, 102 500, 205 000 and 300 000 plants ha^{-1} after thinning in a rain-fed production system.

In this study the main interactions of interests where that of Planting data and either plant density or fertiliser rates.

6.2.6 Model run

For model calibration and testing, the DSSAT sorghum model was run for two consecutive seasons, 2013/14 and 2014/15. During the scenario analyses, the DSSAT ecosystem allows the user to design experimental designs to reduce the margin of errors in the proposed simulations (Hoogenboom et al., 2019). This study used the split-plot design (SPD); plots were divided into main plots, subplots and ultimate plots. In SPD, several factors are studied simultaneously with different levels. The scenario analysis followed three replications, two main plots (planting dates), five subplots (seed rates) and two ultimate (Nitrogen levels). During the scenario analysis, the study adopted the same soil and crop file used during model calibration and validation; however, due to the lack of long-term weather station data for Ukulinga.

6.2.7 Model evaluation and statistical analysis

Model evaluation

The model was evaluated for model calibration and testing by comparing simulated versus observed values for crop phenology and grain yield. Data to validate the model was sourced from Chimonyo et al. (2016). The performance of DSSAT was evaluated using two statistical indicators, namely, the root means square error ($RMSE$) equation 6.2 and normalised RMSE (NRMSE) equation 6.3 (Yang et al., 2014). The target value for $RMSE$ is 0; values close to 0 indicate a good agreement between observed and simulated data. The model performance was categorized as follows; very good when NRMSE ≤ 10%, good when 10% < NRMSE ≥ 15%, acceptable when 15% < NRMSE ≥ 20%, marginal when 20% < NRMSE ≥ 25%, and poor when NRMSE >25% (Yang et al., 2014).$RMSE = \left[\frac{\sum_{i=1}^{n}(S_i - O_i)^2}{n}\right]^{1/2}$ Equation 6.2

$$NRMSE = \frac{\left[\frac{\sum_{i=1}^{n}(S_i - O_i)^2}{n}\right]^{1/2}}{N} \quad \text{Equation 6.3}$$

Where S_i, O_i and $\bar{O}$ Simulated, observed and observed mean values, respectively, and n is the number of measurements (Yang et al., 2014).

Evaluating planting date criteria

Since our calibration data was from the Ukulinga research centre, we tested whether the population mean ranks for the two planting criteria differed using the Wilcoxon rank-sum test. The Wilcoxon rank-sum test is a non-parametric alternative to the two-sample t-test based solely on the order in which the observations from the two samples fall. The tests did not assume that the two planting criteria are typically distributed but assumed that the distributions were of the same shape.

Evaluating scenario performance

Planting density and fertiliser treatments were analysed using an ANOVA, and Fisher's protected least significant difference (LSD, a = 0.05) was used for mean separation. A t-test was used to determine a significant difference between the DAFF and DEPTH planting criteria. The t-test, as a single index of merit, a fitness function, summarises how close a given design solution is to achieving the set aims (Yang et al., 2014).

6.3.0 Results

6.3.1 Model Evaluation

The alignment of both simulated and observed data for sorghum biomass showed that the model could accurately simulate biomass. It showed RMSE of 232.2 kg ha^{-1} and NRMSE of 5.3 % for the sorghum rain-fed production (calibration) and 93.3 kg ha^{-1} (Figure 6.1).

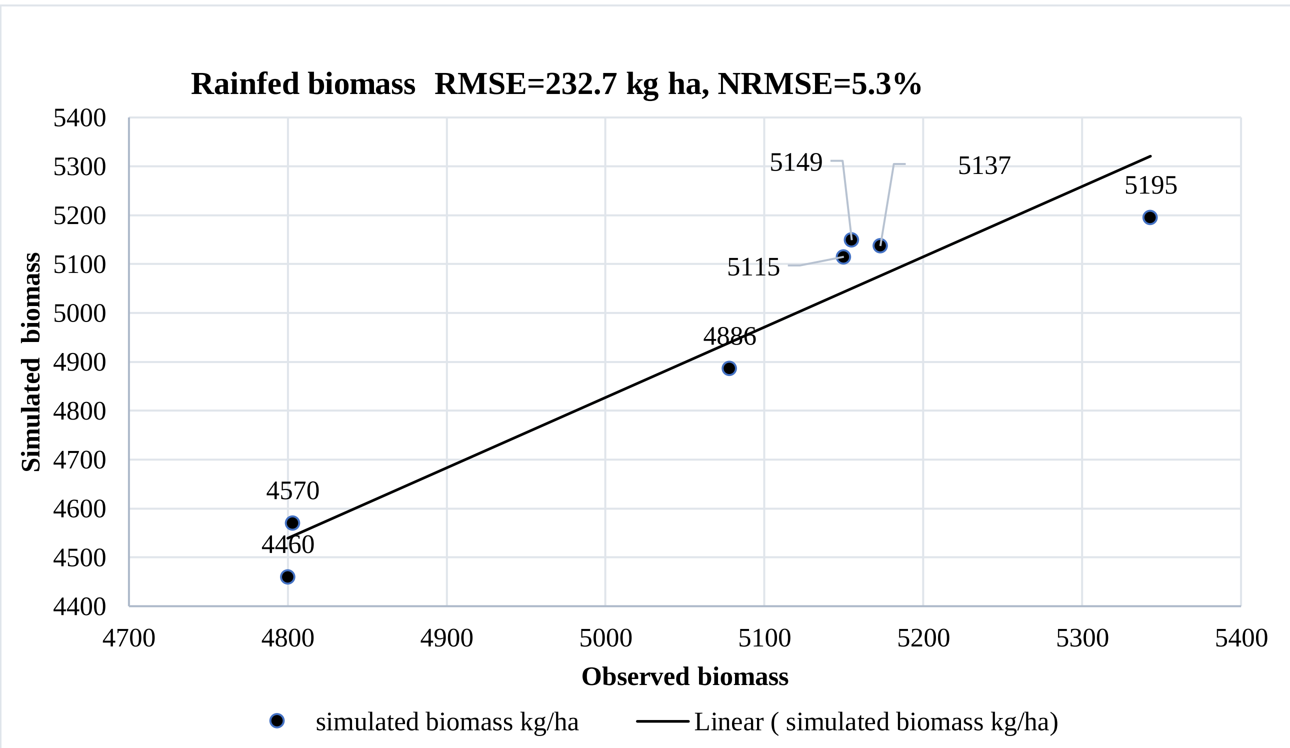

Figure 6. 1 Observed and simulated sorghum biomass kg ha^{-1} for rain-fed production.

The final yield and biomass were consistent with the observed results (Figure 6.1). The RMSE and NRMSE of the measured and simulated yield were 116.6 and 5.4%, respectively (Table 6.2). Similarly, the NRMSE and RMSE values for days to anthesis were 5.6 % and 4.0, respectively (Table 6.2).

Table 6. 2 A comparison of observed and simulated values for days to anthesis, yield and biomass (kg ha^{-1}) for sorghum (PAN 8816) and statistical output for its evaluation.

	Observed (kg ha^{-1})	**Simulated (kg ha^{-1})**	**RMSE**	**NRMSE**
Anthesis in days	71.0	72.0	4.0	5.6%
Yield (kg ha^{-1})	1239.4	1306.0	116.6	5.4%
Biomass (kg ha^{-1})	5285.0	5056.0	229.0	4.3%

6.3.2 Evaluating For both criteria, the averaged long-term starts of the season start earlier from east to west CHIRPS data

The coefficient of determination (R^2), bias, efficiency and a non-parametric Kolmogorov-Smirnov (K-S) significance test with a 95% confidence level were applied to precipitation between climatic data from four automatic weather stations. Based on the results of a K-S test, the CHIRPS precipitation data that significantly (K-S test) matched the in-situ data distribution were identified inside their respective threshold boxes. The CHIRPS evaluation results were presented in chapter 3 (Table 3.5).

6.3.3 Planting criteria

6.3.3.1 Spatial presentation of the start of season map in KwaZulu Natal

The long-term adjusted CHIRPS data set showed a variation in the start of the season across KwaZulu Natal (Figure 6.2). For both criteria, the averaged long-term starts of the season start earlier from east to west. Northeast of KwaZulu showed the late start of the season (2nd dekad of December) on both criteria. Districts such as Zululand, UMzinyathi and UMgungundlovu planting is between the first dekad of November to the last dekad of November. Some districts, such as Sisonke at the northwest of the district season, can start as early as October (Figure 6.2).

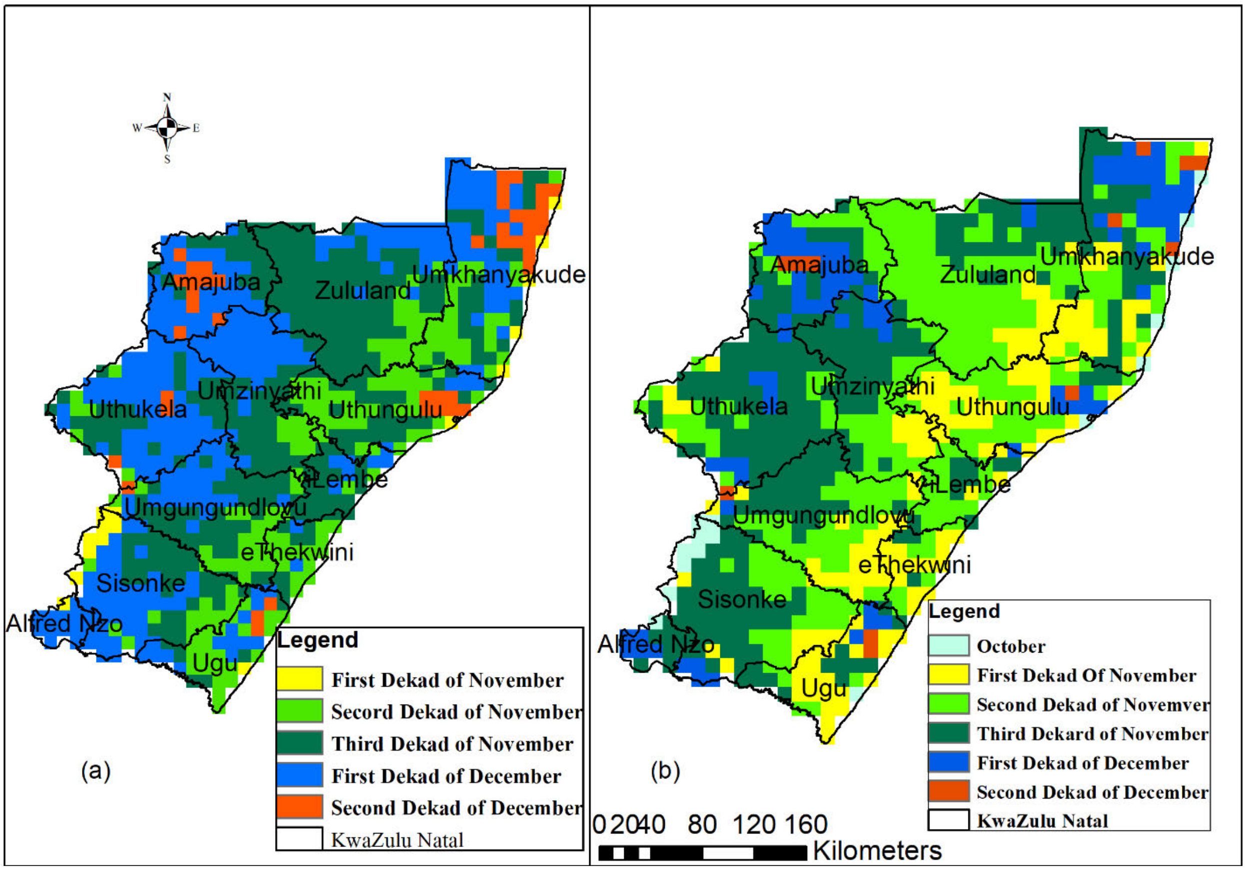

Figure 6. 2 Planting windows (a) DEPTH Criterion 40 mm in 4 days (b) Department of Agriculture, Forestry and Fisheries (25mm in 5 days)

6.3.3.2 Start planting at Ukulinga

The planting dates generated by DAFF and DEPTH criteria are shown in Figure 6.3. The Wilcoxon rank-sum test (P = 0.007) indicated a significant difference in planting dates over the past 38 years. The DAFF criterion generally gave the earliest planting dates compared to the DEPTH criterion. Based on the DAFF criterion, the planting window is between 26 October-third dekad of October (¼ quartile) to 23 November-third dekad of November (3/4 quartile). According to the DAFF criterion, the season started on the 2^{nd} dekad of November (15 November), as indicated by the median. Using the DEPTH criterion, the season usually starts on the 3^{rd} dekad of November (29 November), indicated by the median, and the planting window is between 17 November (¼ quartile) to 6 December (3/4 quartile). In both criteria, there was no start of the season in 1992. DAFF's planting dates are consistent and were always first met, followed by the DEPTH criterion and more variability in the DEPTH criterion. In 1991, 1998, 2009 and 2011, planting dates for DEPTH and DAFF stretched to January (Figure 6.3).

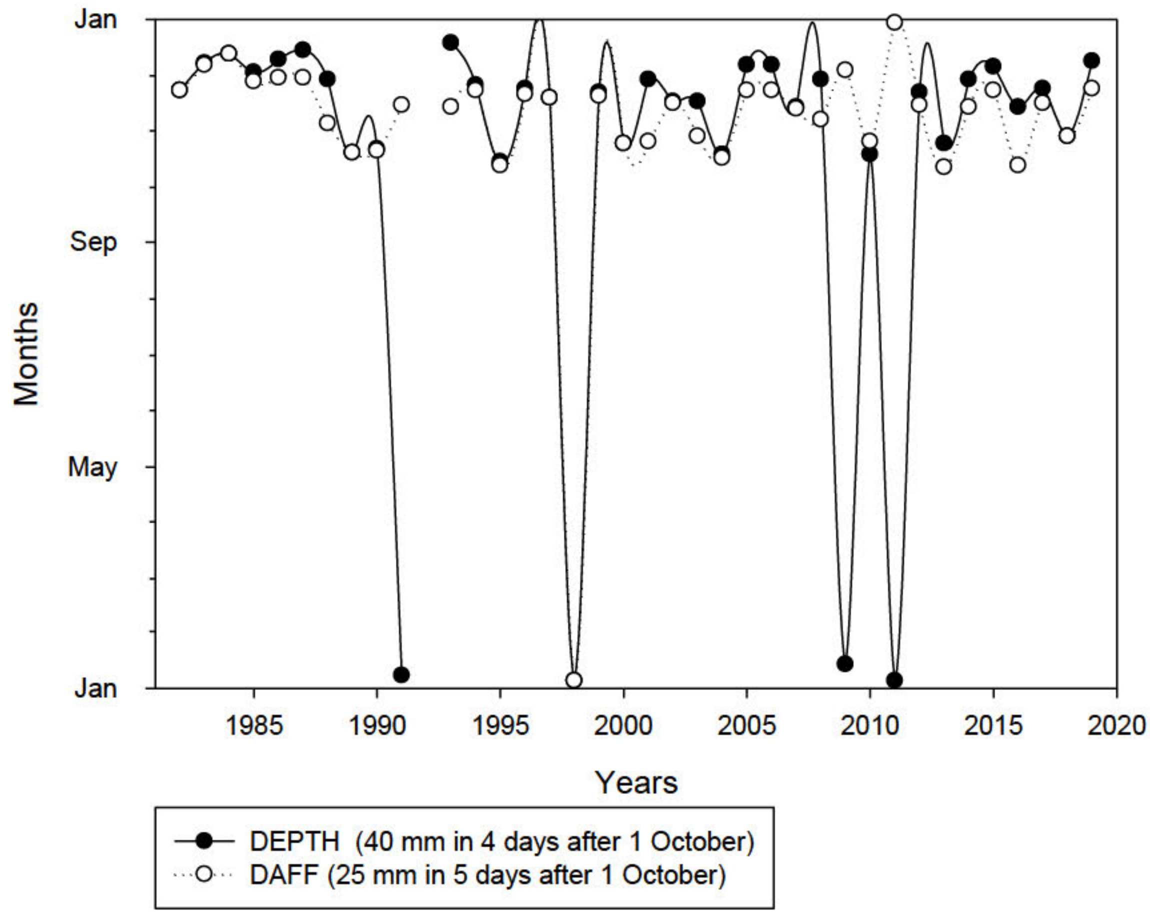

Figure 6. 3 Trend analysis for two planting criteria DEPTH 40 mm in 4 days (Raes et al., 2004) and Department of Agriculture Fisheries and Forestry (DAFF-25 mm in 5 days) from 1981-2019 Ukulinga.

6.3.4 Scenario analysis

6.3.4.1 Optimisation of planting dates

Based on the results of the t-test, there was a significant difference ($p < 0.05$) in simulated sorghum yield between the start of the season from DEPTH and DAFF criteria (Figure 6.4). The fitness function for DAFF was 2.3, and for DEPTH, it was 5.6 (Figure 6.4). In several seasons, planting criteria thresholds were met at different times. In several seasons, the DAFF criterion always starts, followed by the DEPTH criterion except in the 2010 season.

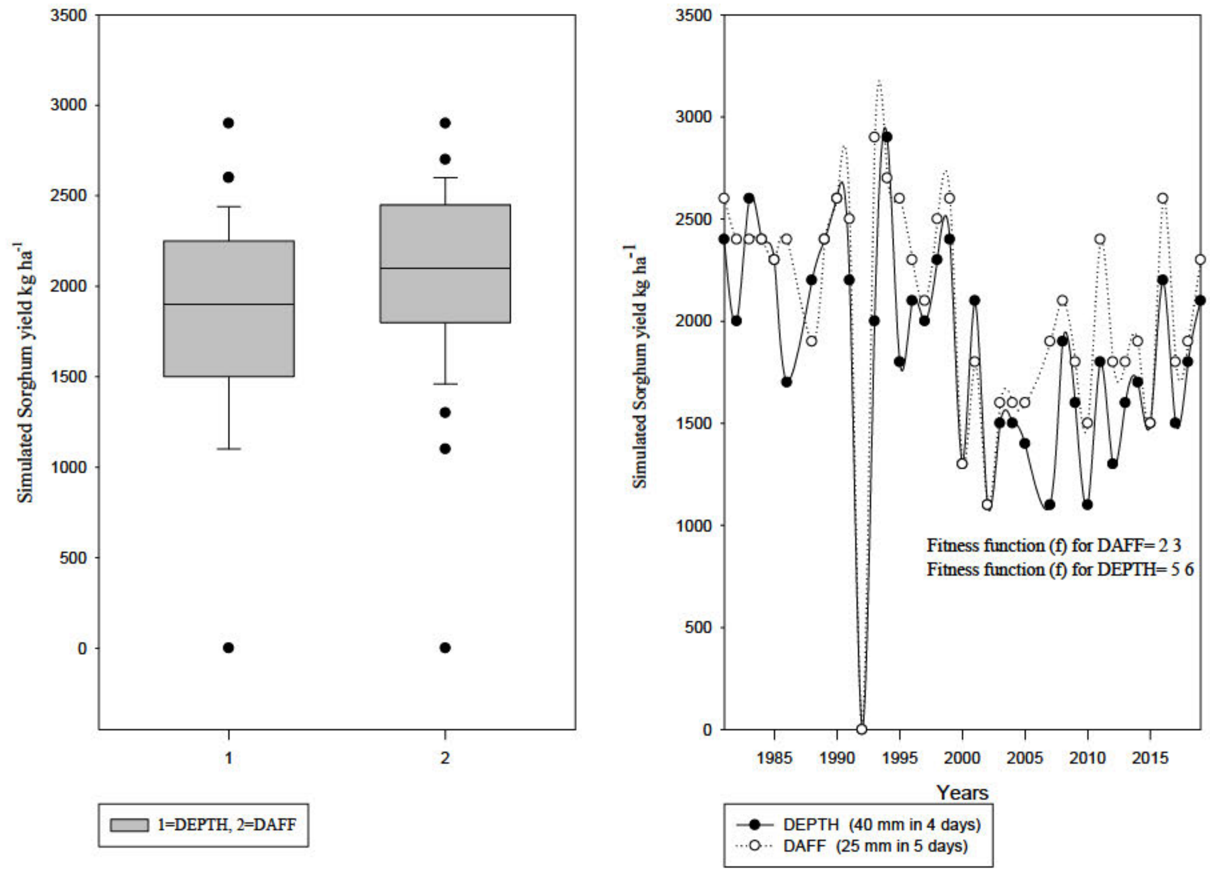

Figure 6. 4 (a) A boxplot showing simulated yield 1=DEPTH criterion 40 mm in 4 days, 2=Department of Agriculture, Forestry and Fisheries (DAFF) (25mm in 5 days) (b) Simulated sorghum yield optimised from 1981 to 2019 for Ukulinga.

6.3.5 Effect of planting density and fertiliser application rate on optimised planting dates

The yield response to planting criteria varied between 465 kg ha^{-1} to 1855.3 kg ha^{-1}. From the simulations, the DAFF criterion simulated higher yields than the DEPTH criterion except in 102 500 plant density (Table 6.5). The lowest sorghum yields were simulated at the 0 N level under both planting criteria (Table 6.5). The highest yield was simulated from 100 kg ha^{-1} N under the DAFF criterion. The low rate of N fertiliser combination of 25 kg ha^{-1} of N applied 28 DAS after basal resulted in significantly lower yields than 50 kg ha^{-1} of N applied 28 DAS after basal (Table

6.5). Sorghum yield increased over the entire range of stand density (Table 6.5). Sorghum was significantly affected by increased plant density at (p=0.05) (Table 6.5).

Figure 6. 5 Effect of planting criteria, planting density and nitrogen application rate under rain-fed production in DSSAT ecosystem in season 2014/15

	Sorghum yield kg ha^{-1}	
Population density	DAFF (25 mm in 5 days)	DEPTH (40 mm in 4 days)
51 100	1469.9^{a}	1284.5^{a}
68 200	2118.2^{c}	1 855.3^{bc}
102 500	1719.3^{b}	1754.6^{b}
205 000	1469.9^{a}	1312.1^{a}
300 000	1405.1^{a}	1323.6^{a}
Nitrogen rate		
Control (0)	550	465
low (25)	1807	1590.8
High (50)	2007.8	1677.7

Means within a column followed by the same letter, and those without letters, are not Significantly different per Fisher's protected least significant difference (P< 0.05). Nitrogen rate: low = 25 kg N ha^{-1} (representing 75 kg ha^{-1}) and high = 50 kg N ha^{-1} (representing 100 kg ha^{-1}).

Highest simulated yield, 2 118.2 kg ha^{-1} obtained from 68 200 plants under rainfed production using the DAFF criterion (Figure 6.5). Yield simulation under DAFF produced higher yields than simulation-based on the DEPTH criterion (Figure 6.5).

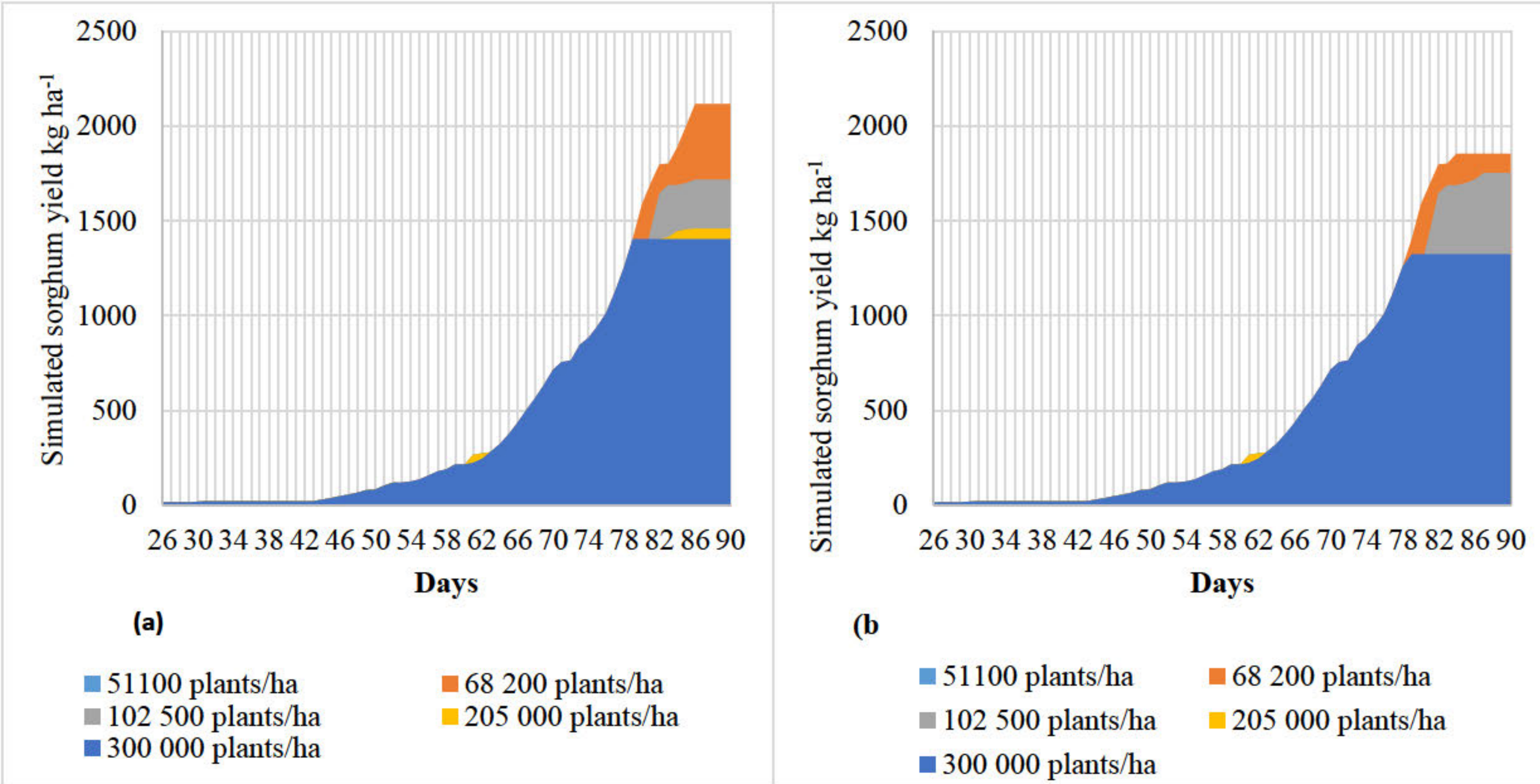

Figure 6. 6 The response of sorghum planting density on grain yield kg ha^{-1} (a) DAFF criterion, plant density and fertilisation and (b) under DEPTH criterion, plant density and fertilisation.

6.4.0 Discussion

Field experiments combined with crop model simulations have been used to design crop production guidelines in recent years. Crop modelling tools have become more helpful in designing crop management guidelines in a short period and at a lower cost than field trials (Jones et al., 2003; Anar et al., 2019). Conventionally, common field trial-and-error methods are used to develop the best crop management practices, yet crop growth models are an option for selecting the optimum combination for best sorghum management (Attia et al., 2021; Rugira et al., 2021). The study used sensitivity analysis and generalised likelihood uncertainty estimation (GLUE) tools in DSSAT. The DSSAT models can dynamically quantify crop growth responses to farmland environments. In DSSAT, the sensitivity analysis and GLUE tools DSSAT combined with R-Instat were used to develop sorghum cropping guidelines. R-Instat was used to upscale the point-based planting window into maps to guide smallholder farmers on planting dates in marginal lands. Therefore, we used the hybrid method as a first step to developing crop management guidelines for sorghum produced under marginal conditions in KwaZulu-Natal. In addition, gridded climatic data was used after it was compared with recordings from an automatic weather station.

DSSAT parameterisation

Calibrated genetic cultivar coefficients closely matched the observed sorghum anthesis grain yield and biomass (Table 6.2). Validation of crop parameters resulted in the best match with the observed data. Results showed a good model simulation of these variables in response to different treatments with nRMSE < 5.6 % for anthesis, sorghum yield 5.4% and biomass 4.3%. The average observed anthesis date in the evaluation was four days less than during calibration (Table 6.2). This indicates a model response to water stress in simulating sorghum phenology.

Nevertheless, the values of the crop phenology parameters reported in this study are closely similar to those reported for sorghum in APSIM in the same environment (Chimonyo et al., 2016). The values for G2 were calibrated to 49.0, and P5 was calibrated to 140.5, indicating that sorghum (PAN8816) is a medium to high-yielding hybrid for arid environments (Bertalero et al., 2013; Chimonyo et al., 2016; Hadebe et al., 2017). The PHINT was set as 81.5, which is closed to the range set by (Araya et al. (2018) and Sannagoudar et al. (2019) of 78-83 in some sorghum, and our cultivar coefficients are within the range of their reported coefficients. Simulation of sorghum times to anthesis, yield and biomass indicated good stability responding to climate, soil and crop management.

Comparison of automatic weather station rainfall data and CHIRPS datasets

Comparisons of CHIRPS data with available climatic records are crucial to determine their strengths and limitations in sorghum production, where availability of climatic is scarce. The analysis of climatic data depends on its distribution pattern, especially in marginal areas. A non-parametric Kolmogorov-Smirnov (K-S) significance test with a 95% confidence level was applied to precipitation between in-situ data, assuming both in-situ data and CHIRPS data have similar distributions (Funk et al., 2015; Dinku et al., 2018). The in-situ data recorded through traditional rain gauges do not accurately measure precipitation events (<2.5 mm/day) because weather station data represents point-scale observations, which is not truly representative of the area-averaged precipitation of the CHIRPS data. Precipitation from infrared and microwave-based algorithms also has limitations due to terrain and wet and dry regional climates (Dinku et al., 2018). The application of corrected remotely sensed climatic data can develop climatic-related guidelines in regions where in-situ data is sparse and unavailable (Ullah et al., 2019).

Planting windows

Sorghum production in marginal areas can be seriously affected by planting and rainfall during the start of the season and the entire growing period. It is imperative to improve the design of sorghum management systems to make productive use of first effective rain and enhance sorghum productivity due to variable inter-and intra-seasonal rainfall distribution. Based on the local average climatic conditions, the results of this study showed that the planting date had a direct impact on sorghum yields. The ideal planting date is a scenario where overall yields are high and there is minor variation over time. The DAFF criterion planting dates simulated higher yields because the sorghum utilises heat units, the growing period's length, and then accumulates more biomass (Chimonyo et al., 2016). Raes et al. (2004) showed that the planting date factor would help delineate the optimum strategy for rain-fed cropping systems. The earlier crops are planted, the higher the probability of having higher yields due to low relative evapotranspiration. The relative evapotranspiration (ratio of actual evapotranspiration, ET, to the potential evapotranspiration, ETc) is an index that expresses the degree of satisfaction of the crop water requirements (Foster et al., 2017). This index strongly correlates with crop yield, and seasonal values are used to obtain reliable estimates of the expected yield reduction resulting from water stress, especially in marginal areas (Mugalavai et al., 2008; Waongo, 2015).

The DEPTH method quantifies a field inspection method often used by smallholder farmers to determine whether conditions favour planting. This is achieved by digging a test hole, usually a day after a rain event (Raes et al., 2004; Mhizha et al., 2014). The logic is to allow the rain to reach deeper soil layers, forming a recognisable wetting front. Planting with the first effective rains improves the chances of the sorghum to utilise heat units for robust growth, and the crop can utilise the length of the growing period. The DEPTH criterion is more difficult to meet because it requires the highest moisture to bring dry topsoil at a wilting point to field capacity and support seed emergence until the next rains are received. There are high chances of having successful sorghum planting as the season progress from the second dekad of November to December in KwaZulu Natal. The success of having effective rains in the last dekad and first dekad of December is attributed to the movement of ITCCZ from the equator to the southern hemisphere. The migration of southern Africa's inter-tropical convergence zone (ITCZ) affects seasonal precipitation patterns across the regions. The ITCZ brings rainfall around December, signalling annual crops.

Planting dates vs planting population and planting dates vs fertiliser management

The highest yield was obtained at the 68 200 planting density. This demonstrates that the stability of sorghum grains depends on plant density and resources provided to the field. Higher populations negatively impacted yield under lower fertiliser 25 kg ha^{-1} 28 days after planting in 2013, which was relatively wetter than the 2014-2015 season (Chimonyo et al., 2016). When rainfall was high, yield increased with population density. Increasing plant density to optimum density was hypothesised to be one way of increasing yields in sorghum production. Optimum density allows sorghum to use available moisture efficiently. Sorghum can be planted at a wide range of population densities; however, a population of about 68 200 plants ha^{-1} would be most reliable under marginal production conditions (Masasi et al., 2019). Reduced row spacing also planting contributes to weed control by a quicker canopy cover and make the sorghum crop more competitive against weeds. Generally, sorghum develops larger stalks and produces enough tillers to fill open spaces when plants are not crowded without water.

Plants do not have room to grow at higher densities and will develop smaller stalks. In this location, and those similar to Ukulinga in South Africa, the N rate on sorghum yield affects production. The more fertiliser that is applied, the lower the utilisation rate of fertiliser. The less fertiliser there is, the higher the fertiliser utilisation rate but, the lower the yield. This paper recommends 100 kg ha^{-1} of nitrogen applied 50 kg ha as basal application and other 50 kg ha^{-1} applied 28 DAS. Araya et al. (2018) recommended a similar fertiliser application. It is important to note that applying recommended nitrogen after soil testing increases sorghum production because of the principle of diminishing benefit.

Smallholder farmers in Sub-Saharan Africa (SSA) have limited options for investment (seed, insurance, fertilisers, pesticides, machines) and irrigation to adapt to climate-related risks (Stads and Beintema, 2012).In semi-arid regions, a few smallholder farmers who grow sorghum exhibit decreasing absolute risk to climate shocks, they are risk-averse, and their concern is how to limit the risk of replanting due to false start of the season, crop failure, and sustain their crop production in moisture stressed environment (Waongo et al., 2015). Smallholder farmers need to adapt to climate-related shocks. One way of adapting to climate-related shocks is by observing planting windows and planting with correct moisture to sustain crop growth (Raes et al., 2004). Predicting a recurring planting window based on successful planting events can improve crop production in SSA. Such climatic information is essential for smallholder farmers; it guides them in choosing crops, varietal selection, planning of labour, on-time land preparations, and when and how much moisture to trigger a planting event in rain-fed crop production. The development of fertiliser blends for different locations should be based on soil nutrient status. The DSSAT model, to be more efficient, should be able to model the effect of pests (Boote et al., 2018). Therefore, the DSSAT ecosystem and many other crop modelling systems are limited in handling the impact of biotic stresses caused by insect pests, diseases, and weeds (Ewert et al., 2019). The DSSAT can be automated to issue real-time guidance to farmers on planting time, planting density, fertiliser application rate and timing according to observed and forecast rainfall.

6.5 Recommendations

- In events where recorded data from weather stations, adjusted gridded climatic data from big data sources can be used to develop crop production guidelines. Before using gridded climatic data, one needs to compare the weather station data and satellite data. One of the choices that must be made in such comparisons is how much averaging of the gauge data and satellite data are needed to reduce the "noisiness" of the comparisons to a level low enough to be informative.
- Smallholder farmers who rely on rain-fed production must increase the use of climatic information from early warning systems to achieve food and nutrition security.

- Optimum planting dates from the DAFF criterion (25 mm in 5 days) simulated the highest sorghum yields in a planting window. They can be considered valid planting criteria in a normal agricultural season in KwaZulu Natal.
- Risk-averse smallholder farmers can use the DEPTH (40mm in 4 days) method, which is based on farmer's practices, the risk of failure drops but, on the other hand, might reduce the NUS yield due to delayed planting.
- The planting criteria generated do not elaborate on a specific planting date. Instead, they suggest a set of reasonable planting rules, leading to a time window for the planting of approximately two weeks. This can help to increase the adaptability of this approach for smallholders who grows sorghum in marginal areas because their decision about planting also depends on other external factors such as land preparation, availability of seeds, labour, machines, short weather forecast (early warning systems), an advisory from extension staff etc.
- Rain-fed sorghum production spacing of 75 * 5 cm, approximately 5-7 kg seed/ha for tiny seed and up to 7 kg for large seed is recommended, and this translates to 68 200 plants ha^{-1}
- Maps generated can be used as a general spatial recommendation to improve sorghum production in marginal areas. On-farm climatic data recording is advisable so that farmers can develop their planting windows, planting density and fertiliser application rates which are farm-specific.

6.6 Conclusion

A hybrid method, DSSAT and R-Instat, are practical and applicable methods for determining the best planting methods in marginal lands of South Africa. The developed sowing guidelines were presented on a map, including optimum planting density and fertiliser application. The developed maps at the start of the season can show a homogenous area with a similar planting window for sorghum production in marginal. However, the set guidelines are still rather general, and their application at the farm level is complex unless they are simplified to the farm level. Since sowing date occurrences vary yearly, and fertiliser application depends on soil analysis, it would be helpful to use climate information like short-term weather forecasts to develop the best crop management. In this study, selecting either DAFF (25 mm in 5 days) or DEPTH (40 mm in 4 days) depends on the risks a smallholder farmer wants to run. Risk-averse smallholder farmers might nevertheless be worthwhile to promote the DEPTH method in sorghum production. However, in a scenario where the planting window is historically known, the DAFF criterion is more consistent and usually simulates higher yields of DSSAT. Identifying optimum planting dates within a planting window, coupled with optimum planting density and fertiliser management practices, can increase sorghum yields. Sorghum can be planted at a wide range of population densities without impacting biomass production; however, a population of 68 200plantsha^{-1} produced economic yield in marginal lands under rain-fed production. The presence of sorghum at correct moisture, optimum planting density, and optimum fertiliser produced the highest economic yields in DSSAT ecosystems. Crop models integrate genotype, environment and management and can serve as an analytical tool to study the influences of these factors on crop growth and agricultural planning.

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CHAPTER 7: GENERAL DISCUSSION, CONCLUSION AND RECOMMENDATIONS

7.1 Introduction

The world population continuously grows, causing overexploitation of natural resources, especially agriculture-related activities leading to food insecurity and poverty (UN DESA, 2017). Shifts in population dynamics and climate change are predicted to put more significant constraints on global food production before 2050 (Bank, 2018). Hence, there is a need for more sustainable agricultural development in marginal lands. It is within this population who resides in marginal lands where food insecurity is high (Reynolds et al., 2015). To achieve food security, smallholder agriculture is supposed to align its targets with the cognition of the four pillars of food security (van Dijk et al., 2021). However, agriculture in these systems is affected by several challenges, including weather uncertainties due to climate change, lack of resources to adapt to weather extremes, poor infrastructure, worsening land degradation, especially declining soil fertility~~,~~ and dwindling arable land (Goldblatt and von Bormann, 2010; Jones et al., 2015). A plausible pathway to increasing food security and resilience within smallholder farming communities is mainstream technologies adaptable to prevailing socio-economic and environmental conditions. One such technology is neglected and underutilised crop species (NUS) (Mabhaudhi et al., 2017a). They provide potential solutions and pathways for resilience, adaptation to food insecurity, environmental degradation and poverty reduction.

Neglected and underutilised crop species are crops that have not been previously classified as major crops, are under-researched, occupy low utilisation levels and are mainly confined to smallholder farming areas (Chivenge et al., 2015). They are well known for tolerating adverse conditions such as climate variability and change in marginal land (Mabhaudhi et al., 2017c, 2019). Despite this, the importance of NUS in rural food systems and information regarding their suitability across diverse agricultural landscapes remains mainly anecdotal, with limited information detailing "where" they can grow and "why" they grow (Ceballos-Silva and López-Blanco, 2003; Sekiyama and Nagashima, 2019). Such information is essential if NUS are to be incorporated into existing cropping systems, increase the productivity of marginal landscapes, and reclaim degraded agricultural land. Further improvements in NUS production can improve food security globally, especially in marginal land where most smallholder farmers are. (Slabbert et al., 2004; Harrison et al., 2010; Motsa et al., 2015).

Information about the suitability of NUS remains untapped in South African agroecology (Nhamo et al., 2018). There are no frameworks for assessing NUS's current and future suitability. Overly, the study hypothesised that NUS are suitable for the current and future agroecology of South Africa. It is reasonable to assume that NUS displays some natural selection and climatic adaptability traits on specified agroecology (Nyadanu and Lowor, 2014; Chivenge et al., 2015; Baldermann et al., 2016; Mabhaudhi et al., 2017b). The study tests the hypothesis that selected NUS are suitable for drought-prone areas in South Africa. A series of modelling approaches were used to test this hypothesis (Figure 7.1).

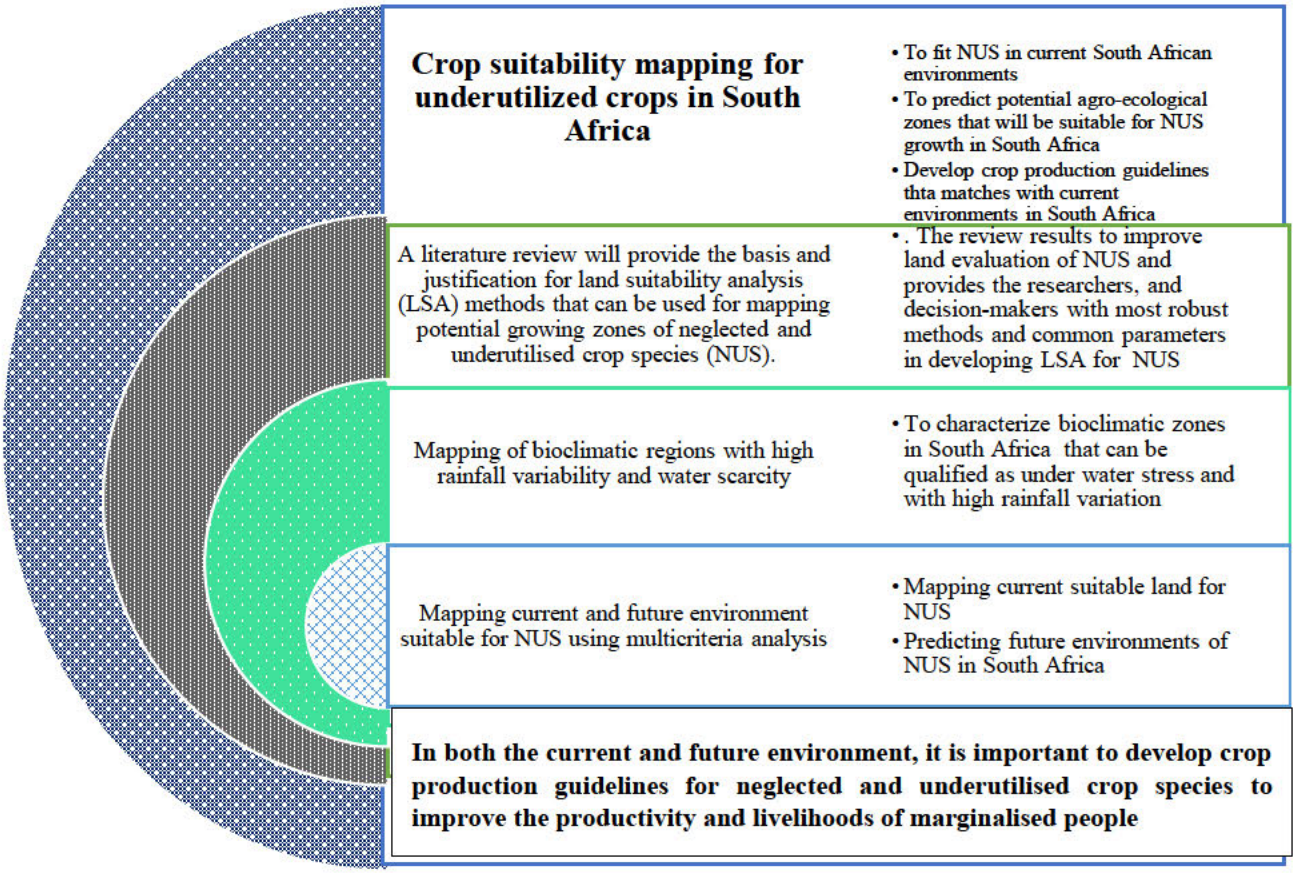

Figure 7. 1 Thesis discussion framework

7.2 Identifying a suitable method for assessing land suitability of underutilised crops

A scoping review was initially undertaken (cf. Chapter 2) to evaluate methodological strategies for land suitability analysis (LSA). In agriculture, land use and classification address questions such as "where" and "why" a particular crop is grown within particular agroecology. There are several LSA methods, but there is no consensus on the best method for crop suitability analysis. The review classified LSA methods reported in articles as traditional (26.6%) and modern (63.4%). Modern approaches, including Multi-Criteria Decision Making (MCDM) methods such as Analytical Hierarchy Process (AHP) (14.9%) and Fuzzy methods (12.9%); crop simulation models (9.9%), and machine learning-related methods (25.7%), are gaining popularity over traditional methods.

The MCDM methods, namely AHP and fuzzy, are commonly applied to LSA, while crop models and machine learning-related methods are gaining popularity. A total of 67 climatic, hydrology, soil, socio-economic and landscape parameters are essential in LSA (Akinci et al., 2013). Many studies have used MCDM techniques for analysing the complexities involved in land capability and suitability evaluation in crop production. However, all land suitability analysis methods are imperfect and require careful testing and evaluation before application (Bagherzadeh and Gholizadeh, 2018; Pecchi et al., 2019). To improve land use planning and give an accurate picture of land use, especially in smallholder farming systems, socio-economic factors should be included where available (Kamilaris and Prenafeta-Boldú, 2018; Sharma et al., 2018). Unavailability and categorical datasets from social sources are challenging (Akpoti et al., 2019). To capture social and economic datasets, using the Internet of Things (IoT) and block chain to store and share data with different organisations will improve the accessibility of data (Sharma et al., 2018). Socio-economic factors are required in hybrid land evaluation. Integrating quantitative simulation modelling and qualitative land evaluation techniques leads to excellent scientific and practical results, which gradually improve the models' accuracy and applicability (McDowell et al., 2018).

Finally, the practical automated application of land evaluation systems is described as a land-use decision support tool that uses information technologies to link integrated databases and various models (Bagherzadeh and Gholizadeh, 2016). Therefore, future research studies should encompass more substantial attributes of NUS LSA's hybrid land evaluation system. The review expects researchers and decision-makers to provide the most robust methods and common parameters required in developing LSA for NUS. Qualitative and quantitative approaches must be integrated into a unique hybrid land evaluation system to improve LSA.

7.3 Identification of bioclimatic regions with high rainfall variability and water scarcity in South Africa

In bioclimatic regions, high rainfall variability and water scarcity are hypothesised to be more suitable for NUS. Mapping high-risk agricultural drought areas are critical for informing policy and decision-making to formulate drought adaptation strategies (cf. Chapter 3). This study used the Vegetation Drought Response Index (VegDRI), a hybrid drought index that integrates the Standardised Precipitation Index (SPI), Temperature Condition Index (TCI), and the Vegetation Condition Index (VCI) to delineate bioclimatic zones with both high rainfall variability and water scarcity for South Africa. Secondary to this, a correlation test between the VegDRI and normalised crop yield data for sorghum was used to test and validate the applicability and usefulness of the VegDRI index. The identification of bioclimatic zones characterised as water-stressed and with high rainfall variability is a pre-requisite to spatial and temporal variation analysis that can inform crop management strategies to improve food security in marginal lands of South Africa (Masih et al., 2014; Shiferaw et al., 2014; Baudoin et al., 2017).

The identified water-stressed bioclimatic zones or agricultural risk zones produced by integrating VCI, TCI, and SPI drought indices indicate that South Africa can be classified into slight, moderate, and severe agricultural drought risk zones, respectively (Brown et al., 2013; Nam et al., 2018). The indices evaluated in this study provide options for identifying the severity and location but do not show the duration, onset, and cessation of drought conditions. The combination of VCI, TCI, and SPI allow us to detect drought in the agricultural areas of South Africa, and VegDRI was found to be more effective than other indices (Brown et al., 2014). Based on the results from the hybrid index, VegDRI can be used for various applications such as agricultural drought detection, drought duration, crop yields, and crop production during the growing season (Brown et al., 2013; Nam et al., 2018).

The VegDRI characterise water-stressed bioclimatic zones with high rainfall variability better than the established drought indices. The VegDRI approach can be adapted for other regions in sub-Saharan Africa using available climate, satellite, and biophysical data. It can be applied to any vegetated area where remote sensing data are accessible, even with limited in situ data availability. Future research can incorporate hydrology, soil water, evapotranspiration, and socio-economic factors to delineate bioclimatic zones with high rainfall variability and water scarcity to improve drought management. Ground truthing is recommended to validate the new VegDRI map in South Africa. The adjusted maps can show homogenous areas with similar water requirements for crop production in marginal areas of South Africa (cf. Chapter 3). The results from this study highlight the potential for using a hybrid index, the VegDRI, in agricultural decision support systems such as drought risk maps for agricultural drought early warning systems, crop yield forecasting models, or water resource management tools.

7.4 Fitting sorghum, cowpea, amaranth and taro into dry regions of South Africa

This study aimed to develop land suitability maps for selected NUS sorghum, cowpea amaranth and taro using Analytic Hierarchy Process (AHP) in ArcGIS. The land suitability of NUS was assessed by using climatic, soil-landscape, and socio-economic factors. The use of AHP provides scope for combining expert opinion with measurements in pairwise comparisons between criteria at each level of the hierarchy to come up with relative weights.

Multidisciplinary factors from climatic, soil and landscape, socio-economic and technical indicators are overlaid using Weighted Overlay Analysis. Validation was done through field visits, and the area under the curve (AUC) was used to measure AHP model performance. The validation showed that the mapping exercises exhibited a high degree of accuracy (i.e., sorghum AUC = 0.87, cowpea AUC = 0.88, amaranth AUC = 0.95 and taro AUC = 0.82) (cf. Chapter 4 results). Rainfall was the most critical variable and criterion with the highest impact on the land suitability of the NUS. According to the local experts' judgment, rainfall was the most critical variable, followed by temperature, while soil depth and distance from the road were the least important.

The introduction of NUS into regions classified as moderately suitable (S3) to highly suitable (S1) could increase the crop choices available and also contribute to biodiversity (SDG 15). The low environmental impacts and increased biodiversity brought about by the introduction of NUS can be viewed as a climate change adaptation strategy (SDG 13) for increasing farmer resilience (Drimie and Pereira, 2016). More so for marginalised farming communities with limited access to improved technologies such as hybrid seed and fertiliser (Modi, 2003). Introducing NUS into existing cropping systems can be viewed as a sustainable intensification approach (Harvey, 2010). Promoting or introducing NUS in mapped zones can be essential for addressing food insecurity, specifically malnutrition, reducing vulnerability to climate variability and change, environmental degradation, and gender inequality (Azam-Ali et al., 2021). It is argued that holistic land suitability maps, which consider several socio-economic indices, could be more helpful to policymakers and enhance the participation of marginalised farmers in the food system (Mabhaudhi et al., 2019). The exclusion of key socio-economic indicators in developing suitability maps might affect the uptake and adoption of these crop species in areas where they are biophysically suitable. Therefore, to generate information on socioeconomic indicators, there is a need for future studies to identify innovative ways to derive maximum value from the possible integration of GIS with blockchain, big data, and Internet of Things (IoT) technologies to mine updated data, especially on climatic data and social-economic factors (Wolfert et al., 2017; Sharma et al., 2018). To achieve this, farmers, the private sector, and the government will need to research NUS value chains further. This study suggests that South Africa has massive potential for NUS production. The maps developed can contribute to evidence-based and site-specific recommendations for NUS and their mainstreaming. Also, the maps can be used to design appropriate production guidelines and support existing policy frameworks that advocate for sustainable intensification of marginalised cropping systems through increased crop diversity and stress-tolerant food crops.

7.5 Projecting future potential growing zones for NUS

We applied an improved and refined scenario for climate change to quantify the potential effects of alterations in climatic factors on localities of NUS sorghum, cowpea, amaranth and taro production, which are an option for food and nutrition security in South Africa (cf. Chapter 5). Several climate models have predicted an increased frequency and intensity in the occurrence of hazards such as droughts, flooding, extreme temperature, and erratic rain distribution. This is of great concern to farmers who rely on rainfed crop production because crop failure incidence will likely increase (Mabhaudhi et al., 2018). This study aimed to assess the application of presence-only data for current and future crop suitability modelling using the MaxEnt model (cf. Chapter 5). The application of a machine-learning, algorithm-based model designed to estimate the likelihood of occurrence based on presence-only data has great potential for use, mainly where extensive land use information is often difficult to obtain. The study identified annual precipitation length of growing period (LGP) maximum and minimum temperature variables that made a relatively higher contribution to the model.

In our spatially explicit characterisation of KwaZulu Natal's biophysical and socio-economic suitability (KZN) ecology for NUS production, 14 covariates/variables were considered in the final model setting (cf. Chapter 5). The current and future NUS production areas in KZN largely depend on biophysical factors, including climate and soil types. As such, climatic conditions play a vital role and influence other biophysical factors such as hydrology and soil conditions. Furthermore, climate change, especially temperature, rainfall and humidity modifications, significantly affects the physiological and ecological characteristics, phenology and geographical distribution of NUS production in South Africa (Mabhaudhi et al., 2018). Compared with current environmental variables, NUS's suitable agroecology in the future was found to be scattered across KZN (Figures 5.2-5.5) (cf. Chapter 5). In the 2050s and 2070s, the suitable distribution areas for sorghum, cowpea and amaranth are predicted to increase gradually. A new suitable site is expected to appear in central, including the east of KZN province. This trend agrees with the promotion of NUS in South Africa to improve nutrition in the marginalised (Mugiyo et al., 2021). Should global warming increase as projected by the scenarios used, currently arable land suitable for maize production may face water shortage and reduced length of the growing period, which means that crop production will increasingly rely on NUS. Promoting NUS in marginal land opens the possibility of exploiting semiarid zones into the green belt to improve food security.

This study indicates that KZN has enough suitable arable to meet its domestic NUS production in future. The analysis shows that sorghum, cowpea, amaranth and taro can be grown in South Africa. Promoting NUS within marginal production areas can create new and sustainable economic pathways and improve the availability and access to nutrient-dense foods. As a result of global climate change, scientists have to develop algorithms to provide valuable data to understand future crop distribution better. The analysis will help predict the future distribution of potential growing areas based on several environmental and social-economic factors.

7.6 Development of crop management guideline

The study aimed to develop crop management guidelines for sorghum produced under marginal conditions (cf. Chapter 6). The study used the Sensitivity Analysis and generalised likelihood uncertainty estimation (GLUE) tools in DSSAT. Crop models integrate genotype, environment and management and can serve as a tool for good agricultural practices to enhance food and nutrition security in marginal lands (Hoogenboom et al., 2019).

Smallholder farmers in Sub-Saharan Africa (SSA) have limited options for investment (seed, insurance, fertilisers, pesticides, machines) and irrigation to adapt to climate-related risks (Stads and Beintema, 2012). In SSA, a few smallholder farmers who grow sorghum exhibit decreasing absolute risk to climate shocks, they are risk-averse, and their concern is how to limit the risk of replanting due to false start of the season, crop failure and to sustain their crop production in moisture stress environment (Raes et al., 2004). Smallholder farmers need to adapt to climate-related shocks, given the roles of smallholder farmers in confronting the challenge of addressing hunger and nutrition insecurity in rain-fed production. One way of adapting to climate-related shocks is by observing planting windows and planting with correct moisture to sustain crop growth c

Predicting a recurring planting window based on successful planting events can improve crop production in SSA. Such climatic information is essential for smallholder farmers; it guides them in choosing crops, varietal selection, planning of labour, on-time land preparations, and when and how much moisture to trigger a planting event in rain-fed crop production. The sowing guidelines were presented on a map, including optimum planting density and fertiliser application. The adjusted maps can show homogenous areas with similar planting windows for sorghum production in marginal. However, the developed guidelines are still rather general, and their application at the farm level is complex unless they are simplified to the farm level.

This study selects DAFF (25 mm in 5 days) or DEPTH (40 mm in 4 days), depending on the risks a smallholder farmer wants to run. Risk-averse smallholder farmers might nevertheless be worthwhile to promote the DEPTH method in sorghum production, but in a scenario where the planting window is historically known DAFF criterion is more consistent and usually simulates higher yields from DSSAT. Crop simulation models can reliably determine 'what if' and 'when' scenarios across a diverse cropping system (Singh, 2004; Lobell, 2013). Identifying optimum planting dates within a planting window, coupled with optimum planting density and fertiliser management practices, can increase sorghum yields. Sorghum can be planted at a wide range of population densities without impacting biomass production; however, 68 100 plants ha^{-1} produced the highest economic yield in marginal lands under rain-fed production. Sorghum can compensate significantly for biomass for low plant populations and inexpensive grain yield (Ramirez-Villegas et al., 2013; Singh et al., 2014). Crop models integrate genotype, environment and management and can serve as an analytical tool to study the influences of these factors on crop growth and agricultural planning. Sorghum is suitable in sub-Saharan Africa's drought-prone environments and low-input cultivation systems (Chimonyo et al., 2016).

7.7 Conclusion

The study successfully mapped current and possible future suitable zones for NUS in South Africa. A scoping review was used to acquire and synthesise possible methods for land suitability for crop species such as NUS. The FAO land evaluation framework provided the guidelines to delineate crop suitability maps in South Africa, where data for mapping NUS suitability is not readily available. Modern land suitability methods are gaining popularity in cropland suitability analysis. The commonly used MCDM methods are AHP and fuzzy. The review is expected to improve NUS land evaluation and provide researchers and decision-makers with the most robust methods for developing LSA for NUS. Robust land suitability methods are essential to developing land suitability maps to improve current and future planning on crop production guidelines, climate change issues and environmental management.

The study mapped drought-prone zone in South Africa. A hybrid drought index, the VegDRI, characterised bioclimatic zones with high rainfall variability and water scarcity in South Africa. The results from this study highlight the potential for using a hybrid index, the VegDRI, in agricultural decision support systems such as drought risk maps for agricultural drought early warning systems, crop yield forecasting models, or water resource management tools.

In addition, the study mapped sorghum, cowpea, amaranth and taro in South Africa. The AHP model in GIS was used to integrate nine multidisciplinary thematic factors from climatic indicators from 1950 to 2000 (seasonal rainfall, seasonal maximum and minimum temperature), soil and landscape attributes (soil depth, slope, elevation), and social-economic (road) and technical indicators (LULC). Rainfall was the most critical variable and criterion with the highest impact on the land suitability of the NUS. Neglected and underutilised crop species can be grown on the marginal land of South Africa.

Further to the current suitability of NUS in South Africa, the study demonstrates the proof concept to predict the future suitability of NUS in KwaZulu-Natal. The study assessed presence-only data for current and future crop suitability modelling using the MaxEnt model. Applying a machine-learning, algorithm-based model to estimate the likelihood of occurrence based on presence-only data has great potential for use, mainly where extensive land use information is often difficult to obtain. MaxEnt could model NUS's current and future suitability in KZN in SA. Topographical variables (elevation and slope), climatic variables such as seasonal precipitation, length of growing period (LGP), and maximum and minimum temperature variables made a relatively higher contribution to the model, as well as soil water content parameters, are significant predictors' suitable KZN condition for rain-fed NUS cultivation. Also, our results showed that proximity to roads and urban centres provides an additional suitable condition for NUS production. This study indicates that KZN has enough suitable arable to meet its domestic NUS production in future. The analysis shows that the areas where sorghum, cowpea and amaranth can be grown in South Africa. Mapping current and future NUS suitable zones in SA is key to promoting NUS production by providing evidence to assist decision-and policymakers on crop choice. Specifically, the results help inform the Climate Smart Agriculture Strategy, National Policy on Comprehensive Producer Development Support and Indigenous Food Crops Strategy currently under development in South Africa. The suitability maps are also helpful in informing decisions on climate change adaptation (climate-smart agriculture) and sustainable agriculture practices and informing decisions on creating markets for NUS.

The findings help inform land-use classification, especially in marginal environments. The method can be adapted to other regions with a similar context for promoting NUS cultivation. Promoting NUS within marginal production areas can create new and sustainable economic pathways and improve the availability and access to nutrient-dense foods. The study concludes that NUS holds significant promise in improving South African food production systems' resiliency to mitigate climate change and alleviate food insecurity in marginal land.

Finally, the study used crop models to integrate genotype, environment and management to develop one of the NUS-sorghum production guidelines in KwaZulu-Natal, South Africa. This study uses DAFF (25 mm in 5 days) or DEPTH (40 mm in 4 days), depending on the risks a smallholder farmer wants to run. Risk-averse smallholder farmers are recommended to use the DEPTH method in sorghum production at the expense of losing heat units and the length of the growing period. Sorghum can be planted at various population densities without impacting biomass production. The best combination of management was when sorghum was planted in the second dekad of November, at a density of 68 200 plants ha^{-1} with a split application of 100 kg of nitrogen split (50% basal, 50% top-dressing 28 days after emergence). Sorghum is a suitable option in drought-prone environments and low-input cultivation systems in South Africa.

Farmers who rely on rain-fed production must increase the use of climatic information from early warning systems to achieve food and nutrition security. Smallholder farmers who rely on rain-fed production must use climate-smart agriculture such as conservation agriculture, agroforestry, and water harvesting techniques to improve productivity in marginal land.

Recommendations

Table 7. 1 Resilience strategies and usefulness of results generated in the study

Strategy	Key findings	Specific use	Proposed adaptation and mitigation strategies	Recommendations
Agriculture and the use of climate information to improve productivity	Identified suitable areas for NUS production	• To indicate where NUS can be promoted as an alternative crop choice • Sustainable transformation of existing farming systems	• To inform site-specific crop diversification recommendations as a sustainable intensification strategy • Ex- and in-situ rainwater harvesting and conservation techniques	• Researchers need to consider the inclusion of more socio-economic parameters in delineating suitable zones for NUS • Any future study on crop suitability should consider crop-specific varieties • Future research should also consider the specificity of NUS varieties and technological advancements in sorghum, cowpea, amaranth and taro suitability modelling. • Smallholder farmers who rely on rain-fed production must use climate-smart agriculture such as conservation agriculture, agroforestry, and water harvesting techniques to improve productivity in marginal land.

		• Early warning action	• Maps can monitor, assess, and forecast the likelihood of drought and wet spells in high-risk areas.	• Gridded climatic data need to be validated with locally generated datasets from South Africa Weather Service
		• Weather index insurance Area yield index insurance	• Insuring smallholder farmers from drought	Maps work as a base map for drought monitoring and initiate weather index claims for insurance companies like Africa Risk Capacity (ARC),
Strategy	**Key findings**	**Specific use**	**Proposed adaptation and mitigation strategies**	**Recommendations**
		• To understand the regions within South Africa at greater risk of drought hazards.	• Livelihood diversification, such as livestock production • Access to microcredit to promote alternative productions that are less vulnerable • Saving and lending groups to caution hazards and puerile	Diversification of crop-livestock systems to spread the risk (intercropping, rearing small livestock, market gardening, and promotion of NUS to complement major crops to improve food and nutrition in marginal lands
Land use land cover	In South Africa, NUS are suitable for all arable and marginal land.	• The review expects researchers and decision-makers to provide the most robust methods and common parameters required in developing LSA for NUS. Qualitative and quantitative	• The review is expected to improve NUS land evaluation and provide researchers and decision-makers with the most robust methods for developing LSA for NUS.	• Future studies should focus more on machine learning models to assess spatial distribution and stimulate the production of crops. Future studies should use algorithms incorporating near-real-time changes in the crop environment, which can be integrated with other

		approaches must be integrated into unique hybrid land evaluation systems to improve LSA.		techniques for improved decision-making. • To efficiently identify homogenous zones, especially for NUS, hybrid methods that combine traditional and modern methods (e.g., MCDM, CSM and MLMs) are needed.
		The suitability maps generated help guide decision-making processes using the integrated climate risk management approach (risk reduction); insurance (risk transfer); livelihoods diversification and microcredit (prudent risk-taking); and savings (risk reserves)	• Investing in climate risk assets such as the construction of dams and irrigation facilities • Mainstreaming weather information into agricultural extension support using bulletins to guide preparedness efforts • Crop diversification at a spatial and temporal scale •	• A higher spatial resolution VegDRI would be more applicable for local-scale monitoring and decision. •
Climate change	In future, in 2050 and 2070, NUS to be more suitable in KwaZulu-Natal, South Africa.	• Promoting green zones for climate action in agriculture	• Promote tolerance crops such as NUS in dry regions to gain agroecosystem services and improve food security in marginal lands in future	• The suitability maps generated in this study can indicate where NUS can be promoted as alternative crop choices or complement the current range of crops grown within marginalised cropping systems. The maps can inform site-specific crop diversification

				recommendations as a sustainable intensification strategy.
		• Identifying the potential spatial distribution of NUS in future	• The developed maps are essential for designing appropriate production guidelines and providing frameworks for policies supporting the sustainable intensification of marginalised cropping systems through increased crop diversification and stress-tolerant food crops in the future.	• In planning for future sustainable crop production, the interactions of biophysical and social-economic factors are critical for detecting areas threatened in terms of the NUS and zones with the potential to support the NUS.
Policy and funding context	In SA, about 16% of arable was classified under extreme/very severe, 34%-severe, 38%- moderate, 11%- slight, and 1%-no drought conditions.	• The findings can be used to formulate evidence-based policy.	• To generate policies that support good agricultural practices.	• Harmonisation of existing policies and institutes that speak to land, environment, agriculture, and health • Policies such as the National Food and Nutrition Security Policy and National Developmental Plan of South Africa (National Planning Commission, 2012) need to give a clear road map for NUS production, especially by explicitly mentioning NUS and targeting them for production on marginal lands that are currently not suitable commercial crops production as a strategy to improve food

and nutrition security within these areas.

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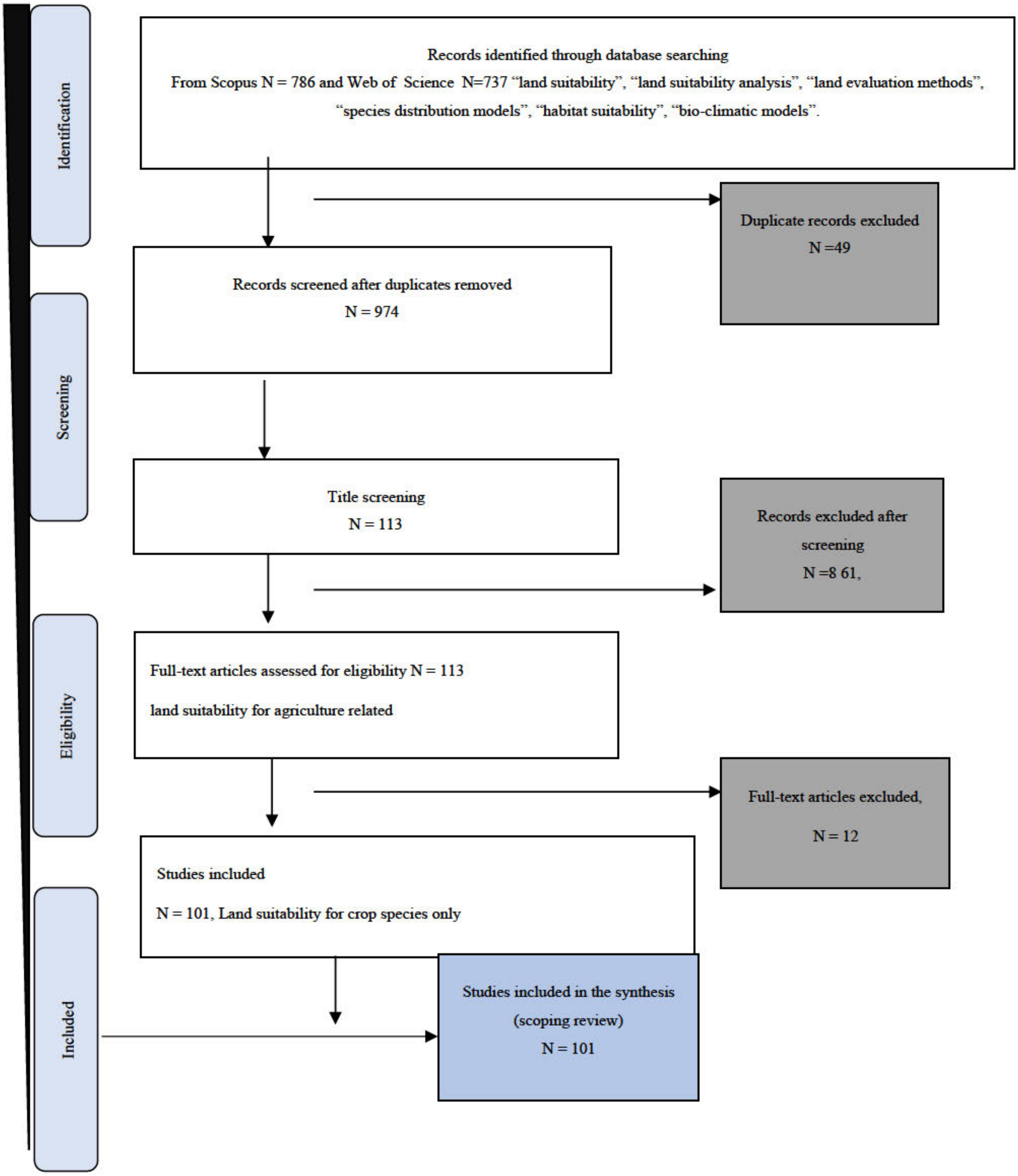
APPENDICES



Appendices 1. 1 Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) flow chart diagram

Supplementary Table 1. 1 Applicability and thematic factors used in traditional methods in crop suitability mapping.

Authors	Country	The objective of the study	Methods used or Model	Crop	NUS (Yes/No)	Thematic factors			
	Country					Climatic	Soil and landscape	Social-economic factors	LULC
(El Baroudy, 2016)	Egypt	Spatial model for land suitability assessment	Parametric	Wheat	No		N-P-K, Zn, D, Tex, Dep, Topo, SS, HP, HC, WHC, EC, ESP, CaCO3, pH	No	No
(Danvi et al., 2016)	Benin	Determine suitable areas for rice production	Boolean Logic, Maximum Limiting factor	Rice	No	P, T, RH, R, Flooding	D, Dep, CEC, BSP, pH, OC	No	No
(Masoud et al., 2013)	Ghana	Most suitable areas for inland valley rice	WLC	Rice	No	P, LGP, Stream order, discharge	S, fertility, pH, N, OC, EC, CEC, BSP land reforms, Tex, ESP	Land tenure, roads, markets, credit systems,	Yes

								incentive benefits	
(Kuria and Waithaka, 2011)	Kenya	Evaluating the suitability of rice	WO	Rice	No	No	ESP, Tex	Land reforms	Yes
(Thenkabail, 2009)	Ghana	Evaluating the suitability of rice	WLC	Rice	No	P, T, LGP, Stream order, discharge	Slope, Dep, fertility	Social-economic	No
(Motuma et al., 2016)	Ethiopia	Land suitability analysis	Square root mean, WLC	Wheat, Sorghum	Yes	P, T	Dep, Tex, OC, D, Soil type, S	No	No
	Iran	Use of a model	Storie, Square root	Wheat, alfalfa, Barley, maize,	No	RH, T SR,	S, Tex, % CaSO4, EC, CEC, ESP, Drain	No	Yes
(Munene et al., 2017)	Zambia	Evaluation of land suitable for soybean	WLC	Soybean	No		Tex, OC, Phosphorus, pH, Drain, S, H	Roads	No
(Diallo et al., 2016)	Senegal	Suitability analysis for rice	Storie, PCA	Rice, Cassava, Groundnut	No	P, T, RH, Wind, SH, PET	S, Drain, Coarse fragment, Dep, Tex, Clay, Silt,	No	No

							sand, CEC, OM, BSP, EC, ESP		
(Kamkar et al., 2014)	Iran	Land suitability analysis	Computer overlay	Canola, Soybean	No	P, T	As, H, S, Tex, pH, EC	No	No
(Martínez-Casasnovas et al., 2008)	Spain	Land evaluation using biophysical factors	FAO, Statistics	Alfalfa, maize, rice, sunflower	No	LGP, SR, T, TWU, hailstorms, winds, Flood risk	Fertility, Dep, Tex, CEC, pH, BSP, OC	No	No
(Hennebert et al., 1996)	Burundi	Land evaluation	Sys	Wheat, Pea bean, maize, potato	No	P, LGP, T, RH, SH	S, Drain, H, Dep, SS, Tex, CEC, pH, BSP, OC	No	Yes
(Bydekerke et al., 1998)		Crop specific suitability	Expert Knowledge, FAO method	Cherimoya	No	P, T, LGP, RH	SG, Tex, Dep, CEC, OM	No	No
(Chen et al., 2013)	China	Land suitability for sustainable development	Qualitative approach	Maize, Pearl millet, Foxtail millet, Potato, Apple, vegetable	Yes		S, As, SG, H	Income	Yes

(Teixeira et al., 2013)	Global	Spatial assessment of heat stress risk	GAEZ	Wheat, maize, rice, Soybean	No	Max and min T,	S, H	No	Yes
(Fischer et al., 2005)	Africa	Impacts of climate change on agro-ecosystem	GAEZ	wheat, maize	No	Min and Max T, P, RH, vapour pressure	SG, H, S	No	Yes

Supplementary Table 1. 2 A list of Analytic Hierarchy Process methods and factors used to delineate land suitability for crops

Authors	Country	The objective of the study	The method used or Model	Crop	NUS (Yes/No)	Thematic factors			
						Climatic	Soil and landscape	Social-economic factors	LULC
(Ceballos-Silva and López-Blanco, 2003)	Mexico	To map areas for maize and potatoes	AHP	Maize, Potatoes	No	P, PET, Max T, Min T,	Tex, Dep, S, H	No	Yes

(Kihoro et al., 2013)	Kenya	Rice suitability	AHP	Rice	No	T, RH	Tex, pH, Drain, S	No	No
(Wali et al., 2016)	Afghanistan	Use of logic scoring to improve AHP	AHP	Safron	No	P, T	SG, S, As, H	Road, economics index	Yes
(Hood et al., 2006)	Australia	To map potential growing areas for grapes	AHP-WLC	Grapes, pasture, Bluegum	No	P, TDD, Frost	S, As, Drain, PH, ESP, Dep, Tex, EC	No	No
(Dadhich et al., 2017)	India	Wheat suitability mapping	AHP-WO	Wheat	No		Tex, pH, ESP, EC, Drain, N-P-K, S, GW	No	Yes
(Benke and Pelizaro, 2010)	Australia	Evaluating the uncertainty of power of AHP	AHP-Fuzzy	Ryegrass, Wheat	No	P, T	PH, WHC, Coarse fragment, Dep, Tex, EC, Drain	No	No
(Alkimim et al., 2015)	Brazil	To map areas that highly suitable for sugarcane	AHP	Sugarcane	No	P, T	SG, H	Infrastructure, Population,	Yes

								Literacy, Labor force	
(Maleki et al., 2017)	Iran	To assess the suitability of saffron	AHP-WO	Saffron	No	P, T, SH, Frost, RH	S, As, H, EC, pH, Tex	No	No
(Chen et al., 2013)	China	Sensitivity analysis for MCE	AHP-OAT-WLC	Wheat	No		Tex, Dep, OM, sand dune waviness, SE, Drain, DWT	No	No

List of abbreviations: Land use land cover (LULC), Topography (Topo), Surface Stoniness (SS), hard pan (HP), hydraulic conductivity (HC), water holding capacity (WHC), Groundwater (GW), Soil moisture (SM), depth to water-table (DTW), Temperature degree day (TDD), aridity index (AI), Temperature (T), dry month/ length of the dry season (DM), Wet month (WM) rainfall (P), soil drainage (Drain), texture (Tex), effective depth (Dep), cation exchange capacity (CEC), base saturation percentage (BSP), soil pH (pH), Organic carbon (OC), Slope (S), Aspect (As), Elevation (H), potential evapotranspiration (PET), solar radiation (SR), Sunshine hours (SH), soil erosion (SE), length of the phenological period (LPP), Gypsum (% $CaSO_4$), Relative humidity (RH), Boron Toxicity (BT), Soil type (ST), Weighed Overlay (WO) and Weighted Linear Combination (WLC). Depth to water table (DWT), Irrigation/Irrigation Water Use (IWU), Length of growing period (LGP), Post-harvest technology (PHT), Growing degree days (GDD), Calcium carbonate equivalent (CCE), electrical conductivity or salinity (EC); sodium adsorption ratio (SAR), Sodicity (ESP), surface stoniness/rockiness (SS), Soil groups/Soil types (SG).

Supplementary Table 1. 3 A list of Fuzzy logic technique methods and common factors used to delineate land suitability for crops

Authors	Country	The objective of the study	The method used or Model	Crop	NUS (Yes/No)	Thematic factors			
				:		Climatic	Soil and landscape	Social-economic factors	LULC
(Zabel et al., 2014)	Global	Global land resources allocation	Fuzzy	16 Crops	Yes	P, T	Tex, Coarse fragments	No	No
(Nisar Ahamed et al., 2000)	India	To evaluate arable land on selected crops	Fuzzy	Finger millet, paddy, groundnut	Yes		Tex, Drain, Gravel, CEC, BSP, pH	No	No

(Avellan et al., 2013)	Global	To evaluate the difference between topsoil properties for the dominant soil mapping units between two global soil datasets.	Fuzzy	Cassava, Groundnut, Maize, Millet, Oil-palm, Potatoes, Rapeseed, Rice, Rye, Sorghum, Soy, Sugarcane, Sunflower, Wheat	Yes	P, T	CaSO4, pH, BSP, OC, EC, ESP	No	No
(Braimoh et al., 2004)s	Ghana	Maize land Suitability evaluation	Fuzzy	Maize	No		OC, CEC, Drain, Clay, pH	No	No

(Bagherzadeh and Gholizadeh, 2018)	Iran	Land suitability for irrigated sugar beet	Fuzzy	Sugar beet	No	T, LGP	H, SE, EC, ESP, OC	No	No
(Holzkämper et al., 2013)	Switzerland	Evaluation of crop-specific climate suitability	Fuzzy	Maize	No	P, T, GDD, SR, AET, LPP	No	No	No
(Baja et al., 2002)	Australia	Evaluating procedures of land suitability	Fuzzy	Barley, cotton, spinach, wheat,	Yes		S, Drain, Gravel, Cobbles,	No	No

evaluation in slope areas	rye, maize, oats, sorghum	EC, ESP, WHC, Tex, Dep, CEC, pH, OM

List of abbreviations: Land use land cover (LULC), Topography (Topo), Surface Stoniness (SS), hard pan (HP), hydraulic conductivity (HC), water holding capacity (WHC), Groundwater (GW), Soil moisture (SM), depth to water-table (DTW), Temperature degree day (TDD), aridity index (AI), Temperature (T), dry month/ length of the dry season (DM), Wet month (WM) rainfall (P), soil drainage (Drain), texture (Tex), effective depth (Dep), cation exchange capacity (CEC), base saturation percentage (BSP), soil pH (pH), Organic carbon (OC), Slope (S), Aspect (As), Elevation (H), potential evapotranspiration (PET), solar radiation (SR), Sunshine hours (SH), soil erosion (SE), length of the phenological period (LPP), Gypsum (% $CaSO_4$), Relative humidity (RH), Boron Toxicity (BT), Soil type (ST), Weighed Overlay (WO) and Weighted Linear Combination (WLC). Depth to water table (DWT), Irrigation/Irrigation Water Use (IWU), Length of growing period (LGP), Post-harvest technology (PHT), Growing degree days (GDD), Calcium carbonate equivalent (CCE), electrical conductivity or salinity (EC); sodium adsorption ratio (SAR), Sodicity (ESP), surface stoniness/rockiness (SS), Soil groups/Soil types (SG).

Supplementary Table 1. 4 A list of Crop models and factors used to delineate land suitability for crops

Authors	Country	The objective of the study	The method used or Model	Crop	NUS (Yes/No)	Thematic factors			
						Climatic	Soil and landscape	Social-economic factors	LULC

(Daccache et al., 2011)	United Kingdom	To delineate current and future land suitability for potato	Pedo-climatic functions, PSMD	Potato	No	P, T, AET, LGP	Dep, Tex, OM, S, SS,	No	No
(Wolf and van Diepen, 1994)	Europe	Agro-climatic suitability	Water deficit Method	Maize	No	P, T, AWC		No	No
(Liu et al., 2008)	Africa	Assessment of current and future hotspots of food insecurity in SSA	GEPIC	Cassava, sorghum, wheat, maize	Yes	P, T, SR, WM	Dep, sand, silt, BD, PH, OC	GDP, population, Undernutrition data	No
(Liambila and Kibret, 2016)	Ethiopia	The impacts of climate change on land suitability for rain-fed crops	Almagra model, Sys	Sweet potato, Sorghum, soybean, wheat, maize	Yes	P, T, PET,	Dep, Tex, Drain, Ec, ESP, CEC, pH, OC	No	No
(Lane and Jarvis, 2007)	Global	To identify regions potentially suitable for crops	ECOCROP	Groundnut, soybean, sugarcane	Yes	P, T		No	No
(Ramirez-Villegas et al., 2013)	Africa	Assessment of climate change on sorghum suitability	ECOCROP	Sorghum	Yes	P, T	No	No	N

List of abbreviations: Land use land cover (LULC), Topography (Topo), Surface Stoniness (SS), hard pan (HP), hydraulic conductivity (HC), water holding capacity (WHC), Groundwater (GW), Soil moisture (SM), depth to water-table (DTW), Temperature degree day (TDD), aridity index (AI), Temperature (T), dry month/ length of the dry season (DM), Wet month (WM) rainfall (P), soil drainage (Drain), texture (Tex), effective depth (Dep), cation exchange capacity (CEC), base saturation percentage (BSP), soil pH (pH), Organic carbon (OC), Slope (S), Aspect (As), Elevation (H), potential evapotranspiration (PET), solar radiation (SR), Sunshine hours (SH), soil erosion (SE), length of the phenological period (LPP), Gypsum (% $CaSO_4$), Relative humidity (RH), Boron Toxicity (BT), Soil type (ST), Weighed Overlay (WO) and Weighted Linear Combination (WLC). Depth to water table (DWT), Irrigation/Irrigation Water Use (IWU), Length of growing period (LGP), Post-harvest technology (PHT), Growing degree days (GDD), Calcium carbonate equivalent (CCE), electrical conductivity or salinity (EC); sodium adsorption ratio (SAR), Sodicity (ESP), surface stoniness/rockiness (SS), Soil groups/Soil types (SG).

Supplementary Table 1. 5 A list of Machine learning related methods and common factors used to delineate land suitability for crops

Authors	Country	The objective of the study	The method used or Model	Crop	NUS (YES /NO)	Thematic factors			
						Climatic	Soil and landscape	Social-economic factors	LULC
(Bagherzadeh et al., 2016)	Iran	Evaluation of land suitability of soybean in semi-arid regions	ANN, Fuzzy	Soybean	No	P, T, LGP	Tex, EC, ESP, CaCO3, Gravel, Dep, Oc, pH, S, Drain, Flood, CaSO4	No	No
(Wang, 1994)	Indonesia	Agricultural land suitability	Artificial neural networks (ANNs) ANN	Rice	No	P, T	DM, Drain, Tex, Dep, CEC, pH, N-P-K, ESP, S	No	No
(Jiao and Liu, 2007)	China	Paddy rice land evaluation	Fuzzy Neural Network, GA	Rice	No		OC, Tex, Thickness of tilth, S, N-P-K, Water conservancy, pH	No	No

(Ranjitkar et al., 2016)	Nepal	bioclimatic conditions to assess the suitability	Global Environmental Stratification Strata, (GenS), ecological niche modelling, Fuzzy	Banana, Coffee	No	P, T. AI, PET,	As S	No	Yes
(Estes et al., 2013)	South Africa	To compare the suitability and productivity of maize	MaxEnt, GAM, DSSAT	Maize	No	P, T, SR, H	SG	No	Yes
(Ovalle-Rivera et al., 2015)	Global	To evaluate potential areas for coffee	MaxEnt	Coffee	No	P, T, Diurnal T	No	No	No
(Austin et al., 2015)	Indonesia	Quantify the potential CO2 emissions reductions	Logistic Regression	Palm oil	No	P, T	H, S, Dep, Drain, pH, OC	Roads	Yes
(Heumann et al., 2011)	Thailand	Use of MaxEnt to map suitability areas for cassava	MaxEnt	Cassava	Yes	SR, PET	H, SG, S, As	No	Yes

(Heumann et al., 2013)	Thailand	Understand factors affecting the suitability of crops	MaxEnt	Cassava, rice	Yes		H, SG	Population, roads	Yes
(Kidd et al., 2015)	Australia	Assessment of soil and enterprise	Regression tree	Potato, Hazelnuts	No	P, T, frost days, Chill hours	Dep, pH, EC, Clay, Drain, SS	No	No
(Mockshell and Kamanda, 2018)	Iran	Suitable cultivable lands and water resources to optimize potential areas for crop production	Goal programming	Wheat, alfalfa, potato, maize	No	P, T	SG, course fragments, EC, pH, CaCO3, GW, water bodies	No	Yes
(Holzkämper et al., 2013)	Switzerland	Evaluating crop-specific climate suitable	Knowledge-based determination of factor suitabilities, rule-based approach, WLC, genetic algorithm (GA)			P, T	H,	No	No
(Läderach et al., 2013)	Africa	To evaluate cocoa-growing regions of	MaxEnt	Cocoa	No	P, T, AEP	No	No	No

		Ghana and Côte d'Ivoire							
	Iran	land allocation	Cellular automata (CA), Markov chain, fuzzy rule-based systems, goal programming, WLC method	Wheat, Barley, Maize, alfalfa, Potato, Wheat	No	P, T, RH	S, Dep, Tex, Flood, Drain	Income	No
(Wang et al., 2011)	China	Evaluate land suitable for wheat	ANN	Wheat	No	P, T, SH	N, OC		

List of abbreviations: Land use land cover (LULC), Topography (Topo), Surface Stoniness (SS), hard pan (HP), hydraulic conductivity (HC), water holding capacity (WHC), Groundwater (GW), Soil moisture (SM), depth to water-table (DTW), Temperature degree day (TDD), aridity index (AI), Temperature (T), dry month/ length of the dry season (DM), Wet month (WM) rainfall (P), soil drainage (Drain), texture (Tex), effective depth (Dep), cation exchange capacity (CEC), base saturation percentage (BSP), soil pH (pH), Organic carbon (OC), Slope (S), Aspect (As), Elevation (H), potential evapotranspiration (PET), solar radiation (SR), Sunshine hours (SH), soil erosion (SE), length of the phenological period (LPP), Gypsum (% $CaSO_4$), Relative humidity (RH), Boron Toxicity (BT), Soil type (ST), Weighed Overlay (WO) and Weighted Linear Combination (WLC). Depth to water table (DWT), Irrigation/Irrigation Water Use (IWU), Length of growing period (LGP), Post-harvest technology (PHT), Growing degree days (GDD), Calcium carbonate equivalent (CCE), electrical conductivity or salinity (EC); sodium adsorption ratio (SAR), Sodicity (ESP), surface stoniness/rockiness (SS), Soil groups/Soil types (SG).

Supplementary Table 1. 6 Common factors used in land suitability analysis and its description

Factors	**Description**

Potential/Actual Evapotranspiration (P/AET)	Climate factors such as rainfall and potential evapotranspiration are among the crucial factors that affect the suitability of an area for irrigation.
Chill hours	Chill hours represent an indicator to ensure cold enough conditions to optimize nut production.
Arity index (AI)	AI links precipitation and evapotranspiration to define climatic zones
Diurnal temp	Suitable diurnal temperature fluctuations ensure seed self-regeneration and, therefore, long-term persistence of the crop.
Growing degree days (GDD)	To represent growing season length and the cumulative heat requirements for plant growth.
Length of growing period (LGP)	LGP represents the number of days when soil moisture and temperature permit crop growth.
Length of the phenological period (LPP)	To account for effects of phenological development on biomass accumulation and crop yields.
Relative Humidity	Some crops must be planted in areas where RH is low. RH is important during the months of flower pollination. High RH results in poor pollination, which in turn leads to a low number of formed fruits
Precipitation	Precipitation and temperature are the two major variables that could greatly impact the growth and final yield of biofuel crops and rain-fed cropping systems. From daily precipitation events like the start of the season, dry spells, end of the season, and wet spells can be calculated.

Temperature (Max and Min)	Precipitation and temperature are the two major variables that could greatly impact the growth and final yield of biofuel crops and the rain-fed cropping system.
Temperature degree day (TDD)	TDD is a measure of heat accumulation, very useful in crop planting and management.
Winds	Agricultural productivity is highly affected by meteorological parameters, including wind speed.
Solar radiation	Solar radiation has an important effect on crop growth and yield. Solar radiation is essential for photosynthesis, but excessive amounts of solar radiation can cause photo-damage to plants.
Sunshine hours	Sunshine hours are used as an estimate of solar radiation.
Indices (WRSI, SPI, VegDRI)	Most of the indices can be calculated using the above climatic factors
Soil and landscape attributes	
Factors	**Justification**
Effective depth	Effective rooting depth is related to soil depth. The shallow soil may restrict the development of plant roots, due to which the plant may suffer adverse conditions in the limited soil volume.
Elevation	Variation in elevation has an impact on soils, microclimatic effects, and other processes that could affect land suitability.

Slope	The slope is a crucial factor affecting vegetation structure and soil erosion. The slope is an important aspect of the surface as well as for internal soil water drainage as both characteristics play a major role in the growth of the crop
Soil depth	Soil depth determines roots growth as well as the presence of a volume of water and air in the soil.
Land Use Land cover-LULC	Knowledge of existing land use provides information about land availability. Land use data helps to identify the productivity of an area for a given cropping system.
Aspect	Aspect influences the degree of sunlight exposure, and thus southern and western aspects are usually assumed to be most capable for agriculture
Base saturation percentage	High values of base saturation limit crop growth.
Boron toxicity	Boron toxicity can limit plant growth in soils of arid and semi-arid environments
Bulk density	Bulk density is an indicator of the compactness of the soil. Bulk density is considered to be a measure of soil quality due to its relationships with other properties (e.g., porosity, soil moisture, hydraulic conductivity, etc.).
Clay	Clay is important in moisture retention for crop growth.
Cation exchange capacity	CEC provides a buffer against soil acidification and can influence the soil's
Fertility (Nitrogen-N, Phosphorus-P, and Potassium-K)	capacity to hold onto essential nutrients. It is frequently included in Asansol fertility is the most important characteristic of the soil, and it has a great impact on crop productivity. N-P-K are the primary nutrients but vary over time based on specific crop cultivation.

Erosion hazard	Erosion is an indicator of soil degradation with a substantial loss of soil nutrients.
Gypsum	Highly gypsic soils (> 10% gypsum) should be avoided as, under irrigation, they may subside as the gypsum is dissolved from the soil under irrigation.
Hardpan	Hardpan or bedrock depth refers to soil depth as a physical restriction that significantly reduces the movement of water and air through the soil.
Hydraulic conductivity	Hydraulic conductivity is an important soil physical property for determining infiltration rate, irrigation, drainage practices, and other hydrological processes. It controls water and solute transport; its assessment at the field scale is important in evaluating agronomic performances.
Organic Carbon/Matter	Ideal source of plant nutrients in soils, important in maintaining soil structure, soil tilth and reducing soil erosion. Soil OC indicates the organic matter content in the soil, which often creates the basis for the successful use of mineral fertilizers. The combination of organic matter and mineral fertilizers provides suitable environmental conditions for the crop as the organic matter improves soil properties and the mineral fertilizer supply the plant is Needed.
Rockiness/Stoniness	Estimate the proportion of surface rock and stone
Salinity (Electrical conductivity)	Soil salinity indicates the total concentration of soluble salts in the soil. In the root zone, the presence of soil with a substantial amount of natural salt leads to a reduction of soil water which is extracted by plant and may cause a to a reduction of soil water which is extracted by plant and may cause a nutrient imbalance that could affect plant growth and limit crop yields by causing the low osmotic potential of the soil solution.
Sand	Cultivation of sandy soil often leads to soil degradation.
Silt	Silt and clay increase the surface area of the soil, and the amount of plant-available water decreases the leaching potential.

pH	An important factor in soil productivity and plant growth. It provides information about the solubility and thus potential availability or phytotoxicity of elements for crops and subsequently specifies the soil suitability for a specific crop. Nutrient availability is also a function of pH.
Texture	The texture is one of the important parameters of soil. Most of the physical properties of the soil depend upon textural class. The soil textural class most capable for agriculture is loam, which contains a mix of sand, silt, and clay particles. Soil textural class influences a soil's ability to drain water, be aerated and hold onto moisture.
Alkalinity/Sodicity (Exchangeable Sodium Percentage-ESP)	Sodicity affects the productivity of crops by reducing the water availability and soil permeability to plant roots.
Soil Drainage	Play a key role in air and soil water regime—well-drained soil results in deeper rooting of crops. Also, it gives an indication of the soil moisture conditions.
Water holding capacity	Water holding capacity estimates the total available water in the root zone and determines the need for irrigation.

Social-economic and technical indicators.

Factors	Justification
Distance to road/accessibility	Land use is often also influenced by the ease of access to networks for the transport of supplies or produce. This factor is usually most important in remote areas.
Female participation in economic activities/Gender	Female participation in economic activities is understood as an indicator of women's empowerment and economic development. Gender inequality increases the susceptibility to sudden changes and threats such as climate change. Integrated conservation agriculture and agroforestry can promote gender equality and improve livelihoods for women and men while supporting mitigation and adaptation.
Literacy rate/Education	The literacy rate is an education indicator. High literacy reflects enhanced adaptive capacity to make informed decisions regarding viable coping strategies under climate change.

Population/Population density	Access to the market is essential to agricultural activities. It is sometimes used as a proxy for market access and transport inputs.
People employed for agricultural activities/Labour force	Considered as people that possess some level of knowledge of agricultural activities
Average income	The expected income per hectare of given crops can influence the choice of which crop to be grown by farmers.
Credit systems	Define the easy access of farmers to credit.
Distance to the source of water	It could be important in a system whereby small-scale farmers have to travel to fetch water for irrigation.
Markets Availability	Market access plays a crucial role in agricultural development in many ways. For instance, a study showed that the relatively limited use of chemical fertilizers in Sub-Saharan Africa has indeed been variously linked to market access constraints.
Extension system/ Technical assistance	Extension systems transfer knowledge from researchers to farmers, advising farmers in their decision making, educating farmers to make similar decisions in the future, enabling farmers to clarify their own goals and possibilities and stimulating desirable agricultural development.

Land tenure	Land tenure is a social concern. Considered important in the case of ALSA for large-scale investment, land tenure is not always systematically included in the modelling process due to lack of data.

Heuristic models

Heuristic-based models are approaches used in problem-solving, learning, or discovery that employ a practical method. They are not guaranteed to be optimal, perfect, logical, or rational, but instead are sufficient for reaching an immediate goal (Mustafa et al., 2011). Heuristic methods can be used to speed up the process of finding a satisfactory solution and works with presence-only data such as Bioclimatic, ANUCLAM, DOMAIN, FEM and HABITAT (Booth et al., 2014; Duan et al., 2014). Such models can be used in NUS where production information is limited. The models are simple to use, but they tend to over-predict (Booth et al., 2014). They require ground-truthing or use of crop simulation models to validate the suitability maps (Heumann et al., 2013). This type of model can operate with a small number of records but can not make quantitative predictions or provide confidence levels (Xu and Hutchinson, 2012, 2013).

a) Decision tree models

Decision tree methods are used for data mining and aid in classifying systems based on multiple covariates or for developing prediction algorithms for a target variable (Pecchi et al., 2019). The algorithm is non-parametric and can accommodate large, complicated datasets without imposing a complicated parametric structure (REF). The model requires one to know machine learning and programming skills. Frequently used algorithms include ACE, S-Plus algorithms CART, C4.5, CHAID, and QUEST(Kotsiantis, 2013). They can be linked with GIS and remote sensing data, SPSS and SAS programs that can be used to visualize tree structure (Pecchi et al., 2019).

b) Genetic algorithms

Artificial Neural Networks (ANNs) are among the most advanced methods in land suitability analysis, a non-linear mapping structure works with presence or absence data (Basse et al., 2014). The model requires a high number of records and can be challenging to use in areas where data is minimal especially in the study of NUS. The models result tend to be general because it depends on the sample frame. The more the number of training data the better the suitability index such as Genetic Algorithm for Rule-Set Prediction (GARP), MaxEnt (Anderson et al., 2003; Phillips et al., 2006). It is a general-purpose machine learning method with a simple and precise mathematical formulation for modelling species geographic distributions with presence data only (Sharma et al., 2018). The assumptions not always evident, some models like Maximum entropy niche-based modelling are often used for environmental studies but the principle of maximum entropy can be used to delineate areas suitable for crops (MaxEnt) (Fourcade et al., 2014; Phillips et al., 2009).

c) Additive statistical models

The Generalised Linear Models (GLM) and Generalised Additive Models (GAM) are additive statistical models, sometimes called ecological niche models (Austin, 2007; Oppel et al., 2012). Generalised linear models are probably the most commonly used statistical methods in bioclimatic modelling and have proven their ability to predict NUS distribution (Heumann et al., 2013). The models require lots of reliable records and knowledge of the ecology (Sillero, 2011; Peterson, 2015).

Considering the limitations of GLM in capturing complex response curves, application of Generalised Additive Models is being proposed for species suitability mapping (Secondi, 2014). The Generalised Additive Model blends the properties of the Generalised Linear Models and Additive models. Generalised Additive Models are based on nonparametric regression, and unlike GLM, which does not impose the assumption that the data supports a particular functional form (normally linear) (Warren, 2012). Here the response variable is the additive combination of the functions of the independent variable. However, transparency and interpretability are compromised to accommodate this greater flexibility. Applications of GLM in NUS land suitability might of less use because NUS are usually grown by smallholder farmers. Therefore, to capture the heterogeneous landscape and dynamic social-economic factors, we need Generalised Additive Models which accommodate nonparametric factorsused to delineate NUS, only 29% used LULC (7).

Supplementary Table 1. 7 Climatic and hydrology factors, soil and landscape, social and economic factors and land use land cover (The results are presented as percentage N=64)

Factor	AHP	CSM	Fuzzy	MLM	TM	Total
Climate						
Temperature	16	9	9	17	20	71
Precipitation	14	11	8	20	14	67
Relative Humidity	8	-	-	2	8	18
Length of the growing period	-	3	2	3	6	14
Growing degree days	-	-	5	3	-	8
PET	-	2	-	2	5	9
SH	3	-	-	2	-	5
SR	-	-	2	2	2	6
AET	-	2	2	-	-	4
Frost	2	-	-	2	-	4
Hydrology						
Flood	-	-	-	-	3	3
AWC	-	2	-	-	2	4

Hail Storms	-	-	-	-	2	2
TDD	2	-	-	-	-	2
Winds	-	-	-	-	2	2
Chill hours	-	-	-	2	-	2
Stream order	-	-	-	-	2	2
Discharge	-	-	-	-	2	2
Drain	-	2	-	-	-	2

Soil and landscape

Factors	AHP	CSM	Fuzzy	MLM	TM	Total
Texture	9	3	8	8	19	47
pH	8	3	8	8	13	40
Slope	5	3	3	11	14	36
Soil depth	6	5	5	8	11	35
EC	5	-	9	6	6	26
OC	-	3	8	6	9	26
CEC	-	-	9	5	11	25
Elevation	3	-	3	8	8	22

ESP	3	-	5	5	5	18
As	5	-	-	3	3	11
N-P-K	3	-	-	3	2	8
Gravel	2	-	2	3	2	9
OM	5	2	-	-	-	7
CaSO4	-	-	2	3	2	7
BSP	-	-	2	-	5	7
Clay	2	-	2	2	2	8
SG	-	-	-	3	3	6
Mg	2	-	3	-	-	5
Ca	2	-	2	-	-	4
Cl	2	-	-	2	-	4
Sand	2	-	-	-	2	4
Silt	-	2	-	-	2	4
Thickness of tilth	-	-	-	2	2	4
Phosphorus	-	-	-	-	2	2
DM	-	-	2	-	-	2

BD	-	2	-	-	-	2
Fertility	-	-	-	-	2	2
Cobbles	-	-	2	-	-	2
Zn	-	-	-	-	2	2
Social-economic factors						
Factor	AHP	CSM	Fuzzy	MLM	TM	Total
Road	3	-	2	2	3	10
Population	2	-	-	2	-	4
Income	-	-	-	2	2	4
labour force	3	-	-	-	-	3
Infrastructure	2	-	-	-	-	2
Literacy	2	-	-	-	-	2
Land tenure	-	-	-	-	2	2
Markets	-	-	-	-	2	2
Credit systems	-	-	-	-	2	2
Incentive benefits	-	-	-	-	2	2
Economics index	2	-	-	-	-	2

Land value	-	-	2	-	-	2
Undernutrition data	-	2	-	-	-	2
GDP	-	2	-	-	-	2
Distance to city	2	-	-	-	-	2
Land use land cover						
Factor	AHP	CSM	Fuzzy	MLM	TM	Total
LULC	6	-	3	9	11	29

List of abbreviations: Land use land cover (LULC), Topography (Topo), Surface Stoniness (SS), hard pan (HP), hydraulic conductivity (HC), water holding capacity (WHC), Groundwater (GW), Soil moisture (SM), depth to water-table (DTW), Temperature degree day (TDD), aridity index (AI), Temperature (T), dry month/ length of the dry season (DM), Wet month (WM) rainfall (P), soil drainage (Drain), texture (Tex), effective depth (Dep), cation exchange capacity (CEC), base saturation percentage (BSP), soil pH (pH), Organic carbon (OC), Slope (S), Aspect (As), Elevation (H), potential evapotranspiration (PET), solar radiation (SR), Sunshine hours (SH), soil erosion (SE), length of the phenological period (LPP), Gypsum (% $CaSO_4$), Relative humidity (RH), Boron Toxicity (BT), Soil type (ST), Weighed Overlay (WO) and Weighted Linear Combination (WLC). Depth to water table (DWT), Irrigation/Irrigation Water Use (IWU), Length of growing period (LGP), Post-harvest technology (PHT), Growing degree days (GDD), Calcium carbonate equivalent (CCE), electrical conductivity or salinity (EC); sodium adsorption ratio (SAR), Sodicity (ESP), surface stoniness/rockiness (SS), Soil groups/Soil types (SG

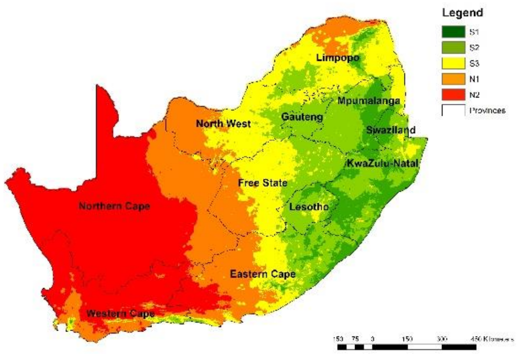
1.1 The Geography of South Africa

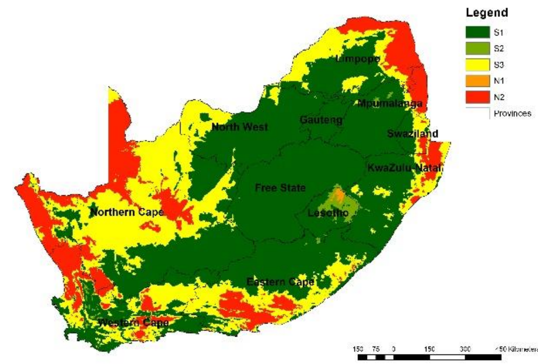
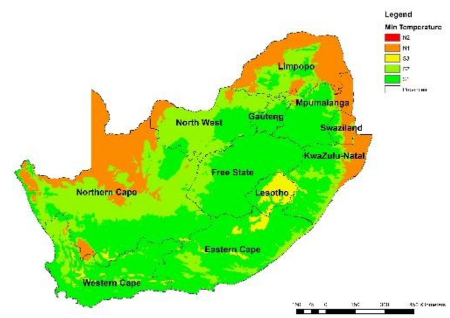
Rainfall is undoubtedly the dominating factor determining crop production, especially in marginal areas where irrigation facilities are limited for smallholder farmers (Tibesigwa et al., 2017). The country is characterized by a mild, temperate climate (Aliber and Cousins, 2013). Precipitation varies spatially across the country with an average annual of 450 mm (compared to a global average of 860 mm), and it is variable across the seasons (Smithers and Schulze, 2000). About 890 mm of precipitation falls yearly in the Eastern Low-veld and the Eastern Uplands as far west as the Drakensberg **Error! Hyperlink reference not valid.** (Smithers and Schulze, 2000) (**Error! Reference source not found.**). The High Veld receives about 380 to 760 mm of precipitation annually, the amount diminishing rapidly toward the west (**Error! Reference source not found.**). About 61% of the country receives rainfall of less than 500 mm rainfall annually, which is considered the minimum for successful dryland farming. Where rainfall exceeds 500 mm, major crops include maize, soybean, tobacco, sugar cane and high-value horticultural crops.

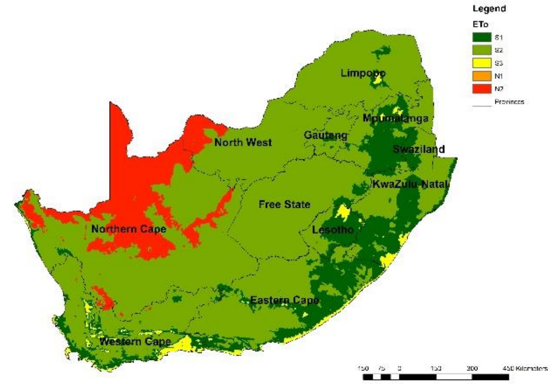
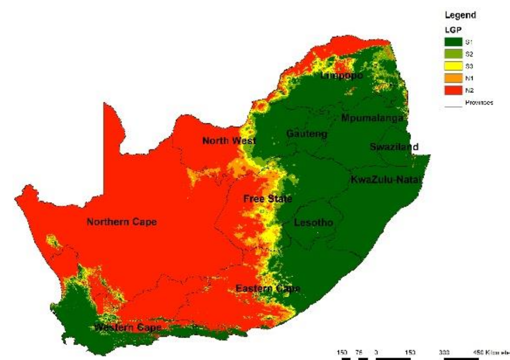
South Africa is characterised by a range of thermal zones and length of rain-fed growing days, which both affect the suitability of crops. A different range of soil depth also characterises the country, the highest percentage of medium-sized soil texture and has the highest mountain range of approximately 3482 m in the east of the country (Aliber and Cousins, 2013). A number South African smallholder farmers who have few financial resources, limited access to infrastructure and disparate access to information are located in marginal areas (Pereira, 2013). Therefore, smallholder farmers need a transformational adaptation (TA) of agricultural systems to climate change and one of TA strategy is to grow NUS on recommended land units in South Africa.

Single factor suitability maps

Supplementary Table 1. 8 climatic factors used to delineate land suitability maps for neglected and underutilised crop species

Factor	**Description**	**Source**	**Single factor suitability maps for South Africa where (S1-Highly Suitable, S2-Moderately Suitable, S3-Marginally Suitable, N1-Currently Unsuitable, N2 Permanently Unsuitable**
Precipitation (mm) 1.7 km resolution	Precipitation is defined as liquid or solid products of the condensation of water vapour falling from clouds or deposited from the air on the ground (Pierrehumbert et al., 2006). Wet periods can be calculated from daily precipitation events like the start of the season, dry spells, end of the season. In SA, precipitation is undoubtedly the dominating factor determining crop production, especially in marginal areas where irrigation facilities are limited for smallholder farmers (Tibesigwa et al., 2017). Precipitation varies spatially across the country with an average annual of 450 mm (compared to a global average of 860 mm), and it is	South African Quaternary Catchments database- Water Research Commission	 Fig 8: Spatial distribution of seasonal precipitation, for period of 1950-2000 for South Africa

	variable across the seasons (Smithers and Schulze, 2000) (Figure 8)	South African Quaternary Catchments database- Water Research Commission	
Temperature 1.7 km resolution	Temperature is a measure of heat accumulation and is instrumental in crop growth and management. Temperature is presented as maximum and minimum of air near the earth's surface; the surface of the ground, the soil at various depths. The optimum temperature for photosynthesis is (25°C), and plants growing in a CO_2 enriched environment thrive in slightly warmer conditions (28°C) (Sage and Kubien, 2007). The photosynthesis rates drop off sharply if temperatures rise above 30 °C, and it also falls if temperatures are cooler (Cannell and Thornley, 1998; Sage and Kubien, 2007) (Figure 9 and 10)		 Fig 9: Seasonal average maximum temperature for South Africa for period of 1950-2000  Fig 10: Seasonal average maximum temperature for South Africa for period of 1950-2000

Reference crop evapotranspiration (ETo) millimeters (mm) or (lm^{-2})) 1.7 km resolution	Reference crop evapotranspiration refers to evapotranspiration rate from a reference surface, not short of water (Doorenbos and Pruitt, 1977). The reference surface is a hypothetical grass reference crop with specific characteristics (Raes, 2017). Climate factors such as rainfall and potential evapotranspiration are among the crucial factors that affect the suitability of an area for irrigation (Raes et al., 2012) (Figure 11).	South African Quaternary Catchments database- Water Research Commission	 Fig 11: Reference crop evapotranspiration (ETo) millimeters (mm) for South Africa
Length of growing period (LGP) 1.7 km resolution	This represents the number of days when soil moisture and temperature permit crop growth (Figure 12). The Adapted FAO Approach was used to determine moisture growing season; it assumed that during the period when $P \geq 0.3Er$ sustained plant growth can take place, where P is median monthly precipitation (mm) and mean monthly Epan is considered as the reference potential evaporation- Er (FAO, 2011). The growing period was calculated using the moisture growing season by applying a	South African Quaternary Catchments database- Water Research Commission	 Fig 12: Length of growing period (LGP) for South Africa

	simple water budgeting approach(Schulze and Maharaj, 1978; FAO, 2011).	
Water Requirement Satisfaction Index (WRSI)-at 1.0-degree resolution	An indicator of crop performance based on the availability of water during a growing season. Important in locations where weather stations or other ground observations are sparse or non-existent. The indices can be calculated using seasonal actual crop evapotranspiration (AETc) to the seasonal crop water requirement, which is the same as the potential crop evapotranspiration (PETc) (Heng et al., 2009; Consoli and Vanella, 2014). PETc is crop-specific potential evapotranspiration after an adjustment is made to the reference crop potential evapotranspiration (PET) by the use of appropriate crop coefficients (Kc) (Singh Rawat et al., 2019). Crop coefficients values define the water use pattern of a crop.	Fewsnet https://earlywarning.usgs.gov/fews

Soil and landscape attributes used to delineate land suitability maps for neglected and underutilised crop species

Factors	Description	Source

Soil depth at 250m resolution	It is the depth of soil to which the roots of a plant can easily penetrate to withdraw water and extract nutrients from the root zone (Bello and Walker, 2017). Soil depth is the most critical soil property affecting the hydrologic properties of soil and its behaviours against erosion. Water-storing capacity and effective rooting depth are related to soil depth. Effective rooting depth is sometimes related to soil depth, and it is most critical, but unavailability of data at spatial was a challenge. Shallow soils may restrict the development of plant root due to which the plant may suffer adverse conditions in the limited soil volume. Soil depth suitability map is shown in (Figure 13)	South African Quaternary Catchments database- Water Research Commission

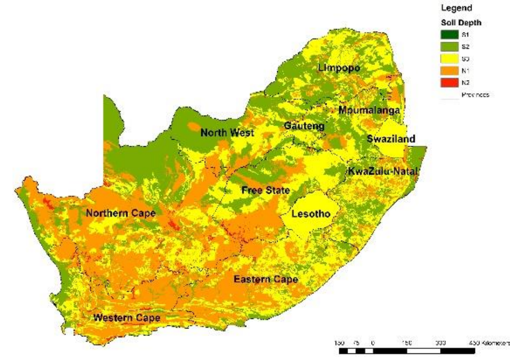
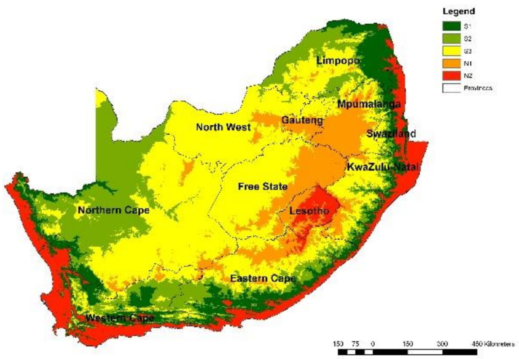
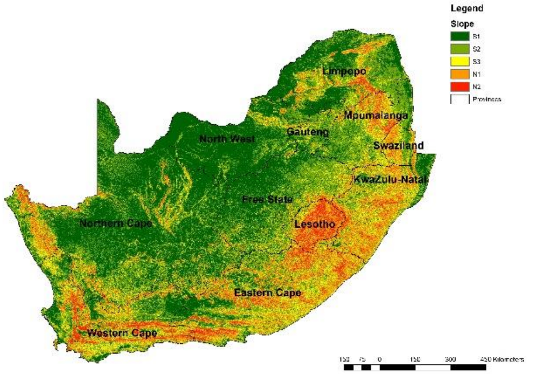
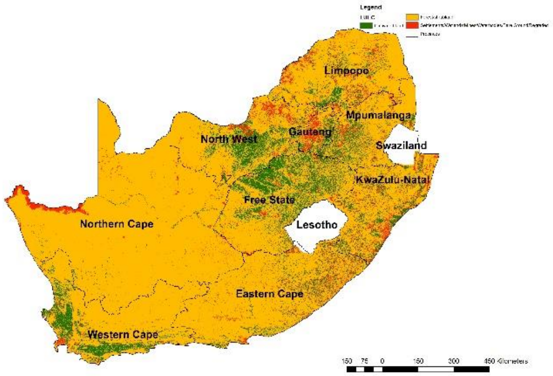
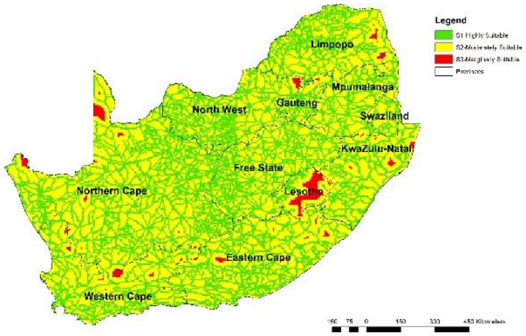


Fig 13: Soil depth suitability map for South Africa

Elevation (mm) 30m resolution	The height of an object above a given level or implied place, especially above sea level (Mendelsohn, 2008). Variation in elevation has an impact on the number of agro-climatic factors like soils, microclimatic effects, and other processes that could affect land suitability (Abera et al., 2018). Elevation affects cropland suitability because of temperature change with an increase of height in the lower troposphere of the atmosphere. The vegetation and vernalisation periods are delayed by 4-6 days for every additional 100 m in elevation on the mountains. In this study, the 30m spatial resolution DEM data of SRTM was acquired from USGS http://earthexplorer.usgs.gov, (Figure 14).	http://earthexplorer.usgs.gov.	 Fig 14: Elevation suitability map for South Africa

Slope	The slope is a crucial factor affecting vegetation structure and soil erosion Table 5. The slope is the essential aspect of the surface as well as for internal soil water drainage as both characteristics play a significant role in the growth of the crop. The general slope suitability map is indicated in (Figure 15)	South African Quaternary Catchments database- Water Research Commission	 Fig 15: Slope suitability for South Africa
Land Use Land cover-LULC of 2016	Knowledge of existing land use provides information about land availability. Land use data helps to identify the productivity of an area for a given cropping system. The land use and land cover (LULC) are a core information layer for a variety of scientific activities and administrative tasks in a given region. Understanding the proportion of land use is essential for the development of control measure, guide planners in making more informed decisions and achieving a balance between urban growth and preservation of the natural environment. The LULC map		 Fig 16: Crop production suitability map for land use land cover map for South Africa

	for cultivated areas in SA is shown in (Figure 16)		
Social and economic factors used to delineate land suitability maps for NUS.			
Distance from road/accessibility	Land use is often also influenced by the ease of access to road networks for the transport of produce to the markets. Road networks play a vital role in remote areas, and the suitability analysis omits informal roads within farms though they play a crucial role in transportations of goods. Figure 17, represent distance from road suitability map for SA.	South African Quaternary Catchments database- Water Research Commission	 Fig 17: Distance from road suitability map for South Africa

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