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Assimilation of SVM-based estimates of land surface temperature for the retrieval of surface energy balance components

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Data-assimilation methods play a crucial role for exploiting remote sensing in dynamic physical models for the prediction of hydrological-process evolution. Here, a novel method is proposed to assimilate land-surface temperature estimates, derived by applying support-vector regression to infrared satellite data, into a variational technique for mass and energy exchange estimation at the soil surface. Recent techniques to fully automate support vector regression and to estimate the pixelwise statistics of the regression error are incorporated in the proposed method.

DESCRIPTION

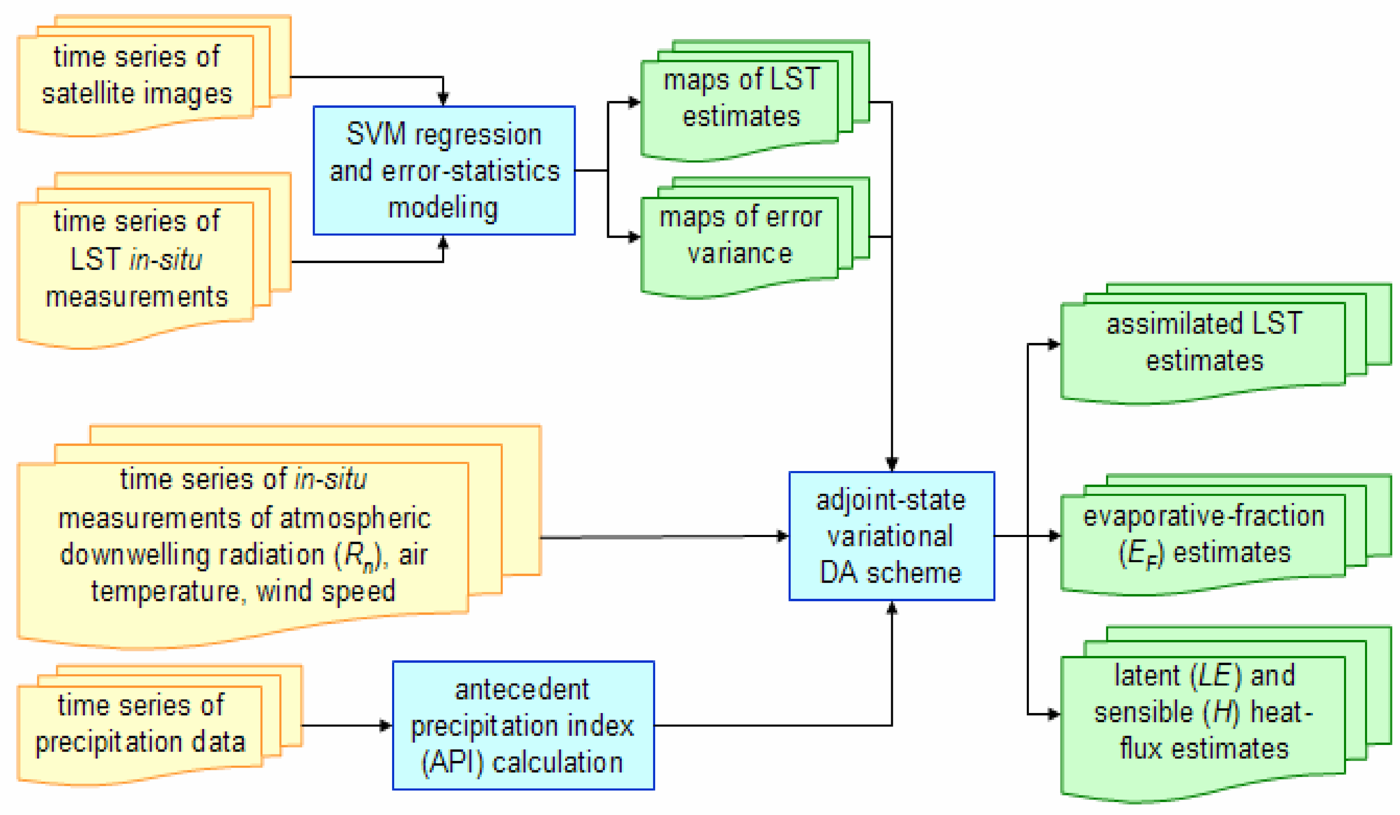

Figure 1. Architecture of the proposed DA-SVM method

$$\hat{T}_s(x) = \sum_{r \in R} \beta_r K(x_r, x) + b$$ → estimate of the LST *Ts* on the feature vector *x* of a generic pixel

$$\begin{cases} \min_{\beta} \left(\frac{1}{2}\beta^T Q \beta - T_s^T \beta + \varepsilon \|\beta\|_1 \right) \\ \mathbf{1}^T \beta = 0, \quad \|\beta\|_\infty \le C \end{cases}$$

where: $Q_{ij} = K(x_i, x_j)$ → kernel function

$$SB(C,\varepsilon,\gamma) = \varepsilon + \frac{1}{\ell}\sum_{r \in R} |\beta_r| s_r^2 + \frac{T_s^T \beta - \varepsilon \|\beta\|_1 - \beta^T Q \beta}{C\ell}$$

Support vector regression:

- kernel-based nonparametric method;
- very good generalization properties;
- improved test-set accuracy, compared to classical LST estimators;
- no need for prior estimates of surface or atmospheric properties;
- need for in-situ temperature measurements (for training);
- regularization and kernel parameters automatically optimized by minimizing a generalization error bound (span bound on the leave-one-out error) by Powell's algorithm (nondifferentiable functional) (3)

DA scheme (1,2):

- adjoint-state variational scheme;
- Lagrangian iterative constrained minimization of a quadratic penalty function that incorporates LST and API dynamics;
- constraints: mass and energy balance;
- quadratic differences between assimilated and SVM-based LST estimates are weighted by pixelwise error variances.

$$J = \int_{\tau i}^{\tau f} [Z - M_w Y]^T C_{\varepsilon,\varepsilon}^{-1} [Z - M_w Y]\, d\tau \; +$$
Quadratic of misfit error between measurements and state prediction.

$$+ [Z - M_w Y]_{\tau f}^T \, C_{\varepsilon,\varepsilon}^{-1} \, [Z - M_w Y]_{\tau f} \; + \; [\Psi - \overline{\Psi}]^T \, C_{\psi,\psi}^{-1} \, [\Psi - \overline{\Psi}] \; +$$
Squared errors of parameters estimations.

$$+ 2 \int_{\tau i}^{\tau f} \Lambda^T(\tau) \left[\frac{dY(\tau)}{d\tau} - F(Y, \Psi | \tau) \right] d\tau$$
Physical constrains adjoined through Lagrange multipliers.

Force-restore equation (energy balance constraint in the DA scheme):

– widely used in land modeling and DA to describe the evolution of T_s due to diurnal variations in radiative-forcing (R_n-H-LE);

– forcing is modified by a restoring term (deep soil temperature):

$$\frac{dT_s}{dt} = 2\sqrt{\pi\omega}\left(\frac{R_n - H - LE}{P}\right) - 2\pi\omega(T_s - T_{deep}),$$

API dynamics (mass balance constraint):

– thermal inertia P is affected by soil water;

– given the intensity of precipitation I, a general and simplified way to estimate the degree of moisture in the ground is given by API (S):

$$\frac{dS}{dt} = -\gamma S + I,$$

EXPERIMENTAL RESULTS

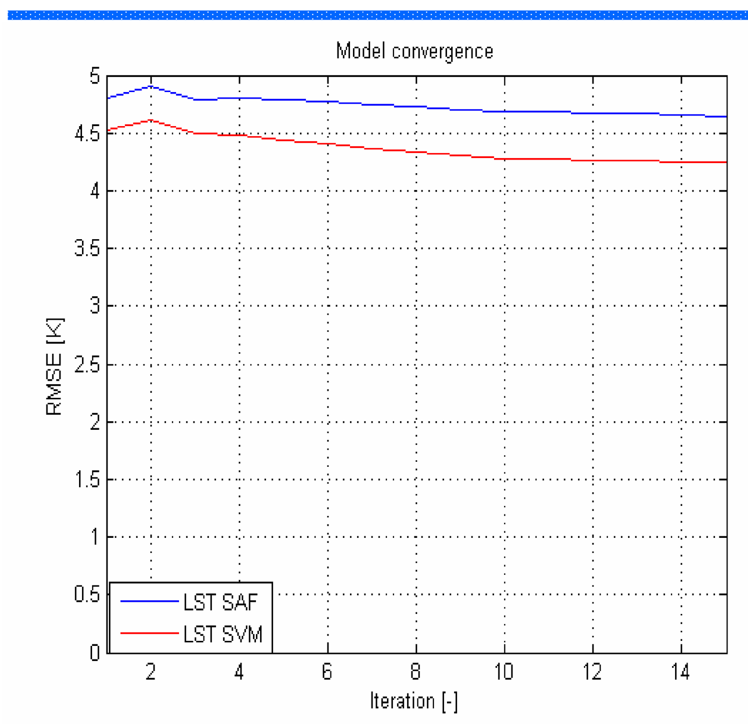

Figure 2. RMSE between DA-based and satellite LST estimates, computed over the considered time period and over all pixels where assimilation was significant (≥ 300 hours of clear sky during the period)

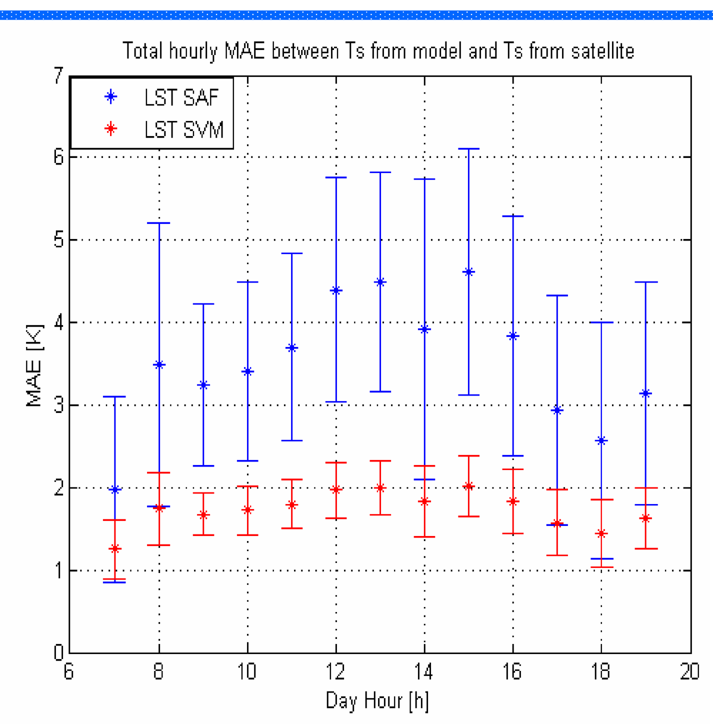

Figure 3. Hourly mean and standard deviation of MAE, computed between DA-based and satellite LST estimates over the considered time period and over all pixels where assimilation was significant

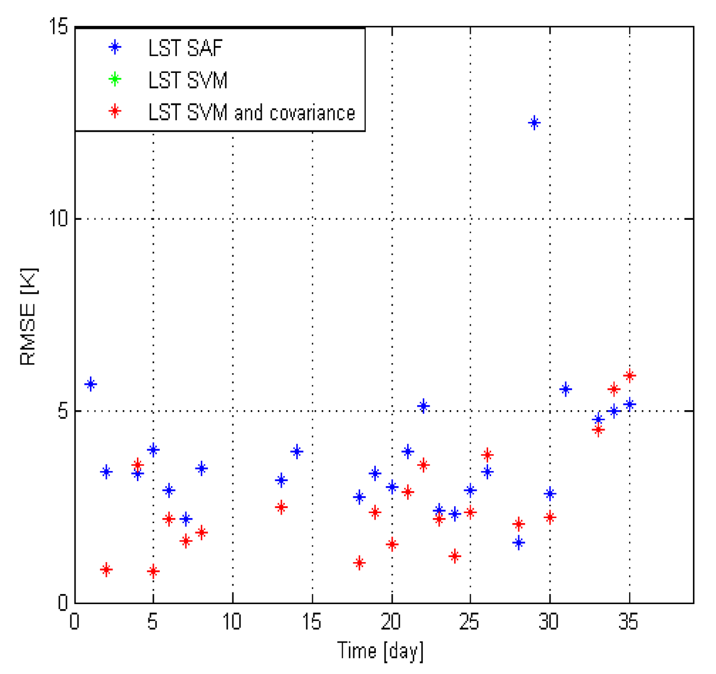

Figure 4. Daily mean RMSE, computed for a single pixel in the Padana Plain between the DA-based and satellite LST estimates

	MAE	RMSE
LST SAF	0,1733	0,2073
LST SVM	0,1578	0,1926

Tab 1. total mean absolute error (MAE) and root mean square error (RMSE) between observed saturation level and evaporative fraction

CONCLUSIONS AND REMARKS

A novel method was proposed to integrate remote-sensing data in physical models for mass-energy exchanges at the soil surface by combining SVM and variational DA.

From the results represented above it is possible to see that it has been:

- improved convergence behavior and matching between assimilated and satellite LST estimates, as compared with classical split-window LST estimates;
- improved matching between ground observations of saturation level and evaporative fraction obtained with assimilation of LST from SVM;

Future extensions:

- estimation of the correlations among regression errors in distinct pixels (full error covariance matrix) and integration in the variational scheme.

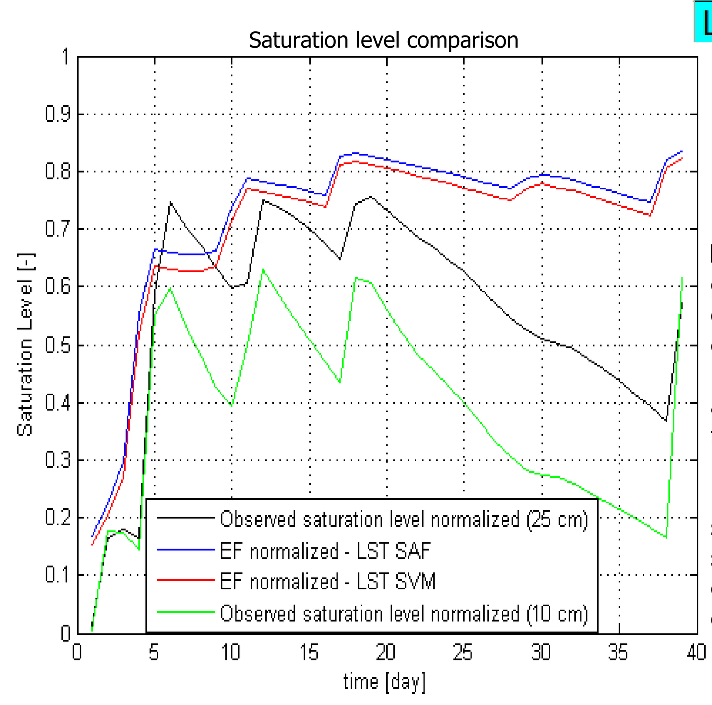

Figure 5. Comparison between ground observations at different depths (green at 10 cm, black at 25 cm) of normalized saturation level and normalized EF obtained from assimilation of LST SAF (blue) and LST SVM (red). EF is representative of a medium soil layer, interested by roots, so EF estimates must be compaired with ground observations at 25 cm depth.

REFERENCES

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