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The Impact of Human Activity on Desertification Dynamics in China: A Meta-analysis

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Abstract

Desertification is a state shift to which global drylands are very sensitive. It has both human and climatic causes which are dependent on the region and time. China is a country which has large areas of dryland that are affected by desertification dynamics. To determine the extent to which human activities contribute to these dynamics in China, a meta-analysis is conducted with recent literature on desertification and its causes. There seems to be a general trend that human factors have a bigger influence on desertification expansion compared to climatic factors, while for reversion of desertification climatic factors are more important.

Samenvatting

Verwoestijning is een *state shift* waar droge gebieden wereldwijd gevoelig voor zijn. Verwoestijning heeft zowel menselijke als klimatologische oorzaken welke afhankelijk zijn van het gebied en periode. China is een land dat grote droge gebieden heeft die aangedaan worden door de dynamieken van verwoestijning. Om te bepalen in welke mate menselijke activiteiten bijdragen aan deze dynamieken in China, is een meta-analyse uitgevoerd van recente literatuur betreffende de oorzaken van verwoestijning. In het algemeen lijken menselijke factoren een grotere invloed te hebben op de uitbreiding van verwoestijning in vergelijking met klimatologische factoren. Voor het verminderen van verwoestijning zijn klimatologische factoren van groter belang.

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1. Introduction

Ecosystems are affected by both natural and human influences which could lead to gradual changes eventually resulting in an ecosystem irreversibly shifting to another state (Kéfi et al., 2007). Drylands are a type of ecosystem that are widely threatened by such a shift in state, in which case the shift is called desertification (Bestelmeyer et al., 2013; Verón, Paruelo & Oesterheld, 2006). The definition of desertification as determined in 1977 by the United Nations Environment Programme is degradation of arid, semi-arid and dry-subhumid land (Le Houérou, 1996). This degradation means that the resource potential of the ecosystem is reduced (Helldén, 1991). Soil fertility and vegetation quality are reduced, which has resulted in giant ecological and economic losses (Zha & Gao, 1997). As approximately 40% of the land surface consists of these drylands and at least one billion people inhabit these areas (Reynolds et al., 2007; Verón et al., 2006), desertification is thus a relevant threat. The severity of the problem is likely to become bigger as population continues to grow and climate change further affects the world's ecosystems (Reynolds et al., 2007). One country which has experienced large population growth over the past decades is China (World Bank, 2018b). Situated in Asia, a large area in this country can be classified as dryland, especially in the northeastern part of the country (Sterk et al., 2016).

Research has been done on possible causes for this degradation of drylands. The causes are generally divided into two categories, natural and human (Zha & Gao, 1997). Examples of human drivers are (over)grazing, crop growing and deforestation, and examples of natural drivers are climate variations such as less rainfall, and wildfires (Geist & Lambin, 2004; Sheikh & Soomro, 2006). Climate variations may be influenced by anthropogenic activity on a larger timescale through climate change (IPCC, 2013). Warming of surface temperatures due to increased emission of greenhouse gases (IPCC, 2013) may lead to changing rainfall patterns and more rainfall extremes around the world (Pascale, Lucarini, Feng, Porporato & Hasson, 2016; Xie et al., 2015). In scientific research used in this thesis, the climate variations may include effects of global anthropogenic origin. Human causes meanwhile include the local anthropogenic activity.

To combat desertification as effectively as possible, it is useful to determine to which extent human activity plays a part in the degradation of drylands, so mitigation and prevention techniques can be targeted most effectively, especially for areas in China that are not irreversibly affected by desertification yet.

Many case studies have been performed on desertification in different locations globally. If academics and policymakers want to find solutions for the growing problem of desertification and prevent land degradation of drylands in China in the future, it needs to be determined which factors are most important in causing this process of desertification. To find out to what extent human activity plays a role in causing further desertification in China, for this research project a meta-analysis was conducted. Data from multiple case studies can be combined to increase the number of available cases for analysis, making it possible to find potentially national trends in the role of humans in causing desertification. To do this, the research question that is central to this thesis is the following:

"What is the extent to which anthropogenic activity contributes to desertification expansion and reversion in China?"

The hypothesis for this question is that anthropogenic activity is more significant than natural climatic drivers in causing expansion of areas affected by desertification. Additionally, for decrease of area affected by desertification, anthropogenic causes play a significantly less important role. Added together this would mean that anthropogenic activity has a net positive effect on the ongoing process of desertification worldwide.

In the following chapters I first present a theoretical framework which explains key concepts, after which the meta-analysis performed as part of this thesis is presented. A discussion of the research follows, and finally the research question is answered.

2. Theoretical framework

Drylands and desertification

Around 40% of the global land surface is covered by drylands (Feng et al., 2015). Drylands can be categorized into four different types (from most dry to less dry): hyper-arid, arid, semi-arid and dry-subhumid (see also figure 1) (Sterk et al., 2016). They generally have low biological activity and dispersed animal and vegetation populations compared to other biomes, which is part of the reason why they are less frequently subject of scientific study (Schimel, 2010). Safriel (2009) describes drylands as ecosystems that are limited in their biological activity by lack of enough water. In coming decades, the total land area covered by drylands is expected to increase globally (Schlaepfer et al., 2017). Despite the limited biological activity, drylands are a habitat for many endemic species (Maestre et al., 2012).

Desertification or (dry)land degradation is as a shift of state or regime that occurs in drylands (Bestelmeyer et al., 2013), defined by the United Nations Convention to Combat Desertification (UNCCD) during the Earth Summit in 1992 as “land degradation in arid, semi-arid and dry-subhumid areas resulting from various factors, including climatic variations and human activities” (Jiang, Lian & Qin, 2014; Sterk, Boardman & Verdoodt, 2016). Drylands are especially vulnerable to these state shifts due to rainfall that is limited and irregular, together with little soil fertility (Bestelmeyer et al., 2013). Desertification cannot occur in areas that are already classified as ‘hyper-arid’ or desert, but only in those drylands of the world that provide mostly livable conditions for humans (Sterk et al., 2016). Around 54 million km^2 or 40% of the world’s land surface is covered by drylands (Feng et al., 2015; Reynolds et al., 2007; Verón et al., 2006). Sterk et al. (2016) estimate the population in the regions that are classified as drylands to be around 2 billion. Much of the population that inhabits these areas is dependent on agriculture for survival (Sterk et al., 2016). Desertification is characterized by loss of vegetation cover, and as desertification continues to affect more land area globally, living conditions for people will be compromised due to decreasing livable habitat (Feng et al., 2015).

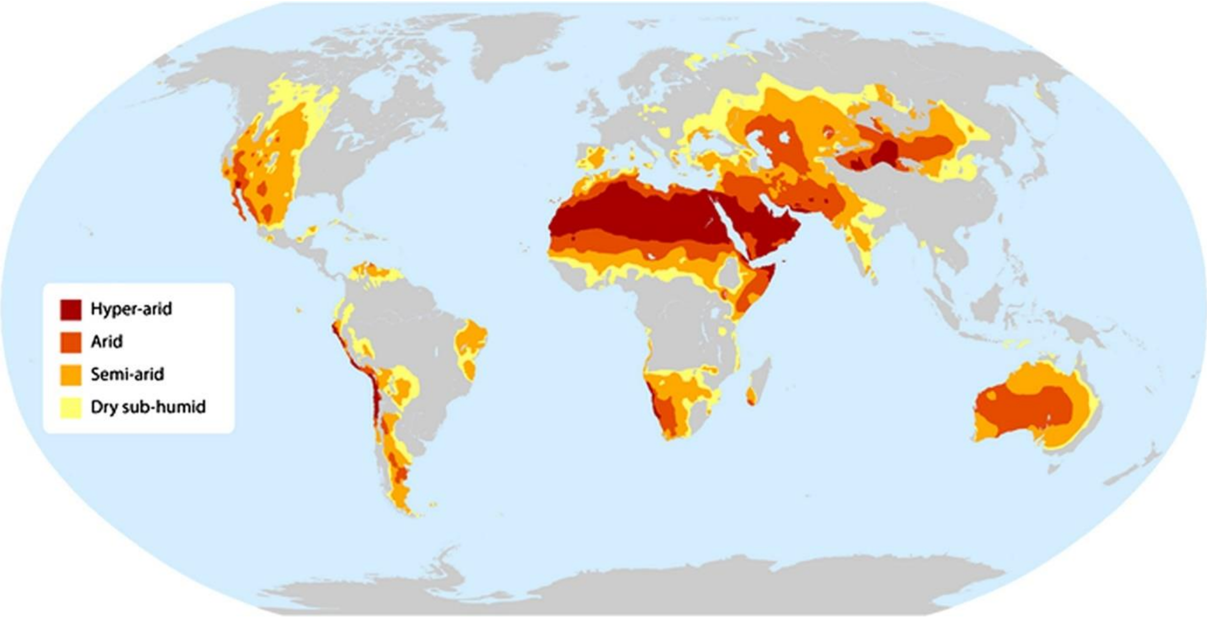

Figure 1: Map of global drylands (Sterk et al., 2016)

Desertification in China

Historically, there have been several periods of desertification in China. According to Li et al. (2018), desertification in the past, before 1700 AD, was mostly caused by climate factors. After 1700 AD, human influence on desertification increased extensively (Li et al., 2018).

China has dealt with a large population increase over the past decades, as well as a sharp increase in economic welfare, with the GDP per capita increasing from a little less than 1 million in the year 2000 to more than 8 million in 2016 (World Bank, 2018a; World Bank, 2018b). These are both considered to be underlying driving forces of desertification (Geist & Lambin, 2004).

Several ecological restoration programs have been set up by the government in an attempt to combat the severe desertification in the country (Guo et al., 2017; Tian et al., 2015). Li et al. (2018) state that since the 1970s large projects and regulations have been put in place. These projects involve afforestation, limiting sand movement and returning farmland to forestry (Li et al., 2018). Regulations that have been put in place mainly concern grazing management in the form of rotational grazing and grazing exclusion, where the last mentioned option prohibits the use of land for grazing completely for a period of time (Li et al., 2018).

Drivers of desertification

Causes of desertification can generally be divided into two categories: human, and natural climatic factors. While this distinction exists, desertification is mostly caused by a combination of both human and natural influences, and it is often not clear what the precise explanation is (Helldén, 1991; Sterk et al., 2016). Geist and Lambin (2004) make a different distinction between the causes of desertification. They broadly divide the anthropogenic causes into two categories: proximate causes and underlying driving forces. The first category is defined as "human activities or immediate actions at the local level (…) that originate from intended land use and directly affect dryland cover" (Geist & Lambin, 2004). Examples they use are agricultural activities such as overgrazing, and deforestation (Sterk et al., 2016). Geist and Lambin define the second category as "fundamental social and biophysical processes (…) that underpin the proximate causes and either operate at the local level or reflect influences at the national or global level" (Geist & Lambin, 2004). Examples of this category included in their research are population density, market growth, and new innovations.

The relationship between the multiple drivers gets more complicated because of two-way influence. Climate change, for example, has been caused by human activity, and influences global weather patterns (IPCC, 2013). Daily temperature and precipitation extremes have increased in intensity and frequency due to climate change (Stott, 2016). The other way around, desertification can influence climate (Sivakumar, 2007). Precipitation patterns are expected to change and rainfall extreme are expected to become more frequent due to anthropogenic climate change (Pascale et al., 2016; Xie et al., 2015). Changes in vegetation cover possibly change the albedo of an area, which influences how much solar radiation is reflected (IPCC, 2013).

Drivers of desertification may differ depending on the location and may vary during time (Sterk et al., 2016). This is why in some regions human activity may be a more significant cause relative to climatic factors.

Reversion of desertification

As well as for drivers of desertification, a distinction can be made between human and climatic causes when it comes to reduction of desertification. Due to desertification being such a widespread problem with serious consequences for local populations, active human intervention has been taking place to try and restore (partly) degraded land area (Guo et al., 2017; Tian et al., 2015). These 'restoration programs' involve large-scale afforestation (Tian et al., 2015), with vegetation that is resistant to cold and dry climates (Guo et al., 2017). Tian et al (2015) describe the goal of these programs to be to increase the vegetation activity in degraded areas. This vegetation (activity) consists of multiple factors, such as the biomass, net primary productivity (NPP), and vegetation coverage (Tian et al., 2015). It is still questionable how effective these types of programs are, especially on a larger timescale. The cause of failed restoration programs may be negligence of important factors, such as climatic, hydrological and landscape factors as Tian et al. (2015) state.

Apart from active attempts to reverse desertification by restoring vegetation, climatic changes may also help with reversion of desertification. Desertification can be partly caused by a lack of rainfall or periods of drought (Bestelmeyer, 2013). As a result, when climatic conditions are warm and humid for a considerable period of time, this can eventually cause a reversion of desertification (Guo et al., 2017). This also become evident when looking at past trends in desertification (Li et al., 2018).

Methods of measuring desertification

Higginbottom and Symeonakis (2014) state that due to the dynamic nature of desertification, accurate, objective and consistent measurements are necessary to study the phenomenon. Earth Observation (EO) is a valid choice according to them, as large areas of the world are affected by desertification and many of these areas are not developed yet, making field measurements harder to justify (Higginbottom & Symeonakis, 2014). EO mostly consists of using remote sensing with satellites to gather data on, amongst others, geological and biological features of the earth. With this method, information on environmental indicators can be gathered. As Higginbottom and Symeonakis (2014) state, for desertification vegetation index data is most often used for analysis. Most common is the Normalised Difference Vegetation Index (NDVI), which has a close correlation with the Net Primary Production (NPP) (Higginbottom & Symeonakis, 2014). This is however, according to Higginbottom and Symeonakis (2014), not sufficient as a standalone method, as desertification is characterized by many factors and causes which should offer multiple possibilities for quantitative analysis. It is however still very limited to EO based data only, as collection of large scale field data is not possible is most cases (Higginbottom & Symeonakis, 2014).

Kairis et al. (2013) describe how environmental indicators have become an often-used approach to measure desertification on different scales. There is however still no scientific consensus on how exactly to measure desertification, as both the definition of desertification (Higginbottom & Symeonakis, 2014) as well as the required indicators (Kairis et al., 2013) are not agreed upon. According to Kairis et al. (2013) is it necessary to combine multiple indicators when analyzing a problem as complicated as desertification. They concluded the most relevant indicators for land degradation to be rainfall patterns, slope gradient, and water availability (Kairis et al., 2013).

Based on the concept described in the previous paragraph above, a basic conceptual framework for the causes of desertification can be created, as visualized in figure 2 below (based on Geist & Lambin, 2004).

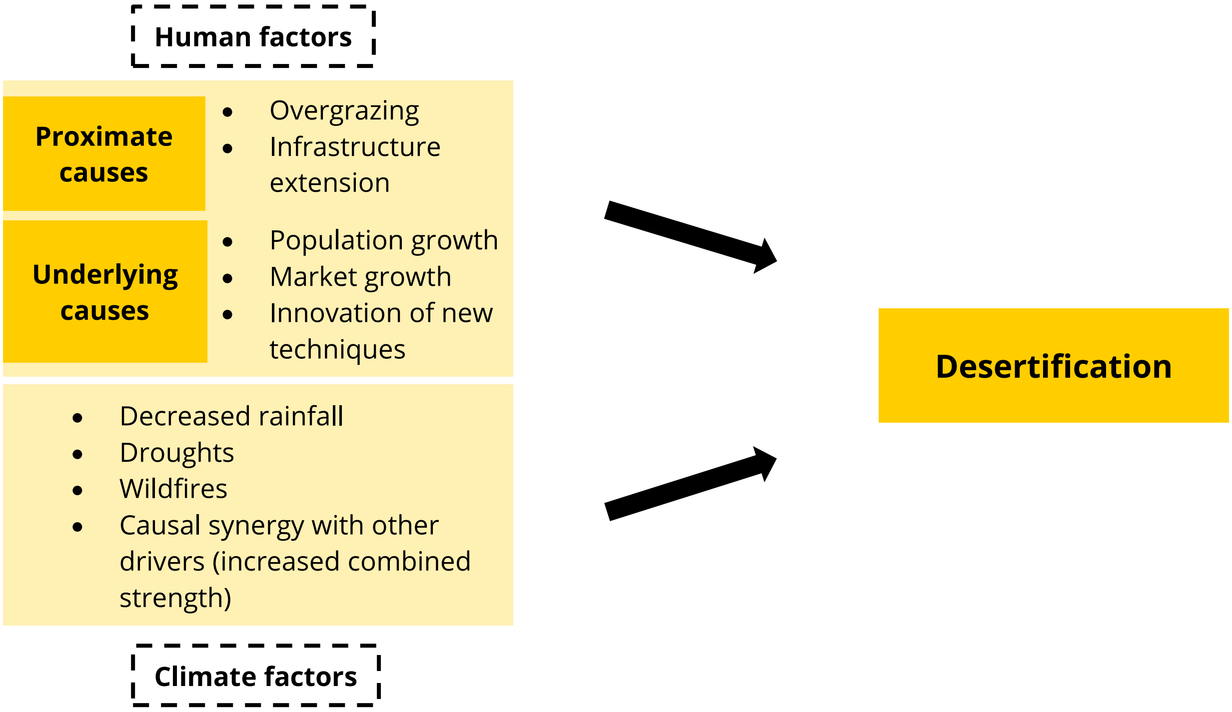

Figure 2: Schematic overview of causes of desertification.

3. Research methods

To evaluate whether there is a significant difference between the impact of human and climatic factors on desertification dynamics in China, a meta-analysis was conducted. The analysis is different in nature because of the existing research on desertification, where an index is often used as a measure of desertification. Criteria for these indices are not always given, and differ between papers. The other variable in this case is qualitative in nature, as it consists of two possibilities 'human' and 'climatic'.

3.1 Data collection

To conduct the meta-analysis, literature cases were collected from different databases such as Google Scholar and Scopus. To find literature cases, key words such as 'desertification', 'land degradation', 'human', 'climate', 'causes', 'China', 'Asia', 'net primary production', and 'NDVI' were used. To further specify the search, literature cases containing quantitative data on the different causes of desertification dynamics were looked for specifically, using key words 'quantitative' and 'relative'. Finally, other papers from already included authors were checked for suitability, and the 'snowball' method was applied to find papers using references at the end of already included papers.

One criterion for definitive selection was that the case included both information on desertification increase and decrease (expansion and reversion). Another important criterion is that the literature case included quantitative data, with a distinction between human and climate causes. This could be either absolute by usage of the total area (in e.g. km^2), or absolute or relative (using percentages). In the case of percentages of the total area, the total research area was additional necessary information. In the case of percentages of either expanded or reversed area, in which case human + climate for both expansion and reversion equals 100%, the additional information necessary was on the area that experienced either expansion or reversion. One final criterion were that the research area had to be in China or include China (i.e. Asia). As a result of this, a selection of 23 cases was made of scientific journal articles. Each of these papers was individually assessed for usefulness for the meta-analysis.

After the elimination of literature cases that did not meet the criteria, 15 cases for the meta-analysis remained, which are listed in table 3. For each of these cases, the data below was extracted from the paper.

- Country/area of research
- Time period of research or data

- In case of multiple temporal intervals within the case, the most recent one was selected.

- Research area in km^2
    - In case the total research area was not mentioned explicitly for a study on the entirety of China, the area as specified most recently in Zhou et al. (2017) was used.
- Resolution or grid size of results in km^2
    - In case the resolution of the results is not included in a paper, the resolution of the used datasets was used. Of these, the largest resolution was selected.
    - In one single case any resolution was missing. For this case the resolution for the analysis has been set at 1 km^2.
- Main used indicator or method
    - While sometimes a combination of multiple methods is used, especially for cases where the indicator for human or natural causes is actual vs. potential net primary production, the main or final method of the paper is mentioned in the table.
- Area with desertification expansion due to human causes (HE)
- Area with desertification expansion due to climatic causes (CE)
- Area with desertification reversion or reduction due to human causes (HR)
- Area with desertification reversion or reduction due to climatic causes (CR)

For the calculation of different areas in the last four columns, in most cases the data was not directly useful. The situations that occurred are listed in table 1 below.

The literature cases and their data are included in appendix A.

Table 1: Possible combinations of data in literature cases, with the solution of how to calculate useable data.

Data on desertification	**Data on causes**	**Solution**
km^2 of area expanded or reversed reversed	km^2 caused by human/climate	Not needed, data directly useful
km^2 of area expanded or reversed reversed	% of area caused by human/climate	Multiply percentage with area
% of total area expanded or reversed reversed	% of area caused by human/climate	Multiply both percentages, and multiply with total research area

3.2 Data analysis

The first step in the data analysis is to convert the data from area to a number adjusted for resolution size. This was done by using the following formula:

$$adjusted\ area = \frac{actual\ area\ (\mathrm{km}^2)}{resolution\ (\mathrm{km}^2)}$$

As a result of this, literature cases which have a smaller and thus more precise resolution of 0.5 x 0.5 km have a relatively larger weight in the analysis than literature cases which have a larger resolution of 8. This means weight in the analysis was determined by the area from the case together with the resolution used in the research.

With the adjusted area data, cumulative data for each category can be calculated. The categories are the combinations in the last four columns of table 6: HE (human-expansion), CE (climate-expansion), HR (human-reduction), and CR (climate-reduction).

To create a 2x2 cross table, the cumulative adjusted data is used. The variable on human or climatic causes determines the column name, while the variable on expansion or reversion determines the row name. This creates four cells with observed values f_o, for the four categories HE, CE, HR and CR (left to right, top to bottom). After this, the total for each row is added to a new cell to its right, and the total for each column is added to a new cell below. The total combined adjusted area in km^2—also from now on referred to as *n*—that was included in the analysis is then calculated by adding the values in the four cells, and this value is put in the lower right corner of the table. A second and third 2x2 cross table are made after calculating the expected values f_e for the four categories, with the expected and combined results.

The expected values represent the values which could be expected from the data should the human or climatic causes have no difference in influence on expansion or reduction of desertification. To calculate the expected data values f_e, the following formula is used, based on Field (2013).

$$expected\ value\ f_e = \frac{row\ total * column\ total}{n}$$

In this case, *n* is the total combined adjusted area in km^2, or the total combined adjusted area from all literature cases. For each of the four f_o values, the total of the row and column the value is in are multiplied. After this, it is divided by the total area *n* to get the expected value f_e for each observed value.

A difference in the observed and expected values can be interpreted in the following ways:

- A higher observed than expected HE or HR means that expansion or reversion of desertification is by a larger extent caused by human factors.
- A higher observed than expected CE or CR means that expansion or reversion of desertification is by a larger extent caused by climatic factors.

To determine whether there is a significant difference between the human and climatic causes, statistical calculations have to be done to determine the effect size. To do this, first the χ^2 statistic must be determined. This can be done using the formula below (Field, 2013).

$$\chi^2 = \sum \frac{(f_o - f_e)^2}{f_e}$$

In this formula, for each value f in the table, in this case HE, HR, CE and CR, f_o is the observed value and f_e is the expected value. Additionally, the degrees of freedom for determining the critical χ^2 value can be calculated from the size of the cross table. In this case however, the degrees of freedom are 1, as it concerns 2x2 tables.

$$df = (no.of\ rows - 1)(no.of\ columns - 1)$$

As the actual values dealt with during the analysis are rather large due to it being the area, a big confidence interval can be applied. At a 99,9% confidence interval, the critical value for χ^2 is 10,8276 ("Chi-square table", 2013). This means that if the χ^2 test statistic in the results is higher than this, there is a significant difference between the two groups.

Because the values used in this analysis are not strictly based on the number of cases but rather on the area, the χ^2 value to be found is expected to be large. As χ^2 is not a measure of the strength of the effect, the value of Cramer's V may be calculated from the χ^2.

$$\varphi_C = \sqrt{\frac{\chi^2}{n}}$$

In this formula, φ_c is the value of Cramer's V, and n is the total combined adjusted area in km^2. The value of Cramér's V is a measure of effect size between 0 and 1, and. Because of this, the large values in the analysis are not a problem. The resulting value can be interpreted according to table 2.

Table 2: Interpretation of Cramer's V value (Cohen, 1988).

Magnitude of Effect Size	Cramer's V/phi
Small	0.1
Medium	0.3
Large	0.5

In addition to the cross-table analysis, a Mann-Whitney U Test was also conducted to test for significance of the difference between human and climatic expansion. For this statistical analysis, IBM SPSS Statistics 24 was used. Two variables were created, one scale variable with the 30 adjusted area values of both categories HE and CE, and one grouping variable indicating for each value whether it belonged to the HE (value 1) or CE (value 2) group. For a confidence interval of 95%, the significance should be lower than 0.05 for it to be considered a significant difference between the two groups.

Finally, a Mann-Whitney U Test comparing the relative contribution of human and climatic causes to desertification expansion was done by calculating the percentage of expansion that was caused by either human or climatic causes for each case. Together this amounted to 100% for each individual set of human and climate expansion. The Mann-Whitney U Test was then done in the same way as described above, except with the relative percentages instead of adjusted area.

Table 3: Meta-analysis table. Each row represents one literature case study, from which data has been taken on the research area and time period, resolution of the results, the main method that was used in the research, and the area for each category in the analysis (HE, CE, HR and CR).

#	Author(s)	Year	Country/ area	Research/data time period	Total research area (km^2)	Resolution of results (km^2)	Main used indicator/method	Degradation dynamics/causes (area in km^2)			
								Desertification expansion		**Desertification reduction**	
								Human (HE)	**Climate (CE)**	**Human (HR)**	**Climate (CR)**
1	D.Y. Xu et al.	2010	China	1980-2000	86,752	1	Actual/potential NPP	2,342	8,068	25,861	6,541
2	T. Wang et al.	2012	China	1991-2000	43,000	8	NDVI	4,858	4,172	9,976	0
3	Zhou et al.	2013	China	2001-2010	128,900	0,5	Actual/potential NPP	71,087	6,761	719	45,030
4	Gang et al.	2014	Asia	2000-2010	3,350,000	1	Actual/potential NPP	642,461	506,017	614,085	488,956
5	D. Xu et al.	2014	China	2000-2010	-	1	Actual/potential NPP	62,723	47,611	52,302	54,570
6	Zhou et al.	2014	China	2001-2010	-	0,5	Actual/potential NPP	1,085,100	329,100	334,100	584,700
7	Feng et al.	2015	China	1983-2012	3,350,000	8	NDVI	1,329,950	345,050	1,329,950	345,050
8	Sun et al.	2015	China	1998-2011	1,565,860	1	NDVI	49,764	355,581	988,264	172,351
9	Tian et al.	2015	China	2000-2012	1,180,000	1	NDVI	17,346	2,006	66,906	69,148
10	Zhou et al.	2015	China	2001-2010	3,500,000	0,5	Actual/potential NPP	1,372,959	423,801	651,287	748,748
11	Li et al.	2016	China	2000-2014	2,603,431	0,5	Actual/potential NPP	46,802	30,343	89,447	216,860
12	Z. Wang et al.	2016	China	2001-2013	1,090,206	1	Actual/potential NPP	84,000	240,000	312,000	139,000
13	Guo et al.	2017	China	2010-2015	86,882	-	Actual/potential NPP	3,706	3,712	9,343	814
14	H. Xu et al.	2017	China	1982-2010	124,000	8	NPP / climate factors	14,508	47,492	14,508	47,492
15	Zhou et al.	2017	China	1982-2010	3,350,000	1	Actual/potential NPP	352,849	364,256	829,383	224,071

4. Results

4.1 Total area per category

First, the total adjusted area for each category was determined. The area in each category for each literature case was adjusted for the resolution that was used in the paper. The results are given in table 4 below, as well as the total areas per category in figure 3.

Table 4: Observed values for each case, adjusted for resolution size

#	HE	CE	HR	CR
1	2,342	8,068	25,861	6,541
2	607	522	1,247	0
3	142,174	13,522	1438	90,060
4	642,461	506,017	614,085	488,956
5	62,723	47,611	52,302	54,570
6	2,170,200	658,200	668,200	1,169,400
7	166,244	43,131	166,244	43,131
8	49,764	355,581	988,264	172,351
9	17,346	2,006	66,906	69,148
10	2,745,918	847,602	1,302,574	1,497,496
11	93,604	60,686	178,894	433,720
12	84,000	240,000	312,000	139,000
13	3,706	3,712	9,343	814
14	1,814	5,937	1,814	5,937
15	352,849	364,256	829,383	224,071
	6,535,752	3,156,851	5,218,555	4,395,195

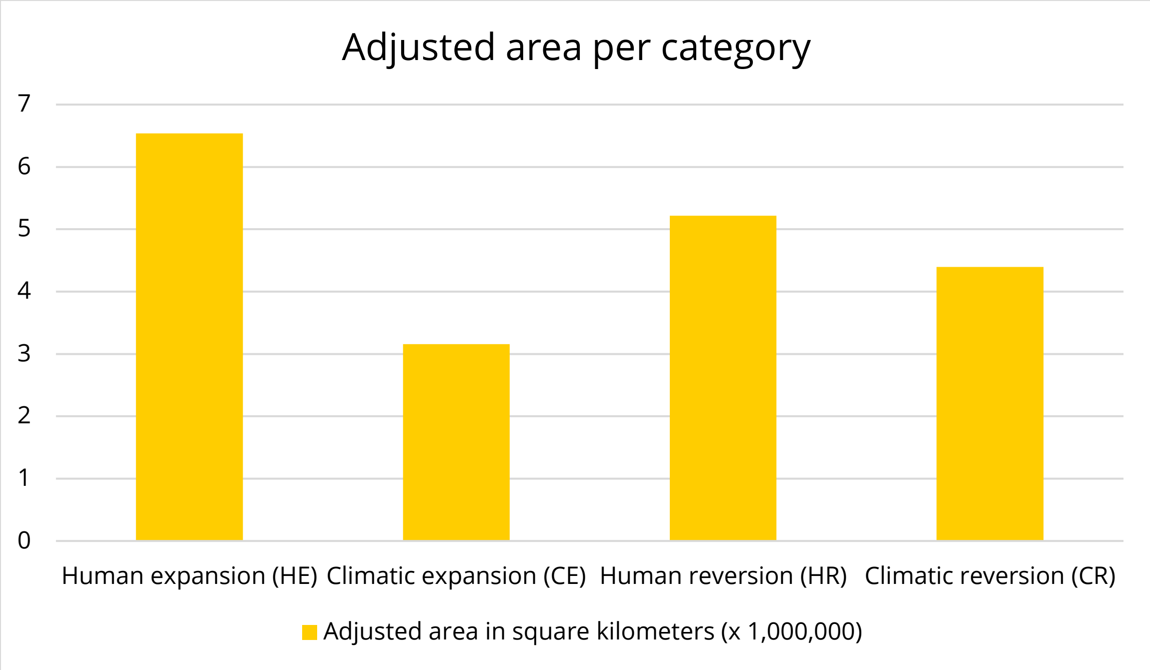

Figure 3: Total area, adjusted for resolution, for the four different categories HE, CE, HR and CR.

Using these total values, the 2x2 cross-tables can be created. Total values for each category from table 4 is put in the corresponding cells in table 5a. After this, the values row and column total can be calculated, as well as the overall total *n*.

4.2 2x2 cross tables

Table 5a: 2x2 cross table of observed values

OBSERVED	**Human**	**Climate**	**Total**
Expansion	6,535,752	3,156,851	9,692,603
Reversion	5,218,555	4,395,195	9,613,750
Total	11,754,307	7,552,046	19,306,353

The analyzed literature cases results in the observed values in table 5a. To be able to conduct statistical analysis the expected values are needed. The expected values can be calculated from the observed values above.

$$Expected\ HE = 5{,}901{,}158$$

$$Expected\ CE = 3{,}156{,}851$$

$$Expected\ HR = 5{,}218{,}555$$

$$Expected\ CR = 4{,}395{,}195$$

Table 5b: 2x2 cross table of expected values

EXPECTED	**Human**	**Climate**	**Total**
Expansion	5,901,158	3,791,445	9,692,603
Reversion	5,853,149	3,760,601	9,613,750
Total	11,754,307	7,552,046	19,306,353

The observed value for HE is larger than the expected value, while the observed value for CE is smaller than the expected value. Meanwhile, the observed value for HR is smaller than the expected value, and the observed value for CR is larger than the expected value. This could mean that human activities have a bigger effect relative to climate changes on the expansion of land that is (to any extent) affected by desertification, while climate changes play a more important role when it comes to the reversion of desertification.

4.3 Calculating effect size

The value of χ^2 can be determined with the observed and expected values.

$$\chi^2 = 350{,}347$$

This value is much larger than the critical value of 10.8267, as was expected. There is thus a significant difference between the observed and expected values.

As χ^2 is not a measure of the strength of the association, Cramer's V for a 2x2 table can be calculated as a measure of effect size with the following formula based on Field (2013):

$$\varphi_C = \sqrt{\frac{350{,}347}{19{,}306{,}353}} = 0.135$$

The value of Cramer's V is 0,135, which indicates a small effect based on the criteria of Cohen (1988).

4.4 Mann-Whitney U test

The two causes of desertification expansion, human and climatic, were tested for any significant differences between the groups. This was done for both the adjusted area and the relative contribution to expansion in percentages. The test results can be found in appendix B.

For the first test, using the adjusted area, the two-tailed significance was 0.820, which is much larger than the 0.05 required for there to be a significant difference at a 95% confidence interval. We can thus say that in this case the difference between the two causes is not significant in this test.

For the test with percentages, the two-tailed significance was 0.171, which is a significant decrease from the first one, but is still far from significant at a 95% confidence interval. For this test, the difference between the two causes (human and climate) was thus also not significant.

5. Discussion

The data resulting from the meta-analysis is mostly in line with the results that were expected, in that anthropogenic activity plays a bigger part in increasing desertification when compared to natural climate changes. The effect size however is not too large with 0.135, being in between 0,1 (small) and 0,3 (medium). The Mann Whitney U Test also did not return any significant results when comparing the influence of human or climate factors on the expansion of desertification.

The research conducted for this thesis functions as a way to determine whether there is a general trend visible in the different literature studies analyzed. As it seems to be a fairly recent type of research, especially for the area of China, there is not a lot of research done yet in this same manner. There does however seem to be somewhat of a trend in the desertification dynamics in China based on the analyzed literature. When looking at individual case differences, there are still some contradictory cases. Many of the used literature cases analyze rather large areas of land for their desertification dynamics. When considering future research, analyzing smaller regions may lead to clear local causes behind desertification. The results from research done on a smaller scale could be more useful for policymaking and education of local population. This may also help to determine whether local initiatives to counteract desertification are indeed useful or not. Meta-analysis for desertification may provide insights in general dynamics, perhaps even globally. The challenge in this case would be to deal with stark differences in research methods.

When looking at the individual literature cases used for the meta-analysis, there are several cases that seem to provide data that is in contradiction with the general trend. In the case of expansion, there are 4 literature cases that have clearly opposing data (1, 8, 12 and 14), and for reduction 5 cases have clearly opposing data (1, 2, 4, 7 and 8). This is a likely reason for the relatively small effect size that resulted from the analysis. When looking at the specifics for these particular cases, the region or temporal research interval is likely not of influence, as there is no clear distinction between the deviating cases mentioned above and the other cases. As far as research method is concerned, for desertification expansion there does not seem to be a clear pattern, as 25% used NDVI and 75% used NPP as main or final indicator. This is in line with the complete set of literature cases, where around 27% of cases used NDVI and 73% NPP. For reduction or reversion however, 3 out of 5 cases used the NDVI method as main or final indicator. This means a ratio of 60% NDVI versus 40% NPP, which is a noteworthy deviation from the total dataset of all cases.

Other than the strongly opposing literature cases, there are also some cases that do not present a clear difference in the impact of human activity or climatic changes on desertification reduction. This may also slightly reduce the magnitude of the effect size.

When looking at the research methods used, there are several limitations that need to be considered. First of all, the total number of cases included in the meta-analysis is very small. The reason behind this was that the cases included in the meta-analysis as conducted were the only existing cases that met all the criteria. The search for literature was in this case exhaustive, and after individual analysis of each case only 15 literature cases remained that were in the intended research area of China, using either NDVI or NPP as main research method or indicator, and, most importantly, included enough data to be able to calculate the needed data for each different one of the four categories. The least recent literature case was published in 2010, which may have provided a starting point for research to be done with this method in the country of China. This is fairly recent, so this could also explain why literature cases are limited. Not all cases explicitly mention desertification often. Rather than doing so, they evaluate vegetation dynamics, and explain in the literature how this is linked to desertification.

The type of classification used for desertification and the human or climate factors does not lend itself well to a classic quantitative meta-analysis, as most case studies do not include and odds ratio or the data necessary to calculate one. This is mainly due to the fact that desertification is often measured according to an index or scale. To make analysis possible, for this thesis the scale is divided into two categories, with increasing and decreasing desertification, in this analysis named 'expansion', and 'reversion' or 'reduction'. This leads to the problem that number of cases is not a possible method of cross-table analysis. To solve this, the total area for each category was chosen as measurement, divided by the resolution used in research to create a more logically weighted comparison. A consequence was that some cases contributed significantly more As a result of the use of area, the χ^2 statistic was not a very useful indicator due to the large numbers in the analysis. This was however solved by finally calculating Cohen's V as the measure of effect size. Cramer's V always has a value between 0 and 1 and corrects for the total *n*, thus likely provided an accurate effect size in this analysis.

In part of the literature cases studies, the whole area was classified as either having increased or decreased desertification. In others however, another possibility was that there was no (significant) change in an area, eventually leading to much smaller category area values for those cases.

For some cases, there was missing data. In most cases, this could be calculated from the data that was included. In two literature cases, 7 and 14, this could not be done, and the same data was used for both expansion and reversion. By doing this, the distinction between human activity and climatic changes was still possible to be made. There was one case in which there was no resolution included, neither on used data or research results. To adapt for this, the most common resolution for the other cases (1 km) was used. Finally, in one case the total area was not given, but was needed to calculate the data for the analysis. For this case, the total area of the most recent case with the same research area was taken as a substitute. These choices could have affected the final results, although it is difficult to determine to which extent this may have happened.

6. Conclusion

The main research question for this thesis is "What is the extent to which anthropogenic activity contributes to desertification dynamics in China?". Following the results of the meta-analysis that was conducted, it can be concluded that human activity plays a bigger role compared to climate changes when it comes to expansion of desertification. On the other hand, for the area that experiences any kind of desertification reversal or reduction, natural climate changes were more important than human factors. It is however not a very large difference that was measured, as is evident from the calculated effect size Cohen's V. This merely indicated a small effect. Further statistical test pointed toward an insignificant difference between human and climate factors as causes for desertification expansion.

In general it can thus be said that in China, it is not possible to say that human activities have a significantly more negative impact on desertification dynamics, in the sense that they contribute to the increase of land area affected by desertification. The human activities may include agriculture or increasing the extent of infrastructure. Due to the complicated nature of desertification causes however, the actual impact of human activities may be larger than these results show, due to the indirect effect of climate change.

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Appendix A: Meta-analysis data sources

Author(s), year	Data used from paper	Missing data and sources used for solution
D.Y. Xu et al., 2010	Total area: 86,752 km^2 Resolution of results: 1 km Results for 1 km scale: - HE: 2,349 km^2 - CE: 8,078 km^2 - HR: 25,897 km^2 - CR: 6,546 km^2	-
T. Wang et al., 2012	Total area: 43,000 km^2 Results: - HE: 53.8% - CE: 46.2% - HR: 119% - CR: -19% - Increased desertification area: 21% - Decreased desertification area: 23.1%	Resolution of results: - Maximum resolution of used data is 8 km Area HE/CE/HR/CR: - Increased/decreased area % - HE/CE/HR/CR % - Total area
Zhou et al., 2013	Total area: 128,900 km^2 Resolution of results: 0,5 km Results: - HE: 71,087 km^2 - CE: 6,761 km^2 - HR: 719 km^2 - CR: 45,030 km^2	-

Gang et al., 2014	Resolution of results: 1 km Results: - HE: 38.94% - CE: 30.67% - HR: 36.12% - CR: 28.76% - Increased desertification area: 49.25% Decreased desertification area: 50.75%	Total area: - Zhou et al. (2017): 3,350,000 km^2 Area HE/CE/HR/CR: - Increased/decreased area % - HE/CE/HR/CR % - Total area
D. Xu et al., 2014	Resolution of results: 1 km Results: - HE: 62,723 km^2 - CE: 47,611 km^2 - HR: 52,302 km^2 - CR: 54,570 km^2	Total area: - Not needed for data analysis
Zhou et al., 2014	Resolution: 0,5 km Results: - HE: 1,085,100 km^2 - CE: 329,000 km^2 - HR: 334,100 km^2 - CR: 584,700 km^2	Total area: - Not needed for data analysis
Feng et al., 2015	Resolution: 8 km Results: - Human impact: 79.4% - Climate impact: 20.6%	Total area: - Zhou et al. (2017): 3,350,000 km^2 Division over expansion/reversion: - Assume equal areas (half of total) Area HE/CE/HR/CR: - Human/climate impact % - Total area (half for each)

Sun et al., 2015	Resolution: 1 km
	Results:
	- Increased vegetation: 74.12%
	- Decreased vegetation: 25.88%
	- HE: 12.28%
	- CE: 87.72%
	- HR: 85.15%
	- CR: 14.85%
		Total area (1,565,860 km^2)
		- Beijing area: 16,800 km^2
		  o Chang, S., & Bonavia, D.M. (2018). Beijing. In *Encyclopædia Britannica*. Retrieved from https://www.britannica.com/place/Beijing
		- Hebei area: 202,700 km^2
		  o Hung, F.F., & Falkenheim, V.C. (2016). Hebei. In *Encyclopædia Britannica*. Retrieved from https://www.britannica.com/place/Hebei
		- Tianjin area: 11,760 km^2
		  o Boxer, B. (2018b). Tianjin. In *Encyclopædia Britannica*. Retrieved from https://www.britannica.com/place/Tianjin-China
		- Shanxi area: 157,100 km^2
		  o Boxer, B. (2018a). Shanxi. In *Encyclopædia Britannica*. Retrieved from https://www.britannica.com/place/Shanxi
		- Inner Mongolia area: 1,177,500 km^2
		  o Falkenheim, V.C., & Cheng, C. (2013). Inner Mongolia. In *Encyclopædia Britannica*. Retrieved from https://www.britannica.com/place/Inner-Mongolia

Tian et al., 2015	Total area: 1,180,000 km^2 Resolution: 1 km Results: - HE: 1.47% - CE: 0.17% - HR: 5.67% - CR: 5.86%	Area HE/CE/HR/CR: - Total area - HE/CE/HR/CR %

Zhou et al., 2015	Total area: 3,500,000 km^2 Resolution: 0,5 km Results: - HE: 70,3% - CE: 21,7% - HR: 42,1% - CR: 48,4% - Total expansion area: 55,8% - Total reversion area: 44,2%	Area HE/CE/HR/CR: - Total area - HE/CE/HR/CR % - Total reversion/expansion area %
Li et al., 2016	Total area: 2,603,431 km^2 Resolution: 0,5 km Results: - HE: 46,802 km^2 - CE: 30,343 km^3 - HR: 27,8% - CR: 67,4% - Total mitigated area: 321,752 km^2	Area HR/CR: - Total mitigated area - HR/CR %
Z. Wang et al., 2016	Resolution: 1 km Results: - HE: 84,000 km^2 - CE: 240,000 km^2 - HR: 312,000 km^2 - CR: 139,000 km^2	Total area: - Not needed for data analysis

Guo et al., 2017	Total area: 86,882 km^2 Results: - HE: 49.0% - CE: 49.1% - HR: 91.7% - CR: 8.0% - Total developed land: 7,562 km^2 - Total reversed land: 10,180 km^2	Resolution of results: - The mode of the other resolutions in the dataset was chosen (1 km) Area HE/CE/HR/CR: - Total developed/reversed land - HE/CE/HR/CR %
H. Xu et al., 2017	Total area: 124,000 km^2 Resolution: 8 km Results: - Climate: 76.6% of variability - Human: 23.4% of variability	Area for reversion/expansion: - Divide total area by 2 Area HE/CR/HR/CR: - Total area divided by 2 - Climate/human %
Zhou et al., 2017	Total area: 3,350,000 km^2 Resolution: 1 km Results: - HE: 46.4% - CE: 47.9% - HR: 78.1% - CR: 21.1% - Total degraded land: 22.7% - Total restored land: 31.7%	-

Appendix B: **Mann-Whitney U Test results**

The first results are from the first test using area. The results below it are from the second test using percentages.

Mann-Whitney Test

Ranks

	cause	N	Mean Rank	Sum of Ranks
expansion_area	human	15	15,87	238,00
	climate	15	15,13	227,00
	Total	30		

Test Statistics[a]

	expansion_area
Mann-Whitney U	107,000
Wilcoxon W	227,000
Z	-,228
Asymp. Sig. (2-tailed)	,820
Exact Sig. [2*(1-tailed Sig.)]	,838[b]

a. Grouping Variable: cause

b. Not corrected for ties.

Mann-Whitney Test

Ranks

	cause	N	Mean Rank	Sum of Ranks
expansion_area	human	15	17,70	265,50
	climate	15	13,30	199,50
	Total	30		

Test Statistics[a]

	expansion_area
Mann-Whitney U	79,500
Wilcoxon W	199,500
Z	-1,369
Asymp. Sig. (2-tailed)	,171
Exact Sig. [2*(1-tailed Sig.)]	,174[b]

a. Grouping Variable: cause

b. Not corrected for ties.