Hochschule für nachhaltige Entwicklung

Forest land-use strategy

A comparative per pixel suitability analysis of the Rabia, Storie, and Square Root method of land evaluation in Suriname, Guyana, and French Guiana

Master Thesis

To gain the Master of Science degree (MSc) in Forest System Transformation from the faculty of Forest and Environment at the University for Sustainable Development in Eberswalde, Germany

Presented by

Stephan M. Playfair

1: Thesis advisor: Dr. Evelyn Wallor, Germany
2: Thesis advisor: Dr. Pierre Couteron, France

1: Referee: Prof. Dr. Carsten Mann, Germany
2: Referee: Dr. Pierre Couteron, France

Eberswalde, 11/02/2022

Acknowledgement

First, I wish to express my gratitude for all the moral support I have had from friends and family in Suriname and across the world during the research and writing phases of this thesis. Surely without the empowerment you have provided, this research would have had a completely different tone.

Next, without the guidance, inspiration, and technical support from the administration, researchers, colleagues, and friends from the Institute de Recherche et Development (IRD), this research would not have been possible at all. Particularly, I would like to thank Dr. Pierre Couteron whom has guided me during my stay in Montpellier, welcomed me to the research facility and gave me the space to learn, interact and engage with some of the brightest minds in the field of ecology and remote sensing. Your support in working out problems have been wholly insightful and contributed to my general growth as a researcher. A special thanks goes out to Pierre Ploton from the IRD who was at any time standby for a discussion on ecology, mathematics, or remote sensing. I take no hesitancy in calling you an inspiration.

The Foundation for Production Control and Forest Management (SBB) is a key component for the initial development of this research topic. Throughout the years, I have been privileged to learn from and work with passionate and individuals from across the globe on efforts pertaining to conserving the enigmatic, delicate, yet impressively vast rainforest. Sarah Crabbe, close friend and colleague has pushed and encouraged me throughout the years to explore the limits of what is technically feasible. To all of you at the SBB, I dedicate this research with the hopes of it contributing a pebble to the mountain of forest protection.

Last, I wish to thank the staff, lecturers, and professors from the University of Sustainable Development (HNEE) for their continued support in not only this master's thesis, but for the entire study period of the Forest System Transformation course. Many concepts covered during many lectures have made their way to this research and for that I am entirely thankful. Special thanks go to my supervisor, Dr. Wallor whom has patiently taken the time to meticulously read through my drafts and pinpoint areas for improvement. The fine attention to detail has greatly improved this work.

Abstract

Good sustainable forestry practices are an effort to yield productivity on an as small as land unit as possible. Parametric land evaluation methods provide a robust and empirical way to assess the suitability of a land unit for a specific land-use. Therefore, in this research, the Rabia, Square Root, and Storie suitability methods are used to assess the degree of suitability for forestry per land unit. First, the Shuttle Radar Topography Mission (SRTM) data was used as raw input data. The SRTM data was corrected for latent canopy height and random noise errors using a bias fitting method of a tree height offset method and Lee sigma smoothing algorithm. The resulting smoothed Digital Elevation Model (DEMs) and Potapov Canopy Height Model were transformed into distinct input features. Using the input features as data source, a scoring scheme conforming the standard FAO method was developed to evaluate the land unit characteristics. The resulting suitability factors were combined into a suitability model using the Rabia, Square Root and Storie method. Lastly, using harvested tree information from the Sustainable Forestry Information System Suriname database, each suitability model was assessed with respect to the total suitable area and percentage of trees harvested on those areas. Results show that the Rabia method has the largest percentage of suitable area, the Square Root method the second highest percentage, and the Storie method has the smallest percentage. However, when the ratio of trees per suitable land unit are compared, the Storie method has the highest ratio of trees harvested in a suitable land unit. The conclusion is that adopting one method of land evaluation over another will shift forest management practices in the direction of conservation or production.

Table of contents

List of tables

List of figures

Abbreviations

AHP:	Analytical Hierarchy Process
ALS:	Airborne Lidar System
CBD:	Convention on Biodiversity
CBL:	Central Bureau for Areal Imagery
COP:	Conference of Parties
DEM:	Digital Elevation Model
DEMh:	Digital Elevation Model hydrologically corrected
DEMs:	Digital Elevation Model smoothed
DSM:	Digital Surface Model
FAO:	Food and Agricultural Organization
FCM:	Forest Canopy Model
GIS:	Geographic Information System
GLASS:	Geoscience Laser Altimeter System
GRASS:	Geographic Resources Analysis Support System
HAND:	Height Above Nearest Drainage
HWSD:	Harmonized World Soil Database
ICESat:	Ice, Cloud, and land evaluation Satellite
IPCC:	Intergovernmental Panel on Climate Change
IRD:	Institute of Research and Development
Lidar:	Light Detection and Ranging
QGIS:	Quantum GIS. An opensource GIS software
R:	software environment for statistical computing and graphics
REDD+:	Reduce Emissions from Deforestation and forest Degradation
RMSE:	Root Mean Square Error
SFISS:	Sustainable Forestry Information System Suriname
SBB:	Foundation for Forest Management and Production Control
SRTM:	Shuttle Radar Topography Mission
UNFCCC:	United Nations Framework Convention on Climate Change

1. Introduction

The natural environment is undergoing significant stresses from manmade climate change (IPCC, 2021), ecosystem degradation through deforestation (Ramirez, 2011), and loss of biodiversity (Pörtner et al., 2021). International agreements such as the COP, CBD conventions, attempt to limit the overall degradation of the natural environment by urging nations to self-regulate their environmental policies (UNFCCC, 2021) while ensuring sustainable usage of natural land resources (Holling, 2001; Foley et al., 2005), preserving cultural significant areas (Taylor, 2010), and providing equitable job opportunities for local and tribal communities (Government of Suriname, 2019). Naturally, such complex goals require intensive decision-making processes in a timely manner before irreversible damage to the natural environment occurs due to improper ecosystem services evaluation (Ehrlich et al., 1997).

Since systemic forestry data collection started in Suriname in the early 2000s (Whiteman, 1999), there has been an increasing trend in forest timber products including an increasing trend of forest degradation (Ramirez, 2011) and proliferation of illegal trade (Playfair, 2007). To reduce the risk of greater environmental damage, the government of Suriname adopted several strategies in line with global expectation for mitigating forest degradation and deforestation such as specifically addressing sustainable forest management guidelines in the Forest management act (Government of Suriname, 1992), implementing biodiversity protection strategies in policies (Government of Suriname, 2006), and continuously monitoring and reporting on the state of the forest for the benefit of international scientific community and other stake holders (Government of Suriname, 2020).

This research explores land evaluation methods which complement existing efforts to systemically enhance sustainable forest management practices. Specifically, this research attempts to utilize internationally accepted data sets and methodologies to optimize input features which are in turn used to evaluate, compare, and match against forest management practices and biodiversity conservation strategies. The aim is to create a comprehensible land evaluation system which should be able to determine the suitability of a land area using the Rabia, Storie, and Square Root method of land evaluation, compare their outcomes and evaluate their implications for current and future sustainable forest management practices.

The following research question is proposed to address the concept of this research: how do the Rabia, Storie, and Square Root method of bio-physical land evaluation using an optimized digital elevation model and hydrological network as primary input dataset reflect on current forestry practices in Suriname?

To address the research-question the hypothesis of this research is that the Rabia, Storie, and Square Root method of bio-physical land evaluation yield in varying degrees of suitable areas for sustainable forestry which in turn reflects the sustainability of past and present timber yield as well as having an influence on future timber production.

To accomplish this hypothesis the following objectives will be taken in successive order:

- Prepare input data for suitability maps
- Setup a framework for land evaluation scoring in close accordance with the FAO method of land evaluation
- Produce suitability factors based on a ranked scoring method
- Calculate final suitability index for the Rabia, Storie, and Square Root method
- Collect tree harvest data from Sustainable Forestry Information System Suriname database
- Evaluate tree harvest data with respect to the Rabia, Storie, and Square Root index.

The flow of this research as seen in figure 1 represents the steps that will be taken in successive order. This research is split into three distinct sections: pre-processing stage, suitability processing stage, and a final post-processing stage. In the pre-processing stage, the raw input data will be prepared with ancillary data using existing methodologies. The core of this research centers around producing suitability scores for the input features, converting those features into factors, and finally producing suitability indexes using the Rabia, Storie, and Square Root methods of land evaluation. Finally, an analysis is performed on the output of the three suitability indexes to assess the performance of current forest management.

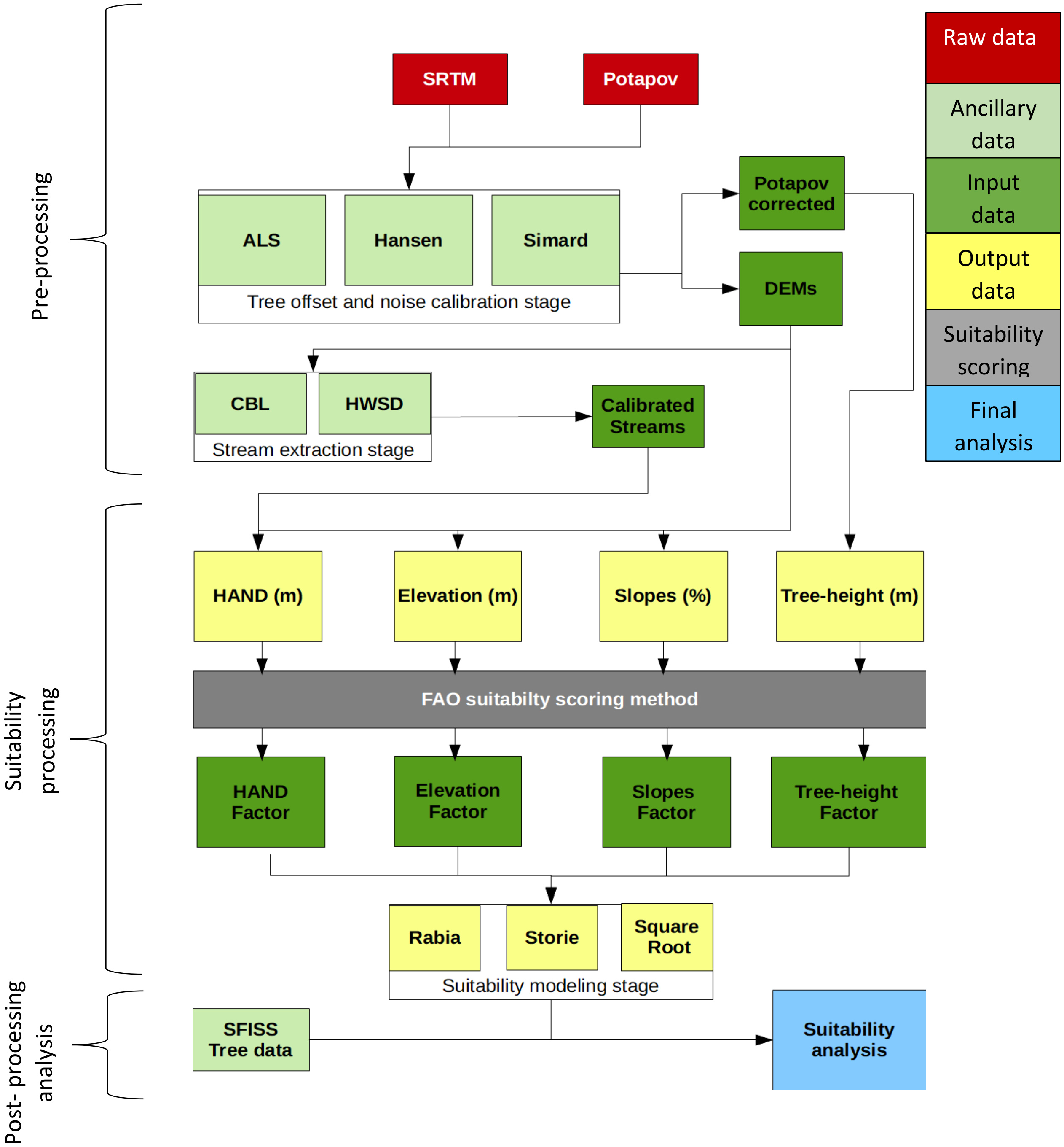

Figure 1: Flow diagram of the research project. The initial raw data goes through a series of refinement and calibration stages and outputs corrected input data for further processing. Input features go through an expert-based suitability scoring method and are transformed into suitability factors. These factors are combined into suitability indexes. A final analysis is performed using the sustainable information system Suriname tree data on the 3 output suitability models.

2. Literature Review

2.1 Transformation process within the forest sector

An important question for any resource management project is to question what the cost of exploitation is on its land units (Cekanavicius, 2003). Additionally, the FAO (1976) argues that the challenge is more in deciding what degree of land utility is permissible on a land unit. To tackle this question, it is necessary to employ some transformation process which will alter the paradigm of the current conventional resource management strategy into a sustainable resource management type (Geels, 2014) which is also able to distinguish between degrees of suitability for each land unit for a given management type (FAO, 1999). However, the conditions for what are considered transformation processes is difficult to narrow down due to its broad definition (Schneidewind, 2016). Nevertheless, this research is classified into establishing suitable areas for production forests as a sustainable socio technical transformation process in the forest sector for its use of existing technologies and methods which fosters and adapts capabilities and opportunities (Hollings, 2001), gives power to actors to challenge existing regimes (Schneidewind, 2016), and maximizes productivity on as small land base as possible (Brand, 2020). The following paragraphs will explore the technologies and methods used and discuss its probable effect on suitable land units for forestry in the study area.

2.2 DEM correction for optimal terrain feature modeling

First, there is a brief exploration and discussion on the technology and methods that are used in this transformation process. The primary input data source in this research is the Shuttle Radar Topography Mission dataset (Reuter et al., 2009). Considerable amount of time was spent understanding the limitations of this dataset prior to it being utilized in further raster calculations, hydrological modeling, and other surface transformations. The two primary areas of concern for many researchers are the tree height effect and random noise (Bock, 2009; O'Loughlin et al., 2015; Reuter et al., 2009). Tree height effect has the potential to alter drainage directions which lead to false drainage networks as well as increased terrain height in dense forested areas (Galant, 2009). Noise in the dataset may cause erratic slope formation as well as false drainage network (Galant, 2011).

Studies in the amazon basin have shown that vegetation error correction or tree height offset have improved modeling accuracies from 24% to 94% (O'Loughlin et al. 2015). Moore et al. (1990) argues that using an optimized Digital Elevation Model (DEM) with as few artifacts is essential for developing high quality terrain surface and hydrological models.

2.3 Sustainable Forestry as a land-use

Sys et al. (1990) define land-use planning as an *"objective to select the optimum land-use for each defined land unit, taking into account both physical and socio-economic considerations and the conservation of environmental resources for future use."* This statement by Sys et al. (1990) is in accordance with many forestry guidelines and research which have sought to explain the need for spatial planning to effectively manage carbon emissions (Houghton, 2017), warn against collapsing ecosystems due to deteriorating ecological services from sustained, unmanaged economic activities (Gretchen et al., 1997), and have suggestions for reducing carbon emissions and environmental degradation by optimizing forestry practices (Zalman et al., 2019). Moreover, the government of Suriname (2018) has acknowledged in their implementation of the National REDD+ strategy that the country's national strategy should be towards robust land-use planning and forest conservation. This willingness to incorporate land-use planning has echoed throughout the history of landscape protection and restoration in Suriname.

The Forest policy of Suriname written in 2003 (Government of Suriname, 2006) has listed several goals to improve sustainable forest management by following guidelines from the FAO. In particular, the forest policy was designed to agree with several international treaties including the Convention on Biological diversity (CBD) protocols. Primarily, the first goal of the policy aims to "*increasing the contribution (of sustainable forestry) to the national economy and the well-being of current and future generations while respecting the conservation of biodiversity."* This goal has been adopted within the national biodiversity strategy as "*Biodiversity will be conserved in Suriname through protection and enhancement of habitats and species at local, regional and national* scales" (Government of Suriname, 2006). These goals and action plans have contributed to diverse research into the geology and ecology of Suriname (Wong et al., 2009), rigid studies and experiments in sustainable forest management procedures (Werger, 2011), and multiple rapid assessments of vulnerable areas (Lim et al., 2012; Solari et al, 2007; O'Shea et al., 2013, Ouboter et al., 2012). The purpose of these studies is to facilitate decision making regarding sustainable forestry among other. More importantly they are supposed to minimize gaps in our understanding of evaluating ecosystem functions which in turn can be mapped using a land suitability analysis (Government of Suriname, 2006).

2.4 Suitability modeling

To address the first goal of the national biodiversity strategy and to fulfill the need for a forest suitability map for sustainable forestry, it is necessary to examine three methods for land evaluation: the Rabia method, the Storie method and the Square Root method. The Rabia method developed by Rabia et al. (2013) is a promising land evaluation method which aims to maximize suitable areas for a specific land-use by utilizing the land factor which has the most influence on the final land-use. In contrast, the Storie and Square Root parametric land evaluation methods attempt to estimate the land suitability score by selecting the land factor with either the lowest suitability score or a selected factor and utilize it to evaluate the remaining factors (Storie, 1978; FAO, 1976). Effectively this subtle change either increases the number of unsuitable areas as in the Square Root method or designates more moderate suitable areas to land units. Though there are many studies which investigate the differences in correlation between land suitability and actual land-use across suitability methods (Ghanbarie et al., 2016; Albaji et al., 2012; Rabia et al., 2013; Verheye, 2009) few found that there are minor differences with each evaluation method. It is therefore necessary to adhere back to the original FAO (1976) land evaluation guidelines which suggest that regardless of the methodology, each land unit should be evaluated with respect to the land-use type in question. This statement by the FAO suggests that there is no one method which suits the need of a particular land-use but that the method should be a function of regional context, land-use type and intensity, and available technologies and data.

3. Materials and Methods

3.1 Study area

As seen in figure 2, this research area is composed out of 4 equal sized extents that span across Suriname, French Guiana, and Guyana named: suitability extent 1 through 4. This was primarily done to decrease processing time. There are 3 smaller study areas to calibrate the SRTM from vegetation effect and random vertical noise (red grid), perform a flow accumulation threshold analysis (blue grid), and final suitability analysis using SFISS tree data was performed in suitability extent 2.

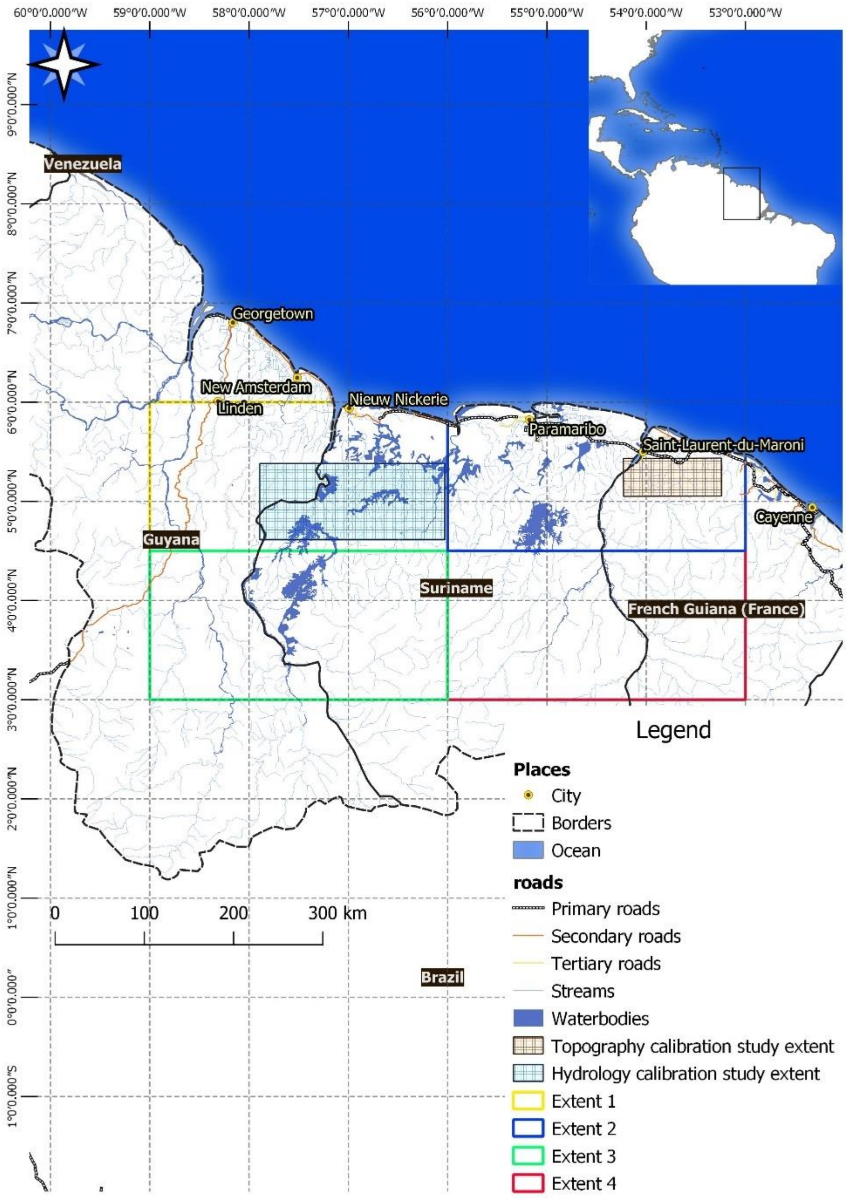

Figure 2: Overview of study area. The study area spans over 80% of the Surinamese land area, nearly 40% of the French Guianese land area and 30% of Guyana land area.

3.2 Materials

From the advent of free and open-source material online, there has been an explosion of new research in many different fields (Onoda et al., 2017). By utilizing these various data sources, it is now possible to conduct simple or advanced investigations in many parts of the world (Jolly, 2017). This research builds on the works of open-sourced and readily available data on the internet. The following is a list of materials used in this research, what their limitations are and how they have been incorporated.

3.2.1 Shuttle Radar Topography Mission 30m (SRTM), 2000

First, the primary input data for this research is the Shuttle Radar Topography Mission (SRTM) data with a spatial resolution of 30 meters (Far et al., 2007). The SRTM is a near global coverage of the earth's topography and has undergone extensive treatment and validation to reduce as many spatial errors as possible (Far et al., 2007). However, no dataset is void of errors or blemishes. The SRTM is derived from an X-Band and C-Band phased radar array and thus contains statistical noise that has been filtered out as much as possible (Reuter et al., 2009; Far et al., 2007). Further in this research the data itself which contains some minor random noise caused by the nature of the phased array that is utilized to capture the terrain (Far et al., 2007) will be discussed. This is a limitation in the dataset that is especially relevant in low-lying, flat regions (Köthe et al., 2009).

Additionally, the radar techniques employed have a crucial limitation of not being able to penetrate forest cover. Furthermore, it is unknown to which depth the radar data can penetrate the canopy layer before returning a bounce signal (Reuter et al., 2009). This could suggest that various forest types could return varying degrees of canopy penetration and thus yield varying degrees of elevation accuracy (Reuter et al., 2009). Either way, the global absolute error of the SRTM data is centered around 6 meters, which falls within the acceptable margins of accuracy (Far et al., 2007).

3.2.2 Potapov Tree height data, 2020

Next, the Global Forest Canopy Height Model (FCM) dataset developed by Potapov et al., (2020) shows the forest canopy height by using a Global Ecosystem Dynamics Investigation (EGDI) lidar instrument aboard the International Space Station (ISS) and in turn used machine learning algorithms to fit its data against Landsat derived indexes which resulted in a 30-meter resolution Global Forest Canopy Height Model (FCM). Their methodology shows that the accuracy of the dataset is related to a few factors: the training data used to train and validate the final product, the number of returns in the EGDI footprint, the topography of the terrain itself, and cloud coverage conditions (Potapov et al., 2020).

The accuracy of the Potapov tree height data can more directly be addressed by analyzing the training data (Potapov et al., 2020). To validate the EGDI dataset, the authors used strategic validation points from a variety of ecosystems. Though this method successfully generalizes the training dataset, it underestimates taller than 30 meters or lower than 13 meters. This limitation of the dataset will become apparent during the DEM processing of the SRTM dataset.

3.2.3 Aerial Lidar System (ALS) data 2016 -2017

For further correction of the SRTM dataset, high resolution, validated topographic and vegetation data is necessary. Airborne Lidar Systems were used from western French-Guiana. This data was provided by the Institute of Recherche et Development (IRD). ALS data were provided by ONF through a partnership with IRD and were acquired through grants from European Union (EAFRD), in the framework of French Guiana Rural Development Programme.

3.2.4 Sustainable Forestry Information System Suriname (SFISS) Tree data, 2021

The Sustainable Forestry Information System Suriname (SFISS), a subsystem of the NFMS, is built to specifically monitor nationwide logging activities (Crabbe et al., 2018). Crabbe et. al further argues that the SFISS was established to provide tools to the Foundation of Forest Management and Production Control (SBB) and the private sector to have a more efficient administration, reduce illegal timber harvesting, and further promote sustainable forest management. The primary source for the

SFISS system is a database that stores among other administrative data, a table containing trees intended for harvest or harvested. This table will be used to analyze the suitability model outputs in the final analysis. For this research a query was developed to extract all harvested trees within the database with their x and y geographic coordinates.

3.2.5 Hansen data, 2020

Over the years Hansen et al. (2013) tree cover data has proven to be especially useful in identifying global landcover changes. This is particularly the case in pan tropical regions where effective monitoring is limited by any number of factors (Achard et al., 2007). The Hansen et al. (2013) tree cover dataset captures global annual vegetation changes based on Landsat images dating back to the year 2000 where each year's change is classified in separate image bands. The authors used the year 2000 as a baseline upon which further yearly vegetation changes are calculated.

However, in this research the Hansen data will primarily be used to offset deforested patches from the Potapov tree height data which in turn will be used to correct the SRTM dataset. Specifically, the year 2000 of the Hansen dataset which corresponds to the year of acquisition of the SRTM is used to substitute deforested areas in the Potapov et al. (2020) tree height dataset.

3.2.6 Globeland30, 2000

Selecting a universal wall to wall landcover map is essential to capturing historical land-use patterns in a region and timeframe (Turner et al., 2007). For this reason, the landcover from Globeland30 may prove to be useful. The Globeland30 dataset has seen widespread adaptations in several fields (Arsanjani et al., 2016) and produced in several studies worldwide (Chen et al., 2017; Perez et al., 2017). The dataset consists of tiles of raster images where each pixel (resolution = 30m) has been assigned a numerical value which in turn corresponds to a given landcover type (Arsanjani et al., 2016). In their product, the land-use types have been classified using a pixel-object-knowledge algorithm that achieved an overall global accuracy of 80% with varying degrees of accuracy between countries. In this research the primary focus shall be on utilizing the global landcover map from the year 2000 which corresponds to the original creation date of the SRTM dataset (Reuter et al., 2009).

3.2.7 Simard global Canopy height data, 2011

Like the Potapov dataset, the Simard global canopy height data set is an attempt to map a wall-to-wall coverage of tree height data (Simard et al., 2006). Simard et al. (2006) created this dataset by using the Geoscience Laser Altimeter System (GLASS) attached to the Ice, Cloud, and land evaluation Satellite (ICESat). Between 2003 and 2009 the GLASS module scanned the complete earth with its lidar system and returned data which could be converted into canopy height. However according to the researchers, due to the limitations of the lidar system, climate and weather conditions, and orbital mechanics, the GLASS module was unable to obtain sufficient surface reflectance in the tropical broad leaf forests. To compensate the lack of data, the researchers attempted to optimize the GLASS data with MODIS data which served as spatially continuous ancillary variables. With this method it was possible to substitute the data where there is a sparce footprint.

The result of these procedures is a seamless, wall-to-wall coverage of canopy height dataset with a 1km pixel resolution (Simard et al., 2006). However, because some modeling has been involved to compensate for the sparse footprints, the researchers state that there is some degree of underestimate in tropical broad leaf forests with a root mean square error (RMSE) of 6.6m. In this research the Simard canopy height is utilized to substitute for missing data in the Potapov dataset.

3.2.8 Harmonized World Soil Database and Map (HWSD), 2010

The World Soils Database is an aggregation of soil related data compiled by the FAO in 2009 (Nachtergaele et al., 2010). Nachtergaele (2010) argues that the database and vector files consist mostly of the submission of soil information from a variety of critically assessed sources. Due to the dataset being a pool of information, there is some variability in the quality of the datasets where Southern and Eastern Africa, Latin America, the Caribbean, and Central and Eastern Europe have the highest quality data (Nachtergaele et al., 2010).

3.2.9 Centraal Bureau voor Luchtkartering (CBL), 1956-1958

Post second world war there was a need to map the interior of Suriname for the purpose of identifying land-use cases such as forestry, mining, and water management (Koeman, 1973). The map published by the Center for Aerial Photography and described by Koeman (1973) was produced by manually interpreting arial photos taken between 1947 and 1948 and later between and 1956 and 1960. The CBL maps were divided into 150 tiles which covers nearly the entire country. Though the accuracy of the map has not been fully assessed the CBL maps have been used as a baseline for all cartographic use-cases including identifying suitable areas for forestry. In this research, the CBL maps will be used as calibration data for stream origins.

3.3 Methods

The methodological workflow of this research is based on the principle that the correct input features are required to produce an accurate model of reality which in turn should produce a valid, accurate, and consistent final product for decision makers, policy advisors, and other relevant actors. To start, the SRTM must be calibrated by removing artifacts in the dataset. The works of Gallant (2016) shows that proper calibration of the dataset is essential for properly utilizing the SRTM, especially where hydrological modeling is required. After the pre-processing steps, the input features for the suitability model will be prepared. Afterwards, each factor for the final suitability analysis will be scored and combined. Lastly, an analysis of the suitability analyses will be conducted by sampling harvested trees from the sustainable forestry information system Suriname (SFISS) database and performing summary statistics.

3.3.1 Pre-processing

First, the SRTM is pre-processed by offsetting vegetation data embedded within the original dataset. To do so, the Potapov dataset is used as a proxy dataset which serves as a “best guess” for the tree height in each pixel. The first step is to analyze the Potapov dataset with higher resolution ALS tree height data to identify the limitations of the Potapov dataset specifically to the study area (study area: SRTM calibration extent). Prior to testing for regularity, a test for homoscedasticity is performed on the ALS tree height data and Potapov data. Images within the sample areas of the ALS data in French-Guiana are resampled to the raster images cell size of the Potapov dataset (30m). The

Potapov data is clipped and masked to correspond to the ALS data to ensure 100% overlap. Next, the ALS data and clipped Potapov data are converted from raster format to a 1-dimensional array and concatenated to form a 2-dimensional matrix where each column in the new matrix corresponds to the Potapov dataset or ALS dataset. The RMSE is calculated between the ALS and Potapov columns, followed by the difference of the dataset to determine the degree of fitness of the Potapov dataset.

After the degree of fitness of the canopy height offset fraction is calculated, the optimal canopy height offset fraction is calculated by iterating over the Potapov dataset and multiplying the raster image with a decimal value between 0.4 and 1 and a step function of 0.1. The residual value, R-squared, and intercept value between the resulting dataset and the ALS tree height data were calculated. The y-intercept was used as a proxy value to determine the degree of fitness. The iteration that produces the lowest intercept and residual value was considered the most optimal offset fraction to use for improving the fit between the Potapov data and ALS data.

The procedure is summarized as follows:

For all

$$\alpha \ in \ i \ to \ 1 \ by \ 0.1$$

given

$$f(\epsilon) = \sum \epsilon^2 = \sum(dem - \hat{d})^2 = \sum(dem - b - m \times als)^2 \rightarrow min$$

where

$$dem = dsm - (\alpha \times tree\_height)$$

and

$$\hat{d} = m \times als + b$$

then

$$f(b) = min(\sqrt{\sum(dem - \hat{d})^2} / _n) = min(\sqrt{\sum(dsm - (\alpha \times tree\_height) - (m \times als + b))^2} / _n)$$

The goal of this procedure is to achieve a perfect linear relationship y = x where y is the DEM and x equals the ALS data. However, in realistic conditions the equation resolves to y = m.x + b + e where the ALS data, x, is multiplied by some variable m, added with some bias b and an error e. It is possible to reduce the bias through bias fitting where the optimal estimation of the linear equation between the ALS and DEM is found i.e., the bias is forced through zero. The optimal DEM is then the result of the subtraction of the Potapov tree height data multiplied by a fraction α from the original SRTM DSM. Through regression analysis, the function of the errors ϵ is minimized such that $\hat{d}$ resolves to $m \times als + b$ where m is a variable that affects the slope of the ALS (als) data plus some bias. The bias is reduced to zero (or close to zero) to achieve the optimal relationship y = m.x + 0 + e by minimizing the RMSE of the ALS data and the created DEM data. This process was achieved by iterating over the α from 0.4 to 1 and a step function of 0.1 in the R program until the RMSE reached as close to zero as possible. The range for α was chosen to be between an arbitrary small nonzero value and 1.

However, in coastal areas with a different vegetation structure and a lack of ALS training data for the model, a comparable method was used to calibrate the SRTM dataset. In those areas an offset fraction of 0.65 was used to calibrate the Potapov data before subtracting from the SRTM dataset. This fraction was chosen after a series of trial and error. The offset fraction which produced the most visually accurate result was chosen as the final value.

The Hansen data is modified into a tree presence and absence map where all areas after the year of SRTM acquisition date are identified. Areas deforested after the acquisition year are mapped as 1 and non-forested areas as 0. The tree presence map was multiplied by the Simard dataset to acquire a map containing Simard tree height data from deforested areas after the acquisition period. The inverse of the tree presence map was multiplied by the Potapov dataset to mask out all the areas that have been deforested after SRTM acquisition date. Finally, the Simard and Hansen data are combined into a consistent tree height map that resembles the SRTM vegetation effect.

After calibrating the SRTM for vegetation, an attempt was made to reduce the random noise in the SRTM dataset. To do so the ALS topography dataset for calibration was used. First, the cell-size of the topography ALS dataset is set to match the vegetation corrected SRTM dataset. Afterwards, the corrected SRTM is clipped and masked to overlap the topography ALS data. To smooth out the random noise of the SRTM dataset the Lee sigma smoothing filtering algorithm (Lee, 1983) was used by setting the window-size to 5 by 5 pixels and iterate over the sigma value between 0.5 and 4 and a step value of 0.5. The Lee sigma smoother filter uses a gaussian distribution to minimize noise in a user defined kernel (Mansourpour, 2006). It is a variable in the gaussian equation that determines its size. As the sigma value increases, the intensity of the gaussian distribution increases and thus decreases the overall variance within the kernel (Lee, 1983). In each iteration the intercept value, slope, and correlation between the SRTM smoothed and ALS topography data was calculated. The iterations which produced the lowest intercept value and correlation would be contestant of being the most optimal smoothing factor for the Lee sigma smoothing filter. Lastly, the slopes of the DEMs and original SRTM dataset assessed to analyze the effects of the Lee sigma smoothing filter.

The final step for optimizing the DEMs was to prepare it for hydrological modeling. Hydrological correction is an attempt to produce more accurate hydrologically models from the DEMs (Pinel et al., 2015). With input of the land-use layer from Glob30, the waterbodies class was filtered and used to “burn” in hydrological features such as lakes, rivers, and streams. However, to do so the filtered hydrological data from Glob30 was converted into a binary map where 0 indicates dry land and 1 water. After some initial tests, a gaussian filter of sigma=2 over a window of 5 pixels was used to smooth out the transition between dry land and water features. The resulting map was multiplied by a constant of 5. The burn map is subtracted from the DEMs to produce a DEMh map.

3.3.2 Suitability processing: input features creation

After the pre-processing phase, the input features for the suitability factors were created using R software. Specifically, the slopes dataset was created using the GDAL slopes algorithm (CERL, 1993). However, to produce accurate input features the correct parameters had to be set up. The first input feature is the height above nearest drainage (HAND) data which shows the relative elevation of a pixel above the nearest stream. This data is useful for identifying hydromorphic and dry areas (Guitet, 2015). However, the HAND requires that a comprehensive hydrological network is computed.

Producing a comprehensive stream network can be computed using the GRASS hydrological module (Ehlschlaeger, 1989; Holmgren, 1994; Montgomery, 1993). After having produced a digital elevation model that has been corrected for vegetation, noise and hydrology, a flow accumulation model where each pixel represents the accumulation or summation of the value of its neighboring pixels was computed in GRASS.

The next step to create a hydrological model was to select a threshold on the flow accumulation map which functions as a global stream origin. However, since the hydrological model covers the extent of varying geological and geomorphological strata (the hypothesis is that this influences the formation of streams) an adaptive flow accumulation threshold per geological stratum is applied.

An adaptive threshold map was created by first utilizing the HWSD soils map to distinguish the geological units by their drainage capacity and slope steepness. The CBL map which shows detailed hydrological information were used to randomly point sample as many stream origins per soil unit. In total, 217 stream origin points were found using the CBL maps. After which, the sample points were buffered into circular polygons 90 meters in diameter. This was done to account for any spatial disparity between the CBL maps and flow accumulation map. The buffered points were subsequently used to derive the maximum flow accumulation value within their perimeter. Summary statistics on the maximum flow accumulation value per buffered points were calculated per drainage class. This yielded information on the flow accumulations minimum, maximum, average, and median flow accumulation value per drainage class. With this information it was possible to convert the soils map containing drainage rate into flow accumulation stratifications map. This map was used as a weighted mask to normalize the flow accumulation map. After accounting for depressions in the weighted flow accumulation map, a comprehensive stream network was created. Finally, the stream network, elevation, and drainage network maps were used in GRASS' hydrology module to produce the height above nearest drainage network map.

The remaining input features require no manual treatment and were easily calculated using GIS functions. The slopes map as input feature was created by utilizing the raster R package. At first the slopes were expressed as degrees. However, to be useful as a suitability factor, the slopes map was converted into percent. Lastly, the corrected Potapov canopy height model was directly used as an input feature.

3.3.3 Suitability processing: Feature transformation and suitability score determination

Individual factor values heavily influence the final suitability of a land unit. Therefore, valuating each individual factor had to be carefully considered. First, the input features were transformed into land suitability orders: Suitable and not suitable. In this thesis the suitability order is based on previous work from the SBB: the binary suitability map for sustainable forestry. The suitable and not suitable areas were classified using commonly applied guidelines for sustainable forest practices (Van der Hout, 2011). For the slopes, hydromorphic, elevation, and canopy height factors the suitability orders were determined primarily by the Code of Practice for Sustainable Forestry in Suriname, the forest policy of 2005, the results of rapid assessments in various regions, and the forest act of 1992.

Next, the orders are further subdivided into suitability classes. The classification for each suitability class was done conforming the FAO (1976) method of suitability class evaluation. A table was constructed which refers to the suitability score and description. Each factor, in turn, was scored accordingly. Classification of the factors was based, among others, on economic feasibility and the preservation of vulnerable areas. The scoring of the suitability classes was primarily executed using a classification assignment function in R where raster values in the input feature were reclassified.

After scoring the suitability factors, final land suitability models were created by combining the factors into a single output. Three models were calculated: the Rabia method, Storie method, and Square Root method. These methods for land evaluation have been tested in applications ranging from various forms of agriculture including agroforestry (Baroudy et al., 2020; Albaji et al., 2017; Rabia et al., 2013). The main principle of the previously mentioned methods is to evaluate a land unit based on its individual factor scores. This evaluation technique is a purely mathematical equation which interprets the product of the individual factors in a specific manner.

The suitability index is calculated per pixel i,j of the factor raster grids in the study extents. In R the factors were combined in a single raster file format containing 4 bands: elevation, slopes, forest canopy height model (FCM), and HAND data. The bands were combined using the R raster calculation function, calc. This effectively performed a per pixel computation on the dataset. The computations of the suitability models are described below.

$$Rabia \rightarrow S_{i,j} = w_{max} \times \sqrt{\left(\frac{x_1}{100}\right) \times \left(\frac{x_2}{100}\right) \times \left(\frac{x_3}{100}\right) \times \left(\frac{x_n}{100}\right)}$$

$$Storie \rightarrow S_{i,j} = x_1 \times \left(\frac{x_2}{100}\right) \times \left(\frac{x_3}{100}\right) \times \left(\frac{x_4}{100}\right) \times \left(\frac{x_n}{100}\right)$$

$$Square\ Root \rightarrow S_{i,j} = x_{min} \times \sqrt{\left(\frac{x_1}{100}\right) \times \left(\frac{x_2}{100}\right) \times \left(\frac{x_3}{100}\right) \times \left(\frac{x_n}{100}\right)}$$

Where $S_{i,j}$ represents the suitability score output for either the Rabia, Storie, or Square Root method, x_1 through x_n represent the individual factors with scores 0 to 100, and x_{min} represents the lowest factor scoring for pixels i,j in factors x_1 to x_n.

Rabia et al. (2013) attempts to maximize suitable areas by utilizing the highest weighted factor as the multiplier and the square root of the product of the remaining normalized factors as the multiplicand. The highest rated factor in the Rabia method is calculated through evaluating the analytical hierarchy process (AHP) method (Saaty, 2008). First a ranking scheme derived from Saaty (1980) was developed specifically for this research. The ranking scheme in this research is numbered 1 to 4 where 4 equals highest importance, 1 indicates equal importance. Next, the input factors were ranked in a pairwise scoring matrix. The resulting matrix was normalized and the eigenvectors for each input factor summed and divided by the total number of input factors. This resulted in a vector of scores. The input factor with the highest weighted score is used as w_{max} in the Rabia method.

In contrast to the Rabia method which uses the highest weighted factor, the Square Root method utilizes the lowest factor scoring per pixel group. To derive the lowest factor score, a vector of length 4 was constructed per land unit. In R, the “min” function was used on this vector to retrieve the factor with the lowest score and used as the multiplier while the square root of the products of the normalized remaining factors are used as the multiplicand.

The Storie method does not take the square root of the product of the normalized factors but instead multiplies any chosen factor by the normalized remaining factors. In this research the slopes factor was chosen to represent the multiplier, x_1.

The resulting suitability maps from the applied models on the input factors are raster data with values between 0 and 100. To analyze the resulting suitability maps, spatial statistics were calculated on the maps to investigate the distribution of suitability per suitability class. The suitability raster data are then reclassified using the classify function within R where each class is reflects the suitability classes determined earlier in the process. Next, the pixel values were counted per raster class with the R table function. The tabled data is normalized to produce a density distribution of the suitability dataset which produces the percentage of pixels designated to each suitability class. This density distribution along with the suitability maps were used to compare against harvested trees in the SFISS trees study extent as seen in figure 2.

3.3.4 Post-processing analysis with harvested SFISS tree data

Finally, after the suitability maps were calculated, spatial statistics were conducted on a test area (SFISS Tree sample area) which include harvested tree information from the Sustainable Forestry Information System Suriname database (Crabbe et al., 2018). The harvested trees contain geolocations which were used to sample the pixel class value of each suitability model. Summary statistics were calculated directly in QGIS on the tree data with their respective suitability score using the point-sample algorithm. Lastly the relative ratio between trees harvested in the suitable order and the total suitable order areas is calculated.

4. Results

4.1 Pre-processing and feature creation

4.1.1 ALS data compared against Potapov data

The higher resolution ALS tree height data within the study area showed some considerable differences with the Potapov dataset. The first notable characteristic is that whereas the ALS tree height data shows a gradual decrease in taller trees (>=30 meters), the Potapov data seemed to taper of rapidly at 32 meters tall. This is reflected in figure 3 which shows most trees cluster around the upper spectrum of the dataset (31 meters).

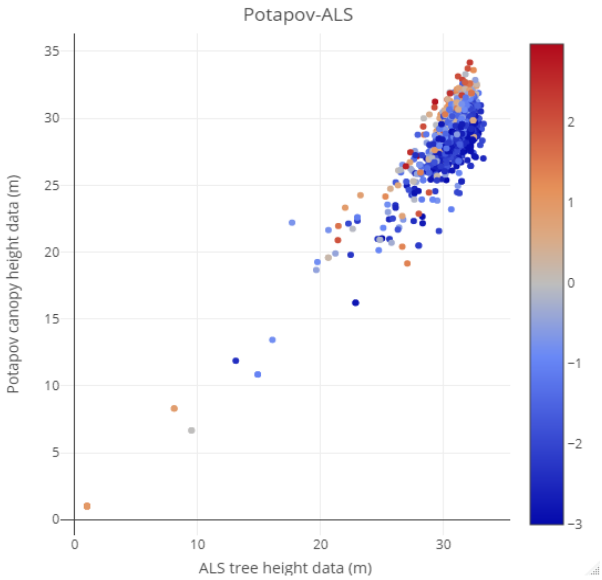

Figure 3: Potapov tree height sample points plotted against lidar tree height data samples show their relative correlation. While there is a vague linear relationship, there is also an upper limit to Potatpov data (32 meters). The color spectrum indicates whether there is an over or under estimation compared to the ALS data set.

Furthermore, this dataset shows that the Potapov dataset is overestimating ALS tree height data as the RMSE between the Potapov, and ALS tree height dataset is around 4 meters. The standard deviation (5m) within the residual data meant that there is some bias in the Potapov data that needs to be corrected. The ALS tree height and Potapov canopy height data show some amount of homoscedasticity ($p > 0.05$) upon which a simple bias fitting model could be applied.

4.1.2 Estimating optimal offset fraction from lidar data using bias fitting method

After temporally adjusting data from the Potapov dataset with the Simard dataset due to deforested areas during the date the Potapov tree height data was acquired compared to the SRTM data acquisition, the objective was to offset the tree height data. Offsetting the tree height required finding the most optimal offset fraction to reduce the overall height parametrically. Over the course of 7 iterations the fraction was increased by a decimal point (0.1) which led the intercept value to decrease from 14.95 to -2.49. As the intercept value decreased the residual decreased to -1.56 and increased back to 4.74. This decreasing trend is observed in figure 4 where there is a rebound in the intercept value as the offset increases to 1. The residual of 4.74 corresponds to having not performed any modifications on the Potapov dataset.

The lowest intercept value (0.41) also corresponds to a low mean residual value (1.59) although still overestimates the ALS tree height dataset by over 1.5 meters. Given that as the offset fraction continually decreases, the intercept increases, a value of 0.9 (which yields the lowest intercept value) as seen in table 1 was used to multiply against the Potapov dataset.

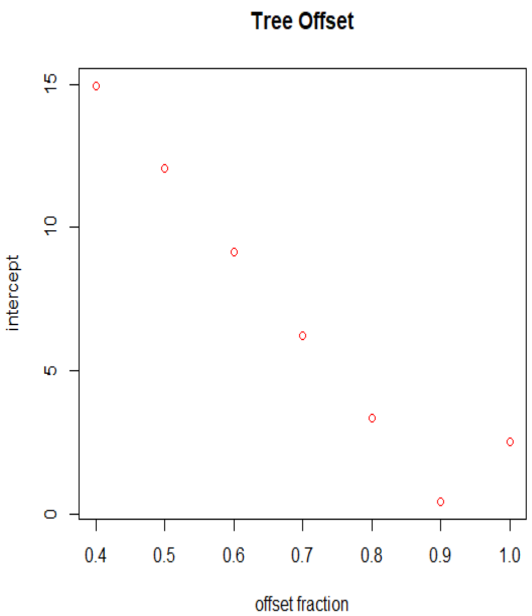

Figure 4: iteration of the tree height offset fraction with a step function of 0.1. the function f(x) = mx + b. Where b equals the relative bias of the origina SRTM data.

Table 1: Multiplier offset fraction and resulting b intercept and tree height residual value. With each attempt, the offset is increased by 0.1 and influences the value of the b-intercept. The mean residual between the ALS and Potapov data changes as a result.

Attempt	Offset Fraction	b-intercept	Mean Residual
1	0.4	14.95	-14.12
2	0.5	12.05	-10.98
3	0.6	9.14	-7.84
4	0.7	6.23	-4.70
5	0.8	3.32	-1.56
6	0.9	0.41	1.59
7	1	-2.49	4.74

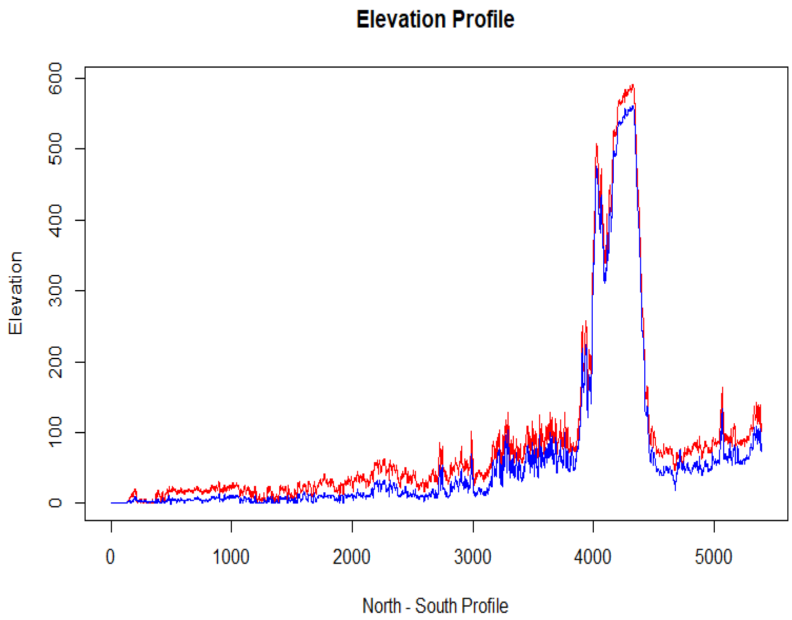

Figure 5: Elevation profile showing DSM uncorrected in red and DEM model in blue after performing tree height offset methods.

For inland trees, an offset fraction of 0.9 yielded acceptable results (free of voids, sinks, null values) with the SRTM dataset. Mountainous regions, medium hilly terrains and savanna areas showed proper removal of canopy height information while leaving non forested areas untouched. In the savanna belt where there are patches of non-forest areas, which influence hydrological models (Reuter et al., 2009), the offset method managed to equalize the forest and non-forest areas with the forest cover areas. A gaussian filter (sigma=2, window=5x5) was necessary to remove edge effects on these areas to make the gradient of the transition less abrupt.

In coastal areas another approach was necessary as using an offset value of 0.9 resulted in negative elevation values in the SRTM data. A lower offset value was used which minimized the negative elevation values in the resulting DEM. After masking the coastal zone in the Potapov dataset, experimenting with the offset fraction showed that an offset of 0.6 yielded desirable results. Though there were still vegetation artifacts visible, there were fewer negative sinks in the DEM while other locations seemed to have been made comparable to a bare earth model.

Figure 5 gives a good impression how the resulting DEM compares to the original SRTM dataset. From the data points it was concluded that there was no significant difference in data quality between the coastal area processing method and inland processing method.

4.1.3 Lee sigma noise reduction of DEM

The Lee sigma noise reduction method was used to minimize noise on the SRTM dataset. Here several sigma values were used on a fixed 5 x 5 pixels window kernel which resulted in increasingly smoother terrain features. As the sigma value increases (step = 0.5), the intercept of the linear model between ALS altitude data and the vegetation corrected SRTM data increases thus signifying a more linear fit. As seen in figure 6 and table 2, at sigma = 3, the intercept of the linear model has reached its lowest value and only steadily increases afterwards. In contrast, the correlation between the ALS dataset and smoothed dataset sits between 0.67 and 0.63 and does not vary more than 0.02 from a mean of 0.65 ($p < 0.001$).

Upon inspecting the ALS data and the SRTM data, it was apparent that the former had clear hydrological features which the SRTM data could not replicate. For that reason, as the smoothing factor increased, the remaining hydrological features blended in with other terrain features. As a result, there was a risk of increasing between group likeness and decrease within group likeness whereas the objective was to minimize between group likeness by preserving as many terrain features as possible after smoothing.

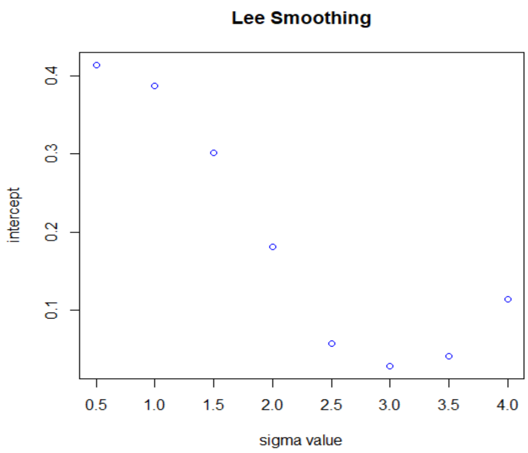

Figure 6: Lee Smoothing Sigma value plotted against b-intercept

Table 2: Sigma value table and corresponding similarity to Lidar dataset

Attempt	Sigma	Intercept	Slope	Correlation
1	0.5	0.41	1.55	0.67
2	1	0.39	1.56	0.66
3	1.5	0.30	1.58	0.64
4	2	0.18	1.59	0.63
5	2.5	0.06	1.59	0.63
6	3	0.03	1.54	0.64
7	3.5	0.04	1.47	0.65
8	4	0.11	1.39	0.66

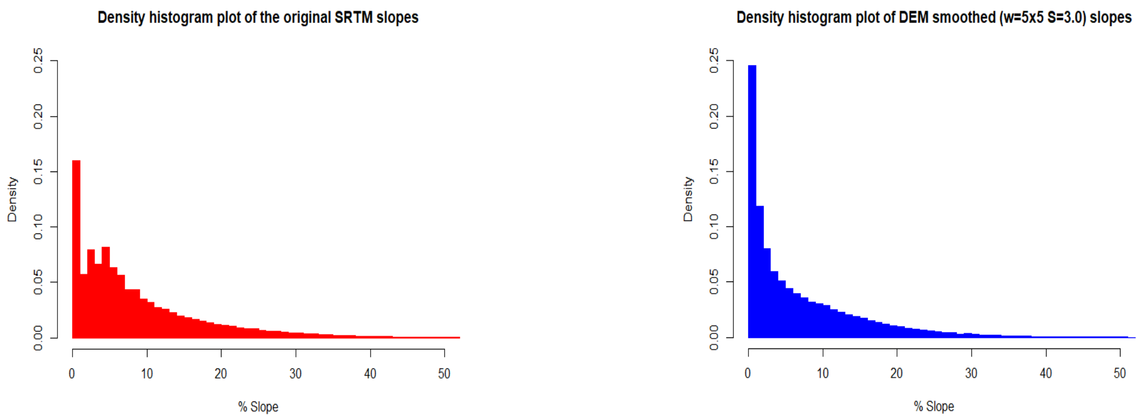

Figure 7: A comparison between slopes computed from the DSM (left) and slopes computed from DEMHs (right). The slopes index an expression of terrain texture of the study area.

One metric to evaluate the effects of the smoothing algorithm is to compare the slopes before and after smoothing the SRTM data. Since the slopes are simultaneous a function of terrain texture and a function of terrain suitability (Rosenbloom et al., 2001; Singh et al., 2019), it was considered a proper evaluation technique. Figure 7 is a slope analysis of suitability extent 2. The slopes after smoothing show a reduction in slopes over 20% compared to having done no smoothing. The smoothed DEM thus has fewer variation in terrain texture which influences the slope steepness and slope length which altered the drainage direction and flow accumulation values. Note that the density of flat areas (0%) is noticeably higher in the DEMHs (density = 0.25) compared to the original SRTM (density= 0.16).

4.1.4 Hydrological Network

After smoothing, a comprehensive hydrological model was created using the smoothed DEM as input feature. Soil profile classes were used as classification units where each class was hypothesized to contain a distinct flow accumulation threshold. Table 4 shows summary statistics of this hypothesis and indicates that each class contains varying flow accumulation thresholds from the predicted stream origin per soil profile class.

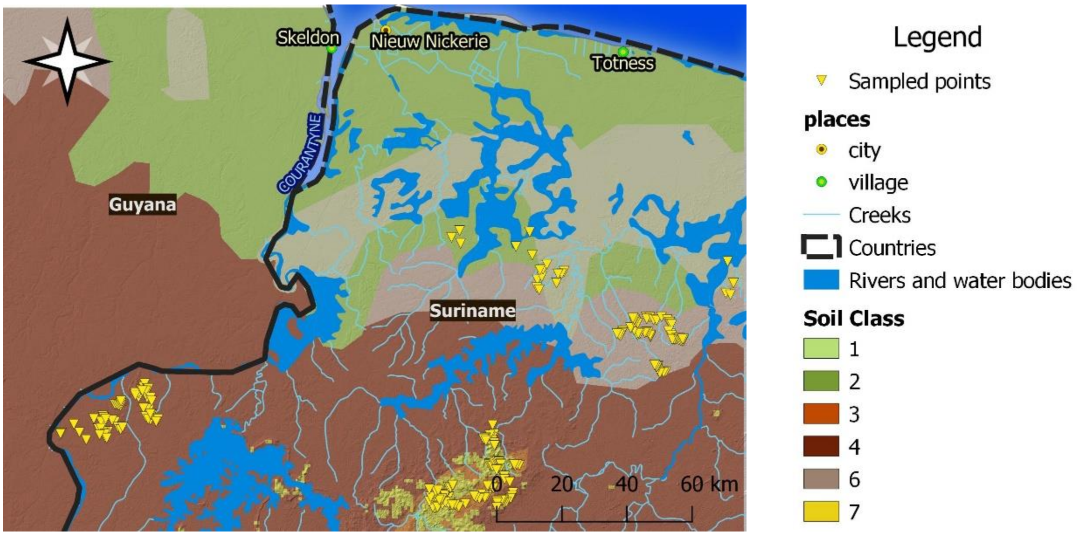

Figure 8: Sampled points distribution on soil profile map. Sampled points are based on CBL maps 14d, 25a, 25d, 26a, 34b, 34c, 34d. Soil class 7 is derived from class 3. However, the main difference is that geomorphic features which have a slope greater than 30% are filtered.

Table 3: Soil profile drainage classification and description

Soil Profile Class	Soil profile(s) name FAO90	Drainage capacity	Soil Characteristics (Gray & Murphy, 2002)
1	Fibric Histosols	Very Poor	Composed of organic materials
2	Albic Plinthosols	Poor	Wet, hard layer of iron, clay, and quartz in subsoil
3	Dystric Leptosols	Imperfectly	Very shallow depth over hard rock, or very gravely
4	Haplic Ferralsols; Dystric Leptosols; Xanthic Ferralsols	Imperfectly to Moderately Well	Deep and strongly weathered physically stable but chemically poor subsoil, and hard bedrock or gravely
6	Albic Arenosols	Somewhat Excessive	Sandy, very weak or no pedologic development
7	Haplic Ferralsols; Dystric Leptosols	Imperfectly	Deep and strongly weathered physically stable but chemically poor subsoil with traces of gravels and hard bedrock

Table 4: Flow accumulation sample points summary statistics

Soil Profile Class	Sample Points	Flow accumulation value (number of pixels)			
		Minimum	Max	Mean	Median
1	10	431.8	1726.37	976.34	850.13
2	6	1582.06	5820.43	4372.93	4635.91
3	8	42.39	310.26	137.18	124.64
4	81	88.5	3010.45	508.35	326.23
6	64	41.55	1964.02	220.54	145.54
7	48	25.38	384.7	102.19	83.64

Sample points were randomly distributed on a soil class map to provide a way to categorically sample the flow accumulation map (figure 8). CBL maps provided ground truth orientation to locate probable stream origin. Each soil profile class contains specific soil characteristic (table 3) which influences overland flow origin, drainage direction, and flux magnitude (Leopold, 1953). Notice in table 4 that each soil class has a unique mean and median flow accumulation threshold denoting a likely stream origin. Also note that the number of samples per class are low (6 samples) in soil profile classes where permeability is low due to the parent material (soil class 1, 2, and 3) and higher where the soil structure contains more granular grains (soil class 4 and 6).

Using the summary statistics, the mean value was selected as a threshold for the GRASS hydrological model. The resulting stream network shows a significant variation between stream density per soil profile class in the young coastal plain (soil class 1, 2 and 6) and in the Amazonian basin (soil class 3, 4, and 7). Particularly in soil profile class 3 through 7, the stream data corresponds well to the CBL maps spatially. In coastal areas, there was often a discrepancy between stream location between the modeled streams and the CBL. Inspection of the stream data show that the model was either hindered by infrastructure and building artifacts in the DEMs data, misled by false drainage direction and uncertainty caused by latent vegetation artifacts in the dataset.

The streams along with the elevation data, and drainage direction were used to compute the Height Above Nearest Drainage model. The HAND model showed proper elevation above stream data, especially in complex geographic terrains. In lower elevations with an almost smooth relief, the HAND model shows extended hydromorphic areas as expected.

4.2 Suitability processing

4.2.1 Factor scoring based on land characteristics

After the input features were generated, classifying, and determining the description of each suitability order and class was the next point of focus. First, the suitability orders were subdivided into 2 parts: Not suitable and suitable respectively. In this research suitable areas are defined as productive forests where some form of sustainable forestry can be performed with degrees of degradation of the natural environment. Not suitable areas are classified as those areas where no sustainable forestry can be performed without bringing unrestorable and/or permanent damage to the natural environment. Table 5 gives an overview of the structure of the orders and classes. Not suitable order ranges from a suitability score of 0 to 25 whereas the suitable order is given a score between 25 and 100.

The orders of the suitability model are subdivided into classes which add some extra dimensionality to the ordered set. The suitability order is divided into three suitability classes where each class represents a score given to the land utilization activity and how it may either impact the natural environment or the quantifiable and non-quantifiable costs of operating on such an area. The terms marginally suitable, moderately suitable, and highly suitable are given to the classes within the suitable order to summarize the impact on the surrounding area given that the land area is used for forestry activities.

Though the scoring and description of the suitability classes are based on the official FAO classification (FAO, 1976), manual adjustments were made in the terminology to reflect current forest land utilization methods. Furthermore, the classification score has been adjusted to reflect current land-use scenarios within Suriname and French Guyana.

The interpretation along with their descriptions guided the scoring of the individual factors. Careful consideration was given to each factor as to portray a realistic overview of how forestry as a land-use is limited by physical characteristics of the terrain. The elevation, forest canopy height model, slopes, and HAND model each relate to specific limitations of the land unit that affect either the drainage capability, soil and slope stability, impact on the ecosystem, health and safety for those operating in that area, and the overall productivity of the land unit.

Table 5: Suitability class descriptions

Suitability order	Suitability Class	Score	Description (FAO, 1976)
S: Suitable	S1: Highly Suitable	75 - 100	Land having no significant limitations to sustained application of sustainable forestry or results only in minor limitation that will not signifactly reduce productivity or other ecological benefits and functions.
	S2: Moderately suitable	50 - 75	Land having some limitations which in aggregate are moderately severe for sustained application of the given land utilization type; the limitations will reduce productivity or the benefits and increase required inputs to the extent that the overal advantage to be gained from the use wull be appreciably inferior to that expected on class S1.
	S3: Marginally suitable	25 - 50	Land having limitations which in aggregate are severe for sustained application of the given land utilization type and will so reduce productivity or benefits, or requires inputs, that this expenditure will only be marginally justified.
N: Not Suitable	N1: Marginally not suitable	10 - 25	Land having limitations which may be surmountable in time but which cannot be corrected with existing knowledge at currently acceptable cost; the limitations are so severe as to preclude successful sustained application of the given utilization type.
	N2: Permanently not suitable	< 10	Land having limitations which appear so severe as to preclude any possibility of successful sustained application for forestry in particular.

The scores of the factors were assigned by substituting the values of the original input data with its corresponding suitability score. Table 6 gives an overview of the assignments of the scores to each input data. The class N2 was determined by taking into consideration those land-use characteristics that are prohibited by law and are contrary to agreed policies for sustained forest applications. In the following paragraphs the limitations and rationalization of the classes N1 through S1 land characteristics are listed.

Table 6: Factor classification table

Suitability Score	Elevation (m)	FCM (m)	Slopes (%)	HAND (m)
N2: 0	0-2 AND >= 400	0 - 5	> 30	0 - 1
N1: 10	2 - 5	5 - 10	25 - 30	1 - 2
S3: 25	5 - 10	10 - 20	20 - 25	2 - 5
S2: 50	--	20 - 25	15 - 20	5 - 10
S1: 75	10 - 25	--	10 - 15	10 - 20
S1: 100	> 25 AND < 400	> 25	0 - 10	> 20

The elevation data was segmented into 5 distinct classes: sea level and biodiversity sensitive areas (N2), coastal strip (N1), young coastal plain (S3), old coastal plain (S2), and inland areas (S1). Coastal strip (0 to 2 meters altitude) is generally considered to be unproductive terrain mostly due to the presence of protected mangrove forests, wetlands and other areas that are considered of no value for sustainable forestry but high value for biodiversity and coastal zone management (Erftemeijer and Teunissen, 2009; Noordam, 1990; Wong, 1986). The young coastal plain is vegetated with trees between 5 and 15 meters however also contains wetlands, agricultural fields, sporadic mangrove forests, build up areas, and generally unfavorably areas for productive, sustainable forestry (Erftemeijer and Teunissen, 2009). The old coastal plain has somewhat taller trees between 10 and 20 meters especially in savanna forests which are actively in use by Amerindian villages for self-sustenance (Werger, 2011). Lastly, the inland areas contain trees between 20 and 40 meters, has the most production forests, and most suitable forest areas for prolonged sustainable forestry (Tropenbos International Suriname, 2015). However, above 400 meters in altitude, rapid assessment studies in strategic locations in Suriname show that there are endangered biomes that are to be preserved from intensive activities such as mining, forestry, and agriculture (Alonso and Berrenstein, 2006).

The Potapov forest canopy height model (FCM) is segmented into grasses and shrubs (N2), low trees (N1), medium trees (S3), secondary forests (S2), primary forests (S1). When trees are classified into a suitability score, several assumptions about the quality of the timber, and their commercial value in each height category are applied. Vegetation in the class "low trees" (trees between 5 to 10 meters) are defined as trees according to the FAO (1976), however, due to their relative diameter at breast height, they are of no considerable commercial value that would warrant any harvesting efforts (Van der Hout, 1999). Moreover, medium trees between 10 to 20 meters could be considered harvestable when trees intended for firewood, and pole-wood are considered (Van Dijk, 2011). Though these trees do offer some functional utility, they are still considered too small for sustainable forestry and therefore receive a marginally suitable class. Trees between 20 and 25 meters are in-between medium and high trees in the medium-high classification scheme. The distinction is that the locality of trees with these characteristics are often attributed to either savanna forests, secondary forests, or previously harvested forests (FAO, 2010). Though there are still some commercially viable trees found in these areas, they are frequently less commercially viable than taller trees or trees found in primary forests and are thus classified as moderately suitable. Primary forests are the most suitable for sustainable forestry since their ecosystems have not been damaged due to previous logging or have experienced enough time to regenerate and contain sufficient commercially viable trees taller than 25 meters and if all conditions are met, contain very few limitations that prohibit timber production (Van der Hout, 1999).

The slopes factor is important for a variety of reasons related to the land characteristics. Slopes influence the rate of soil loss in the universal soil loss equation (Liu et al., 2000), influence the way sustainable forestry can be performed, as well as impacts operational safety and costs (Van der Hout, 2011). In this paper the slopes are segmented into 5 classes: flat terrain (S1), low undulating (S2), medium undulating (S3), high convexity (N2), strong convexity (N1). Flat terrains generally do not contain limitations that would hamper sustainable forest activities and are preferred for planning skid-trail and therefore receive the highest rating. Though it is still possible to perform sustainable forestry on low undulating terrains (10 to 15%), there is extra effort needed to either haul the trees from their origins to the landing site or some amount of hazard during or after felling. Although these areas are still regarded as highly suitable, they are less suitable than flat terrains. Medium undulating terrains (15 – 20% of slopes) are accessible but there is extra effort needed to design proper skid trails to evacuate harvested trees, some environmental damage could occur especially during felling, an increase of risk, and potentially unstable slope conditions limits the extent on which sustainable forestry can be done. For areas with slopes greater than 20% and less than 25% (highly undulating terrains), there are more restrictions towards planning landing sites, skid trail routes, as well as an increased risk of erosion due to the removal of vegetation. Considering the limitations of this class, a classification of marginally suitable for forestry has been assigned to this class. Slopes between 25 and 30% have been designated as marginally unsuitable for sustainable forestry as studies have pointed to the risk of erosion and consequently increased run off from rainfall reaching nearby streams (Zhang et al., 2017). Lastly, by directions in the Code of Practice for Sustainable Forestry in Suriname (2003) it is not allowed to harvest trees on slopes above 30%.

The distribution of phenology depends on a few factors: geomorphology and hydrology (Schietti et al., 2014**;** Guitet et al., 2015). This research was primarily focused on the properties of stream and overland flow and how they relate to effective forest management protocols and how the distribution of tree species may vary to the horizontal and vertical position of the nearest drainage area. The distribution, quantity and quality of tree species is believed to be correlated on the vertical distance to the nearest stream. Guitet et al (2015), and field visits between 2014 and 2018 show a relationship between tree density and their vertical and horizontal proximity to streams. It states that as forest density increases, and tree biomass decreases as you near a drainage path. Therefore, the HAND is used as a proxy tool to differentiate between hydrological zones of suitability: hydromorphic zone (N2), transitional zone (N1), seasonally flooded zone (S3), lower mesophytic zone (S2), upper mesophytic zone (S1). The hydromorphic zones are considered permanently not suitable because of the direct influence the stream has on that zone. The forest act (1992) states that harvesting trees in areas that are directly influenced by the hydrology of a stream to protect the waterway from debris or damage to the soil. Transitional zones are described as those areas that form the boundary between wet and dry land but those that are still under the influence of tides or precipitation and are therefore unsuitable for sustainable forestry. The seasonally flooded land units are given a score of S3 because while they are mostly dry, they are subjected to flooding when prolonged, intense rainfall occurs. The mesophytic zone is split into 2 parts: the lower mesophytic zone and the upper mesophytic zone. Here the following assumption are made: the lower mesophytic zone contains more diversity in tree species however, the upper mesophytic zone may contain higher quality timber species (Schietti et al., 2014). Finally, a full suitable score (S1) is applied for those areas that are 20 meters above the nearest drainage.

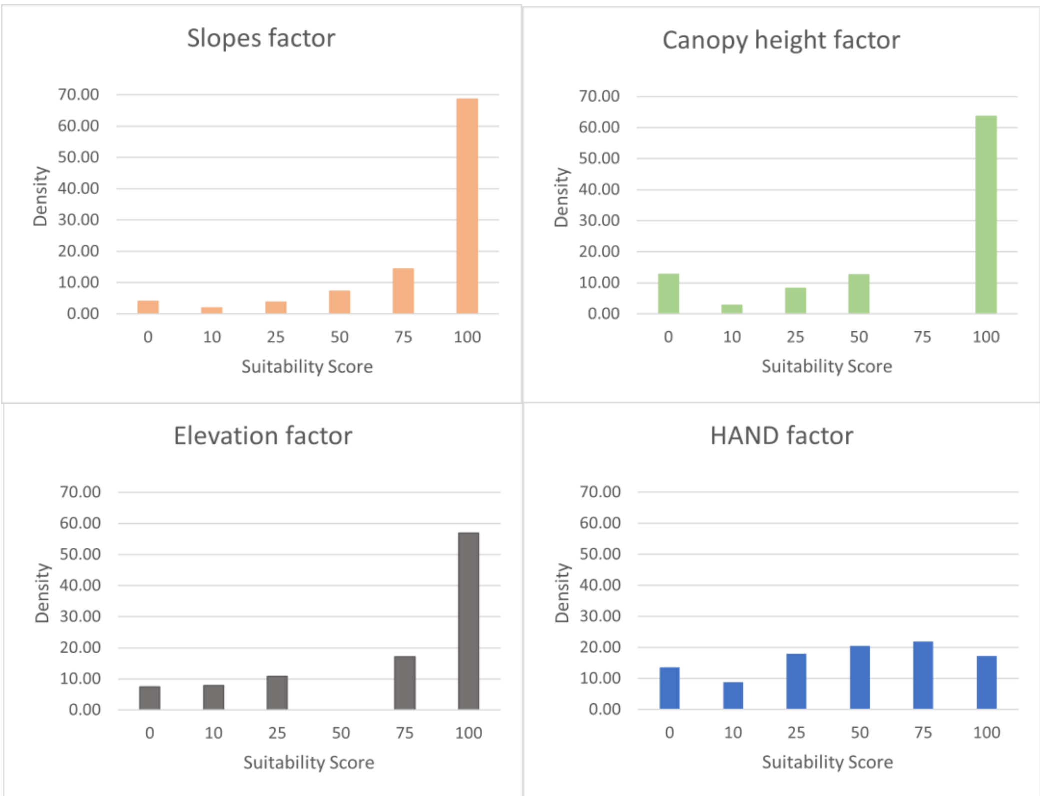

Figure 9: Distribution of suitability score per terrain suitability factor. Factors are classified into permanently not suitable [0-10], marginally not suitable (10-25], marginally suitable (25-50], moderately suitable (50-75], highly suitable (75-100]

As seen in figure 9, when the histogram distribution of the factors is calculated (after applying the class scores to the input features), the results are unique distributions for each factor. Using these distributions values, the scores between factors were inspected. The Potapov forest canopy height factor, slopes, and elevation factors have more suitable order areas (slopes = 90%, FCM = 76%**,** elevation = 74%) for forestry compared to the HAND factor (59%). The slopes factor has increased suitable areas below 15% slopes. Slopes between 0 and 15% make up the majority (83% of the land units) of the moderately suitable and highly suitable areas. The elevation factor has a high percentage (74% of the land units) of moderately and highly suitability as most of the study region lies on elevations above 25 meters.

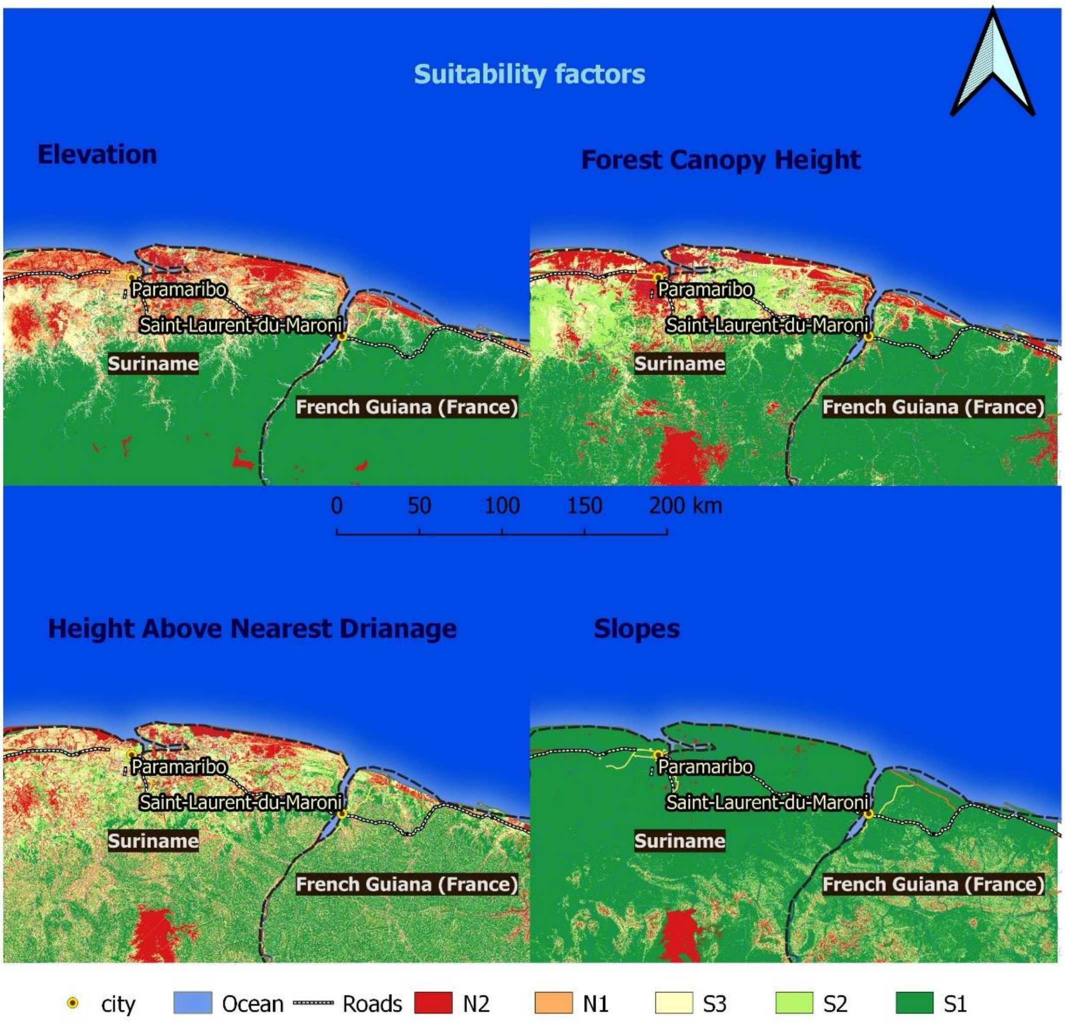

Figure 10: Suitability factors of suitability extent 2 study area

The suitability factors are inspected spatially to have a better understanding of the distribution seen in figure 10. Figure 10 (elevation) shows a discrepancy between suitability in the upper land opposed to the lower regions while masking out mountain ranges higher than 400m higher than sea-level. Swampy areas in coastal regions are mostly unsuitable except areas that have sand ridges. The forest canopy height factor has managed to separate the non-forest areas from the forested inland areas. Build up areas, infrastructure, mining areas, and other low vegetation areas are classified as unsuitable. The slopes factor shows a concentration of unsuitable areas near the mountain ranges while leaving the rest of the study area mostly highly suitable.

4.2.2 Suitability models

The analytical hierarchy process (AHP) was used to determine the feature with the highest weight. As seen in table 7, regarding terrain conditions (the accessibility, and the estimated productivity of the terrain), the slopes factor has been identified as the most important limiting condition. HAND data has been identified as the second most important factor while the height as a factor is regarded as the least important factor. The highest weighted factor is consequently used as the main input variable in the Rabia, Storie, and Square Root method.

Table 7: Analytical Hierarchy Process table

Parameters	Slopes	HAND	FCM	SRTM	Weight
Slopes	1	2	3	4	49%
HAND	0.5	1	2	3	27%
FCM	0.33	0.5	1	2	15%
SRTM	0.2	0.33	0.5	1	9%

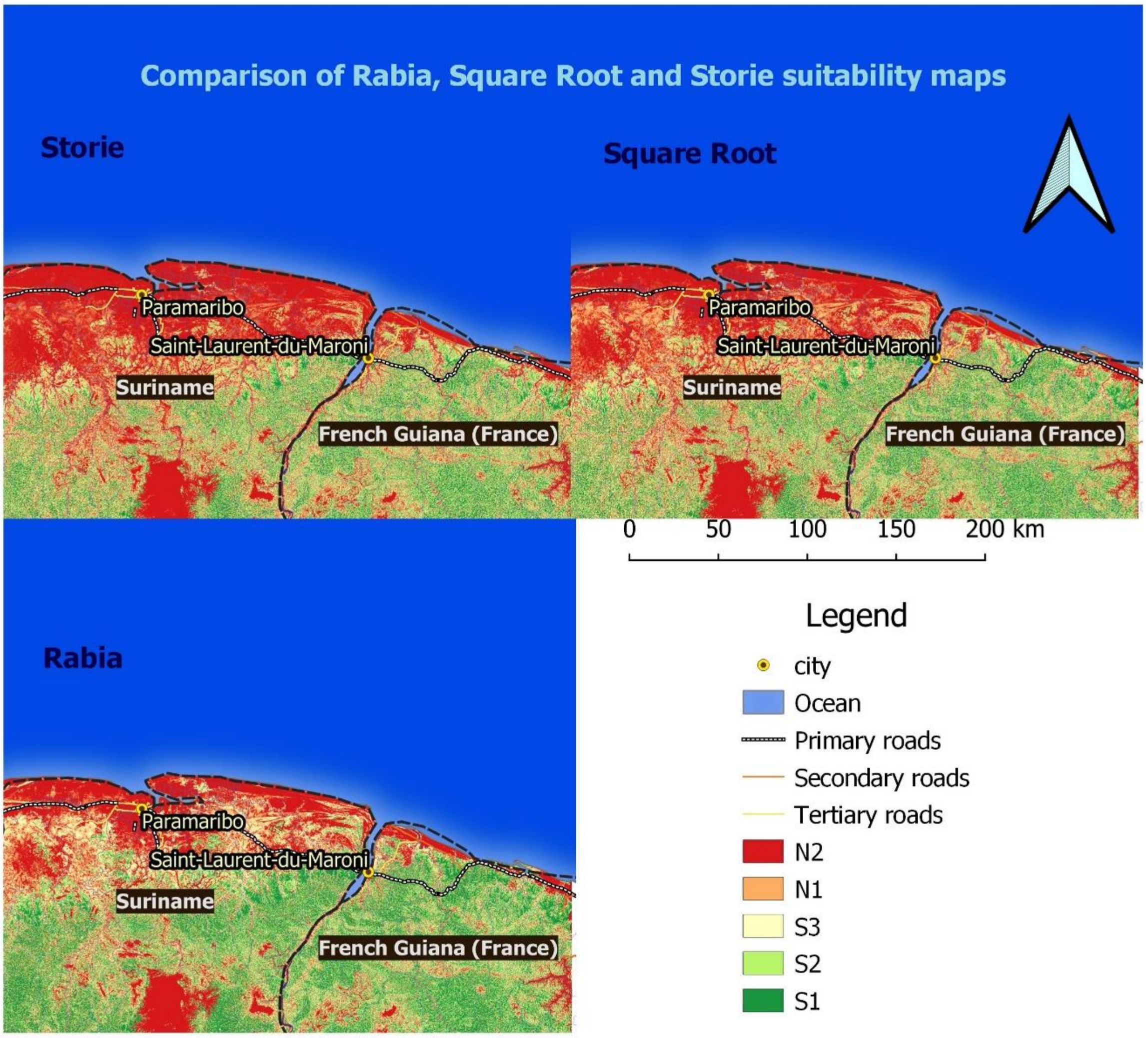

Figure 11: Suitability models of the suitability extent 2 study area

The outputs of the suitability model are raster images where each pixel (pixel resolution= 90 meters) represents part of a land unit and its corresponding suitability score. The figure above shows the outputs of a suitability model using the Rabia method, the Square Root method, and the Storie method. Though the three maps show different intensities of suitability for each land unit, there is good agreement on the permanently not suitable areas in the coastal region, high mountains, hydromorphic regions and near steep hills. Also noticeable is that the permanently not suitable region of the Storie and Square Root method protrudes further inland than the Rabia method.

The difference in the three methods is in how a land unit is evaluated. A land unit which in the Rabia method is assigned a highly suitable class may shift to a moderately suitable or marginally suitable class in the Storie and Square Root method. Of the three methods, the Rabia method yielded the largest percentage (11.9%) of highly suitable land units followed by the Square Root method (3.8%) which is tied with the Storie method. The highly suitable class is also the smallest percentage of area out of all 5 classes. In all three instances, the permanently not suitable areas are the dominant class in their respected dataset. The Rabia method contains the least area of permanently not suitable land units (29.6%) whereas the Storie and Square Root method have 45.1% and 40.3% respectively. The Rabia and Square Root methods produce the highest percentage of land units in the marginally suitable class (Rabia = 22.2%, Square Root = 19.3%) whereas the Storie method has the highest percentage of land units in the moderately suitable areas (17.8%) albeit lower than the Rabia and Square Root method as seen in figure 12.

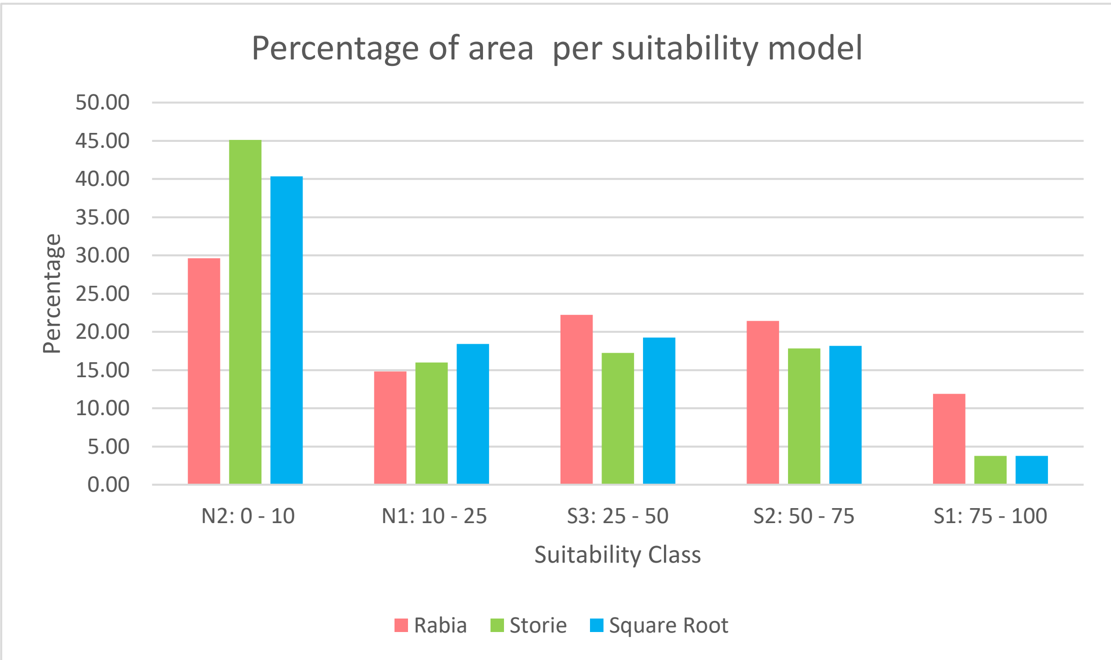

Figure 12: Distribution of the Rabia, Storie, and Square Root suitability model for land evaluation of suitability extent 2.

4.3 Post-processing - Sustainable Forestry Analysis

Figure 13 shows three different interpretations of land suitability in suitability extent 2 where harvested trees on the three suitability models (green markers) were sampled. In total 157,511 trees from separate harvest units spanning over several terrains. Each terrain in turn is subjected to their own harvest management plan with strict oversight from the foundation for forest management and production control. The spatial distribution of the tree, especially in the northern half, are found in suitable regions in the Rabia method and mostly unsuitable areas in the Storie and Square Root method. Important to note as well are the differences in how flood plains are interpreted within each suitability model. The Rabia method returns more suitable land units in flood plains than do the Storie and Square Root method.

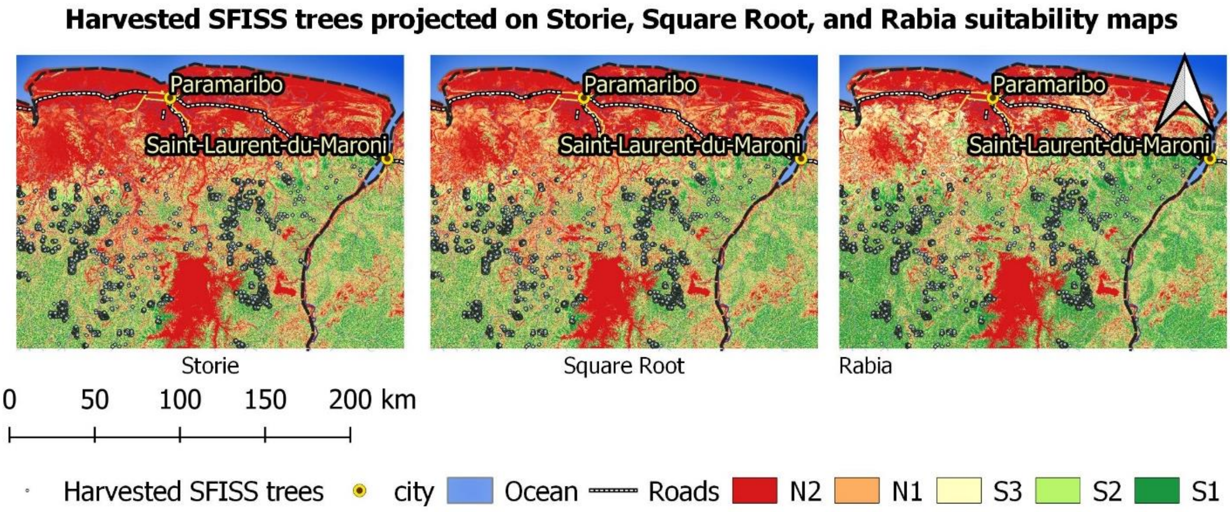

Figure 13: Spatial distribution of harvested trees on the Rabia, Storie and Square Root Suitability maps of the suitability extent 2 study area

Summary statistics were calculated on the harvested trees to investigate how each suitability model would have impacted forestry practices. As seen in table 8, there is a high chance ($p < 0.01$) that a tree is harvested in a suitable order than in an unsuitable order if the Rabia method is used over the Square Root or Storie method. The median and mean statistics highlight this difference between the three methodologies; the mean suitability score of the Rabia method (57) is noticeably higher than the Square Root method (45) and Storie method (43). However, the distribution of the trees for each suitability model presents can be viewed from another perspective.

Table 8: Summary statistics of harvested trees on the Rabia, Square Root, and Storie index of land suitability

Statistic	Rabia	Square Root	Storie
Count	**157,511 trees**		
MIN	0		
Mean	57	45	43
Median	61	43	38
MAX	100		

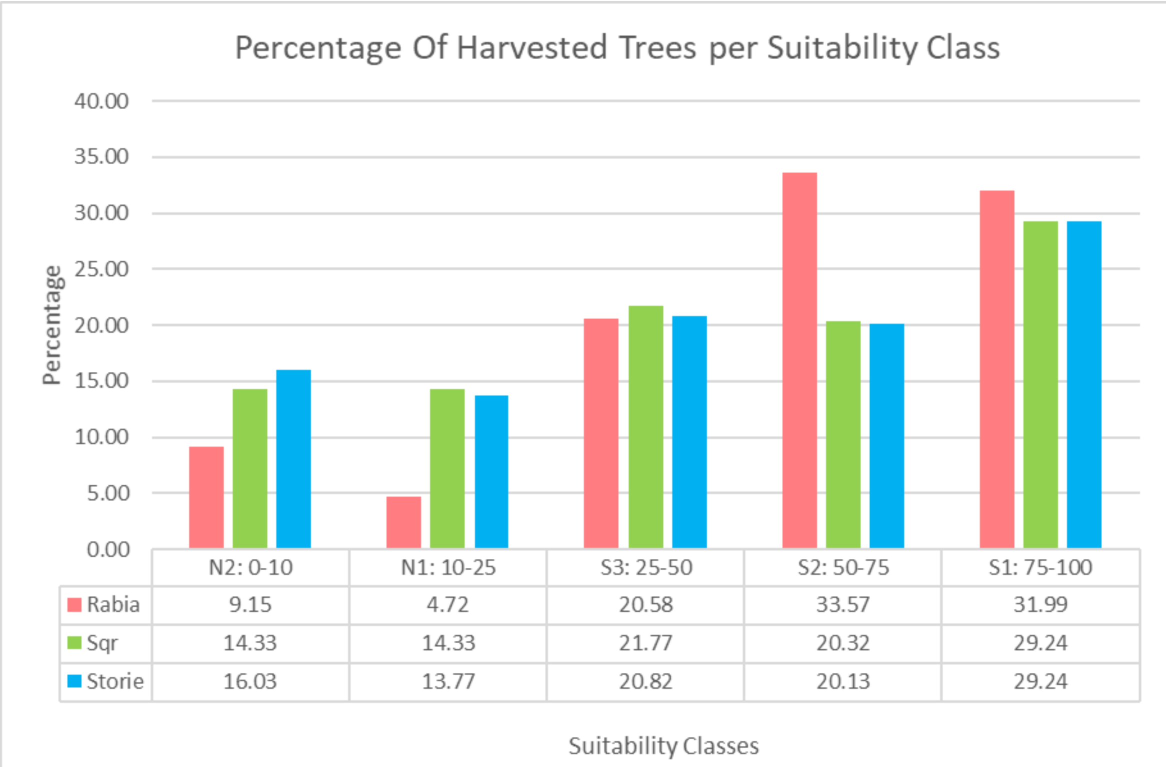

Figure 14: Distribution of harvested SFISS trees per suitability class.

Figure 14 gives an overview of the distribution of harvested SFISS trees in suitability extent 2. When the Rabia method is applied, most trees (33.6% of trees) are harvested in moderately suitable land units followed by 32% of trees in the highly suitable land units. Notice that the Rabia outperforms the Storie and Square Root method in the suitable order opposed to the Not Suitable order where the Square Root and Storie method both have higher values. However, the main take away should be that the largest percentage of trees are harvested within marginally to highly suitable terrain conditions.

To get a more comprehensive understanding how the Rabia, Storie, and Square Root method differ from one another, the next step would be to assess the harvested trees per suitability order (not suitable or suitable). For each suitability model the percentages of harvested trees and the percentage of suitability area are summed per suitability order. Doing so allows for a closer examination of the relative ratio between the suitability models.

Table 9: Percent harvested trees compared with percent total areas per suitability order

	Rabia	**Square Root**	**Storie**
% Trees not suitable	13.87	28.67	29.80
% Area not suitable	44.44	58.75	61.10
% Trees suitable	86.13	71.33	70.20
% Area suitable	55.54	41.23	38.88

Table 9 is split between two orders: not suitable and suitable. Each order has 2 rows pertaining to the percentage of trees and percentage of area of the Rabia, Storie, and Square Root suitability model. The Rabia method has 86.13% of the suitable trees fall within the suitability order. The suitable order represents 55% of the total area. The Square Root method has 71.33% of trees on 41.23% of the total area while the Storie has 70.2% of trees on 38.88% of the total area.

Table 9 is finally used to calculate the relative ratio which provides a way of evaluating the “effectiveness” of a suitability model by stating the ratio between suitable trees per land unit. The ratio between suitable harvested trees and the suitable area for the Rabia method is 1.6 while the ratio for the Square Root method is 1.7 and the Storie, 1.8.

5. Discussion

The output products of this research are only as good as the input products used. Extensive and careful pre-processing procedures were followed to ensure a more realistic output. However, there are some caveats to the pre-processing stage that need to be discussed to have a firm understanding of the strengths and limitations of the final suitability datasets. First, the limitations of the Potapov tree height dataset and how choosing the tree height offset value may have its limitations are addressed. Next, the Lee smoothing algorithm optimal sigma value and how that produces some incongruity in the final output and how that influences further image processing are discussed. The structure of the hydrological network is discussed as well as a discussion on the factor input creation and valuation, and how the SFISS data corresponds to the produced suitability maps.

5.1 Tree height offset

First, the Potapov tree height dataset as stated in the materials paragraph, has significant inherit limitations: there seems to be a flattening of the data above 30 meters in tree height which is suggesting that the algorithm used to develop the dataset is unable to properly distinguish taller trees from the input image. Potapov et al. (2020) states that the predictive model could potentially underfit due to the variety in ecological regimes in the amazon basin alone. To represent tropical forests, data from Costa Rica, Africa, and parts of tropical Asia were used to train the model. The nuances found in tropical regions may explain this sudden flattening of the curve above 30 meters in the dataset. This limitation progresses throughout the tree offset method.

Furthermore, the SRTM dataset has not been calibrated for canopy detection. In effect this means that the radar pulse has penetrated the canopy cover some bit before reflecting to the radar receiver thus resulting in a “near” top of canopy relative height.

To compensate for these limitations only a fraction of the tree height data is used to offset vegetation effect in the SRTM dataset. Although an optimal offset fraction was found, there was more variation when the ALS data was compared to the Potapov data that cannot easily be explained. Therefore, some variation in the dataset may lead to under or overestimating the actual tree height offset fraction. Furthermore, the ALS test dataset does not include coverage in the young coastal plain. This restricts the use of the offset fraction in areas particularly flat and near the coastline. A lower offset was used to finalize the dem. This action leads to greater vegetation offset near the coastline. A trade off was considered between having greater errors in the dataset by not applying an offset and increased false depression in the dataset due to overestimating the offset fraction. A conservative value was chosen to both maintain some vegetation artifacts and some minor false depressions forming in the dataset. Though this action compromises the integrity of the dataset in coastal regions, it does not return exaggerated pit, valleys, or disfigure geological structures.

5.2 Lee Sigma Smoothing

Smoothing has more potential to alter terrain characteristics by decreasing the natural topographical variations (Köthe & Bock, 2009). Therefore, an algorithm was needed that would be able to distinguish true random noise from the natural variation found in the dataset by not over or undersmoothing the original SRTM dataset. The Lee sigma algorithm was used to de-speckle the SRTM image to reduce latent global noise. ALS images captured in French Guyana were used as calibration images to transform the SRTM data to imitate the ALS data. A sigma value of 4 was found to be the most optimal to smooth the SRTM data to resemble the ALS data. The method was chosen to find the most optimal smoothing value is based on iteratively comparing the likeness of the SRTM dataset to the ALS dataset. The limitation of doing so is that while trying to determine the likeness of the dataset, small geological structures that compose terrain characteristics are often lost when the terrains are aggregated together. A more optimized solution would be to determine the terrain likeness per window and perform a smoothing intensity per window. However, doing so would require evaluating the correct window size and then compute the terrain likeness of that window per sigma. Additionally, complete terrain likeness may never achieved due to the difference in data capturing method and resolution. While the SRTM native resolution is a 30-meter pixel, the ALS native resolution is 5-meters. Furthermore, because the ALS data was able to sample true ground samples and the SRTM did not, there were some differences in small terrain characteristics present in the ALS dataset that do not appear in the SRTM dataset. One important terrain feature that is not present in the SRTM dataset are comprehensive hydrological features. These missing features in the SRTM dataset are the major factor why the overall likeness is not above 0.67. Further it was assessed how the smoothing affected slope terrain characteristics and found that the overall slopes above 30% have been reduced suggesting that there is an under estimation of steep slopes. This reduction in slope steepness in the SRTM dataset is regarded as a conservative approach to estimation of the terrain while being aware that there are situations where the overall steepness of the terrain may be higher than reported. Nonetheless, the resulting smoothed DEM showed good correlation with the original SRTM and ALS dataset indicating no loss of larger terrain characteristics necessary for hydrological modeling and further suitability transformations.

5.3 Hydrological network

Producing a highly reliable hydrological network was necessary to produce a valid height above nearest drainage dataset. CBL maps were used as reference images to calculate the flow accumulation threshold per soil-drainage capacity profile. Here three limitations with this process: CBL accuracy, HWSDB units, SRTM flow direction need to be discussed. The first limitation is that the CBL maps themselves were manually produced through stereographic photo interpretations. While they have been in use for many decades by various private and government organizations, the exact accuracy of the dataset has not yet been proven. This limitation could possibly yield false stream origins, stream location, or missing streams. Second, using the world soil database and slope class as explanatory variables is limited. The hydrology of a region is based on complex interactions between soil, climate, and vegetation among others. However, using slopes and soil variables to establish hydrological zones are supported by Montgomery et al. (1993). Additionally, visually inspecting the resulting streams layer showed good coherence with the CBL maps. By taking these extra steps in the pre-processing stages there is higher confidence in the HAND data, slope data, elevation data, and tree height data for use in the suitability factors.

5.4 Feature selection process and the effects on sustainable forestry

The input features, the HAND, slope, elevation, and tree height data for the sustainability analysis were chosen by their relevancy to sustainable forestry. These features had to be especially relevant to both Suriname and French Guyana due to their shared physical environment, history, and goals towards sustained sustainable management and protection of forests. Other criteria for the input features were that they had to be observable, measurable, available, and have proven to be useful for any environmental, biophysical, or forestry analysis. Pure social or economic factors were omitted out of the final factor selection due to the limits of the scope of this research. A more wholistic scope is necessary to include social and economic factors and rationalize their individual scores. Factors suggested by the FAO (1976) are distance from roads, cultural significant sites, tourist sites, villages, towns, and cities. Nevertheless, during the scoring of the individual scoring, some social and economic factors were considered for the evaluation of a land characteristic. For example, basic health and safety protocols, environmental impact assessments, and cost-benefit analysis were used to determine the scoring of the factors in this research.

5.5 Naïve suitability-factor scoring of input features

A direct classification method was used to score the input factors from 0 to 100 where zero represented permanently not suitable and 100 ranks highly suitable. To accomplish this, inference from what is known about the terrain characteristics and how they applied to sustainable forest management was used. For instance, the FAO guidelines (1976) show that low vegetative cover yields low productivity or that steep slopes are hazardous to work on. Despite the abundance of knowledge surrounding forestry, there is no single unified guideline that links terrain characteristics explicitly to forestry guidelines. Therefore, with no empirical or observational data to justify the scoring seen in table 4, a naïve scoring method was designed to emulate the impact of forestry on a land unit given the descriptions. A more robust method would be to investigate each factor intensively, conduct a wholistic study on the impact of forestry on slope stability, hydrology, elevation. Additionally, it would be beneficial to study tree-growth patterns on hydrological and geomorphological zones as well as the productivity of the above ground biomass per tree height class in the study region. The limitation of using expert based, naïve scoring method are that the scores are either too lenient or strict which in turn influences the final suitability score. Moreover, three suitability models were utilized where each in turn interprets the suitability of land units uniquely. To test this, it was apt to compare the resulting suitability maps against real world data to assess the quality of the scoring and to assess the sustainability of forestry practices in the study area.

5.6 Comparison of the Rabia, Storie, and Square Root suitability maps with SFISS tree data

Before the implications of the different suitability models on sampled tree data are discussed, it is imperative to evaluate how each model interprets the suitability score of a region by combining the input factors in some specific manner.

The Rabia method determines the suitability of a land unit by multiplying the highest weighted input factor by the Square Root of the normalized product of the remaining input factors (Rabia, 2013). The highest weighted input factor in this research was the slopes factor. The weight of the slope factor was determined by utilizing the AHP method. The importance of each factor was determined by estimating the effect it has on forestry, impact on the surrounding ecosystems, and reliability of the input dataset and were ranked accordingly. Having the slopes as highest weighted input factor strongly influences how the suitability is classified. Figure 9 shows that the slopes factor has the highest number of suitable areas as compared to the HAND factor. These suitable areas were used as maximizing agents in the final suitability calculations as the highest weighted factor does not undergo normalization. When the slopes are then multiplied against the Square Root of the remaining normalized input factors, they contribute less change on the final suitability area. If another factor was ranked as highest weighted, then the final suitability calculations would result differently. The selected factor would maximize whatever its suitability score is; a high number of unsuitable land units would shift the suitability score towards the lower end.

The Square Root method equation is constructed differently. Whereas the Rabia method preselect the highest weighted factor, the Square Root method maximizes whichever factor has the lowest score in a land unit. Given four factors where each has a different suitability interpretation of the land unit due to their land characteristics, the factor which has the lowest suitability score is used to multiply against the product of the Square Root of the remaining factors. The result is that low suitability scores are weighted higher over suitable areas.

The Storie method is different than the Rabia and Square Root method in that it computes the suitability index by multiplying a chosen factor by the product of the normalized remaining factors (Ghanbarie et al., 2016). In this analysis the slope factor was used as the primary factor. The Square Root of the product from the normalized factors is not performed in the Storie method thus the remaining factors are scaled to smaller values opposed to the Square Root method.

While comparing harvested trees with the three methods used in this research, the expectation was to see that the Rabia method has more trees fall within suitable order than the Square Root and Storie method. Therefore, it could be reasonably to argue that the suitability of a land unit is directly related to the method used to evaluate it. For example, from the results in this research it is possible to argue that the Rabia method is lenient towards production while the Storie and Square Root method favor alternative land-uses such as forest conservation.

The suitability maps provided the tools necessary to evaluate the rate of sustainable forestry in a sample region. A sample from the northeastern region from Suriname was taken and compared the criteria for suitability with the Rabia, Storie, and Square Root suitability indexes. When the number of trees harvested using the Rabia method are compared, fewer trees fall within the Not Suitable order. However, when the ratio between the suitability models and harvested trees is calculated it is apparent that the suitability model which maximizes land units is the Storie method (ratio = 1.8) followed by the Square Root method (ratio = 1.7) and finally the Rabia method (ratio = 1.6). This means that the Storie method has relatively more trees harvested on a smaller area. The argument can be made that trees are predominantly harvested on areas that are deemed accessible, safe, and sustainable as dictated by law and policies. Simply put there already is a tendency to maximize the profitability of a land unit by harvesting trees on suitable areas because of a yet to be determined reason.

5.7 Alternative Land-uses

Rabia and Terribile (2016) argue that their method has increased reliability over the Square Root and Storie method as it forms a more realistic approximation. However, special consideration should be given to what is meant by a realistic approximation. As discussed earlier, the Rabia method seemingly optimizes for a given land-use by minimizing the influence of the lower weighted factors on the final suitability score. Though this in turn yields more suitable land units for forestry purposes, it effectively decreases the suitability for other types of land-use such as ecologically protective sites. Alternative land-uses can be determined in one of two ways: 1. The inverse of suitability for forestry is considered suitable as protected forests or 2. Creating a suitability analysis specifically for nature conservation and protection.

Alternative land-uses are an essential component to a suitability analysis. Alternative land-use analyses such as mining, housing, food production, and tourism are not addressed in this research to concentrate on suitable areas for production forests. However, land units not suitable for timber harvest are, based on their vulnerability to harmful and severe degradation, intended for intensive conservation from logging activities or other intensive land-uses. Which means that suitable production forests are, despite their grade of suitability, still subjected to sustainable timber harvest guidelines as stipulated by country specific rules and regulations but are not held with the same intense scrutiny, observation, or protection as not suitable forested land units.

6. Conclusion

The conclusion of this research addresses the primary research question that was proposed in the introduction: “How do the Rabia, Storie, and Square Root method of bio-physical land evaluation using an optimized Digital Elevation Model and hydrological network as primary input dataset reflect on current forestry practices in the Guianas?” This question was proposed so that it was possible to explore the strength and weaknesses of existing landcover data sets and land evaluation methods to investigate forest management strategies in Suriname and speculate what the possible implications are when a transformation process which utilizes existing policies and current environmental dogmas is applied on a national scale. This question, however, does not answer what the definitive changes will be if any land evaluation method is adopted but merely glances at optimal renditions of forest management strategies.

The first task was to properly address the shortcomings of existing datasets such as the SRTM, the primary input data. It was found that utilizing a biased fitting method to offset vegetation and correct vertical noise from the SRTM data set as well as utilizing an optimized hydrological model yielded acceptably accurate input features for further suitability modeling.

Next, three land evaluation techniques were applied: the Rabia, Storie, and Square Root method and found that each technique yielded varying degrees of land suitability for forestry. Thus, the discussion was on how and why each technique may yield varying degrees of suitability. It was determined that the way individual land units are evaluated and consequently aggregated using specific mathematical calculations altered the outcome of the suitability of a land unit.

While this research makes no claim in which land evaluation method is better than the other, the major implications of each land evaluation techniques compared to real world data suggest that choosing one land evaluation method over the other will have an impact on the total harvestable tree volume and shift the forest management system to favor conservation- by limiting the amount of suitable areas- or economic activities by being lenient in its land evaluation output for suitable areas.

References

Achard, F., DeFries, R., Eva, H., Hansen, M., Mayaux, P., & Stibig, H. J. (2007). Pan-tropical monitoring of deforestation. *Environmental Research Letters*, *2*(4), 045022.

Albaji, M., Papan, P., Hosseinzadeh, M., & Barani, S. (2012). Evaluation of land suitability for principal crops in the Hendijan region. *International Journal of Modern Agriculture*, *1*(1), 24-32.

Albaji, M., & Alboshokeh, A. (2017). Assessing agricultural land suitability in the Fakkeh region, Iran. Outlook on Agriculture, 46(1), 57-65.

Alonso, L. E., & Berrenstein, H. J. (2006). *A rapid biological assessment of the aquatic ecosystems of the Coppename River Basin, Suriname*. Conservation International, Center for Applied Biodiversity Science.

Arsanjani, J. J., Tayyebi, A., & Vaz, E. (2016). GlobeLand30 as an alternative fine-scale global land cover map: Challenges, possibilities, and implications for developing countries. *Habitat International*, *55*, 25-31.

Baroudy, A. A. E., Ali, A., Mohamed, E. S., Moghanm, F. S., Shokr, M. S., Savin, I. & Lasaponara, R. (2020). Modeling land suitability for rice crop using remote sensing and soil quality indicators: the case study of the nile delta. Sustainability, 12(22), 9653.

Cekanavicius, L., Semeniene, D., Oosterhuis, F., & van Ierland, E. (2003). 19. The Cost of Pollution: Environmental Economics.

Chen, J., Cao, X., Peng, S., & Ren, H. (2017). Analysis and applications of GlobeLand30: a review. *ISPRS International Journal of Geo-Information*, *6*(8), 230.

Crabbe, S., Playfair, S (2018). "Sustainability Plan for the Sustainable Forestry Information System." department of research and development for the Foundation for Forest Management and Production Control.

CERL, U. A. (1993). GRASS 4.1 Reference Manual. US Army Corps of Engineers, Construction Engineering Research Laboratories, Champaign, Illinois, 1-425.

Ehlschlaeger, C. (1989). Using the AT Search Algorithm to Develop Hydrologic Models from Digital Elevation Data, Proceedings of International Geographic Information Systems (IGIS) Symposium '89, pp 275-281 (Baltimore, MD, 18-19 March 1989). URL: http://faculty.wiu.edu/CR-Ehlschlaeger2/older/IGIS/paper.html

Ehrlich, G., Alexander, S., Ehrlich, P., Goulder, L., Lubchenco, J., Matson, P., ... & Woodwell, G. (1997). Ecosystem services: benefits supplied to human societies by natural ecosystems. Issues Ecol, 2, 1-16.

Erftemeijer, P., & Teunissen, P. (2009). ICZM plan Suriname-mangrove report. *Analysis of problems and solutions for the management of mangrove forests along Suriname's 'wild coast'. Lievense–Deltares report*.

FAO (1976). A framework for Land Evaluation. *Soils Bulletin*, *32*.

FAO (2010) Global forest resources assessment 2010: country report Suriname. Food and Agriculture Organization of the United Nations, Rome.

Farr, T. G., Rosen, P. A., Caro, E., Crippen, R., Duren, R., Hensley, S., & Alsdorf, D. (2007). The shuttle radar topography mission. *Reviews of geophysics*, *45*(2).

Foley, J. A., DeFries, R., Asner, G. P., Barford, C., Bonan, G., Carpenter, S. R., ... & Snyder, P. K. (2005). Global consequences of land-use. science, 309 (5734), 570-574.

Ghanbarie, E., Jafarzadeh, A. A., Shahbazi, F., & Servati, M. (2016). Comparing parametric methods (the Square Root and the Storie) with the fuzzy set theory for land evaluation of khaje region for wheat. *International Journal of Advanced Biotechnology and Research (IJBR)*, *7*, 343-351.

Government of Suriname (1992). Act of 18 September 1992, containing provisions regarding forest management, forest exploitation and the primary wood-processing sector.

Government of Suriname (2019). National REDD+ Strategy of Suriname. Paramaribo, Suriname

Government of Suriname (2020). First Summary of Information on REDD+ Safeguards of Suriname. Paramaribo, Suriname.

Gray, J., & Murphy, B. (2002, August). Parent material and world soil distribution. In *17th World Congress of Soil Science, Bangkok, Thailand* (Vol. 2215, pp. 1-2215).

Gallant, J. (2011). Adaptive smoothing for noisy DEMs. Geomorphometry 2011, 7-9.

Gallant, J. C., Read, A. M., & Dowling, T. I. (2012). Removal of tree offsets from SRTM and other digital surface models. International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 39(4), 275-280.

Guitet, S., Pélissier, R., Brunaux, O., Jaouen, G., & Sabatier, D. (2015). Geomorphological landscape features explain floristic patterns in French Guiana rainforest. *Biodiversity and Conservation*, *24*(5), 1215-1237.

Hansen, M. C., Potapov, P. V., Goetz, S. J., Turubanova, S., Tyukavina, A., Krylov, A., ... & Egorov, A. (2016). Mapping tree height distributions in Sub-Saharan Africa using Landsat 7 and 8 data. *Remote Sensing of Environment*, *185*, 221-232.

Hout, P. D. (1999). Reduced impact logging in the tropical rain forest of Guyana: ecological, economic and silvicultural consequences. *Reduced impact logging in the tropical rain forest of Guyana: ecological, economic and silvicultural consequences.*

Holmgren, P. (1994). Multiple flow direction algorithms for runoff modelling in grid based elevation models: An empirical evaluation. Hydrological Processes Vol 8(4), pp 327-334. DOI: 10.1002/hyp.3360080405

Holling, C. S. (2001). Understanding the complexity of economic, ecological, and social systems. Ecosystems, 4(5), 390-405.

IPCC (2021). Summary for Policymakers. In: Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate. Cambridge University Press. In Press.

Jolly, C. (2017). Evaluation of Space Programs: Select Findings from the OECD Space Forum. In *Satellite Earth Observations and Their Impact on Society and Policy* (pp. 171-176). Springer, Singapore.

Jonkers, W. B. J. (1987). *Vegetation structure, logging damage and silviculture in a tropical rain forest in Suriname* (Doctoral dissertation, Jonkers).

Koeman, C. (1973). *Links with the past: the history of the cartography of Suriname 1500-1971*. C. Koeman (Ed.). Theatrum Orbis Terrarum.

Köthe, R., & Bock, M. (2009). Pre-processing of digital elevation models–derived from laser scanning and radar interferometry–for terrain analysis in geosciences. *Proc. Geomorph*, 155-161.

Lee, J. S. (1983). Digital image smoothing and the sigma filter. Computer vision, graphics, and image processing, 24(2), 255-269.

Leopold, L. B., & Maddock, T. (1953). *The hydraulic geometry of stream channels and some physiographic implications* (Vol. 252). US Government Printing Office.

Lim, B. K., & Joemratie, S. (2012). Rapid Assessment Program (RAP) survey of small mammals in the Kwamalasamutu region of Suriname. In *A Rapid Biological Assessment of the Kwamalasamutu region, Southwestern Suriname* (p. 144). Conservation International.

Liu, B. Y., Nearing, M. A., Shi, P. J., & Jia, Z. W. (2000). Slope length effects on soil loss for steep slopes. Soil Science Society of America Journal, 64(5), 1759-1763.

Mansourpour, M., Rajabi, M. A., & Blais, J. A. R. (2006). Effects and performance of speckle noise reduction filters on active radar and SAR images. In Proc. ISPRS (Vol. 36, No. 1, p. W41).

Montgomery, D. R., & Foufoula-Georgiou, E. (1993). Channel network source representation using digital elevation models. *Water Resources Research*, *29*(12), 3925-3934.

Nachtergaele, F., van Velthuizen, H., Verelst, L., Batjes, N. H., Dijkshoorn, K., van Engelen, V. W. P., ... & Montanarela, L. (2010). The harmonized world soil database. In *Proceedings of the 19th World Congress of Soil Science, Soil Solutions for a Changing World, Brisbane, Australia, 1-6 August 2010* (pp. 34-37).

Noordam, D. (1993). The geographical outline. In *The Freshwater Ecosystems of Suriname* (pp. 13-28). Springer, Dordrecht.

Onoda, M., & Young, O. R. (2017). *Satellite earth observations and their impact on society and policy*. Springer Nature.

O'Shea, B. J., & Ramcharan, S. (2013). A rapid assessment of the avifauna of the Upper Palumeu watershed, southeastern Suriname. In *A Rapid Biological Assessment of the Upper Palumeu River Watershed (Grensgebergte and Kasikasima) of Southeastern Suriname* (p. 145). Conservation International.

Ouboter, P. E., Jairam, R., & Kasanpawiro, C. (2012). A rapid assessment of the amphibians and reptiles of the Kwamalasamutu region (Kutari/lower Sipaliwini Rivers), Suriname. In *A Rapid Biological Assessment of the Kwamalasamutu region, Southwestern Suriname* (p. 124). Conservation International.

Pérez-Hoyos, A., Rembold, F., Kerdiles, H., & Gallego, J. (2017). Comparison of global landcover datasets for cropland monitoring. *Remote Sensing*, *9*(11), 1118.

Pinel, Sebastien & Bonnet, Marie-Paule & Da Silva, Joecila & Moreira, Daniel & Calmant, Stéphane & Satge, Frederic & Seyler, Frédérique. (2015). Correction of Interferometric and Vegetation Biases in the SRTMGL1 Spaceborne DEM with Hydrological Conditioning towards Improved Hydrodynamics Modeling in the Amazon Basin. Remote Sensing. 7. 16108-16130. 10.3390/rs71215822.

Playfair, M. (2007). Law Compliance, and Prevention and Control of Illegal Activities in the Forest Sector in Suriname.

Pörtner, H. O., Scholes, R. J., Agard, J., Archer, E., Arneth, A., Bai, X., Barnes, D., Burrows, M., Chan, L., Cheung, W. L., Diamond, S., Donatti, C., Duarte, C., Eisenhauer, N., Foden, W., Gasalla, M., Handa, C., Hickler, T., Hoegh-Guldberg, O., ... Ngo, H. T. (2021). *IPBES-IPCC co-sponsored workshop report on biodiversity and climate change*. Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES) and Intergovernmental Panel on Climate Change (IPCC).

Potapov, P., Li, X., Hernandez-Serna, A., Tyukavina, A., Hansen, M. C., Kommareddy, A., ... & Hofton, M. (2021). Mapping global forest canopy height through integration of GEDI and Landsat data. *Remote Sensing of Environment*, *253*, 112165.

Rabia, A. H., & Terribile, F. (2013). Introducing a new parametric concept for land suitability assessment. *International Journal of Environmental Science and Development*, *4*(1), 15.

Ramirez-Gomez, S. O. (2011). Spatial Drivers of Deforestation in Suriname. Center for Agriculture Research in Suriname, Tropenbos Suriname.

Ramirez-Gomez, S. O., Brown, G., & Fat, A. T. S. (2013). Participatory mapping with indigenous communities for conservation: challenges and lessons from Suriname. *The Electronic Journal of Information Systems in Developing Countries*, *58*(1), 1-22.

Reuter, H. I., Hengl, T., Gessler, P., & Soille, P. (2009). Preparation of DEMs for geomorphometric analysis. *Developments in Soil Science*, *33*, 87-120.

Rosenbloom, N. A., Doney, S. C., & Schimel, D. S. (2001). Geomorphic evolution of soil texture and organic matter in eroding landscapes. *Global Biogeochemical Cycles*, *15*(2), 365-381.

Schietti, J., Emilio, T., Rennó, C. D., Drucker, D. P., Costa, F. R., Nogueira, A., ... & Magnusson, W. E. (2014). Vertical distance from drainage drives floristic composition changes in an Amazonian rainforest. *Plant Ecology & Diversity*, *7*(1-2), 241-253.

UNFCCC (2021). Nationally determined contributions under the Paris Agreement-Synthesis report by the secretariat. UNFCCC, Bonn.

Saaty, T. L. (2008). Decision making with the analytic hierarchy process. International journal of services sciences, 1(1), 83-98.

Simard, M., Zhang, K., Rivera-Monroy, V. H., Ross, M. S., Ruiz, P. L., Castañeda-Moya, E., ... & Rodriguez, E. (2006). Mapping height and biomass of mangrove forests in Everglades National Park with SRTM elevation data. *Photogrammetric Engineering & Remote Sensing*, *72*(3), 299-311.

Singh, Y., Bhandari, S., Tamang, D., Basnet, A., Shrestha, R., & Awasthi, B. (2019). Comparison and Suitability Assessment of Slope Calculation Algorithms on Different Terrains Using Aerial Survey. *The International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences*, *42*, 129-136.

Solari, S., & Pinto, M. (2007). A rapid assessment of mammals of the Nassau and Lely plateaus, Eastern Suriname. In *RAP Bulletin of Biological Assessment: A Rapid Biological Assessment of the Lely and Nassau Plateaus, Suriname (with additional information on the Brownsberg Plateau)* (p. 130). Conservation International.

Storie, R. (1978). Storie index soil rating (revised). Special Publication. Div of Agricultural Sciences No. 3203. *Univ of California, Berkeley, CA*.

Taylor, K. (2010). International practice and regional applications in cultural heritage management: whose values?

Tropenbos International Suriname, Van Hall Larenstein University of Applied Sciences (2015). Handleiding: Duurzaam bosbeheer voor dorpsontwikkeling, Paramaribo, Suriname. 108 pp

Turner, B. L., Lambin, E. F., & Reenberg, A. (2007). The emergence of land change science for global environmental change and sustainability. *Proceedings of the National Academy of Sciences*, *104*(52), 20666-20671.

Van Dijk, S. (ed.) (2011) Minor Timber Products, Major Challenges? Tropenbos International Suriname, Paramaribo, Suriname, 48 p.

Van der Hout, P (1999). Reduced impact logging in the tropical rainforest of Guyana. Ecological, economic and silvicultural consequences.

Van der Hout, P (2011)., Praktijkrichtlijnen voor duurzame houtoogst in Suriname. Stichting voor Bosbeheer en Bostoezicht, Paramaribo, Suriname. 97 pp.

Verheye, W. (2009). Land evaluation systems other than the FAO system. *Land-use, Landcover and Soil Sciences-Volume II: Land Evaluation*, 100.

Werger, M. J. (2011). Sustainable management of tropical rainforests: the CELOS management system. *Tropenbos Series*, (25).

Whiteman, A. (1999). A roundwood production cost model for Suriname: Model description and user guide. Forest Finance Working Paper-FSFM/MISC, 6.

Winchell, M. F., Jackson, S. H., Wadley, A. M., & Srinivasan, R. (2008). Extension and validation of a geographic information system-based method for calculating the Revised Universal Soil Loss Equation length-slope factor for erosion risk assessments in large watersheds. *Journal of Soil and Water Conservation*, *63*(3), 105-111.

Wong, T. E. (1986). Outline of the stratigraphy and the geological history of the Suriname coastal plain. *Geologie en Mijnbouw*, *65*(3), 223-241.

Zhang, X. J., & Wang, Z. L. (2017). Interrill soil erosion processes on steep slopes. *Journal of Hydrology*, *548*, 652-664.