558 GEOSPATIAL ANALYSES OF DROUGHT IMPACT AND SEVERITY IN NORTH DAKOTA, USA USING REMOTE SENSING AND GIS

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1. INTRODUCTION

Drought is a complex phenomenon difficult to accurately describe because it is both spatially variant and context dependent (Quiring, 2009). Although many definitions of drought exist, the central theme in documented literature on drought lies behind the context of water deficiency (Cook et al., 2007). Historically, losses from drought events across the world significantly increased with: (a) an increase in number of droughts; or (b) drought severity (Wilhite, 2000). Severe drought is one of the greatest recurring natural disasters in North America (Cook et al, 2007). Drought differs from other natural hazards in many ways especially in the sense that its onset and termination is invariably difficult to quantify or predict (McKee et al., 1993). Drought planners usually rely on acceptable mathematical indices to decide on when to start implementing water conservation or mitigation measures (Sonmez et al., 2005). Most commonly used indices include: (i) Palmer Drought Severity Index (PDSI); (ii) Standardized Precipitation Index (SPI); (iii) Crop Moisture Index (CMI); and (iv) Surface Water Supply Index (SWSI). An understanding of drought frequency and/or severity is critical in drought mitigation and planning in addition to implementing public policies. Geographic Information Systems (GIS) and applied Remote Sensing techniques are an effective set of tools necessary to display, model spatial and temporal drought intensity variation. In addition, use of remotely sensed data presents distinct advantages when determining drought impact on vegetation (Vicente-Serrano, 2007). Vegetation indices derived from processed satellite imagery allow areas affected by drought to be identified (Kogan, 1995). Vegetation indices are derived from various vegetation biophysical variables or biophysical responses to external stimuli. The objectives of this study are to (a) analyze the spatial variance of drought within the state of North Dakota, USA, (b) ascertain drought severity and county-by-county frequency of impact level within the state using GIS, and (c) analyze impact of drought on vegetation using Remote Sensing techniques for the southwestern drought-prone region of North Dakota. Various spatial analyses techniques such as kriging with spherical semivariograms, maximum likelihood and "band math" were used to derive drought-severity areas.

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1.1 Background

North Dakota State is situated in the north-central United States of America. North Dakota State has 53 counties. Figure 1 shows all counties in North Dakota with regional relative directional locations. North Dakota has been significantly impacted by drought in the past. Drought impact is notably varied spatially within state. Identifying regional vulnerabilities may lead to adjustment in practices in water-dependent sectors and can help decision makers to take the drought into account from a hazard-mitigation perspective and include the concept of drought vulnerability into natural resource planning (Sonmez et al., 2005).

2. METHODOLOGY

2.1 Drought Severity

In this study, county-by-county weekly common drought severity and coverage indices (I_{sc}) were calculated from the weekly percentage of areal coverage values of drought intensity, for a period of about nine years (Jan. 2000 – Apr. 2009) to determine the drought severity. These are non-dimensional indices calculated from:

$$\boldsymbol{I_{sc} = 1 \times (D0) + 2 \times (D1) + 3 \times (D2) + 4 \times (D3) + 5 \times (D4)} \quad (1)$$

Where $\boldsymbol{D0, D1, D2, D3}$, and $\boldsymbol{D4}$ are percentage area coverage values for different drought intensity categories, where $\boldsymbol{D0}$ is abnormally dry, $\boldsymbol{D1}$ is moderate drought, $\boldsymbol{D2}$ is severe drought, $\boldsymbol{D3}$ is extreme drought, and $\boldsymbol{D4}$ is exceptional drought. From Eq. (1), a value of 500 can be regarded as the worst possible drought scenario implying that 100% of the county would be deemed under exceptional drought using county-by-county values. A value of

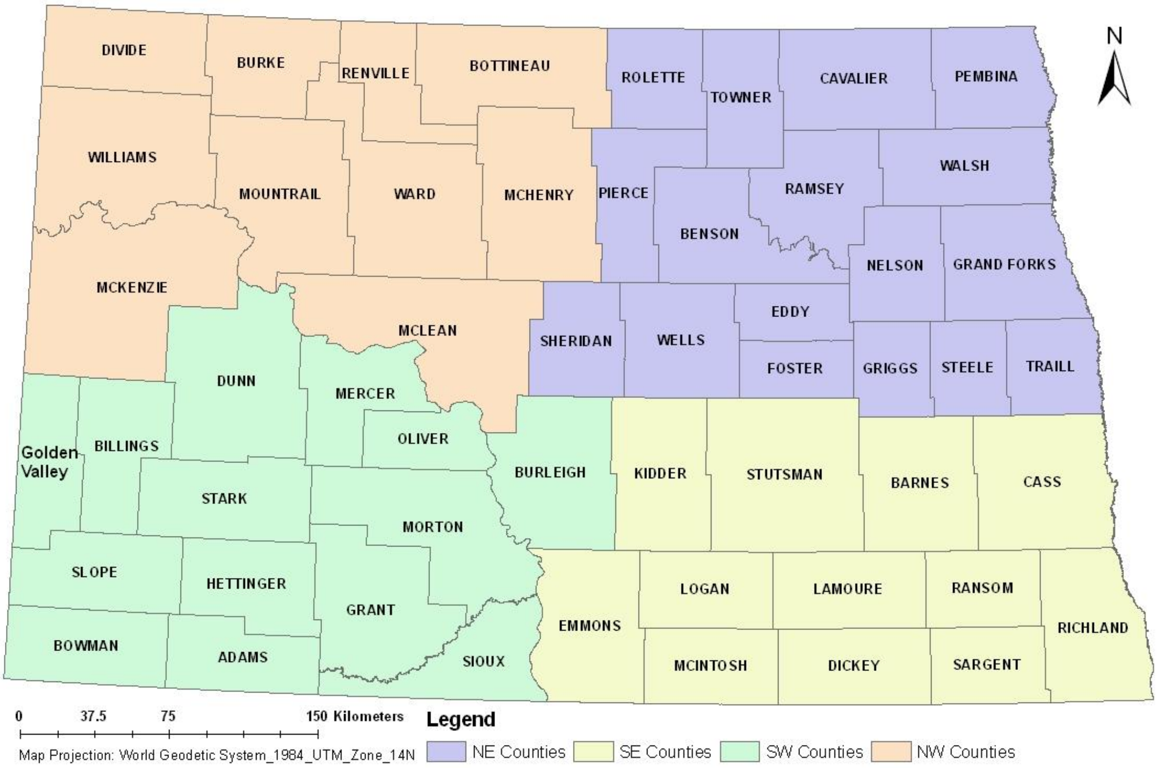


Figure 1: North Dakota Counties

zero would therefore imply that 0% of the county is facing drought. $\boldsymbol{D0, D1, D2, D3,}$ and $\boldsymbol{D4}$ were categorized using Palmer Drought Index, CPC Soil Moisture Model (Percentiles), USGS Weekly Stream flow (Percentiles), Standardized Precipitation Index (SPI), and Objective Short and Long-term Drought Indicator Blends (Percentiles) [see National Drought Mitigation Center (NDMC) site at http://www.drought.unl.edu]. The drought intensity values were derived as weekly percentages for each county for the sampling period (485 weeks). A new attribute representing average I_{sc} values was created in the county GIS shapefile for each predefined county centroid coordinates. The I_{sc} values were thereafter used as input values for basic spatial interpolation. This was done using ordinary kriging technique using a spherical semivariogram model in extension ArcView® version 3.2 with Spatial Analyst extension using a custom Avenue® script.

2.2 Drought Frequency

To analyze the drought frequency, the sum total of drought occurrence, n, within each county under each drought severity category was determined for the sampling period and classified as shown below (Table 1). A graduated symbol map for the classes was generated for each category using ArcGIS-ArcINFO®.

Table 1: Classified categories with I_{sc} ranges (n is number of occurrence associated with I_{sc})

Category	n
A	$n_{I_{sc}} \le 100$
B	$n_{100 < I_{sc} \le 200}$
C	$n_{200 < I_{sc} \le 300}$
D	$n_{300 < I_{sc} \le 400}$
E	$n_{400 < I_{sc} \le 500}$

2.3 Impact of drought on Vegetation

To assess the impact of drought on vegetation remote sensing image processing software ENVI® version 4.5 was used. Landsat 7 ETM+ images were obtained from the USGS archive (http://glovis.usgs.gov/) for the southwest portion of the state since this was an identified drought prone area. The satellite frames encompassed Slope and Bowman counties on the southwest end of North Dakota. Normalized Difference Vegetation Indices (NDVI) for the input imageries were determined for temporal times (Oct .07, 2000; Aug. 07, 2001 and Aug. 26, 2002) within the sampling period window.

The NDVI can be represented as (Rouse et al., 1974):

$$\boldsymbol{NDVI} = \frac{(\rho_{nir}-\rho_{red})}{(\rho_{nir}+\rho_{red})} \qquad (2)$$

Where $\boldsymbol{\rho_{nir}}$ is near-infrared radiant flux and $\boldsymbol{\rho_{red}}$ is red reflected radiant flux. The NDVI derived values can be used to assess seasonal and annual weather related vegetation growth. NDVI can also be used to detect vegetative activity while reducing noise stemming from atmospheric conditions, for example, illumination differences, dark objects, attenuation and/or scattering, topographical variations (Huete et al., 2002a, b). The resultant images were exported to a GIS platform (ArcGIS-ArcINFO® version 9.3). This was done to corroborate drought prone areas located in the southwestern portion of the state.

3. RESULT

3.1 Drought Severity

The spatial variation of the drought impact within North Dakota is depicted using a red to green with a transitional yellow hue colour gradation (Fig. 2).Preliminary results indicated that the following

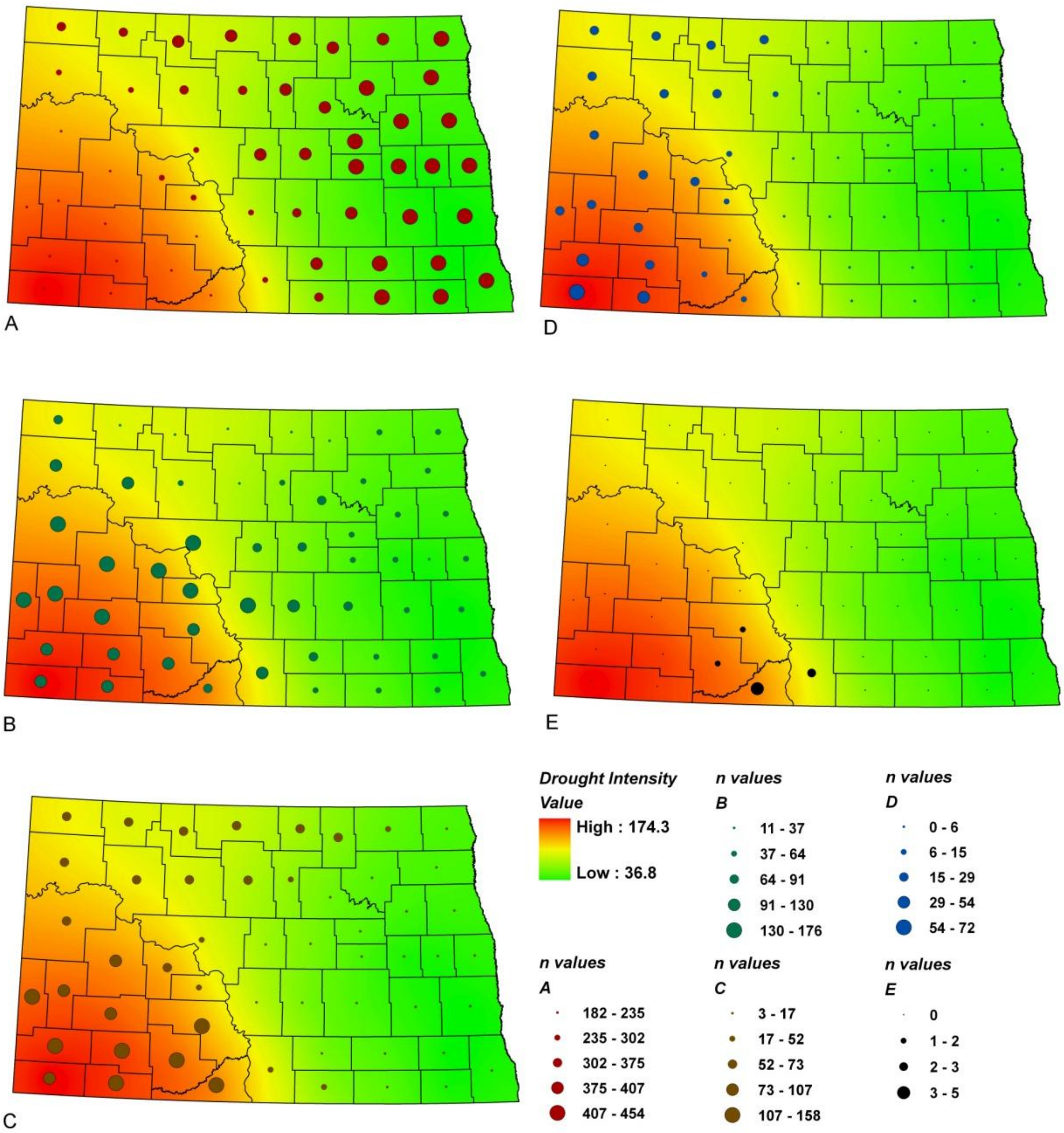


Figure 2: Drought intensity variation using color gradation. Red hue depicts drought prone areas situated mostly on the southwestern portion of the state. Fig. 2A, 2B, 2C, 2D and 2E depict class categories of $n_{I_{sc}\le 100}$, $n_{100<I_{sc}\le 200}$, $n_{200<I_{sc}\le 300}$, $n_{300<I_{sc}C\le 400}$, and $n_{400<I_{sc}\le 500}$ respectively

counties located on the south-western part of the state; Bowman, Slope, Adams, Hettinger, Stark, Golden Valley, Billings, Grant, Sioux and Dunn Counties had a higher than average value of I_{sc} for the sampled period. The maximum average value was 174.3 for Bowman county and minimum value was 36.8 for Cass County.

3.2 Drought Frequency

Fig. 2 depicts spatial distribution of the drought frequency variation within North Dakota for each drought frequency analyses using graduated symbols and hue. We can deduce that: - (i) for category A ($n_{I_{sc} \leq 100}$), the counties that had numerous occurrence values of lower drought incidences in descending order from highest were Steele ($n_{I_{sc} \leq 100} = 454$), Walsh ($n_{I_{sc} \leq 100} = 432$), Nelson ($n_{I_{sc} \leq 100} = 432$), Ransom ($n_{I_{sc} \leq 100} = 432$), and Griggs ($n_{I_{sc} \leq 100} = 431$) (see also Table 2). We can surmise that from the spatial analyses these eastern counties were less vulnerable to drought. (ii) For category B ($n_{100 < I_{sc} \leq 200}$), counties like McKenzie ($n_{100 < I_{sc} \leq 200} = 176$), Burleigh ($n_{100 < I_{sc} \leq 200} = 173$), Billings ($n_{100 < I_{sc} \leq 200} = 167$), Oliver ($n_{100 < I_{sc} \leq 200} = 149$), and Mercer ($n_{100 < I_{sc} \leq 200} = 148$) were most notable. (iii) for category C ($n_{200 < I_{sc} \leq 300}$), the counties that had numerous occurrence values of intermediate drought incidences in descending order from highest were Grant ($n_{200 < I_{sc} \leq 300} = 158$), Sioux ($n_{200 < I_{sc} \leq 300} = 156$), Morton ($n_{200 < I_{sc} \leq 300} = 148$), Slope ($n_{200 < I_{sc} \leq 300} = 133$), Hettinger ($n_{200 < I_{sc} \leq 300} = 133$) and Adams ($n_{200 < I_{sc} \leq 300} = 130$). As much as these n values are in the similar range as in category B, the drought severity can be interpreted as significant. The n values in this case carry a higher weighting in this regard. (iv) Considering a higher drought severity index corresponding to Category D ($n_{300 < I_{sc} \leq 400}$), counties like Bowman ($n_{300 < I_{sc} \leq 400} = 72$), Adams ($n_{300 < I_{sc} \leq 400} = 54$), Slope ($n_{300 < I_{sc} \leq 400} = 40$), Hettinger ($n_{300 < I_{sc} \leq 400} = 29$), and Golden Valley ($n_{300 < I_{sc} \leq 400} = 27$) displayed higher n values. (v) In the highest category E ($n_{400 < I_{sc} \leq 500}$), counties like Sioux ($n_{400 < I_{sc} \leq 500} = 5$), Emmons ($n_{400 < I_{sc} \leq 500} = 3$), Morton ($n_{400 < I_{sc} \leq 500} = 2$), and Grant ($n_{400 < I_{sc} \leq 500} = 2$) were counties that can be classified as prone to drought. Table 2 summarizes the highest and lowest determined n values In Fig. 3, we can see distribution ranges of each drought category. There is a general 'thinning' trend as one moves from lower to higher drought categories. Fig. 4 shows graphical variation for each quarter demarcated region within the state. While the highest corresponding drought severity values were lower in occurrences, the lower relative categories displayed a non-linear trend.

Table 2: Summary table of highest and lowest n values.

Highest		Lowest	
County	n	*County*	n
Category A			
Steele	454	Slope	182
Walsh	432	Bowman	184
Nelson	432	Golden Valley	188
Category B			
McKenzie	176	Rolette	11
Burleigh	173	Renville	19
Billings	167	Bottineau	21
Category C			
Grant	158	Eddy	3
Sioux	156	Foster	3
Morton	148	Grand Forks	3
Category D			
Bowman	72	Eddy	0
Adams	54	Foster	0
Slope	40	Ransom	0
Category E			
Sioux	5	Eddy	0
Emmons	3	Foster	0
Morton	2	Ransom	0

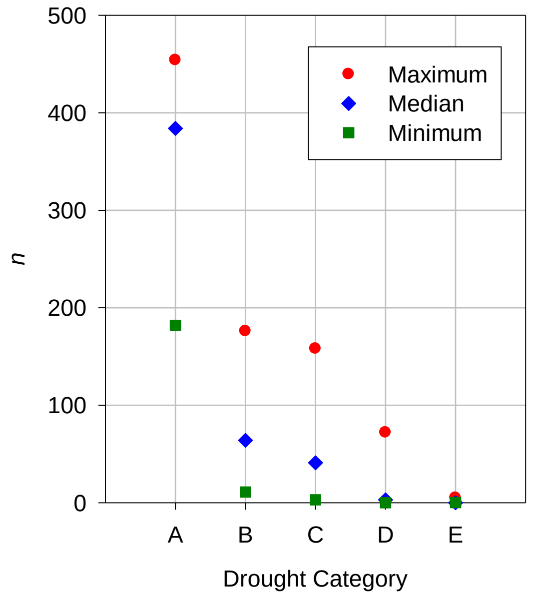
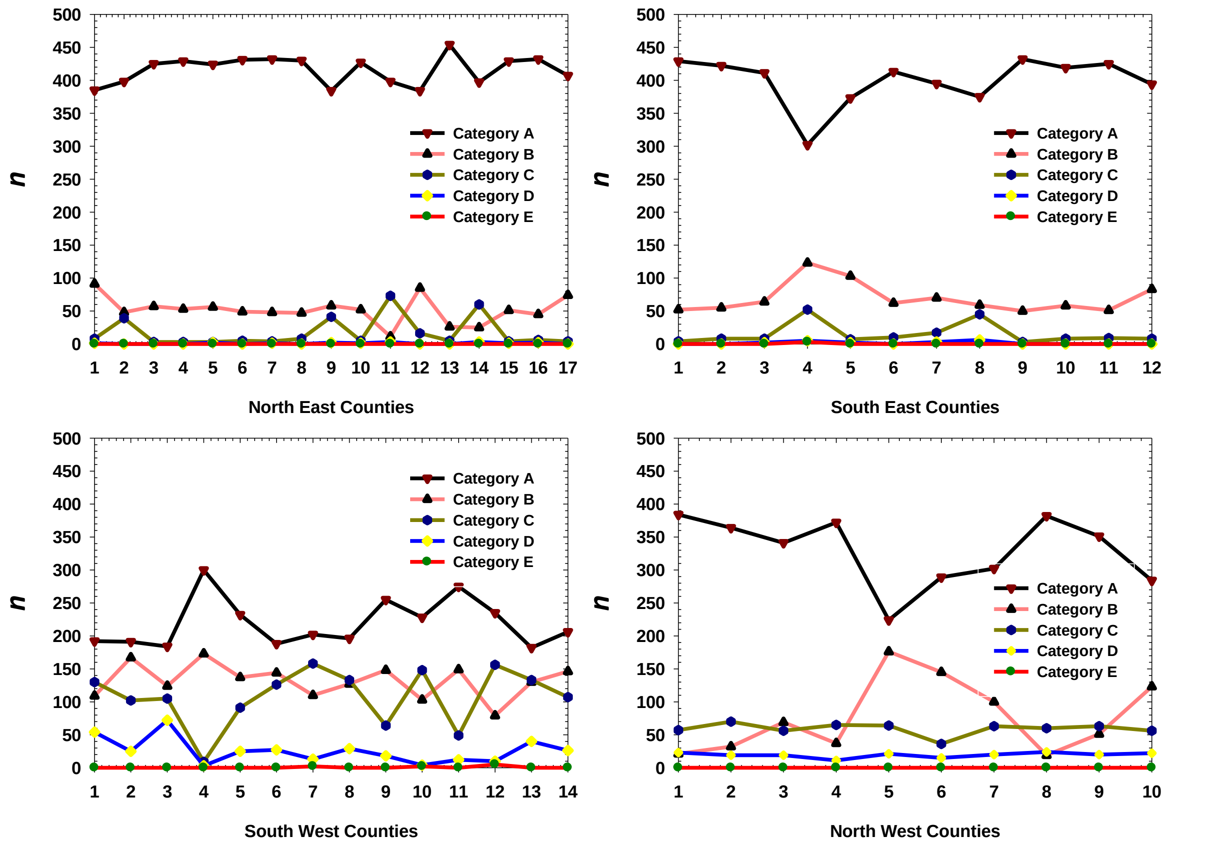


Figure 3: Maximum, median and minimum $\boldsymbol{n}$ Vs Drought category



NE Counties: 1-Benson, 2-Cavalier, 3-Eddy, 4-Foster, 5-Grand Forks, 6-Griggs, 7-Nelson, 8-Pembina, 9-Pierce, 10-Ramsey, 11-Rolette, 12-Sheridan, 13-Steele, 14-Towner, 15-Traill, 16-Walsh, 17-Wells
SE Counties: 1- Barnes, 2- Cass, 3- Dickey, 4- Emmons, 5- Kidder, 6- LaMoure, 7- Logan, 8- McIntosh, 9- Ransom, 10- Richland, 11- Sargent, 12- Stutsman
SW Counties: 1- Adams, 2- Billings, 3- Bowman, 4- Burleigh, 5- Dunn, 6- Golden Valley, 7- Grant, 8- Hettinger, 9- Mercer, 10- Morton, 11- Oliver, 12- Sioux, 13- Slope, 14- Stark
NW Counties: 1- Bottineau, 2- Burke, 3- Divide, 4- McHenry, 5- McKenzie, 6- McLean, 7- Mountrail, 8- Renville, 9- Ward, 10- Williams

Figure 4: Drought frequency value of each category for four regions of North Dakota counties.

For all NE counties, the lower category n values were higher than the higher ordered categories. For some counties, there was a general overlap in n values for categories B and C. From SE county listing, Emmons County displayed a relatively lower Category A n value with correspondingly higher Category B and C. All other SE counties displayed almost similar trends. The identified drought-prone SW counties had characteristic curves that were overlapping in n determinates. The physical significance of this may not be attributed to only a single factor however this region is geographically and geologically different from the entire state with unusual rainfall patterns. The dip in n values for McKenzie county (a NW county) almost coincides with the apparent increase in n value for Category B.

3.3 Impact of drought on Vegetation

Normalized Difference Vegetation Indices (NDVI) were derived from Landsat 7 ETM+ satellite imagery within the sampled period timeframe. And the NDVI images are shown in Fig 5. Table 3 lists corresponding I_{sc} values for two SW counties.

Table 3: I_{sc} Values for the remote sensing study area

Date	Bowman County	Slope County
Aug 07 2001	0	0
Oct 07 2000	100	100
Aug 26 2002	278	200

From Table 3 and Fig. 5 we can surmise that the higher the relative occurrences of severe drought, the

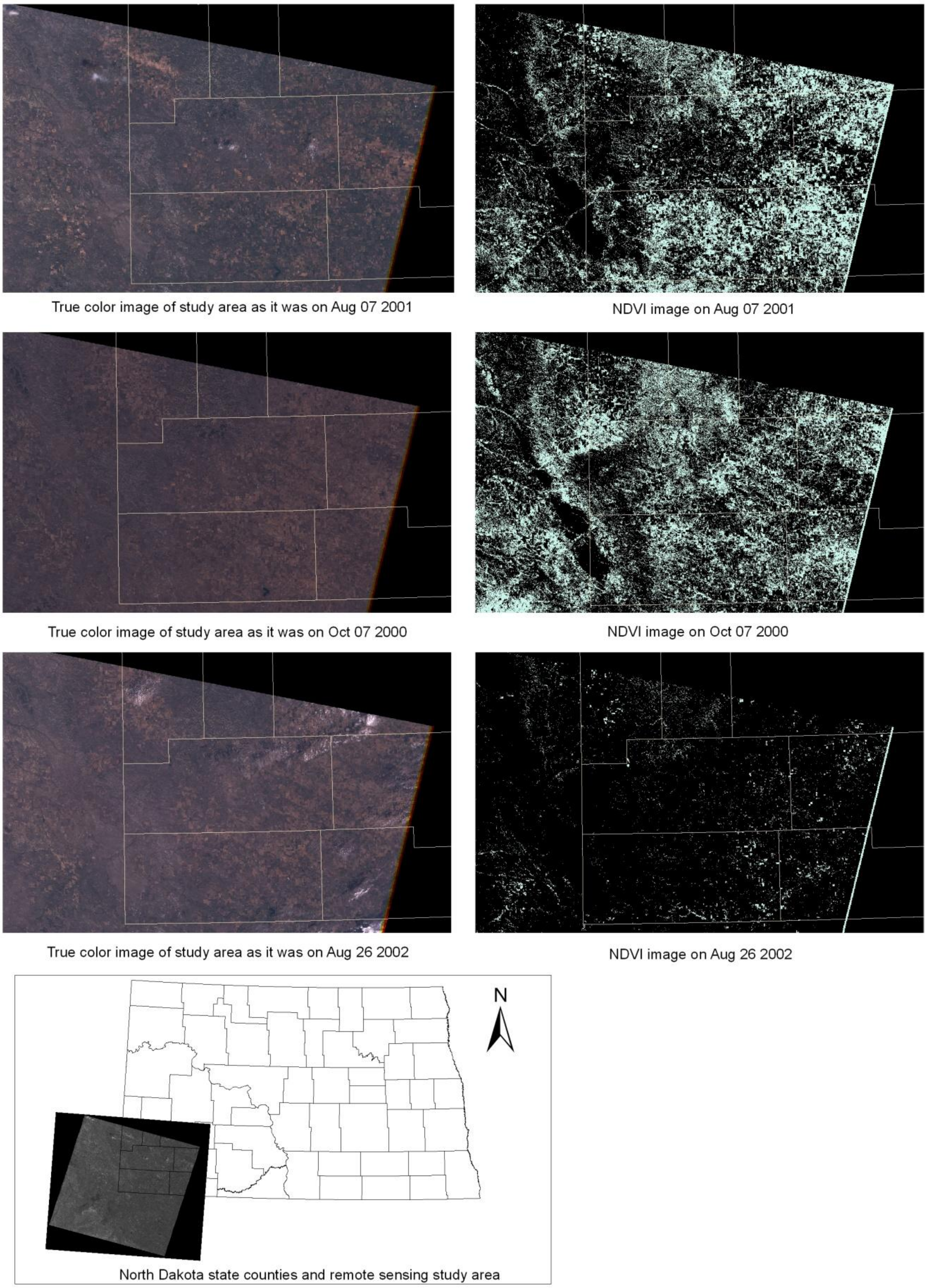


Figure 5: True color images and NDVI images for remote sensing study area

lower the NDVI value. Conversely, the lower the drought severity the higher the relative NDVI value. For example the Aug 07 2001 image appears brighter because this area displayed non-drought related conditions on the day of image acquisition. The Aug. 26, 2002 NDVI image appears much darker than others since this day corresponded to a higher I_{sc} value interpreted as a higher drought severity index.

4. DISCUSSION

In this study, drought data from National Drought Mitigation Center (NDMC) were used. NDMC publishes weekly drought coverage data and disseminate it from the URL: http://www.drought.unl.edu. This data is classified based on multiple drought indices. Using a single set of subjectively defined drought thresholds may be inappropriate since this can lead to a mischaracterization of drought conditions (e.g., over- or underestimating drought severity) and incorrect triggering of drought responses (Quiring,2009). Drought severity and frequency was studied as county-by-county spatial demarcations since most agricultural management is best administered on county basis. Dow et al., (2009) study emphasizes issues that need to be addressed in greater detail in decision- maker scientist dialogs by providing further insight into (1) what units are useful to local drought information and (2) users' awareness and acceptance of the uncertainty and tradeoffs involved in mapping climate information to a ''local'' scale. Landsat 7 ETM+ imagery was used to study the impact of drought on vegetation. A range of vegetation indexes based on remote sensing data have been used to monitor vegetation (Bannari et al., 1995), with the most widely adopted being the normalized difference vegetation index (NDVI) (Tucker,1979). Many studies report that the spatial and temporal differences in the NDVI are closely related to climate in many environments (Eastman and Fulk, 1993). In fact, temporal variations in the NDVI may be representative of the vegetation's response to climatic variability (Nicholson et al., 1990). Vicente-Serrano (2007) studied the effects of drought on the vegetation in the Iberian Peninsula, by using NDVI and also considered spatial and seasonal differences to assess drought impact. Their study further emphasised that NDVI is an attractive vegetation index in assessing or addressing drought impacts.

5. CONCLUSION

This study demonstrated that southwestern counties of North Dakota, US, may be more drought prone and require Best Management Practices (BMPs) to address future drought impacts. Agricultural productivity of the eastern counties within North Dakota may be further increased since these counties do not display higher drought severity indices or frequency of drought occurrences. In case of impact of drought on vegetation it is inherently difficult to draw a concrete conclusion based on derived vegetation indices since in rapidly developing areas, land cover change needs also to be accounted. Land cover transition studies are also usually modeled using Markov Chain Monte Carlo simulations which may incur inherent complexities in fingerprinting drought impacts.

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