MONITORING WITH VEGETATION INDICES HOW VEGETATION RECOVERS ON LANDSLIDES IN DOMINICAN TROPICAL FOREST

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July 2020

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ABSTRACT

Landslides can have high impacts on ecosystem services and people's livelihoods. An increased understanding of vegetation recovery on landslides contributes to the improvement of restoration projects and hazard risk reduction. This study aimed to evaluate with vegetation indices how fast vegetation on hurricane-triggered landslides in Dominican tropical rainforest recovers, and which landscape variables influence it. A landslide inventory that geometrically corresponded with landslide positions on Sentinel-2 imagery has been selected based on the finding that landslides dropped significantly ($p < .05$) more in vegetation index values than non-slided, but hurricane damaged forest. The utility of vegetation indices (ARVI, EVI, FRI2, MSAVI2, NDMI, NDVI and SAVI) has been evaluated by comparing the state of the vegetation on landslides with the surrounding non-slided forest and by analysing the Vegetation Recovery Rate (VRR) of landslides up to 2.5 years after disturbance. EVI was considered the most useful to monitor vegetation recovery in hurricane-prone regions, it had a large drop in values and could differentiate the most between landslides and surrounding forest. A significant multiple linear regression model ($F(5,1136) = 42$, $p < .000$, $R^2 = 0.156$) was found that predicts vegetation recovery time based on remaining vegetation, altitude, slope, aspect, landslide zone (initiation, transport, deposit) and soil type. Vegetation indices can be used to monitor how fast young secondary vegetation recovers on landslides. Therefore, it is recommended to make use of vegetation indices to automatically and continuously monitor vegetation recovery to detect landslides in need for restoration projects, this reveals people and properties that are at risk.

Keywords: landslide succession, tropical rainforest, vegetation indices, landscape variables.

ACKNOWLEDGEMENTS

The founder and first rector and of ITC, Prof. dr. ir. W. Schermerhorn has had an inspirational life. In 1936 he guided the aerial surveying of New Guinea. Schermerhorn's diary about his journey gives the impression that he was more impressed by the urban environment than about the nature. During a stop in Sumatra he states for instance: "Everything is tropical rainforest. This is a very mournful land. No sand and stones to be seen, only inhospitable forest. But Delhi is wonderful, and Medan is a beautiful place. Nice country houses; a good hotel. This is a welcoming land." However, during an aerial survey above Cenderawasih Bay Schermerhorn got to experience the beauty of the tropical landscape. He wrote: "This part of the land was much more peaceful than the swamp forest. Such landscapes suddenly show me the friendly side of the land.". In the footsteps of Schermerhorn, I got the change to deepen my knowledge about tropical forests in the field of earth observation while also seeing the beauty of Earth's nature. An opportunity I am very grateful for. Therefore, I would like to thank the entire ITC Faculty, and in particular its people: the staff and my classmates.

A special word of appreciation to my supervisors Victor Jetten and Thomas Groen, two supervisors with who I agreed upon a thesis topic more than a year ago and who provided continuous support ever since. I learned a lot from the discussions we had.

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1. INTRODUCTION

This study focuses on the recovery of vegetation on landslides in Dominica's tropical rainforests. It evaluates the utility of different remote sensing vegetation indices to monitor how fast vegetation recovers on landslides. In addition, this study analyses the influence of landscape variables on the return of vegetation indices to pre-disturbance values.

1.1. Forest disturbance and recovery

Forest disturbances manifest in different forms, each having its own characteristics. As Frolking et al. put it:

> Forest disturbance can be abrupt (e.g., hurricanes) or chronic (e.g., acid rain); stand-replacing (e.g., clear-cut logging) or not (e.g., selective logging); complete (e.g., landslides) or incomplete (e.g., insect defoliation); natural (e.g., tornados) or anthropogenic (e.g., land conversion); widespread (e.g., fire) or geographically restricted (e.g., avalanches); temporary (e.g., blowdowns) or permanent (deforestation and land use conversion). (2009, p. 2)

Landslides are defined as the downslope movement of soil, rock, and organic materials and the landform that results from it (Highland & Bobrowsky, 2008). They mostly appear as abrupt, stand-replacing, complete, natural or human-induced, widespread and temporary disturbances (Frolking et al., 2009; Haque et al., 2019; Highland & Bobrowsky, 2008).

In most cases, forest starts recovering naturally when there is no human interference after forest disturbance. The recovery capability of forests depends on the resistance and resilience of an ecosystem. The resistance is the ability of an ecosystem to withstand a disturbance. The resilience is the ability of an ecosystem to return to pre-disturbance conditions over time. In practice, these pre-disturbance conditions, also known as the recovered state, are difficult to define because disturbance-prone forests are dynamic, diverse and complex ecosystems of which forest properties cannot straightforwardly be mapped. This is why monitoring and measurements of forest properties are essential to quantify forest recovery (Attiwill, 1994; Frolking et al., 2009).

Forest properties can be divided into the ecological structure of a forest and the ecological functions that a forest has (Attiwill, 1994). Biomass, species diversity and Leaf Area Index (LAI) are examples of structural properties, and can be quantified with measurements. The functions of a forest, of which the capability can be measured, are for instance storing carbon, plant productivity, and the effect vegetation has on slope stability (Frolking et al., 2009; Gray & Sotir, 1996). Forest recovery refers to the reestablishment of the forest structure and functions after the impact of a disturbance (Attiwill, 1994).

For landslides, the recovery of forest functions goes faster than the recovery of the forest structure (Chiu, Hsu, Lin, & Chen, 2016; Myster, Thomlinson, & Larsen, 1997). The findings of Hu & Smith (2018) indicate that this is also the case for hurricane disturbances. After Hurricane Maria made landfall on Dominica and Puerto Rico, they monitored how vegetation recovered using the Normalized Difference Vegetation Index (NDVI). This index is closely related to the greenness and leaf pigments of plants, and is therefore a proxy for the plant productivity vegetation has (Alchanatis et al., 2012). Hu & Smith (2018) concluded that NDVI returned to near normal values within 1.5 months after disturbance. As opposed to forest functions, the forest structure can take much more time to recover. In rainforest in Puerto Rico the restoration of biomass takes 20 to 25 years (Brokaw et al., 2012), and in Jamaica the influence of a severe hurricane on rainforests tree diversity can last up to 101 years (McLaren, Luke, Tanner, Bellingham, & Healey, 2019).

Due to the possible quick recovery of forest functions, the reestablishments of forest structures that have a slope stabilizing function (such as biomass and fractional vegetation cover (FVC)) are often the purpose of vegetation engineering methods (Chiu et al., 2016). However, besides biomass and FVC, also the species composition and plant roots affect the slope stabilizing function of vegetation (Gray & Sotir, 1996). Species that positively influence forest recovery are those that are functionally redundant, can stabilize and fertilize the landslide surface, and grow and reproduce rapidly (Walker et al., 2009). Therefore, successful restoration projects are those that develop early-successional-stage forests with strata and diverse[1] and slope-stabilizing species, and those that take specific local conditions into account (Chiu et al., 2016; Walker, Velázquez, & Shiels, 2009). To conclude, both functional and structural recovery are important for slope stabilisation of landslides, and they have the potential to accelerate each other (Chiu et al., 2016; Laskurain et al., 2016; McDonald et al., 2016).

1.2. Vegetation indices to monitor vegetation recovery on landslides

Ground-based measurements and remote sensing imagery are both used to study forest disturbance and recovery. Ground-based measuring of vegetation properties is a very precise but time, money and resources consuming approach (Jiang et al., 2015). The use of remote sensing imagery plays an increasingly important role in monitoring forest disturbance and recovering due to the rising possibilities. Satellite imagery can be used to retrieve information of forests that are difficult to access as well as to conduct automated analysis. Nowadays, high spatial resolution imagery (< 1 m) together with allometric equations can determine individual tree properties such as crown geometry and height. However, high spatial resolution imagery is constrained by data availability and costs. On the other hand, several medium spatial resolution imagery products (10-30 m) with a high temporal resolution are freely available. These products are sufficient to detect disturbances larger than 1000 m^2, and are sometimes capable of detecting even smaller disturbances in the tropics (Frolking et al., 2009; Masiliūnas, 2017). Medium spatial resolution imagery can also be used "to derive terrain conditions associated with landslides, such as lithology, differences in vegetation, land use [and] soil humidity" (Metternicht & Gogu, 2005, p. 291). Some of the challenges of medium spatial resolution imagery are cloud and shadow interference and monitoring small-scale disturbances (Frolking et al., 2009; Jiang et al., 2015). In addition, the accuracy of medium spatial resolution imagery is lower, and it is difficult to determine structural forest properties such as species composition and tree height (Grainger, 2008).

Remote sensing studies investigating which landscape and biological variables are correlated with landslide susceptibility have been conducted for decades (Metternicht et al., 2005). However, studies analysing the recovery of vegetation on landslides is limited to non-tropical regions. Two of the landslide-prone regions that have had extensive research using remote sensing are the landslides that were caused by the Chi-Chi earthquake in 1999 in Taiwan and those triggered by the Wenchuan earthquake in 2008 in China.

The Chi-Chi earthquake induced landslides at more than 20,000 sites, including landslides in sub-tropical forests. Multiple studies used SPOT imagery (20 m resolution) derived NDVI to monitor vegetation recovery on these landslides. Even though vegetation started recovering rapidly in the first years after the occurrence of landslides, there is still a difference in NDVI values observable between non-slided and

[1] Thom & Seidl (2016) state that diverse forest ecosystems are more resilient and resistant to disturbance impacts.

landslided areas twelve years after the earthquake (Lin, Chou, Lin, Huang, & Tsai, 2005; M.-D. Yang, Chen, & Tsai, 2017). The occurrence of typhoons and the number of days in a year with heavy rainfall negatively correlate with NDVI values (Lin et al., 2005; Yang et al., 2017). Since ridgelines are not able to preserve water very well, landslides on steep hillslopes recovered faster than landslides on ridgelines. This led to the conclusion that soil moisture is a critical stimulating factor for recovery. Because of the dependency of vegetation on soil moisture, slope gradient is not a dominant restrictive factor for recovery in this region (Chou, Lin, & Lin, 2009; Lin et al., 2005). Landslides located near streams recover even slower due to erosion that takes place during rainfall seasons. Field surveys indicate that the recovery pattern is location dependent. Near stream landslides have an invading pattern of species, steep slopes a surviving pattern, and on ridgelines a mixture of both patterns takes place[2] (Chou et al., 2009).

Studies evaluating the recovery of thousands of landslides triggered by the Wenchuan earthquake made use of low-resolution MODIS imagery (250 m resolution) (Jiang et al., 2015; W. Yang, Qi, & Zhou, 2018; Yunus et al., 2020). NDVI values were used to calculate the Vegetation Recovery Rate (VRR). The VRR expresses the vegetation state by calculating to which extent the temperate vegetation of Wenchuan recovered to pre-disturbance values. Jiang et al. (2015) classified the vegetation state into four classes: not recovering, recovering slightly, recovering largely and recovered fully. After 5 years, 41% of the disturbed vegetation had recovered to pre-disturbance NDVI levels. Several factors that possibly influence the recovery speed were evaluated. The higher the earthquake intensity, the more earthquake and landslide damage to vegetation was done. Hence, an inverse relationship was found between the earthquake intensity and fully recovered landslides. Clear differences in recovery speed where found between the different vegetation types within the region. There was expected that soil moisture is an important factor for plant growth. However, there was no clear relationship between clay content in the topsoil and vegetation recovery. It seems that when altitude increases (especially in the range 1840 - 4071 m), the percentage of fully recovered landslides increases as well. Altitude seems to be an influencing, but not decisive factor for plant growth, and "must interact with topography and water supply to affect vegetation growth" (Jiang et al., 2015, p. 8775).

NDVI can be used to monitor vegetation recovery up to at least 10 years for landslides triggered by the Wenchuan earthquake (Yunus et al., 2020) and at least up to 12 years for landslides caused by the Chi-Chi earthquake[3] (Yang et al., 2017). However, forest in the tropics behaves different than the forests in the subtropical and temperate regions of Wenchuan and Taiwan. After a disturbance in the tropics, vegetation recovers in a remarkably short time and a rapid regrowth of canopy leaf area and photosynthetic vegetation takes place (Frolking et al., 2009; Walker et al., 2013; Walker, Zarin, Fetcher, Myster, & Johnsen, 1996). On top of this, "NDVI saturates with the increased leaf area found in older, structurally complex forests" (Clark, Roberts, Ewel, & Clark, 2011, p. 2932). Therefore, monitoring recovery with NDVI to estimate aboveground biomass is limited to young secondary tropical forest (Clark et al., 2011). The fact that tropical forests recover rapidly and that vegetation indices saturate quickly makes deriving functional or structural forest properties challenging in the tropics. In order to overcome those limitations, there is a need to gain more knowledge on how to relate medium spatial resolution remote sensing measurements to ground-based measurements. This allows for more in-depth remote sensing analysis of the functional and structural recovery of forests (Frolking et al., 2009).

[2] The invading pattern is characterised by the wind transportation of lightweight seeds of pioneer plants to a side. The surviving pattern is characterised by the recovery and reproduction of remaining species on sides.
[3] The ability of NDVI to track vegetation recovery on landslides in these regions is possibly even larger, but no research has been done to this (yet).

1.3. Influence of landscape variables on vegetation recovery on landslides

Besides the remote sensing based approach, ground based measurements are used to investigate which variables influence the recovery of vegetation on landslides. Walker et al. (2013) investigated the influence of landscape variables and how this changes over time on the primary succession of seed plants and ferns on six Puerto Rican landslides. The steeper the slopes and the smaller the catchment sizes (landslide area above the plot on the landslide) of plots the higher was the scrambling fern cover. On the other hand, flatter slopes with larger catchment sizes had greater diversity and density of seed plants. East facing slopes exposed to trade winds and hurricanes had higher tree fern densities, while non-east facing slopes had a more rapid regrowth of seed plants and scrambling ferns. Clay-rich and more fertile, volcaniclastic soils have a positive influence on plant composition, especially in the early stages of primary succession. While soils influence vegetation recovery, soil development on landslides is influenced by landscape variables as well. Soils of flatter, wind-facing plots that were located close to the forest edge contained more soil nitrogen and organic matter.

Li et al. (2014) analysed vegetation recovery on landslides in the Longxi-Hongkou Nature Reserve in China using logistic regression models. More, higher and more diverse vegetation was found on plots located on deposit zones, and plots with less gravel cover. The distance of plots to the surrounding forest influenced the vegetation cover and height. Steeper slopes had a lower species diversity and shrub cover. Lastly, remaining vegetation was of significant influence on the shrub cover on landslides.

Myster et al. (1997) examined the predictive power of landscape characteristics on vegetation recovery on Puerto Rican landslides using four different statistical techniques (maximum likelihood logistic regression, multiple regression, Pearson product-moment correlation coefficients and principal components analysis). Based on those techniques, they concluded that "more successional development takes place on landslides which are older, face away from hurricane winds, are at lower elevation, and are on volcaniclastic substrate" (Myster et al., 1997, p. 299).

1.4. Research gap

Natural forest disturbances are fundamental for the development of many forests (Attiwill, 1994), but can have high impacts on ecosystem services and people's livelihoods (Thom & Seidl, 2016). Billons of people depend on forests to meet their needs for income, employment, food, energy, and shelter (FAO, 2014). To preserve forests as healthy ecosystems, it is essential to understand the ecological processes of natural disturbances and recovery in order to manage forests as a renewable resource that retains their diversity, richness and ecosystem services (Attiwill, 1994; Frolking et al., 2009). Understanding this will help in finding out how forests will behave when disturbance regimes change. In addition, with an increased knowledge about forest disturbances and recovery, forest management, restoration projects, and hazard risk reduction can be improved.

To increase our understanding, extensive research has been done towards forest disturbances and gap succession. However, most studies focus on clearcut logging and fire-disturbances and/or forests in North America and Europe (Prach & Walker, 2020; Thom & Seidl, 2016). Findings of those studies are not one-on-one relatable to landslide succession in tropical forests because landslides damages the forest different than other disturbances (Frolking et al., 2009; Prach & Walker, 2020). Landslides damage the forest and soil at the same time and their occurrence is restricted to steep slopes. On top of this, in the area of study landslides are triggered by hurricanes and tropical storms that also damage the surrounding forest around landslides. The damage to the surrounding forest is expected to result in a different recovery behaviour of vegetation on landslides than recovery in non-hurricane prone regions.

Prach & Walker (2020) found 13 studies that have been investigating vegetation succession on landslides in the tropics. No studies have been found that investigate the recovery of tropical forests with the use of remote sensing. The few studies that used vegetation indices to monitor vegetation recovery on landslides are conducted in non-tropical regions and exclusively use NDVI. Tropical forests recover more rapidly than other forest types and NDVI saturates quickly in the tropics (Clark et al., 2011; Frolking et al., 2009; Walker et al., 2013). Therefore, investigating the utility of other indices to monitor vegetation recovery will give insights about how remote sensing can best be used to monitor vegetation recovery in the tropics.

An important aspect that defines the utility of vegetation indices is how well they can explain the time and process of secondary forest succession. A restoration of vegetation during the secondary succession may have a positive effect on slope stability, even when it is not a fully grown forest. Vegetation alters the water balance by means of evapotranspiration (Jetten, 1994), which makes the soil drier and reduces the change on slope failure caused by soil saturation. The presence of plant roots are positive, because the main source of additional soil strength is from tensile strength of smaller roots, and not from larger roots covered in bark (Kuriakose & van Beek, 2011). On top of the positive effects of vegetation on slope stability, interception, infiltration, and the increased surface roughness prevent soil detachment and delay the onset and velocity of runoff (Gray & Sotir, 1996).

Besides the recovery time of vegetation, knowing which landscape and biological variables influence the recovery time even further increase our understanding of gap succession. Several studies investigated the influence of landscape variables on the recovery of vegetation on landslides in tropical regions. However, they made use of ground-based measurements, which is very precise, but does not allow for an investigation of a large number of landslides. In addition, those studies only investigated a small number of landslides and did this for one moment in time, multiple moments with large breaks in between, or used a space-for-time substitution. The lack of extensive research makes it difficult to extrapolate findings beyond the local regions that are studied (Prach & Walker, 2020; Walker et al., 1996). Several studies recommend to further investigate the influence of landscape and biological variables on landslide recovery (Myster et al., 1997; Walker et al., 2013, 1996).

1.5. Research objectives and questions

To fill the identified knowledge gap the main objective of this study is to:

- Evaluate with vegetation indices how fast vegetation on landslides in tropical rainforest recovers, and which landscape variables influence it.

There are several landslide inventories available for the study area. Those inventories are mapped based on different remote sensing products. The correspondence of the mapped landslides with the actual landslide position on the ground varies among the inventories. That is why it is important to select an inventory for this study that corresponds accurately with the landslide position Sentinel-2 imagery[4] indicates.

SO1: Determine which landslide inventory corresponds best with the landslide positions on Sentinel-2 imagery.

↳ RQ 1.1: To what level are landslides detectable on Sentinel-2 imagery?
↳ RQ 1.2: What is the effect of eliminating mixed pixels at the edges of landslides?

After selecting a landslide inventory, the recovery of vegetation on those landslides has been monitored with a diverse selection of vegetation indices. It included an investigation of how long it takes for vegetation indices to reach pre-disturbance values. Because the surrounding forest has been severely affected by the hurricane, a comparison with vegetation on landslides and the surrounding non-slided forest has been made.

SO2: Evaluate the utility of vegetation indices to monitor vegetation recovery on landslides over time in relation to the surrounding forest, and determine which index can best be used to analyse this process.

↳ RQ 2.1: Which areas can be used as a reference for the non-slided forest?
↳ RQ 2.2: How do we determine changes in vegetation regrowth when the surrounding forest is also damaged?

Potentially, factors related to climate, relief, soil and landslide characteristics (hereafter called landscape variables) influence the restoration of vegetation on landslides.

SO3: Determine the influence of landscape variables on the return of vegetation indices to pre-disturbance levels on landslides.

↳ RQ 3.1: Which landscape variables are available that are related to vegetation growth?
↳ RQ 3.2: Which landscape variables have a linear relation with changes in vegetation index values?
↳ RQ 3.3: Which landscape variables should be included in a multiple linear regression?

[4] Sentinel-2 imagery was used in this study to monitor vegetation recovery over time. Selecting a landslide inventory of which the landslides accurately correspond with the positions Sentinel-2 imagery indicates, improved the accuracy of the analysis in this study.

2. STUDY AREA AND DATA

2.1. The Commonwealth of Dominica

The Commonwealth of Dominica is an island country located in the Lesser Antilles in the Caribbean Sea. The 72,000 inhabitants (2019) of Dominica are sharing 750 km^2 of land of which nearly 60% is covered by tropical rainforest (Government of the Commonwealth of Dominica, 2017; United Nations Statistics Division, 2019). Dominica has been exposed to a total of 13 hurricanes and 16 tropical storms between 1950 and 2019 (Acevedo, 2016; CRED & UCLouvain, 2020[5]). The Category 5 Hurricane Maria was the last hurricane that made landfall (18 September 2017). Figure 2.1. Hurricane Maria at peak intensity on 19 September 2017. The white circle highlights the location of Dominica. Figure adapted from Pasch, Penny, & Berg (2019) presents the size of Hurricane Maria as compared to Dominica. These hurricanes and tropical storms trigged a large number of landslides over the years. Hurricane Maria initiated more than 10,000 landslides in Dominica[6].

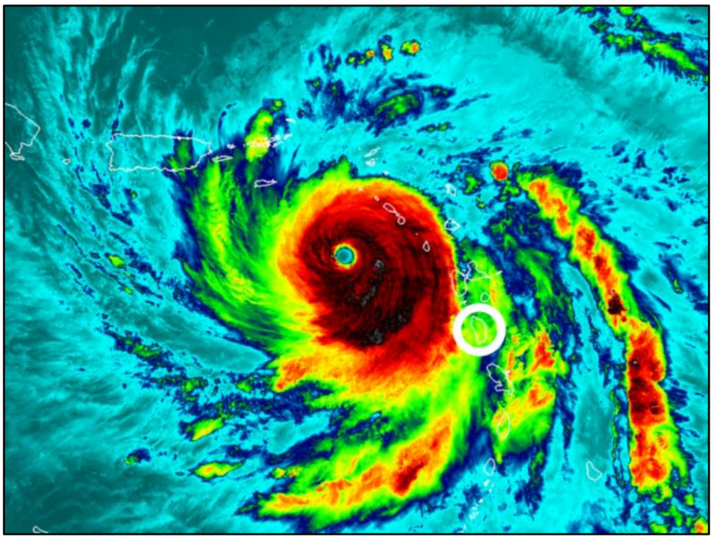


Figure 2.1. Hurricane Maria at peak intensity on 19 September 2017. The white circle highlights the location of Dominica. Figure adapted from Pasch, Penny, & Berg (2019).

Landslides have an impact on the society and environment of Dominica. Between 1925 and 2015, 35 deaths were caused by landslides (Government of the Commonwealth of Dominica, 2017). Landslides, along with floods, contribute to the displacement of woody debris that ends up damaging buildings, infrastructure and bridges. The high wind speeds and intense rainfall of hurricanes as well as the landslides triggered by hurricanes cause severe damage to the forest. Figure 2.2 illustrates that after Hurricane Maria, much of the forest was stripped of leaves and damaged and fallen trees were found all over the island. It also shows how rapidly the vegetation can recover. According to the Government of the Commonwealth of Dominica (2017), Hurricane Maria caused an estimated US$ 30 million of damage and losses to the forestry sector and US$ 182 to transportation infrastructure. Damaged rainforest impacts the economic sectors of Dominica (e.g. tourism and agriculture) and people's livelihoods that (partly) depend on forest resources. Interventions and funding might be needed for erosion control, land stabilisation and to maintain water harvesting facilities (Government of the Commonwealth of Dominica, 2017).

[5] EM-DAT, CRED / UCLouvain, Brussels, Belgium – www.emdat.be (D. Guha-Sapir)

[6] Number based on the Pleiades and DigitalGlobe landslide inventories. The details of those inventories are described in Section 2.3.

Figure 2.2. Photos showing severe hurricane and landslide damage to the Dominican forest and rapid recovery after two years. Photos taken by C.M. Eckelmann in October 2017 (left) and October 2019 (right).

The fact that Dominica is landslide-prone in combination with the majority of the island being covered by forest make Dominica a suitable region to investigate the recovery of tropical rainforest on landslides. Besides this, the outcome of this research could be valuable if interventions focused on erosion control and land stabilisation are conducted.

2.2. The Grand Bay catchment

The Grand Bay catchment is located in the south of Dominica and is selected as the study area. The first reason for selecting is that in the majority of this catchment a large number of landslides were initiated by Hurricane Maria. Even after masking out landslides that are not suitable for analysis, there was still a large number of landslides that could be included. This made it possible to conduct this study with a large sample of the landslide population. Figure 2.3d shows the Grand Bay catchment and the density of landslides triggered by Hurricane Maria.

In addition, the landscape variables of which the influence on recovery has been analysed needed to have some level of variation to be able to conclude whether they influence vegetation recovery. If for instance the whole region has altitudes within a small range, drawing conclusions on the influence of altitude on recovery outside this range becomes difficult. On the other hand, too much variation was not preferable because a minimum number of landslides were needed in each range or class of the landscape variables in order to draw significant conclusions. Figure 2.3 shows the spatial variation of some of the landscape characteristics of Grand Bay.

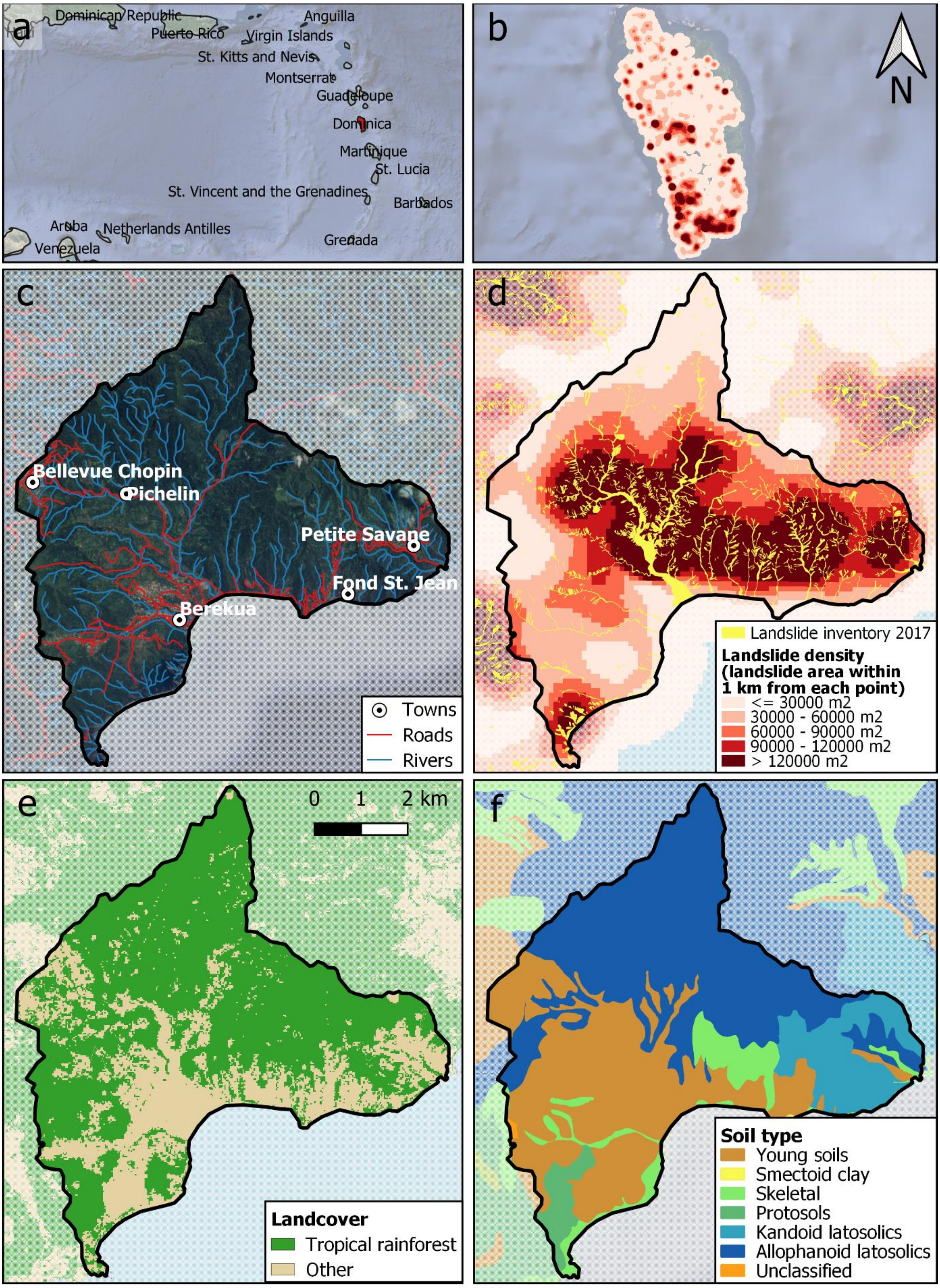


Figure 2.3. Landscape characteristics Grand Bay (a) Location of Dominica in the Caribbean Sea; (b) 2017 landslide density Dominica; (c) Towns, roads and rivers; (d) 2017 landslide density Grand Bay; (e) Tropical rainforest cover; (f) Soil types.[7]

[7] Data sources and details of these maps are provided in Appendix A.

2.3. Landslide inventories

There are four landslide inventories available that contain landslides triggered by Hurricane Maria. Figure 2.4 shows one of the landslides that is mapped in three different inventories. A Lidar DEM from February 2018 shows the vegetation height. Landslides consist of three different zones: the initiation, transport and deposit zone. The initiation zone is where the landslide is initiated and is therefore usually located on steep slopes. The transport zone is where the sliding debris is transported towards a flatter deposit zone. Deposit zones, followed by transport zones, usually contain the most plant growth stimulating nutrients and organic matter (Li et al., 2014; Prach & Walker, 2020; Walker et al., 2013). Vegetation is therefore expected to grow back more rapidly on deposit zones, and the least quick on initiation zones. The distinction between the transport and deposit zone is not always clear, which is why in some cases the two are combined in the inventories. In three of the four inventories these zones were mapped.

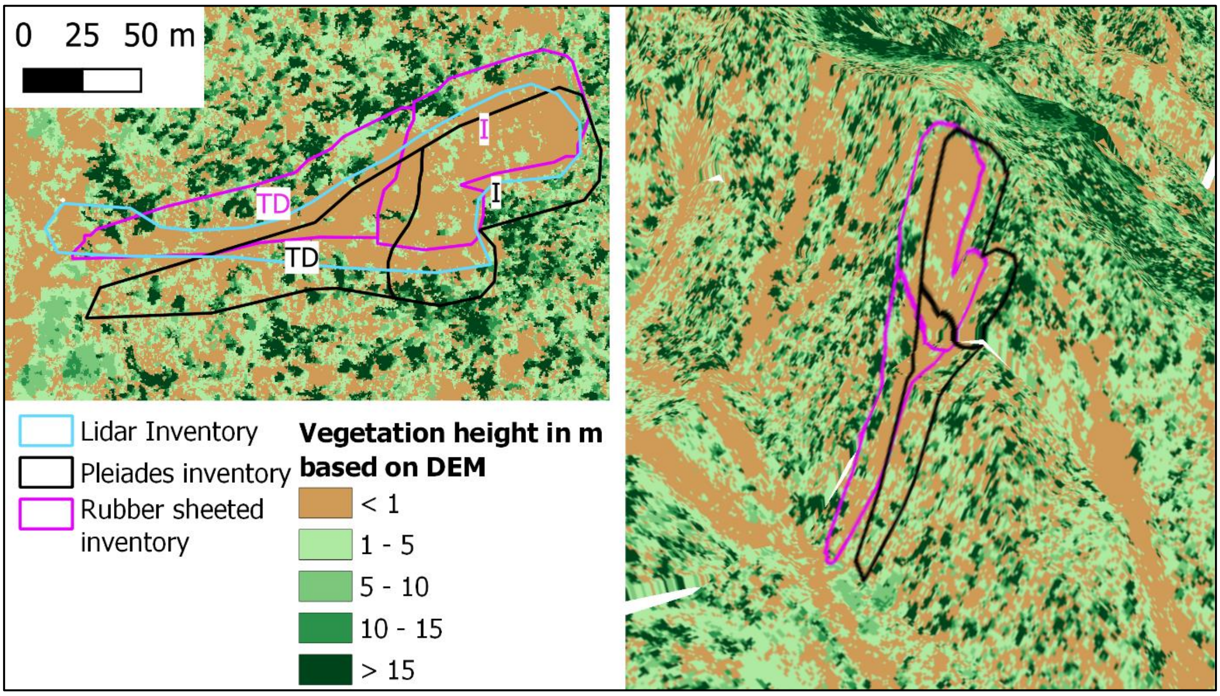


Figure 2.4. Landslide position in different inventories. I stands for Initiation zone and TD stands for Transport/Deposition zone. Left: 2D view. Right: 3D view.

Table 2.1 provides an overview of the properties of the four available landslide inventories. Notable is that the rubber sheeted inventory is based on the Pleiades inventory. The Pleiades inventory has some geometrical distortion due to the quality of the imagery that has been used for landslide mapping. Based on the Lidar DEM 40 control points all over Dominica were used trying to correct for this distortion. Apart from the Lidar inventory, the inventories include for each landslide the type of landslide it is (debris flow, debris slide, rockfall or slipstream).

Table 2.1. Available landslide inventories for Grand Bay.

Properties	Pleiades inventory	Rubber sheeted inventory	DigitalGlobe inventory	Lidar inventory
Mapped based on:	Pleiades imagery (0.5 m resolution) from 23/09/2017	Rubber sheeted Pleiades inventory	DigitalGlobe imagery (~ 1 m resolution) from 11/12/2017	Lidar DEM (0.5 m resolution) from 02/2018
Created by:	C.J. van Westen and J. Zhang (ITC, University of Twente)	C.J. van Westen (ITC, University of Twente)	B. van der Bout (ITC, University of Twente)	B. van den Bout (ITC, University of Twente)
Location of mapped landslides:	The whole study area, except areas covered by clouds on the imagery	The whole study area, except areas covered by clouds on the imagery	The areas covered by clouds on Pleiades imagery	Southern part of the study area (Between Berekua and Fond St. Jean)
Number of landslide polygons in study area:	2,156	2,156	423	134
Other properties:	Each polygon represents one landslide zone (initiation, transport, deposit)	Each polygon represents one landslide zone (initiation, transport, deposit)	Each polygon represents one landslide zone (initiation, transport, deposit)	Each polygon represents one landslide

2.4. Satellite Image Time Series

To extract information of undisturbed and recovering forest on landslides, a medium spatial resolution (10-30 m) satellite product that is available before and after Hurricane Maria was required. Sentinel-1 (SAR) has been considered because it is not affected by cloud cover. However, it uses the C-band which is not very suitable for forestry applications due to their inability to sense through complete vegetation cover. On top of this, the side looking view of radar in combination with the mountainous topography of Dominica results in geometric distortion and shadow problems, especially on steep landslides. To reduce the speckle effect of SAR images, a smoothing function needs to be implemented, which makes the resolution coarser and therefore less suitable for monitoring small landslides.

Because forests recover rapidly in the tropics, it is preferable monitored without large intervals between observations in order to understand the recovery pattern more detailed. Because Dominica is regularly covered by clouds, a product that has a high temporal resolution was needed for aiming to have at least one monthly cloud-free observation. The last requirement is that the product had the spectral bands available that were needed for calculating vegetation index values.

Sentinel-2 imagery has been selected and has the advantage of having a cloud mask band (QA60). However, caution should be taken when using it. Coluzzi, Imbrenda, Lanfredi, & Simoniello (2018) found that the cloud mask performs well, but has, especially for rainforests, difficulties in masking cirrus clouds and the transition zone between the cloud core and cloud-free areas. Sentinel-2 has a spatial resolution of 10 m for the Blue, Red and NIR bands and 20 m for the SWIR1 and SWIR2 bands, which is high enough to measure differences in vegetation on landslides (Frolking et al., 2009; Metternicht et al., 2005). Sentinel-2 is freely available and can be processed in the cloud using Google Earth Engine (GEE). Figure 2.5 shows that Sentinel-2, Level 1C images (top-of-atmosphere reflectance) are available since December 2015. Level 2A imagery (surface reflectance) becomes available from December 2018 onwards. The software Sen2Cor can create L2A imagery by performing atmospheric, terrain and cirrus correction of L1C imagery, which is a time consuming and computational demanding process. Because of the ready to use availability, and the expected sufficiency of the top-of-atmosphere reflectance to measure recovery and differences between non-slided forest and landslides, there was decided to work with L1C imagery.

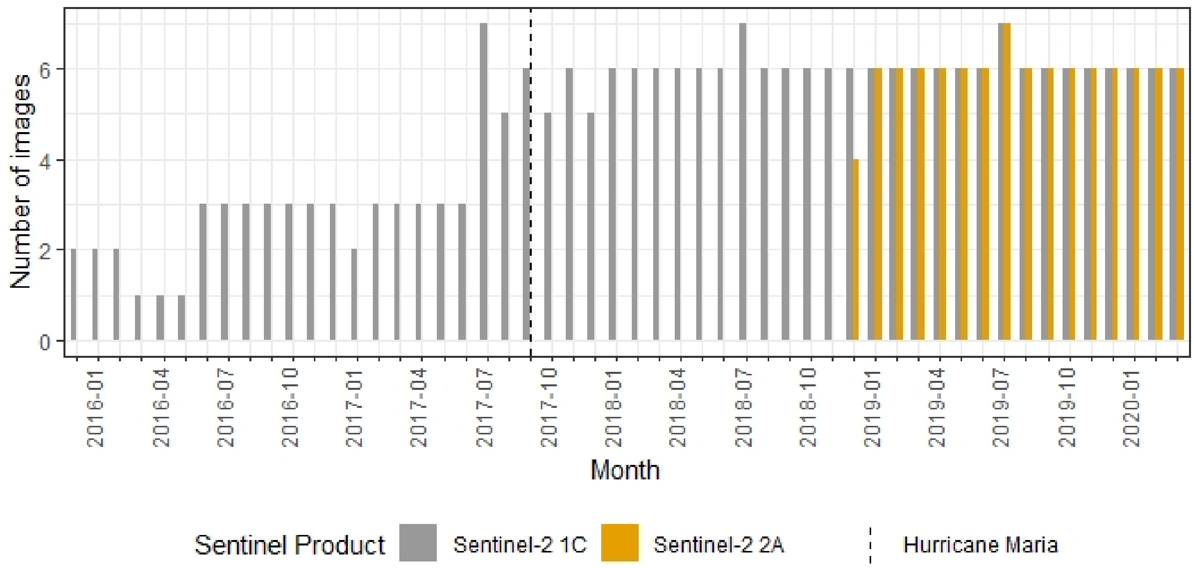


Figure 2.5. Number of available Sentinel-2 images in GEE for the study area per month.

The Sentinel-2 mission consists of two twin satellites. After the launch of the second satellite the number of images increased to on average 6 a month as of from July 2017. There are almost two years of Sentinel-2 images of the study area available before Hurricane Maria made landfall and in the 3.5 months before the hurricane an image is captured every 5 days. This makes it possible to compare the vegetation state after the hurricane with the period before.

3. METHODS

This chapter describes in four sections the methods that have been used to achieve the (sub-)objectives. Those four sections are:

3.1. **Vegetation indices.** This section describes which seven vegetation indices have been used.

3.2. **Selecting a landslide inventory.** Sub-objective 1 is to select a landslide inventory. First, the four available inventories have been modified to create two sets of these four inventories, each set having different properties. Secondly, timeseries data containing vegetation index values of each landslide were extracted. Lastly, the quality of the inventories have been compared, and one inventory was selected.

3.3. **Evaluating the utility of vegetation indices.** Before the ability of vegetation indices to provide information about vegetation recovery on landslides has been evaluated (sub-objective 2), forest buffer zones around the landslides were created. This made it possible to compare the vegetation on landslides with the surrounding forest.

3.4. **Analysing the influence of landscape variables on recovery.** One vegetation index that is best able to monitor vegetation recovery is used to determine the recovery time of the vegetation on landslides. This formed the response variable for a multiple linear regression model of which the landscape variables were the predictors. The outcome of the multiple linear regression provided insights about the influence of landscape variables on vegetation recovery (sub-objective 3).

Figure 3.1 illustrates the main research steps that have been taken.

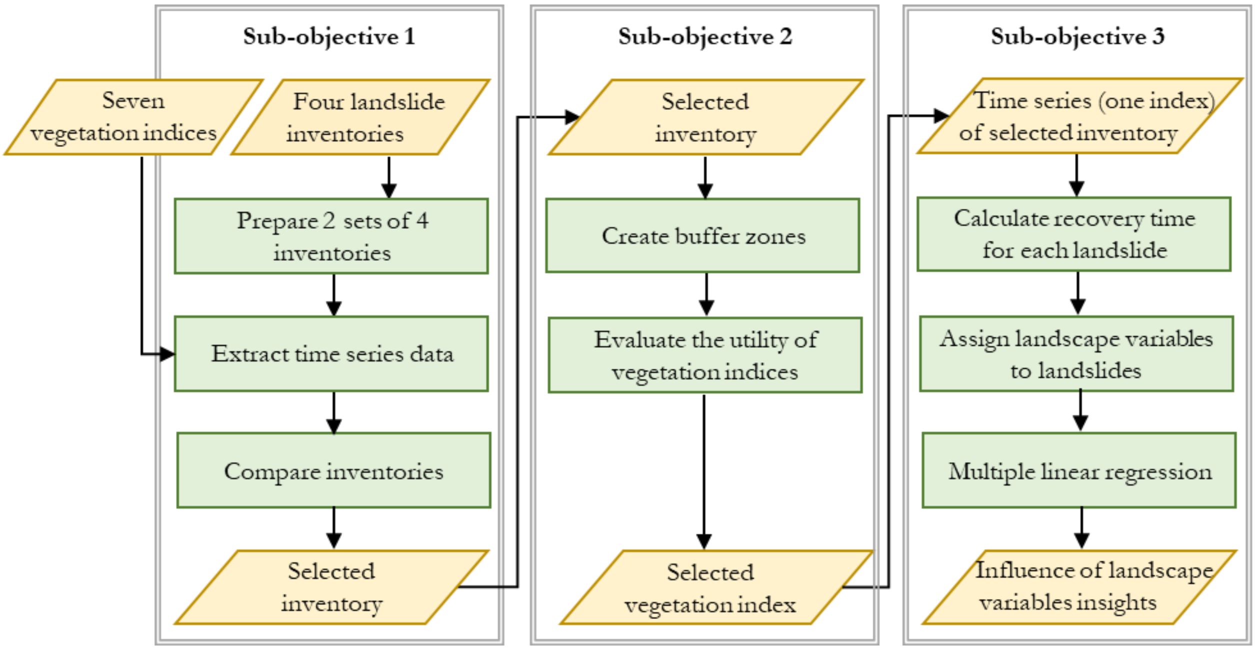


Figure 3.1. Main research steps. Yellow boxes represent input/output and green boxes are processes.

3.1. Vegetation indices

Based on the wavelengths of light absorbed and reflected by vegetation, a large number of vegetation indices have been development and used over the last decades. Each index expresses green vegetation differently and has its own suitability for specific uses and environments. Judged by the usability of vegetation indices to monitor vegetation recovery and by making sure a diverse range of indices is evaluated, seven vegetation indices have been selected for this study. Table 3.1 provides an overview of the indices. Notable is that the IFZ formula is used to derive an input value for the FRI2 formula.

Table 3.1. Vegetation indices evaluated in this study. Bands refer to Sentinel-2 bands.

Vegetation Index	Formula
Atmospherically Resistant Vegetation Index (ARVI)	$ARVI = \frac{((NIR - ((2 * RED) - BLUE))}{(NIR + ((2 * RED) - BLUE)))}$
Enhanced Vegetation Index (EVI)	$EVI = 2.5 * \frac{(NIR - RED)}{(NIR + 6 * RED - 7.5 * BLUE + 1)}$
Forest Recovery Index 2 (FRI2)	$FRI2 = \frac{1}{(IFZ + 1)}$
Integrated Forest Z-score index (IFZ)	$IFZ = \sqrt{\frac{1}{NB}\sum_{i=1}^{NB}\left(\frac{b_{pi} - \bar{b}_i}{SD_i}\right)^2}$
Modified Soil-Adjusted Vegetation Index 2 (MSAVI2)	$MSAVI2 = \frac{(2 * NIR + 1 - \sqrt{(2 * NIR + 1)^2 - 8 * (NIR - RED)})}{2}$
Normalized Difference Moisture Index (NDMI)	$NDMI = \frac{(NIR - SWIR1)}{(NIR + SWIR1)}$
Normalized Difference Vegetation Index (NDVI)	$NDVI = \frac{(NIR - RED)}{(NIR + RED)}$
Soil Adjusted Vegetation Index (SAVI)	$SAVI = \frac{NIR - RED}{NIR + RED + 0.5}\ (1 + 0.5)$

3.1.1. NDVI

NDVI, developed by Rouse, Haas, Schell, & Deering (1974), is one of the oldest and most commonly used vegetation indices. By using the ratio between the Red and NIR spectral bands, it is an index that is closely related to the greenness and leaf pigments of vegetation. The use of NDVI to estimate aboveground biomass is limited to young secondary tropical forests because the NDVI saturates when forests have a LAI of three or more (Clark et al., 2011; Gao, 1996). NDVI is sensitive to soil backgrounds and atmospheric influences. The relative influence of the soil background is higher with dark, wet soils as compared to more brighter soils. For atmospheric influences, the higher the aerosol content the larger the underestimation of NDVI values (Alchanatis et al., 2012; Liu & Huete, 1995). As mentioned in Section 1.4, it is the only index that has been used in several studies to monitor landslide recovery.

3.1.2. ARVI

The Atmospherically Resistant Vegetation Index (ARVI) used the difference in radiation between the Red and blue band to correct for atmospheric influences. According to Kaufman & Tanré (1992), ARVI is on average four times less sensitive to atmospheric effects than NDVI. It is in particular useful in vegetated areas, because ARVI corrects more accurately for atmospheric influence without the influence of soil brightness.

3.1.3. SAVI

The Soil Adjusted Vegetation Index (SAVI) has been developed to mitigate the influence of soil brightness. For NDVI, the influence of soil background decreases with increasing vegetation cover (Huete, 1988). SAVI includes a soil correction factor ranging between 0 and 1 in its formula. This factor should be 1 in case of low vegetation densities and near 0 when the leaf area index (LAI) increases. In this study, landslides and the surrounding forest were analysed. Landslides are expected to have a low vegetation density after occurrence, which tends to increase over time. However, the surrounded rainforest does have high vegetation densities. Therefore, a correction factor of 0.5 was chosen, which reduces soil noise considerably over the range of vegetation densities (Huete, 1988).

3.1.4. MSAVI2

With SAVI the optimal adjustment for the soil effect is found when the correction factor is adjusted based on the LAI of the vegetation. The correction factor is manually adjusted in the SAVI formula, while in the Modified Soil-Adjusted Vegetation Index 2 (MSAVI2) formula the soil correction factor is self-adjusting (Qi, Chehbouni, Huete, Kerr, & Sorooshian, 1994). As a result, the MSAVI2 behaves like NDVI at higher vegetation cover while at lower vegetation cover there is almost no soil correction. When comparing landslides with the surrounding forest, the MSAVI2 might be more suitable than SAVI, because for SAVI only one correction factor can be chosen for both low and high vegetation density each time the formula is applied.

3.1.5. EVI

ARVI, SAVI and MSAVI2 have their advantages when it comes to reducing soil and atmospheric effects. However, as a result of the complex interaction between soil brightness and atmospheric noise, reducing the effect of one might increase the other (Liu & Huete, 1995). To reduce both effects at the same time, the Enhanced Vegetation Index (EVI) has been developed. Another advantage of the EVI is that EVI saturates slower than NDVI when the LAI is increasing, therefore EVI can capture more variation in densely forested areas (Alchanatis et al., 2012; Huete, Liu, Batchily, & Van Leeuwen, 1997). A disadvantage of the EVI is that it is more sensitive than NDVI to topographic conditions (slope and aspect) due to the soil correction factor (Liao, He, & Quan, 2015; Matsushita, Yang, Chen, Onda, & Qiu, 2007).

3.1.6. NDMI

The Normalized Difference Moisture Index (NDMI) is the only selected index that does not include the Red band in its formula. The Red band is located in the strong chlorophyll absorption part of the spectrum, and is therefore sensitive to greenness of vegetation. Different from the Red band is the SWIR1 band, which is sensitive to vegetation density, structure, shadowing and leaf moisture content (Schroeder, Wulder, Healey, & Moisen, 2011). Because NDMI makes use of the NIR and SWIR1 bands it is less sensitive to the greenness of vegetation, which makes it possible to differentiate the LAI up to six leaf layers. The NDMI is less sensitive to atmospheric effects because aerosol scattering effects in the NIR and SWIR1 bands are weak (Gao, 1996). For tropical forest gap monitoring, Masiliūnas (2017) states that NDMI is less sensitive than NDVI to the noise created by shadows from trees surrounding a gap.

3.1.7. FRI2

The Forest Recovery Index 2 (FRI2)[8] can be used to detect forest disturbances and to monitor post-disturbance forest dynamics (Moressi, Vitali, Urbinati, & Garbarino, 2019). The FRI2 uses the outcome of the Integrated Forest Z-score index (IFZ). The Red, SWIR1 and SWIR2 Sentinel-2 bands are sensitive to forest cover changes (Huang et al., 2009) and are used in the IFZ to evaluate the likelihood of pixels being recovered. It compares each pixel (b_{pi}) in an image with healthy, undisturbed forest. The $\bar{b}_i$ and SD_i in the IFZ formula are the mean and standard deviation values of the Red, SWIR1 and SWIR2 bands obtained from healthy, undisturbed forested training pixels.

The spectral signature of healthy, undisturbed forest follows a more or less normal distribution in certain spectral ranges, which is called the forest peak (Huang et al., 2008). There are different approaches used to find the forest peak. One method is to calculate the means and standard deviations of undisturbed forest pixels that have a tree canopy fractional cover higher than 90% (Moressi et al., 2019). Another method is to identify the forest peak in a histogram of substantial forest pixels in an area where non-vegetated areas are already masked out (Huang et al., 2008). Even if not all the bands follow a rigorous normal distribution, an approximate probability interpretation is still applicable to determine the mean and standard deviation values (Huang et al., 2009, 2008).

3.2. Selecting a landslide inventory

The vegetation indices under study were input for extracting time series data. This time series data has been used to compare the quality of the available landslide inventories. As mentioned in Section 2.3, the landslides positions are not accurately matching among the inventories because different imagery has been used to map those landslides. Selecting an inventory of which the landslides correspond accurately with the landslide position on Sentinel-2 imagery improved the quality of the analysis in this study. Based on the following criteria the qualities of the landslides inventories were inspected:

- **Detectability of landslide disturbance.** The drop in vegetation index values of landslide inventories have been compared with non-slided forest. It was expected that when an inventory corresponds with the landslide positions on Sentinel-2 imagery there is a significant difference in vegetation index values between landslides and non-slided forest.
- **Geometrical correspondence of landslides.** Besides comparing the inventories with non-slided forest, the inventories have also been compared with each other. In case inventory 'X' has a larger drop in vegetation index values when the landslide occurred compared to other inventories, inventory 'X' is expected to have a better geometrical correspondence with the landslide positions on Sentinel-2 imagery.

The outcome of this comparison has been used to select an inventory that formed the input for the next research steps. There are four inventories available for the study area. In order to analyse the quality of those inventories, the following data preparation steps were taken: 1. Region of interest masking, 2. Landslide filtering, 3. Creation of two sets of four inventories, and 4. Time series data extraction. The details of those four steps are explained in the next paragraphs.

[8] FRI2 is the revised version of the Forest Recovery Index (FRI), which was developed by Chu, Guo, & Takeda (2016). FRI2 and FRI are both based on the outcome of the Integrated Forest Z-score index (IFZ). In contrast with FRI, FRI2 results in values between 0 and 1 by adding 1 to IFZ at the denominator, which avoids infinite large outcomes when IFZ is close to 0.

3.2.1. Region of interest masking

The first step is that a region of interest was created. This region has been used to exclude the parts of landslides that are not located in tropical rainforest. Landslides, or parts thereof, that have been excluded are those that are located on major roads, grassland, agricultural land, and built-up areas. Secondly, also (parts of) landslides that occurred in 2017 that overlap with landslides in the 2014 and 2015 inventories have been excluded. This is because on those locations the forest was already affected by a large disturbance before, which probably makes the vegetation recovery behave different than forest that was only disturbed in 2017. Around the areas that were excluded, a buffer of 5 m is drawn that was also excluded to correct for geometrical distortion. Even without geometrical distortion, the surrounding forest located close to previous landslides and non-forested landcover is probably not representative of a full-grown tropical rainforest. Appendix A provides a complete overview of the data that was used to create this region of interest.

The Lidar inventory only contains 134 mapped landslides. Although landslides not located in tropical rainforest are excluded, the decision has been made not to exclude landslides that are located on landslides from the 2014 and 2015 inventories. This would even further reduce the size of this inventory, which was unwanted since this would result in an even smaller sample size. During the interpretation of the results this decision was taken into account.

3.2.2. Landslide filtering

For the remaining landslides after the region of interest masking, additional filtering took place. Landslides classified as rockfalls have been excluded, the 23 rockfalls in the study area are all located on coastal cliffs on the edge of regions classified as tropical rainforest. It is unlikely that a tropical rainforest will grow on a coastal cliff that did already not have much vegetation. Landslides classified as slip streams have been excluded as well. Slip streams are large, elongated deposit streams that carry a high amount of debris (like tree trunks) that usually end up in rivers that further transport the debris. On most parts of those slip streams forest is not likely to grow back because there was already not a full-grown forest before and because slip streams still occasionally transport debris during heavy rainfall events. This, plus the fact that slip streams are much bigger than other types of landslides, make it difficult to make a proper comparison between slip streams and other types of landslides.

Sentinel-2 has a 10 m resolution for most of the bands that were used in this study. Satellite products with a medium spatial resolution are not able to monitor small disturbances (Frolking et al., 2009; Metternicht et al., 2005), that is why all landslides smaller than 100 m^2 are excluded. Landslides of which less than 95% of their original size remained after masking the region of interest were excluded, because the remaining landslide polygon should be a good representation of the state of the vegetation on the whole landslide.

3.2.3. Creation of two sets of four inventories

After the region of interest masking and filtering, there were four inventories ready to be used for further analysis. However, when the landslide polygons of those inventories are used, there will be Sentinel-2 pixels that are located on the boundaries of the landslide polygons. Even though only pixels of which the centroid falls within the landslide polygon will be included, there are still boundary pixels[9] (BP) that would not only reflect the state of the vegetation on the landslides, but also the surrounding forest. On top of this, the geometrical correspondence of the inventories with Sentinel-2 imagery is not perfect, and excluding the

[9] Also known as mixed pixels.

outer 5 m results in smaller landslide polygons that are more likely to fall within the position of the landslide that Sentinel-2 imagery indicates. Figure 3.2 visualizes the impact of excluding the outer 5 m of landslide polygons.

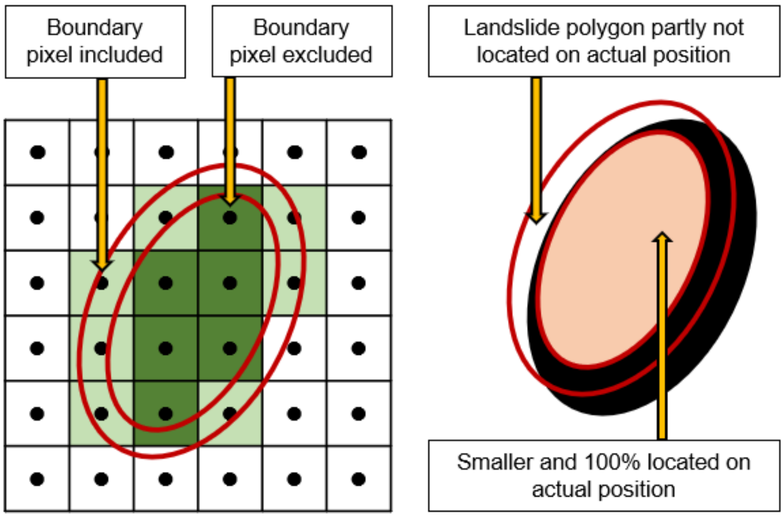


Figure 3.2. The impact of excluding the outer 5 m of landslide polygons. The big red oval represents the original landslide and the small red circle represents the same landslide but with an exclusion of the outer 5 m. Left: when excluding the outer 5m, boundary pixels (light green) will not be measured and pixels that are fully located within the original landslide (dark green) will. Right: improvement of geometrical correspondence (black oval represents the true landslide position on Sentinel-2 imagery).

Excluding the outer 5 m of landslide polygons from the analysis could improve the ability to capture the state of the vegetation located on landslides, without a disturbed reflectance signal of the surrounding forest. That is why an additional set of four inventories have been created that excludes the outer 5 m. This resulted in two sets of the four inventories that will be taken to the next step, one set with an exclusion of the outer 5 m (without boundary pixels) and one set that contains the original size of the landslide polygons (with boundary pixels). Worth mentioning is that the inventories in the set that excludes the outer 5 m contain less landslides due to this exclusion.

3.2.4. Time series data extraction

The two sets of the four inventories have been used to extract Sentinel-2 time series data. In GEE, opaque and cirrus clouds have been masked out using band QA60. For the landslide polygons the vegetation indices values were calculated. This has been done by calculating the mean of the spectral band values of pixels of which the centroid falls inside the landslide polygon. The mean calculation was weighted, which means that the pixels that fall partly into the polygons were included in the mean calculation according to the percentage of the pixels that are located inside the polygons. December 2015 till March 2020 is the time range wherefor vegetation indices values have been extracted.

The on the IFZ formula based FRI2 required input parameters that had to be obtained before the IFZ values of the polygons could be calculated. The input parameters for the IFZ formula are the mean and standard deviation of normally distributed undisturbed forest pixels in the study area, which is used as a reference situation. Some studies use the reflectance values from undisturbed forest at the same moment in time for which FRI2 is calculated as a reference (Chu, Guo, & Takeda, 2016; Huang et al., 2009, 2008). Because Hurricane Maria did severely damage the non-slided forest, the non-slided forest at the same moment in time would for this study not be a proper ‘recovered state’ reference situation. Similar to Moressi et al. (2019), this study used the yearly average reflectance values from a pre-disturbance period as a reference situation. The state of the forest from September 2016 till August 2017 is considered a good reference situation because no hurricane or tropical storm made landfall in Dominica in this period and the months before.

2000 circular polygons with a diameter of 30 m have been randomly created in undisturbed forested areas, excluding areas where landslides happened in recent years, build-up areas, roads, and the 5 m around those excluded areas. From those 2000 polygons, at each moment cloud-free Sentinel-2 imagery is available, reflectance values of the Red, SWIR1 and SWIR2 band have been acquired. For every polygon, the yearly mean for each band has been calculated. The 2000 circular polygon values for the bands have been used to determine the forest peak by making density histograms and normal distribution curves of the spectral reflectance in each band. The normal distribution of the forest peak has been checked using the Shapiro-Wilk test. For every band, the mean and standard deviation of undisturbed forest is calculated and serves as input parameters for the FRI2 formula. The density histograms, normal distribution curves and the outcome of the Shapiro-Wilk tests are shown in Appendix B.

After acquiring the time series data, some additional processing in R had to be done. Because Sentinel-2 does capture some regions twice at the same time, the values measured can have a very small difference. In cases this happened, the mean of those values is used. After that, for each month before and after hurricane Maria the mean of the vegetation index values of each landslide was calculated. This means for example that the first month before hurricane Maria is from 18 August 2017 until and including 17 September 2017. This monthly data has been used to compare the inventories.

3.2.5. Inventory comparison

After the data preparation steps, the detectability of landslide disturbance has been analysed by comparing the drop of vegetation index values of landslides with the 2000 non-slided forest polygons. Also, the non-slided forest polygons were damaged by Hurricane Maria, and it is essential[10] to know whether landslides drop more in vegetation index values than the non-slided forest. A two-sided independent t-test was used to test whether there was a significant drop in vegetation index values between landslide inventories and the non-slided forest polygons in the third month after the hurricane. Hu & Smith (2018) state that NDVI returned to near normal values on the island within 1.5 months. If landslides in inventories are accurately corresponding with the location on Sentinel-2 imagery, this would mean that if there is a difference in vegetation index values between landslides and the non-slided forest, it should be visible in the third month after the hurricane.

If landslide disturbance is detectable, there is expected that the drop in vegetation indices values will be larger when landslides in inventory ‘X’ do more accurately correspond with the positions on Sentinel-2 imagery than inventory ‘Y’. However, not all landslide inventories do contain landslides in the same regions of the study area. Hurricane and landslide damage varies per region, which means a comparison between inventories of different regions in the drop of vegetation index values will not tell anything about the geometrical correspondence. For the landslide inventories that do contain landslides in the same regions,

[10] If there is no difference in vegetation index values between landslides and the non-slided forest, the vegetation indices would tell more about the impact of the hurricane on the region than about the vegetation on individual landslides.

the following comparisons were made for the vegetation indices values in the third month after the hurricane:

- A comparison between the Pleiades and rubber sheeted inventories using a two-sided independent t-test. This made clear if the rubber sheeting did reduce the geometrical distortion of the Pleiades inventory.
- A comparison between the inventories with and without boundary pixels using a two-sided independent t-test. This showed whether the exclusion of the boundary pixels improved the ability to monitor vegetation recovery on landslides.

Finally, one inventory for the whole study area is selected based on the inventory comparison.

3.3. Evaluating the utility of vegetation indices

After selecting a landslide inventory, the ability of vegetation indices to provide information about vegetation recovery on landslides has been evaluated. Based on their abilities, one index has been selected to analyse the influence of landscape variables on recovery.

3.3.1. Creating buffer zones

One way to derive insights about the recovery is to compare landslides with the non-slided forest surrounding landslides. The surrounding forest has been damaged by Hurricane Maria. Unlike the created 2000 non-slided forest polygons, the direct surrounding forest is defined as a buffer zone from 10 to 30 meters located in the forest around landslide polygons (Figure 3.3). Mapped landslides polygons do not always completely represent the actual position, that is why the first 10 meters around the polygons were not included in the buffer zones. Similar to the landslide inventories, the region of interest masking has been applied. One addition to this mask is that also landslides from the 2017 inventory were excluded from the buffers. Buffers should be able to represent the surrounding forest. Therefore, buffers smaller than 300 m^2 were excluded. For all the buffers, the monthly mean vegetation index values were calculated for each month cloud-free Sentinel-2 imagery is available.

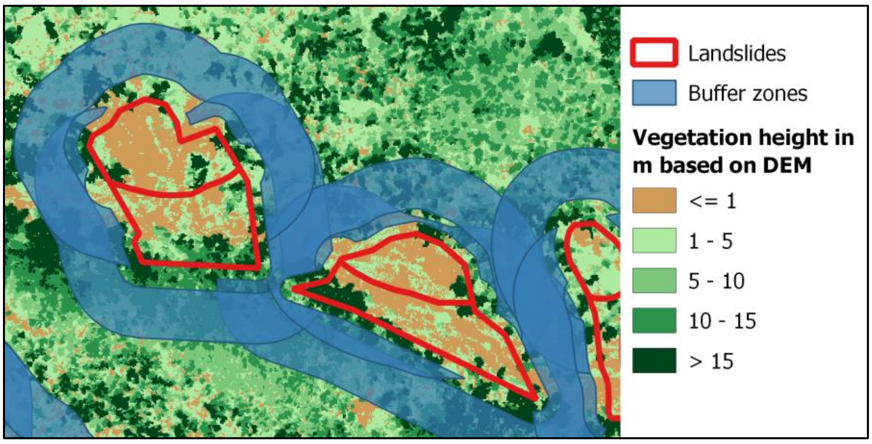


Figure 3.3. Buffer zones around landslides.

3.3.2. Comparing vegetation indices

The behaviour of vegetation indices values over time have been analysed in the following ways:

- By analysing the overall trend in vegetation index values for landslides and their buffers, which made it possible to see their absolute difference.

- By calculating the landslide/buffer ratio for each moment in time (Equation 4.1). In the months before the hurricane this ratio will be around 100% and after the hurricane this ratio is expected to gradually increase to 100%. This analysis gave insight in the relative difference between landslides and buffers, and how long it takes on landslides to reach vegetation indices values similar to the surrounding forest.

$$\frac{(landslide\ vegetation\ index\ value + 1)}{(buffer\ vegetation\ index\ value + 1)} * 100\%$$

Equation 4.1.

- Through investigating the Vegetation Recovery Rate (VRR), which has been used in other studies investigating the recovery of landslides (Jiang et al., 2015; Lin et al., 2005; Yang et al., 2017; Yunus et al., 2020). In Equation 4.2, N_0 is the vegetation index value of a landslide before the landslide disturbance happened, N_1 is the measured value directly after the disturbance of a landslide and N_t is the vegetation index value at 't' months after disturbance. For each landslide, N_0 has been calculated as the average value of the year before the hurricane happened. For N_1, the average value of the first month after the hurricane was used. For N_t, each moment in time to calculate the VRR for was used[11].

$$VRR\ (\%) = \frac{N_t - N_1}{N_0 - N_1} * 100\%$$

Equation 4.2.

The overall trend, the landslide/buffer ratio, and the VRR values are plotted over time. The values from three months before till six months after the hurricane are shown in boxplots in timesteps of months. In several months outside this range there were less than 75% of the total landslides with measured values due to cloud cover. This, in combination the highest rate of change happening in especially the first few months, led to the decision to visualize the landslide values in timesteps of six months from the seventh month onwards. The average values over the year before the hurricane is plotted as a reference situation.

To find out till which extent different indices hold different information, the correlation between vegetation index values of all landslides from 12 months before till 30 months after Hurricane Maria has been analysed by calculating the Pearson correlation coefficients.

3.4. Analysing the influence of landscape variables on recovery

To analyse the influence of landscape variables on vegetation recovery a multiple linear regression model has been used with recovery time as response variable and landscape variables as predictors.

3.4.1. Recovery time as response variable

Based on the utility of the vegetation indices, one index that is best able to quantify vegetation recovery over time has been selected. Other studies have used the VRR of landslides for one moment in time to analyse which landscape variables influenced vegetation recovery. This study deviated from this approach because it would not be possible to differentiate between landslides that are classified as recovered at one specific moment in time. If for example two landslides are recovered, but one much earlier than the other, this approach cannot identify which landscape variables made this one landslide recover faster than the other. Instead, this study used VRR values of the selected index to determine for each landslide how long it takes to recover.

[11] For all the landslides where N_0, N_1 or N_t did not have values due to cloud cover, the VRR could not be calculated.

For each landslide, the month in which the VRR ≥ 100% for on average one month has been used as the response variable. An additional advantage is that the response variable is a continuous variable, and not a categorical variable as opposed to the approach other studies used[12]. Due to cloud cover, there are some landslides that did not have vegetation index values on a regular base. Therefore, 272 landslides with less than 15 months without values in the first 30 months after disturbance have been excluded from the analysis. The landslides that did not recover up to a VRR ≥ 100% in the first 30 months were assigned the label 31 ≥. The length of the recovery of the landslides have been plotted and a threshold has been set at the moment almost no landslides did recover. The few landslides recovering after this threshold are excluded from the analysis because it would not be possible to draw significant conclusions based on this small subset of samples in each monthly timestep.

3.4.2. Landscape variables as predictors

Twelve landscape variables (Table 3.2) have been selected of which the influence on recovery speed has been analysed. Appendix A provides the data sources and details of those variables.

Table 3.2. Landscape variables. Variables with an asterisk are categorical variables, without it are continuous variables[13].

Landscape variable	Explanation
Remaining vegetation	The remaining vegetation is quantified as the EVI value on the landslide in the first month after the hurricane. This indicates how severe the vegetation on the landslide was damaged.
Damage to surrounding forest	The damage done to the buffers around landslides is expressed as the EVI buffer value in the first month after disturbance divided by the EVI buffer value in the month before disturbance times 100%. The higher this percentage, the less damage has been done to the surrounding forest.
Area/perimeter ratio	The area/perimeter is the area of the landslide divided by its perimeter. It is an indicator that expresses the area and shape of the landslide simultaneously.
Altitude	The average height of the landslides expressed in meters above sea-level.
Slope	The average slope of landslides in percentage.
Radiation	Global Horizontal Irradiation is the total amount of shortwave radiation (kWh/m^2) received from above by a surface, the value includes both direct normal irradiance and diffuse horizontal irradiance.
Annual rainfall	The annual rainfall expressed in mm (1 km resolution).
Landslide zone*	The zone of landslides can be initiation, transport, deposit or transport/deposit zone.
Landslide type*	The type of landslides can be debris flow or debris slide.
Aspect*	The aspect is categorised into the eight wind directions.
Soil type*	Landslides took place on five different soil types (in brackets the soil class): 1. skeletal (gravelly sandy loam), 2. protosols (sandy loam with less fine matrix), 3. young soils (sandy loam), 4. allophanoid soils (sandy clay loam), and 5. kandoid latosolics (silty clay). Hereby is 1 to 5 a scale of how far soils are weathered. Skeletal and protosols contain a large part of un-weathered minerals while kandoid latosolics are deeply weathered clay.
Soil depth*	The estimated soil depth in the region of the landslide is taken into account. It has five classes: very shallow (< 0.25 m), shallow (0.25-0.75 m), moderate (0.25-0.75 m), deep (1.25-1.5 m), and very deep (> 1.5 m).

[12] Because the VRR can have infinite low or high values, other studies classified the VRR outcome into classes. The disadvantage of this is that there are still differences in recovery level between landslides that are grouped into the same class.

[13] It is important to note that not all the landslides do have altitude, slope and aspect values. Out of the 1359 landslides, 217 did not have these values. This is because the Lidar DEM was used to obtain those values. Lidar did capture most of the study area, but some parts on the northeast side of the study area were not flown.

Based on the literature review the landscape variables are expected to influence vegetation recovery. However, before a multiple linear regression was executed, those variables have been checked to see if they influence vegetation recovery in the study area. To see of the continues variables significantly correlate with recovery speed, scatterplots and linear regression lines were made. The variables without a $p < .05$ were excluded and not used in the multivariate regression. For categorical variables, boxplots were made., showing the categorical variables on the y-axe and showing the recovery time in months on the x-axe. Categorical variables were there were small or no differences in recovery time among categories were excluded. For the variables, the Pearson correlation coefficients were calculated and from correlating variables only one variable was used for the multiple linear regression. The remaining landscape variables have been analysed in a multiple linear regression. After running the first model, landscape variables with a $p < .05$ were excluded before the final model was ran.

4. RESULTS

4.1. Selecting a landslide inventory

This section is about the usability of the different landslide inventories to monitor vegetation recovery, it discusses the detectability of landslide disturbance and the geometrical correspondence of mapped landslides with Sentinel-2 imagery. For the non-slided forest polygons and the two sets of four inventories, (one set with boundary pixels (BP) and one set without) the monthly averaged vegetation index values are shown in boxplots in Figure 4.1 and Appendix C. All the inventories have significant lower vegetation index values in the first month after Hurricane Maria as compared to the month before (paired, one-tailed t-test, $p < .05$). This is the case for all the vegetation indices apart from FRI2, which is the only index that does not significantly ($p > .05$) drop in values caused by hurricane and landslide disturbance[14]. Before the occurrence of the hurricane, outliers were skewed to lower values, while afterwards, outliers were skewed towards higher values. Although this indicates that not all landslides are damaged severely, the majority of outliers in the first month after disturbance are still lower than the mean values in the months before.

4.1.1. Detectability of landslide disturbance

Apart from FRI2, the indices indicate that the non-slided forest polygons are rapidly recovering from the second month after disturbance onwards. In the third month after disturbance, the vegetation index values of the forest polygons have been compared with the eight landslide inventories. This comparison showed that ARVI, EVI, MSAVI2, NDMI, NDVI, and SAVI all have significantly ($p < .05$) lower values for the inventories than for the non-slided forest polygons (Table 4.1).

Table 4.1. T-test results comparing vegetation indices values forest polygons with landslide inventories in the third month after the hurricane. Meaning of numbers: 1. Pleiades with boundary pixels (BP), 2. Pleiades without BP, 3. Rubbersheeted with BP, 4. Rubbersheeted without BP, 5. DigitalGlobe with BP, 6. DigitalGlobe without BP, 7. Lidar with BP, 8. Lidar without BP.

Independent, two-tailed t-test. Colours represent: $p \geq .05$ | $p < .05$								
Index	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
ARVI	.00	.00	.00	.00	.00	.00	.00	.00
EVI	.00	.00	.04	.02	.00	.00	.02	.00
FRI2	.00	.18	.06	.42	.00	.01	.13	.21
MSAVI2	.00	.00	.05	.03	.00	.00	.02	.01
NDMI	.00	.00	.00	.00	.00	.00	.00	.00
NDVI	.00	.00	.00	.00	.00	.00	.00	.00
SAVI	.00	.00	.02	.01	.00	.00	.01	.01

[14] See Appendix C for the FRI2 boxplots.

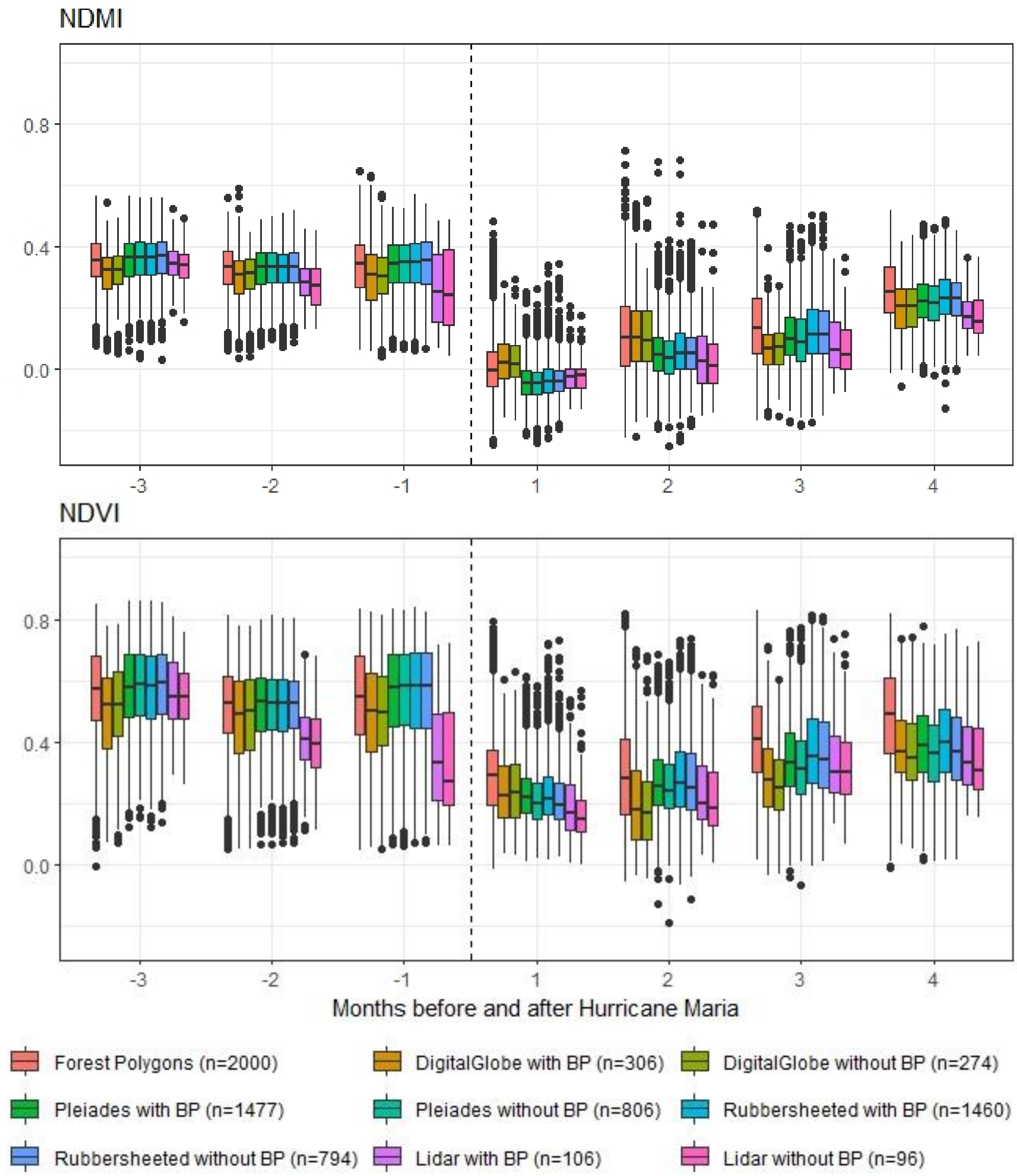


Figure 4.1. Monthly NDMI and NDVI boxplots for months before and after Hurricane Maria. Colours stand for the non-slided forest polygons and two sets of the four inventories (one set with boundary pixels (BP) and one set without). The dotted line represents hurricane Maria that happened on 18/09/2017. Outliers, visualized as dots, are defined as values over 1.5 times the interquartile range above the 75th percentile (Q3) or below the 25th percentile (Q1).

4.1.2. Geometrical correspondence of landslides

Since the rubber sheeted inventories contain landslides in the same region of the study area as the Pleiades inventories, a comparison between the two has been made to see whether one of the two has a larger drop in vegetation index values. In Section 4.1.1 it became clear that the forest polygons recovered more rapidly than landslide inventories. This supports the assumption that the more accurately an inventory corresponds with Sentinel-2 imagery, the lower the vegetation index values will be. This means a smaller portion of landslides is located in non-slided forest, which results in a slower recovery of vegetation index values.

Although there was expected that the rubber sheeted inventory would be better corresponding with Sentinel-2 imagery due to the correction, the ARVI, EVI, MSAVI2, NDMI, NDVI and SAVI values of the Pleiades inventories were significantly lower than the rubber sheeted inventories (Table 4.2). A reason for this could be that the 40 control points for the rubber sheeting were placed all over Dominica, and not specifically in the study area.

Table 4.2. T-test results comparing vegetation indices values for the Pleiades and rubbersheeted inventories in the third month after the hurricane.

Independent, two-tailed t-test. Colours represent: $p \geq .05$ | $p < .05$		
Index	**Pleiades - rubber sheeted (both with BP)**	**Pleiades – rubber sheeted (both without BP)**
ARVI	.00	.00
EVI	.00	.00
FRI2	.29	.66
MSAVI2	.00	.00
NDMI	.00	.00
NDVI	.00	.00
SAVI	.00	.00

To discover if the exclusion of boundary pixels did actually improve the capability of exclusively monitoring the forest recovery on landslides, the inventories with and without boundary pixels are compared with each other. Only in a few cases the inventories without boundary pixels had significantly lower vegetation index values than inventories with boundary pixels (Table 4.3).

Table 4.3. T-test results comparing vegetation indices values between the inventories with and without boundary pixels in third month after the hurricane.

Independent, two-tailed t-test. Colours represent: $p \geq .05$ | $p < .05$				
Index	**Pleiades**	**Rubbersheeted**	**DigitalGlobe**	**Lidar**
ARVI	.00	.14	.27	.78
EVI	1	1	1	.95
FRI2	.30	.51	.61	.99
MSAVI2	.02	.57	.04	.56
NDMI	.19	.93	.39	.33
NDVI	.00	.26	.09	.71
SAVI	.01	.53	.04	.56

4.1.3. Selected landslide inventory

For all the landslide inventories, ARVI, EVI, MSAVI2, NDMI, NDVI, SAVI are able to detect hurricane and landslide disturbance. FRI2 is not able to do this and is therefore not used in the remainder of this study. The Pleiades inventory has significantly lower vegetation index values than the rubber sheeted inventory, which provides an argument to pick the Pleiades inventory over the rubber sheeted inventory. In most cases the exclusion of boundary pixels did not result in lower vegetation index values. In addition, the exclusion of boundary pixels resulted in inventories with a smaller subset, and therefore the inventories with boundary pixels are preferred to maintain a larger sample size. Unlike the Lidar inventory, the Pleiades and DigitalGlobe inventories do together consist out of mapped landslides in the whole study area. That is why the Pleiades and DigitalGlobe inventory, both with boundary pixels, have been selected for the in-depth analysis in the remainder of the study.

4.2. The utility of vegetation indices

The selected landslide inventory has been used to evaluate the utility of different vegetation indices to monitor vegetation recovery on landslides.

4.2.1. Vegetation index values over time

The vegetation indices values dropped severely for both the landslides and the surrounding forest in the buffer zones (Figure 4.2). The buffers dropped less in values and reached pre-disturbance values earlier than the landslides. ARVI, MSAVI2, NDVI and SAVI buffer values reached near pre-disturbance values in the 6th month after the hurricane. EVI and NDMI buffer values take longer and reached near pre-disturbance values in between the 13th and 18th month.

The difference between buffers and landslides is getting smaller within 7-12 months after disturbance for all indices. However, up to 30 months the average of landslides remains consistently lower than the buffer average. ARVI, EVI and NDVI show much larger differences between landslides and buffers in the first half a year than MSAVI2 and SAVI. For NDMI, the differences are even smaller.

EVI and NDVI behave similar in the first four months after the hurricane. Corresponding with the literature (Alchanatis et al., 2012; Huete et al., 1997), NDVI saturates faster than EVI when vegetation recovers. For NDVI, the difference between landslides and buffers is on average 0.01 in the periods 19-24 and 25-30 months. For EVI, the differences in the same periods are 0.02 and 0.04, respectively. Although the differences between landslides and buffers are small for EVI and NDVI, they are still significant (independent, two-tailed t-test, $p < .05$).

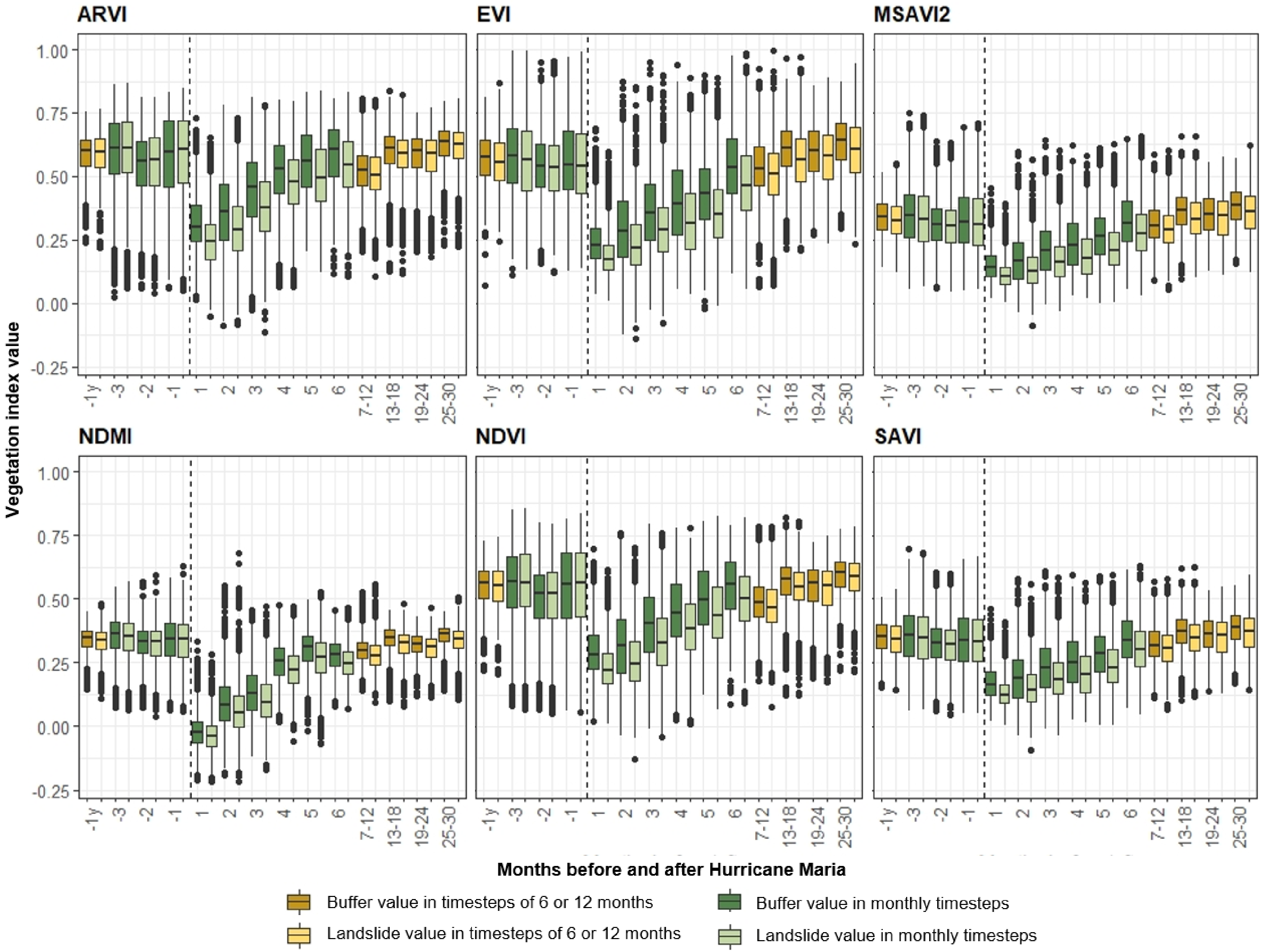


Figure 4.2. Vegetation index values for landslides and buffers over time. The dotted line represents Hurricane Maria. '-1y' stands for the averaged values over the year before the hurricane happened. Outliers, visualized as dots, are defined as values over 1.5 times the interquartile range above the 75th percentile (Q3) or below the 25th percentile (Q1).

4.2.2. Comparing landslides with the surrounding forest

Even though landslides and buffers are recovering from the first month onwards (Figure 4.2) the difference in index values between landslides and buffers remains more or less stable in the first six months after disturbance (Figure 4.3). The landslide/buffer ratio does also show that NDMI behaves noteworthy different than the other indices. Where other indices are fluctuating a bit in the first six months, the difference of NDMI between buffers and landslides is increasing in the first five months.

ARVI, MSAVI2, NDVI and SAVI reach on average values near 100% between the 19th and 24th month period after the hurricane. For EVI and NDMI there is still a small difference observable between landslide and buffer values in the 25th to 30th month period.

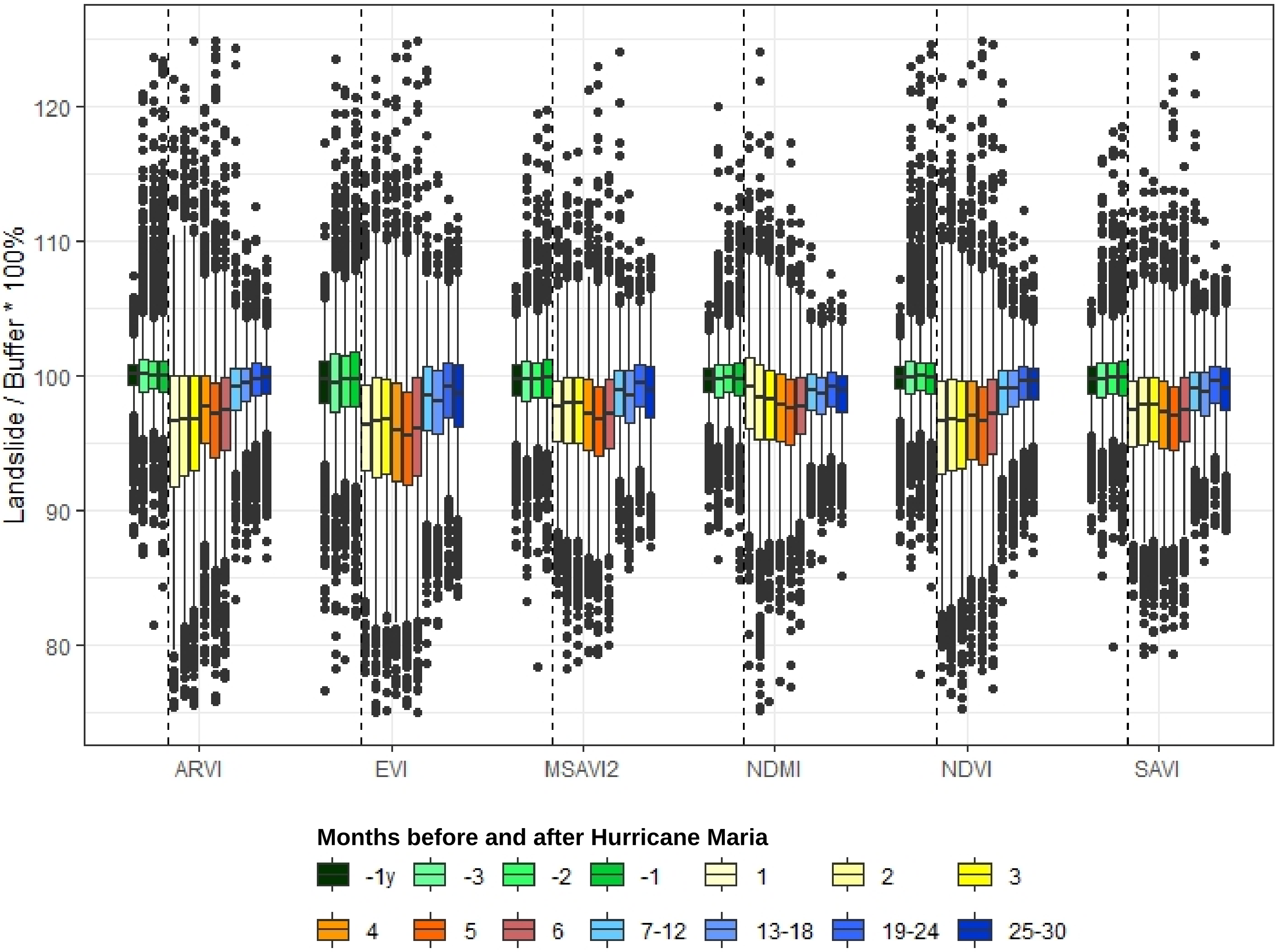


Figure 4.3. Landslide/buffer ratio over time. The dotted line represents Hurricane Maria. '-1y' stands for the averaged values over the year before the hurricane happened. Outliers, visualized as dots, are defined as values over 1.5 times the interquartile range above the 75th percentile (Q3) or below the 25th percentile (Q1).

4.2.3. Vegetation Recovery Rate over time

As opposed to the absolute vegetation index values and the landslide/buffer ratio, VRR expresses more observable how landslides are recovering (Figure 4.4). In the months before the hurricane, it can be seen that the VRR fluctuates around 100% due to forest dynamics, seasonal changes and atmospheric effects. Notable is that ARVI and NDMI reach an average VRR of around 75% more rapidly than the other indices. However, this does not lead to a shorter recovery time because all indices reach an average VRR near 100% in between the 13th and 18th month after the hurricane. Notable is that while all indices are around 110% on average in the 25-30 month period, NDMI is still around 100%. This could have to do with the fact that NDMI possibly better tracks recovery in the long-term.

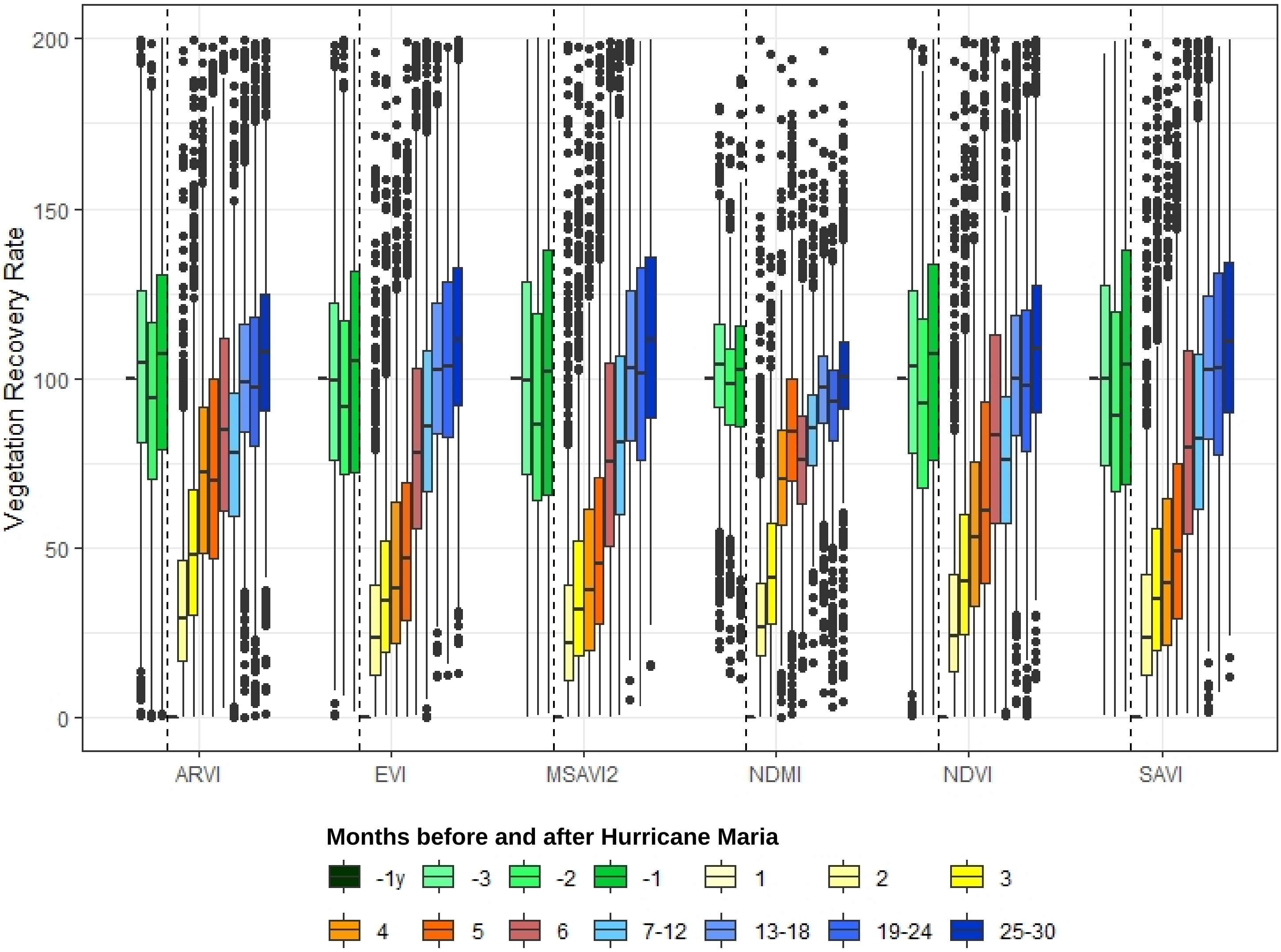


Figure 4.4. Vegetation Recovery Rate over time. The dotted line represents Hurricane Maria. '-1y' stands for the averaged values over the year before the hurricane happened. Outliers, visualized as dots, are defined as values over 1.5 times the interquartile range above the 75th percentile (Q3) or below the 25th percentile (Q1).

4.2.4. Utility of vegetation indices

Although each vegetation index expresses green vegetation differently, they are still correlated to each other (Figure 4.5). SAVI and MSAVI are positively correlated with each other (coefficient of 1), which is also the case for ARVI and NDVI (coefficient of 0.99). The only 'wetness index', NDMI, is the least correlated with other indices. That NDMI behaves different could also be seen in Figure 4.3, where NDMI is the only index of which the difference between landslides and buffers is increasing in the first five months.

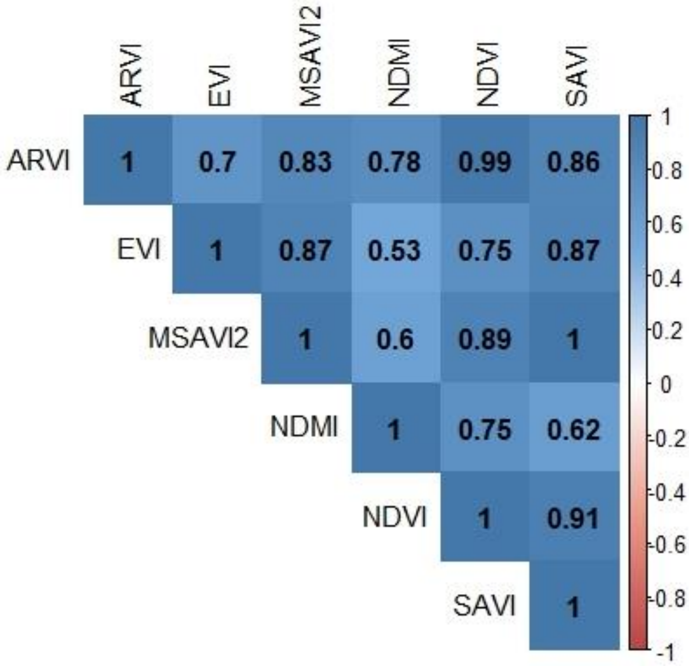


Figure 4.5. Pearson correlation coefficients matrix of monthly vegetation index values of all landslides between 12 months before till 30 months after the hurricane.

Since all indices are positively correlated with each other (coefficients > 0.5), it makes sense that all indices reach on average near 100% VRR values in the same period in time (13-18 months). ARVI, EVI and NDMI show the largest difference between landslides and buffers in the first six months. Of those three indices, EVI has the largest difference between landslides and buffers after the first six months.

EVI has a large drop in values, it is able to differentiate the most between landslides and the surrounding forest and does this up to 2.5 years after landslide disturbance. The ability of EVI to correct for atmospheric noise and soil brightness simultaneously, in combination with slower saturation than NDVI when LAI increases (Alchanatis et al., 2012; Huete et al., 1997) are likely explanations for this. Even though EVI is more sensitive than NDVI to topographic conditions (Liao et al., 2015; Matsushita et al., 2007), it has been selected as the index to investigate which landscape variables influence vegetation recovery.

4.3. The influence of landscape variables on recovery

This section presents the results of the multiple linear regression which has been run to analyse which landscape variables influence vegetation recovery. In the absence of a field investigation, the analysed variables were limited to the available information: meteorological (rainfall, radiation), relief (altitude, slope, aspect), soil (soil type and depth), disturbance impact (remaining vegetation, buffer damage), and landslide information (area/perimeter ratio, landslide zone, landslide type).

4.3.1. Recovery time as response variable

91% of all landslides reach a VRR ≥ 100% in the first 14 months after disturbance (Figure 4.6). 4% did not have a VRR ≥ 100% within 30 months, and does therefore take at least 31 months to recover. The low number of recovered landslides in the 10th month is due to the fact that Sentinel-2 imagery was often covered by clouds. Within 15 to 30 months after disturbance, only 5% of all landslides recovered. Therefore, all landslides that take longer than 14 months to recover have been excluded from the regression analysis.

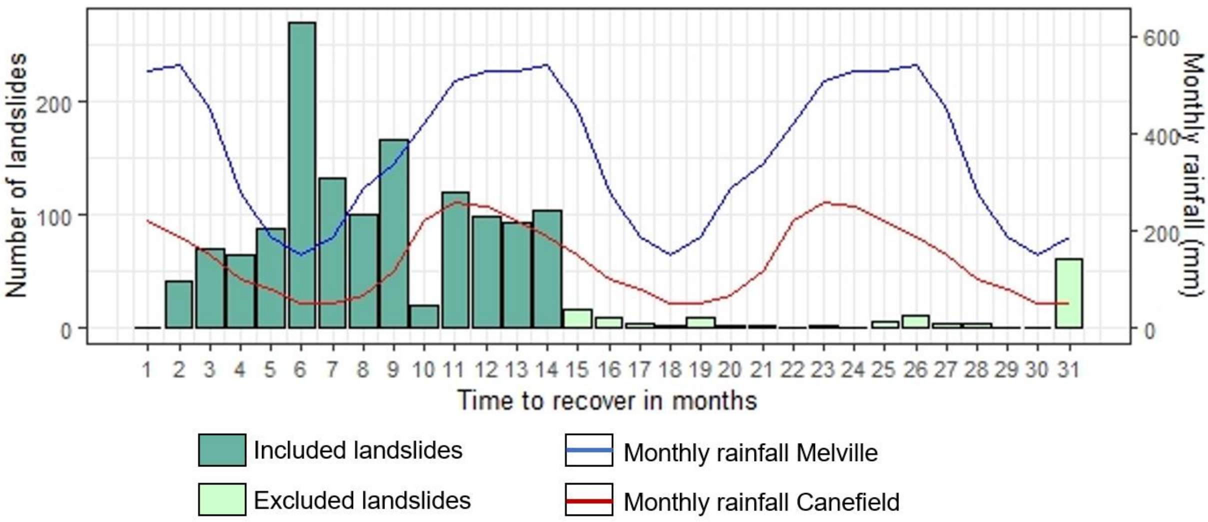


Figure 4.6. Time it takes for landslides to reach a VRR ≥ 100%. Month 31 means that landslides need more than 30 months to recover, but the exact time to recover is unknown.

The two lines in the histogram show the monthly rainfall pattern (average 1982-2013) of two rain gauges in Dominica. The number of landslides recovering each month does not directly seem to correlate with the rainfall season in Dominica.

4.3.2. Selection of landscape variables

To find out if the twelve landscape variables significantly influence vegetation recovery on landslides, the data has been explored. The continues variables have been plotted as single linear regression lines and scatterplots (Figure 4.7). Although rainfall and radiation are both important for plant growth, both do not significantly ($p > .05$) influence the recovery time. Radiation and rainfall are negatively correlated (coefficient of -0.71). High-altitude regions experience more rainfall in Dominica, and are therefore more often covered by clouds (Lang, 1967; Smith, Schafer, Kirschbaum, & Regina, 2008). As a result of the cloud cover, radiation is less. The raise of one stimulating variable causes the other to go down, which seems to cancel out the positive influence radiation and rainfall together have on vegetation recovery.

The area/perimeter ratio has no significant influence on recovery time. This corresponds with Myster et al. (1997), who suggests that landslide revegetation might be heavily seed-driven. Therefore, the size and shape of a landslide might be less of influence on vegetation recovery since recovery does not depend much on the invading vegetation from the surrounding forest. The significantly contributing continues variables, remaining vegetation, buffer damage, altitude and slope have been included in the multiple regression model.

The categorical variables have been plotted as boxplots (Figure 4.8). Only 13 landslides are located in regions with an estimated shallow soil depth (0.25-0.75 m) and only 6 in a very deep soil depth region (> 1.5 m). There was no clear difference in recovery time between landslides located in regions with a moderate (0.75-1.25) and deep soil depth (1.25-1.5). The small number of landslides in two classes and the fact that landslides in the moderate and deep soil class both show the same spread in recovery time, did lead to the decision to exclude this variable from the multiple linear regression. Between debris flows and debris slides no difference in recovery time is observable. A reason could be that debris flows and slides show similarities in terms of the damage they do to the environment (Prach & Walker, 2020), which is supported by the fact that landslide type does not correlate with remaining vegetation (coefficient of 0.05). Landslide type is not an important influencing factor for vegetation recovery and was therefore not included in the multiple linear regression.

The other categorical variables, aspect, landslide zone, and soil type have notable differences among the categories. When it comes to aspect, it seems that slopes facing the north-east and east are recovering faster than other slopes. To investigate if aspect significantly influences recovery it has been treated as a dummy variable in the multiple linear regression where north-east and east facing slopes were coded as '0' and other categories as '1'. Landslides located on skeletal and kandoid latosolics soil types take on average two months longer to recover and were coded as '0' while the other soil types were coded as '1'. Transport and deposit zones have a different average recovery time than initiation and transport/deposit zones. The majority of the samples are initiation zones and were coded as a '0', the other zones were coded as '1'.

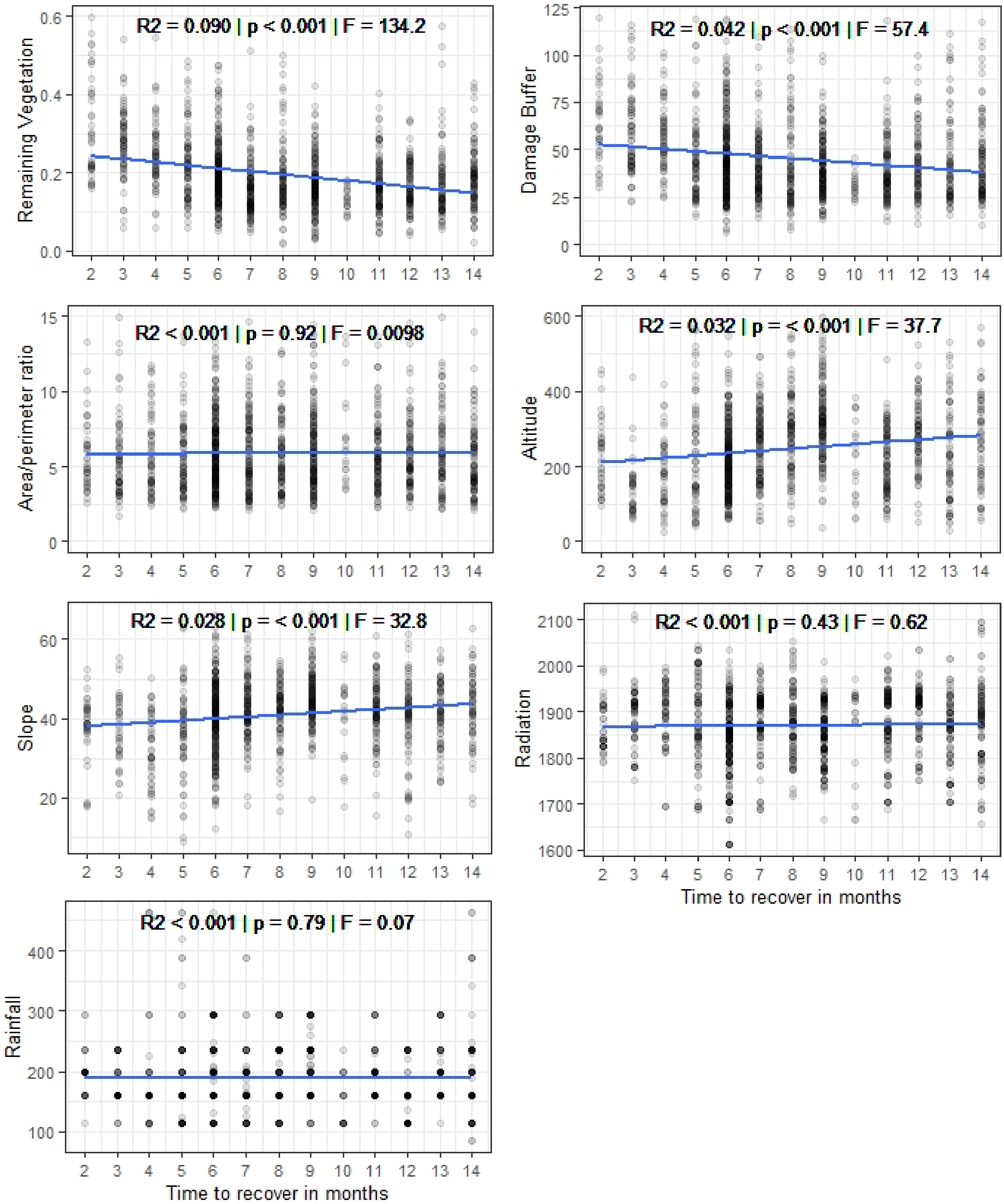


Figure 4.7. Scatterplots of the relationships between landscape variables and time to recover in months. The R^2, p-value and F-statistic are the statistics of the blue single linear regression line.

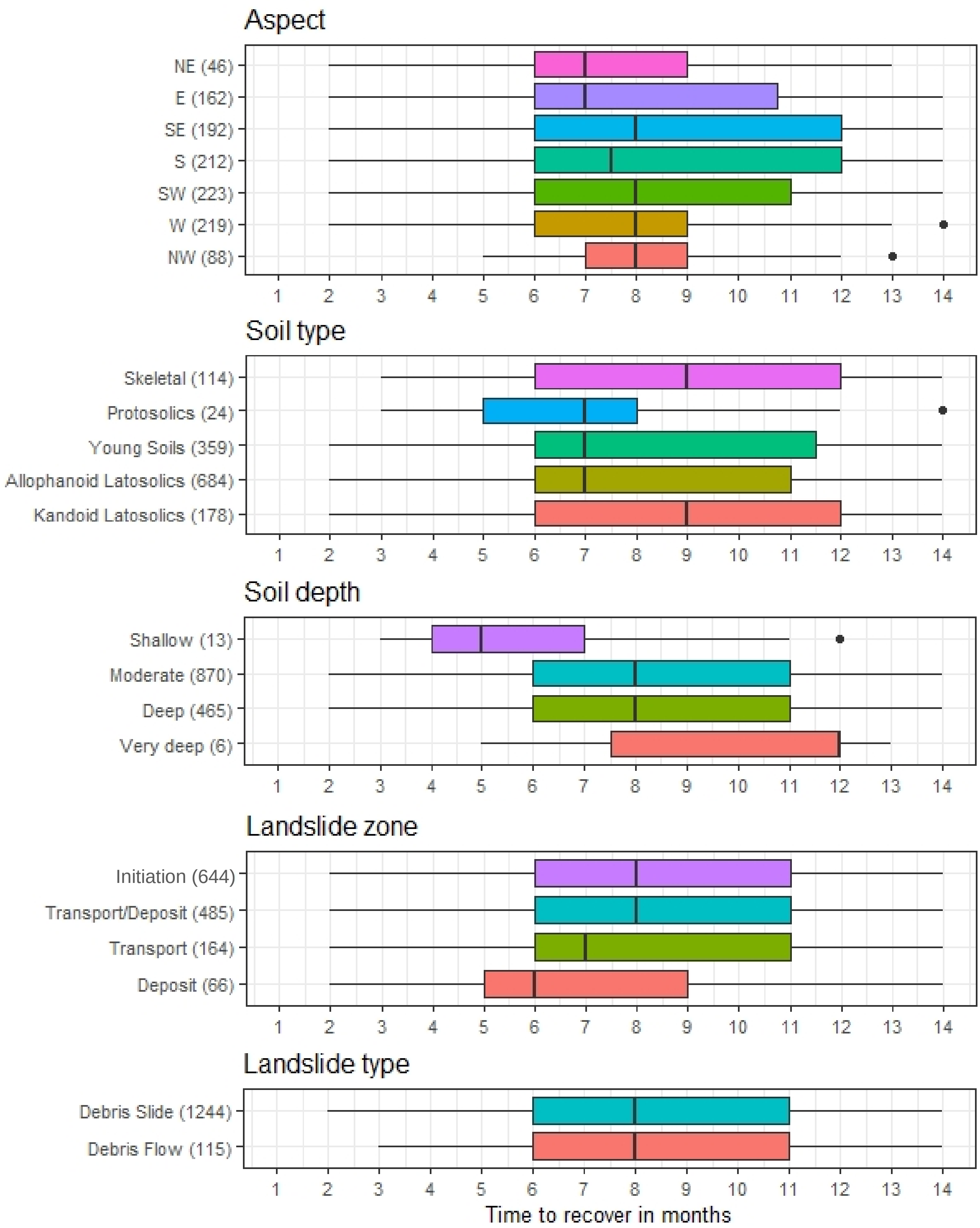


Figure 4.8. Boxplots showing the recovery time in months for the categories of five categorical landscape variables. The number between brackets is the number of landslides in each class. Outliers, visualized as dots, are defined as values over 1.5 times the interquartile range above the 75th percentile (Q3) or below the 25th percentile (Q1).

The remaining continues and categorical variables have been tested on collinearity (Figure 4.9). When the remaining vegetation on landslides is higher, the hurricane damage done to the surrounding forest is generally lower (coefficient of 0.57). Due to this correlation, remaining vegetation was selected as input variable for the multiple linear regression because it had more predictive power. When remaining vegetation was changed to damage buffer as predictor in the final model, the R^2 dropped from 0.156 to 0.103. In this final model, the standardized beta coefficient of remaining vegetation would be -0.298 and that of damage buffer -0.171. This indicates that the surviving recovery pattern of existing vegetation is possibly of more importance than the invading pattern stimulated by the vegetation surrounding landslides. That remaining vegetation was of influence corresponds with Li et al. (2014), who found that remaining vegetation was of influence on vegetation recovery quantified as shrub cover on landslides.

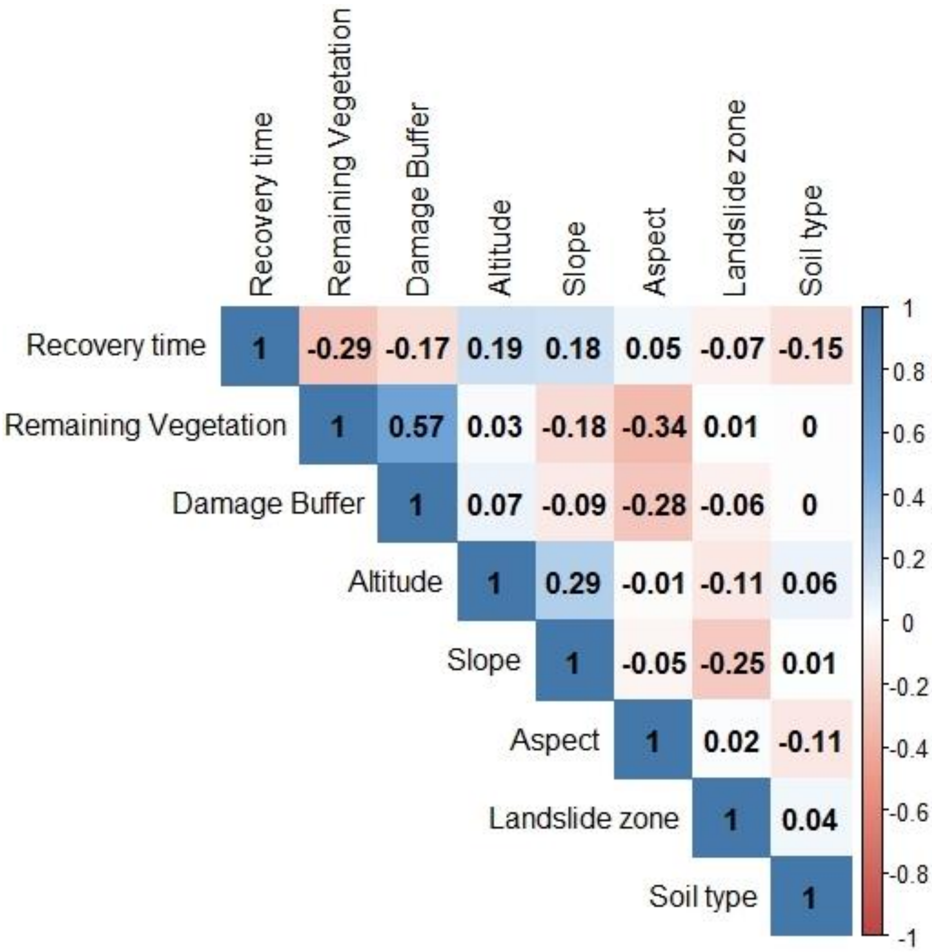


Figure 4.9. Pearson correlation coefficients matrix of recovery speed and landscape variables.

4.3.3. Multiple linear regression outcome

After the exclusion of several variables, a first multiple linear regression model was run to predict vegetation recovery time based on remaining vegetation, altitude, slope, aspect, landslide zone and soil type. Although a significant regression equation was found ($F(6,1135) = 35.1$, $p < .000$, $R^2 = 0.157$), not all predictors were significant. The non-significant predictors ($p > .05$) were slope and landslide zone. Excluding landslide zone as a predictor resulted in the final significant regression equation ($F(5,1136) = 42$, $p < .000$, $R^2 = 0.156$), of which all predictors were significant (Table 4.4).

Table 4.4. Final multiple regression model output

ANOVA		
F	**Significance**	**R^2**
42	.000	0.156
Coefficients		
Landscape variables	**Standardized beta coefficients**	**Significance**
Remaining vegetation	-0.298	.000
Soil type	-0.189	.000
Altitude	0.175	.000
Aspect	-0.069	.019
Slope	0.060	.041

Even though landslide zone was not significantly contributing to the final model, there are differences in recovery between the zones. Deposit zones (n=60) recover on average within 6 months, transport zones (n=164) within 7 months and initiation zones (n=644) within 8 months. This corresponds with Walker et al. (2013) and Li et al. (2014) who state that less steep slopes and deposit zones have the most plant growth stimulating soil nutrients and organic matter and initiation zones the least. However, the zones that were mapped as combined transport/deposit zones (n=485) do not underwrite this, these zones took on average 8 months to recover. This might be due to the fact that those transport/deposit zones have a slope of 41%, which is almost as high as initiation zones (43%) and larger than transport (39%) and deposit zones (30%). This makes the transport/deposit zones possibly less capable of holding soil nutrients and organic matter.

Although the influence of landslide zones seems to be influenced by the slope of those zones, it did not correlate with the slope of landslides (Figure 4.9). Slope had significant predictive power in the final model, but was of low importance (standardized beta coefficients of 0.06). While Lin et al. (2005) reported that slope steepness is slightly stimulating recovery on landslides, Walker et al. (2013) found that it influences the type of vegetation and that it restricts soil development. Li et al. (2014) concluded that it restricts the regrowth of shrub cover and number of species. Lastly, Myster et al. (1997) concluded there was no significant relation between recovery and slope at all. The disagreement between studies shows that the relation between slope and recovery is not clear and that it could be of influence depending on the circumstances.

It was found that landslides recover slower when altitude is higher (standardized beta coefficient of 0.175). This corresponds with studies in tropical forests (Myster et al., 1997; Walker et al., 2013), but not with non-tropical regions where recovery goes faster when altitude increases (Jiang et al., 2015). The predictive power of altitude in previous studies can be explained by more volcaniclastic substrate that was found at lower elevations (Myster et al., 1997) or by the fact that ridgelines on higher altitudes have more difficulties in storing soil moisture than steep slopes at lower altitudes (Lin et al., 2005). However, the exact reason(s) for altitude being of influence is unclear, and could also have to do with the differences in species that grow at different altitudes in Dominica (Nicolson, 1991).

Vegetation on north-east and east facing slopes recovers on average one month faster than slopes facing the south-east, south-west, west and north-west. Contradicting with the results from this study, Myster et al. (1997) concluded that slopes facing away from hurricanes recover faster. Walker et al. (2013) expected ferns to be positively correlated with slopes facing hurricanes due to their low stature and pioneer states on frequently disturbed habitats. However, they did not find this relationship. The shorter recovery time of north-east and east facing slopes in this study corresponds with Crk et al. (2009) who suggests that forest recovery goes faster on north-west to north-east facing slopes due to moisture-bearing north-east trade winds. Remote sensing reflectance values cannot conclude if different species grow on different facing slopes, but this could be a topic for future research. If ferns with a high LAI are mostly present on north-east and east facing landslides due to the north-east trade winds, this might be a reason for the quicker recovery as indicated by vegetation indices who tend to saturate when LAI increases.

Soil types are significantly influencing the recovery time. Landslides located on skeletal and kandoid latosolics recover on average two months slower than protosolics, young soils and allophanoid latosolics. There are two possible explanations for this. First of all, the protosolics, young soils and allophanoid latosolics soils are closely related to each other in texture, while kandoid latosolics and skeletal soils are both more different than the other three. It could be that pioneer species grow well on those three soils, and less well on the others. Secondly, the skeletal and kandoid latosolics are both located on the eastern side of the study area. This area was severely hit by tropical storm Erica in 2015. Although vegetation indices did not reveal that vegetation in this region was still recovering, it is likely that the landslides and surrounding forest were still recovering[15]. Therefore, vegetation on landslides triggered by Hurricane Maria in the eastern side possibly recovered slower due to the severe damage the forest experienced twice (2015 and 2017) in a short time.

[15] This is likely because in this study was found that vegetation indices can monitor vegetation recovery on landslides up to 13-18 months. However, the forest could possibly still be recovering from tropical storm Erica after this period.

5. DISCUSSION

5.1. Selecting a landslide inventory

Using an inventory that geometrically corresponds with landslide positions on Sentinel-2 imagery is an important requirement to monitor vegetation recovery on landslides. The geometrical correspondence could be evaluated based on the finding that landslides dropped more in vegetation index values than the non-slided forest. Landslides can effectively be detected with remote sensing (Frolking et al., 2009; Metternicht et al., 2005), but no studies have been found that do this automatically in hurricane-damaged forests where also the surrounding forest is severely damaged. Therefore, a topic for further studies could be to explore the ability to detect landslides in hurricane-damaged forests automatically with vegetation indices.

Although the inventories evaluated in this study were not perfectly corresponding, excluding boundary pixels did not result in significantly lower index values for most vegetation indices. In addition, excluding boundary pixels would exclude small and elongated landslides from the inventory, which is not preferable. Therefore, the recommendation is not to exclude boundary pixels, but to make use of an inventory which corresponds accurately with satellite imagery. It is advisable to make use of high spatial resolution imagery (0.5 m) to map landslides and to validate or obtain more information about landslides on the ground (e.g. landslide zones, types and depth), especially when the influence of landscape variables is analysed. Although Frolking et al. (2009) states that medium spatial resolution (10-30 m) imagery might have difficulties detecting disturbances smaller than 1000 m^2, this study found that even small landslides (100-400 m^2) were significantly lower than the surrounding non-slided forest. Masiliūnas (2017) supports that Sentinel-2 is capable of monitoring small disturbances in the tropics, but recommends the use of higher resolution so that vegetation is represented by multiple pixels. To conclude, the decision to include all landslides larger than 100 m^2 is advisable given that an inventory accurately corresponds geometrically.

5.2. Utility of vegetation indices to monitor vegetation recovery on landslides

During the landslide inventory comparison, it became clear that FRI2 is not able to distinguish between the vegetation state on landslides and pre-disturbance conditions. FRI2 has not been used in hurricane-prone regions that are highly dynamic and heterogenic, like Dominica. For those dynamic forests, defining a 'recovered state' reference situation is subjective (Attiwill, 1994). Similar to Moressi et al. (2019), this study used the yearly average reflectance values from a pre-disturbance period as a reference situation. FRI2 values close to 1 (indicating a 'recovered state') were expected for the 2000 reference plots during the reference period. However, even without major hurricane and landslide disturbances in this reference period, the 2000 reference plots had an average FRI2 value of 0.54. Only 20% of those plots had reflectance values that fell within the bandwidth of one standard deviation around the mean for all three bands. Moressi et al. (2019) concluded that FRI2 is suitable for tracking long-term forest recovery in non-tropical forests in Italy with yearly average values as a reference situation. This was not the case in this study which was probably due to the highly dynamic nature of the hurricane-prone tropical forests of Dominica that cannot well be represented by yearly average reflectance values.

The utility of the indices that performed well in differentiating between landslides and non-slided forest has been evaluated over time. All indices reached near pre-disturbance values between the 13^{th} and 18^{th} month after disturbance. MSAVI2 and SAVI are highly correlated, which indicates that the self-adjusting soil correction factor in the MSAVI2 formula did not result in much different MSAVI2 values than SAVI values. Hence, the soil correction factor of 0.5 used in the SAVI formula seems to perform well in the study area. This means the soil brightness is of intermediate influence in the study area. If the soil would be of low or high influence, the self-adjusting correction factor of the MSAVI2 formula would be more needed, and the correlation would have been less. Since it seems that soil brightness is of intermediate influence on the reflectance measurements, this could also be an explanation for the high correlation between ARVI and NDVI. When atmospheric effects are reduced in the ARVI formula, the influence of soil brightness can increase (Liu & Huete, 1995), which possibly makes ARVI behave similar as NDVI.

EVI had a large drop in values, was able to differentiate the most between landslides and the surrounding forest and did this up to 2.5 years after landslide disturbance. EVI is the only evaluated index that corrects for atmospheric noise and soil brightness simultaneously. The topographic conditions where EVI is more sensitive for than NDVI (Liao et al., 2015; Matsushita et al., 2007) did not became evident in the spread of the values of the two indices. Therefore, the use of EVI is recommend in studies investigating vegetation recovery on landslides triggered by hurricanes that also severely damage the non-slided forest.

NDMI is the least correlated with the other greenness indices. Although the difference between landslides and their buffers is small in the first month after the hurricane, it is the only index where the difference increases continuously in the first five months. This could indicate that the surrounding forest recovers to pre-disturbance moisture levels rapidly while the growing vegetation on the landslides takes more time. Notable is that the VRR of NDMI is remarkably lower than the other indices from 19-30 months after the hurricane, which is likely to be caused by the ability of NDMI to differentiate the LAI up to six leaf layers (Gao, 1996). This leads to the recommendation to explore the ability of NDMI in regions where landslides happen without severe damage to the surrounding forest. In these regions NDMI is expected to differentiate well between landslides and the surrounding forest, while also being able to monitor vegetation recovery longer than greenness indices do.

5.3. Influence of landscape variables on vegetation recovery on landslides

Multiple studies using a variety of statistical methods found that landscape and biological variables are of influence on vegetation recovery on landslides. This study is the first that analysed the influence of landscape variables in the tropics using vegetation indices. A significant multiple linear regression model ($F(5,1136) = 42$, $p < .000$, $R^2 = 0.156$) was found that predicts vegetation recovery time based on remaining vegetation, altitude, slope, aspect, landslide zone and soil type. These results point out that remote sensing can be used to investigate the influence of landscape variables on recovery. The R^2 from this study is not much lower than Myster et al. (1997), who also used multiple linear regression but made use of ground-based vegetation measurements of Puerto Rican landslides as the response variable ($R^2 = 0.233$). However, my study could not very well explain the variance, and further research would be needed to increase the understanding about vegetation succession on landslides.

The ability to predict recovery time could be improved by including other landscape variables and by making use of more recent and accurate data. Soil depth was included in this study with the expectation that landslides in regions with shallow soil depths would have less soil remaining which restricts vegetation to grow back rapidly. This relationship was not found, and the investigation of landslide depth instead of the soil depth of the region could find out if this expectation holds. An updated and more detailed version of the soil type map could improve the results since it is relatively coarse and created in 1967. The annual rainfall map has a resolution of 1 km and the influence of rainfall could be better investigated with a more detailed map. Other variables that are expected to influence vegetation recovery on landslides that could be further analysed are soil nutrients, organic matter content, and the occurrence of previous landslides in recent years on the same landslide.

The advantage of using remote sensing is that it allows for automated analysis. Therefore, a large number of landslides could be investigated in this study. However, the information retrieved about vegetation is limited to 2D measurements from above. Future studies would be recommended to investigate the relationship between vegetation index values and ground-based measurements on landslides. Ground-based measurements do not only make it possible to obtain more information about vegetation recovery (e.g. biodiversity and the succession pattern) but are also useful to obtain more information about landscape variables (e.g. landslide depth and soil conditions). One concrete topic to investigate would be to find out if the surviving succession pattern of vegetation is of more importance than the invading pattern. A hypothesis that is supported by the fact that the area/perimeter ratio was not of significant influence on vegetation recovery while the remaining vegetation was.

5.4. Potential of remote sensing to monitor vegetation recovery on landslides

The use of remote sensing had some limitations in this study. The tropics do experience seasonality (Gwenzi, Helmer, Zhu, Lefsky, & Marcano-Vega, 2017), which could be seen in the fluctuations in vegetation index values in the months before the hurricane (Figures 4.1-4.4). This made it difficult to define which part of measured vegetation recovery are purely a result of vegetation succession. The seasonality contributes to the subjectivity that comes with selecting a reference situation as the recovered forest state. To correct for this seasonality, a solution would be to compare monthly post-disturbance vegetation index values with pre-disturbance values from the same month of the year. Sentinel-2 images before Hurricane Maria are only limitedly available and Dominica is often covered by clouds, which made it not possible to have monthly reference situations for the majority of landslides. With the launch of the twin Sentinel-2 satellite in March 2017 the revisiting time and the available pre-disturbance imagery will be higher for studies to more recent disturbances. Another possible solution would be to make use of smoothing filters to estimate vegetation index values for moments where there is no (cloud-free) imagery available.

The cloud masking applied to the Sentinel-2, L1C imagery was not perfect and increased the variability of measurements. Coluzzi et al. (2018) found that the L1C cloud masks perform well but have, especially for rainforests, difficulties in masking cirrus clouds and transition zones between the cloud core and cloud-free areas. When making use of Sentinel 2, L2A, there are more bands available to improve cloud masking. Another consideration for further studies would be to use monthly maximum values for each landslide to reduce the influence of cloud cover. However, this is expected to reduce the duration vegetation indices can distinguish between the state of vegetation between landslides and non-slided forest. This is because the vegetation will be classified as recovered, even if only one measurement in a month indicates it is. Therefore, this approach would be sensitive to outliers and seasonal fluctuations.

The use of vegetation indices to monitor vegetation recovery on landslides is limited to the recovery of young secondary tropical forest characterized by fast growing pioneer species (Clark et al., 2011; Walker et al., 2013, 1996). While in non-tropical regions NDVI was able monitor vegetation recovery on landslides up to at least 12 years (M.-D. Yang et al., 2017; Yunus et al., 2020), in this study vegetation indices reached near pre-disturbance values within 13 to 18 months. However, this does not mean the forest is completely recovered, since the restoration of biomass and biodiversity take decades in the tropics (Brokaw et al., 2012; McLaren et al., 2019; Prach & Walker, 2020). Figures 2.2 and 5.1 illustrate that although a rapid regrowth of vegetation takes place on Dominica, the recovery of a full-grown evergreen forest takes much longer. A restoration of vegetation during the secondary succession may already have a positive effect on slope stability by means of evapotranspiration, root tensile strength, interception, infiltration and the increased surface roughness that prevents soil detachment and delays the onset and velocity of runoff (Gray & Sotir, 1996; Jetten, 1994; Kuriakose & van Beek, 2011). That secondary succession contributes to slope stability is supported by the fact that 72% and 85% of the landslide surface from the 2015 and 2014 inventories respectively did not slide again in 2017.

Figure 5.1. The state of the vegetation on two landslides in the Grand Bay catchment triggered by Hurricane Maria (photos taken by K. van 't Loo in November 2019).

Using vegetation indices to monitor vegetation recovery on landslides can be particular useful to find out which landslides are not covered by secondary vegetation, and are therefore more prone to slope failure. Ground-based measurements are time- and money-consuming and are therefore only conducted occasionally. Beneficial is that remote sensing makes it possible to conduct automated analysis continuously. A practical application would for instance be to execute vegetation restoration projects to increase slope stability on the 61 Dominican landslides that did not reach pre-disturbance levels within 2.5 years (Figure 4.6).

Intense hurricanes and tropical storms are likely to increase in frequency in the Caribbean (Bender et al., 2010; IPCC, 2013). Vegetation on landslides in the eastern side of the study area recovered slower, which is possibly due to tropical storm Erica that hit this area severely in 2015. If intense hurricanes and tropical storms increase, this possibly puts pressure on the ability of the forest to recover itself. Hence, vegetation restoration projects could become essential to preserve the Dominican forests and mitigate the possible increase of slope failures. Based on the findings of this study, the use of remote sensing to monitor vegetation recovery can play an important role in doing so.

6. CONCLUSION

This study aimed to evaluate with vegetation indices how fast vegetation on landslides in Dominican tropical rainforest recovers and which landscape variables influence this process. A landslide inventory that geometrically corresponded with the landslide positions on Sentinel-2 imagery proved that landslides had a significantly ($p < .05$) larger drop in vegetation index values than non-slided, but hurricane damaged forest. This difference in vegetation index values between landslides and the surrounding non-slided forest was clearly visible up to 6 months after disturbance.

FRI2 was the only evaluated vegetation index that did not significantly detect hurricane and landslide disturbance. With the other indices (ARVI, EVI, MSAVI2, NDMI, NDVI and SAVI) vegetation recovery on landslides could be monitored up to 13 to 18 months after disturbance. EVI was considered the most useful to monitor vegetation recovery in hurricane-prone regions, it had a large drop in values, could differentiate the most between landslides and surrounding forest, and did this up to 2.5 years. Moisture content of non-slided forest measured with NDMI did drop almost equally as much as that of landslides. However, due to the ability of NDMI to differentiate the LAI up to six layers, it is recommended to explore the use of NDMI in regions where no severe damage is done to the forest surrounding landslides.

A significant multiple linear regression model ($F(5,1136) = 42$, $p < .000$, $R^2 = 0.156$) was found that predicts vegetation recovery time based on remaining vegetation, altitude, slope, aspect, landslide zone (initiation, transport, deposit) and soil type. To increase the understanding about vegetation succession on landslides, further research is needed that makes use of more accurate and recent data that can be obtained with ground-based measurements of landscape and biological variables.

To conclude, vegetation indices can be used to monitor how fast young secondary vegetation recovers on landslides, and it has the potential to find out which landscape variables influence this. Even though the development of full-grown evergreen forest takes decades, the recovering secondary vegetation that can be monitored may have a positive effect on slope stability. Therefore, it is recommended to make use of vegetation indices to automatically and continuously monitor vegetation recovery to detect landslides in need for restoration projects, which would reveal people and properties that are at risk.

LIST OF REFERENCES

Acevedo, S. (2016). *Gone with the wind: Estimating hurricane and climate change costs in the Caribbean* (No. 16/199). Retrieved from https://www.imf.org/external/pubs/ft/wp/2016/wp16199.pdf

Alchanatis, V., Sreekala, G. B., Ben-Dor, E., Bhatnager, D., Boschetti, M., Breuning, F. M., … Zhu, Y. (2012). *Hyperspectral remote sensing of vegetation* (1st ed.; P. S. Thenkabail, J. G. Lyon, & A. Huete, Eds.). Boca Raton, FL: CRC Press.

Attiwill, P. M. (1994). The disturbance of forest ecosystems: The ecological basis for conservative management. *Forest Ecology and Management*, *63*(2–3), 247–300. https://doi.org/10.1016/0378-1127(94)90114-7

Bender, M. A., Knutson, T. R., Tuleya, R. E., Sirutis, J. J., Vecchi, G. A., Garner, S. T., & Held, I. M. (2010). *Modeled impact of anthropogenic warming on the frequency of intense Atlantic hurricanes*. *324*, 454–458. https://doi.org/10.1126/science.1180568

Brokaw, N., Crowl, T. A., Lugo, A., McDowell, W., Scatena, F., Waide, R., & Willing, M. (2012). *A Caribbean forest tapestry: The multidimensional nature of disturbance and response*. New York, NY: Oxford University Press.

CHARIM. (2015). Profile of dominica. Retrieved October 27, 2019, from http://charim-geonode.net/people/profile/dominica/

Chiu, C. A., Hsu, H. S., Lin, S. H., & Chen, W. C. (2016). The trajectory and goal of landslide revegetation: A proposal from the viewpoints of restoration ecology. *Journal of Chinese Soil and Water Conservation*, *47*(2), 104–110.

Chou, W. C., Lin, W. T., & Lin, C. Y. (2009). Vegetation recovery patterns assessment at landslides caused by catastrophic earthquake: A case study in central Taiwan. *Environmental Monitoring and Assessment*, *152*(1–4), 245–257. https://doi.org/10.1007/s10661-008-0312-8

Chu, T., Guo, X., & Takeda, K. (2016). Remote sensing approach to detect post-fire vegetation regrowth in Siberian boreal larch forest. *Ecological Indicators*, *62*, 32–46. https://doi.org/10.1016/j.ecolind.2015.11.026

Clark, M. L., Roberts, D. A., Ewel, J. J., & Clark, D. B. (2011). Estimation of tropical rain forest aboveground biomass with small-footprint lidar and hyperspectral sensors. *Remote Sensing of Environment*, *115*(11), 2931–2942. https://doi.org/10.1016/j.rse.2010.08.029

Coluzzi, R., Imbrenda, V., Lanfredi, M., & Simoniello, T. (2018). A first assessment of the Sentinel-2 Level 1-C cloud mask product to support informed surface analyses. *Remote Sensing of Environment*, *217*, 426–443. https://doi.org/10.1016/j.rse.2018.08.009

CRED, & UCLouvain. (2020). EM-DAT Public. Retrieved June 22, 2020, from https://public.emdat.be/

Crk, T., Uriarte, M., Corsi, F., & Flynn, D. (2009). Forest recovery in a tropical landscape: What is the relative importance of biophysical, socioeconomic, and landscape variables? *Landscape Ecology*, *24*, 629–642. https://doi.org/10.1007/s10980-009-9338-8

Dibaba, M. B. (2019). *The influence of soil depth models on simulating slope instability: The case of southern Dominica* (Master's thesis, ITC, University of Twente). Retrieved from https://library.itc.utwente.nl/papers_2019/msc/aes/dibaba.pdf

Eckelman, C.-M. (2019). *Effects of Hurricane Maria on the forests of Dominica and recovery after two years: Photo documentation*.

FAO. (2014). *State of the World's forests: Enhancing the socioeconomic benefits from forests*. Retrieved from http://www.fao.org/3/a-i3710e.pdf

Frolking, S., Palace, M. W., Clark, D. B., Chambers, J. Q., Shugart, H. H., & Hurtt, G. C. (2009). Forest disturbance and recovery: A general review in the context of spaceborne remote sensing of impacts on aboveground biomass and canopy structure. *Journal of Geophysical Research: Biogeosciences*, *114*(G2), G00E02. https://doi.org/10.1029/2008JG000911

Gao, B. C. (1996). NDWI - a normalized difference water index for remote sensing of vegetation liquidwater from space. *Remote Sensing of Environment*, *58*(3), 257–266.

Government of the Commonwealth of Dominica. (2017). *Post-disaster needs assessment Hurricane Maria September 18, 2017*. Retrieved from https://reliefweb.int/sites/reliefweb.int/files/resources/dominica-pdna-maria.pdf

Grainger, A. (2008). Difficulties in tracking the long-term global trend in tropical forest area. *PNAS*, *105*(2), 818–823. https://doi.org/10.1073/pnas.0703015105

Gray, D. H., & Sotir, R. B. (1996). *Biotechnical and soil bioengineering slope stabilization: A practical guide for erosion control*. New York, NY: John Wiley.

Gwenzi, D., Helmer, E. H., Zhu, X., Lefsky, M. A., & Marcano-Vega, H. (2017). Predictions of tropical forest biomass and biomass growth based on stand height or canopy area are improved by Landsat-scale phenology across Puerto Rico and the U. S. Virgin Islands. *Remote Sensing*, *9*(2), 123. https://doi.org/10.3390/rs9020123

Haque, U., Paula, F., Devoli, G., Pilz, J., Zhao, B., & Khaloua, A. (2019). The human cost of global warming: Deadly landslides and their triggers (1995–2014). *Science of the Total Environment*, *682*, 673–684. https://doi.org/10.1016/j.scitotenv.2019.03.415

Highland, L. M., & Bobrowsky, P. (2008). *The landslide handbook: A guide to understanding landslides*. Retrieved from https://pubs.usgs.gov/circ/1325/pdf/C1325_508.pdf

Hu, T., & Smith, R. (2018). The impact of Hurricane Maria on the vegetation of Dominica and Puerto Rico using multispectral remote sensing. *Remote Sensing*, *10*(6), 827. https://doi.org/10.3390/rs10060827

Huang, C., Goward, S. N., Schleeweis, K., Thomas, N., Masek, J. G., & Zhu, Z. (2009). Dynamics of national forests assessed using the Landsat record: Case studies in eastern United States. *Remote Sensing of Environment*, *113*(7), 1430–1442. https://doi.org/10.1016/j.rse.2008.06.016

Huang, C., Song, K., Kim, S., Townshend, J. R. G., Davis, P., Masek, J. G., & Goward, S. N. (2008). Use of a dark object concept and support vector machines to automate forest cover change analysis. *Remote Sensing of Environment*, *112*(3), 970–985. https://doi.org/10.1016/j.rse.2007.07.023

Huete, A. R. (1988). A soil-adjusted vegetation index (SAVI). *Remote Sensing of Environment*, *25*(3), 295–309. https://doi.org/10.1016/0034-4257(88)90106-X

Huete, A. R., Liu, H. Q., Batchily, K., & Van Leeuwen, W. (1997). A comparison of vegetation indices over a global set of TM images for EOS-MODIS. *Remote Sensing of Environment*, *59*(3), 440–451. https://doi.org/10.1016/S0020-1693(00)85959-9

IPCC. (2013). *Climate change 2013: The physical science basis* (T. F. Stocker, D. Qin, G.-K. Plattner, M. Ignor, S. K. Allen, J. Boschung, … P. M. Midgley, Eds.). Retrieved from https://www.ipcc.ch/report/ar5/wg1/#:~:text=Please use the following reference,Qin%2C G.

Jetten, V. G. (1994). *Modelling the effects of logging on the water balance of a tropical rain forest: A study in Guyana* (Doctoral dissertation, University of Utrecht). Retrieved from https://www.tropenbos.org/resources/publications/modelling+the+effects+of+logging+on+the+water+balance+of+a+tropical+rain+forest.+a+study+in+guyana.

Jiang, W., Jia, K., Wu, J., Tang, Z., Wang, W., & Liu, X. (2015). Evaluating the vegetation recovery in the damage area of Wenchuan earthquake using MODIS data. *Remote Sensing*, *7*(7), 8757–8778. https://doi.org/10.3390/rs70708757

Kaufman, Y. J., & Tanré, D. (1992). Atmospherically resistant vegetation index (ARVI) for EOS-MODIS. *IEEE Transactions on Geoscience and Remote Sensing*, *30*(2), 261–270.

Kuriakose, S. L., & van Beek, L. P. . (2011). Plant root strength and slope stability. In J. Gliński, J. Horabik, & J. Lipiec (Eds.), *Encyclopedia of Agrophysics*. https://doi.org/https://doi.org/10.1007/978-90-481-3585-1

Lang, D. M. (1967). *Soil and land-use surveys: Dominica*.

Laskurain, N. A., García-Mijangos, I., Manzanedo, H., Sesma, J., Ferrari, M., Calvo, T. G., & Loidi, J. (2016). ation: An experiment based in vegetation succession. In E. O. Box (Ed.), *Vegetation structure and function at multiple spatial, temporal and conceptual scales* (pp. 475–497). https://doi.org/10.1007/978-3-319-21452-8_21

Li, B., Zhang, M., Zhao, L., Ran, J., Moermond, T., & Shang, T. (2014). Vegetation recovery on landslides of the Wenchuan earthquake and its influencing factors: a case study in Longxi-Hongkou Nature Reserve. *Chinese Journal of Applied and Environmental Biology*, *21*(3), 533–539. https://doi.org/10.3724/SP.J.1145.2014.10010

Liao, Z., He, B., & Quan, X. (2015). Linear and segmented linear trend vegetation index data in semiarid GIMMS normalized difference detection for vegetation cover using regions of Nigeria. *Journal of Applied Remote Sensing*, *9*(4), 551–556. https://doi.org/10.1117/1.JRS.9

Lin, W., Chou, W., Lin, C., Huang, P., & Tsai, J. (2005). Vegetation recovery monitoring and assessment at landslides caused by earthquake in Central Taiwan. *Forest Ecology and Management*, *210*(1–3), 55–66. https://doi.org/10.1016/j.foreco.2005.02.026

Liu, H. Q., & Huete, A. (1995). Feedback based modification of the NDVI to minimize canopy background and atmospheric noise. *IEEE Transactions on Geoscience and Remote Sensing*, *33*(2), 457–465. https://doi.org/10.1109/36.377946

Masiliūnas, D. (2017). *Evaluating the potential of Sentinel-2 and Landsat image time series for detecting selective logging in the Amazon* (Master's thesis, Wageningen University & Research). Retrieved from https://edepot.wur.nl/426144

Matsushita, B., Yang, W., Chen, J., Onda, Y., & Qiu, G. (2007). Sensitivity of the enhanced vegetation index (EVI) and normalized difference vegetation index (NDVI) to topographic effects: A case study in high-density cypress forest. *Sensors*, *7*(11), 2636–2651. https://doi.org/10.3390/s7112636

McDonald, T., Gann, G. D., Jonson, J., & Dixon, K. W. (2016). *International standards for the practise of ecological restoration - including principles and key concepts*. Retrieved from https://cdn.ymaws.com/www.ser.org/resource/resmgr/custompages/publications/ser_publications/SER_Standards_English.pdf

McLaren, K., Luke, D., Tanner, E., Bellingham, P. J., & Healey, J. R. (2019). Reconstructing the effects of hurricanes over 155 years on the structure and diversity of trees in two tropical montane rainforests in Jamaica. *Agricultural and Forest Meteorology*, *276–277*, 107621. https://doi.org/10.1016/j.agrformet.2019.107621

Metternicht, G., Hurni, L., & Gogu, R. (2005). *Remote sensing of landslides: An analysis of the potential contribution to geo-spatial systems for hazard assessment in mountainous environments*. *98*(2–3), 284–303. https://doi.org/10.1016/j.rse.2005.08.004

Moressi, D., Vitali, A., Urbinati, C., & Garbarino, M. (2019). Forest spectral recovery and regeneration dynamics in stand-replacing wildfires of Central Apennines derived from Landsat time series. *Remote Sensing*, *11*(3), 308. https://doi.org/10.3390/rs11030308

Myster, R. W., Thomlinson, J. R., & Larsen, M. C. (1997). Predicting landslide vegetation in patches on landscape gradients in Puerto Rico. *Landscape Ecology*, *12*(5), 299–307. https://doi.org/10.1023/A:1007942804047

Nicolson, D. H. (1991). Flora of Dominica, part 2: Dictoyledoneae. *Smithsonian Contributions to Botany*, *77*. https://doi.org/10.5479/si.0081024x.77

Pasch, R. J., Penny, A. B., & Berg, R. (2019). *Hurricane Maria*. Retrieved from https://www.nhc.noaa.gov/data/tcr/AL152017_Maria.pdf

Prach, K., & Walker, L. R. (2020). *Comparative plant succession among terrestrial biomes of the world*. https://doi.org/10.1017/9781108561167

Qi, J., Chehbouni, A., Huete, A. R., Kerr, Y. H., & Sorooshian, S. (1994). A modified soil adjust vegetation index. *Remote Sensing of Environment*, *48*(2), 119–126. https://doi.org/10.1016/0034-4257(94)90134-1

Rouse, J. W., Haas, R. H., Schell, J. A., & Deering, D. W. (1974). Monitoring vegetation systems in the great plains with ERTS. *Third Earth Resources Technology Satellite (ERTS) Symposium*, *1*, 309–317. Retrieved from https://ntrs.nasa.gov/archive/nasa/casi.ntrs.nasa.gov/19740022614.pdf

Schroeder, T. A., Wulder, M. A., Healey, S. P., & Moisen, G. G. (2011). Mapping wildfire and clearcut harvest disturbances in boreal forests with Landsat time series data. *Remote Sensing of Environment*, *115*(6), 1421–1433. https://doi.org/10.1016/j.rse.2011.01.022

Smith, R. B., Schafer, P., Kirschbaum, D. B., & Regina, E. (2008). Orographic precipitation in the tropics: Experiments in Dominica. *Journal of the Atmosheric Sciences*, *66*(6), 1698–1716. https://doi.org/10.1175/2008JAS2920.1

Thom, D., & Seidl, R. (2016). Natural disturbance impacts on ecosystem services and biodiversity in temperate and boreal forests. *Biological Reviews*, *91*(3), 760–781. https://doi.org/10.1111/brv.12193

United Nations Statistics Division. (2019). UNData. Retrieved April 15, 2020, from https://data.un.org/en/iso/dm.html

Walker, L. R., Shiels, A. B., Bellingham, P. J., Sparrow, A. D., Fetcher, N., Landau, F. H., & Lodge, D. J. (2013). Changes in abiotic influences on seed plants and ferns during 18 years of primary succession on Puerto Rican landslides. *Journal of Ecology*, *101*(3), 650–661. https://doi.org/10.1111/1365-2745.12071

Walker, L. R., Velázquez, E., & Shiels, A. B. (2009). Applying lessons from ecological succession to the restoration of landslides. *Plant and Soil*, *324*, 157–168. https://doi.org/10.1007/s11104-008-9864-1

Walker, L. R., Zarin, D. J., Fetcher, N., Myster, R. W., & Johnsen, A. H. (1996). Ecosystem development and plant succession on landslides in the Caribbean. *Biotropica*, *28*(4a), 566–576. https://doi.org/10.2307/2389097

Yang, M.-D., Chen, S.-C., & Tsai, H. P. (2017). A long-term vegetation recovery estimation for Mt. Jou-Jou using multi-date SPOT 1, 2, and 4 images. *Remote Sensing*, *9*(9), 893. https://doi.org/10.3390/rs9090893

Yang, W., Qi, W., & Zhou, J. (2018). Decreased post-seismic landslides linked to vegetation recovery after the 2008 Wenchuan earthquake. *Ecological Indicators*, *89*, 438–444. https://doi.org/10.1016/J.ECOLIND.2017.12.006

Yunus, A. P., Fan, X., Tang, X., Jie, D., Xu, Q., & Huang, R. (2020). Decadal vegetation succession from MODIS reveals the spatio-temporal evolution of post-seismic landsliding after the 2008 Wenchuan earthquake. *Remote Sensing of Environment*, *236*, 111476. https://doi.org/10.1016/j.rse.2019.111476

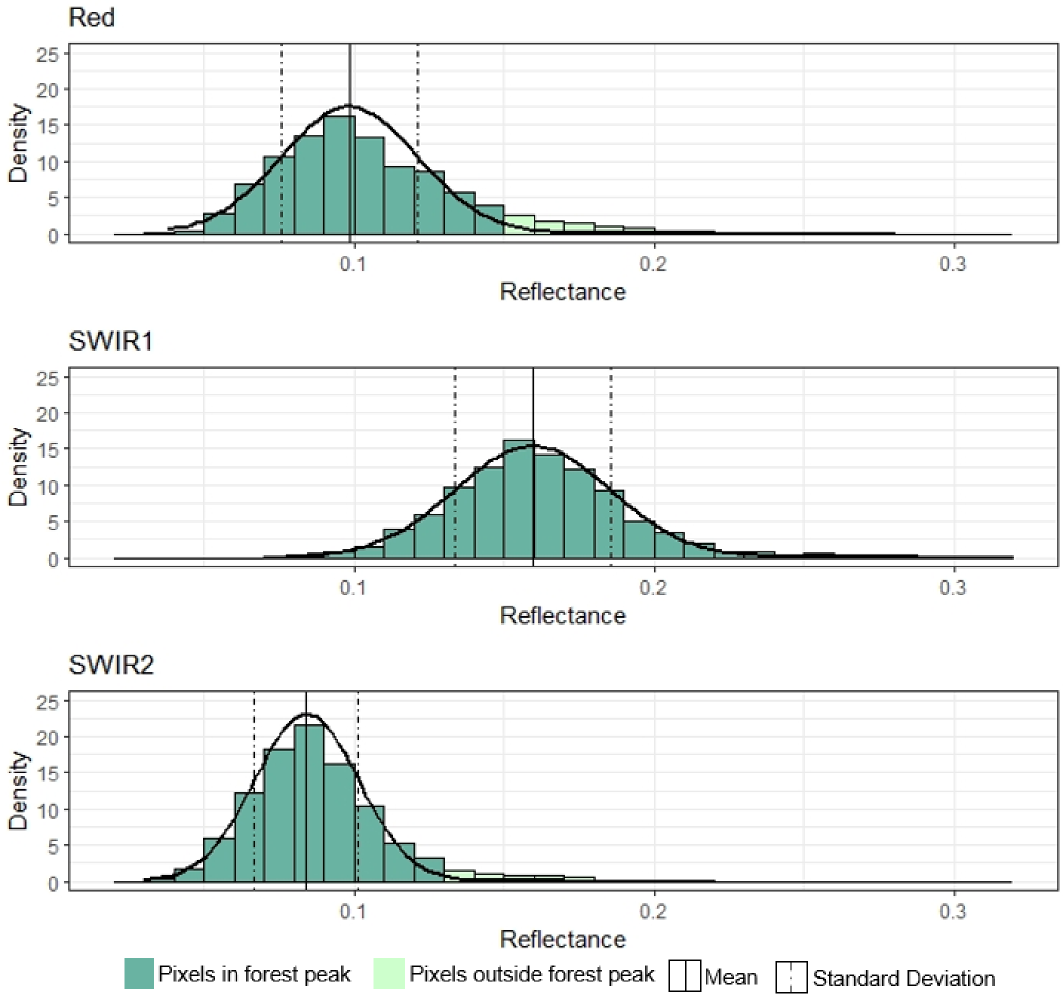
APPENDIX A: DATA SOURCES AND DETAILS

This appendix elaborates on the (spatial) data that has been used for this study. Besides the description and source, it also states at which figures and sections in the report the data was used for (SO1, SO2, and SO3 stand for the three sub-objectives from this study).

Data	Description & year	Source	Figures	SO1	SO2	SO3
Road network	Digitized road network (n.d.).	CHARIM Project	2.3c			
River network	Digitized river network (n.d.).	CHARIM Project	2.3c			
Pleiades landslide inventory	Landslide inventory based on Pleiades imagery (2017).	C.J. van Westen & J. Zhang (ITC, University of Twente)	2.3d, 2.4, 3.3	✓	✓	✓
DigitalGlobe landslide inventory	Landslide inventory based on DigitalGlobe imagery (2017).	B. van der Bout (ITC, University of Twente)	2.3d	✓	✓	✓
Land cover	Land cover map generated by image classification of SPOT imagery (30 m resolution). Originally from 2000, updated in 2015.	CHARIM Project	2.3e	✓	✓	
Soil type	Soil type map from 1967 showing the five major soil types in the study area: 1. skeletal, 2. protosols, 3. young soils, 4. allophanoid soils, and 5. kandoid latosolics.	D.M. Lang	2.3f			✓
Rubber sheeted landslide inventory	Corrected version of the Pleiades inventory (2020).	C.J. van Westen (ITC, University of Twente)	2.4	✓	✓	
Lidar landslide inventory	Landslide inventory based on Lidar DEM (2019).	B. van der Bout (ITC, University of Twente)	2.4	✓	✓	
Lidar DEM	Lidar DEM (0.5 m resolution, 2018) which was used to extract the slope, altitude and aspect of landslides in the study area.	Ministry of Health and Environment (Dominica)	2.4, 3.3			✓
Sentinel-2 imagery	Extracted through GEE and used to obtain vegetation index values.	CHARIM Project	2.5	✓	✓	✓
Raw data OpenStreetMap	Roads, grassland, agricultural land and build-up areas were used to create the region of interest mask.	OpenStreetMap		✓	✓	
2014 landslide inventory	Landslide inventory based on Google Earth Imagery made by C.J. van Westen (2014).	CHARIM Project		✓	✓	
2015 landslide inventory	Satellite-detected landslide inventory based on WorldView-2 imagery (2015).	UNITAR-UNOSAT		✓	✓	
Radiation	Global Horizontal Irradiation is the total amount of shortwave radiation (kWh/m^2) received from above by a surface, the value includes both direct normal irradiance and diffuse horizontal irradiance (2019).	Solargis				✓
Annual rainfall	Digitized averaged daily precipitation over Dominica (March 2007 - February 2008) from Guadeloupe radar measurements (1 km resolution).	R.B. Smith, P. Schafer, D.J. Kirshbaum & E. Regina				✓
Soil depth	Estimated soil depth of Grand Bay divided into five classes: very shallow (< 0.25 m), shallow (0.25-0.75 m), moderate (0.25-0.75 m), deep (1.25-1.5 m), and very deep (> 1.5 m). Estimation based on field work data obtained in 2018.	M. Dibaba				✓
Monthly rainfall	Monthly rainfall averages from 1982-2013 obtained at wo rain gauges: Melville and Canefield.	Dominica Meteorological Service	4.6			✓

APPENDIX B: FRI2 INPUT PARAMETERS

Section 3.2.4 discussed how the FRI2 input parameters were obtained. The density histograms and distribution curves are shown below. The reflectance values that are included in the forest peak for the Red, SWIR1 and SWIR2 band are highlighted.

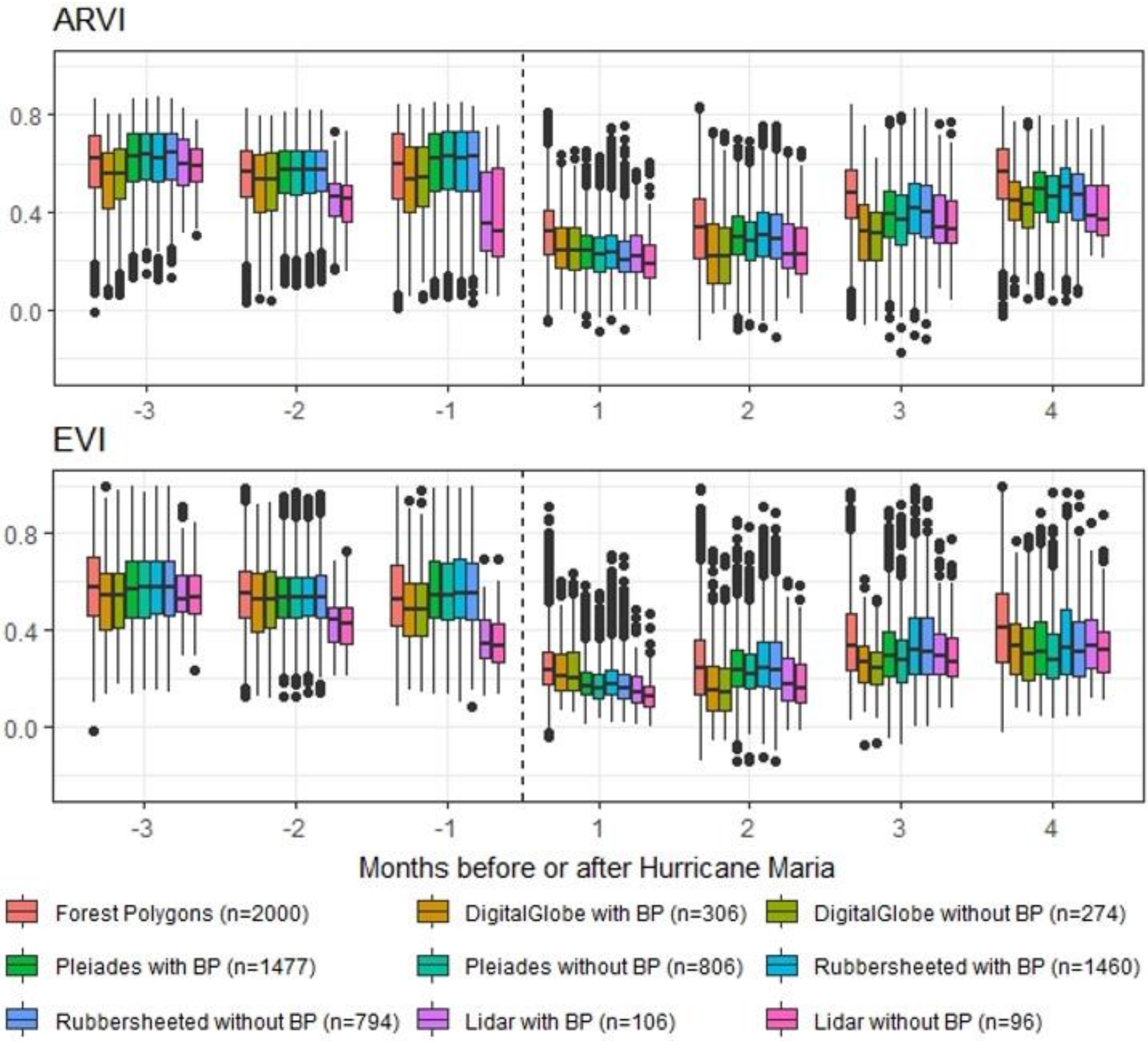


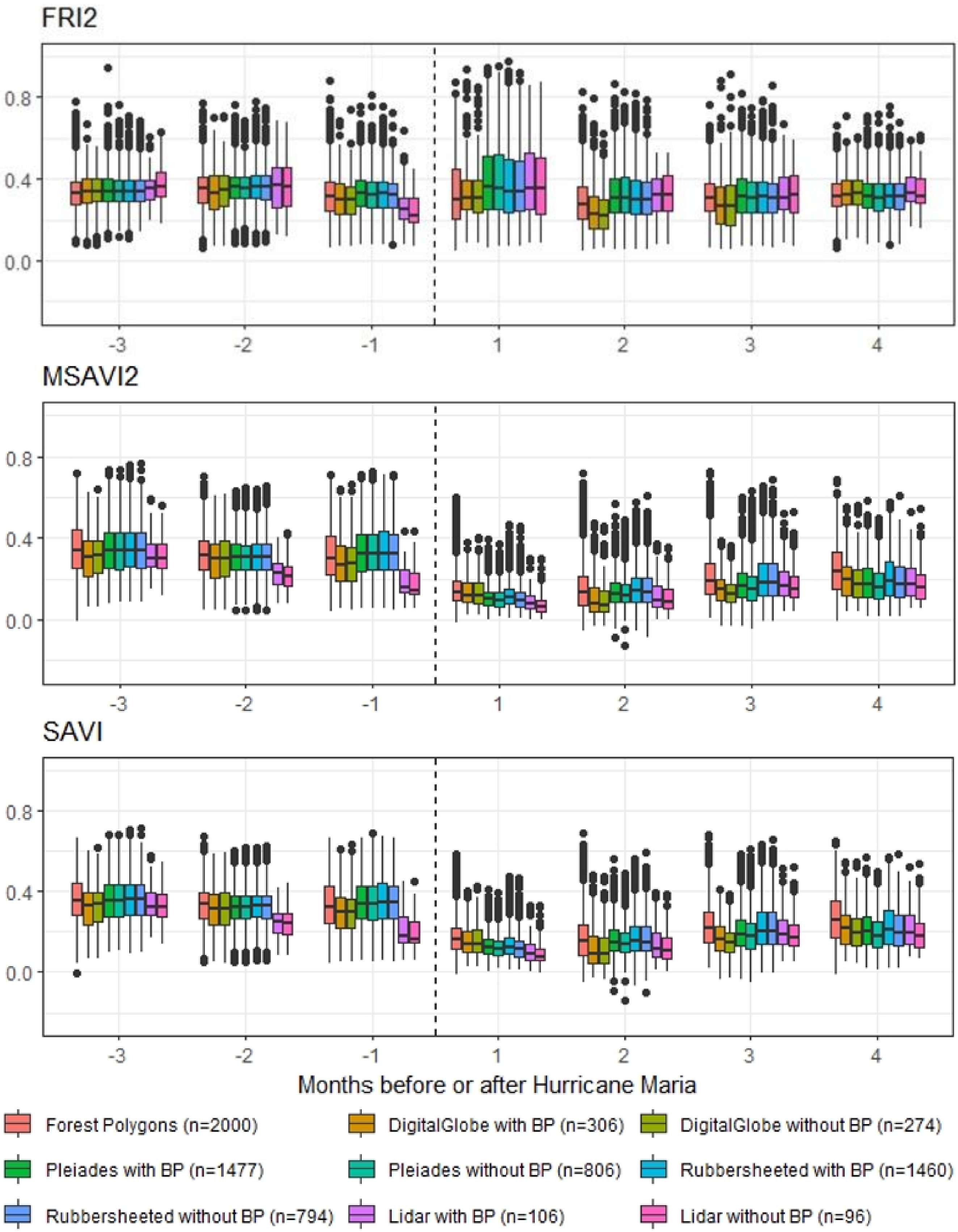
The pixels in the forest peak have been used to calculate the normal distribution curve, mean and standard deviation. The table below shows the calculated mean, standard deviation, and the outcome of the Shapiro-Wilk test. This test indicates that the SWIR1 band does not significantly differentiate from a normal distribution. For the other two bands this is not the case. However, previous research argues that even if not all the bands follow a rigorous normal distribution, an approximate probability interpretation is still applicable to determine the input parameters for the FRI2 equation (Huang et al., 2009, 2008).

Band	Mean	Standard deviation	Shapiro-Wilk test outcome
Red	0.0983	0.0228	.000
SWIR1	0.1595	0.0259	.099
SWIR2	0.0841	0.0173	.000

APPENDIX C: INVENTORY COMPARISON VEGETATION INDICES

Monthly ARVI, EVI, FRI2, MSAVI2, and SAVI boxplots for months before and after Hurricane Maria. Colours stand for the non-slided forest polygons and two sets of the four inventories (one set with boundary pixels (BP) and one set without). The dotted line represents hurricane Maria that happened on 18/09/2017. Outliers, visualized as dots, are defined as values over 1.5 times the interquartile range above the 75th percentile (Q3) or below the 25th percentile (Q1).




FRI2
0.8
0.4
0.0
-3
-2
-1
1
2
3
4
MSAVI2
0.8
0.4
0.0
-3
-2
-1
1
2
3
4
SAVI
0.8
0.4
0.0
-3
-2
-1
1
2
3
4
Months before or after Hurricane Maria
Forest Polygons (n=2000)
DigitalGlobe with BP (n=306)
DigitalGlobe without BP (n=274)
Pleiades with BP (n=1477)
Pleiades without BP (n=806)
Rubbersheeted with BP (n=1460)
Rubbersheeted without BP (n=794)
Lidar with BP (n=106)
Lidar without BP (n=96)