Determining the Presence of Desertification between 1999 and 2019 in Volgograd Russia using NDVI, NDMI, and TGSI

Final Report

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Introduction

Increasing temperatures, changes in precipitation patterns and vegetation composition due to climate change and human activity have given birth to the phenomena of desertification (Yang *et al.* 2005, Feng *et al.* 2015). Desertification refers to the loss of vegetation cover and land degradation in regions that are arid, semi-arid, and dry sub-humid (Feng *et al.* 2015, Lamchin *et al.* 2016). It can lead to detrimental environmental and economic impacts in these areas, rendering previously productive land infertile and thereby affecting trade and farmer livelihoods (Feng *et al.* 2015, Lamchin *et al.* 2016). Anthropogenic factors, such as poor land-use (overgrazing and over-irrigation), logging and deforestation, as well as climate change are accepted in literature to be main contributors to this phenomena (Feng e*t al.* 2015, Lamchin *et al.* 2016).

Remote sensing and GIS applications, along with remote sensing indices, have been traditionally used to map the rate of vegetation loss and therefore detect the magnitude of desertification (Feng *et al.* 2015, Lamchin *et al*. 2016). For instance, Lamchin *et al.* (2016) used remote sensing satellite images, along with indices such as Normalized Difference Moisture Index (NDMI), Topsoil Grain Size Index (TGSI) and Normalized Difference Vegetation Index (NDVI), in ENVI and ArcInfo to determine the degree of desertification and land cover change that had occurred between 1990 and 2011 in an Khogno Khan, Mongolia.

While desertification can be a global problem, the aforementioned definition suggests that it is of particular concern in arid, semi-arid, and dry sub-humid regions that are collectively termed as ‘drylands’ (see Figure 1) (Feng *et al.* 2015, Mcksweeney 2019). Most drylands on earth are typically found in Western United States, China, Australia and Africa, where there has also been an increasing incidence of sandstorms (Feng *et al.* 2015). Thus, it is also not surprising that most of the literature on this topic is also based on the aforementioned regions.

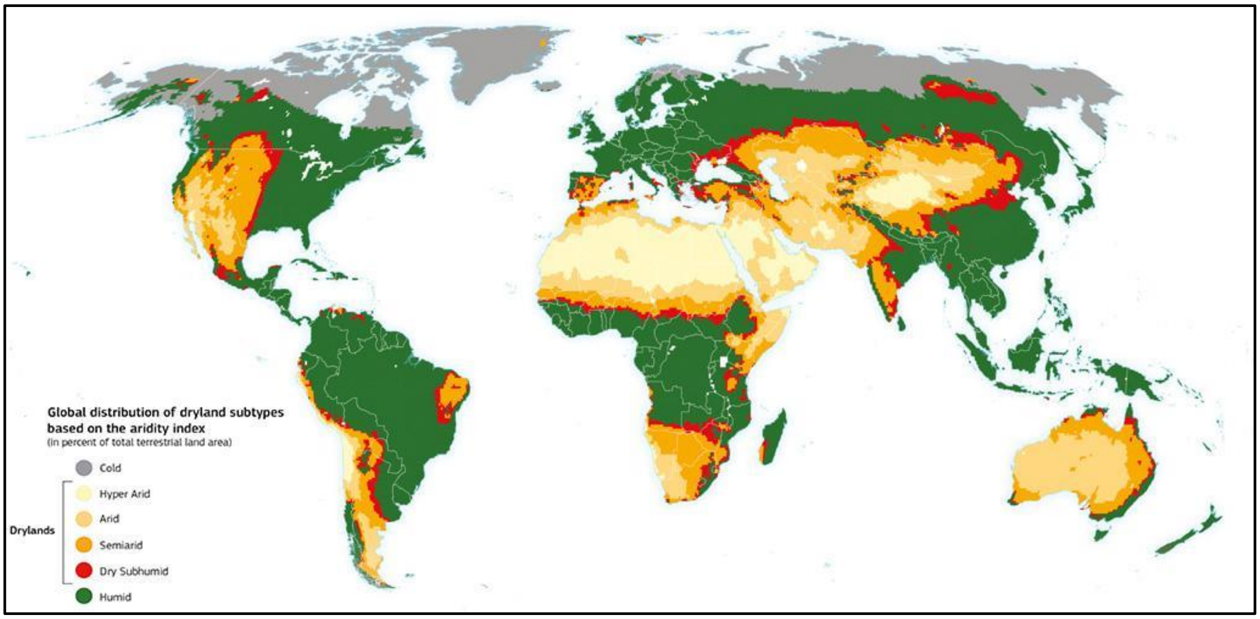

Figure 1. Map showing the distribution of drylands on earth. This figure illustrates the various subtypes of drylands based on an aridity index. Reprinted from *World Atlas of Desertification*, by European Commission's Joint Research Centre, April 25 2019, retrieved from https://wad.jrc.ec.europa.eu/patternsaridity

Although most of Russia can be considered to be cold and humid, there has been increasing literature on regions such as Kalmykia (arid to semi-arid according to the map above) where severe desertification has taken place since the 20th century (Zonn *et al*. 1995). The issue stems back to the old Soviet era, in which land was almost wholly converted to farmland due to a heavy government emphasis on animal production (Zonn *et. al* 1995). Poor farming practices eventually led to degradation and desertification of areas close to Kalmykia (Mirzabaev & Wu 2019). This research project will specifically focus on Volgograd, Russia, an area that has historically faced high human-induced risk of desertification due to grazing, salinization, and recultivation practices (Mirzabaev & Wu 2019). To combat desertification, the national government released the "*General Plan to Combat Desertification of Black Lands and Kizlyar Pastures*" that aimed to improve irrigation and grazing practices, whereas the local government provided more funding to help farmers in Volgograd (Kulik *et. al* 2017)

Using the remote sensing and GIS techniques used in literature, the project aims to answer the research question: Has desertification continued to occur in Volgograd between 1999 and 2019 or has this phenomenon been mitigated by government action/intervention?

Medium spatial resolution imagery from Landsat 8, combined with changes in NDMI, TGSI and NDVI will be used to detect desertification over the span of 20 years on a five-year basis (images from

1999, 2004, 2009, 2014, and 2019 from USGS Earthexplorer). We will also apply the Normalized Difference moisture index (NDMI) to detect changes in moisture content, which may be affected by desertification. Random sampling will be done in the study region and plotted in a regression model to see if the changes are significant.

The results of this project will enable us to confirm whether desertification has been happening in Volgograd since 1999 or have government interventions since this time reduced the degree of desertification. If there is still existence of desertification, the results will provide a rationale for officials to improve remediation efforts. Overall, the methodology and analyses developed in this project can be applied more generally to study other global areas facing desertification.

Methodology

Study Area

The study area for this research project is the area located at 48.70391°N , 44.45235°E , focusing the city of Volgograd and the area around it. Volga river flows from west to east and towards the north part of the study region. A large forested area with low density of agricultural area was located in the east of the study area to the Volga River. High density of agricultural areas were located around Volgograd city, Volga River and the forest area.

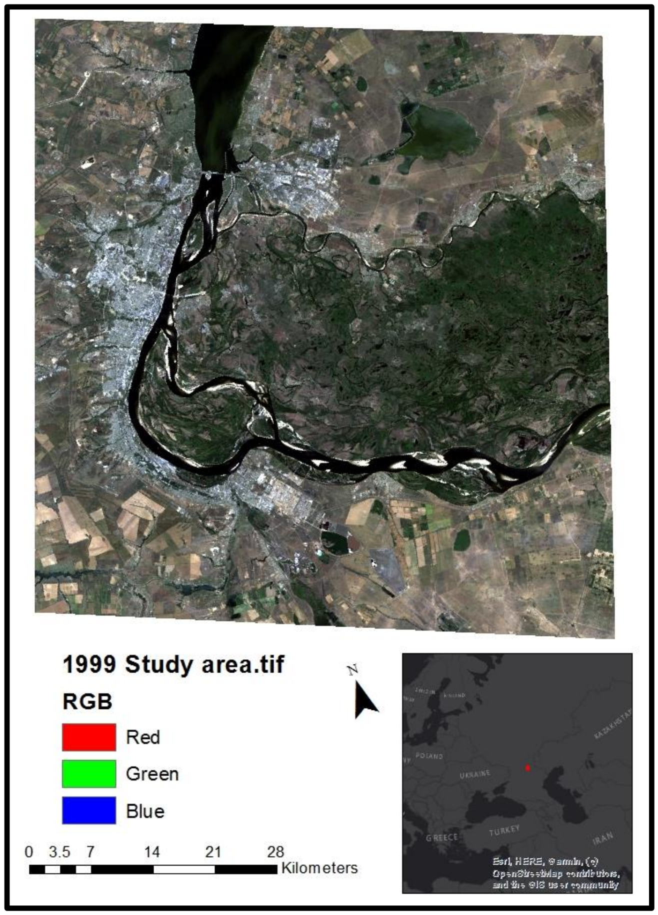

Figure 2. Map of the study area. Inset map is the study area location in Russia.

Remote Sensing and Data Processing

Following the selection of the study area, Level 2 Landsat 5 Thematic Mapper (TM) and Landsat 8 Operational Land Imager (OLI) images were downloaded from Earth Explorer (https://earthexplorer.usgs.gov/). For consistency during spatial analysis, all data were projected to the World Geodetic System 1984 datum (WGS1984) and Universal Transverse Mercator (UTM) zone 38 N. The data acquisition dates were taken every five years from 1999 to 2019. We downloaded three images in the same year with lower than 10% cloud cover and months ranging from May to September (spring and summer season). Clipped it to our study area and then retrieved the median of pixels on each band of the three images to accommodate for the seasonal variation. This will be done to all images producing five images of 30 m resolution for every band (1999, 2004, 2009, 2014 and 2019). We then computed Normalized Difference Vegetation Index (NDVI), Topsoil Grain Size Index (TGSI) and Normalized Difference Moisture Index (NDMI).

Table: Landsat type and the date of the image used, all images have lower than 10% cloud cover.

Sensor	**Month/day/year**
Landsat 5 TM	06/14/1999
Landsat 5 TM	08/17/1999
Landsat 5 TM	09/02/1999
Landsat 5 TM	07/29/2004
Landsat 5 TM	09/08/2004
Landsat 5 TM	06/20/2004
Landsat 5 TM	06/02/2009
Landsat 5 TM	06/09/2009
Landsat 5 TM	09/22/2009
Landsat 8 OLI	07/02/2014
Landsat 8 OLI	08/03/2014
Landsat 8 OLI	09/04/2014
Landsat 8 OLI	07/23/2019

Landsat 8 OLI	09/09/2019
Landsat 8 OLI	06/14/2019

Landsat-based Indices

NDVI was computed following Colwell (1974), where NIR is near infrared and R is red bands. NDVI produces values that range from 1 to -1; values approaching -1 indicate water, values approaching zero indicate no vegetation and values approaching 1 imply high and healthy vegetation.

$$\mathrm{NDVI} = \frac{(\mathrm{NIR} - \mathrm{R})}{(\mathrm{NIR} + \mathrm{R})}$$

TGSI was computed following Xiao *et al.* (2006), where R is red, B is blue, and G is green. This index correlated with the coarse fraction (sand) of the topsoil. Negative value or value approaching 0 indicate high vegetation area or water body and value around 0.20 indicate high sand (fine soil) content.

$$\mathrm{TGSI} = \frac{(\mathrm{R} - \mathrm{B})}{(\mathrm{R} + \mathrm{G} + \mathrm{B})}$$

NDMI was computed following Gao (1996), where NIR is near infrared and SWIR is Shortwave Infrared. For Landsat 8, we used SWIR in band 6 instead of band 7. NDMI produced values range from -1 to 1. Low value indicates low moisture content whereas high value indicates high moisture content.

$$NDMI = \frac{NIR - SWIR}{NIR + SWIR}$$

Data Extraction, Processing and Analyses

Polygons were created around locations that were visually interpreted as agricultural (land use type that shows the most visible impact of desertification) and were merged together into a shape file. After creating the polygon shapefile, we then used the Create Random Points Tool from ArcMap 10.7 to produce

100 random points within the polygon. The points were made to have at least 100 meters distance in-between them in order to reduce any autocorrelation that may have occurred. Values for each index from each year were extracted for each individual point by using extract multi value to points. We repeated these steps five times to improve the accuracy of the index values.

The extracted values of NDVI, NDMI, and TGSI were averaged across point groups for each year and were placed on a time series graph. The time series graph for each index was then fitted to a linear regression model using R Studio. The regression enabled us to model the relationship between year (predictor variable) and the index value (response variable) for each index. As these points were extracted five times, there are five point sets for each year. Finally, maps showing index changes/differences over 20 years maps were produced for NDVI, NDMI and TGSI by subtracting the 1999 median image from the 2019 median image in Raster Calculator in ArcMap.

Results

Results are provided in this section for each index, with the tabular results of each of the point groups found in the appendix. All graphs and data analysis was conducted in R studio.

NDMI

Fitting the results of our study on a linear regression shows a strong (r = 0.658) negative linear relationship between years and the NDMI values. The slope of the line of best fit suggests that average NDMI values are decreasing at a rate of 0.0015 units every year. This relationship has a P value of 0.00034 (<0.05; if using 95% confidence) meaning that the relationship is statistically significant. The R squared of the linear regression is 0.4092 which indicates that years since 1999 can explain 41% of the variability in the average NDMI values.

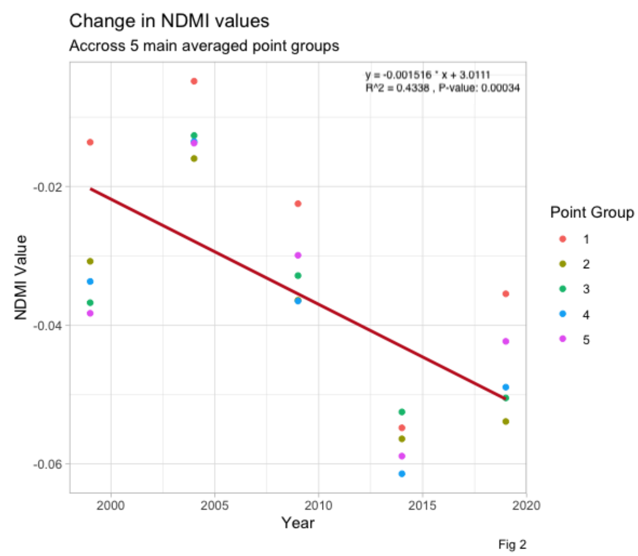

Figure 3. Graph showing NDMI values extracted from different point groups across 20 years. Produced in R Studio

The middle area of the study area appears to be relatively improved in terms of NDMI, while areas in the south and north appear to decrease. NDMI value for water bodies such as the south part of Volga river and ponds near agricultural areas appear to be highly decreasing in the period of 20 years. Agricultural areas in the south appear to also experience improvement but are mostly dominated by degradation in NDMI.

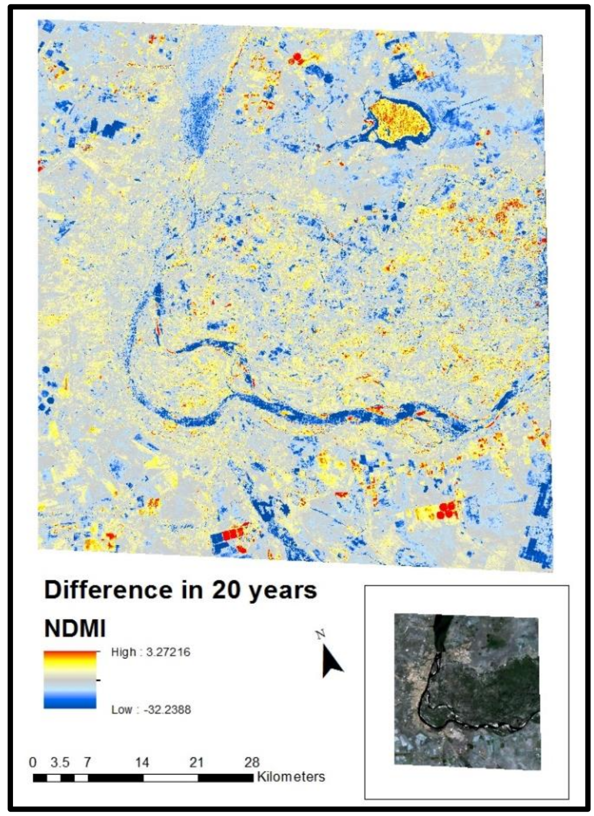

Figure 4. Difference in NDMI value in 20 years, from 1999 to 2019. Inset map is the true colour image in 1999.

TGSI

Fitting the results of our study on a linear regression shows a strong (r = 0.846) positive linear relationship between years and the TGSI values. The slope of the line of best fit suggests that average TGSI values are increasing at a rate of 0.00381 every year. This relationship has a P value of 9.55e-08 (<0.05) meaning that the relationship is statistically significant. The R squared of the linear regression is 0.7045 which indicates that years since 1999 can explain 70% of the variability in the average TGSI values.

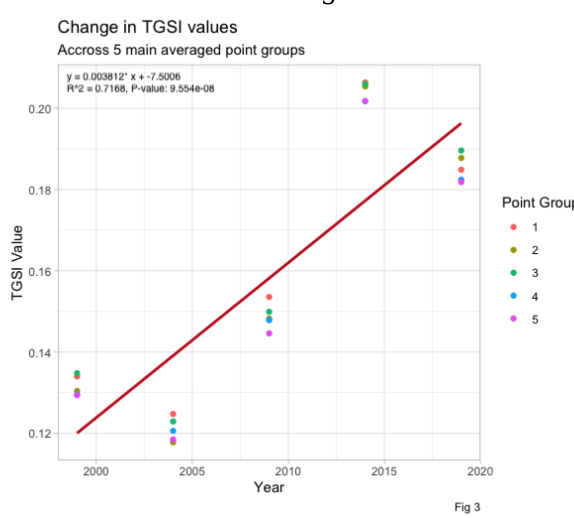

Figure 5. Graph showing TGSI values extracted from different point groups across 20 years. Produced in R Studio.

Area west of Volga river shows increases of TGSI value, indicating soil in this area to be coarser in 2019 compared to 1999. The intensity of desertification, via mechanical composition of the topsoil (soil texture) shows that the effects were greater as distance from the water body increases. This can be observed as some area in the west, near the boundary of our study area, shows a red colour (high changes in soil texture). This is also the same for the area in the east of the study region, however, the intensity is lesser compared to the area in the west. Area in the south of the study area shows mixed effects in terms of TGSI.

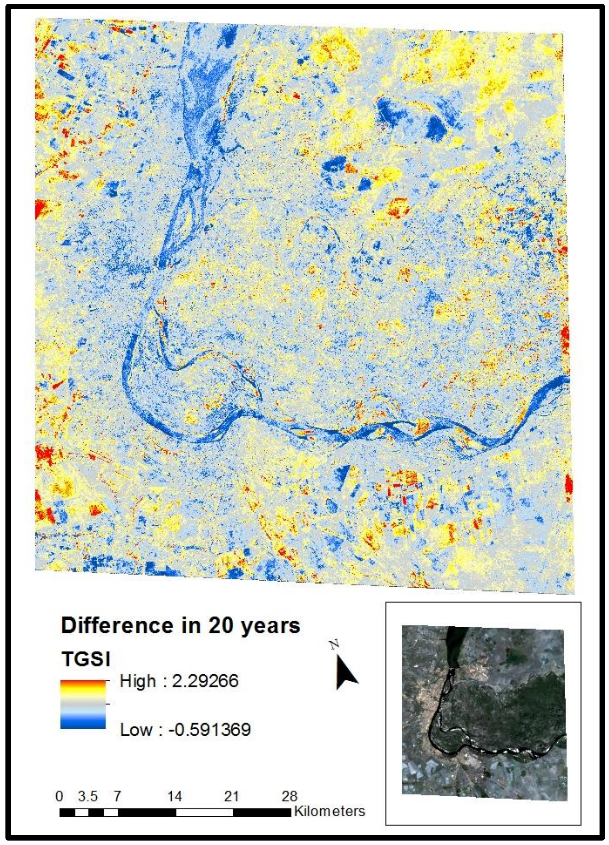

Figure 6. Difference in TGSI value in 20 years, from 1999 to 2019. Inset map is the true colour image in 1999.

NDVI

Fitting the results of our study on a linear regression shows a positive relationship between years and the NDVI values. Meaning the average NDVI values are increasing at a rate of 0.002 every year. This is further supported by the fact that this relationship has a P value of 0.007 (<0.05) meaning that the relationship is actually the least statistically significant relationship we have observed so far. The R squared of the linear regression is 0.239 which indicates that years since 1999 can explain 23% of the variability in the average NDVI values.

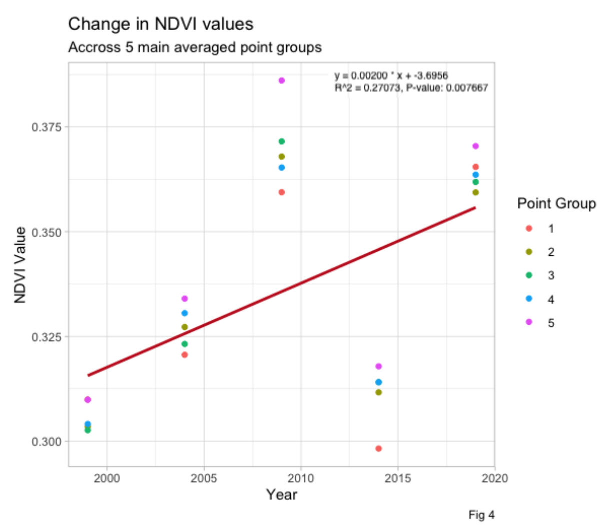

Figure 7. Graph showing NDVI values extracted from different point groups across 20 years. Produced in R Studio.

In the study region, most areas show improvement in terms of NDVI followed by areas with no changes. Areas that experience negative value are mostly water bodies in an agricultural area, see figure 8. Low NDVI value was observed in the Volga river. Some agriculture in the south shows improvement in NDVI value (red colour) while others appear or remain unchanged.

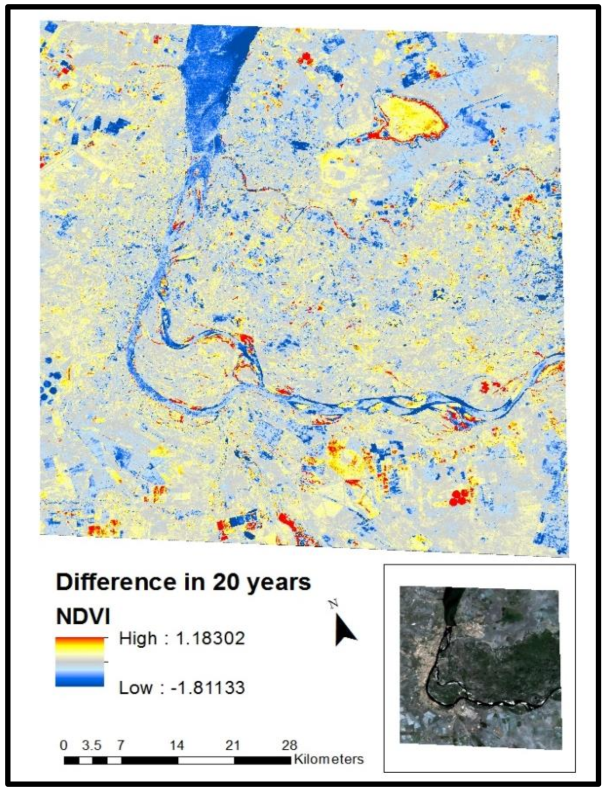

Figure 8. Difference in NDVI value in 20 years, from 1999 to 2019. Inset map is the true colour image in 1999.

Discussion

The interpretation of the regression of each of the indices, as well as the difference maps, will be provided through connections made to literature. The section will conclude with an explanation of the significance of our results.

NDVI

The average NDVI in our study area changes (Figure 7) from approx. 0.313 in 1999 indicating Mid-high canopy cover to approx. 0.355 in 2019 also indicating Mid-high canopy cover (Antognelli n.d.). Improvement in NDVI in 20 years was also detected as most areas in the study region appear to be warm colour as opposed to dark colour (Figure 8). While the increase in NDVI values is contrary to our hypothesis of increasing desertification rates in Volgograd, Lamchin *et al.* (2017) suggest that indices such as NDVI do not provide an accurate estimate of the true extent of desertification. This is because indices such as the NDVI are heavily influenced by precipitation and crop cycles, both of which are irregular in arid regions such as Volgograd (Xiao *et al.* 2006). Thus, it is difficult to determine whether NDVI changes are due to climate or seasonal harvest, which may also be the additional variables that can explain the change in NDVI values and improve the low R squared.

NDMI

The average NDMI in our study area changes (Figure 3) from -0.020 in 1999 indicating 'low canopy cover, dry or very low canopy cover, wet' to -0.050 in 2019 indicating 'Very low canopy cover'

(Antognelli n.d.). Furthermore, area around the Volga river appears to increase in NDMI value, however, this is not the case for agricultural areas further from the river (Figure 4). Overall, the decreasing values of the index suggest that the area is losing canopy cover and that it is water stressed (Antognelli n.d.). Decreasing canopy cover is a leading cause of soil desertification as it exposes bare soil directly to the sun (Guo *et al.* 2017). Thus, this index supports our hypothesis of increasing desertification rates in Volgograd. The R squared value indicates that even though years can explain a large amount of the variability in NDMI, there may be other variables that can help further explain the changing average NDMI values. These variables may include population of volgograd or agricultural output.

TGSI

The average TGSI in our study area changes (Figure 5) from 0.12 in 1999 indicating mid moisture and mid sand content to 0.195 in 2019 indicating high content of sand and very low moisture (Xiao *et al.* 2006). Decreasing moisture and increasing coarse particle (sand) content of soil are clear indications of desertification. The agricultural area in Volgograd experiences an increase in coarse particles in the top soil and the severity increases on areas located further away from water bodies (Figure 6). The R squared value indicates years explain a large variability in TGSI (71.6%), however some other factors may also influence the changes in TGSI value. On that note, TGSI is also useful and reliable in measuring the long term impact of desertification (Lamchin *et al.* 2017).

Significance of Results

As stated in the introduction of this report, previous studies suggested that Volgograd was afflicted with desertification in previous years. Our findings confirm that desertification has been taking place in the study area in Volgograd, as indicated by the changing values of the indices. In particular, the NDMI averages decline from -0.02 to -0.05 (refer to Figure 3) meaning that the study area has lost canopy cover and become increasingly water stressed, and TGSI values increase from 0.12 to 0.195 (Figure 5), indicating a decrease in soil moisture and increased proportion of sand content (Antognelli n.d., Xiao *et al.* 2006). Increasing NDVI values, suggesting an increase in vegetation in the study area, contradict our findings but may be attributable to variations in precipitation and crop cycles (Xiao *et al.* 2006).

In order to combat desertification, Volgograd has attempted a number of methods to replenish its farmlands. When the initial reports of Volgograd's desertification were publicized, the Government of the Russian Federation began working on a plan known as the "*General Plan to Combat Desertification of Black Lands and Kizlyar Pastures*", which consisted of multiple measures that were to be enacted over the coming years, such as the "displacement of farm animals from degraded pastures" and "works on irrigation and the improvement of pastures" (Kulik *et. al* 2017). In addition to the integration of the plan, Volgograd has also been investing more funds towards infrastructure for farms in the area, mainly to help the farmers produce more yield, it may take some time before the results show (FAO and EBRD 2009). According to a 2009 report, Volgograd still ranks behind in cereal and sunflower seed production, despite the fact that the city is investing the most towards farming infrastructure: Volgograd's 19% versus Stravropol's 3%, Krasnodar's 6%, and Rostov's 8% (FAO and EBRD 2009). Volgograd's methods seem to be ineffective, since our results find that desertification is still an increasing problem throughout the land. Since replenishing Volgograd's farmland will take a long time, Volgograd should also maintain its current farmland through sustainable land and resource use, active protection of existing farmland, and try other, alternative methods of farming, such as dryland aquaculture. (Borgen Project, n.d.)

Future Work

The results of this investigation can be improved with more imagery; either using the same time interval of 5 years for a longer duration of time or using a shorter year interval (e.g. each year) for a duration. The interval of 5 years was chosen for this study due to time limitations related to image processing. A yearly interval of images collected, however, can provide for more accurate results.

Conclusion

Overall, the results of our study confirm that desertification is happening in Volgograd, Russia as determined by changes in NDMI and TGSI averages respectively. NDVI results implied the opposite case but is not an accurate estimator of desertification due to variations in precipitation and crop cycles (Xiao *et al.* 2006). Even though Volgograd has introduced the plans above, these measures seem to be ineffective as farmland in Volgograd is producing less grain-based products such as cereal when compared to other farmlands in Russia. It is likely that Volgograd will continue to produce low agricultural yields, unless effective government intervention takes place to remediate the area. In general, Volgograd is one of the many cases of desertification affecting the local populace across the world. The methods and tools applied in this study can be applied to other arid regions in the world such as Mongolia and the Sahel region of Africa.

Appendix

Table 1. Tabular Format of Final Research Results

Year	Average of TGSI	Average of NDMI	Average of NDVI	Point Group
1999	0.13402044	-0.0136282	0.30994363	1
1999	0.1304321	-0.0307912	0.30346168	2
1999	0.13480925	-0.0367566	0.30263145	3
1999	0.12953411	-0.0336981	0.30409904	4
1999	0.12941742	-0.0382784	0.30989864	5
2004	0.12478568	-0.0048283	0.32062379	1
2004	0.11781499	-0.0159774	0.32725222	2
2004	0.12294364	-0.0126582	0.32321235	3
2004	0.12062048	-0.0135203	0.33055002	4
2004	0.11853104	-0.0137542	0.33401658	5
2009	0.1535838	-0.0224868	0.35942126	1
2009	0.14825149	-0.0364045	0.36791082	2
2009	0.14991401	-0.0328519	0.37154957	3
2009	0.14787087	-0.0365176	0.36530241	4
2009	0.14461808	-0.0299211	0.38608003	5
2014	0.20636791	-0.0547927	0.29824975	1
2014	0.20536075	-0.056382	0.31166312	2
2014	0.20594373	-0.0525055	0.31409697	3
2014	0.20172352	-0.0614129	0.31408013	4
2014	0.20175413	-0.0588699	0.31786898	5
2019	0.18488471	-0.0354727	0.36546534	1

2019	0.18776708	-0.0538782	0.35938006	2
2019	0.18959947	-0.0504878	0.36185616	3
2019	0.18242904	-0.0489345	0.36358827	4
2019	0.18184148	-0.0423263	0.37042442	5

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(Note: the above is the recommended IPCC citation)

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