The use of geostatistics in relating soil moisture to RADARSAT-1 SAR data obtained over the Great Basin, Nevada, USA

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Abstract

Block kriging is applied to geographically register digital images from the RADARSAT-1 satellite to soil moisture samples. Both satellite and soil moisture data are interpolated in this process to obtain precise registration. Median and adaptive Lee filtering of images are also used to correlate pixel values with soil moisture. A case study is presented using a playa in the western Great Basin, Nevada, of North America. A statistically significant correlation is found between interpolated RADARSAT-1 digital numbers and interpolated soil moisture. Results indicate that RADARSAT-1 is sensitive to median soil moisture levels; however, filtering does not significantly improve this sensitivity. The study results indicate the ability of synthetic aperture radar to delineate and map temporal soil moisture variability with the use of geostatistical methods to interpolate values over pixel areas.

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1. Introduction

Radar remote sensing has been targeted as a viable tool for soil moisture measurement since pioneering work in the 1970s (e.g. Ulaby, 1974). Typically, field soil moisture measurements are used to calibrate and establish a relationship between in situ and remote sensing estimates. Relating point measurements with radar responses over an aerially averaged pixel scale can be difficult. Furthermore, point measurements typically cannot address the spatial and temporal variability inherent to soil moisture (Van Oevelen, 1998). For example, soil moisture estimation at medium to large scales is essential for hydrologic and climatic models that require timely input for assessing such parameters as infiltration and carbon dioxide distribution. Conventional ground-based field measurements, such as from time domain reflectometers (TDR), neutron probes, or grab samples, cannot effectively cover the spatial or temporal variability needed for these types of models.

Point measurements of soil moisture may be made in the field; however, remote sensors measure soil moisture over an area equal to the pixel size. One approach to relating point-based field measurements with aerially averaged pixel measurements from radar backscatter is to use geostatistics (block kriging) for interpolation between scales. The research presented here entails using geostatistics to relate soil moisture values at field scales to radar responses at pixel scales. Images were acquired from the Canadian Space Agency’s and RADARSAT International’s (RSI) RADARSAT-1 satellite, a synthetic aperture radar (SAR) system, in conjunction with field soil sampling in an arid to semiarid environment of the western Great Basin, NV.

The current paper addresses the following aspects: (1) image processing of the SAR data for use with field
data; and (2) the use of geostatistics in relating point field measurements to SAR responses and determining spatial variability effects on aerial soil moisture values.

2. Background

2.1. Previous work

Van Oevelen (1998) emphasizes the use of geostatistics and remote sensing for estimating soil moisture for field locations that cannot be visited and to characterize transport and flow processes that affect soil moisture. Volumetric soil moisture in the top 10 cm of the soil profile typically has wide variability and he suggests the use of spatial interpolation for weighting of elements that contribute to the point measurement. Van Oevelen (1998) was able to downscale high-resolution aerial soil moisture estimates to low-resolution soil moisture estimates from the HAPEX-Sahel 1992 (Goutorbe et al., 1994) and Washita 1994 (Jackson et al., 1995) experiments. Other studies incorporating geostatistics in radar remote sensing of soil moisture include the works of Dempsey et al. (1998a, b). These studies use kriging and principal component analyses to discriminate variations in soil texture in the profile and soil moisture over time and space.

2.2. Field area and sampling

The data used in this study include RADSARSAT-1 SAR data and field soil moisture sampling over an area on the Winnemucca Lake Playa, Great Basin, NV (Fig. 1). The area is topographically flat with no vegetation and uniform, minimal, surface roughness. This site was chosen because of these features: the lack of research on remote sensing soil moisture on playas, and its close proximity to laboratory facilities at the Mackay School of Mines, University of Nevada, in Reno, NV. The impetus for this project was to develop a geostatistically based model to characterize soil moisture that may be used along with snow moisture, snow cover, and snow extent to predict snowmelt runoff in arid mountain watersheds (i.e. high topographic relief and vegetation effects).

Soil samples were collected on July 30 and August 9, 1999, to relate soil moisture conditions to the radar response of the RADSARSAT-1 satellite. Images were also acquired on these dates. Soil samples were collected within 6 h of the satellite overpass. Soil moisture contents of the grab samples were determined by the oven-dried method in accordance with ASTM D 2216–90. The moisture content is defined herein as the ratio of mass of water present in a soil mass to the mass of soil solids.

Soil samples were collected in a grid pattern at 10 m spacing (Fig. 2). A total of 36 samples were collected on each date. The samples were collected from the upper 5 cm of the soil profile. Previous studies have shown that soil moisture can most accurately be detected in the upper 5 cm of the soil profile using SAR (e.g. Schmugge, 1983; Engman and Chauhan, 1995). Moisture conditions were predominantly uniform within the upper 5 cm of the soil profile. Random locations were sampled at greater depths and in some cases, up to 40 cm below the ground surface. These samples were not used in analyses but provided an indication of the moisture behavior of the field area with depth.

Fig. 1. Location of Winnemucca Lake, Great Basin, NV.
Soil surface roughness was measured using a 1 m long bar leveled horizontally over the soil surface after Griffiths and Wooding (1996). Vertical measurements were made perpendicular to the level bar and between the bar and soil surface. These measurements were made over 5 cm horizontal intervals for the entire length of the bar. Average roughness measurements of less than 1 cm over five random 1 m transects were obtained in both the east-west and north-south directions in the field area.

Rainfall had not occurred in the area since the first week of June 1999, more than 50 days prior to the July 30, 1999, field collection day. However, rainfall occurred during the 3 days prior to sampling on August 9, 1999, amounting to a total of 21 mm between the July 30 and August 9 sampling dates. No rainfall was recorded between the time of satellite acquisition and soil sample collection on August 9, 1999.

2.3. Satellite images

RADARSAT-1 was chosen for this study for its availability, educational pricing, timely repeat coverage (temporal resolution) for the specified field area, and its relatively recent availability. RADARSAT-1 operates at C-band, 5.6 cm wavelength, and 5.3 GHz frequency with HH polarization. One SAR image was acquired on July 30, 1999, at 13:58 Universal Coordinated Time (UTC) in Fine 2 (F2) beam mode, descending at an incidence angle of 40.7°. The second image was acquired on August 09, 1999, at 01:53 UTC and in Fine 1 Near (F1N) beam mode, ascending at an incidence angle of 37.9°. Both images have pixel resolution of 6.25 m × 6.25 m. The Fine beam modes were the highest-resolution images available from RADARSAT-1 at the time of data acquisition. Fine beam positions have higher incidence angles, greater resolution, and smaller imaging areas, than other RADARSAT-1 beam positions, such as the Standard and Wide beam positions. The two images are single-look images in both the azimuth and range directions. These images were processed as RADARSAT Path Images (SGF), in which the image product is aligned parallel to the satellite’s orbit path and latitude and longitude positional information has been added to represent the first, middle, and last pixel positions of each line of data.

3. Image processing

3.1. Georeferencing

It was first necessary to reference each RADARSAT image to known latitude and longitude control points. Georeferencing was completed in ENVI 3.1 with the second-order polynomial warping function for georeferencing an image to map (ENVI 3.1 User's Guide, 1998). Ground control points were used to ensure accurate georeferencing. This included 3–5 known latitude and longitude coordinates on the ground that were used to confirm coordinates assigned to image pixels. After georeferencing was complete, 100 pixel × 100 pixel subsets were selected from the original images to match the field area of Winnemucca Lake where field sampling took place (Figs. 3 and 4). The images were cropped to this size for ease in data processing, to highlight the most sampled grid (50 m × 50 m) area of the field site, and to match field moisture sampling locations.

3.2. Filtering

The images were filtered with a 3 × 3 median filter and a 3 × 3 adaptive Lee filter to reduce the influence of speckle and to enhance the images for interpretation. These filtering techniques were implemented before the kriging process which in itself smoothes data and reduces speckle. Speckle is an inherent characteristic of SAR images. Synthesis of aperture is achieved by recording Doppler shifts in radar frequency returned by ground targets. There are, however, many ground targets that return reflections. These multiple reflections, because they are wave phenomena, interact causing many wave cancellations and additions. These interactions impart a salt-and-pepper texture to radar images, darker and brighter pixels depending on whether
reflections cancel or add. This texture is the noise known
as speckle.

Studies have shown median filters to be useful in
reducing speckle without altering the original radar
response captured in the pixels (Lewis et al., 1998;
Toll, 1985). The Lee adaptive filter, a standard deviation
(or sigma)-based filter, has been used in several soil
moisture studies (e.g. Van Oevelen, 1998; Soulis et al.,
1998). The Lee filter was chosen in this study because
it models multiplicative noise which is often found in
SAR images. Multiplicative noise in SAR images is
expressed as

\[ z = \frac{x - r}{\sigma} \]  

where \( z \) is the observed image pixel, \( x \) the noise-free
image pixel, and \( r \) the multiplicative noise.

The Lee filter computes the standard deviation of
the pixels in the filter window, then replaces the target pixel
with the original value of that pixel minus the standard
deviation multiplied by a constant:

\[ z' = z - k\sigma, \]  

where \( z' \) is the replaced image pixel, \( z \) the observed
image pixel, \( k \) the constant, empirically derived, and \( \sigma \)
the standard deviation of pixels in window.

The constant, \( k \), in Eq. (2) is an empirically derived
value and is determined by the amount of smoothing
needed. Often \( k \) depends upon the number of looks
the satellite takes of the same scene, as larger numbers
of looks induce more speckle (Martin and Turner,
1993; Raney, 1998). In this study, \( k \) was chosen to have a
value of 1 based on the single-look complex of
the RADARSAT-1 satellite. Lee filters can produce
large variations in the mean and, because the user
determines the constant value, a wide range of
filtered values may arise. In addition, the Lee filter
can reduce white additive noise while not reducing
speckle.
### Table 1
Statistical summary of July and August soil moisture and DN values

<table>
<thead>
<tr>
<th></th>
<th>Field soil moisture (%)</th>
<th>Raw DN values</th>
<th>Median filtered DN values</th>
<th>Lee filtered DN values</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>30 July 1999</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>16.2</td>
<td>84.8</td>
<td>84</td>
<td>84.4</td>
</tr>
<tr>
<td>Median</td>
<td>15.2</td>
<td>80.5</td>
<td>71.5</td>
<td>78.5</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>7.1</td>
<td>43.3</td>
<td>30.7</td>
<td>32.1</td>
</tr>
<tr>
<td><strong>9 August 1999</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>33.8</td>
<td>139</td>
<td>147.1</td>
<td>138.4</td>
</tr>
<tr>
<td>Median</td>
<td>34</td>
<td>129</td>
<td>138.5</td>
<td>134</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>3.8</td>
<td>75</td>
<td>58.1</td>
<td>56.5</td>
</tr>
</tbody>
</table>

The filtered images indicate that the median filter smoothed the image more and highlighted the trends of high and low digital number (DN) values more than the Lee filter. The Lee filter better preserves image similarity to the original pre-filtered image.

### 4. Geostatistical interpolation

#### 4.1. Introduction

Data analyses were performed with the georeferenced images and the 36 field-collected soil moisture samples of the top 0-5 cm soil profile (from the 50 m × 50 m grid). The objective of the analyses was to relate field-scale soil moisture to image-scale RADARSAT-1 pixel DN values. The statistical analysis consisted of descriptive statistics, semivariograms, block kriging, correlation coefficients, and hypothesis testing of the field soil moisture, and the raw and filtered pixel DN values (Table 1).

#### 4.2. Descriptive statistics

The mean-field soil moisture values for the July and August data are 16% and 34%, respectively. The median-field soil moisture values for July and August are 15% and 34%, respectively. By comparison, the mean raw pixel DN values for July and August are 85 and 139, respectively (these DN values represent single-byte integers in the range 0–255). The median values are 81 and 129 for July and August, respectively. The larger mean and median values for the August raw pixel values are interpreted to indicate an enhanced response of the radar reflectivity due to the higher moisture content in the soil (and a higher dielectric constant of the soil–water mixture).

#### 4.2.1. Scatter plots: the need for geostatistical registration

A preliminary comparison between raw pixel DN values and observed soil moisture (Fig. 5A and 5B, respectively) revealed little evidence of linear correlation between soil moisture and DN values, thus no statistical correlation was inferred between the two. Likewise, no distinct relationship was found between the median and Lee filtered pixel DN and field moisture values.

Pixel DN values are aerial measurements for each pixel spacing (6.25 m × 6.25 m), while the field soil moisture measurements are point measurements for discrete field locations (10 m spacings). Because of this difference, correlating these two variables, both geographically and analytically, is difficult. Moreover, no geographical registration via geostatistics was yet affected. Consequently, block kriging was applied to geographically register the RADARSAT images and field moisture data to yield new digital images of both.
consisting of pixels representing average values over 6.25 m × 6.25 m cells.

Variograms for raw and filtered DN value, moreover field moisture data are presented (Figs. 6–9). Block kriging was applied using these variograms. This procedure has been used previously (Schowengerdt, 1997, pp. 139; Magowe and Carr, 1999). Scatter plots were developed for the kriged, raw, median, and Lee filtered pixel DN values and the kriged field soil moisture data for July and August (Figs. 10–12). The July kriged raw pixels and moisture values show a positive linear correlation for the kriged estimated values. The August data show little correlation within the data set.

Fig. 6. (A) Semivariogram model for July 30, 1999, field soil moisture, x-axis: h is lag distance (in degrees latitude/longitude); y-axis: γ(h) semivariogram values. (B) Semivariogram model for August 09, 1999, field soil moisture, x-axis: h is lag distance (in degrees latitude/longitude); y-axis: γ(h) semivariogram values.

Fig. 7. (A) Semivariogram model for July 30, 1999, raw pixel DN values, x-axis: h is lag distance (in degrees latitude/longitude); y-axis: γ(h) semivariogram values. (B) Semivariogram model for August 09, 1999, raw pixel DN values, x-axis: h is lag distance (in degrees latitude/longitude); y-axis: γ(h) semivariogram values.

Linear regression was applied to the scatter plots. The method of regression analysis applied is that which assumes equal error on x and y (cf., Carr, 2002). Hypothesis testing on results from regression was performed using an F-test based on the ratio, (regression variance)/(standardized error variance). Given the sample size of 36 and assuming a 95% confidence level. Prob [F_{1,34} ≤ 4.15] = 0.95.

The regression analysis of the kriged raw pixel DN values and kriged soil moisture values for the July data has an F statistic of 61 (R^2 = 0.38), whereas the August data has an F statistic of 10.5 (R^2 = 0.1). F statistics for the median and Lee filtered July data are 140 and 84, respectively.
Fig. 8. (A) Semivariogram model for July 30, 1999, median filtered DN values, x-axis: h is lag distance (in degrees latitude/longitude); y-axis: γ (h) semivariogram values. (B) Semivariogram model for August 09, 1999, median filtered DN values, x-axis: h is lag distance (in degrees latitude/longitude); y-axis: γ (h) semivariogram values.

Fig. 9. (A) Semivariogram model for July 30, 1999, Lee filtered DN values, x-axis: h is lag distance (in degrees latitude/longitude); y-axis: γ (h) semivariogram values. (B) Semivariogram model for August 09, 1999, Lee filtered DN values, x-axis: h is lag distance (in degrees latitude/longitude); y-axis: γ (h) semivariogram values.

A regression analysis was also applied to the combined July and August data. F statistics are 1057, 1441, and 1544 for the regressions using the raw, median, and Lee filtered pixel data. $R^2$ values of 0.84, 0.87, and 0.88 are computed for the raw, median and Lee filtered pixel data. The regression equation of the combined data is similar to the July regression equation. Combined July and August data are modeled well by the line ($y = 5.5x - 13.2$), whereas the July data are modeled well by the line ($y = 6.8x - 33$).

The effects of filtering the pixel data are best illustrated in the July data (vs. the regressions of the combined July and August data). The raw data has a $R^2 = 0.38$. The median and Lee filtered data have an $R^2 = 0.58$ and 0.46, respectively. The filtering may affect the regressions using the July data alone more than the regressions using the combined July and August data because of the differences in data sample set size (36 vs. 72).

For the combined data set regressions, the $F$ test indicates that the null hypothesis is rejected and the regressions are considered significant. More importantly, the $F$ statistic is much higher for the regression of the combined data than for the regressions of the individual July and August data sets.
5. Discussion

5.1. Regression analysis

The most significant regression occurs after combining the July and August data. The best fit regression line for the July and August data is visually superior. Statistically, the $R^2$ value is much larger than for either data set used alone. The large $F$-test statistic also indicates that the regression is statistically significant. These results indicate that RADARSAT-1 is sensitive to median soil moisture levels, returning low brightness values for low moisture contents and high brightness values for high moisture contents. Furthermore, the results indicate the ability of the SAR to delineate and map moisture variability between images (temporally).

These statements are based, however, on only two sampling dates. Two defenses are offered. First, at the time of image acquisition, RSI offered two images maximum for educational discount. Images past this
limit are acquired at full cost, an amount prohibitive for this study. Second, the July regression model, alone, represents both the July and August results well. In this sense, the August data validate the July model. Using this model, a DN value of 129, the median for the August image, indicates a moisture value of \((129 + 33)/6.8\) or 23.8%. Using the combined equation, a DN value of 129 yields a soil moisture estimate of \((129 + 13.2)/5.5\) or 25.8%.

5.2. Filtering

At the onset of this study, it was assumed that filtering of the images would be necessary to remove noise speckle and local variation in pixel DN values. This assumption was based on literature reviews and image processing experience of the authors. The median filter and adaptive Lee filter were chosen. Visually, these filters provide a smoother image while preserving spatial resolution. Statistically, they reduce the data variability resulting in more “conformable and agreeable” data values. However, in this study, they provided very little help in correlating pixel values with soil moisture. In fact, the filtered pixel values had only a slightly larger \(R^2\) value (0.88) with the soil moisture than the raw pixel values (0.85). These results indicate that (1) the filters chosen were not capable of filtering the noise speckle or reducing the interference in the pixel values or (2) the images had very little noise speckle present at the onset of image processing or (3) any filtering performed by the median or Lee algorithms does not affect the sensitivity of the brightness values to soil moisture, or (4) the dielectric constant of the soil medium had a large enough influence on the brightness value of the pixels that it overrode any background or noise effects. In conclusion, the filtering algorithms provide a visually pleasing image but for this particular study are not necessary.

6. Conclusion

Radar backscatter is affected by the dielectric constant of surface materials. Water has a high dielectric constant. Soil, if dry, has a very low dielectric constant. The more water that is present in soil, the higher is its dielectric constant. Consequently, radar backscatter should be greater for moist soil and lesser for dry soil. Many factors interfere with this concept. Vegetation, if present and in sufficient quantity, can influence radar backscatter more than underlying soil, especially if vegetation moisture content is high. Furthermore, surface topography influences radar backscatter dependent upon the orientation of the surface to the radar sensor. If a slope faces the sensor, its radar backscatter will be higher simply because of this geometry. On the other hand, slopes facing away from the radar sensor are shadowed. These characteristics may outweigh in magnitude the influence of dielectric constant on radar backscatter. For these reasons, we chose a dry lake bed as a field site for assessing the sensitivity of the RADARSAT sensor to soil moisture. Interpolation was necessary to precisely register RADARSAT pixels to measured values of soil moisture. Block kriging was chosen for this effort because interpolated values represent averages over an area. Once registration was
achieved. RADARSAT DN values were found to correlate well with field measures of soil moisture.

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