Disaggregation of Soil Moisture Measurements Using SAR and Optical Remotely Sensed Data

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by

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Abstract

There is growing interest about soil moisture (SM) estimation using remotely sensed imagery due to its large spatial coverage. Conventionally, SM measurement is carried out in small area using ground instrument in which measurement is not possible for a large area within same time frame. Estimation of SM from microwave region gives more precise result than from optical region but finer resolution microwave satellite images are costly and have coarser temporal resolution.

The main objective of this study is to adapt and evaluate downscaling cokriging technique using finer resolution optical satellite image and coarser resolution microwave image for SM estimation as they are acquired from different sensors with different properties. SM image estimated from Envisat ASAR at 180 m resolution and Land Surface Temperature (LST) from Terra ASTER at 90 meter resolution are used as inputs to obtain SM at 90 m resolution. Cokriging provides the spatial details at finer resolution optical image into the coarser resolution microwave image. The formulation of cross semivariogram between different supports is done using linear system theory. Estimation of point to point semivariance and cross semivariance between images from experimental semivariance makes it possible to predict the soil moisture or other spatial information at any spatial resolution. Downscaling cokriged products are compared with downscaling using regression equation and trivial downscaling methods. Universal Triangle method is used for SM estimation from ASTER. Similarly, for Envisat ASAR method developed by Loew (2006) is used to calculate dielectric constant ($\varepsilon$) and for inversion of $\varepsilon$ into volumetric SM equation derived for C-band by Brisco et al. (1992) is used.

Downscaling cokriging technique is applied with two convolution windows i.e. $4 \times 4$ and $6 \times 6$ on LST and ASTER soil moisture image. The performance of cokriging technique is compared to original SM estimated from ASAR at 90m resolution with simple downscaling techniques. The downscaling cokriging techniques produce lower ME and RMSE than the other two techniques. The RMSE of downscaling cokriging techniques for SM is only 0.74% volume by volume for both ASTER SM and LST as co variable. The correlation analysis shows that there is significant positive correlation ($r=0.55$ with $p<0.01$) between ASAR SM and downscaling SM image. Application of different window sizes i.e. $4 \times 4$ and $6 \times 6$ on LST for SM prediction has no effect on SM prediction. For simplicity, use of one small window size based on data requirement is enough to apply downscaling cokriging technique. Overall, the downscaling cokriging technique provides an ample opportunity to predict soil moisture or other application at finer resolution with reasonable accuracy on concerned sensor type.

Keywords: Soil moisture, Envisat ASAR, Terra ASTER, downscaling/disaggregation, cokriging, semivariance, cross semivariance, image fusion
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1. Introduction

1.1. Background

Soil moisture (SM) is an important variable that affects agricultural production and influences hydrological, ecological, and meteorological processes ranging from local land-atmosphere interaction to global water cycle. Agriculture is mainstay of developing countries, where irrigation scheduling is an important tool for optimizing the use of water resources for productive agriculture. Thus, prediction of soil moisture is crucial task for economic development of such countries.

SM is highly variable in the spatial and temporal dimensions and thus, significant amount of in situ and remote sensing research has been conducted to observe and characterize soil moisture at various spatial and temporal scales (Das and Mohanty, 2008). Gathering information on soil moisture through in situ field measurement is time consuming and expensive. Recent technological advances in remote sensing can provide a variety of techniques to estimate SM. It offers a means of measuring SM across wide areas continuously over time instead of at discrete point locations that are inherent with ground measurements (Wang, 2008). The moisture content change in soil and vegetation can leave significant signatures in remote sensing measurements.

SM is not easily measured, by comparison to atmospheric properties such as temperature, humidity, and wind speed (Santanello et al., 2007), because it varies greatly over time and space. Soil water content and its variability over space are critical inputs to agricultural management practices. In fact, various efforts have been made to utilize optical and microwave image data to monitor soil water content as well as other geophysical parameters such as soil texture, organic matter content, run-off properties and so on.

Use of microwave remotely sensed imagery emerges as a vital tool for SM estimation. SM estimation from such imagery considers various sensor parameters such as polarization and incidence angles and surface factors such as surface roughness, vegetation type, topography, and so on. Based on these factors, numerous theoretical and empirical models have been developed to retrieve surface SM information from active and passive microwave data (Baghdadi et. al, 2006; Moran et. al, 2005; Walker et al., 2004; Dubois et al., 1995; Chauhan, 1994). These models are used to estimate SM on the basis of a contrast existing between the dielectric constant values for dry and wet soils. SM estimation depends on the ability of the applied methodology to define the complex relationship that exists between the backscattered energy and the characteristics of topographic and land-cover conditions; and instrument characteristics such as angle of incidence, polarization, and frequency (Lakhankar et al., 2008).

The passive microwave sensor measures the intensity of emission in microwave spectrum (at wavelengths of 1-30 cm) from land surfaces. Its measurement is related to moisture content as dielectric constant is very sensitive to soil moisture. However, Moran et al. (2005) identified the
limitation of space-borne passive microwave measurements for SM mapping because of its coarser spatial resolution (e.g., 40 km × 40 km). Information on SM from such images is not applicable for agricultural and meso-scale watershed management (Li et al., 2008). Similarly, the information available from aircraft-based passive sensors gives limited spatial coverage and is usually expensive. The positive aspect of coarser resolution satellites images are often easier and cheaper to obtain.

It is well documented that microwave signals are sensitive to the dielectric properties, surface geometry, surface roughness and materials with which they come in contact (Tansey, 2005). There is a strong correlation between volumetric SM and Synthetic Aperture Radar (SAR) backscatter (Dobson and Ulaby, 1986). The spatial resolution of 10 m. by 10 m. is desirable to estimate SM and plant biomass, although about 100 meter by 100 meter pixel resolution still provides useful information on degree of contrast in range in moisture and vegetation condition (Li et al., 2008). The satellite systems that currently meet the spatial resolution and coverage required for agricultural management are active microwave sensors. The most common imaging active microwave configuration is the SAR such as Radarsat (8-100 m), Envisat Advanced Synthetic Aperture Radar (ASAR, 30m), ALOS Phased Array type L-band Synthetic Aperture Radar (PALSAR, 7-88 m) with swath width of 50 to 500 km, thus is applicable at local scale. If we are working for SM estimation for agriculture management, routine application is hindered by the low frequency of repeated coverage (35 days) as continuous SM data is needed for better management practices. Another problem associated with SAR data to estimate quantitative data is the presence of the speckle within the scene (Zagolski et al., 2007). Moreover, compared to passive microwave imagery, imagery from active microwave sensors is expensive to use in developing countries.

Alternatively, optical remotely sensed images can also be used to estimate SM. The reflectance from various surface as well as physical parameters is used to estimate SM from optical remotely sensed images. Wang et al., (2007) used Normalized Difference Vegetation Index (NDVI) and Land Surface Temperature (LST) calculated from Moderate Resolution Imaging Spectroradiometer (MODIS) to estimate surface SM. Similarly, Chauhan (2003) applied surface albedo along with LST and NDVI calculated from Advanced Very High Resolution Radiometer (AVHRR) for optical images and brightness temperature for microwave images to estimate SM. He used fine resolution optical image and coarser resolution microwave images and predicted SM at fine resolution that agreed reasonably with coarser resolution.

One of the better options for SM estimation will be from Terra MODIS as suggested by Wang et al. (2007), which is free source image and spatial resolution is also fine (1 km) as compared to Soil Moisture and Ocean Salinity (SMOS, ~37 km) and Advanced Microwave Scanning Radiometer-EOS (AMSR-E, ~56 km). The spatial resolution of MODIS is not sufficient to estimate SM for agriculture purpose as well as for resource management at watershed level. The problem of its spatial resolution can be solved by a disaggregation technique, which is the process of converting coarser resolution imagery to finer resolution with the help of ancillary information from fine resolution. However, the challenge results from the large discrepancy between the coarse spatial scales of available data and the fine scales of application needs (Kim and Barros, 2002).

Pardo-Igúzquiza et al. (2006) developed and applied disaggregation technique namely downscaling co-kriging in Landsat ETM+ only for general purpose, there is no specific application (for example,
land cover mapping, land surface temperature estimation and so on). They used sub-pixel information except for the spatial correlation imposed by the modelling of the set of co-variances and cross co-variances (Atkinson et al., 2008). They illustrated the efficacy of co-kriging technique to downscale image at optical region, in which they use the information of spatial variability from finer resolution image in coarser resolution to generate finer resolution image from coarser one. Cheaper satellite remote sensing technique to estimate soil moisture at finer resolution can be achieved if one can use the information of optical and microwave imagery. Thus, this study will attempt to use multi sensor imagery as inputs for downscaling co-kriging for SM estimation.

1.2. Objectives

The objective of this proposed study is to develop and evaluate downscaling co-kriging technique using finer resolution optical satellite image and coarser resolution microwave image for SM estimation.

The specific objectives of the study will be as follows:

1. Identify and apply suitable soil moisture estimation algorithm for Envisat ASAR and ASTER imagery
2. Adapt and evaluate disaggregation technique, namely downscaling co-kriging from coarser resolution satellite image for soil moisture estimation using microwave and optical imagery

1.3. Research Questions

To achieve the specific objectives, following questions are to be addressed in this research:

1. What is the relation between soil moisture with surface roughness, surface temperature and soil properties?
2. How can we validate soil moisture predicted from remotely sensed imagery against field measurements?
3. Is downscaling co-kriging technique effective for soil moisture estimation from optical and microwave imagery?
4. What is the level of accuracy of downscaling co-kriging to estimate soil moisture at finer scale?
5. Which method is more appropriate to estimate soil moisture that is disaggregating first and estimate soil moisture or the other way around?

1.4. Thesis Structure

The thesis consists of seven chapters. The rationale behind the study, existing problems in soil moisture estimation with objective and sub-objectives are provided in chapter 1. Chapter 2 reviews the influence of various parameters those affect the estimation of SM from microwave and optical imagery. The review of SM estimation methods from different microwave and optical images is also covered in this chapter. Information about Eagle campaign and data description that are used in this
study is provided in Chapter 3. Similarly, Chapter 4 gives insight of methods adopted for SM estimation from optical and microwave imagery and downscaling or disaggregation technique. Chapter 5 shows the result coming from application of method applied, its analysis and thorough discussion of research findings with supportive documents. Finally, Chapter 6 summarizes the results from previous chapters, gives limitations and directions for further study. Chapter 7 provides the reference of literature used for this study.
2. Literature Review

SM is an important parameter for many natural resource applications such as hydrological modelling, stream flow forecasting, and flood forecasting. SM is a measure of liquid water occupying in the pore spaces between soil particles in relation to the amount of soil, which can be defined in the following ways:

- Gravimetric water content: ratio of the weight of water to the weight of dry soil;
- Volumetric water content: ratio of the volume of water to the volume of soil; and
- Degree of saturation: the ratio of the amount of water currently in the soil to amount of water that would be in the soil if the soil were completely saturated.

Near surface SM can be estimated using satellite images with reasonable accuracy and volumetric water content is usually derived from Remote Sensing (RS) imagery. Images from both optical as well as from microwave radiometer can be used to estimate SM and various parameters influence the accuracy of estimation of SM.

This chapter attempts to review the influence of these parameters and SM estimation methods from microwave as well as optical sensors.

2.1. Parameters for SM Estimation from Radar

Active microwave remote sensing for SM estimation is based on differences in the electromagnetic dielectric properties between dry and wet soils. An electromagnetic signal produced by satellite is propagated through space to the target, and is partially reflected back to sensor. The sensor records the phase and amplitude of the return signal. Backscatter cross section refers to the strength of the signal reflected by the target and scattered back to the radar sensor, which is measured in term of $\sigma$ (sigma), usually expressed in decibels (dB). Elachi (1988) defined backscatter cross section as “the ratio of the energy received by the sensor over the energy that the sensor would have received if the surface scattered the energy incident on in an isotropic fashion”. Backscatter cross section of a target can be viewed as a comparison of the strength of the reflected signal from a target to the reflected signal from a perfectly smooth metal sphere of cross section area. These expected returns are derived during sensor calibration. Backscatter cross section in decibels can be calculated by:

$$\sigma = 10 \log \left[ \text{energy ratio} \right]$$

The backscattering coefficient ($\sigma\$, sigma naught) is the amount of radar cross section per unit area on the ground (Jensen, 2000) corrected by calibration constant. Characteristic backscatter coefficients of different surfaces depend on wavelengths, incidence angle and polarization characteristics of sensor. In addition, the amount of SM influences the return signal by affecting the amplitude of the backscatter coefficient (Tansey, 2005). Backscattering on an active microwave image is influenced by
sensor parameters and target or surface parameters, which makes SM estimation from radar complicated.

### 2.1.1. Sensor parameters

Radar systems can be active or passive. Passive radar systems sense microwave radiation emitted by all objects in the natural environment (CCRS, 2008). Active radar systems transmit short pulses of electromagnetic energy in the direction of target and record strength of the backscatter received from objects within the system's field of view. Active microwave systems use its own energy source and have advantage to estimate SM over passive one as it

- can penetrate cloud cover due to these use their own energy,
- have fine spatial resolution and
- strong function of dielectric constant

The characteristics of the active microwave radar instruments are critical along with parameters in determining the strength and direction of scattering from the soil. Radar sensors are defined by three characteristics viz. frequency (or wavelength), polarization and incidence angle. These parameters have influenced on estimation of SM from active microwave systems, descriptions of which are given below:

#### 2.1.1.1. Wave length and frequency

Most of the imaging radar systems operate on single band that is defined either by wavelength or frequency. There is unique relationship between wavelength and frequency, which is given as:

$$ c = \lambda \cdot \nu $$

(2)

Where,

- $c$ = speed of light (299,790,000 $\approx$ 3 x $10^8$ m/s)
- $\lambda$ = wavelength in meter (m)
- $\nu$ = the frequency in hertz (Hz)

<table>
<thead>
<tr>
<th>Bands</th>
<th>P</th>
<th>L</th>
<th>S</th>
<th>C</th>
<th>X</th>
<th>K</th>
</tr>
</thead>
<tbody>
<tr>
<td>Frequency (GHz)</td>
<td>0.220-0.39</td>
<td>1-2</td>
<td>2-4</td>
<td>4-8</td>
<td>8-12</td>
<td>12-40</td>
</tr>
<tr>
<td>Wavelength (cm)</td>
<td>77-136</td>
<td>15-30</td>
<td>15-7.5</td>
<td>3.75-7.5</td>
<td>2.5-3.75</td>
<td>0.75-2.5</td>
</tr>
</tbody>
</table>

The relation between wavelength of different bands and their frequency are given in Table 2-1. The penetration depth of a radar signal in soil and vegetation cover is proportional to the wavelength of the signal and inversely proportional to the moisture content of soil. Longer wavelengths can penetrate more into the soil and thus respond to moisture conditions over a deeper volume. These longer wavelengths are also able to penetrate through a vegetation canopy and provide more direct information on the soil conditions under vegetation. For moist soil, the penetration depth is approximately equal to the wavelength of the signal; therefore, radar platforms are only capable of
detecting SM in the top layer of soil (5-20 cm depending on signal wavelength). For C-band SAR instruments, such as ERS-1 and RADARSAT, the penetration depth for moist soil is less than 5 cm (Ulaby et al., 1986).

The contribution of surface roughness to backscatter also depends on the radar wavelength. The effect of roughness on backscattering is reduced as wavelength increases. Thus, C-band or L-band images are highly preferred for SM estimation (Martin et al., 1989; Dobson and Ulaby, 1986). At these longer wavelengths, most surfaces will appear to have a similar roughness; thereby effect on roughness is less important for SM estimation.

2.1.1.2. Incidence angle (θ)

Incidence angle describes the relationship between radar illuminations to the ground surface. It is the angle between the radar beam and a target object (Figure 2-1). The variation of incidence angle is directly related with the flying height of sensor platform and helps to determine the appearance of a target on an image. Incidence angle affects the relative contribution of each surface characteristic to radar backscatter. Moreover, various land covers such as trees, rivers, buildings, other structures can create changes in the local incidence angle, which may cause variations in pixel brightness (Figure 2-2). Local incidence angle account the topographical variation in the terrain. Satellite incidence angles vary less than airborne incidence angles due to their greater altitude and produce more uniform illumination on satellite images than airborne radar images (CCRS, 2008).
Figure 2-2 Local incidence angle influence on pixel brightness (CCRS, 2008)

Figure 2-3 illustrates the importance of the incidence angle on total backscattering due to vegetation canopy from that of the underlying soil. Each curve represents the simulated response, with C-band VV polarisation, of a soybean canopy for varying gravimetric SM ranging from 20% to 30%. Whilst the backscatter at 20° incidence angle is still sensitive to underlying soil conditions, that at 40° is stable and invariant with respect to SM (ESA, 2007).

Figure 2-3 Relation between Incidence angle and backscattering coefficient (dB) (adopted from ESA, 2007, Figure 1.36)
When incidence angle is small (less than 30°), the greatest contribution to the signal is from SM. On the other hand, the contribution from soil roughness and vegetation dominate the signal at larger angles. For example, Ulaby et al. (1986) suggested that an incidence angle value between 10° ad 20° would be optimal for SM estimation in C-band signal, which produces the highest correlation between radar backscatter and SM. Thus, use of incidence angle is one option that can be used to minimize the contributions of both surface roughness and vegetation to radar return for estimating soil water. Similarly, study of Martin et al., (1989) showed that viewing angles of 30° and 45° also produced strong correlations with SM measurements of a tall-grass prairie in C-band radar signal.

2.1.1.3. Polarization

The polarization indicates the orientation of the electric field vector in a reference plane perpendicular to the direction of wave propagation as a function of time. A radar system can work in different polarization mode. Backscatter power received by the radar can be calculated for any combination of polarizations such as VV, HH, VH or HV of the transmitting or receiving antennas, where first letter represent the transmitted energy and second refers to the received energy.

The polarization of the transmitted microwave signal also influences which components of the crop and soil contribute to the total amount of energy scattered back to the radar sensor. Vertically polarized microwaves interact with the predominant vertical structure of the most crops and as a result, the microwave signal is attenuated to a greater extent. Thus, crops like wheat tend to appear darker on the image. Corn leaves appear much brighter on the image because leaves are large relative to the wavelength and is more randomly oriented. Horizontally (H) polarized microwaves are not as easily attenuated and therefore these microwaves tend to penetrate the crop canopy to a greater extent. As a result, more information is provided about the underlying soil condition when a horizontal polarization is used (McNairn et al., 2002).

For retrieval of SM studies of bare soil, different polarization modes are used to improve the inversion into soil parameters. Cross polarizations provide an important improvement for SM retrieval since the radar backscatter is less sensitive to surface roughness, row direction (ESA, 1998). However, Brisco et al. (1992) suggested that the co- and cross polarization ratios were not as effective for SM estimation as the data in HH or VV polarizations; although they have been used successfully elsewhere to help reducing the impacts of soil roughness and vegetation for data acquired at shallower incidence angles. Thus, cross polarization image has indirect effect on SM estimation by reducing the effect of surface roughness.

2.1.2. Surface parameters

The most important surface parameters for extracting accurate SM estimates from microwave data are the dielectric constant, the surface geometry of the soil (random roughness related to tillage, soil aggregation and weathering; tillage row direction; and micro-topography), the vegetation characteristics and other soil properties such as texture and bulk density (Dobson and Ulaby, 1986).
2.1.2.1. Dielectric constant

Microwave techniques for estimation of SM rely on clear distinction between dielectric properties of water and those of the soil particles (Walker et al., 2004). Dielectric constant ($\varepsilon$) is highly dependent on SM content (due to the large difference in dielectric property of dry soil i.e. 2-3 and water i.e. approximately 80) and to a smaller degree by soil composition. Thus, the dielectric constant of the target increases in proportion to moisture content in soil increases.

Soil is composed of soil matrix, air and water (Brady and Weil, 2001). Water in soil is either bounded with soil matrix or free in pore space. Free water has the highest dielectric properties as water molecules are free to rotate at microwave frequencies, while water molecules those adsorbed by soil particle are immobilized and have therefore lower dielectric properties. The clay particles have high specific surface per unit area providing immense adsorption capacity. Similarly, silt has intermediate adsorption capacity, whilst sand has less specific surface thereby the lowest adsorption capacity. The specific surface area of different soil texture is given in Figure 2-4. The dielectric constant, thus, depends on soil texture.

The dielectric constant also determines how deep the microwaves penetrate into the soil. When the soil is moist, radar return is primarily from a shallow depth of about 0-5cm for L-band (Jackson and Schmugge, 1989) and this penetration depth range depends on degree of wetness of soil. But as a general rule, radars are sensitive to soil water to a depth approximately equal to the wavelength of the applied microwave signal (Boisvert et al., 1995). Moreover, the radar signal becomes less sensitive to SM when soil is very wet having moisture contents larger than 35% by volume (Bruckler et al., 1988).
2.1.2.2. Surface roughness

Surface roughness is the most limiting factor for estimation of SM from active microwave (Wang et al., 1987) and is equal to or greater than the effect of SM on backscatter (Engman and Chauhan, 1995). Two fundamental parameters commonly used to characterize surface roughness are standard deviation of roughness and the surface correlation length \( l \). The standard deviation of surface height \( s \) represents the root mean square surface variations with respect to a mean surface. Thus, it is also termed the Root Mean Square (RMS) height of the surface. The surface correlation length \( l \) is defined as the displacement perpendicular to or along the sensor look direction for which the normalized autocorrelation function \( e^l \). For most surfaces, the autocorrelation function can be approximated as exponential or Gaussian. The correlation length is a measure of statistical independence of two points on the surface. For a given frequency, a surface with higher RMS height appears rougher than a surface with lower RMS height. For the extreme case of a perfectly smooth surface, \( l = 1 \) and \( s = 0 \) (Narayanan and Hirsave, 2001).

2.1.2.3. Vegetation

Soil moisture estimation from radar backscatter is simple when the soil is bare. For surfaces with significant vegetation cover, microwaves transmitted by the radar will interact with the vegetation cover. The microwaves are scattered and attenuated by the vegetation, therefore, the strength of the signal reaching the soil surface is reduced. Moreover, the energy scattered back towards the sensor is a combination of scattering directly from the vegetation canopy and directly from the soil, as well as multiple scattering that results from the signal interacting with both the soil and the canopy. Estimating soil water content under a vegetation canopy is difficult and requires separating the contribution of the soil itself, from that of the vegetation (McNairn et al., 2002).

2.2. SM Estimation Algorithm from Microwave SAR

The detection of SM using active microwave has been an active area of research for last few decades (Ulaby et al., 1986). There are various techniques developed for SM estimation using microwave images, choice of which depends on available band, polarization, amount of in situ field observation, land cover type and incidence angle. Most efforts to estimate soil water from radar backscatter are based on one of three modelling approaches.

2.2.1. Statistical/empirical method

The statistical or empirical methods are the simplest, and probably the most widely used approach. These methods need huge amount of SM observation data from the target field from which relation between SM against surface backscatter is developed. For active microwave, sample sites are located on the image and backscatter values for each site are taken directly from the image and estimate regression coefficients. Based on the radar backscatter, this regression model can be inverted to predict SM across the entire image.

Several studies had been carried out based on empirical approach for both airborne and satellite sensors. For example, Loew (2006) reported a significant correlation between Envisat ASAR C-VV
backscatter and water content with R value 0.92, 0.90, 0.88, 0.81, and 0.84 for grassland, bare soil, cereals, harvested field and root crops, respectively with different regression coefficient for each land cover type. The relationship given by Loew (2006) is based on an extensive empirical database from two test sites in Germany 1992 to 1997. The investigations were made on fields with different surface roughness conditions. The resulting relationship between the dielectric constant and the backscattering coefficient is therefore considered to represent the mean surface roughness of a given land-use type. Boisvert et al. (1996) observed similar results using Earth Resource Satellite-1 (ERS-1) imagery.

Empirical approach is the most common one used for SM estimation; though several limitations are associated with it. The SM measurements taken in the field to establish the regression model usually represent only point field observation (usually area of core ring) compared to pixel size. Integration of field measurement with radar backscatter values of pixel resolution of the sensor imposes the difference in scale between the ground measurements and the radar imagery introduces errors in the regression model. The regression model developed is site specific, thus can be used in particular area. Therefore, large errors can occur when a model developed for one test site is applied to other regions, particularly when soil texture varies across the region of interest (McNairn, 2002).

2.2.2. Theoretical/physical method

Physical methods are directly related to radar instruments and classified based on the surface roughness of their validity. Several physical models have been developed to characterize backscatter response from soil. The most common models include the small perturbation model (SPM), physical optics and geometrical optics model. The physical optics model is used on relatively smooth surfaces, and SMP is used in slightly rough surfaces whereas geometric optics model is used on relatively rough surfaces (Ramnath, 2003).

These physical models are well suited for investigating backscatter responses from soil as a function of radar configuration, and for exploring the sensitivity of backscatter to target characteristics. However, physical models are complex and are either difficult or impossible to invert (Oh et al., 1992). Thus, Oh et al. (1992) questioned on the performance of these models when comparing backscatter derived from these models to measured backscatter.

2.2.3. Semi-empirical method

Semi-empirical model is a combination of both empirical and physical approaches. In this approach, large number of roughness and soil water observations from the target field along with incidence angle and polarization information from radar is used to retrieve SM.

One of the widely used semi-empirical models was developed by Oh et al. (1994) based on theoretical backscattering models (SPM and Kirchhoff model) along with large experimental data. The authors used L, C, and X band spectrometer data with incidence angle range from 10° to 70° for their study. They used experimental data to determine unknown constants.
The Dubois and co-workers developed a model using Scatterometer data. The model optimized for bare and sparse vegetated surfaces and has frequency validity between 1.5 and 11 GHz. The mathematical expression for the two co-polarized channels is expressed below:

\[
\sigma_{hh}^0 = 10^{-2.75} (\cos^{1.5} \theta / \sin^2 \theta) 10^{0.28 \varepsilon \tan \theta} (k h \sin \theta)^{1.4} \lambda^{0.7} \\
\sigma_{vv}^0 = 10^{-2.37} (\cos^{3} \theta / \sin^3 \theta) 10^{0.046 \varepsilon \tan \theta} (k h \sin \theta)^{1.1} \lambda^{0.7}
\]

(3)

(4)

Where, \(\sigma_{hh}^0\) and \(\sigma_{vv}^0\) are the backscattering coefficient, \(\theta\) is the incidence angle, \(\varepsilon\) is the real part of the dielectric constant in decibels, \(h\) is the RMS height of the surface (cm), \(k\) is the wave number and \(\lambda\) is the wavelength in cm. The model is comparatively easier to invert for parameter estimation than the mathematically complex models. If both \(\sigma_{hh}^0\) and \(\sigma_{vv}^0\) are known, then Eqs. (3) and (4) can be solved simultaneously for \(h\) and \(\varepsilon\). The general backscattering behaviour with surface roughness given by Eqs. (3) and (4) is similar to that predicted by the small perturbation model (SPM) and physical optics model (Ulaby et al., 1986). In the above expressions, the RMS height of the surfaces is introduced via the \(kh \sin \theta\) factor which is a dimensionless form of the projected roughness on the wave incident plane.

Dubios model gives best results for \(kh \leq 2.5\), \(\theta \leq 30^o\) and when the volumetric SM is less than 35%. The algorithm has been successfully applied to areas with NDVI<0.4 when using L-band data (Dubois et al., 1995).

### 2.3. Parameters for SM Estimation from Optical Image

Remote sensing of SM estimation using the optical/IR spectrum with wavelengths between 0.4 and 2.5 \(\mu\)m measures the reflected radiation of the sun from the Earth’s surface, known as albedo (Sadeghi et al., 1984). Soil albedo is defined as the ratio of reflected to incoming radiation and has been influenced by SM along with numerous other factors.

There are some physical models to link soil biophysical and geophysical parameters with sensor measurements in optical/IR region. Vegetation and land surface temperature directly depend on SM. Gillies et al. (1997) showed that there is a unique relationship among SM, the normalized difference vegetation index, and the land surface temperature.

#### 2.3.1. Normalized Difference Vegetation Index

The Normalized Difference Vegetation Index (NDVI) is a numerical indicator that can be used to analyze remote sensing measurements from air or space platform to assess whether the target being observed contains live green vegetation and calculated as:

\[
NDVI = (NIR - RED)/(NIR + RED)
\]

(5)
Where,
RED = spectral reflectance in the red band
NIR = spectral reflectance in the near-infrared band

NDVI measurement is the ratios of the reflected radiation over the incoming radiation in each spectral band individually and hence they take on values between -1.0 and 1.0. Healthy vegetation absorbs most of the incident radiation in the visible range, and reflects a large portion of the near-infrared light and reaches near to 1. Similarly, unhealthy or sparse vegetation reflects more visible light and less near-infrared region (NASA, 2008).

2.3.2. Land Surface Temperature
Land Surface Temperature (LST) is a key parameter for many remote-sensing applications, which can be determined by measuring the radiation emitted by the surface landscape including the top of the canopy for vegetated surfaces as well as other surfaces such as bare soils, ice cover, etc. This radiation will be converted into brightness temperature using the inverse of Planck’s radiation equation. Planck’s law is based on blackbody. Unfortunately, natural objects do not behave like a blackbody and land surfaces have emissivity less than 1.

The radiation measured by the satellite also includes radiation emitted by the atmosphere and radiation reflected by the land surface. Gases and suspended particles in the atmosphere may absorb radiation emitted from objects, resulting in a decrease in the energy reaching a thermal sensor (Batatia and Bessaih, 1997). Ground objects appear colder on radar sensor due to atmospheric absorption and scattering. Thus, conversion of thermal emission into LST is difficult task and requires complicated mathematics. For this reason, measurements are usually made in two atmospheric absorption free regions of the electromagnetic spectrum lying between 3.5 mm to 3.9 mm and 10 mm to 13 mm (Batatia and Bessaih, 1997). LST can be measured either by using radiative transfer model or by using presently established atmospheric and emissivity algorithms.

Information of LST can be applied on variety of purposes. It can be applied for water and energy balance modelling (Griend et al., 1993), monitoring on vegetation health (Karnieli et al., 2006), SM estimation (Chauhan, 2003) etc.

2.4. SM Estimation Algorithm from Optical/IR Images
Optical/IR techniques can provide a means for SM estimation, despite the difficulty in separation of signatures from soil type and SM. Vegetation and land surface temperature have a close dependency on SM. Schematic description of the relationship between LST and NDVI is sometimes referred to as the “Universal Triangle” (Figure 2-5), where SM varies from low value in right to high value in left side in the triangle (Chauhan, 2003). The abscissa and the ordinate are satellite SM estimation appropriately scaled versions of temperature and NDVI, respectively such that:

\[ T^* = \frac{(T - T_o)}{(T_s - T_o)} \]

(6)
\[ N^* = \frac{(NDVI - NDVΙ_o)}{(NDVΙ_s - NDVΙ_o)} \]  \hspace{1cm} (7)

Where,
\( T \) = observed soil temperature
\( T_o \) = minimum soil temperature values over area
\( T_s \) = maximum soil temperature values over area
\( NDVI \) = observed NDVI
\( NDVΙ_o \) = minimum NDVI value over study area
\( NDVΙ_s \) = maximum NDVI value over study area

The idea behind the triangle is that the vegetation radiometric temperature is always close to air temperature, but that the surface radiant temperature of bare soil varies depending on the soil water content. This implies that the spatial variation in surface radiant temperature will be small (except for emission from underlying bare soil) over a full vegetation but will vary from warm to cold surface moisture availability ranges from zero to one for bare soil (URL 1).

Carlson (1994) established the relation among SM (\( M_v \)), \( LST^* \) (or \( T^* \)) and \( NDVI^* \), which can be expressed in a regression model as:

\[ M_v = \sum_{i=0}^{n} \sum_{j=0}^{n} a_{ij} \cdot NDVI^{*i} \cdot T^{*j} \]  \hspace{1cm} (8)

In terms of second order polynomial, Eq. (8) can be expanded (Chauhan, 2003) as:

\[ M_v = a_{00} + a_{10}NDVI^* + a_{20}NDVI^{*2} + a_{01}T^* + a_{02}T^{*2} + a_{11}NDVI^*T^* + a_{22}NDVI^{*2}T^{*2} + a_{12}NDVI^*T^{*2} + a_{21}NDVI^{*2}T^* \]  \hspace{1cm} (9)
Figure 2-5 Schematic relationship between SM temperature and NDVI (Universal Triangle)

2.5. Disaggregation/Downscaling of Images

2.5.1. Introduction

As mentioned in previous section SM can be estimated from remotely sensed imagery. There is always a question; what should be the level of spatial and temporal resolution needed for SM estimation in field level. This is very crucial question as SM varies greatly over time and over space and time. The choice of spatial as well as temporal resolution depends on the application. If we are talking about economic agricultural production or for meso-scale watershed management task, finer spatial resolution estimation is needed so far as possible. Li et al. (2008) suggested the spatial resolution of 10 m by 10m is desirable to estimate SM and vegetation, although about 100 m by 100 m pixel resolution still provides useful information on degree of contrast in range in moisture and vegetation condition for such condition. Similarly, Townshend & Justice (1988) showed that for a wide variety of landscapes, pixel resolutions on the order of 100 m are required to monitor land use/land cover changes. However, the challenge results from the discrepancy between the coarse spatial scales of available data and the fine scales of application needs (Kim and Barros, 2002).

Moran et al. (2005) identified the limitation of space-borne microwave measurements for SM mapping as the spatial resolution is inherently coarse. Similarly, the information available from aircraft-based passive sensors gives limited spatial coverage and is expensive. The positive aspect of coarser resolution satellites images are often easier and cheaper to obtain. However, information on SM from such images is coarse (e.g., 40 km × 40 km) and is not applicable for agricultural management.

The satellite systems that currently meet the spatial resolution and coverage required for agricultural management are active microwave sensors. The configuration of most common active microwave SAR is given in Table 2-2. The radar system such as Radarsat (8-100 m), Envisat ASAR (30m) and
ALOS PALSAR (7-88 m) with swath width of 20 to 360 km is, thus applicable in local scale. If we are working for SM estimation for agriculture management, routine application is hindered by the low frequency of repeated coverage (35 days) as continuous SM data is needed for better management practices. Another problem associated with SAR data to estimate quantitative data is the presence of the speckle within the scene. Moreover, compared to passive microwave imagery, imagery from active microwave sensors is expensive to use in developing countries.

Table 2-2 The configuration of most common active microwave and optical sensors

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Platform (Altitude)</th>
<th>Spatial Resolution</th>
<th>Temporal Resolution</th>
<th>Swath</th>
<th>Wave Bands/ Band width</th>
</tr>
</thead>
<tbody>
<tr>
<td>Envisat ASAR</td>
<td>Space borne (786.18 km)</td>
<td>30m-2km</td>
<td>35 days</td>
<td>56-400 km</td>
<td>C</td>
</tr>
<tr>
<td>Radarsat-1</td>
<td>Space borne (793-821 km)</td>
<td>8-100m</td>
<td>24 days</td>
<td>45-500 km</td>
<td>5.3 GHz</td>
</tr>
<tr>
<td>Radarsat-2</td>
<td>Space borne (798 km)</td>
<td>3-100m</td>
<td>24 days</td>
<td>20-500 km</td>
<td>C</td>
</tr>
<tr>
<td>ALOS Palsar</td>
<td>Space borne (691.65 km)</td>
<td>7-88m</td>
<td>46 days</td>
<td>20-360 km</td>
<td>5.405 GHz</td>
</tr>
<tr>
<td>SMOS*</td>
<td>Space borne (763 km)</td>
<td>35 km</td>
<td>2-3 days</td>
<td>1000-3000km</td>
<td>L</td>
</tr>
<tr>
<td>LANDSAT 5TM</td>
<td>Space borne (705.3 km)</td>
<td>15-60m</td>
<td>16 days</td>
<td>170-183 km</td>
<td>7 Bands</td>
</tr>
<tr>
<td>TERRA ASTER</td>
<td>Space borne (705 km)</td>
<td>15-90m</td>
<td>16 days</td>
<td>60 km</td>
<td>15 Bands</td>
</tr>
<tr>
<td>TERRA MODIS</td>
<td>Space borne (705 km)</td>
<td>250-1000m</td>
<td>1-2 days</td>
<td>2330 km</td>
<td>36 Bands</td>
</tr>
</tbody>
</table>

Note: 1ESA, 2007, 2URL2, 3URL3, 4ERSDAC, 2006, 5URL5, 6URL6, 7URL6, 8URL7

One of the better options for SM estimation will be from Terra MODIS as suggested by Wang et al. (2007), which is free source and spatial resolution is also finer (1 km) as compared to SMOS (37 km) and AMSR-E (56 km). Synergetic use of SMOS with coarse spatial resolution and MODIS with finer resolution is better opt for developing as both are economic thus can easily be used to estimate SM at finer scale. The problem of their spatial resolution can be solved by **disaggregation/downscaling technique**, which is the process of converting coarser resolution imagery to finer resolution with the help of ancillary information from fine resolution.

### 2.5.2. Disaggregation techniques

There are various disaggregation methods available to estimate SM from radar or from optical imagery. Some of the examples are Regression predictor (Price, 1999; Loew and Mauser 2008), wavelet transform and multiscale Kalman filter (Simone et al., 2002), fractal interpolation (Kim and Barros 2002), multiresolution wavelet analysis (Nuñez et al., 1999; Das and Mohanty, 2006), downscaling cokriging (Pardo-Igúzqui et al., 2006; Pardo-Igúzqui and Atkinson 2007), Vector
Machine (SMV)-based assimilation (Kahiel et al., 2008), and deterministic approach (Merlin et al. 2008).

Kim and Barros (2002) presented fractal interpolation for downscaling with providing unique fractal surface for soil, vegetation and terrain data. They applied linear combinations of spatial distributions of ancillary data as scaling function. They disaggregated 10 km to 825 m spatial resolution and found the method had significant contribution to produce SM at finer spatial resolutions.

Das and Mohanty in 2006 worked on polarimetric scanning radiometer (PSR) at 800 m x 800 m resolution data. They applied wavelet-based multi-resolution technique to decompose the SM into large-scale mean SM fields and fluctuations in horizontal, diagonal, and vertical directions at hierarchical spatial resolutions i.e. from 6400 m x 6400 m to 800 m x 800 m. Results suggested that the wet fields show almost similar variance for all the resolutions signifying the strong spatial correlation. However, the dry soil exhibit a log-log linearity of moments with various scales, and the slopes of these relationships exhibit a concave functional form with the order of moments, typically representing a multi-scaling process.

Loew and Mauser (2008) applied linear regression model on passive microwave SMOS with using prior information about spatial and temporal persistent SM fields for the disaggregation of coarse-scale SM data, assuming SM dynamics are driven by meteorological forcing at scales on the order of tens of kilometers. They found high correlations for a linear regression model relating fine (1 km) and coarse-scale (37 km) SM data. Some differences are identified as due to different land-cover types, soil conditions, and local topography.

Recently, a new efficient technique for downscaling SM data has been devised by Kahiel et al. (2008). They fused the information from point measurements using Support Vector Machine (SMV)-based assimilation process that greatly improved the capability of the model to reproduce the coarse-scale behaviour at the finest scale. They downscaled airborne 800 m x 800 m resolution image to 50 m x 50m resolution and the correlation coefficient before and after downscaling was highly significant ($R^2=0.91$).

All the above mentioned downscaling methods were applied on microwave images. Some works on optical/IR and microwave synergistic approaches have also been developed. Among them, the work of Chauhan et al. (2003) was drawn the most attention in this field. They used AVHRR (~1 km) data as a finer resolution and Spatial Sensor Microwave Imager (SSM/I, ~25km) as coarser resolution. An error budget analysis performed on the estimation procedure shows that the root mean square error in the estimation of SM is of the order of 5%. Predicted SM results at fine resolution agree reasonably well with coarse resolution. Similarly, Merlin et al. (2008) developed deterministic approach on SMOS and MODIS using National Airborne Field Experiment 2006 (NAFE’06) as optical and microwave synergistic approach. They developed four different downscaling relationship and overall root mean square difference between downscaled and observed SM value varied between 1.4% volume by volume (v/v) and 1.8% v/v depending on the downscaling algorithm used.

Similarly, Pardo-Igúzquiza et al. (2006) developed and applied disaggregation technique namely downscaling co-kriging in Landsat ETM+ only for general purpose, there is no specific application
(for example, land cover mapping, land surface temperature estimation and so on). They used sub-pixel information except for the spatial correlation imposed by the modelling of the set of co-variances and cross co-variances (Atkinson et al., 2008).

Cokriging is a multivariate geostatistical spatial predictor, which may be of use in image processing problems like spatial resolution. It has solid statistical foundation (Atkinson et al., 2008). Pardo-Igúzquiza et al. (2006) advocated the advantages of downscaling cokriging technique over other image fusion techniques as “cokriging provides an unbiased prediction with minimum prediction variance and takes into account i. the support effect (pixel size), ii. the form of point spread function of the sensor, iii. the spatial correlation within an image, and iv. the cross-correlation between images.”

Downscaling cokriging explicitly takes into account pixel sizes, correlations, cross-correlations and the point spread function of the sensor. In addition, downscaling cokriging can incorporate information provided by ancillary and sparse experimental data (Pardo-Igúzquiza and Atkinson, 2007). For increasing the spatial resolution of remote sensing images the downscaling cokriging procedure requires the definition of covariance and cross-covariance that are not accessible experimentally, and the linear model of co-regionalization (LMC) to empirical data was used to solve this problem. It is based on area-to-point kriging used by Kyriakidis and Yoo (2005) which considers the problem of predicting from areal supports to points, where they only apply univariate case. One of the major advantages of this method is to induce point support variogram model from which one can downscaled image at desired resolution based on resolution of co variable.

This study will attempt to use multi-sensor imagery as inputs for downscaling co-kriging to estimate SM.
3. Study Area and Data Descriptions

To apply downscaling cokriging technique to estimate soil moisture from optical and microwave imagery for SM estimation, it is necessary to gather satellite observation data along with field measurements for validation of techniques used. Acquisition of remotely sensed data at various spatial resolutions combined with real-time ground truth SM measurement is a difficult task. There are numbers of SM campaigns, which gather huge amount of such datasets. SM campaign data is available to those who are interested to study or develop new technique in relation to SM and these campaigns provide all necessary data that is needed. Thus, data from Eagle Campaign have been used for this study purpose and details of this campaign and data are provided in this chapter.

3.1. Eagle Campaign

EAGLE 2006, Netherlands is a multi-purp ose, multi-angle and multi-sensor, in situ, airborne and space borne campaigns over grassland and forest. The campaign was carried out to generate database for the understanding of bio-geophysical parameter retrieval from optical and SAR data as well as the direct modelling of the underlying physical processes in forests and grassland by supplying appropriate observation data. In EAGLE 2006 an intensive field campaign was carried out using different airborne sensors for an optical imaging sensor, an imaging microwave radiometer, and a flux airplane - for data acquisition and to collect extensive ground measurements simultaneously over one grassland (Cabauw) and two forest sites (Loobos & Speulderbos), in addition to acquisition of multi-angle and multi-sensor satellite data. The datasets are both unique and urgently needed for the development and validation of models and inversion algorithms for quantitative surface parameter estimation and process studies (Su et al., 2009).

3.2. Study area

The data from Cabauw grassland area is chosen for this study as it resembled agricultural landscape (Figure 3-1). Cabauw grassland area is situated approximately at the central western part of the Netherlands, nearly the village of Cabauw and geographically it lies on 51°58’00”N and 04°54’00”E.

3.2.1. Climate and soil

Cabauw grassland falls in humid, temperate climate with average annual temperature approximately 10°C and annual precipitation is approximately 750 mm. The vegetation cover at Cabauw is close to 100% all year round. Even in winter, after mowing or after a dry spell it is unusual to see any bare soil (Timmermans et al., 2008). Soil composition is fairly heavy clay in top 18 cm depth having turf zone (0-3 cm) and 35% - 50% clay with 8% - 12% organic matter content (Jager et al., 1979 as referred by Beljaars and Bosveld, 1997). The surface minimum, maximum and average temperature and precipitation for first fortnight of June 2005 at Cabauw grassland is given in Figure 3-2.
The soil of Cabauw grassland is fine grained with high organic matter content and water holding capacity of the soil at the site is also high. The ground water level in the whole catchment area is artificially managed through narrow, parallel ditches spaced 40 m apart from each other. The water level in the ditches is always kept at 40 cm below the surface level maintaining the level of the ground water table near the surface. Due to the rich supply of water and the fine grained soil, the evaporative fraction rarely falls below 0.6 (Timmermans et al., 2008).
3.2.2. Data used

3.2.2.1. Field observation data
SM was measured in the field for calibration and validation of SM measurements through remotely sensed data. The measurements took place during the entire day on 8, 12, 13, 14, and 15th of June 2006. Due to limitation of acquisition time of remotely sensed data, measurements on 8th June were used in this study. In 8th June SM, the time measurements were taken during 14:48 to 17:12. SM measurements were carried-out using the Hydra Probe (Stevens Water Monitoring Systems Inc.). More information on Hydra Probe and SM measurement procedure is available on URL 8. The points of measurements were distributed in the four fields and marked with numbered sticks to repeat the measurements in the same position every time. The exact locations of the points were taken via the GPS station to reference them to the satellite images.

3.2.2.2. Satellite data
The Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) image acquired on June 8 at 10:44:29 am has been used as optical images. The ASTER is an advanced multispectral imager that was launched on board NASA’s Terra spacecraft in December, 1999. ASTER covers a wide spectral region from visible to the thermal infrared region.

The ASTER products used for this study are Level 1B (AST09: at-surface radiance in the VNIR and SWIR regions) to derive NDVI and Level 2 (AST08: land surface temperature obtained with the TES algorithm). The spatial resolution of AST09 for band 1-3 is 15 m. Similarly, AST08 product has 90 m spatial resolution. These data were used to derive scaled NDVI and LST, respectively for SM estimation using universal triangle.

Envisat ASAR APP product is selected for microwave image. The Advanced SAR (ASAR) sensor on board of the Envisat platform operates at C-band (5.3 GHz), which built up on the experience gained with the ERS-1/2 active microwave instrument (AMI) to continue and extend Earth observation with SAR. In Alternating Polarization Precision mode (APP), transmit and receive polarization can be selected allowing scenes to be imaged simultaneously in two polarizations (ESA, 2007). Details of acquisition of ASAR image are given in Table 3-1.

<table>
<thead>
<tr>
<th>Table 3-1 Details of acquisition of ASAR image</th>
</tr>
</thead>
<tbody>
<tr>
<td>Orbit</td>
</tr>
<tr>
<td>-------</td>
</tr>
<tr>
<td>22356</td>
</tr>
</tbody>
</table>
4. Methods

This chapter covers the method for data processing; algorithms used for SM estimation from optical as well as microwave imagery and application of downscaling cokriging technique for disaggregation of coarser resolution to finer spatial resolution.

4.1. SM Estimation from Optical Imagery

The ASTER images have been used as optical image to derive scaled NDVI and LST, respectively for SM estimation using universal triangle. The steps of which are given as:

1. The ASTER data acquired through Eagle Campaign were initially in EOS HDF (Hierarchical Data Format). Those are imported to ERDAS Imagine as IMG format.

2. Double Stereographic projection is applied (Spheroid: Bassel, Datum: Amersfoort-1; Dutch Coordinate System) for geometric correction of the ASTER data product L1B (AST09) with Root Mean Square Error (RMSE) 0.407 meter. For geometric correction, the digital topographic maps (Scale 1: 25000) are used as base map. This output Image is used as base image for geo-referencing ASTER data product L2 (AST08) and Envisat ASAR.

3. Surface reflectance is calculated for band 2 and 3N of ASTER data product L1B (AST09). Surface reflectance values for these bands are used as the input for the NDVI calculation. Detail of this process is given by Milder (2008).

4. Calculated images are degraded to 90 m spatial resolution using ERDAS Imagine software to make comparable spatial resolution to LST and NDVI is calculated (Eq. 5).

5. Scaled LST and scaled NDVI are calculated using Eqs. (6) and (7), respectively. The regression relationships are identified by combining the ground truth measurements of SM ($M_v$) and ASTER scaled NDVI and LST. The flowchart of the SM estimation algorithm for optical image is given in Figure 4-1.

The equation for SM ($M_v$) is

$$M_v = 0.41281 - 0.09738 T^* + 0.24222 NDVI^* + 0.04616 (T^*)^2 - 0.26776 (NDVI^*)^2 - 0.06243 T^* NDVI^*$$  \hspace{1cm} (10)

6. The roadside and buildings are masked out from ASTER products so that there is no effect of reflectance from road and building materials.
4.2. SM Estimation from Microwave Imagery

Envisat ASAR APP product is selected as microwave image. SAR data processing is complex, thus special care is taken for processing the SAR data sets. The following steps are carried-out for processing and SM estimation from SAR Image:

1. SAR image is subset covering the study area and applied Lee adaptive filter to remove high frequency noise/speckle (Chen and Kasilingam, 1999) with preserving high frequency features using a 7x7 window of pixel. The number of looks applied for the filtering is 1.8 and Rat image processing software tool is used (URL 11). The data was initially in Envisat file format (.N1), which is export as ENVI raster file (.hdr) after filtering.

2. The filtered image is co-registered using georeferenced ASTER L1B product with root mean square (RMS) error 1.013 meter.

3. SAR image was spatially degraded using areal average method in ERDAS Imagine software to 90 m and 180 m target spatial resolution. Degraded image at 180 m resolution is used as coarser resolution input in the application of downscaling cokriging technique and that of 90 m resolution image is used for comparison of downscaling products.

4. Radar images are composed of many pixels, which represent an estimate of radar backscatter for the area on the ground. Backscatter for a target area at a particular wavelength is vary for a variety of conditions, such as physical size of the scatterers in the target area, the target’s electrical properties, wavelength and polarization of the radar pulses, and the observation angle. Backscattering coefficient ($\sigma^0$), which is unit less representing radar cross section was calculated using (ESA, 2007):

$$\sigma^0 = \frac{A^2}{K} \sin \alpha_D$$  \hspace{1cm} (11)
Where,

- $A$ = Average pixel intensity
- $K$ = Absolute calibration constant (426351.38, acquired from Envisat header of scene used in this study)
- $\alpha_D$ = Distributed target incidence angle (15.58° - 15.59° for subset used in this study, the terrain is flat and spatial extent of the subset is relatively small, so 15.58° is used in this calculation)

5. This unitless backscattering coefficient may exhibit a wide dynamic range, and thus need to present in decibels (Ulaby et al., 1996). To convert $\sigma^0$ into decibels ($\sigma_{dB}^0$), the following equation is used (ESA, 2007):

$$\sigma_{dB}^0 = 10\log_{10} \sigma^0$$

(12)

6. Conversion of backscattering coefficient ($\sigma_{dB}^0$) to dielectric constant ($\varepsilon$) was carried-out using empirically derived land-use-specific relationships as provided by Loew (2006). The relationship is given as:

$$\varepsilon = a + b(\sigma_{dB}^0) + c(\sigma_{dB}^0)^2$$

(13)

Where $a$, $b$, and $c$ are land-use-specific model parameters, which are 40.94, 5.33, and 0.18, respectively for grassland. This equation applies only on VV polarized image and for incidence angle of 23°. These coefficients were derived from grassland in Germany. Assumption of using these coefficients is the similar climatic condition of both sites. The application of other semi empirical model (such as Dubios, Oh model) was not suitable for calculation of dielectric constant because Cabauw grassland area had high NDVI value and soil roughness ($h$) was range from 1.2 to 7.0 cm, when solving Eqs. (3) and (4). SM measured in field also range from 22 to 50 per cent, and most of the inversion equation do not work on higher SM content (Dubios et al., 1995, McNairn et al., 2002). Thus, the method prescribe by Loew is used to calculate dielectric constant. However, the incidence angle at Cabauw site from ASAR scene was at the range of 15.58-15.59, thus correction factor 15.59/23 (0.6773) is used during inversion of dielectric constant to volumetric water content.

7. The inversion of dielectric constant to volumetric SM was carried out by applying the equation developed by Brisco et al. (1992). The equation is given as:

$$Mv = a + b \cdot \varepsilon + c \cdot \varepsilon^2 + d \cdot \varepsilon^3$$

(14)

Where, $a$, $b$, $c$, and $d$ are band-specific model parameters, which are $-1.01 \times 10^2$, $2.62 \times 10^2$, $-4.71 \times 10^{-4}$, and $4.12 \times 10^{-6}$, respectively for C-band.
8. Application of SM estimation algorithm is for grassland. Thus, SM image from ASAR is also masked to avoid multiple backscattering from building and different nature of backscattering from road compared to grassland.

4.3. Application of Downscaling cokriging Technique

The main task of this study is to estimate SM for resource management. Nowadays, various satellites have been available to get information of the land surface. The spatial resolution of 10 m by 10m is desirable to estimate SM and vegetation, although about 100 m by 100 m pixel resolution still provide useful information on degree of contrast in range in moisture and vegetation condition (Li et al., 2008). Different satellite sensors acquire information on the surface of the Earth at different spatial resolutions and for different sensors with various wavebands of the electromagnetic spectrum in a same area. The problem in this case is, some posses finer spatial resolution, while coarser temporal resolution and vice versa. A common choice is the combination of a relatively finer resolution, with a sensor with a relatively coarser resolution to derive information from fine spatial as well as temporal resolution. The problem of its spatial resolution can be solved by downscaling technique. For this study, SM estimated from Terra ASTER and Terra ASTER LST product as a finer spatial resolution and degraded Envisat ASAR APP product as coarser spatial resolution were used for SM estimation applying downscaling cokriging technique.

For simplicity, the process of derivation of co-kriging equation with the evaluation of the required covariance and cross-covariance models first. In remote sensing, supports are the pixel sizes of image, where each spatial variable is modelled as a Random Function (RF) and particular image is interpreted as a realization of that RF. Each realization images are assumed to be co-registered so that the different pixels at different resolutions are placed exactly within each other. Then, the LST image and SM estimated from ASTER at 90 meter spatial resolution (ASTER) and SM estimated from ASAR at 180 meter resolution (ASAR) are used to of as example and details of derivation process as described by Pardo-Igúzquiza et al. (2006) images is given as:

$$Z^l_u(x)$$ RF of ASTER \(l\) for pixel size \(u\) at location \(x\), where the superscript gives the type of image and the subscript gives the support of the variable. For two-dimensional images, \(x = \{x_1 + x_2\}\) is the two-dimensional location of pixels, with the components \(x_1\) and \(x_2\) being the coordinates of the pixel

$$Z^l_{x_0}(x)$$ Random Variable (RV) defined at location \(x_0\). The set of all RVs for all the different locations of the image is a RF

$$Z^l_{v_0}(x)$$ RV of ASAR at spatial resolution \(V\) (\(V>u\)) for location \(x_0\). In general, the side of \(V\) is an integer multiple of the side of \(u\). Thus, the pixel \(V\) contains an integer number of small pixels \(u\). Furthermore, the variables are assumed to be (at least locally) second order stationary with constant mean:

$$E\{Z^l_{x_0}(x)\} = m^l$$

(15)
Such that the covariances are the function of the distance and direction vector (or lag) $s$ between two locations but not on the locations themselves:

$$C_{uu}(s) = E\{Z_u^l(x), Z_u^l(x+s)\} - (m^l)^2$$

(17)

$$C_{VV}(s) = E\{Z_v^k(x), Z_v^k(x+s)\} - (m^k)^2$$

(18)

Where, $s$ is a two-dimensional vector $s = \{s_1, s_2\}$ joining the centre of two pixels (which may have supports $u$ or $V$).

The cross-covariance between $Z_u^l(x)$ and $Z_v^k(x)$ is also a function of the lag vector $s$ only:

$$C_{VU}(s) = E\{Z_v^k(x)Z_u^l(x+s)\} - m^k m^l$$

(19)

These covariances can be inferred from the empirical information given by two images.

Our objective is to get the finer spatial resolution image as ASAR ($k$) calculated from a coarse spatial resolution image ($k$) and a fine spatial resolution image ASTER ($l$), thus, cokriging predictor is given by:

$$\hat{Z}_u^k(x_o) = \sum_{i=1}^{N} \hat{X}_i^k Z_v^k(x_i) + \sum_{j=1}^{M} \beta_j^o Z_u^l(x_j)$$

(20)

Where,

$\hat{Z}_u^k(x_o)$ Random variable (RV) of pixel of areal size $u$ (ASTER), with spatial location $x_o = \{x_1, x_2\}$ and SM estimated from ASAR image ($k$) estimated by cokriging

$Z_v^k(x_i)$ RV of pixel of the coarse spatial resolution image with areal size $V$ (ASAR) and image $k$. The weight assigned to the random variable of the $i^{th}$ pixel is $\hat{X}_i^k$.

$Z_u^l(x_j)$ RV of pixel of the fine spatial resolution image with areal size $u$ and SM estimated from image ($l$). The weight assigned to the random variable of the $j^{th}$ pixel is $\beta_j^o$.

$N$ Number of values of $k$ with support $V$ used in the prediction of $Z_u^k(x)$. For example, $N = 3 \times 3$ window of pixels.

$M$ Number of values of $l$ with support $u$ used in the prediction of $Z_u^l(x)$. For example, $M = 4 \times 4$ window of pixels.
The set of weights \( \{ \lambda_i^0, i = 1, \ldots, N; \beta_j^0, j = 1, \ldots, M \} \) is determined by solving ordinary cokriging system, which is a linear system with \( (\sum_{i=1}^{N} \sum_{j=1}^{M} ) + N \) equation and the same number of unknowns (the weights plus N Lagrange multipliers introduced for constrained minimization, which is taking into account conditions for having an unbiased predictor) (Atkinson et al., 1992). The cokriging system may be written in matrix form as:

\[
CL = B \tag{21}
\]

Where, C and B are covariance matrix (the detail information on covariance matrix and point-to-point cokriging is given by Pardo-Igúzquiza et al. (2006)) and L which includes weights, is only the unknown parameter and is calculated by

\[
L = C^{-1}B \tag{22}
\]

The set of weights must be unbiased and must minimize the prediction variance and for that data must have:

\[
E\{ \hat{Z}_u^k (x) \} = E\{ Z_u^k (x) \} = m^k \tag{23}
\]

Then,

\[
E\{ \hat{Z}_u^k (x) \} = \sum_{j=1}^{N} \lambda_j^0 Z_v^k (x_i) + \sum_{j=1}^{M} \beta_j^0 Z_u^l (x_j) \tag{24}
\]

From the Eqs. (23) and (24),

\[
m^k = m^k \sum_{i=1}^{N} \lambda_i^0 + m^l \sum_{j=1}^{M} \beta_j^0 \tag{25}
\]

Which implies the \( \sum_{i=1}^{N} \lambda_i^0 = 1 \) and \( \sum_{j=1}^{M} \beta_j^0 = 0 \) i.e. the sum of the weights of the variable \( Z_v^k \) must be one, while the sum of weights of the variable \( Z_u^l \) must be zero.

The weight factors i.e. \( \lambda_i^0 \) and \( \beta_j^0 \) may be interpreted as low pass filter and high pass filter, respectively. Once the weights are calculated they can apply as a moving window for desired fine spatial resolution image as:

\[
\hat{Z}_u^k (x_0) = L[Z_v^k (x_i)] + H[Z_u^l (x_j)] \tag{26}
\]

Where,

\( L[.] = \) Low pass filter operator
\( H[.] = \) High pass filter operator
Figure 4-2 Convolution windows with different weight for neighbouring pixels on coarser and finer resolution image during application of downscaling cokriging technique.
For this study, the experimental semivariogram from SM estimated from ASAR and that of ASTER and LST is calculated using R-statistical using ‘gstat’ and ‘sp’ libraries. For crossvariogram calculation, SM image derived from ASAR (180 m) is degraded by naïve approach (breaking down a pixel into four having same value for downscaling scaling factor 2). This degraded image (90m resolution) is used to calculate crossvariogram between LST (and SM estimated from ASTER) and SM estimated from ASAR. These semivariogram and cross variogram are used to obtain weighted cokriging windows. The origin of pixel setting for ASAR and ASTER image in the process of weight calculation is given in Appendix-1. The main point to be considered during the process of weight calculation, is the cokriging matrix must be positive definite. The software provided by Pardo-Iguzquiza is used in this study to guarantee this. Once the weights are calculated they were applied as a moving window in both input images and fusion of convolved images (Eqs. 20, 26) gave the predicted fine spatial resolution cokriged image for SM estimation from ASAR (Figure 4-2).

4.4. Downscaling using Regression Equation

In the regression downscaling technique, finer resolution ASTER SM image (90 m) is degraded by areal average approach to match coarse resolution SM image estimation from ASAR (180 m). In areal approach, four adjoining pixels of finer resolution image are averaged to get one pixel of coarser resolution image. Linear regression coefficients are then predicted based on these images at the same resolution. The process of downscaling using regression equation method is given in Figure 4-3.

4.5. Trivial Downscaling Method

Two trivial downscaling techniques have been applied in this study. In first method, downscaling is done by giving equal weight to both finer and coarser image to produce finer resolution image (Figure
4–4). For simplicity, the term TDA is used for this downscaling method hereafter. Similarly, a simple downscaling approach is applied to disaggregate coarser resolution SM image from ASAR at 180 m resolution. In this method one coarser pixel is broken down into four pixels and value of original pixel is given to all pixels. The term TDR is used for this downscaling method in this paper and method is illustrated in Figure 4-5.

![Figure 4-4 Trivial downscaling method using SM estimated from both ASTER and ASAR (TDA)](image)

![Figure 4-5 Trivial downscaling method using SM estimated from ASAR at 180 m (TDR)](image)

### 4.6. Validation of Result

SM estimated from satellite imagery covers a large area in continuous fashion, which is not possible in point field observation. The SM estimated by microwave image accounts for soil moisture from few centimetres under the surface. On other hand, soil moisture from such images give average estimation over a pixel. There is large spatial and temporal variability exists in SM. Due to this heterogeneity, the conditional spatial distribution of soil moisture estimated from remotely sensed data is difficult to validate with *in situ* measurement (Chauhan, 2003).
The results are compared using mean error, root mean square error, and correlation coefficient between SM estimated from ASAR at 90 meter resolution and SM after application of various downscaling techniques. Similarly, same statistical tools were applied to compare SM estimated using remotely sensed data with *in situ* measurement. The spatial dimension of point field observation was for 8th June 2006 about 146 m. by 180 m., thus; only five pixels from remotely sensed image are used to compare with field observation.

The calculation of these statistics is given as:

**Mean Error (ME):**

\[
ME = \frac{1}{N} \sum_{i=1}^{N} (P_i - O_i)
\]  

(27)

**Root Mean Square Error (RMSE):**

\[
RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (P_i - O_i)^2}
\]  

(28)

**Correlation Coefficient (r):**

\[
r = \frac{N \sum_{i=1}^{N} P_i O_i - \sum_{i=1}^{N} P_i \sum_{i=1}^{N} O_i}{\sqrt{N \sum_{i=1}^{N} P_i^2 - (\sum_{i=1}^{N} P_i)^2} \sqrt{N \sum_{i=1}^{N} O_i^2 - (\sum_{i=1}^{N} O_i)^2}}
\]  

(29)

where, ME and RMSE are in percentage by volume $P$ is the field or simulated variable, $O$ the estimated variable, and $N$ number of data, $r$ is dimensionless value of which ranges from 0 to 1.

### 4.7. Summary of Methods

The Figure 4-6 depicts the overall methods applied during this study. The ENVI (with IDL), ERDAS Imagine, R-statistical software using *gstat* and *sp* libraries, Rat v 0.20 along with Microsoft Office 2003 packages are used in the study.
Figure 4-6 Schematic diagram of overall methods for disaggregation to estimate SM at finer resolution
5. Result and Discussions

5.1. SM Estimation from Remotely Sensed Images

A number of techniques utilizing the electromagnetic spectrum have been used to retrieve SM in remote sensing. The methods for such estimation vary greatly in accordance with sensor types. The optical/IR and microwave frequency have been used widely for soil moisture studies. Thus, Envisat ASAR as microwave image and Terra ASTER as optical/IR image have been used separately for SM estimation in this study.

5.1.1. ASTER SM estimation

The “Universal Triangle” method (Chauhan, 2003; Wang et al., 2007) is used to estimate SM from ASTER image. To calculate SM, the regression coefficients are estimated by using ground truth measurements of SM and ASTER scaled NDVI and LST (Eq. 10). The SM estimated image from ASTER is shown in Figure 5-1.

Figure 5-1 SM estimated (%, volume/volume (v/v)) from ASTER image at Cabauw grassland at 90 m resolution (the white colour in the image is masked area)
Figure 5-2 shows the relationship between SM, NDVI and LST. There is no unique relationship between SM and land surface temperature (Coefficient of determination, $R^2=0.01$), but a stable relationship is found between NDVI and land surface temperature ($R^2=0.50$). The observed relationship between NDVI with SM is a stable 2nd order polynomial relationship to soil moisture with $R^2=0.69$. Carson et al. (1994) also found a stable relationship between soil moisture and NDVI.

\[ y = -117.3x^2 + 125.25x + 8.5199 \]

\[ R^2 = 0.69 \]

Correlation analysis shows that relationship between SM and NDVI value is negative ($r=-0.45$) and significant ($p<0.01$). In Figure 5-2(A), it can be clearly seen that relation between NDVI and SM is positive for NDVI <0.50 and negative when NDVI >0.50. Cabauw grassland area is always covered with dense vegetation due to sufficient soil moisture (Beljaars and Bosveld, 1997; Timmermans et al., 2008) and most of NDVI value of the pixels has more than 0.5. In higher moisture condition, all soil pores are occupied with water restricting air circulation and high SM can effect vegetation health due
to poor root respiration. Thus, the relation between NDVI is negatively defined in Cabauw site. Relationship between NDVI and LST is negative but highly significant at $p < 0.01$ (Table 5-1).

<table>
<thead>
<tr>
<th></th>
<th>LST</th>
<th>NDVI</th>
<th>Aster SM</th>
</tr>
</thead>
<tbody>
<tr>
<td>NDVI</td>
<td>-0.71</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>p-value</td>
<td>0.000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ASTER SM</td>
<td>-0.10</td>
<td>-0.45</td>
<td>0.000</td>
</tr>
<tr>
<td>p-value</td>
<td>0.001</td>
<td>0.000</td>
<td></td>
</tr>
<tr>
<td>ASAR SM</td>
<td>0.31</td>
<td>-0.36</td>
<td>0.13</td>
</tr>
<tr>
<td>p-value</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
</tbody>
</table>

5.1.2. **ASAR SM estimation**

SM estimation from microwave image is complicated process because radar backscatter depends on various surface parameters. Microwave backscattering from soil is the integration of the reflected radiation from certain depths. The backscattering recorded by the sensor depends on the wavelength of the sensor and dielectric property of soil. The empirical model developed by Loew (2006) is based on such parameters at various land use types in Germany using Envisat ASAR for $23^\circ$ incidence angle. Same method is applied in this study using coefficient for grassland. The SM image estimated from ASAR is given in Figure 5-3. The volumetric SM from ASAR ranges from 30.30% to 37.17%.

![Figure 5-3 SM estimated (% v/v) from Envisat ASAR image at Cabauw grassland at 90 meter resolution (the white colour in the image is masked area)](image.png)
The correlation analysis shows that there is a significant negative relationship between ASAR SM estimation and NDVI \((r=-0.36 \text{ at } p<0.01)\) at 90 m resolution, while with LST is significant and positive \((r= 0.31 \text{ at } p<0.01)\) (Table 5-1). The relationship between SM estimated from ASAR with ASTER NDVI and LST is illustrated in Figure 5-4.

![Figure 5-4 Relationship between volumetric SM estimated by ASAR with ASTER NDVI and LST at 90 m resolution](image)

### 5.1.3. Comparison between ASAR and ASTER SM estimation

Table 5-2 shows the basic statistics of SM estimated from ASAR and ASTER at 90 m resolution. The SM estimated from ASTER is higher than that from ASAR. Optical sensor measures radiation reflected from ground surface, while microwave sensor records backscattering from certain depth, which depends on wavelength or frequency of microwave emission and dielectric property of soil. Microwaves can penetrate vegetation canopy to certain depth, while optical sensors have no such properties. These factors account variations in soil moisture estimated from these two different image types.

<table>
<thead>
<tr>
<th>Table 5-2 The statistics of SM (%, v/v) estimated from remotely sensed images (90 meter resolution)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>ASAR SM estimation</strong></td>
</tr>
<tr>
<td>Maximum</td>
</tr>
<tr>
<td>Minimum</td>
</tr>
<tr>
<td>SM Range</td>
</tr>
<tr>
<td>Mean</td>
</tr>
<tr>
<td>Skewness</td>
</tr>
<tr>
<td>1st quartile</td>
</tr>
<tr>
<td>Median</td>
</tr>
<tr>
<td>3rd quartile</td>
</tr>
<tr>
<td>Standard Deviation</td>
</tr>
</tbody>
</table>

Test of skewness shows that ASAR SM estimation is positively skewed and narrow range (32.15 to 33.21) fall under 1st to 3rd quartile. Similarly, ASTER SM estimation is negatively skewed and inter-
quartile range is from 39.18 to 41.86. There is very narrow inter-quartile range in ASAR SM estimation.

The correlation analysis shows that there is significant positive relationship ($r = 0.13$ at $p<0.01$) between ASTER and ASAR SM estimation (Table 5-1). Figure 5-5 shows the relationship between SM estimated from ASTER and ASAR images, which is weak despite the correlation is significant. The coefficient of determination of this relationship is only 0.016. This may be due to the acquisition time difference between these two source images. The time lag between acquisitions of those images was 33 hours covering two full sun-shining days.

5.2. Comparison of SM Estimated from Remotely Sensed Imagery with Field Measurement

Validation of soil moisture estimation result is difficult particularly when estimation is from satellite images. The difficulty arises not only in the estimation process but also in the measurements of in situ soil moisture (Chauhan, 2003). SM estimated from satellite imagery covers a large area in continuous fashion, which is not possible in point field observation. On the other hand, soil moisture from such images gives average estimation over an area of pixel.

The comparison of soil moisture estimated from remotely sensed data with field observation is given in Table 5-3. There were 20 field observation recorded on June 8, which covers 5 pixels at 90 m resolution. The number of these field observations is not sufficient for the accuracy assessment of remotely sensed data. However, it gives a rough idea about SM estimation from remotely sensed data. Therefore, ME and RMSE are calculated based on field measurement. Figure 5-6 shows that both ME and RMSE are lower in ASTER SM estimation than ASAR estimation. This may be due to difference in acquisition time of ASAR and field observation. The time difference between ASAR acquisition and field observation is 27 to 30 hours. Two full sunshine days fall during those periods.
temperature during those days were more than 25° Celsius (Figure 3-2), which may cause high evapo-
transpiration and SM estimated from ASAR is lower than field observation and ASTER SM.

Table 5-3 The basic statistics of SM measurement from remotely sensed data with field measurement

<table>
<thead>
<tr>
<th></th>
<th>ASTER SM</th>
<th>ASAR SM</th>
<th>Field Measurement</th>
</tr>
</thead>
<tbody>
<tr>
<td>Maximum</td>
<td>40.93</td>
<td>33.32</td>
<td>50.00</td>
</tr>
<tr>
<td>Minimum</td>
<td>38.84</td>
<td>32.54</td>
<td>26.50</td>
</tr>
<tr>
<td>Mean</td>
<td>39.90</td>
<td>32.93</td>
<td>40.60</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>0.93</td>
<td>0.24</td>
<td>6.46</td>
</tr>
</tbody>
</table>

![Figure 5-6 ME and RMSE of SM estimated from ASAR and ASTER](image)

5.3. Application of Downscaling Techniques

Three downscaling techniques are applied in this study. Among them downscaling using regression equation and trivial downscaling technique are used to compare downscaling cokriging technique.

5.3.1. Downscaling cokriging technique

To derive ASAR soil moisture at finer spatial resolution, i.e. at 90 m, from coarser resolution input i.e. 180 m, LST image at 90 m spatial resolution is used as a co-variable. The downscaling cokriging method requires covariance and cross-covariance models from input images. The experimental variograms are estimated from ASAR SM image and LST image. For cross-variogram, SM estimated from ASAR is degraded by trivial/naive method and cross-variogram is estimated by using spatially degraded product as main variable and LST image as a co-variable. The experimental variogram and cross variogram is estimated from R-statistical software using sp and gstat libraries. R-code for variogram and cross variogram estimation is given in Appendix-2. These tentative variogram models are used to generate a point support covariance and cross-covariances from the experimental images.
For each input dataset, two nested exponential models are selected. Point support models are obtained by the use of the tentative variograms and cross-variogram from DSCOKRI software by a deconvolution process. The point variogram model obtained by a deconvolution process is given in Table 5-4. These induced point models are comparable to experimental variograms. Comparisons of experimental variogram and induced point models are shown in Figure 5-7.

Figure 5-7 The experimental variograms (circle) with induced variogram model (solid line) A. Cross-variogram B. variogram estimated from LST image, and C. variogram estimated from ASAR SM image
Deconvolution process is repeated to achieve common range for all structure. The experimental variograms and induced point support variogram models are fitted in corresponding plots and comparison is done to get optimal structure. The range estimated for cross-variogram model i.e. 157.3 for first structure and 296.7 for second structure is found optimal. Thus, a short range of 157.3 and a long range of 296.7 are fixed for all variograms. With these fixed ranges and sills given in the Table 5-5 for nested exponential structure are used for further downscaling cokriging process. Comparisons of experimental variogram and induced point models are shown in Figure 5-8.

### Table 5-4 The point variogram model obtained from input images

<table>
<thead>
<tr>
<th></th>
<th>LST 90m</th>
<th>ASAR SM 180 m</th>
<th>Cross</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>First structure</td>
<td>Second structure</td>
<td>First structure</td>
</tr>
<tr>
<td>Sill</td>
<td>3.572</td>
<td>9.669</td>
<td>0.532</td>
</tr>
<tr>
<td>Range (X)</td>
<td>76.1</td>
<td>163.3</td>
<td>131.03</td>
</tr>
<tr>
<td>Range (Y)</td>
<td>76.1</td>
<td>163.3</td>
<td>131.03</td>
</tr>
</tbody>
</table>

### Table 5-5 Variogram models adopted in downscaling cokriging

<table>
<thead>
<tr>
<th></th>
<th>LST 90m</th>
<th>ASAR SM 180 m</th>
<th>Cross-variogram</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>First structure</td>
<td>Second structure</td>
<td>First structure</td>
</tr>
<tr>
<td>Sill</td>
<td>9.086</td>
<td>3.357</td>
<td>0.476</td>
</tr>
</tbody>
</table>
These point support models are used to calculate weight for both LST and ASAR SM images. In this study, there are two window sizes applied on LST i.e. 4×4 windows (CK44) and 6×6 windows (CK66). The example of weight for 4 by 4 windows applied on LST is given in Table 5-6 and Table 5-7. The weight of high pass filters applied on ASAR SM estimated image are nearly 1.0 (0.99999 to 1.00001 and 0.99998 to 1.00002 for CK44 and CK66, respectively) and those of low pass filter are nearly zero (-2.00E-05 to 1.00E-05 and -3.31E-18 to 1.00E-05 for CK44 and CK66, respectively). The fusion of images using Eq. (26) gives the downscaled image at 90 meter resolution. Thus, two disaggregated images are produced. The statistics of these images is given in Table 5-10.

Table 5-6 The 3x3 window (high pass filter) for coarser resolution image (ASAR)

<table>
<thead>
<tr>
<th></th>
<th>a11</th>
<th>a12</th>
<th>a21</th>
<th>a22</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.03</td>
<td>0.172</td>
<td>-0.031</td>
<td>-0.032</td>
<td>0.176</td>
</tr>
<tr>
<td>0.172</td>
<td>0.978</td>
<td>-0.158</td>
<td>-0.166</td>
<td>0.987</td>
</tr>
</tbody>
</table>

Table 5-7 The 4x4 window (low pass filter) for finer resolution image (ASTER)

<table>
<thead>
<tr>
<th></th>
<th>a11</th>
<th>a12</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.0004</td>
<td>0.0005</td>
<td>0.0022</td>
</tr>
<tr>
<td>0.0002</td>
<td>0.0003</td>
<td>0.0014</td>
</tr>
<tr>
<td>-0.0018</td>
<td>-0.0010</td>
<td>-0.0125</td>
</tr>
<tr>
<td>-0.0036</td>
<td>-0.0034</td>
<td>0.0339</td>
</tr>
</tbody>
</table>

Table 5-10 The 4x4 window (low pass filter) for finer resolution image (ASTER)

<table>
<thead>
<tr>
<th></th>
<th>a11</th>
<th>a12</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.0008</td>
<td>-0.0001</td>
<td>-0.0027</td>
</tr>
<tr>
<td>-0.0001</td>
<td>-0.0001</td>
<td>-0.0028</td>
</tr>
<tr>
<td>-0.0027</td>
<td>-0.0028</td>
<td>0.0355</td>
</tr>
<tr>
<td>0.0003</td>
<td>0.0001</td>
<td>-0.0109</td>
</tr>
</tbody>
</table>
Comparison between SM predicted from with and without fixing the range

Before comparing SM predicted from various downscaling methods, comparison between SM predicted from point support variograms with and without fixing the range is carried-out. Table 5-8 shows the ME and RMSE of these two products comparing with ASAR SM at 90 m resolution. RMSE values produced by these two approaches are same, while ME is lower when range is fixed same to all inputs.

<table>
<thead>
<tr>
<th>Without fixed range</th>
<th>With fixed range</th>
<th>Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>CK44</td>
<td>CK66</td>
<td>CK44</td>
</tr>
<tr>
<td>ME</td>
<td>0.012</td>
<td>0.015</td>
</tr>
<tr>
<td>RMSE</td>
<td>0.742</td>
<td>0.740</td>
</tr>
</tbody>
</table>

Comparison between SM predicted from downscaling cokriging using ASTER SM and LST as co-variable

In this study, SM image estimated from ASTER is also applied to downscale SM estimated from ASAR. In this process, the common range for all structure is achieve through repeated deconvolution process and 131.03 for first structure and 366.51 for second structure found optimal. The window sizes for ASTER SM are same as that for LST. The comparison of downscaling cokriging product using SM estimated from ASTER and LST is given in Table 5-9. There is negligible difference between soil moisture predictions using different inputs. Pardo-Igúzquiza (2006) also advocated that the cokriging can incorporate secondary information from thematic map or field observational data to increase spatial resolution. Thus, cokriging technique offers choice of inputs for increasing spatial resolution of target image.

<table>
<thead>
<tr>
<th>Without fixed range</th>
<th>With fixed range</th>
<th>Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>CK44</td>
<td>CK66</td>
<td>CK44</td>
</tr>
<tr>
<td>ME</td>
<td>0.009</td>
<td>0.010</td>
</tr>
<tr>
<td>RMSE</td>
<td>0.739</td>
<td>0.744</td>
</tr>
</tbody>
</table>

From Table 5-8, we can conclude that there is no difference in SM prediction, while fixed range structure give lower ME. Similarly, Table 5-9 shows SM prediction at 90 m resolution from ASTER SM image is nearly equal that predicted from LST image. Thus, SM predicted from LST image as co-variable in downscaling cokriging technique with fixed range (a short range of 157.3 and a long range of 296.7) is used for comparison with other downscaling products.

5.3.2. Application of Trivial downscaling and Regression equation methods

Two types of trivial downscaling methods are applied to compare downscaling cokriging technique. In first method, half weight is given to finer resolution image and remaining half weight is supplied to the coarser resolution pixel comparable to finer resolution (this method is termed TDA hereafter).
Similarly, second trivial approach (TDR) used by disaggregating a coarser pixel into four pixels and value of original pixel is given to all pixels. The statistics of downscaled image produced by this method is provided in Table 5-10.

In regression equation method, a linear regression equation is derived from degraded SM estimated from ASTER image equivalent with pixel resolution to the coarser resolution SM estimated from ASAR. The relationship between these two images is given in Figure 5-9. The statistics of downscaled image produced by regression equation are provided in Table 5-10.

Regression equation soil moisture estimation for ASAR is given as:

$$M_v = 30.67 + 0.0488 \times (\text{ASTER } M_v)$$  \hspace{1cm} (30)
5.3.3. Comparison among downscaled images

Table 5-10 shows the basic statistics of input images and downsampling products. The mean of SM predicted from various downsampling approaches are near to the mean from ASAR SM estimation except for the TDA method. The range of SM value predicted by the Regression method is the narrowest (0.57), which is followed by TDR (3.53), downsampling by 6×6 windows on LST (CK66) with the value of 5.03 similar to downsampling by 4×4 windows on LST (CK44) with the value of 5.08. The SM predicted by the TDA has the widest range (6.51).

<table>
<thead>
<tr>
<th>Downscaling using</th>
<th>Regression Equation</th>
<th>TDR</th>
<th>TDA</th>
<th>CK44</th>
<th>CK66</th>
</tr>
</thead>
<tbody>
<tr>
<td>Maximum</td>
<td>44.79</td>
<td>34.86</td>
<td>32.86</td>
<td>34.86</td>
<td>39.15</td>
</tr>
<tr>
<td>Minimum</td>
<td>33.20</td>
<td>31.33</td>
<td>32.29</td>
<td>31.33</td>
<td>32.64</td>
</tr>
<tr>
<td>SM range</td>
<td>11.59</td>
<td>3.53</td>
<td>0.57</td>
<td>3.53</td>
<td>6.51</td>
</tr>
<tr>
<td>Mean</td>
<td>40.45</td>
<td>32.71</td>
<td>32.64</td>
<td>32.71</td>
<td>36.58</td>
</tr>
<tr>
<td>Skewness</td>
<td>-0.60</td>
<td>0.49</td>
<td>-0.59</td>
<td>0.49</td>
<td>-0.60</td>
</tr>
<tr>
<td>1st quartile</td>
<td>39.18</td>
<td>32.26</td>
<td>32.58</td>
<td>32.26</td>
<td>35.96</td>
</tr>
<tr>
<td>Median</td>
<td>40.75</td>
<td>32.70</td>
<td>32.66</td>
<td>32.70</td>
<td>36.75</td>
</tr>
<tr>
<td>3rd quartile</td>
<td>41.86</td>
<td>33.08</td>
<td>32.71</td>
<td>33.08</td>
<td>37.35</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>1.77</td>
<td>0.63</td>
<td>0.09</td>
<td>0.63</td>
<td>1.03</td>
</tr>
</tbody>
</table>

Test of third central moment shows that downsampling using regression equation and trivial methods are slightly negatively skewed, while other downsampling SM images are slightly positively skewed. The inter quartile range of various downsampling product are given in Table 5-10. Comparison histogram of downscaled soil moisture product is illustrated in Figure 5-10.

Histogram maps clearly indicate that frequency distribution of downsampling by cokriging method is close to ASAR input than trivial and regression equation methods.
The SM map produced by downscaling approaches and two original images are given in Figure 5-11. The SM map after downscaling by regression equation, TDA and that estimated from ASTER visually looks similar. However, while comparing statistics, all images are quite different in their mean value and range. The statistics of SM estimated from ASAR 180 m and TDR method is same. The SM map after downscaling by CK44 and CK66 looks similar and basic statistics is also in reasonable agreement with ASAR SM at 180 m and 90 m resolution.
5.4. Validation of Result

The soil moisture estimated from ASAR at 90 m resolution is used as a reference image for the validation of downscaled SM image products at the same (90 m) spatial resolution. Table 5-11 shows the ME and RMSE value of different downscaling methods. Both ME and RMSE values are the lowest in downscaling using CK 66 windows and CK 44 windows compared to the TDA and the Regression equation method. The highest ME and RMSE value produced by the TDA method. The ME and RMSE value of the TDR is comparable with downscaling cokriging methods. However, SM
predicted by TDR method has no practical implication because it has same value for downscaled pixel as original coarser pixel.

The SM estimated from ASAR at 90 m spatial resolution is 6.87 (% v/v), while Regression method has very narrow range very narrow range (0.57 %, v/v). Range of SM predicted by downscaling cokriging methods are more than 5% v/v and that from TDR method is 4.50% v/v, which is comparable to original ASAR SM estimation (Table 5-10).

<table>
<thead>
<tr>
<th>Downscaling using</th>
<th>Regression Method</th>
<th>TDR Method</th>
<th>TDA Method</th>
<th>CK44 Method</th>
<th>CK66 Method</th>
</tr>
</thead>
<tbody>
<tr>
<td>ME</td>
<td>-0.072</td>
<td>0.014</td>
<td>3.867</td>
<td>0.008</td>
<td>0.010</td>
</tr>
<tr>
<td>RMSE</td>
<td>0.821</td>
<td>0.703</td>
<td>3.997</td>
<td>0.743</td>
<td>0.739</td>
</tr>
</tbody>
</table>

The relation among SM value estimated by ASAR and ASTER with SM predicted by various downscaling methods is given in Table 5-12. The effect of SM estimated from ASTER in downscaling product can be observed and correlation between the TDA method with ASTER SM is the strongest with r= 0.947. Similar relationship is found between TDA method and the Regression equation (r= 0.947). Such a high correlation is due to use of ASTER SM data directly to both type of downscaling product. Similarly, relation between ASTER SM with CK44 and CK66 is positive and significant at p<0.01, however relationship is weak showing r=0.15 for CK66 and r=0.10 for CK44 (Table 5-12).

<table>
<thead>
<tr>
<th>Downscaling using</th>
<th>ASTER SM</th>
<th>ASAR SM</th>
<th>TDA</th>
<th>TDR</th>
<th>Regression</th>
<th>CK66</th>
</tr>
</thead>
<tbody>
<tr>
<td>ASAR SM</td>
<td>0.276</td>
<td>(0.000)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TDA</td>
<td>0.947</td>
<td>0.430</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>TDR</td>
<td>0.133</td>
<td>0.585</td>
<td>0.444</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Regression</td>
<td>-</td>
<td>0.267</td>
<td>0.947</td>
<td>0.135</td>
<td></td>
<td></td>
</tr>
<tr>
<td>-</td>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>CK66</td>
<td>0.114</td>
<td>0.549</td>
<td>0.406</td>
<td>0.935</td>
<td>0.116</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>CK44</td>
<td>0.097</td>
<td>0.544</td>
<td>0.391</td>
<td>0.937</td>
<td>0.099</td>
<td>0.992</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.001)</td>
<td>(0.000)</td>
</tr>
</tbody>
</table>

Note: The value given in parenthesis shows probability value
The correlation analysis for ASAR SM at 90 m resolution shows that the closest relationship is between ASAR SM with TDR \((r=0.585)\) followed by CK66 \((r=0.549)\) CK44 \((r=0.544)\). The correlation between CK66 and CK44 is strong and positive \((r=0.99)\). The main aim to apply these different size windows is whether there effect of neighbouring pixels to SM estimation or not. The weights for neighbouring pixels are calculated by introducing spatial details that is supported by experimental data (Pardo-Igúzquiza et al., 2006). The weights are different according to window size. The result from both window sizes is same (Table 5-14), as all windows sizes have same spatial detail from experimental data.

Overall, both bias (ME) and accuracy (RMSE) are lower in cokriged image compared to regression equation and TDA. There is strong correlation between downscaling cokriging with ASAR SM at 90 m resolution than other two methods.

<table>
<thead>
<tr>
<th>Table 5-13 The statistics of residuals</th>
</tr>
</thead>
<tbody>
<tr>
<td>Downscaling using Regression method</td>
</tr>
<tr>
<td>Maximum</td>
</tr>
<tr>
<td>Minimum</td>
</tr>
<tr>
<td>Range</td>
</tr>
<tr>
<td>Mean</td>
</tr>
<tr>
<td>Skewness</td>
</tr>
<tr>
<td>1\text{st} quartile</td>
</tr>
<tr>
<td>Median</td>
</tr>
<tr>
<td>3\text{rd} quartile</td>
</tr>
<tr>
<td>Inter Quartile Range</td>
</tr>
<tr>
<td>Standard deviation</td>
</tr>
</tbody>
</table>

There is a large difference in residual error value of output images with respect to SM estimated from ASAR (Figure 5-12). Comparison of residual error shows that SM moisture predicted by CK44 windows produces the highest variation in error range followed by CK66. Downscaling using regression equation gives the lowest residual range. Though residual error seems to be high in all observations, concerning the main quartiles (median, first and third quartiles) do not exceed 1.36% for downscaling products (Table 5-13). Besides, the inter quartile range of downscaling cokriging products are only 0.84 to 0.85 for CK66 and CK44, respectively. Comparison of mean of residual error of downscaled products is in following order: downscaling CK44 \(\geq\) CK66 \(>\) TDR \(>\) TDA \(>\) Regression equation method.
Finally, to compare difference of using sizes of windows on LST image pair t-test is used. The comparison between SM predicted by these two methods is given in Table 5-14. The result from pair t-test shows that there is no sufficient evidence to suggest difference between SM predicted from CK44 and CK66 at 95% confidence interval. This may be resulted as weight calculation only considered global variance of spatial information from experimental data. Thus, there is no difference of using different size window for downscaling cokriging technique.
Table 5-14 Comparison between SM predicted by CK66 and CK44 methods

<table>
<thead>
<tr>
<th></th>
<th>No. of samples</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Standard Error of Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>CK66</td>
<td>1178</td>
<td>32.73</td>
<td>0.70</td>
<td>0.02</td>
</tr>
<tr>
<td>CK44</td>
<td>1178</td>
<td>32.72</td>
<td>0.70</td>
<td>2.03E-02</td>
</tr>
<tr>
<td>Difference</td>
<td>1178</td>
<td>2.30E-03</td>
<td>0.09</td>
<td>2.60E-03</td>
</tr>
</tbody>
</table>

95% Confidence interval for mean difference is -0.0028 to 0.0074, $t$-value = 0.87 ($p$-value = 0.38)
6. Conclusion and Recommendations

6.1. Conclusions

The main objective of this study is to adapt and evaluate downscaling cokriging technique using finer resolution optical satellite image and coarser resolution microwave image for soil moisture estimation. To achieve this objective, five research questions put forward in the study. Answer of research questions is tried to be solved and conclusion for each question is given as:

1. What is the relation between soil moisture with surface roughness, surface temperature and soil properties?

Soil moisture estimation from remotely sensed images is influenced by various surface and sensor parameters, which is described in chapter 2.1 and 2.2. For SM estimation from optical images, LST and NDVI are the most important parameters. Similarly, for SM estimation from microwave images, sensor parameters such as incidence angle, polarization, and wavelength and surface parameters like surface roughness, dielectric constant, vegetation and soil composition are important. Among them dielectric property is the most important one, which is highly dependent on moisture content of soil.

2. How can we validate soil moisture predicted from remotely sensed imagery against field measurements?

SM estimated from satellite imagery covers a large area and gives an average SM estimation over an area covered by a pixel. The SM estimated by microwave image accounts soil moisture from few cm below the surface, which depends on wavelength of sensor. On the other hand, soil moisture from field measurement is based on point measurement. SM content varies greatly over space and time. In this study, there is only a small fraction of the area covered by field moisture measurement, which corresponds to only five pixels of 90 m resolution images. Time of SM field measurement was not coinciding with image acquisition time. Thus, validation of soil moisture with field measurement is limited in this study.

3. Is downscaling co-kriging effective for SM estimation from optical and microwave imagery?

4. What is the level of accuracy of downscaling co-kriging to estimate SM at finer scale?

Downscaling cokriging technique is an efficient technique for increasing spatial resolution. It takes spatial details from input images and thus preserves the SM variability in space. The downscaling cokriging techniques along with TDR method produce lower ME and RMSE. The RMSE of TDR method is 0.70, while downscaling cokriging techniques is 0.74% SM volume by volume for both LST and ASTER SM image as co-variable and different window sizes. However, SM predicted by TDR method has no foundation of spatial information and has no practical application because it has same value for downscaled pixel as original coarser pixel. The correlation analysis also shows that
there is significant positive correlation ($r = 0.55$ with $p < 0.01$) between ASAR SM and downscaling SM image. Application of different window sizes *i.e.* 4x4 and 6x6 on LST for SM prediction has only a small effect. For simplicity, use of one small window based on data requirement is sufficient to apply downscaling cokriging technique.

5. **Which method is more appropriate to estimate soil moisture that is disaggregating first and estimate soil moisture or the other way around?**

Application of active microwave depends on various parameters and various complicated processing steps are involved to get usable microwave images product. There are many intermediate images produced during processing. Due to complicated processing, application of disaggregation first may cause propagation of error and SM estimation thereafter introduces more errors. Thus, it is wise to estimate soil moisture first and apply downscaling cokriging technique.

In conclusion, the downscaling cokriging technique provides an ample opportunity to predict soil moisture or other application at finer resolution with reasonable accuracy. The synergetic use of optical and microwave sensors to increase spatial resolution by cokriging technique may be better choice. Users can choose convenient image product in accordance with their requirement and budget.

### 6.2. Limitations of study

The limitations of the study are time, space and number of field soil moisture measurement. The spatial coverage of measurement was 146 m by 180 m and numbers of measurement were only 20 points. The acquisition time of active microwave data was not matching with field measurements. Moreover, downscaling cokriging technique needs spatial information from co-variable for disaggregation. Due to difference in acquisition time of ASTER and Envisat ASAR errors in spatial information are expected.

### 6.3. Recommendations

The downscaling cokriging technique performs well for SM estimation at the considered resolution. Downscaling cokriging technique offers generation of point support variogram model. Due to limitation of resolution of LST product of ASTER, disaggregation is carried-out by scale factor 2 in this study. In principle, it is possible to apply this technique at desired resolution in accordance with resolution of co-variable. Co-variable can be secondary information from thematic map or field measurements. Thus, this method provides ground of using different source of information to increase spatial resolution for future study.
References


ESA, 1998. ASAR science and applications. European Space Agency (ESA), SP-1225


**Reference from websites**

URL1, [http://www.essc.psu.edu/~tnc/howto.html](http://www.essc.psu.edu/~tnc/howto.html), online document access on December 15, 2008

URL4, http://www.esa.int/esaLP/ESAL3B2VMOC_LPsmos_0.html, online document access on November 15, 2008
Appendix

Appendix 1: Assigning the origin of pixels for LST (and ASTER SM) and ASAR SM images, and X and Y of pixels to be estimated during application of weight filter.
Appendix 2: R-code for estimation of experimental variogram and cross-variogram (using gstat and sp libraries)

> Res.180<-read.table('D:/Data/R/sm180.txt',header=T)
> Res.90<-read.table('D:/Data/R/90all.txt',header=T)
> coordinates(Res.180)<-~X+Y
> coordinates(Res.180)<-~X+Y

For variogram

> v.sm180<-variogram(sm180~1, loc= Res.180)
> v.lst<-variogram(lst~1, loc= Res.90)

For crossvariogram of degraded ASAR (lst used as covariable)

> g <- gstat(NULL, id = "raddeg", form = raddeg ~ 1, data= Res.90)
> g <- gstat(g, id = "lst", form = lst ~ 1, data= Res.90)
> v.cross.lst <- variogram(g)