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Geospatial data assimilation and mapping groundwater vulnerability in high plains aquifer using DRASTIC Model

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ABSTRACT

High Plains Aquifer is one of the most important aquifers in the United States, accounting for one-fourth of total annual freshwater withdrawal, and one-fifth of crop production of some major crops. But the area above this aquifer has not been extensively researched for determining the risk of groundwater pollution. Therefore, this study was undertaken to determine the groundwater pollution potential using the DRASTIC model in a Geographic Information System (GIS) environment. Despite the limited data availability, DRASTIC model proved effective in delineating areas of High Plains Aquifer susceptible to groundwater contamination. The results from the model indicated that large portions of southwestern Texas, central Kansas, eastern Colorado, eastern Wyoming, western and north-western Nebraska were highly vulnerable to groundwater pollution whereas Oklahoma had the lowest vulnerability.

Keywords: Irrigation, high plains aquifer, ArcGIS, DRASTIC model, Ogallala aquifer, groundwater vulnerability

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1 Introduction

Groundwater (GW) withdrawal accounted for more than 50% of total water withdrawal in the United States (U.S.) in 2015 (Dieter et al., 2018). Being one of the most valuable resources, GW is not only crucial to agricultural production and sustaining global water supply, but also, it helps nourishing streamflow between wet and protracted drought periods and has a significant impact on the ecosystem. Among all groundwater bodies in the U.S., also known as aquifers, High Plains Aquifer (HPA) is the largest source of GW, which is also the primary source of water for many communities in eight states in the Great Plains region. This aquifer is known as "bread-basket". for providing 25% of total water supply for agricultural production in the whole U.S. (Houston et al., 2013), contributing $7 Billion to the economy annually. Therefore, the HPA is the most important groundwater resource in the U.S.

Since the 1960s, the HPA, especially Southern Great Plains (SGP) is facing several challenges due to various reasons (Masasi et al., 2019): high depletion in water level because of continuous irrigation (Datta et al., 2017; Rudnick et al., 2019); contamination by numerous organic and inorganic pollutants such as nitrates, heavy metals, pesticides, precipitation variability due to ongoing climate change (Datta et al., 2018), soil erosion due to water runoff, etc. Due to the lack of direct observation and frequent measurement of different quality and quantity indicators of water in HPA, these challenges are not getting addressed as fast as they should be. Multiple campaigns were undertaken by U.S. Geological Survey (USGS) to monitor the groundwater and determine the vulnerability of the aquifer, but these methods are time-consuming, costly and sometimes unrealizable because of different geographic constraints. This potentially leads to a loss of valuable resources at a considerable economic cost. Therefore, determining the vulnerability of GW in this region is of paramount importance to decide how the groundwater resources can be managed in a more sustainable way.

Aquifer vulnerability can be affected by various factors including aquifer chemistry, temperature, transmissivity, tortuosity, gaseous phase transport, etc. But not all of these data can be obtained easily and are not readily accessible. Considering the availability of mappable data, Aller (1985) proposed a numerical ranking model, DRASTIC, for determining the vulnerability of aquifers to contamination. This model uses Depth to water table, net Recharge, Aquifer media, Soil media, Topography, Impact on vadose zone, and hydraulic Conductivity to estimate the vulnerability of aquifers. One of the best ways to represent the results from DRASTIC model is to combine the results with Geographic Information System (GIS) software such as – ArcGIS (ESRI, Redlands, CA, USA). By combining several thematic layers of the factors involved in the model, the DRASTIC index produces vulnerability scores of the areas that are most susceptible to pollution and carries a high risk for intended users (Babiker et al., 2005).

Previously several pieces of research have demonstrated the use of the DRASTIC model, combined with GIS, for determining aquifer vulnerability. Babiker et al. (2005) conducted a study in central Japan assessing aquifer vulnerability and reported GIS to have provided an efficient environment for having high capabilities of handling large-scale spatial data and making the result from DRASTIC model easier to interpret. The aquifers reported in that study had moderate to high vulnerability according to DRASTIC model. Lathamani et al. (2015) carried out a similar study in India and determined that most of the aquifers during last quarter of a year showed very high vulnerability impacting agricultural and municipal practices in the area. Fritch et al. (2000) investigated the Paluxy aquifer in north-central Texas using DRASTIC model and found that more than 45% area covered by aquifer had moderate to high groundwater pollution potential. A statewide study in Nebraska, USA was conducted to delineate regions with higher vulnerability to groundwater pollution potential and DRASTIC model was implemented using raster-based information as input (Rundquist et al., 1991). Other examples include studies conducted in Iran (Neshat et al., 2013), China (Huan et al., 2012), Turkey (Sener and Davraz, 2012), and many other countries. Gurdak and Qi (2012) conducted a water-quality assessment in the HPA region by determining nitrate concentration and found northern and southern parts of HPA have a high probability of contamination. However, to the best knowledge of the authors, there has been no study implementing the DRASTIC model to assess the vulnerability of HPA. Therefore, this study was conducted primarily to develop an ArcGIS based geodatabase for HPA containing all feature datasets relating to parameters needed to run the DRASTIC model. The secondary objective was to use the DRASTIC model to find the regions in the HPA region that are vulnerable to groundwater contamination.

2 Materials and Methods

2.1 Study area

This study addressed HPA region that underlies eight of U.S. states in the great plains, with an area exceeding 450,000 km^2 and serves as a primary source of water for millions of people in Wyoming, South Dakota, Nebraska, Kansas, Colorado, Oklahoma, New Mexico, and Texas (McGuire, 2009). The HPA has different precipitation regimes, ranging from wet areas in eastern Nebraska to arid areas in Texas panhandle. HPA states rely extensively on agriculture, 60% of their agricultural related sales depends on the water extracted from the HPA (Perrin et al., 2018) and accounts for about 20% of corn, wheat and cotton production in the United States (Steward and Allen, 2016).

2.2 DRASTIC Model

The DRASTIC model uses a numerical index that is obtained from ratings and weights assigned to each of the seven model parameters. Each of the parameters will have raster files that will be reclassified from 1 to 10 based on their relative effect on the vulnerability of the aquifer (Babiker et al., 2005). After that, the parameters are assigned relative weights spanning from 1 to 5. A weight of 1 means the low impact on the vulnerability of a parameter whereas a weight of 5 has the highest possible impact on aquifer vulnerability. Then, the DRASTIC index (DI) is calculated according to the following formula:

$$\begin{aligned} DI = D_r D_w + R_r R_w + A_r A_w + S_r S_w \\ + T_r T_w + I_r I_w + C_r C_w \end{aligned} \quad (1)$$

where, D, R, A, S, T, I, and C are the seven DRASTIC parameters; r and w are the corresponding rating and weights, respectively. These numerical ratings and weights were established using the Delphi technique

Table 1. Data layers and sources for HPA

Data Layer †	Source	Description
US states layer	US Census Bureau (https://www.census.gov/data/datasets.All.html)	Feature dataset of conterminous US states (polygon; updated in 2017)
Depth to water table	US Geological Survey (https://pubs.er.usgs.gov/publication/sir20175040)	Depth from the ground surface to water table in feet. These are location values (point shapefile)
Net recharge	US Geological Survey (https://pubs.usgs.gov/ds/777/)	Amount of water from land surface reaching saturated zone (raster, a digital image).
Aquifer media	USGS Geologic Map Data Portal (https://mrdata.usgs.gov/geology/state/)	Consolidated or unconsolidated rock that serves as saturated zone material.
Soil media	Web soil survey (STATSGO2 database) (https://catalog.data.gov/dataset/u-s-general-soil-map-statsgo2-for-the-united-states-of-america)	Top-weathered portion of unsaturated zone controlling recharge.
Topography	Digital elevation map from USGS data hub (https://www.mrlc.gov/)	The slope of the land surface dictating runoff and/or percolation of water.
Impact of vadose zone	Web soil survey (STATSGO2 database) (https://catalog.data.gov/dataset/u-s-general-soil-map-statsgo2-for-the-united-states-of-america)	The unsaturated zone material controlling the passage, attenuation of the water to saturated zone.
Hydraulic conductivity	US Geological Survey (*.E00 file) (https://pubs.er.usgs.gov/publication/ofr98548)	This specifies the ability of an aquifer to transmit water. This may be good if water has minimal contaminant, bad if it has a high concentration of contaminants.

† All projections were already in or were converted to NAD_1983_Albers geographic coordinate system

by Aller (1985) and are well-defined and these same values were used in this study.

2.3 Data collection

The data used in this study and respective sources are listed in Table 1.

2.4 Setting parameters for DRASTIC Model

The DRASTIC parameters and their reclassification are outlined in Table 2. The depth to water table (D) was obtained from USGS and reclassified according to values from Rahman (2008) (Fig. 1). It is one of the most important parameters in the DRASTIC model as it depicts the distance the water must travel from land surface to reach the saturated zone of water, the aquifer. High water table depth indicates higher protection potential. Thus, a rating of 10 for D means the water table is close to the ground surface and 7 means it is deep down. The recharge (R) raster was classified according to value ranges set by Babiker et al. (2005). More recharge, rated as 8, means that the probability of contamination is high (Fig. 1). The aquifer media (A) refers to the consolidated or unconsolidated rock that serves as an aquifer (Lathamani et al., 2015). Larger grain size and a high number of fractures mean that more water will infiltrate to the aquifer media. The GIS layer for aquifer media was collected from USGS geological map website and the mineralogy data was collected and reclassified with information obtained from Lathamani et al. (2015), Babiker et al. (2005) and Rahman (2008) (Fig. 3). Soil media (S) information was collected from USGS Web Soil Survey STATSGO2 database (WSS, 2016). The “hydgrp” column in the components table was used to extract information about the soil medium (Fig. 4).

Topography data (T), 30 m digital elevation map (DEM), were downloaded from the USGS GIS data portal for 8 states of interest. Then, these images were mosaiced and extracted by the mask to represent the

HPA boundary. Mosaicing is a technique that allows analysts to merge the adjacent raster images together, and area of interest is separated from the image via extracting by mask. The reclassification was done according to values obtained from (Babiker et al., 2005; Rahman, 2008) (Fig. 5). The characteristics of the impact of the vadose zone layer (I) is similar to the soil media. A different column, "taxpartsize", from components table was used to extract soil texture information. Coarser textured soil was classified with a high rating and fine-textured soils with low ranking (Fig. 6). The hydraulic conductivity (C) raster was also obtained from USGS (Cederstrand and Becker, 1998) and reclassified from low to high rating indicating low conductivity to high conductivity values, respectively (Fig. 7). After the reclassification was done on all of the rasters, the raster calculator was used to generate the vulnerability layer, DRASTIC Index, using equation 1. The reclassification criteria are often set arbitrarily, according to several past studies (Huan et al., 2012; Lathamani et al., 2015; Rahman, 2008). This trend was also followed in this study.

3 Results and Discussion

In general, the DRASTIC values ranged from 56 to 184 and the raster cells in the map covered an area of 370,452 km^2 (Fig. 8). For ease of interpretation, the DRASTIC Index (DI) values were classified into three categories: 56-80 as low vulnerability zones, 80-120 as moderate vulnerability zone, and 120-184 as high vulnerability zone. Previous studies also used arbitrary ranges of DRASTIC values to describe the vulnerability of aquifers (Babiker et al., 2005; Fritch et al., 2000; Lathamani et al., 2015). Only 0.6% (2,321 km^2) of the total area covered by layer was in low vulnerability zone, whereas 53.4% area (197,908 km^2) was under moderate vulnerability and the rest 46% area (170,223 km^2) was under high vulnerability of groundwater getting contaminated. As seen in Fig. 8, Oklahoma had low to moderate vulnerability of contamination. Southwest Texas had a higher portion of areas under high pollution potential. Also, the high vulnerability can be observed in central Kansas, eastern Colorado, most of Wyoming, northern and northwestern Nebraska and some of South Dakota. Overall, the whole HPA region is dominated by moderate vulnerability values.

Interpreting from Fig. 1 and Fig. 8, the depth to water table had a high impact on DI as expected. More vulnerable areas can be observed in case of low depth to groundwater table. In addition, the impact of the vadose zone layer indicates that the areas with loamy and sandy loam soils, they also face more vulnerability and as expected, has high Dr values. The hydraulic conductivity values are low for Colorado and Wyoming, but we still see high Dr values because of the impacts of depth to groundwater table, soil texture and annual recharge of water. Most of the HPA region has been dominated by agriculture since the 1800s. Agriculture makes the soil loose, usually performed on plain land (little to no slope), situated where the depth to water table is low. So, combined with everything, agriculture can multiply the risk of groundwater contamination ten-fold and Dr values could increase greatly.

From the perspective of implications, the DI values show that there is a higher probability of potential groundwater contamination due to anthropogenic activities e.g., irrigation, land use, waste disposal, agricultural practices, etc. on the vulnerable regions of HPA, although the model does not factor these activities in calculation. Since the largest water user of HPA is irrigated agriculture, the susceptibility of the aquifer would also be highly associated with the application of water that could cause the percolation of undesirable chemicals into the groundwater formations. Fig. 9 shows the spread of irrigated and rainfed cropping area across HPA (Salmon et al., 2015). A significant proportion of cropping lands can be seen in Nebraska, that is followed by Kansas and Texas. It is important to note here that most of these areas are situated above the regions that are classified as moderate to highly vulnerable for contamination according to DRASTIC index.

Moving on, the vulnerability of the HPA can also be viewed through the lens of climate anomalies such as droughts. The dry years in aquifers like HPA could raise the overall scale of vulnerability because of a reduced recharge and a greater concentration of agricultural chemicals that infiltrate with lesser dilution due to reduced availability of water. It is important to mention here that due to uninterrupted groundwater supply, the agricultural water consumption usually does not face any considerable decline in drought years (Ajaz et al., 2018). For example, the comparison of the actual evapotranspiration (ETa) in HPA during drought and non-drought years, 2013 (Fig. 10a) and 2016 (Fig. 10b), respectively, demonstrated that there was only 20% variation in ETa from 2013 to 2016. Also, during drought years the dryland farmers tend to supply supplemental water to their crops amid non-occurrence of anticipated precipitation spells. This infers that the evaporative demand of crops is met during drought years, while the possibility of the pollutants staying in the lower vadose-zone during drought years escalates, and those would eventually trickle down into the aquifer in wet season along with an augmented load of wet-year chemical application.

Table 2. Reclassification, ratings and index values of DRASTIC parameters

		Rating	Weight	*DI*
Depth to water table (m)	0 – 4.9	10	5	50
	4.9 – 15	9		45
	>15	7		35
Recharge (mm yr^{-1})	102 – 381	8	4	32
	51 – 102	3		12
	<51	1		4
Aquifer media (Minerals)	Sand	9	3	27
	Gravel/Coarse-detrital	8		24
	Sandstone	7		21
	Unconsolidated/ Silt/ Sandstone-Mudstone	6		18
	Sandstone-mudstone	6		18
	Siltstone/ Mudstone/ Conglomerate-sandstone	5		15
	Siltstone-mudstone/ Sedimentary	4		12
	Limestone	3		9
	Basalt/ Fine-detrital	2		6
	Shale/Claystone/Clay	1		3
Soil media (Materials)	Sands/gravel	6	2	12
	Moderately coarse materials	5		10
	Moderately finer materials	4		8
	Fine	3		6
	Finer materials	2		4
	Clay	1		2
Topography (Slope in %)	0 - 2	10	1	10
	2-Jun	9		9
	6-Dec	5		5
	Dec-18	3		3
	18 – 181	1		1
Impact of vadose zone (Soil texture)	Sandy	8	5	40
	Sandy loam	6		30
	Loamy	5		25
	Silty	4		20
	Clay	1		5
Hydraulic Conductivity (m d^{-1})	0 – 11.4	2	3	6
	11.4 – 22.9	5		15
	22.9 – 45.7	8		24
	45.7 – 137.2	10		30

† *DI* = DRASTIC Index

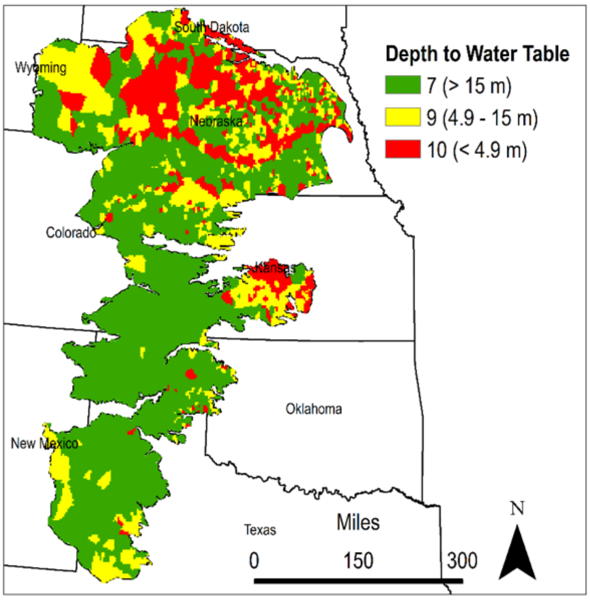

Figure 1. Depth to water table (DWT) raster classification

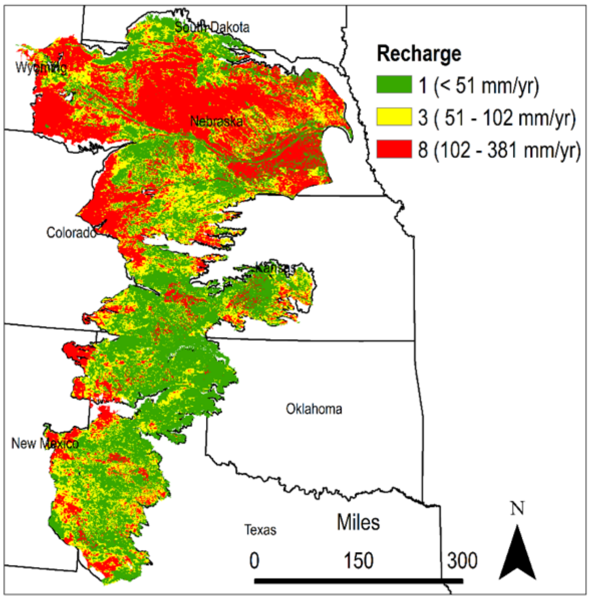

Figure 2. Annual recharge raster classification

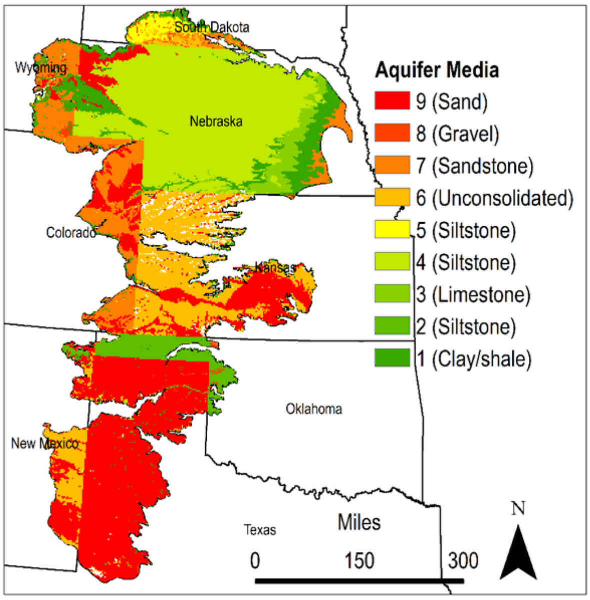

Figure 3. Aquifer media raster classification

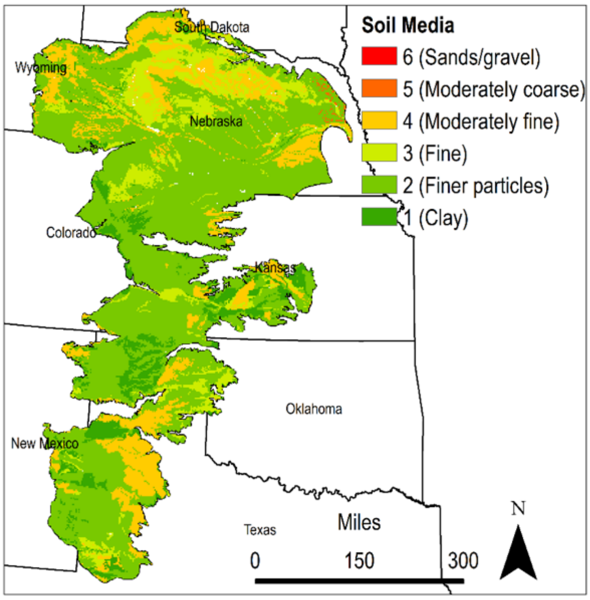

Figure 4. Soil media raster classification

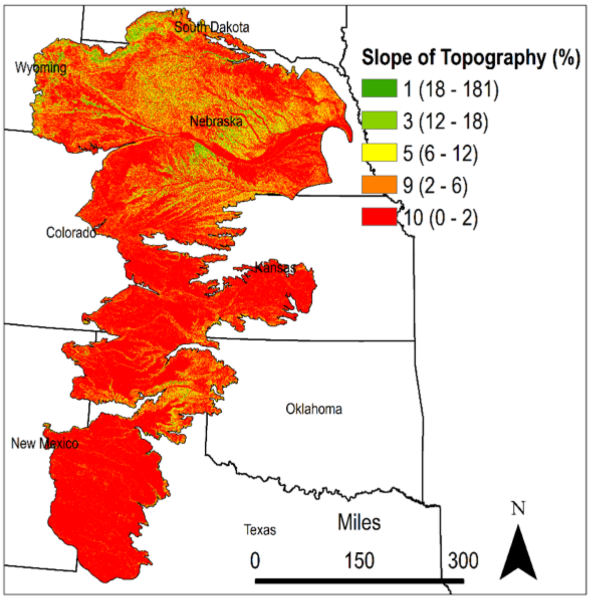

Figure 5. Topography (% Slope) raster classification

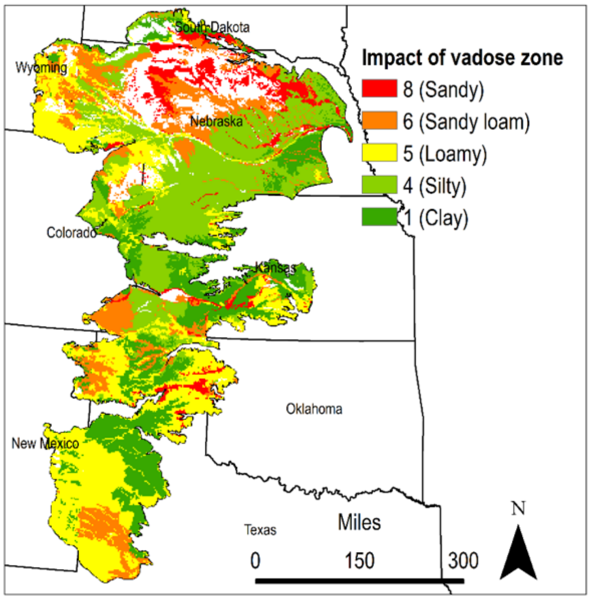

Figure 6. Impact of vadose zone raster classification

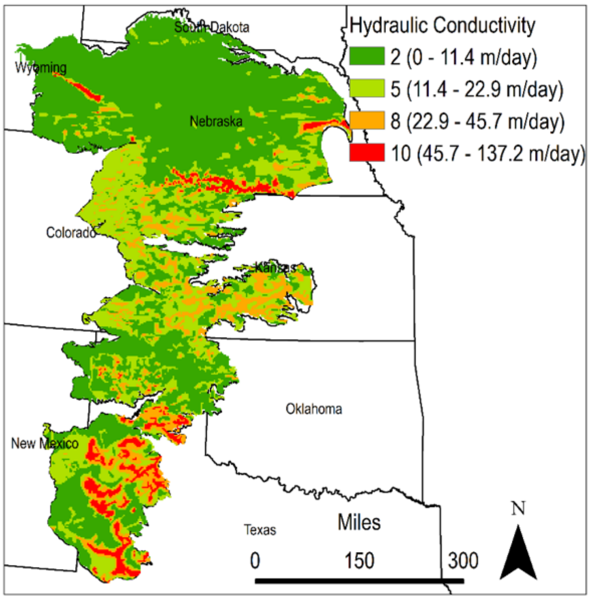

Figure 7. Hydraulic conductivity raster classification

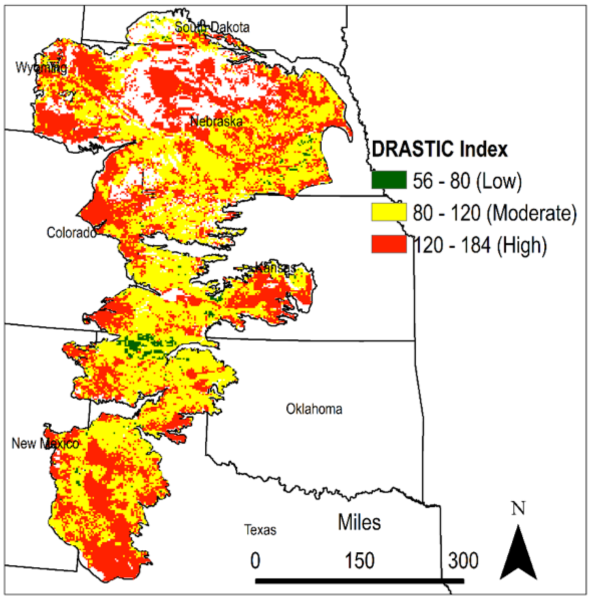

Figure 8. DRASTIC Index raster for High Plains Aquifer

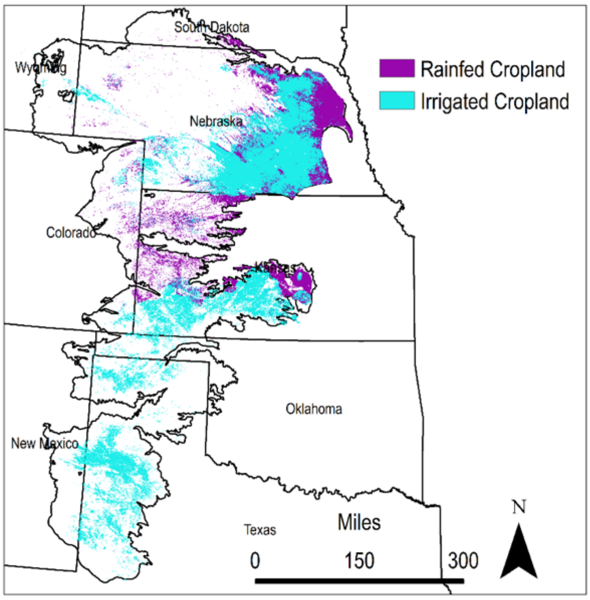

Figure 9. Irrigated and rain-fed agriculture in High Plains Aquifer (HPA) region (Source: Salmon et al. (2015)

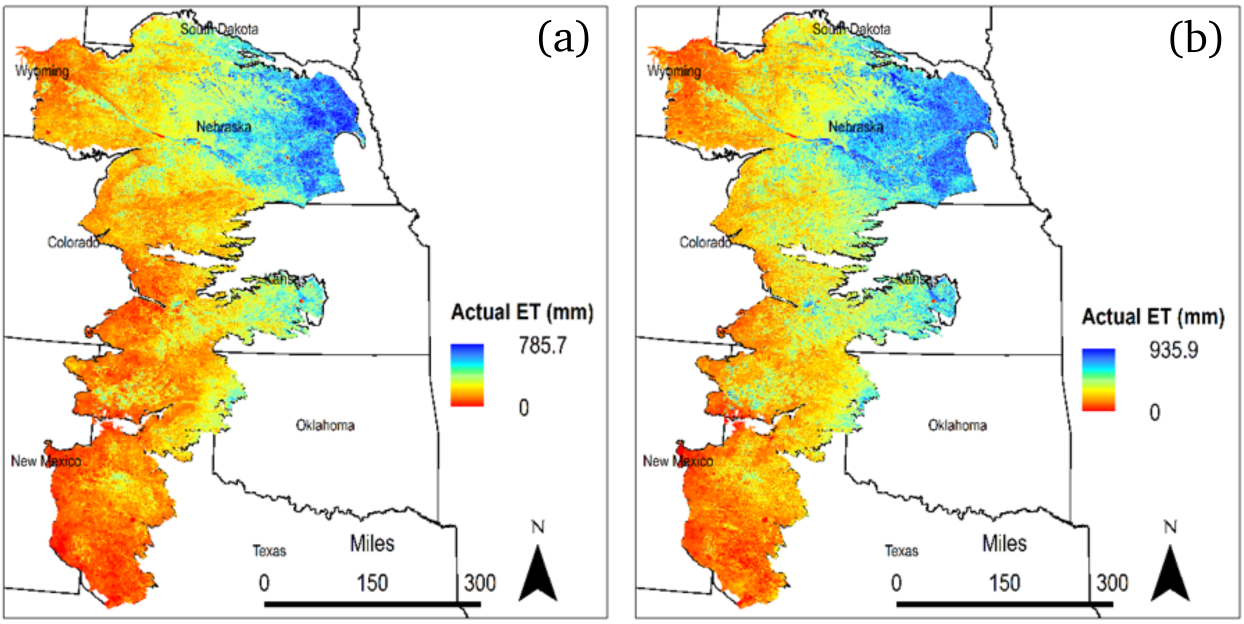

Figure 10. (a) Cumulative Actual ET during year 2013-Drought Year (b) Cumulative Actual ET during year 2016-Non-drought Year (Source: MOD16A2.006, 500 m, 8 day)

4 Conclusions

The DRASTIC model was successfully integrated with GIS to map the vulnerability of High Plains Aquifer (HPA). All of the required layers were reclassified using values from relevant literature and also, by arbitrary classification. The DRASTIC index was calculated and ranged from 56 to 184. Less than 1% of the area in HPA was under low vulnerability and the rest of the areas had Dr values of more than 80 making these areas vulnerable to groundwater pollution. The continuous agricultural operations in these areas could substantially add to the vulnerability of HPA. A limitation in this study is the classification of parameters needed for calculation of DRASTIC index. More effort could be made to more accurately reclassify these parameters. The categorization of DRASTIC index is also arbitrary with no widely accepted range of values. Further research is needed for proper categorization to match different geographic locations.

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Conflict of Interest

The authors declare that there is no conflict of interests regarding the publication of this paper.

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