DInSAR Measurement of Soil Moisture

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***Abstract*—Differential interferometric sythetic aperture radar (DInSAR) measurements using the European Remote Sensing 2 (ERS-2) satellite in a high-plains region of Colorado show intriguing spatial variations in millimeter-scale path-length change that may correspond to variations in soil moisture of a few percent by volume, in both farm fields and uncultivated terrain. The observed signal is hypothesized to result from both changes in penetration depth and the swelling of clay-rich soils, both due to changes in soil moisture. Comparisons with our field measurements of soil moisture cannot conclusively verify this, but strong support is found from prior and complementary research as well as the visual correlation with hydrological features such as stream channels and watershed boundaries on a 50-m scale. Detection of these subtle signals was facilitated using a digital elevation model with high vertical accuracy. If our interpretations are correct, C-band DInSAR is a promising new tool for the remote sensing of soil moisture in a variety of terrain.**

***Index Terms*—Hydrology, penetration depth, microwaves, soil moisture, synthetic aperture radar (SAR), synthetic aperture radar (SAR) interferometry.**

I. Motivation and Hypothesis

THE WATER CONTENT of the thin band of soil covering our earth's land surface plays a major role in global climate and human affairs and, therefore, merits the considerable attention it receives from the scientific community. Because we walk, drive, and build on this upper layer of soil, understanding the relationship between soil moisture and ground, stability is an important aspect for many engineering projects. Soil moisture also largely controls the success or failure of agricultural crops, whether or not forest fires will occur or spread, and the run-off volume following precipitation or snow-melt events. Because of the high latent heat of water and its phase change at 0 °C, soil moisture also largely controls the mass and energy exchange between land and atmosphere, strongly influencing global climate and its many feedback mechanisms. Unfortunately, soil moisture is difficult to measure over large spatial areas, and a successful remote sensing technique that combines high spatial resolution with high accuracy has remained elusive [1].

The initial motivation of the research presented here was to determine whether we could measure soil moisture using spaceborne synthetic aperture radar (SAR) for the purposes of facilitating military-vehicle trafficability-planning in remote regions, with both the instrument and initial study area being preselected by the funding agency. Spaceborne SAR [European Remote Sensing 2 (ERS-2)] was selected because of its relatively high spatial resolution (tens of meters), near-global coverage, and its all weather, day/night measurement capability. The 1000-km^2 Pinon Canyon Maneuver Area (PCMS) [Fig. 1(A)] in south-central Colorado was selected as the study area both because large-scale tank maneuvers occur there several times per year and because it is sparsely vegetated and has gently sloping terrain making it suitable for SAR research. To avoid long-term ecological damage, the PCMS range-managers restrict maneuvers to areas in which tank treads will not permanently damage the soil. Such decisions are based largely on qualitative assessments of soil moisture (i.e., muddiness), and an accurate near-real-time spaceborne measurement technique was desired. Therefore, PCMS served the military's long-term goals of theater planning and short-term goals of maneuver-site preservation. Given these two constraints, SAR and PCMS, we were free to develop our own methods.

In this paper, we provide validation for the hypothesis that C-band differential interferometic SAR (DInSAR) is a promising tool for the measurement of soil moisture. A common working hypothesis within the microwave remote sensing community is that a *useful* soil moisture phase (SMP) signal can *not* be derived from C-band, spaceborne DInSAR techniques. Our research largely invalidates this hypothesis, though significant research gaps need to be filled before the technique can reach a useful state.

II. Methods and Data Sources

To examine the relationship between SAR phase and soil moisture, we processed a time-series of eight consecutive differential interferograms (DIGs) of the PCMS area spanning ten months from August 1999 to May 2000 using ERS-2 data. The two-pass DInSAR methods we used in this study are standard in every way [2], [3], except that the accuracy of the digital elevation model (DEM) is substantially higher than typically used. We used the commercial InSAR processing software "PHASE" (Vexcel Corporation, Boulder, CO) to produce all of the DIGs presented here. The DEM used to create the synthetic interferogram was identical in each DIG and was created by Intermap Technologies Corporation's Star3i airborne, X-band, single-pass InSAR system [Fig. 1(A)]. It has a spatial resolution of 5 m and nominal vertical accuracy of 3 m, though we found the actual accuracy to be better than 2 m using D-GPS. This DEM was resampled for SAR processing, and the final DIGs have a 50-m posting; how this resampling affects the DIGs is discussed later. We did not employ the permanent scatterer (PS) technique [4] in this rural area; therefore, we had no direct means of accounting for atmospheric phase anomalies; the significance of this is discussed later as well. As a crude

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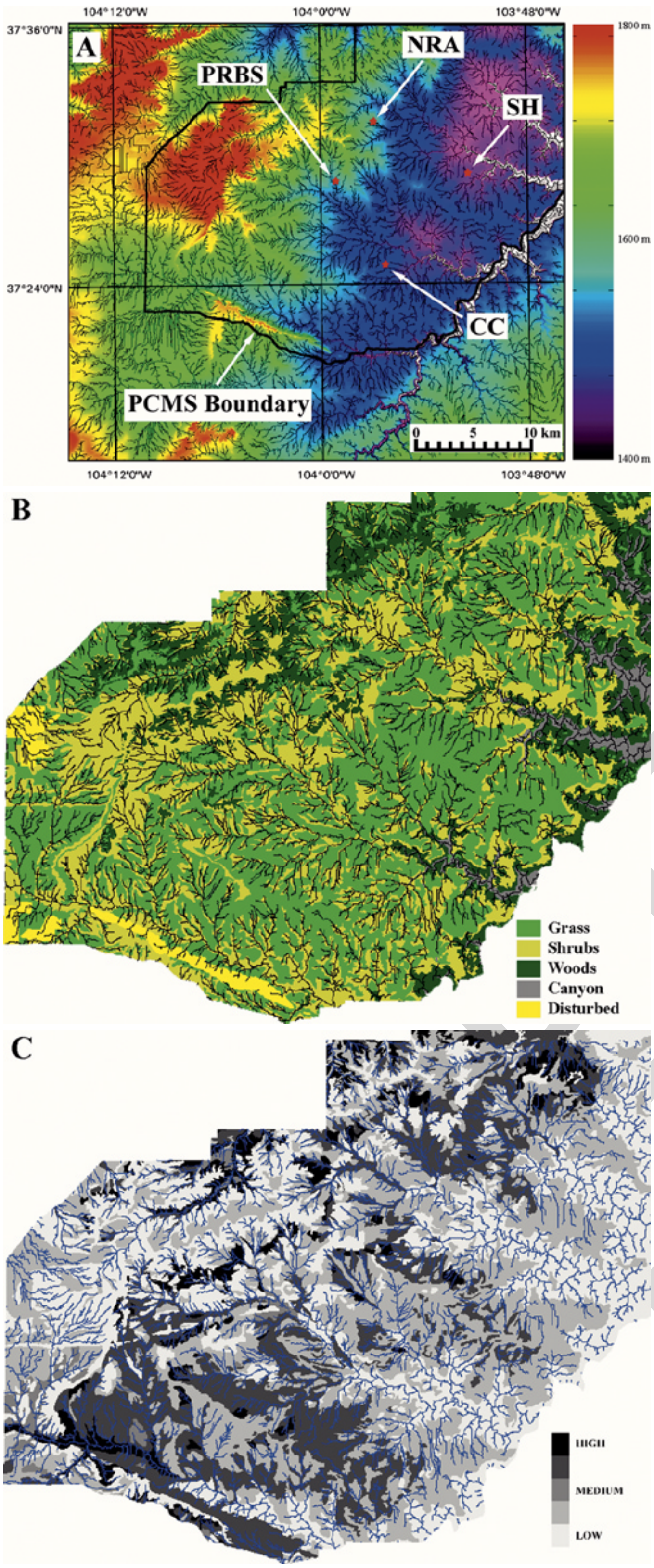

Fig. 1. Location maps of PCMS in Southern Colorado. (A) Color slice of DEM with the locations of four meteorological stations and the PCMS boundary. (B) Simplified vegetation map of PCMS. Grass consist of four units (e.g., Bouteloua gracilis). Shrubs consist of 11 units (e.g., Opuntia imbricata and Yucca glauca). Woods consist of four units, with varying densities of Juniperus monosperma. Black lines indicate stream channels. (C) Map of potential for clay swelling. Soils data were used to rank potential for clay swelling, as described in text.

approximation for atmospheric distortion, we reduced each DIG individually to zero mean change, as is commonly done [5], preserving the relative phase change within each DIG but limiting comparisons between DIGs, such that cumulative maps of change cannot be created, and the color mapping indicates relative change in path length within a *single* image. For example, within any DIG, a red pixel means a relative path length increase of 10 mm compared to a yellow pixel in that DIG, but the actual path length to that red pixel could have decreased between acquisitions. The parameters used to reduce each raw DIG to zero-mean are presented in Table I (an offset, a ramp in the range direction, and a ramp in the along-track direction), along with the perpendicular baselines for these pairs.

We installed four meteorological stations to provide quantitative ground truthing for these DIGs. These stations [PRBS, CC, SH, and NRA; see Fig. 1(A)] continuously recorded air temperature, relative humidity, wind speed and direction, net solar radiation, and soil moisture. Mean annual air temperature is approximately 10 °C (with annual extremes of +35 °C and −20 °C), and annual precipitation ranges between 200 and 330 mm, depending on site. Each station had multiple time domain reflectometry (TDR) soil moisture probes (Model CS615, manufactured by Campbell Scientific), at a variety of depths and locations, with a minimum of two at about 50 mm beneath the soil surface. Probes only several meters apart and placed at the same depth with careful attention to uniformity showed volumetric soil moisture differences as high as 20% (i.e., 10% versus 30%) consistently throughout the measurement period (Fig. 2).

Vegetation and soils maps of PCMS indicate that vegetation should largely not interfere with the soil phase signal and proved useful in qualitative spatial comparisons with the DIGs. These maps were obtained digitally from the Directorate of Environmental Compliance and Management (DECAM) of Fort Carson, CO, and were created as part of their environmental assessment and restoration efforts, based partially on previously existing unpublished maps. Vegetation within the regions consists of 25 units, which we have simplified into grasses, shrubs, trees, and rock in Fig. 1(B). PCMS is largely covered by sparse grasses, even sparser cactus bushes, and isolated groves of relatively open canopy Juniper trees. Mean percentage bare ground is 15.3% for grassland, 12.3% for shrubland, and 9.6% for woodland. Except for tree-covered regions, above-ground biomass is approximately 0.25 $\mathrm{kg/m^2}$. Ulaby *et al.* [6] indicate that an above-ground biomass of less than 0.5 $\mathrm{kg/m^2}$ has a negligible affect on C-band backscatter from the soil surface; thus, most of our study area should be unaffected by vegetation. Soils contain 31 units, and information on these units is derived largely from unpublished reports [7] created by the Los Animas County local U.S. Department of Agriculture (USDA) National Resource Conservation Service (NRCS) in Trinidad, CO. Rather than present a map of the units themselves (as mapped by DECAM), we derived a new map [Fig. 1(C)] based on the NRCS classification of the tendency of the soil unit to swell with increases in moisture. The tendency of each unit to swell was ranked as a function of depth as low, medium, or high, though the nominal depths tested varied for each unit (10 cm was typical). Because the actual depths are

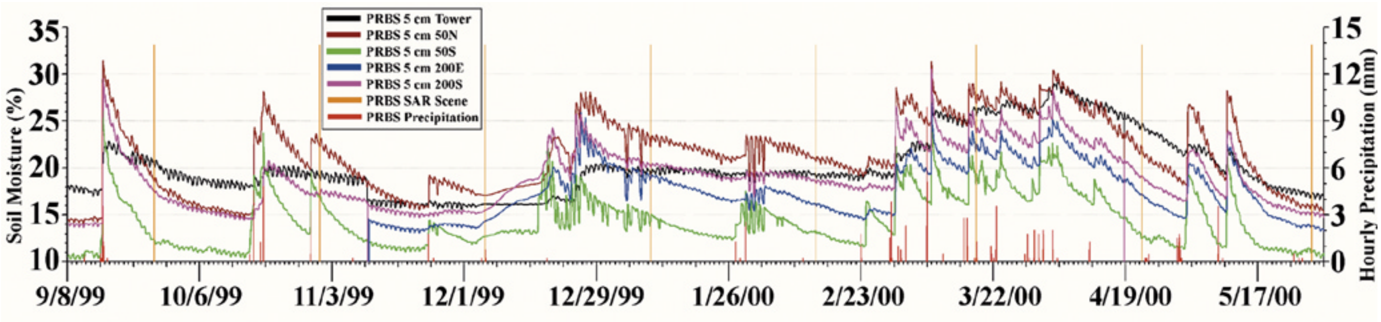

Fig. 2. Example TDR soil moisture measurement at site PRBS. Vertical orange lines indicate time of SAR acquisitions. Probe 200E experienced data loss in September and October. Each of these probes was placed horizontally, approximately 5 cm below the soil surface, at locations within the same SAR pixel. Other than a slight surface slope (downward toward the southwest), no differences in ground morphology were observed. While the overall trends are similar, significant differences in overall values are observed throughout the record, as well as different responses to rainfall and character of drying/redistribution. These subtle differences produce a wide range of correlation coefficients when compared to DInSAR measurements.

TABLE I
DETAILS OF ERS-2 INTERFEROMETRIC PAIR PROCESSING. GOLDSTEIN "ALPHA" VALUE IS DESCRIBED IN [2]. OTHER COLUMNS ARE DESCRIBED IN THE TEXT

DIG	Perpendicular Baseline (m)	Goldstein alpha	Vertical Offset (mm)	Slant Tilt (mm/pixel)	Azimuth Tilt (mm/pixel)
Aug-Sep99	532	0.8	373.44	0.007	0.02
Sep-Oct	124	0.8	-0.5	-0.002	-0.001
Oct-Dec	435	1.2	78.24	0.01	-0.001
Dec-Jan00	79	1.6	23.72	-0.004	0.003
Jan-Feb	-470	1	27.08	-0.011	-0.017
Feb-Mar	-431	1	26.2	0.05	-0.018
Mar-Apr	-229	0.4	27.06	-0.003	0.014
Apr-May	182	0.4	27.061	0.005	-0.018

likely different than the nominal depths (but with no means of determining this short of thousands of soil cores), we simplified this classification into five categories: low/low, low/medium, medium/medium, medium/high, and high/high, where the first rank is above the nominal 10 cm and the second below 10 cm. Most of the study area ranks low to medium.

III. Hypothesis Validation

We have pursued four independent lines of investigation to validate our hypothesis that a viable soil moisture phase (SMP) signal can be retrieved from C-band data. First, we examine the literature to find that prior research has demonstrated that L-band DIGs contain an SMP signal and that theory strongly supports that the same is possible for C-Band. Second, a qualitative inspection of the DIGs provides numerous examples of what appears to be SMP signal. Third, we conclusively refute the alternative possibilities for all phase sources previously identified in the literature that are unrelated to soil moisture. Finally, having demonstrated the likely presence of an SMP signal, we use our DIGs and field data to lend support to two mechanisms by which soil moisture could affect phase in the manner observed.

A. Prior Research

Prior DInSAR observations convincingly demonstrate that spaceborne L-band DIGs contain an SMP signal. Gabriel *et al.* [8] were first to describe the technique of three-pass DInSAR and its potential for soil moisture measurement. They used the L-band Seasat satellite to demonstrate the technique, measuring changes related to soil moisture in agricultural fields in California. Their DIGs revealed path-length changes on the order of several centimeters over a nine-day interval, with spatial variations in phase change occurring primarily between farm fields that individually had relatively uniform phase. After reviewing irrigation records of about 50 of these farm fields, they found that nearly all of the phase variation between the fields could be explained by differences in soil moisture. Their explanatory hypothesis, which remains untested, was that increases or decreases in water content caused swelling or contraction of clay rich soils, causing a change in surface elevation (and the SAR scattering centers within the soil) that is measurable using DInSAR. Their study leaves little doubt that an SMP signal exists, at least in farm fields using L-band, though their hypothesized mechanism would only be valid in areas with suitable clay mineralogy [9]. Despite this initial success 15 years ago, however, there has not been a single DInSAR study to our knowledge that has specifically attempted to exploit this technique for quantitative assessment of soil moisture [10].

Prior theory and empirical studies indicate that DInSAR measurement of soil moisture should also be possible in soils with little or no clay, using C- or L-band [11]. Because of the water content's effect on the soil's permittivity, the penetration depth of SAR microwaves is dependent on soil moisture. It was found that both clay swelling and penetration depth affect phase with the same sign (e.g., both positive). For example, wetting the

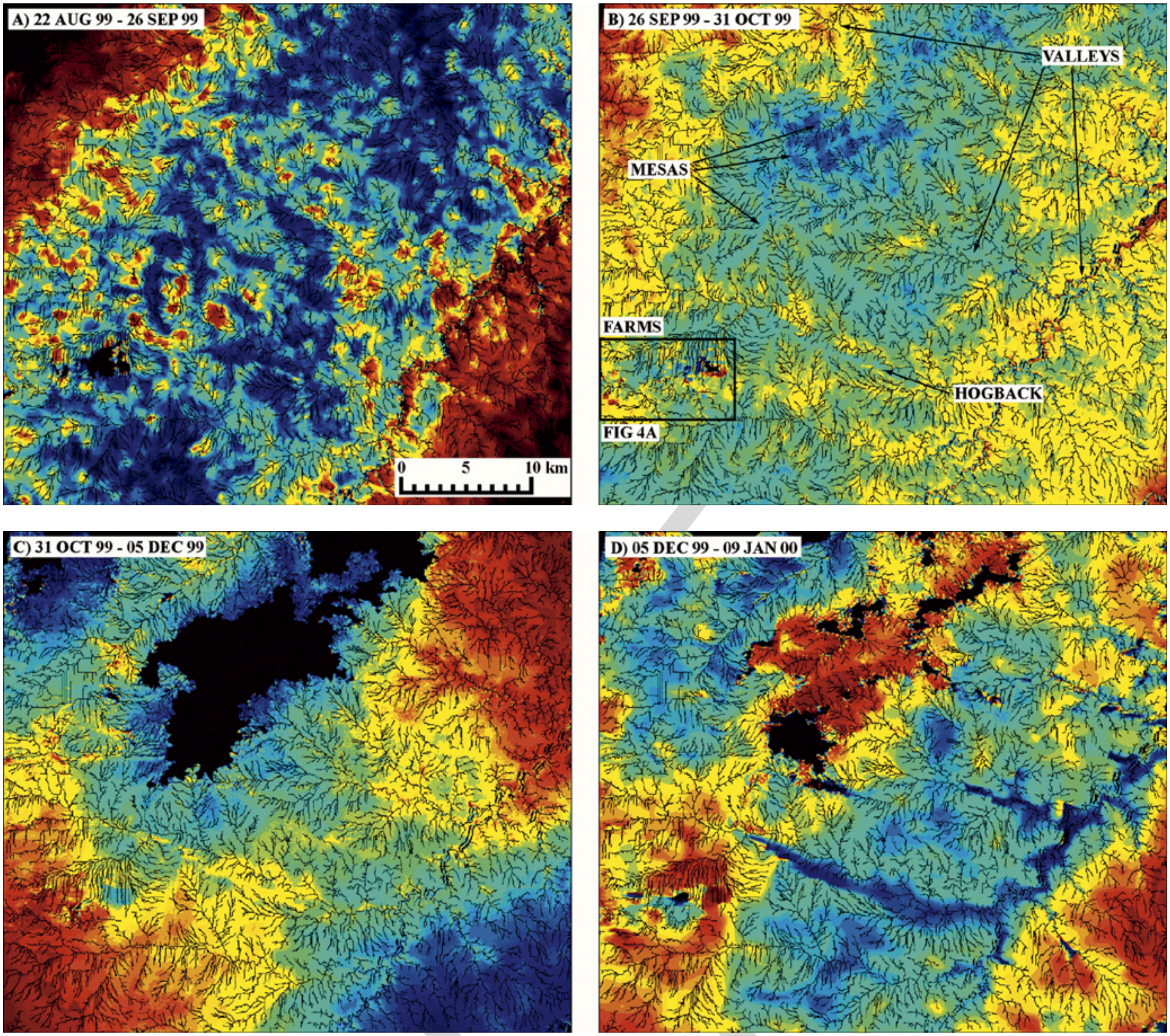

Fig. 3. DIGs of the PCMS area. (A)–(G) Time-series of DIGs from August 1999 to May 2000 on 35-day intervals, as annotated. Color mapping is shown in units of both millimeters and relative wetting and drying, as described in the text. Black lines indicate stream channel locations. Black regions indicate decorrelation due to poor coherence, except in (D), where a phase-unwrapping error occurred due to the canyon in the southeastern corner. Image width is 42.5 km. North is up.

soil both increases surface elevation and decreases penetration, both of which decrease path length. Clay swelling, while a valid mechanism, was found not to be a viable *proxy* because the complexity of swelling phenomenon prevents an inversion for soil moisture, at least given the current state of research. A change in penetration depth, however, should occur regardless of soil composition and has a smoothly varying relationship with soil moisture. Unfortunately, this relationship is nonlinear [11], making inversion difficult. For example, a 1-mm change in penetration depth could represent a change from 6.0% to 6.5% or from 20% to 23% volumetric soil moisture (VSM) using C-band SAR. For C-band SAR, it was found that the typical range of path length variation due to soil moisture change should be less than 20 mm; by comparison, this is about the noise floor of most DInSAR studies until recently, largely due to topographic noise. Subwavelength changes in penetration depth should not necessarily cause interferometric decorrelation, since many stable DIGs have been created in regions that must have changed in soil moisture due to evaporation or redistribution over the 35-day acquisition interval of ERS (e.g., [3], [10], and [12]); we discuss the effects of clay swelling on decorrelation below.

Theory and examples also exist that show that path-length variations on a submillimeter scale should be observable using DInSAR if DEMs of sufficient vertical accuracy are used, further indicating that C-band DInSAR can detect a useful SMP signal. It was shown [13] that vertical RMS accuracies of 2 m or better facilitate the measurement of subtle signals like soil moisture in irregular terrain. The primary advantage of high-accuracy DEMs is that they largely counteract the problems associated with using interferometric pairs with large perpendic-

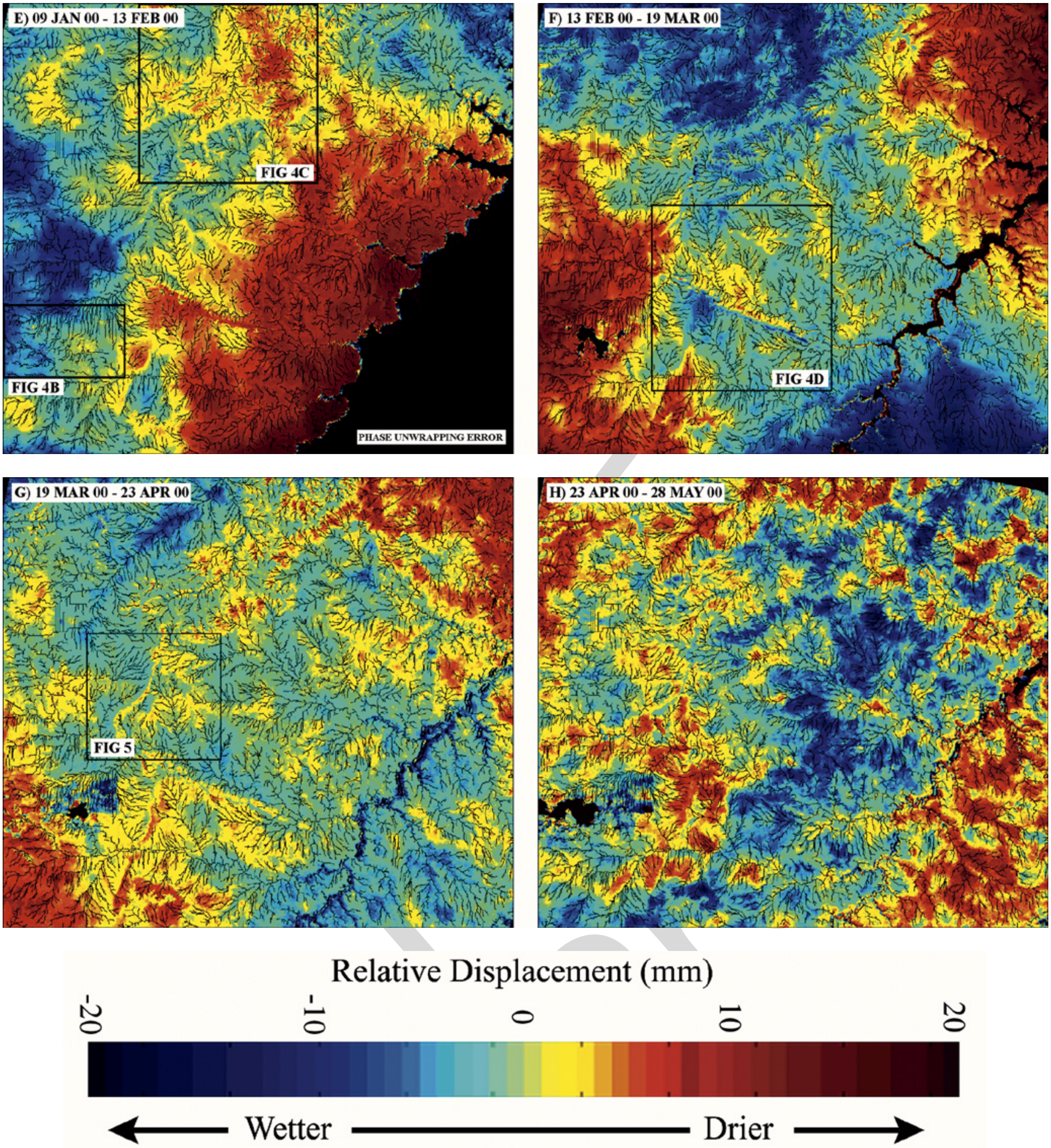

Fig. 3. *(Continued).* DIGs of the PCMS area. (A)–(G) Time-series of DIGs from August 1999 to May 2000 on 35-day intervals, as annotated. Color mapping is shown in units of both millimeters and relative wetting and drying, as described in the text. Black lines indicate stream channel locations. Black regions indicate decorrelation due to poor coherence, except in (D), where a phase-unwrapping error occurred due to the canyon in the southeastern corner. Image width is 42.5 km. North is up.

ular baselines, allowing for more usable pairs. A variety of new DEMs of PCMS (including the Shuttle Radar Topography Mission (SRTM) DEMs, the U.S. Geological Survey's (USGS) new National Elevation Database (NED), and the Star3i airborne SAR of Intermap Technologies Corporation) were tested and found sufficient. Standard USGS DEMs and those made by repeat-pass ERS-2 interferometry were found insufficient, though they may be adequate at other sites or with multiple-pair averaging for the latter. The most important variable, however, was hypothesized to be relative vertical accuracy between adjacent

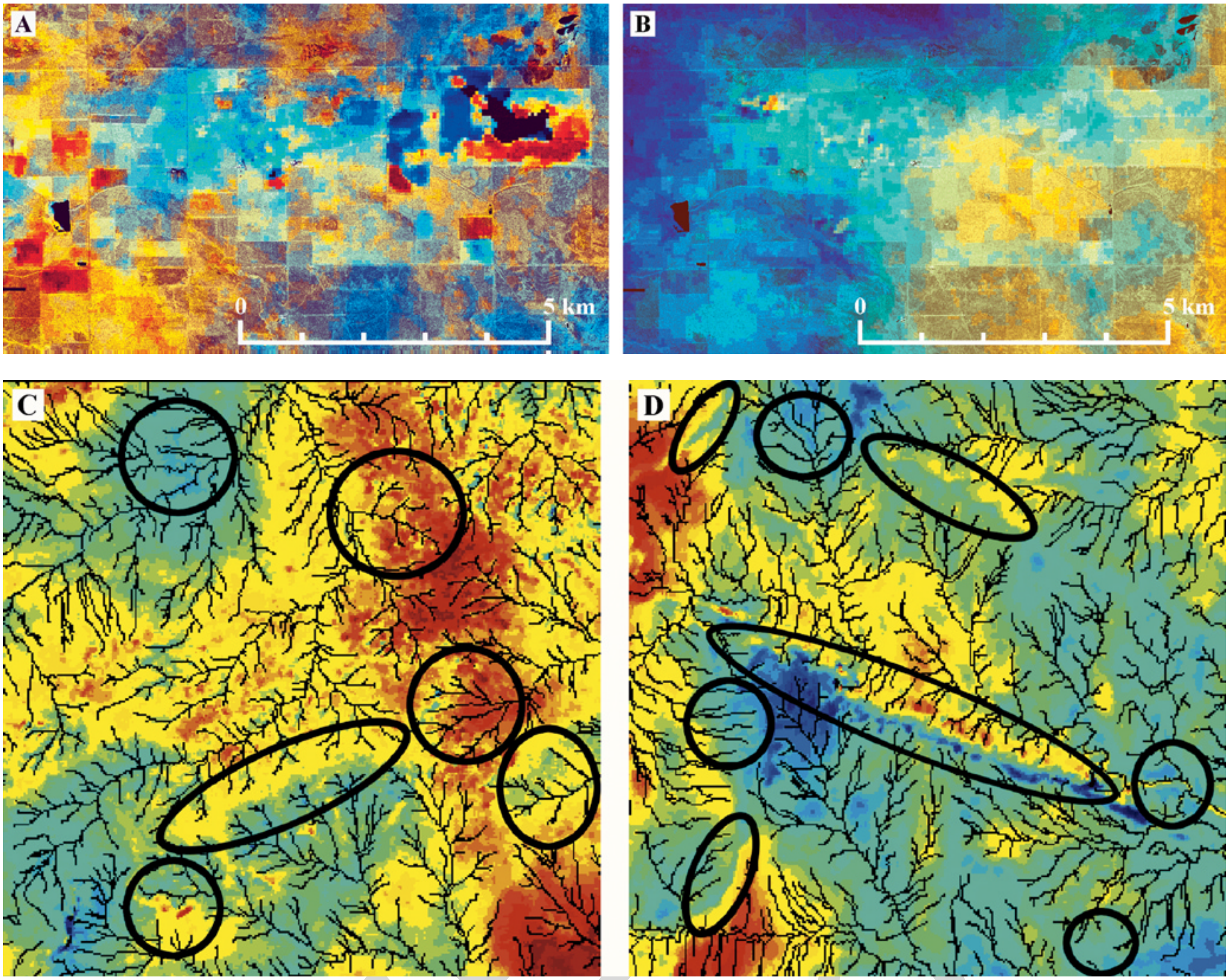

Fig. 4. Example highlights of visual correlations between phase change and hydrology. (A) and (B) Example DIG cutouts (Fig. 3(B) and (E), respectively) of the farm fields of Model, CO. Cutouts are approximately 11 km tall. Color mapping is the same as in Fig. 3(B), except that the Star3i radar amplitude image is used to modulate color intensity, which accentuates field boundaries. No causal mechanisms other than soil moisture have been identified that can explain changes across such linear boundaries. Soil moisture is expected to vary between fields because of differences in evaporation and drainage due to cover crops, soil type, and farming practices, irrespective of the irrigation events, which would obviously cause an immediate difference. (C) and (D) Example DIG cutouts (Fig. 3(E) and (F), respectively) in uncultivated areas. Circles highlight examples of phase change correlated with stream channels (black lines), and ellipses highlight phase change correlated with ridges that separate watersheds. Similar to cultivated regions, atmospheric phase delays are insufficient to explain the full variation seen here.

pixels (i.e., slope accuracy), but this metric was not published for the DEMs tested. Slope accuracy in the case of Star3i approaches the sensor limitations of 30 cm, as it is a relative accuracy that is not tied to real-world coordinates, suggesting soil moisture resolutions of less than 1% VSM. Resampling high-accuracy DEMs to lower spatial resolutions did not seem to affect the quality of the result, likely because both the slope accuracy is preserved and the SAR scene is resampled to match DEM resolution within the InSAR processor.

Thus, there is substantial background to suggest that an SMP signal exists (either due to penetration depth or clay swelling) in both L- and C-band and that accurate DInSAR measurement of it should be possible using available technology.

B. Qualitative Inspection

Qualitatively, the eight DIGs shown in Fig. 3 are consistent with a soil moisture source explanation. The colorbar in Fig. 3 indicates phase change reduced to path length change, as well as qualitatively indicating our soil moisture interpretation. This colorbar is based on the results of [11], which discusses that penetration depth should decrease with wetter soil and increase with drier soil. Each individual DIG is the difference in phase between two acquisitions; thus, spatial differences within a DIG indicate that some property has changed spatially between acquisitions. The stream channel overlay (black lines) reveals that the phase-change variations are often visually correlated to watershed features such as stream channels, subdrainages, and watershed divides. Fig. 4 presents cutouts that highlight a few of these correlations, but many more exist in the full scenes. A useful way to explore the detail found in these DIGs is to follow a particular feature, such as the hogback or one of the circled regions in Fig. 4(C) and (D), through time and note the differences. Note that topography can be inferred from the stream channels; for example, ridges exist at the loose ends of stream channels. A key qualitative feature of these DIGs is that they show temporal differences in spatial patterns, but in such a way that they often correspond with hydrologic features.

Why should soil moisture be correlated with stream channels and watershed boundaries? Water, of course, flows downhill, and its direction is, therefore, a function of terrain, so intuition suggests that valleys should be wetter than ridges, all else being equal. This particular terrain, however, is characterized by mesas and hogbacks, created by the differential erosion of bedding layers that also have water retention properties that vary along the flow path. Soil types, and thus water retention properties, are, therefore, a function of this topography as well. Vegetation [Fig. 1(B)], in turn, is also correlated with watershed features in this arid region, likely due to a feedback with soil moisture and soil type (in fact, most soils maps use vegetation as a proxy for soil type); thus, a correlation between vegetation and DInSAR phase should be expected if soil moisture is the phase signal source. Fig. 5(A)–(C) gives an example of such spatial correlations, but many more can be found by comparing Fig. 1(B) to the DIGs. It is important to note that vegetation itself could not be the phase signal source unless it *changed* between acquisitions. Such a signal source is unlikely because most of the vegetation here is sparse grass and shrubs that are essentially invisible to C-band microwaves. Soil type or surface roughness boundaries likewise could not be signal sources in DInSAR unless they *changed* over time, and did so in a spatially smooth manner. These possibilities are discussed below.

The phase variations themselves are smoothly varying down to the submillimeter scale with a pattern that is clearly related to vegetation and soils boundaries, indicating that these subtle patterns are useful data and not simply a processing artifact. Fig. 5(D) indicates that patterns related to vegetation and soils are present down to a 0.5-mm resolution, with a minimum between 0.3 and 0.4 mm; if these patterns were an artifact of interferometric filtering, we would except no such correspondence with vegetation and soils (which we assume are actually soil moisture patterns controlled by the water retention properties of the soil boundaries). Because 1-mm resolution represents 0.5% to 4% volumetric water content change [11], submillimeter resolution suggests that subpercentage soil moisture resolution at nearly any initial soil moisture, though entire scenes would be difficult to view at this resolution. Such submillimeter signal resolution is predicted for the 0.3-m Star3i sensor accuracy, as described previously [11].

Though the patterns of phase change visually correspond to many hydrological features that we would expect them to, many of the patterns themselves do not match the canonical model of soil moisture, where ridges should dry more quickly than hill slopes that dry more quickly than valley bottoms. Given uniform rain conditions, uniform soil properties, and uniform vegetation, this model is likely a good first approximation. Fig. 3(B) is the closest our full-size DIGs come to this canonical model, with mesas generally showing more drying than valleys (though many exceptions exist). However, rainfall in this area is dominated by brief, intense convective storms with narrow footprints. Further, 25 vegetation types and 31 soil types characterize PCMS, with terrain varying greatly in slope and aspect; thus, the infiltration, redistribution, and evaporation rates likely vary spatially considerably. This heterogeneity in rainfall and surface properties contributes to the heterogeneity in soil moisture patterns. That is, in this location it would be surprising to find that the canonical model held in every scene and every location.

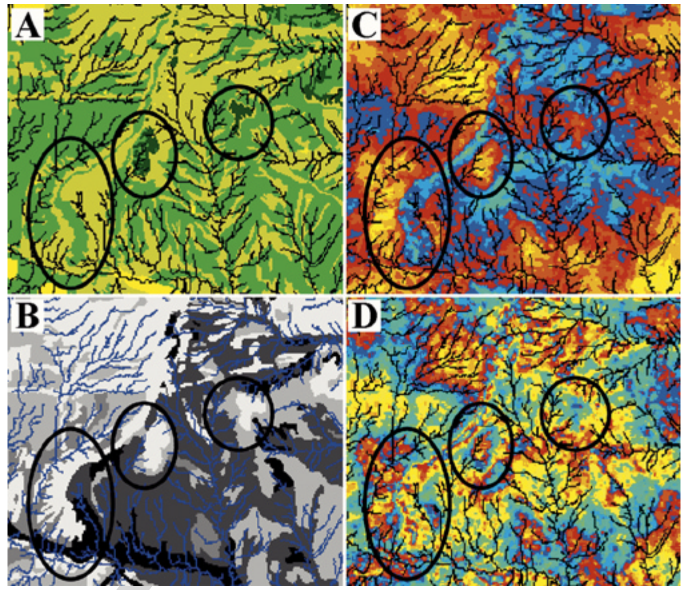

Fig. 5. Spatial and vertical resolution of DInSAR signal. (A) Vegetation map [cutout of Fig. 1(B)] and (B) soil swelling potential map [cutout of Fig. 1(C)] corresponding to cutouts in (C) and (D). (C) and (D) A cutout of the March–April DIG [Fig. 3(G)] is shown with several different colormaps. Color intervals are 1 mm [same interval but different colors than Fig. 3(G)] and 0.4 mm, respectively. Note that the shape of the ridge-line running north-south and the Woods (circles) seen in the vegetation map are reproduced in the DIGs, indicating a correspondence to surface features. Red/blue boundary at central circle in C is at 0-cm displacement. This correspondence to surface features is maintained down to a signal resolution of about 0.3 mm (not shown), which appears to be the noise floor. Note that while DInSAR filtering can smooth noise down to any level, the resulting DIG is not likely to correspond to differences in vegetation and soils in the manner seen here.

C. Refutation of Possible Alternatives

We examined all sources of InSAR phase variation previously identified in the literature and found them insufficient to explain the full range of variation we see in Fig. 3, though they may be contributors to it as noise. The following is an overview of our considerations of atmospheric/ionospheric anomalies, topographic residuals, vegetative interaction with wind, vegetative growth, surface roughness, frost, and dew; we dismiss phenomena such as plate tectonics, volcanic inflation, and well-pumping without discussion.

1) Atmospheric and Ionospheric Anomalies: Atmospheric and ionospheric anomalies are the only other potential phase contributor that we have identified that can create smoothly varying patterns of phase change of the magnitude and spatial-scale observed in our DIGs. The majority of atmospheric anomalies, caused by spatial variations in water vapor, occur high within the troposphere and on spatial scales on the order of kilometers or more [14]–[16], though there is recent

TABLE II
RELEVANT METEOROLOGICAL CONDITIONS ON ERS-2 ACQUISITION DATES

Date	Wind Speed (m/s)	Temp (ºC)	Relative Humidity (%)	Possible Frost?	Possible Dew?
22-Aug-99	no data	no data	no data	no	no
26-Sep-99	3	25	26	no	no
31-Oct-99	3.7	10	31	no	no
5-Dec-99	6.8	-3	98	no (snow on ground)	no
9-Jan-00	3.7	6	26	no	no
13-Feb-00	1.2	0	88	yes	yes
19-Mar-00	3.1	1	91	yes	yes
23-Apr-00	9	23	12	no	no
28-May-00	2	20	30	no	no

indication of even smaller scale anomalies [4], [17]. However, while such anomalies were likely present on some of our acquisition dates, they can explain neither the visual correlation of the small spatial-scale (100 m) variations with watershed features [Fig. 3 and highlighted in Fig. 4(C) and (D)] nor the linear phase-change boundaries that map directly to farm boundaries [Fig. 4(A) and (B)], as in [8]. In these farms fields, we would expect differences in irrigation and evaporation rates (due to cover crop differences) to cause differences in soil moisture between fields. Because the shape of these fields is so easily identifiable and the phase change so abrupt, perhaps our strongest qualitative evidence for a soil moisture source explanation comes from the temporal variations seen in these fields. Use of the PS technique [4] or equivalent, where the scatterers used are rock or building that are unaffected by soil moisture, would substantially reduce the possibility for misinterpreting atmospheric noise as SMP signal, without affecting the SMP signal itself. Thick fogs that conform to the topography, causing phase delays related to topography, could not have been present in this arid environment.

2) Topographic Residuals: Topographic residuals are unlikely to be the dominant signal source for several reasons. Topographic phase signals include the so-called flat-earth phase (an artifact of the side-looking radar) and topographic phase (an artifact of elevation differences). The interferometric processor developed by Vexcel Corporation has undergone numerous tests and years of successful processing to properly flatten these phases. We repeated the analyses with several DEMs of high vertical accuracy (Star3i, SRTM, and USGS NED) and with nearly the same results [13] (differences were largely confined to steep areas and were relatively minor), indicating that the phase patterns we see are not some unidentified bug related to the DEM. If topographic residuals were dominating the DIGs, then two pairs with the same baseline should yield a similar result, and this does not seem to be the case. While we do not have two identical baselines to compare, several pairs with close baselines (Table I) have very different phase patterns and comparison of all records gives no indication that the patterns are the same but simply scaled by baseline (i.e., phase change is not directly related to baseline). Even if residual topographic errors were still present in our DIGs, they could not explain the small-scale variation we observe, as most residuals would likely appear as ramps or warps on the scale of the DEM used. For example, the displacement value may gradually increase going from east to west, or the corners of the map may tend to dip up or down. There is some evidence of this corning-warping effect in our data, though it is difficult to determine because each corner is also topographically different. This possibility of large-scale warping, however, could not induce the fine-scale variation endemic in these maps; it could not account for the variations observed in the farm fields of Model (Fig. 4), nor could it explain why the same topographic features (such as the hogback) have such large temporal differences. Small errors in baseline refinement could allow a variety of topographically induced noise into the DIGs, but again, the variety of the phase change along adjacent hillslopes of the same elevation and aspects cannot be explained solely by this mechanism, though no doubt such artifacts are subtle contributors in some of the DIGs.

3) Wind, Vegetation Growth, and Surface Roughness: A common source of temporal error and decorrelation in interferometry relates to wind or growth-induced changes in locations of vegetative surface scatterers, though such effects are not likely to be significant in our study. There is not enough vegetation in most of the area to act as above ground scatterers, let alone scatterers affected by wind or growth. Wind speeds measured locally were typically fairly low (Table II). Further, it is reasonable to believe that wind-induced phase change would be random and, therefore, unlikely to produce the smoothly varying patterns found on our DIGs. Thus, while wind or growth may be affecting some small regions of densely populated trees, it cannot account for the bulk of the spatial variations seen in Fig. 3. Because these are measurements of temporal *change*, spatial differences in vegetation type or crop type *alone* cannot cause these variations (though their effects on shading and evapotranspiration likely would). Similarly, surface roughness could not be the signal source unless it varied spatially smoothly and did so continuously throughout the ten-month study period and without causing decorrelation; none of these possibilities seem likely to us.

4) Other Surface Phenomena: Frost or dew could also not explain the phase variations we observed. SAR acquisitions occurred at 10:37 A.M. local time, and there were several instances when frost or dew may have been present on the ground during winter (Table II). To our knowledge, dew or frost has never been documented as a DInSAR observable, but it seems likely that dew would cause decorrelation similar to wet snowfall. However, there were no instances of substantial temporal decorrelation within the PCMS boundary, except that related to a snow event on December 5, 1999. And of the eight scenes, meteorological data indicates that frost or dew was only possible on two dates. Thus, while frost or dew may have contributed to the phase differences on those dates, it cannot explain any of the variability on the other dates.

D. Confirmation of Possible Mechanisms

At this point we can be conclusive about several things and map a strategy for our remaining work. Clearly variations in phase exist in our DIGs and those of [8]. These variations cannot be explained by conventional sources and they clearly have some qualitative relationship with ground-related phenomena and hydrologic features. Prior research and theory suggest that phase is related to irrigation of farm fields and that changes in penetration depth and clay swelling (soil moisture related phenomena) should cause changes in the range that we observe in our DIGs [11]. Before we can positively attribute the observed phase change to one of these mechanisms, however, we must show some statistically significant correlation with ground-based measurements of them, and in this section, we discuss why our attempts to do so are inconclusive.

First we statistically test the validity of the penetration depth model described in [11] against our SAR measurements. Nolan and Fatland [11] developed a quantitative relationship between soil moisture and penetration depth that can be inverted for soil moisture under certain conditions and we use those here. These quantitative comparisons are restricted to tests of covariance between changes in soil moisture and changes in penetration depth, noting that the validity of this analysis may be in question due to the presence of an independent mechanism, clay swelling, which may be affecting both measurements. ERS-2 acquisitions were made at 10:37 A.M. local time; we used the hourly TDR recording at 11 A.M., which is the average of four measurements (10:15, 10:30, 10:45, and 11 A.M.). Comparing the unconverted TDR values to DInSAR produced no statistically useful linear correlation coefficients, presumably due to their nonlinear relationship. It was also not possible to convert the DIGs to soil moisture without some knowledge or assumptions about initial soil moisture, due to the nonlinearities involved [11]. Instead, we therefore used the TDR data to calculate the permittivity of the soil using empirical relationships [11], then converted that into penetration depth using an algorithm described in [11]. Here we assumed uniform soil moisture and soil properties over the upper 50 mm, and a soil composition of 51% sand and 13% clay, though the results described here were insensitive to composition. These converted field data were then differenced to correspond to the acquisition dates of the DIGs, so that we are comparing the difference in field measured soil moisture (converted to penetration depth) to the difference in SAR phase (converted to penetration depth). Because our field measurements began after the first SAR acquisition, we can only compare the last seven of the eight DIGs to field data. The number of TDR probes within 50 mm of the surface varied between the four sites. Covariance analysis resulted

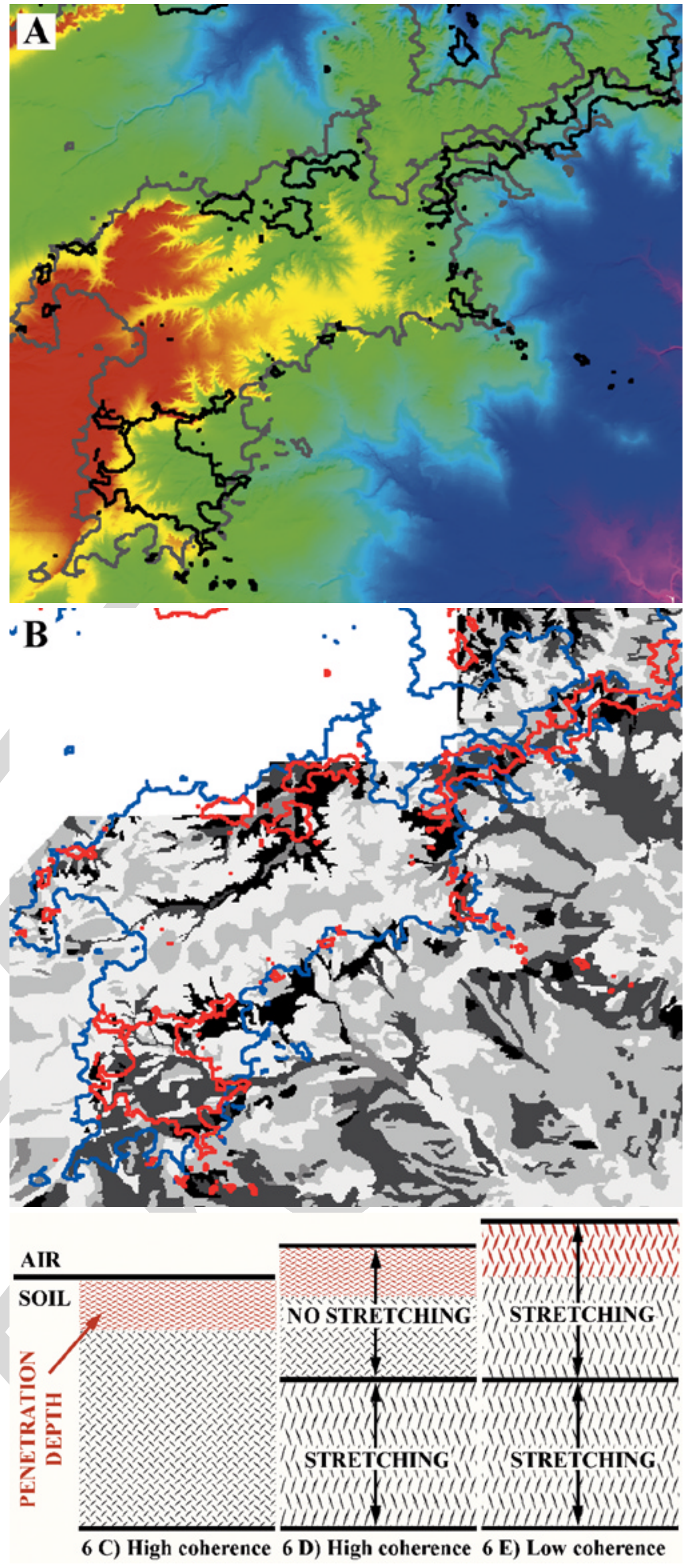

Fig. 6. Observations of clay swelling. (A) Decorrelated regions superimposed on elevation map [same color scale as in Fig. 3(A)]. Gray line indicates decorrelated regions in the October-December DIG and black lines indicates the December-January DIG. (B) Same boundaries superimposed over map of potential for clay swelling [same color scale as in Fig. 1(C)]. Note that the largest area of decorrelation in December–January corresponds with a watershed that has high potential for clay swelling. (C)–(E) Schematic illustrating that coherence would remain high if the upper scatterers (red dots) were simply translated upward (D), but would likely decrease if the upper scatterers stretched (E) if clay swelling occurred within the depth of penetration.

in r^2 values of 0.4296, 0.2650, 0.1231, 0.3045, 0.0876 for CC probes, 0.7938 and 0.5784 for NRA, 0.3230, 0.066, and 0.2714 for PRBS, and 0.24 and 0.16 for SH. Only an NRA probe had a nonrandom correlation at 95% significance ($p = 0.05$). Once the study period ended, we carefully dug out the probes and qualitatively rated their placement (while embedded, there is no way to assess actual placement). The correlations for each site are presented in the order that the probes were ranked.

Several factors are likely keeping these correlations weaker than otherwise possible. The minimum operational depth of our TDR probes was 50 mm, yet the penetration depths are likely less than 20 mm [11]. The upper few centimeters of soil over much of this area is qualitatively different than the soil below, as it is a wind-blown dust that dries to near zero soil moisture but turns into a "gumbo" following the short, intense rainfalls that characterize the area. Therefore, TDR and SAR measurements may not be physically measuring exactly the same soil moisture dynamics. A large metal windmill near SH may have help explain the poor correlations there; the many metallic corners moving with the wind likely affect the signal from nearby pixels. Geolocation errors may also be playing a role in lowering the correlation coefficients; we estimated an accuracy of 150-m (three pixels) and so examined a 5×5 neighborhood, but found no statistically different results. An improvement in correlation might also result if we were to repeat the empirical measurements of [18] on the local soils and use those to calculate the dielectric properties based on our TDR measurements, particularly as the local soils may be higher in ionic content than the prior lab measurements; that is, the probe itself is assuming a nonlinear relationship that may invalidate our differencing approach. Differing levels of DInSAR filtering were required to ensure proper phase unwrapping (Table I), with the unavoidable side-effects on correlations. Another factor in reducing correlations may be the permanent alteration of soil scatterers following rainfall. Our eight DIGs demonstrate that sufficient coherence is maintained between observations that phase unwrapping is usually possible without heavy filtering, despite rain and snow falls throughout the ten-month period and the potential for stretching and rebound of the soil scattering centers due to clay action.

Despite these exterior factors, however, our soil moisture probes indicate that the natural variability on the subpixel scale may be too large to use these data for validation. That is, no matter how well some probes correlate with DInSAR measurements, other probes in that same area will have poor correlations. Part of this variability is related to the whether the probes are placed into bare ground or into organic matter, since the vegetative mat is not continuous here. Given that Bell *et al.* [19] suggest that a minimum of 25 measurements are required to properly characterize a uniform farm field, our several measurements per site are clearly insufficient to characterize a region with substantial heterogeneity; thus, we have no meaningful way of combining these data into an aggregate value. And given the nonlinear relationship between penetration depth and soil moisture, there is some reason to believe that a simple spatial average of TDR probes is not the most accurate approach (i.e., wetter areas may need to be weighted more heavily to produce an aggregate pixel value), but this not clear at this stage in our research. With no physically valid means of distinguishing which of our probes, if any, are representative of the entire DIG pixel, we selected one probe ($n = 7$) of the best rated probes (correlations shown above) from PRBS, NRA, and CC, combined them together ($n = 21$), and recalculated covariance. Such grouping of spatially distributed data is possible because our stations are separated by several kilometers allowing the associated SAR data to be treated as independent measurements [20]. Selecting those probes that had the highest individual correlations (i.e., when $n = 7$) resulted in an r^2 of 0.4339, which is statistically a nonrandom correlation at 95% significance ($p = 0.05$). It could be argued that there are physical reasons why those particular probes should be selected, but those arguments are strained at best, since placement was as uniform as possible. This essentially arbitrary selection of data thus invalidates its use as true validation, but nonetheless indicates that the potential of the technique is high, and warrants further research, particular in field validation techniques.

We would like to test the clay swelling mechanism quantitatively, as we did for penetration depth, but we cannot. To invert for soil moisture, we need millimeter-scale measurements of surface elevation change over a 50 m $\times$ 50 m SAR pixel and a model of how the microwave scatterers within the soil would move with increased moisture. We have neither—the former might be possible with D-GPS, but the latter is a complex function of clay mineralogy, vertical distribution of grain sizes, strain history, surface charge density of the clay particles, concentration and valence of counter-ions, and pH [9], [21], [22], such that any such relationships must be derived empirically using local soil types. Our literature review could find no such quantitative relationships, with the most related analyses restricted to confined soil pressure as a function of water content in swelling soils. Thus, we are limited to qualitative analysis at this point.

The only observational evidence that we could find related to clay swelling is found from scenes involving the December 5, 1999, acquisition, but due to the snowfall on that date, we cannot untangle the contributions of the two phenomena. About 20 cm of snow fell on December 4 and 5, with air temperatures ranging from $+4$ °C to -3 °C and ground temperatures always above freezing, such that the snow could have been wet but leaving no possibility for frost heaving. Further, measured soil moisture showed no increases until after the acquisition, presumably when the snow began melting in earnest. If wet snow blocked penetration of the microwaves from the soil (which was snow free on the scenes before and after the snowfall), then the decorrelated areas on DIGs before and after the snow [Fig. 3(C) and (D)] should be roughly the same size and shape, regardless of improvements in baseline separation between DIGs, and they are not. Fig. 6(A) reveals that most of the decorrelated regions in Fig. 3(D) are a subset of the larger area of decorrelation found in the October 30–December 5 [Fig. 3(C)] DIG, and that this larger region largely follows the boundaries of the mesa structures. Fig. 6(B) reveals that most of the regions that remained decorrelated in the December 5–January 9 DIG (including the largest) are regions that the soils maps indicate have a high tendency toward clay-swelling phenomena, suggesting the two may be related. That is, if the decorrelation was due to snow fall alone, why do the decorrelated areas occur preferentially in area predisposed to clay swelling? Unfortunately, not enough field measurements were made at the time of the event, so all we can do is speculate about explanatory scenarios. However, these observations at the least indicate that further research into this phenomena is warranted and opens up questions about whether low coherence and decorrelation may be a means to detect clay swelling.

While a full scattering model is beyond the scope of this paper, we offer several lines of reasoning to suggest that most changes in penetration depth related to soil moisture will not cause decorrelation, unlike clay swelling, which might. Most fundamentally, there have been hundreds of successful interferograms created in the past decade that show no decorrelation, and in a great many of thes, soil moisture likely changed to some extent due to evaporation, drainage, or even rainfall. If a change in soil moisture did indeed occur in these interferograms, then a change in penetration depth also *must* have occurred (albeit too small to have been noticed or below the noise threshold), all without causing decorrelation [11]. A change in penetration depth does not necessarily imply that the *position* of the scatterers has changed, only that the relative *attenuation* of the scatterers has changed or new ones have been added, all else being equal. Indeed, if the soil matrix remains undisturbed (as is likely in the case of evaporation or redistribution), then most scatterers will remain in place with only a change in sign or strength, or the addition or loss of new scatterers (water droplets). The case may be different for clay swelling, however, as illustrated in Fig. 6(C). If the swelling occurs in deeper soil substantially below the penetration depth of the SAR microwaves, the upper soil where the microwave scatterers are located is simply translated upward with no stretching between them. However, if the swelling occurs within the region of the penetration, the scatterers located here should stretch apart from each other, changing the superposition of phase returned from each and, thus, changing the net phase measured at the satellite in a spatially random manner, independently of the spatially coherent increase in surface elevation. If the random contribution is significant, the temporal change reduces coherence and, thus, makes the spatial gradients in phase unusable. If the stretching is minimal within the penetration depth but the surface elevation changes, we might expect this to be measureable interferometrically.

Our quantitative efforts are insufficient to validate either mechanism as the cause of phase variations in our DIGs. However, since the majority of the land area in our DIGs is composed of soils with a low or negligible tendency toward clay swelling, such swelling could not be responsible for the phase variations we observe there. Note that our study does not suggest clay swelling is an unimportant mechanism in suitable soil types, but rather points to the fact that further research is required before we can both measure it and then use it as a proxy for soil moisture.

IV. Conclusion

Our research supports the hypothesis that a soil moisture phase signal exists within our C-band DIGs of both cultivated and uncultivated terrain, though we have not been able to verify whether they are actually useful for quantitative soil moisture research. We did this by first reviewing prior research that validates that a soil moisture phase signal exists in farm areas using L-band [8], as well as prior research that indicates that C-band penetration depth is a viable proxy for soil moisture [11]. We then presented DIGs that contain intriguing patterns of phase change that often visually correlate well with hydrological features that we expect to drive soil moisture levels, such as stream channels, drainages, ridges, soil properties, and vegetation types (Figs. 3–5). These DIGs also contain abrupt changes in phase change patterns at farm field boundaries, where we would expect soil moisture to vary due to differences in irrigation, tilling, and evaporation [Fig. 5(A) and (b)]. We then discussed all alternative explanations such as atmospheric phase delays, topographic residuals, vegetative growth, wind, surface roughness, fog, dew, or frost and found them insufficient to explain the full range of variation, though some of these may be contributing factors. Finally, we looked at the data quantitatively. Here, we found that the range of variation of field measurements and DInSAR agree well with each other and with theory, and the DIG noise floor of roughly 0.3 mm is consistent with our DEM slope-accuracy. Unfortunately, we found our field data insufficient to validate the penetration depth mechanism (though this may have been more a problem with the field data itself, as some correlations were significant at 95% confidence), but determined that we could rule out clay swelling as a mechanism in most of the study area (though it may be important in some regions). Our results indicate that even if we are never able to quantitatively bridge the gap between SMP detection and a useful technique for measuring soil moisture, that SMP does exist and must be considered as a potentially significant noise source in many interferometric studies.

V. Discussion

Substantial further research will be required before a DInSAR technique becomes practical on anything but an academic research level. We did not account for atmospheric anomalies in this study; the permanent scatterer technique [4] currently holds the most promise for these corrections, but it may not be applicable in many remote areas lacking man-made objects unaffected by soil moisture. Use of this technique would also allow cumulative maps of soil moisture to be made, largely overcoming the problem of needing to know the initial soil moisture of each scene to calculate the final—only once will initial levels need to be estimated if cumulative maps are possible. Proxy development (penetration depth and particularly clay swelling) needs to be substantially improved and tested in a wide variety of soil types. Finally, validation techniques need to be substantially improved, especially in uncultivated areas. In addition to the classic problem of spatial heterogeneity when comparing point data to spatial data, the penetration depth of C-band is typically shallower than many automated probes can operate, possibly invalidating their use. Choosing farm fields near urban areas (with permanent scatterers) as research sites may largely overcome many of these problems until the technique becomes better established, but its application to remote areas will eventually require these problems to be solved rather than avoided.

Even with these obstacles, however, DInSAR remains a most promising remote sensing technique for the measurement of soil moisture. It has potential for spatial resolutions on the order of tens of meters with a potential accuracy of less than 1% volume water content and can likely be applied at any location meeting basic DInSAR constraints (e.g., minimal vegetation, no shadowing) and where DEMs of sufficient accuracy exist. Because there is currently no way to measure soil moisture on large spatial scales with this resolution, and no other techniques have been identified that can, there is no way to validate models of it and our basic understanding of soil moisture redistribution remains seriously lacking [1]. Thus, in addition to being a monitoring tool, further development and use of this DInSAR technique could also allow for improved model development and an improved understanding of the processes involved.

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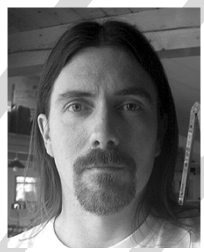

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