SAR imagery used for soil moisture monitoring: the potential

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Abstract A series of soil moisture measurements were taken in a 15 ha unvegetated field on the Essex coast (UK) at times to coincide with seven ERS-1 overpasses during a wetting period in autumn and winter. The results show that the calibrated SAR values have a strong correlation with soil moisture. Analysis of the spatial variability (using semi-variograms) suggests that the SAR data are able to distinguish spatial continuity of soil moisture that the field programmes could not detect. Analysis suggests that the optimum spatial resolution of the SAR data for soil moisture assessment is approximately 1 ha. One-hectare spatial resolution is of great use in hydrology as it is well within the scale of catchment modelling schemes. The paper discusses how such data may be made operational by hydrologists using new satellite platforms and combined modelling approaches.

Key words ERS-SAR; Essex, UK; semi-variograms; soil moisture variability

INTRODUCTION

The ability to assess soil moisture distribution in a spatially distributed fashion is of great importance for hydrological modelling. The amount of data required to set initial conditions in a distributed model are vast and it has been suggested that remote sensing may offer a way of overcoming the problem (Grayson et al., 1992). Several studies have demonstrated the ability of ERS-SAR (European Remote Sensing Satellite–Synthetic Aperture Radar) data to predict soil moisture at the field scale (Griffiths & Wooding, 1996). The nominal spatial resolution within a SAR image would suggest that it might offer the potential of assessing soil moisture at a scale finer than a single field. This paper is an attempt to find the smallest scale for interpreting soil moisture from ERS-SAR data.

METHODS

A series of soil moisture measurements were taken within a 15 ha unvegetated field (Fig. 1) to coincide with ERS overpasses during an autumn and winter period. The
location was chosen to provide the optimum conditions for soil moisture interpretation of SAR data, i.e. unvegetated and flat. The intention of this research was to find out how well soil moisture could be detected under ideal conditions and then these findings can be related to the needs for hydrological modelling.

At times concurrent with the satellite overpasses, volumetric soil moisture was measured gravimetrically using an undisturbed core sampler. The sampling strategy (Fig. 1) was designed to obtain the maximum number of samples to evaluate the total field soil moisture in addition to any small-scale variability. There are three scales of measurement: 13 samples 1 m apart in a crucifix shape; samples within lines transecting the field 30 m apart; and the transect lines themselves, which are approximately 100 m apart.

The SAR PRI (Precision Image) data extracts for the study area were filtered using an enhanced Lee sigma filter and calibrated to provide a relative backscatter coefficient. They were geolocated using recognizable ground control points and co-registration of images.

For the period of measurement an automatic weather station was set up nearby and, using these data, a simple model of surface soil moisture devised. The model treats the top 5 cm of the soil as a bucket with rainfall as input and evaporation and seepage as losses. Potential evaporation is modelled using the Penman equation and related to actual evaporation through a nonlinear relationship with soil moisture. The field is underdrained and therefore the assumption was made that the water table never rises to the surface. The seepage of water from the surface is modelled using the Richards approximation of Darcy’s Law for unsaturated flow. The model calculates the soil moisture content on a daily timestep. Since it is not always possible to have the

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**Fig. 1** Location of the field site and sampling pattern. Within the intensive sampling square 13 samples were taken in a crucifix shape.
field measurements coincide with the satellite overpass (three field programmes were mistakenly seven days late), the soil moisture model is sometimes used as a comparison.

**RESULTS**

The measurements of soil moisture carried out in the field were at three different scales to try and capture some of the variability that might be expected. Analysis of these data is carried out using semi-variograms to investigate whether there is any connectivity between the points. Figure 2 shows that there is no obvious nugget variance or sill. Any trough or peak evident in the semi-variogram is as much a factor of the sampling design as of any within-field variability. Therefore, it is reasonable to assume that the field sampling of soil moisture was not able to detect any inherent variability. However, this may be a function of sampling density, or a lack of spatial correlation in the soil moisture overall.

It is clear from Fig. 3 that there is a sill in the semi-variograms for the ERS-SAR data, which for the majority of images is reached within seven lags i.e. 87.5 m. This suggests a spatial dependency of soil moisture as detected by the satellite signal variability, of around 90 m, considerably less than shown by Biftu & Gan (1999). In this case it appears that the satellite has detected a spatial dependency in soil moisture that could not be seen through the field measurement programme.
In a secondary analysis, the SAR imagery was spatially filtered, using progressively larger neighbourhood windows to compare against measured values of soil moisture. This is shown in Fig. 4, in which the size of neighbourhood is on the x-axis and the correlation coefficient (between measured soil moisture and averaged radar backscatter) is shown on the y-axis. A flattening off of this curve occurs at approximately 1 ha, caused by a large reduction in the variability of backscatter when averaging above this level. This suggests that the majority of signal variability in the SAR data occurs at a scale of less than 1 ha, and therefore that it should not be used to interpret soil moisture below this resolution.

By combining the data from different days of observation it is possible to derive a relationship between radar backscatter and soil moisture. The field was left fallow and undisturbed throughout the measurement period and therefore it has been assumed that surface roughness does not change between satellite overpasses. In Fig. 5 the ERS-SAR imagery has been spatially averaged to a 1-ha resolution using kriging and compared to the measured soil moisture values. The measured soil moisture values remain as point measurements, as it was not possible to krig the data sensibly due to the lack of spatial continuity discussed above. The main groups of data are at either end of the relationship, which reflects the coincident field programme being at the start and end of the period that corresponds to the wettest and driest. For the period when the field programme was not coincident with the satellite overpass, model results are used. The model treats the field as a single averaged unit and therefore it is compared to a single averaged SAR backscatter value. In Fig. 5 there is a strong relationship
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Fig. 4 Area of pixels from neighbourhood integration plotted against corresponding correlation coefficient ($R$) values for the neighbourhood averaged backscatter vs soil moisture relationship. The thick solid line marker shows the 1 ha area.

Fig. 5 Relationship between averaged SAR backscatter and point measurements of soil moisture for the measurement period. Points marked as a circle (o) are averages for the total field with soil moisture values derived from the model.

between radar backscatter and measured soil moisture, confirming previous studies such as Griffiths & Wooding (1996).

**DISCUSSION**

An understanding of the surface soil moisture based on radar backscatter at a spatial resolution of 1 ha is very encouraging for hydrological modelling. It would appear to offer the hope of setting initial conditions for a model at a resolution well within the current modelling capability. However all of the results shown here have been in a situation ideal for the interpretation of soil moisture from SAR backscatter, not a real world situation that requires investigation by the hydrologist. The field site was flat to negate the effect of radar shadow. It was fallow because vegetation is known to attenuate the microwave signal and may also interfere with the signal through changing surface roughness. The measurement period was also at a time when the field was left untouched so that surface roughness did not alter significantly.

The limitations on the data outlined above do not mean that this approach is totally without use. It is undoubtedly the presence of vegetation cover and changing surface
roughness that are the largest barriers in the operational usage of SAR data for soil moisture interpretation. Su et al. (1997) inverted a theoretical backscattering model to derive effective surface roughness parameters for a site. This allows surface roughness to be derived using multiple SAR imagery and solving for roughness as a series of simultaneous equations, i.e. lessening the requirement for surface roughness measurement. The presence of vegetation is more complicated to overcome. Chauhan (1997) uses a combination of active and passive microwave data to estimate soil moisture under a range of different vegetation covers. This works well but is difficult from an operational point of view in terms of obtaining both datasets simultaneously. Vegetation is sometimes modelled as a “vapour cloud” (Taconet et al., 1996), which allows some understanding of the effect of the vegetation on backscatter signal. This type of approach offers a way of accounting for vegetation as part of the overall backscatter signal but tends to treat the plant as static, i.e. no change with growth. It is important that a better understanding is gained of how radar backscatter changes as a vegetation cover such as an arable crop grows.

Combined sensor approaches will likely provide information for operational use of satellite data in hydrology. New satellite systems such as Envisat will allow such multisensor modelling approaches. Skriver et al. (1999) use a combination of C and L-band SAR at different polarizations on an airborne platform to derive “polarimetric signatures” of arable crops in Denmark. If this type of data were available from satellite platforms then it is feasible that large-scale evaluation of ground cover could be carried out simultaneously with soil moisture assessment.

Finally it must be acknowledged that the soil moisture evaluation is for the extreme surface, although this is still of hydrological importance through control of infiltration rates. Under optimum conditions surface soil moisture can be assessed at a scale of great use to hydrology; the challenge now is to find techniques so that the range of conditions can be extended to be of operational use to hydrology.

Acknowledgements The authors would like to thank Mr S. H. Fowler for access to the field site at Hockley Farm. A College research grant from Queen Mary & Westfield College supported the work and the European Space Agency enabled access at low cost to the ERS-SAR PRI image archive.

REFERENCES


