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Water table level in relation to EO-1 ALI and ETM+ data over a mountainous meadow in California

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Abstract. In an effort to map water table levels in an irrigated high mountain meadow, we explored the potential of the spectral reflectance of meadow surface covers. Multispectral data acquired from the earth observing-1 (EO-1) advanced land imager (ALI) and Landsat enhanced thematic mapper plus (ETM+) with similar band specifications and the same spatial resolution of 30 m were tested. Preliminary regression analysis reveals that the blue, red, and near-infrared bands all correlate strongly with water table levels. The visible bands have negative correlations and the near-infrared band has a positive correlation. During the early half of the growing season, weekly water table levels averaged on a monthly basis show strong correlations with spectral data of the meadow. The normalized difference vegetation index (NDVI) has a better correlation with water table level than several other linear transformation features obtained with principal component analysis and the Kauth–Thomas transform.

Résumé. Dans le but de cartographier les niveaux de la nappe phréatique dans une zone de prairie irriguée en haute montagne, nous avons exploré le potentiel de la réflectance spectrale des couverts de surface de la prairie. Des données multispectrales acquises à l'aide des capteurs ALI (« advanced land imager ») de EO-1 (« earth observing-1 ») et ETM+ (« enhanced thematic mapper plus ») de Landsat avec des caractéristiques de bandes similaires et la même résolution spatiale de 30 m ont été testées. Une analyse préliminaire de régression révèle que les bandes du bleu, du rouge et du proche infrarouge sont fortement corrélées avec les niveaux de la nappe phréatique. Les bandes du visible affichent une corrélation négative et la bande du proche infrarouge présente une corrélation positive. Au début de la première moitié de la saison de croissance, les niveaux hebdomadaires de la nappe phréatique moyennés sur une base mensuelle montrent des corrélations fortes avec les données spectrales de la prairie. L'indice NDVI (« normalized difference vegetation index ») montre une meilleure corrélation avec le niveau de la nappe phréatique que plusieurs autres caractéristiques de transformation linéaire obtenues à l'aide de l'analyse en composantes principales et de la transformée de Kauth-Thomas.
[Traduit par la Rédaction]

Introduction

Water table level is an important parameter in the study of soil productivity, hydrology, ecology, biogeochemistry, and global change of various environments, particularly wetlands and meadows (e.g., Regina et al., 1996; Martin et al., 1997; Krebs et al., 1999; Munoz-Reinoso, 2001; Seybold et al., 2002; Heyer et al., 2002; Bliss and Comerford, 2002). Water table level data in arid agricultural lands are critical in water resource management and precision agriculture. For instance, irrigated pastures and meadows are an important source of summer forage for livestock in the arid western United States. In northern California, concerns exist about negative associations between irrigation management practices and the health of water resources. Many streams that provide irrigation water and receive runoff from irrigated pastures also provide critical habitat for cold-water fisheries. There are concerns that the removal of water from streams reduces streamflow below natural levels, reduces available in-stream habitat, and leads to increased stream temperature and concentration of pollutants. Excessive irrigation rates can generate runoff of polluted and higher temperature water to streams and lakes. In an attempt to study the grazing impact on stream water temperature and nutrients for better management of irrigation and nutrient transport, we chose the high mountain meadow in Bridgeport Valley of eastern California, USA. Like many complex irrigation systems, field-based monitoring in the Bridgeport Valley to comprehensively assess sources of excessive irrigation and pollution is both difficult and expensive.

Alternative approaches are desirable. Boucneau et al. (1996) developed a model-based method, requiring a limited number of dip wells and related mapped soil information, to describe

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water table depth fluctuations in time and space. Their dip-well-specific, regressive model was developed with meteorological data as input. To successfully model the water table level condition, however, it is necessary to have information about soil structure and detailed topographic and bedrock conditions. Such data are not readily available. Allen-Diaz (1991) suggested an indirect approach that uses plant species as indicators of water table. This method requires mapping of grassland at the specific-species level, which cannot be easily accomplished without extensive fieldwork. Al Saifi and Qari (1996) analyzed Landsat thematic mapper (TM) imagery over salt-enriched flat areas of the Red Sea coast and suggested that water table level was one of three soil parameters that can be differentiated by image colors. However, no quantitative analysis was done. Al-Khudhairy et al. (2002) estimated the width of wet water channels from Landsat TM data to correlate with water level in the ditch. In this paper, we report some of our initial analysis of water table levels in relation to Landsat TM data and the earth observing-1 (EO-1) advanced land imager (ALI) data.

Study area

The Bridgeport Valley (38°15′N, 119°12′W) covers an area of approximately 100 km^2, with elevations ranging between 2100 and 2200 m. Nine headwater streams of the East Walker River leave the high-elevation lakes and streams of the Sierra Nevada Mountains and are first used for irrigating the meadow–grassland in a sage scrub community. This irrigated land supports 8 000 – 10 000 beef cattle during the summer months. Irrigation of meadows has been traditionally manually controlled by local ranchers on an intuitive basis. The irrigation system affects the natural water table levels, and thus pattern of grass growth, and the grazing causes high loadings of nitrate and phosphate, which in turn affect the downstream fishery. The growing season for meadow begins in mid-May and ends in late August. Since the temperatures during the growing season over the entire valley are similar, water availability is the primary control of vegetation growth. Water availability is also the primary determinant of soil color. When the soil is wet, it is darker. Therefore, we investigated the relationship between water table and the spectral properties of the meadowland in the valley.

Data processing

We chose the year 2002 and obtained the following data: (*i*) two scenes of EO-1 ALI imagery (acquired on 31 May and 16 June); (*ii*) one scene of Landsat-7 enhanced thematic mapper plus (ETM+) imagery (2 August); (*iii*) piezometer data (during the growing season on a weekly basis for 2002); and (*iv*) field spectrometer data and water table level data (at 28 sites) collected between 14 and 20 July.

ALI has nine spectral bands, and seven of the bands cover spectral ranges similar to those of the six TM optical bands. ALI does not have the thermal band. It has two bands in blue (bands 1′ and 1) and two bands in near infrared (bands 4 and 4′), one entirely new band (1.2–1.3 μm), and the other bands are similar to TM bands (bands 2, 3, 5, and 7). The spatial resolution is also the same as that for TM. The sensors are at the same orbit as Landsat-7, with a local overpass time that is 30 min earlier. The major difference is that the radiometric resolution of ALI is better than that of TM (16 bits versus 8 bits). For this application, the high radiometric precision of ALI is not very critical. The two types of data are comparable. The different ranges of digital values have been converted to reflectance using pseudo-invariant targets (water bodies and road surfaces). We treated the spectral properties of water and paved road over selected locations as not variable during the period of satellite data acquisition (Gong et al., 1994). Ground reflectances of the pseudo-invariant targets are obtained from field spectrometer measurements in mid-July 2002. The field spectral data were taken with an Analytical Spectral Devices, Inc. (ASD) field spectrometer. The spectral resolution was less than 10 nm. ALI and TM bands are several times wider. Spectrometer bands were extracted corresponding to the spectral wavelength ranges of ALI or TM. Their spectral values were then averaged to derive the spectral data accordingly.

The water table levels are from two sources. The first source is the weekly piezometer data, and the second source is the field-measured water table data. During the field measurement, the surface conditions of each measurement site were noted, such as grass height and coverage and grazing intensity. All measurement locations were measured with a field global positioning system (GPS) with a positioning accuracy of better than 1 m.

Exploratory analysis between piezometer data and satellite data

Piezometer data were collected during the growing season at eight sites in the valley since 2000. At each site, 10 water-level reading wells were set along a transect of approximately 80 m in the vertical direction to stream flow. The distribution of well locations is denser near the stream than farther away from the stream. Two of the eight sites are outside the meadow area and one site has a large number of missing readings (due to low water levels). These three sites were not included in the analysis. We chose the remaining five sites within the meadow and averaged all 10 piezometer readings on a weekly basis. The piezometer well locations at each site were surveyed with a GPS at an accuracy of less than 1 m. The GPS surveys were averaged to represent the site location. **Table 1** shows the average water table levels for the five selected sites collected on a weekly basis. Data were chosen 1 month before the satellite data acquisition. ALI and TM spectral data corresponding to the average location of each site were extracted from the images. The exploratory regression analysis results are shown in **Table 2**. Recognizing that the May imagery only records the irrigation effects in May, whereas later in the year an image would reflect the cumulative effect of irrigation, we did not calculate correlation coefficients with water table data collected after the image acquisition date.

The correlation coefficient matrix in **Table 2** shows a number of general patterns: (*i*) May and June water levels have a stronger correlation with the spectral data; (*ii*) bands 1–3 (in the visible spectral region) usually have high correlations (mostly negative, i.e., the deeper the brighter) with water table levels; (*iii*) band 4 in the near infrared tends to produce high positive correlations with water table levels, i.e., the shallower the brighter; (*iv*) the May and June spectral data are usually highly correlated with water table levels 2–3 weeks before the image acquisition date, but the August image does not have this property; and (*v*) the August image has its highest correlation with some of the May and June water level data.

In general, a negative correlation between spectral data in the visible range and water table level is reasonable because a higher water level results in low spectral values of surface soil or healthier vegetation absorbs more visible light. A positive correlation with the near-infrared band is also reasonable because a higher water level leads to better vegetation growth and thus higher near-infrared reflectance. However, **Table 2** shows that the water level on a single date may not follow this general trend (e.g., 15 May and 17 July). This is quite possible,

Table 1. Average piezometer readings (in m) taken over five sites in Bridgeport Valley in 2002.

Site	May 1	May 8	May 15	May 22	May 29	June 5	June 12	July 3	July 10	July 17	July 24	July 31
1	–0.10	–0.33	–0.42	–0.11	–0.08	–0.15	–0.20	–0.10	–0.11	–0.42	–0.52	–0.21
2	–0.34	–0.49	–0.56	–0.03	–0.19	–0.02	–0.02	–0.26	–0.34	–0.53	–0.71	–0.32
3	–0.53	–0.45	–0.40	–0.62	–0.37	–0.16	–0.39	–0.61	–0.64	–0.05	–0.14	–0.65
4	–0.48	–0.32	–0.26	–0.46	–0.56	–0.13	–0.28	–0.02	–0.25	–0.49	–0.16	–0.47
5	–0.53	–0.68	–0.09	–0.06	–0.46	–0.64	–0.05	–0.54	–0.60	–0.56	–0.20	–0.47

Table 2. Correlation of multitemporal piezometer readings with spectral data from ALI (bands MS1′, MS1–MS4, MS4′, MS5′, MS5, and MS7) and TM (bands TM1–TM4, TM5, and TM7).

(A) May 30 and June 15 ALI images									
For the week starting	MS1′	MS1	MS2	MS3	MS4	MS4′	MS5′	MS5	MS7
May 30 image									
May 1	–0.43	–0.41	–0.45	–0.43	0.00	0.01	–0.08	–0.25	–0.25
May 8	–0.70	–0.71	–0.81	–0.74	–0.78	–0.78	–0.70	–0.72	–0.72
May 15	0.85	0.88	0.76	0.89	0.08	0.10	0.32	0.55	0.61
May 22	0.42	0.39	0.48	0.36	0.85	0.85	0.83	0.68	0.67
May 29	–0.51	–0.49	–0.45	–0.49	0.23	0.22	–0.03	–0.27	–0.29
June 15 image									
May 1	–0.85	–0.86	–0.82	–0.85	0.65	0.63	–0.26	–0.96	–0.92
May 8	–0.30	–0.45	–0.67	–0.49	–0.15	–0.16	–0.49	–0.44	–0.34
May 15	0.71	0.81	0.83	0.87	–0.65	–0.65	–0.27	0.63	0.75
May 22	–0.35	–0.24	–0.03	–0.25	0.67	0.63	–0.16	–0.60	–0.55
May 29	**–0.98**	**–0.95**	**–0.84**	**–0.94**	**0.91**	0.92	0.23	–0.87	–0.97
June 5	–0.44	–0.61	–0.75	–0.69	0.23	0.22	–0.07	–0.49	–0.51
June 12	–0.09	0.00	0.21	–0.03	0.55	0.50	–0.10	–0.36	–0.33
(B) August 2 TM image									
For the week starting		TM1	TM2	TM3	TM4			TM5	TM7
May 1		0.48	0.25	0.06	0.46			0.01	–0.10
May 8		0.32	0.13	0.39	–0.39			–0.15	0.24
May 15		–0.16	–0.14	–0.21	0.04			–0.53	–0.27
May 22		0.58	0.57	0.12	**0.99**			0.42	0.08
May 29		0.18	0.04	–0.18	0.45			0.19	–0.23
June 5		0.27	0.22	0.47	–0.33			0.40	0.48
June 12		0.55	0.65	0.25	**0.93**			0.61	0.28
July 3		0.85	0.70	0.75	0.18			0.17	0.55
July 10		0.79	0.58	0.54	0.32			0.10	0.33
July 17		**–0.84**	–0.86	–0.58	**–0.81**			–0.44	–0.49
July 24		–0.57	–0.54	–0.31	–0.63			–0.67	–0.31
July 31		0.76	0.60	0.31	0.75			0.26	0.15

as irrigation plans change from time to time and the vegetation has a delayed response to irrigation. Overall, the June data produced the greatest correlation with the water table data. The May imagery may be a little early in the growing season, and the August imagery records the flowering season in the meadow. The maturity of the meadow as recorded in the August imagery may have a lower response to changes in the water table level than in July. This may explain the lower correlation with water table level when compared with the correlations for the May and June data.

This analysis suggests that it is critical to have a good water supply during May and June. It may not be as productive to continue irrigating the meadow in July. The analysis also indicates that water table information for a particular date cannot be directly estimated with a single-date satellite image. It seems helpful to examine the effect of cumulative water levels on spectral data. **Table 3** shows the correlation coefficients for the relationship between monthly average water table level and spectral data.

Since the near-infrared and red bands seem to be highly correlated with water table conditions, we further explored the potential of vegetation indices in estimating cumulative water table conditions. Some additional analyses are discussed as follows.

We calculated the normalized difference vegetation index (NDVI) and several other spectral indices such as brightness, greenness, and wetness using the Kauth–Thomas (KT) transform (Jensen, 1996). Because the KT indices did not show strong correlation results, we only report the results obtained with the NDVI. NDVI values were calculated from the spectral reflectance data. The weekly water table data were averaged over time and then correlated with the NDVI data obtained from the satellite images. **Table 4** shows some of the results.

Table 4 shows that NDVI does not have much better predicting power than some of the single spectral bands but shows similar results. NDVI values obtained from the June image have the greatest correlation with cumulative water table levels, and those obtained from the August image had little correlation with the water table data. This low correspondence with water level data may be caused by flowering or grazing.

The foregoing analysis has the following disadvantages. First, the number of piezometer sites is small. Second, there are fewer image scenes than desirable. Because of cloudiness, it was hard to acquire more images during the growing season in 2002. We tried to overcome the first shortcoming with additional water table measurements.

Correlating field-measured water table levels with ALI and TM data

We selected 28 water table measurement sites and located them with a GPS between 14 and 18 July 2002. Manual drilling was used to measure water table level. Although all sites were chosen with relatively homogeneous grass growing conditions, the water level could not be reached at a number of the sites after 4 ft (1 ft = 0.3048 m) of drilling. Three of the 28 sites were

Table 3. Correlation of monthly average water table level with spectral data.

Four week average before	MS1′	MS1	MS2	MS3	MS4	MS4′	MS5′	MS5	MS7
Image data from 30 May 2002									
May 29	0.15	0.16	0.15	0.13	**0.48**	**0.49**	0.47	0.34	0.35
Image data from 15 June 2002									
May 29	–0.59	–0.51	–0.37	**–0.49**	**0.64**	**0.60**	–0.34	–0.82	–0.74
June 12	–0.72	–0.71	–0.57	**–0.75**	**0.88**	**0.84**	–0.05	–0.89	–0.91
Image data from 2 August 2002									
May 29		0.60	0.44	0.05	**0.87**			0.09	–0.11
June 12		0.60	0.55	0.27	**0.73**			0.60	0.24
July 31		–0.03	–0.29	–0.08	–0.45			–0.69	–0.28

Table 4. Correlation of monthly average water table data with NDVI data.

				Two week prior total average[a]		Prior average[b]	
NDVI	May average	June average	July average	May 29	July 17	Until June	Until July
May	0.33			0.41			
June	0.57	0.825		0.69		0.79	
August	0.40	0.163	–0.18	0.34	–0.14	0.11	–0.15

[a]All water table data 2 weeks prior to the corresponding image acquisition date were averaged.
[b]All water table data prior to image acquisition date were averaged.

Table 5. Correlation of field-measured water table levels with satellite data.

	MS1′	MS1	MS2	MS3	MS4	MS4	MS5	MS5	MS7	NDVI
June ALI	–0.60	–0.52	–0.46	–0.56	0.19	0.18	–0.12	–0.38	–0.51	0.62
August TM		0.05	0.23	0.08	0.29			–0.09	–0.15	0.18

also heavily grazed. As a result, only 21 sites were used in the analysis.

The GPS locations of the 21 sites were used to locate the corresponding pixels in the June ALI and August TM images. Located pixel values were extracted for correlation analysis. Before extraction of the pixel values, we applied principal component analysis and KT transform to the ALI and TM images. Therefore, a series of derivative data was available for analysis. However, none of these derivatives except the NDVI produced high correlation coefficients. **Table 5** shows the correlation results.

It is interesting to note that, although the water table level measurements were taken 1 month after the June ALI image was acquired, the blue bands and the red band of the ALI data are highly correlated with the July water level data (**Figure 1**). **Figure 1c** shows that the NDVI does not reach the highest value when the water level is near the surface. Instead, it reaches its maximum when the water table is at a depth of between 10 and 20 cm. In fact, a nonlinear fitting of the data distribution would give even better results in this case. This can be explained from two aspects: some plants do not grow best when the soil is saturated or under water; the dark soil background may have caused a reduction in NDVI when the soil is under water or saturated. In general, it seems that the June satellite data reflect well the water conditions in the study area. On the contrary, the August TM data are poorly correlated with the water level data. Nonetheless, the highest correlation was achieved between the water level data and the NDVI difference for the August TM and June ALI data. The NDVI increment between June and August (i.e., delta NDVI) is better correlated with the July water level measurements in this case (see **Figure 2**). Additional water level data measured during the earlier growing season and more early-season satellite data are necessary to further examine the relationship between water table and meadow growth in the Bridgeport Valley.

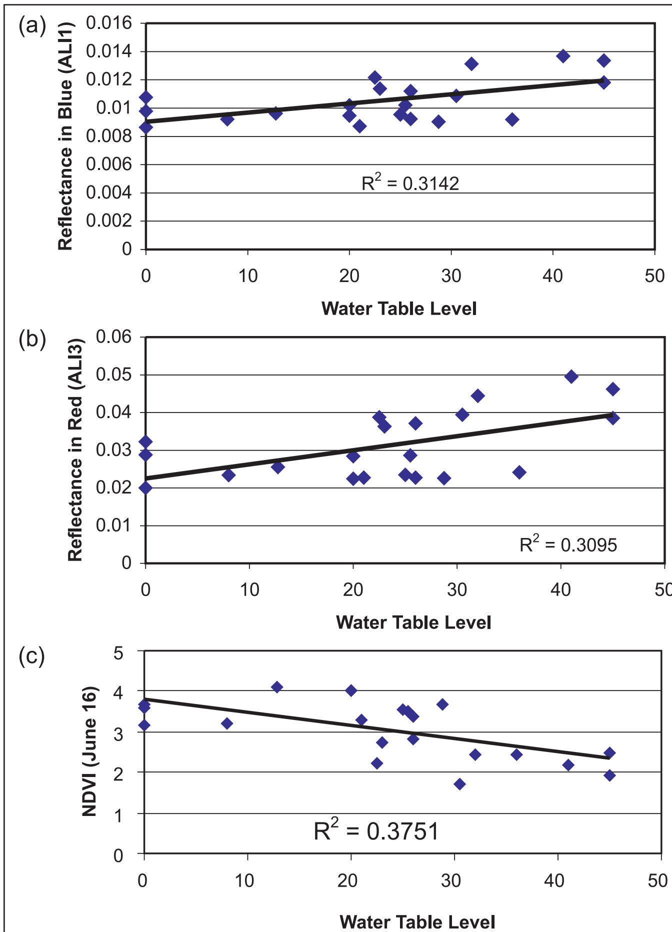

Figure 1. Correlation between field water table measurements (depth in cm) and the June ALI spectral data: (a) with blue; (b) with red; (c) with NDVI.

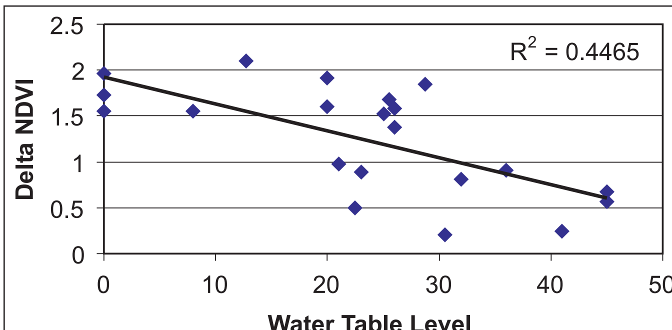

Figure 2. Correlation between field water table measurements (depth in cm) and the NDVI difference (Delta NDVI) of the August TM and June ALI data.

Conclusions

Preliminary results over the irrigated Bridgeport Valley meadow area show that, during the early half of the growing season, vegetation growth as manifested by the spectral properties in the blue, red, and near-infrared bands has a good correlation with average water table level. Use of the NDVI slightly enhances the correlation. For relatively large and flat areas, remote sensing is an important alternative water table level monitoring tool for site-specific measurements. It is necessary to further investigate these relationships with more field data and more frequent satellite data acquisition.

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