Mapping tea plantation health in proportion to invasive alien plants and climate change in Tshivhase Tea Estate, South Africa: A remote sensing approach

By

FHULUFHEDZANI NEMBAMBULA

20020600

Supervisor: Dr. Oupa Malahlela

Co-supervisor: Dr. Lutendo Mugwedi

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Declaration

This study was undertaken in fulfilment of a Master's Degree in Environmental Sciences and presents the original work of the author under the supervision of (i) and (ii). Any work taken from other authors' or organizations is duly acknowledged within the text and references section.

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Ms Fhulufhedzani Nembambula

(Student)

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General Abstract

Invasive alien plants (IAPs) pose substantial threats to agriculture, biodiversity, and ecosystem services delivery globally. IAPs decrease species richness and abundance through competition, predation, hybridization, and indirect effects. Tea plantations like any other agricultural entity are threatened by invasive alien species. Tea is important as it contributes significantly to job creation and export earnings in many developing countries as well as its tasteful flavour and health benefits. The control and removal of these invaders require accurate mapping. In recent years, many countries have adopted the use of satellite remote sensing to map tea health at various scales. The increasing effects of climate change threaten the health and production of tea. This study assessed the co-occurrence of IAPs present in the Tshivhase Tea Estate and mapped the dominant species (*Solanum mauritianum*) using geostatistics techniques (Inverse Distance Weighting (IDW), kriging, and regression splines). The study also explored the potential of SPOT 7 and Sentinel 2 satellite data in mapping the occurrence of *S. mauritianum*, *Lantana camara* and the co-occurrence amongst *S. mauritianum*, *L. camara*, and *Chromoleana odorata* in the Tshivhase Tea Estate in Limpopo, South Africa. The Vegetation Condition Index (VCI) has been used to assess tea plantation health and climate data to assess climate change. Tea plantation health was then related to *S. mauritianum* distribution. The most frequently occurring species was the *S. mauritianum* with a 53% occurrence proportion and 73% likelihood of occurrence followed by the *L. camara* at 25% proportion of occurrence. None of the geostatistic methods were significant in mapping the occurrence of alien invasive plants species with IDW yielded R^2=0.04; the root mean square error (RMSE) =0.48; the mean absolute deviance (MAD) =0.42; kriging (R^2=0.02; RMSE=0.47; MAD=0.45) and regression splines (R^2=0.004, RMSE=3.95; MAD=1.81). The presence/absence and remotely sensed environmental data were used to generate a logistic regression model in R for *S. mauritianum* and *L. camara* occurrence as well as the observed and conditional co-occurrence probability of *S. mauritianum* (P1), *L. camara* (P2) and *C. odorata* (P3). The logistic regression model coefficients were then mapped on QGIS to produce invasive alien plant species (IAPs)' occurrence frequency and co-occurrence probability maps. The SPOT 7 model performed the highest receiver-operating characteristic (ROC) in the area under the curve (AUC) of 0.94 in predicting the conditional co-occurrence of *S. mauritianum* and *L. camara* whereas the sentinel 2 model performed a ROC AUC of 0.86. This could be because SPOT 7 has a spatial resolution than Sentinel-2. The VCI was high throughout the Tshivhase Tea Estate with a 50-100% range. The *S. mauritianum* occurred in areas of high VCI thereby affecting the health of tea plantations through the competition of nutrients and other things. The temperature and precipitation showed a positive or significant correlation with VCI in 2015. The study has attempted to map tea health concerning invasive plant species using high-resolution satellite images. The study has concluded that geostatistics methods are not suited for mapping the occurrence of alien invasive plants in homogenous plantations especially when the area of study is small and with scattered invasive alien plant species distribution. On the other hand, remote sensing variables and co-occurrence in combination with logistic regression are well suited for mapping the prediction occurrence of alien invasive plants in the homogeneous plantation, especially when using high and spectral resolution satellite images.

Keywords: Alien Invasive Plants; Geostatistic techniques; Logistic Regression; VCI

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CHAPTER ONE

Introduction

1.1 Study background

Tea, obtained from the leaves of *Camellia sinensis*, is one of the most popular and commonly consumed beverages in the world (Yilmaz *et al*., 2019). Tea is an important commodity as it contributes significantly to job creation and export earnings for many developing countries (Khumalo *et al*., 2015) as well as its health benefits such as reducing cancer and heart diseases risk, improving immune function as well as treating diarrhea (Trevisanatto and Kim,2000). Biodiversity, ecosystem functioning, and human well-being are threatened by invasive alien plants (IAPs) worldwide (Ahdhikari *et al*., 2019). Climate change is expected to expand the climatically suitable ranges for IAPs. There are studies about determining the IAPs species distribution (Higgins *et al*., 1999; Rejmanek, 2000; Urban *et al*., 2016). IAPs are a major cause of crop loss thereby adversely affecting food security (Sheppard *et al*., 2016).

Recently, there is substantial attention globally towards the occurrence, spatial distribution, and abundance of IAPs detection and mapping (Royimani *et al*., 2019). There are many studies on IAPs distributions or occurrence and impacts on forests and agriculture using different methods. The five mechanism impact of IAPs on forest regeneration included competition as well as chemical, physical, structural and indirect impacts with other species were identified using a systematic review approach in the European Temperate forests (Langmaier and Lapin, 2020). On the other hand, Malahlela *et al*., (2015) mapped the occurrence of *C. odorata* in the subtropical forest gaps and highlighted that WorldView 2 spectral bands have the capability of detecting the presence and absence of *C. odorata* in forest canopy gaps. More recently, agricultural areas' vulnerability to invasive alien plant species invasion was assessed using climatic suitability maps and found that multiple plant invasions across the agricultural land differ with land use types (Champika *et al*., 2021). Although there are a lot of studies on the impact of IAPs on forests, there are also few studies about the impact of IAPs on tea plantations.

Remote sensing (RS) is one of the precision agriculture technologies that serve as an early indicator to detect potential problems by enabling farmers to collect, visualize, and evaluate crop and soil health conditions at various stages of production conveniently and cost-effectively. RS also provides opportunities to address farming problems at an early stage (Khanal *et al*., 2020). Tea plantations could be well monitored and measured using multispectral sensors (Dutta *et al*., 2008).

Different methods of RS have been applied in mapping homogeneous vegetation such as tea plantations. Different vegetation indices such as Normalized Difference Vegetation Index

(NDVI), Fraction of Photosynthetically Active Radiation (FPAR), and Transformed Vegetation Index (TVI) are widely used to monitor and map crop health which is also directly proportional to yield (Acharya, 2018). The Green Normalized Difference Vegetation Index (GNDVI), Soil Adjusted Vegetation Index (SAVI), and Modified Soil Adjusted Vegetation Index 2 (MSAVI2) are some of the popular vegetation indices used for monitoring crop health status (Ali *et al*., 2017). For example, the Normalized Difference Vegetation Index (NDVI) and the Soil Adjusted Vegetation Index (SAVI) derived from Landsat 8 and Sentinel-2 were effective in predicting potato tuber yield in agricultural fields of Saudi Agri-cultural Development Company (INMA) in Wadi Al-Dawasir area south of Riyadh, the capital city of Saudi Arabia(Al-Gaadi *et al*., 2016). There is proof of the association of NDVI and Leaf Area Index (LAI) in plant life monitoring research. LAI is an important parameter that controls the physiological process of the vegetation canopy closely related to biomass and crop yield (Hasan *et al*., 2019). Factors such as temperature, irrigation facilities, and soil health conditions are important in monitoring the health, growth, and production of the crop.

Based on the above background, this study explores the capability of Sentinel 2 and SPOT 7 in mapping tea plantation health to IAPs in the Tshivhase Tea Estate in Limpopo, South Africa. The objectives of the study are as follows:

- To assess the frequency of *Solanum mauritianum* co-occurrence within the tea plantation using Geostatistical techniques.
- To explore the capability of medium to high-resolution satellite data in delineating the potential distribution of common IAPs species in the Tshivhase Tea Estate.
- To assess the extent of climate change using climate data in proportion to the tea health plantation and IAPs distribution.

1.2 Outline of the Thesis

This thesis consists of five (5) chapters: Chapter 1 presents the background of the study, aims, and objectives of the study. Chapters 2, 3, and 4 were written in the form of paper publication submissions. Chapter 2 presents the geostatistical assessment of the frequency of *S. mauritianum* co-occurrence within the tea plantation in the Tshivhase Tea Estate. Chapter 3 presents the exploration of medium to high-resolution satellite data capability in delineating the potential distribution of common invasive alien plant species in the Tshivhase Tea Estate. Chapter 4 presents the assessment of the extent of climate change using climate data for tea health plants. Chapter 5 presents the conclusion of the study. The aims and the objectives of the study are discussed in detail. The recommendations for future studies are outlined at the end of this chapter.

CHAPTER TWO

The geostatistical assessment of the frequency of *Solanum mauritianum* co-occurrence within the tea plantation in the Tshivhase Tea Estate in South Africa

2.1 Abstract

Invasive alien plants (IAPs) can considerably impact global agriculture which influences food security continuously worldwide. The ongoing invasion of IAPs demands efficient and economic resolutions of their management. Therefore, this study assessed the co-occurrence of IAPs present in the Tshivhase Tea Estate and mapped the dominant IAP (*Solanum mauritianum*) using geostatistics techniques (inverse distance weighting (IDW), kriging, and regression splines). Co-occurrence matrices were used to assess the distribution of IAPs species in the Tshivhase Tea Estate. The most frequently occurring IAP species in the Tshivhase Tea Estate was an *S. mauritianum* with a 53% proportion of occurrence and 73% likelihood of occurrence. The marginalized co-occurrence probability between *S. mauritianum*, *Lantana camara*, and *Chromolaena odorata* was the same as the proportional probability of occurrence of these species. The observed co-occurrence probability indicated the association between *S.mauritianum* and *L. camara* (P1, 2), *S. mauritianum* and *C. odorata* (P1, 3), and *L .camara* and *C. odorata* (P2, 3) as 0.74, 0.5 and 1 respectively. The *S. mauritianum* also had the highest chance of occurring as a single invader. On the *n*=124 occurrence frequency dataset, 60% (n=74) of the dataset have been used in the interpolation models. The IDW has surpassed kriging and spline models with R^2=0.04; RMSE=0.48; MAD=0.42 compared to kriging (R^2=0.02; RMSE=0.47; MAD = 0.45) and Spline (R^2=0.004, RMSE=3.95; MAD=1.81). These results are not sufficient enough to map the frequency of species occurrence. The model should have higher R^2 and lower RMSE and MAD to be considered a good fit. The interpolation models' predictive accuracy was assessed by calculating the co-efficient of determination (R^2), root mean square error (RMSE), and mean absolute deviation (MAD). The findings of the study further indicated that there is a high occurrence frequency of *S. mauritianum* in the central part of the tea plantation and low in areas where there are no tea plants or trimmed tea plants. The geostatistics methods were not sufficient enough in mapping the occurrence frequency of IAPs even when high spatial and spectral resolution images (SPOT 7) have been used. This could be because the study area was small and the invasive alien plants were scattered within the tea plantation and not evenly distributed.

Keywords: inverse distance weighting (IDW), kriging, regression splines

2.2 Introduction

Invasive alien plants (IAPs) everywhere pose solid threats to farming, biodiversity, and ecosystem services delivery (Witt *et al*., 2018). The IAPs contest, attack, and breed with other species resulting in a decrease in the richness and abundance of the other species (Blackburn *et al*., 2004; Gaertner *et al*., 2009). The essential starting point to quantify the IAPs threats is to gather information about their occurrence and distribution and inform the development of appropriate responses (Witt *et al*, .2018). Tea plantations like other agricultural entities are also threatened by invasive alien species. Tea contributes significantly to job creation and export earnings in many developing countries (Khumalo *et al*., 2015), as well as its good taste and numerous health benefits (Chen *et al*.,2020), such as reducing heart diseases risk, stress reduction, weight loss, cancer risk reduction (Trevisanato and Kim, 2000).

However, the global tea industry is faced with other challenges besides the obvious threat of IAPs, and these challenges range from higher production costs, competition from cheap tea imports, low skills, and production levels, the removal of tariffs, lack of government support, high competition of world market, and tea market price fluctuation of tea market price to the risk of exchange-rate among others (Khumalo, 2012). Furthermore, tea is also faced with climate change threats that negatively affect species' health and quality (Carnazzi, 2014). Various types of annual and everlasting weeds may also infest tea plantations. The tropical climate, which is the same as that experienced at the Tshivhase Tea Estate, also influences the flourishment and growth of weeds through plentiful sunshine, heat, and moisture. These weeds contest for space, water, and nutrients, with other plants, and their energetic growth overshadows tea plants, especially when tea plants are juvenile (Mukhopadhyay and Mondal, 2017). Weeds create conditions that are vulnerable to plant diseases by increasing the humidity in the plantation thereby promoting the presence of pests and bacteria that may kill the tea plantation (Hasselo and Sandanam, 1965; Parent, 2021). Quality tea productivity can be achieved by detecting its infestation early, such as early detection of weed infestation stress thereby providing an opportunity for the planters to control and efficiently manage the spread of weeds.

The *S. mauritianum* is one of the IAP infesting tea plantations. The *S. mauritianum* is an evergreen, noxious shrub with branches that invades several tropical, subtropical, and warm temperate regions (Olckers, 2011; ISSG 2006). It is known by various common names, such as bugweed, tree tobacco, and woolly nightshade (Florentine *et al*., 2003; ISSG 2006; PIER 2010). In South Africa, the IAPs are promoted in the farming land, plantations of the forest, riparian zones, and areas of conservation through the rapid growth, plentiful fruit production, a large number of native fruit-eating birds as well as seed banks covering a large area of these IAPs (Henderson 2001; ISSG 2006; Witkowski and Garner 2008). The *C. odorata* on the other hand is an enduring, temporary, and multi-stemmed shrub that originated from South and Central America (Mugwedi, 2020). In South Africa, *C. odorata* is commonly known as "triffid" or "paraffin weed" (Naidoo, 2013). It has become a prolific weed in riverine ecosystems, crop plantations, grasslands, and natural forests (Goodall and Erasmus, 1996). The rapid spread of *C. odorata* is related to seed production affecting a large area as well as how these seeds are dispersed (Erasmus, 1985; Liggitt, 1983; Macdonald and Frame, 1988). The small spines on the seeds can adhere to wet clothes, fur, and feathers (Wilson, 2003). The invasion of *C. odorata* in Cote d'Ivoire led to the abandonment of cocoa and coffee plantations (Zebeyou, 1991). The *C. odorata* has been indicated to be problematic during the establishment of young oil palm, cocoa, and rubber plantations in Nigeria (Sheldrick, 1968; Ivens, 1972; Ikuenobe and Ayeni, 1998) and Ghana (Timbilla, 1996). The weed can cause a decline in the farming output and increase management costs at both subsistence and commercial scales (Lucas 1989; Prasad *et al*., 1996).

The IAPs species co-occurrence theory is needed to analyze and interpret IAPs co-occurrence (presence-absence) data in the community. The species co-occurrence theory analyzes the interactions between species distribution (Blanchet *et al*., 2020). This theory focuses on the relationship between occurrences and abiotic factor and work out assumptions for unlike community congregation techniques (Cazelles *et al*., 2016). The presentation of the presence/absence data matrix over a set of sites is the first step in the analysis of species co-occurrences. The co-occurrence quantitative study has two features, 1. A metric used to measure the association strength between pairs of species, 2. The null model is worked out based on Diamond's analysis (Cazelles *et al*., 2016). Currently, there is no multi-species communities' co-occurrence theory (Cazelles *et al*., 2016). This theory will help in understanding the relationship between the IAPs species available in the Tshivhase Tea Estate.

On the other hand, a Geographic Information System (GIS) can be used to monitor the abundance and spatiotemporal spread of IAPs across different areas (Caffrey *et al*., 2006). Invasive plant abundance maps are particularly useful in clearly indicating the extent of IAPs distribution problem to relevant beneficiaries such as farmers, policymakers, and other relevant stakeholders (Bradley and Martin, 2011). The abundance and distribution of IAPs species data for mapping are mostly collected using GPS (Bois *et al*., 2011). The accuracy of remotely-sensed data has been assessed using GPS units (Abella *et al*., 2009).

The detailed analysis of IAPs species extent and dynamics can be achieved through the use of GIS, remote sensing, and geostatistics techniques. These can also be adopted in the preparation of activities aiming at fighting the spread of invasive alien plant species (Bzdega *et al*., 2021). The geostatistical modeling and remote sensing data were successfully used to estimate the Spatio-temporal dynamics of the vegetative cover (Zhukov et al., 2013) as well as to describe the subtropical forests' spatial variations in Leaf Area Index (LAI) (Zhu *et al*., 2016). Geostatistical methods such as IDW and kriging have been widely used in predictive weed mapping (Heisel *et al*., 1996, 1999; Jurado-Exposito *et al*., 2009; Kalivas *et al*., 2010, 2012). Simple kriging, indicator kriging, universal kriging, and co-kriging are the types of kriging that have different degrees of success in the interpolation of environmental attributes. Ordinary kriging is the most common used kriging method (van Groenigen, 2000; Guti´errez de Rav´e *et al*., 2014). Although geostatistical methods such as ordinary kriging have proven to be useful in natural sciences, there are still a small number of geostatistical methods applications in natural science studies (Bzdega *et al*., 2021). The current chapter explored the frequency of *S. mauritianum* invasive plant using the geostatistical methods, co-occurrence matrices, and GIS at the Tshivhase Tea Estate in South Africa.

2.3. Material and methods

2.3.1 Study Area

The study was undertaken at Tshivhase Tea Estate in Thulamela Municipality which falls within 22.8922° S, 30.6200° E -22.97276° S, 30.37697° E(Lower right corner), and -22.94597° S,30.3195° E(Upper Left corner), in the Vhembe District Municipality of the Limpopo Province of South Africa (Figure 1). The Tshivhase Tea Estate is traded by Venteco, which took over the business from British firm Sapeco after it withdrew from the country in 2004 as it was operating at a loss. The Tshivhase and Mukumbani are the two sub-estates under the Tshivhase Tea Estate. The cultivation, production of tea (*Camellia sinensis*), and packaging of bulk black and rooibos (*Aspalathus linearis*) tea are the main activities in the Tshivhase Tea Estate Tshivhase packages the rooibos tea. The study will focus only on the Tshivhase sub-estate. This study area was chosen because it is one of the agricultural enterprises that provide job plantations to sustain the quality and production of tea plantations, thereby sustaining job opportunities and improving food security. This study has the potential to effectively contribute to a cost-effective and reliable approach for monitoring and managing tea plantations to sustain the quality and production of tea plantations, thereby sustaining job opportunities.

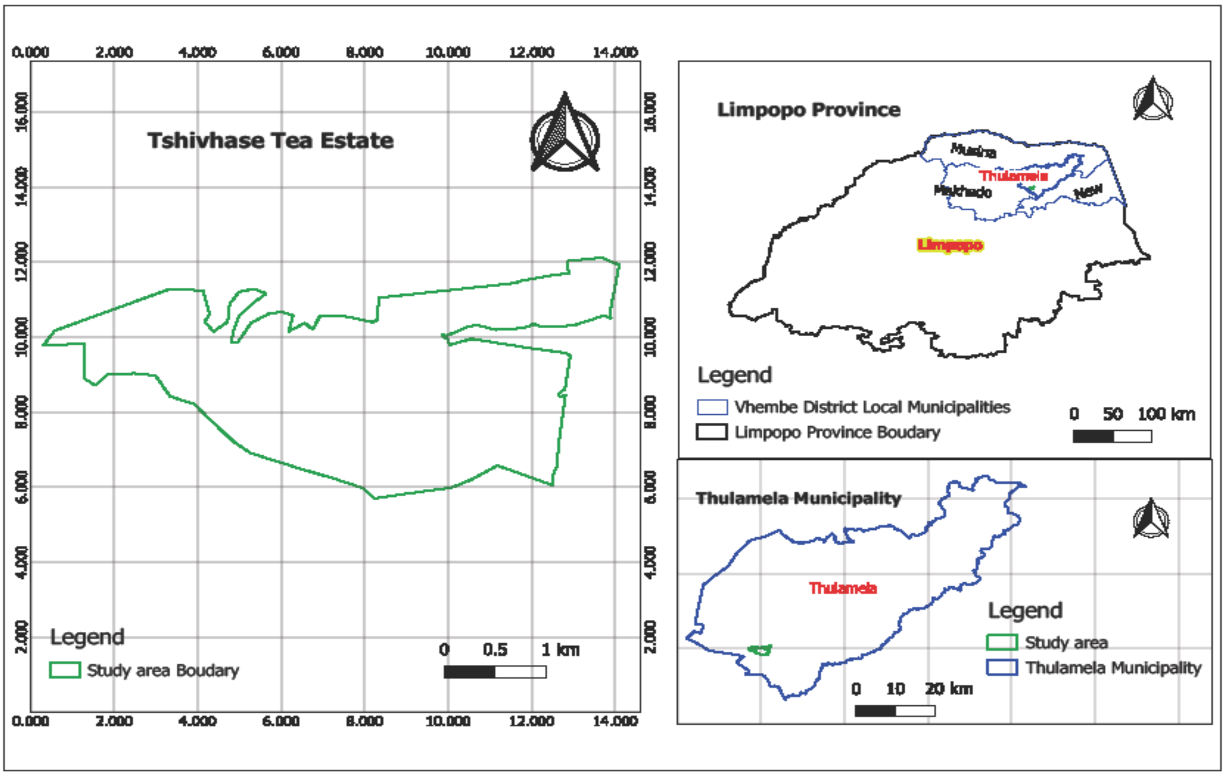

Figure 1: Tshivhase Tea Estate, Thulamela Municipality, Limpopo Province.

2.3.2 Field data collection

Randomly sampled points were surveyed within the Tshivhase Tea Estate boundary. A total of 124 points were collected in a field survey. The locations of surveyed sites were recorded using Garmin eTrex Global Positioning System receiver with a maximum spatial accuracy of 4m. The presence and absence of IAPs were observed visually on the randomly sampled points for six days between the 1st and 8th days of October 2021. The date was chosen based on the phenological condition (green and ready for harvest) of the tea during that time.

2.3.3 Co-occurrence analysis

The community assembly could be understood by co-occurrence (presence-absence) data (Blanchet *et al*., 2020) which is the study that analyzes the interactions between species distribution (Blanchet *et al*., 2020). The observed and conditional co-occurrence probability was used to assess the co-occurrence of Species 1(*S. mauritianum*), Species 2 (*L. camara*) and Species 3 (*C. odorata*). The observed co-occurrence between species *i* and *j* is the joint probability $p\ i, j = (X_i = 1 \cap X_j = 1)$ representing the number of sites where the two species occur together across all possible species set in the data (Cazzelles *et al*., 2016).

The conditional co-occurrence between species i and j is $pi|j$ = p $(Xi = 1|Xj = 1)$ representing the probability of observing i, knowing that species j is already present (Cazelles *et al*., 2016). This is similar to quantifying the association between two species as it is independent of the marginal occurrence probability of both species. The conditional co-occurrence is marginalized over the set of all other species from the community as soon as there is a presence of other species (Cazelles *et al*., 2016).

The occurrence frequency was also determined through calculations of the proportion of presence of each species using equation 1 and the likelihood of occurrence amongst all the species using equation 2.

$$Pr_i = \frac{p}{|p + a|} \times 100$$

Equation 1

$$F = \frac{p}{|pK_1| \ + |pK_2| + |pK_3|)} \times 100$$

Equation 2

where Pr_i is the probability of species presence in a site i, F is the presence frequency (co-occurrence) for species K_j when species presence $p = 1$, a is species absence.

2.3.5 Spatial interpolation

The collected field data were interpolated using the inverse distance weighting (IDW), kriging, and regression splines to predict the co-occurrence frequency of an *S. mauritianum* in the Tshivhase Tea Estate. These interpolations have been applied to determine their efficacy in mapping the occurrence of *S. mauritianum*. Interpolation is the prediction of the unknown value of a feature using the measurements of the known value of the feature within the same area (Krahmer *et al*., 2020). The interpolation was conducted on ArcGIS Pro. The IDW interpolation method estimates the unknown point values by averaging the values of nearby known sample data points with distance-based functions as weight. The equation to calculate IDW is as follows (Roberts *et al*., 2004):

$$Z_{(x_0)} = \sum_{i=1}^{n} \lambda_i Z_{(xi)}$$

Equation 3

where $Z_{(x_0)}$ is the unknown value, $Z_{(xi)}$ is the known sample value; and λ_i is the weighting value quantified as below(Roberts et al, 2004).

$$\lambda_i = [d_{(x_i x_0)}]^p / \sum_{i=1}^{n} [d_{(x_i x_0)}]^p$$

Equation 4

where $d_{(x_i x_0)}$is is the Euclidean distance between x_i and x_0 and p is a power value. The IDW interpolation results will vary depending on the selection of power value and the neighbourhood strategy (Watson and Philip, 1985; Roberts *et al*., 2004).

On the other hand, kriging is an advanced geostatistical technique that estimates the surface from a dispersed set of points with z-values (Wang, 2017). Kriging also provides some measure of the certainty of prediction accuracy in producing and interpolating surfaces (Munyati and Sinthumule, 2021). Data that is well distributed and with no discontinuities is best suited for kriging (Akkala *et al*., 2010). The ordinary kriging formula is the same as the IDW equation in Equation 1 with the difference in that the λi, in IDW depends entirely on the distance to the prediction location whereas in kriging; it depends on the overall spatial arrangement of the measured points in addition to the distance (Munyati and Sinthumule, 2021).

Spline creates a smooth surface that passes along the input points using a mathematical function (Wang *et al*., 2017). The map surface is allowed to undershoot and overshoot input points to maintain smooth curvature accordingly (Valley *et al*., 2005). The spline model is expressed as (Ali *et al*., 2011):

$$C(h) = h^k$$ **Equation 5**

where *C(h)*is the covariance function, h is the distance between the points, *k*=*m*-1, and *m* is observed points order of relative derivation.

The IDW model was set to the power of 2 and for the kriging, the ordinary kriging method and semivariogram were chosen. The IDW and kriging model radius search was set to a variable.

2.3.6 Validation

To validate the accuracy of the interpolation models, the ground observations dataset (*n*=124) presence/absence of an *S. mauritianum* dataset) was divided into two random datasets, that is, the training dataset (60%, *n*=74) and a validation dataset (40%, *n*=50). The training dataset was used to interpolate the occurrence frequency *of S. mauritianum* while the validation dataset was used to check the model accuracy by calculating co-efficient of determination (R^2), mean absolute deviation(MAD), and root mean square error which was calculated as (Wang *et al.*,2017):

$$R^2 = \frac{\{\sum_{k=1}^{n}[(Y_k - \underline{Y})(O_k - \underline{O})]\}}{\sum_{k=1}^{n}[(Y_k - \underline{Y})]^2 \sum_{k=1}^{n}[(Y_{k-}\underline{O})^2]}$$

Equation 6

where n represents the number of validation data,

Yk represents the in-situ frequency occurrence data in validation site k,

Ok represents the predicted frequency occurrence data in validation site k,

Y represents the mean value of in-situ frequency occurrence data for all validation sites, and

O represents the mean value of the predicted frequency occurrence data for all validation sites.

The lower the RMSE (0.2- 0.5) and the higher the R^2 (0.6 - 1) the superior the model in fitting the dataset (Statology, 2021; Saeedi, 2019). The RMSE closer to Zero (0) and R^2 closer to one (1) indicates high accuracy of the model performance (Mwenda, 2019).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(p_{i-}a_i)^2}$$

Equation 7

$$MAD = \frac{1}{n}\sum_{i=1}^{n}(p_i - a_i)$$

Equation 8

where n is the validation dataset values, p_i is the predicted value and a_i is the actual (measured) value (Malahlela *et al*., 2019).

2.4. Results

2.4.1 Co-occurrence frequency

Three invasive alien plants were observed in the Tshivhase Tea Estate, i.e. *S. mauritianum*, *C. odorata* and *L. camara*. The *S. mauritianum* is the one that occurs mostly when walking throughout the Tea Estate. As shown in Figure 2, *S. mauritianum* had the higher proportion of occurrence with 53.2% followed by *L. camara* at 18.6%. The *C. odorata* had the lowest proportion of occurrence. There is a high chance of finding *S. mauritianum* in the Tshivhase Tea Estate plantation.

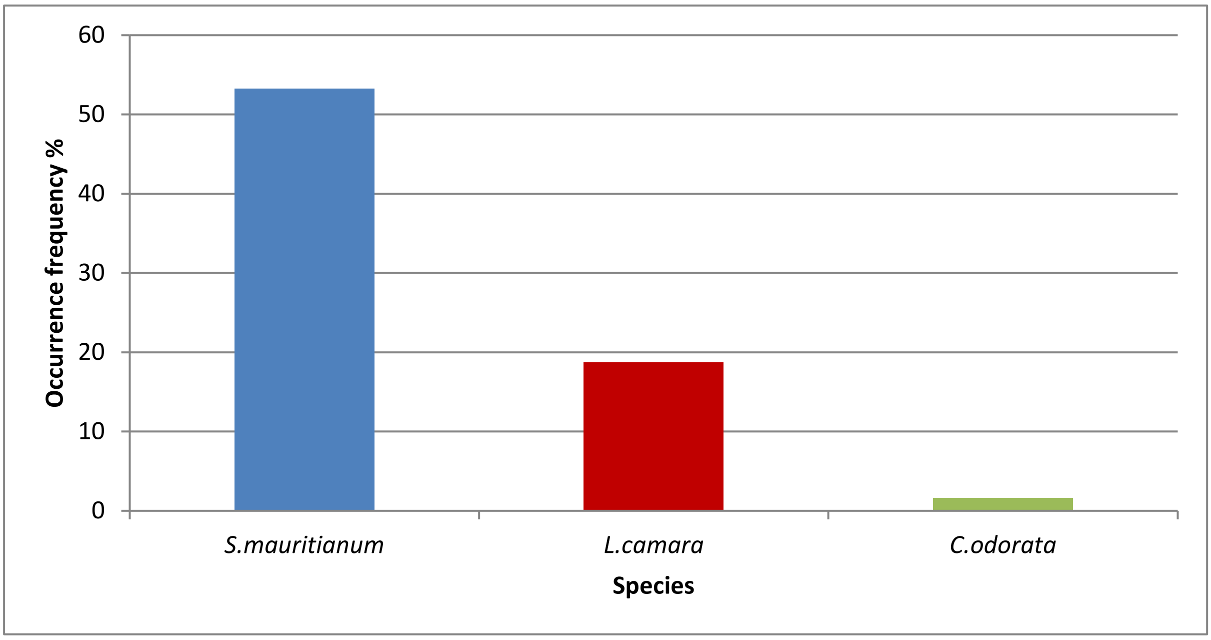

Figure 2: Proportion of occurrence of *Solanum mauritianum*, *Lantana camara* and *Chromoleana odorata* in the Tshivhase Tea Estate.

The likelihood of occurrence between *S. mauritianum*, *L. camara* and *C. odorata* is shown in Figure 3, where *S. mauritianum* has the highest likelihood of occurrence with 72.53 %. The *S. mauritianum* is followed by *L. camara* with a 25 % likelihood of occurrence within the tea plantation. Likewise, *C. odorata* has the lowest likelihood of occurrence among other species.

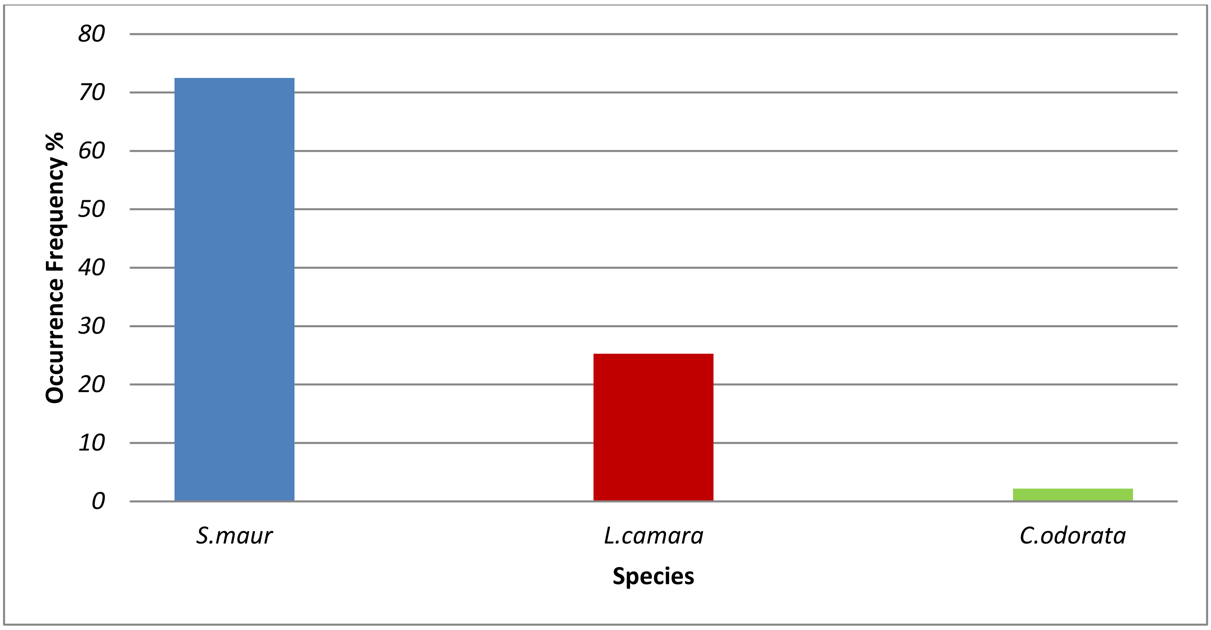

Figure 3: Likelihood of co-occurrence between *Solanum mauritianum*, *Lantana camara* and *Chromoleana odorata* in the Tshivhase Tea Estate.

Figure 4 below represents the proportion of occurrence between the IAPs found in the Tshivhase Tea Estate (*S. mauritianum*, *C. odorata*, and *L. camara*). The frequency of occurrence for all the three IAPs ranged from 0; 0.33; 0.50 and 100 where 0 indicated areas in the tea plantation where it is pure (no IAPs), 0.33 indicated areas in the tea plantation where there are all three IAPs, 0, 50 indicated areas in the tea where is only two invaders of IAPs and 100 indicated areas in the tea where there is one IAP. It was observed that at a frequency of 0, there is a high chance (122 cases) of not finding *C. odorata* followed by *L. camara* with 101 cases of absence. *S. mauritianum* has a low chance of not being found at 0 frequencies (pure tea areas) with 58 cases. At the frequency of occurrence of 0.333 (Three invaders occurrence), there is the lowest chance of finding all the three IAPs in one area, with each having 1 case of occurrence. At the frequency of 0.50 (Two invaders), there is a high chance of finding *S. mauritianum* and *L. camara* at 16 and 17 cases, respectively. At the frequency of 100, there is a high chance of finding *S. mauritianum* and the least chance of finding *L. camara* as a single invader in one area.

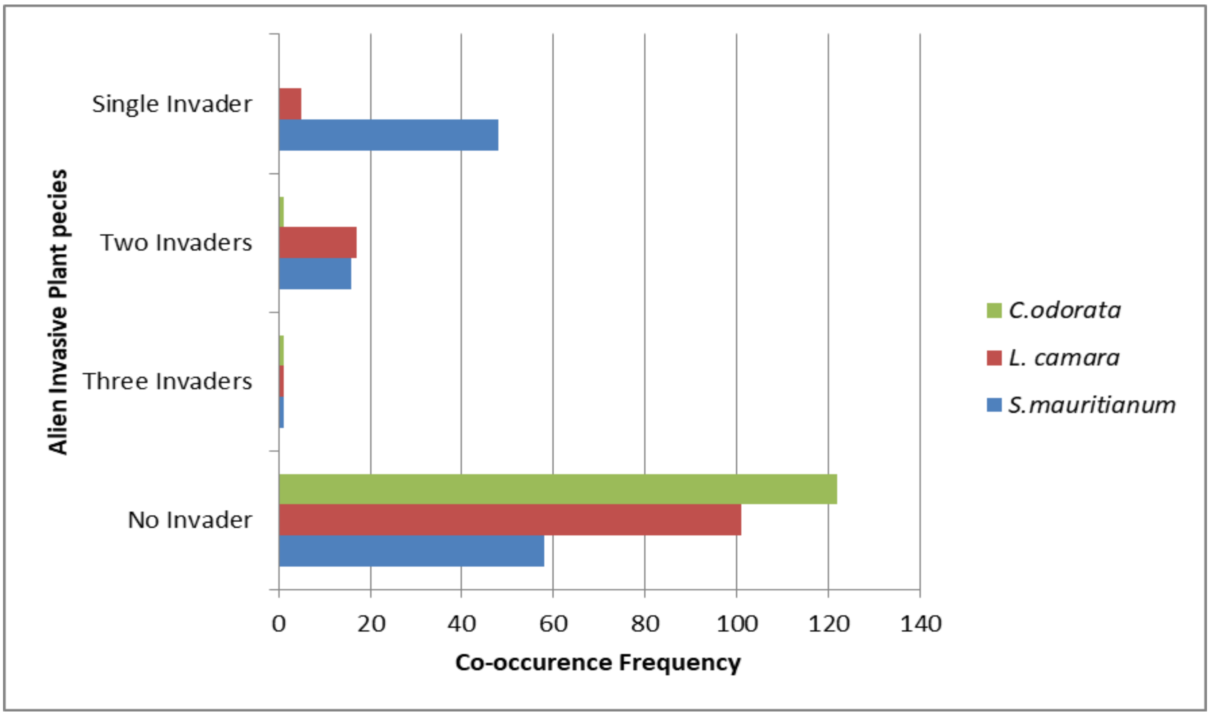

Figure 4: Co-occurrence frequency between *Solanum mauritianum*, *Lantana camara* and *Chromolaena odorata* in the Tshivhase Tea Estate.

The marginalized co-occurrence matrix has indicated the probability co-occurrence of *S. mauritianum* (P1), *L. camara* (P2) and *C. odorata* (P3) of 0.53, 0.19 and 0.016, respectively (Figure 5). This is in agreement with Figure 2 (likelihood of occurrence) above. On the other hand, the observed co-occurrence matrix indicated the association between species wherein P1, 2 (*S. mauritianum* and *L. camara*), P1, 3 (*S. mauritianum* and *C. odorata*) and P2, 3 (*L. camara* and *C. odorata*) have a probability of 0.74, 0.5 and 1, respectively. Finally, the conditional co-occurrence between *S. mauritianum*, *L. camara* and *C. odorata* in the absence of any other species indicated that given that *S. mauritianum* (P1), the probability of *L. camara* (P2) occurring is 0.65. There is a high chance of finding *S. mauritianum* and *L. camara* co-occurring together in one site. The probability of co-occurrence of P3 (*C. odorata*) in the presence of P2 (*L. camara*) is 0.5 which means that there is a 50/50 chance of occurrence between P2 and P3. In the case where *S. mauritianum* is present, there is no chance of co-occurrence of *C. odorata* indicated by 0 probabilities (Figure 5).

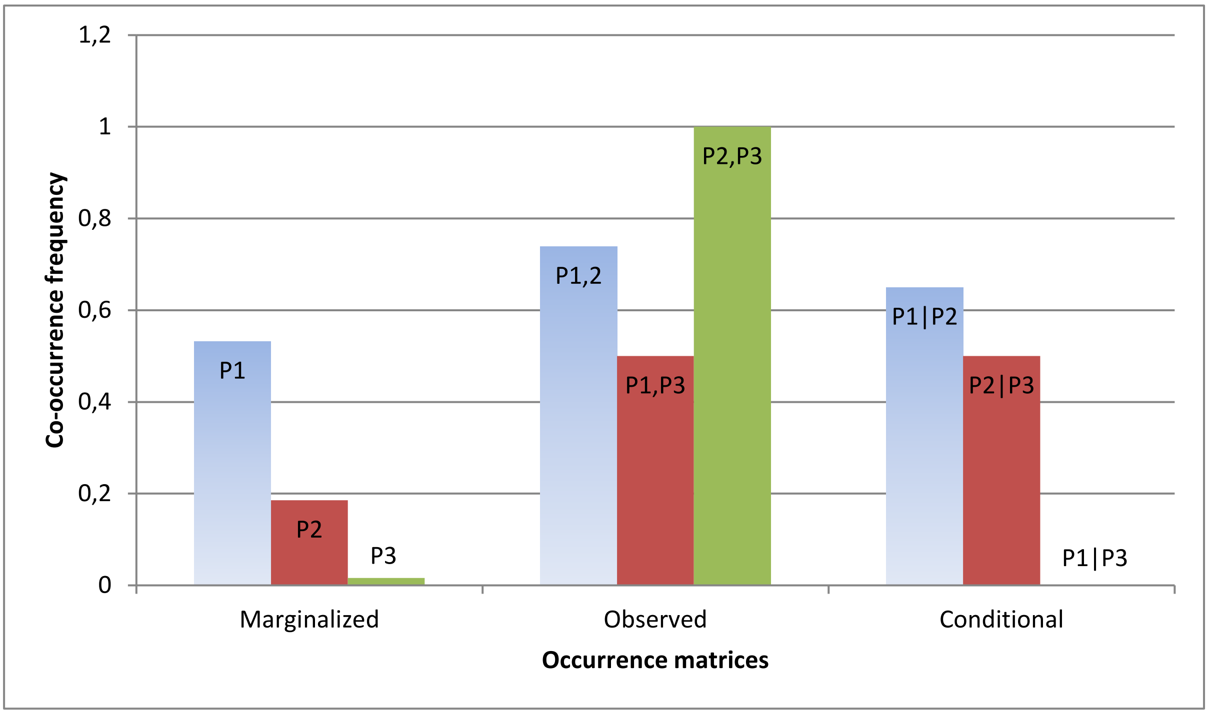

Figure 5: The co-occurrence frequency distribution of *Solanum mauritianum*, *Lantana camara* and *Chromolaena odorata* in the Tshivhase Tea Estate.

2.4.2 Spatial Interpolation

The IDW, kriging and regression splines spatially mapped the distribution of a *S. mauritianum* (dominant species) from the validation dataset (*n*=74). The IDW yielded the R^2 of 0.04 (*n*=50); RMSE=0.48; MAD=0.42 frequency occurrence of *S. mauritianum*. Table 1 shows the results of interpolation models. On the other hand, the kriging model yielded an R^2 =0.02; RMSE=0.47 and MAD=0.45 occurrence frequency of *S. mauritianum*. The spline yielded the lowest correlation with the occurrence frequency of a *S. mauritianum* (R^2= 0.004, RMSE=3.95, and MAD=1.81).

Table 1: Interpolation comparison of Inverse Distance Weighting (IDW), Ordinary kriging (OK), and regression splines

	Validation		
Method	R^2	**RMSE**	**MAD**
IDW	0.04	0.48	0.42
kriging	0.02	0.47	0.45
Spline	0.004	3.95	1.81

R^2 = Coefficient of determination, RMSE=root mean square error, MAD= mean absolute deviance, MAD=mean absolute deviance.

The resulting maps of a *S. mauritianum* frequency occurrence obtained from the IDW, kriging and regression splines interpolation model tested in the Tshivhase Tea Estate are shown in Figure 6, 7 and 8 respectively. The low frequency occurrence of *S. mauritianum* is indicated by an orange colour. Areas with no *S. mauritianum* in the Tshivhase Tea Estate are indicated by the red colour which in most cases is the buildings and water bodies. The moderate frequency occurrence of *S. mauritianum* in the Tshivhase Tea Estate is indicated by a yellowish color and the high occurrence frequency is indicated by the blue colour. It can be observed from the map that the occurrence frequency of *S. mauritianum* is high in the centre or middle of the tea plantation and low along the edges of the tea plantation as well as along the Thathe Vondo dam banks. The occurrence frequency of *S. mauritianum* is also low in areas where there is no tea plantation and where the tea has been trimmed.

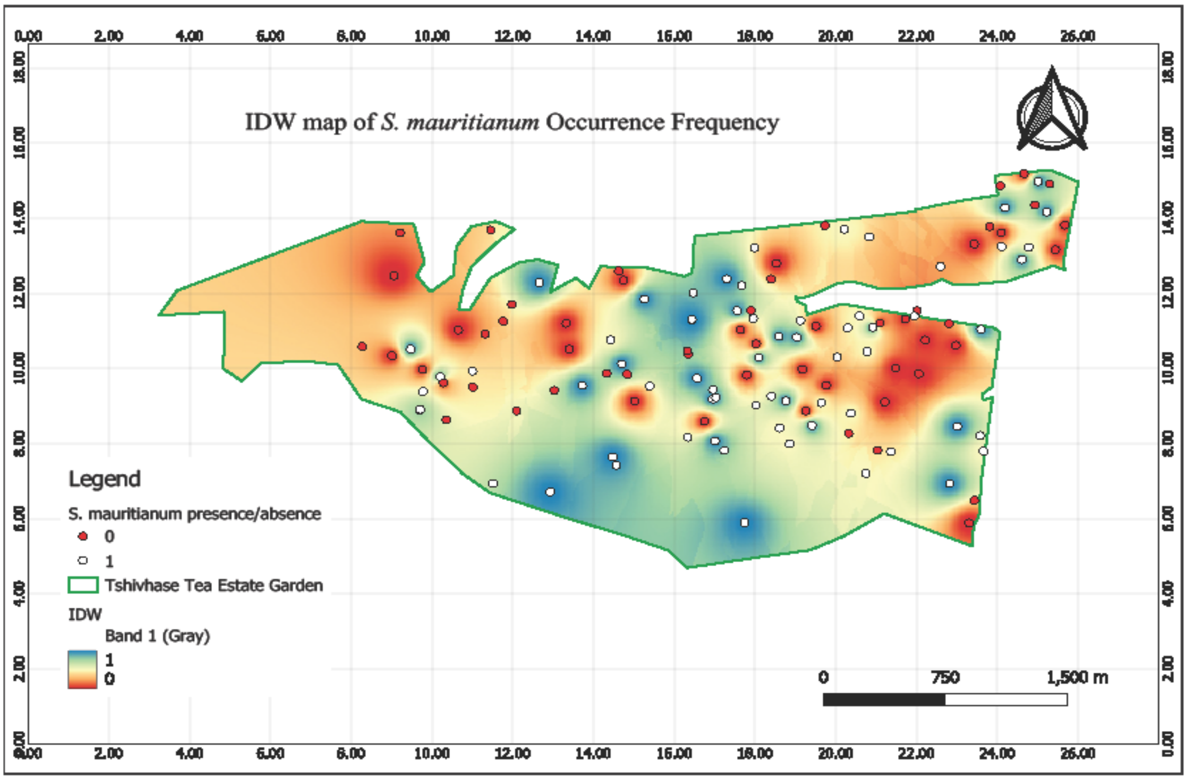

Figure 6: IDW interpolation model map of a *Solanum mauritianum* frequency occurrence in the Tshivhase Tea-Estate.

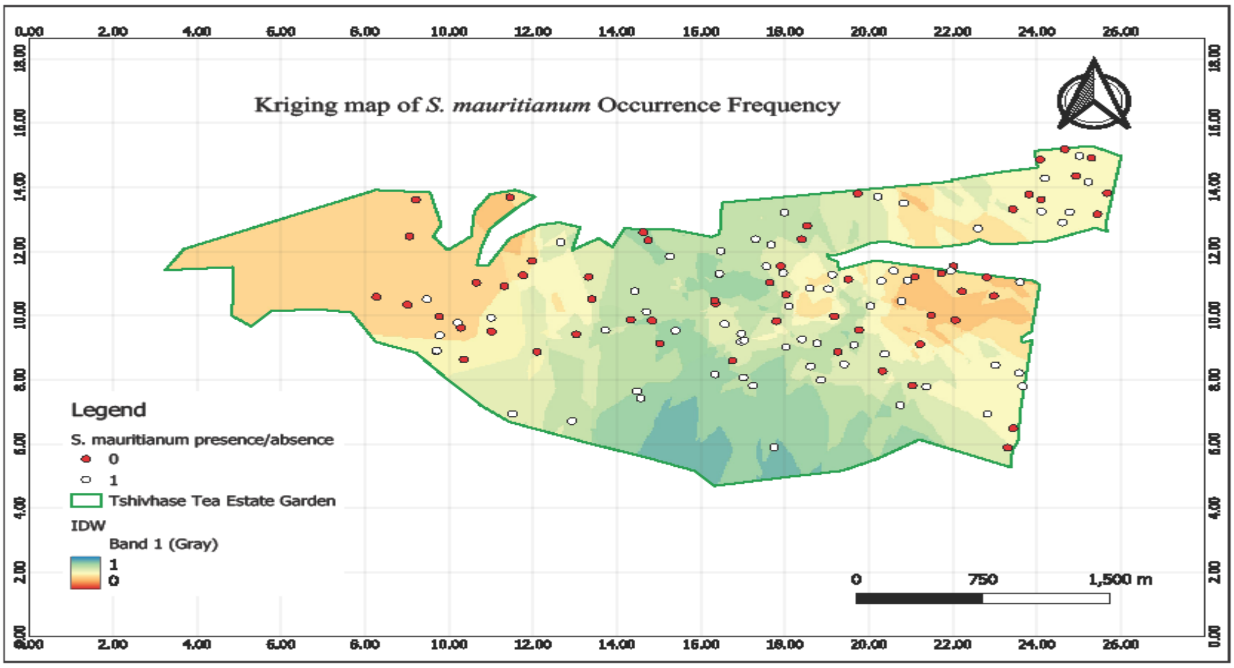

Figure 7: kriging interpolation model map of a *Solanum mauritianum* frequency occurrence in the Tshivhase Tea Estate.

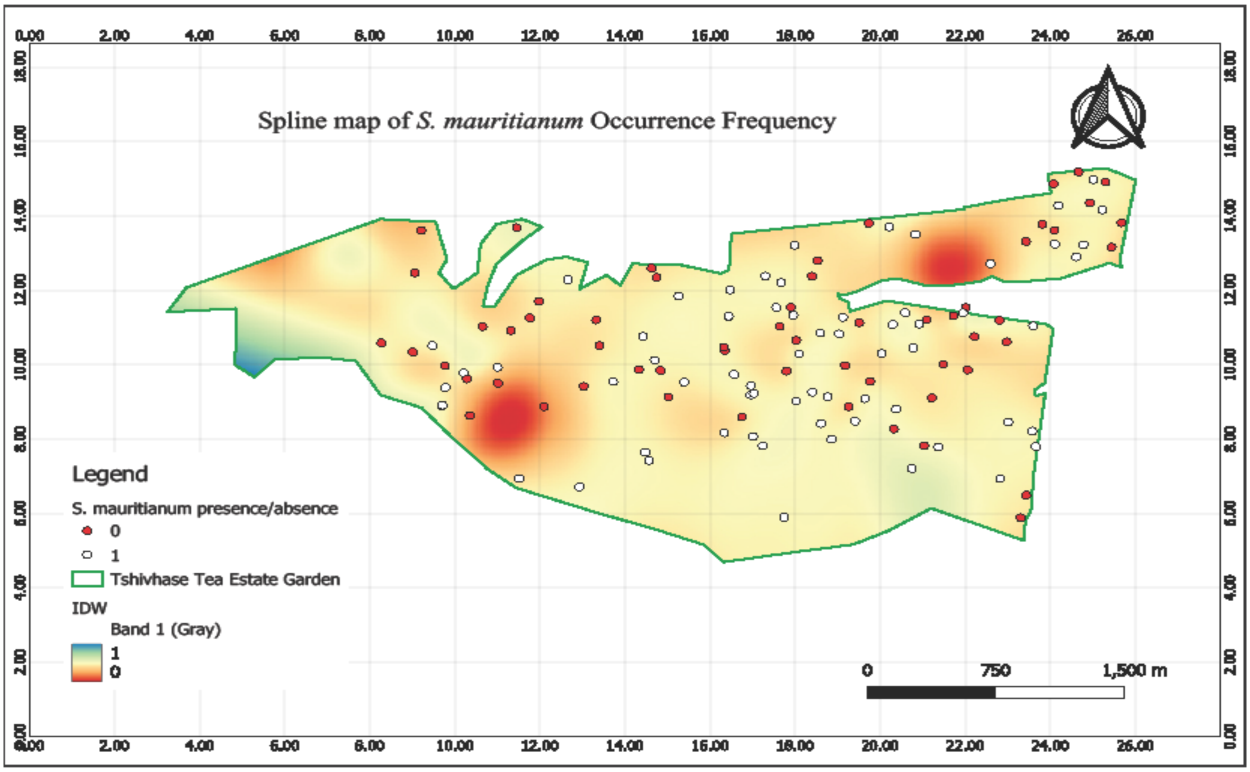

Figure 8: Regression splines interpolation model map of a *Solanum mauritianum* frequency occurrence in the Tshivhase.

2.5 Discussion

2.5.1 Co-occurrence of alien invasive plants in the Tshivhase Tea estate

The three alien invasive plant species observed in the Tshivhase Tea Estate were *S. mauritianum*, *L. camara* and *C. odorata*. It was observed from the co-occurrence frequency analysis that *S. mauritianum* is the most frequently occurring species in the Tshivhase Tea Estate. The *S. mauritianum* had the higher proportion of occurrences at 53% followed by *L. camara* with 18.6%. The *S. mauritianum* also had the highest likelihood of occurrence of 72.53% as compared to *L. camara* with 25% and *C. odorata* with 1.6%. *C. odorata* was the least occurring species in the Tshivhase Tea Estate.

It is likely to find *S. mauritianum* and *L. camara* co-habiting in the same area and least likely to find *S. mauritianum* and *L. camara* together in one area (Figure 4). The following was the same with the observed and conditional co-occurrence matrices. They have indicated the probability of co-occurrence of *S. mauritianum* and *L. camara* of 0.74, meaning that there is a high probability of finding these two species together in one site. On the other hand, there was a low co-occurrence probability of *S. mauritianum* and *C. odorata*. There is the lowest chance of finding all these three species together. The marginalized co-occurrence probabilities of all the species were the same as the proportional occurrence results.

The birds prefer feeding on tall trees or plant fruits than on short plants or tree fruits (Lee *et al*., 2005) and it could be the reason why *S. mauritianum* is the most distributed species within the tea plantation than the other species. Additionally, monkeys also feed on *S. mauritianum* fruits (Scholar *et al*., 2014) contributing to the dispersal of seeds throughout the study area. The *S. mauritianum* survives in high water retention soil and is shade tolerant (CABI.org, 2019). This is true in the case of the Tshivhase Tea Estate, where the tea plantation has grown taller and produced seeds with high water retention soil. It is always moist within the tea plantation because the ground is always covered or enclosed by the tea plants' canopies minimising the rate of water evaporation. This favours the survival of *S. mauritianum*. The *S. mauritianum* survives in moist habitats and in high rainfall areas, especially areas that receive summer rainfalls (CABI, 2019), just like the Tshivhase Tea Estate climatic condition.

The *S. mauritianum* occurrence in forest margins, open areas, and riparian zones was successfully mapped with accuracies of 91.33%, 85.08%, and 67.90% using the unsupervised method and satellite image (Peerbhay *et al*., 2015). The occurrence or distribution of *S. mauritianum* has been studied more on commercial forest plantations (Peerbhay *et al*., 2015; Lotterning *et al*., 2020; Atkinson et al., 2013 and others). These studies have used GIS and remote sensing techniques in assessing the distribution of *S. mauritianum* in forest plantations. The classification accuracy in detecting *S. mauritianum* densities had improved by 10% and 11.6% when using AISA Eagle and World-view image (Peerbhay *et al*., 2015) unlike in this study where the geostatistics interpolation maps have yielded low accuracies. This could be because they have used hyperspectral data over multispectral data used in this study (SPOT 7).

The second species to occur frequently is the *L. camara*. It is very likely to find *L. camara* and *S. mauritianum* co-occurring in one area in the Tshivhase Tea Estate. The co-occurrence frequency analysis consisted of ground observations. It adapts to habitats such as open and unshaded areas, such as pastures and crop fields as well as disturbed areas, such as roadsides, railway tracks, and fired forests (Sharma *et al*., 2005; Dogra *et al*., 2009). Millions of hectares of pastureland and infested major crop plantations, such as tea, coffee, sugarcane, and cotton plantations are invaded by *L. camara* (Sharma *et al*., 2005; Priyanka and Joshi, 2013). There are few *L. camara* in the Tshivhase Tea Estate because *L. camara* has been said to adapt to unshaded areas and the Tshivhase Tea Estate is shaded. The low height of *L. camara* influences the birds to feed more on *S. mauritianum* fruits than on *L. camara* fruits and therefore minimising its seed distribution all over the Tshivhase Tea Estate. In this study, the *L. camara* has been observed along the edges of the tea plantation and along open areas where there is no tea plantations.

The *C. odorata* occurs less frequently in the Tshivhase Tea estate. It is very unlikely to come across the *C. odorata* in the Tshivhase Tea Estate. There is a probability of 0 for *C. odorata* to co- occur with *S. mauritianum* and a probability of 0.50 for *C. odorata* to co-occur with *L. camara*. This is true based on the ground observation, *C. odorata* were only co-occurring with *L. camara* in open areas. It has become a prolific weed in riverine ecosystems, crop plantations, grasslands, and natural forests (Goodall and Erasmus, 1996). Tshivhase Tea Estate as a crop plantation is also invaded with *C. odorata*. The extensive seed production and wind dispersal architecture are directly related to the rapid spread of this species (Erasmus, 1985; Liggitt, 1983; Macdonald and Frame, 1988). The small spines on the seeds of *C. odorata* can adhere to wet clothes and fur (Wilson, 2003). The cocoa and coffee plantations were left abandoned due to the invasion of *C. odorata* in Cote d'Ivoire (Zebeyou, 1991). The *C. odorata* has been indicated to be problematic during the establishment of young oil palm, cocoa, and rubber plant plantations in Nigeria (Sheldrick, 1968; Ivens, 1972; Ikuenobe and Ayeni, 1998) and Ghana (Timbilla, 1996). The weed result in the decline of farming products thereby increasing management costs at both subsistence and commercial scales (Lucas 1989; Prasad *et al*., 1996). Since the invasion of *C. odorata* can cause abandonment of the crop plantations, the low occurrence of it in the Tshivhase Tea Estate will have little to no impact on tea production.

2.5.2 Spatial interpolation

The geostatistical methods were not significant in mapping the occurrence of *S. mauritianum* in the Tshivhase Tea Estate. The IDW yielded an R^2 value of 0.043, an RMSE value of 0.48, and a MAD value of 0.42. The kriging model performed an R^2 value of 0.0153, an RMSE value of 0.473775, and MAD (0.45). Finally, the regression splines yielded an R^2 of 0.004, RMSE of 3.95, and MAD value of 1.81. The *S. mauritian*um has been chosen because it is the most frequently occurring species in the Tshivhase Tea Estate. The model that produces low RMSE and higher R^2, the superior it is in fitting the dataset (Statology, 2021). In other studies, the ordinary kriging performed finer than IDW interpolation in the higher variability nature of the tree cover when interpolating the woody cover variables at the dispersed tree woodland site (Munyati and Sinthumule, 2021). Based on this statement, ordinary kriging performs well in dense plant species than in scattered plant species. In the case of the Tshivhase Tea Estate, the poor performance of kriging might be attributed to *S. mauritianum* being scattered all over the Tshivhase Tea Estate. The regression splines, on the other hand, are well suited for gently varying surfaces and which is a different case in the Tshivhase Tea Estate (Environmental Research Institute Inc, 1996). This has resulted in poor performance of the regression splines model in mapping the occurrence frequency of an *S. mauritianum*. Perhaps, the geostatistic models could have yielded improved accuracies if other variables such as soil condition, DEM (Digital Elevation Model), climatic condition and remote sensing derived variables were used for interpolation, e.g. co-kriging.

2.6 Conclusion

The study aimed to assess the co-occurrence frequency of invasive alien plants present in the Tshivhase Tea Estate and map the dominant species (*Solanum mauritianum*) using geostatistical methods. Below are the conclusions drawn from the study:

- Of the three invasive alien plants observed in the Tshivhase Tea Estate, *S. mauritianum* occurs frequently because the climatic condition in the Tshivhase Tea Estate favours its vigorous establishment.
- All of the spatial interpolation techniques used in this study performed poorly in estimating the distribution of dominant tea invasive alien plants. The IDW yielded predictive accuracy of the occurrence frequency of an *S. mauritianum* in the Tshivhase Tea Estate with an R^2 of 0.043. The IDW further yielded low predictive errors with RMSE of 0.48 and MAD value of 0.42 using the validation dataset.
- The IDW interpolation map indicated *S. mauritianum* frequently occurring in the central or middle part of the Tshivhase Tea Estate and low in areas where there are no tea plantations.

This study provides the Tshivhase Tea Estate with information about the IAPs present in the tea plantation. The interpolation models all performed poorly in validation and cannot be recommended for mapping the occurrence of IAPs, especially in the small study area where IAPs are dispersal spread. Further research is needed in identifying other IAPs within the tea plantation using geostatistics techniques, remote sensing, and GIS.

CHAPTER THREE

Exploring the capability of high resolution satellite data in delineating the potential distribution of common invasive alien plant species in the Tshivhase Tea Estate

3.1 Abstract

Invasive alien plants (IAPs) continue to exert significant impacts on agriculture in many countries, resulting in food insecurity. IAPs reduce agricultural production through competition and parasitism with planted crops. Tea plantations are also invaded by invasive alien plant species. The control and removal of these invaders require accurate mapping. This study has explored the potential of SPOT 7 and Sentinel 2 satellite data in mapping the occurrence of *S. mauritianum*, *L. camara* and the co-occurrence between *S. mauritianum*, *L. camara*, and *C. odorata* in the Tshivhase Tea Estate in Limpopo, South Africa. The presence/absence and remotely sensed environmental data were used to generate a logistic regression model in R for *S. mauritianum* and *L. camara* occurrence as well as the observed and conditional co-occurrence probability of *S. mauritianum* (P1), *L. camara* (P2) and *C. odorata* (P3). The logistic regression model coefficients were then mapped on QGIS to produce invasive alien plant species (IAPs) occurrence frequency and co-occurrence probability maps. The Brightness Index (BI) was significant in most SPOT 7 logistic regression models at $P<0.05$ whereas the blue, Red, and NIR band and standard deviation were significant at $P<0.05$ in most of the Sentinel 2 models. The SPOT 7 model performed the highest receiver-operating characteristic (ROC) under the curve (AUC) of 0.96 in predicting the conditional co-occurrence of *S. mauritianum* (P1) and *L. camara* (P2) whereas the Sentinel 2 model performed a ROC AUC of 0.83. This could be because SPOT 7 has a high spatial and spectral resolution compared to Sentinel 2. Therefore, SPOT 7 and Sentinel 2 are capable of delineating the potential distribution of alien invasive plants in the tea plantation.

Keywords: Alien Invasive Plants; *S,mauritianum*, SPOT 7, Sentinel-2; Logistic Regression

3.2 Introduction

IAPs, everywhere pose substantial warnings to farming, biodiversity, and the delivery of ecosystem services (Lyimo *et al*., 2019). IAPs species have caused great economic and ecological damage around the world (Das and Duarah, 2013). They have been reported to reduce agricultural productivity through various mechanisms such as competition (for light, nutrients, and water), allelopathy, and parasitism (Bajwa *et al*., 2019; Fried *et al*., 2017). Tall IAPs are known for shading out juvenile crops and hampering their growth (Burgos and Ortuoste, 2018).

One of the noxious IAP in the subtropical environment is known as *S. mauritianum* (wormwood). It is a species that is native to South America and has naturalized in Africa, Australasia, India, and islands in the Atlantic, Indian and Pacific oceans (Roe, 1972). The *S. mauritianum* has an armed branched shrub or small tree that can be 2-4 m tall (Olckers, 1999). The *S. mauritianum* has been present for 135 years in South Africa invading farming lands, forestry plantations, riverine areas, and conservation areas, especially in the higher rainfall regions (Olckers, 1999). The presence of *S. mauritianum* in South Africa is promoted by excessively high production of fruit set and long extent of seed dispersal by fruits-eating birds (Olckers, 1999). The dense form of *S. mauritianum* overcrowds and shades other species, subsequently disturbing their growth (Haley, 1997). The *S. mauritianum* plant parts are poisonous to humans, particularly green berries (ESC, 2003). The fine hair on the leaves can be an irritant particularly when they are forced out during the removal operation (Wildy, 2002). The biological control of *S. mauritianum* was initiated in South Africa as conventional control methods such as hand pulling of seedlings, and ring barking of trees are either ineffective or unsustainable over the long term (Olckers and Zimmermann, 1991). Although chemical control is more effective in controlling *S. mauritianum*, the method is considered unsustainable looking at the density and the rate of infestation at which cleared areas are invaded by seedlings dispersed by the birds (Olckers, 2009). It is expensive to remove *S. mauritianum* for example; 15 billion rands has been spent by the Working for Water program in South Africa over alien plant control operations since 1995 where the amount spent per year has risen dramatically since 2010, reaching around 2 billion rands per year (van Wilgen *et al*., 2020).

Early detection of weed infestation will provide relevant stakeholders such as farmers to control the spread of IAPs in their farming lands. High spatial resolution images have been proved in many studies to delineate and map IAPs, as they are capable of visually detecting the spatial distribution of IAPs through the direct remote sensing method (Huang and Asner, 2009). New and old very high spatial resolution (VHR) aerial photographs are capable of identifying invasive alien plant species of interest through the use of appropriate period images and good time series(Brook and Bowman, 2006, Laliberte *et al*., 2004). This approach is better than the traditional field monitoring of IAPs which is difficult and expensive (Lourenco *et al*., 2021). Many studies have used high spatial resolution multispectral sensors in detecting and mapping IAPs, for example, the *Pinus* spp. was successfully mapped in mountainous regions of the Western Cape, using SPOT-6 imagery (Forysyth *et al*., 2014). Malahlela *et al*., 2015 also successfully mapped the probability of invasive *Chromolaena odorata* in subtropical forest gaps using WorldView-2 vegetation indices.

Currently, there is no study as yet about the assessment of the occurrence or distribution of IAPs in tea plantations using remote sensing and GIS. Based on the above statement, this study aims to test the capability of high- medium resolution satellite images in mapping the occurrence of *S. mauritianum*, *L. camara,* and the co-occurrence probability between *S. mauritianum*, *L .camara* and *C. odorata* in the Tshivhase Tea Estate using SPOT 7 and Sentinel-2 images. Knowledge of the *S. mauritianum* and other alien invasive plant species occurrence and its extent will assist Tshivhase Tea Estate managers in controlling the infestation of the IAPs within the tea plantation.

3.3 Methods

3.3.1 Study Area

Please refer to Chapter 2 (2.3.1).

3.3.2 Image data acquisition and pre-processing

The SPOT 7 data was acquired on 18 October 2021 with 4 spectral bands: blue (0.455 µm – 0.525 µm), green (0.530 µm – 0.590 µm), red (0.625 µm – 0.695 µm), and near-infrared (0.760 µm – 0.890 µm) (European Space Agency), as well as Sentinel 2 acquired on 28 September 2021 at level 1 with 12 spectral bands, was used to map the presence/absence of *S. mauritianum* at the Tshivhase Tea Estate (Table 2). The spatial resolution of Sentinel-2 is dependent on the particular spectral band (refer to Table 2). SPOT 7 provides data up to 1.5 m spatial resolution panchromatic and multispectral. The date was chosen based on the phonological condition of the tea during that time at the Tshivhase Tea Estate.

The SPOT 7 data was pre-processed for any geometric and radiometric distortions by the South African National Space Agency (SANSA). On the other hand, Sentinel-2 was radiometrically and geometrically corrected by the European Space Agency (ESA) (Pandzic *et al*., 2016). Further, Sentinel-2 was pre-processed using the open-source software QGIS for atmospheric correction via the Semi-Automatic Classification Plugin (SCP). To run the indices and perform image analyses, SCP in QGIS takes Sentinel-2 imagery metadata, and individual bands and converts the imagery from Digital Numbers(DN) to the physical measure of Top of Atmosphere reflectance (TOA), which is the application of a simple atmospheric correction using the DOS1 method (Dark Object Subtraction 1) (Congedo, 2016).

Table 2: SPOT 7 and Sentinel 2 spectral bands

Image	Band name	central wavelength(**µm**)	Resolution(m)
	1-Blue	0.455 µm – 0.525 µm	6
	2-Green	0.530 µm – 0.590 µm	6
	3-Red	0.625 µm – 0.695 µm	6
	4-Near-Infrared	0.760 µm – 0.890 µm	6
Sentinel-2	Band 1 - Coastal aerosol	0.443	60
	Band 2 - Blue	0.490	10
	Band 3 - Green	0.560	10
	Band 4 - Red	0.665	10
	Band 5 - Vegetation Red Edge	0.705	20
	Band 6 - Vegetation Red Edge	0.740	20
	Band 7 - Vegetation Red Edge	0.783	20

	Band 8 - NIR	0.842	10
	Band 8A - Vegetation Red Edge	0.865	20
	Band 9 - Water vapour	0.945	60
	Band 10 - SWIR - Cirrus	1.375	60
	Band 11 - SWIR	1.610	20
	Band 12 - SWIR	2.190	20

3.3.3 Field data collection

Please refer to Chapter 2, 2.3.2 Field data collection. The Figure 9 below shows the sampled survey sites in the study.

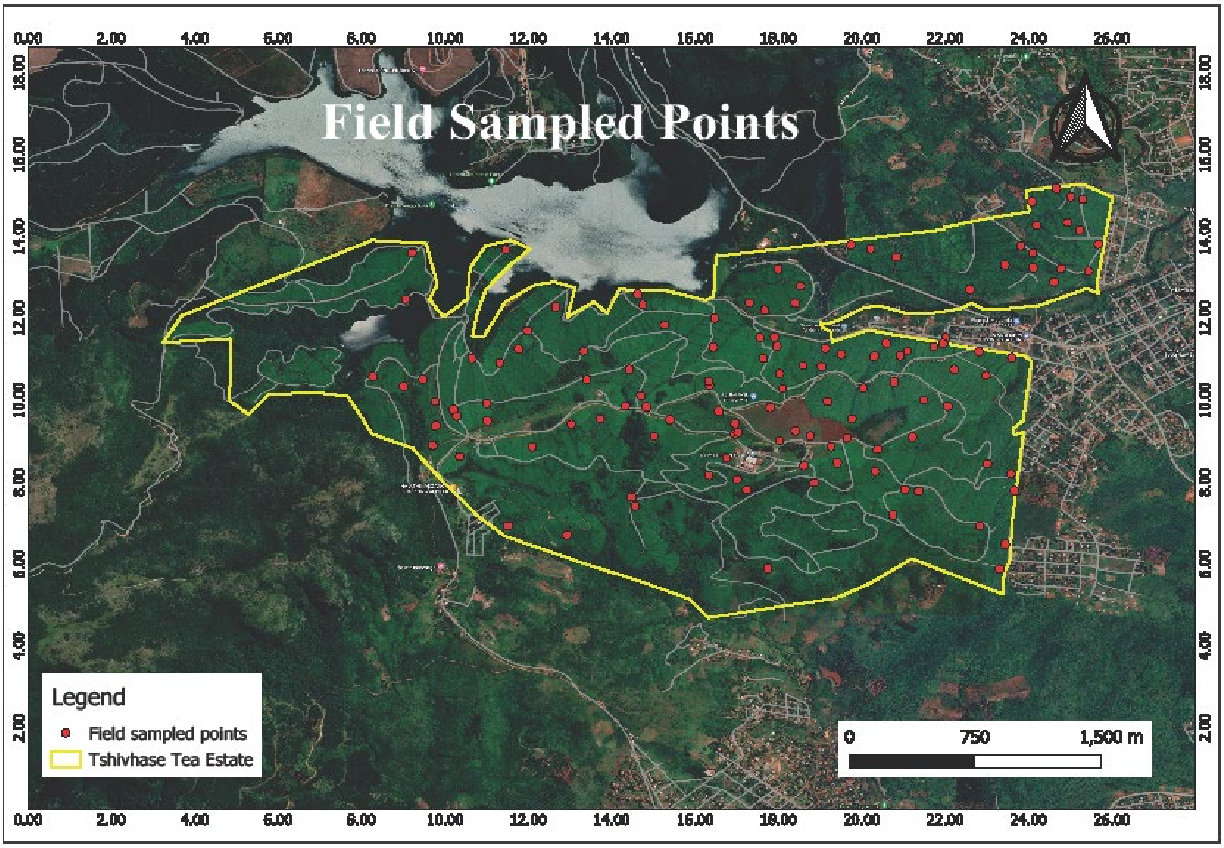

Figure 9: Sampled Points Visited in the Tshivhase Tea Estate

3.3.4 Spectral indices

Spectral indices used for characterizing the brightness, health, and moisture status of tea plantation in the Tshivhase Tea Estate are (Normalized Difference Vegetation Index (NDVI), Brightness Index (BI), and Modified Normalized Difference Water Index (MNDWI) (Table 3). The NDVI uses the red and near-infrared bands of the electromagnetic spectrum to assess changes in vegetation phenology as it uses the highest absorption and reflectance of the chlorophyll region (Oumar, 2016). NDVI has been chosen as it is a successfully commonly used vegetation index in monitoring vegetation conditions (Cropin, 2021). The MNDWI uses the green and near-infrared to extract water bodies (McFeeters, 1996) and to delineate the amount of water present in vegetation (Gao, 1996). NDWI is useful in determining plant water stress which can have a major impact on the general plant development, and crop failure resulting in lower production in agricultural areas (Factsheet, 2011. MNDWI is not widely used in crop health monitoring and it has been used in this study to determine tea plant water stress. The Brightness Index (BI) is related to the brightness of soils influenced by soil moisture, the presence of salts, and the organic matter content of the soil surface (Escadafal, 1989). The BI was used to determine the soil moisture in the study area.

.Table 3: Spectral Indices

Vegetation Index	Formula	Reference
Normalized Difference Vegetation Index(NDVI)	$\frac{\rho NIR - \rho RED}{\rho NIR + \rho RED}$	(Basso *et al*.,2004)
Modified Normalized Difference Water Index (NDMI)	$\frac{Green - NIR}{Green + NIR}$	Qiao *et al*., 2020
Brightness Index(BI)	$\frac{\sqrt{(Red^2 + Green^2)}}{2}$	Marques et al.,2020

3.4 Data analysis

The relationship between *S. mauritianum* presence /absence and the remotely-sensed environmental data was modelled using the logistic regression technique in R statistical software. The observed and conditional co-occurrence probability was also modelled using logistic regression in R statistical software. The logistic regression model is the regression method that can be used when a response variable is binary, and the predictor variable is continuous or categorical (Sahragard and Ajorlo, 2016). Logistic regression uses the logit function to describe the relationship between response variables and predictor variables (Miller and Franklin, 2002). Logistic regression is widely used for distribution modelling of plant species in the general linear Model (Rushton *et al*., 2004). Generalised Linear Model (GLM) functionality in R statistical software was used to model the relationship between *S. mauritianum* and the environmental remotely sensed data as well as the relationship between the co-occurrence probability of *S. mauritianum*, *L. camara*, and *C. odorata* and the remotely sensed environmental data. GLM is a generalization of ordinary linear regression that allows for response variables that have error distribution models other than a normal distribution (DataCamp, 2020). The coefficients of the models were then used in QGIS to generate the distribution of plant species map together with the co-occurrence probability map.

3.5 Model calibration

60% of the total dataset (*n*=124) was used in the logit model calibration. The calibration dataset was used to train the model for invasive species occurrence using the R statistical software. Stepwise logistic regression was achieved by including all input variables in the model and the statistically insignificant variables were eliminated. Logistic regression is given by the following equation from Higgins *et al*., (1999):

$$y = \frac{e^{\beta_0+\beta_1 x_1+\beta_2 x_2+\cdots\beta_n x_n}}{1+e^{\beta_0+\beta_1 x_1+\beta_2 x_2+\cdots\beta_n x_n}} \qquad \text{Equation 9}$$

where y is the probability of species occurrence, $x_n$is the explanatory variable, β_n is the coefficient of x_n, β_0 is the intercept and e is the exponent function of the model.

The area under the curve (AUC) statistic was used for the assessment of generated models by R statistical software. The AUC statistic shows the power of the model in the distinction between presence and absence. The value of the statistics closer to 1.0 indicates superior agreement between the model and the real environment (Sahragard and Chahouki, 2015).

3.6 Model validation

40% of the total dataset (*n*=124) was used for validating the predictive model. The predicted probabilities (y), which ranged from values 0 and 1, represented the increasing probability of *S. mauritianum* in Tshivhase Tea Estate. A range of thresholds was explored to determine the optimum threshold level for predicting *S. mauritianum* presence/absence (P/A) in Tshivhase Tea Estate. The probability thresholds of 0.2–0.9 were tested where a 2×2 error matrix table with rows indicating predicted cases and columns indicating observed cases was plotted for a threshold value that yielded the highest mapping accuracy. The overall mapping accuracy is defined as the total number of correctly predicted test cases to the total number of test samples and is presented as a percentage (Fielding and Bell 1997). The table compares the predicted values from an optimum threshold value with the observed field data of *S. mauritianum* distribution. The receiver operator characteristic (ROC) curves are used to show how a predictor compares to the true outcome (Muschelli, 2019). In ROC analyses, the predictive capabilities of a variable are commonly summarized by the area under the curve (AUC), which can be found by integrating areas under the line segments(Muschelli,2019).

The area under the curve (AUC) statistic was used for the assessment of generated models by R statistical software. The AUC statistic shows the power of the model in the distinction between presence and absence. The value of the statistics closer to 1.0 indicates superior agreement between the model and the real environment (Sahragard and Chahouki, 2015). On the other hand, the AUC value of 0.5 indicates that the model accuracy is equal to the random prediction (Baldwin 2009). Negative values indicate extremely poor agreement between the observed occurrences and predicted occurrences (Monserud and Leemans

1992). The AUC has a quantitative measure of 0.0-1.0 scale grading the following levels: poor (0.6), pass (0.6-0.7), good (0.7-0.8), and excellent (0.9) (Malahlela *et al.*, 2015).

3.7 Results

3.7.1 Logistic regression

3.7.1.1 *S. mauritianum* occurrence

Prediction of *S. mauritianum* occurrence using SPOT 7 spectral bands, and vegetation indices as independent variables in stepwise regression final model indicated B1-B3 and standard deviation as significant at *P*>0.05 with a positive relationship towards the presence of *S. mauritianum* in the Tshivhase Tea Estate. Other spectral variables (NDVI, BI and MNDWI) are shown as significant at *P*<0.05 with a negative relationship towards the presence/absence of *S. mauritianum* in Tshivhase Tea Estate (Table 4). B1-B4 and standard deviation were insignificant at *P*>0.05.

Table 4: The results of Logistic regression models of *S. mauritianum* occurrence SPOT 7

Data source	Predictor	Estimate	SE	*Z* Value	*P* value
Final Model(SPOT)	(Intercept)	752.56	340.83	2.21	0.03*
	B1	2.76	1.60	1.72	0.09.
	B2	1.04	0.72	1.45	0.15
	B3	2.92	1.54	1.90	0.06.
	B4	-6.33	3.63	-1.74	0.08.
	Standard deviation	12.59	7.24	1.74	0.08.
	NDVI	-1648.06	835.35	-1.97	0.05*
	BI	-1401.64	621.03	-2.26	0.02*
	MNDWI	-1939.71	961.16	-2.02	0.04*

Significance codes: °0.1;* 0.05; **0.01

The logistic regression model with Sentinel-2 spectral variables indicated B8 as significant at *P*<0.05 with a negative relationship towards the presence/absence of *S. mauritianum* at the Tshivhase Tea Estate (Table 5). On the other hand, B2, B4 and standard deviation were highly significant at *P*<0.05 with a positive correlation towards the presence/absence of *S. mauritianum* in the Tshivhase Tea Estate. The good part is that the model was significant in predicting the probabilities of occurrence of *S. mauritianum* just like with the SPOT model.

Table 5: The results of Logistic regression model of *S. mauritianum* Sentinel 2

Data Source	Predictor	Estimate	SE	Z Value	P value
	(Intercept)	-4.39	8.63	-0.51	0.61
	B2	719.98	215.74	3.34	0.00***
	B4	1156.90	308.41	3.75	0.00***
	B8	-1933.80	485.30	-3.99	0.00***
	Standard deviation	4110.43	1023.71	4.02	0.00***

Significance codes: * 0.05; **0.01;*0.001**

3.7.1.2 *Lantana camara* occurrence

The logistic regression model for the relationship between the presence/absence of *L. camara* and the remotely sensed environmental data indicated B3 spectral band, standard deviation, variance, Modified Normalized Difference Water Index (MNDWI) and Brightness Index (BI) as significant at *P*<0.05 with B3 having a positive relationship and others with a negative relationship towards the presence/absence of *L. camara* in the Tshivhase Tea Estate (Table 6).

Table 6: The results of logistic regression model of *L. camara* occurrence SPOT 7

Data Source	Predictor	Estimate	SE	Z Value	P value
SPOT 7	(Intercept)	-100.70	42.32	-2.38	0.01729*
	B3	0.55	0.17	3.206	0.00135**
	Standard deviation	-0.65	0.24	-2.753	0.00591**

variance	0.00	0.00	2.074	0.03808*
BI	-412.00	130.60	-3.154	0.00161**
MNDWI	-797.90	253.40	-3.148	0.00164**

Significance codes: °0.1;* 0.05; **0.01;*0.001**

The sentinel 2 logistic regression model indicated B4, B8 and standard deviation as insignificant at *P*>0.05 (Table 7). On the other hand, B2 was highly significant at *P*<0.05 with a negative relationship towards the presence/absence of *L. camara*. BI was significant at *P*<=0.05 with a positive relationship towards the presence/absence of *L. camara* in the Tshivhase Tea Estate.

Table 7: The results of Logistic regression models of *L. camara* occurrence Sentinel 2

Data source	Predictor	Estimate	SE	*Z* Value	*P* value
Sentinel 2	(Intercept)	-111.26	81.16	-1.37	0.17
	B2	-1523.95	648.30	-2.35	0.02*
	B4	-5688.89	3121.29	-1.82	0.07.
.	B8	5830.76	3121.20	1.87	0.06.
	Standard deviation	-12025.16	6448.30	-1.87	0.06.
	BI	370.91	191.63	1.94	0.05.

3.7.1.3 Observed Co-occurrence

The SPOT 7 logistic regression model for observed co-occurrence between *S. mauritianum* (P1) and *L. camara* (P2) indicated B1 as significant with P<0.05 and showed a positive correlation toward the co-occurrence of species P1 and P2 (Table 8). The B3, B4, variance, BI and MNDWI were insignificant at P>0.05 towards the co-occurrence of species 1 and 2.

Table 8: The results of Logistic regression model of Observed co-occurrence SPOT 7 (P1, P2)

Data source	Predictor	Estimate	SE	*Z* Value	*P* value
SPOT 7	(Intercept)	-70.94	47.02	-1.51	0.13
	B1	0.15	0.07	2.25	0.02*
	B3	0.93	0.58	1.61	0.11
	B4	-0.41	0.26	-1.58	0.11
	variance	0.00	0.00	1.38	0.17
	BI	-575.00	342.60	-1.68	0.09
	MNDWI	-979.20	560.60	-1.75	0.08

Significance codes: 0 '*' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1**

The Sentinel 2 logistic regression model indicated B2, B4, B8, standard deviation, and BI as significant at $P<0.05$ with B2, B4, and standard deviation showing a negative correlation whereas B8 and BI are indicated as significant at $P<0.05$ with positive correlation towards the co-occurrence of P1 (*S. mauritianum*) and P2 (*L. camara*). The variance was insignificant at $P>0.05$ (Table 9).

Table 9: The results of logistic regression model of observed co-occurrence Sentinel 2 (P1, P2)

Data source	Predictor	Estimate	SE	*Z* Value	*P* value
Sentinel 2	(Intercept)	-233.50	127.20	-1.84	0.07.
	B2	-2759.50	1265.10	-2.18	0.03*
	B4	-11899.20	5947.80	-2.00	0.05*
	B8	12146.40	6029.70	2.01	0.04*
	Standard deviation	-25787.00	12852.10	-2.01	0.04*
	variance	4302.40	2734.30	1.57	0.12

	BI	752.70	365.50	2.06	0.04*

Significance codes: 0 '*' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1**

The observed co-occurrence of *S .mauritianum* (P1) and *C. odorata* (P3) logistic model for SPOT 7 and Sentinel 2 were insignificant in correlating the co-occurrence of P1 and P3 species in the Tshivhase Tea Estate present by "ObsP1P3~1".

3.7.1.4 Conditional co-occurrence

The SPOT 7 conditional co-occurrence logistic model of *S. mauritianum* (P1) and *L. camara* (P2) indicated B1 as significant at P<0.05. The B3, B4, variance, BI and MNDWI were insignificant at P>0.05 (Table 10).

Table 10: The results of logistic regression model of SPOT 7 conditional co-occurrence probability (P1P2)

Data source	**Predictor**	**Estimate**	**SE**	***Z* Value**	***P* value**
SPOT 7	(Intercept)	-68.67	46.28	-1.48	0.14
	B1	0.15	0.07	2.09	0.04*
	B3	1.00	0.63	1.60	0.11
	B4	-0.43	0.28	-1.54	0.12
	variance	0.00	0.00	1.39	0.16
	BI	-597.30	369.70	-1.62	0.11
	MNDWI	-994.20	597.70	-1.66	0.10.

Significance codes: 0 '*' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1**

The sentinel 2 logistic regression model for conditional co-occurrence of *S. mauritianum* and *L. camara* indicated B2, B8, standard deviation, and BI as significant at P<=0.05 with B2 and standard deviation showing a negative correlation towards the co-occurrence of P1 and P2 species. On the other hand, B8 and BI were significant at P<0.05

with a positive relationship in the co-occurrence of P1 and P2 when species P3 is not occurring in the Tshivhase Tea Estate. The variance was insignificant at $P>0.05$ (Table 11).

Table 11: The results of logistic regression model of Sentinel 2 conditional co-occurrence probability (P1P2)

Data source	**Predictor**	**Estimate**	**SE**	***Z* Value**	***P* value**
Sentinel 2	(Intercept)	-237.70	134.40	-1.77	0.08.
	B2	-2997.50	1369.20	-2.19	0.03*
	B4	-12385.50	6329.20	-1.96	0.05.
	B8	12748.00	6437.70	1.98	0.05*
	Standard deviation	-27027.60	13725.60	-1.97	0.05*
	variance	4265.30	2950.30	1.45	0.15
	BI	780.70	388.50	2.01	0.04*

Significance codes: 0 '*' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1**

The conditional co-occurrence of *S. mauritianum* (P1) and *C. odorata* (P3) for SPOT 7 and Sentinel 2 logistic regression model was insignificant in predicting the co-occurrence of *S. mauritianum* and *C. odorata* (P3) given that P2 species is not occurring. The model result was "ConP1P3 ~ 1".

3.7.2 Model Validation

3.7.2.1 *S. mauritianum* occurrence

The *S. mauritianum* predictive model was validated using probability threshold values as shown in Table 12 for SPOT 7 logistic regression. The highest prediction accuracy was obtained at a threshold of 0.2 at 70%. The highest sensitivity rates were observed at the same threshold range of 0.2 at 96 %. The highest specificity is at a threshold range of 0.9 at 88%. On the other hand, Sentinel-2 logistic regression produced the highest prediction accuracy at a threshold range of 0.5 and 0.6 at 66 % (Table 13). The highest sensitivity rates were observed at the threshold range of 0.2 at 66% and the highest specificity at the threshold range of 0.9 at 100%.

Table 12: Statistics for evaluating model performance across probability threshold values (SPOT 7)

	Probability threshold							
	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
SPOT 7								
Prediction accuracy (%)	0.7	0.66	0.64	0.64	0.66	0.74	0.74	0.64
Sensitivity (%)	0.958333	0.875	0.833333	0.833333	0.791667	0.791667	0.708333	0.375
Specificity (%)	0.461538	0.461538	0.461538	0.461538	0.538462	0.692308	0.769231	0.884615

Table 13: Statistics for evaluating model performance across probability threshold values (Sentinel-2)

	Probability threshold							
	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Sentinel-2								
Prediction accuracy (%)	0.6	0.64	0.64	0.66	0.66	0.64	0.58	0.52
Sensitivity (%)	0.666667	0.583333	0.541667	0.458333	0.375	0.291667	0.125	0
Specificity (%)	0.538462	0.692308	0.730769	0.846154	0.923077	0.961538	1	1

A probability of 0.2 was chosen for further validation steps. The 2 ×2 error matrix table for a probability threshold of 0.2 is shown in Table 14 and Table 15.

Table 14: Predicted outcomes from logistic regression on *S. mauritianum* versus the observed field data at probability threshold of 0.2 (*P*=0.2)

SPOT 7	Predicted occurrences		
	Presence	Absence	Total
Observed occurrences			
Presence	23	1	24
Absence	14	12	26
Total	37	13	50

Table 15: Predicted outcomes from logistic regression *on S. mauritianum* versus the observed field data at probability threshold of 0.2 (*P*=0.2)

Sentinel-2	Predicted occurrences		
	Presence	Absence	Total
Observed occurrences			
Presence	16	8	24
Absence	12	14	26
Total	28	22	50

The strength of the model was measured by the Area under the Curve (AUC) of the operating characteristic curve (ROC) (Figure 10 and Figure 11). SPOT 7 ROC AUC scored 0.94 whereas the Sentinel 2 ROC AUC scored 0.86. The value of 0.93 and 0.86 for AUC indicate that the model used for prediction was significant. The strategy of randomly guessing a class is represented by a diagonal line in the model (Fawcett, 2006). A poor model is represented by the curve bending towards or below the diagonal line (decreasing sensitivity) whereas a good model is represented by the curve bending towards the north-western direction of the plot (Fawcett,2006). Our ROC shows the curve bending towards the north-western direction, and hence an AUC of 0.8 and 0.93.

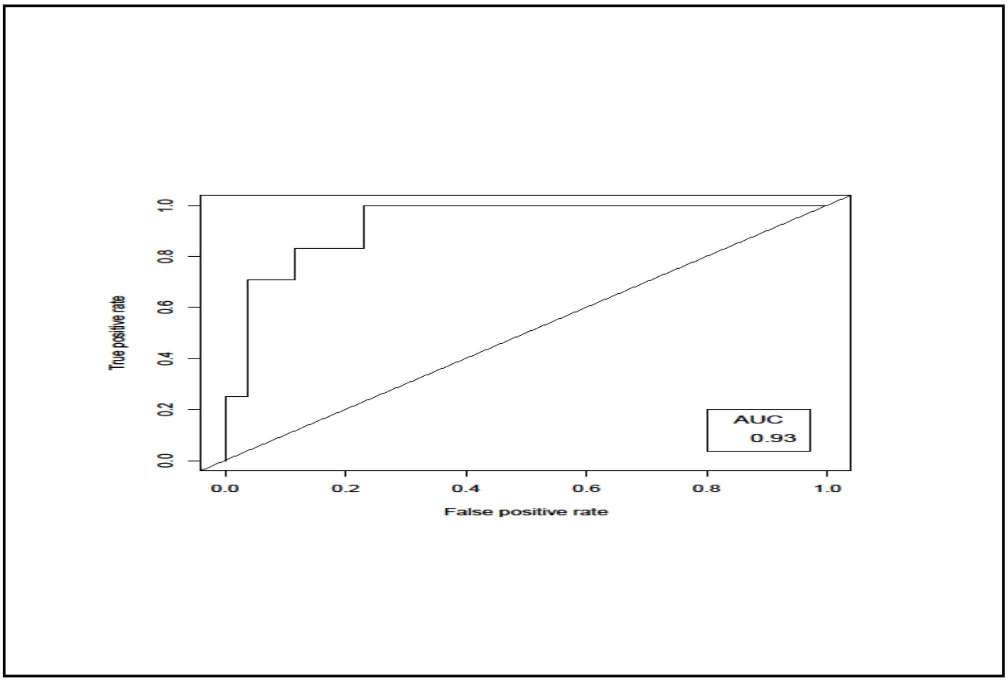

Figure 10: *Solanum mauritianum* SPOT 7 Logistic Regression model ROC Curve

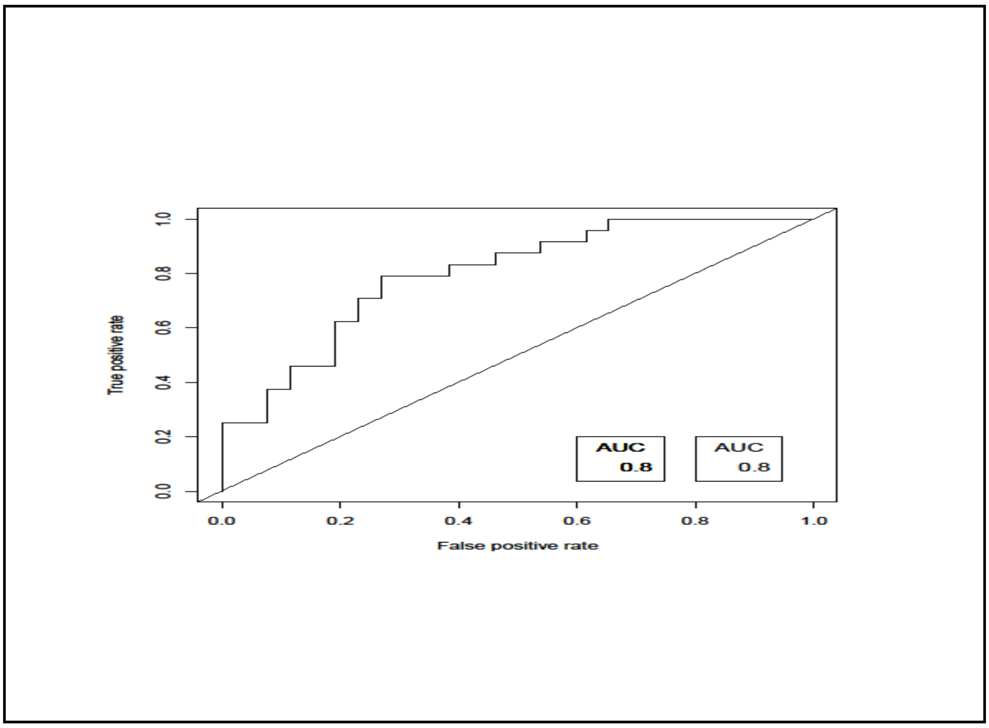

Figure 11: *Solanum mauritianum* Logistic Regression model ROC Curve (Sentinel 2)

3.7.2.2 *Lantana camara* Occurrence

The *L. camara* SPOT 7 model was validated using the area under the curve (AUC) of the receiver characteristic operator curve (ROC) (Figure 11). The *L. camara* model yielded 0.87 which is a high prediction of *L. camara* occurrence (Figure 11). On the other, hand the Sentinel 2 model yielded the ROC AUC of 0.61 which is a poor prediction of *L. camara* (Figure 12).

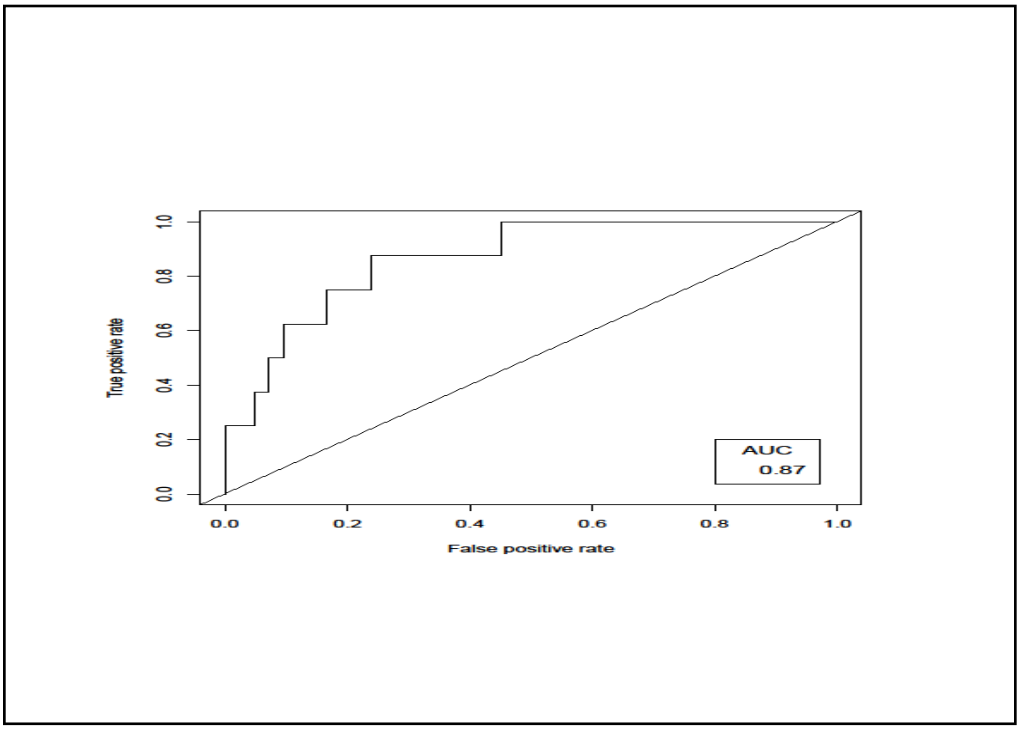

Figure 12: *Lantana camara* occurrence Logistic Regression model ROC Curve (SPOT 7)

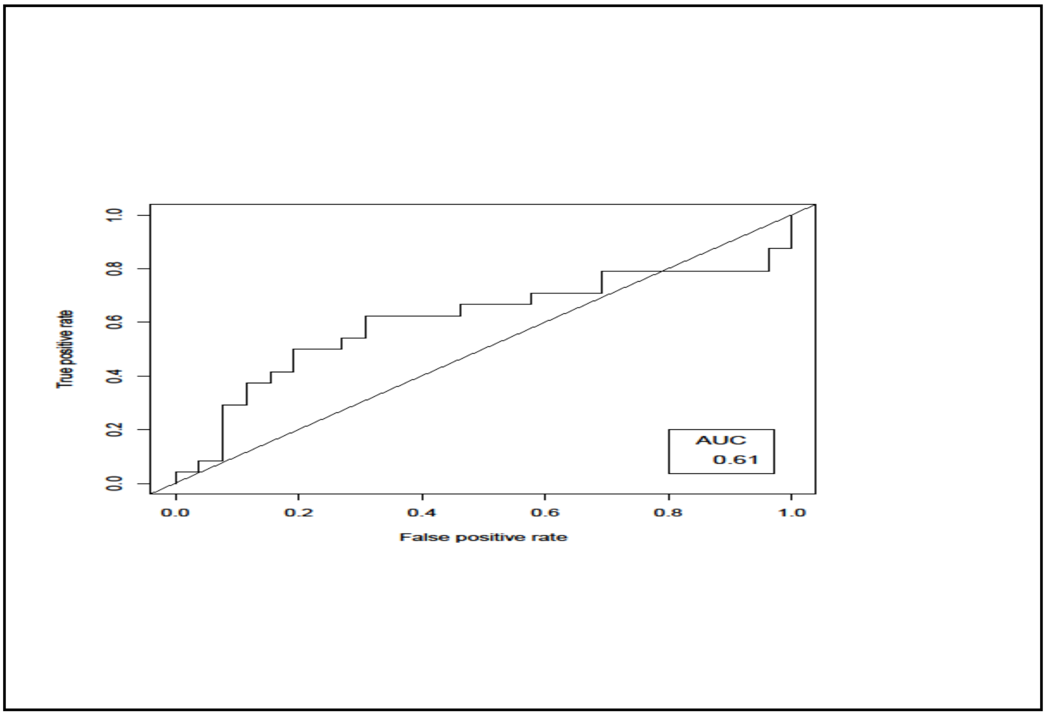

Figure 13: *Lantana camara* occurrence Logistic Regression model ROC Curve (Sentinel 2)

3.7.2.3 Observed co-occurrence probability

The observed co-occurrence probability of *S. mauritianum* (P1) and *L. camara* (P2) SPOT 7 model yielded 0.91 ROC AUC which is a high prediction performance (Figure 14). On the other hand, sentinel 2 produced a ROC AUC of 0.82 which was only 0.09 different from the SPOT 7 model (Figure 15). Based on these results, observed co-occurrence of P1 and P2 species in both SPOT 7 and Sentinel 2 performed high in predicting the co-occurrence of species P1 and P2 in the Tshivhase Tea Estate.

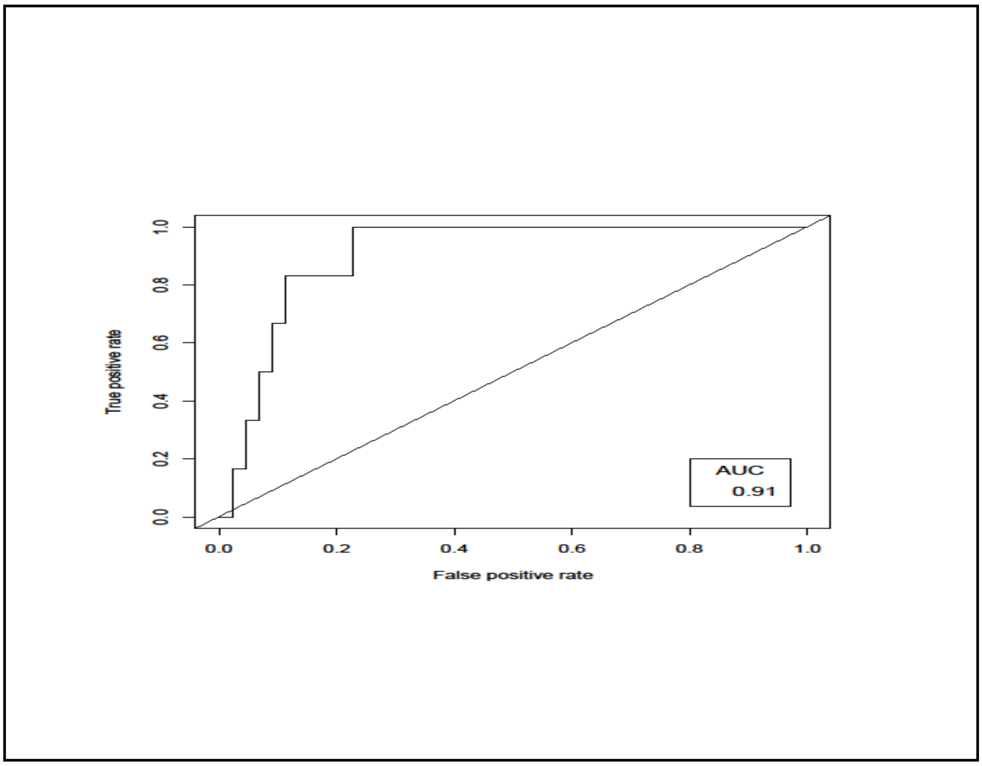

Figure 14: Observed co-occurrence probability (P1P2) ROC curve (SPOT 7)

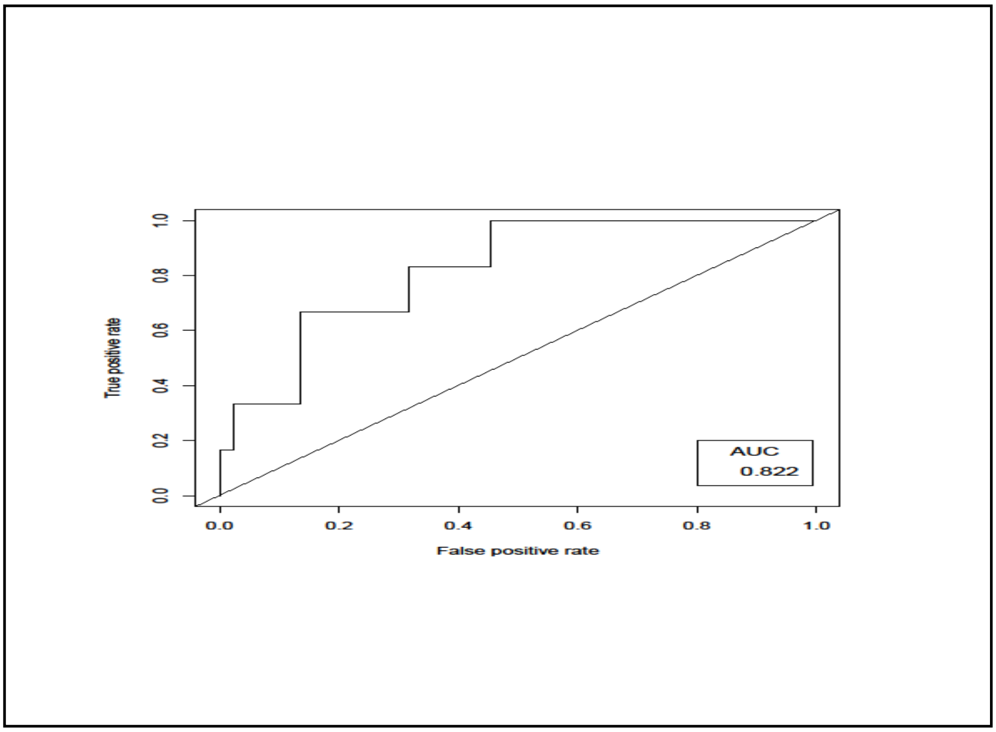

Figure 15: Observed co-occurrence probability (P1P2) ROC curve (Sentinel 2)

The observed co-occurrence probability model of *S. mauritianum* (P1) and *C. odorata*(P3) for Sentinel 2 could not be validated as it was invalid for binary logistic models. On the actual presence/absence data in validation data, there was no co-occurrence of P1 and P3 species.

3.7.2.4 Conditional co-occurrence probability

The conditional co-occurrence probability model of *S. mauritianum*(P1) and *L. camara*(P2) for SPOT 7 yielded ROC AUC of 0.96 which was an excellent performance in predicting the co-occurrence of species P1 and P2 in the Tshivhase Tea Estate(Figure 16).On the other hand, sentinel 2 conditional co-occurrence probability models of P1 and P2 species yielded 0.83 ROC AUC which is also a high prediction performance (Figure 17).

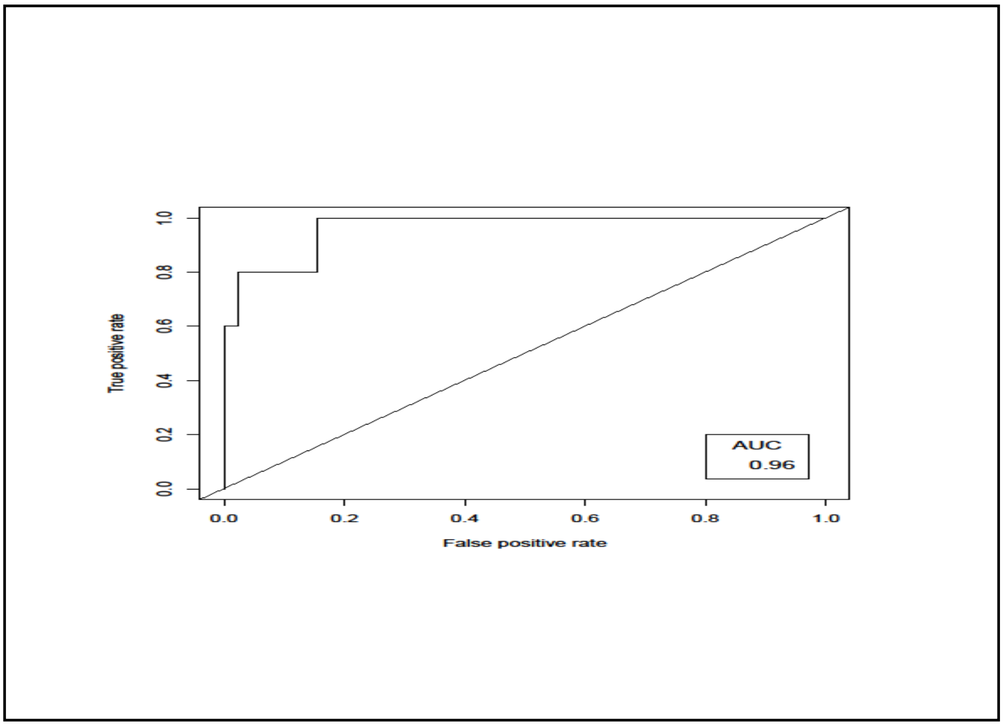

Figure 16: Conditional co-occurrence probability (P1P2) ROC AUC (SPOT 7)

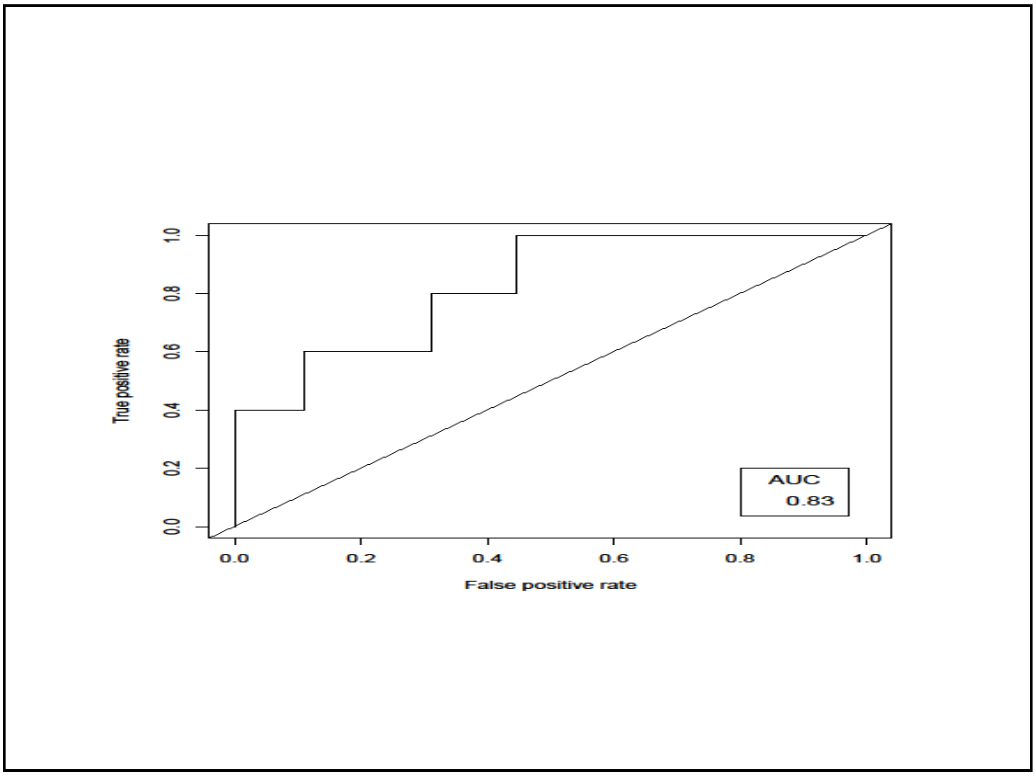

Figure 17: Conditional co-occurrence probability (P1P2) ROC AUC (Sentinel 2)

The Observed co-occurrence probability model *of S. mauritianum* (P1) and *C. odorata* (P3) for SPOT 7 could not be validated as it was invalid for binary logistic models. On the actual presence/absence data in validation data, there was no co-occurrence of P1 and P3 species.

3.8 Predictive Maps

Below are the logistic regression maps showing the distribution of *S. mauritianum* in the Tshivhase Tea Estate indicated by the values 0(absence) and 1(presence) (Figures 18 and 19). The Sentinel 2 map indicated *S. mauritianum* occurring on the northern and western sides of the Tshivhase Tea Estate (Figure 18). On the other hand, the SPOT 7 map (Figure 19) indicated the occurrence of *S. mauritianum* all over the tea plantation with high occurrence in the northern and the western part of the tea plantation. The areas with red colour with a value of 0 indicated areas where *S. mauritianum* never occurred. These are path areas, Thathe Vondo Dam, and where there are buildings in the study area.

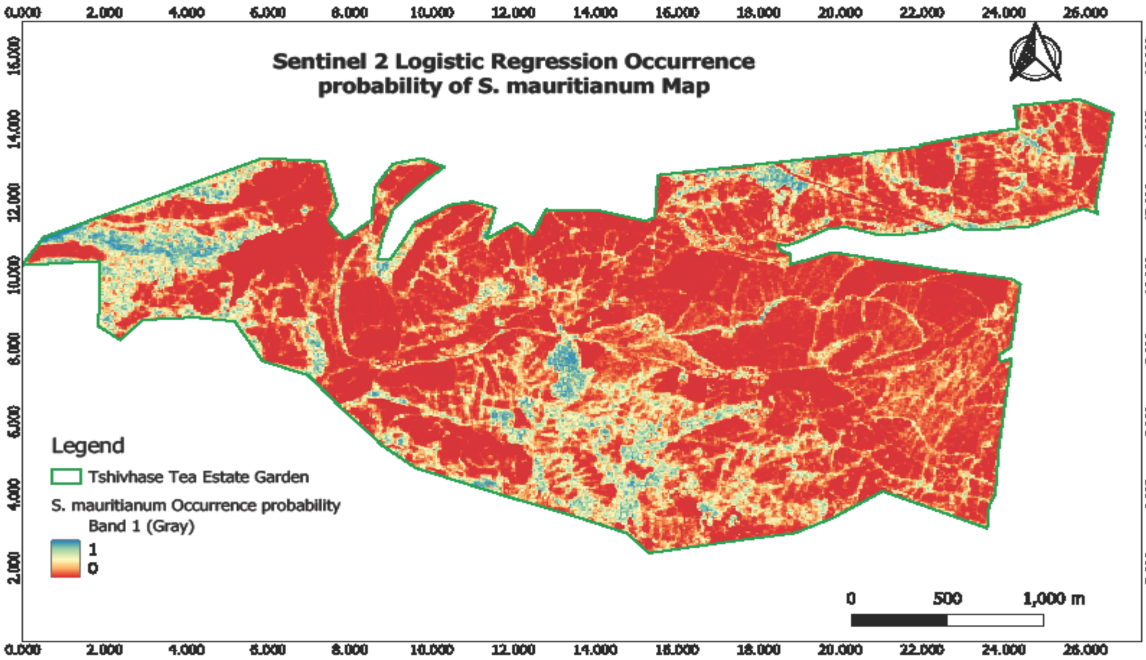

Figure 18: Occurrence probability of *S. mauritianum* in the Tshivhase Tea Estate for Sentinel-2

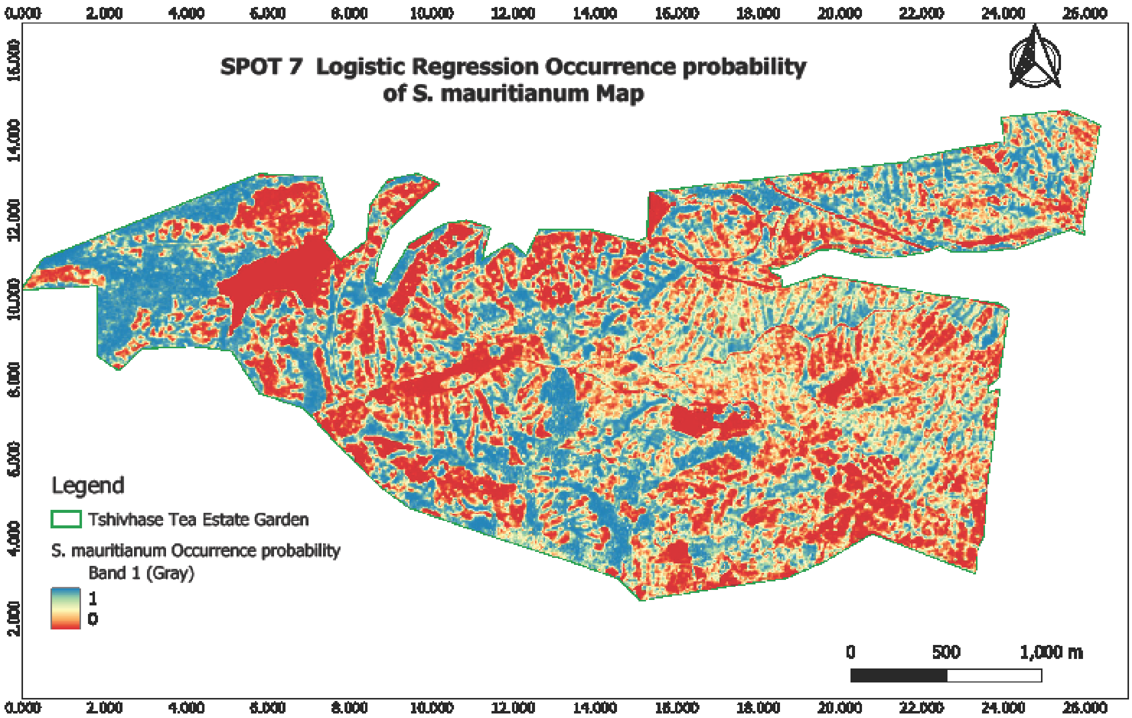

Figure 19: Occurrence probability of *S. mauritianum* in the Tshivhase Tea Estate for SPOT 7

Figures 20 and 21 below represent the occurrence of *L. camara* in the Tshivhase Tea Estate. It can be observed from the Sentinel map (Figure 20) that *L. camara* slightly occurs in open areas such as along the paths and areas closer to the buildings. From the SPOT 7 map (Figure 21), it can also be well observed that *L. camara* occurs along the path areas, open areas as well as in the edges of the tea plantation presented by a blue colour (1).

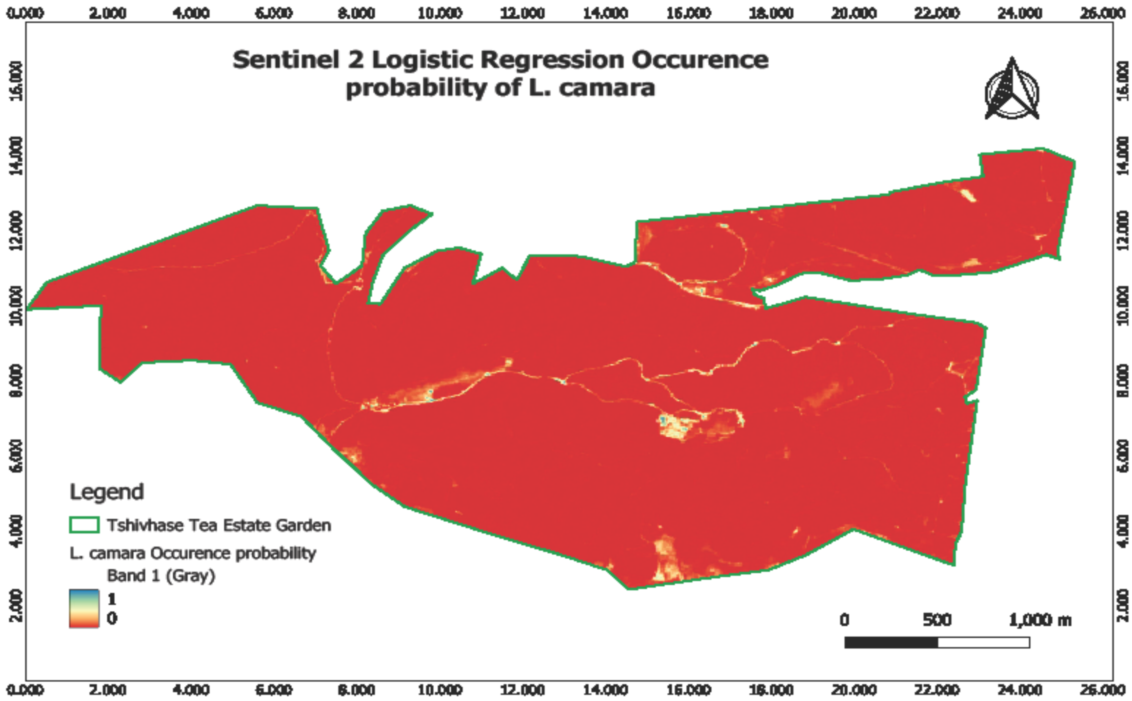

Figure 20: Occurrence probability of *L. camara* in the Tshivhase Tea Estate for Sentinel-2.

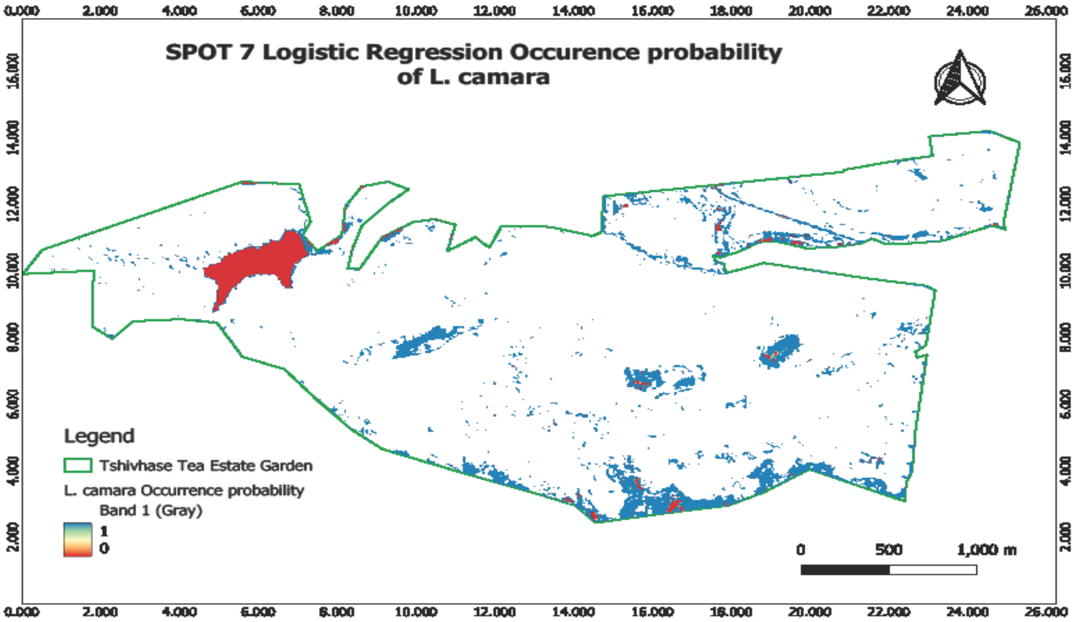

Figure 21: Occurrence probability of *L. camara* in the Tshivhase Tea Estate for SPOT 7

Figure 22 shows the observed co-occurrence between *S. mauritianum* (P1) and *L. camara* (P2) in the Tshivhase. Sentinel 2 maps showed a poor distribution of P1 and P2 species. They were indicated as co-occurring only in the centre of the tea plantation, represented by blue colour. The SPOT 7 map (Figure 23) indicated the distribution of P1 and P2 species occurring along the tea paths and open areas which is not the case in the real world.

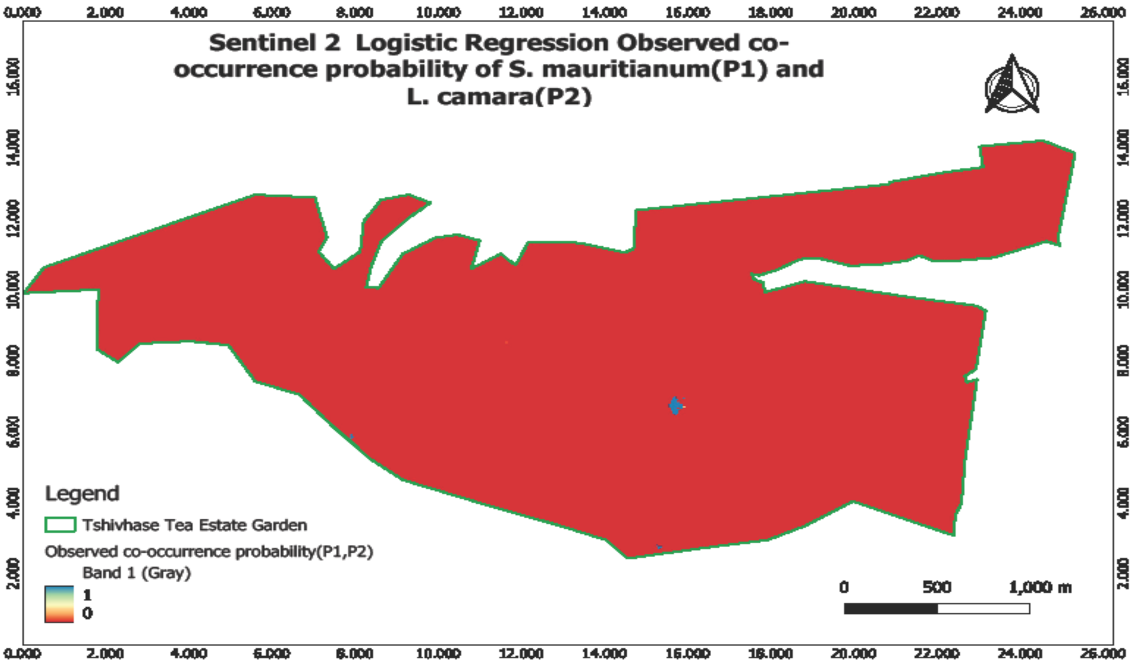

Figure 22: Observed co-occurrence probability of *S. mauritianum* (P1) and *L. camara* (P2) in the Tshivhase Tea Estate for Sentinel-2.

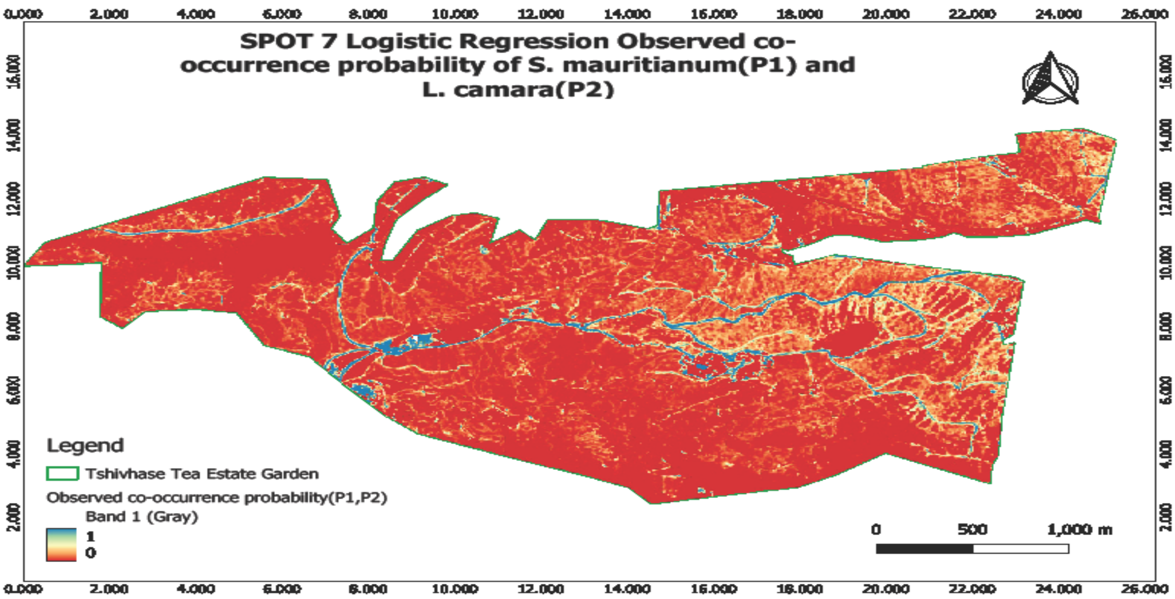

Figure 23: Observed co-occurrence probability of *S. mauritianum* (P1) and *L. camara* (P2) in the Tshivhase Tea Estate for SPOT 7.

The Sentinel 2 logistic model was not successful in mapping the observed co-occurrence (P1P3) and conditional co-occurrence (P1, P2) and P1, P3. SPOT 7 also was not successful in mapping conditional co-occurrence (P1, P3) as the validation dataset could not fit a binary model.

3.9 Discussion

3.9.1 *S. mauritianum* occurrence

The findings of the study indicated the relationship between the presence/absence of *S. mauritianum*, spectral bands, and vegetation indices. The logistic model with SPOT 7 spectral bands as independent variables indicated B3 (Red band), variance and Brightness Index as significant at $P<0.05$. The other variables such as B1 (blue), B2 (green), B4 (Near-Infrared), standard deviation, and Modified Normalized Water Difference Index (NMDWI) were insignificant at $P>0.05$. The ROC AUC of the SPOT 7 model yielded 0.94 and the Sentinel 2 one was 0.86. The SPOT 7 model performed excellently in predicting the presence/absence of *S. mauritianum*. The best model had the higher AUC and therefore the better the model in predicting the presence (1) and absence (0) classes (Narkhede, 2018). In this study, the "0" classes are absent whereas the "1" classes are the presence of *S. mauritianum* in the Tshivhase Tea Estate. The SPOT 7 and Sentinel-2 models are excellent as their AUC is closer to 1 especially the SPOT 7 model with 0.94 AUC. There is a slight difference of 0.08 in the AUC of SPOT 7 and Sentinel-2 making Sentinel-2 to be still considered for logistic regression occurrence mapping of IAPs. The *S. mauritianum* occurrence in the forest margins, open areas and riparian zones were effectively mapped at 91.33%, 85.08%, and 67%, respectively, using WorldView-2 and unsupervised methodology (Peerbhay *et al*., 2016). Based on these results, the logistic regression model is still superior in mapping the occurrence of *S. mauritianum*.

3.9.2 *L. camara* occurrence

The logistic regression model with SPOT spectral bands indicated green band, standard deviation, variance, BI and MNDWI as significant at $P<0.05$ with standard deviation, BI and MNDWI showing a negative correlation towards the presence and absence of *L. camara*. The Sentinel 2 model on the other hand indicated standard deviation as significant at $P<0.05$ with a negative correlation towards the presence/absence of *L. camara*. The ROC AUC of SPOT 7 model yielded a performance prediction of 0.87 whereas Sentinel 2 produced a prediction performance of 0.63. In predicting the occurrence of *L. camara* in the Tshivhase Tea Estate, the SPOT 7 model was superior. The potential of satellite remote sensing in weed detection and mapping in South Africa using readily available multispectral data has been proven in the assessment of the SPOT 6 sensor in detecting and mapping *L. camara* for a community clearing project in the KwaZulu-Natal study (Oumar,2016). This study is in agreement with Omar's (2016) study as it has also mapped the occurrence of *L. camara* using SPOT 7 successfully. Sentinel 2 was also used successfully in mapping the distribution of IAPs in a water-limited catchment with higher overall accuracy of 71% (Mtengwana, 2020).

3.9.3 Observed co-occurrence probability

The observed co-occurrence probability of *S. mauritianum* and *L. camara* SPOT model indicated all variables as insignificant at *P*>0.05. According to this model, B2, B3, B4, B8, standard deviation, mean, variance and BI do not have a relationship with the presence/absence of *S. mauritianum* and *L. camara* co-occurring in the Tshivhase Tea Estate. Other variables such as soil condition and the Digital Elevation Model (DEM) could correlate with the presence/absence of *L. camara* in the Tshivhase Tea Estate. The SPOT 7 model produced 0.86 ROC AUC performances in predicting the co-occurrence of *S. mauritianum* and *L. camara* in the Tshivhase Tea Estate whereas sentinel 2 yielded 0.82. Both models have performed superior in predicting the co-occurrence of these two species.

In predicting the observed co-occurrence of *S. mauritianum* and *C. odorata*, the SPOT 7 model indicated non-significant of B2, B4, standard deviation, NDVI, and MNDWI at *P*>0.05 meaning that there is no correlation between the observed co-occurrence probability of *S. mauritianum* and *C. odorata*. The Sentinel 2 model on the hand also showed no significance in B2, B3, B4, B8, mean, and BI at *P*>0.05. The SPOT 7 model yielded a ROC AUC of 0.96 which was an excellent performance in predicting the co-occurrence of *S. mauritianum* and *L. camara* in a condition where *C. odorata* does not occur. The Sentinel 2 on the other hand yielded a ROC AUC of 0.83 which is still a superior performance.

3.9.4 Conditional co-occurrence probability

The SPOT 7 model indicated only B1 as significant and B3, B4, variance, BI, and MNDWI as non-significant in predicting the co-occurrence of *S. mauritianum* and *L. camara*. The sentinel 2 also indicated all the spectral bands, standard deviation, mean, variance and BI as non-significant at *P*>0.05. This means that these variables do not influence the co-occurrence of *S. mauritianum* and *L. camara* in the Tshivhase Tea Estate. Other variables such as soil condition, climate, and DEM could have an influence on the co-occurrence of *S. mauritianum* and *L. camara* in the condition where *C. odorata* does not occur.

The conditional co-occurrence probability model of both SPOT 7 and Sentinel 2 were insignificant in predicting the co-occurrence of *S. mauritianum* and *C. odorata* given that *L.*

camara does not occur. There was no probability that *S. mauritianum* and *C. odorata* co-occur in one area in the Tshivhase Tea Estate.

To the best of my knowledge, there are no studies as yet about the observed and conditional co-occurrence probability mapping of IAPs in the tea plantation. Moreover, B1, B2, B3, B4, standard deviation, Variance, MNDWI, and BI were positively significant in determining the presence/absence of occurrence of *S. mauritianum* in the SPOT 7 model. On the other hand, B8 and MNDWI were negatively significant in determining the presence/absence of *S. mauritianum*. SPOT 7 and Sentinel-2 were successful in mapping the occurrence of *S. mauritianum* in the Tshivhase Tea Estate.

3.10 Conclusion

In conclusion, the study aimed at exploring the capability of high-resolution satellite data in mapping the occurrence of alien invasive plant species in the Tshivhase Tea Estate. Below are the highlights from the study:

- Logistic regression models can successfully predict the occurrence of IAPs, especially when also using SPOT 7 spectral bands as independent variables
- SPOT 7 outperforms Sentinel 2 in predicting and mapping the occurrence of IAPs because it has a higher spatial resolution.
- SPOT 7 and Sentinel 2 can successfully map the occurrence of alien invasive plant species.
- Observational and conditional co-occurrence probability mapping can be successfully modelled in the logistic regression model and be mapped to show the co-occurrence of alien invasive plant species within the tea plantation.

The combination of logistic regression and remote sensing variables was significant in mapping the prediction of *S. mauritianum*, especially when using a higher spatial and spectral resolution like SPOT 7. The observational and conditional matrices were also successful in mapping the co-occurrence between the IAPs species and therefore they can assist the tea plantation managers with information about the invasive IAPs species that co-occur within the tea plantation and plan for clearance thereof. Through the use of logistic regression and remote sensing variables, the location of these IAPs species will be easily identifiable providing the opportunity to target directly areas infested by these species saving time of walking all over the tea plantation and locating areas invaded by invasive alien plant species.

CHAPTER FOUR

Assessing the extent of tea plant health in relation to invasive alien plants and climate data in the Tshivhase Tea Estate in South Africa

4.1 Abstract

Tea is one of the widely consumed beverages globally, with various tea species found in different parts of the world. However, the increasing effects of climate change threaten the health and production of this beverage. On the other hand, climate change is expected to modify IAPs by potentially reshuffling the ecological areas favouring the species. This, unfortunately, results in shifts and adaptations by plant species including the aggressive invasive alien plants. It remains to be seen how various climatic factors in subtropical environments are related to the invasive plant distribution and the general health of *C. sinensis* plantations. Thus this study aimed at assessing the extent of climate change using climate data considering tea health in the Tshivhase Tea Estate in South Africa. In this study, the Vegetation Condition Index (VCI) was used to assess tea plantation health in proportion to climatic conditions for multiple years including 2015, 2017, and 2021. The VCI was derived from SPOT and Sentinel 2 images in 2015, 2017, and 2021. The relationship between the VCI and the climate variables (temperature, precipitation, and relative humidity) was obtained through the use of linear regression. The climate variables were further used to assess climate change. The results of the study showed that VCI was generally high throughout the Tshivhase Tea Estate with a 50-100% range. The *S. mauritianum* was observed in areas of high VCI thereby affecting the health of the tea plantation through the competition of nutrients and other things. In 2015, the maximum temperature (Tmax) showed a positive significant correlation in 2015 of 0.54 and 1.91 in Sentinel 2 and SPOT 6 models respectively. For every 0.54°C and 1.91°C, there was an increase in maximum temperature (Tmax) by 1 in 2015. In 2017, Tmax showed a negative correlation towards VCI by -0.01°C in the Sentinel 2 model whereas the SPOT 7 model indicated Tmax with a positive correlation of 6.30 meaning that for every -0.01 there was a decrease in Tmax by 1°C and for every 6.30 °C there was an increase in Tmax by 1°C. On the other hand, relative humidity showed a negative correlation with VCI in all the Sentinel 2 models in 2015-2021 with -10.74,-0.68, and --6.31% respectively. Precipitation showed a positive correlation in 2015-2021 in the Sentinel 2 model with 1.53, and 46.19 mm respectively. The increase in Tmax and precipitation favours the distribution of *S. mauritianum* as it strives well in moist areas with high temperatures thereby putting a strain on tea plantation health through competition of nutrients and sunlight. The period of 2015-2021 did not indicate the extent of climate change in the Tshivhase Tea Estate as the temperature, precipitation, and relative humidity have been decreasing from 2017-2021. The Tshivhase Tea Estate managers can

adopt the use of readily available high spatial resolution images in monitoring drought throughout the tea plantation.

Keywords: VCI; SPOT; Sentinel-2; Climate Change; Linear Regression

4.2 Introduction

Vegetation dynamics and the distributions of plant species and vegetation are driven by the climate (Sykes, 2009). Impacts of climate change and global warmings such as temperature, precipitation, and recurrent drought contribute to vegetation change (Na-U-Dom, 2017 *et al*., 2017). Moreover, these aspects of climate change are the key drivers of the geographical distribution of species resulting strongly in the spread of IAPs (Kariyawasam *et al*., 2021). IAPs have a significant impact on agriculture (Kariyawasam *et al*., 2021). The *S. mauritianum* is one of the invasive alien plant species that invade agricultural lands. It is a shrub with branches that invades some tropical and warm temperate regions globally (Roe 1972; ISSG, 2006). Through observations in South Africa, *S. mauritianum* can adjust to a wide extent of habitats, climates, and natural conditions (CABI, 2019). It occurs in a range of climatic conditions from the Mediterranean to coastal subtropical to high-altitude temperate climates (CABI, 2019). *S. mauritianum* like any other IAPs spread is being facilitated by climate change resulting in crop health reduction (IUCN, 2021). The increasing temperature was listed as one of the reasons linked to the decline in tea production in the study about the effect of global warming on tea production in Indonesia (Indahsari, 2016). The increased summer temperatures and excessive rainfall in India caused by climate change were found to be disastrous for tea yield (Mallik and Ghosh, 2021).

There is a global increment within the utilization of remote sensing and geographic information systems (GIS) technology in identifying the patterns in spatial data and vegetation dynamics based on the time arrangement of satellite imageries (Anderson *et al*., 2010; Xie *et al*., 2015). Geospatial technology provides better methods of studying vegetation dynamics than the traditional methods of mapping large areas based on field surveys (Xie *et al*., 2008). The vegetation change trends and drought assessment have been analysed using the available remotely- sensed time-series of vegetation indices (Anderson et al., 2010). In addition, remote sensing can identify areas that are invaded by IAPs or areas that are vulnerable to being invaded in the future (Current Science, 2005). Further, the IAPs are abundant and tolerant to a broad range of climatic conditions making them easy to adapt to a new climatic condition (Shrestha *et al*., 2018).

Vegetation Condition Index (VCI) has been widely used in drought monitoring and analysis with verified reliability by many studies (Baniya *et al*., 2019). The relationship between VCI and temperature as well as precipitation has also been studied (Baniya *et al*., 2019). The monitoring of drought using remote sensing to determine the probability of occurrence and relationships with climates on different time scales is important for improving agricultural production, protecting the environment, and promoting sustainable socio-economic development (Gu *et al*., 2011). VCI can estimate the status of vegetation vigor over a particular period in different years giving a more accurate result as compared to the

Normalized Difference Vegetation Index (NDVI) while monitoring drought at a regional scale (Bajgiran *et al*., 2008).

This study evaluated the ability of the satellite-based Vegetation Condition Index (VCI) with climate variables to monitor the distribution of *S. mauritianum* and tea plantation health. The objective of the study was as follows:

- To evaluate the performance of SPOT 7 and Sentinel 2 derived VCI with climate data in assessing tea plantation health.
- To assess the extent of climate change in the Tshivhase Tea Estate using temperature and precipitation data.
- To assess the effect of climate change on the distribution of *S. mauritianum* in the Tshivhase Tea Estate to tea health.

4.3. Methods

4.3.1 Study Area

Please refer to Chapter 2 (2.3.1)

4.3.2 Image data acquisition and processing

Please refer to Chapter 3(3.3.2). The image acquired in the year 2015 and 2017 was also used to calculate Vegetation Condition Index (VCI) for tea plantation in the Tshivhase Tea Estate.

4.3.3 Field data collection

Please refer to Chapter 2 (2.3.2).

4.3.5 Climate and remote sensing data

The climate data from the years 2015, 2017, and 2021 were obtained from the South Africa Weather Services and NASA power Data Access viewer (https://power.larc.nasa.gov/data-access-viewer/). The climate data obtained were the maximum and minimum temperature, precipitation, and humidity. These climate data were analysed with the Vegetation

Condition Index (VCI). The VCI was derived from Sentinel 2 and SPOT 7 satellite images for the years 2015, 2017, and 2021. The VCI was used to monitor the tea plantation vigour in the Tshivhase Tea Estate. The VCI was calculated using the below equation (Pei, 2017):

$$VCI = \frac{(NDVI_i - NDVI_{min})}{(NDVI_{max} - NDVI_{min})}$$ **Equation 10**

where *NDVI*, $NDVI_{max}$ and $NDVI_{min}$ represent the yearly NDVI, their absolute maximum and minimum values in a given period, respectively.

The VCI indicates vegetation conditions in a value range of 0 to 100 where values close to zero indicate severe dryness conditions while those close to 100 indicate optimal humidity conditions (Kogan *et al*., 2003). The below table indicates the VCI classification of vegetation conditions.

Table 16: VCI Classification

VCI Range	Numeric Index	Vegetation condition
(0-20)	5	Extreme
(20-40)	4	Severe
(40-60)	3	Moderate
(60-80)	2	Good
(80-100)	1	Very Good

4.4 Data analysis

The relationship between tea Vegetation Condition Index (VCI) and climate data (temperature, rainfall and humidity) was modelled in the linear regression using MS Excel. The linear regression equation is as follows:

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots \beta_n x_n$$ **Equation 11**

Where Y=VCI (dependent variable), β_0 is the y intercept and β_1, β_2 are the regression coefficient of the independent variables. x_1, x_2 are the independent variables (minimum and maximum temperature, precipitation and relative humidity).

4.5 Results

4.5.1 2015 VCI

The Sentinel 2 and SPOT 6 VCI for the year 2015 is shown in Figure 24 below. The annual VCI values for the year 2015 derived from Sentinel 2(A) and SPOT 6(B) show the drought condition in the Tshivhase Tea Estate. In 2015, the drought condition in the Tshivhase Tea Estate was normally ranging from 50-100 %. The VCI values (0-25%) indicate areas that have a severe drought but in this case, these are the areas that cannot be considered by VCI as they are not vegetation such as the water bodies and built areas. Moreover, the presence and absence of *S. mauritianum* are indicated in figure 24 where the low presence of *S. mauritianum* occurs where there are low VCI values (25-50%) along the tea paths and open areas. The high presences of *S. mauritianum* are in areas with high VCI values (75-100%) where there are neglected tea plants.

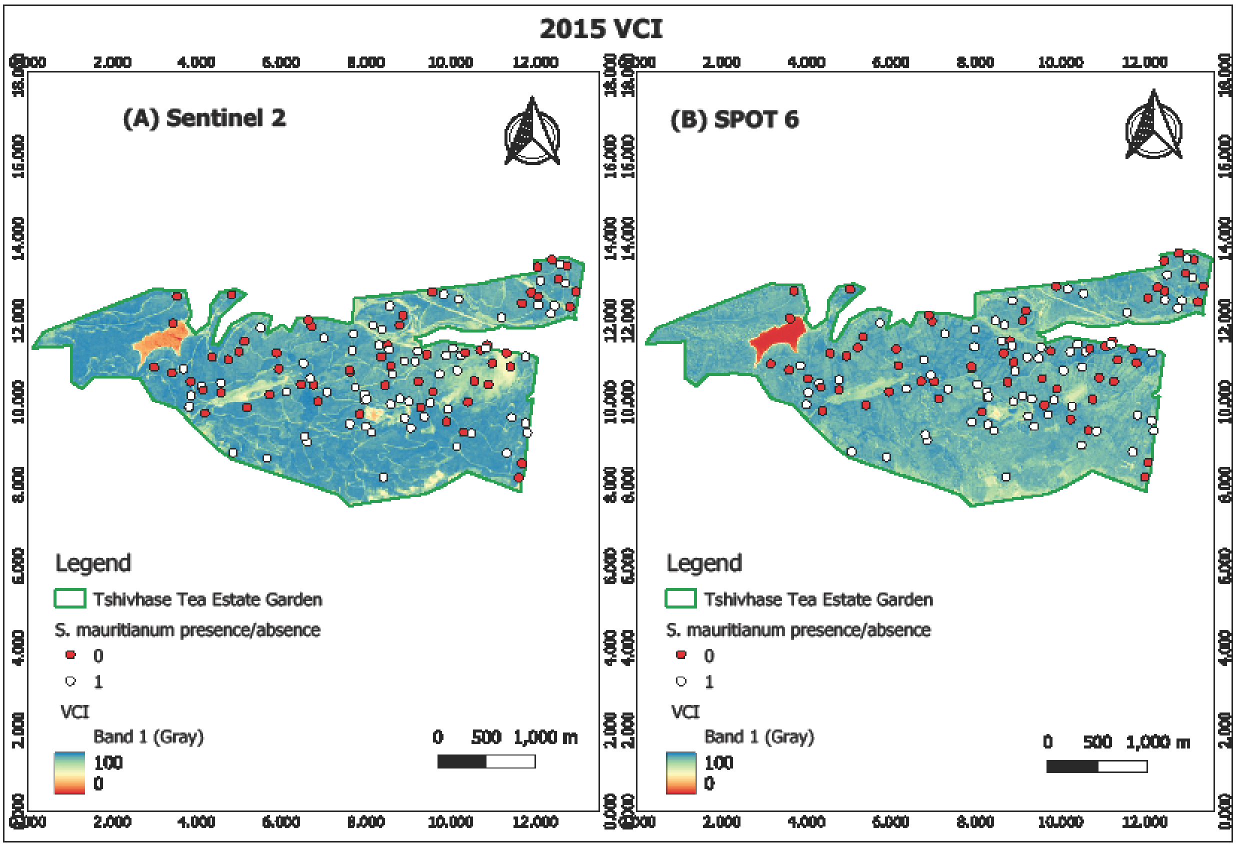

Figure 24: 2015 Sentinel 2 (A) and SPOT 6(B) VCI

4.5.2 2017 VCI

Figure 25 shows the VCI derived from Sentinel 2(A) and SPOT 6(B) acquired on 2017/11/14 and 2017/10/19, respectively. There is a slight difference in VCI conditions between 2015 and 2017. Like in the year 2015, the S. *mauritianum* was present in areas with high VCI and also absent in areas with high VCI. Areas with low VCI are tea paths and open areas. The bottom left side of the tea plantation had low VCI in 2017. The presence of *S. mauritianum* was low with a high absence in areas along the paths and within the tea plantation.

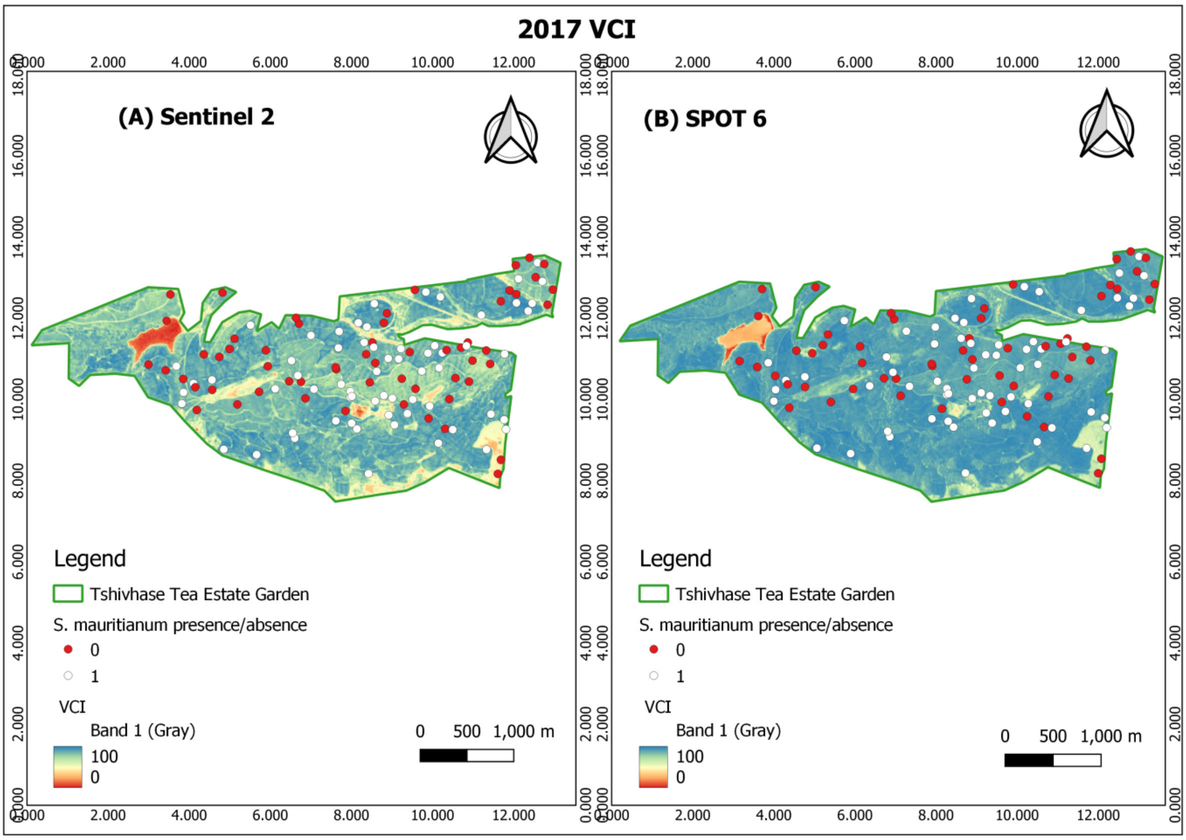

Figure 25: 2017 Sentinel 2 (A) and SPOT 6(B) VCI

4.5.3 2021 VCI

Figure 26 below indicates drought conditions derived from Sentinel 2 and SPOT 7 acquired on 2021/09/28 and 2021/10/09 respectively. Both SPOT 7 and Sentinel 2 show high VCI all over the Tshivhase Tea Estate. The moderate drought is found in tea paths and open areas. The *S. mauritianum* occurs in areas where there is high VCI as indicated in other figures.

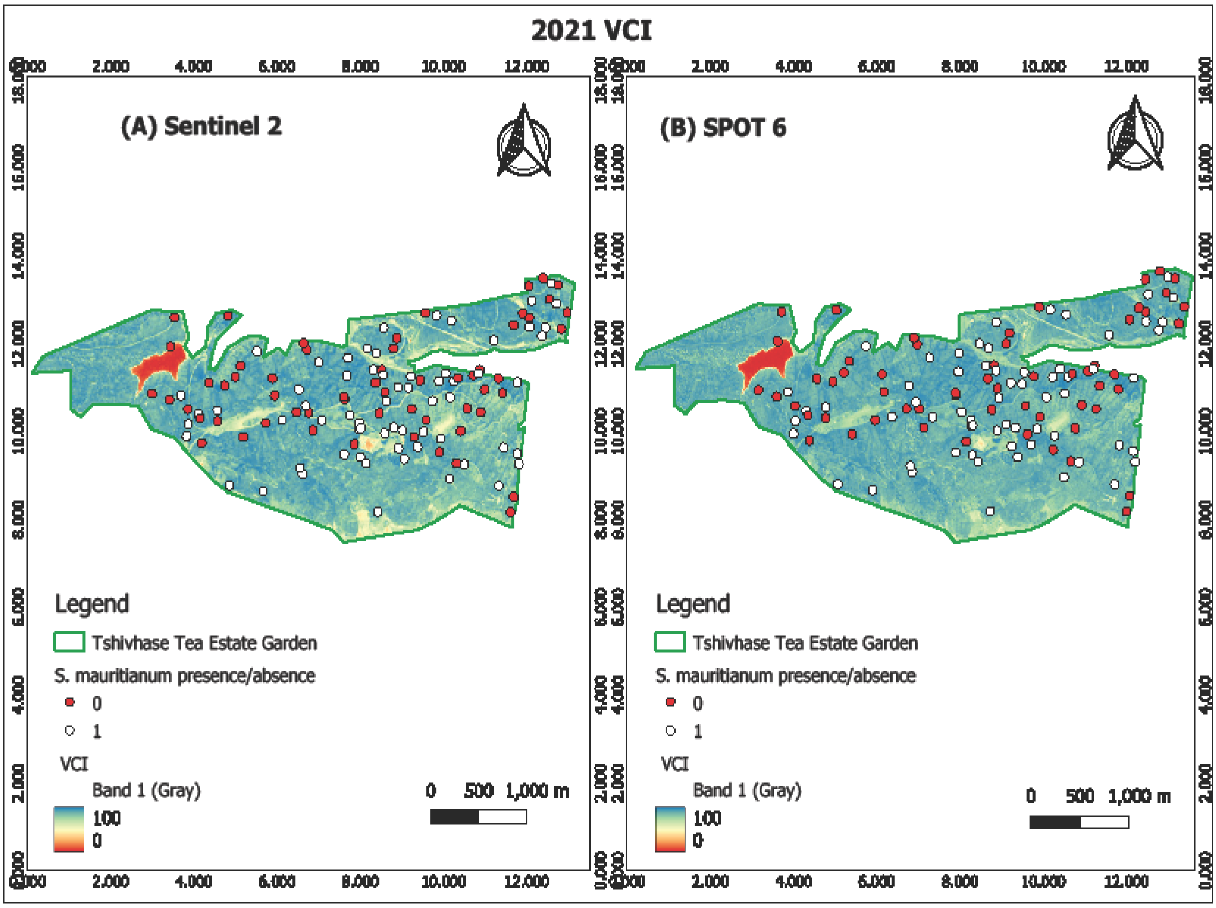

Figure 26: 2021 Sentinel 2 (A) and SPOT 6(B) VCI

4.5.4 Climate data

Figure 27 below indicates the month of February and November has the highest maximum temperatures with June month having the lowest maximum and minimum temperatures. The humidity was high in April and September 2015 with November having the lowest humidity. The rainfall was high in January and in September with June-August having the lowest rainfall.

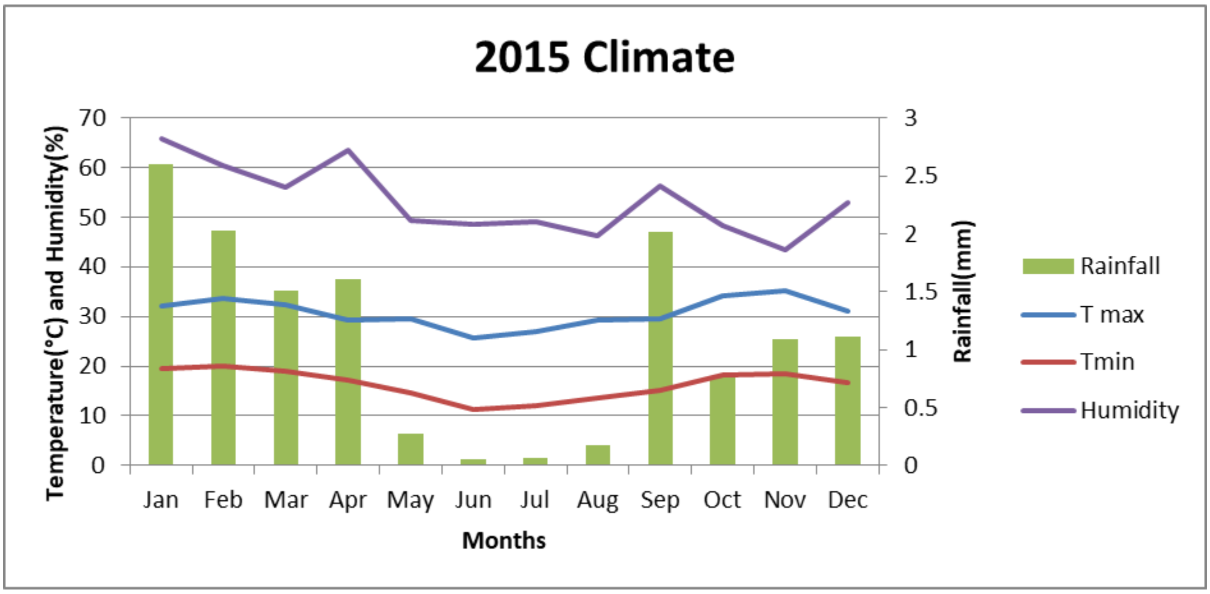

Figure 27: 2015 Climate in the Tshivhase Tea Estate

The 2017 climate is shown in Figure 28. The maximum temperature was slightly lower in 2017 as compared to the year 2015. Rainfall was low with February having the highest rainfall compared to all the months. The minimum temperatures were very low in 2017 as compared to the year 2015. The humidity was very low with January having the highest humidity.

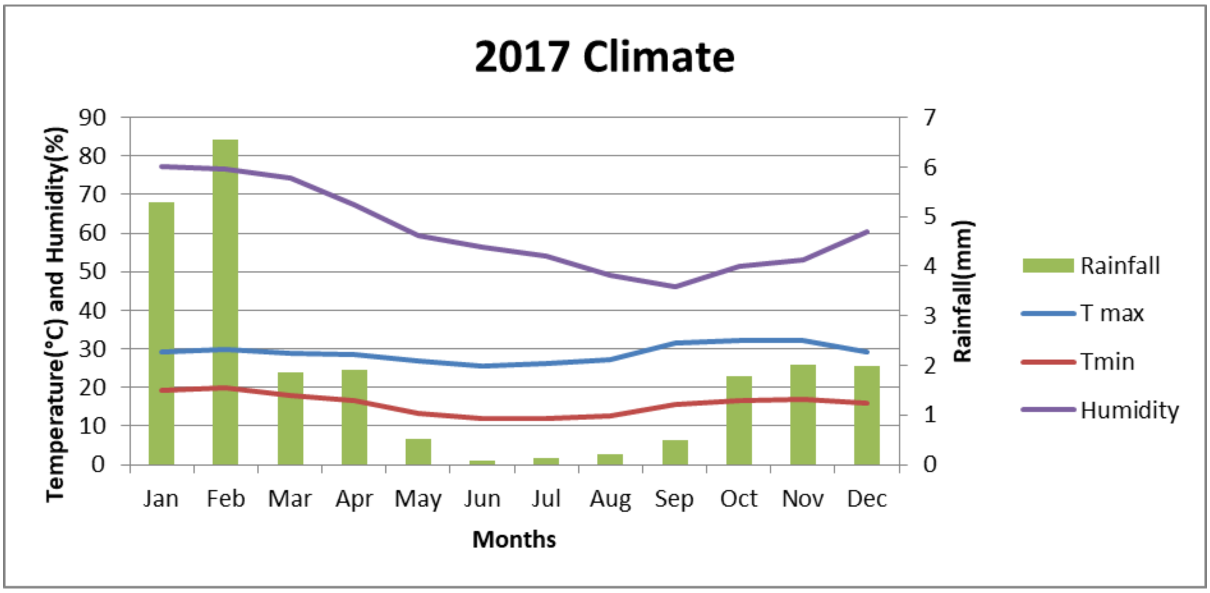

Figure 28: 2017 Climate in the Tshivhase Tea Estate

Figure 29 below shows climatic conditions in the Tshivhase Tea Estate in the year 2021. It shows high maximum temperatures in November with insufficient rainfall in 2017. The humidity was high in February just like in the year 2015. The rainfall was high in January and February.

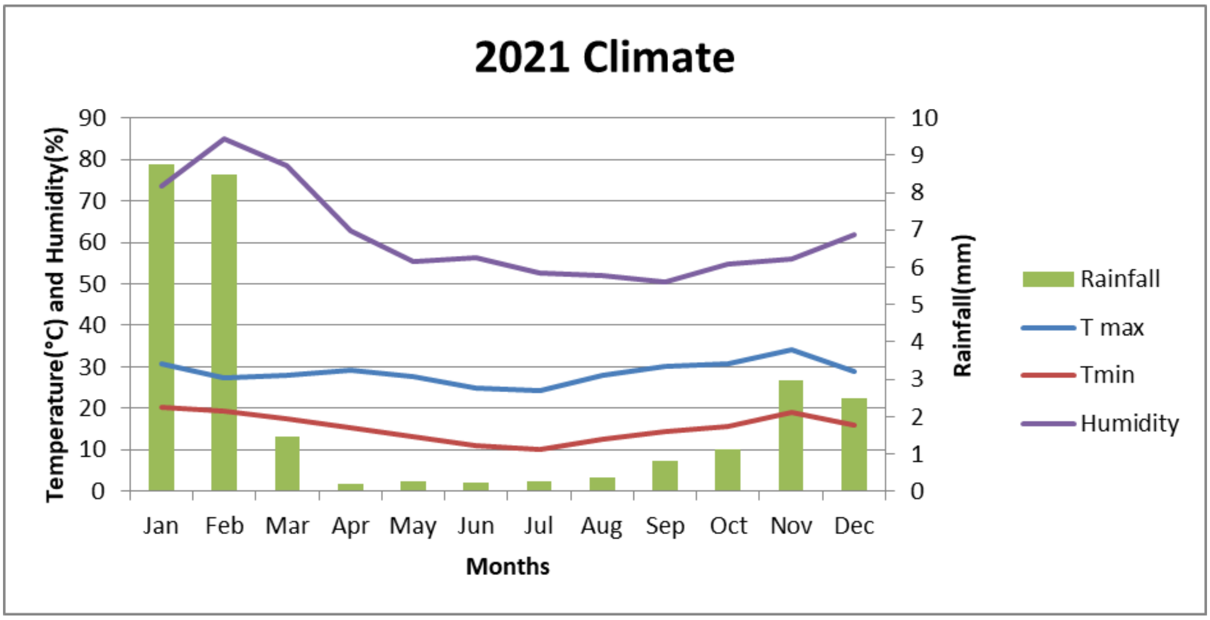

Figure 29: 2021 Climate in the Tshivhase Tea Estate.

From the year 2015-2021, the average maximum and minimum temperatures dropped together with rainfall and humidity. The year 2015 had the highest temperatures, humidity, and rainfall as compared to the years 2017 and 2021. The year 2021 had the lowest maximum and minimum temperatures, rainfall, and humidity as compared to the other years.

4.5.5 Linear Regression

The relationship between the Vegetation Condition Index (VCI) and climate data was modelled in the linear regression model in Excel. Table 17 below shows the relationship between Sentinel 2 and SPOT 6 VCI in 2015 with maximum temperature (Tmax), minimum temperature (Tmin), precipitation, and relative humidity (RH). Tmax and Tmin have a positive relationship with VCI. Precipitation and RH have a negative correlation toward VCI in both Sentinel 2 and SPOT 6. The increase in Tmax and Tmin will lead to an increase in VCI by 1.

Table 17: 2015 VCI Regression model coefficients for Sentinel 2 and SPOT 7

	Coefficients	Standard Error	t Stat	P-value
Sentinel 2				
Intercept	468.35	742.83	0.63	0.53
Tmax	0.54	23.00	0.02	0.98
Tmin	2.00	14.28	0.14	0.89
Precipitation	27.76	57.34	0.48	0.63
RH	-10.74	16.73	-0.64	0.52
SPOT 6				
Intercept	55.65	387.87	0.14	0.89
Tmax	1.91	12.01	0.16	0.87
Tmin	-4.59	7.45	-0.62	0.54
Precipitation	-2.73	29.94	-0.09	0.93
RH	1.25	8.74	0.14	0.89

Table 18 below indicates the relationship between Sentinel 2 and SPOT 7 VCI with maximum and minimum temperature (Tmax and Tmin), precipitation, and Relative Humidity (RH) in 2017. The Tmax and RH have a negative relationship toward the VCI meaning when they increase, VCI decreases. The Tmin and precipitation have a positive relationship.

Table 18: 2017 VCI Regression model coefficients for Sentinel 2 and SPOT 7

	Coefficients	Standard Error	t Stat	P-value
Sentinel 2				
Intercept	0.26	206.42	0	1
Tmax	-0.01	0.02	-0.41	0.68
Tmin	1.97	14.29	0.14	0.89
Precipitation	1.53	6.99	0.22	0.83
RH	-0.68	1.69	-0.4	0.69

SPOT 7				
Intercept	280.94	649.91	0.43	0.67
Tmax	6.30	20.12	0.31	0.76
Tmin	-7.69	12.49	-0.62	0.54
Precipitation	4.26	50.17	0.08	0.93
RH	-6.31	14.64	-0.43	0.67

The correlation of VCI and climate data in 2021 for SPOT 7 and Sentinel 2 is shown in Table 19. Precipitation and relative humidity have a negative relationship toward VCI whereas Tmax and Tmin have a positive relationship. The relationship between VCI and Tmax and Tmin is the same as the one in 2017.

Table 19: 2021 VCI Regression model coefficients for Sentinel 2 and SPOT 7

	Coefficients	**Standard Error**	**t Stat**	**P-value**
Sentinel 2				
Intercept	-458.00	591.98	-0.77	0.44
Tmax	19.89	18.33	1.09	0.28
Tmin	-10.49	11.38	-0.92	0.36
Precipitation	46.19	45.70	1.01	0.32
RH	-0.26	13.33	-0.02	0.98
SPOT 7				
Intercept	58.56	362.38	0.16	0.87
Tmax	1.79	11.22	0.16	0.87
Tmin	-4.29	6.96	-0.62	0.54
Precipitation	-2.55	27.97	-0.09	0.93
RH	1.17	8.16	0.14	0.89

4.6 Discussion

4.6.1 VCI

The Tshivhase Tea has a high VCI in general and the distribution of *S. mauritianum* occurs where there is high VCI. Both Sentinel 2 and SPOT 7 were successful in mapping the VCI with SPOT 7 clearly showing more ground details than Sentinel 2. This is because SPOT 7 has higher spatial and spectral resolution than Sentinel-2. Measho *et al*., (2019) used VCI and standard precipitation Index (SPI) to assess drought patterns in Eritrea where VCI and precipitation showed a positive correlation with the drought condition. In this study, precipitation showed a negative relation towards VCI in 2015 and 2021 in both SPOT and Sentinel 2 models. In 2017, that's when precipitation showed a positive correlation with VCI in both SPOT and Sentinel 2 models. VCI was also calculated using the long-term NDVI images and revealed the occurrence of drought-related crop stress in the year 2002 (Dutta *et al*., 2015). In this study, the VCI indicated that Tshivhase Tea Estate is in good condition with a healthy tea plantation. The only issue was that high VCI contributed to the occurrence and distribution of *S. mauritianum*. Invasive alien plants reduce agricultural productivity through several mechanisms such as competition (for light, nutrients, and water), allelopathy, and parasitism, and decrease the yield of crops (Bajwa *et al*., 2019; Fried *et al*., 2017). Tall IAPs are known for shading out juvenile plants and hampering their growth (Burgos and Ortuoste, 2018). Based on this statement, *S. mauritianum* occurrence in the Tshivhase Tea Estate is competing with tea plants for light, nutrients, and water thereby inhibiting its growth. The climate variables (temperature and precipitation) contribute to the occurrence of *S. mauritianum* and can tolerate any climatic condition.

4.6.2 Climate change

There was a severe decrease in temperature from the year 2015 to 2021. The year 2015 had the highest maximum and minimum temperature, precipitation, and relative humidity whereas in the year 2021, the temperature in November decreased from 35.24 °C to 32.18. The period studied did not show climate change trends from the year 2015-2021. The period should have been longer to give a clear climatic condition trend.

Through the use of VCI, the Tshivhase Tea Estate can identify areas that are affected by drought and take necessary measures thereof such as irrigation planning. The climatic condition in the Tshivhase Tea Estate favours the survival of *S. mauritianum* and therefore it is spreading and outgrowing the tea plants thereby negatively affecting tea health and production.

4.7 Conclusion

In conclusion, the study aimed at evaluating the performance of SPOT 6 and Sentinel 2 images in mapping the VCI and assessing the relationship between VCI and climate variables. The distribution of *S. mauritianum* was also related to tea health and climate change. The highlights of the findings are as follows:

- SPOT and Sentinel 2 images can perform well in mapping vegetation condition Index with SPOT 7 showing more ground details due to having higher spatial and spectral resolution than Sentinel 2.
- VCI can successfully measure drought conditions in which the Tshivhase Tea Estate is indicated as having no drought.
- There is a relationship between precipitation, temperature, and VCI. The increase in temperature and precipitation increase VCI.
- *S. mauritianum* occurs in high VCI areas and good VCI contributes to the occurrence and distribution of *S. mauritianum* in the Tshivhase Tea Estate.
- The presence of *S. mauritianum* affects tea health via competition of space, water, nutrients, and sunlight. *S. mauritianum* is further overshadowing tea plantations.

More research needs to be conducted such as on the effects of IAPs in tea production using high spatial resolution images.

CHAPTER FIVE

Conclusions and Recommendations

5.1 Introduction

Detailed spatial tea plantation information is extremely useful in developing and implementing effective agricultural practices for tea plantations and management (Xu *et al*., 2018). Recently, detecting and mapping the occurrence, spatial distribution, and abundance of invasive alien plants (IAPs) have gained substantial attention globally (Royimani *et al*., 2019). Although a combination of remote sensing and field data has been conducted on a very coarse resolution scale previously, it has proved to be crucial in mapping the occurrence of invasive species (Rew *et al*., 2005; Joshi *et al*., 2006; Masocha and Skidmore, 2011). This study indicates the improvement in spatial and spectral resolution capability of satellite imageries in detecting and mapping the accuracy of IAPs such as *S. mauritianum* occurrence probability. The main aim of the study was to map tea health concerning IAPs using high-resolution satellite images. The main objectives of the study were (i) to explore the capability of SPOT 7 and Sentinel 2 in mapping the co-occurrence of alien invasive species in the Tshivhase Tea Estate,(ii) to evaluate the relationship between tea health plantation and climate change and (iii) to assess the extent of climate change in the Tshivhase Tea Estate using temperature and precipitation data as well as (iv)to assess the effect of climate change on the distribution of *S. mauritianum* in the Tshivhase Tea Estate with tea health.

5.2 Exploring the capability of high resolution satellite data in delineating the potential distribution of common IAPs in the Tshivhase Tea Estate.

Logistic regression models were successful in predicting the occurrence of IAPs, especially when using SPOT 7 spectral bands as independent variables. Observation and conditional co-occurrence probability are possible to be modelled on logistic regression and mapped. The SPOT 7 model yielded the highest ROC AUC than Sentinel 22 as it has the highest spatial and spectral resolution of 1.5m.

5.3 The geostatistical assessment of the frequency of *S. mauritianum* co-occurrence within the tea plantation in the Tshivhase Tea Estate in South Africa.

The presence/absence data was successful in presenting the co-occurrence frequency of IAPs species in the Tshivhase Tea Estate. *S. mauritianum* had a higher proportion of occurrence (53%) compared with *L. camara* (25%) and *C. odorata*(1.6%). It is highly likely to find *S. mauritianum* and *C. odorata* co-occurring in one area in the Tshivhase Tea Estate. On the other hand, the geostatistical techniques were not sufficient enough in mapping the occurrence of IAPs in the Tshivhase Tea Estate with low R^2 and higher RMSE as well as MAD with IDW improved.

5.4 Assessing the extent of tea plant health in relation to invasive alien plants and climate data in the Tshivhase Tea Estate.

Climate change was not well indicated using climate data from 2015-2021. The period was too short to quantify climate change. There was also a slight difference in temperature, precipitation, and relative humidity from 2017 to 2021. The year 2015 had the highest temperature, precipitation, and relative humidity in some months. Vegetation Condition Index (VCI) was successful in indicating the tea health plantation together with the presence/absence data of *S. mauritianum*. There was a high VCI in the Tshivhase Tea Estate and thus contributed by the presence of *S. mauritianum* which is further contributing to favourable conditions that can lead to the development of tea diseases.

5.5 Recommendation

Remote sensing was used more efficiently in mapping vegetation including tea plantations as seen in the results of this study and by Dutta (2006) who studied bush tea health determination and yield estimation using GIS and remote sensing techniques. Tshivhase Tea Estate needs to adopt the use of GIS and remote sensing in monitoring and managing tea plantations. Remote sensing and GIS allow for better decision-making with less cost and greater efficiency. Further studies need to be carried out on the following:

- The effect of IAPs on tea quality and production using GIS and remote sensing.
- Determining the role of texture and tone in determining tea health.

Time to time monitoring of the tea plantation is very important as problems such as pest and crop infestation can be detected at an early stage and be quickly addressed.

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