Student thesis series INES nr 421

Linkages between land degradation and economic inequality in global drylands

Neija Maegaard Elvekjær

2017

Department of
Physical Geography and Ecosystem Science
Lund University
Sölvegatan 12
S-223 62 Lund
Sweden

Neija Maegaard Elvekjær

Linkages between land degradation and economic inequality in global drylands

Bachelor degree thesis, 15 credits in *Physical geography and ecosystem science*

Department of Physical Geography and Ecosystem Science, Lund University

Level: Bachelor of Science (BSc)

Course duration: *March 2017* until *June* 2017

Disclaimer

Linkages between land degradation and economic inequality in global drylands

---

Neija Maegaard Elvekjær

Bachelor thesis, 15 credits, in *Physical geography and ecosystem science*

Supervisor:

Jonathan Seaquist, Lund University

Exam committee:

Ulrik Mårtensson, Lund University

Petter Pilesjö, Lund University

Abstract:

Land degradation has a negative effect on agriculture, food security and ecosystems. It severely impacts the livelihood of the many people directly depending on agriculture around the world. Drylands are some of the most vulnerable areas around the world. Population increase and climate change add strain on the food production of these areas, making them especially vulnerable to land degradation. The aim of this thesis was to explore possible linkages between land degradation and economic inequality. The residual trend method was applied for global drylands, and the resulting vegetation trends were correlated with three measures of income inequality: the Gini coefficient, the income quintile ratio and the decile dispersion ratio. All three correlations showed significant negative relationships, meaning that land degradation can be associated with economic inequality.

No other research could be found that quantifies the association between land degradation and economic inequality. The results underline the importance for policy makers to tackle inequality and land degradation simultaneously, since they are interconnected. Further research is needed to determine the nature of this relationship, and how the understanding of this relationship could help combat inequality and land degradation in the future.

Keywords: Land degradation, socio-economic inequality, restrend, inequality index, Mann Kendall trend analysis, NDVI, global drylands, Gini coefficient, income inequality, desertification

Contents

List of figures:

List of tables:

1 Introduction

Drylands occupy 45% of earths terrestrial area (Pravalie 2016) and is the home of more than 38% of the total global population (Reynolds et al. 2007). Feng and Fu (2013) predicted drylands to expand by 11-23% by the end of the century, under future IPCC climate scenarios (RCP4.5 and RCP8.5 respectively). This expansion will mainly occur in developing countries where drylands are likely to cover 60% of the countries' area (Huang et al. 2016).

Land degradation is defined as a reduction of the capacity of the land to deliver ecosystem goods, and perform functions and services (Higginbottom and Symeonakis 2014). It occurs in almost all terrestrial biomes (Nkonya et al. 2016). It has a negative effect on global agriculture, food security and ecosystems and severely impacts the livelihood of the many people directly depending on agriculture around the world (Hazell and Wood 2008). It is considered one of the main environmental problems today (Reynolds et al. 2007; Nkonya et al. 2016). About 30 % of the global land area shows signs of land degradation and 3 billion people are affected by this (Le et al. 2016). Out of global land degradation 22% occur in drylands (Bai et al. 2008)

The most vulnerable to land degradation in drylands are the poor as they do not have the economic power to mitigate or adapt to the challenges of land degradation. Degraded areas are home to 42% of the world's very poor (Nachtergaele et al. 2013). As shown by Barbier and Hochard (2016) land degradation diminishes the poverty-reducing impact of per capita income growth, widening the gap between rich and poor. Nkonya et al. (2016) argued that poor farmers tend to use indigenous methods, instead of intensive and unsustainable agricultural practices that induce land degradation. So how does economic inequality relate to land degradation? Does land degradation cause inequality or vice versa? These are some essential questions that need to be answered in order to combat land degradation and promote sustainable development in future drylands.

Environmental degradation, especially land degradation has many impacts on society. For example, land degradation reduces agricultural productivity, forcing intensification of agriculture to meet food demand, further degrading the land. Due to various causal relationships and feedback loops such as this, the relationship between inequality and land degradation is not easily quantified. Linkages between land degradation and different aspects of socio-economic inequality have been debated in

previous studies (Barbier et al. 1997; Grepperud 1997; Scherr 2000; Gerber et al. 2014; Mirzabaev et al. 2015; Nkonya et al. 2016). However, quantifications of the relationship between land degradation and economic inequality are still missing. This study attempts to fill this gap.

1.1 Aim

This study aims to investigate possible relationships between land degradation and economic inequality in global drylands. The null hypothesis is that there is no relation between land degradation and economic inequality. The alternative hypothesis is that there is a relationship between land degradation and economic inequality. The aim will be accomplished by the following objectives:

1. To quantify the magnitude of vegetation residual trends in global drylands, with the effect of climate removed, using the residual trend method.
2. To quantify the linkages between land degradation and income inequality by correlating the vegetation residual trends with three income inequality measures.

2 Background

2.1 Definitions

2.1.1 Land degradation

Various definitions for land degradation exist in the literature. The complexity of the many processes and feedbacks leading to land degradation makes it hard to exactly define the term. It is generally agreed that land degradations means a reduction in land quality, which will have a negative impact on soil fertility, food production, water quality, etc. (Omuto et al. 2014). Land degradation is a result of both natural drivers such as climate, erosion and natural disasters; and anthropogenic drivers such as land-use change and land management.

2.1.2 Socio economic inequality:

Socio-economic inequality refers to differences in both economic and social resources within a society. Inequality takes the whole population into account as opposed to poverty measures, such as poverty lines and poverty gaps, which only include the population beneath a certain threshold. Socio-economic inequality can be seen in many aspects of society. The metric to capture inequality can thereby reflect social inequality such as education and health care or economic inequality, such as income and wealth distribution. For the sake of simplicity, this thesis will only look at income inequality, a measure of the

distribution of the accumulated income throughout the population. However it is logical that income inequality will relate to other areas of inequality in society; such as health care and education (Nkonya et al. 2016).

This study will look at three different income inequality measures, see table 4 for details. All measures compare different parts of the accumulated income. Using three different measures will provide insight into inequalities between income groups and within income groups. All measures are useful but none of them give an exhaustive understanding of income inequality (Trust 2011; Alfonso et al. 2015) All income inequality measures are calculated from the accumulated income distribution (see section 3.2.)

2.2 Land degradation and vegetation trends

2.2.1 Causes of land degradation

There are many causes of land degradation, both human and biophysical. Table 1 shows the different drivers of land degradation. The drivers can be divided into proximate causes, where the relationship is easily defined; and underlying causes, which affect land degradation by reinforcing loops and interdependent relationships. For example: land degradation leads to food insecurity, and in the process of filling this resource gap, the land can be further degraded. The underlying causes of land degradation are debated, and some studies find opposite relationships (see table 1). In some cases, increase in population could lead to land degradation, and in other cases it doesn't. The increase in population might lead to intensification of agriculture with unsustainable methods or it might lead to farmers adapting more sustainable methods to protect the fertility of the land, which becomes even more important with more mouths to feed. Many of the mechanisms behind land degradation and its effect on society depend on local conditions, attempts to determine these mechanisms at global scales often fail (Svensson 2007).

Table 1: Drivers of land degradation and some examples of the causality. Based on Mirzabaev et al. (2016) and Gerber et al. (2014)

Driver	type	Causality
Topography	Proximate cause (Natural)	Steep slopes are more vulnerable to water erosion and landslides
Climate	Proximate cause (Natural)	Wildfires lead to soil erosion Heavy rain leads to flooding and erosion Infrequent rainfall lead to erosion
Soil type	Proximate cause (Natural)	Some soil types are more prone to erosion than others.

Driver	type	Causality
Pest and diseases	Proximate cause (Natural)	Leads to biodiversity loss
Land cover change	Proximate cause (Natural and anthropogenic)	Conversion of grasslands to agriculture and deforestation can lead to soil erosion and nutrient loss
Unsustainable management	Proximate cause (anthropogenic)	Land clearing, overgrazing, damaging cultivation techniques and intensification of agriculture leads to land degradation (Allan et al. 2007)
Population density	Underlying cause (anthropogenic)	Bai et al. (2008) and Nachtergaele et al. (2013) found no global relationship. Grepperud (1997) found that increasing population density lead to land degradation. However, Mirzabaev et al. (2016) found that population density positively correlated with sustainable land management.
Market access	Underlying cause (anthropogenic)	Mirzabaev et al. (2016) found that as the distance to the market increased, the land degradation decreased Hazell and Wood (2008) found that high market access leads to increased cost of labor, which makes the farmers choose less labor intensive non-sustainable land management
Land tenure	Underlying cause (anthropogenic)	Mirzabaev et al. (2016) found that tenure insecurity leads to land degradation
Poverty	Underlying cause (anthropogenic)	Barbier and Hochard (2016) found that land degradation would mostly affect the poorest in a society. Mirzabaev et al. (2016) found that a decrease in child mortality correlated with a decrease in land degradation
GDP	Underlying cause (anthropogenic)	Mirzabaev et al. (2016) found no relationship Vu et al. (2014) found that areas with low GDP per capita corresponded with server land degradation
Socio-economic development	Underlying cause (anthropogenic)	Mirzabaev et al. (2016) found that higher night time light intensity, a proxy for development, correlated with higher land degradation

2.2.2 Vegetation trends

Global trends in vegetation can be assessed by analysis of Normalized Difference Vegetation Index (NDVI) images (Higginbottom and Symeonakis 2014). NDVI is computed from Advanced Very High Resolution Radiometry (AVHRR) data, see Equation 1 in the appendix. The AVHRR sensors are sensitive to the reflectance of plants in the near infrared spectrum, which means that the images give a

good estimation of how dense the vegetation is in an area. The trends in NDVI is therefore used as a proxy for the development of plant cover in an area (Evans and Geerken 2004; Wessels et al. 2007; Higginbottom and Symeonakis 2014).

Vegetation trends are mostly driven by climate (Higginbottom and Symeonakis 2014). Precipitation is the most important factor globally but vegetation is limited by different factors around the world, such as nutrient and light availability.

Several studies look at vegetation trends and drivers, both on a global and local scale, in order to quantify land degradation. Time series satellite images provide the overview of trends over time which is further enhanced by field studies considering local conditions, processes and drivers. An overview of some studies into land degradation trends can be seen in table 2. Positive and negative vegetation trends are distinguished by these studies, however studies on local and global scales do not always agree.

Three different methods could be used to isolate changes in vegetation caused by land degradation from the climatic induced change: the residual trend analysis (Restrend) (Evans and Geerken 2004; Wessels et al. 2007; Wessels et al. 2012; Omuto et al. 2014; Ibrahim et al. 2015), the trend-correlation stepwise method (trend-correlation)(Vu et al. 2014; Le et al. 2016) or the trend-correlation with the use of rain-use efficiency (Bai et al. 2008; Swinnen et al. 2013; Kundu et al. 2017). The first two methods looks at the relationship between NDVI and precipitation.

The Restrend method determines land degradation from a linear regression between NDVI and precipitation. The vegetation change due to land degradation is found from a time series analysis of the residuals of this relationship (see section 3.3.1). By extracting the residuals, the climatic effect on the vegetation trends is removed and the remaining trends are due to other factors both natural and anthropogenic. The remaining trends are used as a proxy for land degradation.

The trend-correlation defines which vegetation trends are due to climatic factors by looking at the strength of the correlation between NDVI and climatic variables, with the use of a Pearson's correlation. The RUE method looks at the correlation between the NDVI and the rain-use efficiency(RUE). RUE is the ratio between above ground net primary productivity and rainfall. However studies from Wessels et al. (2012), Prince et al. (2007) , Khaldoun and Stephen (2016) and

Higginbottom and Symeonakis (2014) have criticized the RUE method for being too dependent on above ground primary productivity. These studies propose Restrend as the most accurate method to determine vegetation trends as a proxy for land degradation.

Table 2 Overview of some previous attempts to quantify vegetation trends and land degradation with remotely sensed data. The studies use different spatial extent and methods, see section 3.3.

Extent	Method	Conclusion	reference
Global	RUE	Both positive and negative trends	Bai et al. (2008)
Global	RUE	Both positive and negative trends	De Jong et al. (2011)
Global	Restrend	Both positive and negative trends, drylands more susceptible to land degradation	Allan et al. (2007)
Global	Trend-correlation	29% of global land area is degraded	Le et al. (2016)
Drylands	RUE	Mostly positive trends	Fensholt et al. (2012)
Drylands	Restrend	Both positive and negative trends	Nachtergaele et al. (2013)
Sahel	RUE	Mostly no change	Prince et al. (2007)
Sahel	Restrend and RUE	8% showed significant negative trends, otherwise no change	Khaldoun and Stephen (2016)
Sahel	RUE	Positive vegetation trends. Most trends are explained by climate	Swinnen et al. (2013)
Sahel	Restrend with soil moisture	Negative vegetation trends found in sub-Saharan west africa	Ibrahim et al. (2015)
India	Restrend and RUE	35% of the study area showed negative trends	Kundu et al. (2017)
Somalia	Restrend	30% negative trends 10% positive trends 60% no change	Omuto et al. (2014) and Omuto et al. (2010)

Extent	Method	Conclusion	reference
Syria	restrend	Negative vegetation trends in the central parts of the country	Evans and Geerken (2004)
South Africa	restrend	Negative trends corresponded well with field studies	Wessels et al. (2007)

2.2.3 Link between land degradation and socio-economic inequality

A consensus exists in regards to the proximate causes of land degradation (D'Odorico et al. 2013; Mirzabaev et al. 2016). But the mechanisms of the underlying causes are difficult to quantify. Social and economic factors affect land management decisions, and can thereby lead to increases or decreases in land degradation. As seen from table 1 several studies contradict each other when trying to define the underlying anthropogenic drivers.

Few studies have tried to quantify the relationship of various socio-economic variables and land degradation: Barbier and Hochard (2016) investigated if land degradation leads to poverty or vice versa. They looked at the population density on degraded lands in developing countries. They found that the poverty reducing impact is higher in degraded areas and concluded that high population density and poverty on degraded lands might impede economic growth thereby reinforcing poverty, especially in locations with limited market access. Mirzabaev et al. (2016) correlated several socio-economic factors to land degradation in order to find underlying drivers. Child mortality, market access and higher night time light intensity where found to have a correlation with land degradation. The trends found on a global scale were similar to trends found on a continental scale and when grouping countries according to socio-economic factors.

3 Study area, data and methods

3.1 Study area

Global drylands cover 45% of the world's land area (Pravalie 2016). These areas are characterized by having an aridity index (AI) of less than 0.65. The aridity index is used to classify the world into humidity classes, see figure 1. AI is the ratio between precipitation and potential evapotranspiration (UNEP 1997)

The study area was limited to global drylands where precipitation is likely to be the limiting factor (Fensholt et al. 2012; Ibrahim et al. 2015) (see section 3.3.1). Hyper arid and arid regions were excluded due to high uncertainty when vegetation is too scarce (Beck et al. 2011; Fensholt et al. 2012; Tian et al. 2015). The study area was therefore defined by having an aridity index of 0.2-0.65; including both semi-arid and dry sub-humid areas, see figure 2. The study area was derived from the CGIAR-CSI Global-Aridity and Global-PET Database (Trabucco et al. 2008; Zomer et al. 2008), see table 3.

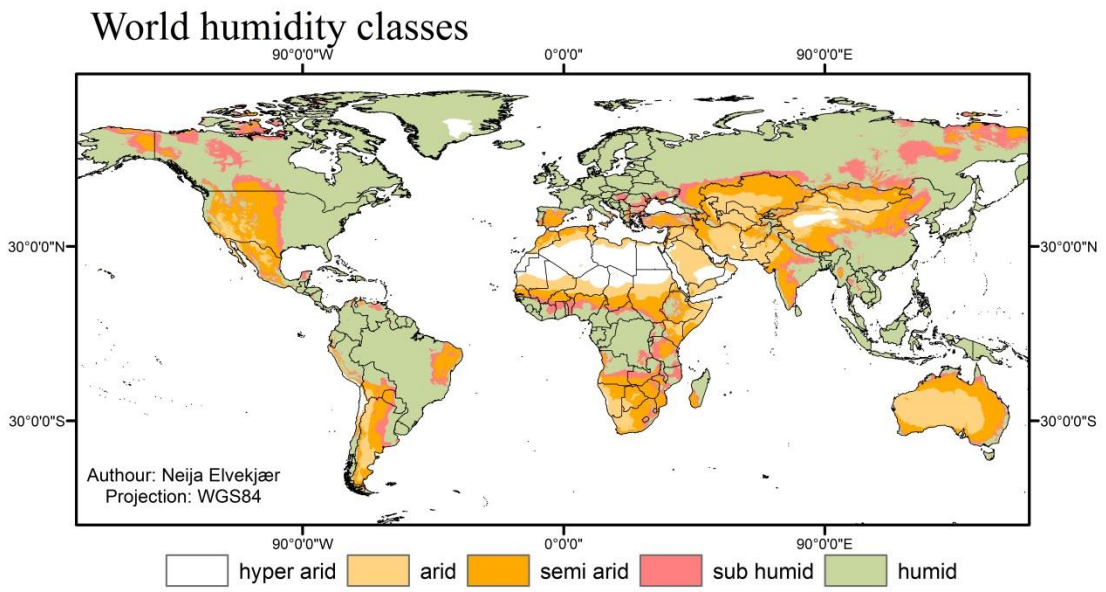


Figure 1: World humidity classes according to UNEP (1997). Data Source: CGIAR-CSI Global-Aridity and Global-PET Database (Trabucco et al. 2008; Zomer et al. 2008)

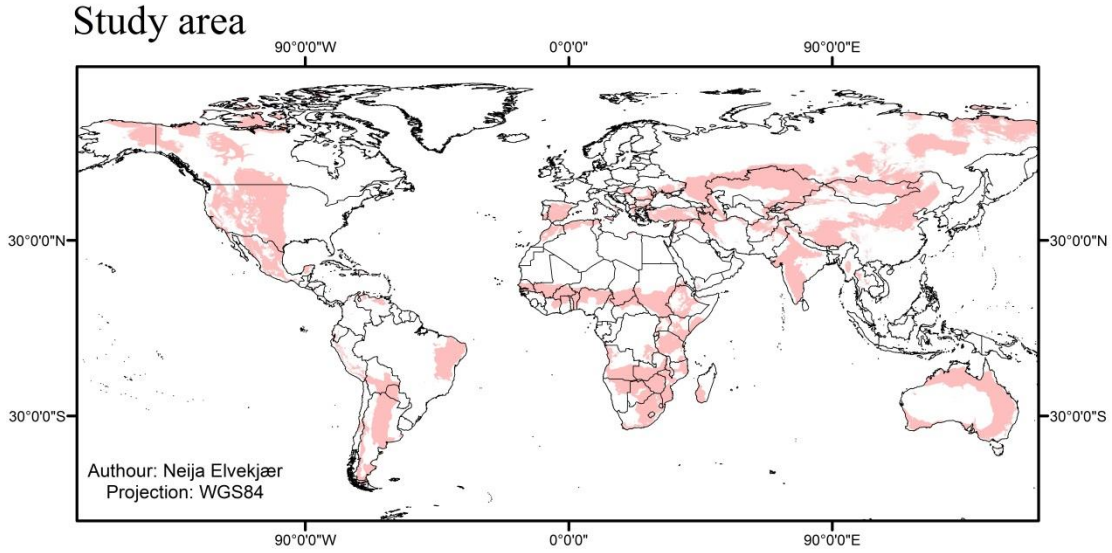


Figure 2: Study area, the colored areas have an AI of 0.2-0.65 and include the humidity classes of semi-arid and dry sub-humid, defined by UNEP (1997). Data source: CGIAR-CSI Global-Aridity and Global-PET Database (Trabucco et al. 2008; Zomer et al. 2008)

3.2 Data

Several datasets were used to explore the relationship between land degradation and inequality, see table 3. The study area was derived by reclassifying a global aridity index dataset (Trabucco et al. 2008; Zomer et al. 2008) into the humidity classes defined by UNEP (1997). Vegetation trends were derived from GIMMS NDVI images (Tucker et al. 2005) and GPCC precipitation data (Schneider et al. 2015).

The AVHRR GIMMSg NDVI dataset is considered most suitable when analyzing long term vegetation trends (Beck et al. 2011). This is due to the timespan of the global dataset, covering 1982-2013. Tian et al. (2015) found the GIMMS3g to have the highest temporal consistency between the three NDVI datasets tested: the GIMMS, VIP3 and LTDR4, though inconsistencies between the sensors where found in semi-arid and hyper arid areas. Similarly, Fensholt and Proud (2012) evaluated the GIMMS NDVI quality, and found strong correlation between the GIMMS datasets and the higher resolution MODIS dataset. However, they found lower correlations in arid and hyper arid areas.

The rainfall data comes from GPCC Full Data Reanalysis Version 7.0. This is a global dataset of monthly precipitation, with a time span of 1901-2013. The dataset is based on quality-controlled data from 75000 stations, each with over 10 years of measurements. The accuracy of the interpolated

surface primarily depends on the distribution density of the measurement stations. The CPCC dataset reaches the requirement of more than 40000 stations distributed globally, and is therefore a good global measure of rainfall (Becker et al. 2013).

The inequality measures were derived from the UNU-WIDER (2017) World Income Inequality Database (WIID3.4). The income quintile ratio (IQR) and the decile dispersion ratio (DDR) were calculated from the income distribution data, with the formulas found in the appendix. The Gini coefficient was given by the database. The WIID 3.4 is a compilation of inequality estimations from various sources. It is the most complete compilation of inequality measures globally. However, the data has been collected from different sources, so the methods of data collection might be inconsistent (Svensson 2007). Inequality measures form 1982-2013 were used in this analysis.

To further explore the linkages between land degradation and economic inequality, details about the individual countries and their dependency on agriculture where retrieved from the world bank. This includes, income level of the country, which continents, rural population, employment in agriculture, agricultural land, and the agricultural sectors part of the country's GDP.

Table 3: Overview of data used for analysis

Dataset	Source and details
Global Aridity index	CGIAR-CSI Global-Aridity and Global-PET Database (Trabucco et al. 2008; Zomer et al. 2008) Downloaded from: http://www.cgiar-csi.org/data/global-aridity-and-pet-database WGS84 1 km resolution
AVHHR GIMMS-g (NDVI dataset)	Tucker et al. (2005) Normalized Difference Vegetation Index (NDVI) generated from NOAA's Advanced Very High Resolution Radiometer (AVHRR) 15-day NDVI composites Timespan: 1982-2013 WGS84 8 km resolution
GPCC Full Data Reanalysis Version 7.0	Schneider et al. (2015) Monthly Land-Surface Precipitation from Rain Gauges built on GTS based and Historic Data; WGS84 0.5° grid resolution
GINI coefficient and income distribution data	UNU-WIDER (2017) World Income Inequality Database (WIID3.4) Downloaded from: https://www.wider.unu.edu/database/world-income-

Dataset	Source and details
	inequality-database-wiid34
Country details:	All downloaded from the World Bank. Original sources of the individual data series are listed below
Agriculture (% of GDP)	Source: World Bank national accounts data, and OECD National Accounts data files.
Employment in agriculture (% of total employment)	Source: International Labour Organization, ILOSTAT database. Data retrieved in March 2017.
Rural population (% of total population)	Source: World Bank staff estimates based on the United Nations Population Division's World Urbanization Prospects.
Agricultural land (% of land area)	Source: Food and Agriculture Organization, electronic files and web site.

3.3 Methods

The method used to accomplish the two objectives was divided into two steps:

1. The Restrend method: determine the relationship between NDVI and precipitation, by a linear regression between the independent variable (precipitation) and the dependent variable (NDVI) for each year. Then, extract the residuals from the NDVI/precipitation relationship. These are used as a measure of land degradation. For each pixel determine the trend of the residuals over time.
2. The Correlation: Calculate averages of three inequality measures for each country. Correlate land degradation trends and inequality averages.

A graphical summary of the method used can be seen in figure 3.

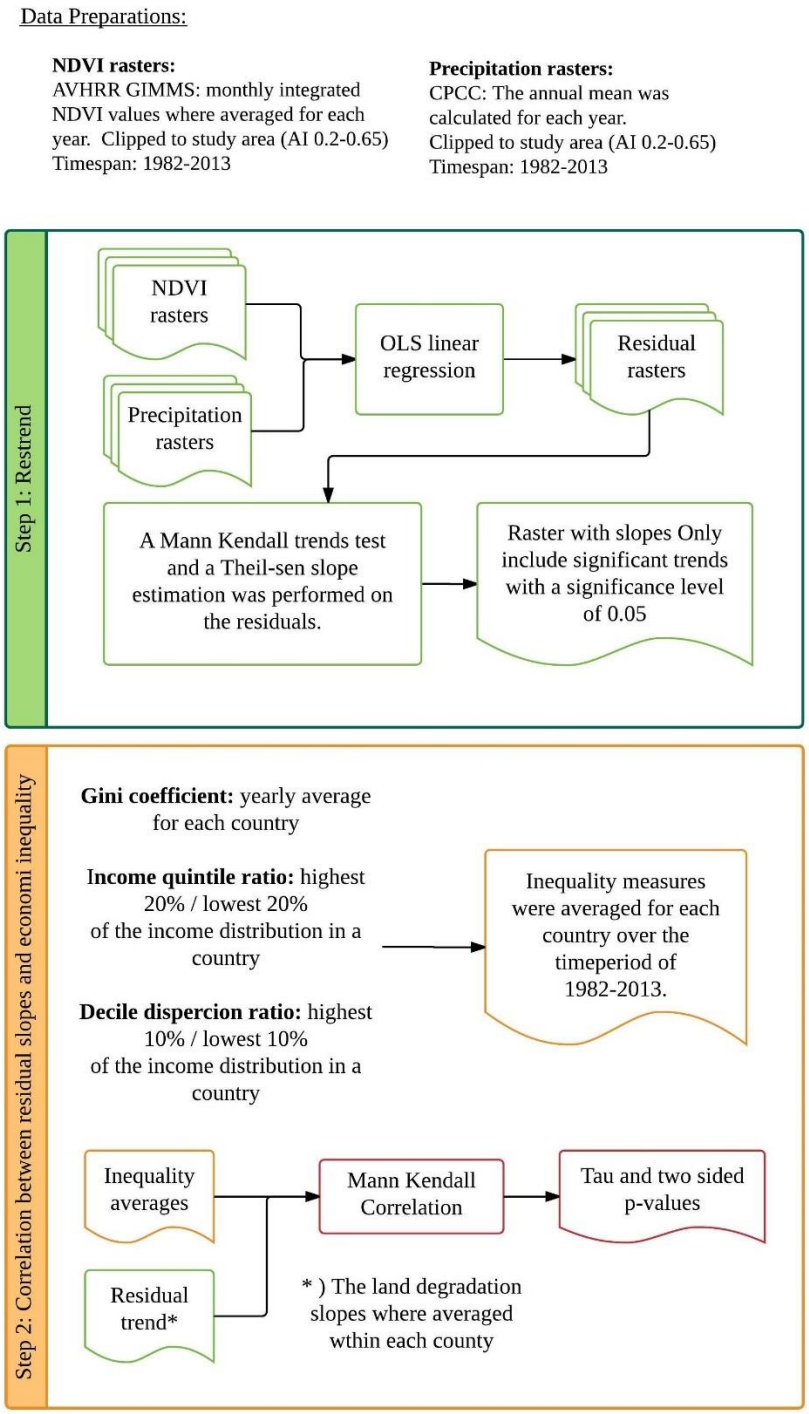


Figure 3: Flow chart showing the steps taken in analyzing the correlation between land degradation and economic inequality in global drylands. The method is divided into two steps in order to accomplish the two objectives.

3.3.1 Vegetation residual trend analysis

This study will implement Restrend, a method that was developed by Evans and Geerken (2004) for Syria. The method uses time-series remotely sensed data in order to discriminate between climate and human induced land degradation (Evans and Geerken 2004). Restrend was selected as the better method to determine land degradation in semi-arid areas out of the three methods mentioned in section 2.2.2 (Wessels et al. 2007; Wessels et al. 2012; Higginbottom and Symeonakis 2014).

The climate induced vegetation trends were removed from the time series to analyze the change in vegetation due to land degradation. This was done by regressing rainfall against NDVI with a linear regression for each year and extracting the residuals for each pixel. The residuals from this relationship represent the NDVI observations that cannot be explained by rainfall and is assumed to be due to land degradation, both human induced and naturally occurring. The trend of the residuals throughout the time series can then be used to estimate the change in land degradation over time. The regression was performed with the monthly integrated NDVI and the monthly average of precipitation, for each year of the analysis, 1982-2013.

3.3.1.1 Evidence for assumptions

The method is based on two main assumptions: (i) the linear relationship between rainfall and NDVI. Studies have shown that precipitation and NDVI can be accurately modeled by a linear relationship (Nicholson et al. 1990). A study by Fensholt et al. (2012) compared non parametric (Mann Kendall trend test) and parametric (Ordinary Least Squares/OLS) trend test for the NDVI/precipitation relationship. Both trend tests produced similar results, however OLS generally described trends in semi-arid areas best. Therefore, an OLS was used to determine vegetation/rainfall relationships. (ii) Land degradation causes reduction in vegetation due to soil erosion, soil degradation and changes in vegetation species (Wessels et al. 2007) and the trend in NDVI can therefore be used as a proxy for land degradation (Bai et al. 2008; Higginbottom and Symeonakis 2014)

Other assumptions for the Restrend method are 1) that the data is normally distributed 2) homogeneity of the variance, 3) that there is no autocorrelation (Higginbottom and Symeonakis 2014). In reality, assumption 2 and 3 are not met. Spatial autocorrelation in drylands result in strongly correlated NDVI, making the residuals dependent on one another (Higginbottom and Symeonakis 2014). Furthermore, the residuals produced by the NDVI/precipitation regression are also not normally distributed.

To avoid violation of the assumptions, non-parametric tests were applied in further analysis. The Mann Kendall trend test is used to find trends in time series data. The variable, in this case the residuals, are ranked according to the time series. The test returns a tau-value (τ) measuring the strength of the relationship. The Theil-Sen test estimates the slope of the relationship by calculating all possible trends between the points in the data series and thereafter returning the median slope value. These two tests were used for finding trends in the residuals, as suggested by Fensholt et al. (2012).

The Mann Kendall trend test calculates a two tailed p-value. With a 0.05 significant level, if the trends had a p-value between -0.025-0.025 then they were considered significant

3.3.2 Correlations between vegetation residual trends and inequality measures

3.3.2.1 Inequality measures

The measures of inequality were averaged for the period of the analysis 1982-2013. Following measures for economic inequality were used: the Gini coefficient (GC), the income quintile ratio (IQR) and the decile dispersion ratio (DDR). See table 4 for more details.

The average of inequality measures was deemed suitable due to the time lag between the two variables. Both variables are complex and it would therefore take time before any affect between the two to be noticeable. Therefore, the average inequality measure was selected for the analysis, instead of the inequality trends or the newest measured inequality.

Table 4: Overview and description of inequality measures used for the analysis of the relationship between inequality and land degradation.

Inequality measure	Description
Gini coefficient	The most widely used index for income inequality. It is based on the Lorenz curve, a cumulative frequency curve that compares the distribution of a specific variable (e.g. income) with a distribution that represents equality. The coefficient ranges from 0 = complete inequality to 1 = complete equality. However as mentioned by the Gini coefficient tend to be mostly influenced by the middle income group (Rogerson 2013). Changes in the extreme poor or rich part of the population will not affect the overall Gini very much. Furthermore, it is not possible to see where in a population the inequality occurs. The Gini-coefficient used was provided by the WIID3 database.
Income Quintile	20% richest vs. the 20% poorest. It is more robust against outliers; which is why it is

Ratio	used by the United nations development program human development report. The IQR was calculated according to Equation 2 in the appendix.
Decile dispersion ratio	The ration between the 10% richest and 10% poorest in a country. It is useful to see the changes in the tails of the distribution; however this ratio is very sensitive to outliers, and does not take into account the middle of the distribution (Haughton and Khandker 2009). The DDR was calculated according to Equation 3 in the appendix.

3.3.2.2 The correlation of inequality and land degradation

For the final step, a Kendall tau correlation was performed to investigate the association between land degradation and income inequality. The Kendall tau is a non-parametric correlation techniques which compares two columns of ranked data, in this case income inequality and residual slopes. The test returns a tau value between 0 and +/-1; where 0 is no correlation and 1 is perfectly correlated. The land degradation trends were averaged for each country and afterwards correlated to the inequality averages.

Countries with higher dependency on agriculture might be more sensitive to the association between land degradation and inequality. Geographical or political factors, might lead to some continents having higher correlations than others. Finally, some countries with lower income might be more susceptible to the consequences of land degradation and its effect on society (D'Odorico et al. 2013; Mirzabaev et al. 2016). To further investigate the relationship, a similar correlation was performed by grouping the trends by income group, size of agricultural sector and continent. Data from the World Bank provide the basis for grouping the pairs of inequality and residual slopes by the various attributes, see table 1. Only some pairs with specific attributes were included in the correlations, e.g. only high income countries were included in the correlation. The four measures of the importance of agriculture were grouped by quartiles

Same p value as the vegetation trends was used to determine if the correlation was significant. However, to further explore the association in question, correlations within a significance level of 0.1, e.g. a p-value between -0.5-0.5 were also noted.

4 Results

4.1 Vegetation residual trends in global drylands

From this analysis, the proportion of negative and positive trends found is almost equal. However, when excluding statistically insignificant trends only 3% of the global drylands remain. The residual trends are shown in Figure 4 and the trends are summarized in Table 5.

On average, the countries with the largest negative residual trends are Botswana, Zimbabwe, Zambia and Madagascar. The countries with the largest positive residual trends are Peru, Ecuador, Uzbekistan and Ethiopia.

Generally, Africa shows the highest frequency of occurrence of negative trends in residuals, especially in Sahel and in the south of Africa (Figure 5). Both North and South America (Figure 6) show primarily greening trends. Asia (Figure 6) and Australia (Figure 4) show both positive and negative trends,

Table 5: Trends found from restrend analysis of the study area (AI 0.2-0.65) between 1982-2013. The proportion of trends are given in percentages of total drylands. Trends are included within a significance level of 0.05. No change is defined by a trend between +/- 1%

	All trends (%)	Significant trends (%)
No change	37.27	0.00
Positive trends	31.91	1.14
Negative trends	30.82	1.65

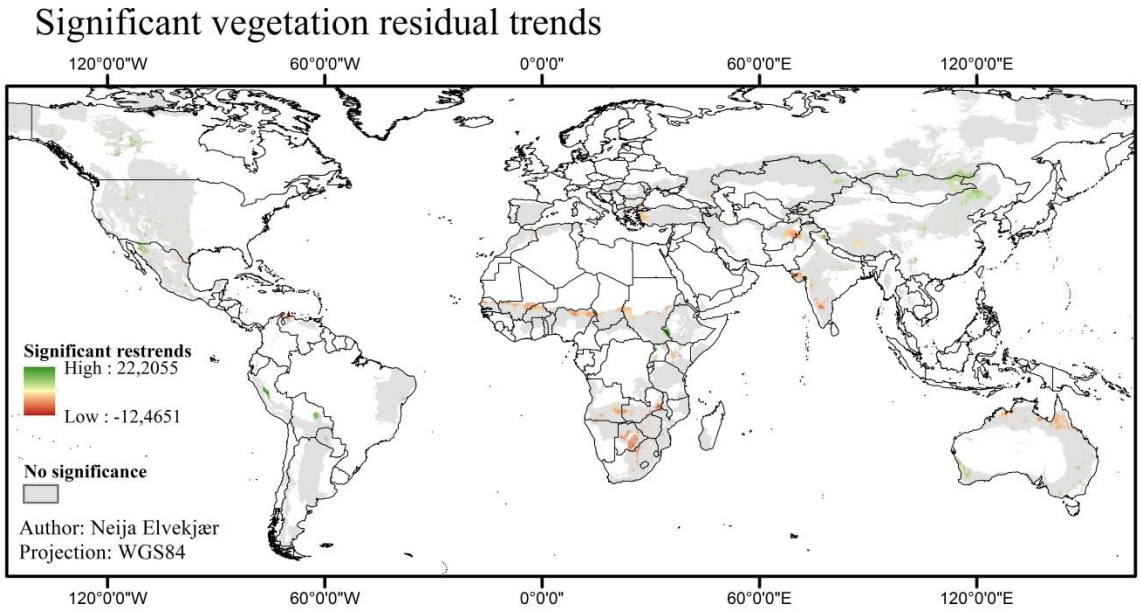


Figure 4: Trends of vegetation residuals as a proxy for land degradation. Result from application of restrend method on GIMMS NDVI data in the period of 1982-2013. The trends produced in the grey areas were insignificant.

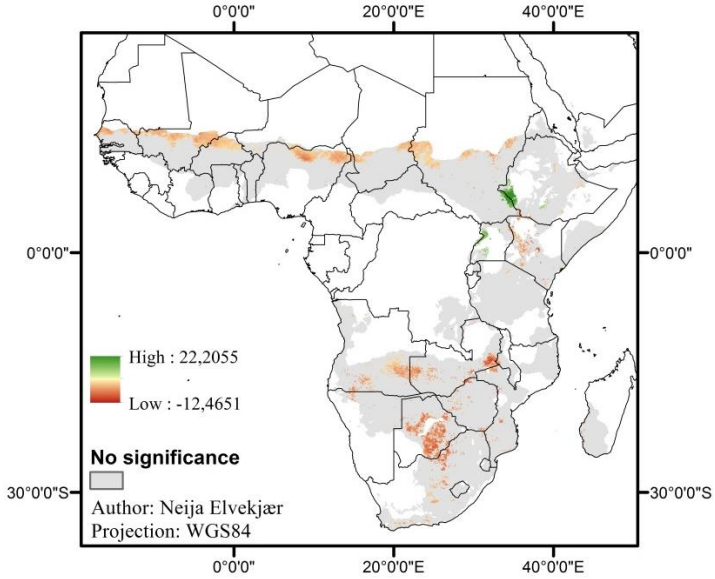


Figure 5: Residual trends for Africa's drylands. Result from application of restrend method on GIMMS NDVI data in the period of 1982-2013. The trends produced in the grey areas were insignificant. (Zoom in on figure 4)

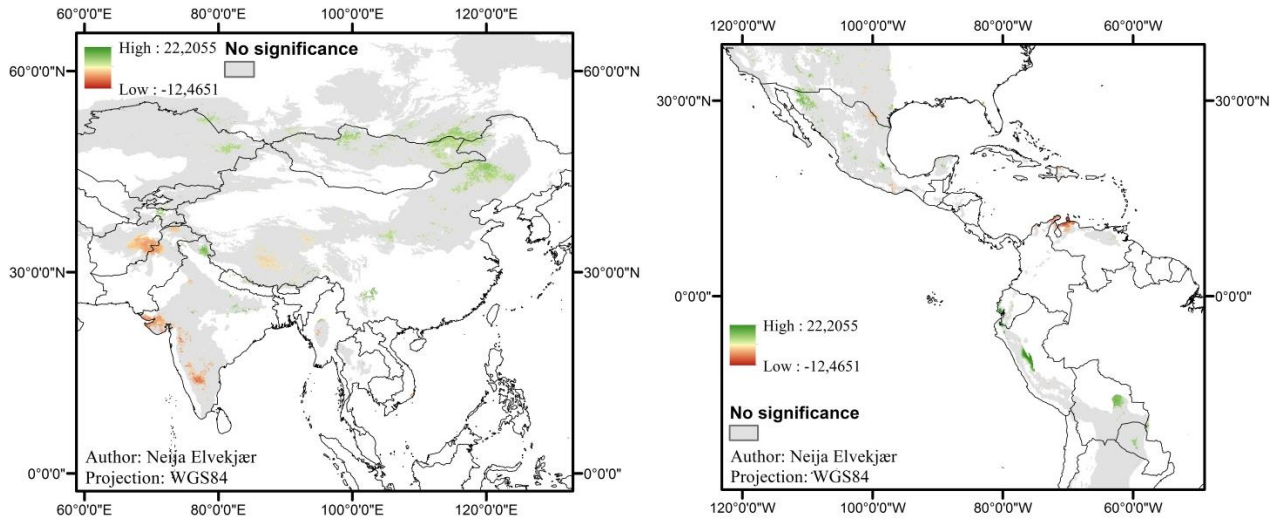


Figure 6: Left: Residual trends for Asia's drylands. Right: residual trends from some of America's drylands. Result from application of restrend method on GIMMS NDVI data in the period of 1982-2013. The trends produced in the grey areas were insignificant. (Zoom in on figure 4)

4.2 Correlation of residual trends and inequality measures

The association between residual trend slopes and income inequality measures was explored with scatterplots. The countries included in this part of the analysis had to show significant residual trends within the studyarea and had to have inequality data available within the selected time period. A total of 71 countries fit these to criteria for the gini and the IQR, and 67 countries fit for the DDR. Figure 7 shows the three income inequality indices plotted against the average residual slopes. All three indices show nonlinear inverse relationships, where high inequality is associated with negative residual slopes. The Gini coefficient shows more scattering than both IQR and DDR. All three inequality measures show a negative association for the degrading slopes, however from 0 all three plots scatter, and no clear association can be noted.

Several clusters of outliers are visible from the scatterplots. In appendix 2, a more detailed version of the scatterplots can be seen, with country labels included. Several African countries (Zimbabwe, Zambia, South Africa and Mauritania) have very high inequality coefficients and negative residual trends and can therefore be distinguished in the top left of the plot. Several countries in South America (Brazil, Bolivia, Paraguay, Argentina, Ecuador and Peru) have positive residual trends but high inequality. East Timor shows negative residual trends and low inequality; Ethiopia and Uzbekistan shows relatively high positive residual trends.

The three measures of inequality show similar τ from the results of the Kendall correlations. However the Gini coefficient shows significance at a lower p-value. The Gini correlations also show the largest τ, whereas several τ values from IQR- and DDR- correlations are close to zero. Global drylands showed significant negative trends with a significance level of 0.05 for the Gini coefficient and with a significance level of 0.1 for the correlation with the IQR and the DDR.

For further exploration, correlations were also performed by grouping the countries according to different attributes. The results from these correlations were not plotted, but can be seen in table 6. All significant correlations had negative tau values.

All inequality measures where significant with a significance level of 0.05, when correlating only negative vegetation trends with the inequality averages The correlations for each income group only showed significant results for the low-middle income group, with a significance level of 0.1. The remaining groups also varied between the inequality measures. When performing the correlations for each continent individually, only Africa showed significant results. Grouping by the dependency on agriculture only yielded significant results in the highest quintile. These correlations showed more variations between the three inequality measures. The three first quartiles did not consistently show any significant correlations.

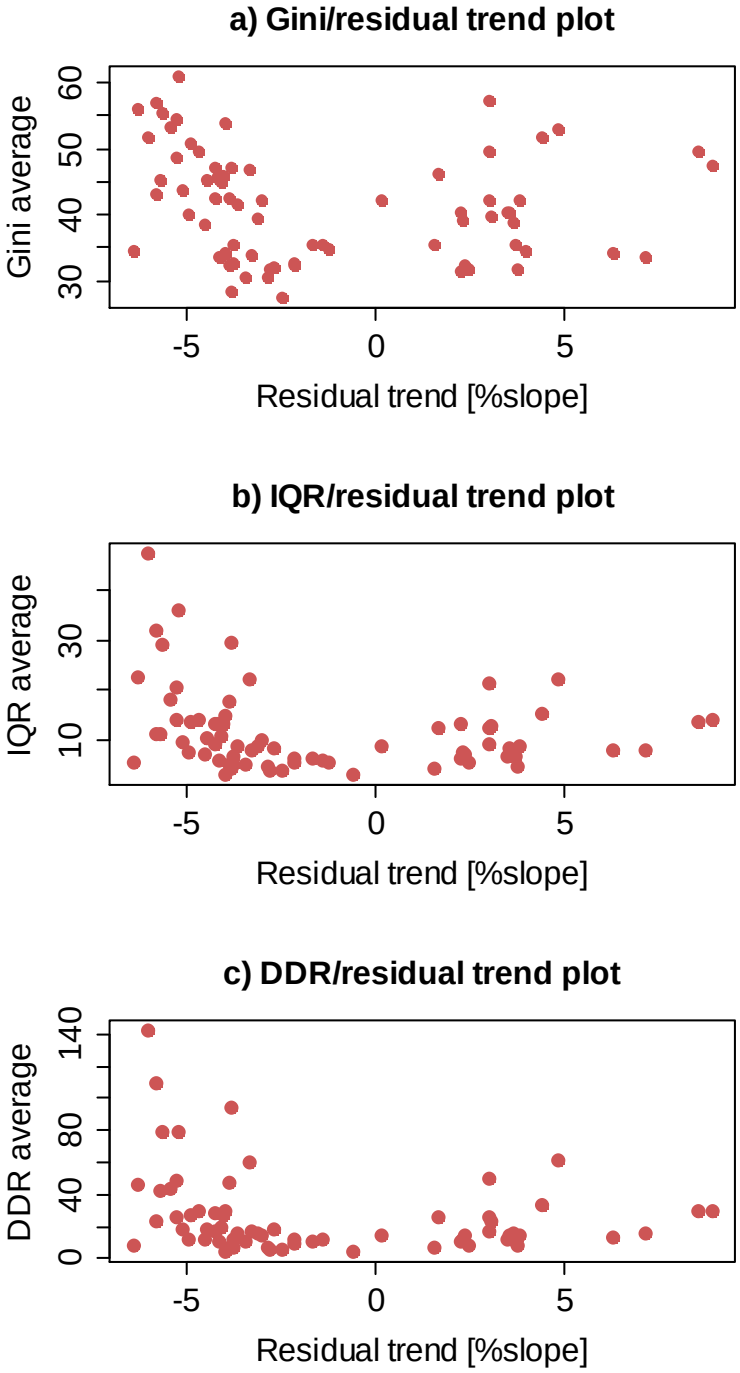


Figure 7: Average income inequality and vegetation residual trends plotted for the three different income inequality variables: a) Gini coefficient b) income quintile ratio (IQR) and c) decile dispersion ratio (DDR). Vegetation residual trends where derived from NDVI and precipitation data during 1982-2013; and thereafter averaged for each country. Available income inequality data was averaged over the period of analysis for each country. More detailed view of plots including labels is seen in appendix 2.

Table 6: Resulting Tau and P values for Mann Kendall correlation test between the average of the three measures of income inequality and the vegetation residual trends. Correlations was also performed in various groupings: continents, country income group. The value of agricultural sector, employment in agricultural sector, rural population and agricultural land were all grouped by their quartiles. The values marked with green showed significant correlations with a significance level of 0.05. The values marked with yellow showed significant correlations with a significance level of 0.1. Source of grouping data: World Bank

	Gini			IQR			DDR		
	tau	p-value	npoints	tau	p-value	npoints	tau	p-value	npoints
Global drylands	-0.218	0.007	71	-0.173	0.034	71	-0.180	0.032	67
Negative residual slopes	-0.484	0.000	46	-0.439	0.000	47	-0.416	0.000	44
Positive residual slopes	0.056	0.726	25	0.196	0.189	24	0.225	0.139	23
Correlations with countries grouped by income									
high income	-0.099	0.661	14	-0.026	0.951	13	-0.127	0.640	11
high-middle income	-0.124	0.450	21	-0.095	0.566	21	-0.074	0.673	20
low-middle income	-0.305	0.057	21	-0.352	0.037	22	-0.325	0.037	22
low income	0.213	0.297	15	-0.213	0.296	15	0.233	0.272	14
Correlations with countries grouped by continent									
Africa	-0.493	0.001	25	-0.393	0.006	25	-0.353	0.014	25
Americas	-0.113	0.499	16	-0.010	1.000	15	-0.231	0.300	13
Asia	0.053	0.780	19	0.147	0.381	20	0.124	0.495	18
Europe	0.056	0.917	9	0.000	1.000	9	0.111	0.754	9
Oceania	Na	Na	2	Na	Na	2	Na	Na	2
Correlations with countries grouped by the quartiles of the agricultural proportion of GDP [% of total GDP]									
GDP_1	-0.118	0.537	17	-0.176	0.343	17	-0.588	0.007	13
GDP_2	-0.118	0.537	17	-0.132	0.484	17	0.061	0.837	12
GDP_3	-0.162	0.387	17	0.000	1.000	17	-0.347	0.121	13
GDP_4	-0.464	0.008	18	-0.386	0.028	18	0.103	0.669	13
Correlations with countries grouped by the quartiles of employment in agriculture [% of total workforce]									
emp_1	-0.200	0.322	15	-0.086	0.692	15	-0.124	0.553	15
emp_2	-0.105	0.621	15	0.048	0.843	15	0.033	0.913	14
emp_3	-0.257	0.198	15	-0.124	0.553	15	-0.011	1.000	14
emp_4	-0.467	0.013	15	-0.433	0.022	16	-0.505	0.010	15
Correlations with countries grouped by the quartiles of rural population [% of total population]									
rur_1	-0.046	0.820	18	-0.033	0.880	18	-0.132	0.484	17

	Gini			IQR			DDR		
	tau	**p-value**	**npoints**	**tau**	**p-value**	**npoints**	**tau**	**p-value**	**npoints**
rur_2	-0.147	0.434	17	-0.132	0.484	17	-0.067	0.753	16
rur_3	-0.503	0.004	18	-0.281	0.116	18	-0.309	0.091	16
rur_4	-0.346	0.049	18	-0.346	0.049	18	-0.367	0.029	17
Correlations with countries grouped by the quartiles of agricultural land [% of total area]									
agr_1	-0.111	0.545	18	-0.033	0.880	18	-0.103	0.592	17
agr_2	-0.279	0.127	17	-0.279	0.127	17	-0.283	0.137	16
agr_3	-0.124	0.495	18	-0.098	0.596	18	-0.044	0.837	17
agr_4	-0.503	0.004	18	-0.346	0.049	18	-0.368	0.044	17

5 Discussion

5.1 Vegetation residual trends in global drylands

5.1.1 Residual trends established

The vegetation residual trends in global drylands were mostly insignificant. Only 3% of the study area showed significant residual trends within a p-value of 0.05. From this, 1.65% showed negative trends, and are therefore assumed to be affected by land degradation. The positive trends could indicate recovery of vegetation due to various factors, such as recovery of soil fertility or application of fertilizers and irrigation. Many factors could cause over/under estimation of the vegetation residual trends. This is discussed in the next sections.

5.1.2 Comparison with previous studies

This study found a smaller proportion of significant residual trends compared to other studies. Various studies have estimated global land degradation to cover 15-63% of total land area and dryland degradation to cover 4-74% of the total drylands (Allan et al. 2007). In this study 3% of global drylands showed significant vegetation residual trends (with 1.14 % positive trends and 1.65 % negative trends.)

On a global scale, this study found fewer statistically significant trends, than a similar study conducted by Fensholt et al. (2012). Fensholt included both RUE and incoming solar radiation as climatic variables, thereby more accurately depicting vegetation in drylands limited by other factors than precipitation. Both positive and negative vegetation trends were found in the analysis. This agrees with studies done on global scale (sources from table 2).

The negative residual trends in Sahel established by this study, contradicts the positive vegetation trends found in the Sahel by Fensholt et al. (2012) and Swinnen et al. (2013). However, these two studies also concluded that the greening trend found in Sahel was mainly attributed to climate.

5.1.3 Possible explanations for trends

The vegetation residual trends vary in both significance and magnitude. The residual trend method can only point out areas with vegetation anomalies, which could potentially be linked to land degradation. The mechanisms behind land degradation depend on many local factors. To explain the trends found, it is necessary to refer to more localized studies of different regions.

Land degradation could be underestimated when using the restrend method. Factors that positively affect the vegetation hide the otherwise negative vegetation trend coupled with land degradation. Areas with nutrient loss and soil degradation might be hidden beneath application of fertilizers (Le et al. 2016). China, India and the United States rank highest in fertilizer consumption, and use almost ten times as much fertilizers as Africa (Le et al. 2016). Irrigation also leads to an underestimation of land degradation or even trends of vegetation recovery, since irrigation eliminates water as a limitation to plant growth. The recovering vegetation trend found in Asia can be attributed to irrigation and other human influences hiding the land degradation (Allan et al. 2007) However, northern parts of China have been suffering from land degradation for a long while, and measures have been put in place to "green" the area and this could be another explanation for the vegetation recovering trend (Zaichun et al. 2016)

The effects of CO2 fertilization can hide degraded soils. Higher levels of CO2 in the air increases the water use efficiency of plants. This means that higher CO2 will result in more biomass, and a greening trend could be from the NDVI images, eventhough the precipitation does not change. This effect could hide possible areas of land degradation. However, Fensholt et al. (2012) argue that the positive effect of CO2 fertilization is cancelled out by declining vegetation trends due to climate change.

Land-use changes might produce an increase/decrease in NDVI that does not reflect the productivity and health of an ecosystem, but a change in abundance of species in the area (Wessels et al. 2012). Furthermore, using NDVI as a proxy for land degradation fails to account for changes in species composition, which is considered by most as another sign of land degradation (Higginbottom and Symeonakis 2014).

5.2 Correlation of residual trends and inequality measure

5.2.1 Associations established

From the analysis, several correlations between vegetation residual trends and inequality were found. A negative correlation means that land degradation, represented by negative residual trend slopes correlates with high inequality values. A positive correlation means that land degradation is associated with low inequality.

Generally the three inequality measures showed similar correlations. However, the Gini coefficient resulted in the most statistically significant correlations. The Gini coefficient also showed more scattering and a higher average τ. This does not necessarily mean that the Gini coefficient is a better measure of inequality; the scattering of the Gini correlation is clearly more scattered than the other two indices in figure 7. However the IQR and DDR portray the inequality between two groups within the society, whereas the Gini coefficient looks at the whole population. That Gini correlated better with residual trends could therefore indicate that land degradation affects all groups in the society, rather than just the extremes.

The correlation over the whole study area showed a significant negative correlation. This means that in global drylands land degradation can be associated with income inequality. This correlation becomes especially convincing if only the negative residual trends are used for the correlation. When only using the positive residual trends no correlation was found, meaning that vegetation recovery could be associated with either inequality or equality depending on other factors.

When grouping by the income groups defined by the World Bank, negative correlations were found for the middle-low income group, with a significance level of 0.05. The other income groups did not show any significant results. Therefore grouping into income groups did not strengthen the understanding of the association between vegetation residual trends and inequality.

When grouping according to continents, only Africa resulted in a strong correlation, showing a negative relationship, meaning that land degradation and inequality are related for Africa. Other parts of the world might have factors unaccounted for that impacts this relationship, resulting in no correlation.

All four variables representing the countries dependence on agriculture showed significant negative relationships in the highest quintile group. This means that 25% of the countries that depend highest on agriculture show an association between land degradation and inequality measures.

As seen in the results several clusters and outliers could be mentionable. Several countries in South America do not follow the general negative association found. This could be due to some of the mentioned factors masking the effect of land degradation. Furthermore, some outliers such as Ethiopia, could show a positive association, due to land abandonment.

5.2.2 Comparison with previous studies

Previous studies indicate a relationship between other aspects and environmental degradation (Gregory et al. 2007; Holland et al. 2009; Islam 2015). However, no previous attempt to link land degradation to income inequality was found during the literature search. Many studies debate how land degradation affects society, but quantification of this is not easy (D'Odorico et al. 2013; Gerber et al. 2014; Mirzabaev et al. 2016; Nkonya et al. 2016)

5.2.3 Possible explanations for correlations

The negative correlation between residual trends and inequality measures can be explained by several potential linkages between environment and society. It has been argued that the relationship between land degradation and economic inequality is bidirectional (D'Odorico et al. 2013; Gerber et al. 2014) The following examples confirm this.

Land degradation could be a driver of poverty. It has indirect impacts on poverty, through agricultural productivity and income. It is an obstacle in reducing poverty and increasing equality since economic growth might bypass poor families coping with land degradation, especially in remote locations with limited market access (Barbier and Hochard 2016). Mirzabaev et al. (2016) found that decrease in child mortality correlated with a decrease in land degradation, showing that a decrease in poverty and inequality correlates with a decrease in land degradation. This supports the findings in this thesis.

Poverty could be a driver of land degradation. Poverty and economic mobility further affects land degradation by determining the farmers' choice of land management. Gerber et al. (2014), found poor farmers think short term, since they do not have the luxury of choosing sustainable agricultural methods that produce less yield, which suggests a negative correlation where inequality and land degradation go hand in hand. This could be supported by the negative correlation found in middle-low

income countries. However, the opposite was argued by Mirzabaev et al. (2015) and Scherr (2000). Poor farmers practice indigenous methods that are more sustainable. Conflicting arguments in the literature is supported by the lack of correlation within the income groups.

The correlation between the inequality indices and the positive residual trends did not show any significant results. In some countries, high inequality and insecurity might lead to land abandonment and rehabilitation of degraded lands. This was seen by the positive residual trends of South Sudan. In contrast, other countries, with high income and income equality, might have more room in their economy to focus on environmental problems and restoration of degraded lands.

5.3 Limitations in this study

5.3.1 Limitations in quantifying vegetation residual trends

The diverging estimations of land degradation on a global scale are far from perfect. The restrend method tends to underestimate the land degradation in some areas and overestimate in other.

Restrend assumes a linear relationship between climatic variable and vegetation (Wessels et al. 2007). Reality is more complex, a better fit for the regression might be achievable with other regression models. Furthermore, interannual variation in rainfall is still unaccounted for. This could be a problem, especially in areas affected by weather phenomena such as the oscillations, where some years would be more wet than others (Allan et al. 2007; D'Odorico et al. 2013).

Some studies suggest that the natural factors have a larger influence on the degradation of the land, than the human influence (Higginbottom and Symeonakis 2014). Therefore, assuming that the degradation trends produced by this analysis accurately depict human induced land degradation could lead to errors. Furthermore, a non-degraded reference period does not exist, so the climatic component and the land degradation component of the vegetation trend cannot be separated completely (Wessels et al. 2007).

5.3.2 Limitations with the correlation

The difference in spatial extent of the variables weakens the correlation. Vegetation residual trends were found on pixel basis with the resolution of 8 km; whereas the inequality averages could only be distinguished on a country by country basis. In order to match these two extents, an average was taken of negative and positive residual trends. When averaging, these trends could have cancelled each other out, resulting in land degradation trends close to zero.

5.4 Further studies and future perspective

The relationship between land degradation and human society needs further exploration. Impacts of land degradation could be reduced and human management of the land could be improved with better understanding of the phenomenon and its importance. In order to further explore the relationships between income inequality and land degradation, a smaller scale is needed. On a smaller scale, understanding of local conditions would allow disentanglement of causes and effects of land degradation.

The Restrend method does not capture all aspects of land degradation, it must be used together with field studies in order to get a deeper understanding of the exact magnitude of land degradation and what the main drivers in the process are (Wessels et al. 2007; Omuto et al. 2014).The restrend method is a good tool to point out land degradation/recovery "hotspots" for further study in the field (Bai et al. 2008). It is therefore the first step in assessing land degradation, that should be followed by field validation of the magnitude of land degradation.

6 Conclusion

This thesis made the attempt to link land degradation and inequality by the help of two objectives.

Objective 1: Vegetation residual trends were quantified throughout global drylands. Due to limitations of the method and interannual variations, only 3% of the area had significant trends

Objective 2: The correlation between the vegetation residual slopes and income inequality averages showed significant negative correlations, meaning that land degradation and inequality goes hand in hand.

The null hypotheses can be rejected. A significant correlation was found between a land degradation proxy and income inequality measures. Land degradation and human society can be associated with each other. The further exploration of this relationship within different groupings did not yield any convincing result. The next question is what is the nature of this relationship? Does land degradation lead to inequality and poverty or does inequality and poverty lead to land degradation? Further studies into the drivers and consequences of land degradation could provide inside into these questions.

This thesis found quantifiable evidence for the hypothesis that land degradation and economic inequality are related. This underlines the importance to tackle the problems of land degradation and economic inequality simultaneously, as they are linked.

7 Acknowledgements

I would like to thank my supervisor Jonathan Seaquist at Lund University for guiding me throughout the process of outlining, analyzing and writing this thesis. Secondly, I would like to thank my opponent Caroline Hall and my examinators Ulrik Mårtensson and Petter Pilesjö. Their comments and constructive criticism has helped me improve my performance. Thirdly, I would like to thank the whole department of Physical geography and ecosystem science at Lunds University for three great years, where I have had the opportunity to learn, develop and expand my horizon within the field. Finally, I would like to thank my classmates for accompanying me these past three years and for supporting me both academically and socially.

8 References

Alfonso, H., M. LaFleur, and D. Alarcón. 2015. Inequality Measurement. Development Issues.

Allan, R., U. Förstner, W. Salomons, M. V. K. Sivakumar, N. Ndiang'ui, and U. N. Safriel. 2007. The Assessment of Global Trends in Land Degradation. 1.

Bai, Z. G., D. L. Dent, L. Olsson, and M. E. Schaepman. 2008. - Proxy global assessment of land degradation. - 24**:** - 234.

Barbier, E. B., and J. P. Hochard. 2016. Does Land Degradation Increase Poverty in Developing Countries? *PLOS ONE*, 11**:** e0152973. DOI: 10.1371/journal.pone.0152973

Barbier, E. B., P. Sanchez, R. Thomas, and A. Wagner. 1997. The Economic Determinants of Land Degradation in Developing Countries [and Discussion]. 891. The Royal Society.

Beck, H. E., T. R. McVicar, A. van Dijk, J. Schellekens, R. A. M. de Jeu, and L. A. Bruijnzeel. 2011. - Global evaluation of four AVHRR-NDVI data sets: Intercomparison and assessment against Landsat imagery. - 115**:** - 2563.

Becker, A., P. Finger, A. Meyer-Christoffer, B. Rudolf, K. Schamm, U. Schneider, and M. Ziese. 2013. - A description of the global land-surface precipitation data products of the Global Precipitation Climatology Centre with sample applications including centennial (trend) analysis from 1901-present. - 5**:** - 99.

D'Odorico, P., A. Bhattachan, K. F. Davis, S. Ravi, and C. W. Runyan. 2013. - Global desertification: Drivers and feedbacks. - 51**:** - 344.

De Jong, R., S. De Bruin, M. Schaepman, and D. Dent. 2011. Quantitative mapping of global land degradation using earth observations. *International Journal of Remote Sensing*, 32**:** 6823-6853. DOI: DOI: 10.1080/01431161.2010.512946.

Evans, J., and R. Geerken. 2004. Discrimination between climate and human-induced dryland degradation. *Journal of Arid Environments*, 57**:** 535-554. DOI: 10.1016/S0140-1963(03)00121-6

Feng, S., and Q. Fu. 2013. - Expansion of global drylands under a warming climate. - 13**:** - 10094.

Fensholt, R., T. Langanke, K. Rasmussen, A. Reenberg, S. D. Prince, C. Tucker, R. J. Scholes, Q. B. Le, et al. 2012. Greenness in semi-arid areas across the globe 1981-2007 - an Earth Observing Satellite based analysis of trends and drivers. *Remote Sensing of Environment*, 121**:** 144-158. DOI: 10.1016/j.rse.2012.01.017

Fensholt, R., and S. R. Proud. 2012. Evaluation of Earth Observation based global long term vegetation trends - Comparing GIMMS and MODIS global NDVI time series. *Remote Sensing of Environment*, 119**:** 131-147. DOI: 10.1016/j.rse.2011.12.015

Gerber, N., J. Von Braun, and E. Nkonya. 2014. *Land degradation, poverty and marginality*. Springer Netherlands.

Gregory, M. M., G. Andrew, and D. P. Garry. 2007. Economic inequality predicts biodiversity loss. *PLoS ONE, Vol 2, Iss 5, p e444 (2007)***:** e444. DOI: 10.1371/journal.pone.0000444

Grepperud, S. 1997. Poverty, Land Degradation and Climatic Uncertainty. 586. Oxford University Press.

Haughton, J., and S. Khandker. 2009. Handbook on Poverty and Inequality Chapter 6: inequality measures. *World Bank*.

Hazell, P., and S. Wood. 2008. Drivers of change in global agriculture. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 363**:** 495-515. DOI: 10.1098/rstb.2007.2166

Higginbottom, T. P., and E. Symeonakis. 2014. - Assessing Land Degradation and Desertification Using Vegetation Index Data: Current Frameworks and Future Directions. - 6**:** - 9575.

Holland, T. G., G. D. Peterson, and A. Gonzalez. 2009. A Cross-National Analysis of How Economic Inequality Predicts Biodiversity Loss. *Conservation Biology,* 23**:** 1304-1313. DOI: 10.1111/j.1523-1739.2009.01207.x

Huang, J., H. Yu, X. Guan, G. Wang, and R. Guo. 2016. Accelerated dryland expansion under climate change. *Nature Climate Change,* 6**:** 166-171. DOI: 10.1038/nclimate2837

Ibrahim, Y. Z., H. Balzter, J. Kaduk, and C. J. Tucker. 2015. Land Degradation Assessment Using Residual Trend Analysis of GIMMS NDVI3g, Soil Moisture and Rainfall in Sub-Saharan West Africa from 1982 to 2012. *Remote Sensing,* 7**:** 5471-5494. DOI: DOI: 10.3390/rs70505471.

Islam, N. S. 2015. Inequality and environmental sustainability. *DESA Working paper*.

Khaldoun, R., and D. P. Stephen. 2016. Environmental and Anthropogenic Degradation of Vegetation in the Sahel from 1982 to 2006. *Remote Sensing, Vol 8, Iss 11, p 948 (2016)***:** 948. DOI: 10.3390/rs8110948

Kundu, A., N. R. Patel, S. K. Saha, and D. Dutta. 2017. Desertification in western Rajasthan (India): an assessment using remote sensing derived rain-use efficiency and residual trend methods. *Natural Hazards,* 86**:** 297-313. DOI: 10.1007/s11069-016-2689-y

Le, Q. B., E. Nkonya, and A. Mirzabaev. 2016. Biomass Productivity-Based Mapping of Global Land Degradation Hotspots. *Economics of Land Degradation & Improvement - A Global Assessment for Sustainable Development***:** 55.

Mirzabaev, A., E. Nkonya, J. Goedecke, T. Johnson, and W. Anderson. 2016. Global Drivers of Land Degradation and Improvement. In *Economics of Land Degradation and Improvement – A Global Assessment for Sustainable Development,* eds. E. Nkonya, A. Mirzabaev, and J. von Braun, 167-195. Cham: Springer International Publishing.

Mirzabaev, A., E. Nkonya, and J. von Braun. 2015. Economics of sustainable land management. *Current Opinion in Environmental Sustainability,* 15**:** 9-19. DOI: 10.1016/j.cosust.2015.07.004

Nachtergaele, F., R. Biancalani, M. Petri, and S. Bunning. 2013. Land degradation assessment in drylands - methodology and results.

Nicholson, S. E., M. L. Davenport, and A. R. Malo. 1990. A comparison of the vegetation response to rainfall in the Sahel and East Africa, using normalized difference vegetation index from NOAA AVHRR. *Climatic Change,* 17**:** 209-241. DOI: 10.1007/BF00138369

Nkonya, E., A. Mirzabaev, and J. von Braun. 2016. Economics of Land Degradation and Improvement: An Introduction and Overview. In *Economics of Land Degradation and Improvement – A Global Assessment for Sustainable Development,* eds. E. Nkonya, A. Mirzabaev, and J. von Braun, 1-14. Cham: Springer International Publishing.

Omuto, C. T., Z. Balint, and M. S. Alim. 2014. A FRAMEWORK FOR NATIONAL ASSESSMENT OF LAND DEGRADATION IN THE DRYLANDS: A CASE STUDY OF SOMALIA. *Land Degradation & Development,* 25**:** 105.

Omuto, C. T., R. R. Vargas, M. S. Alim, and P. Paron. 2010. Mixed-effects modelling of time series NDVI-rainfall relationship for detecting human-induced loss of vegetation cover in drylands. *Journal of Arid Environments,* 74**:** 1552-1563. DOI: 10.1016/j.jaridenv.2010.04.001

Pravalie, R. 2016. Drylands extent and environmental issues; a global approach. *Earth-Science Reviews,* 161**:** 259-278. DOI: 10.1016/j.earscirev.2016.08.003

Prince, S. D., K. J. Wessels, C. J. Tucker, and S. E. Nicholson. 2007. - Desertification in the Sahel: a reinterpretation of a reinterpretation. - 13**:** - 1313.

Reynolds, J. F., D. M. S. Smith, E. F. Lambin, B. L. Turner, M. Mortimore, S. P. J. Batterbury, T. E. Downing, H. Dowlatabadi, et al. 2007. Global Desertification: Building a Science for Dryland Development. 847. American Association for the Advancement of Science.

Rogerson, P. A. 2013. The Gini coefficient of inequality: a new interpretation. *Letters in Spatial and Resource Sciences*: 1-12. DOI: 10.1007/s12076-013-0091-x

Scherr, S. J. 2000. A downward spiral? Research evidence on the relationship between poverty and natural resource degradation. *Food Policy*, 25: 479-498. DOI: 10.1016/S0306-9192(00)00022-1

Schneider, U., A. Becker, P. Finger, A. Meyer-Christoffer, B. Rudolf, and M. Ziese. 2015. GPCC Full Data Reanalysis Version 7.0 at 0.5: Monthly Land-Surface Precipitation from Rain-Gauges built on GTS-based and Historic Data. . In *FD_M_V7_050*, ed. h. g. d. d. a. D. W. Global Precipitation Climatology Centre (GPCC.

Svensson, L. 2007. Socio-economic indicators for causes and consequences of land degradation.

Swinnen, E., S. Horion, P. Kaspersen, S. Huber, R. Fensholt, and K. Rasmussen. 2013. Assessing Land Degradation/Recovery in the African Sahel from Long-Term Earth Observation Based Primary Productivity and Precipitation Relationships. *Remote Sensing, Vol 5, Iss 2, Pp 664-686 (2013)*: 664. DOI: 10.3390/rs5020664

Tian, F., R. Fensholt, J. Verbesselt, K. Grogan, S. Horion, and Y. Wang. 2015. Evaluating temporal consistency of long-term global NDVI datasets for trend analysis. *Remote Sensing of Environment*, 163: 326-340. DOI: 10.1016/j.rse.2015.03.031

Trabucco, A., R. J. Zomer, D. A. Bossio, O. van Straaten, and L. V. Verchot. 2008. Climate change mitigation through afforestation/reforestation: A global analysis of hydrologic impacts with four case studies. *Agriculture, Ecosystems & Environment*, 126: 81-97. DOI: https://doi.org/10.1016/j.agee.2008.01.015

Trust, T. E. 2011. Income inequality: Trends and Measures. *Equality Trust Research Digest*, 2: 1-8.

Tucker, C. J., J. E. Pinzon, M. E. Brown, D. A. Slayback, E. W. Pak, R. Mahoney, E. F. Vermote, and N. El Saleous. 2005. An extended AVHRR 8-km NDVI dataset compatible with MODIS and SPOT vegetation NDVI data. *International Journal of Remote Sensing*, 26: 4485.

UNEP, N. M., and David S. G. Thomas. 1997. *World atlas of desertification* London: Arnold.

UNU-WIDER. 2017. World income inequality database (WIID 3.4).

Vu, Q. M., Q. B. Le, and P. L. G. Vlek. 2014. Hotspots of human-induced biomass productivity decline and their social-ecological types toward supporting national policy and local studies on combating land degradation. *Global and Planetary Change*, 121: 64-77. DOI: 10.1016/j.gloplacha.2014.07.007

Wessels, K. J., S. D. Prince, J. Malherbe, J. Small, P. E. Frost, and D. VanZyl. 2007. Can human-induced land degradation be distinguished from the effects of rainfall variability? A case study in South Africa. *Journal of Arid Environments*, 68: 271-297. DOI: 10.1016/j.jaridenv.2006.05.015

Wessels, K. J., F. van den Bergh, and R. J. Scholes. 2012. - Limits to detectability of land degradation by trend analysis of vegetation index data. - 125: - 22.

Zaichun, Z., P. Shilong, R. B. Myneni, H. Mengtian, Z. Zhenzhong, J. G. Canadell, P. Ciais, S. Sitch, et al. 2016. Greening of the Earth and its drivers. *Nature Climate Change*, 6: 791-795. DOI: .DOI: 10.1038/nclimate3004.

Zomer, R. J., A. Trabucco, D. A. Bossio, and L. V. Verchot. 2008. Climate change mitigation: A spatial analysis of global land suitability for clean development mechanism afforestation and

reforestation. *Agriculture, Ecosystems & Environment*, 126**:** 67-80. DOI: https://doi.org/10.1016/j.agee.2008.01.014

9 Appendix

Appendix 1: formulas used in this thesis

Equation 1: Formula to calculate NDVI from satellite images

$$NDVI = \frac{Near\ Infrared\ Radiation - Visible\ radiation}{Near\ Infrared\ Radiation + Visible\ radiation}$$

Equation 2: Formula used to calculate the income quintile ratio from World Bank data

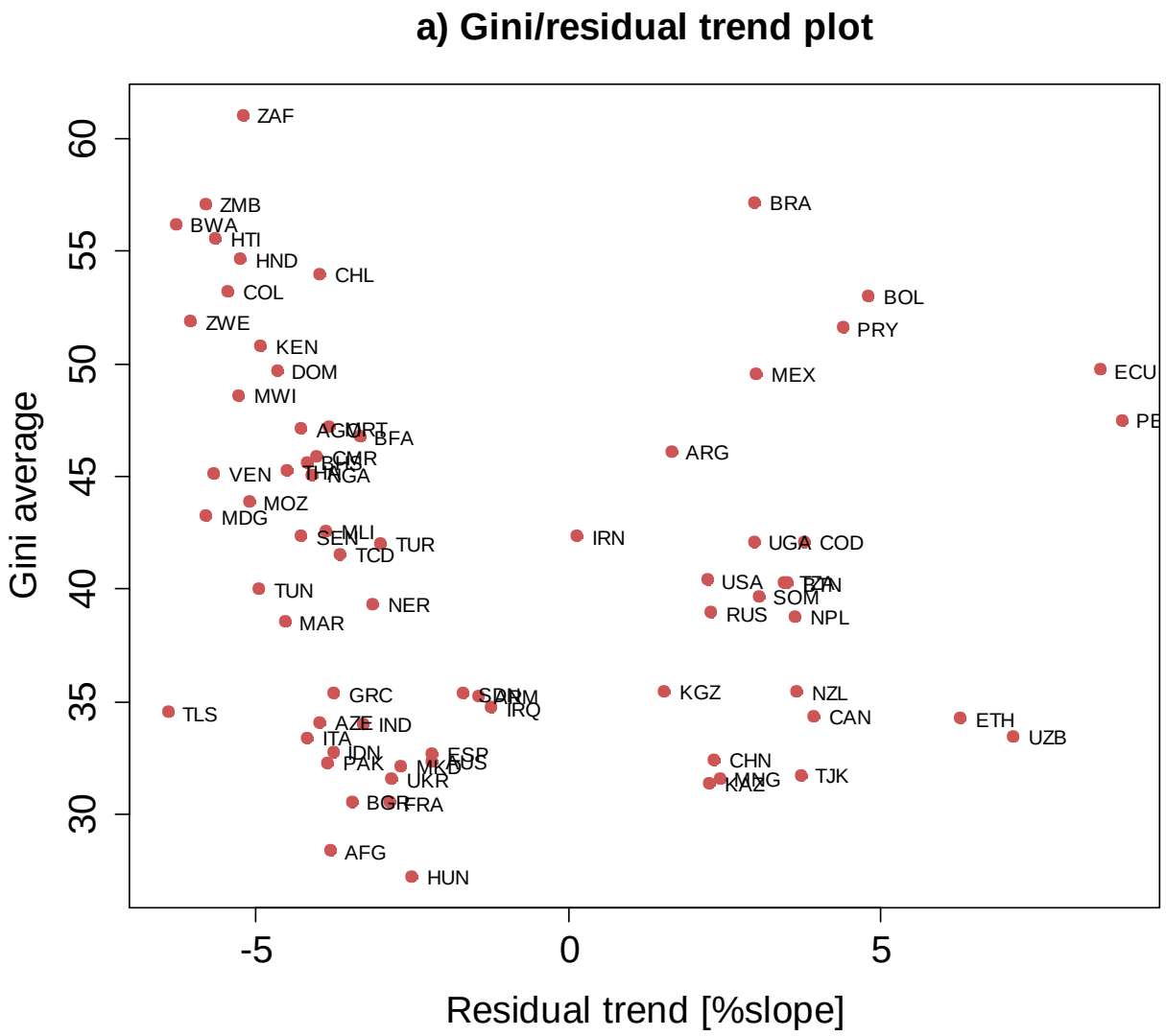
$$IQR = \frac{richest\ quintile\ of\ accumulated\ income\ distribution}{poorest\ quintile\ of\ accumulated\ income\ distribution}$$

Equation 3: Formula used to calculate the decile dispersion ratio from World Bank data

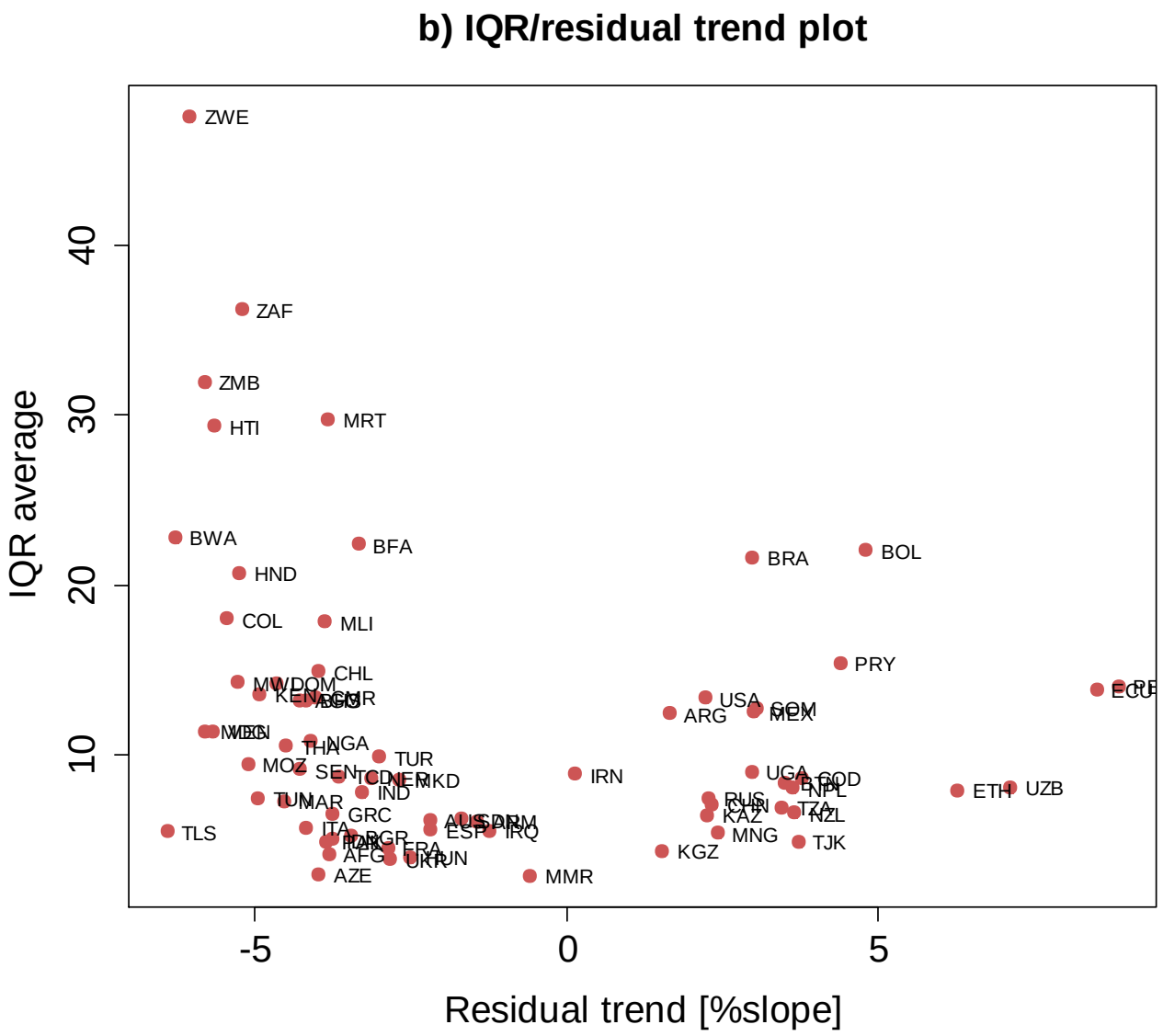
$$DDR = \frac{richest\ decile\ of\ accumulated\ income\ distribution}{poorest\ decile\ of\ accumulated\ income\ distribution}$$

Appendix 2A: More detailed version of figure 5. The ISO (see appendix 3) is included to label points.

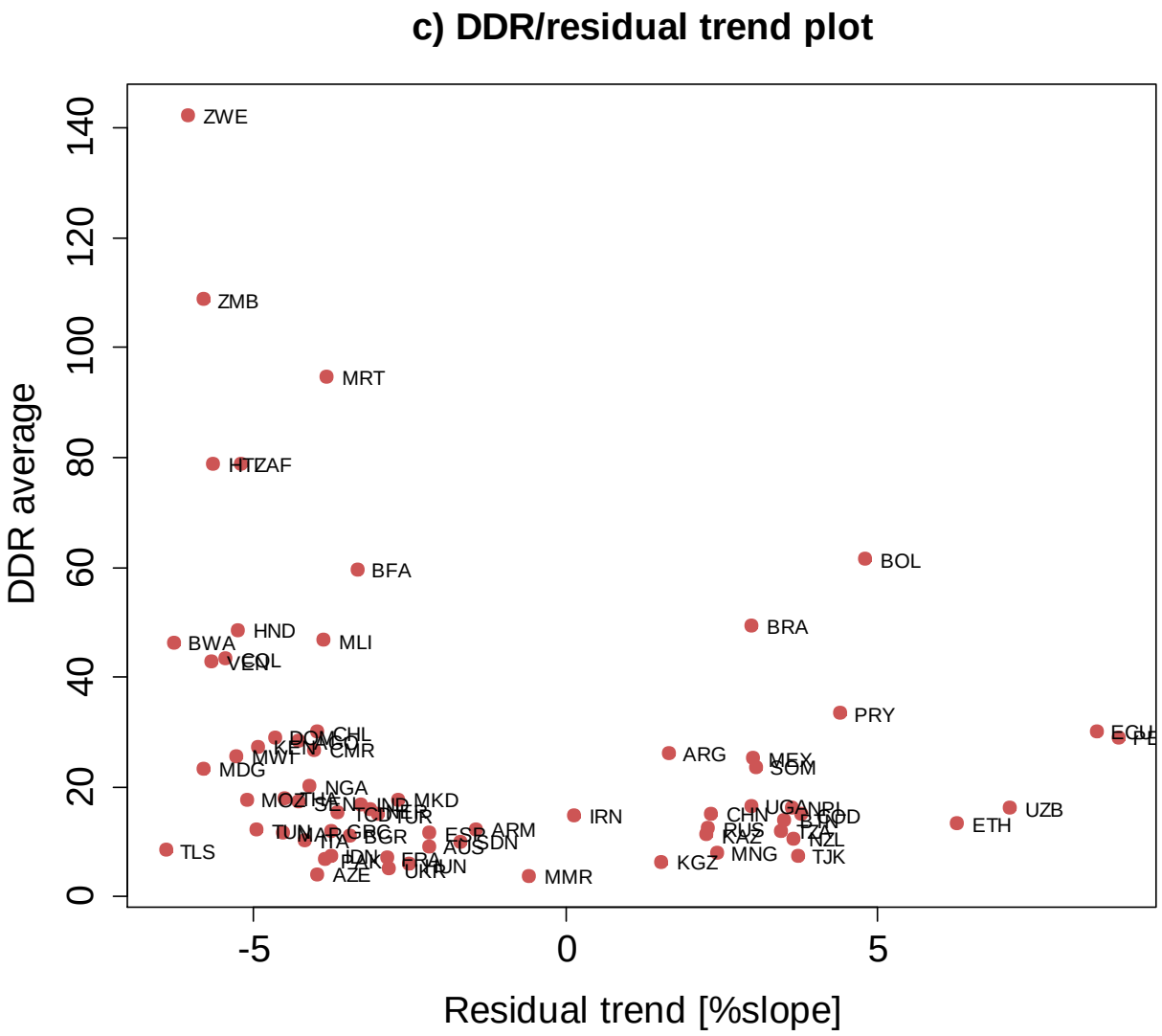
A) Gini coefficient plotted against residual slopes



Appendix 2B: More detailed version of figure 5. The ISO (see appendix 3) is included to label points. B) IQR coefficient plotted against residual slopes



Appendix 2C: More detailed version of figure 5. The ISO (see appendix 3) is included to label points. C) IQR coefficient plotted against residual slopes



Appendix 3: country names and abbreviations.

Source: https://unstats.un.org/unsd/tradekb/Knowledgebase/Country-Code

ABW Aruba
AFG Afghanistan
AGO Angola
AIA Anguilla
ALA Åland Islands
ALB Albania
AND Andorra
ANT Netherlands Antilles
ARE United Arab Emirates
ARG Argentina
ARM Armenia
ASM American Samoa
ATA Antarctica
ATF French Southern Territories
ATG Antigua and Barbuda
AUS Australia
AUT Austria
AZE Azerbaijan
BDI Burundi
BEL Belgium
BEN Benin
BFA Burkina Faso
BGD Bangladesh
BGR Bulgaria
BHR Bahrain
BHS Bahamas
BIH Bosnia and Herzegovina
BLM Saint Barthélemy
BLR Belarus
BLZ Belize
BMU Bermuda
BOL Bolivia
BRA Brazil
BRB Barbados
BRN Brunei Darussalam
BTN Bhutan
BVT Bouvet Island
BWA Botswana
CAF Central African Republic
CAN Canada
CCK Cocos (Keeling) Islands
CHE Switzerland
CHL Chile
CHN China
CIV Côte d'Ivoire
CMR Cameroon
COD Congo, the Democratic Republic of the
COG Congo
COK Cook Islands
COL Colombia
COM Comoros
CPV Cape Verde
CRI Costa Rica
CUB Cuba
CXR Christmas Island
CYM Cayman Islands
CYP Cyprus
CZE Czech Republic
DEU Germany
DJI Djibouti
DMA Dominica
DNK Denmark
DOM Dominican Republic
DZA Algeria
ECU Ecuador
EGY Egypt
ERI Eritrea
ESH Western Sahara
ESP Spain
EST Estonia
ETH Ethiopia
FIN Finland
FJI Fiji
FLK Falkland Islands (Malvinas)
FRA France
FRO Faroe Islands
FSM Micronesia, Federated States of
GAB Gabon
GBR United Kingdom
GEO Georgia
GGY Guernsey
GHA Ghana
GIB Gibraltar
GIN Guinea
GLP Guadeloupe
GMB Gambia
GNB Guinea-Bissau
GNQ Equatorial Guinea
GRC Greece
GRD Grenada
GRL Greenland
GTM Guatemala
GUF French Guiana
GUM Guam
GUY Guyana
HKG Hong Kong
HMD Heard Island and McDonald Islands
HND Honduras
HRV Croatia
HTI Haiti
HUN Hungary
IDN Indonesia
IMN Isle of Man
IND India
IOT British Indian Ocean Territory
IRL Ireland
IRN Iran, Islamic Republic of
IRQ Iraq
ISL Iceland
ISR Israel
ITA Italy
JAM Jamaica
JEY Jersey
JOR Jordan
JPN Japan
KAZ Kazakhstan
KEN Kenya
KGZ Kyrgyzstan
KHM Cambodia
KIR Kiribati
KNA Saint Kitts and Nevis
KOR Korea, Republic of
KWT Kuwait
LAO Lao People's Democratic Republic
LBN Lebanon
LBR Liberia
LBY Libyan Arab Jamahiriya

LCA Saint Lucia
LIE Liechtenstein
LKA Sri Lanka
LSO Lesotho
LTU Lithuania
LUX Luxembourg
LVA Latvia
MAC Macao
MAF Saint Martin (French part)
MAR Morocco
MCO Monaco
MDA Moldova, Republic of
MDG Madagascar
MDV Maldives
MEX Mexico
MHL Marshall Islands
MKD Macedonia, the former Yugoslav Republic of
MLI Mali
MLT Malta
MMR Myanmar
MNE Montenegro
MNG Mongolia
MNP Northern Mariana Islands
MOZ Mozambique
MRT Mauritania
MSR Montserrat
MTQ Martinique
MUS Mauritius
MWI Malawi
MYS Malaysia
MYT Mayotte
NAM Namibia
NCL New Caledonia
NER Niger
NFK Norfolk Island
NGA Nigeria
NIC Nicaragua
NIU Niue
NLD Netherlands
NOR Norway
NPL Nepal
NRU Nauru
NZL New Zealand
OMN Oman
PAK Pakistan
PAN Panama
PCN Pitcairn
PER Peru
PHL Philippines
PLW Palau
PNG Papua New Guinea
POL Poland
PRI Puerto Rico
PRK Korea, Democratic People's Republic of
PRT Portugal
PRY Paraguay
PSE Palestinian Territory, Occupied
PYF French Polynesia
QAT Qatar
REU Réunion
ROU Romania
RUS Russian Federation
RWA Rwanda
SAU Saudi Arabia
SDN Sudan
SEN Senegal
SGP Singapore
SGS South Georgia and the South Sandwich Islands
SHN Saint Helena, Ascension and Tristan da Cunha
SJM Svalbard and Jan Mayen
SLB Solomon Islands
SLE Sierra Leone
SLV El Salvador
SMR San Marino
SOM Somalia
SPM Saint Pierre and Miquelon
SRB Serbia
STP Sao Tome and Principe
SUR Suriname
SVK Slovakia
SVN Slovenia
SWE Sweden
SWZ Swaziland
SYC Seychelles
SYR Syrian Arab Republic
TCA Turks and Caicos Islands
TCD Chad
TGO Togo
THA Thailand
TJK Tajikistan
TKL Tokelau
TKM Turkmenistan
TLS Timor-Leste
TON Tonga
TTO Trinidad and Tobago
TUN Tunisia
TUR Turkey
TUV Tuvalu
TWN Taiwan, Province of China
TZA Tanzania, United Republic of
UGA Uganda
UKR Ukraine
UMI United States Minor Outlying Islands
URY Uruguay
USA United States
UZB Uzbekistan
VAT Holy See (Vatican City State)
VCT Saint Vincent and the Grenadines
VEN Venezuela, Bolivarian Republic of
VGB Virgin Islands, British
VIR Virgin Islands, U.S.
VNM Viet Nam
VUT Vanuatu
WLF Wallis and Futuna
WSM Samoa
YEM Yemen
ZAF South Africa
ZMB Zambia
ZWE Zimbabwe

Institutionen för naturgeografi och ekosystemvetenskap, Lunds Universitet.

Student examensarbete (Seminarieuppsatser). Uppsatserna finns tillgängliga på institutionens geobibliotek, Sölvegatan 12, 223 62 LUND. Serien startade 1985. Hela listan och själva uppsatserna är även tillgängliga på LUP student papers (https://lup.lub.lu.se/student-papers/search/) och via Geobiblioteket (www.geobib.lu.se)

The student thesis reports are available at the Geo-Library, Department of Physical Geography and Ecosystem Science, University of Lund, Sölvegatan 12, S-223 62 Lund, Sweden. Report series started 1985. The complete list and electronic versions are also electronic available at the LUP student papers (https://lup.lub.lu.se/student-papers/search/) and through the Geo-library (www.geobib.lu.se)

400 Sofia Sjögren (2016) Effective methods for prediction and visualization of contaminated soil volumes in 3D with GIS

401 Jayan Wijesingha (2016) Geometric quality assessment of multi-rotor unmanned aerial vehicle-borne remote sensing products for precision agriculture

402 Jenny Ahlstrand (2016) Effects of altered precipitation regimes on bryophyte carbon dynamics in a Peruvian tropical montane cloud forest

403 Peter Markus (2016) Design and development of a prototype mobile geographical information system for real-time collection and storage of traffic accident data

404 Christos Bountzouklis (2016) Monitoring of Santorini (Greece) volcano during post-unrest period (2014-2016) with interferometric time series of Sentinel-1A

405 Gea Hallen (2016) Porous asphalt as a method for reducing urban storm water runoff in Lund, Sweden

406 Marcus Rudolf (2016) Spatiotemporal reconstructions of black carbon, organic matter and heavy metals in coastal records of south-west Sweden

407 Sophie Rudbäck (2016) The spatial growth pattern and directional properties of *Dryas octopetala* on Spitsbergen, Svalbard

408 Julia Schütt (2017) Assessment of forcing mechanisms on net community production and dissolved inorganic carbon dynamics in the Southern Ocean using glider data

409 Abdalla Eltayeb A. Mohamed (2016) Mapping tree canopy cover in the semi-arid Sahel using satellite remote sensing and Google Earth imagery

410 Ying Zhou (2016) The link between secondary organic aerosol and monoterpenes at a boreal forest site

411 Matthew Corney (2016) Preparation and analysis of crowdsourced GPS bicycling data: a study of Skåne, Sweden

412 Louise Hannon Bradshaw (2017) Sweden, forests & wind storms: Developing a model to predict storm damage to forests in Kronoberg county

413 Joel D. White (2017) Shifts within the carbon cycle in response to the absence of keystone herbivore *Ovibos moschatus* in a high arctic mire

414 Kristofer Karlsson (2017) Greenhouse gas flux at a temperate peatland: a comparison of the eddy covariance method and the flux-gradient method

415 Md. Monirul Islam (2017) Tracing mangrove forest dynamics of Bangladesh using historical Landsat data

416 Bos Brendan Bos (2017) The effects of tropical cyclones on the carbon cycle

417 Martynas Cerniauskas (2017) Estimating wildfire-attributed boreal forest burn in Central and Eastern Siberia during summer of 2016

418 Number reserved for BSc thesis

419 Clara Kjällman (2017) Changing landscapes: Wetlands in the Swedish municipality Helsingborg 1820-2016

420 Raluca Munteanu (2017) The effects of changing temperature and precipitation rates on free-living soil Nematoda in Norway.

422 Petra Oberhollenzer, (2017) Reforestation of Alpine Grasslands in South Tyrol: Assessing spatial changes based on LANDSAT data 1986-2016

423 Femke, Pijcke (2017) Change of water surface area in northern Sweden

424 Alexandra Pongracz (2017) Modelling global Gross Primary Production using the correlation between key leaf traits

425 Marie Skogseid (2017) Climate Change in Kenya

426 Ida Pettersson (2017) Ekologisk kompensation och habitatbanker i kommunalt planarbete

427 Denice Adlerklint (2017) Climate Change Adaptation Strategies for Urban Stormwater Management – A comparative study of municipalities in Scania

428 Johanna Andersson (2017) Using geographically weighted regression (GWR) to explore spatial variations in the relationship between public transport accessibility and car use : a case study in Lund and Malmö, Sweden

429 Elisabeth Farrington (2017) Investigating the spatial patterns and climate dependency of Tick-Borne Encephalitis in Sweden

430 Maja Jensen (2017) Hydrology and surface water chemistry in a small forested catchment : which factors influence surface water acidity?

421 Neija Maegaard Elvekjær (2017) Assessing Land degradation in global drylands and possible linkages to socio-economic inequality