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Spatially distributed evapotranspiration estimation using remote sensing and ground-based radiometers over cotton at Maricopa, Arizona, USA

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Abstract Spatially distributed estimates of evapotranspiration (ET) could be valuable for monitoring croplands. Recently various ET estimation approaches have been developed that include visible and near infrared for vegetation indices and thermal infrared for surface temperatures. However, these approaches rely on high-resolution remotely sensed data (<100 m) that are too infrequent for operational use. To help fill the gap, a two-part ground and remote sensing approach is developed. The first part projects vegetation cover from the latest NDVI scenes using a simplified crop model. The second part projects spatially distributed surface temperatures using cover projections and ground-based radiometers. The projections from both parts are then input to a two-source energy balance model. The approach is demonstrated using data over a 2003 cotton experiment conducted in Maricopa, Arizona, USA. Using soil moisture depletion observations for validation, estimates were usually accurate to within 1 mm/d for two weeks beyond the latest remote sensing acquisition.

Key words evapotranspiration; surface energy balance; surface temperature; remote sensing; Maricopa, Arizona, USA

INTRODUCTION

Knowledge of evapotranspiration (ET) over irrigated crop lands is important for conserving and managing water resources in arid environments. Without this knowledge it would be especially difficult to effectively allocate water when supplies become severely constrained. While ET estimation has been feasible for many years, only recently has it become possible to retrieve spatially distributed ET estimates, where variability within and between fields could be evaluated by interpreting high resolution (<100 m) remotely sensed image data. These data typically include visible- near infrared (VNIR) images for constructing vegetation indices and sometimes include thermal infrared observations for estimating land surface temperatures. The combination of these two main data streams allows modelling of the surface energy flux, and subsequently the flux of water vapour. Because of their availability and wide geographic coverage, remote sensing data usually are derived from satellite-based platforms such as Landsat TM. Clearly, image data from these satellites are valuable and will become increasingly important as ET-retrieval techniques mature. Nevertheless, there is a significant obstacle to their use operationally, namely coverage is too infrequent. For example TM data have a 16-day repeat period, an interval that could readily increase given cloudy skies. Clearly such intervals are inadequate for crop water management, where ET estimates are needed at least weekly.

While additional satellites may remove this shortcoming, none of the kind and quality such as Landsat are expected to be launched soon, and thus alternative ET estimation approaches are needed. Proposed here is an ET modelling scheme based on combining ground-based radiometric data with remote sensing image data as they become available. The basis of the scheme is to spatially model ET at hourly time steps using episodic images and continuously recorded land surface temperatures (LST) at fixed ground locations. Provided that vegetation cover densities can be forecast for up to two-week intervals, and further that strong relationships exist between diurnal LST values over soils and vegetation, then accurate, spatially distributed daily ET estimates are feasible.

The ET estimation approach is illustrated in three parts. First, the energy balance model used to retrieve ET is described. Second, the forecasting methodology is described, where the two main modelling inputs, vegetation cover and LST, are respectively projected at daily and hourly time intervals. Third, some results from a cotton field experiment are shown.

ESTIMATION OF EVAPOTRANSPIRATION

An effective way to estimate ET using remote sensing data is to resolve the land surface energy balance considering the four most important components: net radiation, R_n, soil heat, G, sensible heat, H, and latent heat, LE:

$$R_n - G = H + LE \tag{1}$$

where the left-hand side represents available energy and the right-hand side turbulent flux. Equation (1) represents the instantaneous flux, which can be re-written in terms of ET by solving for LE and dividing by the product of water density and latent heat of vaporization. With remote sensing, R_n can be estimated by using VNIR and solar radiation data (Campbell & Norman, 1995) and strongly constrained by the fractional cover of vegetation. G, a small term at daily time intervals, can be estimated as a fraction for R_n (Choudhury *et al.*, 1987). H can be determined from the temperature gradient (ΔT) between vegetation and the overlying atmosphere:

$$H = \rho c_p \frac{\Delta T}{r} \tag{2}$$

where ρ is moist air density, c_p is specific heat of air and r is transport resistance. Determining three of the four terms in equation (1) allows estimation of LE (plus residual errors), and hence ET.

The ET modelling for this study is a modified form of the two-source approach (TSEB, Norman *et al.*, 1995), where computations for equations (1) and (2) are accomplished by separating soil from vegetation fractions. The modification avoids use of Priestley-Taylor parameterization (Priestley & Taylor, 1972) by using temperature observations to solve the energy budget for the vegetation canopy. Having solved for LE at frequent time steps, daily ET estimates can then be directly computed by summation over 24-hour intervals. Thus, assumption of constant evaporative fraction (Lhomme & Elguero, 1999) is not needed.

FORECASTING COTTON COVER FRACTION AND TEMPERATURE

For well-established surface energy balance models such as TSEB, the needed input data are derived from three main sources: vegetation index maps (e.g. NDVI), LST maps, and surface observations including land cover conditions and meteorology. Remote sensing data supply images for the first two sources, while point-based observations supply data for the third source. The approach described here utilizes the most recently available remote sensing image data set and forecasts vegetation cover at daily time steps and LST at ½-hourly time steps.

Cover fraction

To estimate the fractional cover of vegetation an initial remote sensing image of NDVI is needed, which is then transformed to cover (f) via the semi-empirical equation of Choudhury (1987):

$$f = 1 - N^{*p} \tag{3}$$

where N^{*p} is a normalized NDVI scaled between bare soil and full cover, and p is a leaf angle distribution parameter. Cover fraction is then forecast by modelling small areal patches that are uniformly planted and managed according to beta distribution functions. What constitutes a small patch is determined by the particular experiment. In this study, the plot treatment design dictated size. Beta functions are a flexible and realistic way to model the spatial distribution of plant cover because they are smooth and bounded. Similar to Normal distributions, two shape parameters are needed (denoted by α and β) and can be uniquely defined by cover mean ($\bar{f}$) and variance (f_{var}) from the method-of-moments estimators:

$$\alpha = \bar{f}\left[\frac{\bar{f}\left(1-\bar{f}\right)}{f_{\mathrm{var}}} - 1\right] \tag{4}$$

$$\beta = (1-\bar{f})\left[\frac{\bar{f}(1-\bar{f})}{f_{\mathrm{var}}} - 1\right] \tag{5}$$

Assuming that cover fraction changes slowly at daily scales, vegetative cover can be forecast by linearly projecting the mean plant growth and assuming that relative density differences within a patch do not change. In the Maricopa experiment, ground-level photography provided samples of mean cover between remote sensing data sets, while airborne VNIR remote sensing data provided cover variability information. Operationally, mean cover could instead be estimated from plant growth modelling. Thus the cover forecast method followed these steps: (a) transform remote sensing image data to fractional cover from equation (3), (b) estimate beta shape parameters using equations (4) and (5) and moment observations output from step (a), (c) extrapolate cover estimates by updating mean cover, but retaining the initial cover variance, and (d) repeat steps (b) and (c) until a new remote sensing scene becomes available, at which point return to step (a).

Diurnal LST

Modelling ET with remote sensing either requires accurate knowledge of LST or an assumed relationship between cover fraction and plant transpiration. Difficulties are encountered with either. In the first case, high quality, high-resolution thermal infrared image data are often lacking. In the second case, plant water stress cannot be readily detected. One way that can help reduce these problems is to observe plant and dry soil LST values continuously at ground level and spatially scale these according to the cover estimates previously solved. As shown in Fig. 1, LST values of the two surface types have a consistent relationship. Provided representative ground observations, soil LST (T_{soil}) can be forecast at frequent intervals by dynamically calculating a cover scaling function:

$$T_{soil} = T_{veg}(1 + (k-1)\sin\left[\frac{\pi}{12}(t - 6 - \varphi)\right] \tag{6}$$

where vegetation LST is T_{veg}, k is the empirical scale factor relating the component temperatures, t is local time in hours, and φ is sinusoidal phase. Hence diurnal LST values are forecast by daily modelling of ground-based LST observations of vegetation and dry soil to determine the k factor.

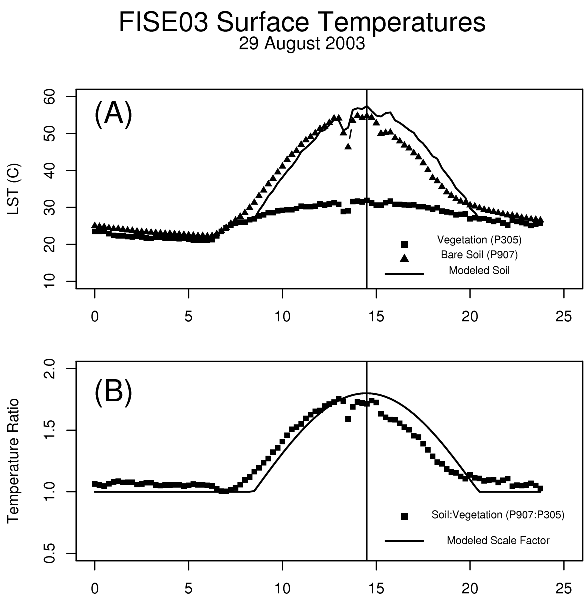

Fig. 1 Land surface temperature scaling model. Fifteen-minute ground-based observations of vegetation and dry bare soil are displayed in (A) as squares and triangles, respectively. Maximum daily LST is indicated by the vertical lines at ~14.5 hours. The scaling function is shown in (B), which considers daytime sinusoidal variations and isothermal night-time conditions.

Phase shift φ is modelled by observed time of maximum vegetation LST. To extend equation (6) to any value within the land cover patch, a mixing model utilizing previously forecast fractional cover estimates is used:

$$T_{composite} = \left[fT_{veg}^4 + (1-f)T_{soil}^4\right]^{1/4} \quad (7)$$

THE MARICOPA FISE03 EXPERIMENT

Implementation of the ET forecast approach was tested using experimental data collected over a cotton field study known as FAO Irrigation Scheduling Experiment 2003 (FISE03; Hunsaker *et al.*, 2005). FISE03 included a ground field site, meteorological, soil, agronomic, and hydrological instruments, plus 10 remote sensing overflights with a helicopter-based platform. The primary objective for FISE03 was development of remote sensing based irrigation scheduling techniques, and thus ET throughout the growing season was closely monitored.

The site (Fig. 2) is a 1.3 ha field at the University of Arizona Maricopa Agricultural Center (MAC, 33.067°N, 111.967°W). Cotton was planted in a 4 × 8 matrix of 32 randomized plots. The water budget in each plot was monitored at daily and weekly time scales using volumetric soil moisture observations derived from neutron probes. Estimated daily ET was calculated for all plots using the FAO-56 dual crop coefficient procedures (Allen *et al.*, 1998).

To monitor plant canopy temperatures, infrared thermometers were deployed in 11 plot locations at different times during the cotton-growing season. Of these nine were pointed towards cotton plants and two pointed towards the soil.

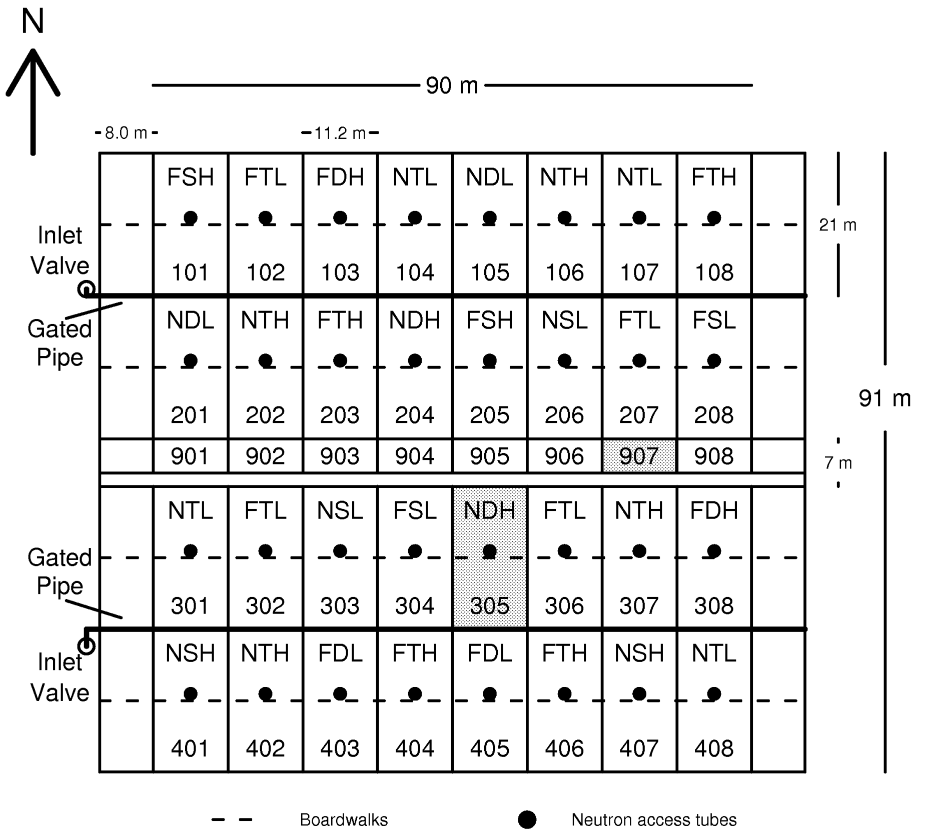

Fig. 2 FISE03 plot design. The 1.3 ha site was planted in cotton in 32 main, and 8 ancillary plots. Identification codes for each plot represent irrigation schedule treatments, planting density, and nitrogen levels. The shaded plots indicate locations for reference LST values over vegetation and bare dry soil.

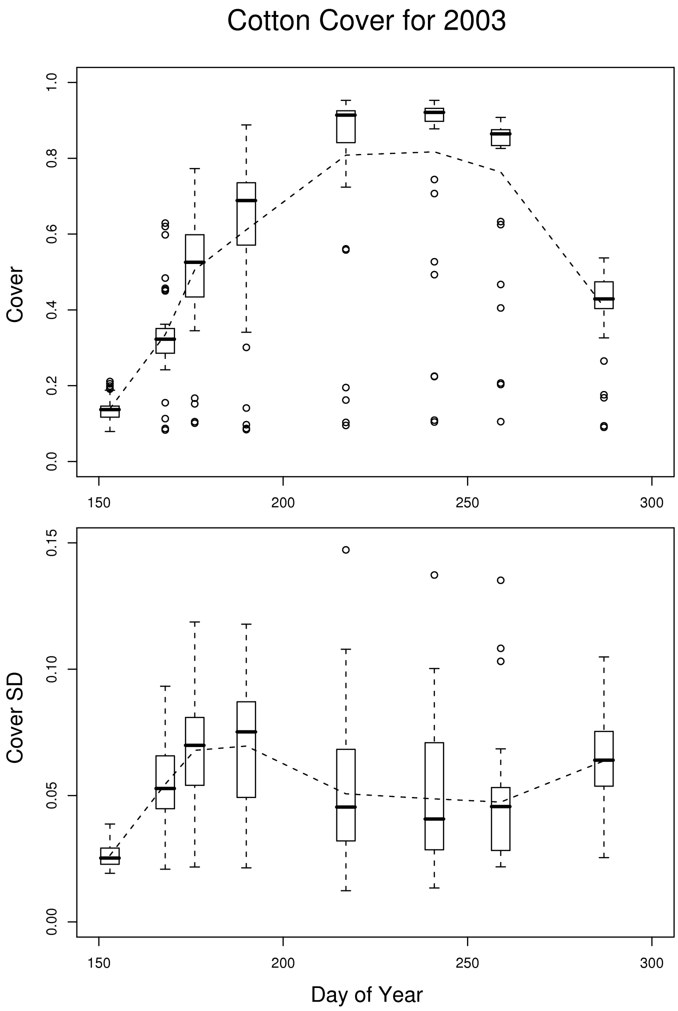

Fig. 3 Temporal changes in FISE03 fractional cotton cover (top) and standard deviation of cover (bottom). Box plots denote quantile statistics on each remote sensing observation day, with whiskers extending to outlier values. The connected dashed lines represent mean trends.

Table 1 Forecast ET *vs* observed soil moisture depletions on 3 July 2003 (DOY 184).

Plot	101	102	103	108	203	205	207	208	302	304	306	308	403	404	405	406	Mean
ET soil moisture	11.1	11.0	11.4	11.0	10.9	11.3	11.2	11.3	10.9	11.3	11.2	11.4	11.0	10.7	11.1	12.2	11.2
ET remote sensing	9.0	8.9	9.1	9.1	9.0	9.0	9.1	8.9	9.1	9.0	9.1	9.1	9.1	9.0	9.2	9.1	9.0

Remote sensing data at FISE03 were collected on ten occasions between 7 May and 13 October 2003 using a helicopter platform. Data acquired included composite LST from a thermal infrared camera and vegetation indices from a visible near infrared camera. Seasonal change in fractional cover (Fig. 3, top) shows density change from bare soil in May, to full cover in July, followed by senescence in September.

Using the ET forecasting approach, initial non-comprehensive results show fair agreement between modelled daily values and estimates derived from soil moisture depletions. As shown in Table 1, modelled ET on day of year (DOY) 168 was mostly within ~20% of soil moisture estimates. These modelled results are outcomes for predicting ET on 3 July 2003, 16 days beyond the most recently available remote sensing data set (DOY 152). Assessment of the full growing season will be needed to determine where the approach can be improved and also to evaluate how much prediction bias is due to the energy balance model, rather than from forecast errors.

Viewing variability in cotton cover trends retrospectively (Fig. 3, bottom) shows that the beta distribution modelling approach can be significantly improved given knowledge of the crop phenology. In this instance, assuming constant variance within a plot was only correct for the mid-season. At early growth, and during senescence, cover variability increased with time by a factor of 2. Thus fractional cover modelling, which did not change the beta shape factors accordingly, likely under-estimated spatial ET variability.

CONCLUSION

An ET forecasting approach developed to cope with episodic remote sensing observations was shown to predict daily ET with accuracy on the order of 1 mm/d. The approach extended fractional cover by using spatial means and variances according to empirical fits to the beta distribution function. LST values were then spatially forecast by using ground LST observations, dynamically-calibrated scale factors, and previously modelled cover estimates. Fractional cotton cover, LST, and meteorological data were then combined with a two-source surface energy balance model to yield time-integrated ET estimates. Comprehensive testing of the approach for the full cotton season is needed to establish the relative accuracy of this forecast approach compared with more conventional approaches using only instantaneous observations.

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