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WATER SCARCITY, CONFLICT, AND THE IMPACT OF HYDROELECTRIC DAMS IN THE GANGES-BRAHMAPUTRA-MEGNA RIVER BASIN

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by

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Abstract

Water Scarcity is frequently cited as a potential cause for conflict. Reduced freshwater can lead to crop failure, societal tensions, and potential mass migrations. The UN estimates that approximately 1.8 billion people will live in water scarce areas by 2030. An unlikely contributor to reduced freshwater supply are Large Scale Water Transfer Projects. As many as 3,700 Large Scale Water Transfer Projects are planned or under construction globally. This study examines the relationship between climatic variables and conflict, and the potential impact Large Scale Water Transfer Projects have on water security via a case study of the Ganges Basin in India. To do so, it analyzes Climate Hazards Center InfraRed Precipitation with Station data, Global Land Data Assimilation System, Hydrosheds and conflict data using GIS and statistical techniques. The paper finds a statistical relationship between water scarcity and conflict, with water storage capacity changes having the greatest influence on conflict events. This has implications for the potential of the future production of water-related conflicts in watersheds undergoing the construction of large-scale water transfer projects.

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Introduction

Freshwater is a fickle resource. At times, it is too abundant, overflowing riverbanks and destroying livelihoods. During extended dry periods, crops wither, freshwater sources dry up and drought events occur. In the last fifty years, water use has increased at over twice the rate of population growth and freshwater extractions have tripled (United Nations, 2012). A 2012 Intelligence Community Report estimated that by 2030 climate change could reduce water resources between 10-30% in already water scarce areas. The United Nations (2012) estimates that as many as 1.8 billion residents will live in water scarce areas by 2030. When water resources are reduced, competition for water can occur between both industries as well as inhabitants. Population growth and migration in arid areas prone to drought and water scarcity have the potential to present not only humanitarian crises, but also lead to conflict and civil insecurity (Homer-Dixon, 1994). Glieck (2014) argues that environmental factors, specifically water scarcity, were the driving factor causing migrations in the lead up to the Syrian Civil War. Additionally, The United States Intelligence Community Assessment (2021) states that destruction of environmental resources will increase water security and the potential for conflict due to competition over reduced resources. Currently, water protests in Iran due to an inadequate allocation of water have resulted in harsh crackdowns from the government (Fahissi, 2021). Despite agreement among scholars (Klare, 2020),and policy makers (Busby, 2017), (Intelligence Community Assessment, 2012), (United Nations, 2012) that water scarcity will become an increasingly prominent global issue, there is no consensus as to whether water scarcity can be directly linked to conflict, whether localized or at a larger multistate level (von Uexkulla et al. 2016).

The increasing variability of precipitation and surface water sources is occurring at a time when much of the developing world is investing heavily in hydroelectric power to generate electricity (Lehner, et al., 2011). Existing and planned hydroelectric dams have the potential to drastically alter the available freshwater resources to down-stream communities as well as disrupt the ecological and social livelihoods of populations at the dam site. Not only do reservoirs deplete water resources through evaporation (Gleick, A Guide to the World's Freshwater Resources, 1993), but also disrupt sediment transfer, leading to saltwater intrusion and loss of agricultural land (Moore, 2014; Mekonnen & Hoekstra, 2011).

This project examines the relationship between water scarcity and conflict, and the implication that future hydroelectric dams will have on water scarce regions. Specifically, the analysis performed in this project will attempt to establish a methodology to predict locations that will experience an increase in conflicts due to changes in climatic variables and the construction of hydroelectric dams. The next section offers a review of the literature on water scarcity and conflict. The third section details the data and methodology used to complete the analysis, and the fourth section provides the results of the analysis.

Literature Review

What is Water Scarcity?

The United Nations (2012) defines an area as water scarce when per capita access to freshwater is less than 1700 cubic meters on an annual basis. The per capita water availability is based on the Falkenmark

Indicator (Rijsberman,2006). The use of the Falkenmark Indicator is beneficial because it is easy to interpret, and data is readily available. However, it does not account for small-scale scarcities, regional water usages or for infrastructures that modify availabilities (dams, pipelines etc.). Additional widely used water scarcity metrics include the Water Resource Vulnerability Index (Rijsberman, 2006), the Water Poverty Index (Sullivan, et al., 2003) and the Water Stress Index (Damkjaer & Taylor, 2017). Among these, the Water Resource Vulnerability Index (WRVI) was developed by the United Nations as the standard for examining water scarcity. The WRVI attempts to measure the available water resources in each water system and compare that availability to the consumption needs of the population in a given water system. When the consumption needs outpace the water systems ability to regenerate, the area is considered vulnerable (Huang & Ca, 2009) Water Scarcity and Conflict in the Literature

Homer-Dixon (1994) was among the first scholars to examine the relationship between water scarcity and conflict and provided three hypotheses related to environmental indicators and violent conflict. The first is scarcity of physical resources leads to intrastate resource wars. Second, migration due to resource scarcity creates ethnic clashes and "group identity." Third, extreme scarcity will increase economic disparities and lead to civil strife and insurgency (Homer-Dixon, 1994). From the viewpoint of Homer-Dixon, environmental scarcity is fundamentally connected to population growth and unequal economic distribution. Homer-Dixon (1994) argues that as the quantity and quality of a resource are reduced, those resources will inevitably be unequally distributed, pointing to land ownership restrictions in Mauritanians banning ethnic groups from owning land near freshwater sources, and the policy in the West Bank banning the establishment of new wells by Arab inhabitants. More recently, the Syrian Civil War has been attributed in part to drought and water scarcity (Gleick 2014). Gleick (2014) argues that the social and economic breakdown in Syria were the direct result of ongoing drought and water scarcity. As agricultural workers migrated into urban areas to flee failing crops and drought. This created tensions in the urban areas between residents and migrants as resource availability and job prospects were reduced in these spaces.

Homer-Dixon and others primarily focus on a logical progression of resource conflicts and do not rely on empirical evidence to support their claims. As Jägerskog & Swain (2016) note, contributing conflicts and migrations to drought and climate is simplistic: local governance and poor resource management are likely the root causes of instability. A study by Eklund & Thompson (2017) supports this opinion. Using remotely sensed landcover data, the vegetation health of Syria, Iraq, and Turkey were evaluated using the NDVI and EVI (an indicator of soil moisture) in the years prior to the Syrian Civil War. Eklund & Thompson (2017) found that the while the entire study area was subject to a prolonged drought, the Syrian government's water policies had a significant impact on water resources relative to neighboring Turkey, which did not feel the effects of the drought as drastically as Syria. According to Jägerskog & Swain (2016), the Syrian government's water and agricultural policies caused the drought to be more severe than it should have been. Kelley et al. (2014) examined precipitation and temperature trends as well as population growth in Syria from 1931 to 2008. While the results indicated that precipitation decreased, temperatures increased, and population grew in the years leading up to the war. Kelley et al. concluded that agricultural policies were the driving factor in migrations from the rural areas into the urban centers and resulting civil tensions.

Among the first to attempt to attribute a statistical link between water scarcity and conflict was a study conducted by Stalley (2003). Stalley used a regression model for all nation states from 1980 – 1992, in which the dependent variable was Militarized International Dispute (MID), and the unit of measurement was one year. Independent variables included population density and environmental variables (Stalley did not evaluate water scarcity alone, but also looked at soil properties, food availability etc.). Water availability was measured on a per capita basis. This study did not find a statistically significant relationship between water scarcity and international conflict. However, when conflict is viewed at the intrastate level, studies have shown a relationship between water scarcity and conflict.

According to von Uexkulla et al. (2016), intrastate conflicts increased when droughts occurred during the growing season of a region's primary crop. In the study, ethnic population data, land use datasets, and monthly remotely sensed drought metrics (Standardized Precipitation Evapotranspiration Index) were overlaid using a GIS to determine how drought conditions correlated to conflict. Reuveny (2007) analyzed the statistical relationship between environmental scarcity, migration, and violence. Of 38 migration case studies reviewed, 17 percent were the result of drought and 15 percent were the result of water scarcity. Conflicts were identified in 19 of the 38 migration case studies, half of which were intrastate conflicts, while the other half were interstate. Interstate conflicts included the migration of 12-17 million Bengalis to India due to the diversion of the Ganges within India that deprived Bangladesh. The study also found that unequal sharing of water resources on the Indus River, as well as substantial Hindu-Muslim (intrastate) violence resulting from water scarcity in Islamabad and Kirachi Pakistan in the 1980's and 90's, resulting in resource struggles and urban violence. Raleigh and Urdal (2007) took a unique approach to the problem of water scarcity and conflict. Instead of analyzing at the country scale, the globe was divided into grid consisting of 100 km x 100 km cells. GIS was used to create buffers around conflict areas, and precipitation, temperature, and water availability rasters were then used in a linear regression to identify their relationships to conflicts. The regression results indicated that decreasing freshwater resources created a higher risk for civil conflict.

Additionally, Hendrix & Glaser (2007) used a statistical model to calculate the probability a country would engage in conflict based on a variety of variables, including population, GDP, land degradation, and freshwater resources per capita. While the study was focused on the African continent, the methods could be reproduced for any region. The study concluded that short term variations in precipitation and freshwater resources did impact the onset of civil conflict, although only mildly. According to Hendrix & Glaser (2007), variability of interannual rainfall had a greater impact on conflict onset than did freshwater resources. However, given that rainfall is the primary source of freshwater in arid regions, it is hard to differentiate the two in many instances.

If a mass migration does occur as the result of drought or food and water scarcity, communities accepting the refugees will suffer increased resource competition (Homer-Dixon, 1994). To determine the increase in water demands in Lebanon following an influx of Syrian refugees, Jaafar et al. (2020) examined water usage prior to the Syrian migration and compared that usage to after the arrival of Syrian refugees using GIS and remotely sensed data. As with other studies in this review, precipitation and evapotranspiration rasters datasets were compared to determine available freshwater. The freshwater availability was then compared to industrial, domestic, and agricultural withdrawals for both pre- and post-Syrian refugee populations. According to the analysis, the spatial resolution at which water consumption was viewed greatly affected the outcome. When viewed at the national level, water consumption only increased by 6%. However, when viewed at a regional and local levels, domestic water usage increased by 20% in areas with a larger number Syrian migrants. One of the primary ways that governments around the world seek to ameliorate water scarcity is through the construction of new water infrastructure as a supply-side solution.

Large Water Transfer Projects (LWTPs)

While typically well intentioned, resource allocation from Large Water Transfer Projects (LWTPs) is not always evenly distributed (Wang, Nixon, Erwin, & Ma, 2020). As Ioris (2016) notes, most LWTPs benefit industrial trades and urban areas, while the source areas receive little economic or water resource benefits. Additionally, LWTP's require a large amount of land, and alter the natural course of the river system, threatening traditional land uses such as agriculture and husbandry (Wang, Nixon, Erwin, & Ma, 2020). For example, the Melamchi Water Supply Megaproject in Nepal has reduced river flows, endangering the livelihoods of 90% of the population who rely on agriculture and fishing (Domenech, March, & Saurí, 2013). Not only are agricultural lands and fishing grounds lost to flooding, but entire populations can also be forced to move because of LWTP's. Moore (2014) states that approximately 300,000 residents will be displaced as a result the Chinese South-North Water Transfer Project. Additionally, large dams inhibit rivers from the natural deposition of sediment in deltas (Moore, 2014; Mekonnen & Hoekstra, 2011) further disrupting traditional and subsistence livelihoods down river from dams. Zarfl et al. (2014) estimate that the construction of large (greater than 1 MW) hydroelectric dams will decrease the number of free-flowing rivers by 21% in the future. The decrease in free-flowing rivers has the potential to adversely affect down-stream populations. In doing so, they could cause water scarcity, food shortages, a reduction of sediment transport, and potential mass migrations (Zarfl et al., 2014). As Figure 1 indicates, the number of hydroelectric dams has steadily increased throughout the past one hundred years and construction is expected to increase rapidly in the next decade.

Among future hydroelectric dams, 414 are expected to be built in the Ganges-Brahmaputra-Meghna (GBM) River Basin (Zarfl et al., 2014). As seen in Figure 2, the GBM River Basin has a high concentration of planned dams or dams already under construction.

Given the high concentration of planned hydroelectric dams in the GBM Basin, this region was chosen to examine the relationship between water scarcity and conflict and the potential impacts of hydroelectric dams on the Ganges-Brahmaputra-Meghna River Basin. As the literature details, governmental water policy has significant impact on how freshwater is allocated and used by various industries. Using data from LWTPs provides a bridge between an emerging water policy and climatic variables such as temperature, precipitation, and water storage. Six datasets were utilized to assess the impact of LWTPs and climate variables on water scarcity and conflict. The data sets include: Global Dam and Resivoir Database, HydroBasin, Climate Hazards Center InfraRed Precipitation with Station data (CHIRPS), Global Land Data Assimilation System (GLDAS), and the Armed Conflict Location and Event Project (ACLE).

Data

Global Dam and Reservoir Database

The Global Dam and Reservoir Database (GranD) data is a comprehensive dataset that includes the georeferenced locations and attributes of 7,320 dams throughout the world. In addition to completed dams, GRanD contains the latitude and longitude of planned dams, dams currently under construction, and reservoirs associated with dams.

There are currently 83 completed dams and 414 planned dams in the GBM Basin. The attributes available for the existing dams includes attributes related to location, administrative properties, storage properties, construction notes, size, degree of regulation, and source. In this study, the degree of regulation was the attribute of interest. The attributes of future dams contain only expected construction specifications, location, and construction start dates.

HydroSheds

HydroSheds (Lehner, Verdin, & Jarvis, 2008) data was developed by the USGS, using data collected during the 2000 Shuttle Radar Topography Mission. HydroSheds is the source for river, basin, and DEM data sets. Hydrosheds provides vector and raster layers for stream networks, watershed boundaries, lakes, and accumulation data. The primary use of the dataset in the analysis was providing the GBM subbasins and stream networks. Spatial resolution of the DEM is approximately 30 Km at the equator.

Climate Data

Climate data is provided by two separate sources. First, precipitation data was primarily derived from Climate Hazards Center InfraRed Precipitation with Station (CHIRPS) data (Funk, et al., 2015). CHIRPS is provided by the Climate Hazards Center at the University of California, Santa Barbara. The data set used for this investigation details annual precipitation averages from 1981 to 2021. The spatial resolution is approximately 0.05 degrees, or 28 square kilometers per pixel. Precipitation is measured in mm.

Second, the project relies on water storage and temperature data (Rodell, et al., 2004) obtained from the NASA Goddard Earth Sciences Data and Information Services Center and Global Land Data Assimilation System (GLDAS). The spatial resolution of the datasets is 28 km. Data in the GLDAS dataset is collected using satellite and ground collected data. Data is collected in three-hour intervals and aggregated into monthly averages. GLDAS data is only available from 2000 to present. GLDAS data is hosted on the ArcGIS Pro server and no download is required.

Both the CHIRPS data and the GLDAS datasets are multidimensional raster datasets with a temporal dimension.

Conflict Data

Conflict data was obtained from the Armed Conflict Location and Event Project (ACLE). Data is provided in tabular format (Microsoft Excel) and is obtained from publicly available data sources and tracked by longitude and latitude. The ACLE data is available for the years 2010-2020. The data was accessed in August of 2020. Currently an access key is required to access the data which can be obtained from https://acleddata.com/data-export-tool/. At the time of the data download, no access key was required.

Methodology

The primary step in pre-processing to enable analysis was determining the appropriate size of subbasins in the HydroSheds Data. HydroSheds basin data is available in 12 different levels of detail, known as the Pfafstetter level. The Pfafstetter system allows for a nested breakdown of river basins from largest area to smallest area. According to Linke et al. (2019), Pfafstetter level one displays basins as large as one million square kilometers, while level 12 may be as small as ten square kilometers (Linke, et al., 2019). In this study, The Pfafstetter Level 6 to was used determine the sub-basin areas. Level one consisted of the entire GBM basin and contained all river stretches within the GBM. The Pfafstetter Level Six subbasins in the study area can be seen in Figure 3. The geographic area of the subbasins represented in Pfafstetter Level 12 were, in some cases, smaller than the spatial resolution of the climate raster data sets. Given this, Level 6 was chosen as it provided a similar spatial resolution for the input raster data sets, as well as an appropriate geographic area to analyze the data within the study area. With the appropriate size of subbasins identified, the subbasins associated with the GBM were identified using an attribute selection on the HYDROID field in the HydroSheds dataset. All subbasins with the attribute MainBasin 4060025450 make up the greater GBM basin. The GBM basin data was then joined with GRanD version 1.3 by HydroID to amend the attributes of the dam data to the subbasin data. The attribute of interest in the GRanD data was the degree of regulation (DOR). The DOR is the ratio of total upstream storage capacity divided by total annual flow volume (J, Grill, & Hartman, 2015). After the join on the two datasets was completed, the cumulative DOR of each subbasin could be calculated using the Summarize Within method in ArcGIS Pro. Figure 4 represents the DOR for each subbasin in the study area.

Following the calculation of the cumulative DOR, the subbasin polygons were converted to points and a DOR raster was created using an Inverse Distance Weighted (IDW) Interpolation. A dam was not present in all subbasins, and therefore these subbasins did not have a DOR value. Instead, the IDW was used to estimate the continuous DOR value. The results of the interpolation on DOR can be seen in Figure 5.

To complete the trend analysis of the climate data, the multidimensional raster datasets were examined with the Multidimensional Tool in ArcGIS Pro. Each raster dataset contains a time slice for each month from roughly 1981 to 2020. The time slices represent a monthly average for each raster cell for a given climate variable. For example, a multidimensional raster for precipitation representing one year of rainfall would have twelve individual time periods contained within the single raster.

Using the temporal properties of the multidimensional rasters, the average value of each cell could be calculated for the duration of available data to create a trend analysis map. The results of the trend analysis for water storage, temperature, and precipitation can be found in Figures 6-8.

Additionally, several output statistics are available in ArcGIS Pro. For this study, the output statistics used were derived from the Seasonal-Kendall model to ensure desired statistical values as the output. The Seasonal-Kendall model returns rasters with five bands including the slope of the trend, RMSE, P-Value, and the Z-Score. For this study the Z-Score was used to determine areas with increasing or decreasing climate trends. The Z-Score was done because the climate variables are in different units (e.g., centimeters, milimeters, and Celsius) and the Z-Score provided a normalized method to analyze the trends of each of the variables as a standard deviation from their respective means.

Finally, the conflict data was modified to be compared to the climate trends and DOR values. First, the desired conflict data was queried by the Type2 attribute to filter for conflicts only with keywords related to violence or weapons using. The attribute query resulted in a total of 12,000 conflict data points. Upon visual analysis of the conflict data, there appeared to be significant clustering of conflicts around areas with higher populations. To determine if the visual analysis was correct, a Moran's I test for spatial autocorrelation and hotspot analysis were conducted on the conflict data.

The Moran's I (Figure 9) confirmed that the conflict data was clustered. The Z- score of 221 indicates that there is almost 100% chance that the conflicts did not occur at random locations. The optimized hotspot analysis indicated that two hotspots existed near Dhaka and Dehli, as seen in Figure 10.

Additionally, the conflict data did not contain any quantitative data to compare to the other variables in the project. Using the Kernel Density tool, a quantitative value representing the occurrence of conflicts over a given unit area was created with the same raster cell size as the climate and DOR datasets.

In this case, cells with a higher kernel density value were areas with higher conflict rates, and those with a lower kernel density value had lower conflict rates. Because the data was heavily affected by spatial autocorrelation, certain areas of the study area had extremely high values as opposed to their neighboring cells. Therefore, a logarithmic transformation was used to create a kernel density map with a more normal distribution.

With the conflict data normally distributed, three random subsets of conflict data were created to further reduce the effects of spatial autocorrelation and randomize the data points. Each subset of conflict data contained fifty percent of the original data. For each of the three subsets of conflict data, an Extract Multiple Cell Values function was performed in ArcGIS Pro using the values of the precipitation, temperature, water storage, DOR, and conflict density rasters. This function allowed raster values at each conflict point to be appended to the conflict point data attributes.

To complete the analysis, an ordinary least squares regression was conducted on all three of the conflict subset features with temperature, precipitation, water storage, and DOR as the independent variables and the conflict density value as the dependent variable.

Results

The R^2 values of the regression ranged from .20 to .22 when all variables were considered, as shown in Table 1. All variables except for temperature had a negative relationship with the occurrence of conflict. In other words, as temperature decreased, the occurrence of conflict increased. Water storage was the most influential variable in the model with a coefficient averaging -.24 among the three regressions.

Subset1 (R^2 = .22)				
Variable	Coef	StdError	t_Stat	Prob
Intercept	3.055	0.018	166.946	0.000
DOR	-0.011	0.000	-34.218	0.000
WATER_STORAGE	-0.251	0.010	-24.680	0.000
PRECIPITATION	-0.030	0.004	-8.045	0.000
TEMPERATURE	0.015	0.003	4.892	0.000002
Subset2 (R^2 = 0.21)				
Variable	Coef	StdError	t_Stat	Prob
Intercept	3.040	0.018	165.374	0.000
DOR	-0.011	0.000	-33.638	0.000
WATER_STORAGE	-0.244	0.010	-23.885	0.000
PRECIPITATION	-0.030	0.004	-8.239	0.000
TEMPERATURE	0.016	0.003	5.411	0.000
Subset 3 (R^2 = 0.2)				
Variable	Coef	StdError	t_Stat	Prob
Intercept	3.071	0.018	167.091	0
DOR	-0.011	0.000	-33.738	0
WATER_STORAGE	-0.233	0.010	-22.947	0
PRECIPITATION	-0.027	0.004	-7.453	0
TEMPERATURE	0.012	0.003	3.864	0.000122

Table 1-Regression Analysis Results

Interestingly, the climate variables Precipitation and Temperature had very little impact on the outcome of the of the model, with temperature having approximately the same coefficient as the Degree of Regulation in all the iterations of the regression, and precipitation had slightly higher coefficients than temperature in all iterations.

Additionally, output data provided by the Regression tool in ArcGIS Pro did not indicate the presence of collinearity among the independent variables.

Independently, degree of regulation did not appear to be a significant factor in generating conflicts in the GBM. However, it is important to note that DOR and water storage are related. The function of a dam is to store water to be used when it is needed, or to protect downstream areas from flooding. As more dams are constructed in the GBM, the more likely it is that the study area will see an increase in DOR, and likely a decrease in water storage in communities downstream from large water infrastructure projects. Given the anticipated increase in large hydroelectric dams in the GBM, specifically in the Himalayan region, water storage rates are likely to be heavily impacted. These reductions in water storage could eventually lead to conflict. Again, the coefficient for water storage in the model was -0.24. This means that for every reduction in one centimeter of water storage, the conflict density value increased by 0.24. This may seem to be a small increase. However, large scale water projects can greatly reduce downstream water storage capacity by much greater amounts than one centimeter. Could we predict density value of conflict based on certain increments of decreased storage capacity say in intervals of 10 cm? This would get into inferential statistics, maybe the relationship becomes non-linear? Tipping point?

Discussion and Conclusion

When all variables are considered in the analysis, they do explain roughly one-fifth of all conflicts observed in the study area. The results of the regression are in agreement with the literature reviewed as part of this project, in that climate variables on their own are not a singular cause of conflict (Jägerskog & Swain ,2016; Kelley et al., 2014; Eklund & Thompson,2017). However, as this analysis indicates, they do play a significant role in the potential evolution of conflicts. As the literature details, it is often a combination of government policy and climatic variables which cause a conflict to occur. Resource conflicts are complex relationships between climate, government policy, and social/economic conditions. In the GBM, the climatic variables (primarily water storage) and DOR could explain nearly a quarter of the conflicts recorded by the Armed Conflict Event Tracking organization. That is significant. History has shown that regions with weak governments, social and/or economic issues being pushed over the edge by the introduction of water scarcity. As was the case in Syria, groundwater storage was declining while the government mandated an emphasis on using groundwater for irrigation. As a result, crops failed leading to mass migrations and civil unrest.

Large water infrastructure projects decrease downstream water availability (Wang, Nixon, Erwin, & MA, 2020; Loris, 2016) and damage a river's ecological system (Moore, 2014; Mekonnen & Hoekstra, 2011). This analysis showed that water storage was the greatest contributor in explaining the regression model. According to Zarfl et al. (2014), the GBM region is expected to experience significant construction of hydroelectric dams. This construction may alter the historic distribution of water storage. As (Wang, Nixon, Erwin, & Ma, 2020) state, these water infrastructure projects usually benefit urban areas rather than rural. With rural areas seeing a reduction in water resources, those populations may be forced to migrate to more populous areas, increasing tensions and leading to conflict, as was the case in Syria.

In conclusion, this paper has examined the statistical relationship between climate trends, degree of regulation introduced by hydroelectric dams, and the occurrence of conflict using an ordinary least squares regression on a cell-by-cell basis. Based on the results of the analysis, the methodology used in the project does provide a meaningful procedure for predicting the locations vulnerable water conflicts. Conflicts in this analysis were closely related to water storage changes. As more large water infrastructure projects are completed, water storage is likely to decrease in downstream locations resulting in water conflicts. This is especially true in regions with ongoing cultural tensions where a significant increase in the construction of large water transfer projects is expected.

Future Research and Lessons Learned

Throughout this project, numerous obstacles were met. Among them, the spatial autocorrelation of the conflict data proved to be the most significant to the analysis. Despite the transformation of the original data, and the creation of three randomized subsets of the conflict data, the residuals of the regression remained clustered around three distinct regions (Figure 11). Intuitively, conflicts are bound to occur more frequently in regions with higher populations than in sparsely populated regions. Additional methods could be used in the future to minimize the effects of spatial autocorrelation in the analysis. Additionally, Pfafstetter Level 6 used in the analysis was chosen based on the size of the study area. Lower levels appeared too generalized and only contained a few subbasins. The higher levels had small spatial areas and did not provide a proper scale to conduct an analysis on a study area a basin the size of the GBM. There was no literature found to aid in choosing the Pfafstetter Level. The size of the study area dictates the level chosen. In a smaller study area, a higher level may have been appropriate. However, it is probable that using a different Pfafstetter Level would have resulted in a different outcome of the analysis.

An additional research topic would be to apply the same methodology used in this analysis to other river basins throughout the world and determine if the results of this analysis were consistent with other regions of the earth.

Also, this analysis focused on long term climate trends. The climate data is available in monthly intervals. A possible area of future research would be to examine the relationship between short term climate anomalies and the occurrence of conflicts.

Finally, given the coefficient of -0.24 for water storage and its importance to the model, could this coefficient be utilized with the Raster Calculator in ArcGIS to predict a conflict density value by decreasing water storage values by a set increment until a conflict is guaranteed to occur.

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Figures

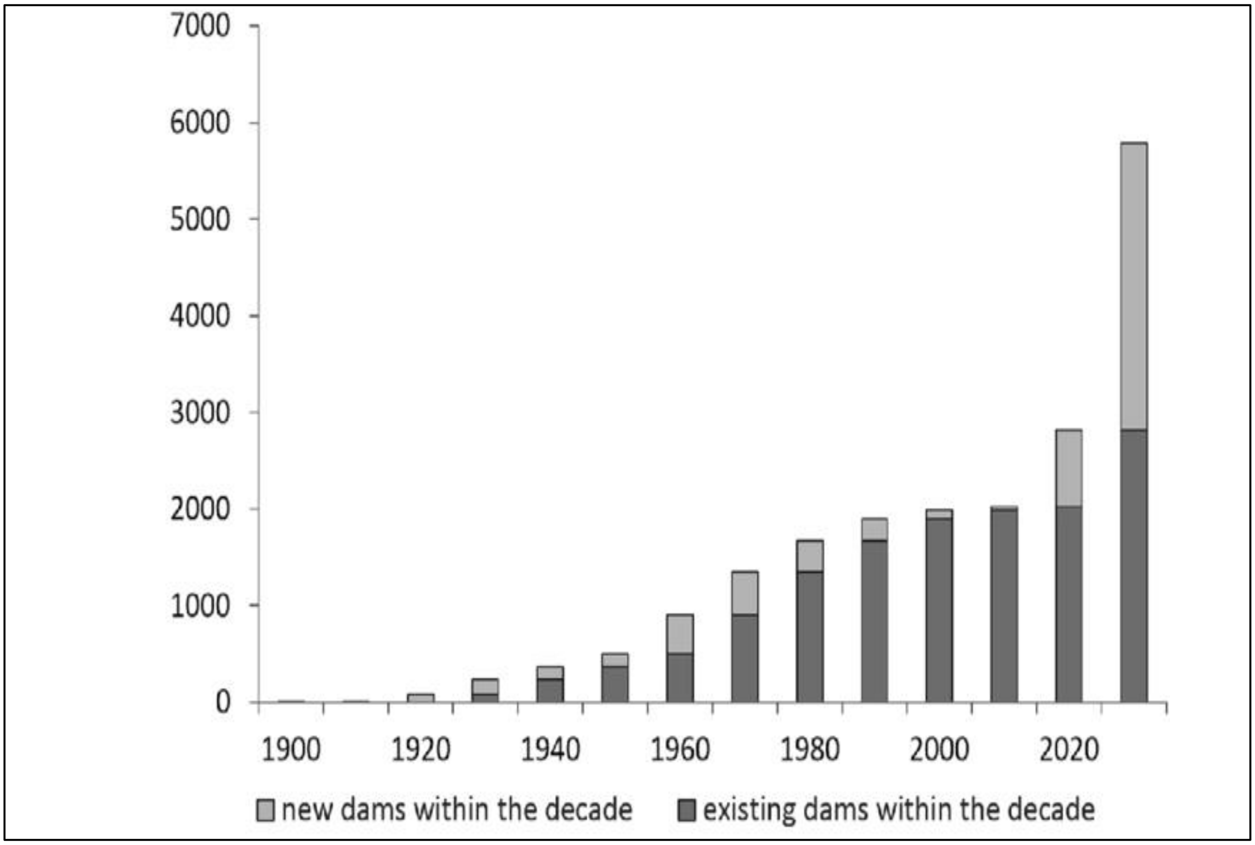

Figure 1 Hydroelectric Dam use by Decade

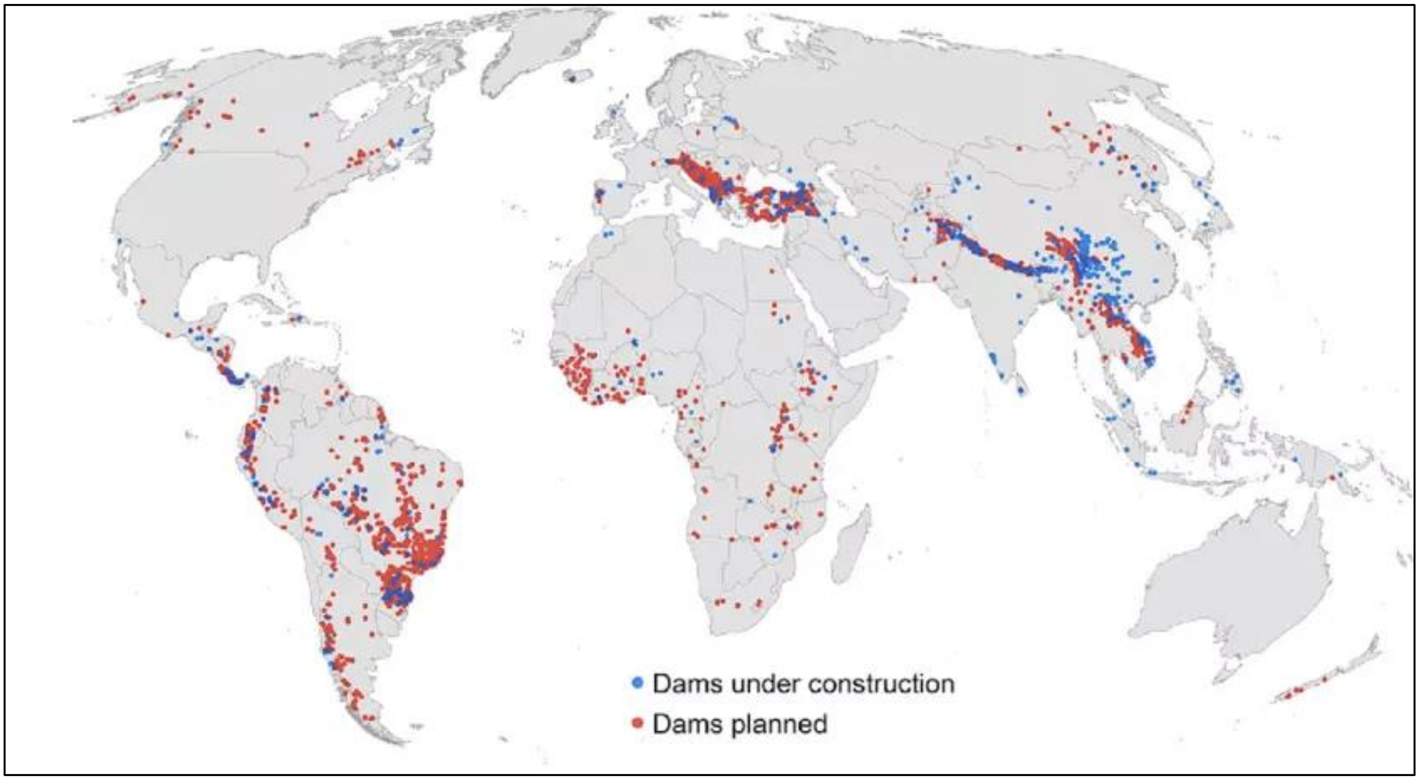

Figure 2 Global distribution Future Hydroelectric Dams. From Zarfl et al., 2014.

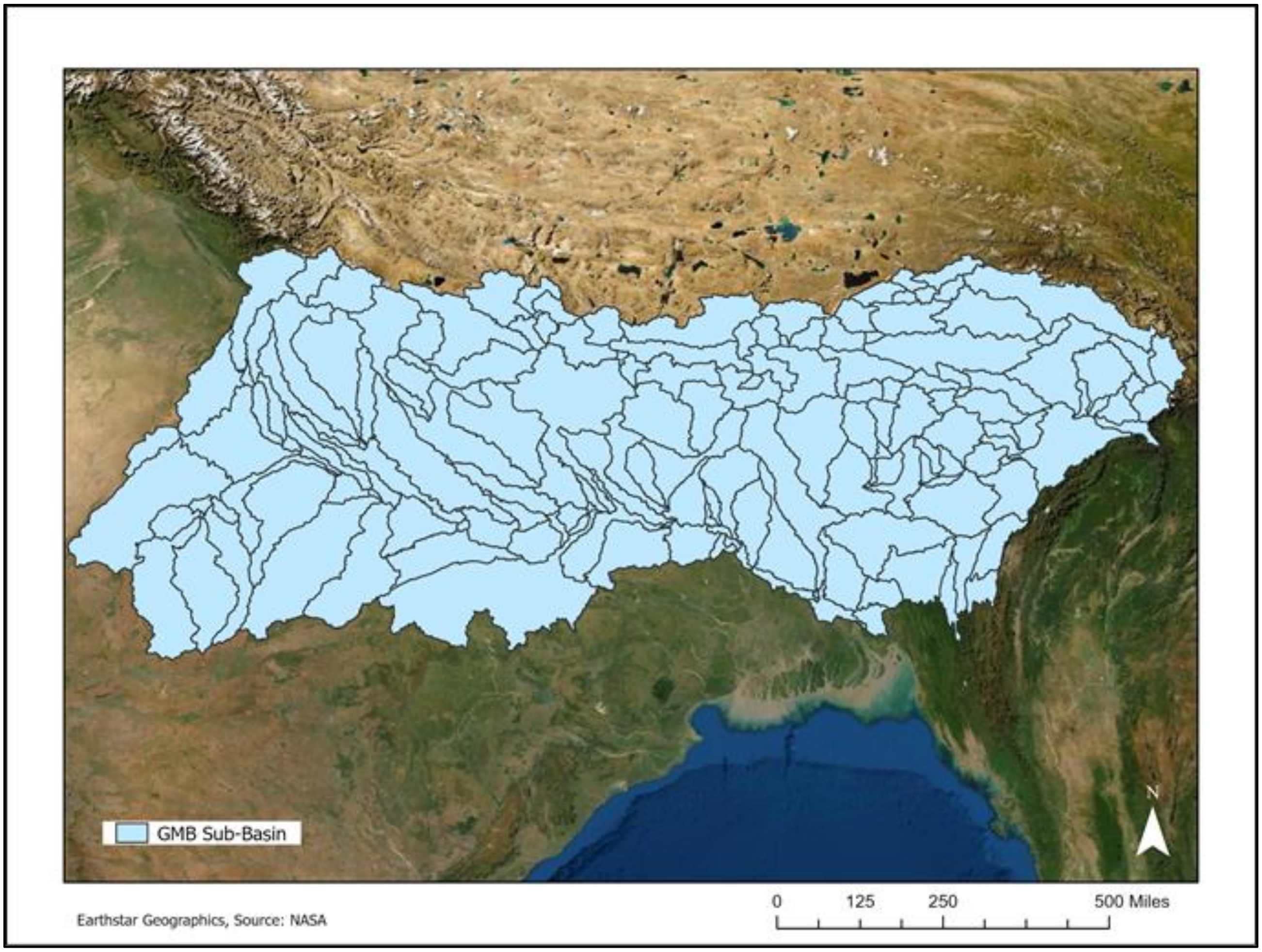

Figure 3 The GBM Study Area and Subbasins Displayed at Pfafstetter Level 6

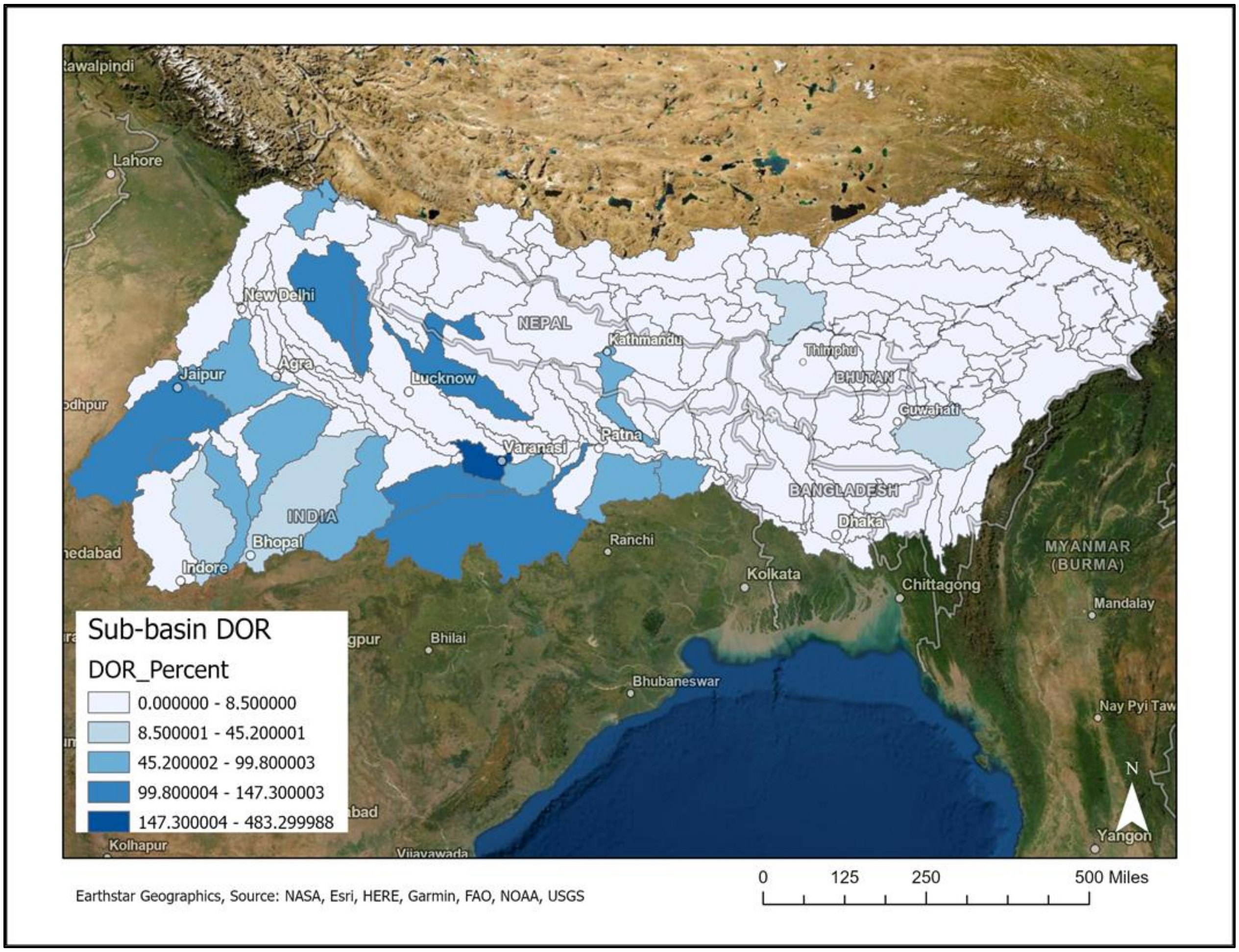

Figure 4 - Degree of Regulation by Subbasin. Darker shades of blue represent a higher DOR.

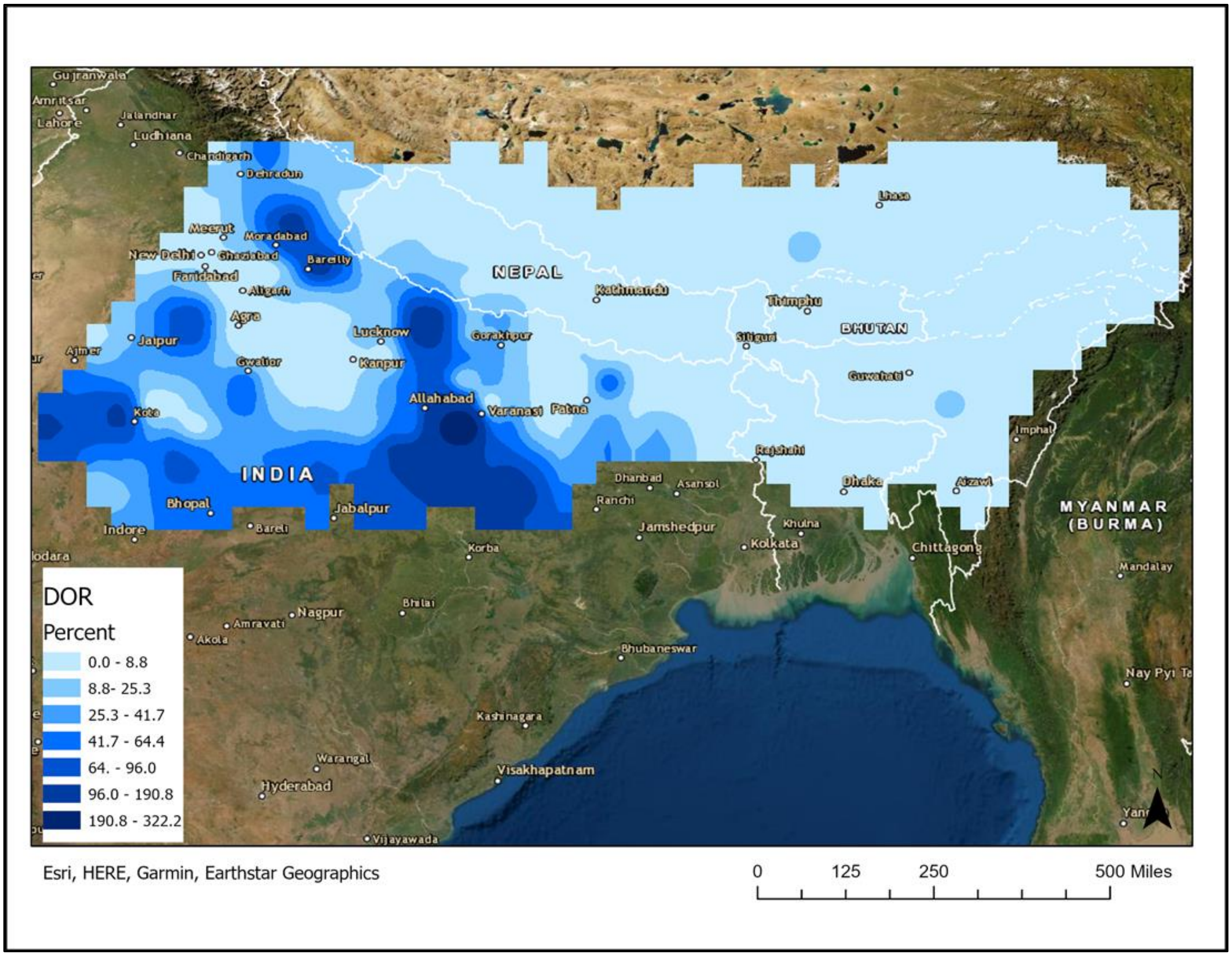

Figure 5 Study Area DOR as a Continuous Surface. Derived from IDW interpolation of DOR points. Areas with dark blue coloring represent locations with a high degree of regulation and the water availability is more likely to be impacted by hydroelectric dams

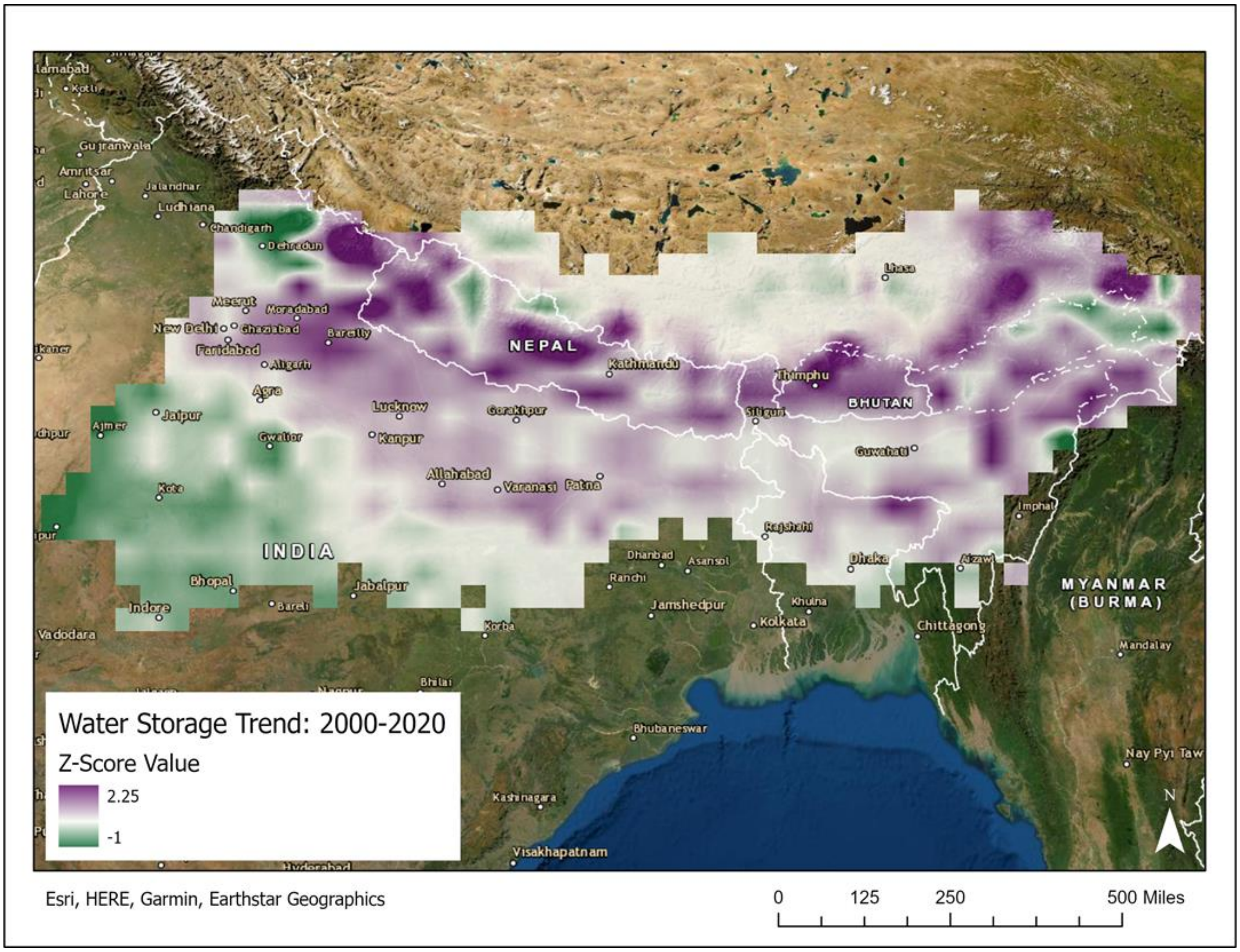

Figure 6 Trend Analysis of Water Storage. Dark purple areas are indicative of locations with an increasing trend in water storage from 2000 to 2020. Green areas represent locations with a decreasing trend in water storage capacity.

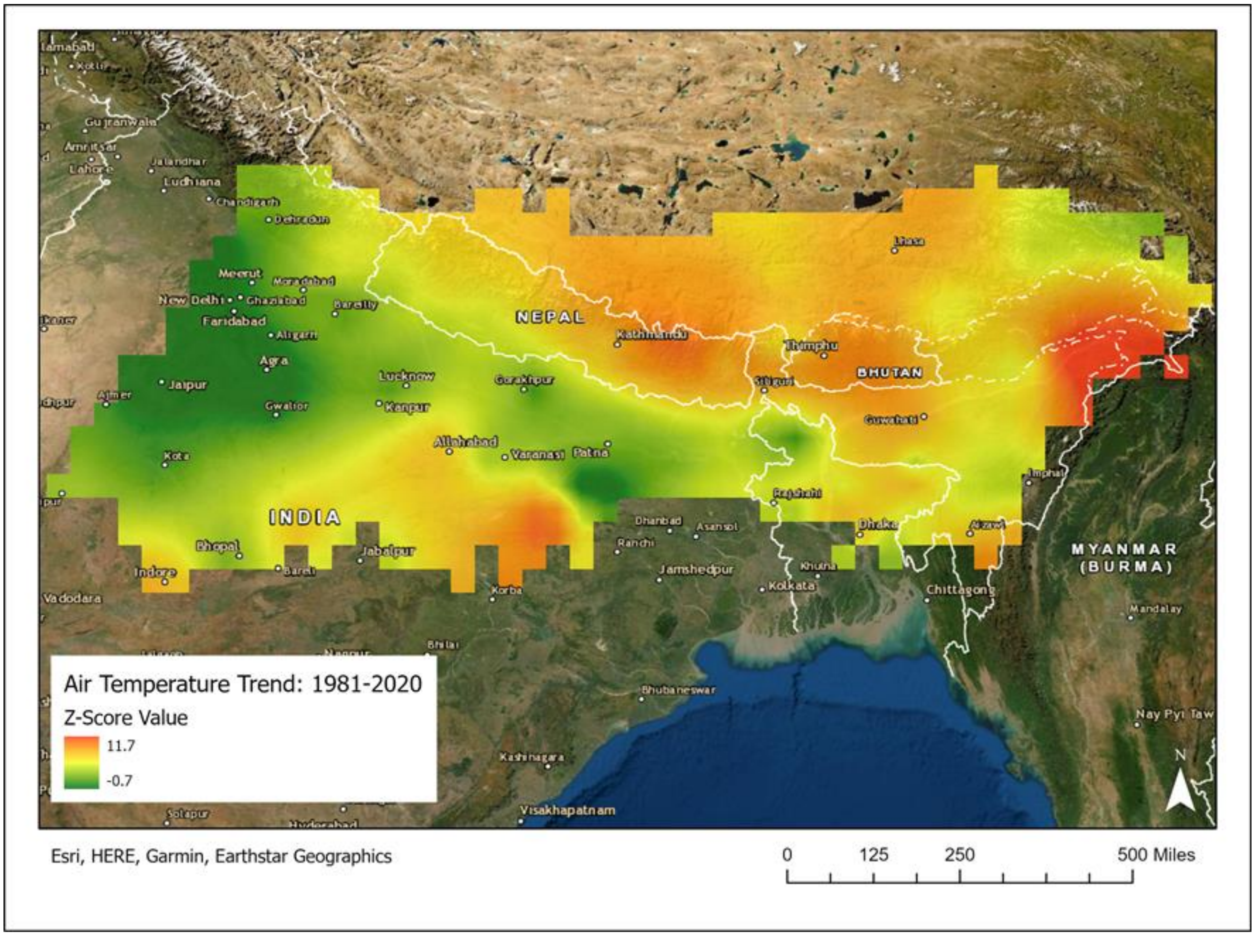

Figure 7 Temperature Trend Analysis. Red areas are representative of locations with a temperature above the expected average while areas in green represent locations with little to no change relative to the expected mean.

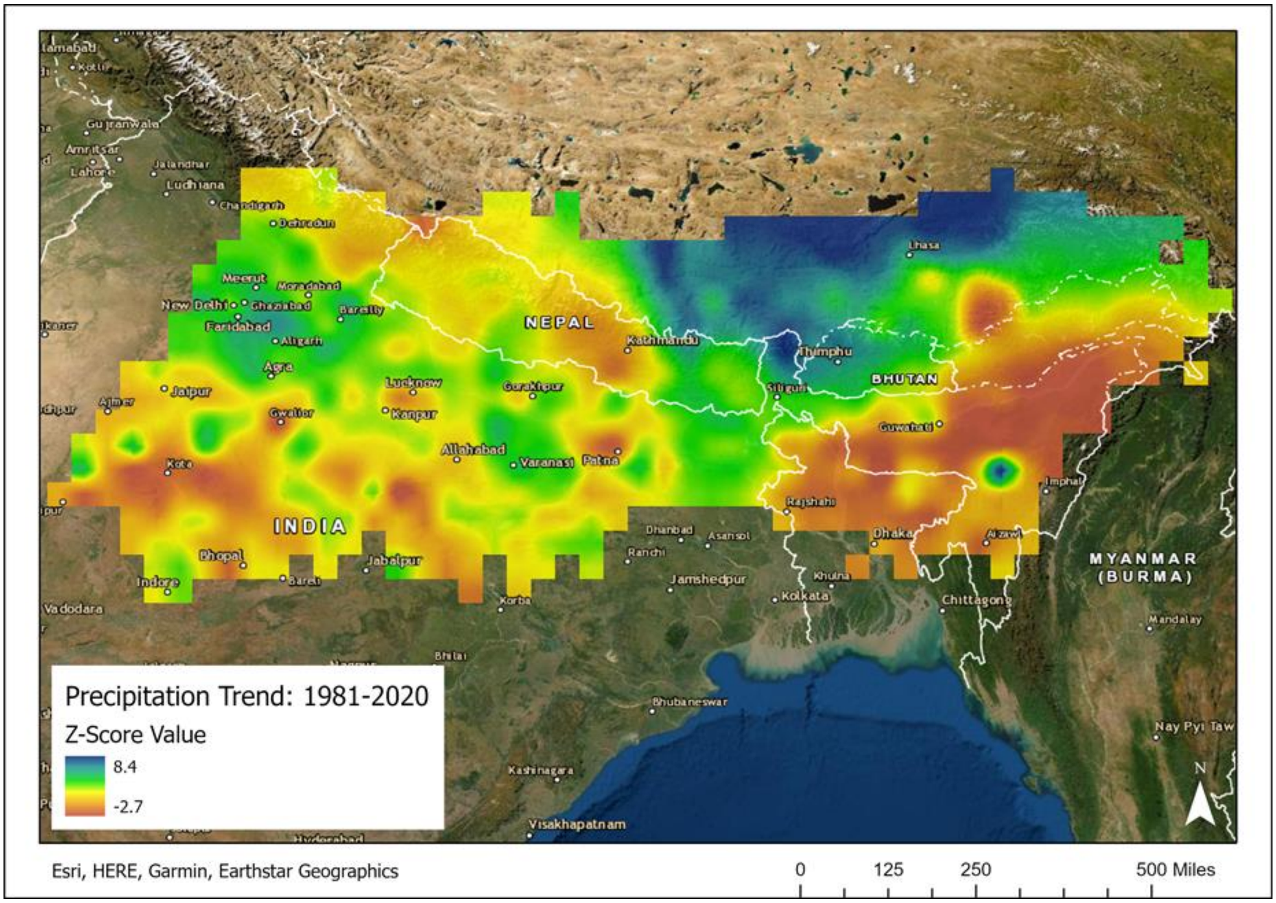

Figure 8 Precipitation Trend Analysis. Areas in blue have a high z-score indicating an increase in temperature in those regions. Areas in red represent locations with a decreasing precipitation trend. Green areas indicate little to no change above or below the mean.

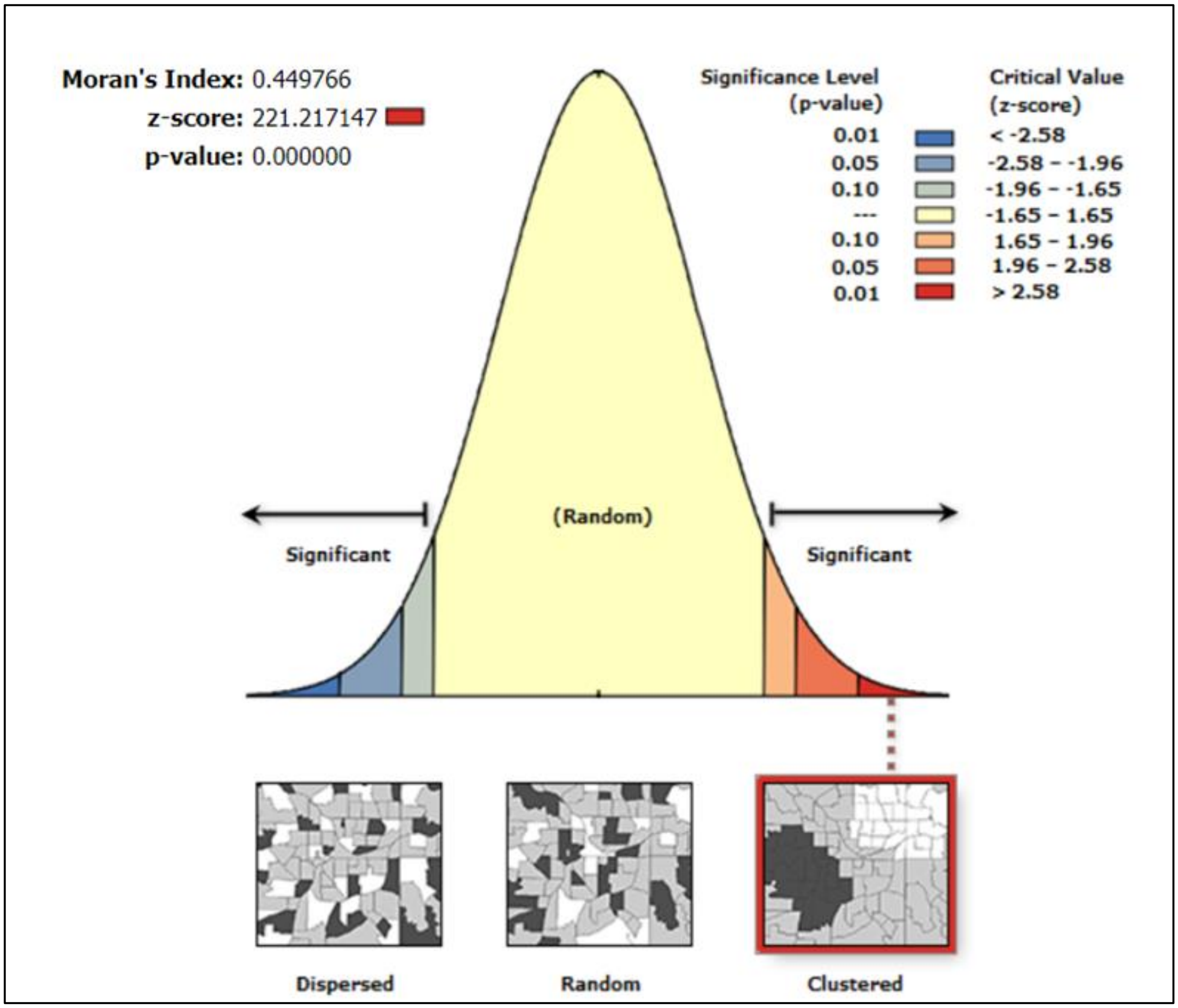

Figure 9 Results of Moran's I Test for Spatial Autocorrelation. The z-score and p value indicate that there is almost no chance that the location of the conflicts is randomly occurring.

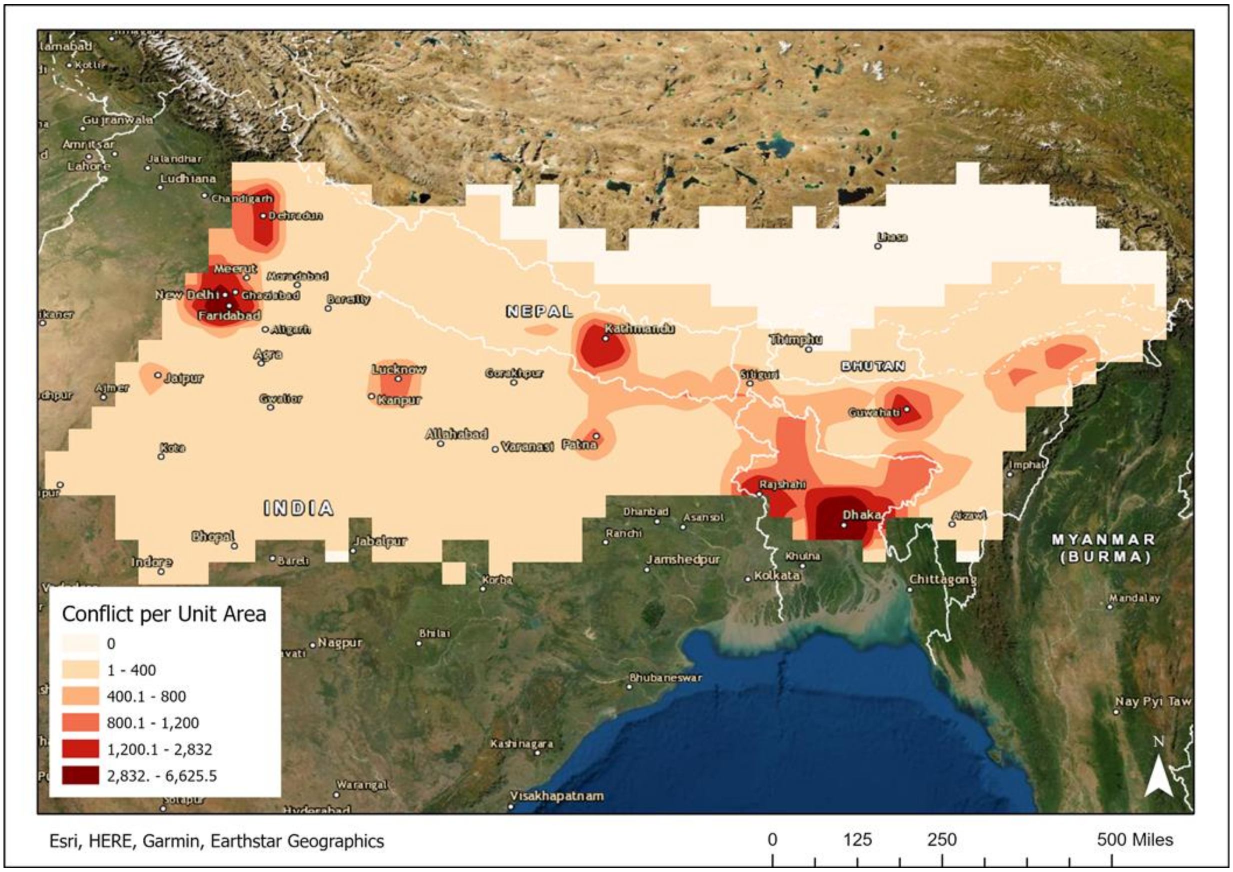

Figure 10 Number of Conflicts per 30 km2. Areas with red and dark red have a high occurrence of conflict while lighter shades of red and brown have lower occurrences of conflict.

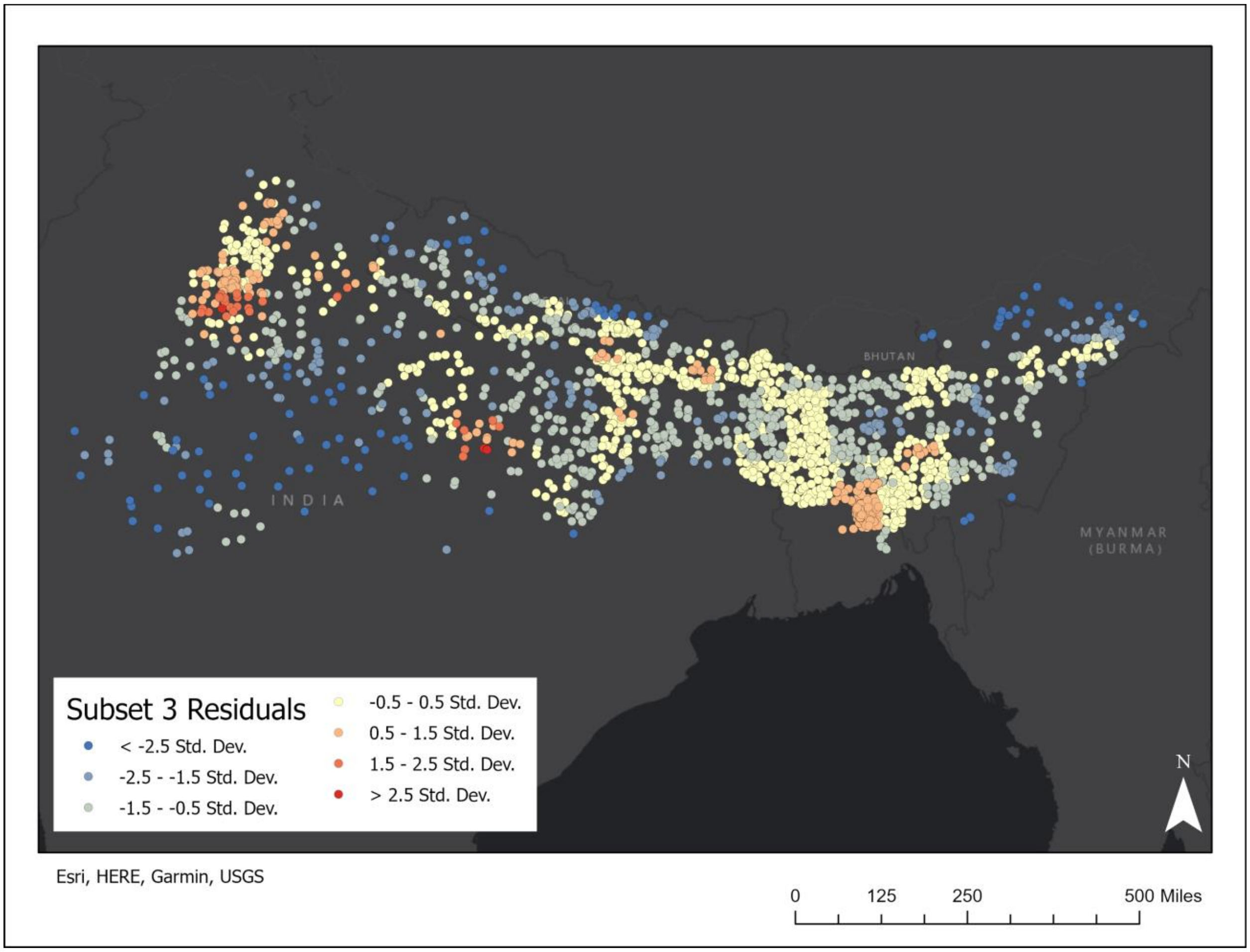

Figure 11- Residuals of Subset 3 of conflict data. Red circles indicate locations where the model is over predicting the outcome. This is a result of spatial autocorrelation.