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Characterising Turning Points and Their Drivers in Moroccan Dryland Ecosystems Over the Last 20 Years

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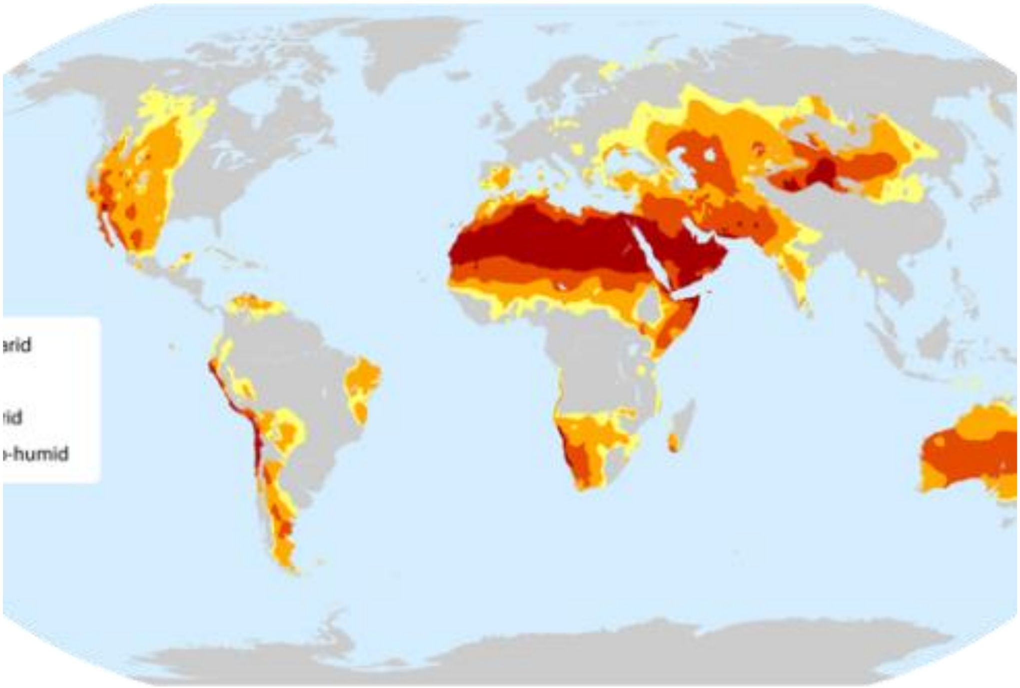

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Characterising Turning Points and Their Drivers in Moroccan Dryland Ecosystems Over the Last 20 Years

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Acknowledgements

This master thesis report is the result of a six months study on ecosystem functioning in Moroccan drylands. More specifically, identifying turning points and characterising their drivers. The research consists of a technological part and an explanatory part. Respectively, using remotely sensed data as a source of information and using informed judgement as a source of information. For me personally, this report reflects my interest in remote sensing, migration, social geography and explanatory analysis, as well as a combination of them all.

My recognition goes out to Paulo Bernardino MSc from the Wageningen University and Research, for his practical suggestions, continuous feedback and brainstorming sessions. I also want to thank Dr. Nandika Tsendbazar and Dr.ir. Jan Verbesselt, also both from the Wageningen University and Research, for their supervision, constructive criticism and valuable advice during meetings.

I gratefully acknowledge Prof.dr. Hein de Haas, from the University of Amsterdam, for his extensive knowledge and inspiring lectures regarding migration studies. His lectures very much sparked my interest in migration studies, which led to the combination of remote sensing and migration as part of this thesis.

On a personal note, I want to thank my girlfriend for her unconditional support and resilience throughout these tumultuous months; *sumus inseperabilia.*

Finally, I want to thank my parents for their love and for being a source of inspiration ever since. Thank you both, this one is for you.

Rick Heger

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Abstract

Among the Sustainable Development Goals (SDG), SDG 15.3: "end desertification and restore degraded land" is of great importance, yet challenging, for drylands all over the world. Especially in Morocco, of which a vast area is dryland, and thus vulnerable to desertification and land degradation. By understanding turning points (i.e., key moments in the ecosystem development where its functioning is significantly changed or altered) in Moroccan dryland ecosystem functioning and their effects on desertification and land degradation, valuable information is produced for better dryland ecosystem conservation.

This research aimed to (1) identify and classify turning points in Moroccan dryland ecosystem functioning and (2) to establish a relationship between turning points and their drivers. Moreover, this research intended to (3) identify and classify abrupt changes in vegetation greenness trends on a sub-national scale, namely in the Todgha valley, and to investigate the explanatory value of migration to characterise the detected changes.

By applying BFAST01 (a time series segmentation technique) on a 19-year rain-use efficiency time series, turning points were detected. Next, a typology developed for the classification of turning points was used to characterize ecosystem functioning changes in Moroccan drylands. Results showed a hotspot of turning points in the northern part of Morocco, in 2009, encompassing the Moulouya River basin. The majority of turning points (63.2%) were characterized by a steady increase in ecosystem functioning up to the turning point occurrence, after which the increase in ecosystem functioning slowed down. The Hassan II dam might explain the occurrences of these turning points, as the dam possibly led to a reduction of water availability downstream.

Further analysis, by means of a binary logistic regression, showed that a combination of proximate (i.e., cropland abandonment, changes in sparse herbaceous land cover, and built-up expansions) and underlying causes (i.e., the occurrence of abnormally dry months and population density increase) had influence over the probability of a turning point occurrence in Moroccan dryland ecosystem functioning. However, the model resulted in a McFadden pseudo-R^2 of only 0.015, so interpretation should be done with care.

Moreover, by applying BFAST01 on a 20-year NDVI time series and classifying the outputs, similarly to what was done with the rain-use efficiency data, the identification and classification of abrupt changes in vegetation greenness trends was performed. Abrupt changes were detected across the whole Todgha valley in a very patchy pattern, with a peak in the year intervals of 2005 – 2006, 2009 – 2010, and 2013 – 2014. The impact of migration on the

detected abrupt changes was found to be substantial. Migration and the accompanied remittances lead to local development in the form of investments in diesel pumps for agriculture. People who receive remittances have the ability to continue or expand their agriculture activities, which likely results in positive vegetation greenness trends, while the opposite case can potentially lead to negative vegetation greenness trends.

Keywords: abrupt changes, rain-use efficiency, ecosystem functioning, turning point, drylands, drivers.

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1. Introduction

1.1 Background

Drylands are, defined by the United Nations, land areas with one specific characteristic: the low amount of precipitation they receive (United Nations Environment Programme, 2011). Drylands cover approximately 40% of the total earth surface and give a place to live for over two billion people. After Asia, Africa has the highest percentage of its population living in drylands (42% and 41%, respectively; Reynolds et al., 2007). Drylands also account for roughly 40% of the global net primary productivity (Wang et al. 2012), the energy stored in biomass by vegetation and used by the ecosystem. They are located in the dry sub-humid, semi-arid and arid climates of the world. In terms of carbon storage efficiency, drylands are as efficient as humid areas (Laban et al., 2018). Global climate change, human activities, and severe droughts in the Sahel region have led to a significant increase in scientific interest in dryland ecosystems and their functioning both in the Sahel region and around the globe (Fensholt et al., 2015b). The biophysical characters of drylands, dependent on precipitation and vulnerable to drought, makes this type of ecosystem vulnerable for human-induced soil degradation and anthropogenic activities (Saco et al., 2018; Zika & Erb, 2009).

These vulnerabilities can lead to abrupt changes in dryland ecosystems functioning. Abrupt changes in ecosystem functioning are changes that occur over a short period of time, with respect to the nominal rates of change, and can be identified by detecting turning points. Turning points are key moments in the ecosystem development where its functioning is significantly changed or altered (Horion et al., 2016). By identifying turning points in dryland ecosystems functioning and characterising the drivers of these turning points, a contribution to the Sustainable Development Goals (SDG) of the United Nations can be made, in particular to SDG-15.3: end desertification and restore degraded land (United Nations, 2017). Research by de Jong, Verbesselt, et al. (2012) and de Jong, Verbesselt, et al. (2013) revealed that, between 1982 and 2008, the global area with greening trends was decreasing, while the global area with browning trends increased. This increase in browning trends suggest a decline in vegetation activity in dryland ecosystems. However, other studies (Dardel et al., 2014; Eklundh & Olsson, 2003; Heumann et al., 2007) showed particular greening in the Sahel region, paradoxically.

Drivers of these changes in dryland ecosystems emerge as naturogenic and anthropogenic, which are both of importance when analysing drivers of ecosystem change. Knowing the drivers of change is important in order to mitigate the effects of desertification and land degradation. Policies with an aim on, for example, land management, water management, and agriculture could benefit from a clear view on the most important drivers of change.

A country that is vulnerable to desertification and land degradation, due to the presence of large dryland areas, is Morocco. Next to the large dryland areas in Morocco which have an important role in shaping the country, emigration (i.e., leaving the country of origin) and its associated effect on land cover change has been paramount in shaping Morocco's society (Castles et al., 2013). As a result, arable and irrigated land will be abandoned, which makes it vulnerable to turning points. Compared with the positive net-migration of 80,000 in The Netherlands in 2017, Morocco presented a net-migration of -257,096 in the same year (The World Bank, 2019). An area within Morocco which consists of large dryland areas and present an inherent nature of migration patterns is the Todgha valley (de Haas, 2003). These two factors makes the Todgha valley an interesting area to investigate.

1.2 Problem definition

Several global scale studies (de Jong, Schaepman, et al., 2013; IPCC, 2007; Li et al., 2012; Maestre et al., 2012) have shown that climate change is a major driver of the changes in vegetation trends over the course of time, potentially leading to desertification and land degradation.

Besides natural drivers, more and more research focusses on anthropogenic drivers of change in dryland ecosystems. A previous study carried out by Lioubimtseva and Henebry (2009) indicated that water, demanded for irrigation, leads to human-induced desertification of drylands in Central-Asia. Fensholt, et al. (2014) have shown that human factors influence the NDVI trends. Especially on a smaller scale, it is important to take human factors into account. This is also suggested by others (Bégué, Vintrou, Ruelland, Claden, & Dessay, 2011; Seaquist, Olsson, Ardö, & Eklundh, 2006). Yet, the complex relation between changing vegetation trends, climate change, human impact (e.g., migration, population density, land management) and other drivers has to be established. This is also advocated by others as a relevant field of study (Bürgi et al., 2010; de Jong, Verbesselt, et al., 2013; Fensholt et al., 2015a; Levick & Rogers, 2011; Sohl et al., 2010). However, in depth studies of this complex relation have not been performed before at a national scale, such as Morocco.

The GIMMS Normalized Difference Vegetation Index (NDVI) from the Advanced Very High Resolution Radiometer (AVHRR) sensors has been the standard NDVI product to detect turning points in multiple studies (Dardel et al., 2014; Fensholt et al., 2013, 2015a; Horion et al., 2016). However, with a spatial resolution of ~9 km this product is too coarse to relate turning points to a particular driver. The MODIS NDVI products with a finer spatial resolution, 500 and 250 m, have the potential to relate turning points to particular drivers, as suggested by Rasmussen et al. (2014).

Considerable research has been done on detecting vegetation trend changes and turning points in dryland from earth observation data (Bernardino et al., 2020; de Jong, Verbesselt, et al., 2013; Horion et al., 2016). But a national and more detailed assessment of turning points and their drivers in Morocco is still missing. Such a national assessment is essential in order to get a better understanding of dryland ecosystem functioning on both a local and global scale (Geist & Lambin, 2004; Rasmussen et al., 2014; Sohl et al., 2010).

The effects of migration on Morocco and specifically on the Todgha valley in terms of, e.g., increased globalization, increased wealth, and decreasing birth rates, has been established in several studies (de Haas, 1998, 2003, 2007; Jones, 1998). However, the connection between migration and shifts in vegetation activity trends has never been studied on such a small scale as the Todgha valley. On the one hand, migration can give people the possibility to pursue their aspirations, a livelihood in the city, for example. On the other hand, migration can lead to local development, as remittance flows directly to the people who need it. In Morocco, this may lead to, e.g., the investment in irrigation pumps, which then may result in more agricultural activity. This pathway of development has been proven to be important in the Todgha valley (de Haas, 2006).

In general, dryland regions in Morocco remain poorly studied and deserve more research (Maestre et al., 2012).

1.3 Research objective and research questions

The objective of this research is to identify and classify turning points in Moroccan dryland ecosystem functioning and to have a detailed look at the drivers of these turning points, both naturogenic and anthropogenic. In order to achieve this objective, the following main research question is defined:

"How can turning points and their drivers in Moroccan dryland ecosystem functioning over the last 20 years be characterised?"

To answer the main research question, three sub-questions have been formulated:

- Which dryland areas in Morocco experienced turning points in ecosystem functioning over the last 20 years and how can these be categorised?
- To what extent does a combination of proximate causes (i.e., agricultural activities, increased aridity, infrastructure extension and wood extraction) and underlying causes (i.e., climate and demographic factors) explain the detected turning points in Moroccan drylands on a national scale?

- Which areas of the Todgha valley experienced abrupt changes in vegetation greenness trends over the last 20 years and what is the explanatory value of migration on the detected changes?

A working hypotheses was formulated in order to investigate the socio-economic drivers of abrupt changes in vegetation greenness trends, and in this way addressing the third sub-question. The working hypotheses states that:

"The pumping of water for cropland irrigation in the western part of the Todgha valley (zone b) leads to a lowering of the groundwater table in the eastern part of the Todgha valley and further downstream in the Tinejdad-Ferkla oasis (zone c & d), and thus, to desertification."

This working hypothesis was provisionally accepted as a basis to investigate the socio-economic drivers of abrupt changes in vegetation greenness trends in the Todgha valley. It is a follow up of former research by de Haas (2003) regarding the disparate socio-economic impacts of out-migration on the Todgha valley.

1.4 Report structure

This thesis consists of two parts and two study areas. In the first part, a national analysis has been performed to identify and classify turning points in ecosystem functioning. Complementary to this analysis, a national driver analysis has been done in order to characterise the drivers of these turning points. This first part addresses sub-questions 1 and 2. The second part of the thesis consists of a sub-national analysis to identify and classify abrupt changes in vegetation greenness trends in the Todgha valley. On this sub-national scale, the focus has been on the explanatory value of migration to characterise the detected changes. This analysis leads to answering sub-question 3.

The distinction between the terms turning point (i.e., used in the first part of this thesis) and abrupt change (i.e., used in the second part of this thesis) has been deliberately made. As defined by Horion et al. (2016), a turning point is a key moment in the ecosystem development where its functioning is significantly changed or altered, which can be assessed by using the Rain-Use-Efficiency. In the second part of this thesis, NDVI was used to detect changes in vegetation greenness trends. As these changes do not imply a shift in ecosystem functioning, the term abrupt changes was used here instead of the term turning point.

Chapter 2 describes the theoretical background to support this report. This chapter includes information that assists in understanding the methodology, interpreting the results and placing the research in a scientific context. The study areas and a detailed explanation of the data can be found respectively in Chapters 3 and 4. The methodology that was used to answer each sub-question and finally, the main research question, is presented in Chapter 5. The results, which are shown in Chapter 6, are presented per sub-question, and are discussed in Chapter 7. Finally, the conclusions of this research and recommendations for further research are featured in Chapter 8.

2. Theoretical background

In order to understand the methodology, interpret the results, and to place the present research in a scientific context in the best way possible, additional information on four fundamental concepts is required. These four concepts are: Rain-Use-Efficiency, Break For Additive Season and Trend, a framework with causes of desertification and land degradation, and lastly, binary logistic regression. They are indispensable for this research and will be elaborated upon in the following sub-sections.

2.1 Rain-Use-Efficiency

The turning points in Moroccan dryland ecosystem functioning are identified by means of using the Rain-Use-Efficiency (RUE; Le Houérou, 1984), which is a key indicator for measuring the response of plant production to precipitation. RUE is defined as the ratio between the Net Primary Productivity (NPP) and precipitation, and can be used as an indicator for dryland ecosystem functioning (Horion et al., 2016). The small integral of the NDVI growing season was used as a proxy for the NPP (Fensholt et al., 2013), following (Bernardino et al., 2020). The denominator in this ratio is the sum of the precipitation in the growing season.

$$RUE = \frac{NPP}{Precipitation}$$

Because NPP is highly correlated with precipitation in arid and semi-arid drylands, RUE provides a way to normalise NDVI to NDVI per unit precipitation. As this research included investigating both naturogenic and anthropogenic drivers of turning points, this normalisation is essential. By using the RUE, precipitation and other drivers of turning points in ecosystem functioning are differentiated from each other (Orr, 2011). This has been proven to be a method with high potential (Fensholt et al., 2015a; Horion et al., 2016)

2.2 BFAST, BFAST01 and BFAST01classify

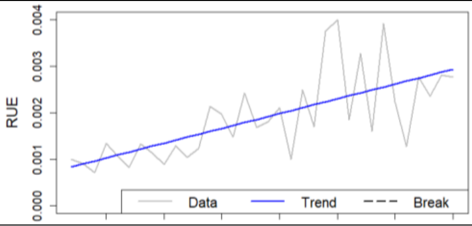
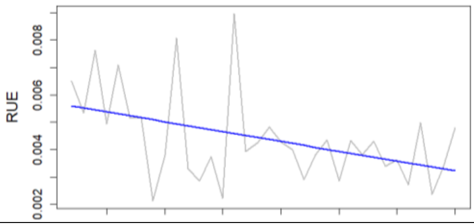
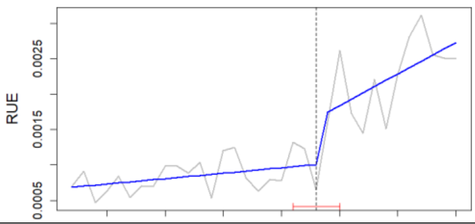
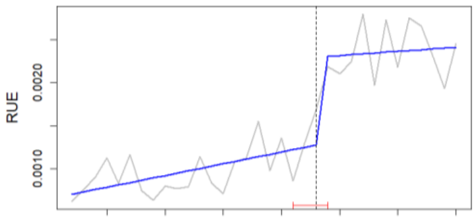
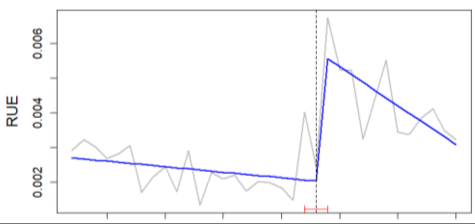
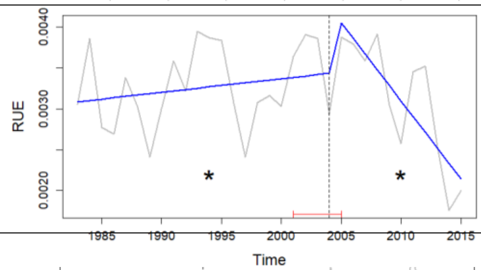
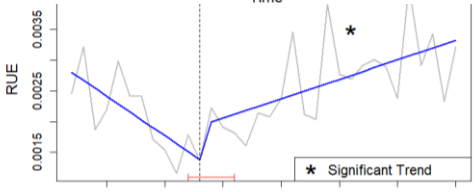
A time series is as a sequence of satellite images, acquired within a certain time frame, with the same spatial coverage and resolution. Time series are ideally fit to monitor vegetation and detect shifts in vegetation activity. A time series object operates as the input of Break For Additive Season and Trend (BFAST) and Break For Additive Season and Trend 01 (BFAST01) algorithms.

A way to analyse time series is Break For Additive Season and Trend (BFAST), proposed by Verbesselt, Hyndman, Newnham, & Culvenor (2010). This method iteratively estimates the time step and amount of abrupt changes in the trend and seasonal components within a time series and has been proven to effectively detect changes in vegetation dynamics in different ecosystems, including drylands. De Jong et al. (2012) used BFAST to detect both abrupt and gradual vegetation trend changes in shrubland and grassland biomes. Two other studies have shown the effectiveness of using BFAST to detect vegetation trends in dryland areas (Fensholt et al., 2015b; Watts & Laffan, 2014).

A variant of BFAST, and another way to analyse time series, is Break For Additive Season and Trend 01 (BFAST01). BFAST01 (de Jong, Verbesselt, et al., 2013) is different from BFAST (Verbesselt et al., 2010) in the sense that it only detects the most prominent trend shift within the time series, while BFAST detects all the potential. Thus, a turning point is identified if and when the most prominent trend shift in RUE is detected.

To not only identify, but also classify turning points and abrupt changes in dryland ecosystems, Bernardino et al. (2020) developed an improved typology for BFAST01classify (de Jong, Verbesselt, et al., 2013). This improved typology divides the detected turning points and abrupt changes into six types and four subtypes. Moreover, the new typology also provides information about the rate of change in functioning before and after the shift, besides of only the direction of change. Table 1, extracted from Bernardino et al. (2020), gives an overview of the possible types and subtypes.

Table 1 Typology of types and subtypes of changes in ecosystem functioning, extracted from Bernardino et al. (2020)

Type	Subtype	Example	Illustration of ecological inference
Stable increase	No subtype		Gradual increase in ecosystem functioning due to increased temperature or CO_2 fertilization (e.g., Horion et al., 2016)
Stable decrease	No subtype		Gradual land degradation, such as long-term loss in soil organic matter content (e.g., Horion et al., 2019)
Interrupted increase	Accelerating		Species composition shift towards a faster ecosystem functioning increase (e.g., Chapin et al., 2000)
Interrupted increase	Slowing down		Species composition shift towards a slower ecosystem functioning increase (e.g., Chapin et al., 2000)
Interrupted decrease	Accelerating		Extreme drought leads to high RUE, but subsequent plant mortality decreases ecosystem productivity by reducing vegetation
Negative reversal	Complete		Deforestation leading to a decrease in ecosystem functioning in north-eastern Brazil.
Positive reversal	Transition		Cropland abandonment followed by natural vegetation regeneration (e.g., Horion et al., 2016; Bernardino et al., 2020))

2.3 Framework causes of desertification and land degradation

After analysing 132 case studies on the causes of desertification and land degradation in dryland ecosystems, Geist & Lambin (2004) developed a framework of desertification and land degradation causes. In this framework, a distinction between proximate and underlying causes of desertification is made. They define proximate causes as immediate actions at the local level (e.g., agricultural activities, increased aridity, infrastructure extension and wood extraction). Underlying causes are fundamental social and biophysical factors (e.g., demographic factors, economic factors, technological factors, climatic factors, policy and institutional factors, cultural factors). These proximate and underlying causes are divided per continent, based on occurrence in the 132 case studies. In this way, it becomes clear for each continent which proximate and underlying causes are important to investigate, in terms of desertification and land degradation.

The four proximate causes which have potential to explain the occurrence of turning points in Moroccan drylands are agricultural activities, increased aridity, infrastructure extension, and wood extraction. Former research showed that these causes have a strengthening effect on desertification and land degradation in Morocco (Hammouzaki, 2013; Karmaoui, 2019; Karmaoui et al., 2014). The underlying causes which have been treated as probable drivers of turning points are climate and demographic related factors.

2.4 Binary logistic regression

A binary logistic regression allows us to better understand how proximate and underlying causes are related with turning points occurrence. It looks for the most optimal relationship between the dependent variable and one or more independent variables by estimating probabilities using the maximum likelihood method. It is a powerful statistical way of modelling a binomial outcome with one or more explanatory variable. A binary logistic regression differs from the regular logistic regression in the sense that it is optimized to deal with a binary response variable. Its model is defined as follows:

$$P(Yi = 1\ |Xi = xi) = \frac{e^{(\beta 0 + \beta 1 xi)}}{1 + e^{(\beta 0 + \beta 1 xi)}}$$

By using turning points occurrence as the binary dependent variable (turning point/no turning point), a binary logistic regression has the potential to establish a relationship between the proximate and underlying causes (independent variables). Different studies have used this regression method to related topics successfully (Dargaso Dana, 2018; Mandal & Mandal, 2018; Pourghasemi, 2016), making the binary logistic regression an analysis method with high potential.

3. Study area

3.1 National study area

The first part of this research focused on a specific area within the undisputed territory of Morocco. The Western Sahara, the territory occupied mostly by Morocco as its Southern Provinces, is excluded from this research. The Köppen-Geiger climate classification (Beck et al., 2018), with a 1 km spatial resolution, combined with the World Atlas of Desertification (Cherlet et al., 2018), were used to define the study area. The study area consists of drylands with an arid and semi-arid climate (BWh, BWk, BSh, and BSk). The remaining parts of Morocco are also excluded from this research, because these areas do not match the definition of drylands by the United Nations (United Nations Environment Programme, 2011). The open source QGIS software was used to extract the study area. This specific area is shown in black on the inset map of Figure 1.

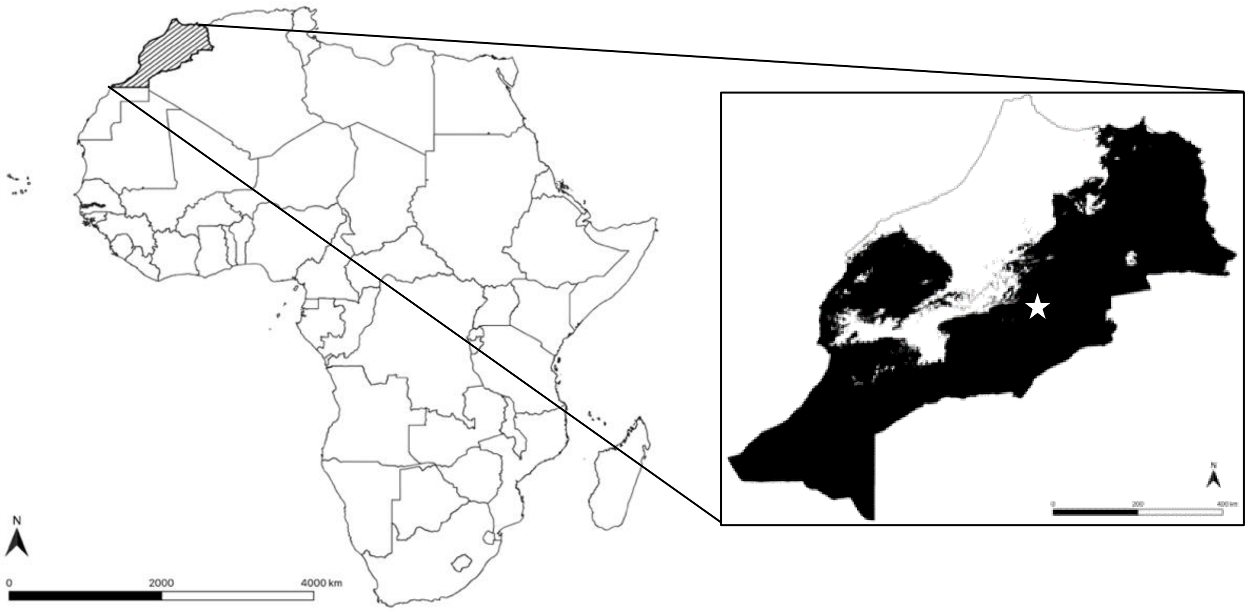


Figure 1 The national study area relative to the undisputed territory of Morocco (black area) and the Todgha valley relative to the national study area (white star).

3.2 Sub-national study area

The second part of this research concentrated on a specific area within the national study area: the Todgha valley. This area has been selected based on the presence of multiple oases, its significance on the migration numbers of Morocco and because we had access to expertise knowledge for this area (de Haas, 1998, 2001a, 2003, 2006, 2007). The Todgha valley is located in the middle of Morocco's main oasis regions, the Draâ valley and the Tafilalt. The Todgha valley is indicated with the white star on the inset map of Figure 1.

3.2.1 An introduction to the Todgha valley

The Todgha is a river valley on the Southern slopes of the High Atlas Mountains that drain the melt- and rainwater captured in the high mountains south- and eastward to the Sahara desert. In this arid/semi-arid climate, the High Atlas Mountains provides a continuous supply of fresh water, which explains the existence of numerous oases south of the Atlas. The Todgha valley stretches from the main town Tinghir in the west to Tinejdad in the east. Zooming in on the actual Todgha Valley, roughly four zones can be distinguished based on the discrepancy in water availability and irrigation methods (Figure 2). This distinguishing has been made throughout the analysis to identify abrupt changes in vegetation greenness trends as well as the explanatory analysis.

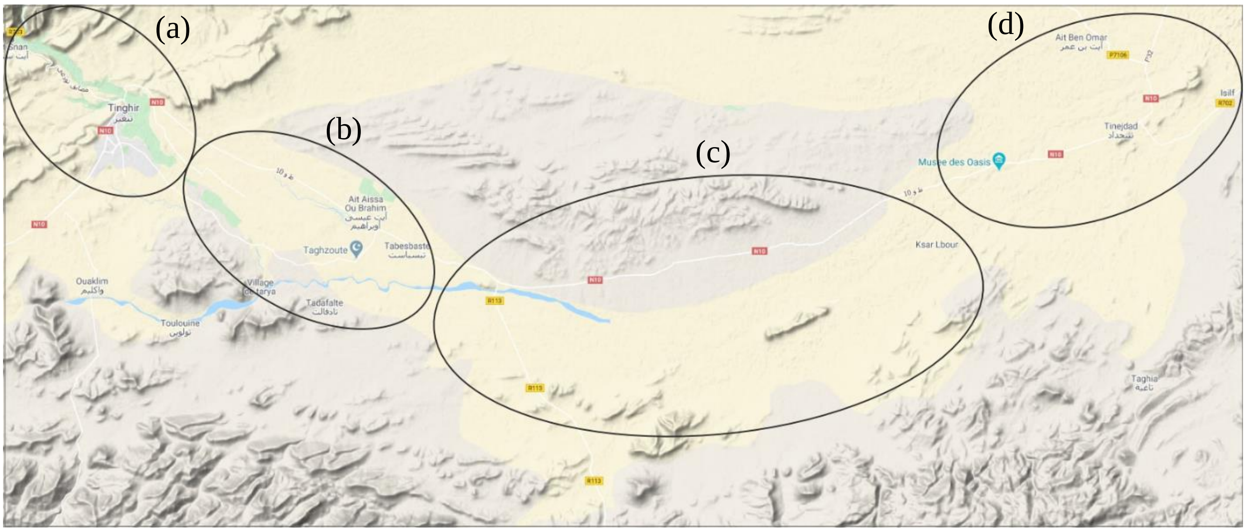


Figure 2 The four zones of the Todgha valley. Based on the discrepancy in water availability and irrigation methods.

The Upper Todgha valley (Figure 2a) starts at the point where the Todgha leaves the gorges. This zone has the most elevated relief from all zones and is characterised by its abundance in perennial water sources. From here on downstream, the Todgha flows further in a south-eastern direction and the valley gently widens. At this point, in the Middle and Lower Todgha valley (Figure 2b), khettara[1] and mechanical irrigation becomes more important because of the subsidence of the Todgha. The most eastern point of this zone marks the end of the old Todgha valley. Newly irrigated plains of Ghallil and Bour Tinedjad (Figure 2c) emerge in this zone since the 1980s particularly. This zone is increasingly reclaimed for relatively large-scale agriculture. Here, farmers are dependent on the use of diesel engines to pump up subsurface water of the Todgha. Further eastwards, the fourth zone of the Todgha valley, the traditional

[1] A traditional irrigation method to access subsurface water via a network of tunnels, shafts and dams.

oasis of Tinejdad-Ferkla (Figure 2d), can be distinguished. The valley widens up again and the contrast with the traditional oasis of the Todgha valley (zones a and b) is clear. This zone suffers from lowering of water tables, caused by pumping in zones b and c, leading to drying out of sources and water tables (de Haas, 2003).

4. Data description

All data used in this research originates from satellites and can thus be referred to as remote sensing data. Data from two different sources were used for the identification and classification of turning points in ecosystem functioning, namely Moderate Resolution Imaging Spectroradiometer (MODIS) and Climate Hazards Group InfraRed Precipitation with Station (CHIRPS). In order to characterise the drivers of the identified turning points, data from several different sources were used, all remotely sensed. To identify abrupt changes in vegetation greenness trends on a sub-national scale, MODIS data were used. The data for both the national and the sub-national will be discussed in the following sub-sections and are summarised in Table 2 and 3

4.1 Identification of turning points in ecosystem functioning

To identify turning points in ecosystem functioning on a national scale, the NDVI product of MODIS and the rainfall estimates product from CHIRPS were used. As suggested by Rasmussen et al. (2014), the use of MODIS NDVI products with a finer spatial resolution (i.e., 500 and 250 m), has the potential to relate turning points in ecosystem function to particular drivers.

4.1.1 MODIS

The 6th version of the Terra MODIS NDVI product (Didan, 2015b) was used. For the national turning point analysis, a spatial resolution of 500 m was chosen. This dataset has a temporal resolution of 16 days, ranging from February 2000 to the present time. Additionally, the complementary Quality Assessment (QA) product of MODIS was utilised to assess the quality of the images.

4.1.2 CHIRPS

CHIRPS data was used for the precipitation estimates (Funk et al., 2015). CHIRPS provides monthly rainfall estimates with a spatial resolution of ~5 km. Covering the entire globe and with a temporal extent ranging from 1981 up to the present time, this dataset is very suitable for long-term analysis.

Table 2 Summary of the data used in the national turning point analysis and the sub-national greenness trend analysis.

Data product	Spatial resolution (m)	Spatial extent	Temporal resolution	Temporal extent
MODIS NDVI	500 / 250	Global	Bi-monthly	2000 - present
MODIS QA	500 / 250	Global	Bi-monthly	2000 – present
CHIRPS	5500	Global	Monthly	1981 – present

4.2 Characterisation of turning points in ecosystem functioning

The possible drivers of the detected turning points are divided into proximate and underlying causes. For each proximate and underlying cause, different datasets were use. These datasets are discussed in the following sub-sections, starting with the datasets for the proximate causes (4.2.1, 4.2.2, 4.2.3) and ending with the underlying causes (4.2.4 and 4.2.5).

4.2.1 CCI Global Land Cover

The CCI Global Land Cover product was used in order to investigate ‘agricultural activities’ as a possible proximate cause of turning points in ecosystem functioning. The European Space Agency (ESA) initiated a programme to monitor essential variables regarding climate change, called Climate Change Initiative (CCI; ESA, 2017). Part of this program was to monitor land cover, resulting in the CCI Global Land Cover product. As land cover data is accompanied with a standardised legend, agricultural areas can be detected and analysed from this product.

4.2.2 Global Human Settlement Built-Up

The Global Human Settlement product was used to derive information about infrastructure, in order to investigate the proximate cause ‘infrastructure expansion’. The Global Human Settlement product, provided by the Joint Research Team (JRT) of the European Commission (EC), contains information on the human presence on the planet (Corbane et al., 2018). The Built-Up layer specifically, provides information on the presence of built-up areas around the world.

4.2.3 Forest loss

Hansen et al. (2013) developed a global forest change product. This product provides multiple layers, containing information about both forest gains and losses. To analyse the possible proximate cause ‘wood extraction’, the year of gross forest cover loss event (“lossyear”) layer was used. This layer contains forest loss, defined as a stand replacement disturbance, or a change from a forest to non-forest state.

4.2.4 *Standardized Precipitation-Evapotranspiration Index and TerraClimate Soil Moisture*

In order to analyse climate related factors as underlying drivers of turning points, two different datasets regarding climate indicators were used. Firstly, the Standardized Precipitation-Evapotranspiration Index (SPEI). SPEI provides long-time, robust information on drought conditions and shows deviations of the current climatic balance with respect to the long-term balance (Vicente-Serrano et al., 2010) . The other product that was used is the TerraClimate Soil Moisture, providing soil moisture estimates (Abatzoglou et al., 2018).

4.2.5 *Population Density Grid*

To address the demographic factor as underlying cause of turning points, population density extracted from the Gridded Population of the World product was used. This dataset provides estimates of the population density around the globe (Center for International Earth Science Information Network - CIESIN - Columbia University, 2016).

Table 3 Summary of the data used in the national driver analysis.

Data product	Spatial resolution (m)	Spatial extent	Temporal resolution	Temporal extent	Assessed driver
CCI Global Land Cover	300	Global	Annual	1992 - 2018	Agricultural transition
Global Human Settlement Built up	250	Global	15-yearly	1975, 1990, 2000, 2014	Infrastructure expansion
Forest loss	30	Global	Annual	2000 - 2018	Wood extraction
SPEI	0.5°	Global	Monthly	1901 - 2015	Climate factor
TerraClimate Soil Moisture	0.04°	Global	Annual	1958 - 2019	Climate factor
Population Density Grid, V4	1000	Global	Demi-decadal	2000, 2005, 2010, 2015, 2020	Demographic factor

4.3 Identification of abrupt changes in vegetation greenness trends

To identify abrupt changes in vegetation greenness trends on a sub-national scale, the 6th version of the Terra MODIS NDVI product with a spatial resolution of 250 m (Didan, 2015a) was used. This dataset has a temporal resolution of 16 days, ranging from February 2000 to December 2019. Additionally, the complementary Quality Assessment (QA) product of MODIS was utilised to assess the quality of the images.

5. Methodology

Working with remotely sensed data to identify and classify turning points, accompanied by a characterisation of their drivers, requires multiple steps, such as data acquiring, data pre-processing, turning point analysis, driver analysis, and validation. All steps, except the data acquiring and deriving the growing season, were performed in the programming language R. This chapter describes, per research question, the methodological steps which were followed to get the required results to answer them and are summarised in Figure 3.

5.1 Identification and classification of turning points in ecosystem functioning

5.1.1 Downloading and pre-processing MODIS

All available NDVI layers of MODIS, with a spatial resolution of 500 m, for the period 2000/01/01 – 2020/01/01 were downloaded via Google Earth Engine. This resulted in 457 images, ranging from 2000/02/18 to 2019/12/19. Additionally, the complementary QA layers of MODIS were downloaded, also resulting in 457 images. The first step was to pre-process the QA layers in such a way that the pixels with bad quality remained and could be used as a mask later on. The VI quality layer was investigated first. Pixels labelled as ‘VI produced, but check other QA’, were further investigated using the VI usefulness layer. From these pixels, pixels marked as ‘Lowest Quality’, ‘Quality so low that it is not useful’, ‘L1B data faulty’ and ‘Not useful for any other reason/not processed’ were added to the mask with bad pixel quality. Next, the QA land/water was used to make a mask that was used to exclude water bodies from the study area. The pixels labelled as “Land (nothing else but land)” by the land/water QA layer were kept.

The pre-processing of the NDVI layers of MODIS was done as follows. Starting with masking non-dryland areas of the undisputed territory of Morocco, by using the Köppen-Geiger classification data was cropped, re-projected and resampled to fit NDVI layers specifications. The climate classification data were resampled using the nearest neighbour method. Water bodies and pixels with bad quality were masked out of the NDVI layers of MODIS as explained before. To match the same temporal extent as the CHIRPS data, monthly composites were made, using the *max* function, resulting in 239 images. This also decreased the number of missing values in the NDVI dataset. Finally, the NDVI dataset was re-scaled, by dividing it by 10,000, and pixels with a value lower than 0.1 were excluded. This was done in order to remove areas with sparse/absent vegetation (de Jong, Verbesselt, et al., 2013).Which resulted in NDVI values ranging from 0.1 up to 1.

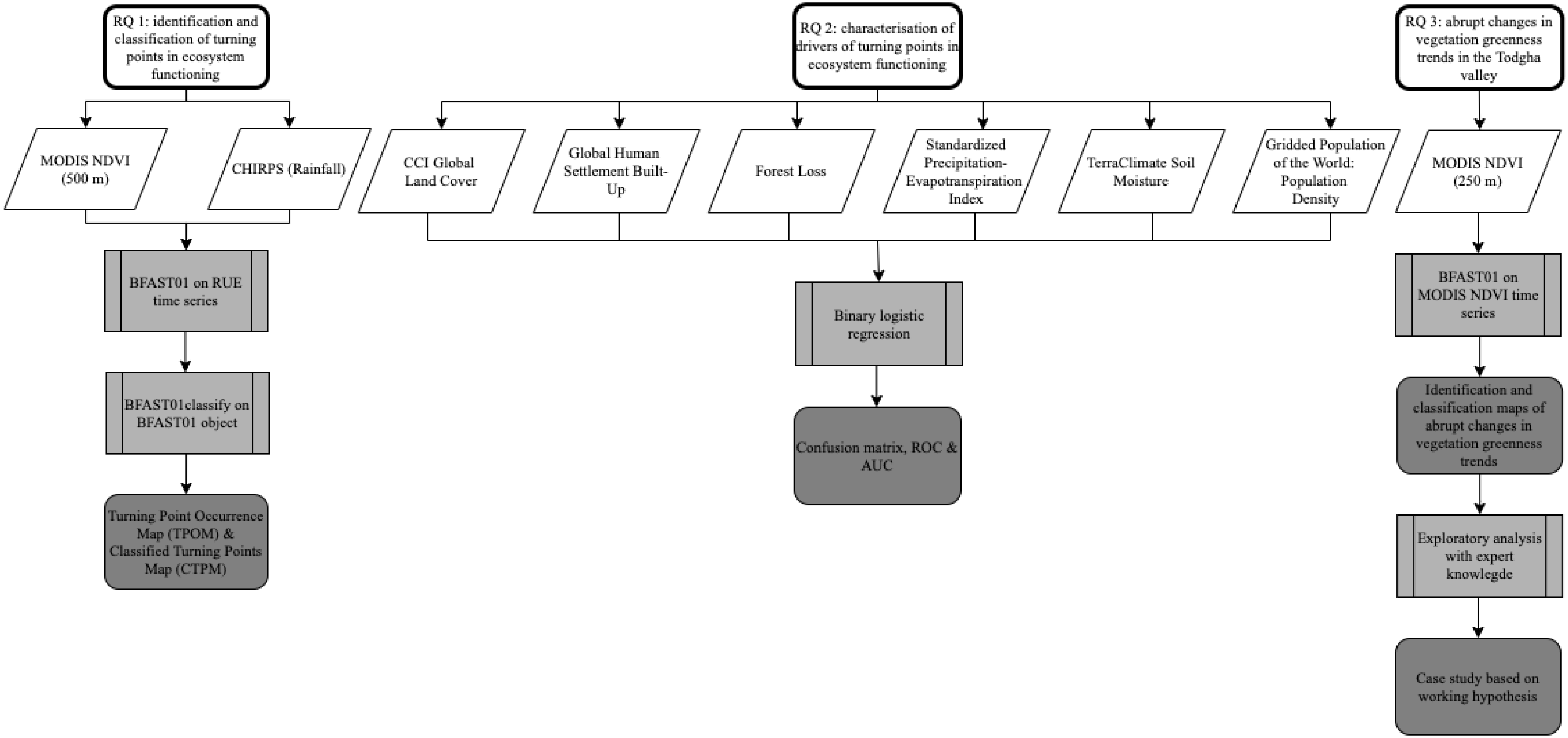


Figure 3 Conceptual frameworks of the followed methodology. Horizontally distributed based on the three sub-questions.

5.1.2 *Downloading and pre-processing CHIRPS*

The monthly composites of the rainfall estimate of CHIRPS were downloaded from the CHIRPS directory (Funk et al., 2015). The dataset has 239 images, ranging from 2000/02 – 2019/12, which matches the temporal extent and spatial coverage of the NDVI layers of MODIS. The rainfall estimates of CHIRPS were cropped, re-projected and resampled to match the NDVI layers specifications. The rainfall dataset was resampled using the nearest neighbour method, assuming that there will not be much variation in rainfall in a ~5 km pixel.

5.1.3 *Growing season and small integral*

For each pixel, the annual growing season small integral value was derived for the whole time series, and was used as a proxy of the NPP (Fensholt et al., 2013). The small integral can be seen as the total vegetation greenness during the growing season. To determine the start and end of the growing season, and to extract the small integral value, the TIMESAT software was used (Jönsson & Eklundh, 2004). The same settings were used as the ones specified by (Horion et al., 2016), and following (Bernardino et al., 2020). Nineteen growing seasons were extracted from the twenty years of NDVI data. As the used dataset goes from February 2000 to December 2019, it was not possible to estimate the last growing season (i.e., the 2019 - 2020 growing season).

5.1.4 *Extracting sum of precipitation*

The per pixel sum of the precipitation in the growing season, which acts as the denominator for calculating the RUE, was extracted based on the nineteen NDVI growing seasons. The start and end time of the NDVI growing seasons, per pixel, were also obtained from TIMESAT (i.e., as an index), and were used to determine which months were included in the precipitation sum for each season. By summing the precipitation estimates for these months, the growing season precipitation sum was derived.

5.1.5 *Turning Point Occurrence Maps*

The next step was to create the Turning Point Occurrence Map (TPOM). To do this, the RUE, which is described in more detail in section 2.1, was calculated as the ratio between the small integral and the sum of precipitation per pixel. This was done for all pixels of the study area. Then, BFAST01, discussed in more detail in section 2.2, was applied on the RUE time series. The formula argument of BFAST01 was set to “response ~ trend”, as a yearly time series with no seasonality was used. The bandwidth argument, which determines the size of the data window for the break detection in relation to the sample size, was set to 3/19, which is a well suited window for the proper detection of breaks in a relatively short (i.e., 19 time steps) time series. Default settings were used for the remaining arguments. Finally, pixels where no turning points in ecosystem functioning were detected were excluded, leaving only significant turning points ($p < 0.05$), resulting in the TPOM (section 6.1.1) .

5.1.6 Classified Turning Point Map

Furthermore, the Classified Turning Point Map (CTPM) were created. An improved typology, discussed in more detail in section 2.2, was used for making the maps. The direction of the trends and rates of change in RUE, before and after the detected turning points, were used to classify the changes in ecosystem functioning, according to the typology proposed by Bernardino et al. (2020). Which makes it possible to characterise not only the rate of change, but also the status of the detected turning point in the trend. The typology argument of BFAST01classify was set to ‘drylands’, as this enables the new typology with type and subtype. Default settings were used for the remaining arguments. In this case, the pixels where no turning point in ecosystem functioning was detected were included. These pixels were classified either as ‘stable increase’, ‘stable decrease’ or ‘no change’. This resulted in two CTPM’s, one showing the type of change and the other showing the subtype of change (section 6.1.2).

5.2 Characterisation of drivers of turning points in ecosystem functioning

In order to characterise the drivers of the detected turning points, by means of the binary logistic regression, it is necessary that the data of each driver is summarised into one raster layer. This resulted in six raster layers, which acted as the input of the binary logistic regression.

5.2.1 Downloading and pre-processing CCI Global Land Cover

The CCI Global Land Cover product was downloaded from the CCI download page (ESA, 2017) for the period 2000 – 2018, resulting in 19 images. The data were cropped, reprojected, and resampled to the NDVI dataset specifications. Next, the cropland areas were extracted. The values used to extract these areas were 10 (cropland, rainfed), 20 (cropland, irrigated or post-flooding) and 30 (mosaic cropland (>50%)), according to the UN-LCCS legend (FAO, 2000). The cropland pixels which ever underwent a change to any other land cover type, from the start till the end of the available data, were extracted using the *sum* function. After applying the *sum* function, the pixels with values 19 (i.e., cropland pixels which never underwent a change) and 0 (i.e., pixels that were never cropland) were given the value 0. All the other pixels (i.e., cropland pixels that underwent a change) were given the value 1. Resulting in a binary raster layer which made it possible to investigate if cropland abandonment had an influence on the detected turning points.

5.2.2 Downloading and pre-processing Global Human Settlement Built-Up

Two epochs, 2000 and 2014, of the Global Human Settlement (GHS) Built-Up layer were downloaded from the GHS datasets page (Corbane et al., 2018). These two layers were cropped, reprojected, and resampled as described before. One GHS Built-Up growth raster layer was created by subtracting epoch 2000 from epoch 2014. In this way, the pixels where built-up area was developed between 2000 and 2014 were made visible, which made it achievable to analyse the influence of built-up development on the detected turning points.

5.2.3 Downloading and pre-processing Forest Loss

The forest loss layer, for the period 2000 – 2018 was downloaded from the data download page, hosted by the University of Maryland (Hansen et al., 2013) The data was cropped, reprojected and resampled as outlined before. One binary raster layer was created by means of assigning the pixels which underwent a loss in forest to the value 1, and assigning the pixels which did not underwent a loss in forest to the value 0. Resulting in a raster layer which made it possible to investigate the loss in forest as driver of the detected turning points.

5.2.4 Downloading and pre-processing Standardized Precipitation-Evapotranspiration Index

Monthly SPEI data, for the period 2000 – 2018 were downloaded from the Global SPEI database (Vicente-Serrano et al., 2010). The Global SPEI database provides time-scales between 1 and 48 months. For this research, a time-scale of 9 months was downloaded, as drought events before and after the detection of a turning point are interesting to investigate, and following (Bernardino et al., 2020). First, the data was cropped, reprojected, and resampled as described before. Consecutively, The number of abnormally dry months (i.e., SPEI values lower than or equal to -1.5, representing moderate to extreme drought conditions), according to Spinoni et al. (2013) and following Bernardino et al. (2020) were counted. Resulting in one raster layer in which the pixels represent the total number of dry months in the time series, and resulting in a way to investigate drought events as a driver of the detected turning points.

5.2.5 Downloading and pre-processing TerraClimate Soil Moisture

The monthly TerraClimate Soil Moisture data, for the period 2000 – 2018 were downloaded from the website of the Climatology Lab (Abatzoglou et al., 2018), which is the producer of this dataset. The data was cropped, reprojected, and resampled as described before. The first step was to aggregate the monthly data to yearly data and to extract the yearly average for the time series. One soil moisture raster layer was created by calculating the Sen's slope, by means of the *eco.theilsen* function. Which is a nonparametric method for estimating trends in univariate time series (Sen, 1968; Theil, 1992). This resulted in a raster layer where the slope is visualised, indicating negative and positive soil moisture trends.

5.2.6 Downloading and pre-processing Population Density

Two epochs (i.e., 2000 and 2015) of the Population Density dataset from the Gridded Population of the World collection were downloaded (Center for International Earth Science Information Network - CIESIN - Columbia University, 2016). The data was cropped, reprojected, and resampled as described before. One population density growth raster layer was created by subtracting epoch 2000 from epoch 2015. In this way, the pixels where population expanded between 2000 and 2015 were extracted, which made it possible to analyse the influence of population growth on the detected turning points.

5.2.7 Binary logistic regression

The former pre-processing of the driver data resulted in a dataset of 4.412.130 rows and 9 columns. To model the relationship between the detected turning points and their potential drivers, NA (i.e., Not Available) values were removed from this dataset. After this alteration, the dataset contained 752.399 rows and still 9 columns, of which the first column operated as the dependent variables (i.e., turning point = 1, no turning point = 0). A random sample was used in order to compose a training dataset of 526.679 rows, which equates to 70% of the dataset. After sampling, the train dataset consisted of 524.916 rows without a detected turning point and 1.763 rows with a detected turning point. The remaining 30% of the dataset was used to create the test dataset (i.e., 225.720 rows). Of this dataset, 224.936 rows were without a detected turning point, the reaming 784 rows did include a detected turning point, which is inevitably unbalanced.

The fitting of the binary logistic regression was done by using the *glm* function. To ensure a logistic regression was fitted, the family argument was set to 'binomial'. As the selection of independent variables to incorporate in the model is essential to prevent (e.g., multicollinearity, overfitting or redundancy), both forward and backward variable selection was used. This was executed by setting the direction argument of stepAIC to 'both'. Resulting in a binary logistic regression model using 5 of the 9 independent variables (i.e., 'GHS_Builtup', 'Cropland', 'Sparse_Herbaceous', 'Pop_Density', and 'SPEI'). Based on this model, the McFadden pseudo-R^2 was calculated in order to assess the goodness of fit (i.e., 0 indicates a bad fit, 1 indicates a perfect fit). Finally, a Likelihood ratio test was done, which is a goodness of fit test to compare between two models; the null model and the final model.

Next, the just created binary logistic regression model was used on the test dataset, to investigate how the model functioned on unseen data. As both the train and test dataset are very unbalanced, due to the relatively small amount of detected turning points, the Receiving Operating Characteristic (ROC) curve and the Area Under the Curve (AUC) were used to evaluate the model performance. The predicted class (i.e., 0: no turning point, 1: turning point) was determined by means of the cutoff value. The cutoff value was determined in an incremental fashion, based on the ROC curve. The cutoff value used was 0.0038. The classification accuracy was obtained by calculating the precision, recall, and F1-score. The precision is a metric that quantifies the number of correct positive class predictions (i.e., 1: turning point). Consecutively, recall quantifies the number of positive class predictions made out of all positive examples in the dataset. Finally, the F1-score provides a single score that balances both the concerns of precision and recall in one number.

5.3 Identification and classification of abrupt changes in vegetation greenness trends

5.3.1 Downloading and pre-processing MODIS

All available NDVI layers of MODIS, with a spatial resolution of 250, for the period 2000/01/01 – 2020/01/01 were downloaded via Google Earth Engine. This resulted in 457 images, ranging from 2000/02/18 to 2019/12/19. Additionally, the complementary QA layers of MODIS were downloaded. The first step was to crop both the NDVI layers as the QA layers to the sub-national study area (-531500, -472000, 3487000, 3513000). The following pre-processing steps were similar to the steps taken to pre-process the NDVI layers of MODIS with a spatial resolution of 500 m, which are described in more detail in section 5.1.1. This resulted in 239 monthly NDVI composites. Monthly composites have been made in this case not to match the temporal extent of other data sources, but to reduce the amount of missing values and of data in general (reducing computing time in the next steps).

5.3.2 Abrupt changes in vegetation greenness trends

The pre-processed NDVI time series, with a spatial resolution of 250 m, functioned as the input for the BFAST01. The formula argument of BFAST01 was set to “response ~ trend + harmon”, as a monthly time series with seasonality was used. Default settings were used for the remaining arguments. Next, pixels where no abrupt change in vegetation greenness trends were detected were excluded, leaving only significant changes ($p < 0.05$), resulting in the map showing the abrupt changes in vegetation greenness trends in the Todgha valley (section 6.3.1).

5.3.3 Classification of the abrupt changes in vegetation greenness trends

The identified abrupt changes in vegetation greenness trends were classified by using the same typology used in the national turning point analysis. The direction of the trends and rates of change in NDVI, before and after the detected turning points, were used to classify the changes in vegetation greenness, according to the typology proposed by Bernardino et al. (2020). Which makes it possible characterise not only the rate of change, but also the status of the detected turning point in the trend. The typology argument of BFAST01classify was set to ‘drylands’, as this enables the new typology with type and subtype. Default settings were used for the remaining arguments. In this case, the pixels where no abrupt change in vegetation greenness trend was detected were included. These pixels were classified either as 'stable increase', 'stable decrease' or 'no change'. This resulted in two maps of the Todgha Valley (section 6.3.2). One showing the type of change in vegetation activity trends and the other showing the subtype of change in vegetation activity trends.

5.3.4 Literature review

In order to judge the validity of the working hypotheses, stated in section 1.3, a literature review was carried out. This literature review combined the results of this section with literature from multiple migration scholars, of which Prof.dr. H.G. de Haas plays an important role. Additional information was acquired through personal communication with Prof.dr. H.G. de Haas. The literature review resulted in an explanatory analysis, together with a proposed theory to clarify the desertification patterns in the Todgha valley.

6. Results

The results of this study are presented and described in this chapter. First, the results of the identification and classification of turning points in ecosystem functioning are presented. Then, the results regarding the characterisation of the drivers of the detected turning points are presented. This chapter ends by presenting the results of the identification and classification of turning points in vegetation activity trends on a sub-national scale, focusing on the Todgha valley.

6.1 Turning points in ecosystem functioning

6.1.1 Spatial and temporal distribution of turning points in ecosystem functioning

The TPOM highlights dryland areas in Morocco which experienced significant turning points in ecosystem functioning over the last nineteen years, from 2000 up to and including 2018. Most turning points occurred in 2009 (Figures 4 and 5). Turning points in ecosystem functioning were primarily detected in the north of Morocco (Figure 4a). These turning points were mainly concentrated in a single region of the country, although some turning points, were detected as individual pixels. It is noteworthy that the BFAST01 algorithm does not allow to detect turning points in the beginning and end of the time series. This is why there are no turning points detected before 2005 and after 2013 (de Jong, Verbesselt, et al., 2013). In general, the amount of dryland areas in Morocco showing turning points in ecosystem function was 0.34%. No significant ($p < 0.05$) change in ecosystem functioning was detected in 91.63% of the dryland areas in Morocco. Monotonic changes were seen in the remaining 8.03%.

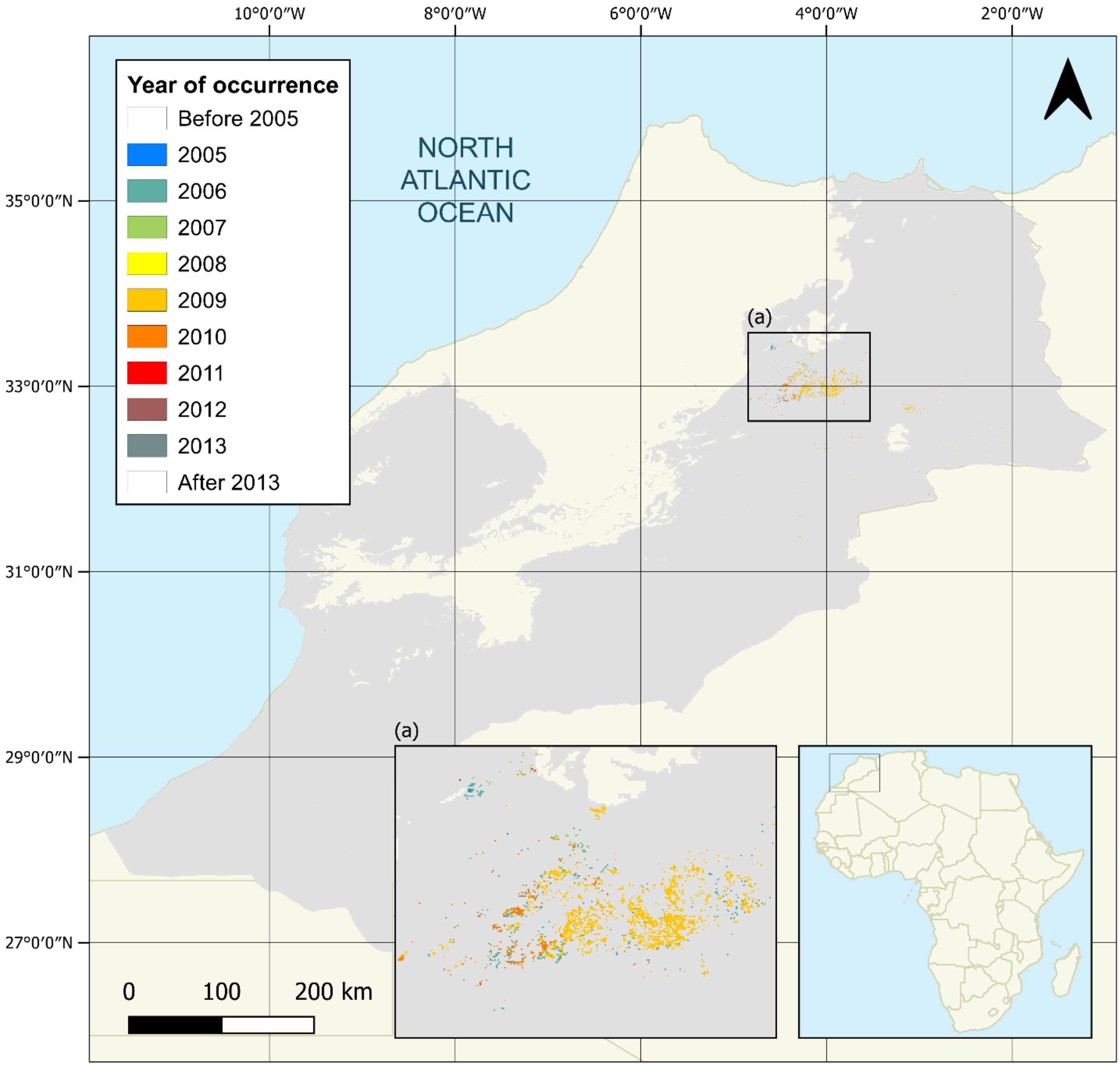


Figure 4 The TPOM in ecosystem functioning. The area in the northeast of Morocco where the turning points were primarily detected is highlighted with a black rectangle and referred to as Figure 4a.

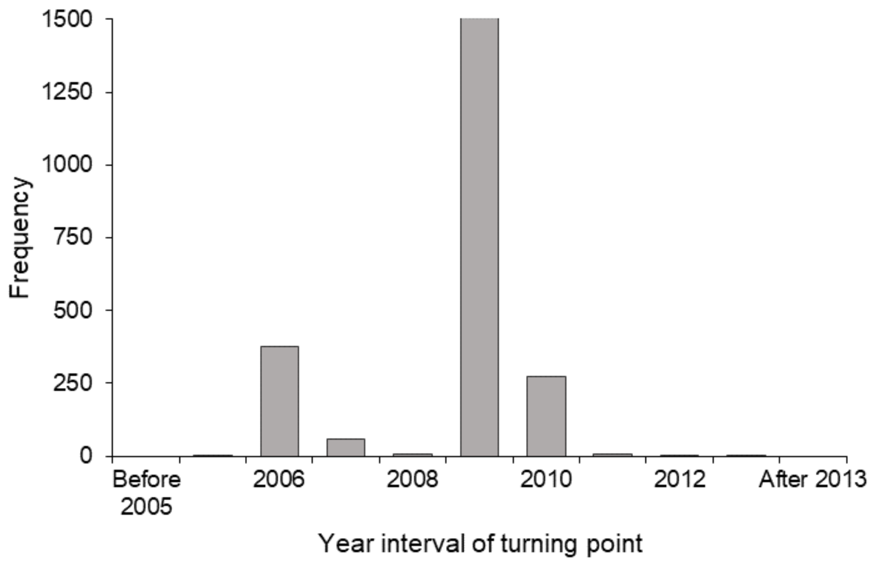


Figure 5 The frequency of turning points in ecosystem functioning. Although the analysis was made from 2000 to 2018, no turning points were detected before 2005 and after 2013.

6.1.2 *Classification of the detected turning points in ecosystem functioning*

The most outstanding type of change was interrupted increase (63.2%), followed by negative reversal (i.e., from increase to decrease in ecosystem functioning; 20.3%) and interrupted decrease (16.4%). With only 0.08% of the pixels, a positive reversal (i.e., from decrease to increase in ecosystem functioning) hardly occurred (Figure 6).

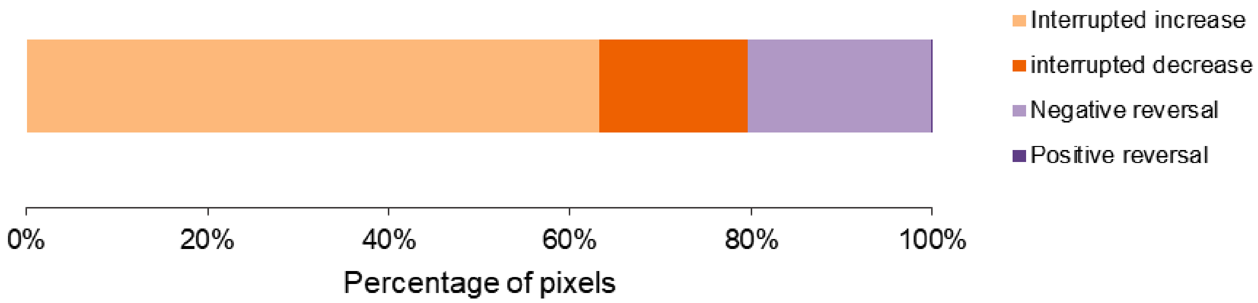


Figure 6 The percentage of pixels for each type of change in ecosystem functioning, for pixels that presented a turning point in Morocco.

The CTPM (Figure 7) revealed the change type of the pixels which underwent a turning point in ecosystem functioning. A hotspot of turning points in ecosystem functioning was observed in the northern part of Morocco, which overlaps with the cities of Missour, Sidi Boutayeb, Teggour, and partially El Ksabi (Figure 7a). Furthermore, this area belongs to the basin of the Moulouya River. The sources of the Moulouya are in the Almssid region and drains both the Middle and High Atlas Mountains. This area was used to investigate the classification of the detected turning points in more detail.

The western part of the hotspot area (hereafter, simply "western part") showed a dominance of turning points classified as interrupted decrease. The eastern part of the hotspot area (hereafter, the "eastern part") revealed a combination of two types of changes: interrupted increase and negative reversal, with a dominance of the former.

Lastly, a coherent area in the centre of the hotspot showed a dominance of the negative reversal change type (hereafter, the "central part").

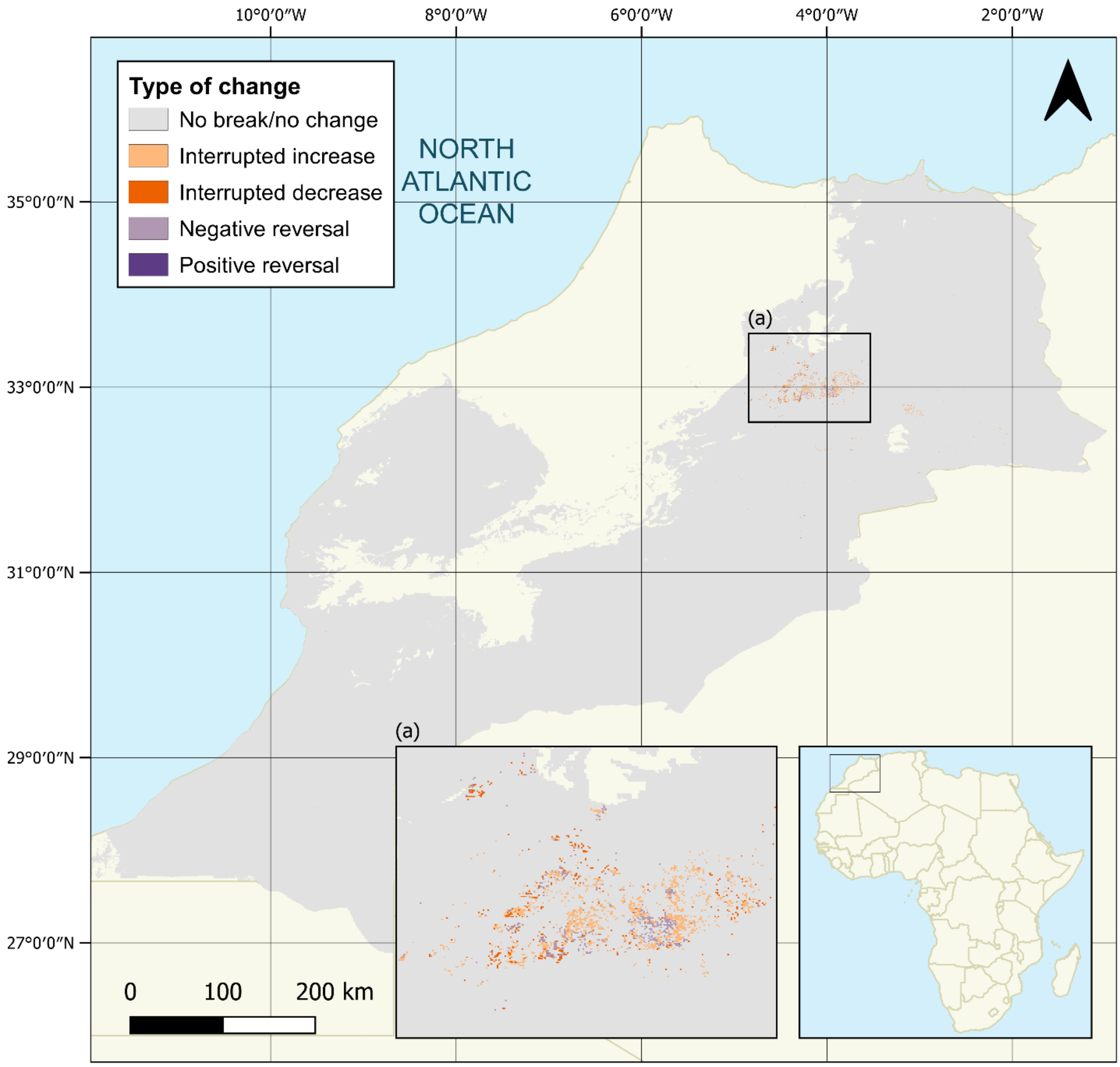


Figure 7 The type of turning points in ecosystem functioning. The area in the northeast of Morocco where the turning points were primarily detected is highlighted with a black rectangle and referred to as Figure 7a.

The four types of change can be further investigated by looking at the subtypes (Figure 8 and 9). From the turning points that were classified as interrupted increase, the great majority (99.4%) showed the subtype "slowing down". The remaining 0.6% showed the subtype "accelerating". From the turning points that were classified as interrupted decrease, 49.0% revealed the subtype "slowing down", where the subtype "accelerating" was found in 51%. Next, from the turning points that were classified as negative reversal, 99.8% displayed the subtype "transition". All turning points that were classified as positive reversal, revealed the subtype "transition".

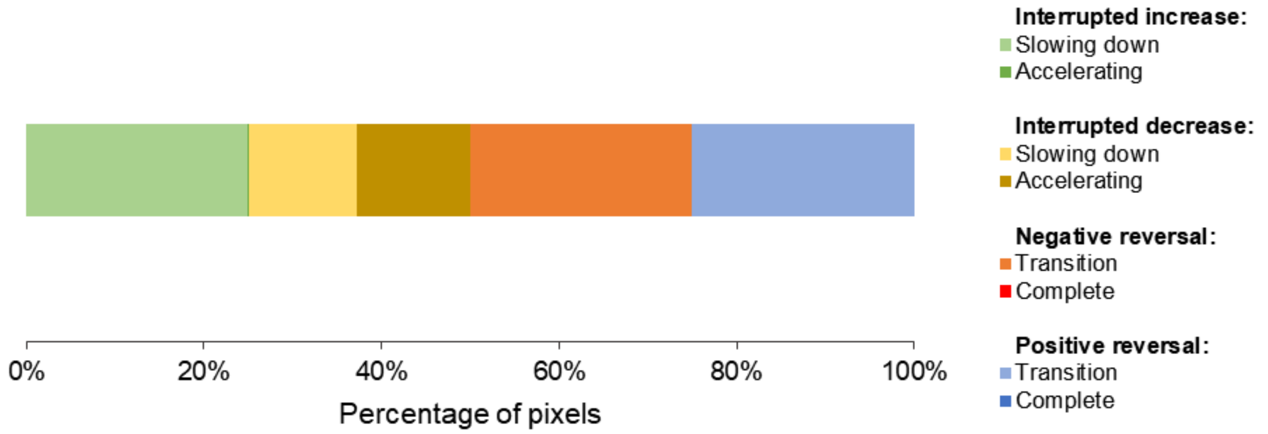


Figure 8 The sub(type) of turning points in ecosystem functioning for Morocco. The percentage of pixels for each possible combination of type and subtype of change are presented.

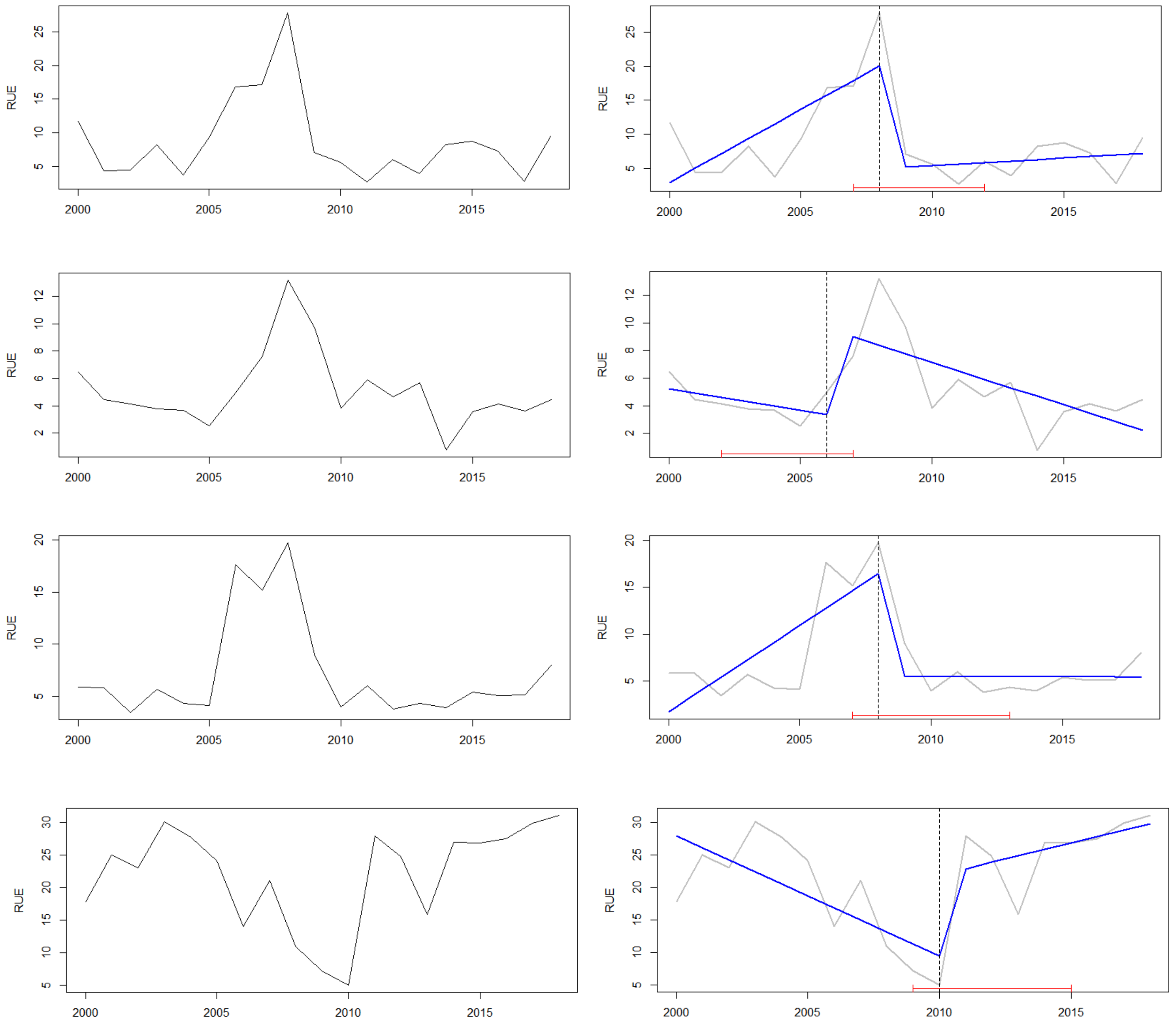


Figure 9 The RUE time series and BFAST01 results for those time series, visualising the type and subtype of change in ecosystem functioning. A peak in RUE can be seen around 2009. From the top row to the bottom row: interrupted increase with a slowing trend, interrupted decrease with an accelerating trend, negative reversal which is in transition, and positive reversal which is in transition.

In the western part of the hotspot, an equal share of the turning points that showed an interrupted decrease were sub-classified as either slowing down or accelerating (Figure 10). Most of the turning points which were classified as an interrupted decrease occurred from 2005 up to and including 2007. The same happens in the areas showing an interrupted decrease with a deceleration after the turning point, but with a smaller magnitude.

The eastern part of the hotspot was classified as interrupted increase with a deceleration after the turning point. These turning points occurred mainly in 2009 and 2010, with a very high occurrence of turning points in 2009.

In the central part of the hotspot, reversals from increasing to decreasing trends in ecosystem function were revealed. Almost all trends were in a transitional stage. These reversals occurred also primarily in 2009.

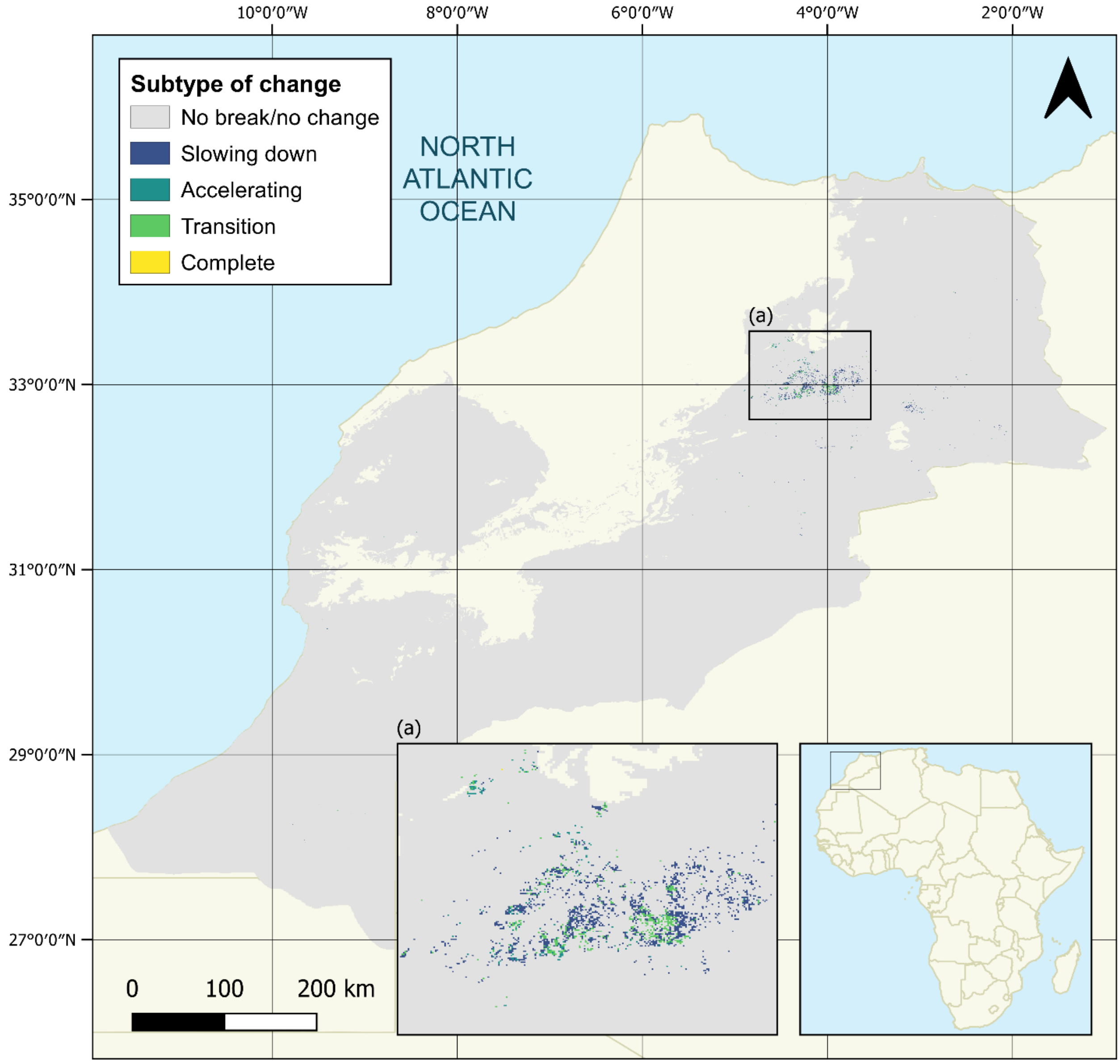


Figure 10 The subtype of turning points in ecosystem functioning. The area in the northeast of Morocco where the turning points were primarily detected is highlighted with a black rectangle and referred to as Figure 10a.

6.2 The drivers of turning points

Knowing the drivers of turning points in dryland ecosystem functioning is important to mitigate the effects of desertification and land degradation. By means of the binary logistic regression, insight was given into the influence of proximate and underlying causes on the detected turning points. The proximate drivers that turned out be most important to explain the detected turning points is ‘Cropland’ (i.e., cropland abandonment). Subsequently, the underlying drivers that emerge as most important are ‘Pop_Density’ (i.e., an increase in population density) and ‘SPEI’ (i.e., the occurrence of abnormally dry months). These three variables revealed a significant influence ($p < 0.05$) on the detected turning points. The binary logistic regression showed that underlying drivers are important to explain turning point in ecosystem functioning in Morocco, as two of the three significant variables are underlying drivers (i.e., ‘Pop_Density’ and ‘SPEI’).

The model summary in Appendix II gives an overview of the constructed binary logistic regression. The coefficients table within the model summary showed the significance of ‘Cropland’, ‘Pop_Density’ and ‘SPEI’. The model fit statistics (Appendix III) revealed a McFadden pseudo-R^2 of 0.015, which indicates a bad model fit. However, the likelihood ratio test showed that the log-likelihood difference between intercept only model (i.e., null model) and model fitted with all independent variables is 183.44, indicating improved model fit. This improvement of fit is also significant ($p < 0.05$).

The Receiver Operating Characteristic (ROC) curve (Figure 11) showed an Area Under the Curve (AUC) of 0.6318, indicating a model that is acceptable in discriminating between pixels where a turning point occurred and pixels where no turning point occurred.

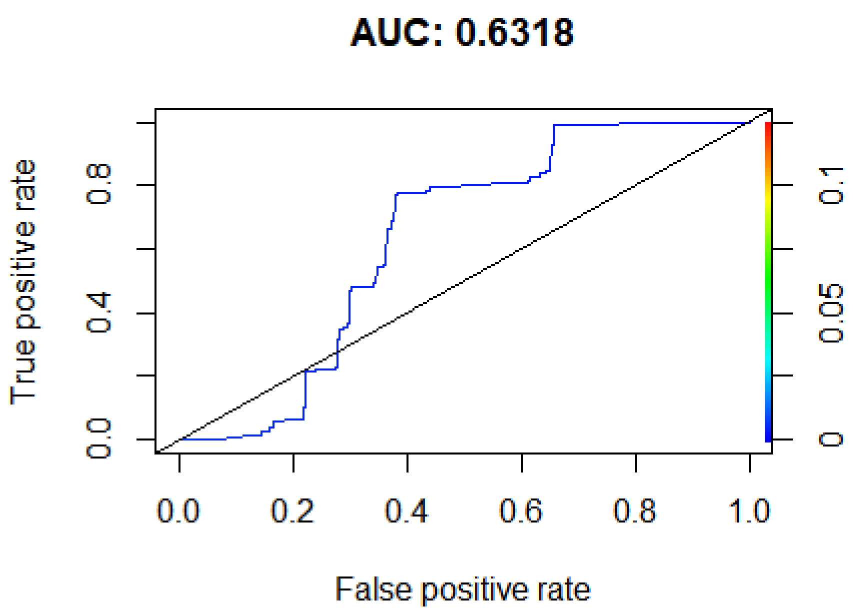


Figure 11 Receiver Operating Characteristic curve and the Area Under the Curve of the created model

The confusion matrix (Table 3) revealed that the model classified 605 turning point occurrences correctly (i.e., true positives), 179 turning point occurrences were not classified correctly (i.e., false negatives). Furthermore, 138.726 observations were correctly classified as an observation were no turning point occurred (i.e., true negatives). 86.210 observation were wrongly classified as observation were a turning point occurred (i.e., false positives). The confusion matrix revealed precision (i.e., correct positive class predictions) and recall (i.e., correct positive class predictions out of all positive examples in the dataset) values of, respectively, 0.772 and 0.007. The F1-score was 0.138, which indicated that the trained model had a classification strength of around 14%.

Table 4 The confusion matrix of the created model on unseen data.

	Reference	
Predicted	**0**	**1**
0	138726	179
1	86210	605

6.3 Abrupt changes in vegetation greenness trends in the Todgha valley

6.3.1 Spatial and temporal distribution of abrupt changes in vegetation greenness trends

The map on Figure 12 shows the detected abrupt changes in vegetation greenness trends from the beginning of 2000 until the end of 2019 in the Todgha valley. The Upper Todgha valley showed a patchy pattern with abrupt changes occurring between 2003 and 2016 (Figure 12a). Most abrupt changes in the Upper Todgha valley appeared between 2005 and 2006 and between 2009 and 2010.

Following the valley eastwards, a less patchy pattern was observed. The Middle and Lower Todgha valley disclosed abrupt changes in vegetation greenness trends mainly between 2003 and 2006 (Figure 12b).

The newly irrigated plains of Ghallil and Bour Tinedjad presented abrupt changes primarily between 2005 and 2010 (Figure 12c). It is conspicuous that, the most recent created irrigated plains revealed abrupt changes in vegetation greenness trends nearly solely between 2011 and 2014.

The traditional oasis of Tinejdad-Ferkla revealed the same patch like pattern as the Upper Todgha valley, with abrupt changes between 2005 and 2016 (Figure 12d).

It is noteworthy that the BFAST01 algorithm does not allow to detect abrupt changes in the beginning and end of the time series. This is why there are no abrupt changes detected before 2003 and after 2016 (de Jong, Verbesselt, et al., 2013). In general, the year intervals

2005 – 2006, 2009 – 2010 and 2013 – 2014 revealed the most abrupt changes (Figure 13). The amount of dryland pixels in the Todgha valley showing abrupt changes in vegetation greenness trends was 89.2%. No significant ($p < 0.05$) change in vegetation activity trends was detected in 7.7% of the dryland areas in the Todgha valley. Monotonic changes were seen in the remaining 3.1% of the pixels.

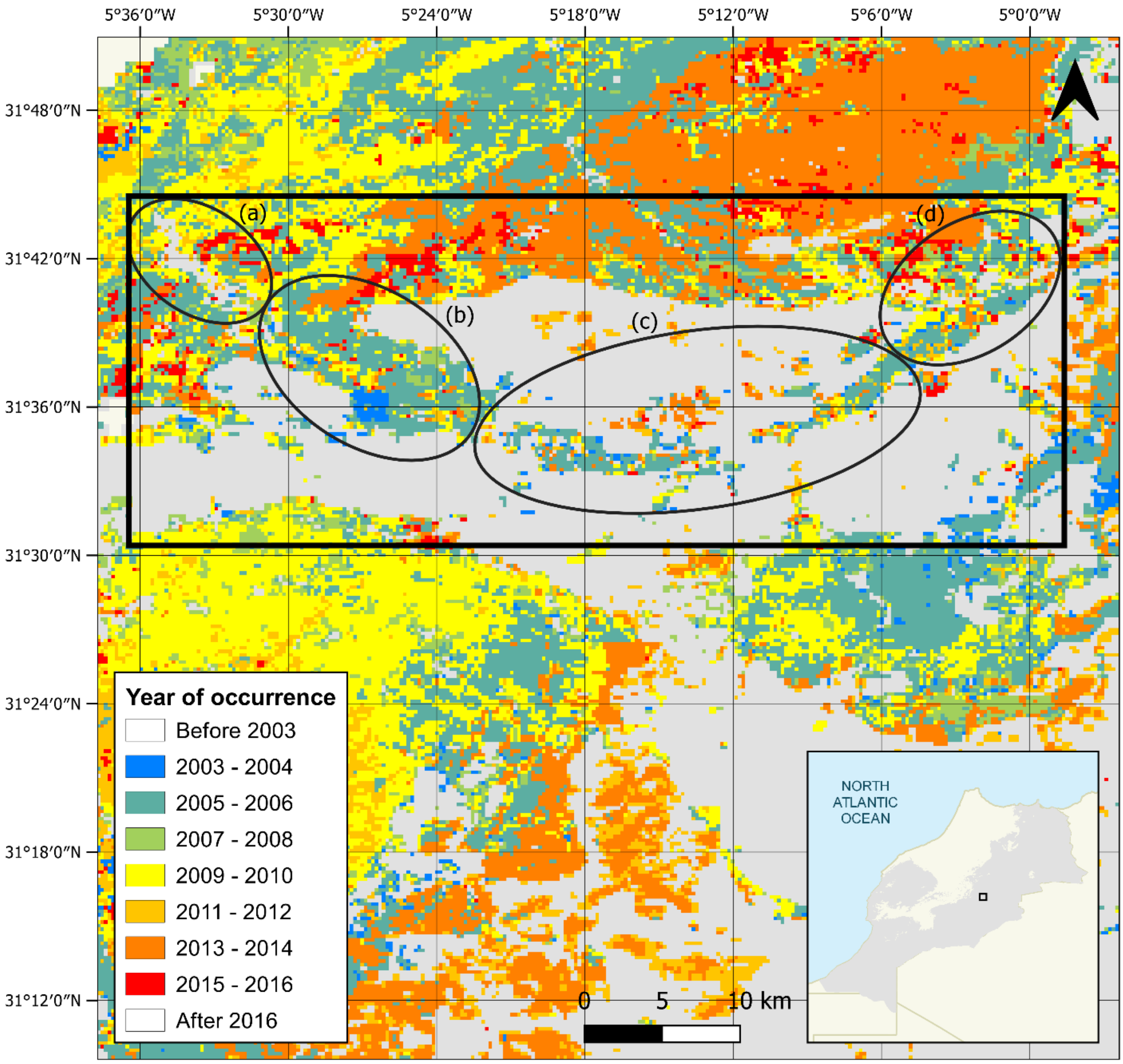


Figure 12 The time of occurrence of abrupt changes in vegetation greenness trends. The Todgha valley is highlighted with a black rectangle in both the main map as the inset map.

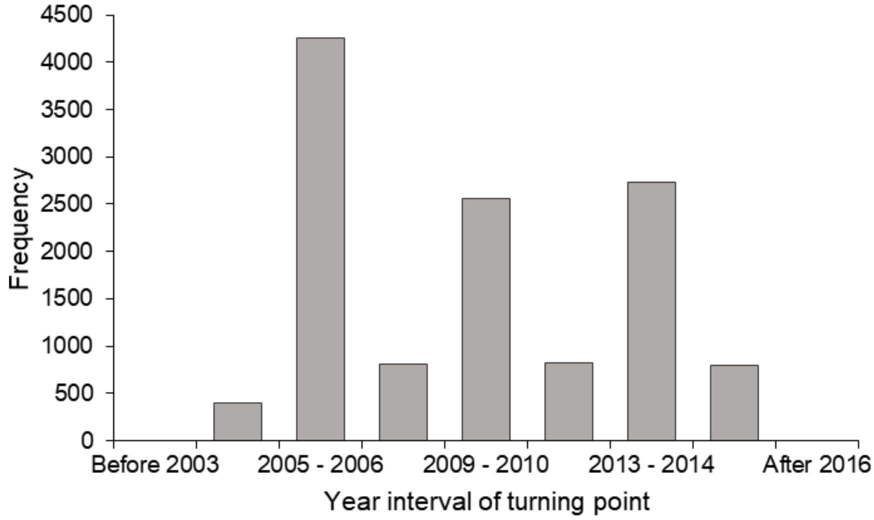


Figure 13 The frequency of abrupt changes in vegetation greenness trends. Although the analysis was made from 2000 to 2019, no turning points were detected before 2003 and after 2016.

6.3.2 Classification of the detected abrupt changes in vegetation greenness trends

From the pixels that underwent an abrupt changes, the two prominent types of change were negative reversal (i.e., from increase to decrease in vegetation activity; 55.7%) and interrupted increase (36.1%). The least number of detected abrupt changes are classified as interrupted decrease (4.1%) and positive reversal (i.e., from decrease to increase in vegetation activity; 4.1%) (Figure 14)[2].

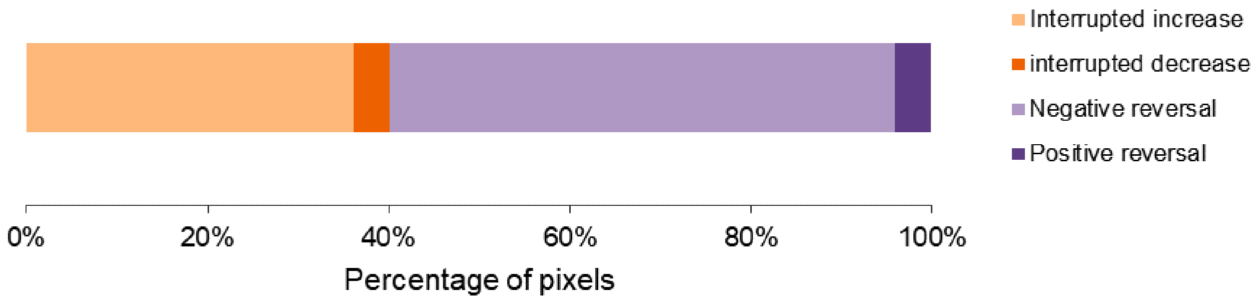


Figure 14 The percentage of pixels for each type of abrupt change in vegetation greenness trends, for pixels that presented an abrupt change in the Todgha valley.

The type of changes can be seen in Figures 15. The Upper Todgha valley revealed a dominance of interrupted increase and negative reversal, but also showed a strip where no abrupt changes were detected.

Moving to the east, to the Middle and Lower Todgha valley, positive reversal and interrupted decrease occurred the most. Particularly at the more downstream ends, where khettara irrigation is relatively important, interrupted decrease is the dominant type of change.

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[2] The statistics have been calculated based on all the pixels within the black rectangle, this calculation is not based on the exact borders of the Todgha valley nor the different zones of the Todgha valley.

The newly irrigated plains of Ghallil and Bour Tinedjad presented a patchy pattern with primarily a mix of interrupted increase and decrease. The most recent created irrigated fields were characterised by a negative reversal. This mix also presented itself in the traditional oasis of Tinejdad-Ferkla, accompanied by a relative vast area where no abrupt changes were detected.

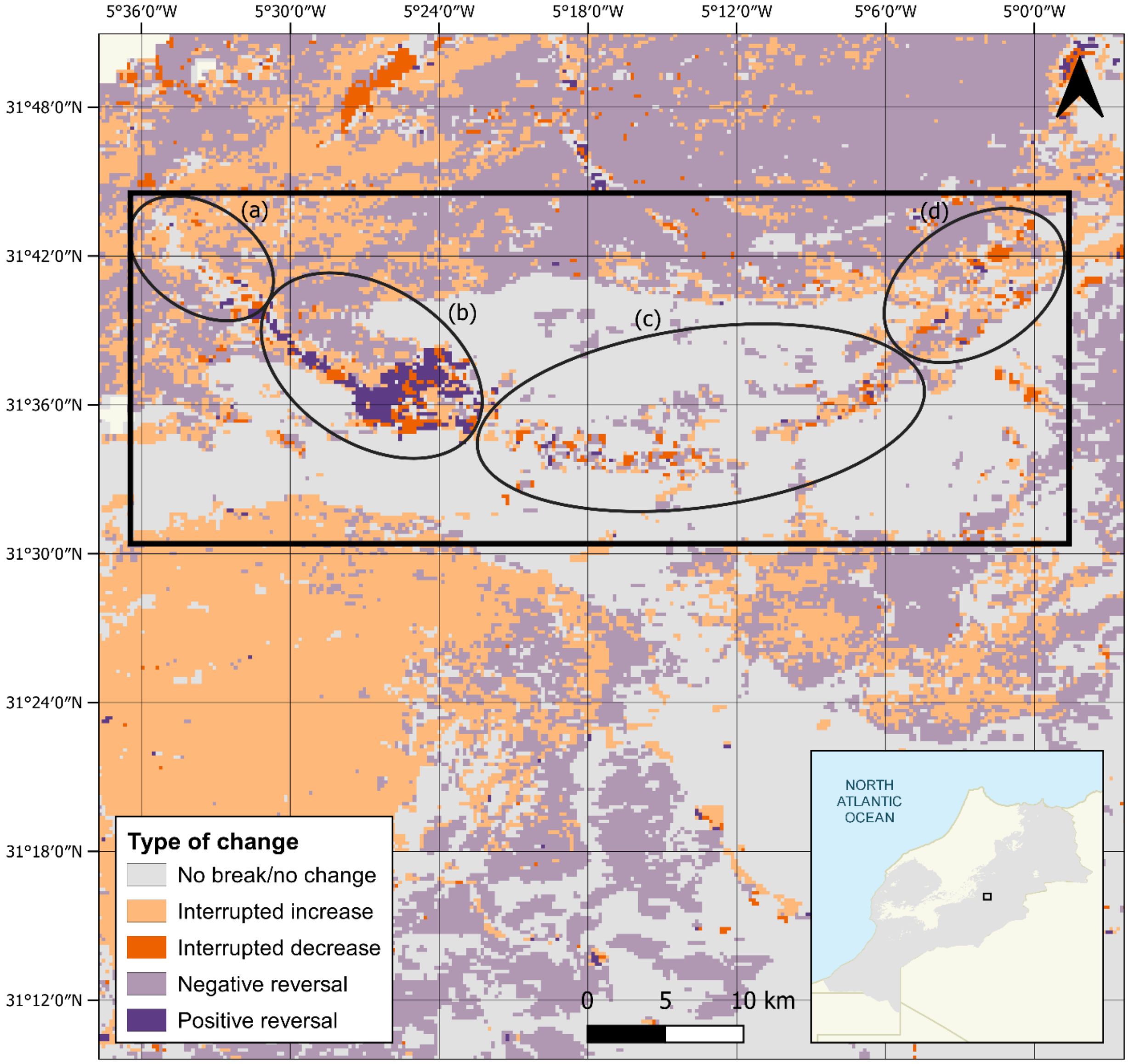

Figure 15 The type of abrupt changes in vegetation greenness trends. The Todgha valley is highlighted with a black rectangle in both the main map as the inset map.

The four types of change can be further investigated by looking at the subtypes (Figure 16). From the abrupt changes that were classified as interrupted increase, 78.6% showed the subtype “slowing down” and 21.4% showed the subtype “accelerating”. From the abrupt changes that were classified as negative reversal, 34.0% were assigned to the subtype “transition” and 57.0% to the subtype “complete”. To elaborate on this, a dominance of the subtype “slowing down” was revealed regardless of the direction of change (interrupted increase or interrupted decrease). The NDVI time series and the BFAST01 output of the two most prominent types of change are visualised on Figure 17.

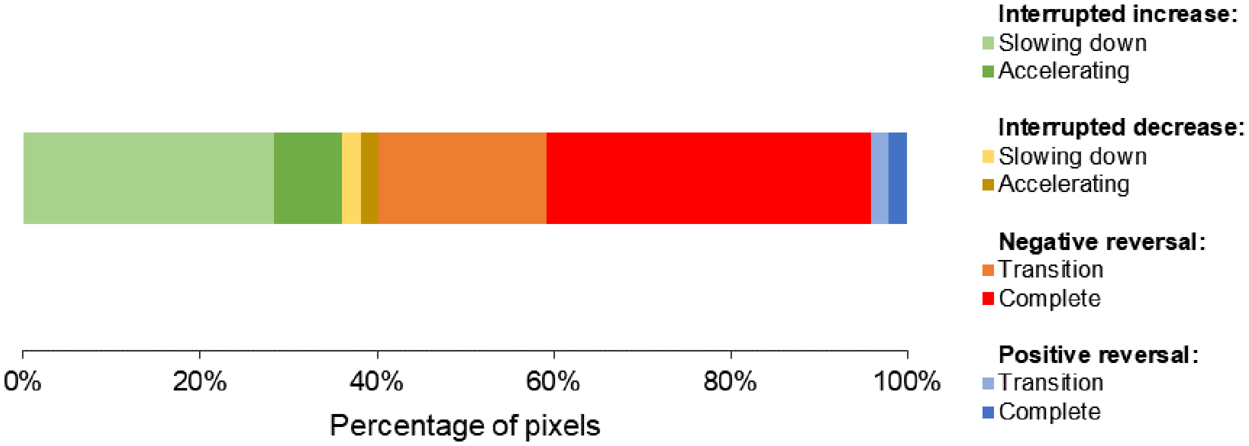

Figure 16 The sub(type) of abrupt changes in vegetation greenness trends for the Todgha valley. The percentage of pixels for each possible combination of type and subtype of change are presented.

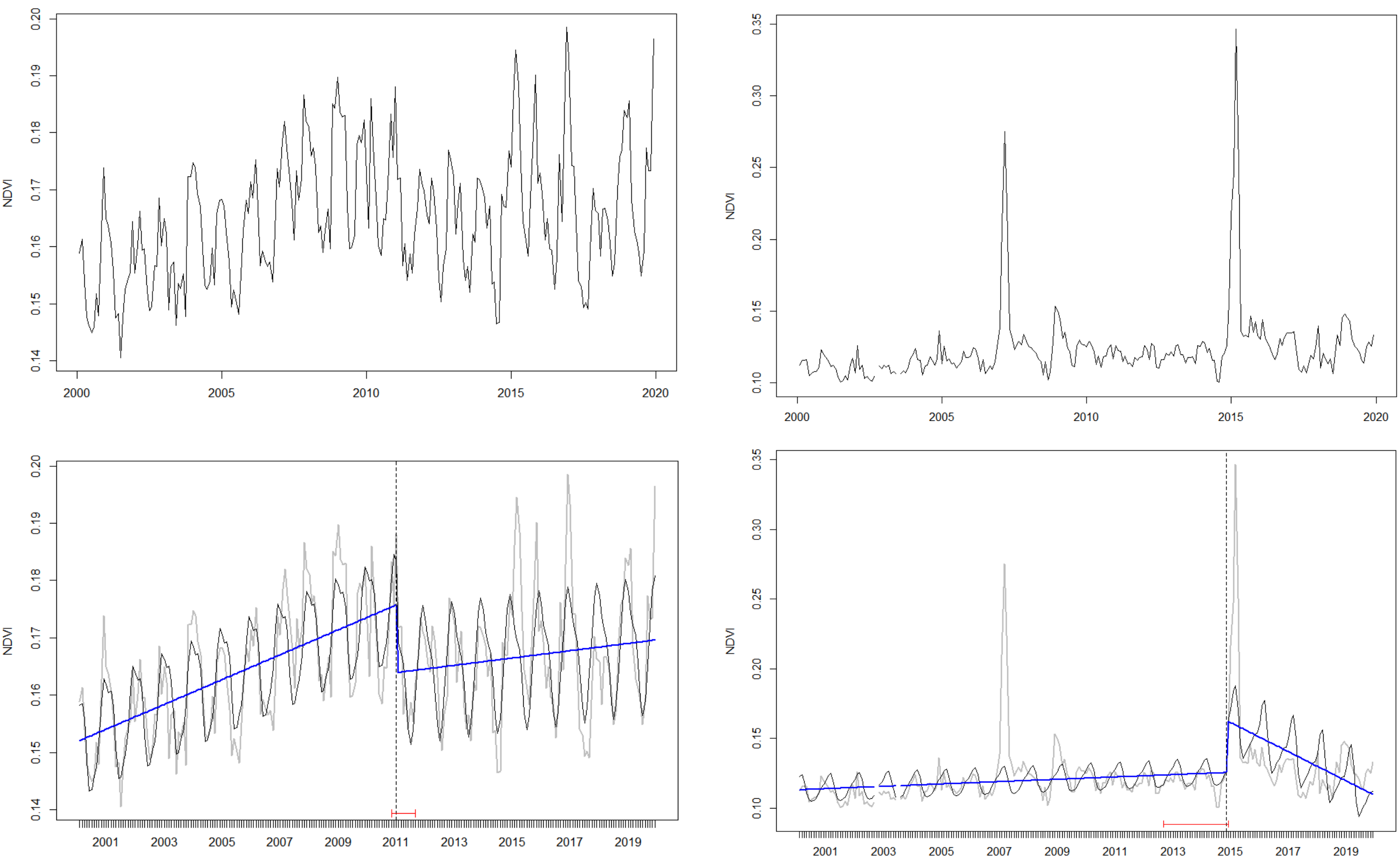

Figure 17 The NDVI time series and BFAST01 output of the two most prominent types and subtypes of change. The left column shows the type interrupted increase, with a slowing down after the turning point. The right column shows the type negative reversal, with the subtype complete.

In the Upper Todgha valley, the abrupt changes that were classified as interrupted increase were sub-classified mostly slowing down (Figure 18). Reversals from increasing to decreasing trends in vegetation activity were observed as another important type of change of this area. Those trends were mostly completely reversed, which indicates a profound change in vegetation activity. Most of the turning points that happened in the Upper Todgha valley happened between 2005 – 2006 and 2009 – 2010.

In the Middle and Lower Todgha valley, a large area revealed reversals from decreasing to increasing trends in vegetation activity. Some trends were sub-classified as transitional, whereas most of the trends had completely reversed in a positive way. Those turning points occurred mostly in 2005 – 2006. The areas which showed an interrupted decrease revealed a slowing trend after the abrupt change, and happened in 2009 – 2010.

Moving further east, the newly irrigated plains of Ghallil and Bour Tinejdad showed a mix of interrupted increases and decreases. From this mix of reversals, the trends were sub-classified as both slowing down and accelerating. However, the area where the most recent created irrigated fields are located revealed reversals from increasing to decreasing trends in vegetation activity, from which most of them had completely reversed between 2013 – 2014.

The situation of the traditional oasis of Tinejdad-Ferkla is comparable with that of the Upper Todgha valley. It is noteworthy that some areas, around the cities of Tinejdad and Isilf, were classified as interrupted decrease with a slowing down after the abrupt change. These abrupt changes happened in 2005 – 2006.

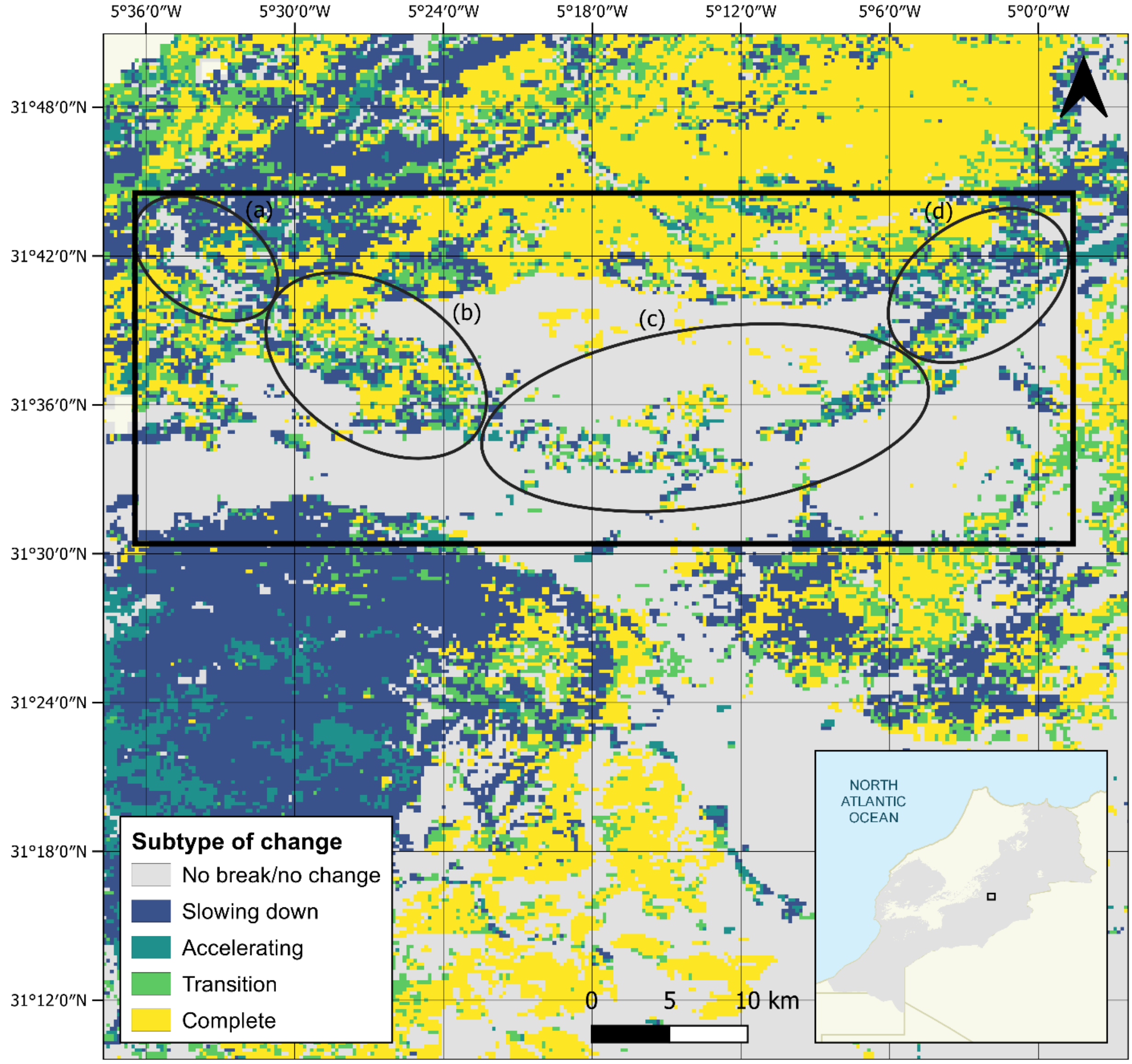

Figure 18 The subtype of abrupt changes in vegetation greenness trends. The Todgha valley is highlighted with a black rectangle in both the main map and inset map.

7. Discussion

This chapter reviews the methods used and results per sub-question. At the start of this research, the following problem was defined: the contemporary knowledge on turning points in ecosystem functioning and their effects on desertification and land degradation is lacking, on both a local and global scale. A national and more detailed assessment of turning points in ecosystem functioning and their drivers is needed. This led to the proposed objectives: identify and classify turning points in Moroccan dryland ecosystem functioning, and have a detailed look at the drivers of these turning points. By answering the three sub-questions (section 1.3), these objectives were achieved:

7.1 Identifying and classifying turning points in ecosystem functioning in Moroccan dryland

This study resulted in the first nationwide identification and classification of turning points in dryland ecosystem functioning, with such a fine spatial resolution (i.e., 500 m), and provides a perspective on the distribution of small-scale RUE disturbances over a 19-year period. A hotspot of turning points were identified in the northern part of Morocco, which overlaps with the cities of Missour, Sidi Boutayeb, Teggour, and partially with El Ksabi. This area belongs to the basin of and depends on the Moulouya River for freshwater and thus determines environmental conditions and human activities (e.g., agricultural) (Snoussi et al., 2002; V. Tekken et al., 2009; Vera Tekken & Kropp, 2012). Furthermore, this hotspot is located directly downstream of the Hassan II dam, which was inaugurated in 2009 (IUCN & Centre for Mediterranean Cooperation, 2010). The sources of the Moulouya are in the Almssid region and drains both the Middle and High Atlas. This hotspot is generally in line with the hotspot of turning points detected in the global study of (Bernardino et al., 2020). However, these turning points were mainly discovered in the period 2002 – 2006. Besides this hotspot, the study of (Bernardino et al., 2020) showed other turning points around the country which were not discovered in this study. Bernardino et al. (2020) revealed a total number of 235 turning points in Morocco, where this study discovered 2547 turning points. Yet, we expected to identify more turning points in Moroccan drylands compared to the global study, because of the higher number of pixels used in the analysis (i.e., caused by the finer resolution used in this study, 500 m versus 8000 m). Possibly this was also caused by the short time series used in the analysis (i.e., 2000 - 2018).

We were able to appoint 2009 as a crucial year for altered functioning in dryland ecosystems in the Moulouya River basin, which is visualised in the peak in RUE in the time series plots (section 6.1.2). A typical pathway to explain such a peak in RUE is that extreme droughts leads to a high RUE, but subsequent plan mortality decreases ecosystem functioning by reducing vegetation (Bernardino et al., 2020). However, no extreme droughts were reported in 2009, so it is unlikely that extreme droughts caused this peak in RUE. Moreover, these kind of peaks in RUE are difficult to interpret when no environmental disaster is reported, because RUE includes both rainfall as vegetation. This makes it hard to conclude if the peak was caused by variations in rainfall or by variations in vegetation.

The turning points in 2009 represented an increase in ecosystem functioning, with a slower increase in ecosystem functioning after the turning point was detected. Which is in line with multiple studies regarding the re-greening of the Sahel (Dardel et al., 2014; Eklundh & Olsson, 2003; Heumann et al., 2007). However, the study of (Bernardino et al., 2020) classified the majority of the turning points in Morocco as negative reversal which were in transition. The Moulouya River basin has been struggling with rising temperatures and decreasing precipitation which started in the 1970s (Vera Tekken & Kropp, 2012). However, these changes in temperature and precipitation turned out to be rather small (V. Tekken et al., 2009). Besides, from the turn of the century, neighbouring river basins (i.e., High, Ziz River basin and Tensift River basin) experienced their wettest periods between 2002 and 2011 (Diani et al., 2019; Meliho et al., 2019). These wet periods might explain the increasing trends in ecosystem functioning until the turning point, as water availability is not restricting vegetation growth. Notwithstanding, that the most significant drought in the period 1968 – 2015 was observed in 2006 – 2007 (Meliho et al., 2019). However, almost no turning points were detected in this period. As many other areas in Morocco which belong to a certain river basin (i.e., the Draa valley, the Todgha Valley), the area of the Moulouya river basin highly relates on natural water resources for agricultural production (Ait Kadi, 2004). Because of this high demand for water, which is not likely to settle in the near future, the Moulouya River basin suffers from water scarcity (Vera Tekken & Kropp, 2012). In their global study, Di Baldassarre et al. (2018) shed light on the fact that dams lead to water shortages downstream resulting in environmental degradation, called the ‘the supply-demand cycles’. Which is also proven by studies specially focused on the Moulouya River basin (IUCN & Centre for Mediterranean Cooperation, 2010; Snoussi et al., 2002). This suggests that the inauguration of the Hassan II dam in 2009, which was in the same year as most of the turning points were detected, has an explanatory factor on the detected turning points. For example, decreasing water supplies downstream caused by the construction of the Hassan II dam has led to a reduction of water of water allocated to irrigation, which might explain the slower increase in ecosystem functioning in the Moulouya River basin.

Which have been proven to be a pathway in the Moroccan Tensift watershed (Meliho et al., 2019).

This study used the rainfall estimates dataset of CHIRPS. However, another promising dataset could be used for identifying turning points in dryland ecosystems in Africa. Namely, the 3th version of TAMSAT, derived from Meteosat TIR. This dataset provides monthly rainfall estimates of Africa with a spatial resolution of 4 kilometre (Maidment et al., 2014, 2017; Tarnavsky et al., 2014), which is slightly finer than the spatial resolution of CHIRPS. With a spatial extent of the continent of Africa and a temporal extent ranging from 1983 to the present time, this dataset could be promising substitute of CHIRPS in the research of turning points in African dryland ecosystems.

7.2 Characterising drivers of turning points in ecosystem functioning in Moroccan dryland ecosystems

The binary logistic regression showed the difficulties regarding the characterisation of drivers of turning points in ecosystem functioning, with a McFadden pseudo-R^2 of only 0.015. In this light, it is important to note that model interpretation should be done with care. The model, which incorporated ‘Cropland’, ‘Pop_Density’, ‘SPEI’, ‘Sparse_Herbaceous’, and ‘GHS_Builtup’, showed an improved model fit compared to the intercept model only. ‘Cropland’, ‘Pop_Density’, and ‘SPEI’ were identified by the model as most important variables.

Cropland abandonment was found to be an important factor on the detected turning points. The study by Geist & Lambin (2004) supports this, by stating that desertification happens when cropland changes into rangelands. Which is in line with many drylands around the world, whom are negatively affected by a change in vegetation cover, resulting in a loss of ecosystem functioning (Wang et al., 2012). An increase in population density is a known driver of change in dryland ecosystem functioning (Cherlet et al., 2018), which this study supports. It has been proven that an increase in population together with an increase in per capita water use is affecting drylands (FAO, 2006; Wang et al., 2012). The increase in population could also lead to an NDVI decline, which might affect the ecosystem functioning (de Jong et al., 2012). Climate related factors are one of the most described drivers of altered ecosystem functioning, including dryland ecosystems (Bastiaansen et al., 2020; Mainguet & Da Silva, 1998; Rogers & McCarty, 2000). Drought conditions, which is studied in this research, were revealed as in important driver of the detected turning points. This is supported by a recent study in the Sahel (Bernardino et al., 2020).

Despite the fact that climate related factors are so important to explain changes in dryland ecosystem functioning, the independent variable ‘Soil_Moisture’ was not included in the model.

However, soil moisture is a very interesting and highly potential driver of turning points in African dryland ecosystem functioning, as shown previously (Bradford et al., 2019; Wei et al., 2019). The use of the Sen's slope as pre-processing method might be sub optimal. Another way to pre-process the soil moisture data is to use the soil moisture anomaly, which is often used to analyse droughts (Anderson et al., 2012; Mao et al., 2017). The soil moisture anomaly can be calculated by subtracting the yearly soil moisture values from the average soil moisture value for the whole time series. Negative values indicate dry years, while positive values indicate wet years. These values could then be averaged, per pixel, over the whole time series to produce one raster layer as input for the binary logistic regression. Also, the cropland data could also be pre-processed in another way, to potentially result in a better model fit. By generating a continuous pre-processed dataset instead of a binary dataset, more valuable data would be included. This continuous dataset could consist of the amount of times a cropland pixel underwent a change to another land cover type within the time series.

Even though five potential drivers were investigated by means of six different datasets, other factors can offer interesting opportunities to further explain the occurrence in turning point in dryland ecosystems, based on the framework of desertification (Geist & Lambin, 2004). For example livestock production and migration (i.e., in- and out-migration). The three versions of the Gridded Livestock of the World (GLW; Gilbert et al., 2018) dataset provides a subnational livestock distribution for 2002, 2006, and 2010, with a spatial resolution of ~10 km. This dataset would be very interesting if its spatial resolution improved, as an aggregation from 10 km to 500 m leads to a lot of uncertainties. The European Commission published a report which describes a global dataset on estimates of net migration, with a spatial resolution of 25 km (Alessandrini A., Ghio, D., Migali, 2020). The dataset encompasses the period 1975 – 2015 with a five year interval. Although that they state that the data is aggregable to country-level, aggregating this dataset accurately to 500 m would be a challenge.

The dependent variable of the model is exclusively composed of the pixels that underwent a turning point (i.e., interrupted increase, interrupted decrease, positive reversal, and negative reversal). As there were a lot more pixels showing no turning point (i.e., 752.399) than showing a turning point (i.e., 2547) in the current used dataset, the model had a hard time to train properly. This might have caused the bad McFadden pseudo-R^2 of 0.015. When including also monotonic trends (i.e., monotonic increase and monotonic decrease) in the dataset, it will be less unbalanced, potentially resulting in a better model fit. Another possibility is to exclusively include monotonic trends in the dataset. In this case, the pixels which showed monotonic trends should be given the value 1, and all the other pixels should be given the value 0. However, in this case the relationship between monotonic trends and their drivers will be modelled instead of turning points and their drivers.

A binary logistic regression is a widely used technique in ecology to establish the relationship between multiple dependent variables and one dependent variable (Chao et al., 2009; Kumar et al., 2014). However, the use of a binary logistic regression also has its downsides. Research by Salas-Eljatib et al (2018) revealed that an unbalanced input dataset will lead to higher variances for the maximum likelihood estimates and therefore to more uncertainty in identifying the driver variables for modelling the response variable. This problem could potentially be solved by using a support vector machine to pre-process the unbalanced data before training the binary logistic regression (Farquad & Bose, 2012). Koziarski et al., (2019) proposed a Radial-Based Oversampling (RBO) algorithm to estimate local distributions of both the minority and majority class and this way reduce the problem of unbalanced data. By considering these methods, the model might result in a better fit and thus in a better a McFadden pseudo-R^2.

As an alternative to the binary logistic regression, random forest could be considered as regression and classification technique. Random forest is a widely used technique in studies regarding the functioning of ecosystems (Chrysafis et al., 2017; Heung et al., 2014), and is a technique to regress when the predictions of all the grown trees are averaged (Liaw & Wiener, 2001). However, the "black box" nature of random forest, which makes it hard to interpret the relationship between the dependent and independent variables, is a considerable disadvantage of this technique (Prasad et al., 2006).

7.3 Social-economic drivers of abrupt changes in vegetation greenness trend

The final section of the discussion investigates the socio-economic drivers of abrupt changes in vegetation greenness trends and answers the working hypotheses, which is also stated in section 1.3. This working hypothesis states that:

"The pumping of water for cropland irrigation in the western part of the Todgha valley (zone b) leads to a lowering of the groundwater table in the eastern part of the Todgha valley and further downstream in the Tinejdad-Ferkla oasis (zone c & d), and thus, to desertification."

The oases in the Todgha valley (and oases in general) can be defined as agricultural areas in an arid/semi-arid climate, where agriculture is normally not possible without irrigation. However, due to social, economic and cultural processes, in which migration played a significant role, the traditional functioning of oasis agriculture in the Todgha valley has been under pressure. The cumulative causation theory (Massey, 1990), hypothesizes that this process can be explained due to out-migration causing agricultural labour shortages. In contrast to this, the new economics of labour migration theory (Stark & Bloom, 1985) hypothesizes that migration enables migrant households to overcome local market constraints and to invest in local agriculture in order to heighten agricultural production.

For centuries, the dwellers of the Todgha valley developed advanced techniques to capture surface water or to extract groundwater for irrigational purposes. Based on the location in the valley, the water source they and the irrigation techniques that they use differ. Three main oasis types can be distinguished: river, groundwater and source oasis (de Haas, 2001b), two of which occur in the Todgha valley. The river oases can be found alongside a perennial rivers (zone a). Groundwater oases lie in areas where groundwater is close enough to the surface to be extracted (zone b, c & d). As the traditional irrigation technique used in zone b and to a lesser extent in zone c, khettaras, require a lot of maintenance of irrigation channels, dams and other water works, a collective water management was put into place. The deterioration of power of this collective water management, caused by a growing autonomy of households enabled by migration, has contributed to the decline of the khettaras (de Haas, 2003), and thus to the availability of water. However, when khettaras are well managed and maintained, mostly on a very local scale, it still remains an effective irrigation method.

The growing autonomy of households led to the decline of khettaras on the one hand, but to an increase in installations of diesel pumps for irrigation, in the same area, on the other hand. Caused by mainly two factors: (1) the general water scarcity in this part of the valley, (2) international migration to European countries (de Haas, 2003). The second factor was initiated around the 1960s and 1970s, when international migration from Morocco to European began to boom. It was mainly due to remittances, the money which is send back by the migrant to the country of origin, that households could afford to buy a diesel pump, and to develop economical in general (de Haas, 2006). As international migration and migration in its principle requires an investment up front, the poorest of the poorest people are not able to migrate, and thus not able to buy a diesel pump. Resulting in a fragmentation of diesel pump around the Todgha valley, where only the people who receive remittances are able to invest in the installation of diesel pumps, and continue or extent their agricultural practices (de Haas, 2003). This might explain the very patchy pattern in the different maps (Figures 12, 15 and18). However, in a water scares valley, the increase in diesel pumps to extract more groundwater for agricultural irrigation also has its dangers. This increased use of diesel pumps for pumping groundwater for irrigation led to a decrease of water tables, which has resulted in a water crisis in zone b, c, and d, endangering the continuation of the agriculture practices (de Haas, 2001b, 2003; Otte, 2000). The pathway of lowering water tables due to the extensive pumping of water for irrigation was also proven in the Souss-Massa River basin (Choukr-Allah et al., 2017).

To conclude, the eastern part of the Todgha valley and the Tinejdad (zone c & d) suffered from the pumping of water for cropland irrigation in the western part of the Todgha valley (zone b), which led to the lowering of groundwater tables and resulting in desiccation and ultimately possibly desertification. Moreover, this area also suffered from water management problems around khettara irrigation. Seeing that the overall patchy patterns of changes in vegetation greenness are rather localised, which are strongly influenced by social (i.e., water management) and economic (i.e., pumping purchasing power) and factors, desertification in the Todgha valley is a profoundly localised phenomenon.

Thus, the relation between the pumping of water in the western part of the Todgha valley and localised desertification in the eastern part of the Todgha valley is causal and supports the working hypothesis, resulting in the above justified *localised desertification theory*.

Three fundamental differences between the analysis of this sub-question and that one of the first sub-question are the spatial resolution of the NDVI dataset, the temporal resolution of the time series, and the used formula argument of BFAST01. While this analysis used NDVI data with a spatial resolution of 250 m, the first sub-question used NDVI data with a spatial resolution of 500 m. Using the NDVI data with a spatial resolution of 250 m could potential lead to the detection of more turning points in dryland ecosystem functioning. A finer spatial resolution also has a better potential to relate turning points in ecosystem functioning to particular drivers (Rasmussen et al., 2014). Next, this sub-question used monthly NDVI data as input of the BFAST01 algorithm, while the first sub-question used yearly RUE data as input of the BFAST01 algorithm. Logically, a time series with a finer temporal resolutions (i.e., monthly vs. yearly) offers a higher probability to detect a significant break. Finally, this difference in temporal resolution of the time series resulted inevitably in the difference in the formula argument of BFAST01. This sub-question made use of the formula argument to "response ~ trend + harmon" as a monthly time series was used with seasonality. The first sub-question made use of a yearly time series without seasonality, so the formula argument of BFAST01 was set on "response ~ trend".

These fundamental differences led to the discrepancy in the number of detected abrupt changes (i.e., analysed in this sub-question) and turning points (i.e., analysed in the first sub-question). This discrepancy also shows that changes in vegetation greenness trends do not necessarily imply changes (e.g., positive or negative) in the state of Moroccan dryland ecosystems, as no turning points were discovered within the Todgha valley.

8. Conclusion and recommendations

8.1 Sub-questions

In this section, the sub-questions introduces in section 1.3 are answered.

- **Which dryland areas in Morocco experienced turning points in ecosystem functioning over the last 20 years and how can these be categorised using BFAST01?**

By applying the BFAST01 algorithm on the RUE time series from 2000-2018, turning points in ecosystem functioning were mainly detected in the northern part of Morocco, encompassing the river basin of the Moulouya River. Most of these turning points occurred in 2009, possibly caused by commissioning the Hassan II dam. A likely pathway could be that a decrease in water supply downstream, caused by the dam, and led to a reduction of water and to land degradation.

Consecutively, by using the BFAST01classify algorithm, while enabling the dryland typology, on the BFAST01 output, 63.2% of the detected turning points showed a steady increase in ecosystem functioning up to the detection of the turning point. After the detecting of the turning point, the increase in ecosystem functioning slowed down in 99.4% of the cases. Reversals from an increase to a decrease in ecosystem functioning comprised 20.3% of the detected turning points. From which 99.8% was transitioning to a further decrease in ecosystem functioning. 16.4% of the detected turning points revealed a decrease in ecosystem functioning up to the turning points, from which an equal share was slowing down and accelerating. Reversals from a decrease to an increase in ecosystem function were only found in the remaining 0.08% of the detected turning points, from which all completed the transition to a decrease in ecosystem functioning.

- **To what extent does a combination of proximate causes and underlying causes explain the detected turning points in Moroccan drylands on a national scale?**

A combination of proximate (i.e., changes in cropland land cover, changes in sparse herbaceous land cover, and built-up expansions) and underlying causes (i.e., the occurrence of abnormally dry months and population density increase) to explain the detected turning points resulted in a McFadden pseudo-R^2 of only 0.015. The main reason for this bad model fit is the unbalanced dataset which functioned as input for the binary logistic regression. Also, the way some drivers were pre-processed could influence the model in a negative way. Changes in cropland, increases in population density, and abnormally dry months turned out to be the most important variables. However, the relationship between turning points and proximate and underlying causes turned out be very hard to establish.

- **Which areas of the Todgha valley experienced abrupt changes in vegetation greenness trends over the last 20 years and what is the explanatory value of migration on the detected shifts?**

Abrupt changes in vegetation greenness trends were detected across the whole Todgha valley. The year intervals 2005 – 2006, 2009 – 2010 and 2013 – 2014 revealed the most abrupt changes. Moreover, the abrupt changes were detected in a very patchy pattern, with only small areas of the Todgha valley showing the abrupt changes in the same year. The impact of migration on the detected abrupt changes is substantial. Migration, which results in remittances, leads to very local development in the form of investments in diesel pumps for agriculture, as not everyone has the means to migrate. In this way, people who receive remittances have the ability to continue or expand their agriculture activities. People who do not receive remittances do not have the ability to continue their agriculture activities, which can result in negative vegetation greenness trends. This pathway of development can be summarised in the developed *localised desertification theory*.

8.2 Main research question

After discussing the three sub-questions, the main research question can be answered:

"How can turning points and their drivers in Moroccan dryland ecosystem functioning over the last 20 year (2000-2019) be characterised?"

Turning points in Moroccan dryland ecosystems can be detected by applying BFAST01 on the 19 year rain-use efficiency time series. The rain-use efficiency is calculated by dividing the net primary productivity by the sum of the precipitation, both in the growing season. Consecutively, the turning points could be classified by applying BFAST01classify on the BFAST01 output. By means of a binary logistic regression some potential drivers could be analysed. However, the created model needs major improvements to establish an accurate relationship between turning points and their drivers in Moroccan dryland ecosystems.

8.3 Further research

Further research should firstly focus on the complicated relationship between turning points and their drivers. The presented binary logistic regression should first of all be expanded with more potential drivers (i.e., soil moisture and migration). Next, as the ratio of turning points and no turning points is very unbalanced which resulted in the bad model fit, the Radial-Based Oversampling technique is worth investigating. As this method reduce the problem of unbalanced data. Moreover, pre-processing the driver data in another way could also influence the model in a positive way. Also, investigating other machine learning techniques (i.e., random forest) to model this complicated relationship should be considered. These potential steps for improvement of the binary logistic regression model are worth investigating, and may lead to a better modelled relationship between turning points and their drivers. This relationship provides crucial insights for a better decision-making process for dryland ecosystem conservation and management.

Secondly, as most of the turning in ecosystem functioning were detected in the year that the Hassan II dam was brought into us. Further work should focus on the exact influence of lowering water availability (both above ground as ground water) due to a dam on turning points in ecosystem functioning.

Finally, further research could focus on the use of two different datasets to compute the RUE. As an alternative to MODIS to provide the necessary NDVI data, Landsat 7 and 8 could be used. These two Landsat products cover the temporal extent used in this study, but with a finer spatial resolution (i.e., 30 m instead of 500 m). As alternative to CHIRPS to provide the required precipitation estimates, Tropical Applications of Meteorology using SATellite (TAMSAT) could be used. Encompassing also the temporal extent used in this study, but also with a finer spatial resolution (i.e., 4 km instead of ~5 km).

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Appendix I: Model summary

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Call:
glm(formula = TPOM_TP ~ GHS_Builtup + Cropland + Sparse_Herbaceous +
    Pop_Density + SPEI, family = binomial, data = train)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.5098  -0.0913  -0.0837  -0.0674   5.6217

Coefficients:
                    Estimate Std. Error z value Pr(>|z|)
(Intercept)        -3.297315   0.146355 -22.530  < 2e-16 ***
GHS_Builtup        -0.433547   0.289318  -1.499  0.13400
Cropland1          -1.609645   0.578267  -2.784  0.00538 **
Sparse_Herbaceous1 -0.238888   0.128537  -1.859  0.06310 .
Pop_Density        -0.012409   0.001657  -7.490 6.91e-14 ***
SPEI               -0.047980   0.003059 -15.683  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 23617  on 526678  degrees of freedom
Residual deviance: 23250  on 526673  degrees of freedom
AIC: 23262

Number of Fisher Scoring iterations: 11
```

Appendix II: Model fit statistics

```
Model: "glm, TPOM_TP ~ GHS_Builtup + Cropland + Sparse_Herbaceous + Pop_Density + SPEI, binomial, train"
Null:  "glm, TPOM_TP ~ 1, binomial, train"

$Pseudo.R.squared.for.model.vs.null
                             Pseudo.R.squared
McFadden                          0.015535100
Cox and Snell (ML)                0.000696365
Nagelkerke (Cragg and Uhler)      0.015880400

$Likelihood.ratio.test
 Df.diff LogLik.diff  Chisq    p.value
      -5     -183.44 366.89 4.0396e-77
```