Applying social factors in spatial analysis for planted forest ecosystems

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Abstract

Forestation originated in the planting of forest plantations with timber-sourcing as a goal. The practice has since changed to include a much wider number of forest types and aims. In recent years, forestation efforts are increasingly focused on forest ecosystem generation. These forest ecosystems can have a wide variety of goals, including Climate Adaptation and Ecosystem-based Disaster Risk Reduction. Forest ecosystems can help in Disaster Risk Reduction in two ways; they can decrease exposure to disasters (for example through increasing soil stability and decreasing landslides) as well as increase community resilience (for example through diversifying the income of local communities). These forest ecosystems require a different project approach than forest plantations as they need to be sustained on a much longer time-scale and their success often depends on interaction with the surrounding communities.

One part of the planning- and decision-making process of forestation projects is spatial analysis. Large scale spatial analysis used in the initial phases of forestation projects to identify suitable areas for forestation. Most current analyses focus on bio-physical factors for single tree species. However, forest ecosystems projects include a wider variety of species and social factors are crucial in their success. Therefore, this research aims to understand the possibility of using socio-economic factors as spatial indicators in the planning of forest ecosystem projects.

In order to understand the possibility of using different indicators for forest ecosystem suitability analysis, a number of bio-physical and socio-economic indicators are compared to forestation success for existing forestation projects in Ethiopia. Forestation projects are assessed from 5 different organizations with a total of 12 projects and 67 forestation sites. A literature review is conducted to understand factors influencing forestation success. From all identified factors influencing forestation success, 11 indicators are chosen based on data availability and limiting overlap in effects. Despite its lack of representation of social and economic success, vegetation growth, using Normalized Difference Vegetation Index or NDVI is identified as the most reliable way to determine forestation success because of the availability of consistent data for all projects.

The suitability indicators selected are: soil texture, drainage, pH of soil, minimum monthly rain, solar radiation, elevation, distance to closest road, population, GDP, land cover and district. The forestation sites show a minimal average increase in NDVI. However, it is also found that areas without forestation projects with similar environmental and social factors show an increase in NDVI as well. When the success indicators of the reference sites are compared to the increase in NDVI, we see that the suitability indicators do not show a significant relationship with the NDVI increase over active project years.

The study shows the importance of standardized monitoring of forestation projects in order to gather not only bio-physical improvement but also social success, especially for projects with a social purpose. The use of satellite imagery to make forestation success assessments do not only give an incomplete understanding of the forestation project, the data availability in temporal and spatial scale and resolution limit the assessment. Additionally, the study shows the difficulty in comparing varying project types with different aims, timespans and sizes.

More research is needed that includes a larger number of forestation projects that have similar goals, methods, timespan and sizes, as well as a standardized reporting of social and environmental success. This could be achieved by combining data from several similar countries and by working closely together with forestation organizations that have standardized monitoring of their projects on both social and environmental success.

List of figures

Table of contents

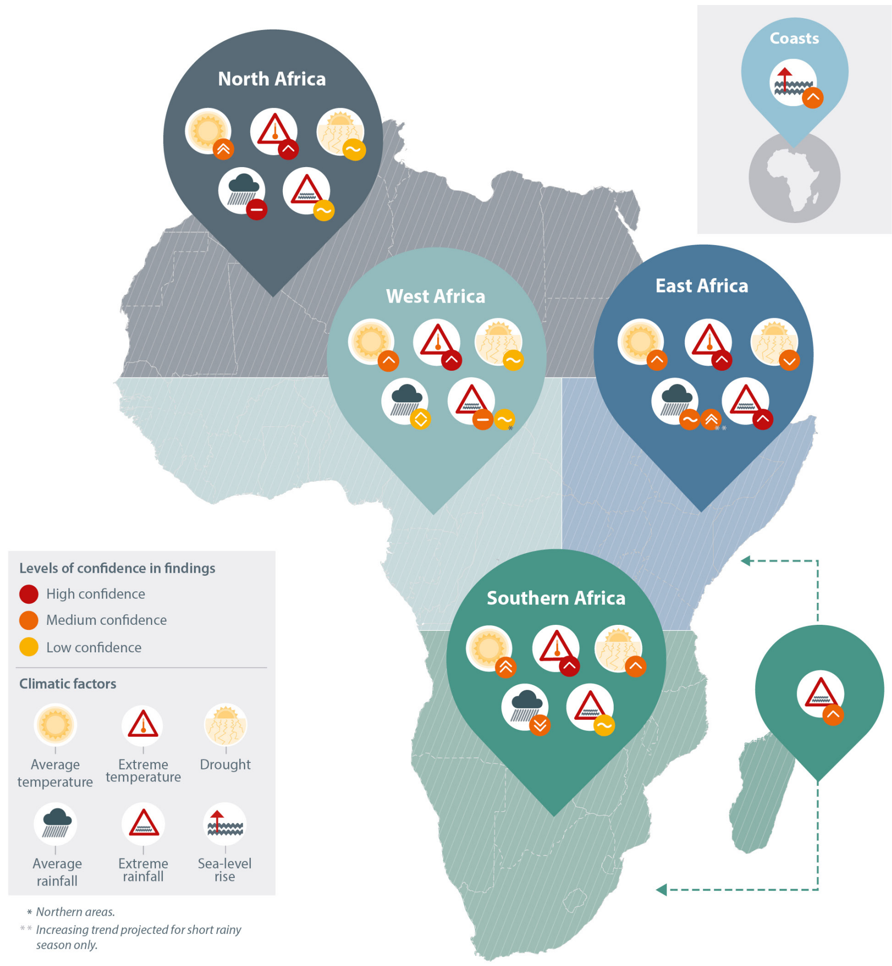
List of tables

1. Introduction and problem definition

1.1 Climate change and the need for adaptation

The growing human population, still-increasing industrialization and astonishing consumption rates have great impact on the earth and her climate. The effects of our changing climate will create challenges for communities worldwide as the natural systems that are the basis of human societies are under pressure. Mitigating human impact and reducing the effects of our society on natural systems is therefore crucial to secure a sustainable future. Large efforts are made globally in the energy sector, materials sector and ecosystem services. In spite of numerous projects, conferences and agreements, climate change cannot be averted altogether.

Climate change will affect people around the world in varying ways. One of the main effects of climate change is an increase in the amount and intensity of natural disasters worldwide, from droughts to floods to typhoons (Triyanti & Chu, 2018). In Figure 1 the effects of climate change are illustrated for different areas of Africa, including climatic factors such as extreme rainfall and droughts, sea level rise and an increase in temperature.



Symbol	Rainfall	Temperature	Extreme rainfall, extreme temperature, sea-level rise
	up to 30% increasing trend	1–6°C increasing trend	–
	up to 10% increasing trend	1–4.5°C increasing trend	increasing trend
	both increasing and decreasing trends	–	both increasing and decreasing trends
	up to 10% decreasing trend	–	decreasing trend
	up to 30% decreasing trend	–	–
	inconsistent trend	inconsistent trend	inconsistent trend
	no or only slight change	inconsistent trend	inconsistent trend

Figure 1. IPCC prediction of future climate trends for Africa including prospects for average temperature, average rainfall, sea level rise and droughts until 2100 (Field et al., 2014)

Poorer communities are at higher risk of these extreme weather events and experience more negative consequences from them (Singer, 2018), which further increases social inequality. Disadvantaged groups are more vulnerable, for example because they are more dependent on natural systems that are affected by climate change and do not have the means to overcome the damage done by disaster events. Climate Change Adaptation measures are actions that are taken to reduce these negative effects that communities experience from a changing climate.

1.1.1 Climate Change Adaptation and the field of Industrial Ecology

The field of Industrial Ecology looks at sustainability problems from multiple perspectives, in the aim to reduce the environmental impact of human actions. Industrial Ecology systematically examines human activity within the context of the natural environment with which it interacts (Lifset, 1997). The field contributes to solutions to sustainability problems by changing the consumption and emissions behavior of socio-technical systems. The multi-perspective approach of Industrial Ecology is suited both for assessing climate change mitigation as well as climate change adaptation challenges. The Journal of Industrial Ecology even dedicated an issue to this overlap between Industrial Ecology and Climate Adaptation, specifically asking for studies about climate adaptation.

As climate change results in an increase of disasters, one important aspect of Climate Adaptation is Disaster Risk Reduction. The multi-perspective approach of Industrial Ecology can contribute to Climate Adaptation and Disaster Risk Reduction in the same way in which the field examines sustainability issues: through examining the human system and the natural environment with which it interacts.

1.1.2 The role of ecosystems in Climate Change Adaptation and Disaster Response

A disaster is a physical hazard event, such as a typhoon or a flood, whose impacts surpasses the local society's ability to cope with the damages (Marisol & Saalismaa, 2013). Impacts of disasters are determined by a combination of the vulnerability of the society and the exposure to the hazard. Vulnerability is described by a range of factors including physical, economic, environmental and political factors (Marisol & Saalismaa, 2013). From this definition we can understand that impacts of disasters can be reduced by decreasing the vulnerability of a society or to lower exposure to hazards. Activities to reduce disaster impact are called Disaster Risk Reduction (DRR).

One of the methods to reduce impacts of disasters is through strengthening local ecosystems. Ecosystem-based Disaster Risk Reduction (Eco-DRR) is the sustainable management, conservation and restoration of ecosystems to reduce disaster risk, with the aim of achieving sustainable and resilient development (Marisol & Saalismaa, 2013). Many other terms are used for similar concepts, such as 'ecosystem-based Climate Change Adaptation', 'Ecosystem-based approaches for Adaptation' and 'nature-based solutions' (Renaud et al., 2016).

The role of ecosystems in DRR, sustainable development and climate change mitigation and adaptation is recognized by many organizations. This is reflected within agreements such as the Sustainable Development Goals (UN), the UNFCCC Climate agreement and the Sendai Framework of DRR (Renaud, Sudmeier-Rieux, Marisol, & Nehren, 2016). Ecosystem management can not only help mitigate hazards and reduce exposure, it can additionally provide benefits to local communities and therefore increase the resilience of communities exposed to hazards (Abedin & Shaw, 2015). Such benefits obtained from ecosystems are called Ecosystem Services (Pramova et al., 2012).

1.1.3 Forestation as an Eco-DRR measure

Forestation is one of the practices that is used to strengthen forest ecosystems for Disaster Risk Reduction. The term forestation can refer to different concepts such as Forest Landscape Restoration (FLR) and sustainable forest management. ecosystem services that can be achieved from forest ecosystems are: reducing local temperatures, providing additional income, providing food and fodder in times of scarcity and protecting against several environmental risks such as soil erosion, landslides, avalanches, flooding events and water quality problems (Pramova, Locatelli, Djoudi, & Somorin, 2012). Smallholder farmers are often dependent on rainfed agriculture and experience great difficulties from climate change and weather variability. Planting trees in agricultural fields can help regulate local climate and waterflow (Pramova et al., 2012).

1.2 A change in forestation

Forestation efforts have increased over the past decades and are expected to continuously increase in the coming years. Great effort already goes into forestation practices; Pistorius, Carodenuto, & Wathum (2017) identify the first Bonn Challenge, where countries that had previously already been involved in the Global Partnership for Forest Landscape Restoration participated, as a landmark for the field of forestation. It is one of the biggest forestation initiatives worldwide, with 43 countries participating and an aim of reforesting a total area of 350 million hectare. Additionally, there is no lack of opportunity for forestation projects in the future. The World Resource Institute states that globally, over 2 billion hectares of land has potential for restoration. (Minnemeyer, 2014).

However since their start, forestation practices have changed in focus and aim. In their beginning, large scale forestation projects were focused around large single species plantations and had carbon sequestration or the sourcing of timber for industrial purposes as a goal ((Liu, Kuchma, & Krutovsky, 2018). In the late 1990's, a growing understanding that conservation practices were not enough in light of the depletion of natural resources made for an increasing interest in restorative practices (Mansourian, Stanturf, Derkyi, & Engel, 2017). Currently, forestation projects are used for a much wider range of goals, including DRR. Many NGO's, such as Treesisters and the Eden Project, work with local communities in order to create ecosystem improvement and poverty alleviation at the same time (Barkham, 2019).

The increasingly social focus of forestation projects ask for a different understanding of forestation than before. The term forestation is at risk of being interpreted as covering large areas with trees (Mansourian et al., 2017), which can be problematic when the goal is biodiversity or DRR. The broad range of definitions in forests, forestation and connected activities is a representation of the misalignment and misunderstanding in forestation projects, e.g. between conservationists and policy makers (Lewis, Wheeler, Mitchard, & Koch, 2019). The term ‘forest’ can describe a variety of ecosystems; uncut primary forest, regenerating natural forest or monoculture plantations of non-native trees (Yang, 2011). All of the different types of “forests” offer a different range of ecosystem services and have different characteristics. A plantation is often harvested in 15-20 years while natural forests can last for decades (Lewis et al., 2019).

This distinction is not always recognized in the field. A clear example of this are the parameters of the definitions of forest by several large authorities in the field of forestation, which are shown in Table 1. It is clear that these factors vary widely, agroforestry being counted as forest by one authority but not in the other. Additionally, factors like biodiversity are not mentioned in any of the definitions. According to these definitions, the two types of vegetation in Figure 2 can both be identified as forests. However, there is a big difference between these types of forest. Forest plantations require a lot of fertile land, they often require pesticides and fertilizers which can harm ecosystems (Liu et al., 2018). Large monoculture projects in China are referred to as “green deserts”, as they have little in common with natural ecosystems (Luttikhuis, 2019). Besides the quickly growing trees that have economic benefit, such as eucalyptus, rubber or fruit trees, these plantations are not suitable for the interaction with native species; birds, bees, snakes and other animals (Luttikhuis, 2019). The monoculture plantations are often preferred because they provide more income in less time as all land can be used to plant one quick growing commercial species (Liu et al., 2018). FAO recognizes these shortcomings and the fact that these definitions are seen as lacking environmental and social criteria, especially for forest plantations (FAO, n.d.).

Table 1. Parameters of Definitions of ‘Forest’ by (FAO, n.d.)

Type	Parameter	UNFCCC	CBD	FRA
Binary parameters	Young stands	1	1	1
	Temporarily unstocked areas	1	0	1
	Non-forest land uses	0	1	1
	Agroforestry	0	?	1
Threshold parameters	Min. area (ha)	0.05-1.0	0.5	0.5
	Min. height (m)	2-5	5	5
	Crown cover (%)	10-30	10	10
	Temporary (years)	n/a	n/a	10
	Strip width (m)	n/a	n/a	20

1.2.1 Spatial data analysis for forestation

These forest ecosystem projects with social goals require a different approach from monoculture plantation projects. Monoculture plantations can be planted, monitored and harvested by an organization alone. Social oriented forestation projects require collaboration with local communities in order to achieve their social goals such as poverty alleviation and diversification of income and ensure sustainable forest management over a longer time span.

These different requirements in planning can be seen in the spatial data analysis that is used to identify the suitable areas for the forestation projects. For monoculture plantations, the sites environmental characteristics need to be suitable for one specific type of tree and the surrounding of the plantation site is of limited importance. However, for ecosystem generation, many more aspects are important (Le, Smith, & Herbohn, 2014). Apart from environmental characteristics, there are numerous factors that determine the success of forest ecosystem projects. Adams, Rodrigues, Calmon, & Kumar (2016) find that the effects of forestation on socio-economic factors vary depending on different variables including availability of jobs outside farming, housing type and the availability of markets for forest products.

Figure 2. Both the left and the right side of this picture might be considered forest (MAAP, 2018)

1.3 Factors that influence forest-ecosystem suitability

In order to get a better understanding of which factors are influential in forestation success, a literature review is done.

1.3.1 Bio-physical forestation suitability factors

There are numerous bio-physical factors that determine the suitability for forestation growth. Plants needs four main resources: light, air, nutrients and water (water and air can be considered nutrients as well). This paragraph provides an overview of the different bio-physical factors that determine the availability of these resources.

1.3.1.1 Soil texture

Soil texture refers to the size of the mineral particles in the soil. There are three classifications of soil particles: sand (1 to 0.5 mm), silt (0.5 to 0.002 mm) and clay (less than 0.002 mm). The size of these particles determines a number of characteristics of the soil, such as aeration and drainage. On average, a soil with a good balance of sand, silt and clay particles is considered a soil that is easy to work with and is suitable for a big variety of vegetation. This soil is called a loamy soil. Soil texture (% sand, silt and clay) is used in literature studies on the suitability of forestation (Carver, Danskin, Zaczek, Mangun, & Williard, 2004).

1.3.1.2 Soil drainage

The drainage capacity of the soil is important for the availability of resources for the plants. The drainage class describes how quickly (rain)water is "drained" through the depth of the soil in which the roots of the plants are growing into a deeper level. There are 5 types of drainage classes (well drained, moderately well drained, somewhat poorly drained, poorly drained and very poorly drained). Well-drained soils make it possible for plants to grow deeper roots as the water table does not limit the oxygen exchange (Cornell University, 2010).

1.3.1.3 Depth to bedrock/soil layer thickness

Soil layer thickness or depth to bedrock (cm) is identified as factor in forestation success (Le, Smith, & Herbohn, 2014) and used in forestation suitability studies (Apan & Peterson, 1998) (Chen et al., 2019).

1.3.1.4 Organic matter content or soil organic carbon

There are three different types of organic matter; living organisms, fresh residues and well-decomposed residues. Living organic matter includes roots, fungi, worms, bacteria and insects. Organic matter influences soil characteristics such as the stability of the soil and contributes to the recycling of nutrients (Cornell University, 2010). Very dead organic matter or humus is able to hold and release important plant nutrients. Soil organic carbon density (g/dm3) is used in existing tree suitability studies (Justdiggit, 2020).

1.3.1.5 pH of the soil

Acidity or basicity of the soil, can promote or hinder nutrient intake of the plant (Cornell University, 2010). A number of studies use soil water pH as indicators of forest suitability (Schwarz, Fahey, & McCulloch, 2003) (Carver et al., 2004).

1.3.1.6 Precipitation

One of the most important determinants of the availability of water is, naturally, rain. The average precipitation per month (mm), the precipitation in the driest month (mm) and the precipitation in the wettest month (mm) are important determinants as they give an indication of the plant available water. Next, the prolonged availability of the rainwater for the plant is determined by the evapotranspiration of water as well as the water drainage in the soil. Many literature resources describe precipitation level (in the watershed) as a determining factor in forest success (Cruz-Bello & Sotelo-Ruiz, 2013) (Justdiggit, 2020).

1.3.1.7 Solar irradiance

There are several effects of the amount of sunlight available for the plant. Firstly, plant use light as their source of energy and need it in order to grow. However, there are other ways in which the availability of sunlight can have effects on vegetation growth. Sunlight has effect on the local temperature and can increase the water uptake by the air. The variability of solar irradiance on the earth surface (w/m2) mostly varies based on latitude. However, in addition to this, the amount of sunlight varies based on the landscape. In the northern hemisphere, South facing slopes get more sunlight than North-facing slopes. Therefore, aspect direction (E - NE - N – NW – W – SW – S – SE or degrees) is an additional indicator that can affect plant growth.

1.3.1.8 Air temperature

As the temperature increases, the water uptake in the air increases as well. Therefore, plants give off more water to the air in higher temperatures. Additionally, high temperatures can overheat the plant whereas low temperatures can freeze the plant. Therefore, important indicators are not only average temperature (^{0}C) but also maximum temperature in warmest month (^{0}C) and minimum temperature in coolest month (^{0}C).

1.3.1.9 Air humidity

When air humidity is high, less water is taken up by the air. Some plants need a high air-humidity in order to keep the leaves from drying out. As transpiration is needed for nutrients to travel through the plant, too high air humidity can decrease the uptake of nutrients. Water vapor pressure (kPa) or relative air humidity (%) are not used in the example studies.

1.3.1.10 Wind speed

Wind speed can cause vegetation to be damaged. Depending on the tree type the strain experienced at different wind speeds might differ and thus also the critical wind speed might differ. Additionally, the availability of wind affects the evapotranspiration: If there is more wind, more water can be taken up by the air. Wind affects the moisture content of the air surrounding the vegetation as well as the temperature.

1.3.1.11 Elevation
Elevation (m) has an effect on several aspects important for plant growth. Temperature is limiting when growing in higher altitudes as plants need a certain temperature to be able to grow. However, vegetation in higher areas receive more sunlight needed for their growth than vegetation in lower areas. In addition, plants in lower regions are more affected by drought as they receive more rainfall whereas the plants in lower regions that are dependent on water in the forms or streams and rivers might dry up. Elevation is used in several suitability studies for forestation (Apan & Peterson, 1998) (Schwarz et al., 2003) (Chen et al., 2019).

1.3.1.12 Slope
The steepness of the slope (%) affects the physical support of the ground for the plant as well as the available water and nutrients in the ground. Many studies identify slope (%) as a factor for forestation success (Chen et al., 2019) (Schwarz et al., 2003) (Le et al., 2014).

1.3.1.13 Aspect
Aspect (in E – NE – N – NW – W – SW – S – SE) largely determines the amount of sunlight received in a certain area, especially in mountainous areas. Aspect becomes less important closer to the equator. The variability in sunlight and time of sunlight has a large influence on the temperature as well. (Chen et al., 2019) (Schwarz et al., 2003) (Apan & Peterson, 1998)

1.3.2 Socio-economic forestation suitability factors
Next to bio-physical factors, numerous societal or human factors determine the success of forest ecosystem projects. Demographics, infrastructure, and governmental aspects can all influence the way in which a forestation project is adopted within society. This paragraph provides an overview of some of these socio-economic factors.

1.3.2.1 Population density
The population density of an area determines both if there is actual space for a forestation project and also determines the use of the forest ecosystem, for the sourcing of e.g. timber or NTFP's. In Ethiopia, the quick population growth is identified as one of the main drivers for deforestation Stern (2016) (through (Kedir et al., 2018)). A densely populated area might therefore be less suitable for forestation as the demand for the use of the forest ecosystem challenges the possibility for sustainable forestry. Population density is a factor currently already in use for the 510 forestation suitability factor.

1.3.2.2 Income
For community-based social forestry projects with a goal to diversify incomes of local communities, the success of a forestation project partly depends on the dependence of local communities on the forest for their income (Le et al., 2014); when people are more dependent on the forest, their participation increases. Studies show that poorer households are more reliant on forests for their income (Pramova et al. 2012). Therefore, local income is expected to influence forestation success. However, intensive use of the forest resources can cause forest depletion and hinder the possibility for sustainable forestry. Therefore, a highly populated area with an average low income is expected to decrease forestry success.

1.3.2.3 Land use
An important factor that is already used widely in spatial assessments of forestation suitability is land use. Land use or landcover data helps to understand the current application of the land which can indicate the possibilities for further development. It can consist of different variety of classes, separating different vegetation types (forest, shrubs), different uses of the land (urban, agricultural land) and other "land covers" such as waterbodies or snow. Some land use classes can also indicate if the land is used for crops or pastoral farming. Additionally, the recent history of land use, as is used in the LULC change analysis that is already done by 510, can identify suitable sites as recently degraded sites are often promising for restoration as beneficial factors for forestation, such as soil structure and organic matter in the soil, often remain for some time (Justdiggit, 2020).

1.3.2.4 Corruption
In many studies, absence of corruption is seen as a greatly important requirement for forestation success (Le, Smith, Herbohn, & Harrison, 2012).

1.3.2.5 Land tenure
One of the most important factors in the success of forestation projects is the local rights for the use of the forest and the regulation/enforcement of these rights (Baynes, Herbohn, Smith, Fisher, & Bray, 2015). In Ethiopia these rights are determined nationally but enforcement is mostly done per area. For example, three regional states have identified PFM as the main forest management principle to be applied in the area.

1.3.2.6 Road conditions
Good road conditions are reported to have possible beneficial effects on forest growth (Le et al., 2014) as well as negative effects (Kaczan, 2020). The benefits of good road conditions can be explained through the support of the forestation project: good road conditions reduce transportation costs and accessibility to the project which eases maintenance work

on the project (Le et al., 2014). Additionally, roads can increase productivity of non-agricultural sectors, therefore reducing agricultural activity and facilitate price convergence across regional forest-product markets (Kaczan, 2020). On the other hand, new roads are often linked with deforestation as they provide access to the forest area (Kaczan, 2020).

1.3.3 Project characteristics

This research is aimed at identifying suitable areas for all types of forestation projects. However, many studies show that the project characteristics such as economic objective, education, capacity building, largely influence the success of forestation activities (Pramova et al., 2012) (Le et al., 2014). For example, the 'Eden project' reforestation projects in Ethiopia were cancelled in 2015 because of fraudulent behavior of the local staff. Naturally, such challenges can affect the project in many ways. Therefore, it is important to identify and highlight the effect of the project characteristics on the forestation success. Because it is difficult to gather information on all of the aspects of forestry projects, for now the organizations and the project sites are taken as categorical indicators for the statistical analysis.

1.4 Problem definition and Research Questions

It is clear that in spite of the focus on environmental factors in spatial data analysis for forest ecosystem planning, many social factors are crucial for success of forestation projects. Therefore the main research question becomes:

> **Can a combination of bio-physical and socio-economic spatial data predict planted forest ecosystem success?**

In order to research this main research question, it is split up into three sub-research questions. First the factors that influence forestation success as described in the introduction need to be translated to spatial data (suitability indicators) Next, in order to test the influence of the socio-economic factors on forestation success, it is needed to understand how forestation project success can be measured. This results in the following three sub-research questions:

> **What bio-physical and socio-economic spatial data (suitability indicators) can represent factors that influence planted forest ecosystem success?**

> **How can the success of planted forest ecosystem projects be measured?**

1.5 Case of 510 forestation assessment

This thesis project is done in collaboration with the Netherlands Red Cross and more specifically their data team; 510. 510 has the aim to improve humanitarian aid by providing data and digital products (510global, 2016). The team uses data to help improve aid, both for projects of the Red Cross-National Societies (the country branches of the International Federation Red Cross) and their local partners, including other NGO's and governments.

Partners for Resilience (PfR) is an NGO that contributes to the resilience of communities by integrating Climate Change Adaptation, ecosystem management and ecosystem restoration into Disaster Risk Reduction (DRR). One of the ways in which PfR does this is through Eco-DRR projects in five different countries. These Eco-DRR projects are part of their goal to demonstrate the full potential of community-based Eco-DRR. This is done by 5 projects in different countries that are implemented across large areas. Besides demonstrating the possibilities of Eco-DRR, the goal is also to develop methods for scaling up community based Eco-DRR. 510 is proposing to help in decision making for several PfR Eco-DRR activities, among which forestation.

1.5.1 510 forestation suitability assessment

Currently, the selection of reforesting areas is assisted by 510 through 3 analyses. Firstly, the Community Risk Assessment is used to identify districts with high disaster risk. For the selected areas, a historical forest cover and a climate and soil assessment is done.

1. The methodology behind the Community Risk Assessment is based upon the widely accepted and used INFORM framework, which describes disaster risk based on three dimensions; Hazard & Exposure, Vulnerability and Lack of coping capacity (Figure 3). The components are based on several indicators that are found in databases from reliable sources with global coverage such as the World Bank, WHO and UNICEF. For the Community Risk Assessment, more detailed data needs to be found in order to provide the same methodology on district level

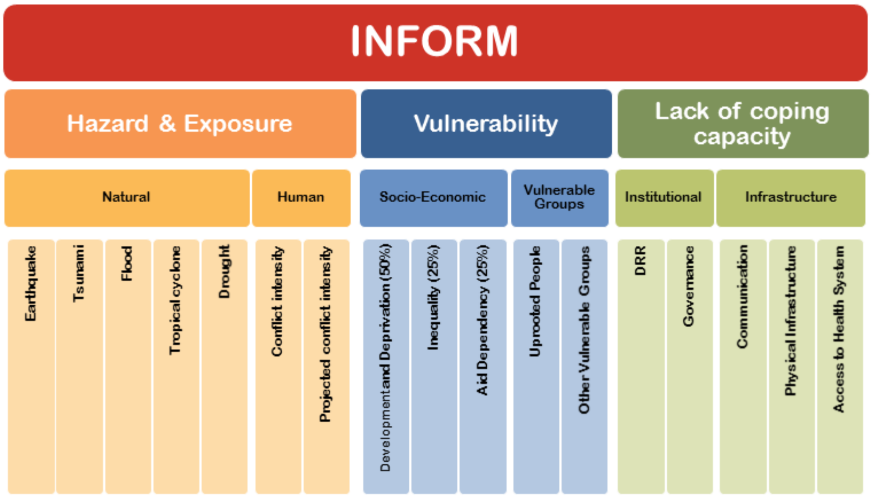


Figure 3. INFORM methodology

2. Based on satellite imagery an automatic identification of different land use classes is made and the difference between satellite imagery of different years is analyzed to find areas in which natural forest has degraded.

3. 510 makes use of several indicators such as rock depth, temperature and population density (see Table 2). These indicators are used to set boundary values for a certain tree type in order to identify suitable locations for forest growth.

Table 2. Geospatial indicators used in tree suitability analysis proposed by 510

Geospatial indicator	Unit
Population Density	1000 people/km2
Elevation	m
Rock-depth	m
Slope	%
average T	^{0}C
maximum T	^{0}C
minimum T	^{0}C

1.5.2 Elaboration of current method

It is clear that 510 takes into account social factors in their forestation planning. Because of the use of the INFORM framework, the analysis covers a number of socio-economic factors. However, these socio-economic factors are only taken into account in the disaster risk prediction. This is not done in the same way for forestation suitability; in the suitability analysis, only one social factor is included (population density). However, from literature it is clear that there are many additional socio-economic factors that influence forestation that are now not included in the spatial analysis of 510. Therefore, the suitability analysis method is less suited for ecosystem-based DRR activities for two reasons: First, the bio-physical analysis is more suited for single species rather than a variety of species included in an ecosystem as it works with boundary values. Second, the limited use of social factors in the suitability analysis makes the analysis more suited for top-down forestation projects rather than participatory forestation projects in which interaction with the local community is crucial.

Because of the large number of forestation projects, it can be expected that 510 will have the opportunity to help these projects more frequently. This project can help 510 gain insight into a more holistic approach towards spatial data analysis for forest ecosystem projects. The research can elaborate on the current methodologies used by 510 while incorporating a more holistic approach.

1.6 Case study country

As forestation is one of the Eco-DRR measures selected for the project plans of PfR in Ethiopia, this country is chosen as a case study. The goal of the Eco-DRR project in Ethiopia is to prevent drought, diseases and conflict over water sources. Forestation is an identified method to contribute to achieving these goals.

Ethiopia is a landlocked country located in the Horn of Africa neighboring Eritrea, Somalia, Kenya, South Sudan and Sudan. The country is 1,1 million km2 and has around 100 million inhabitants (World Bank, n.d.). The capital is Addis Ababa. Ethiopia's population is young and quickly growing. From 1983 to 2018 the population grew from 33,5 million to 108 million, averaging at 3,4% of growth per year. The quick population growth results in a median age of 19.5 years. Ethiopia is predicted to have a 205 million inhabitants in 2050 (UN, 2019 through (Worldometer, n.d.).

1.6.1 Economy

Ethiopia is the fastest growing African economy after Nigeria, with a 7.7% GDP growth in 2017. Despite its strong economic growth, the country's poverty levels are still high, because of previous wars with neighboring countries. The per capita income is 790 US dollar per person (World Bank, n.d.). Although its importance is decreasing, agriculture is still the biggest contributor to the economy and makes up half of Ethiopia's GDP, (Britannica, n.d.).

1.6.2 Geographic and climate

Ethiopia is split through the middle by the Ethiopian Highlands with the highest mountain being 4550 meters. These highlands cause a range of climates. The variety of climate types can be seen in Figure 4. Because of the elevation in the highlands, some areas have quite a temperate climate despite Ethiopia's latitude close to the equator. However, there are also regions with a dry and hot climate. An extreme example is the Danakil depression (-125 meters) which is the hottest human settlement on earth with an average of 41 degrees Celsius.

Ethiopia has three seasons; (1) a dry season from September to February, (2) a rainy season in March and April with a break in May to then be followed by a longer rain season in June, July and August (Britannica, n.d.). However, Ethiopia has four different yearly rainfall patterns in different areas of the country (Britannica, n.d.). Figure 5 shows the rainfall per month for 4 different meteorological stations in Ethiopia.

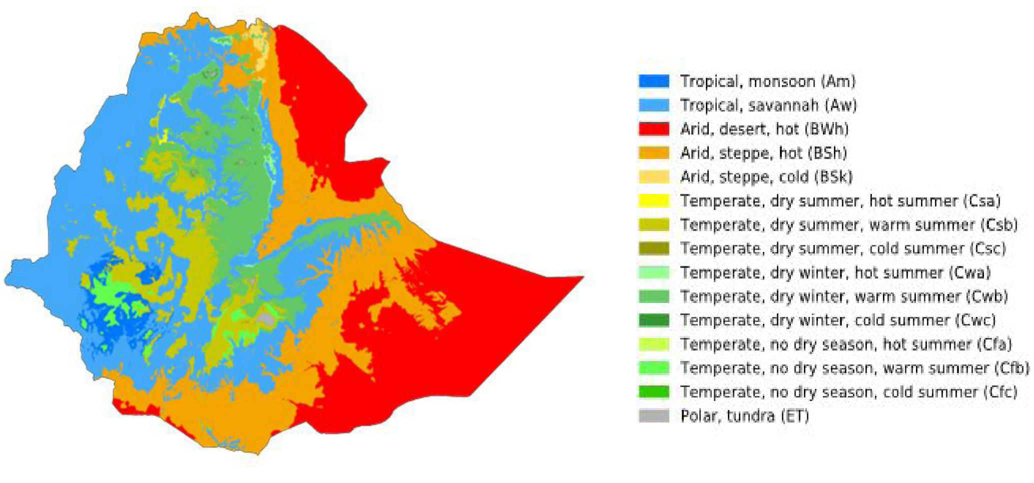


Figure 4. Map of Ethiopia according to the Köppen climate classification (2018).

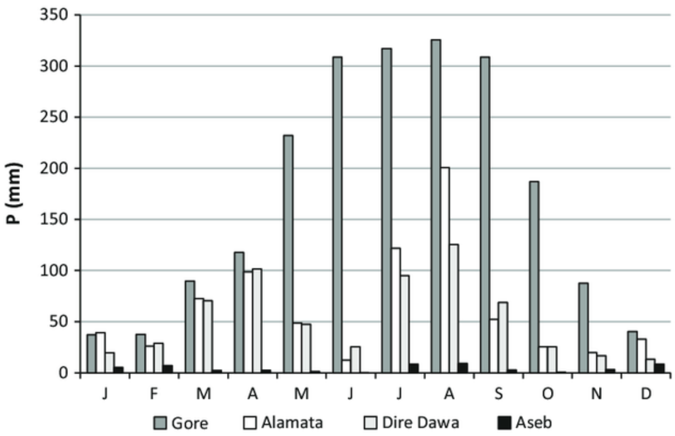


Figure 5. Typical monthly rain patterns in Ethiopia as illustrated by four representative meteo-stations: Gore, mono-modal; Alamata, bimodal with a smaller peak in March/May and a more prominent peak in July/ August; Dire Dawa, bimodal with two peaks almost equivalent; Aseb, diffused pattern. (Billi, Alemu, & Ciampalini, 2015)

1.6.3 Agriculture

Next to a varying climate, Ethiopia knows varying farming regions with more crop and livestock production in the highlands and more agro-pastoralism in the lowlands. Smallholder farmers account for 74% of total farmers (FAO, 2018). Coffee accounts for 26% of the country's export and there are five cereals (teff, wheat, maize, sorghum, and barley) which are Ethiopia's main crops (FAO, 2018). Since 2019, Ethiopia's agriculture has suffered from desert locust outbreaks (Reliefweb, 2019), (FAO, 2020).

1.6.4 Forests

Deforestation has been a pressing topic for many years for Ethiopia. Although the reported numbers vary, it is recognized widely that forest cover has declined rapidly in the past decades. Deforestation and forest degradation are results of free livestock grazing, fodder use, and fuel wood collection/charcoal production, farmland expansion, fires, and construction wood harvesting. The underlying causes of deforestation and degradation based on an analysis by Stern (2016) (through (Kedir, Negash, Yimer, & Limenih, 2018)) are population growth, insecure land tenure and poor law enforcement. The national land-policy and forest management approaches in Ethiopia have changed multiple times over the past decades. This uncertainty regarding land tenure has caused local communities to have lost interest in forest conservation (Kedir et al., 2018).

An increase in awareness on the forest decline has created incentive for a number of forestation projects. The Participatory Forest Management approach was introduced in 1995 in Ethiopia through different organizations such as FARM Africa (Gobeze, Bekele, Lemenih, & Kassa, 2009). More recently, the government has started the green-legacy campaign with the goal of planting 4 billion trees to the end of 2019. The start was in 29 July with 350 million trees in a day (UN Environment, 2019).

2. Methodology

In order to understand the effect of suitability factors on forestation succes, existing forestation projects are used as a reference. Existing forestation projects are selected within a case study country in order to limit the effect of geographic and national differences. From the selected reference forestation project sites, the socio-economic and bio-physical forest suitability factors are determined as well as their forestation success. From these grades the relationship between these suitability factors and forest success scores is determined. Therefore, the research consists of three parts:

- Data indicators are selected to represent important factors that influence forestation suitability and the indicator values are extracted for each reference forestation site
- The forestation success is determined for each reference forestation site
- The relationship between the forestation suitability indicators is analyzed

2.1 Reference forestation projects

Forestation projects are found through desk-research and literature review. A number of different ecosystem-based forestation approaches are included in the analysis in order to increase the number of forestation sites. However, only multi-species projects with a social purpose are included rather than monoculture plantations. An overview of the forestation sites can be seen in Table 3. In total there are 67 forestation sites used in the analysis with diverse sizes, timespans and species. However as can be seen from the description in Appendix A, all projects have social project goals and include a number of tree species.

Table 3. Overview of forestation projects

Organization	Project	Nr. of sites (included)	Start year	End year
Weforest	Amhara	31	2017	n.a.
	Seret	1	2018	n.a.
	Desa'a	1	2017	n.a.
Eden Projects	Rift Valley	1	2004	2014
	Sidama Highlands	3	2004	2014
	Shalobele	3	2004	2014
United Nations	Lake Tanu	1	2014	n.a.
	Sheka	6	2012	n.a.
	Yayu	4	2010	n.a.
	Majang	5	2017	n.a.
	Kafa	5	2010	n.a.
Farm Africa	unnamed	1		n.a.
n.a.	Gebradima	3	2000	n.a.

In order to use the reference forestation projects in the spatial analysis, they need to have a location description. A combination of area descriptions is used depending on the type of reporting of the projects. If available, a project map is projected in the GIS software through the georeference function in QGIS using either coordinate references or location (cities, villages, roads) references (Figure 6). If no map is available of the forestation site, the project coordinate description is turned into an area that can be used for analysis by creating a buffer surrounding the point location (creating an area of approximately 2,5 hectares).

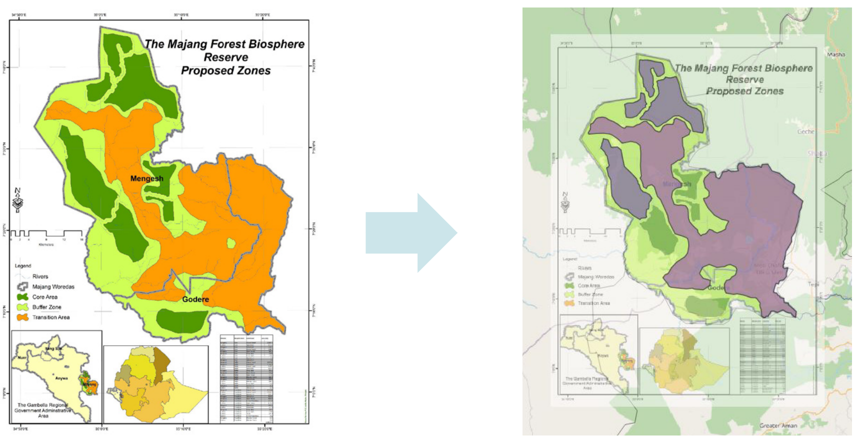


Figure 6. Mapping of a biosphere reserve map. Original map from Unesco (2018).

2.2 Forestation suitability indicators

Several academic and grey literature sources are used to gather potential forestation suitability and priority factors that influence the success of forestation projects, as is discussed in sub-chapter 1.3. In order to quantify these factors, spatial data is found to represent the factors (the suitability indicators). Indicator data is gathered through a number of platforms; Data from the Google Earth Engine data catalog is used, as well as data from ISRIC, UN OCHA, NASA SEDAC and BioClim.

This data is not an exact representation of the success factors but rather an indication of them. Depending on the availability of data on different topics, the indicators can be more or less closely related to the indicator. For example, no spatial data was available on land-tenure rights. However, it is found that these rights differ per district. Therefore, the districts themselves are used as categorical indicators in order to represent this success factor. If no related data is found, the factor is not included in the spatial analysis. From the resulting indicator data, a selection of final indicators is determined based on uniqueness and predicted importance. For example, for several indicators that are closely related, such as minimum and maximum rainfall, only one indicator is included in the analysis.

2.2.1 Preparing indicator data

Before extracting the median indicator values per forestation site, some of the indicator data has to be adapted. For example, for solar radiation, the 12 raster files for each month of the year are averaged using raster calculator tool in QGIS. The indicator data has to be in a raster format in order to use zonal statistics to gather median values. Therefore, for the district data the vector file is turned into a raster file using the vector to raster tool by QGIS.

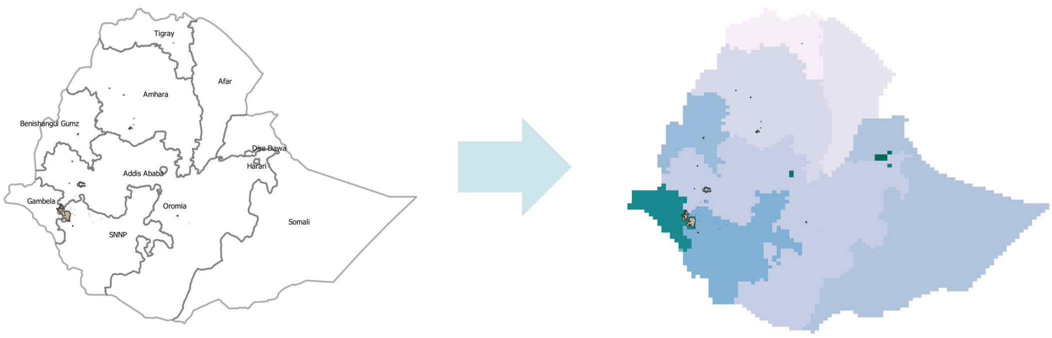


Figure 7. Adapting a vector shapefile to a raster file

The factor data is extracted using the median per forestation site in order to limit the effect of possible faulty cells. The data is extracted in various ways depending on the type of indicator. For numeric data of factors that occur within the forestation site, such as rainfall, the median is taken of the project area. For numeric data of indicators that are relevant both inside and outside the forestation site, such as population or GDP, the median of a larger area that the project site is used. For these indicators, a buffer is created surrounding the forestation site of 4 km and the median of values within the area was extracted. For one indicator, nearest road, a nearest neighbor analysis is done of the road vector and the forestation site vector using the function NNJoin. For categorical indicators, the most occurring category per project site is used.

2.3 Forestation success assessment

The success of a forestation project is determined by measuring the change in vegetation density over the active project years. The vegetation density is measured using NDVI values, as has been done in exemplary studies (Takahashi & Todo, 2012). NDVI is the most widely used measure to quantify vegetation (Lawley, Lewis, Clarke, & Ostendorf, 2016) through remote sensing methodologies. The Normalized Differenced Vegetation Index or NDVI is an indicator for vegetation growth based on two spectral bands. Whereas plants absorb visible light as they use it for photosynthesis, they reflect near infrared light, as can be seen in the spectral reflectance curves in Figure 8. NDVI makes use of this difference in order to determine the density of vegetation. Chlorophyll, which is present in plant leaves, strongy absorbs red light but the cell structure in leaves strongly reflects near-infrared light (NASA, 2000). Therefore, if an area reflects much more NIR than (red) visible light, the area is likely to have vegetation. The bigger this difference is, the more the vegetation is likely to be. The formula for NDVI is: NDVI = (NIR — VIS)/ (NIR + VIS). Calculations of NDVI for a given pixel always result in a number that ranges from -1 to 1. A value of 0 indicates no vegetation and close to +1 (0.8 - 0.9) indicates the highest possible density of green leaves.

For the assessment of existing forestation projects the NDVI data is retrieved for the relevant project years over the different forestation areas. Per NDVI image, the median value is extracted for each project site for all available images within the selected time period. For each forestation site, the mean value per calendar year (or month, as is further explained in paragraph 2.3.1) is calculated. For the project's active years, the mean improvement in NDVI is calculated. This mean improvement is used as the "success score" of the forestation project.

This approach to scoring the forestation site's success holds a number of assumptions. First, the time-span of the reference forestation projects differs largely between project. However, the type of success depends on the timespan: whereas short term success can be seen as the successful initial planting phase (such as survival rate of seedling), long term success can be indicated by social factors such as socio-economic benefits for the community (Le, Smith, Herbohn, & Harrison,

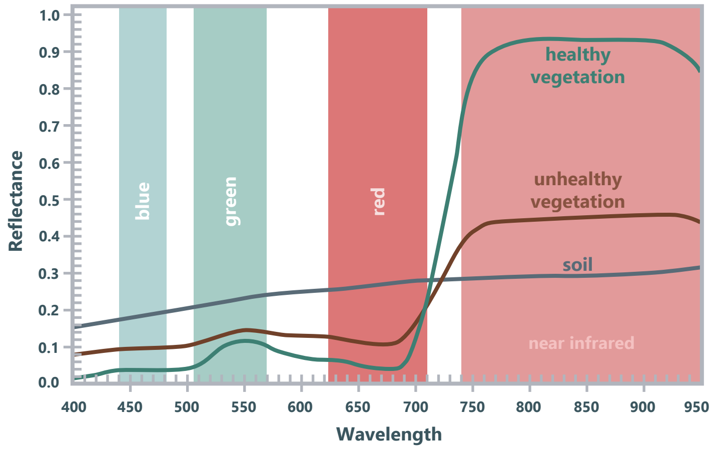


Figure 8. Spectral reflectance signature of healthy vegetation, unhealthy vegetation and soil

2012). Both recently started forestation projects and more established forestation projects are used because of the limited number of reference forestation projects available. Second, the assessment of the reference forestation projects was aimed to be done by comparing a number of different factors that could represent both ecological and social success. However, the social success factors of the project (people engaged, kg harvested products per ha, etc.) are not used as they were not available for all projects and the consistency of the data available could not be guaranteed. Therefore, in order to ensure the availability of data for the different projects, satellite imagery is used for the forestation assessment. This data only represents a small number of ecological indicators such as survival rate of seedlings and area planted. Concluding, because of data availability, for this study it is assumed that short term success can indicate long term success and that ecological success can indicate social success of forestation.

A dependent t-test is used to calculate the difference between forested areas before and after forestation projects.

2.3.1 NDVI improvement comparison

In order to better understand the NDVI improvement of the forestation sites, two iterations to the NDVI improvement analysis are explored; the satellite imagery of which the NDVI values are extracted and the timespan of which the NDVI values are extracted within a year.

The first NDVI data that is used is the MODIS Combined 16-Day NDVI product. This index is not calculated from a single satellite image but rather composited of daily NDVI images which are atmosphere-corrected. The spatial resolution is 250 meters and the temporal scale of the product is from 2000 to 2020. In addition to this MODIS data, a comparison is made using Sentinel-2 data. MODIS data is chosen because of the large temporal range and the publicly available 16-day composite NDVI product. However, the resolution of the MODIS imagery is relatively rough (250 m) in comparison to the scale of some of the project areas, as can be seen in Figure 9. Sentinel-2 data has a much higher resolution (10 m for the red and infrared bands) but has some disadvantages. Firstly, it is only available since 2015, which means that it does not cover much of the time-span of the forestation projects in the study. Additionally, Sentinel-2 has a global coverage every 10 days (since 2017 every 5 days). Because of this lower temporal resolution, for cloudy months such as September and August, there is no data available for the forestation sites. Additionally, for the Sentinel-2 imagery there is no NDVI composite available. Therefore in this research the Sentinel-2 data is used without an extensive correction. The NDVI image is calculated from the Red and Infrared bands and a cloud-cover mask provided by Sentinel is used. Because of the limited temporal range, only WeForest Amhara sites are included in the Sentinel-2 data analysis.

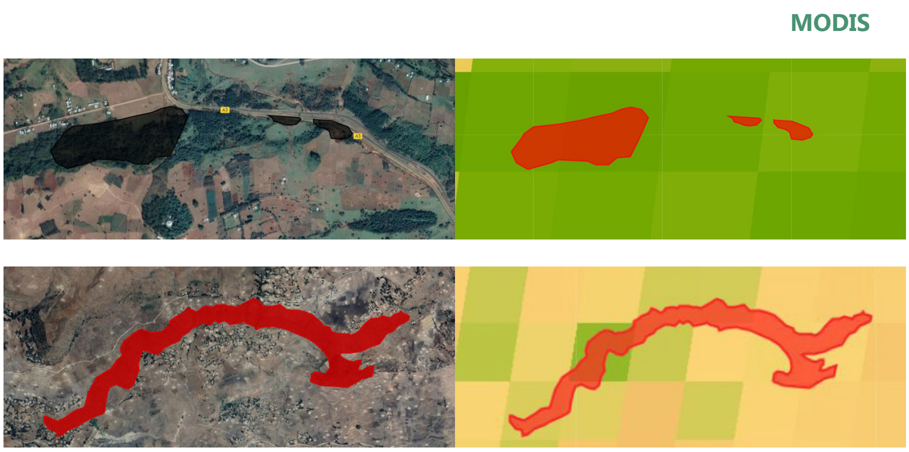


Figure 9. An example of two project sites in red and the relatively low-resolution MODIS NDVI product (visible light RGB image on the left)

Sentinel

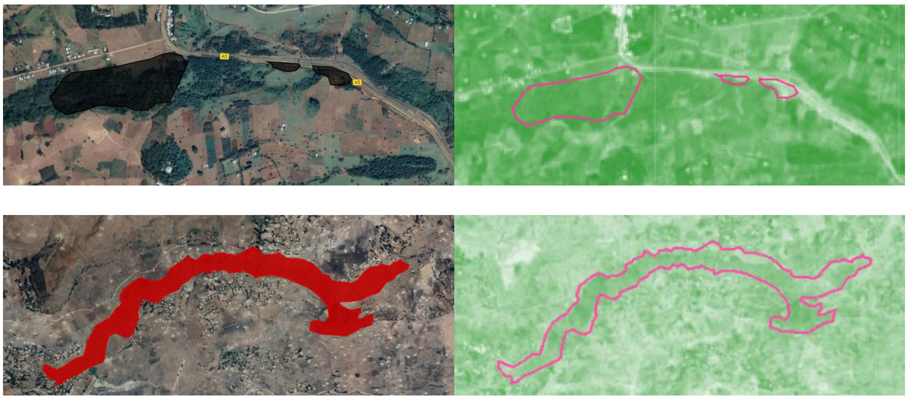


Figure 11. An example of two project sites highlighted in pink and the relatively high resolution Sentinel NDVI image (visible light RGB image on the left)

Initially, the yearly average NDVI value is taken in order to calculate the average increase in NDVI over the active project years. However, for many areas and types of vegetation, the NDVI value varies widely within a year. This can be seen in Figure 10, which shows a filmstrip of MODIS 16-day NDVI composite product for the year 2016 around the WeForest Amhara sites. Around July/September/October, the vegetation is more dense and thus the images show a higher NDVI around these months. The forestation projects used in the analysis include decidious tree species such as Acacia polyacantha and Croton macrostachyus. In order to see their growth clearly in the success scores, an option is to only look at one or several months per year (instead of all 12 months) in which the most leaves, and thus the highest NDVI is expected. Therefore, as an iteration on the yearly average analysis, the average NDVI in October is calculated as well. October is chosen because July and September are part of the rain season in Ethiopia which results in high cloud-coverage for these months and consequently less chance of clear satellite imagery, especially for the lower temporal resolution and non-composited Sentinel imagery.

2.4 Finding possible relationship

The indicators can be divided into categorical indicators (district, project, land use) and numeric indicators (minimum rain, pH, Root Zone Moisture Content). For the different types of indicators, a different approach is used:

2.4.1.1 Numeric indicators

Scatter plots are made to explore the relationship between the numeric indicators and the yearly NDVI improvement.

2.4.1.2 Categoric indicators

Botplots are made to explore the average and range of the yearly average NDVI scores across the different categories of the categorical indicators. A categorical regression is done in R using the lm function.

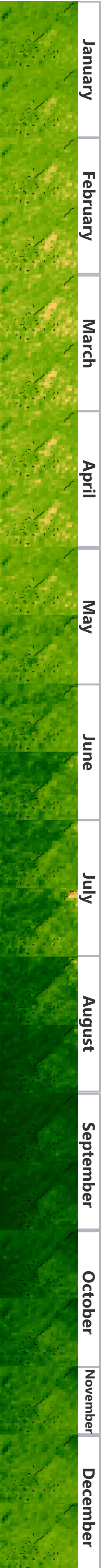


Figure 10. An overview of all 16-day modus products for 2016 surrounding the WeForest Amhara sites, from januari on the top to december at the bottom (around 2 images per month)

3. Results

3.1 Forest-ecosystem suitability indicators

From the various factors found (Sub-chapter 1.4), a selection is made to use in spatial analysis based on relevance, uniqueness, availability of representative data. The socio-economic factors were mostly limited by data availability and therefore no selection had to be done for these indicators. An overview of the final data used can be found in Table 4.

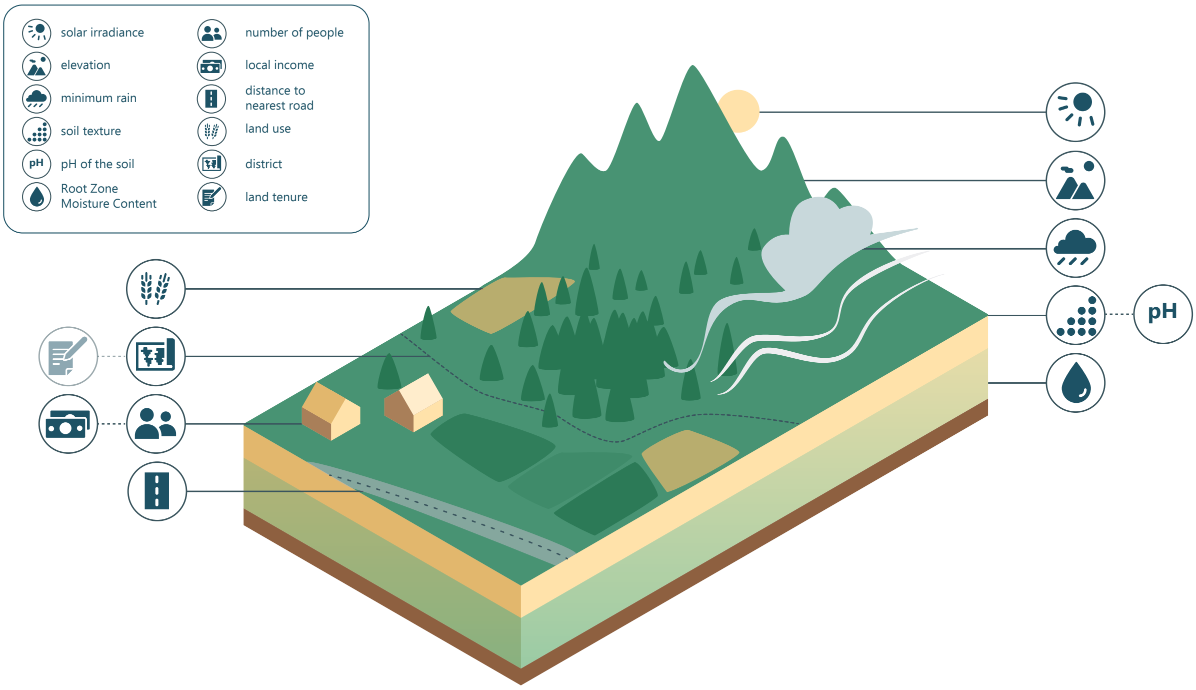


Figure 12. Visual overview of selected forestation suitability indicators

From the bio-physical factors, six factors are chosen:

- Soil texture is represented by the indicator silt percentage. As mentioned in sub-chapter 1.3, soils with a good balance of sand, silt and clay particles is suitable for a larger variety of vegetation.
- The available groundwater is represented by the indicator Root Zone Moisture Content, which shows the volumetric percentage of water in the soil. As large parts of Ethiopia face droughts (Reliefweb, 2020), it is assumed a higher RZMC is associated with a higher NDVI increase.
- The water pH of the soil is seen as an important factor in Ethiopia as Ethiopia contains highly acidic land (pH below 5.5) (Gurmessa, 2020) as can be seen in Table 4. It is expected the optimum pH of the soil is in between 5,5 and 7 (University of Vermont Department of Plant and Soil Science, n.d.).
- Minimum monthly rainfall is chosen because in most areas (determined by climate type) water limits plant growth (NASA, 2000) and Ethiopia faces frequent longer periods of droughts (Reliefweb, 2020).
- Solar radiation is chosen as an additional climatic indicator to represent availability of sunlight for the plant.
- Elevation is added as an indicator as it is used in almost all examples of spatial analysis for forestation suitability analysis.

For socio-economic factors, five factors are determined;

- Road conditions are represented by the indicator distance to nearest road, which is calculated from a vector-file containing all roads in Ethiopia.
- Population density is represented by the indicator population per pixel.
- Income is represented by GDP.
- Land use is represented by the MODIS land cover classification, which uses satellite imagery to determine 17 land cover classes.
- No spatial data is available on tenure rights. However, it is found that in Ethiopia Forest Management is determined by regional authorities. Because of this, tenure rights are represented by the first administration levels.

An overview of the suitability indicators per project site is provided in Appendix B.

Table 4. Bio-physical factors and indicator data overview showing the minimum and maximum value in Ethiopia

	Factor	Indicator	Units	Resolution	Data source	Min	Max
Bio-physical factors							
1	Soil texture	Silt	%	1 km	ISRIC	7	42
2	Drainage	Root Zone Moisture Content	%	1 km	ISRIC	31	56
3	pH of soil	pH soil water	pH * 10	1 km	ISRIC	49	88
4	Rain	minimum monthly rainfall	mm/month	30 sec = 1 km	BioClim (WorldClim)	0	59
5	Solar radiation	average solar radiation per year	kJ m-2 day-1	30 sec = 1 km	WorldClim	17179	23037
6	Elevation	Digital Elevation Model	m	30 sec = 1 km	NASA SEDAC	-124	4291
Socio-economic factors							
7	Road conditions	Distance to nearest road	radial degrees	vector	UN OCHA	n.a.	n.a.
8	Population density	Population	People per pixel	3 sec = 100 m	Worldpop	0	516
9	Income	GDP	US dollars	1 km	NASA SEDAC	0	18278
10	Land use	Land cover	17 classifications	500 m	MODIS	n.a.	n.a.
11	Tenure rights	Regions/ administrations	12 different regions	vector -> 1500 km	UN OCHA	n.a.	n.a.
Project factors							
12	Project characteristics	Project	5 projects		n.a.	n.a.	n.a.

3.2 Forestation assessments

3.2.1 MODIS yearly-average NDVI improvement

As discussed in the methodology, the Normal Difference Vegetation Index (NDVI) is used in order to assess the forestation projects. The NDVI values from the MODIS product have a factor 0,001, meaning instead of 1 the NDVI shows 10,000. Additionally, the MODIS product does not include NDVI values lower than -0,2 (or -2000). Initially, the 16-day NDVI product by MODIS is used for the years 2000 to 2019 which results in a total of 817 images. For each reference forestation site (67 sites), the median NDVI is calculated per image. The yearly average NDVI was calculated for each project site.

Figure 13 shows the yearly NDVI values combined for the different forestation organizations (so in this graph, the average NDVI's are taken for all forestation sites combined per forestation organization instead of for each project site). The additional No project are not from an organization, but are selected sites in which no forestation project occurs (as is explained further in methodology). The forestation sites are grouped in order to make observations on the differences per forestation organization. First of all, it is clear that the forestation projects start at notably different NDVI values. Additionally, they do not increase or decrease a lot in almost 20 years. Furthermore, different projects behave similarly in certain ranges of time. For example, between 2006 and 2008 the Eden Project projects and the Farm Africa project behave similarly. Similarly, the United Nations projects, the Eden Project projects and the no projects sites all show a similar decrease in 2018 and increase in 2019.

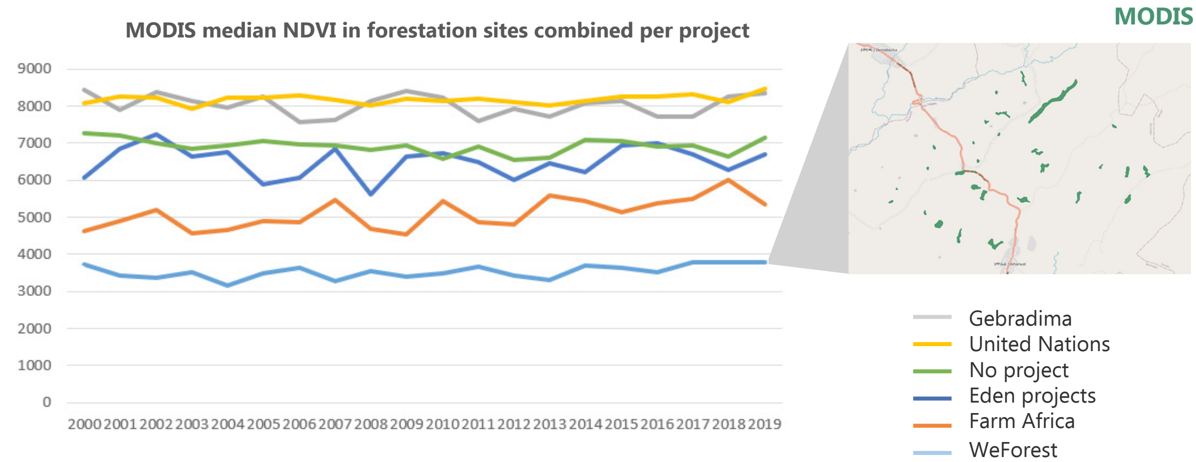


Figure 13. Median NDVI for forestation sites combined per organization from 2000 to 2019

The yearly NDVI values per project site are used to calculate the average increase in NDVI over the active years. Figure 14 shows a histogram of the average yearly NDVI improvements for the 67 reference forestation sites. The histogram shows a normal distribution for the NDVI improvement. The results are summarized in Table 5. The NDVI improvement values range between -125 (so decrease in NDVI) and 425 and an average change of 46.

MODIS (yearly average)

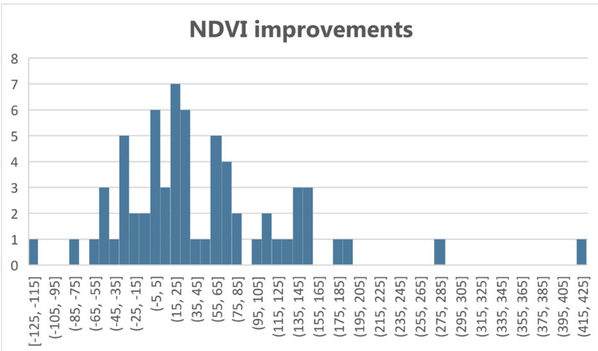


Figure 14. Yearly average NDVI improvement histogram

Table 5. Summary NDVI improvement for all project sites

	Average yearly NDVI change for active project years
average	45.84
maximum	415.10
minimum	-124.98
standard deviation	85.19
average yearly improvement in % compared to year before start project	0.97

Figure 16 and Figure 17 show the average yearly NDVI improvement for two different project organizations: WeForest and the United Nations biosphere reserves. The graphs show that the WeForest projects have a larger deviation, ranging from around -125 to 415, whereas the United Nations projects yearly average NDVI improvement range from around -45 to 78.

MODIS (yearly average)

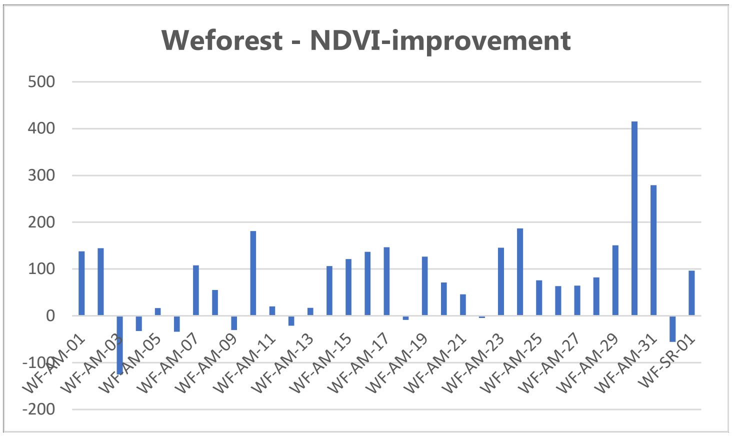


Figure 16. WeForest sites yearly average NDVI improvement

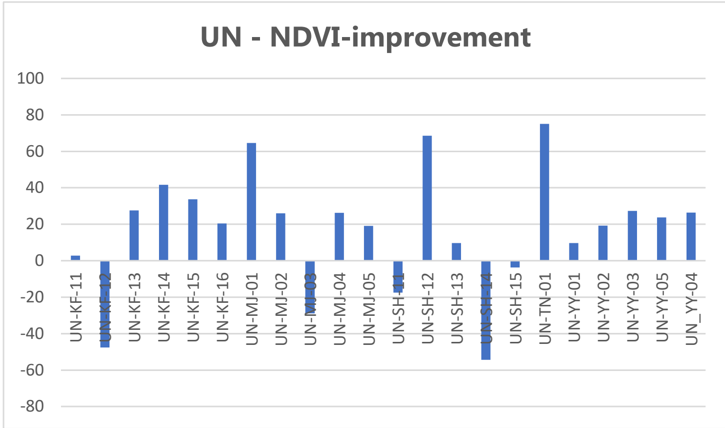


Figure 17. UN Biosphere reserve sites yearly average NDVI improvement

In order to verify that there is an average increase in NDVI after the start of forestation practices, the NDVI values before and during the forestation projects are compared using a paired t-test. The t-test shows a p-value of 4.341 e-09, meaning the result is significant. It is found that during active project years, forestation areas have an NDVI value of 164 (on a scale to 10,000 or 0.016 on a scale to 1) higher than before forestation. The average NDVI value is 6696 so the improvement of 164 is a 2.44% total increase.

3.2.2 No-project areas and time-range comparisons

Seven sites outside of the forestation projects are selected in order to test the trend in NDVI change for areas without forestation efforts. These sites were selected to be in areas that could represent the reference forestation site; an area in Ethiopia with the same values of suitability indicators as are measured in the reference site is determined (the maximum and minimum values found in the reference forestation sites are taken). Within the found area, six random sites are drawn. In order to understand the effect of timespans on the yearly NDVI increase, a comparison of timespans is made using the non-forestation sites as well. Figure 15 shows the average NDVI improvement of sites that are not part of forestation projects, for different time spans which represent the time spans of the reference forestation projects.

MODIS (yearly average)

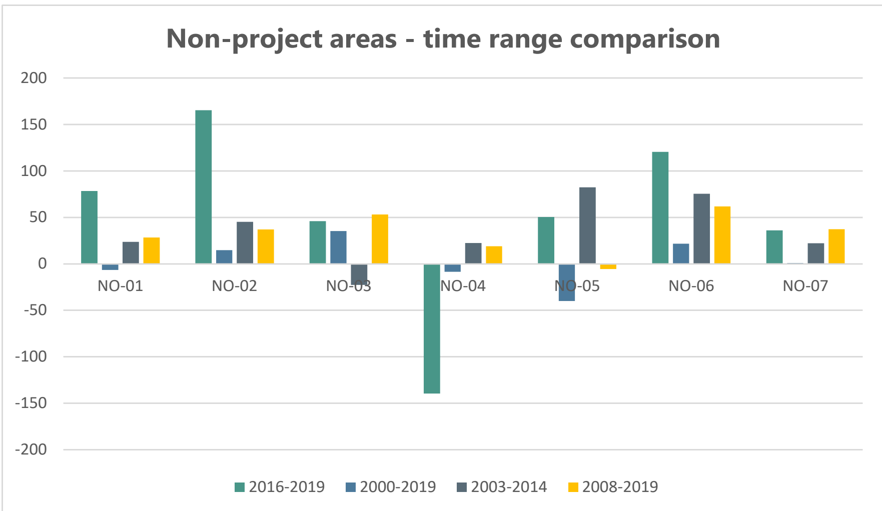


Figure 15. NDVI changes of non-forestation projects over different time-spans

It is clear that the average NDVI increases for sites that are not part of a forestation project, whereas it was expected that forest areas outside of forestation projects either decline or be constant in vegetation. Additionally, it is clear that the average yearly NDVI increase largely depends on the timespans used. Especially the 2016-2019 average differs from the average value over a longer time period. This shows that the project timespan greatly influences the project improvement regardless of the quality of the forestation project.

3.2.3 NDVI improvement comparison

In order to explore the NDVI improvement of the forestation sites, two different iterations are compared as is discussed in more detail in sub-chapter 2.3. Firstly, the average NDVI in October is taken in order to calculate the average yearly increase in NDVI. These same calculations (yearly average NDVI and October NDVI) are done using Sentinel-2 data for the WeForest-Amhara sites.

Figure 19 and Figure 20 show NDVI measurements of MODIS and Sentinel (the values of the MODIS product are a factor 10.000 higher than that of Sentinel). The graphs show the change in NDVI measurements for the different WeForest Amhara sites over a year and the variance in measurements between the different reference sites. The Sentinel measurements

MODIS

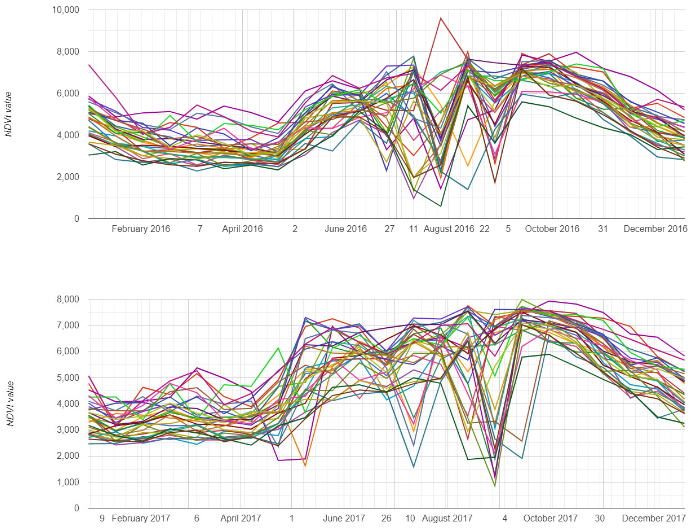


Figure 20. WeForest Amhara sites NDVI values throughout the year 2016 (above) and 2017 (below) using MODIS 16-day NDVI product

Sentinel

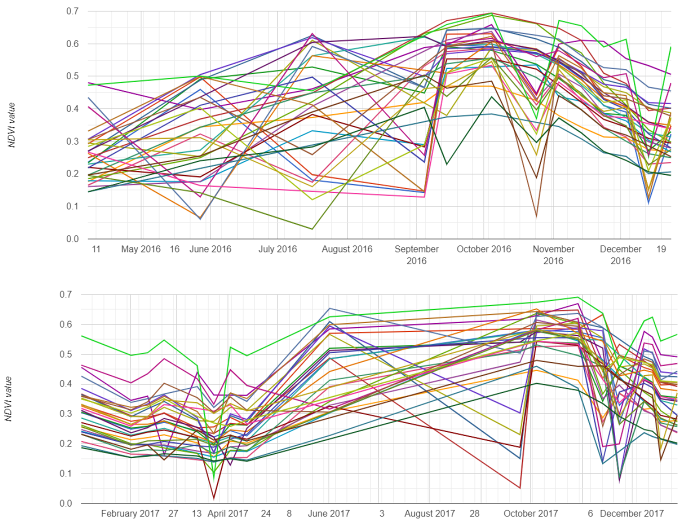


Figure 19. WeForest Amhara sites NDVI values throughout the year 2016 (above) and 2017 (below) using Sentinel imagery

show less constant values than the MODIS measurements. The MODIS measurements show higher variability around the month of August as well. The Sentinel data for 2016 (the year before the start of the Amhara sites) only start from April. Therefore, for the yearly average comparison for Sentinel, only the months April - December are included.

Figure 18 shows a comparison between the different methods of assessing the NDVI change (oct-yearly and MODIS-Sentinel) for the WeForest Amhara sites. It is clear that the average value in October of Sentinel is the highest average increase in NDVI. MODIS yearly average NDVI shows the second highest and MODIS October NDVI the lowest. The Sentinel data shows a higher standard deviation than the MODIS data. All yearly values per site are provided in Appendix C (MODIS yearly), Appendix D (MODIS October), Appendix E (Sentinel yearly) and Appendix F (Sentinel October). A comparison summary is provided in Appendix G.

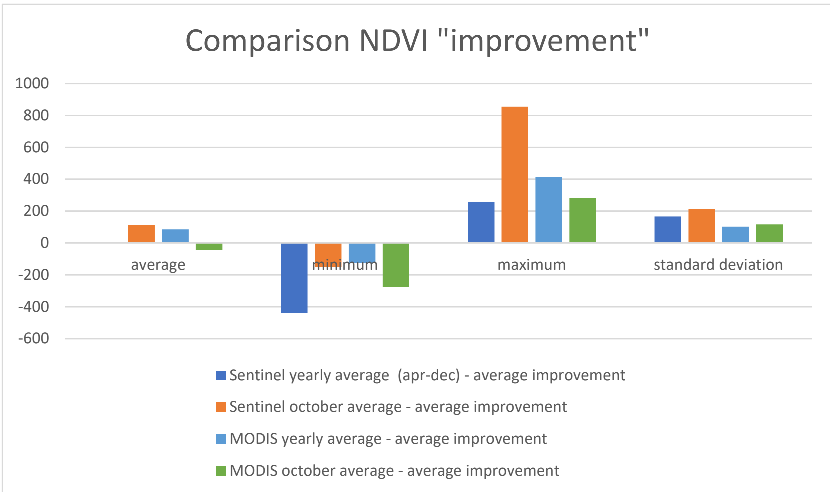


Figure 18. NDVI changes for different NDVI imagery (Sentinel and MODIS) and for different timespans within the compared years (yearly averages and October)

Because the results vary, in addition to the MODIS yearly average values, Sentinel data will also be used for the relationship analysis. Because of the large variability in the yearly data, which might be caused by frequent cloud cover, the October average of Sentinel is used to compare to the suitability indicator data. Because of timerange of the Sentinel data, this is

3.3 Forestation success indicator correlations

In order to understand the relationship between the forest suitability indicators and the forest success scores, the NDVI values were mapped against the suitability indicators. If the results showed a possible relationship, a statistical analysis was done in order to understand if this relationship was significant. The indicators are analyzed separately for the categoric indicators and the numeric indicators as they required a different type of analysis.

3.3.1 Categoric indicators

In order to get a first understanding of the relationship between the categorical variables and the average yearly NDVI improvements (in the active project years), the categorical values were mapped in boxplots.

In the boxplot in Figure 21 the different districts show varying average yearly NDVI improvement. District 3 has the highest NDVI improvement and district 9.5 has the lowest NDVI improvement. In the boxplot in Figure 22 the yearly average NDVI improvement of the project sites is divided per organization. The graph shows that the average NDVI improvement is highest for WeForest projects and lowest for Eden Project projects.

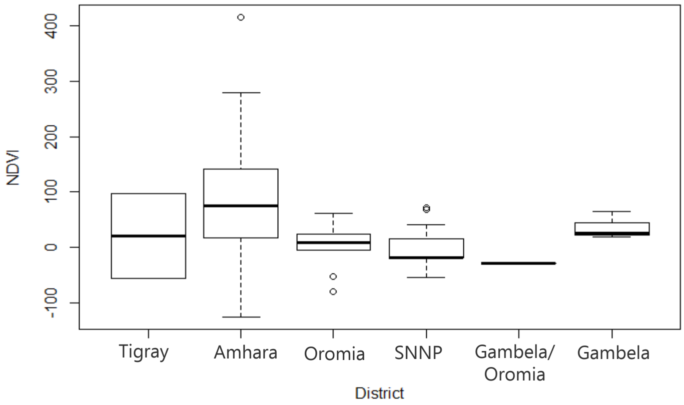


Figure 21. yearly average NDVI improvement divided per district

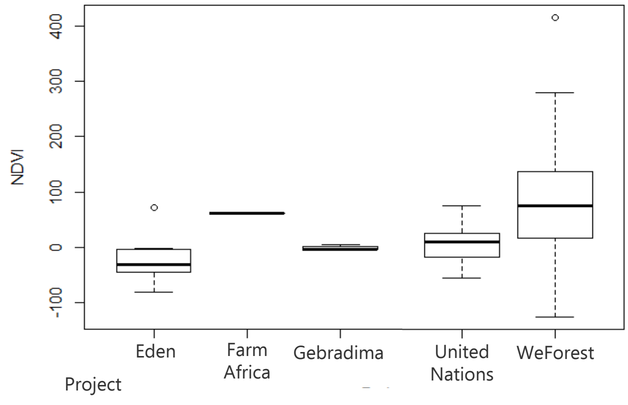


Figure 22. yearly average NDVI improvement divided per project

In the boxplot in Figure 23, the yearly average NDVI improvement of the project sites is divided per landcover class. The plot shows that all forestation projects fall within 4 different landcover classes. The yearly average NDVI improvement is highest for projects within landcover class 10 (grasslands).

In order to evaluate the significance of the different average values across the categorical indicators, a categorical regression was done using the lm function in R. The results can be seen in Table 5. No significant relation was found as no P value is below 0.05

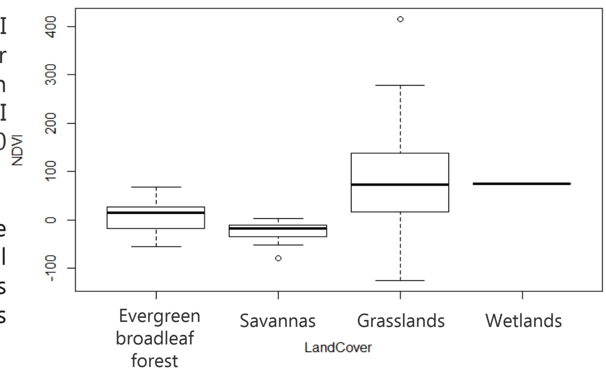


Figure 23. yearly average NDVI improvement divided per Landcover Class of the project sites

Table 6. Categorical regression results

	Estimate	Std. Error	t value	Pr
Intercept	-13.951	106.409	-0.131	0.896
Organization: Farm Africa	-18.225	112.556	-0.162	0.872
Organization: Gebradima	13.431	66.463	0.202	0.841
Organization: United Nations	24.219	48.887	0.495	0.622
Organization: WeForest	-56.685	110.678	-0.512	0.610
District 3: Amhara	64.750	55.705	1.162	0.250
Disrict 4: Oromia	1.933	98.910	0.020	0.984
District 7: SNNP	-4.786	96.616	-0.050	0.961
District 9: Gambela/Oromia (border)	-39.223	121.503	-0.323	0.748
District 12: Gambela	23.727	101.934	0.233	0.817
Landcover Class 9: Savannas: tree cover 10-30% (canopy >2m).	-18.918	39.595	-0.478	0.635
Landcover Class 10: Grasslands: dominated by herbaceous annuals (<2m).	91.216	94.350	0.967	0.337
Landcover Class 11: Permanent Wetlands: permanently inundated lands with 30-60% water cover and >10% vegetated cover.	NA	NA	NA	NA

3.3.2 Numeric indicators

In order to get a first understanding of the relationship between the NDVI improvement and the numeric forestation suitability indicators, the average yearly NDVI improvement is mapped against the median indicator value for each project site.

In Figure 24, the average NDVI improvement is plotted against the silt percentage of the soil per forestation site. From the graph, the silt percentage seems to have an optimum value around 27%, even though it was assumed a higher percentage of silt would create an increase in NDVI improvement.

Along the projects that are nearby a road, the NDVI improvement varies widely (Figure 25). As the projects get further away from the roads, the NDVI improvement slightly increases.

The number of people living near the forestation site (a buffer zone with a 4 km radius was used in order to retrieve this value) seemingly shows an optimum value at around two people per pixel (around 1 km^2) (Figure 26).

The same is done for all numeric indicators (Figure 27). It is notable that all indicators seem to show peaks in NDVI values. This is therefore furter explored in the following paragraph.

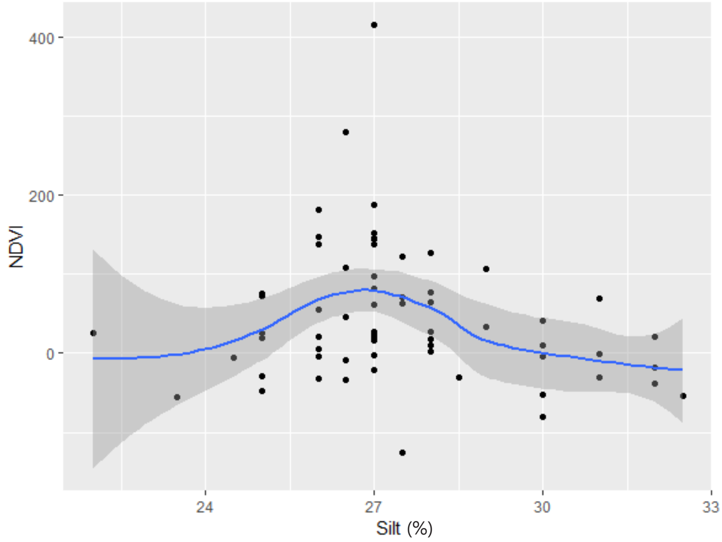


Figure 24. The yearly average NDVI improvement mapped against the silt percentage of the soil per forestation site

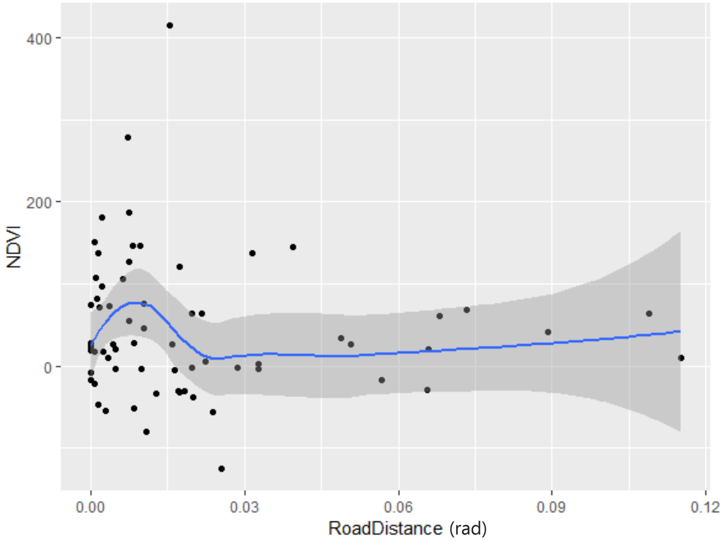


Figure 25. The yearly average NDVI improvement mapped against the distance to the nearest road per forestation site

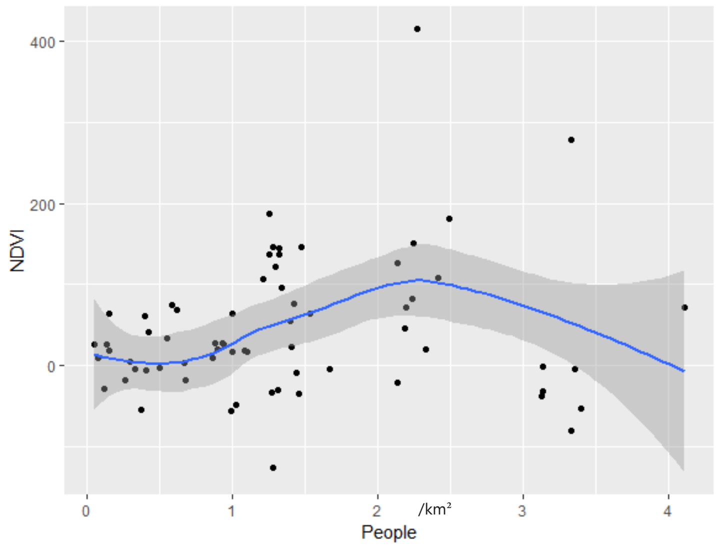


Figure 26. The yearly average NDVI improvement mapped against the number of people/km2 in a 4 km radius (approximate distances) per forestation site

only used for the WeForest Amhara sites.

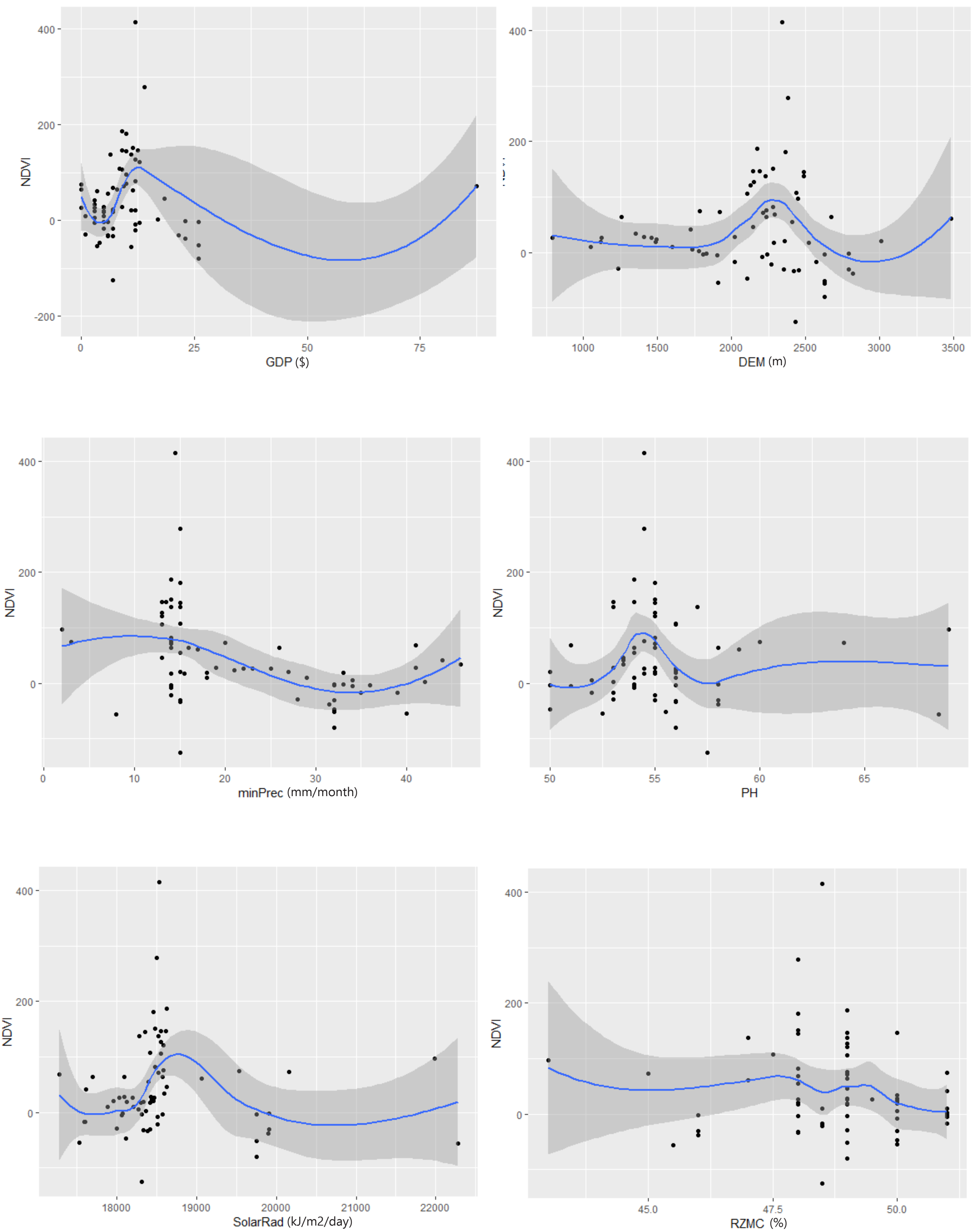


Figure 27. Scatterplot with trendlines of average yearly NDVI improvement mapped against numeric suitability indicator averages

In order to better understand the differences in results per projects, scatterplots were made that show how the different values are divided per project. As was already clear from the forestation assessment, the average yearly NDVI improvement of the WeForest projects are much more disperse than the values of the other projects. However, these different values of the WeForest sites for NDVI assessment are mostly quite close together in the suitability factor values. Because of this, the NDVI improvement shows a peak around the indicator value range of the WeForest projects are. For the indicators silt percentage, this is between 26 and 28 (Figure 28). For the indicator road distance, this is between 0.00 and 0.03 (Figure 29). For the indicator people per pixel, this is between 1 and 3.3 (Figure 30).

On the following page, the rest of the numeric indicators are mapped against the NDVI increase as well (Figure 31).

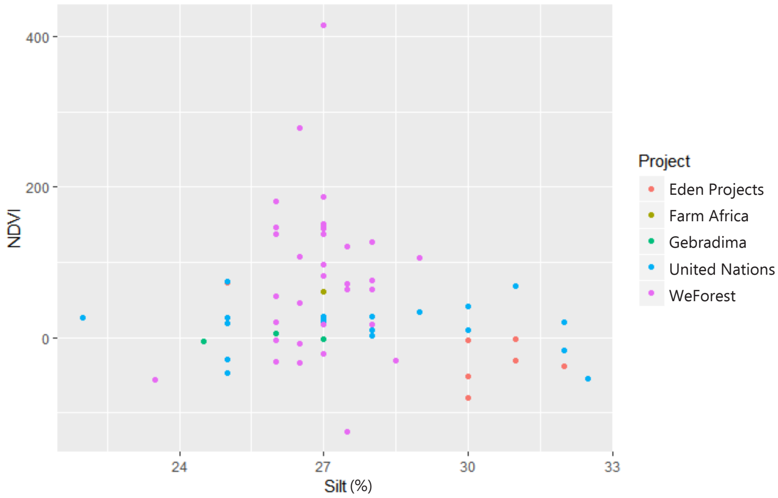


Figure 28. The yearly average NDVI improvement mapped against the silt percentage per site (colored per project/organization)

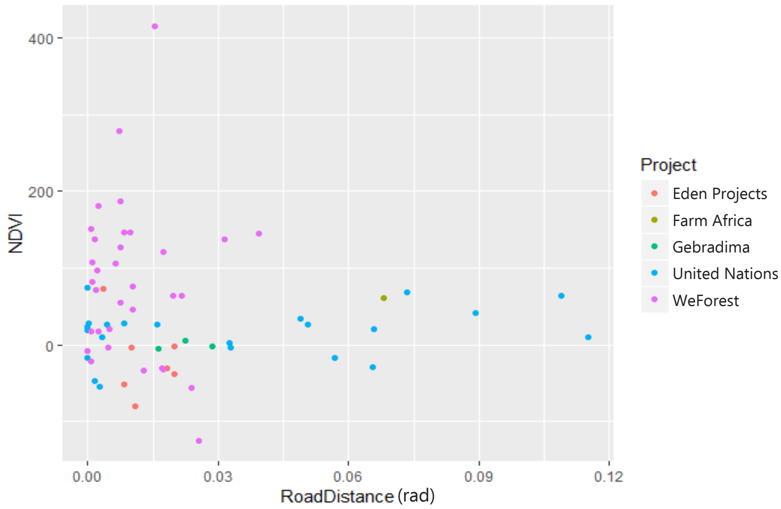


Figure 29. The yearly average NDVI improvement mapped against the minimum distance to a road per site (colored per project/organization)

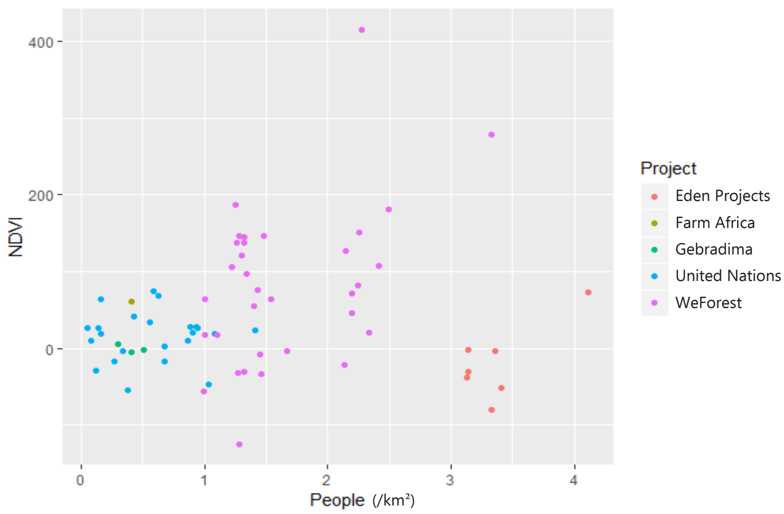


Figure 30. The yearly average NDVI improvement mapped against the median people per pixel in a 4 km radius (colored per project/organization)

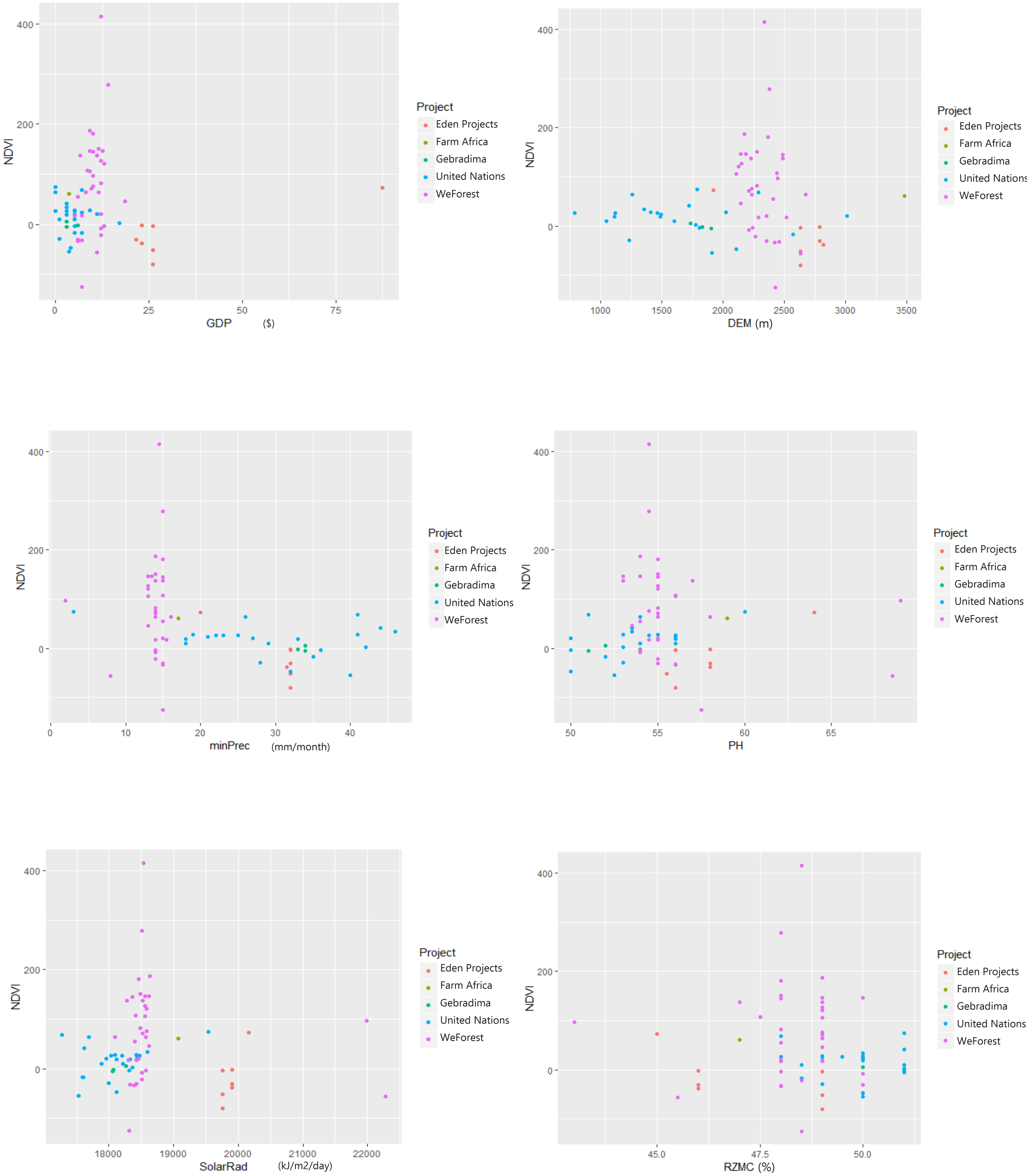


Figure 31. Scatterplots of numeric indicators and average yearly NDVI improvement colored per project

3.3.3 Sentinel imagery

In addition to the MODIS NDVI values, the indicator scores are compared to the Sentinel NDVI improvement. Whereas for MODIS a yearly average was chosen, because of the irregularities in data, for Sentinel the October NDVI values are used. Because of the temporal range of the Sentinel imagery, only WeForest Amhara sites are included in this analysis.

Figure 32 shows the yearly average NDVI improvement mapped against the silt percentage of the soil (%). In comparison to the graph with the MODIS data, in which the NDVI increase seemed to peak around a silt percentage of 27%, in this graph the NDVI seems to decrease as the silt percentage increases. Again this goes against the assumption that a higher silt percentage would increase the NDVI improvement.

The distance to the nearest road shows widely varying results in NDVI increase (Figure 33). There is a small overall trend of higher NDVI improvement as the distance to the road increases, however the variability is quite wide.

The forestation sites taken into account seem to be divided between two ranges of values for the number of people living in a 4 km radius; between 10 and 17 and between 22 and 25. There is no clear difference in NDVI increase between these two groups.

As for the MODIS data, the same plots for all numeric indicators can be seen on the next page (Figure 35). A linear regression analysis does not show significant relationships (Appendix I). As was the case for the MODIS data, the scatterplots do not show convincing relations that can help identify non-linear correlations.

Sentinel (October average)

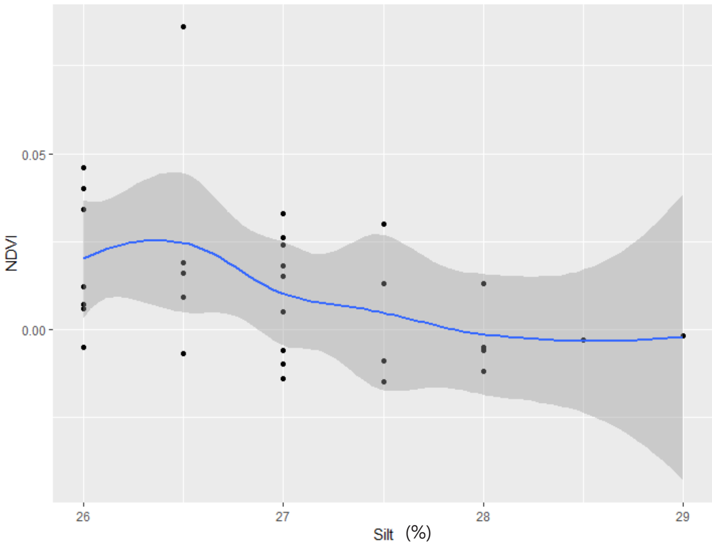


Figure 32. The yearly average NDVI improvement mapped against the silt percentage of the soil per forestation site

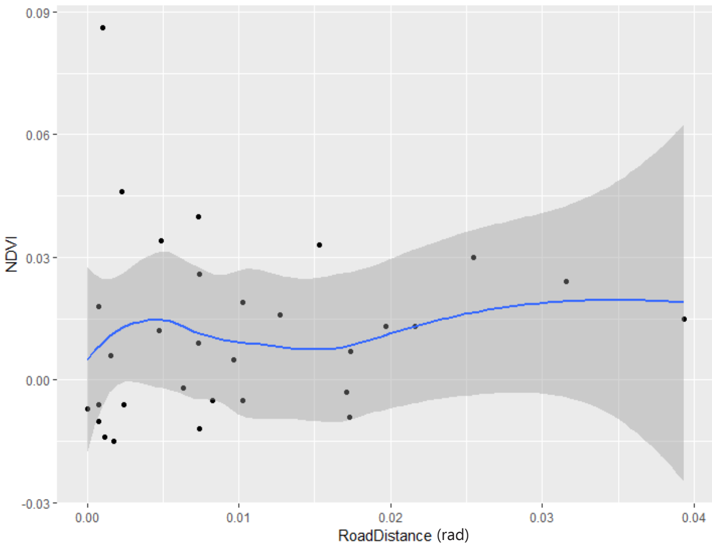


Figure 33. The yearly average NDVI improvement mapped against the distance to the nearest road per forestation site

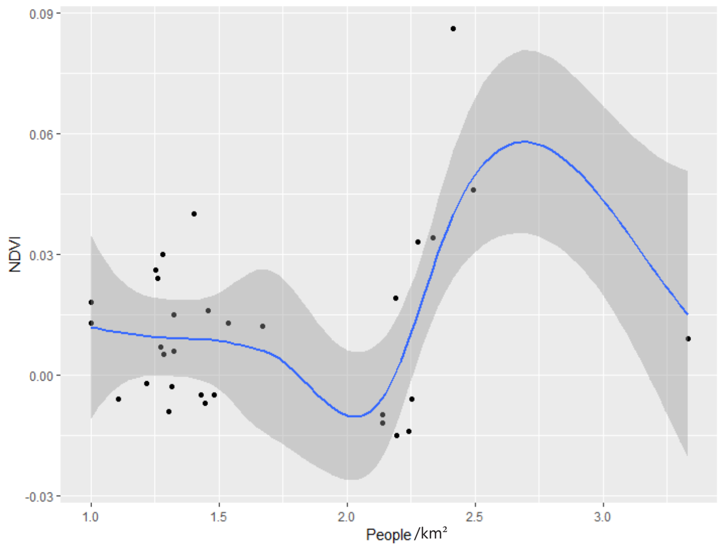


Figure 34. The yearly average NDVI improvement mapped against the number of people/km2 in a 4 km radius (approximate distances) per forestation site

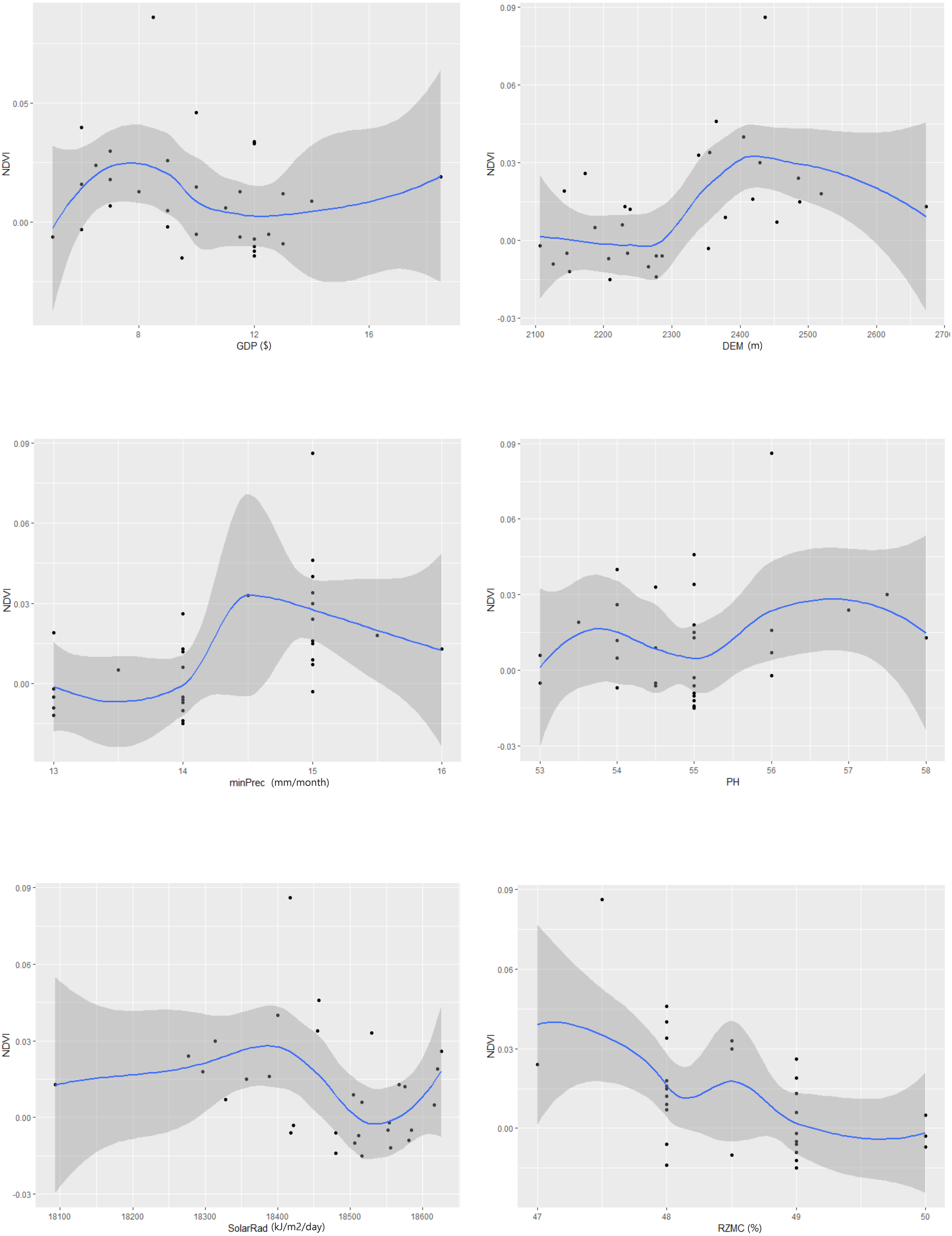


Figure 35. Scatterplot of average NDVI improvement mapped against suitability indicator values for WeForest Amhara sites

4. Discussion

Suitability indicators
The suitability indicators determined to represent suitability factors found in literature are: soil texture, drainage, pH of the soil, minimum monthly rain, solar radiation, elevation, distance to closest road, population, gross domestic product, land cover and district.

Limitations were encountered in data collection. Whereas many factors that influence forestation suitability are described in literature, many of these factors, such as perception of local communities on forest importance, were not found in data. Whereas bio-physical data is globally available from satellite imagery, socio-economic data is less widely available. Because of this, socio-economic factors are more challenging to research.

Forestation “success”
Vegetation increase in the form of NDVI was chosen as a measureof forest ecosystem success because more elaborate progress data about the forestation projects, such as people involved or product from forest sold, was difficult to gather. Although there were projects that were able to provide a lot of data on their project sites, this information could not be used the availability varied within and between organizations.

From the NDVI results it is clear that the forestation sites show a small increase in vegetation during the active project years. Several observations can be made regarding the NDVI results:

A large diversity is seen between the forestation projects. First of all, the different projects have considerably different initial NDVI values; the WeForest areas start with an NDVI of 0.4, meaning there was very little vegetation in the beginning. The UN projects, however, started with a much higher NDVI of around 0.8. The Eden projects and the Farm Africa projects are somewhere in between these two extremes. This reflects the difference in approach and aims of the projects; whereas the UN projects aim to conserve existing forests, the WeForest projects aim to plant new forest. This difference is also reflected in the size of the projects. Conservation is done on a much larger scale than planting of new forest. This can hinder clear results; it can be expected that the NDVI increases quickly for forestation projects in relatively low-vegetated areas. However, if the forestation activities occur within an already dense forest with a dense canopy cover and a high NDVI, the increase in green is less notable on satellite imagery as the reflected Red and Infrared light do not increase much. Additionally, the NDVI improvements of non-forestation sites suggest that it could be useful to separate the forestation projects based on time span when exploring the relation between the spatial indicators and the NDVI improvement. In order to test this, the WeForest projects were removed from the scatter plots (Appendix H). These did not show more clear relations either.

Forestation projects with a shorter timespan show more varying results. From the MODIS results it is shown that projects that have a longer timespan have less deviation in NDVI increase per year. This can be explained by the large yearly variability in NDVI across all projects. This indicates that a lot of the yearly change in NDVI is not caused by forest planting or management but rather by weather variability. Exceptional good or bad years have less influence on the average NDVI increase over a longer time span. Additionally, for both the MODIS and the Sentinel results it is clear that a number of forestation projects even show a decrease in NDVI in the first project years. This might be explained by the preparation of the ground for forestation, which decreases vegetation. In addition, for projects that are started with seedlings there might be a low seedling survival rate. For projects that have started with seeds rather than seedlings, the first project year can show little increase. In combination with the initial preparation of the ground and removal of initial vegetation, this can result in limited NDVI improvement for young projects. Because of this variability in the young projects, it is probable giving a reliable success score can only be done after the initial stage of the forestation project.

The NDVI products represent a weigh-off between temporal scale, temporal scale and resolution or spatial resolution. Because of the long timespan of many of the forestation projects, the lower resolution MODIS data is used for most of the analysis. For more recent forestation projects the Sentinel-2 data has a much higher resolution and is therefore able to show a better NDVI for small forestation sites. However, because of the lower temporal resolution (every 5 days) of this data the higher resolution does not necessarily give a more accurate NDVI; cloud cover can hinder many of the images and, with less chance for correction, give incomplete insights. Because of the smaller size of many afforestation projects, this means that monitoring based on satellite imagery remains limited.

It can be concluded that the possibility of giving success scores based on satellite imagery depends on several aspects of the forestation projects and the data used;

- similarity between the different forestation sites - regarding starting NDVI values, method, size and time-span of the projects
- the years in which the project has been active – for younger projects the variability is very high and often negative NDVI values are seen, which could be caused by site-preparation and does not necessarily reflect a lack of success
- the temporal and spatial resolution and scale of the NDVI product compared to the size and the duration of the forestation projects and the accuracy of the NDVI product

It should be noted that even if the NDVI values had shown clear results, a higher increase in NDVI cannot be compared one-to-one to the success of the project. As forest ecosystem plantations have a wide range of goals, such as disaster management, combatting soil degradation, engaging local communities and providing a source of income, their success cannot be expressed by increase in NDVI alone.

Predicting success

From the categorical regression analysis and the multiple linear regression analysis, no significant relationship was found between the NDVI increase and the suitability indicators. This can be linked to the limitations in the NDVI increase measurements as are mentioned in the previous paragraph.

5. Conclusion

This research aimed to understand the possibility of using socio-economic indicators in addition to bio-physical data in spatial analysis for forest ecosystem planning. This was done by analyzing the success (measured by change in NDVI) and socio-economic and bio-physical characteristics of refernce forestation sites. The results were used to explore possible relationships between these variables.

From all identified factors influencing forestation success, 11 indicators are chosen based on data availability and limiting overlap in effects. The suitability indicators determined are: soil texture, drainage, pH of the soil, minimum monthly rain, solar radiation, elevation, distance to closest road, population, gross domestic product, land cover and district.

The study finds a small average statistical increase in NDVI for the forestation areas. However, numerous sites show a decrease in NDVI and the change in NDVI varies significantly when the analysis is done with different NDVI products.

The analysis does not show significant relationships between the forestation success and the indicators. Whereas literature indicates that social factors play a large role in the success of forest ecosystem projects, this was not shown by the results. Similarly, a correlation was not found for widely accepted and used bio-physical factors such as rain.

Limitations in the research method are the selection of forestation sites, the spatial and temporal resolution of the NDVI data and the use of NDVI as a measure of success for the projects.

The results show an attempt to find a relationship between forestation success and social indicators. However, what the results mostly show is the difficulties encountered in quantifying forestation success and social factors that influence it. They show the difficulty in the use of satellite data as an indication of conservation projects that reach far back in time as well as for forest ecosystem plantation projects that have been started recently which is used to the availability of data on social factors and because of the delay in physical results. Additionally, the data inquiry reflects the lack of standardized data availability for forestation projects. The results indicate a need for an increase of openness in monitoring of forestation success for expansion of knowledge in the field of forest ecosystem generation. More available data can contribute to understanding how social factors influence forestation success and therefore increase the effectiveness and efficiency of planted forest ecosystem projects.

Before moving further towards a more automated decision-making process in forestation projects for climate adaptation or community resilience, it is important to increase the availability of social data factors and forestation project assessments in order to find meaningful relationships. What can already be done as an addition to current practices is to include social factors based on literature and estimates of suitable values. In this case, it should remain clear that the areas selected are based on estimates rather than proven relations.

Based on this study, recommendations for further research are to include a larger number of forestation projects that are similar in terms of aims, method, size and timespan. This could be achieved by combining projects from multiple similar (for example neighboring) countries. In addition, forestation success should be measured based on social success in addition to vegetation growth, based on data captured by the forestation project.

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Appendix A. Forestation projects description

This appendix provides more in-depth explanation on the different forestation projects that are used as reference projects.

6.3.1 WeForest projects

The forestation areas from the WeForest project are part of one of three projects: the Amhara project, the Desa'a project and the Seret project. The WeForest projects are based on community involvement and are currently still active. Their locations are by tracing available online maps.

The Desa'a forest (in Tigray and Afar region) is a dry Afromontane forest that is exposed to desertification with a resulting loss of 74% of the natural forest cover. Forests are degraded because the large number of people living below the poverty line who are reliant on the forest for resources. The government views this area as a priority area and Weforest works together with the local Tigray government on this project (WeForest, n.d.-b). The restoration approaches reported for this area are assisted natural regeneration and framework planting. The species planted are: Juniperus procera, Olea europaea, Cadia purpurea, Carissa edulis, Dracaena ombet, Erica arborea L., Acacia abyssinica, Maytenus obscura, Rhus natalensis.

The Amhara project is aimed at engaging the local communities. The project includes planting indigenous trees on community land, gullies, rever banks and farmlands. In total there are 654 restored hectares and the restoration approaches reported are 'framework planting', 'assisted natural regeneration' and 'enrichment planting: agroforestry'. Species planted are Faidherbia albida, Juniperus procera, Moringa stelapolata, Olea Europea, Pinus patula, Podocarpus spp. For this project, 6 individual project sites are reported (WeForest, n.d.-a).

The Seret project by WeForest in the Tigray region consists of 56 hectares of framework planting and assisted natural regeneration. WeForest reports that currently only 1% of the Afromontane forests in Tigray are left because of cattle grazing, agricultural practices, timber production and illegal charcoal production. In the larger Tigray area the government, communities and NGO's work together to improve local ecosystems. Restoration for the Seret project is done in assigned areas, called exclosures, where cattle grazing is prohibited. A wide range of species is planted; Acacia abyssinica, Acacia etbaica, Cordia africana, Croton macrostachyus, Dodonaea angustifolia, Dovyalis abyssinica, Faidherbia albida, Grevillea robusta, Juniperus procera, Leucaena leucocephala, Olea europaea, Pennisetum pedicellatum, Ziziphus spina-christi

6.3.2 Eden projects

Like the WeForest projects, the 7 project sites from Eden forest can be divided into three forestation projects; Sidama highlands, Shalobele, Koksa and Rift valley. Eden projects reports that local sites were deforested in order to cultivate crops and produce charcoal for cooking and heating. The Eden projects in Ethiopia started in 2005 and uses a similar approach as WeForest by involving local communities in planting trees (Eden Projects, 2018). In 2014 the projects in Ethiopia were terminated as a result of fraudulent behavior on the part of local leaders. It is reported that in total 15,998,000 trees were planted in Ethiopia by Eden projects. The Udo 3 Hills Project site was completed in 2014 with 12,533,000 trees planted. Information on species planted is not available. Point locations of the forestation efforts were found through the web-map provided (Eden Projects, n.d.).

6.3.3 Farm Africa – Sustainable Forestry

Farm Africa has worked on Participatory Forest Management work in the Bale forest region together with other forestation partners. Farm Africa reports that between 2012 and 2015, a total of 12,496 hectares of forest was saved (avoided deforestation) in the area of 333,924 hectares. The project aims to improve the lives of over 350.000 people living in the Bale area (Farm Africa, n.d.).

6.3.4 Gebradima Forest

The Gebradima forest site is an Afromontane forest in southwest Ethiopia with a moderately hot and humid climate. The total forest area is around 76.418 hectares (Tadesse, Woldetsadik, & Senbeta, 2016). The study forest is commonly known as moist evergreen Afromontane forest; and dominated by Albizia gummifera (J.F.Gumel.) C.Asm, Millittia ferruginea (Hochst.) Baker, Pouteria adolfi-friederici (Eng.) Baehni, Schefflera abyssinica (Hochst.ex.A.Rich.) Harms, Sapim ellipticum (Krauss) Pax, Ficus Sur Forssk, and Croton macrostachyus A.Rich (Tadesse et al., 2016). The Gebradima forest has been part of several forest management efforts starting as early as 2000. Farm Africa guided a participatory forest management project in this area together with the Oromia Forest and Wildlife Enterprise, which was active between 2010 and 2015. Around 29,901 ha of forest was managed in this project (Tadesse et al., 2016).

6.3.5 UNESCO

The UN biosphere reserves are areas in which the UN actively supports sustainable development with a goal to find solutions to help with conservation of biodiversity through sustainable use of the landscape. Several biosphere reserves are found in Ethiopia.

6.3.5.1 Kafa Biosphere reserve

The Kafa Biosphere reserve is a large area of 540.631 hectares of Afromontane forest that has been assigned as a UNESCO biosphere reserve in 2010. It houses over 600.000 people and the local main economic activity is agriculture. The Kafa area is 'the birthplace' of Coffea Arabica and contains over 5000 varieties of this species. One of the key focus areas of the reserve is the protection of genetic resources of this Coffea Arabica and its associated ecosystems. Between 2009 and 2014 NABU's Kafa Zones Department of Agricultural Development have established 59 tree nurseries at the Kafa Biosphere Reserve. More than 500 hectares of degraded forest have been reforested with indigenous tree species and almost 300 hectares of farm land have been planted with native multi-purpose agro forestry trees and crops, involving hundreds of people from local communities. The core zone extends over 41,391 hectares and consists of 11 Protected Forest Areas. (NABU, n.d.)

6.3.5.2 Yayu Biosphere reserve

The Yayu coffee forest biosphere reserve consists of an area of 167.021 hectares and was designated in 2010. It includes forest, agricultural land, wetland and grazing land. The forest is one of the last montane rainforests with wild Coffea arabica. The complete biosphere reserve houses around 154.500 residents. Most economic activity consists of agriculture. (UNESCO, 2010)

6.3.5.3 Sheka Forest Biosphere reserve

The Sheka forest biosphere reserve is part of the Afromontane rainforests in Ethiopia's southwestern highlands. The forest is rich in plant life, including 300 species of plants of which 55 are endemic. The reserve contains a diverse area including forests, wetlands, agricultural lands and rural settlements and towns. The Sheka forest was designated in 2012 and covers an area of 238750 hectares. Timber, coffee, and medicinal plants are reported as important products from the forest.

UNESCO provides a list of species: Broadleaved tree species: Pouteria adolfi-friederici, Syzygium guineense, Polyscias fulva, Olea welwitschii, Diospyros abyssinica, Manilkara butugi and Cordia africana. smaller trees (less than 10 m): Allophylus abyssinicus, Chionanthus mildbraedii, Clausena anisata, Coffea arabica, Deinbollia kilimandischarica. And shrub: Acanthus eminens, Dracaena fragrans, Lobelia giberroa, Senecio gigas.

6.3.5.4 Lake Tana Biosphere reserve

The lake Tana project site consists of the largest lake of Ethiopia (which alone is 50% of the total inland waters of the country). The lake is surrounded by wetlands which UNESCO describes to be important breeding nesting and feeding grounds for bird populations. The main economic activities include fishing, agriculture and sand mining. The Papyrus (cyperus papyrus) is an important product from the wetlands surrounding the lake.

UNESCO provides a list of plant species in the area including many indigenous trees and indigenous agricultural crops: Sesa (Albizia gummifera), Birbira (Millettia ferryginea), Wanza (Cordia Africana) (Guizotia abyssinica), teff (Eragrostis tef). Wild coffee (Coffea arabica) occurs naturally in the area, especially in the Zegie Peninsula.

6.3.5.5 Majang Forest biosphere reserve

The Majang forest is a part of Afromontane forest in Ethiopia which is severely threatened. The landscape of 225.490 hectares is dissected by several small streams and includes wetlands and marshes. 52.000 people live in the biosphere reserve area (Unesco, 2018). UNESCO reports that the area is rich in biodiversity, including over 550 plant species including species providing products such as the ensete (ensete fentricosum) and yam (dioscoria bulbifera). Above an elevation of 1000 meters the vegetation is dominated by ferns and bamboo and there can be relatively steep slopes, while lower areas are more covered with palm trees and are relatively flat.

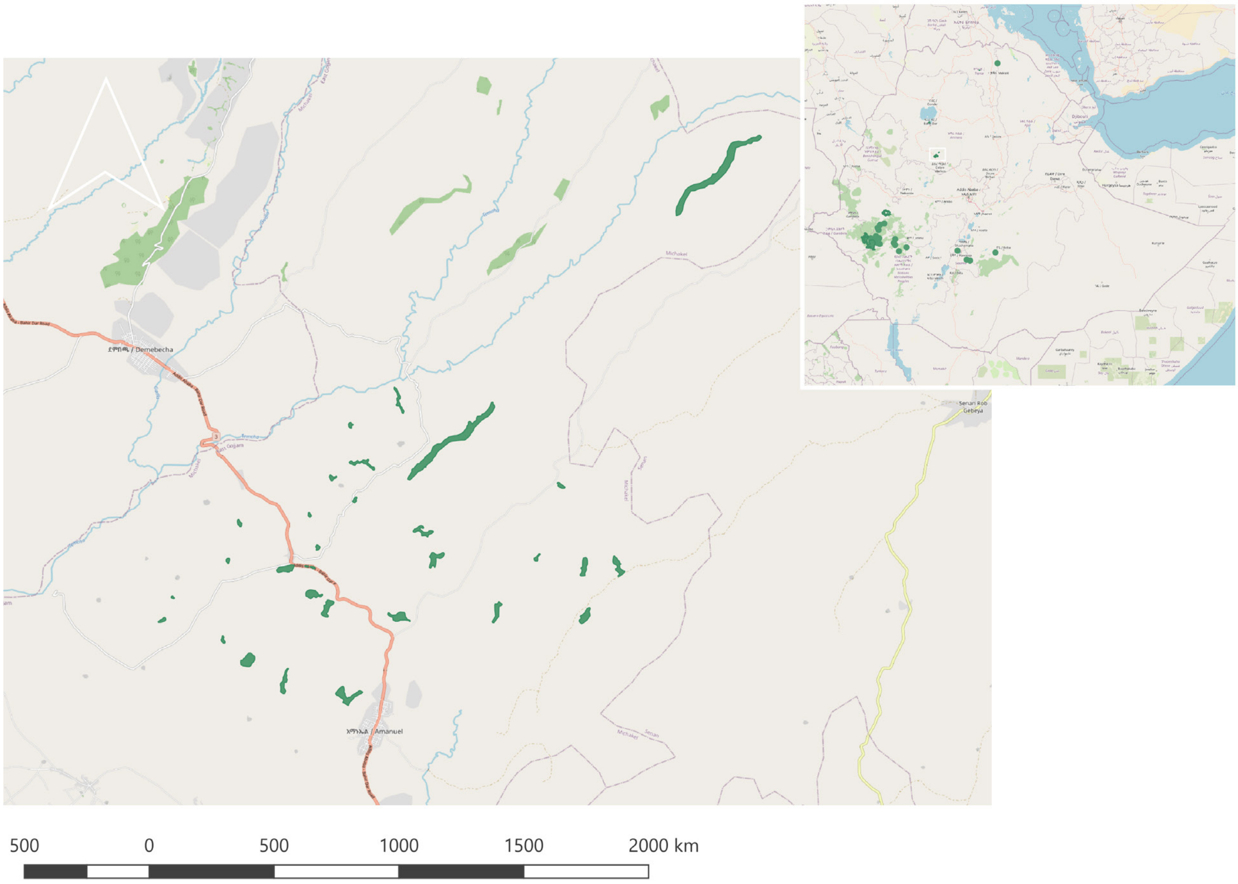


Figure 36. WeForest Amhara forestation sites

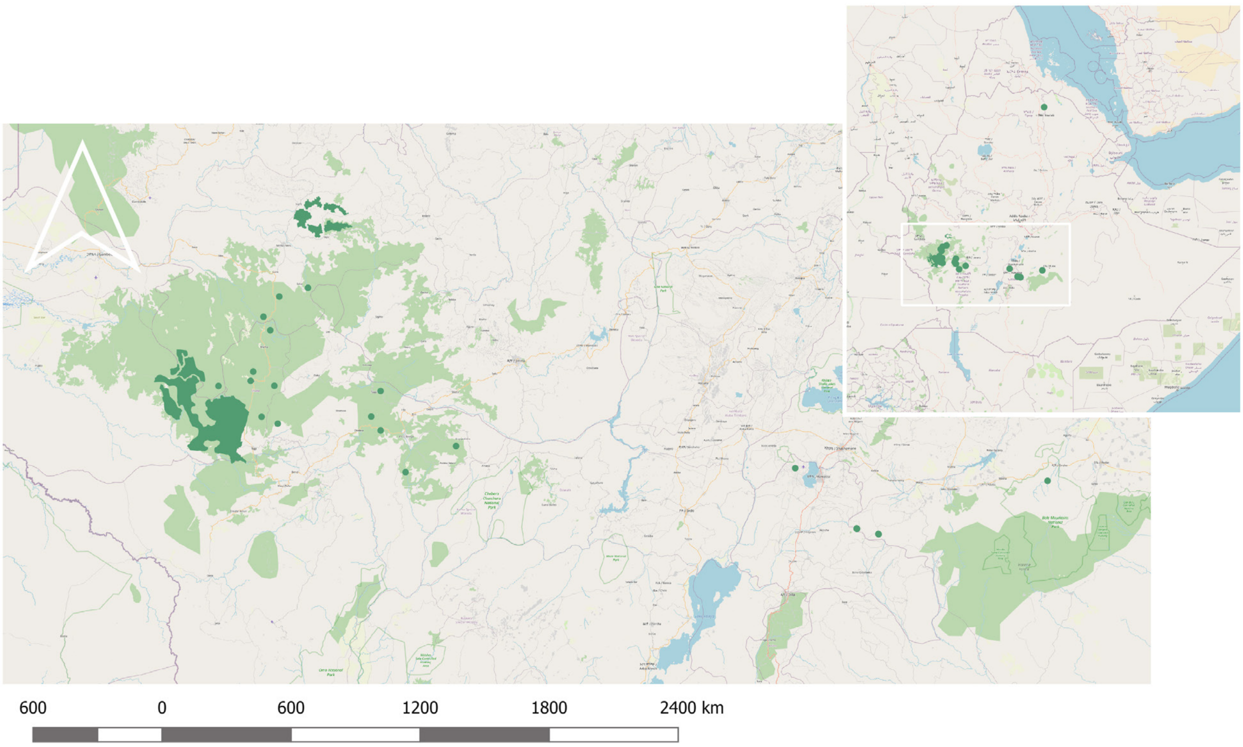


Figure 37. Map of various forestation sites used in the study

Appendix B. Suitability indicators overview

Table 7. Overview suitability factors and NDVI increase per project site

Site ID	Project	Method	Landcover	District	Distance to road (rad*1000)	GDP	People	DEM	PH	minPrec	RZMC	Silt	SolarRad	MODIS NDVI (yearly)
ED-01	ED	AFOR	10	7	3.63	87.5	4.11	1918	64	20	45	25	20156	72.48
ED-02	ED	AFOR	9	7	19.78	23	3.14	2789	58	32	46	31	19909	-1.72
ED-03	ED	AFOR	9	7	19.96	23	3.13	2816	58	31.5	46	32	19903	-37.68
ED-04	ED	AFOR	9	7	18.22	21.5	3.13	2789	58	32	46	31	19909	-31.04
ED-05	ED	AFOR	9	4	10.90	26	3.33	2629	56	32	49	30	19752	-79.77
ED-06	ED	AFOR	9	4	9.96	26	3.35	2629	56	32	49	30	19752	-3.44
ED-07	ED	AFOR	9	4	8.41	26	3.40	2629	55.5	32	49	30	19752	-52.12
FA-01	FA	CONS	10	4	68.13	3.5	0.41	3483	59	17	47	27	19068	60.97
GB-01	GB	CONS	2	4	22.43	3	0.30	1731	52	34	50	26	18270	5.27
GB-02	GB	CONS	2	7	28.68	6	0.50	1830	54	33	51	27	18070	-2.58
GB-03	GB	CONS	2	4	16.23	3	0.41	1902	51	34	51	24.5	18061	-5.17
UN-KF-11	UN	CONS	9	7	32.68	17	0.67	1776	53	42	51	28	18364	2.81
UN-KF-12	UN	CONS	2	7	1.44	4	1.03	2106	50	32	50	25	18116	-47.60
UN-KF-13	UN	CONS	2	7	8.33	9	0.94	2022	53	41	50	28	18093	27.62
UN-KF-14	UN	CONS	2	7	89.15	3	0.43	1723	53.5	44	51	30	17616	41.68
UN-KF-15	UN	CONS	2	7	48.92	3	0.55	1351	53.5	46	50	29	18599	33.66
UN-KF-16	UN	CONS	2	7	65.81	11	0.90	3011	50	27	48	32	17954	20.48
UN-MJ-01	UN	CONS	2	12	108.92	0	0.16	1259	54	26	49	28	17694	64.65
UN-MJ-02	UN	CONS	2	12	50.74	0	0.14	1119	54.5	25	49	25	18030	26.03
UN-MJ-03	UN	CONS	2	9.5	65.52	1	0.12	1235	53	28	49	25	17998	-28.95
UN-MJ-04	UN	CONS	2	12	15.96	3	0.05	789	56	23	48	22	18201	26.22
UN-MJ-05	UN	CONS	2	12	0.00	3	0.16	1113	55	33	49	25	18122	19.08
UN-SH-11	UN	CONS	9	7	0.00	5	0.27	2571	52	35	48.5	32	17588	-17.50
UN-SH-11	UN	CONS	9	7	0.00	7	0.68	2022	53	39	51	32	17598	-17.50
UN-SH-11	UN	CONS	9	7	56.80	5	0.27	2571	52	35	48.5	32	17588	-17.50
UN-SH-11	UN	CONS	9	7	56.80	7	0.68	2022	53	39	51	32	17598	-17.50
UN-SH-11	UN	CONS	2	7	0.00	5	0.27	2571	52	35	48.5	32	17588	-17.50
UN-SH-11	UN	CONS	2	7	0.00	7	0.68	2022	53	39	51	32	17598	-17.50
UN-SH-11	UN	CONS	2	7	56.80	5	0.27	2571	52	35	48.5	32	17588	-17.50
UN-SH-11	UN	CONS	2	7	56.80	7	0.68	2022	53	39	51	32	17598	-17.50
UN-SH-12	UN	CONS	2	7	73.39	7	0.62	2291	51	41	48	31	17279	68.54
UN-SH-13	UN	CONS	2	7	115.22	1	0.08	1049	54	29	48.5	30	17881	9.71
UN-SH-14	UN	CONS	2	7	2.82	3.5	0.37	1909	52.5	40	50	32.5	17534	-54.42
UN-SH-15	UN	CONS	2	7	32.73	5	0.33	1808	50	36	51	26	18312	-3.69
UN-TN-01	UN	CONS	11	3	0.00	0	0.59	1786	60	3	51	25	19535	75.02
UN-YY-01	UN	CONS	2	4	3.32	5	0.87	1599	56	18	51	28	18210	9.63
UN-YY-02	UN	CONS	2	4	0.00	5	1.09	1486	56	18	50	27	18328	19.25
UN-YY-03	UN	CONS	2	4	0.05	5	0.89	1405	55	19	49	27	18425	27.27
UN-YY-05	UN	CONS	2	4	0.00	7	1.41	1492	56	21	50	27	18433	23.68
UN_YY-04	UN	CONS	2	4	4.31	5	0.95	1459	56	22	49.5	27	18468	26.43
WF-AM-01	WF	AFOR	10	3	31.57	6.5	1.26	2486	57	15	47	27	18277	137.74
WF-AM-02	WF	AFOR	10	3	39.32	10	1.32	2487	55	15	48	27	18357	144.51
WF-AM-03	WF	AFOR	10	3	25.48	7	1.28	2429	57.5	15	48.5	27.5	18313	-124.97
WF-AM-04	WF	AFOR	10	3	17.39	7	1.27	2454	56	15	48	26	18328	-32.55
WF-AM-05	WF	AFOR	10	3	0.73	7	1.00	2519	55	15.5	48	27	18297	16.84

Site ID	Project	Method	Landcover	District	Distance to road (rad*1000)	GDP	People	DEM	PH	minPrec	RZMC	Silt	SolarRad	MODIS NDVI (yearly)
WF-AM-06	WF	AFOR	10	3	12.72	6	1.46	2419	56	15	48	26.5	18389	-33.74
WF-AM-07	WF	AFOR	10	3	1.05	8.5	2.41	2437	56	15	47.5	26.5	18417	107.94
WF-AM-08	WF	AFOR	10	3	7.35	6	1.40	2406	54	15	48	26	18400	55.29
WF-AM-09	WF	AFOR	10	3	17.06	6	1.32	2354	55	15	50	28.5	18422	-30.32
WF-AM-10	WF	AFOR	10	3	2.28	10	2.49	2365	55	15	48	26	18457	181.01
WF-AM-11	WF	AFOR	10	3	4.84	12	2.34	2355	55	15	48	26	18455	20.39
WF-AM-12	WF	AFOR	10	3	0.75	12	2.14	2265	55	14	48.5	27	18506	-21.04
WF-AM-13	WF	AFOR	10	3	2.40	5	1.11	2286	54.5	14	49	28	18418	17.06
WF-AM-14	WF	AFOR	10	3	6.34	9	1.22	2106	56	13	49	29	18554	106.33
WF-AM-15	WF	AFOR	10	3	17.29	13	1.30	2126	55	13	49	27.5	18581	121.54
WF-AM-16	WF	AFOR	10	3	1.56	11	1.33	2227	53	14	49	26	18517	137.06
WF-AM-17	WF	AFOR	10	3	8.23	12.5	1.48	2146	53	13	49	26	18552	146.71
WF-AM-18	WF	AFOR	10	3	0.00	12	1.45	2207	54	14	50	26.5	18512	-8.42
WF-AM-19	WF	AFOR	10	3	7.41	12	2.14	2149	55	13	49	28	18556	126.70
WF-AM-20	WF	AFOR	10	3	1.72	9.5	2.19	2210	55	14	49	27.5	18516	71.29
WF-AM-21	WF	AFOR	10	3	10.25	18.5	2.19	2143	53.5	13	49	26.5	18621	45.94
WF-AM-22	WF	AFOR	10	3	4.72	13	1.67	2239	54	14	48	26	18576	-4.26
WF-AM-23	WF	AFOR	10	3	9.65	9	1.28	2187	54	13.5	50	27	18616	145.81
WF-AM-24	WF	AFOR	10	3	7.38	9	1.25	2173	54	14	49	27	18626	187.04
WF-AM-25	WF	AFOR	10	3	10.28	10	1.43	2235	54.5	14	49	28	18585	76.16
WF-AM-26	WF	AFOR	10	3	19.67	11.5	1.54	2231	55	14	49	27.5	18568	63.59
WF-AM-27	WF	AFOR	10	3	21.63	8	1.00	2673	58	16	49	28	18093	64.36
WF-AM-28	WF	AFOR	10	3	1.13	12	2.24	2277	55	14	48	27	18480	82.30
WF-AM-29	WF	AFOR	10	3	0.78	11.5	2.25	2277	55	14	48	27	18480	150.88
WF-AM-30	WF	AFOR	10	3	15.32	12	2.28	2339	54.5	14.5	48.5	27	18530	415.10
WF-AM-31	WF	AFOR	10	3	7.31	14	3.33	2379	54.5	15	48	26.5	18504	278.93
WF-DS-01	WF	AFOR	10	1	23.85	11	0.99	2629	68.5	8	45.5	23.5	22281	-55.59
WF-SR-01	WF	AFOR	10	1	2.05	10	1.34	2447	69	2	43	27	21988	96.75

Appendix C. MODIS - yearly NDVI values

Table 8. Yearly average NDVI values per project site from MODIS 16-day NDVI composite product (NDVI -1 to 1)

year	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
ED-01	0.45	0.51	0.44	0.46	0.51	0.49	0.48	0.50	0.45	0.45	0.53	0.53	0.45	0.50	0.54	0.47	0.49	0.48	0.54	0.54
ED-02	0.60	0.67	0.66	0.64	0.65	0.66	0.59	0.66	0.61	0.66	0.67	0.67	0.63	0.62	0.64	0.66	0.73	0.68	0.63	0.69
ED-03	0.61	0.68	0.73	0.66	0.68	0.59	0.61	0.68	0.56	0.66	0.67	0.65	0.60	0.65	0.62	0.69	0.70	0.67	0.63	0.67
ED-04	0.60	0.67	0.66	0.68	0.65	0.66	0.59	0.66	0.61	0.66	0.67	0.67	0.64	0.62	0.64	0.66	0.73	0.68	0.63	0.69
ED-05	0.69	0.78	0.74	0.79	0.77	0.76	0.74	0.76	0.66	0.73	0.75	0.72	0.71	0.70	0.71	0.74	0.73	0.73	0.75	0.78
ED-06	0.71	0.79	0.77	0.79	0.75	0.79	0.75	0.82	0.68	0.77	0.79	0.74	0.71	0.71	0.79	0.76	0.77	0.75	0.77	0.79
ED-07	0.64	0.74	0.74	0.78	0.63	0.76	0.66	0.73	0.65	0.75	0.78	0.70	0.69	0.63	0.72	0.72	0.76	0.72	0.74	0.74
WF-AM-01	0.41	0.37	0.40	0.34	0.32	0.35	0.38	0.39	0.38	0.38	0.34	0.39	0.35	0.40	0.37	0.41	0.38	0.41	0.43	0.42
WF-AM-02	0.38	0.35	0.36	0.35	0.32	0.36	0.39	0.38	0.37	0.35	0.35	0.39	0.35	0.37	0.36	0.39	0.35	0.38	0.42	0.39
WF-AM-03	0.42	0.40	0.45	0.39	0.42	0.42	0.42	0.43	0.40	0.41	0.39	0.44	0.38	0.42	0.41	0.43	0.44	0.44	0.43	0.41
WF-AM-04	0.42	0.37	0.38	0.37	0.32	0.36	0.43	0.41	0.43	0.40	0.37	0.41	0.36	0.43	0.42	0.45	0.47	0.43	0.45	0.46
WF-AM-05	0.41	0.35	0.35	0.33	0.33	0.32	0.34	0.32	0.34	0.37	0.33	0.37	0.29	0.34	0.38	0.37	0.37	0.37	0.42	0.37
WF-AM-06	0.44	0.47	0.46	0.42	0.42	0.44	0.46	0.47	0.50	0.45	0.42	0.49	0.44	0.47	0.45	0.50	0.47	0.49	0.48	0.46
WF-AM-07	0.43	0.49	0.43	0.43	0.44	0.44	0.44	0.45	0.46	0.43	0.46	0.48	0.42	0.47	0.50	0.50	0.50	0.49	0.52	0.53
WF-AM-08	0.47	0.45	0.45	0.42	0.41	0.46	0.44	0.42	0.46	0.45	0.43	0.48	0.41	0.45	0.45	0.48	0.49	0.47	0.49	0.50
WF-AM-09	0.55	0.51	0.54	0.54	0.45	0.52	0.51	0.48	0.52	0.51	0.50	0.57	0.50	0.56	0.57	0.57	0.59	0.59	0.55	0.58
WF-AM-10	0.55	0.50	0.51	0.46	0.47	0.51	0.52	0.50	0.52	0.52	0.50	0.53	0.51	0.52	0.57	0.55	0.55	0.56	0.54	0.60
WF-AM-11	0.46	0.44	0.46	0.44	0.44	0.46	0.45	0.43	0.46	0.46	0.42	0.44	0.46	0.47	0.47	0.50	0.47	0.50	0.51	0.47
WF-AM-12	0.52	0.52	0.51	0.49	0.46	0.49	0.51	0.47	0.51	0.49	0.48	0.52	0.51	0.53	0.54	0.55	0.52	0.55	0.55	0.52
WF-AM-13	0.60	0.56	0.54	0.49	0.53	0.54	0.52	0.49	0.51	0.52	0.52	0.55	0.47	0.53	0.54	0.56	0.55	0.51	0.56	0.55
WF-AM-14	0.44	0.40	0.41	0.38	0.40	0.41	0.41	0.40	0.42	0.42	0.41	0.42	0.38	0.42	0.43	0.45	0.44	0.45	0.43	0.47
WF-AM-15	0.52	0.45	0.49	0.43	0.48	0.48	0.48	0.48	0.46	0.49	0.50	0.52	0.46	0.51	0.52	0.53	0.53	0.55	0.52	0.56
WF-AM-16	0.46	0.41	0.44	0.39	0.42	0.43	0.44	0.43	0.45	0.43	0.44	0.46	0.42	0.47	0.49	0.48	0.47	0.50	0.47	0.51
WF-AM-17	0.56	0.47	0.51	0.45	0.49	0.49	0.51	0.52	0.52	0.51	0.50	0.55	0.49	0.54	0.55	0.54	0.53	0.56	0.54	0.57
WF-AM-18	0.50	0.44	0.45	0.43	0.43	0.41	0.45	0.44	0.46	0.45	0.47	0.46	0.42	0.47	0.47	0.48	0.48	0.50	0.49	0.48
WF-AM-19	0.50	0.50	0.52	0.50	0.50	0.50	0.51	0.52	0.51	0.50	0.51	0.55	0.48	0.54	0.55	0.56	0.53	0.57	0.56	0.57
WF-AM-20	0.53	0.44	0.50	0.47	0.46	0.48	0.49	0.50	0.49	0.49	0.48	0.53	0.48	0.51	0.50	0.51	0.50	0.54	0.54	0.53
WF-AM-21	0.43	0.45	0.41	0.42	0.42	0.43	0.42	0.41	0.45	0.42	0.42	0.44	0.44	0.45	0.44	0.44	0.45	0.46	0.47	0.46
WF-AM-22	0.49	0.49	0.46	0.47	0.48	0.49	0.49	0.49	0.48	0.48	0.44	0.51	0.48	0.50	0.48	0.53	0.50	0.50	0.50	0.49
WF-AM-23	0.51	0.45	0.48	0.45	0.47	0.47	0.50	0.46	0.48	0.49	0.47	0.51	0.45	0.50	0.50	0.50	0.46	0.50	0.48	0.51
WF-AM-24	0.49	0.44	0.45	0.42	0.44	0.44	0.45	0.40	0.43	0.43	0.42	0.43	0.42	0.45	0.44	0.44	0.40	0.45	0.44	0.45
WF-AM-25	0.50	0.46	0.44	0.46	0.44	0.44	0.48	0.46	0.47	0.47	0.46	0.50	0.45	0.48	0.50	0.51	0.51	0.49	0.49	0.53
WF-AM-26	0.46	0.44	0.42	0.42	0.43	0.43	0.45	0.43	0.42	0.41	0.40	0.42	0.40	0.44	0.45	0.46	0.44	0.44	0.44	0.46
WF-AM-27	0.55	0.53	0.54	0.50	0.52	0.53	0.49	0.50	0.54	0.54	0.49	0.55	0.48	0.53	0.53	0.57	0.56	0.54	0.58	0.58
WF-AM-28	0.47	0.43	0.44	0.41	0.39	0.42	0.35	0.38	0.41	0.40	0.39	0.44	0.41	0.48	0.48	0.49	0.49	0.49	0.49	0.51
WF-AM-29	0.46	0.40	0.42	0.39	0.36	0.37	0.36	0.37	0.40	0.39	0.36	0.45	0.40	0.45	0.43	0.49	0.47	0.49	0.49	0.52
WF-AM-30	0.60	0.53	0.54	0.55	0.57	0.57	0.57	0.54	0.55	0.54	0.53	0.59	0.51	0.55	0.57	0.59	0.52	0.60	0.60	0.64
WF-AM-31	0.48	0.43	0.43	0.40	0.42	0.41	0.42	0.39	0.42	0.39	0.40	0.44	0.40	0.43	0.47	0.46	0.46	0.50	0.50	0.55
WF-DS-01	0.48	0.49	0.45	0.44	0.44	0.47	0.49	0.47	0.45	0.40	0.47	0.47	0.46	0.47	0.47	0.51	0.53	0.52	0.53	0.51
WF-SR-01	0.37	0.34	0.34	0.35	0.32	0.35	0.36	0.33	0.35	0.34	0.35	0.37	0.34	0.33	0.37	0.36	0.35	0.38	0.38	0.38
FA-01	0.46	0.49	0.52	0.46	0.47	0.49	0.49	0.55	0.47	0.45	0.54	0.49	0.48	0.56	0.54	0.52	0.54	0.55	0.60	0.53
GB-01	0.80	0.79	0.81	0.78	0.80	0.79	0.78	0.80	0.80	0.81	0.78	0.80	0.76	0.81	0.83	0.81	0.81	0.78	0.78	0.81
GB-02	0.80	0.69	0.81	0.78	0.78	0.79	0.69	0.76	0.73	0.78	0.77	0.80	0.71	0.76	0.76	0.77	0.74	0.73	0.76	0.79
GB-03	0.84	0.79	0.84	0.81	0.80	0.83	0.76	0.76	0.81	0.84	0.82	0.76	0.79	0.77	0.81	0.82	0.77	0.77	0.83	0.83
UN-KF-11	0.68	0.67	0.70	0.66	0.66	0.65	0.66	0.65	0.66	0.66	0.64	0.66	0.63	0.66	0.65	0.66	0.68	0.59	0.67	0.68
UN-KF-12	0.74	0.70	0.69	0.72	0.77	0.76	0.75	0.66	0.70	0.77	0.70	0.75	0.75	0.69	0.74	0.77	0.73	0.66	0.68	0.71
UN-KF-13	0.73	0.64	0.77	0.73	0.76	0.75	0.76	0.68	0.71	0.68	0.74	0.71	0.76	0.76	0.72	0.70	0.69	0.70	0.72	0.71
UN-KF-14	0.76	0.83	0.82	0.78	0.80	0.77	0.79	0.75	0.77	0.77	0.78	0.77	0.76	0.70	0.75	0.73	0.79	0.77	0.76	0.82
UN-KF-15	0.81	0.82	0.80	0.82	0.77	0.80	0.80	0.78	0.79	0.80	0.75	0.81	0.80	0.81	0.78	0.80	0.79	0.80	0.79	0.84
UN-KF-16	0.61	0.52	0.68	0.68	0.64	0.68	0.64	0.65	0.67	0.67	0.70	0.73	0.66	0.64	0.65	0.70	0.68	0.64	0.72	0.69

year	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
UN-MJ-01	0.76	0.75	0.75	0.79	0.80	0.79	0.80	0.77	0.77	0.80	0.78	0.82	0.77	0.79	0.82	0.81	0.79	0.81	0.78	0.81
UN-MJ-02	0.79	0.77	0.79	0.78	0.81	0.77	0.81	0.79	0.79	0.80	0.80	0.80	0.79	0.79	0.81	0.81	0.81	0.81	0.80	0.82
UN-MJ-03	0.76	0.76	0.78	0.77	0.80	0.78	0.80	0.77	0.76	0.79	0.79	0.80	0.76	0.79	0.82	0.80	0.81	0.79	0.78	0.80
UN-MJ-04	0.79	0.77	0.77	0.78	0.80	0.76	0.80	0.81	0.81	0.80	0.78	0.79	0.79	0.80	0.82	0.80	0.80	0.80	0.81	0.81
UN-MJ-05	0.80	0.80	0.80	0.80	0.81	0.79	0.81	0.81	0.80	0.80	0.80	0.80	0.79	0.80	0.80	0.80	0.80	0.80	0.80	0.81
UN-SH-11	0.62	0.68	0.67	0.75	0.68	0.74	0.72	0.71	0.65	0.72	0.73	0.71	0.70	0.75	0.73	0.67	0.76	0.67	0.71	0.69
UN-SH-12	0.50	0.56	0.61	0.64	0.60	0.67	0.62	0.58	0.60	0.52	0.61	0.59	0.60	0.63	0.55	0.58	0.64	0.55	0.58	0.66
UN-SH-13	0.78	0.74	0.79	0.81	0.80	0.81	0.79	0.78	0.75	0.82	0.79	0.81	0.75	0.79	0.80	0.78	0.82	0.81	0.79	0.82
UN-SH-14	0.64	0.64	0.77	0.75	0.75	0.77	0.75	0.70	0.70	0.73	0.71	0.75	0.69	0.69	0.71	0.75	0.77	0.71	0.74	0.70
UN-SH-15	0.79	0.79	0.81	0.81	0.82	0.81	0.84	0.85	0.83	0.80	0.82	0.83	0.80	0.81	0.82	0.84	0.82	0.84	0.84	0.82
UN-TN-01	0.72	0.72	0.74	0.69	0.70	0.72	0.68	0.72	0.72	0.70	0.68	0.71	0.71	0.70	0.74	0.74	0.70	0.70	0.73	0.74
UN-YY-01	0.79	0.83	0.83	0.82	0.83	0.84	0.82	0.79	0.83	0.84	0.81	0.83	0.83	0.81	0.80	0.84	0.84	0.81	0.83	0.85
UN-YY-02	0.80	0.83	0.82	0.80	0.83	0.83	0.83	0.82	0.82	0.83	0.81	0.83	0.82	0.81	0.81	0.83	0.84	0.81	0.82	0.85
UN-YY-03	0.80	0.82	0.80	0.78	0.81	0.81	0.82	0.80	0.81	0.81	0.79	0.81	0.78	0.81	0.79	0.81	0.82	0.82	0.80	0.84
UN-YY-05	0.83	0.83	0.84	0.80	0.83	0.83	0.84	0.82	0.80	0.83	0.83	0.83	0.83	0.80	0.82	0.83	0.84	0.84	0.83	0.86
UN_YY-04	0.81	0.83	0.82	0.79	0.82	0.82	0.83	0.82	0.80	0.82	0.82	0.82	0.81	0.80	0.81	0.82	0.83	0.83	0.81	0.85

Appendix D. MODIS - October NDVI values

Table 9. October NDVI values per project site from one selected MODIS 16-day NDVI composite image (NDVI -1 to 1)

year	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
ED-01	0.47	0.66	0.48	0.54	0.49	0.66	0.57	0.59	0.56	0.53	0.57	0.58	0.50	0.59	0.61	0.60	0.59	0.56	0.62	0.63
ED-02	0.83	0.74	0.75	0.77	0.76	0.78	0.17	0.77	0.75	0.74	0.39	0.82	0.82	0.76	0.82	0.30	0.86	0.54	0.82	0.78
ED-03	0.84	0.74	0.73	0.79	0.68	0.34	0.58	0.75	0.75	0.76	0.22	0.80	0.77	0.73	0.79	0.71	0.38	0.24	0.85	0.78
ED-04	0.83	0.74	0.75	0.77	0.76	0.78	0.17	0.77	0.75	0.74	0.39	0.82	0.82	0.76	0.82	0.30	0.86	0.54	0.82	0.78
ED-05	0.87	0.86	0.83	0.85	0.85	0.86	0.77	0.84	0.82	0.79	0.38	0.86	0.84	0.84	0.57	0.85	0.85	0.84	0.85	0.87
ED-06	0.78	0.86	0.82	0.85	0.85	0.86	0.66	0.86	0.83	0.81	0.70	0.86	0.85	0.85	0.85	0.86	0.86	0.85	0.86	0.87
ED-07	0.85	0.81	0.81	0.81	0.80	0.83	0.28	0.82	0.83	0.80	0.83	0.86	0.85	0.80	0.85	0.78	0.84	0.84	0.84	0.86
WF-AM-01	0.62	0.66	0.56	0.58	0.50	0.51	0.47	0.47	0.51	0.61	0.52	0.46	0.47	0.58	0.53	0.59	0.56	0.59	0.55	0.57
WF-AM-02	0.58	0.65	0.49	0.56	0.48	0.48	0.52	0.45	0.45	0.57	0.50	0.43	0.46	0.53	0.48	0.58	0.48	0.54	0.48	0.57
WF-AM-03	0.66	0.69	0.57	0.64	0.57	0.58	0.53	0.53	0.55	0.62	0.55	0.55	0.47	0.60	0.58	0.65	0.61	0.64	0.58	0.59
WF-AM-04	0.67	0.58	0.58	0.56	0.50	0.55	0.65	0.53	0.60	0.74	0.55	0.57	0.59	0.64	0.58	0.67	0.62	0.65	0.61	0.61
WF-AM-05	0.62	0.63	0.56	0.55	0.51	0.51	0.50	0.44	0.52	0.61	0.53	0.44	0.43	0.54	0.48	0.59	0.60	0.58	0.60	0.53
WF-AM-06	0.66	0.69	0.59	0.67	0.56	0.60	0.60	0.53	0.97	0.66	0.62	0.59	0.56	0.63	0.60	0.63	0.64	0.63	0.59	0.56
WF-AM-07	0.65	0.61	0.55	0.58	0.54	0.55	0.56	0.54	0.52	0.61	0.62	0.53	0.55	0.62	0.62	0.66	0.64	0.69	0.66	0.60
WF-AM-08	0.63	0.59	0.52	0.57	0.62	0.63	0.54	0.44	0.60	0.67	0.54	0.54	0.55	0.60	0.57	0.62	0.60	0.65	0.67	0.60
WF-AM-09	0.70	0.70	0.68	0.75	0.73	0.67	0.67	0.58	0.67	0.71	0.68	0.62	0.60	0.66	0.66	0.71	0.68	0.72	0.72	0.65
WF-AM-10	0.72	0.64	0.54	0.75	0.65	0.66	0.71	0.67	0.67	0.72	0.70	0.66	0.71	0.75	0.67	0.68	0.74	0.74	0.71	0.73
WF-AM-11	0.72	0.65	0.58	0.72	0.67	0.71	0.66	0.57	0.69	0.73	0.64	0.59	0.71	0.68	0.63	0.66	0.67	0.70	0.67	0.68
WF-AM-12	0.74	0.69	0.65	0.75	0.67	0.70	0.65	0.56	0.67	0.75	0.67	0.61	0.67	0.67	0.66	0.65	0.68	0.71	0.71	0.65
WF-AM-13	0.75	0.75	0.66	0.66	0.72	0.73	0.64	0.64	0.62	0.70	0.64	0.64	0.63	0.64	0.65	0.68	0.69	0.72	0.68	0.65
WF-AM-14	0.62	0.58	0.50	0.55	0.60	0.60	0.55	0.53	0.59	0.64	0.53	0.52	0.47	0.55	0.52	0.61	0.56	0.63	0.56	0.59
WF-AM-15	0.68	0.66	0.56	0.61	0.70	0.70	0.48	0.57	0.65	0.72	0.64	0.62	0.56	0.68	0.64	0.70	0.64	0.69	0.68	0.67
WF-AM-16	0.67	0.64	0.53	0.70	0.62	0.64	0.60	0.55	0.63	0.69	0.62	0.60	0.52	0.65	0.61	0.66	0.65	0.67	0.61	0.66
WF-AM-17	0.67	0.68	0.58	0.63	0.63	0.67	0.65	0.55	0.68	0.71	0.62	0.62	0.55	0.63	0.60	0.66	0.63	0.69	0.68	0.60
WF-AM-18	0.69	0.67	0.56	0.74	0.66	0.65	0.62	0.51	0.65	0.73	0.60	0.54	0.53	0.64	0.57	0.69	0.62	0.67	0.63	0.61
WF-AM-19	0.67	0.72	0.60	0.77	0.67	0.69	0.68	0.57	0.68	0.74	0.67	0.60	0.55	0.68	0.62	0.71	0.69	0.70	0.69	0.64
WF-AM-20	0.71	0.70	0.61	0.69	0.68	0.71	0.68	0.64	0.70	0.75	0.64	0.62	0.58	0.67	0.65	0.72	0.69	0.72	0.69	0.69
WF-AM-21	0.67	0.62	0.54	0.62	0.65	0.65	0.61	0.51	0.70	0.74	0.61	0.56	0.57	0.65	0.62	0.62	0.65	0.72	0.64	0.61
WF-AM-22	0.67	0.68	0.60	0.77	0.67	0.71	0.69	0.58	0.69	0.76	0.62	0.61	0.59	0.67	0.64	0.64	0.68	0.69	0.67	0.66
WF-AM-23	0.72	0.71	0.66	0.70	0.70	0.70	0.66	0.60	0.65	0.77	0.64	0.60	0.69	0.70	0.64	0.67	0.70	0.70	0.72	0.63
WF-AM-24	0.73	0.68	0.66	0.67	0.71	0.69	0.65	0.56	0.66	0.74	0.61	0.60	0.68	0.68	0.64	0.62	0.64	0.71	0.68	0.62
WF-AM-25	0.71	0.69	0.54	0.72	0.70	0.71	0.64	0.62	0.69	0.77	0.65	0.66	0.72	0.69	0.65	0.66	0.69	0.75	0.68	0.71
WF-AM-26	0.61	0.63	0.53	0.65	0.59	0.60	0.65	0.56	0.62	0.65	0.58	0.52	0.63	0.60	0.59	0.58	0.61	0.62	0.55	0.58
WF-AM-27	0.67	0.78	0.67	0.74	0.73	0.74	0.67	0.70	0.75	0.81	0.74	0.71	0.68	0.79	0.71	0.79	0.80	0.78	0.79	0.76
WF-AM-28	0.63	0.53	0.50	0.69	0.47	0.55	0.41	0.33	0.42	0.59	0.46	0.43	0.51	0.61	0.56	0.59	0.58	0.60	0.62	0.56
WF-AM-29	0.59	0.53	0.48	0.60	0.41	0.52	0.37	0.32	0.42	0.59	0.43	0.43	0.47	0.58	0.53	0.56	0.58	0.63	0.61	0.59
WF-AM-30	0.74	0.70	0.66	0.82	0.77	0.78	0.71	0.69	0.71	0.81	0.74	0.61	0.77	0.80	0.72	0.71	0.73	0.73	0.76	0.72
WF-AM-31	0.70	0.65	0.52	0.65	0.61	0.61	0.58	0.54	0.56	0.68	0.63	0.48	0.57	0.61	0.57	0.62	0.61	0.66	0.64	0.66
WF-DS-01	0.62	0.66	0.51	0.52	0.47	0.57	0.57	0.59	0.53	0.53	0.58	0.58	0.48	0.53	0.58	0.51	0.61	0.55	0.62	0.63
WF-SR-01	0.47	0.37	0.31	0.35	0.35	0.40	0.40	0.36	0.39	0.37	0.42	0.40	0.39	0.41	0.48	0.36	0.43	0.41	0.44	0.47
FA-01	0.65	0.64	0.55	0.64	0.55	0.59	0.70	0.63	0.54	0.60	0.67	0.71	0.68	0.69	0.72	0.60	0.43	0.70	0.67	0.76
GB-01	0.85	0.84	0.82	0.85	0.84	0.85	0.84	0.84	0.82	0.83	0.84	0.86	0.85	0.84	0.81	0.85	0.85	0.83	0.63	0.95
GB-02	0.90	0.89	0.84	0.87	0.87	0.85	0.85	0.87	0.25	0.86	0.88	0.87	0.87	0.93	0.86	0.80	0.87	0.84	0.81	0.92
GB-03	0.85	0.85	0.81	0.85	0.85	0.83	0.35	0.85	0.67	0.82	0.79	0.87	0.87	0.86	0.90	0.61	0.88	0.85	0.85	0.75
UN-KF-11	0.69	0.71	0.74	0.71	0.69	0.74	0.74	0.69	0.78	0.64	0.75	0.74	0.68	0.68	0.67	0.71	0.69	0.76	0.74	0.79
UN-KF-12	0.87	0.78	0.86	0.79	0.84	0.85	0.72	0.85	0.86	0.87	0.85	0.81	0.86	0.86	0.86	0.86	0.87	0.88	0.86	0.88
UN-KF-13	0.86	0.78	0.84	0.87	0.87	0.85	0.72	0.87	0.86	0.87	0.87	0.86	0.87	0.85	0.85	0.88	0.89	0.81	0.82	0.92
UN-KF-14	0.91	0.89	0.86	0.89	0.87	0.89	0.29	0.88	0.83	0.87	0.84	0.85	0.87	0.83	0.88	0.69	0.23	0.85	0.88	0.65
UN-KF-15	0.83	0.83	0.81	0.80	0.81	0.81	0.82	0.84	0.84	0.82	0.80	0.81	0.83	0.80	0.82	0.87	0.85	0.85	0.86	0.85
UN-KF-16	0.84	0.84	0.86	0.80	0.83	0.85	0.77	0.83	0.82	0.86	0.83	0.85	0.86	0.82	0.80	0.85	0.83	0.85	0.82	0.82

year	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
UN-MJ-01	0.79	0.82	0.84	0.86	0.85	0.85	0.86	0.83	0.81	0.87	0.86	0.86	0.85	0.85	0.85	0.87	0.87	0.84	0.86	0.76
UN-MJ-02	0.88	0.86	0.86	0.86	0.85	0.87	0.87	0.84	0.84	0.86	0.86	0.87	0.85	0.88	0.85	0.88	0.87	0.88	0.88	0.79
UN-MJ-03	0.85	0.86	0.84	0.84	0.83	0.85	0.85	0.84	0.82	0.85	0.85	0.86	0.84	0.87	0.85	0.87	0.86	0.87	0.85	0.78
UN-MJ-04	0.86	0.87	0.85	0.87	0.85	0.87	0.89	0.87	0.85	0.85	0.86	0.87	0.86	0.88	0.88	0.88	0.87	0.87	0.87	0.87
UN-MJ-05	0.83	0.85	0.85	0.86	0.85	0.86	0.87	0.87	0.84	0.85	0.85	0.86	0.85	0.85	0.85	0.85	0.86	0.87	0.86	0.85
UN-SH-11	0.91	0.41	0.84	0.88	0.86	0.86	0.74	0.88	0.84	0.86	0.87	0.87	0.87	0.89	0.86	0.88	0.89	0.87	0.88	0.64
UN-SH-12	0.19	0.60	0.86	0.81	0.84	0.20	0.32	0.31	0.75	0.71	0.78	0.00	0.85	0.81	0.87	0.55	0.00	0.24	0.70	0.36
UN-SH-13	0.69	0.90	0.89	0.84	0.81	0.87	0.88	0.87	0.84	0.87	0.87	0.88	0.86	0.88	0.84	0.89	0.88	0.88	0.88	0.83
UN-SH-14	0.12	0.93	0.82	0.83	0.87	0.82	0.71	0.54	0.87	0.89	0.67	0.75	0.81	0.80	0.79	0.60	0.65	0.21	0.88	0.58
UN-SH-15	0.78	0.86	0.82	0.86	0.86	0.84	0.79	0.86	0.85	0.85	0.86	0.87	0.86	0.86	0.74	0.88	0.86	0.85	0.87	0.72
UN-TN-01	0.80	0.80	0.80	0.79	0.80	0.80	0.81	0.78	0.80	0.82	0.79	0.78	0.81	0.81	0.81	0.80	0.74	0.82	0.82	0.82
UN-YY-01	0.87	0.88	0.86	0.87	0.88	0.88	0.89	0.88	0.86	0.87	0.83	0.88	0.87	0.86	0.87	0.87	0.87	0.88	0.88	0.87
UN-YY-02	0.87	0.88	0.87	0.86	0.87	0.88	0.88	0.87	0.85	0.88	0.84	0.87	0.86	0.86	0.85	0.87	0.86	0.87	0.88	0.90
UN-YY-03	0.85	0.85	0.85	0.85	0.85	0.87	0.87	0.86	0.84	0.85	0.84	0.86	0.86	0.85	0.86	0.85	0.85	0.86	0.86	0.87
UN-YY-05	0.87	0.87	0.87	0.86	0.86	0.88	0.87	0.87	0.85	0.87	0.86	0.87	0.87	0.87	0.85	0.87	0.86	0.88	0.87	0.90
UN_YY-04	0.86	0.87	0.87	0.85	0.86	0.88	0.87	0.87	0.85	0.86	0.85	0.87	0.86	0.86	0.86	0.86	0.86	0.88	0.87	0.90

Appendix E. Sentinel - yearly NDVI values

Table 10. Sentinel yearly average for the months april untill december (NDVI -1 to 1)

	2016	2017	2018	2019	Total improvement	Average improvement	% improvement compared to before start
WF-AM-01	0.35	0.34	0.37	0.32	-0.03	-0.01	-2.82
WF-AM-02	0.28	0.26	0.30	0.25	-0.03	-0.01	-4.11
WF-AM-03	0.37	0.40	0.39	0.37	0.01	0.00	0.46
WF-AM-04	0.34	0.35	0.37	0.37	0.03	0.01	3.33
WF-AM-05	0.28	0.24	0.31	0.28	-0.01	0.00	-0.83
WF-AM-06	0.38	0.43	0.44	0.43	0.05	0.02	4.58
WF-AM-07	0.42	0.42	0.47	0.46	0.04	0.01	3.53
WF-AM-08	0.36	0.39	0.45	0.44	0.08	0.03	7.25
WF-AM-09	0.47	0.43	0.55	0.52	0.06	0.02	4.06
WF-AM-10	0.54	0.59	0.61	0.51	-0.04	-0.01	-2.29
WF-AM-11	0.42	0.48	0.44	0.45	0.03	0.01	2.15
WF-AM-12	0.43	0.36	0.43	0.40	-0.03	-0.01	-2.35
WF-AM-13	0.51	0.49	0.50	0.53	0.02	0.01	1.59
WF-AM-14	0.39	0.34	0.37	0.37	-0.02	-0.01	-1.97
WF-AM-15	0.49	0.39	0.47	0.44	-0.04	-0.01	-2.96
WF-AM-16	0.38	0.34	0.38	0.38	0.00	0.00	0.19
WF-AM-17	0.50	0.43	0.50	0.52	0.02	0.01	1.23
WF-AM-18	0.45	0.41	0.46	0.45	-0.01	0.00	-0.42
WF-AM-19	0.51	0.45	0.52	0.50	-0.01	0.00	-0.71
WF-AM-20	0.48	0.37	0.45	0.34	-0.13	-0.04	-9.20
WF-AM-21	0.37	0.35	0.37	0.41	0.04	0.01	3.87
WF-AM-22	0.43	0.43	0.49	0.49	0.06	0.02	4.67
WF-AM-23	0.46	0.45	0.48	0.46	0.01	0.00	0.59
WF-AM-24	0.39	0.35	0.38	0.37	-0.03	-0.01	-2.18
WF-AM-25	0.50	0.42	0.48	0.39	-0.11	-0.04	-7.38
WF-AM-26	0.37	0.32	0.36	0.29	-0.09	-0.03	-7.68
WF-AM-27	0.54	0.52	0.52	0.52	-0.02	-0.01	-1.52
WF-AM-28	0.44	0.41	0.42	0.43	-0.01	0.00	-0.88
WF-AM-29	0.35	0.31	0.33	0.37	0.02	0.01	1.43
WF-AM-30	0.41	0.47	0.51	0.47	0.06	0.02	4.83
WF-AM-31	0.39	0.41	0.49	0.46	0.07	0.02	6.41

Appendix F. Sentinel - October NDVI values

Table 11. Sentinel October average (NDVI -1 to 1)

	oct 2016	oct 2017	oct 2018	oct 2019	Total October improvement	Average October improvement	% improvement October compared to before start
WF-AM-01	0.34	0.47	0.46	0.41	0.07	0.02	7.06
WF-AM-02	0.37	0.39	0.42	0.41	0.05	0.02	4.09
WF-AM-03	0.40	0.57	0.40	0.49	0.09	0.03	7.38
WF-AM-04	0.48	0.56	0.55	0.50	0.02	0.01	1.36
WF-AM-05	0.38	0.42	0.40	0.44	0.05	0.02	4.63
WF-AM-06	0.44	0.56	0.55	0.49	0.05	0.02	3.75
WF-AM-07	0.34	0.60	0.61	0.59	0.26	0.09	25.31
WF-AM-08	0.43	0.54	0.49	0.55	0.12	0.04	9.14
WF-AM-09	0.59	0.60	0.63	0.58	-0.01	0.00	-0.55
WF-AM-10	0.53	0.68	0.67	0.67	0.14	0.05	8.67
WF-AM-11	0.52	0.62	0.59	0.63	0.10	0.03	6.46
WF-AM-12	0.58	0.56	0.45	0.55	-0.03	-0.01	-1.68
WF-AM-13	0.64	0.63	0.65	0.62	-0.02	-0.01	-1.01
WF-AM-14	0.53	0.51	0.55	0.52	-0.01	0.00	-0.34
WF-AM-15	0.60	0.57	0.64	0.57	-0.03	-0.01	-1.46
WF-AM-16	0.54	0.54	0.55	0.56	0.02	0.01	1.16
WF-AM-17	0.58	0.58	0.62	0.56	-0.02	-0.01	-0.93
WF-AM-18	0.58	0.56	0.62	0.56	-0.02	-0.01	-1.19
WF-AM-19	0.63	0.62	0.66	0.60	-0.03	-0.01	-1.84
WF-AM-20	0.67	0.62	0.67	0.63	-0.05	-0.02	-2.25
WF-AM-21	0.53	0.57	0.47	0.59	0.06	0.02	3.49
WF-AM-22	0.60	0.61	0.45	0.63	0.04	0.01	2.02
WF-AM-23	0.58	0.60	0.46	0.60	0.01	0.00	0.81
WF-AM-24	0.53	0.60	0.59	0.61	0.08	0.03	4.82
WF-AM-25	0.69	0.65	0.24	0.68	-0.02	-0.01	-0.75
WF-AM-26	0.50	0.53	0.56	0.54	0.04	0.01	2.56
WF-AM-27	0.55	0.65	#DIV/0!	0.59	0.04	0.01	2.29
WF-AM-28	0.56	0.54	0.38	0.52	-0.04	-0.01	-2.49
WF-AM-29	0.45	0.43	0.32	0.43	-0.02	-0.01	-1.40
WF-AM-30	0.54	0.59	0.66	0.64	0.10	0.03	6.22
WF-AM-31	0.59	0.58	0.59	0.61	0.03	0.01	1.52

Appendix G. NDVI increase/decrease comparison

Table 12. NDVI average yearly increase/decrease per active project year for the WeForest Amhara sites

Site-ID	MODIS yearly average	MODIS October average	Sentinel yearly average (apr-dec)	Sentinel October average
WF-AM-01	0.014	0.003	-0.010	0.024
WF-AM-02	0.014	0.028	-0.012	0.015
WF-AM-03	-0.012	-0.005	0.002	0.030
WF-AM-04	-0.003	-0.003	0.011	0.007
WF-AM-05	0.002	-0.025	-0.002	0.018
WF-AM-06	-0.003	-0.027	0.017	0.016
WF-AM-07	0.011	-0.013	0.015	0.086
WF-AM-08	0.006	0.002	0.026	0.040
WF-AM-09	-0.003	-0.010	0.019	-0.003
WF-AM-10	0.018	-0.002	-0.012	0.046
WF-AM-11	0.002	0.002	0.009	0.034
WF-AM-12	-0.002	-0.009	-0.010	-0.010
WF-AM-13	0.002	-0.011	0.008	-0.006
WF-AM-14	0.011	0.007	-0.008	-0.002
WF-AM-15	0.012	0.010	-0.014	-0.009
WF-AM-16	0.014	0.003	0.001	0.006
WF-AM-17	0.015	-0.012	0.006	-0.005
WF-AM-18	-0.001	-0.003	-0.002	-0.007
WF-AM-19	0.013	-0.016	-0.004	-0.012
WF-AM-20	0.007	0.002	-0.044	-0.015
WF-AM-21	0.005	-0.013	0.014	0.019
WF-AM-22	0.000	-0.007	0.020	0.012
WF-AM-23	0.015	-0.025	0.003	0.005
WF-AM-24	0.019	-0.008	-0.009	0.026
WF-AM-25	0.008	0.006	-0.037	-0.005
WF-AM-26	0.006	-0.012	-0.028	0.013
WF-AM-27	0.006	-0.013	-0.008	0.013
WF-AM-28	0.008	-0.007	-0.004	-0.014
WF-AM-29	0.015	0.005	0.005	-0.006
WF-AM-30	0.042	-0.002	0.020	0.033
WF-AM-31	0.028	0.016	0.025	0.009

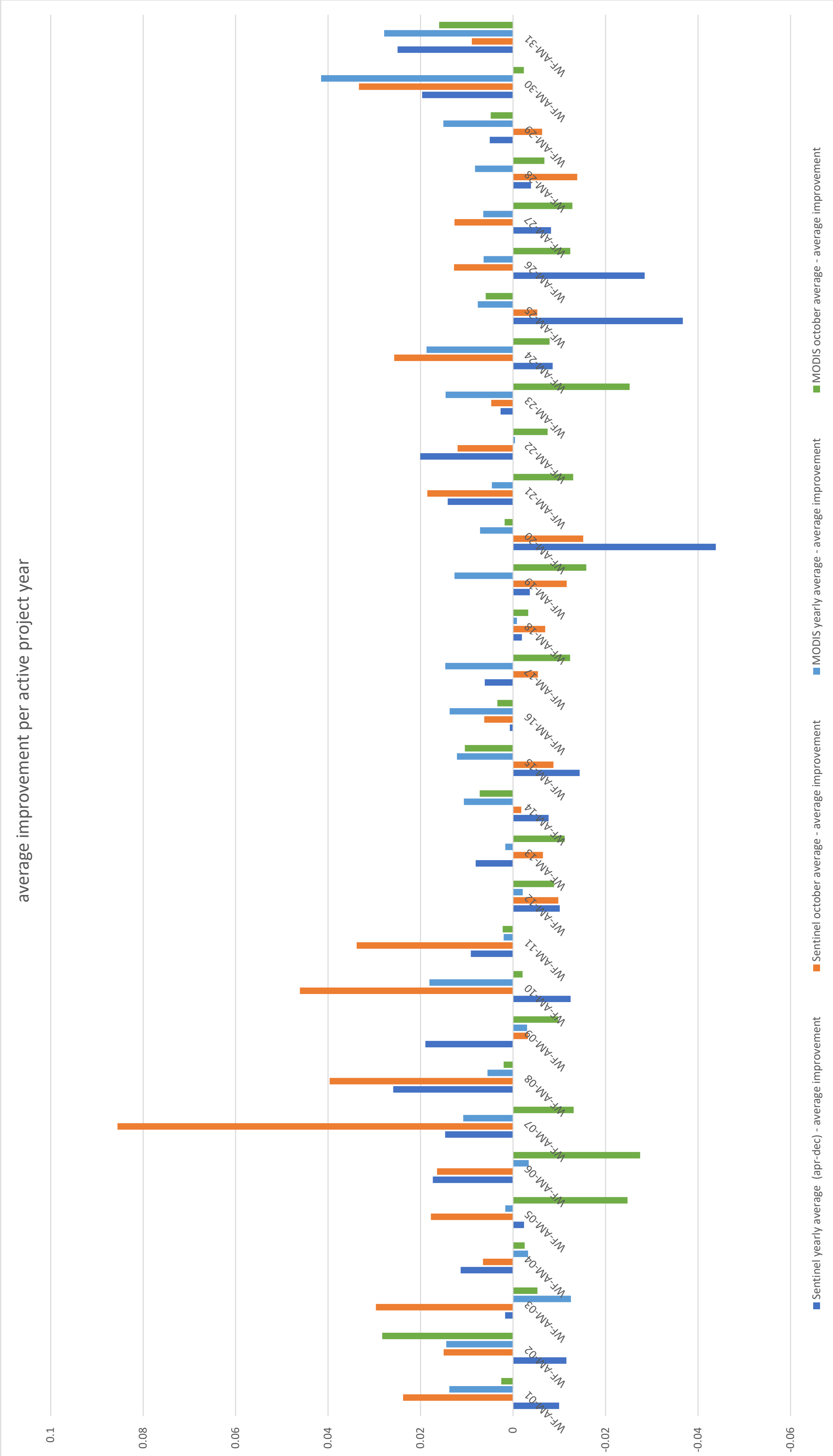
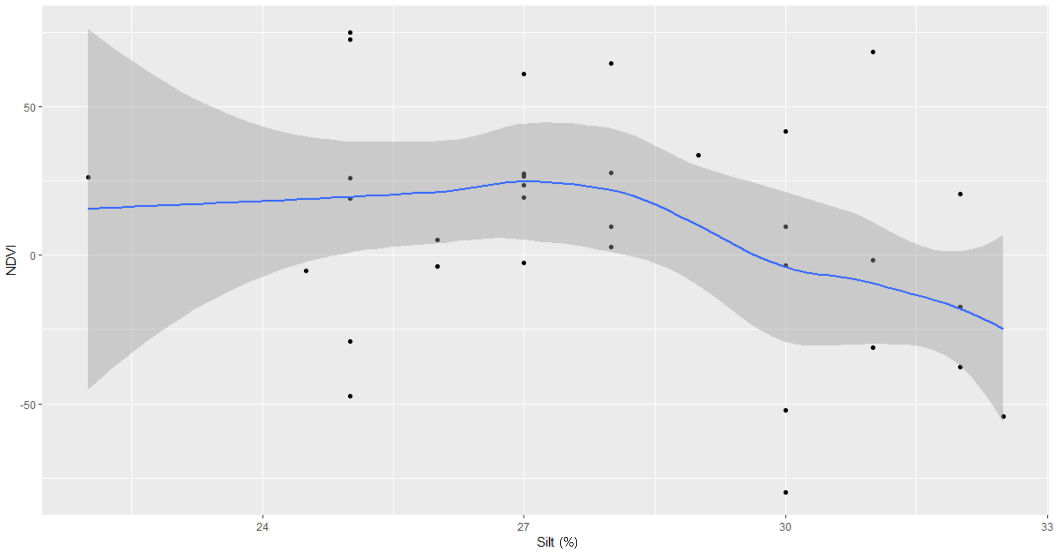
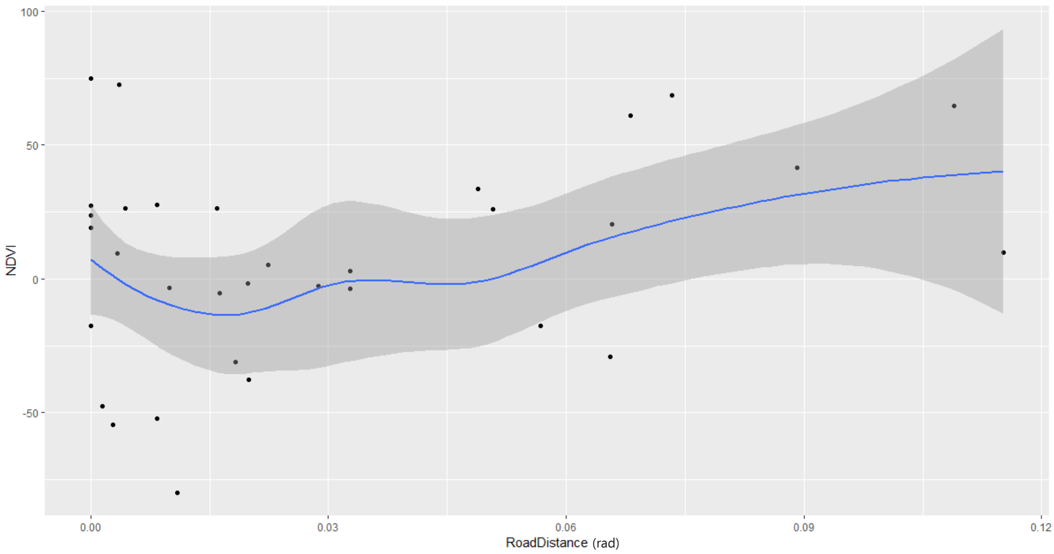


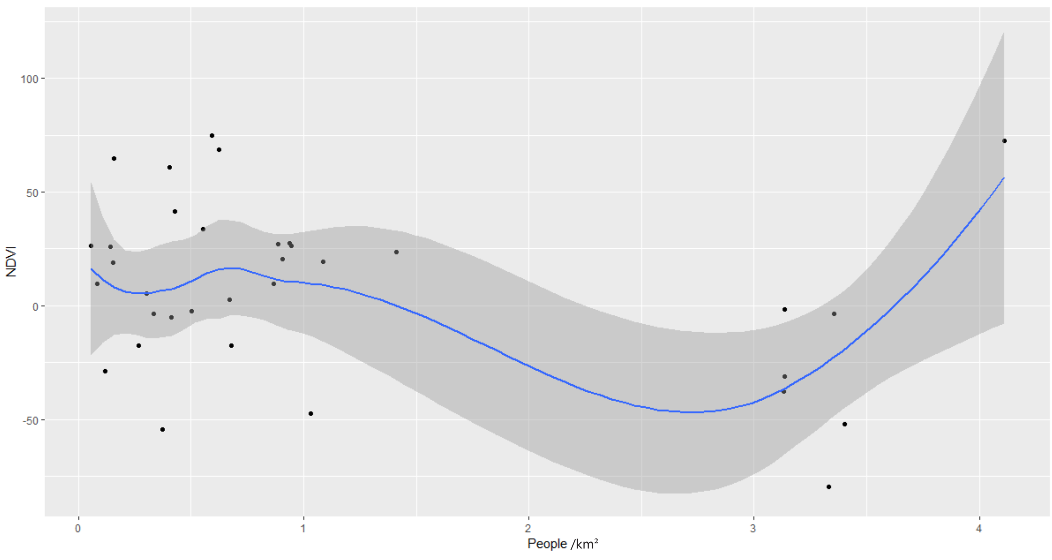
Figure 38. Graph with different NDVI improvement results for the same WeForest Amhara project sites.

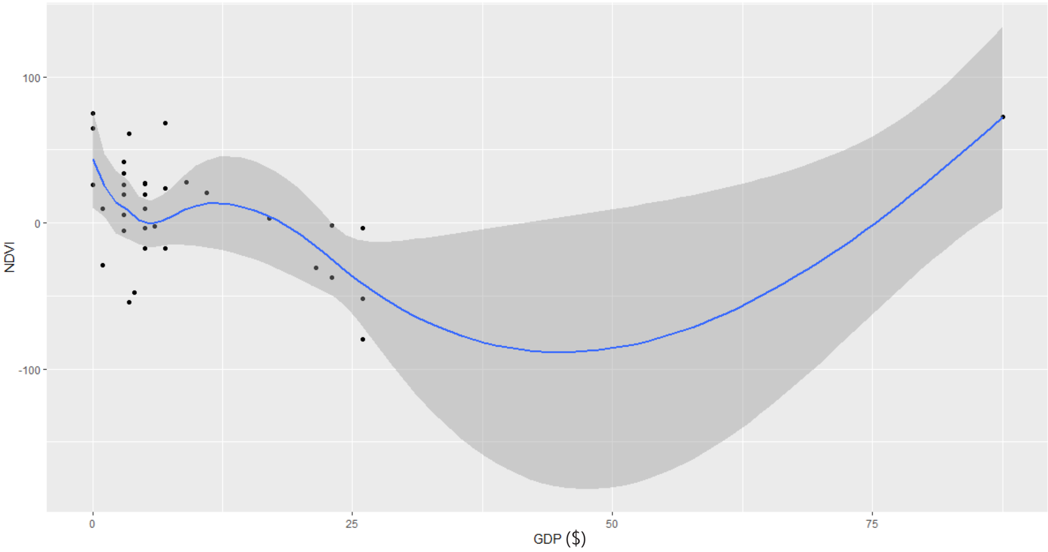
Appendix H.

Scatterplot with trendlines of yearly average NDVI improvement excluding the WeForest projects

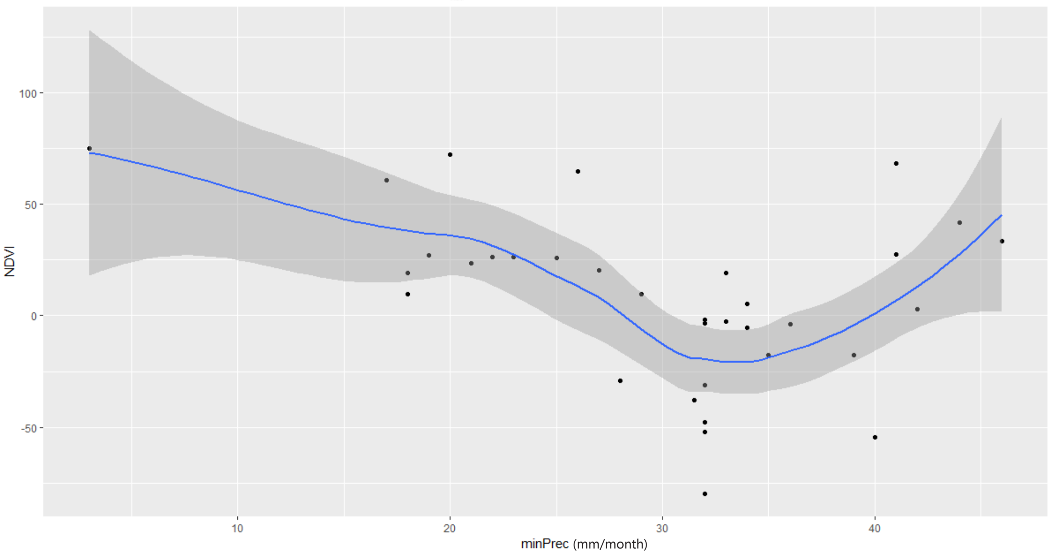




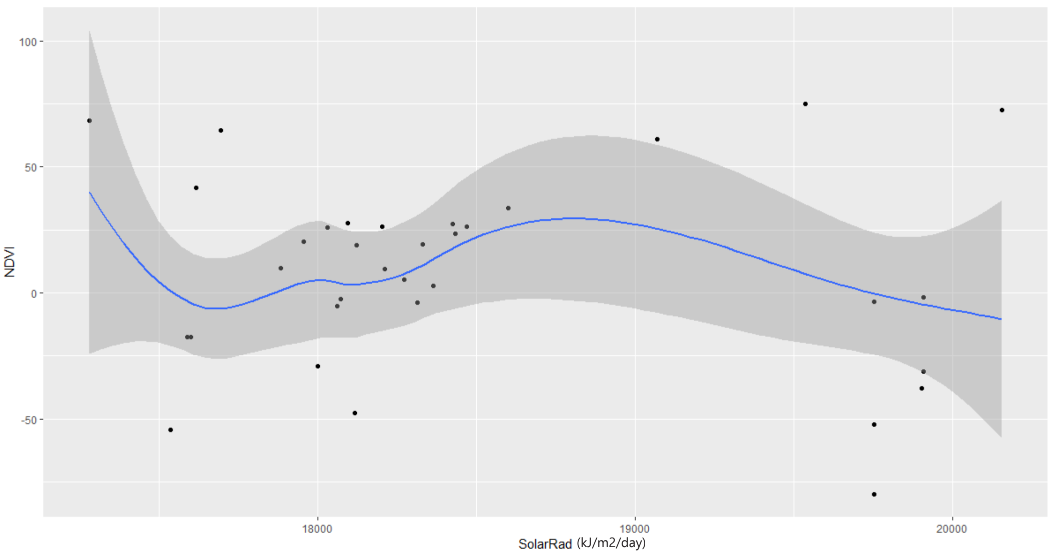




100
0
-100
NDVI
0
25
50
75
GDP ($)



100
50
0
-50
NDVI
10
20
30
40
minPrec (mm/month)



100
50
0
-50
NDVI
18000
19000
20000
SolarRad (kJ/m2/day)

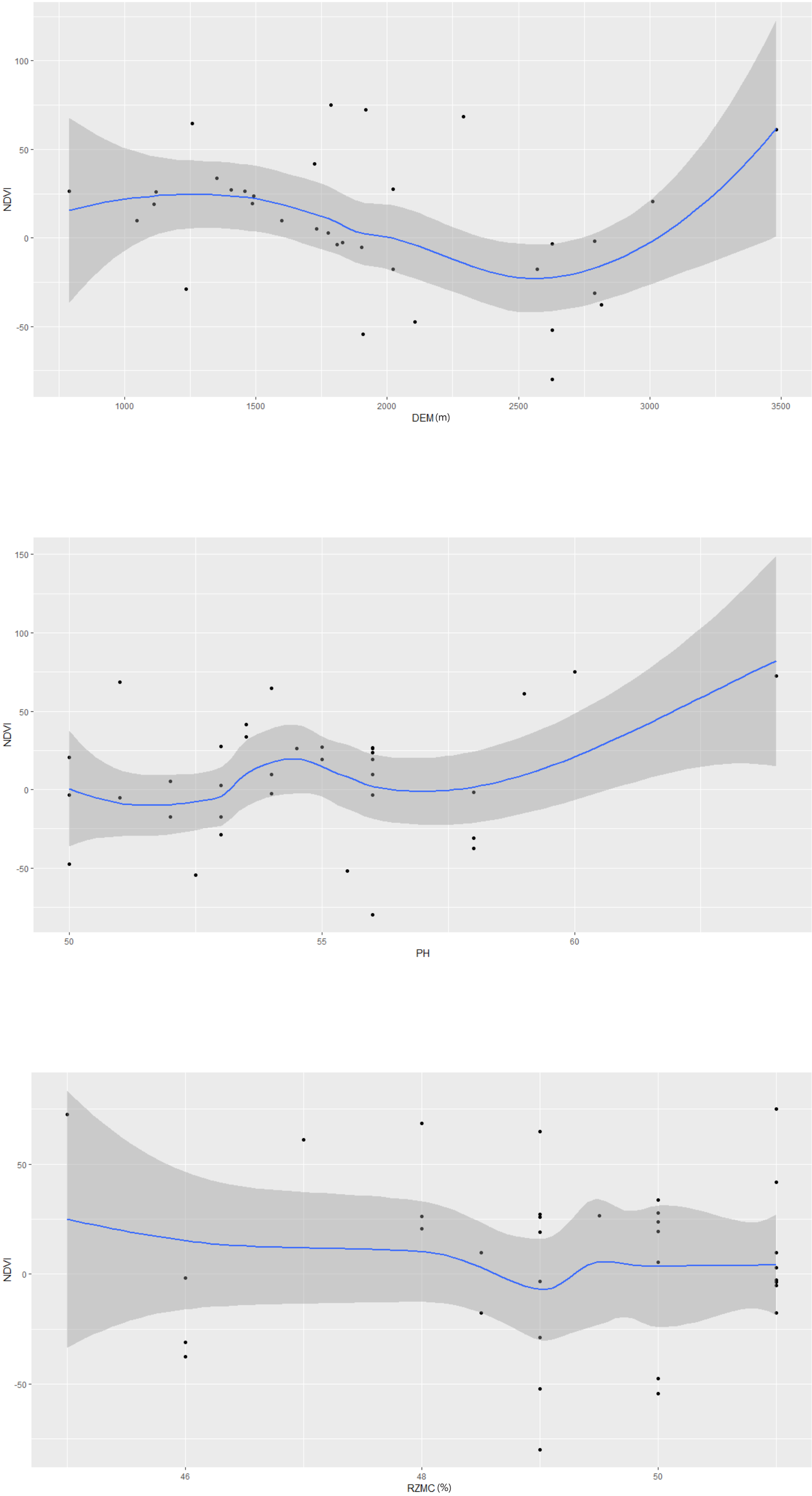


Figure 39. Scatterplot with trendlines of numeric indicators with yearly average NDVI improvement excluding the WeForest projects

Appendix I.

Multiple linear regression results for Sentinel October average NDVI increase against the numeric suitability indicators for the WeForest Amhara sites.

Call:
lm(formula = NDVI ~ RZMC + minPrec + PH + DEM + RoadDistance + People + GDP, data = mlvr)

Residuals:

Min	1Q	Median	3Q	Max
-318.64	-109.10	-6.72	133.16	267.02

Coefficients	**Estimate**	**Std. Error**	**t value**	**Pr(>|t|)**
(Intercept)	-1874.495	4332.410	-0.433	0.669
RZMC	53.441	67.144	0.796	0.435
minPrec	110.982	140.758	0.788	0.439
PH	3.578	41.820	0.086	0.933
DEM	-1.115	1.002	-1.112	0.278
RoadDistance	8.841	14.729	0.600	0.554
People	5023.881	4192.699	1.198	0.244
GDP	12.104	79.832	0.152	0.881

Residual standard error: 176.4 on 22 degrees of freedom
Multiple R-squared: 0.2276, Adjusted R-squared: -0.0181
F-statistic: 0.9264 on 7 and 22 DF, p-value: 0.5058