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Hydrology and Earth System Sciences Discussions

HESSD

4, S866–S879, 2007

Interactive Comment

Interactive comment on "Unsupervised classification of saturated areas using a time series of remotely sensed images" *by* D. A. DeAlwis et al.

D. A. DeAlwis et al.

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We would like to thank the three reviewers' for their helpful reviews. We have taken these reviews seriously and rewritten sections of the paper to clarify points of concern. We were able to make changes to the text, tables, and figures to address nearly all the reviewers' comments; there were only one or two with which we disagreed. Below, pertinent points from the reviews are given with our responses to the comments. We have chosen not to show all the specific comments regarding grammar and use of language, but did incorporate all off the reviewers' suggestions and done a careful review of the paper for other discontinuities in language.

Anonymous Referee #1 Comments General Comment The paper suffers to some extent from the same problem that many modeling-remote sensing comparisons have. The conclusion is always that there seems to be a good correspondence between the satellite images and the modeled area but one does not know why the errors are where they are, if there are structural errors, to what extent parameters have been tuned to provide similar patters (in this case moisture class limits and number of NDWI classes). One can not blame the authors for that; it is just a general problem with this type of studies. Fortunately, here one has tried to come to some quantification and the result (78% accuracy) does look good. Unfortunately, the same does not seem to hold for the comparison with actual field data. It is clear that no one-on-one comparison is possible but the careful quantification of the differences between models and NDWI is not repeated for the differences between field observations and NDWI. In the text, an accuracy of 75% is claimed for the latter, but this does not seem to be substantiated by Figure 6. Perhaps this can be clarified. The applicability elsewhere of the presented method in its exact present form is probably limited. The paper, would, however, encourage researchers to see what a NDWI time series can do for their area, and as such the article should be published.

We agree and have followed the reviewer's suggestion and incorporated an error of omission and commission matrix for the validation of NDWI-based predictions of saturated areas with field mapped saturated areas. Since the field survey was undertaken on 28-30-April-2006 we decided to compare the survey map to the NDWI predictions of a single image (7-May-2001 scene), taken in a similar hydrological season in order to assemble highest comparability. The methodological steps and results of this revised validation are described in section 3.1 and shown in Table 4 and Fig. 6 (see specific comment #5).

Specific Comment #1 The abstract repeats to a large extent the justification of the study, not the content. Please change that because the abstract is often the only part researchers see in a database. Those looking for saturated areas are already convinced of their importance but would like to know what can be found in the paper.

We have modified the abstract accordingly, to focus on the content of the research by removing some of the justification and adding more discussion of the results and implications.

Specific Comment #2 p 1678: There seems to be some confusion about what is overestimated. According to the table, the NDWI overestimates but according to text NDWI underestimates, and an explanation for this is given. Please fix this. I addition, it may not hurt to define "producer" and "user" accuracies (in remote sensing literature, these are often referred to as errors of omission and commission).

The reviewer is correct; we have fixed the discrepancy between the text and table.

Specific Comment #3 The comparison between measured profiles and model outcomes, including Figure 7, does not seem to be useful here. Model validation is not the objective here and even if it serves to increase the trust in the models, we can not really use that information to value the NDWI product.

We agree and have removed the transect data discussion and figure from the paper.

Specific Comment #4 In the discussion, it would be worth mentioning that Landsat 7 images are no longer being acquired. Alternatives may be mentioned such as Landsat 5 (expensive), Aster, IRS (?).

We have made the suggested changes and added to the text in section 4: “It is likely that either or both the Landsat 7 and Landsat 5 satellites could fail after several more years of operation and both satellites will likely run out of fuel before the end of 2010. The Earth observation community is facing a probable gap in Landsat data continuity before the Landsat Data Continuity Mission (LDCM) data arrive in approximately 2011. However, several other sensors can provide promising sources of Landsat-like data, including the China/Brazil Earth Resources Satellite (CBERS-2), and the Indian Remote Sensing (IRS-P6) ResourceSat-1 satellite.”

Specific Comment #5 Figure 6 is not very clear: It seems the wet NDWI part is much larger than the mapped saturated area. What one would like to see is where NDWI and GPS overlap and where they do not (both omission and commission). We have made the suggested changes, replaced Fig. 6, and added to the text in section 3.1: “Due to the uncertainty inherent in the spatial predictions of any model we conducted a field survey of saturated areas in the south eastern portion of Town Brook on 28-30-April-2006 using a Garmin GPS (GPSmap 60C, Garmin Inc.) with 2 m horizontal accuracy. Areas were deemed saturated if there were signs of surface saturation or water tables close to the ground surface (e.g. bootprints would fill with water). Manual delineations of HAAs from the field mapping survey of the Town Brook watershed are shown in Fig. 6. The produced map of saturated areas was converted into a raster file with 30m x 30m resolution and classified according to the land cover types derived from the remote sensing data (de Alwis, 2007). This map was compared with the 7-May-2001 NDWI derived image. The area of each specific land cover from the May NDWI image within the survey area was calculated and a ratio of total mapped saturation area to NDWI saturated area was derived, with the corresponding errors of omission and commission calculated (Table 4). Since saturated areas generally occur in the same location from year to year, we expected a general agreement on the location of these saturated areas but not necessarily on the extent of the saturated areas, since measurements taken in 2006, were made under relatively wet conditions and the NDWI values, were taken on 7-May-2001, following two weeks of dry conditions. Indeed, we found that the general location of the saturated areas were predicted well but the mapped the extent agreed less well with an overall accuracy of 49% (Fig. 6, Table 4). As Table 4 shows, the NDWI predicted a generally larger extent of saturated areas compared to the field survey. Similar to the comparison with the simulation model, the coniferous forest was predicted poorly with low user’s accuracies (Table 4). The correspondence between field observation and NDWI based predictions for land cover classes of deciduous forest and shrub show good agreements with accuracies of 48% and 71% respectively. As Fig. 6 illustrates, most of the spatial disagreement between NDWI derived and mapped saturated areas results from an over-prediction of satura-

HESSD

4, S866–S879, 2007

Interactive Comment

tion areas in the grass land cover classes and an under-prediction in the deciduous forest and shrub land cover classes. The main discrepancy between the NDWI saturated areas and the mapped saturated area extents occurs in the coniferous forest land cover class, where the NDWI reached the highest (positive) value because of the high LAI. Similar to deciduous forest during the growing season, the leaf water status of the coniferous forest is most likely less affected by short term changes in soil saturation as in other vegetation classes (grass/pasture, shrub, deciduous forest)." Fig. 6 has been replaced with a more clear representation of overlapping areas of NDWI derived saturated areas and field mapped saturated areas. In addition we added Table 4 with the error of commission and omission for the comparison of field mapped saturated areas and NDWI predictions.

Anonymous Referee #2 Comments Specific Comment #1 It would be helpful to define "unsupervised clustering," "producer accuracy," and "user accuracy."

We have added the following definitions to the paper in section 2.4: "In an unsupervised classification, statistical clustering algorithms are used to analyze the digital values in each image to determine the number of statistically distinct features (clusters) in the image. In this study, an unsupervised iterative self-organizing data analysis (ISODATA) clustering algorithm was used. ISODATA is a widely used clustering algorithm that makes a large number of passes through an image using a minimum spectral distance formula to form clusters. It begins with both arbitrary cluster means and each time the clustering repeats, the means of these clusters are shifted. The new cluster means are used for the next iteration. This iterative process continues until statistically distinct features emerge."

And section 2.6: "In order to validate the remotely sensed saturated areas the producer's and user's accuracies were calculated for the comparisons with simulated data and field surveys. The producer's accuracy for a saturated area within a land cover type is defined as the probability within a land cover type that a pixel truly belonging to a saturated area within a land cover type is also mapped as a saturated area within the land cover type, while the user's accuracy for a saturated area within a land cover type is the probability that a pixel mapped as a saturated area is truly of a saturated area."

Anonymous Referee #3 Comments Comment #1 The (general) assumption that atmospheric water vapor is homogeneous over relatively small areas and on clear days could be wrong, particularly in areas with abrupt topography in which valleys have more atmospheric water content. In the future, the authors could check if the estimated field of path radiance has any trace of spatial structure that could be related to terrain patterns.

Atmospheric correction of the radiation received at the satellite is by far the most difficult correction to make (Liang et al. 2001). Electromagnetic radiation collected by satellites is modified by scattering and absorption by gasses, water vapor, and particulate aerosols (Song et al. 2003). A number of radiative transfer models based on ray tracing algorithms have been developed for correcting the atmospheric effects. Studies have shown that these models can accurately correct for the atmosphere (Holm et al., 1989, Moran et al. 1992). However, these corrections require accurate measurements of atmospheric optical properties (Song et al. 2001). The requisite measurements are rarely available both coincident with the overpass and in the vicinity of the study area. Lacking sufficient information for full atmospheric correction, it would be best to avoid those bands that are most affected by the atmosphere (i.e., bands in the blue and green portions of the spectrum) and to rely on band combinations that will minimize atmospheric effects. The red and infrared bands are significantly less affected by the atmosphere. In particular, vegetation indices based on Infrared/Red ratios both capture key characteristics of vegetation and also tend to compensate for many complicating factors, e.g., illumination effects due to topographic effects (Lillesand & Kiefer, 2000). Song and Woodcock (2003) found that vegetation indexes are resistant to topographic effects at all illumination angles. The ratio of bands used in the NDVI and NDWI vegetation indices reduces the topographic effects thereby minimized. One indicator (not proof) that the path radiance is not varying a great deal with the topography would be

HESSD

4, S866–S879, 2007

Interactive Comment

to select a collection of pixels from one cover type that spans a range of altitudes, e.g., across a valley. If the reflectance is uniform and the path radiance is negligible one would expect little variation in the visible channel. On the other hand, in an area with haze, there is likely to be a substantial variability in the visible. As an example, I took a slice of data across a valley that looked like it might have uniform vegetation (green), and another slice through an area in the cloudy region where it looked as if there were thin clouds or haze (red). Note the spread of the "hazy" data in the visible. The blue, by the way, is the locus of the clouds in the scene.

Comment #2 I do not like using the NDVI courses to derive landcover maps at such a detailed scale in general, because NDVI phenology is often not enough information to discriminate among some landcover types. Nevertheless, it could be appropriate in this particular case, as the landcover types are very distinct. Unfortunately, the authors do not mention the classification method they use (are they using supervised classification in this case?) and, most important, they do not validate their landcover map. Also, how sensitive are the results (detected HAAs) to errors in the landcover map? If they are sensitive, devoting more effort to produce a better landcover map in the future would make sense.

While the reviewer raises a valid point, we feel that the methodology used to derive the land cover map used in this application circumvents many of the issues raised. We have added a section to the text explaining this: “The images were used to identify spatial differences and temporal changes that occurred due to the phenological cycle of vegetative cover over the study site. By analyzing the variations NDVI of clusters of pixels over time phenological patterns were obtained and distinctive land cover types were identified accordingly. The obtained land cover map was validated using ground truth and air borne imagery. The land cover map based on the phonological variations proved to be better than the available land cover map derived based on spectral classification (de Alwis, 2007). The land cover map based on phenology was able to distinguish the shadowed areas that are often misclassified as evergreen in spectral

HESSD
4, S866–S879, 2007
Interactive Comment

EGU

classification. This was a major advantage of using a classification based on phenology rather than a spectral based classification." Further discussion not included in the paper follows below. Land cover classification is most commonly based on spectral differences among the various land cover types (Cihlar et al. 2000). Spectral classification is most effective when the scene used is collected at a time of year when the spectral differences among land cover types is most pronounced. The appropriate time will depend on the specific land cover categories that are desired and may depend on the natural growing season (e.g., distinguishing maple from oak), the local crop calendar (e.g., distinguishing corn from wheat), or other such characteristics. In other words, choosing the correct time of year allows discrimination among land covers that might otherwise be virtually identical in their spectral character (Vierling et al 1997). This is particularly true of vegetated areas, since species dependent, seasonal changes in appearance and structure (phenology) will enhance the ability to differentiate one type of vegetation cover from another. It is the premise of this paper that, since different vegetated land covers appear spectrally distinct from each other at different times of the year, a time sequence of images will be more effective for land use classification than will the spectral differences observed at one point in time. Phenological changes can be monitored by means of time sequences of remote sensing imagery. This has a special significance since the spectral changes are very closely linked to plant physiology as the plants experience chemical, physical and biological changes. In general these changes occur more or less simultaneously in both the visible (red) and the near infrared (NIR) regions, although changes in NIR reflectance are often more noticeable. Reflectance in the NIR region is apparently controlled at the small scale by the variations in the size, shape and distribution of the cells and air spaces in the mesophyll layer within the leaves and at large scale by the multiple reflections among leaves in a canopy (Lillisand & Kiefer, 1987). While these changes are visible in aerial photography over relatively small areas at a reasonable cost, satellite imagery has proven to be more cost effective for larger areas and could be used to monitor over a time period. Time sequences of remotely sensed images have been used to observe change

HESSD

4, S866–S879, 2007

Interactive Comment

over time of a particular land cover type (Lawrence, 1999; Peterson, 1992; Markon, 2001), insect defoliation in pine forest, Wisconsin (USA) (Radeloff 1999); detection of forest cover change with multi year Landsat data in western Oregon (Cohen & Fiorella, 1998, Cohen et al. 1998); vegetation abundance changes in Semiarid environments 1984-1998 (Elmore 2000) and for similar applications. Vegetation indices derived from satellite data are one of the primary sources of information for operational monitoring of the Earth's vegetation cover (Teillet, et al. 1997). There are a number of vegetation indexes that have been developed over the years primarily for the purpose of ecological assessment  not directly for determining land cover. Of these, the NDVI (Normalized Difference Vegetation Index) is the most commonly used index for ecological assessment (Elmore et al. 2000; Rouse et al. 1973; Jackson, 1983; Purerdorj et al. 1998). The NDVI has been shown to have a 'reasonable correlation' (Elmore et al. 2000) with vegetation abundance and other important ecological parameters such as leaf area index (LAI) (Fassnacht, 1997) and the fraction of absorbed photosynthetically active radiation (fPAR) (Veroustraele, 1996), CO2 uptake (Ludeke, 1991), productivity rates, leaf biomass (Birky, 2001), leaf density and process rates (such as photosynthesis and transpiration). Multi-temporal, multi-spectral Landsat ETM+ images were used to identify spatial differences and temporal changes that occurred due to the phenological cycle of vegetative cover over the study site. Cloud-free images were processed for 7 different months: January 2000, April, May, June, July September and October in 2001. The year 2001 was a relatively dry year for this study region. By analyzing the variations NDVI of clusters of pixels over time phenological patterns were obtained and distinctive land cover types were identified accordingly. The obtained land cover map was validated using ground truth and air borne imagery. The land cover map based on the phonological variations proved to be better than the available land cover map derived based on spectral classification (de Alwis, 2007). The land cover map based on phenology was able to distinguish the shadowed areas that are often misclassified as evergreen in spectral classification. This was a major advantage of using a classification based on phenology rather than a spectral classification.

HESSD

4, S866–S879, 2007

Interactive Comment

Comment #3 I think that the statement in p. 1667 “However, the clustering portion of unsupervised classification operates without a priori information of the wetness index classification and groups samples based on the inherent similarity of individual spectral signals” is not correct. If the authors were really using the spectral signals, they would be including SWIR and NIR reflectance in the classification along with the rest of bands, and thus both classifications would not have been independent. Maybe the authors meant “of individual NDVI time courses”?

Yes, the reviewer is correct, we have fixed the text.

Comment #4 Including the contingency table for SMDR wet and VSLF wet in table 3 would be a good idea: do both simulations agree more between them than with NDWI wet? Also, although the authors are right at stating that the disagreements can be abstracted (not sure this is the correct term here) from the user’s accuracy, the reader would prefer the authors just adding a column to the tables.

We have included the accuracy assessment of the two models in Table 4.

Comment #5 I understand that field validation is more difficult and I’m not a field hydrologist, but I think that you could make a better analysis of the field data you have to validate the NDWI wet results. At the end you are paying a disproportionate attention to the simulation results. Figure 6 is insufficient, why not providing a contingency table equivalent to Table 3?

The reviewer is correct. We replaced Fig. 6 with a more clear representation of overlapping areas of NDWI predicted saturated areas and field surveyed saturated areas. We also included a calculation of errors of commission and omission for each land cover class between NDWI derived saturated areas and field mapped saturated areas, given in Table 4.

Comment #6 I miss a spatial analysis of the disagreements between the different methods (at this point, we cannot speak of errors because the field data are scarce), which could provide interesting clues on why the disagreements are where they are and, with fortune, about their nature. Perhaps the authors could consider a deeper validation and error analysis for a future article?

The reviewer is certainly correct, and researchers lack field data to validate many of these types of models. We are working to obtain more ground truth validation data to corroborate these models.

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HESSD

4, S866–S879, 2007

Interactive Comment

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HESSD

4, S866–S879, 2007

Interactive Comment

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Interactive comment on Hydrol. Earth Syst. Sci. Discuss., 4, 1663, 2007.