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Appropriate scale of soil moisture retrieval from high resolution radar imagery for bare and minimally vegetated soils

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Abstract

This research investigates the appropriate scale for watershed averaged and site specific soil moisture retrieval from high resolution radar imagery. The first approach involved filtering backscatter for input to a retrieval model that was compared against field measures of soil moisture. The second approach involved spatially averaging raw and filtered imagery in an image-based statistical technique to determine the best scale for site-specific soil moisture retrieval. Field soil moisture was measured at 1225 m^2 sites in three watersheds commensurate with 7 m resolution Radarsat image acquisition. Analysis of speckle reducing block median filters indicated that 5 × 5 filter level was the optimum for watershed averaged estimates of soil moisture. However, median filtering alone did not provide acceptable accuracy for soil moisture retrieval on a site-specific basis. Therefore, spatial averaging of unfiltered and median filtered power values was used to generate backscatter estimates with known confidence for soil moisture retrieval. This combined approach of filtering and averaging was demonstrated at watersheds located in Arizona (AZ), Oklahoma (OK) and Georgia (GA). The optimum ground resolution for AZ, OK and GA study areas was 162 m, 310 m, and 1131 m respectively obtained with unfiltered imagery. This statistical approach does not rely on ground verification of soil moisture for validation and only requires a satellite image and average roughness parameters of the site. When applied at other locations, the resulting optimum ground resolution will depend on the spatial distribution of land surface features that affect radar backscatter. This work offers insight into the accuracy of soil moisture retrieval, and an operational approach to determine the optimal spatial resolution for the required application accuracy.
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Keywords: Radar; Soil moisture; Scale

1. Introduction

The distribution of near surface soil moisture is an important factor in hydrologic cycles, floods, climate, and ecosystem production. Resource managers can use such knowledge for a wide range of decision making related to prescribed burns, animal stocking rates, rangeland health and off road trafficability. Space based synthetic aperture radar (SAR) imagery can provide broad scale information on near surface soil moisture because radar signal return is responsive to changes in soil moisture. However, signal return is strongly affected by other variable surface features such as topography, roughness, and constructive and destructive wave interference that result in speckle inherent with active microwave systems (Mattia et al., 2003). To account for variable surface factors and image speckle, numerous approaches have been developed to derive estimates of soil moisture from imagery.

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The methods designed to account for physical surface factors and radar geometry can be grouped into empirical, semi-empirical and physically based models (Baghdadi et al., 2004; Bindlish & Barros, 2000; Oldak et al., 2003; Shoshany et al., 2000) that account for surface feature influence on return signal by different means. However, regardless of retrieval method, imagery is typically filtered using one of several potential speckle reduction filters (e.g., Frost et al., 1982; Kuan et al., 1985; Lee et al., 1994). Most image filtering techniques are applied using relatively small (several pixels) moving windows and are evaluated in terms of image metrics without determining the relationship between filter window size and retrieval accuracy.

In spite of spatial filtering, even with high resolution imagery (1 to 25 m), studies have shown generally poor relationships existed between modeled and measured soil moisture at site (<1 ha) or field (1 to 10 ha) scales and only improved at broader watershed scales (>10 ha) (Kelly et al., 2003; Le Conte & Brissette, 2004; Thoma et al., 2006). The improvement in accuracy of soil moisture retrieval after filtering and at broader scales results largely from isolating central tendencies (i.e., average backscatter values) that are concealed by speckle at finer scales. Only the large pixel sample sizes associated with watershed scale allowed the central tendency in backscatter to be clearly related to surface features (Kelly et al., 2003). These and other researchers also showed that including a temporal component improves prediction results at finer scales (Oldak et al., 2003). But, this is unfortunate since many applications require relatively fine resolution (at site or field scales) soil moisture data at points in time.

Our hypothesis is that the central tendencies in radar backscatter and the appropriate scale for soil moisture retrieval can be determined through a combination of stepwise median filtering that reduces speckle and spatial averaging over increasingly larger areas to isolate central tendencies in image statistics. In this paper, we demonstrate a technique to determine the minimum level of filtering and spatial averaging necessary to determine backscatter with known confidence using an image-based approach.

The objectives of this research were to test these methods using field measurements and statistical analysis at multiple watersheds. The first step was to validate soil moisture retrieval from radar imagery using watershed scale validation sites in Georgia, Oklahoma and Arizona. Then, the proposed methods of filtering and spatial averaging were applied to images at the field scale and evaluated for speckle removal and signal enhancement. Finally, we demonstrated an image-based approach for determining an appropriate resolution for soil moisture retrieval at the site scale. This study offers a protocol for determining the minimum spatial resolution for soil moisture retrieval from radar imagery with known confidence.

2. Study areas and data sets

2.1. Study areas

The three study areas used in this research were the 150 km^2 Walnut Gulch (AZ) Experimental Watershed (31° 43′N, 110° 41′W) in southern Arizona, the 334 km^2 Little River (GA) Experimental Watershed (83° 40′W, 31° 36′N) in southern Georgia, and the 611 km^2 Little Washita (OK) Experimental Watershed (98° 3′W, 34° 52′N) in central Oklahoma, all operated by the United States Department of Agriculture, Agricultural Research Service.

The AZ Experimental Watershed is a semi-arid rangeland supporting low density grass and shrub vegetation (Renard et al., 1993). Soils are composed primarily of alluvium and contain 0 to 60% rock fragments by volume in the top 5 cm of soil profiles. The topography consists of rolling and heavily dissected terrain. Forty-two field sites were selected from grass and shrub dominated landscapes.

The GA Watershed is in a sub-humid coastal plain region that is heavily vegetated with a mixture of forest, crops, and pastures (Bosch et al., 2006). Slopes are gentle and soils are sandy with no rock fragments but may contain iron and manganese concretions less than 1 cm diameter near the soil surface depending on the extent of erosion. Twenty-two field sites were selected from among pasture and fallow row crop fields, and measurements were made when vegetation was senescent.

The OK Experimental Watershed is in a humid region dominated by forest and pasture land (Allen & Naney, 1991). Soils are composed primarily of wind deposited loess and residuum and the topography is gently rolling. Sixteen field sites were chosen within rested or actively grazed pastures, and like GA, measurements were made when vegetation was senescent. A single exception was a winter wheat field that experienced significant phonological change between image acquisitions.

2.2. Imagery

Radarsat images used in this study were F5F fine beam, 46° incidence angle, HH polarization, with 6.25 m resolution. This is one of 5 fine beam modes used in applications that require the highest spatial resolution (Radarsat International, 2000). At AZ, four images were acquired coincident with field measures of soil moisture in 2003 on 19 January, 30 July, 31 August, and 16 September. An additional image from 04 August 2002 was also obtained for AZ. At GA, images were acquired coincident with field measures of soil moisture in 2004 on 27 February, and 22 March. At OK, images were acquired coincident with field measures of soil moisture in 2004 on 19 February, 14 March, and 7 April. For the AZ, GA and OK study areas, one of the images was selected to represent ‘dry’ or ‘reference’ soil moisture conditions used in the delta index, described below. The reference images were acquired on 19 January 2003, 22 March 2003, and 19 February 2003 for AZ, GA, and OK respectively. Image resolution was rounded up to 7 m at import using nearest neighbor resampling and was georeferenced by matching clearly visible buildings and road intersections with 1 m resolution USGS digital orthophotographs. Registration error (RMSE) was kept below 4 m using between 26 and 44 ground control points.

2.3. Vegetation water content and biomass

Earlier research in the AZ watershed indicated that the sparse, rangeland vegetation there had little influence on radar backscatter (Moran et al., 2000) and research in Kansas prairies indicated grass had little effect on backscatter (Hutchinson, 2003). However, because the biomass was denser in many GA and OK pasture sites than it was in the AZ range sites, it was sampled destructively for vegetation water content and biomass to determine if vegetation water content affected soil moisture retrieval. At each GA and OK field site, four 0.25 m^2 quadrats were clipped and weighed wet and after 48 h of forced air drying at 60 °C to determine vegetation water content.

2.4. Surface roughness and soil moisture measurements

Thirty replicates of correlation length and root mean square of surface heights were determined from field measurements with a pin meter (Bryant et al., 2007) at each field site in AZ. Twenty measurements were made at each field site in GA and OK. Because AZ was rangeland and the sites in GA and OK were in pasture or fallow row crops that had already over wintered, we assumed that surface roughness did not change between image acquisitions. The roughness measurements were not needed for use with the delta index retrieval model, but were included to describe the watersheds and make inference about the influence of roughness on image statistics.

For all but three image dates, soil moisture measurements at field sites were made over an integrated 0 to 5 cm depth using capacitance-based moisture probes at 30 to 50 locations on a grid within each 1225 m^2 field site for each watershed. All field measurements of soil moisture were made within 4 h of the 6:30 PM satellite overpass times.

For the Radarsat image acquisition on 04 August 2002 in the AZ watershed, soil moistures were retrieved from continuously recording in situ capacitance sensors installed at 5 cm depth at 13 locations in the watershed (Keefer et al., submitted for publication). Similarly, watershed average soil moisture was determined from continuously operating moisture probes installed at 5 cm depth on 22 Mar 2004 in GA (18 sites) (Bosch et al., 2004) and from time domain reflectometry soil moisture sensors on 19 Feb 2004 at OK (7 sites) (Starks et al., 2006).

3. Methods

3.1. Delta index for soil moisture retrieval

In this study, we chose to use the recently proposed delta index to retrieve soil moisture from radar images (Thoma et al., 2006). The delta index implicitly accounts for topography and other surface features including vegetation and roughness that would be exceedingly difficult to measure accurately at broad scales (Callens & Verhoest, 2004) as long as they remain unchanged between image acquisitions. Delta index was calculated using wet and dry image pairs obtained at different times of the year for bare, fallow, or senescent field site pixels in the three study areas. These delta index values were then compared to soil moisture measured on the ground at 35 m.

The delta index on a per pixel basis is defined as,

$$\text{Delta index} = \left|\frac{\sigma^{o}_{wet} - \sigma^{o}_{dry}}{\sigma^{o}_{dry}}\right|, \qquad (1)$$

where σ^{o}_{dry} = radar backscatter from dry soil obtained from a reference image (Table 1), and σ^{o}_{wet} = radar backscatter from the same location when soil is wet obtained from imagery other than the reference image (Table 1).

The delta index requires that vegetation and surface roughness remain unchanged between image acquisitions and that imagery have the same incidence angle and foot print. In this study, the delta index was calculated on a per pixel basis using unfiltered and filtered imagery for selected field sites where changes in vegetation and roughness were negligible (senescent pastures and fallow fields, except for one wheat field in OK). This was ensured by selecting validation sites in AZ rangelands and fallow fields and pastures in GA and OK study areas and by using imagery that had the same viewing geometry at each acquisition.

For mapping applications, users should consider masking by land use if significant crop growth or cultivation takes place between image acquisitions. Change in either vegetation indices or backscatter across whole fields in agricultural areas would indicate that delta index calculations may be invalid. In practice, images are filtered or spatially averaged before computing the delta index to minimize effects of speckle. If reference scenes are chosen after long dry periods and vegetation and surface roughness remains unchanged, then the computed delta index values result from changes solely due to soil moisture and speckle. Speckle effects can be minimized via filtering and or spatial averaging described below.

Table 1
Range in calibrated volumetric soil moisture measured at field sites at times of satellite overpass

Study area	Date	Probe Sm min (m^3 m^{-3})	Probe Sm max (m^3 m^{-3})	Probe Sm avg (m^3 m^{-3})	Reference image	Watershed Sm range (m^3 m^{-3})
AZ	Jan_19_03[1]	0.00	0.24	0.06	x	0.24
AZ	Jul_30_03	0.02	0.20	0.14		0.18
AZ	Aug_23_03	0.04	0.17	0.07		0.13
AZ	Sep_16_03	0.03	0.07	0.05		0.04
AZ	Aug_04_02[a]	0.15	0.47	0.23		0.32
GA	Feb_27_04	0.12	0.37	0.19		0.25
GA	Mar_22_04[a]	0.00	0.27	0.06	x	0.27
OK	Mar_13_04	0.18	0.31	0.24		0.13
OK	Apr_16_04	0.06	0.18	0.12		0.12
OK	Feb_19_04[a]	0.05	0.23	0.14	x	0.18

[a] Soil moisture was determined for the watershed using in situ continuously recording capacitance or time domain reflectometry soil moisture sensors. Data from these sensors were used to determine average watershed soil moisture for selection of reference images in the delta index calculations. These data were used for validation in AZ only once (aug_04_02) because they were point measurements. In GA and OK the in situ sensors were located at field edges to avoid farming operations and thus could not be used for validation. The average RMSE for soil moisture measured with portable probes versus soil moisture measured by in situ sensors near the sensors was 0.02 m^3 m^{-3}.

3.2. Image filters and statistics

The block median filter was chosen because of its simplicity and it does not require a priori knowledge of speckle statistics. In this study, four levels of a block median filter (3 × 3, 5 × 5, 7 × 7, 9 × 9 pixels) were applied to the 7 m resolution Radarsat backscatter images from the three study areas producing 50 backscatter images including the unfiltered imagery. Block filtering degraded resolution by multiples of 7 m; for example, raw 7 m resolution imagery passed through a 3 × 3 block median filter resulted in a 21 m resolution filtered image product.

Filtering changes delta index values at different resolutions because of the absolute operator in the equation. Speckle shifts the delta index in the positive direction in less aggressively filtered imagery and at finer scales. The delta index in practice can be used with or without the absolute operator because it is an empirical relationship with soil moisture. This issue does not change the findings of this research related to appropriate site-specific spatial scale for input to soil moisture retrieval models because the appropriate site-specific scales were determined from analysis of power values without the need to compute a delta index.

The 95% confidence interval (CI) for the mean power value centered over each field site at each step in the growing region procedure was determined using the percentile bootstrap method. The bootstrap method has been shown to be a robust technique for computing confidence intervals around the mean of lognormal data (Helsel, 2005; Singh et al., 2006). The bootstrapped 95% confidence interval is the 2.5th and 97.5th percentiles of the estimates of the mean. The ordered means were determined by sampling with replacement from the original set of n observations. In this study we computed 500 means on pixel power values for determining the confidence interval on the mean for each step in the growing region process. The confidence interval widths were plotted versus the number of pixels used in the calculation which translates directly to ground area.

Confidence intervals have been used to establish the suitability of backscatter estimates for soil moisture retrieval

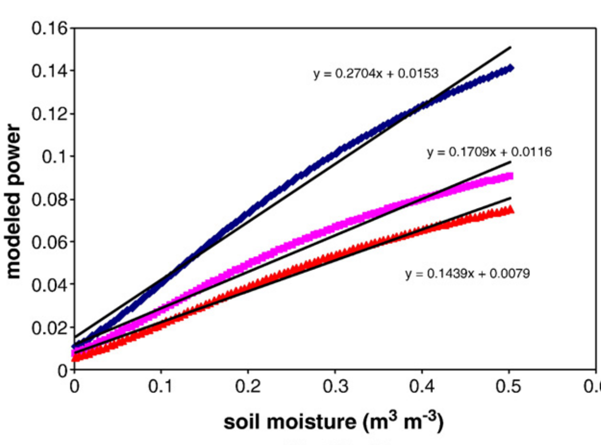


Fig. 1. Sensitivity of observed power to change in soil moisture according to the advanced IEM model using watershed averaged roughness parameters for the three watersheds (Table 2). This relationship was used to determine the allowable uncertainty in power that would limit retrieved soil moisture error to +/−0.03 m^3 m^{-3}. Solid lines represent best fit linear regression.

Table 2
Watershed averaged surface roughness parameters measured once at each field site during the course of the study

Study area	RMS surface height (cm)	Correlation length (cm)	SD RMS surface height (cm)	SD correlation length (cm)	Slope of power vs. soil moisture [a]	Cutoff value [b] (power)
AZ	0.79	8.20	0.29	2.47	0.2704	$8.112 \cdot 10^{-3}$
GA	0.76	15.05	0.36	11.80	0.1439	$4.317 \cdot 10^{-3}$
OK	0.99	19.41	0.25	13.67	0.1709	$5.127 \cdot 10^{-3}$

[a] Power was calculated using the IEM model (Fung et al., 1992) with watershed averaged surface roughness characteristics and radar parameters matching the imagery.
[b] Cutoff value is user set to correspond with +/−3% allowable error in estimated soil moisture.

(Griffiths & Wooding, 1996; Mattia et al., 2003) but have not been used in the inverse sense to determine the spatial scale over variable surfaces required for an estimate of known quality.

3.3. Image-based approach for determining confidence

The image-based approach to determine optimum filter and cluster sizes is based on a sensitivity analysis of observed power versus soil moisture using watershed averaged surface roughness in the Integral Equation Method model (Fig. 1) (IEM; Fung et al., 1992). In this study, an error of +/−0.03 m^3 m^{-3} soil moisture was deemed acceptable. The cutoff value for 95% confidence interval range on mean power values (cu) used to determine the optimum growing region size was determined as,

$$cu = m \cdot 0.03, \tag{2}$$

where m is the slope of the power versus soil moisture relationship.

Cutoff values for each watershed are presented in Table 2. Users can set the threshold depending on the required level of certainty, but should be aware that the accuracy of the radar sensor is approximately 1 dB (Staples & Branson, 1998), and the accuracy of the soil moisture sensors under field conditions with variable soil types is approximately 0.05 m^3 m^{-3} (Dynamax Inc., 1999).[1]

4. Results and discussion

4.1. Field and laboratory calibration of soil moisture sensors

Field calibration of the portable capacitance probes was made using three soil cores collected from the top 5 cm of field sites in GA and OK. A laboratory calibration of the portable probes was developed for the AZ study area using soil collected from the top 5 cm at each field site (Fig. 2). The sandy surface soils and loose structure minimized the influence of disturbance in the laboratory. The calibrated probe readings were used for validation.

[1] Use of trade names in this report is for information purposes only and does not contitute an endorsement bt the USDA-ARS.

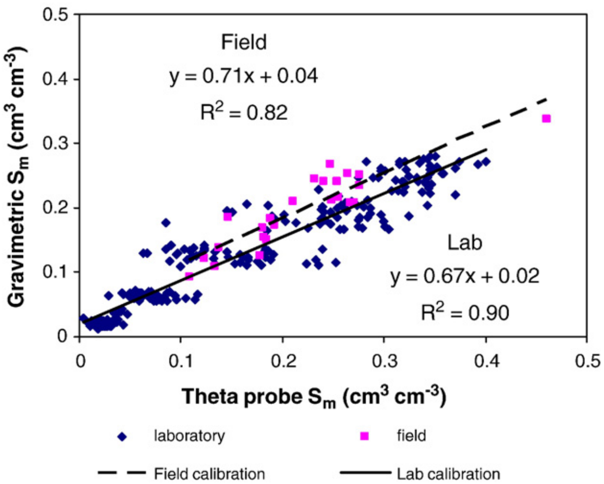


Fig. 2. Laboratory and field calibration of the capacitance probe used in validation. Laboratory calibration was made using 44 soils collected from AZ field sites. Field calibration was made at GA and OK watersheds against gravimetric moisture from three soil cores per field. Capacitance probe soil moisture was determined volumetrically. Confidence intervals (90%) for regression coefficients in both calibrations overlap indicating the coefficients may be from the same population.

The laboratory calibration of probes using AZ soils indicated that soil moisture was typically underestimated (Fig. 2). The accuracy of the probes in the laboratory (RMSE = 0.058 $m^3\ m^{-3}$, r^2 = 0.90) was consistent with manufacturer claims that the probe accuracy would be +/−0.05 $m^3\ m^{-3}$ when used in the field with variable soil types (Dynamax Inc., 1999). Spread in the field data may be due to differences in soil type, and non-uniform distribution of water content and rock fragments. In the dry condition, rocks and soil have little difference in moisture content. As the soil becomes wetter the disparity between rock and soil moisture content becomes greater. The random insertion of probe spikes that may or may not be near rocks further increases variability in measurement values. Additional scatter may result from air pockets created when probes displace pebbles in wet soils creating air filled voids. Both voids and rock fragments cause underestimation of soil matrix water content, but over estimation of bulk moisture content. Furthermore, there is increased spatial variability in the field under moist conditions due to non-uniform drainage, and evapotranspiration. Probe calibrations were made with rock fragments in laboratory samples to account for these interacting effects.

4.2. Accuracy and scale of field measurements of soil moisture

Field measured soil moisture at 35 m was used to validate soil moisture retrieved from individual pixels of filtered imagery at scales varying from 7 to 63 m. For each image date and filter level, the RMSE was calculated on a site-by-site basis for the watersheds. The data were then grouped by filter level for comparison across watersheds. The validation was made on individual pixels because 1) it was difficult to accurately measure soil moisture in the field in expansive nested extents, 2) individual pixels in filtered imagery represent the highest spatial resolution possible in filtered imagery, and 3) information from many pixels in the raw image product is effectively summarized in filtered pixels.

We recognize that the scale of field measured soil moisture does not match the scale represented in the imagery for all validation scales but suggest that the chosen measurement scale is a good approximation of soil moisture at scales between 7 and 63 m. This is primarily based on results presented in Fig. 3a and b, where as few as 10 measurements provided a good estimate of soil moisture that changed little with the number of measurements increasing as the 35 × 35 m area was traversed. Furthermore, field soil moisture measured in 3 ad hoc 100 m plots centered over three 35 m AZ plots differed by less than 2% when intra-site soil moisture varied between 0.06 and 0.15 $m^3\ m^{-3}$.

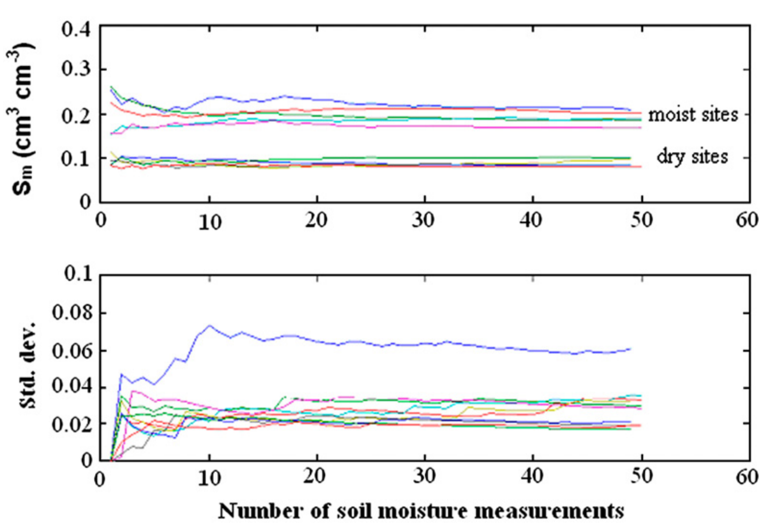


Fig. 3. (Upper) Cumulative mean volumetric soil moisture related to the number of soil moisture measurements made in a 35 × 35 m area on 29 Jul 2003 in AZ. Ten sites are presented, five moist and five drier. Moist site and dry site cumulative mean stabilized after 30 and 15 measurements, respectively. (Lower) Cumulative standard deviation stabilized to +−1% at most sites after 15 soil moisture measurements regardless of site moisture status.

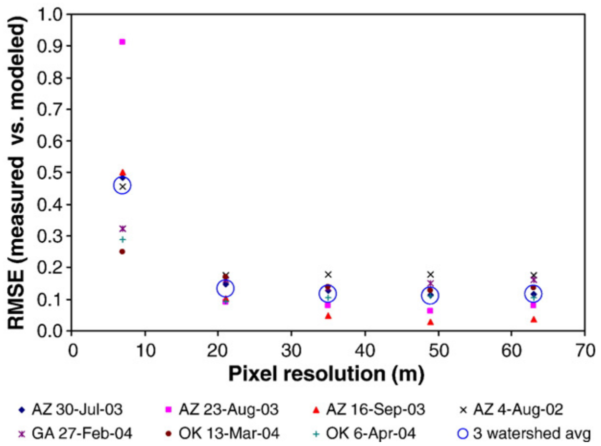


Fig. 4. Soil moisture retrieval accuracy assessed as the difference between measured and delta index modeled soil moisture for three watersheds at 7, 21, 35, 49, and 63 m resolution. RMSE was computed for each site in the watershed then averaged up to the watershed scale. All field measurements were made at 35 m ground resolution. Delta index was calculated using one dry image and one wet image pixel centered over the field site.

A high level of accuracy in measured soil moisture is critical for assessing the validity of retrieval algorithms. Preliminary investigation of spatial soil moisture variability in the field at 35 m was made by over-sampling several field sites to determine the sample size that achieved stable cumulative mean soil moisture and cumulative standard deviation that varied by less than 0.01 $m^3\ m^{-3}$. An appropriate sample size for a 35 m area depended on the moisture status of the site. In general, wetter sites had greater intra-site variability and thus required more soil moisture measurements to reach stable cumulative mean while cumulative standard deviation stabilized at approximately 20 measurements regardless of site moisture status (Fig. 3).

For a range in moisture content between 0.01 and 0.17 $m^3\ m^{-3}$, comparison between in situ sensors and portable sensors at 35 m indicated the in situ sensors were a reliable approximation of area averaged portable sensor measurements with RMSE ranging from 0.00 to 0.04 $m^3\ m^{-3}$ with an average RMSE of 0.02 $m^3\ m^{-3}$. The over-sampling of soil moisture at the field sites and calibration ensured high precision and accuracy of field measured soil moisture at the 35 m scale sampled in the field. This made it possible to use measured soil moisture as model validation with confidence at 35 m scale.

4.3. Effect of vegetation water content and phenology on soil moisture retrieval

Dry biomass averaged 625 and 97 kg ha^{-1} for GA and OK field sites respectively. The average water content in above ground vegetation that was sensed by the radar but not measured by field methods using soil moisture probes during validation was 59.8 and 10.4 g m^{-2} for GA and OK watersheds respectively. This represents 0.60 and 0.10% of the soil moisture in the top 1 cm of the soil profile. The small amount of vegetation moisture was expected as the GA and OK sites were chosen to represent bare soil or pasture in a senescent state. In the single winter wheat field sampled in the OK study area, the vegetation water content was 0.25% of the soil moisture in the top 1 cm of the soil profile, and the dry biomass for this field was mid-range for all sites sampled.

Although some structural change occurred between image acquisitions in the watersheds which would seem to violate the delta index assumptions, we feel it would be minimal based on conclusions of Moran et al. (2000) that vegetation structure had little effect on backscatter in the AZ watershed and Hutchinson (2003) that indicated Kansas prairie grasses had little effect on backscatter. The impact of change in vegetation structure in humid environments is more difficult to evaluate because it changes rapidly. Although we used imagery from winter and early spring in most cases to mitigate structural effects, there may still be some influence. For this reason, we suggest the amount of change in vegetation structure that occurred in this study would be near the upper allowable limit when using the delta index method. We concluded that the minimal amount of vegetation moisture in all sites in all study areas and the minimal phenological change between image acquisitions did not unreasonably violate delta index assumptions and hence had a negligible effect on retrieval accuracy.

4.4. Soil moisture retrieval at the watershed- and site-scales

Surface soil moisture was retrieved using the Delta Index (Eq. (1)) from individual pixels centered over each field site for block median filters of increasing size, from unfiltered (7 m) to 9×9 pixels (63 m). For each image acquisition date and pixel resolution the modeled and measured soil moistures for each site were used to compute an RMSE by site (Fig. 4). This differs from our earlier work (Thoma et al., 2006) where we determined the RMSE as watershed averaged soil moisture versus watershed averaged delta index for several dates at 91 m resolution. The lowest RMSE (0.03) for the collection of field sites in a single watershed was obtained for the very dry 16 Sep 03 AZ image at 49 m resolution. Retrieval accuracy for other

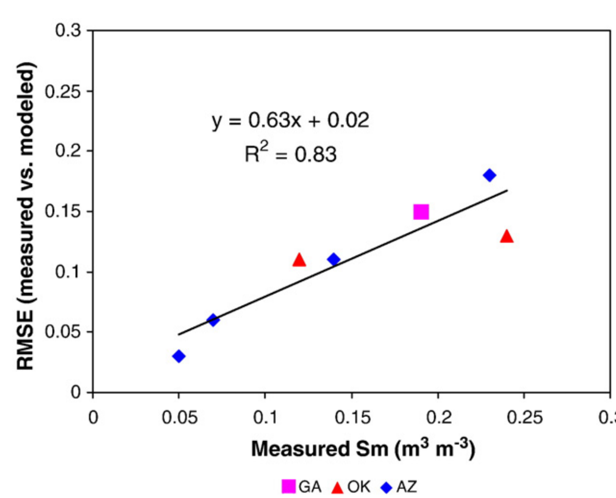


Fig. 5. Relationship between watershed averaged soil moisture retrieval accuracy and field moisture conditions. Soil moisture retrieval accuracy decreases as soil moisture increases.

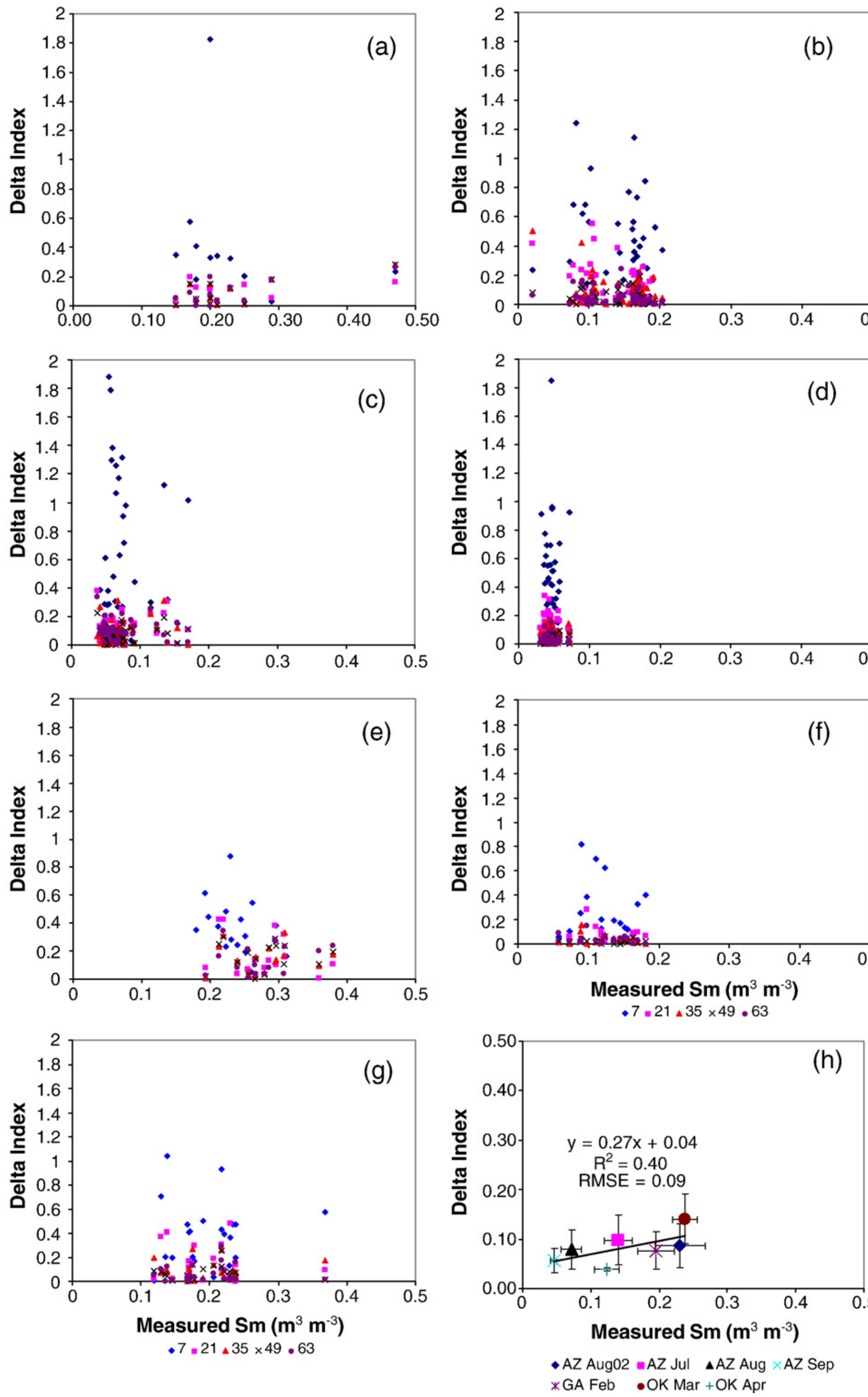


Fig. 6. Soil moisture retrieval accuracy at 7, 21, 35, 49, and 63 m for the three watersheds validated at 35 m. Error statistics are presented in Table 3. Figures are a) AZ — 04 Aug, 2002, b) AZ — 30 Jul, 2003, c) AZ — 23 Aug 2003, d) AZ — 16 Sep 2003, e) OK — 13 Mar 2004, f) OK 16 Apr 2004, g) GA — 27 Feb 2004, and h) retrieval accuracy at watershed scale determined from 35 m Delta Index and 35 m soil moisture at the field sites.

dates and watersheds varied by scale but generally decreased with increasing filter size until pixel resolution was degraded to 49 m (7×7 pixel filter), beyond which no substantial improvement occurred.

The 3-watershed average RMSE that included a range in surface conditions through space and soil moisture through time provided an indication of expected accuracy over varied terrains in the three watershed study areas. The decrease in 3-watershed averaged RMSE between unfiltered (7 m) (RMSE = 0.46) and 5×5 median filtered (35 m) imagery (RMSE = 0.12) was attributed primarily to speckle reduction. The best 3-watershed average RMSE (0.11) was obtained with a 7×7 filter resulting in 49 m resolution. Further improvement was not observed with a larger filter window. Although for all dates and watersheds the RMSE on a site basis was not excellent, it still may be sufficiently accurate for applications that require soil moisture data over large heterogeneous areas.

The disparity between measured and modeled soil moisture may in part be related to field soil moisture content (Fig. 5). Agreement was generally least for the wettest AZ image on 4 August 2002, and greatest for the driest AZ images on 16 September 2003 and 23 August 2003. In dry conditions, the spatial uniformity of soil moisture explained the good agreement between measured and modeled soil moisture after speckle was minimized via filtering. As noted in the field and laboratory calibration of capacitance probes (Fig. 2), wetter conditions were more variable and difficult to characterize due to differences in drainage and evapotranspiration. Residual error due to mis-match in spatial variability of soil moisture and filtered image resolution requires a different approach discussed in the next section.

Analysis at the watershed scale masks variability in site specific agreement between modeled and measured soil moisture on a site-by-site basis (Fig. 6). It should be noted that our estimate of "watershed" soil moisture is restricted to the type of fields validated and does not apply to urban, forest or cropped areas that occur in some of the watersheds. Model performance was poor at all site specific scales (Table 3) for all study areas, which indicated that speckle effects which are readily apparent when validated at 7 m resolution may have still not been entirely removed even at the broadest filter level (Fig. 6a–g). Other factors such as natural variability in soil moisture and subtle change in roughness and vegetation may confound results in spite of our careful selection of bare, fallow, or senescent pasture fields intentionally selected to avoid phonological change between image acquisitions. Still other sources of error result from using two images in the delta index calculation. This introduces potential error from registration, slight satellite view angle differences and the choice of image filter which may select geographically different pixels from within the same geographic block for wet and dry imagery. There are other radar retrieval models or filtering algorithms that may yield better results at the scales investigated in this study. However, in this study results for site specific soil moisture retrieval at 35 m averaged to watershed scale indicate that even when retrieval scale and field measurement scale are identical results are poor on a watershed basis (Fig. 6h). This result supports the need for an image-based approach that considers both natural variations in surface features that drive backscatter response, and speckle to determine the appropriate scale for site specific soil moisture retrieval. The technique demonstrated in the next section has general applicability regardless of model choice.

4.5. Results of combined filtering/averaging on image statistics

Spatially averaging observed power across larger areas after block median filtering offers a means to account for variability at extents broader than the largest 9×9 pixel filter window (63 m). Because the extents that result from spatial averaging power values were large, it was not possible to validate results using our ground based measurements that represented much smaller areas. Instead, a statistical approach was used to assess the combined method.

Considering first the AZ watershed imagery only, the combined effect of median filters and spatial averaging is presented using imagery from 5 dates representing conditions from dry to moist (Fig. 7). The confidence interval range for power was generated from growing regions centered on each of 42 field sites. The spatial scale where a combination of filtering and averaging resulted in 95% confidence interval less than the cutoff (user set based on sensitivity analysis) was called the 'optimum' cluster size (Table 2). Circles indicate the optimum cluster size determined as the growing region size where observed power is less than the cutoff value set by the sensitivity analysis.

Based on the relative position of the curves, it is apparent that unfiltered imagery had the largest and most variable range in power at most spatial scales, while larger block median filters

Table 3
Error statistics for Fig. 6

Figure	Study area	Date	Scale	Slope	Intercept	r^2	RMSE
6a	AZ	4-Aug-02	7	−1.15	0.67	0.04	0.45
		4-Aug-02	21	0.17	0.17	0.08	0.18
		4-Aug-02	35	0.78	−0.09	0.55	0.18
		4-Aug-02	49	0.78	−0.09	0.55	0.18
		4-Aug-02	63	0.71	−0.07	0.53	0.18
6b	AZ	30-Jul-03	7	−0.33	0.45	0.00	0.48
		30-Jul-03	21	−1.14	0.30	0.13	0.15
		30-Jul-03	35	−0.85	0.22	0.12	0.13
		30-Jul-03	49	−0.21	0.08	0.03	0.11
		30-Jul-03	63	−0.27	0.09	0.04	0.12
6c	AZ	23-Aug-03	7	−1.50	0.70	0.00	0.91
		23-Aug-03	21	0.31	0.08	0.01	0.09
		23-Aug-03	35	0.46	0.05	0.03	0.08
		23-Aug-03	49	0.29	0.06	0.02	0.06
		23-Aug-03	63	−0.15	0.11	0.00	0.08
6d	AZ	16-Sep-03	7	3.31	0.26	0.01	0.50
		16-Sep-03	21	−0.96	0.15	0.01	0.10
		16-Sep-03	35	0.59	0.03	0.01	0.05
		16-Sep-03	49	0.75	−0.01	0.08	0.03
		16-Sep-03	63	−0.55	0.05	0.03	0.04
6e	OK	13-Mar-04	7	−1.98	0.84	0.12	0.29
		13-Mar-04	21	−1.01	0.40	0.06	0.09
		13-Mar-04	35	0.30	0.07	0.01	0.10
		13-Mar-04	49	0.30	0.08	0.01	0.11
		13-Mar-04	63	0.77	−0.04	0.06	0.10
6f	OK	16-Apr-04	7	−0.63	0.37	0.01	0.31
		16-Apr-04	21	−0.07	0.08	0.00	0.10
		16-Apr-04	35	−0.26	0.07	0.05	0.05
		16-Apr-04	49	−0.01	0.02	0.00	0.12
		16-Apr-04	63	−0.40	0.09	0.15	0.11
6g	GA	27-Feb-04	7	0.54	0.28	0.01	0.32
		27-Feb-04	21	−0.28	0.20	0.01	0.16
		27-Feb-04	35	0.15	0.06	0.01	0.14
		27-Feb-04	49	−0.01	0.07	0.00	0.15
		27-Feb-04	63	−0.02	0.06	0.00	0.16

Slope, intercept and Pearson's correlation coefficient values are for linear regression.

resulted in lower magnitude and less variable power until large areas were added in the region growing procedure. In most cases, variation stabilized with larger growing regions as the effects of outlying pixel values were mitigated. However, in a few of the field locations larger growing regions encompassed greater variability as evidenced by spikes in the curves. These are interpreted as dramatic changes in roughness or vegetation when growing regions became large enough to cross field, topographic or vegetation-type boundaries. For the most part, variation in the confidence interval range varied predictably with filter level where more aggressively filtered images required fewer pixels centered on each field site to achieve a high level of confidence in parameter estimate. However, the smaller pixel count did not translate to a smaller optimum ground area, because filtered imagery had coarser resolution pixels.

The confidence interval analysis applied to all three study areas (Fig. 7 a–c) indicated that in general, for any filter level and growing region size, the 95% confidence interval range was $CI_{AZ} < CI_{OK} < CI_{GA}$. This relationship mirrored the variation if not the magnitude of RMS surface heights for the three watersheds (Table 2). As expected, variability increased with increasing variation in surface roughness. The most likely explanation for the trend in required ground area for the three watersheds is that roughness effects due to oriented tillage operations in GA induced greater range and variability in backscatter by field while lack of tillage and random orientation of roughness elements in the rangeland study sites (AZ and OK) made for more consistent backscatter response as region growing areas increased in size.

The ground area necessary for good parameter estimation is related to the soil moisture–power relationship in Fig. 1. Less sensitivity reflected in a smaller slope value in this relationship results in larger ground areas necessary to achieve a good parameter estimate. It is important to note, especially with the GA watershed that it may not be possible to obtain a good estimate of observed power with this type of imagery at field scales common in this watershed. In a practical sense, either the confidence level for parameter estimate must be lowered, or very large areas that cross field boundaries must be included thus dramatically increasing the minimum resolution for good parameter estimates. This finding may explain the high degree of variation reported in the literature when observers regress soil moisture on backscatter (Griffiths & Wooding, 1996; Hutchinson, 2003; Shoshany et al., 2000). It is likely, but difficult to ascertain from these studies that the strength of the relationship was indirectly related to the variation in surface roughness or other varying surface properties.

Many combinations of filter level and spatial averaging can be used to achieve a 95% CI range on the mean observed power (Fig. 8). Each point on each of the lines represents such a condition but the spatial extent of the different combinations varies widely due to intra-pixel variance that remained after different levels of filtering. Examination of the resulting ground area necessary to achieve the optimum spatial area for retrieval indicated that the most aggressive filter did not translate to the smallest usable ground area. This counterintuitive finding resulted from growing regions increasing into contrasting surfaces more quickly when image resolutions were low.

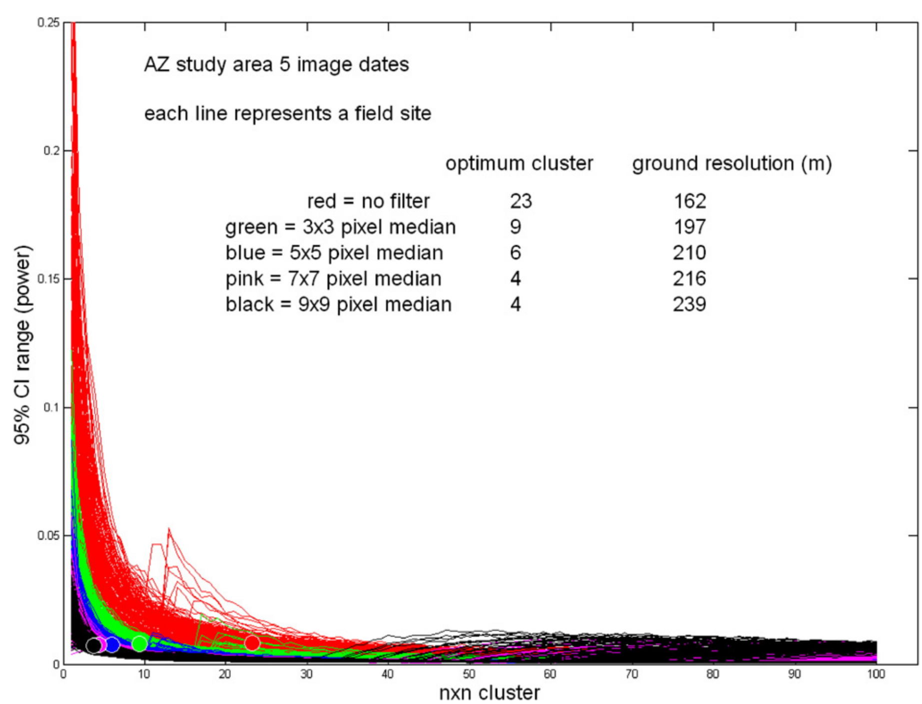
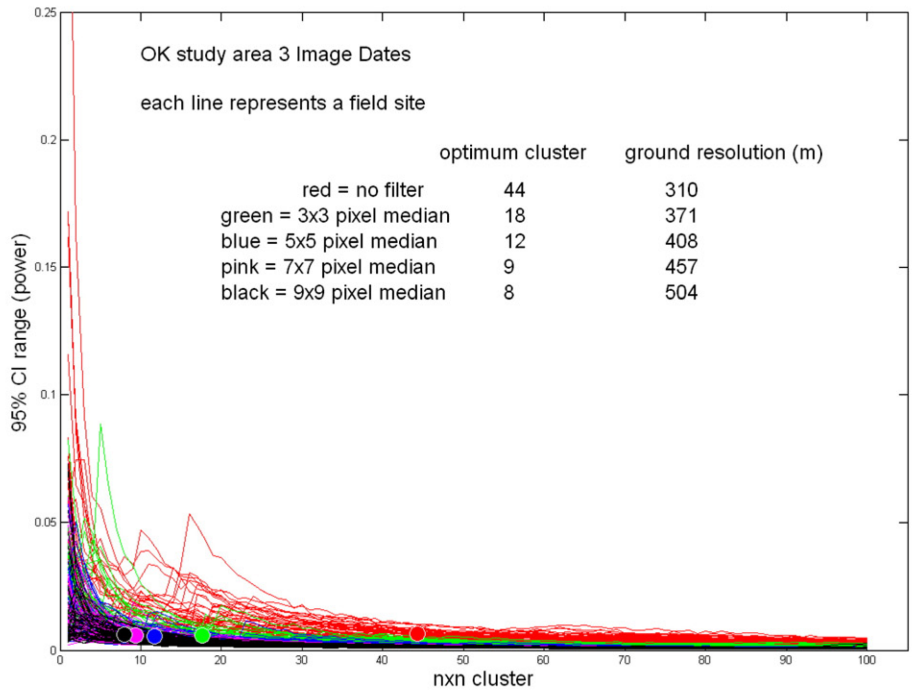


Fig. 7. Using multi-date imagery representing a broad range in soil moisture, we show the reduction in magnitude and variation of confidence intervals for power as growing regions increase around study sites in (Upper) AZ watershed, (Middle) OK watershed and (Lower) GA watershed. The optimum cluster size is the number of pixels necessary to obtain a 95% confidence interval on observed power less than the cutoff value (user set based on sensitivity). The ground resolution is determined as the (cluster size) × (filter level) × (raw image resolution).



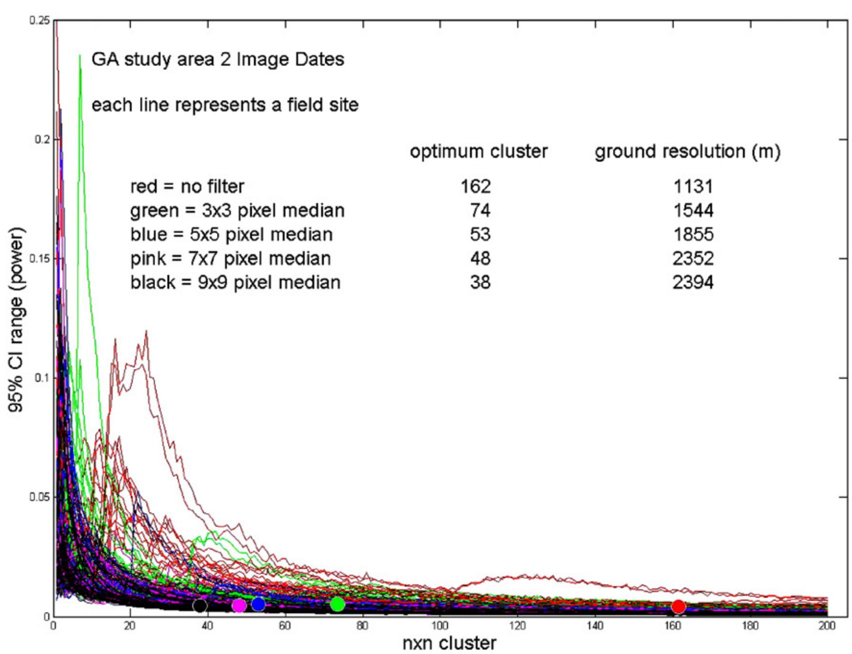


Fig. 7 (*continued*).

4.6. Image-based optimization of scale for site specific estimates

Evaluation of spatial averaging and filtering necessary to derive 95% CI for mean observed power indicated the smallest spatial extent was derived from unfiltered imagery for all three study areas (Fig. 7) and was 162 m, 310 m, and 1131 m for AZ, OK and GA watersheds, respectively. The ground area represented by the optimum cluster size in imagery increased with filter level and was largest at all filter levels for GA and least for AZ as evidence by right-shifted points in Figs. 7 and 8. This trend corresponds to greater variability in roughness at the field sites as indicated in roughness statistics (Table 1). Although field sites were selected in the centers of large fields, the GA fields were not typically as expansive as the rangelands in the OK and AZ watersheds. In the confidence interval method optimum ground resolutions derived from filtered imagery are larger than those derived from unfiltered imagery

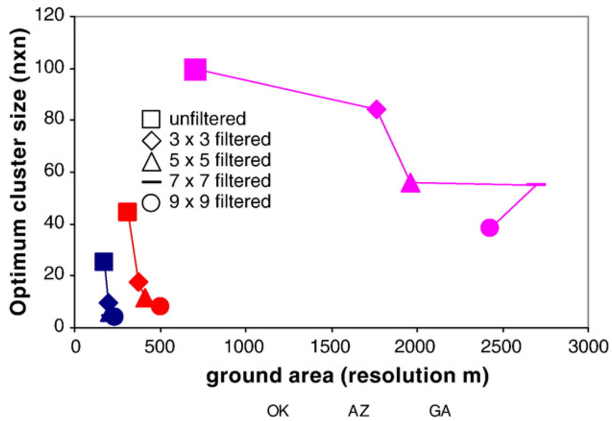


Fig. 8. Ground area required to obtain a high confidence estimate of observed power for soil moisture retrieval for three study areas. Each point on the lines represents a 95% confidence in observed power estimate. Square, diamond, triangle, dash and circle represent unfiltered, 3 × 3, 5 × 5, 7 × 7, and 9 × 9 filtered imagery respectively.

due to more rapid reduction in pixel sample size relative to spatial variation as filter level increases. Therefore users of this technique should be aware of landscape heterogeneity represented in imagery over which spatial averaging occurs.

5. Conclusions

There are multiple studies reporting good results of soil moisture retrieval from radar imagery at the watershed scale, but there are few studies claiming similar results at the field or site scale. Results presented in this study confirmed the spatial limitation of high resolution radar imagery for estimating site scale surface soil moisture. The results herein offer both an explanation for this dichotomy and a procedure to determine the best possible spatial resolution with known confidence.

Site scale soil moisture retrieval from high resolution radar imagery using only filtering to minimize backscatter variability had limited utility (Fig. 6). The best 3-watershed average RMSE (0.11) for a range in soil moisture conditions was obtained at 35 m resolution using a 5 × 5 pixel block median filter (Fig. 4) with results directly related to scale and indirectly related to soil moisture (Fig. 5). That is, results were best at the broadest scales under the driest conditions. While this level of accuracy may be sufficient for watershed applications where data from many pixels are averaged up for a single watershed estimate, improvement in soil moisture prediction at true site scales with SAR imagery will likely only be achieved via spatial averaging and thus a further reduction in resolution.

The image-based approach for determining optimum retrieval for site scale evaluated spatial averaging and filtering to minimize speckle effects and variation in other surface factors that influenced backscatter. The 95% confidence interval range on mean observed power was used to determine the optimum filter window and cluster size associated with the smallest usable ground area. The smallest effective ground resolution was obtained with unfiltered imagery and was 162 m, 310 m, and 1131 m for AZ, OK and GA watersheds, respectively. Filtering reduced small scale variation in observed power, but increased the effective ground area for the same confidence level due to a tradeoff between sample size and filtered image resolution.

The optimum ground area, which is between 25 and 160 times the original SAR image spatial resolution, is based on the assumption that product confidence must be high (95%). This is the case for hydrologic model calibration in which calibration success requires high accuracy of satellite products (e.g. Peters-Lidard et al., 2003).

The CI method represents a technique for deriving input for retrieval models in the absence of field validation when there is significant speckle noise and variation in land surface characteristics. It is valid only for images acquired when the site has minimal vegetation cover with negligible attenuation of the radar response. In this study, the assessment of the CI method was based solely on image statistics because it could not be validated against the ground moisture data due to mismatched scales. This method can be used with imagery from different radar satellites, different raw image resolutions, and other retrieval models. If possible it should be validated at appropriate scales against field measured soil moisture.

This study offers a statistically sound approach for determining the optimal spatial resolution for soil moisture retrieval customized for a given site and given application accuracy. The approach demonstrated here relies on the sensitivity of the soil moisture–power relationship, but perhaps could be modified to a purely image-based approach if some knowledge of surface roughness or land surface features was available. This will shed some light on the mixed performance of soil moisture retrieval approaches using SAR imagery at site to watershed scales. It will also open the door to use of soil moisture maps for model calibration and parameterization which often require both fine spatial resolution and high input accuracy.

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