Downscaling of Satellite-Derived Soil Moisture Using Land Surface Temperature and Vegetation Index

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Downscaling of Satellite-Derived Soil Moisture Using Land Surface Temperature and Vegetation Index

Master of Science Thesis
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Abstract

Soil moisture measurement from remote sensing is mostly available at coarse resolution 10-60 km. Applications at local scale such as agricultural water management requires this information at finer scale (less than 1 km). The objective of this study was to downscale soil moisture data from 12.5 km resolution to 1 km using ASCAT soil moisture dataset available daily. The study involved use of land surface temperature (LST), normalized difference vegetation index (NDVI) and land use map for the study area. The study has been conducted for the whole state of Nebraska with an area of over 200,000 square kilometers. The study involved review of: (1) triangle method, (2) trapezoidal method and (3) ETlook method for soil moisture downscaling. Harmonic time series was used to reconstruct data to obtain continuous daily datasets and to mask clouds. Overall, the soil moisture at coarse scale showed better correlation $R=0.47$ compared to the implemented methods with $R=0.29$ for ETlook method and $R=0.17$ for triangle method. The seasonal variations were observed to be the key drivers to soil moisture variations with an improved accuracy RMSE=0.09 obtained during summer compared to winter which had the lowest accuracy RMSE=0.13 m$^3$/m$^3$. A downscaling method that combines dryness index from triangle method, land use and a sinusoidal correction of seasonal bias was developed. The method improved the annual the temporal correlation from $R=0.1$ to $R=0.5$ and spatio-temporal correlation from $R=0.47$ to $R=0.54$ and when compared to data at coarse scale. The method also improved the accuracy during winter RMSE=0.13 to RMSE=0.10. Thus the downscaling method successfully improved the resolution without degrading the accuracy. This accuracy was found to be within the threshold required for global climate observation systems (GCOS) which is set at 20% of the saturated water content. The methods performed better in Rangelands with $R=0.53$ compared to cultivated areas with $R=0.49$. Global soil dataset was used for the study which largely had a saturated water content of 0.40-0.45 m$^3$/m$^3$. When local soil data from the validation sites were used, the correlation improved from $R=0.54$ to $R=0.67$. The method performance can thus be further improved with availability of higher resolution soil data.

Key Words: HANTS, Downscaling, ASCAT, Land Surface Temperature, NDVI
Acknowledgements

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### Abbreviations

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<th>Description</th>
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<tbody>
<tr>
<td>ASCAT</td>
<td>Advanced Scatterometer (Metop)</td>
</tr>
<tr>
<td>DOY</td>
<td>Day of the year</td>
</tr>
<tr>
<td>DEM</td>
<td>Digital Elevation Model</td>
</tr>
<tr>
<td>EUMETSAT</td>
<td>European Organisation for the Exploitation of Meteorological Satellites</td>
</tr>
<tr>
<td>HANTS</td>
<td>Harmonic Analysis of Time Series</td>
</tr>
<tr>
<td>GLDAS</td>
<td>Global Land Data Assimilation System</td>
</tr>
<tr>
<td>HiHydrosoils</td>
<td>High Resolution Soil Map of Hydraulic Properties</td>
</tr>
<tr>
<td>LAI</td>
<td>Leaf Area Index</td>
</tr>
<tr>
<td>LST</td>
<td>Land Surface Temperature</td>
</tr>
<tr>
<td>MBE</td>
<td>Mean Bias Error</td>
</tr>
<tr>
<td>NDVI</td>
<td>Normalized Difference Vegetation Index</td>
</tr>
<tr>
<td>NIR</td>
<td>Near Infra-Red</td>
</tr>
<tr>
<td>NRT</td>
<td>Near Real Time</td>
</tr>
<tr>
<td>NSE</td>
<td>Nash–Sutcliffe model efficiency coefficient</td>
</tr>
<tr>
<td>QFLAG</td>
<td>Quality Flag</td>
</tr>
<tr>
<td>R</td>
<td>Correlation Coefficient</td>
</tr>
<tr>
<td>RMSE</td>
<td>Root Mean Square Error</td>
</tr>
<tr>
<td>SSM</td>
<td>Surface Soil Moisture</td>
</tr>
<tr>
<td>SWI</td>
<td>Soil Water Index</td>
</tr>
<tr>
<td>TAIR</td>
<td>Air Temperature</td>
</tr>
<tr>
<td>TAMU</td>
<td>Texas A&amp;M University</td>
</tr>
<tr>
<td>TVDI</td>
<td>Temperature Vegetation Dryness Index</td>
</tr>
<tr>
<td>UNL</td>
<td>University of Nebraska Lincoln</td>
</tr>
<tr>
<td>VTCI</td>
<td>Vegetation Temperature Condition Index</td>
</tr>
<tr>
<td>WDI</td>
<td>Water Deficit Index</td>
</tr>
<tr>
<td>WGS84</td>
<td>1984 World Geodetic System</td>
</tr>
</tbody>
</table>
CHAPTER 1
INTRODUCTION

1.1. Background
Soil moisture is a paramount component for crop growth and development. According to Igor Shiklomanov’s, (1993), it represents 0.05% of the world’s freshwater resources and affects hydrologic events that include evapotranspiration, vertical and lateral infiltration and time required to transform rain events to runoff. Thus proper quantification of soil water content is necessary for water management applications such as controlling the amount of water applied to plants. The quantity of soil moisture affects parameters that are closer to the land surface including runoff, the rate of evapotranspiration, surface temperature and water vapour in the atmosphere. This is because it affects the heat transfer between water, soil and the atmosphere closer to the land surface (Schneider et al., 2014). These parameters influence crop production and provides an indication of the crop management practices that need to be applied. For instance, crop water stress at critical crop growing stages can be overcome by ensuring that the soil water content do not fall to a given critical point hence ensuring higher crop yields. In as much as the information on the soil water content is paramount, there is a limited availability at finer spatial and temporal scales. This is because in-situ soil moisture measurements are expensive and requires considerable amount of time to obtain (Shin & Mohanty., 2013).

Remote sensing techniques for soil moisture retrieval provide an alternative to direct measurement as they can be easily accessed. However, as has been reported by Ranney et al, (2014) much as the soil moisture products from satellites are available at resolutions of (20-60km), the main challenge is that for irrigation water management, this data is required at a finer scale. Some of the examples of satellites that provide the data at coarse scale include Windsat available at 25km resolution; Soil Moisture Active and Passive (SMAP) which continues to provide maps at 9km resolution despite its radar mission which was available at 3km resolution coming to a halt in July 2015; Soil Moisture and Ocean Salinity (SMOS) available at 35-50km resolution and ASCAT soil moisture satellite product available at 25km and 12.5km resolution (Merlin et al., 2005, Ranney et al., 2014, Bastiaanssen et al., 2012). It is therefore evident that downscaling techniques are required to make the data available at finer resolutions. Furthermore, the halting of SMAP soil moisture products that were available at 3km resolution in 2015 implies that the soil moisture resolution from satellites may not improve in the near future.

Downscaling techniques that make use of satellite data derived from visible and thermal infrared region of the spectrum have been applied for downscaling coarse resolution to intermediate resolutions of 1km (Merlin et al., 2008, Kim & Barros, 2002). Similarly, surface energy balance algorithms have been used for estimating soil moisture at intermediate-resolution (500m) using optical and thermal remote sensing (Bastiaanssen et al., 1998).
1.2. Problem Statement

In agricultural water management, managers want to understand how much water is available in the field. This enables them to maximise crop production by avoiding crop water stress. There is an opportunity to increase crop yield by making this information available on a daily scale as it enables them to make informed decisions. Whereas in-situ soil moisture measurements provide reliable information, the instruments are expensive to manage and time consuming to obtain daily datasets from the field. The spatio-temporal distribution of soil moisture can be obtained from remote sensing by comparing archived imagery through time. Many soil moisture satellite products, however, provide soil moisture data at coarse resolutions (10-60km). However, applications such as crop water management require finer resolution (Ranney et al, 2014). In agriculture LANDSAT imagery, for instance, can provide sufficient data with fine spatial resolution (30m) but would provide data with 16-days separating two sequential images. This is further impeded by clouds cover making it more difficult to obtain more cloud free images in the cropping period. MODIS instruments view the entire earth surface at least twice a day and imaged at 36 spectral bands: bands 1 and 2 at 250m resolution (620-876nm), band 3 to band 7 at 500m resolution (459-2155nm) and band 8 through to band 36 at 1000m resolution (405nm-14.3µm)(U.S Geological Survey, 2014). However, despite the high spatial and temporal characteristics, the limitation is that it requires cloud-free conditions.

Soil moisture measurements from microwave remote sensing mainly focuses on the top 2 cm. For agriculture, however, this information is required for the crop root zone which vary from one crop to another and with the stage of development; generally taken as 100cm for most established crops(Scott, Bastiaanssen, & Ahmad, 2003). Therefore, in as much as soil moisture data from microwave sensor (ASCAT) will allow monitoring at all-weather conditions, products from optical and thermal satellites available higher resolution such as vegetation and land surface temperature could to be used to deduce the quantity of soil moisture both at the top soil(bare soils) and over the plant root depth (vegetated areas).

Downscaling methodologies that use topography, soil and vegetation have been applied using aerial photography and with fine resolution data (Ranney et al., 2014,Hendrickx et al., 2011). However, the study did not use coarse resolution data but rather fine resolution data from aerial photographs. Similarly, most downscaling methodologies that employ the LST/NDVI based methods have relied on the visual interpretation of the LST/NDVI plots and also cloud free conditions. This study will thus focus on developing downscaling methodology that uses daily NDVI and land surface temperature to downscale ASCAT soil moisture data from a coarse resolution of 12.5km to a resolution of 1000m.
1.3. Objective
The overall objective of the study was to use land surface temperature and vegetation to downscale satellite derived soil moisture data from ASCAT and evaluate the proposed methodology with an existing ground soil moisture dataset in the State of Nebraska.

1.3.1. Specific Objectives
I. Review existing methodologies for downscaling coarse resolution satellite imagery such as using land surface temperature and vegetation indices and propose a methodology for downscaling ASCAT’s 12.5 km resolution.
II. Apply the methodology developed in (I) to produce finer resolutions of 1000m that can be used in agriculture
III. Validate the methodology using in-situ soil moisture measurements obtained from 45 stations in Nebraska

1.4. Research Questions
How can we downscale ASCAT soil moisture product from a spatial resolution of 12.5km to a resolution of 1000m that for applications at local scale such as agricultural water management?

1.4.1. Specific Research Questions
• What are the limitations of current downscaling methodologies and how can we improve them?
• How does the fine resolution data obtained in this study compare to the in-situ soil moisture measurements and to coarse resolution data (12.5km)?
• How does the performance of the methodology compare with different seasons, land use and with soil type?
CHAPTER 2

LITERATURE REVIEW

In this chapter an overview of remote sensing instruments from the various windows of the spectrum is provided. Secondly, indices that include land surface temperature based indices, vegetation based indices and soil water indices are discussed. Thirdly, a review of various downscaling methodologies that have been applied including a summary is provided. Validation and reconstruction of time series data is also briefly discussed.

2.1. Overview of remote sensing instruments

According to Sabin, (1997) remote sensing is defined as “methods that employ electromagnetic energy such as light, heat, and radio waves as a means of detecting and measuring target characteristics”. There exists a sizable number of satellites orbiting planet earth that have continuously been used to provide valuable information for atmospheric, oceanic and land surface studies. The partitioning of electromagnetic energy based on the transmitted energy, absorbed energy and reflected energy is used to infer properties of the land surface.

Remote sensing instruments use various windows of the electromagnetic spectrum to record earth surface reflectance properties. Instruments that include Multi-Spectral Scanner (MSS), MODIS and Advanced Very High Resolution Radiometer (AVHRR) use visible and infrared regions (wavelength 620nm-14μm)(Fang et al., 2013). The MODIS instrument operate on Terra and Aqua satellites. Terra orbits the earth from North to south in the morning while Aqua passes in the afternoon over the equator but from south to north. It acquires data over 36 bands at three spectral resolutions of 250,500 and 1000m. MODIS viewing swath width is 2,330km and has the ability to cover the entire surface in 1 or 2 days(U.S Geological Survey, 2014). The data for land is provided by LP DAAC (Land Process Distributed Active Archive) that include vegetation indices, surface reflectance and temperature and fire products. In this study, we used Land Surface Temperature and NDVI products from MODIS.

Other instruments such as Synthetic Aperture Radar (SAR), Advanced Microwave Scanning Radiometer for Earth Observing System (AMSR-E), Soil Moisture and Ocean Salinity (SMOS), Soil Moisture Active Passive (SMAP) and ASCAT use microwave regions of the spectrum (wavelength 0.15-30cm). The principle behind microwave remote sensing being the large difference that exist between the dielectric properties of liquid water and dry soils (Parinussa, 2013).
The table 2-1 below presents some advantages and disadvantages of using remote sensing for measurement of soil moisture using different parts of the electromagnetic spectrum.

**Table 2-1: Soil Moisture Measurement Using Remote Sensing, synthesized from (Scott et al., 2003)**

<table>
<thead>
<tr>
<th>Spectrum</th>
<th>Advantages</th>
<th>Disadvantages</th>
<th>Wavelength(λ)</th>
<th>Uses</th>
</tr>
</thead>
<tbody>
<tr>
<td>Visible</td>
<td>• Easy to operate</td>
<td>• Strong empirical character</td>
<td>620nm-876nm</td>
<td>• Determining the vegetation land cover</td>
</tr>
<tr>
<td></td>
<td>• Can be applied to a range of temporal and spatial scales</td>
<td>• Require cloud free conditions</td>
<td></td>
<td>• Quantify amount of clouds</td>
</tr>
<tr>
<td>Thermal infrared</td>
<td>• Good Physical basis</td>
<td>• Cloud free conditions required</td>
<td>3.0-14μm</td>
<td>• Surface temperature</td>
</tr>
<tr>
<td></td>
<td>• Can be used on a wider spatial and temporal scale</td>
<td>• Depth of the rootzone is variable across an image</td>
<td></td>
<td>• Forest fires and Volcanoes</td>
</tr>
<tr>
<td></td>
<td>• Provides an assimilated soil moisture value for the root zone</td>
<td></td>
<td></td>
<td>• Cloud fraction</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>• Troposphere Humidity</td>
</tr>
<tr>
<td>Active Microwave</td>
<td>• Can be applied on all weather conditions</td>
<td>• Surface roughness affects estimation of soil moisture</td>
<td>3-25 cm</td>
<td>• Soil Moisture estimates</td>
</tr>
<tr>
<td></td>
<td>• Good physical basis</td>
<td>• Soil moisture can only be retrieved for top few centimeters</td>
<td></td>
<td>• Wind direction and speed</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• The are expensive</td>
<td></td>
<td>• Snow cover</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>• Flooding under canopies</td>
</tr>
<tr>
<td>Passive Microwave</td>
<td>• Applicable for all weather conditions</td>
<td>• Affected by dense vegetation</td>
<td>0.15-30cm</td>
<td>• Soil moisture</td>
</tr>
<tr>
<td></td>
<td>• Good physical basis</td>
<td>• Retrieves on top 0-5cm</td>
<td></td>
<td>• Sea Ice</td>
</tr>
<tr>
<td></td>
<td>• High temporal scale</td>
<td>• Large pixel size from satellites</td>
<td></td>
<td>• Sea surface parameters (wind speed, rainfall rate, surface temperature)</td>
</tr>
</tbody>
</table>

Source: (Scott et al., 2003)
2.2. The Advanced Scatterometer (ASCAT)

This study will focus Soil Water Index product from ASCAT operated by EUMETSAT (European Organisation for the exploitation of Metrological Satellites). ASCAT uses a radar system which operates at C-band. It illuminates a swath width of 550km aboard METOP satellites at an altitude of 837km and conveys a long pulse with Linear Frequency Modulation (‘chirp’). Soil moisture is retrieved from backscattering of the pulses. The soil moisture retrieval algorithm was developed by TU Wein (Albergel et al., 2012).

ASCAT succeeded ERS Scatterometer (EUMETSAT, 2015). Its main improvements are that the backscattering coefficient for daily global coverage increased from 41% to 82% and a better resolution of 25km instead of 50km at similar radiometric accuracy was achieved. Daily soil moisture maps are produced (near real time) with resolutions of 12.5km, 25km and 50km. This data can be obtained from the month of December 2008 to present (Wagner et al., 2010). Soil water index reformatted as Time series product SWI-TS at 12.5km resolution has recently been made available with data from the year 2007 to present for analysis at local scales. The product was downloaded from (Copernicus Global Land Service, 2016)

The Scatterometer measure the backscattering coefficient. This coefficient depend on soil layer dielectric properties, vegetation and surface roughness. Thus, ASCAT provides valuable data for ice and land applications. Due to the ability of scatterometer radar signal to penetrate the land surface, ASCAT can observe subsurface/sub-canopy climate-related features. ASCAT has a global coverage and its ability to provide frequent data makes it a great tool for long term climatic studies (EUMETSAT, 2015, Bartalis et al., 2007). The backscatter from the C-band depends on the amount of soil moisture in the top 2 cm; this basis makes it possible to use backscattered measurements to estimate soil moisture. Scientific studies that focused on ASCAT validation and assessments have had a positive outcome (Wagner et al., 2013)

The sensitivity of backscattering coefficient is such that there are smaller variations on tropical forests or on more dense vegetation. The best soil moisture estimates, however, can be found in grasslands and agricultural areas (Wagner et al., 2013).

Thus this study will focus on developing a methodology for downscaling soil moisture products from the 12.5km spatial scales to finer resolutions for agriculture.
2.3. Soil moisture from remote sensing

In this study, land surface parameters has been used for downscaling ASCAT soil water index. These parameters exhibit a relationship with soil moisture that can be used to estimate variations at local level. A brief discussion of how some land parameters have been used to derive moisture at local scales is presented below.

I. Land Surface Temperature

Land Surface Temperature (LST) is an essential variable that can be used to deduce soil moisture. The main principle being areas that have lower LST relative to the surrounding are deemed to have higher moisture/water content. The cooling effect being mainly brought about by evaporation/evapotranspiration. Besides playing a salient role in processes occurring on the land surface, LST is the basis within which the earth’s energy budget is drawn from. The following two methods that rely on surface temperature for estimating soil moisture are discussed:

a) Evaporative Fraction Method for soil moisture mapping

Modelling applications that rely on energy balance on the land surface to determine soil moisture availability have been developed (Roerink, 2000; Bastiaanssen et al., 1998; Van Der Kwast, 2009; Zhao & Li, 2013). The primary energy balance equation (1) below has been widely used for energy balance on the land surface skin.

\[ \lambda E = R_n - G - H \]  

Where \( \lambda E \), \( R_n \), H, and G represent latent heat flux, net radiation, sensible heat flux and soil heat flux respectively. Evapotranspiration consumes most available energy \( (R_n - G) \) in moist soils. On the other hand, when the soil has no water, energy consumed is mainly towards heating the soil (Hendrickx et al., 2011). Radiation energy can be portioned as the evaporative fraction (\( \Lambda \)) as expressed by Brutsaert, (1992) in equation (2) below.

\[ \Lambda = \frac{\lambda E}{\lambda E + H} = \frac{\lambda E}{R_n - G} \]

According to Entekhabi et al., (2001) evaporative fraction exhibit a relationship with soil moisture that can provide soil moisture inferences at local scale. Land surface temperature based methods that employ this relationship were implemented during this study. The empirical relationship that was derived by Ahmad and Bastiaanssen (2003) has been employed. They used ground based soil moisture measurements in the Indus River to develop the equation (3) below.

\[ s = \frac{\theta}{\theta_s} = e^{\Lambda - 1} \]  

Where S represents saturation degree (0 min - 1 max), \( \theta \) represent water content by volume while \( \theta_s \) represents the volumetric water content at saturation. Evaporative fraction (\( \Lambda \)) estimates can be derived from processing remotely sensed images and used to infer the soil moisture content within the plant rooting depth (Scott et al. 2003, Roerink, 2000, Ahmad & Bastiaanssen, 2003, Bastiaanssen et al., 2005). The technique has shown that land surface temperature has a significant relationship with soil moisture and thus has been employed in this research as a key parameter for downscaling coarse resolution data from ASCAT.
b) **Trapezoidal Method**

It is possible to infer soil moisture based on land surface temperature from both the vegetated area and bare soil using the temperature of the cold pixel and hot pixel (Carlson, et al 2009). The principle is such that on a vegetated land surface, the temperature is affected by the evapotranspiration therefore cold pixel will imply water availability in the root zone; a hot pixel will mean that the there is less or no evapotranspiration from plants (i.e water stressed). However, this may not be true on the top soil. Similarly, a cold pixel on bare soil imply that water is available in the top soil and a hot pixel means that the soil is dry. Therefore, in general, temperature increase with a reduction in vegetation cover and with decreasing soil moisture. However, this should be used cautiously as the deeper soil layers over bare soil surface does not influence the surface temperature considerably. The figure below shows representation of the relation between vegetation cover and surface temperature. A method employed for drawing an inference on soil water content based on this relationship is called trapezoidal method.

![Figure 2-1: Trapezoidal Method, Source: Wang et al, 2011](image)

This method not only shows the relationship between land surface temperatures with soil moisture but goes further to show the difference between a vegetated surface and bare soil. However, the main limitation to land surface temperature measurements to estimate soil moisture is the difficulty in obtaining the true skin land surface temperature values over differing land surface and that it requires clear sky conditions when using optical and thermal imagery.

II. **Land Surface Vegetation Index**

The status of the vegetation can be used give an indication of the soil moisture content in a particular location. However, the vegetation has to be compared to other areas and should be over a relatively larger area. For instance, if the area is near a water body, the vegetation along a river channel can be observed to have a higher vegetative index compared to those further away. This can imply the soil moisture in this particular place is higher compared to other areas. A similar situation is observable in irrigated areas compared to non-irrigated areas.
Normalized Vegetation Index (NDVI) has been commonly used because of its strength of rationing concept which reduces the noise caused by multiple bands (Hemakumara, 2007). Two vegetation indices that have been used are presented in equation (4) and (5) below:

\[
RVI = \frac{\rho_{NIR}}{\rho_{RED}} \tag{4}
\]

\[
NDVI = \frac{RVI - 1}{RVI + 1} \tag{5}
\]

Where RVI is the Ratio Vegetation Index, \(\rho_{NIR}\) is NIR reflectance and \(\rho_{Red}\) is Red reflectance, while NDVI is the ratio given by difference in radiation \(((NIR-RED)/(NIR+RED))\) as shown in the equation (5) above. The table below show some NDVI values and the land cover which the given values represent.

**Table 2-2: Typical NDVI Values (source Holben, 1986)**

<table>
<thead>
<tr>
<th>Cover Type</th>
<th>RED</th>
<th>NIR</th>
<th>NDVI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dense Vegetation</td>
<td>0.1</td>
<td>0.5</td>
<td>0.7</td>
</tr>
<tr>
<td>Dry Bare Soil</td>
<td>0.269</td>
<td>0.283</td>
<td>0.025</td>
</tr>
<tr>
<td>Clouds</td>
<td>0.227</td>
<td>0.228</td>
<td>0.002</td>
</tr>
<tr>
<td>Snow and Ice</td>
<td>0.375</td>
<td>0.342</td>
<td>-0.046</td>
</tr>
<tr>
<td>Water</td>
<td>0.022</td>
<td>0.013</td>
<td>-0.257</td>
</tr>
</tbody>
</table>

In a study conducted by Lakhankar et al., (2009) on the variability of NDVI from active remote sensing, heterogeneous vegetation cover affects soil moisture estimation. As such, we discuss briefly two methods: a) which uses NDVI and b) which uses Leaf Area Index (LAI) to infer soil moisture:

**a) Vegetation and temperature condition index**

Kogan, (1994) investigated how NDVI relate with Brightness Temperature (BT) over 52 weeks of the year with the aim of quantifying drought conditions. He estimated the fluctuations in both temperature and vegetation in the year with relation to maximum and minimum NDVI and BT using Vegetation and Temperature Condition Indices (VCI and TCI). He used the following relations for vegetation to temperature:

\[
VCI = 100(NDVI - NDVI_{min})/(NDVI_{max} - NDVI_{min}) \tag{6}
\]

\[
TCI = 100(T_{max} - T)/(T_{max} - T_{min}) \tag{7}
\]

He found that the two indicators gave a good real-time assessment of the vegetation stress and quantifies the impact of varying weather conditions on the crop. The TCI-VCI relation with water stress had a strong correlation and could be used in areas with varying ecological conditions. The same indices were considered for estimation of soil moisture in this research study.
b) ETlook Method
Water uptake by plants depends on water availability within the root zone. Bastiaanssen et al., (2012) used the relationship expressed in equation (8), embedded in the ETlook evapotranspiration model to estimate water content at the subsoil. This is obtained from a relationship that exists between water content in the top soil and observed recent photosynthetic activity of the plants which is used for expressing water content in the subsoil.

\[ S_{e_{sub}} = 0.1LAI + (1 - 0.1LAI)(1 - \exp\{S_{e_{top}}(-0.5LAI - 1)\} \]  

Where, \( S_{e_{sub}} \) is the effective saturation in the subsoil and \( S_{e_{top}} \) is the effective saturation in the top soil. Overall, vegetation indices provide information on the soil moisture status. Crops that exhibit water stress depict low vegetation index while those that have no water stress show a higher vegetation index. This method was found to be more promising as it uses soil moisture at the top layer which could be obtained from ASCAT. Additionally, Chen et al., (2015) studied the how LAI variations with seasons is affected by soil moisture and concluded that it is a function of soil parameters and that is superior to other cases. The LAI is obtained from optical and thermal remote sensing. The only challenge is that the LAI data is not available daily. In this study LAI has been used through review of ETlook method for downscaling.

III. Land Surface Wetness Index from ASCAT
Microwave remote sensing can directly estimate soil moisture on the land surface. This research entailed using Soil Water Index (SWI) from coarse resolution satellite image (ASCAT). The surface soil moisture (SSM) is directly measured from ASCAT remote sensing instruments. The result is given as degree of saturation varying from (0-1), where 0 indicates dry soil and 1 indicates soil moisture at full saturation. It is a product of the Copernicus Global that gives daily soil moisture at 12.5km resolution and uses surface soil moisture product as the input. The algorithm for retrieving soil moisture shown in equation (9) below, uses infiltration model that gives the relation between the soil moisture at the land surface and the soil moisture in the soil profile from the surface as a function of time (Ersion, 2013).

\[ SWI(t_n) = \frac{\sum_i^n SSM(t_i)e^{\frac{t_n-t_i}{T}}}{\sum_i^n e^{\frac{t_n-t_i}{T}}} \text{ for } t_i \leq t_n \]  

Where \( t_n \) is the observation time of current measurement, SSM represents measured Surface Soil Moisture, and \( t_i \) refer to observation time of previous measurement in Julian days. \( T \) is a factor determining influence of previous measurements on the current soil moisture conditions and is mostly dependent on the soil type. The limitation to using this product as it is that the resolution is still coarse for use in agriculture and the texture of the soil is not considered thus \( T \) value has to be decided by the user.

This study used already retrieved soil moisture product from ASCAT as its scope did entail assessment of the soil moisture derivation algorithm. We however recognize that there exists a number of soil moisture retrieval algorithms. Gruber et al., (2014) compared five fundamental soil moisture retrieval models and concluded that no single model was found to be best or better than the other. This research intended to couple Soil water index with LST and NDVI to produce fine resolution soil moisture datasets.
2.4. Soil Moisture Downscaling Techniques

Soil moisture differs spatially due to discontinuity brought about by a number of aspects among them: precipitation amount, land-use, topographic divides, vegetation, slope, physical soil properties, and human intervention that include irrigation, drainage, and flooding (Hendrickx et al, 2011; Shin and Mohanty 2013, Ranney et al 2014, Zhao and Li 2013). There has been continuous development of soil moisture downscaling models. A review of some of the methods is provided below.

Kim & Barros., (2002) developed a soil moisture downscaling model that used fractal interpolation of soil and vegetation to give spatial relations of soil moisture with time. Availability of soil, vegetation and terrain data however was required at resolutions of 10km globally and it downscaled soil moisture to a resolution of 850m. The results of the study showed that incorporation of soil and vegetation data at finer resolutions generated unique relationships. However, the area considered for the study was smaller, 10,000km² and the number of images considered were only 16 soil moisture maps and not for the entire year. There was therefore a possible bias the images as they covered only two months of the year that is June and July. In this research we consider yearly datasets (365 days).

Pellenq et al., (2003) used topography and soil depth to disaggregate soil moisture. The results showed a satisfactory soil moisture at local scale. The results however cannot be directly used as a representative of larger catchment scale as the results were based on a small area of 6 ha. The method also showed a poor correlation due to difference in observed and simulated scales. It however showed a good correlation when soil moisture is averaged over a 100m length. However, it is difficult to get soil depth information over a larger catchment as this requires comprehensive soil survey hence not only cumbersome but also expensive.

Scott et al., (2003) used optical data to develop a method based on energy balance on the land surface that provided soil moisture maps in the field. The method uses a standard regression curve to relate volumetric soil moisture to the evaporative fraction. The principle is that due to the different rooting depths of plants, we can be able to deduce root zone soil moisture by comparing actual and potential evapotranspiration. Despite the method being independent of soil and vegetation type, the fact that it requires the days to be cloud free remains a major limitation. Moreover, there also exists the time lag between successive images. This research aims to build on this study using continuous data based on similar standard regression curves.

Wilson et al., (2004) carried out analysis of soil moisture patterns based on terrain attributes considering soil moisture averaged with depths. He came up with relations that were determined empirically for different terrains. He particularly notes that is almost impossible to use a static attribute like topography to predict continuously a dynamic parameter like soil moisture. The model performed well at the study location but the relationships were not expected to be applied to other regions as he concludes that the model can get unstable with time. The state of Nebraska is largely flat/gently sloping thus topography based index may not have significant impact.
Merlin et al., (2005) downscaled SMOS soil moisture data which is available at a resolution of 40km using 1km resolution auxiliary data from optical and thermal bands. The algorithm depicts stability but is limited by the uncertainty of SMOS observations. The approach relies on relationships between radiometric soil temperatures from microwave and thermal soil moisture. The algorithm however focuses on the top 5 cm of the soil. Additionally, the study considered only the month of June and July and not the entire 12 months of the year.

Hemakumara, (2007) used a method that combined LST and VI (Vegetation Index) to estimate wetness indices from AMSRE satellite product and found that it provided a good measure of soil moisture compared to using either vegetation or LST alone. In this method, a weighting factor is calculated for every cell whereby the each pixel value is divided by the mean of all the pixels and the factor is multiplied by the low resolution pixel value as shown in equations (10) and (11).

\[
\theta_{RNTI_i} = \theta_{AMSR-E_j} \times \frac{1 - RNTI_i}{\sum_{i=1}^{n} 1 - RNTI_i}
\]  
(10)

\[
\theta_{VTCI_i} = \theta_{AMSR-E_j} \times \frac{VTCI_i}{\sum_{i=1}^{n} VTCI_i}
\]  
(11)

Where \(\theta_{RNTI_i}\) and \(\theta_{VTCI_i}\) are the soil moisture contents computed at higher resolution. The RNTI is a dryness index thus the residual (1-RNTI) is considered while VTCI is a wetness index that incorporates vegetation and requires no conversion. \(\theta_{AMSR-E_j}\) is the soil moisture at low resolution. Whereas the study showed that the above indices could be used to disaggregate soil moisture using both land surface temperature and vegetation index, the area considered was also quite small (50*40km).

Busch et al., (2011) employed methodology that stems from Empirical Orthogonal Functions (EOF) for downscaling soil moisture. In this study, the method produced reasonable results on a number of catchments and performed well in areas within which it were developed. There were also notable inconsistencies in the quantitative estimates. One of his key recommendations was that to improve the EOF method, attributes such as vegetation and soil information can be included in the stepwise linear regression. The study thus depicted the significance of vegetation data has been considered in this study although with a different approach.

Hendrickx et al., (2011) downscaled Landsat scale (30m) soil moisture map to QuickBird scale (2.7m) with and without stratification. He observed that stratification resulted in improved and more reliable soil moisture map. The study shows that by classifying the land and using regression equation for each class, it became possible to downscale Landsat 30m resolution to a resolution of 2.7m. He further concluded that one equation is not sufficient for determining soil moisture across a heterogeneous landscape, and that if regression equations are developed specific land type at finer scale say m-scale, a more reliable soil moisture image at m-scale can be obtained. In this study a set of equations based on land use have been proposed for downscaling approach.
Shin & Mohanty, (2013) developed a deterministic soil moisture downscaling algorithm using soil and vegetation classification. The aim was to account for relatively more uncertainties caused by heterogeneity of land surface. The study used Electronically Scanned Thinned Array Radiometer footprint (ESTAR). This approach uses genetic algorithm (OMEGA) and soil, water, plant and atmosphere model (SWAP) to simulate water flow. Although the downscaled soil moisture showed good performance and demonstrated robustness, there exists uncertainties as showed by the higher MBE values ranging from -0.16 to 0.12.

Zhao & Li, (2013) developed a downscaling method for AMSR-E soil moisture product with the need to cover for uncertainty of determining absolute land surface temperature. The study introduced temperature variation parameters employed in traditional methods. In their study, they introduced the daily maximum temperature time and mid-morning rising rate to replace land surface temperature. The study was validated using REMEDHUS soil moisture network. This technique however was observed to have systematically degraded overall accuracy of the original moisture dataset.

Equilibrium Moisture from Topography (EMT) by Ranney et al., (2014) has also been tested with additional soil and vegetation data. In general, the performance has shown to be similar the EOF method. However, it showed improvements when soil and vegetation data were incorporated. When interpolated soil data was used, the performance was worse than EOF method implying that for better performance, the data for soil is required at finer scale for it be useful. Fine resolution vegetation indicated substantial influence and it greatly increased soil moisture estimation accuracy. Based on the success shown by the inclusion of vegetation data, this research has built on the same by using high resolution soil data and continuous vegetation data reconstructed to provide a higher temporal scale (daily).

According to Wang-Erlandsson et al., (2016) by making an assumption that the vegetation optimises root zone moisture, and by making use of evaporation data, offers an opportunity to estimate global scale soil moisture at the root zone. The method is presented to be scale independent and require neither vegetation nor soil data. The main limitation however is that the approach considers accessible water in the root zone despite rooting density varying with depths for different plants. Similarly, the method did not consider land cover change. The vegetation cover however changes with time.

Most of the studies that have been conducted have been to downscale soil moisture to a resolution of about 1 km for use in hydrologic models from coarser resolutions. Whereas this information can still be used for agricultural purposes, the temporal resolution is low for most methods and requires cloud free conditions. A number of the methods have also been tested using aerial photography at fine resolutions but have not considered larger areas (over 200,000 square kilometres). This literature review reveals that for soil moisture downscaling to be determined at both fine temporal and spatial resolutions there is need to consider vegetation data. Spatial heterogeneity causes difficulties in estimation of soil moisture, however by using fine resolution data from optical and thermal remote sensing this could be improved. The images however are often with a time lag of between 8 and 16 days and often with clouds. This study thus aims to use continuous datasets for downscaling considering the entire season.
The table 2.3 below shows a summary of reviewed soil moisture downscaling methodologies.

**Table 2-3: Summary of Downscaling Techniques**

<table>
<thead>
<tr>
<th>No.</th>
<th>Methodology</th>
<th>Strength</th>
<th>Weakness</th>
<th>Data</th>
<th>Reference</th>
</tr>
</thead>
</table>
| 1   | Modified fractal Interpolation | • Makes use of spatially and temporarily varying scaling functions  
• Can capture dry and wet conditions well | • Requires soil and vegetation data at desired resolutions  
• The method wasn’t tested for complex topography | Soil, Terrain and vegetation data | Kim and Barros, 2002 |
| 2   | Empirical Orthogonal Function (EOF) | • Performs well in locations it was developed  
• More efficient at using topographic information | • Performance degrades when applied to other catchments | Topography data | Busch et al 2010  
Perry and Nieman 2008 |
| 3   | Equilibrium Moisture from Topography (EMT) | • Simpler to use as it requires only topographic data | • Shows limited variability of soil moisture at local scale | LST Topography data | Ranney et al 2014 |
| 4   | Stratification based on finer resolutions e.g Quickbird | • Improved reliability of soil moisture product | • Fine scale resolution is expensive  
• Optical imagery is affected by clouds | Auxiliary data from a finer resolution | Hendrickx et al 2011  
Merlin et al 2005 |
| 5   | Equilibrium Moisture from Topography (EMT)+vegetation | • The results are more realistic as compared to EMT  
• More effective at capturing temporal variability  
• Less cumbersome as it does not need soil data | • Simple representation of vegetation can introduce errors  
• Fixed portion of transpiration is assumed neglecting changes resulting from water stress | LST Vegetation data | Ranney et al 2014 |
| 6   | Topography and soil depth | • Considers lateral flows due to topography thus can be used for estimating runoff | • Interpolated soil data performs poorly  
• Getting information on soil depth at finer resolution is expensive | Topography Soil data | Peng et al 2003  
Ranney et al 2014 |
2.5. Harmonic Analysis of Time Series (HANTS)

The remote sensing images mainly from the visible and infra-red region of the spectrum is often impeded by cloud conditions. In this study, the remote sensing images for Land Surface Temperature (LST) and Normalized Difference Vegetation Index (NDVI) were required to be cloud free. Efforts have been put towards removal of images that have cloud cover for investigation of land surface parameters (Rossow et al., 1982, Simpson & Gobat, 1996). These algorithms normally gives datasets with gaps for days with cloud cover. Therefore, Fourier analysis was later used to reconstruct datasets. The analysis discards the outliers and fill the gaps with the values generated from the Fourier series. The analysis however required an equal spacing between successive images which is not always the case for a typical dataset (Menenti et al., 1993).

The images that were used for the downscaling study entailed yearly images of LST and NDVI. Therefore, being cognizant of the time lag between successive images and possibility of cloud conditions, it was foreseen that this would require reconstruction that caters for images with un-equal spacing. Harmonic Analysis of Time series has been used for reconstruction NDVI with registered success in removal of clouds and replacing the affected images with values interpolated with time (Roerink et al., 2010). Therefore, in this study, Harmonic Analysis of Time series has been used to provide continuous data. The general equation employed is presented in equation (12) below.

\[
y(t) = a_0 + \left[ \sum_{1}^{n_f} a_i \cos(2\pi f_i t_y) + b_i \sin(2\pi f_i t_y) \right]
\]  
(12)

Where \(y(t)\) is the reconstructed time series data, \(a_i\) and \(b_i\) are the coefficients of the trigonometric functions that has a frequency \(f\) and \(t_y\) is the time that the image is observed. This analysis was implemented in MATLAB. The section below describes some of the parameters that are required as inputs:

- **Number of Frequencies (NOF):** This value represents the number of frequencies within a given time period. The input values given by the user represent the number of sine functions. The output will be \(2^n\)NOF-1 (Roerink et al., 2010). The user also specifies the period of interest days.
- **Hi/Lo (Suppression Flag):** The user has to specify the range that the dataset will be within. For instance NDVI values are within -1 and 1. In this case Hi means the max value (1) and Lo means the low value (-1). The user indicates values outside which range will be discarded during the curve fitting.
- **Fit Error Tolerance (FET):** This represents the absolute values within which the data will be considered. Much as the range will have been set above(Hi/Lo) this parameter gives tolerance for consideration while feeding harmonics at each time step. It paramount that this value ought not to be set a very low values lest few observed values will be considered.
- **DOD (degree of over-determinedness):** The iteration will stop once this value is reached. This is thus a safety value.
2.6. Validation
Validation was done using in-situ soil moisture measurements. The common ways for
determining the level of soil wetness include gravimetric method, volumetric method and soil
water potential method. Gravimetric soil moisture (w) is obtained by weighing a wet soil
sample, drying to remove the water and weighing the dry soil to give the mass of water per unit
mass of soil. Volumetric water content (θ) represents volume of voids occupied by water
relative to the total volume of the soil. The soil water potential is a measure of how strongly
water is attached to the soil particles and is expressed in kilopascals (kPa).

The measurement technique employed in the proposed validation sites in Nebraska uses
volumetric water content and were downloaded from Texas A&M University website, the
dataset of interest being North American Database (Texas A&M Geoservices, 2013). The
dataset is quality controlled and available for validation of global land surface soil moisture
simulation models. They consist of 50 stations operated by different soil moisture networks:
four (4) operated by Ameriflux; one (1) operated by cosmic ray observing station; four (4) by
climate reference network; forty (40) automated weather data network and one (1) climate
analysis network. The stations provide data on a daily basis at depths of 10cm, 25cm, 50cm
and 100cm from the soil surface. A map showing station locations is presented in the Appendix
A of this report.

The overall soil moisture measurement technique is the indirect soil measurement method. This
method uses soil physical properties such as electrical conductivity, water potential, and water
vapour to estimate the water content in the soil. Use of electrical conductivity property and
adoption of nuclear methods is an approach used by most automated weather stations in the
study area. In these regions neutron probes are used to estimate the volumetric moisture content
of the soil by measuring the amount of hydrogen.

The merits of using indirect soil moisture estimation methods that soil water content is
determined with depth, it is temperature independent and can accommodate automatic reading.
The dielectric technique use soil dielectric constant (Kd) measurements to estimates soil
moisture content. Differences between dielectric constants of water and other properties of the
soil are generally significantly larger, thus making it possible to detect small differences in the
change of water content using the technique (Hemakumara, 2007).
Whereas the state Nebraska is covered by over 50 soil moisture networks, the some stations had missing data for our period of interest (2007-2008). To this end, a total of 45 stations were used for validation of this research study. Some of the networks in Nebraska include:

i. **Automated Weather Data Network:** The soil moisture measurements are available only for the state of Nebraska through this network. The measurements are done on rainfed conditions and mostly under grass cover at 10, 25, 50 and 100cm and the instruments used are theta probes (Wang et al., 2015).

ii. **Climate Reference Network:** The stations are equipped with soil probes that provide moisture measurements at depth of 5cm, 10cm, 20cm, 50cm and 100cm. The dielectric measurements are converted to fractional volumetric water content and are available as cubic metres of water per cubic meters of soil (m$^3$/m$^3$).

iii. **Ameriflux Network:** The stations use theta probes to measure soil moisture at 18, 25, 50 and 100cm. The soil moisture measurements are given in volumetric water content.

The soil moisture in the root zone at depths of 10cm, 25cm, 50cm and 100cm were used for validation. This is because different vegetation have differing rooting depths and thus vegetation indices depict soil moisture at different depths and this dataset provided an opportunity to test the layer which has a better correlation with the vegetation indices. The focus however is on the top soil, thus the soil moisture measurements at 10cm and at 25cm were mostly used.
2.7. Conceptual Framework

![Diagram of Conceptual Framework](image)

*Figure 2-2: Conceptual Framework*
CHAPTER 3

STUDY AREA DESCRIPTION

3.1. Overview
This study has been conducted in the state of Nebraska. This is because the nature of the study required validation of the soil moisture measurements retrieved from remote sensing and state of Nebraska and the United States in general have sufficient in-situ soil moisture measurements available for free and over sufficiently long period of time (2001-2015) and can be accessed at (Texas A&M Geoservices, 2013)

3.2. Topography and Location
Nebraska State is located in the northern part of United States of America with a total area of 200,356 square kilometres. It lowest point is at an elevation of 256m above sea level to the south east and it rises gently to the highest point in the north west with an elevation of 1653m. The state is divided into two main geographic regions being the till plains to the east and the great plains consisting: loess plains (7,948 square miles), sand hills (20,000 square miles) and loess hills lying in the north of Platte River (Dappen, Merchernt, Ratcliffe, & Robbins, 2007). The figure below shows the slope in percent rise for the study area. It can be observed that the area is largely flat/gently sloping.

![Slope in % rise for Nebraska State](image)

*Figure 3-1: Slope in % rise for Nebraska State calculated from DEM obtained from HydroSHEDS*

The state is largely flat with slope less than 10% rise. The Nebraska sand hills to the North West and the edges of river Missouri to the east comprise the areas with relatively higher slope.
3.3. Climate

The figure 3-2 below shows average precipitation for the state of Nebraska (Oregon State University, 2017). It comprises averages in millimetres in resampled grids at 4km from the year 1981 to 2010. The map shows that the western part of the country is drier compared to the Eastern part and thus the reason most areas towards the east are rainfed while the west comprise rangelands and irrigated fields as reported by Dappen et al, (2007). The humidity follows from the precipitation, gradually dropping from the south east to the north west.

![Figure 3-2 Precipitation Map for Nebraska (synthesized from Oregon State University, 2017)](image)

Similar to the precipitation pattern, the temperature of Nebraska gradually drops from the west to the south east to with exception of the cold months, Dappen et al (2007).
3.4. Land Use

Nebraska is predominantly agricultural state with a major part in the west being under irrigated agriculture (centre pivots) and the eastern part is mainly dominated by rain fed agriculture. The main crops grown are corn and soybeans which are grown in rotation. The western part also consist of rangelands that are used for production of beef cattle. According to Dappen et al, (2007) a great part of the Nebraska sand hills encompass grass stabilized soils favourable for ranching.

The image below shows the land use for the whole state derived from University of Nebraska Lincoln, (2007) for the year 2005. This land use map has been used for clustering soil moisture stations into five groups consisting: cultivated or cropped areas, range or grassland areas, forest and woodlands, wetlands and urban areas. In the table below, a full list of the different land uses is shown. It can be observed that the dominant land use is range/grasslands. Irrigated land comprise over thirty thousand square kilometres (>30,000km$^2$) accounting for about 15% of the total land in the state.

![Figure 3-3: Land use for Nebraska, year 2005 synthesized from (University of Nebraska Lincoln, 2007).](image-url)
3.5. Soil Information

The soil data was obtained from HiHydrosoils (high resolution soil maps), which are available for averages of top soil layer (constitute 0-30cm) and sub soil layer (30-100cm). The property of interest in this study is soil porosity. This being that different soil types can hold different amount of water at full saturation depending on how much pore space is available in the soil. The indices that were used in this study are based on soils at full saturation and when the soil is completely dry. The figure below shows the saturation water content for the topsoil in the study area resampled to 1km resolution for use in this study. Beside water content at saturation, maps of the residual soil moisture at top soil from HiHydrosoils was also used in the study.

![Saturated Soil Moisture Content for Nebraska State](image)

*Figure 3-4: Saturated Soil Moisture Content for Nebraska State*

It can be observed from the HiHydrosoils map that the saturated water content is largely between 0.40 and 0.45m$^3$/m$^3$. This saturated water content corresponds to loess loams and sandy loams.
CHAPTER 4
METHODOLOGY

4.1. Implemented Methodology

4.1.1. Methodology review.

The review entailed identification and implementation of a select set of methods. The following three methods were implemented: (1) Triangle method, (2) Trapezoidal method and (3) ETlook model. The three methodologies were implemented and compared with ASCAT soil moisture dataset representing the top 10cm of the soil. This is because the closest validation dataset closer to the top soil was available were at 10cm. The following dataset were used for this study:

- **Soil Water Index (SWI):** Our primary data input was daily soil moisture estimates (SWI) from Copernicus Global Land Services derived from ASCAT-SWI with 12.5km resolution. They include soil water index maps made available at eight separate T values ranging from 1 to 100 representing the vertical profile of the soil with the larger T values used for inferring soil moisture at deeper soil layers. The images come with respective quality parameter (flag) that which give us an indication of the number of available moisture measurements at top soil used to calculate SWI. The data was downloaded from (Copernicus Global Land Service, 2016). Only soil moisture estimates free from ice/snow conditions were used for this study. For ice/snow conditions the value of 0 is recorded.

- **Leaf Area Index:** The data for this component was obtained from MODIS, (MOD15). LAI variable defines the proportion of leaf layer area relative to the ground. The variable is used to calculate evapotranspiration. LAI composites with spatial resolutions of 500m with 8-day temporal resolution were used (R. Myneni, Y. K., & T.Park, 2015). The study targeted achieving 1km spatial resolutions. Therefore the datasets were resampled to 1 km resolution using bilinear interpolation. This data was required for implementation of ETlook method

- **Terrain Data:** The elevation data was obtained from HydroSHEDS. The digital elevation data was originally produced by NASA through Shuttle Radar Topography Mission (SRTM). The data was obtained from U.S Geological Survey website(USGS HydroSHEDS, 2016). The sample spacing comprise 90 metre resolutions available globally.

- **Land Surface Temperature (LST):** The LST data was required for the implementation of both triangle and trapezoidal methods. Land Surface temperature composites was obtained from MODIS (MOD11A2) at temporal resolution of 8 days and at a spatial resolution of 1 km (Z. Wan et al., 2015).
• **Air Temperature:** Air temperature from Global Land Data Assimilation Systems were used in this study. The data is available at a higher temporal resolution (daily) but at a coarse resolution of 25 km (GSFC, 2016). This data was used alongside land surface temperature to implement trapezoidal method. The resolution however was resampled to 1km to ensure both datasets had the same resolutions.

• **Normalized Difference Vegetation Index (NDVI):** The data for this component was obtained from MODIS (MOD13Q1). This index was used for implementing both triangle and trapezoidal method. The product is available every 16 days with a spatial resolution of 250m (USGS LP DAAC, 2016). The dataset was resampled to 1000m for use in this study.

Upon implementation of the selected methods, the results were analysed for the two years (2007 and 2008) considered for this study using performance metrics that included Mean Bias Error, Bias, Root Mean Square Error and the correlation coefficient. The year 2008 showed better agreement with ground data were used in the detailed analysis.

4.1.2. Downscaling method development
The scope of this study involved developing soil moisture downscaling methodology using vegetation, land surface temperature and soil moisture data from coarse resolution. This was done by first implementing the selected methodologies above then based on their assessments, a methodology for soil moisture downscaling was developed. Land Surface Temperature available during clear sky conditions were required, but the cloud conditions necessitated reconstruction both the LST and NDVI datasets. Harmonic Time Series Analysis was used to reconstruct both NDVI and LST data. The method proposed uses Soil Water Index from ASCAT, land surface temperature based index (TVDI), Land Use and a sine function of the day of the year to downscale ASCAT-010 soil moisture product from a resolution of 12.5km to a resolution of 1km. The land use map was used to generate classes/groups within which various relationships between vegetation indices and soil moisture were explored. Finally, the determined relations were applied for the year 2008.

4.1.3. Implementation of the methodology
The relationship between the various indices and soil moisture was determined empirically using optimization model from excel spreadsheet (Solver). Since the process involved working with multiple images, tools that include but not limited to Python, ArcGIS, R statistical package, MATLAB and Excel were used to implement various algorithms for batch processing of the satellite data. A code implemented in python was used to generate the final soil moisture maps at resolution of 1km based on the determined relations for each land use class. The retrieved low resolution soil moisture from ASCAT was downscaled to 1000m resolution.
4.1.4. Validation of the proposed methodology

The soil moisture downscaled to 1km resolution was validated with ground data obtained from 45 soil moisture stations in Nebraska. The methodology was validated with a dataset that had at least one full year ground measurements available to enable analysis of the seasonal variations. There are a number of performance metrics that can be used to assess the satellite measurements agreement with ground data. In this study we employed a metric proposed by Merlin et al., (2015). The metric is based on the recognition that in-situ measurements are not always representative of the entire area being studied. It also recognizes there exists uncertainty caused by the input data of different resolutions. Variation were analysed both in time and space. The metrics that were applied include:

i. The Root Mean Square Error (RMSE)

This metric has been employed to evaluate downscaling technique performance relative to the ground soil moisture measurements due to its extensive use and acceptability. The metric is error based and gives the model’s ability to predict soil moisture. RMSE units used for this study was volumetric soil moisture (m$^3$/m$^3$). It is given by equation (13) below:

$$RMSE_{XR} = \sqrt{\frac{\sum_{i=1}^{N}(SM_{XR} - SM_{IS})^2}{N}}$$  \hspace{1cm} (13)

Where, SM$_{XR}$ is the moisture retrieved either at higher (HR) or lower (LR) resolution, and SM$_{IS}$ is the in-situ soil moisture measurements at local scale (Hu et al., 2015).

ii. G$_{DOWN}$ Performance metric

This is the performance metric proposed by Merlin et al., (2015). The metric involves calculating slope of the regression curve(S), arithmetic mean of the Bias (B), and Correlation coefficient (R). A regression analysis of both soil moisture at coarse and fine resolution was conducted in relation to the in-situ measurements. The relation is as given in equation (14) below:

$$G_{DOWN} = \frac{G_{EFFI} + G_{PREC} + G_{ACCU}}{3}$$ \hspace{1cm} (14)

Where the $G_{EFFI}$ is the downscaled soil moisture a higher resolution (S$_{HR}$) gain in linear fit slope (S) with regard to low resolution (S$_{LR}$) obtained from satellite imagery as shown in equation (15).

$$G_{EFFI} = \frac{|1 - S_{LR}| - |1 - S_{HR}|}{|1 - S_{LR}| + |1 - S_{HR}|}$$ \hspace{1cm} (15)

Where the $G_{PREC}$ is the downscaled soil moisture resolution (S$_{HR}$) gain with respect to time series correlation (R) when compared to low resolution (S$_{LR}$), given by equation (16).

$$G_{PREC} = \frac{|1 - R_{LR}| - |1 - R_{HR}|}{|1 - R_{LR}| + |1 - R_{HR}|}$$ \hspace{1cm} (16)

And $G_{ACCU}$ is the accuracy of downscaled soil moisture resolution (B$_{HR}$) gain with respect to mean bias (B) relative to the low resolution (B$_{LR}$) scenario, given equation (17) below.

$$G_{ACCU} = \frac{|B_{LR}| - |B_{HR}|}{|B_{LR}| + |B_{HR}|}$$ \hspace{1cm} (17)

The main advantage of this $G_{DOWN}$ metric over other metrics is its computation relative to non-disaggregation gives it a better measure in relative comparison and sensitivity is lower to a given bias in mean (Merlin et al., 2015).
Beside GDOWN metric, the correlation coefficient (R), Nash-Sutcliffe coefficient (NSE), Mean Bias Error (MBE) and Bias were also used.

### iii. Pearson Correlation Coefficient (R)

This coefficient was used to measure the strength of relationship between in-situ soil measurements and satellite derived data. A value of positive one (+1) would imply a strong positive/increasing relationship while a value of negative one (-1) would imply a strong negative/decreasing relationship. Zero (0) represents a situation where there is no relationship. In this study the model \((SM_{Mo})\) values refer to the satellite data while the observations \((SM_{Is})\) refer to in-situ measurements. The relationship is given in equation (18) below:

\[
R = \frac{\sum_{i=1}^{n} (SM_{Is} - \bar{SM}_{Is})^2 \cdot (SM_{Mo} - \bar{SM}_{Mo})^2}{\sqrt{\sum_{i=1}^{n} (SM_{Is} - \bar{SM}_{Is})^2 \cdot \sum_{i=1}^{n} (SM_{Mo} - \bar{SM}_{Mo})^2}}
\]  

(18)

### iv. Nash-Sutcliffe coefficient (NSE)

This coefficient was used to assess the capability of the satellite data to predict the soil moisture in the ground. A value of one (1) indicates an exact prediction. The closer the value is to one the better the prediction. A value of zero means the prediction was as good as the mean of the observed values, while less than zero indicate a lower performance. The values range from \(-\infty\) to 1 given be equation (19) below.

\[
NSE = 1 - \frac{\sum_{i=1}^{n} (SM_{Is} - SM_{Mo})^2}{\sum_{i=1}^{n} (SM_{Is} - \bar{SM}_{Is})^2}
\]  

(19)

### v. Mean Bias Error (R) and Bias

This error metrics were used to determine the deviation of satellite data from the observed value. The MBE takes the absolute value while the bias considers the sign. Bias error metric were used to determine whether there was an overall underestimation or overestimation by the satellite derived data. They are obtained by determining the difference between the in-situ data and the model derived measurements. The closer they are to zero, the better the prediction.
4.2. Summary of the Implemented Methodology in this study

- **Research Proposal**
- **Data pre-processing**
- **HydroSHEDS DEM, MOD15_LAI, ASCAT SWI 12.5KM, MOD11_LST & MOD13_NDVI**
- **Data Processing using HANTS. Tools employed included MATLAB, Python, R, ArcGIS and Excel**
- **Implementation of select methods: Trapezoidal, ETook and Triangle Method**
- **Analysis of the implemented methods based on RMSE, R, NSE, Bias and MBE**
- **Development of a downscaling methodology based on the implemented methods**
- **Development and submission of Thesis Draft**
- **Incorporation of comments and submission of draft final Thesis_Examination version**
- **Thesis Defense Presentation**
- **Incorporation of comments from Thesis presentation**

*Figure 4-1: Summary of the Methodology*
5.1. Data Collection and Processing
In order to implement the methodologies, land surface temperature, Normalized Difference vegetation index (NDVI), leaf area index (LAI), ASCAT soil water index at top soil and at subsoil and soil information were obtained. The temperature based methods proposed required cloud free conditions for implementation. However, visual inspection of the LST and NDVI images revealed that there was substantial cloud cover and this necessitated cloud masking to provide sufficient values for implementation of the methodologies. The two methods (Trapezoidal Method and Triangle method) require clear sky conditions. To remove cloud cover, Harmonic Analysis of Time Series (HANTS) was used. HANTS takes into account measured values within a given range and interpolates/reconstruct data based on available measurements across the year per pixel. This required that that the raster dataset be converted to netCDF files to obtain point data. For the State of Nebraska, netCDF files containing 244,148 points were used representing 1km pixel resolution. The figure 5-1 below shows the land surface temperature results from implementation of HANTs from MATLAB and a fitted curve for one pixel with different frequencies (nf=1, nf=3, nf=5 and nf=8). Where nf represents the number of frequencies in the year. The figure 5-1 below shows a plot of one pixel across the year with different frequencies considered and drawn on the same graph for the year 2007.

![Figure 5-1: Various number of frequencies applied to LST data for one pixel](image-url)
The figures 5-2 below further shows the number of frequencies (nf) tested for use in reconstructing time series data for Land Surface Temperature for the year 2007. The figures are based on the same pixel but with different frequencies.

**Figure 5-2: Number of frequencies applied for the reconstruction of LST**

There are a number of parameters that can be changed to ensure best fit to the data as explained in section 2.5. Whereas there are no set conditions that must be met, NOF was experimentally found to be the most sensitive and it was observed that NOF of 3 gave the best fit to the data. This was thus used for the entire dataset. The curve also fitted well with 2008 data. The image overleaf shows a comparison of the downloaded satellite image with cloud cover and a reconstructed image with masked clouds.
The figures 5-3 and 5-4 below shows original and reconstructed images respectively for January 1 2007. It is notable that over 70% of the area was covered by clouds. With HANTS, these images could be reconstructed to obtain cloud free conditions.

**Figure 5-3: Original Image with cloud cover for January 1st 2007**

Land surface Temperature was interpolated with time such that for every pixel, all the available measurements within the range(260-325k) and a fit error tolerance of 5k were considered for feeding harmonics based on HANTS. However, it was noted that there were still some outliers as observed from the the figure above being data above 290k during the above date expected to be winter time as shown in figure 5-4 below. Also present were some outliers with data below 260 degree kelvin.

**Figure 5-4: Reconstructed LST image for January 1st 2007**
Similar to LST data, the NDVI data was also reconstructed using Hants. The two frequencies \( nf=2 \) and \( nf=3 \) were applied as shown in figure 5-5 below. The \( nf=2 \) was selected for application on the dataset. Graphs of two different pixels are given in figure below:

![Graphs of two different pixels](image)

**Figure 5-5: Reconstructed NDVI with \( nf=2 \) and \( nf=3 \)**

The results from HANTS depicted unique cycles between LST and NDVI for different pixels depending on land use classes. In figure 5-6 show four pixels (2) from cropped area and (2) from grassland area for the year 2007. The pixels depict unique cycles across the year due to the different vegetation types. These cycles offer an opportunity to ascertain the land use classes assigned to the soil moisture stations. In appendix F of this document, the LST-NDVI plots for all the soil moisture stations used in this study has been presented for the year 2008. The data was used to counter-check the land use as the land use map used in the study was developed in 2005 for the state of Nebraska while the study focused on the year 2008.

![LST NDVI plots for different vegetation cover](image)

**Figure 5-6: LST NDVI plots for different vegetation cover**
5.2. Implementation of selected Methodologies

5.2.1. Triangle Method

Triangle method is based on a scatter plot of NDVI and LST. There should however be sufficiently large number of pixels that contain varying NDVI values and LST to allow formation of a triangular shape. Temperature Vegetation Dryness Index (TVDI) can be calculated using the extreme values of temperatures for a given vegetation index (wet and cold edges). This index can be used to infer soil moisture at a given pixel value. The figure below shows triangular space obtained from NDVI-LST graph for summer 2007.

$$TVDI = \frac{N}{D}$$

In order to implement Triangle method, the pixel values for both land surface temperature and NDVI were plotted to obtain the near triangular space above. For the State of Nebraska, a total of 244,178 scatter points were used to generate the plot above. Only plots with NDVI greater than 0.2 were used, this is because the lower values indicate water body surfaces and would produce a substantial number of outliers. This process was repeated for each day for the year 2007 and 2008 using a code implemented in R statistical software.
The figure below shows a raster image for the indices obtained from the triangular space as observed figure 5-7 above for the whole state for August 20, 2008. The regression fit from the plot of NDVI against Temperature resulted in obtaining TVDI indices outside the expected range of between zero and one. This was rectified by normalizing the data using 99 percentile for maximum and 1 percentile for minimum. The result gave the map with TVDI indices between zero and one as shown in the figure 5-8 below.

![Temperature Vegetation Dryness index for August 20th, 2008](image)

The above diagram depicts temperature vegetation dryness index in Nebraska State in summer. The value of 0 indicates highest soil moisture and 1 indicating lowest soil moisture as the surface has the highest temperature and thus near dry conditions. To obtain how much soil moisture is in the soil (wetness index), the above index is subtracted from 1. The soil moisture however differs with soil type, therefore to obtain the volumetric water content, the wetness index is multiplied by the soil porosity. Soil data from HiHydrosoils were used.

5.2.2. Trapezoidal Method

Figure 5-7 represents the plot of NDVI against the difference between land surface temperature and air temperature for all pixels at a resolution of 1000m for the State of Nebraska on 1st of January 2007. The figures/fits were drawn for every day of the year. Since 1st January falls within winter the number of points with NDVI greater than 0.2 is much lower compared to the figure below obtained during summer. This is because during winter, most trees shed leaves and thus have low NDVI values. It can also be observed that the trapezoidal space could not be clearly obtained. Therefore, the indices generated for winter period are expected to have a lower correlation to the soil moisture compared to those obtained with the trapezoidal space in summer.
Figures 5-9 and 5-10: Scatter plots of NDVI against difference between LST and air temperature in winter and summer, respectively, based on (G. Petropoulos, Carlson, & Wooster, 2009).

The figure 5-9 above shows WDI indices obtained from the trapezoidal space for the 20th of August in the year 2008. Since the date falls within summer, the trapezoidal space could be obtained. The data infers that warm and cold edges obtained from a regression fit were more representative of the pixel points in the study area.
The figure 5-10 shows the water deficit indices (WDI) obtained from the trapezoidal space in summer. Similar to triangle method, since the warm and cold edges were obtained from a regression fit, some data were outside the trapezoidal space and thus it was possible to get indices outside the expected range of 0-1. The indices were normalized based on 99 percentile and 1 percentile. The value 0 represents residual soil moisture conditions while 1 represents saturated water content.

![WDI index for August 20th, 2008](image)

The figure 5-10, depicts the western part of Nebraska as drier compared to the eastern part which is expected during this time of the year. It is similar to figure 5-7 obtained on the same date indicating that both land surface based methods gave comparable outputs.

- Volumetric Soil Moisture from LST/NDVI based methods

At any given point within the triangle or trapezoidal space, an index based on wet and cold edges is obtained. This index is related to the evaporative fraction which indicates the soil moisture condition at a given location. The relationship between soil moisture and evaporative fraction (from the temperature based indices) is non-linear. Curve-fitting parameters developed by Scott et al., (2003) were used for the initial run. The relationship in equation (20) was applied to obtain volumetric water content:

\[
\frac{\theta}{\theta_{sat}} = \exp\left\{\frac{\Lambda - a}{b}\right\}
\]

\(\theta = \text{Volumetric water content of the soil (m}^3\text{m}^{-3})\)

\(\theta_{sat} = \text{Satured water content of the soil}\)

\(\Lambda = \text{Evaporative fraction}\)

\(a = \text{Curve fitting parameter equal to 1.0 for normalized soil moisture}\)

\(b = \text{Curve fitting parameter equal to 0.421}\)

Soil moisture values obtained from equation (20) were compared to in-situ soil moisture datasets and to soil moisture at coarse resolution.
• **Comparison between Triangle and Trapezoidal methods**

The two temperature based methods showed a similar trend across the year for all the stations. The graph below shows the time series plot of volumetric soil moisture data representing moisture values obtained from the trapezoidal method (WDI) and triangle method (TVDI) for two stations (Gothenburg and Arthur). The soil moisture data from trapezoidal method (WDI) shows more variation because the index was obtained from the difference between land surface temperature and air temperature, which showed more variation with time. The TVDI however, shows minimal variations because the index was obtained from subtraction of minimum temperature, which was obtained from regression of minimum temperature at 0.05 percentile. The position of this line did not change significantly between succeeding days. Thus resulting smooth curve compared to WDI.

![Graph showing time series plot](image)

*Figure 5-12: Time series plot of LST/NDVI based methods*

For this study, because of the similarity shown by the two methods, only one method has been used in the preceding analysis. Due to the uncertainty brought about by input data, method chosen is TVDI method since it only requires two inputs LST and NDVI while the WDI on the other hand requires LST, NDVI and air temperature.
5.2.3. ETlook Method

ETlook method developed by Bastiaanssen et al., (2012) uses Leaf Area Index and soil water index at coarse resolution to downscale soil moisture to low resolution. The relationship that is employed by this Model was used to determine the degree of saturation at the subsoil. The effective saturation at top soil (0-5cm) is first calculated based on Van Genuchten definition of degree of saturation at top soil which is given by the equation (21) below:

\[ S_{e}^{\text{top}} = \frac{\theta_{\text{ASCAT}_\text{Top}} - \theta_{\text{res}}}{\theta_{\text{sat}} - \theta_{\text{res}}} \]  

(21)

Where: \( \theta_{\text{ASCAT}_\text{Top}} \) is the soil moisture from ASCAT’s top layer, \( \theta_{\text{res}} \) is the residual soil moisture content and \( \theta_{\text{sat}} \) is the soil moisture at saturation. Then using the effective saturation at the top soil the equation (8) was used to obtain the degree of saturation at the subsoil. The LAI images are available every eight days, and thus for the year, a total of 45 satellite images were used for application of the ETLook method. The images are at 500m resolution while the ASCAT images are available at 12.5 km resolution. Thus, resampling for both images was done to 1km for implementation of this method. The figure 5-12 below show the degree of saturation of the top soil (ASCAT_001) from equation (21) and the degree of saturation of the sub-soil from equation (8) on June 1\textsuperscript{st} 2008. A time series plot for one of the soil moisture stations is also included for the year 2008. The plots of all soil moisture stations used in this study are presented in appendix E of this document:

Time series plot of ASCAT_Top, groundata and Etlook

Figure 5-13: Implemented ETlook method
5.2.4. ASCAT SWI

The ASCAT products are made available in 8 T values (001,005,010,015,020,040,060,100). In this study the focus will be on downscaling ASCAT_010 from a resolution of 12.5km to a resolution of 1km. The soil moisture measurements from microwave remote sensing measures the top 5cm. The top-most layer in ASCAT is ASCAT_001. The estimates from three products were compared against the soil moisture measurements at 10cm and the results were as shown below.

<table>
<thead>
<tr>
<th>PRODUCT</th>
<th>BIAS</th>
<th>MBE</th>
<th>RMSE</th>
<th>R</th>
</tr>
</thead>
<tbody>
<tr>
<td>ASCAT_001</td>
<td>-0.01</td>
<td>0.08</td>
<td>0.10</td>
<td>0.40</td>
</tr>
<tr>
<td>ASCAT_010</td>
<td>-0.02</td>
<td>0.08</td>
<td>0.09</td>
<td>0.47</td>
</tr>
<tr>
<td>ASCAT_060</td>
<td>0.00</td>
<td>0.07</td>
<td>0.09</td>
<td>0.58</td>
</tr>
</tbody>
</table>

In the figure 5-13 below, time series plot of the above three products for year 2008 from ASCAT at two soil moisture stations are presented. It is observed that the variations at the topsoil are much higher and compared to ASCAT_010 and ASCAT_060. Since the top most soil moisture available for validation were at 10cm, ASCAT_010 was selected for this downscaling study.

![Figure 5-14: Time series plots of the different ASCAT products](image-url)
5.2.5. TAMU Soil Moisture

In-situ soil moisture measurements were obtained from online sources (Texas A&M Geoservices, 2013). It was thus paramount to check the soil moisture measurements response to precipitation. The time series plot below shows the in-situ soil moisture measurements plotted with rainfall for Kearney and Holdrege soil moisture stations. The rainfall data was obtained from the High Plains Regional Climate Centre (HPRCC) and downloaded from university of Nebraska (HPRCC, 2017).

Figure 5-15: Ground data response to precipitation for the year 2008

Figure 5-14 shows that the soil moisture values respond to precipitation as illustrated the peaks on days 150, 200 and 300. It also indicates that the precipitation curves in both stations were congruent. This is because they are both located within the same region (central Nebraska). It can be observed that the soil moisture increases between day 50 and day 100 without significant increase in precipitation. This is because of snow melt that occur in the month of February. The soil moisture also varies with depth; soil moisture at 10cm showing more variation with time compared to the deeper layer at 25cm as observed in Kearney station. Beside the variations, the soil moisture response at 10cm was at large analogous to the response at 25cm.
5.3. Analysis of Implemented methodologies

5.3.1. Seasonal Comparison

i. Annual

Table 5-2: Annual comparison of implemented methodologies for the year 2008

<table>
<thead>
<tr>
<th>Retrieval Method</th>
<th>BIAS</th>
<th>MBE</th>
<th>RMSE</th>
<th>NSE</th>
<th>R</th>
</tr>
</thead>
<tbody>
<tr>
<td>10cm</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ASCAT_010</td>
<td>-0.02</td>
<td>0.08</td>
<td>0.09</td>
<td>-0.06</td>
<td>0.47</td>
</tr>
<tr>
<td>ETlook</td>
<td>-0.04</td>
<td>0.09</td>
<td>0.11</td>
<td>-0.38</td>
<td>0.29</td>
</tr>
<tr>
<td>TVDI</td>
<td>0.07</td>
<td>0.10</td>
<td>0.13</td>
<td>-0.79</td>
<td>0.14</td>
</tr>
<tr>
<td>25</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ASCAT_010</td>
<td>-0.01</td>
<td>0.08</td>
<td>0.10</td>
<td>0.14</td>
<td>0.48</td>
</tr>
<tr>
<td>ETlook</td>
<td>-0.03</td>
<td>0.09</td>
<td>0.11</td>
<td>-0.13</td>
<td>0.32</td>
</tr>
<tr>
<td>TVDI</td>
<td>0.08</td>
<td>0.11</td>
<td>0.14</td>
<td>-0.66</td>
<td>0.17</td>
</tr>
</tbody>
</table>

Overall, ASCAT derived soil moisture values at coarse resolution showed a better correlation with in situ measurements. The temperature based methods showed a weaker correlation 0.14-0.17 compared to the ASCAT 0.47-0.48. This is attributed to the bias introduced by position of the regression lines triangular space for determining the cold edge (wet soil and well-watered vegetation) and the dry edge (dry soil and vegetation at wilting point). Additionally, for a good part of the year (December-April) there are low NDVI values making it harder to obtain sufficient points above NDVI of 0.2 to create the required plot.

ii. Winter

Table 5-3: Comparison of Implemented Methodologies during winter

<table>
<thead>
<tr>
<th>Retrieval Method</th>
<th>BIAS</th>
<th>MBE</th>
<th>RMSE</th>
<th>NSE</th>
<th>R</th>
</tr>
</thead>
<tbody>
<tr>
<td>10cm</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ASCAT_010</td>
<td>-0.10</td>
<td>0.11</td>
<td>0.13</td>
<td>-1.12</td>
<td>0.36</td>
</tr>
<tr>
<td>ETlook</td>
<td>-0.09</td>
<td>0.11</td>
<td>0.13</td>
<td>-1.06</td>
<td>0.19</td>
</tr>
<tr>
<td>TVDI</td>
<td>-0.08</td>
<td>0.12</td>
<td>0.14</td>
<td>-1.43</td>
<td>0.14</td>
</tr>
<tr>
<td>25cm</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ASCAT_010</td>
<td>-0.06</td>
<td>0.10</td>
<td>0.12</td>
<td>-0.06</td>
<td>0.41</td>
</tr>
<tr>
<td>ETlook</td>
<td>-0.05</td>
<td>0.10</td>
<td>0.12</td>
<td>-0.12</td>
<td>0.27</td>
</tr>
<tr>
<td>TVDI</td>
<td>-0.05</td>
<td>0.11</td>
<td>0.13</td>
<td>-0.39</td>
<td>0.23</td>
</tr>
</tbody>
</table>

During this time of the year, some parts of the land surface is covered with ice and the soil water get frozen in other areas. ASCAT is thus not able to retrieve soil moisture data for top soil. Similarly, the land surface temperature based methods had a poor correlation (0.05-0.23). During this period, most of the trees shed leaves and thus characterised by low NDVI values, highest being NDVI of 0.45. As such, there are no sufficient NDVI values to obtain a clear triangle or trapezoidal space, thus the R values are lower than the yearly mean.
iii. **Summer**

*Table 5-4: Comparison of implemented methodologies during summer*

<table>
<thead>
<tr>
<th>Retrieval Method</th>
<th>BIAS</th>
<th>MBE</th>
<th>RMSE</th>
<th>NSE</th>
<th>R</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>10 cm</strong> ASCAT_010</td>
<td>-0.01</td>
<td>0.08</td>
<td>0.09</td>
<td>0.09</td>
<td>0.45</td>
</tr>
<tr>
<td>ETlook</td>
<td>-0.06</td>
<td>0.10</td>
<td>0.12</td>
<td>-0.53</td>
<td>0.22</td>
</tr>
<tr>
<td>TVDI</td>
<td>0.04</td>
<td>0.08</td>
<td>0.10</td>
<td>-0.11</td>
<td>0.37</td>
</tr>
<tr>
<td>25 cm ASCAT_010</td>
<td>0.00</td>
<td>0.08</td>
<td>0.09</td>
<td>0.18</td>
<td>0.49</td>
</tr>
<tr>
<td>ETlook</td>
<td>-0.05</td>
<td>0.10</td>
<td>0.12</td>
<td>-0.20</td>
<td>0.30</td>
</tr>
<tr>
<td>TVDI</td>
<td>0.05</td>
<td>0.09</td>
<td>0.11</td>
<td>-0.11</td>
<td>0.42</td>
</tr>
</tbody>
</table>

The temperature based method showed a better correlation to in situ measurements during summer compared to all other seasons. This is because at this time of the year the crops are actively growing and there is sufficient NDVI values spread from 0.0-0.9, thus the trapezoidal/triangular space could be obtained.

**5.3.2. Performance by vegetation clusters**

The vegetation type was grouped based on the land use map presented in chapter 3, figure 3-1, a total of five clusters were used namely: cropped/cultivated land, rangeland/grasslands, wetlands, woodlands and urban/barren land. Then for each station, an annual comparison was done between measured and simulated values from Julian day 1 to Julian day 353 of the year. The table 5-5 below presents the performance metrics based on bias, mean bias error (MBE), root mean square error (RMSE) and correlation coefficient(R) for each land use type.

*Table 5-5: Methods performance by land use*

<table>
<thead>
<tr>
<th>Land Use</th>
<th>ASCAT_010</th>
<th>TVDI</th>
<th>Etlook</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Cropped</td>
<td>0</td>
<td>0.01</td>
<td>-0.02</td>
<td>0.08</td>
<td>0.09</td>
<td>0.07</td>
</tr>
<tr>
<td>Rangeland</td>
<td>-0.03</td>
<td>-0.03</td>
<td>-0.06</td>
<td>0.10</td>
<td>0.09</td>
<td>0.07</td>
</tr>
<tr>
<td>Wetland</td>
<td>0.03</td>
<td>0.06</td>
<td>0.08</td>
<td>0.11</td>
<td>0.13</td>
<td>0.11</td>
</tr>
<tr>
<td>Woodland</td>
<td>-0.06</td>
<td>-0.08</td>
<td>-0.04</td>
<td>0.11</td>
<td>0.09</td>
<td>0.07</td>
</tr>
<tr>
<td>Urban/Barren</td>
<td>-0.035</td>
<td>-0.08</td>
<td>-0.06</td>
<td>0.09</td>
<td>0.09</td>
<td>0.08</td>
</tr>
</tbody>
</table>

**DATA ANALYSIS AND RESULTS** 41
Overall, the RMSE values of about 0.1 were obtained. Since soil moisture values range from 0.05(m^3/m^3) for residual soil moisture to about 0.45 for full saturation for most soils, this error represents varies from 20% for saturated soil to 100% for dry soils. This can be attributed to the fact that ASCAT products does not put into consideration soil texture. Additionally, the T values given does not directly relate to depth and different t values relate differently at different locations. In order to show the difference/variance of the methods with vegetation type, figures showing time series plots of cropped areas and rangelands are presented in part (i) and (ii) below. Graphs of each soil moisture station are presented in the appendix E, showing a time series plot of soil moisture against time for the year 2008 from Julian day 1 to day 353 for 43 stations.

i. Cropped/cultivated areas

The cultivated areas are mainly under irrigation towards the west and rainfed towards the eastern part of the country. The figure 5-16 below show a time series plot for Brunswick station which falls within a cultivated area.

![Figure 5-16: Soil moisture estimates from cropped area]

The ground data at 10cm and 25cm were plotted with the volumetric soil moisture obtained from the Temperature Vegetation Dryness Index (TVDI), Etlook method and the soil moisture derived from ASCAT. In this case ASCAT_010 represents the soil moisture at the top 10cm. ETlook moisture estimates derived from soil moisture at top most layer 0-5cm was observed to agree more with ground data between day 60 and day 175. However, in cases where there were overestimates, this was attributed to original estimates from ASCAT_001. The zero measurements from this method implies snow/ice conditions at soil surface. Soil moisture graphs for all stations are presented in Appendix E part (1) for cropped/cultivated areas. The TVDI index showed general overestimate during winter and part of summer. In spring through to early summer there was underestimate. This bias was observed to be systemic and observable in more cultivated areas.
ii. Rangeland/Grasslands

The figure 5-17 below shows the a plot of ground data at 10cm depth and averaged water content at top soil for Gordon soil moisture station in the year 2008.

![Figure 5-17: Soil moisture estimates from rangeland](image)

The ground data at 10cm and 25cm were plotted with the volumetric soil moisture obtained from the temperature vegetation dryness index from the triangle method and ASCAT derived soil moisture. It is observable that during winter the relationship between the TVDI indices and the ground data is not consistent. However for the month of April to October, the trend in both methods show shows some similarity especially at 25cm depth. This is expected to be due to vegetation development from the start of spring through to mid-autumn. ASCAT_010 represents the soil moisture at the top 10cm. However, we are cognizant that this is not always the case and these estimates can represent different depths for different soils. Soil moisture graphs for all stations within grassland areas are presented in Appendix E part (2) of this report.

5.3.3. Performance by soil type

Soil moisture varies directly with the soil porosity and thus the soil type is an important parameter in soil moisture determination. The soil map used in the implementation of the methodologies were derived from HiHydrosoils and are mostly averaged values. The soil percentage of clay, silt and loam was obtained from every station. The soil type was obtained using the soil texture classification triangle. The water content at saturation was inferred based on Rijtema (1965). The soil data is attached in Appendix C of this document. Table 5-6 shows performance of the soil-moisture retrieved from satellite data based on the two datasets.

<table>
<thead>
<tr>
<th>Retrieval Method</th>
<th>BIAS</th>
<th>MBE</th>
<th>RMSE</th>
<th>NSE</th>
<th>R</th>
</tr>
</thead>
<tbody>
<tr>
<td>HiHydrosoils Data</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ASCAT_010</td>
<td>-0.02</td>
<td>0.08</td>
<td>0.09</td>
<td>-0.06</td>
<td>0.47</td>
</tr>
<tr>
<td>ETlook</td>
<td>-0.04</td>
<td>0.09</td>
<td>0.11</td>
<td>-0.38</td>
<td>0.29</td>
</tr>
<tr>
<td>TVDI</td>
<td>0.07</td>
<td>0.10</td>
<td>0.13</td>
<td>-0.79</td>
<td>0.14</td>
</tr>
<tr>
<td>Derived Station Data</td>
<td></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ASCAT_010</td>
<td>-0.06</td>
<td>0.08</td>
<td>0.10</td>
<td>0.00</td>
<td>0.60</td>
</tr>
<tr>
<td>ETlook</td>
<td>-0.08</td>
<td>0.10</td>
<td>0.12</td>
<td>-0.74</td>
<td>0.49</td>
</tr>
<tr>
<td>TVDI</td>
<td>0.06</td>
<td>0.10</td>
<td>0.12</td>
<td>-0.42</td>
<td>0.28</td>
</tr>
</tbody>
</table>
5.3.4. Topography and soil moisture
According to Zhu & Lin., (2011), soil moisture is influenced by slope if the slope is considered to be greater than 8% and less significant if the slope is less than 8%. In order to determine the soil moisture response to slope variations, the DEM was classified into two clusters representing the fairly steep and gently/relatively flat areas according to figure 3-2, presented in chapter 3. It was obtained that 99.4% of the area has a slope with less than 8% when the resampled to a resolution of 1km, while the remaining 0.6% was more than 8%. With this result, the effect of slope was thus deemed negligible to the soil moisture variations across the state of Nebraska.

Figure 5-18: Percent (%) slope for Nebraska State
5.4. Downscaling based on TVDI

Downscaling of soil moisture borrows from the implemented methods. The downscaling focus on the top soil layer assumed to be the top 30cm. Based on the implemented methods, a temperature based index, ASCAT soil water index (SWI) and land use map were selected to develop a set of equations that can be applied to different land use types. Some of the key findings that were used to develop the method were:

- **Soil moisture varied with seasons**

  As observed in chapter 5.3, overall the best estimates were obtained during summer for land surface temperature based methods, while ASCAT derived products provided the best estimates during spring and autumn. Since the crop production is mostly during summer, the temperature based indices were selected as it showed improved estimate during this time of the year.

- **Soil Moisture varied with vegetation type**

  Overall, both ASCAT and LST based indices showed an improved estimate with soil moisture for rangelands/grassland areas compared to cropped areas. Estimate from TVDI method depicted unique response with vegetation classes. There was thus a need to enhance this by taking into consideration land use to obtain relationships for various vegetation types. Figure 5-19 shows clustered land uses that were used to generate the relationships between the various vegetation classes with soil moisture.

![Clustered Land use classes used for downscaling](image)

*Figure 5-19: Clustered Land use classes used for downscaling*
- **ASCAT derived soil moisture was in agreement with ground data**

ASCAT derived soil moisture estimates agreed better with the in-situ measurements as compared to the other implemented methods. The downscaling of the volumetric soil moisture would thus be prudent to provide the variations within each pixel both temporally and spatially.

- **Soil moisture estimates varied with depth**

The LST/NDVI based index has been used for development of the downscaling methodology. The index however indicates different depths with different NDVI values. For vegetated areas, the TVDI index is related to soil moisture at the subsoil while for bare soil, it indicates moisture at topsoil. In the coming the study will focus on soil moisture estimation on the top 10 cm. It was important that first, estimates from TVDI index be compared with in-situ measurements at different depths during summer as most areas have full vegetation. The results shown in figure 5-20 indicate improved performance of TVDI with soil in situ measurements at a depth of 10 and 25 cm compared to deeper soil layers at 50 and 100 cm. We are however cognizant that a depth of 25cm does not necessarily indicate an exact depth of 25cm but rather a sphere of influence for instance from 20-30cm.

![Triangle Method (TVDI)](image)

*Figure 5-20: TVDI performance with depth*

### 5.4.1. Methodology Formulation

Soil moisture at local scale is a function of soil moisture at coarse scale. In order to take into consideration variation within each pixel, the soil moisture is expressed as a function of both the soil water index at coarse scale and the temperature vegetation dryness index such that:

\[
S_m = ASCAT_{m} (a \ast SWI + b \ast TVDI) \tag{22}
\]

Where \(S_m\) is the volumetric soil moisture at local scale, \(ASCAT_{m}\) is the volumetric soil moisture at coarse scale, \(SWI\) is the degree of saturation derived from ASCAT, while TVDI is the temperature vegetation dryness index obtained from triangle method.
From the implemented methodologies, it was observed that the soil moisture estimation from the temperature based indices varied with seasons. For instance, from figure 5-16, above for Brunswick soil moisture station, an overestimation is observed from Julian day 1 to day 50. The overestimation is diminishing with time. Similarly, from day 100 to day 200, the soil moisture estimates are underestimated with the bias value diminishing with time. The same applies to day 200 to 300 and day 300 to day 353 where there is an overestimate followed by an underestimate respectively.

Therefore to correct for bias, a sine function is introduced as a function of Day of the year to give figure 5-21 shown below for bias correction. There are four seasons within the period (365 days). This sine function offered opportunity to correct the different biases for each season.

![Sine Function](image)

**Figure 5-21: Sine function employed for downscaling**

This function however only affects the TVDI index. Therefore, to correct for the same the sine function is introduced in equation (23) below:

$$TVDI_{corrected} = (TVDI + (\sin(Radians(DOY) * Ns) * c)$$  \hspace{1cm} (23)

Where *DOY* is the Julian day of the year, *Ns* is the number of seasons expressed as number of phases. This study has four unique cycles. A value of 2 is thus used to obtain the two periods within 360 days, and the parameter c determines the amplitude of the sine function. Substituting *TVDI* with *TVDI_{corrected}* in equation (22) gives equation (24) below.

$$Sm=ASCAT_{sm}(a*SWI+b*(TVDI+(\sin(Radians(DOY)*2)*c)))$$  \hspace{1cm} (24)

A constant is added to the equation to provide for curve fitting that is to shift the curve up or down depending on whether there exists a negative or positive bias in the overall soil moisture derived from the above equation to give the final equation (25) below:

$$Sm = ASCAT_{sm}(a * SWI + b * (TVDI + (\sin(Radians(DOY) * 2) * c))) + d$$  \hspace{1cm} (25)

The parameters *a*, *b*, *c*, and *d* were optimized for the clustered land use types (figure 5-19) above using soil moisture data from stations representing each cluster. Solver minimization tool in excel was used. The results were applied on the remaining 38 stations without calibration.
The table 5-6 shows the coefficients that have been used for downscaling. The coefficients based on equation (23) and were determined for each land use. The areas of interest are mainly the rangeland areas and the cultivated/cropped areas. This is because a large part of the study area (95%) is either cropped or rangeland area. There are 21 stations within rangelands, 19 stations within cropped areas, and two stations in urban areas, two stations in riparian forest and one station within a wetland area. For both rangelands and cropped areas, three stations were selected to generate the optimal coefficients using excel spreadsheets. While for urban areas, wetland and riparian woodland, only one station per land use was used as there are few stations with the land use.

Table 5-7: Coefficients for different land use

<table>
<thead>
<tr>
<th>Coefficients</th>
<th>a</th>
<th>b</th>
<th>c</th>
<th>d</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cultivated areas</td>
<td>0.6</td>
<td>0.7</td>
<td>0.55</td>
<td>0.13</td>
</tr>
<tr>
<td>Rangelands/grassland</td>
<td>0.6</td>
<td>0.7</td>
<td>0.15</td>
<td>0.10</td>
</tr>
<tr>
<td>Wetland areas</td>
<td>0.5</td>
<td>0.7</td>
<td>0.55</td>
<td>0.13</td>
</tr>
<tr>
<td>Woodland Forests</td>
<td>0.5</td>
<td>0.65</td>
<td>0.5</td>
<td>0.13</td>
</tr>
<tr>
<td>Urban areas</td>
<td>0.54</td>
<td>0.2</td>
<td>0.2</td>
<td>0.13</td>
</tr>
</tbody>
</table>

The coefficients $a$ and $b$ were identical for both cultivated and rangeland areas. However, the amplitude size differed more. This is because the seasonal correction required for cropped areas was larger compared to the grassland for the TVDI. This can be observed in Appendix E of this report. The grassland areas have more uniform cover across the year but for cropped areas, the NDVI values change rapidly with seasons. This can be observed for LST-NDVI graphs presented in Appendix F of this report. The set of equations were then implemented in an algorithm developed in python on 353 days for the year 2008.
The figure 5-22 gives the results from one of the stations (Beatrice) showing correlation at fine scale, coarse scale, and a time series plot of the in situ soil moisture (TAMU) at 10cm, downscaled soil moisture and soil moisture at coarse resolution (ASCAT_010).

![Image showing results from Beatrice station](image)

**Figure 5-22 Performance of the downscaled soil moisture at 1km for Beatrice Station.**

Figure 5-22 shows the improvements realized with the proposed downscaling technique. The sinusoidal correction successfully reduced the bias while maintaining the peaks obtained from coarse resolution.
5.5. Results of the implemented downscaling methodology

The figures 5-23 show the soil moisture maps of Nebraska State on 25\textsuperscript{th} July 2008. A map of ground data has been generated for comparison using kriging method. The date falls within summer season. The patterns observed at coarse resolution were successfully reproduced with the downscaling approach. The western part of the state was generally drier compared to the eastern part. When compared to in-situ data, the western part of the state was closer to ground data compared to the eastern part. This lower values were attributed to the original dataset.

![Soil Moisture Maps](image)

*Figure 5-23: Soil Moisture map for 25 July 2008*
The figure 5-24 below show the soil moisture maps of Nebraska State on 5\textsuperscript{th} April 2008. The day falls within spring season. The soil moisture spatial distribution pattern from coarse scale was successfully captured by the downscaling approach but with higher values. When compared to ground data, the eastern part which is mainly dominated by agricultural areas was found to be closer to the in-situ measurements. This being the crucial season for crop production, the method shows improved performance relative to coarse resolution.

**Figure 5-24: Soil Moisture maps for 5\textsuperscript{th} April 2008 (spring)**
5.5.1. Seasonal Comparison
The tables below present the seasonal variations for the implemented method. The performance is based on simulated data relative to in situ measurements for all the stations (45 in number) for the whole year 2008 and the respective seasons in this case summer and winter has been selected.

The table 5-5 below shows the performance of the downscaling method across the year. There was improvement in the spatio-temporal correlation coefficient from 0.47 to 0.54 annually, 0.36 to 53 in winter and 0.45 to 0.54 in summer for the measurements at 10cm, with a similar range with measurements at 25cm depth.

Table 5-8: Performance of the downscaling method

<table>
<thead>
<tr>
<th>Season</th>
<th>Depth</th>
<th>Retrieval Method</th>
<th>BIAS</th>
<th>MBE</th>
<th>RMSE</th>
<th>NSE</th>
<th>R</th>
</tr>
</thead>
<tbody>
<tr>
<td>Annual</td>
<td>10cm</td>
<td>ASCAT_010</td>
<td>-0.02</td>
<td>0.08</td>
<td>0.09</td>
<td>-0.06</td>
<td>0.47</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Downscaled</td>
<td>-0.03</td>
<td>0.08</td>
<td>0.10</td>
<td>0.11</td>
<td>0.54</td>
</tr>
<tr>
<td></td>
<td>25cm</td>
<td>ASCAT_010</td>
<td>-0.01</td>
<td>0.08</td>
<td>0.10</td>
<td>0.14</td>
<td>0.48</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Downscaled</td>
<td>-0.02</td>
<td>0.09</td>
<td>0.10</td>
<td>0.16</td>
<td>0.51</td>
</tr>
<tr>
<td>Winter</td>
<td>10cm</td>
<td>ASCAT_010</td>
<td>-0.10</td>
<td>0.11</td>
<td>0.13</td>
<td>-1.12</td>
<td>0.36</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Downscaled</td>
<td>-0.024</td>
<td>0.07</td>
<td>0.09</td>
<td>0.124</td>
<td>0.53</td>
</tr>
<tr>
<td></td>
<td>25cm</td>
<td>ASCAT_010</td>
<td>-0.06</td>
<td>0.10</td>
<td>0.12</td>
<td>-0.06</td>
<td>0.41</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Downscaled</td>
<td>0.013</td>
<td>0.09</td>
<td>0.10</td>
<td>0.196</td>
<td>0.54</td>
</tr>
<tr>
<td>Summer</td>
<td>10cm</td>
<td>ASCAT_010</td>
<td>-0.01</td>
<td>0.08</td>
<td>0.09</td>
<td>0.09</td>
<td>0.45</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Downscaled</td>
<td>0.01</td>
<td>0.07</td>
<td>0.09</td>
<td>0.22</td>
<td>0.54</td>
</tr>
<tr>
<td></td>
<td>25cm</td>
<td>ASCAT_010</td>
<td>0.00</td>
<td>0.08</td>
<td>0.09</td>
<td>0.18</td>
<td>0.49</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Downscaled</td>
<td>0.01</td>
<td>0.07</td>
<td>0.09</td>
<td>0.3</td>
<td>0.59</td>
</tr>
</tbody>
</table>

Similarly, NSE coefficient improved from a -0.06 to 0.11 annually, from -1.12 to 0.124 in winter and from 0.09 to 0.22 in summer. Whereas the MBE and RMSE showed smaller improvements compared to gains in correlation, the implemented methodology was successfully able to produce fine resolution data without degrading the accuracy.
The figure 5-25 shows maps depicting the spatial distribution of correlation, RMSE and bias based on yearly comparison of in-situ measurements at the stations and downscaled data.

The downscaling study’s aim was to achieve a higher correlation and a lower RMSE. The above figures show that the correlation is not related to the Bias Error and to the RMSE. This is because while it is possible to have an improved correlation it could still have a negative or a positive bias. The RMSE spatial distribution show some relation with the Bias. The pixels with overall negative bias showed a larger RMSE while areas with positive bias had lower RMSE values.
5.5.2. Performance with vegetation/land use
Nebraska is largely an agricultural state. The cropped/cultivated areas cover 37% of the land while 58% is under grasslands/rangelands or shrubs. The wetlands cover 3%, woodlands at 2% and the urban areas occupy 1% of the land.

Table 5-9: Performance of downscaling method to vegetation

<table>
<thead>
<tr>
<th></th>
<th>BIAS</th>
<th>MBE</th>
<th>RMSE</th>
<th>Mean R</th>
<th>Min R</th>
<th>Max R</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Downscaled</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rangeland</td>
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<td>0.09</td>
<td>0.53</td>
<td>-0.09</td>
<td>0.81</td>
</tr>
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<td>0.01</td>
<td>0.08</td>
<td>0.10</td>
<td>0.49</td>
<td>-0.22</td>
<td>0.82</td>
</tr>
<tr>
<td>Wetland</td>
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<td>0.06</td>
<td>0.08</td>
<td>0.76</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Woodland</td>
<td>-0.06</td>
<td>0.09</td>
<td>0.10</td>
<td>0.60</td>
<td>0.51</td>
<td>0.70</td>
</tr>
<tr>
<td>Urban/Barren</td>
<td>-0.03</td>
<td>0.06</td>
<td>0.07</td>
<td>0.09</td>
<td>-0.33</td>
<td>0.51</td>
</tr>
<tr>
<td><strong>ASCAT_010</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rangeland</td>
<td>-0.03</td>
<td>0.07</td>
<td>0.08</td>
<td>0.05</td>
<td>-0.39</td>
<td>0.59</td>
</tr>
<tr>
<td>Cropped</td>
<td>0.00</td>
<td>0.08</td>
<td>0.09</td>
<td>0.10</td>
<td>-0.30</td>
<td>0.54</td>
</tr>
<tr>
<td>Wetland</td>
<td>0.03</td>
<td>0.06</td>
<td>0.07</td>
<td>0.18</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Woodland</td>
<td>-0.06</td>
<td>0.10</td>
<td>0.11</td>
<td>-0.22</td>
<td>-0.24</td>
<td>-0.19</td>
</tr>
<tr>
<td>Urban/Barren</td>
<td>-0.04</td>
<td>0.05</td>
<td>0.07</td>
<td>0.32</td>
<td>0.14</td>
<td>0.51</td>
</tr>
</tbody>
</table>

In general, there was considerable improvement in the temporal correlation coefficient (R) for the different vegetation types. For instance, for rangeland areas and cropped areas, the values improved from 0.1 to 0.5 and from 0.05 to 0.49 respectively. This was attributed to the bias correction that was specific to the vegetation type. Temporally, the correlation was thus improved significantly. The Bias, MBE and RMSE showed minimal changes.

5.5.3. Performance by soil type
When the station derived soil data was used the correlation coefficient improved from 0.54 to 0.67. The RMSE and MBE increased by 0.01. This is attributed to increased bias from -0.03 to -0.079. The saturation water content also was higher for more stations relative to HyHydrosoils data (Appendix C). In terms of percentage error relative to saturation water content, there was no significant change hence the downscaling approach did not degrade the accuracy.

In general, there was considerable improvement in the temporal correlation coefficient (R) for the different vegetation types. For instance, for rangeland areas and cropped areas, the values improved from 0.1 to 0.5 and from 0.05 to 0.49 respectively. This was attributed to the bias correction that was specific to the vegetation type. Temporally, the correlation was thus improved significantly. The Bias, MBE and RMSE showed minimal changes.

In general, there was considerable improvement in the temporal correlation coefficient (R) for the different vegetation types. For instance, for rangeland areas and cropped areas, the values improved from 0.1 to 0.5 and from 0.05 to 0.49 respectively. This was attributed to the bias correction that was specific to the vegetation type. Temporally, the correlation was thus improved significantly. The Bias, MBE and RMSE showed minimal changes.

Figure 5-26: Downscaling method performance by soil type
The soil types were grouped into four clusters consisting of clay, silt, sand and loam. There were 22 stations with silt, 11 stations with sand, 9 stations with loam and one station with clay. We are however cognizant that the clustered soil types do not entirely have the same properties for instance silty clay and silty loam have different properties. For this study, soils with more than 50% sand were clustered as sand, those with 50% silt were considered as silt, while those with neither silt, clay nor more than 50% were considered loam. Soils that had over 40% clay were considered clay soils.

![Corelation coefficient graph](image1)

**Figure 5-27: Performance with soil type**

### 5.5.4. G\textsubscript{DOWN} performance metric

The performance metric proposed by Merlin, 2015 was used to obtain one metric that combines the Bias, Correlation and slope of linear regression to examine the overall contribution of the downscaling method to the coarse resolution data. The annual correlation (R), Mean Bias Error (MBE) and Slope of linear regressions for each station were used. The method is explained in section 4.1.4 part (ii) in the applied methodology. \( G_{\text{EFFI}} \) is the gain in terms of its bias in the slope (S) of linear fit relative to the low resolution, the \( G_{\text{PREC}} \) is the downscaled soil moisture resolution gain with respect to time series correlation (R) and \( G_{\text{ACCU}} \) is the accuracy of downscaled soil moisture resolution gain with respect to mean bias (MBE):

![G\textsubscript{DOWN} Metric graph](image2)

**Figure 5-28: G\textsubscript{DOWN} Performance metric**

A positive value was obtained for the \( G_{\text{DOWN}} \) in 85% of the stations thus implying that the downscaling method was effective.
CHAPTER 6
DISCUSSIONS

6.1. Indices used for downscaling method

6.1.1. Temperature based index TVDI

The downscaling method used LST/NDVI based TVDI index from triangle method. Overall, the land surface temperature variations were larger in bare soil compared to areas with full vegetation cover as observed in figure 5-7. This was in agreement with (G. Petropoulos et al., 2009). The R values varied from -0.5 to 0.5 with a mean of 0.28. This was lower than the mean R values reported by Wan et al. (2004) at 0.47 using the similar vegetation temperature condition index (VTCI). This is because average values for the whole year were used. For summer, where the TS/NDVI space could be clearly obtained, the mean R value was found to be 0.42 for 25 cm depth and 0.37 for 10cm depth. These values were closer to those obtained by Wan et al., (2004). When the Soil data from the stations were used, the mean R values for summer were found to be 0.48 at 10cm depth and 0.54 at 25 cm depth. The R values obtained from this index was thus found to be in agreement with what has been done before. The main improvement is that soil moisture can be obtained on a daily scale and the limitations of cloud cover were overcome while obtaining similar levels of precision as those of cloud free conditions.

The RMSE values for TVDI ranged from 0.04 (m$^3$/m$^3$) to 0.17 (m$^3$/m$^3$). According to a study done by G. P. Petropoulos et al., (2014), the estimates obtained from the implementation of the triangle method from ASTER satellite data, an RMSE of 0.19 and MBE of 0.08 was found. The spatiotemporal study conducted in Italy, Portugal and Spain was thus found to be in agreement with this research as an average MBE of 0.08 and RMSE of 0.14 were obtained from this research from TVDI. The high RMSE values were attributed to bias introduced by changing seasons manifested in the changing positions of the regression lines with time. The discrepancy with in-situ soil moisture can also be attributed to the differing resolutions between satellite derived soil moisture (1km) and the point scale measurements which are a few metres. Notable was the great improvement observed in summer where the accuracy was observed at RMSE of 0.10(m$^3$/m$^3$). Since this is the period within which cultivation of crops is undertaken in the fields, this offered a good opportunity to use this index for downscaling for agriculture.
6.1.2. Soil Water Index

Soil Water Index Version 3 (SWIV3) product from ASCAT was used in this study. The ASCAT products are available at eight different T values ($T=1$, $T=5$, $T=10$, $T=15$, $T=20$, $T=40$, $T=60$ and $T=100$) with lower T values representing top soil and higher values represent deeper soil. The focus of the study was on the top soil. The soil moisture measurements available for validation were at 10 cm, 25 cm, 50 cm and 100 cm for soil moisture network in Nebraska. Therefore, T value of $T=10$ was selected for this study. The data was compared with in-situ soil measurements from 45 stations at depths of 10 cm and 25 cm. A correlation coefficient R, of 0.47 and 0.6 were obtained when soil data from HiHydrosoils was used and soil information derived from the stations were used respectively. This is similar to value obtained by Paulik et al., (2014), who found an R value of 0.54 when he compared SWIV2 with 664 soil moisture stations from International Soil Moisture Network (ISMN). A mean RMSE of 0.09 (m$^3$/m$^3$) was found for depth of 10 cm depth and 0.10 (m$^3$/m$^3$) for 25 cm depth. According to quality assessment report for SWIV3 2015, the RMSE varied from 0.03 to 0.11 (m$^3$/m$^3$).

6.2. Soil Moisture Spatio-Temporal Variation

6.2.1. Soil Moisture variation with Land Use

In the study site, 95% of the total land is either cultivated or under grasslands/rangeland. A total of 22 soil moisture stations represented cropped areas while 18 stations represented rangeland areas. The remaining five stations were either within urban, wetland or woodland areas. Therefore more meaningful relationships could be derived from range and cropped areas as there were more field observations for validating the downscaling method. The mean R was higher for rangeland areas R=0.53 compared to cropped areas with a mean of 0.49. The RMSE values RMSE values were also better for rangeland areas at 0.09 compared to 0.10 for cropped areas. This was because the NDVI values for grass do not vary significantly across the year.

6.2.2. Soil moisture variation with soil texture/soil type

The correlation coefficient improved from 0.54 to 0.67 when the method was applied using data from HiHydrosoils and Station data respectively. This is because the soil information was resampled to 1 km resolution thus the accuracy of the soil data was affected. The RMSE values degraded from 0.09 to 0.11 (m$^3$/m$^3$). This is because soil data from HiHydrosols were used in the derivation of the downscaling method thus using different set of soil data led to an increase in bias from -0.03 to -0.08. The determination of surface soil moisture is strongly dependent on the soil type. However, the soil water indices derived from ASCAT do not account for soil texture. Thus different T values would imply different depths for different soils. For instance, according to product user manual for ASCAT issued August 2016, in a study conducted in Spain, the best estimate was obtained with $T=40$ for the depth of 0-25 cm (C. W. Paulik, 2016). Since the correlation improved, a variation of the coefficient for bias correction $d$ to a smaller value is expected to increase the accuracy.
The performance in sandy soils was generally low. This is also attributed to the fact that the soil moisture derived from ASCAT does not take into account the soil texture. According to appendix C and appendix F, it can be observed that all soil moisture stations with sandy soils had the values overestimated by ASCAT. Since the downscaling does not take into consideration the soil type but takes the moisture derived from ASCAT as being closer estimates, this accuracy was thus not expected to improve significantly. The downscaling approach effectively produced fine resolution soil moisture data without further reducing the accuracy. Notable is the fact the soil moisture derived from silty soils had higher precision relative in-situ measurements. The interpolated soil from HyHydosoils were largely within a saturated water content of between 0.4-0.45Vv/Vs which was not representative of sandy soils and clay soils.

6.3. Soil Moisture Temporal Variation

The best estimate was found during summer with an R of 0.60 at a depth of 25cm while the lowest R was obtained during winter at 0.53 at 25cm depth. The range was found to be similar to ASCAT original dataset which varied from 0.41 to 0.49 within the same time and at the same depths. The method was thus found to be consistent with time and showed improved correlation. The NSE coefficient also was also higher during summer at 0.3 compared to annual average of 0.159. Similarly the RMSE remained constant during summer with at 0.09 m^3/m^3. The better correlation at deeper depth can be attributed to the TVDI index, whereby the full vegetation cover can be attained at this time of the year and the land surface temperature on the surface is associated with root zone soil moisture.

The lowest RMSE for ASCAT was observed during winter. This is because the Scatterometer ability to derive soil moisture is hampered by frozen conditions. The soil moisture retrieval is dependent on the dielectric properties. This property is affected by frozen states resulting in low backscatter.

The temporal improvements in correlation was also due to the bias correction that was introduced by the sine function. As observed in figure 5-19, the function transforms the time series plot such that the seasonal variations are covered while at the same time maintaining the peaks from ASCAT_010 product. The risk however was with determining the amplitude size as the variations in cropped areas was large compared to rangelands and using the exact same amplitude for a range of vegetation could bring about systematic error. This however can be improved creating more clusters based on land use type and also by observing the LST-NDVI plots for different vegetation types as presented in Appendix F of this report.
6.4. Overall performance of the downscaling methodology

For the overall performance of the downscaling method the $G_{DOWN}$ metric was used. The method was found to improve the effectiveness since gain with respect to slope of linear fit for high resolution was positive in 91% of the stations. The precision was also improved in 93% of the stations while accuracy was improved in 47% of the soil moisture stations. Based on the average of the three metrics obtained from appendix D of this document, $G_{DOWN} = 0.22$ was obtained. According to Merlin, (2015), if this value is found to be positive, then the method contributed positively relative to non-disaggregation. This method considers time series correlation for each station for the entire season. The downscaling method was thus considered effective.

The RMSE was minimally degraded in some soil moisture stations. This can be attributed to the fact that the soil moisture derived from satellite data were compared to in-situ which differ in scale. Both the downscaled and satellite data have a much coarser resolution compared to point measurements for field data. Similarly, in as much as the TVDI index showed better correlation with in-situ data at 25cm depth, the different vegetation depict soil moisture at different depths as the have varying root zones depths.

It is paramount that soil moisture downscaling requires representative soil properties information for validation. Whereas the soil properties could be inferred from the textural classification of the stations data, the soil data used to derive the downscaling method was based on HiHydrosoils data. Therefore, the errors contributed by inaccurate representation as shown in Appendix C were transferred into the method. This led an introduction of Bias that also could have led to the degraded RMSE values in some stations. The areas with sandy soils such as Elgin, North Platte, Gothenburg among others, had significant negative bias while areas with clay soils such as Mead Irrigated had a significant positive bias as shown in both appendix B and appendix F. This is due to the soil porosity, as sand has a lower saturated water content (0.365) compared to clay (0.5).
6.5. Downscaling method application

The soil moisture product developed will be useful for different applications among them agricultural crop production forecasting, surface run-off determination and flood forecasting, navigability of the roads (earth roads) and determining the likelihood of mudslides and landslides. The global climate observations systems have put forward requirements for soil moisture derivation from satellites. The requirements are based on the saturated soil moisture content with a threshold set at 20%, targeted accuracy at 10% and the optimum set at 5% (C. W. Paulik, 2015). However the requirements often have to be used cautiously as the limits vary depending on the soil type and the soil water content especially for agricultural water management. The table 6-1 considers all the soil types that have been used in this study, the accuracy obtained in this study for growing season (m³/m³) and a proposed critical range limits (plus or minus RMSE) based on the available water content for the soils for agricultural applications. The Nebraska growing season considered is day 150 to day 270 of the year 2008. The field capacity is assumed to be pF of 2 while the permanent wilting point is assumed to be pF of 4.2. The difference between soil moisture at field capacity and soil moisture at wilting paint gives the available soil moisture (AM). The readily available moisture (RAM) is assumed to be 55% of the available soil moisture.

<table>
<thead>
<tr>
<th>Soil Type</th>
<th>No of Stations</th>
<th>Threshold accuracy (m³/m³)</th>
<th>Downscaled accuracy (m³/m³)</th>
<th>Available Moisture (AM)</th>
<th>RAM (m³/m³)</th>
<th>Critical Limit (m³/m³)</th>
<th>Downscaled Soil moisture critical range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Clay Loam</td>
<td>1</td>
<td>0.1</td>
<td>0.03</td>
<td>0.16</td>
<td>0.09</td>
<td>0.33</td>
<td>0.3-0.36</td>
</tr>
<tr>
<td>Loam</td>
<td>7</td>
<td>0.09</td>
<td>0.05</td>
<td>0.32</td>
<td>0.17</td>
<td>0.25</td>
<td>0.2-0.25</td>
</tr>
<tr>
<td>Loamy Sand</td>
<td>2</td>
<td>0.07</td>
<td>0.11</td>
<td>0.12</td>
<td>0.07</td>
<td>0.11</td>
<td>0.0-0.22</td>
</tr>
<tr>
<td>Sand</td>
<td>9</td>
<td>0.07</td>
<td>0.10</td>
<td>0.13</td>
<td>0.07</td>
<td>0.08</td>
<td>0.0-0.18</td>
</tr>
<tr>
<td>Sandy Loam</td>
<td>5</td>
<td>0.09</td>
<td>0.08</td>
<td>0.2</td>
<td>0.11</td>
<td>0.15</td>
<td>0.07-0.23</td>
</tr>
<tr>
<td>Silt Loam</td>
<td>17</td>
<td>0.10</td>
<td>0.07</td>
<td>0.37</td>
<td>0.20</td>
<td>0.26</td>
<td>0.19-0.32</td>
</tr>
<tr>
<td>Silt Clay Loam</td>
<td>5</td>
<td>0.10</td>
<td>0.09</td>
<td>0.20</td>
<td>0.11</td>
<td>0.28</td>
<td>0.19-0.37</td>
</tr>
</tbody>
</table>

The higher RMSE values were primarily from sandy soil soils and were overestimated from coarse resolution (ASCAT) hence the larger values. For agricultural crop production, we consider loam and silty soils. The average RMSE from these regions was 0.7 m³/m³ or lower. The critical range for the downscaled soil moisture values can be used to predict crop stress. This values can also be used to predict crop production depending on how long the soil moisture conditions for a given location has been below or within the critical range.
7.1. Conclusions

The objective of the study was to review existing downscaling methodologies, implement a select set of methods and based on their performance develop a methodology for downscaling ASCAT from a resolution of 12.5km to a resolution of 1km. From literature review, three methodologies were implemented namely triangle method, trapezoidal method and ETlook method. Downscaling method that uses ASCAT SWI at coarse resolution, Land Surface Temperature (LST), NDVI and a Land Use map was developed. Overall, combining the LST/NDVI to obtain a Temperature Vegetation Index with ASCAT improved the spatio-temporal correlation from an R of 0.47 to 0.54 without decreasing the accuracy of the measurement with an average RMSE of 0.09 m$^3$/m$^3$ obtained.

The performance of the method varied with seasons with the best results obtained during summer which had a mean spatio-temporal correlation R of 0.59. The aim of the study was to downscale for agriculture. The growing season covers the entire summer period thus the method was found to be effective. The introduction of the sine function to correct for seasonal bias improved the temporal correlation from 0.08 to 0.50 when temporal correlation from each station was averaged. Seasonal changes were thus observed to be the primary drivers of soil moisture variations across the year.

The method gave a higher precision on Silty soils with a mean R of 0.55 and higher accuracy on loam soils with RMSE=0.05m$^3$/m$^3$. This comprise soils predominantly used for agricultural production. The downscaling method uses interpolated soil data from HiHydrosoils. When point scale soil data derived at soil moisture stations were used, the method precision was found to improve with correlation coefficient improving from 0.54 to 0.67. Soil data used for method derivation was found to be critical for the accuracy of downscaling method. The RMSE and MBE degraded by 0.01 and the bias increased from -0.03 to -0.07 when point scale soil data was used.

The downscaling method was also observed to perform better in rangeland areas. The mean R was higher for rangeland areas R=0.53 compared to cropped areas with a mean of 0.49. The RMSE values were also improved for rangeland areas at 0.09 compared to 0.10 for cropped areas. This accuracy was found to be within the threshold required for global climate observation systems, which is set at 20% of the soil saturated water content. The downscaling was thus found to be effective as it successfully produced fine resolution data and improved the correlation without degrading the accuracy.
7.2. Recommendations

- HANTS uses data at one pixel over the whole year to reconstruct data. As much as this method is useful for time series data, it does not take into consideration the nearby pixels making it susceptible to having outliers. An improvement on this method to take into consideration the nearby pixels will be minimise the outliers.

- This data was generated based on the data reconstructed using number of frequencies (nf); nf=3 for Land Surface Temperature and nf=2 for Normalized difference Vegetation Index; where nf represents number of cycles within a year. However the variations within the year may be more. The methodology can be applied with data reconstructed using a range of number of frequencies to determine the performance.

- This method has been implemented on an area that is largely flat with gentle slopes. Therefore the effect of topography could not be foreseen and thus was not considered. However, this relationship should be tested on places with rough terrains to determine its consistency.

- Land use map used in this map was developed in 2005. The study focused on the year 2008. Whereas the land use may not change much within the two year gap the year, it will be interesting to see the effect if the land use map for the same year can be used. Similarly, the study area does not have thick forests or arid areas thus a need to test the method on these areas. The set of relationships used in this study were based on 5 clusters of land use. More clusters could be added to take into consideration more land use types.

- It is notable that the study area is characterised by clear/distinct seasons which are winter, spring, summer and autumn. However, in the tropics, this is not the case and the temperatures remain high throughout the year. Therefore the sine function employed for this study can be altered such that there are only two or one season in the year.

- The seasonal LST/NDVI relationships observed in from the Trapezoidal and Triangle methods produced unique signatures that can be further investigated to determine its use in land use classification. Its robustness could be observed in that it takes into consideration the entire season.
REFERENCES


Appendix A  Soil Moisture stations

The stations below were used to validate the methodology developed for this study.

Figure 8-1: Study Validation Site
The performance metrics of each soil moisture stations.

<table>
<thead>
<tr>
<th>Station</th>
<th>ASCAT soil moisture at 12.5km</th>
<th>Downscaled Soil Moisture Data</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>BIAS</td>
<td>MBE</td>
</tr>
<tr>
<td>Rogers Farm #1</td>
<td>0.06</td>
<td>0.08</td>
</tr>
<tr>
<td>Ainsworth</td>
<td>-0.02</td>
<td>0.04</td>
</tr>
<tr>
<td>Alliance North</td>
<td>-0.04</td>
<td>0.06</td>
</tr>
<tr>
<td>Arthur</td>
<td>-0.05</td>
<td>0.06</td>
</tr>
<tr>
<td>Barta</td>
<td>-0.1</td>
<td>0.1</td>
</tr>
<tr>
<td>Beatrice</td>
<td>0.01</td>
<td>0.09</td>
</tr>
<tr>
<td>Brunswick</td>
<td>-0.07</td>
<td>0.09</td>
</tr>
<tr>
<td>Cedar Point</td>
<td>0.04</td>
<td>0.05</td>
</tr>
<tr>
<td>Central City</td>
<td>0.02</td>
<td>0.06</td>
</tr>
<tr>
<td>Champion</td>
<td>-0.01</td>
<td>0.06</td>
</tr>
<tr>
<td>Clay Center (SC)</td>
<td>0.04</td>
<td>0.06</td>
</tr>
<tr>
<td>Cozad</td>
<td>-0.04</td>
<td>0.07</td>
</tr>
<tr>
<td>Curtis (UNSTA)</td>
<td>0.03</td>
<td>0.06</td>
</tr>
<tr>
<td>Elgin</td>
<td>-0.18</td>
<td>0.18</td>
</tr>
<tr>
<td>Gordon</td>
<td>-0.06</td>
<td>0.06</td>
</tr>
<tr>
<td>Gothenburg</td>
<td>-0.16</td>
<td>0.16</td>
</tr>
<tr>
<td>Grand Island</td>
<td>0.01</td>
<td>0.05</td>
</tr>
<tr>
<td>Halsey</td>
<td>-0.1</td>
<td>0.1</td>
</tr>
<tr>
<td>Higgins Ranch</td>
<td>-0.11</td>
<td>0.11</td>
</tr>
<tr>
<td>Holdrege</td>
<td>0</td>
<td>0.07</td>
</tr>
<tr>
<td>Holdrege 4N</td>
<td>-0.02</td>
<td>0.06</td>
</tr>
<tr>
<td>Kearney</td>
<td>-0.01</td>
<td>0.05</td>
</tr>
<tr>
<td>McCook</td>
<td>0.08</td>
<td>0.09</td>
</tr>
<tr>
<td>Mead</td>
<td>0.05</td>
<td>0.09</td>
</tr>
<tr>
<td>Mead Agrofarm</td>
<td>0.06</td>
<td>0.09</td>
</tr>
<tr>
<td>Merna</td>
<td>-0.11</td>
<td>0.11</td>
</tr>
<tr>
<td>Merritt</td>
<td>-0.06</td>
<td>0.06</td>
</tr>
<tr>
<td>Minden</td>
<td>0.01</td>
<td>0.06</td>
</tr>
<tr>
<td>Mitchell Farms</td>
<td>-0.03</td>
<td>0.04</td>
</tr>
<tr>
<td>Nebraska City</td>
<td>-0.01</td>
<td>0.05</td>
</tr>
<tr>
<td>Newport</td>
<td>-0.13</td>
<td>0.13</td>
</tr>
<tr>
<td>Concord (NE)</td>
<td>0</td>
<td>0.06</td>
</tr>
<tr>
<td>North Platte</td>
<td>0</td>
<td>0.03</td>
</tr>
<tr>
<td>O'Neill</td>
<td>-0.11</td>
<td>0.11</td>
</tr>
<tr>
<td>Ord</td>
<td>0.03</td>
<td>0.06</td>
</tr>
<tr>
<td>Red Cloud</td>
<td>0.01</td>
<td>0.07</td>
</tr>
<tr>
<td>Scotts Bluff</td>
<td>-0.05</td>
<td>0.05</td>
</tr>
<tr>
<td>Shelton</td>
<td>-0.01</td>
<td>0.06</td>
</tr>
<tr>
<td>Sidney</td>
<td>0.01</td>
<td>0.06</td>
</tr>
<tr>
<td>Smithfield</td>
<td>0</td>
<td>0.06</td>
</tr>
<tr>
<td>West Point</td>
<td>0.01</td>
<td>0.07</td>
</tr>
<tr>
<td>York</td>
<td>0.07</td>
<td>0.09</td>
</tr>
<tr>
<td>Mead Irrigated</td>
<td>0.06</td>
<td>0.08</td>
</tr>
<tr>
<td>Mead Irrigated Rotation</td>
<td>0.1</td>
<td>0.11</td>
</tr>
<tr>
<td>Mead Rainfed</td>
<td>0.08</td>
<td>0.09</td>
</tr>
</tbody>
</table>

**Appendix B**
Appendix C  Saturation water content derived from the stations data and HiHydrosils.

<table>
<thead>
<tr>
<th>Station Name</th>
<th>%sand</th>
<th>%Silt</th>
<th>%Clay</th>
<th>Soil Type</th>
<th>Station Derived</th>
<th>HiHydrosils</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rogers Farm #1</td>
<td>3.1</td>
<td>56.3</td>
<td>40.6</td>
<td>silty clay</td>
<td>0.507</td>
<td>0.3779</td>
</tr>
<tr>
<td>Ainsworth</td>
<td>43.3</td>
<td>39.7</td>
<td>17</td>
<td>Loam</td>
<td>0.503</td>
<td>0.4001</td>
</tr>
<tr>
<td>Alliance North</td>
<td>33.3</td>
<td>44.2</td>
<td>22.5</td>
<td>Loam</td>
<td>0.503</td>
<td>0.4033</td>
</tr>
<tr>
<td>Arthur</td>
<td>96.3</td>
<td>0.7</td>
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<td>Sand</td>
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Appendix E  Implemented Methodologies Soil Moisture Graphs.

1. Agricultural/cropped areas (20 Stations)
2. Rangeland/Pasture/Grassland (18 Stations)
3. **Wetland/Swamps/Near Waterbody(1 station)**

---

**Appendix E**
4. Riparian Forest/Woodland (2 Stations)

![Newport Soil Moisture Graph](image1)

![Westpoint Soil Moisture Graph](image2)

5. Urban Area (1 Station)

![Scotts Bluff Soil Moisture Graph](image3)
Appendix F  Downscaled Soil Moisture Graphs.

1. Cropped/Cultivated Area

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Appendix F

Soil Moisture Graphs

Champion

Clay Centre SC

Elgin

Holdrege 4N

LST-NDVI Graphs

Champion

Clay Centre (SC)

Elgin

Holdrege 4N
Appendix F

Soil Moisture Graphs

Mitchell Farms

[Graph showing Soil Moisture content in m$^3$ per m$^3$ over Julian Days for Mitchell Farms, with lines for ASCAT_Top, Ground_Data_10cm, and Downscaled.]

Nebraska City

[Graph showing Soil Moisture content in m$^3$ per m$^3$ over Julian Days for Nebraska City, with lines for ASCAT_Top, Ground_Data_10cm, and Downscaled.]

Concord (NE)

[Graph showing Soil Moisture content in m$^3$ per m$^3$ over Julian Days for Concord (NE), with lines for ASCAT_Top, Ground_Data_10cm, and Downscaled.]

O’Neill

[Graph showing Soil Moisture content in m$^3$ per m$^3$ over Julian Days for O’Neill, with lines for ASCAT_Top, Ground_Data_10cm, and Downscaled.]

LST-NDVI Graphs

Mitchell Farms

[Graph showing LST (K) and NDVI over Julian Days for Mitchell Farms, with a curve for LST (K) and a line for NDVI.]

Nebraska City

[Graph showing LST (K) and NDVI over Julian Days for Nebraska City, with a curve for LST (K) and a line for NDVI.]

Concord (NE)

[Graph showing LST (K) and NDVI over Julian Days for Concord (NE), with a curve for LST (K) and a line for NDVI.]

O’Neill

[Graph showing LST (K) and NDVI over Julian Days for O’Neill, with a curve for LST (K) and a line for NDVI.]
Soil Moisture Graphs

Smithfield

York

Mead Rainfed

Mead Irrigated

Grand Island

LST-NDVI Graphs

Smithfield

York

Mead Rainfed

Mead Irrigated

Grand Island

Legend:
- ASCAT_Top
- Ground_Data_10cm
- Downscaled
2. GRASSLANDS/SHRUBS/RANGE

Soil Moisture Graphs

LST-NDVI Graphs

Arthur

Cozad

Hasley

Gordon

ASCAT_Top, Ground_Data_10cm, Downscaled
### Soil Moisture Graphs

**Higgens Ranch**

- Soil Moisture (m$^3$/m$^3$)
- Julian Days

**Holdrege**

- Soil Moisture (m$^3$/m$^3$)
- Julian Days

**Mead**

- Soil Moisture (m$^3$/m$^3$)
- Julian Days

**Merrit**

- Soil Moisture (m$^3$/m$^3$)
- Julian Days

### LST-NDVI Graphs

**Higgens Ranch**

- LST (K)
- NDVI

**Holdrege**

- LST (K)
- NDVI

**Mead**

- LST (K)
- NDVI

**Merrit**

- LST (K)
- NDVI

Legend:
- ASCAT_Top
- Ground_Data_10cm
- Downscaled
Appendix F

Soil Moisture Graphs

North Platte

ASCAT_Top  Ground_Data_10cm  Downscaled

Ord

ASCAT_Top  Ground_Data_10cm  Downscaled

Red Cloud

ASCAT_Top  Ground_Data_10cm  Downscaled

Shelton

ASCAT_Top  Ground_Data_10cm  Downscaled

LST-NDVI Graphs

North Platte

Red Cloud

Shelton

ASCAT_Top  Ground_Data_10cm  Downscaled
3. WETLAND AREA

4. RIPARIAN FOREST/WOODLAND

5. URBAN AREA