VALIDATION OF FINE RESOLUTION LAND-SURFACE ENERGY FLUXES DERIVED WITH COMBINED SENTINEL-2 AND SENTINEL-3 OBSERVATIONS

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ABSTRACT

A methodology for deriving land-surface energy fluxes estimated with the use of Sentinel-2 and Sentinel-3 observations is validated in a savannah landscape in central Spain. The fluxes are derived at two spatial resolution: fine (20 m) and coarse (around 1 km). At both resolutions the thermal observations from Sea and Land Surface Temperature Radiometer (SLSTR) on Sentinel-3 and optical observations from Multi-Spectral Instrument (MSI) on Sentinel-2 are used within a Two-Source Energy Balance (TSEB) modelling scheme. For the fine resolution estimates, the thermal observations acquired by SLSTR at around 1 km resolution are sharpened using high-resolution (20 m) optical observations taken by MSI and a machine learning algorithm. The results indicate that it is possible to derive fluxes with similar accuracy at both spatial scales, while obtaining more detailed separation of fluxes originating from individual landscape features at the fine scale.

Index Terms— land-surface energy fluxes, thermal sharpening, machine learning, Sentinel-2, Sentinel-3

1. INTRODUCTION

Accurate parameterization of water use in natural and agricultural landscapes requires estimates of actual evapotranspiration (ET) at the predominant landscape scale. This implies a spatial resolution of tens of meters. ET derived at such fine resolution could, among other applications, be utilised in agriculture (e.g. field-scale water use monitoring and optimizing water consumption in crops) and environmental monitoring (e.g. health of wetlands, grasslands or riparian areas). Most methods which utilise satellite observations for actual ET modelling require land surface temperature (LST) information, in order to establish boundary conditions of energy transfer between land surface and atmosphere [1]. This information is derived from Thermal-Infrared (TIR) observations. In addition, the ET models require parameterisation of vegetation conditions (e.g. leaf area index and fractional vegetation cover) which can be obtained from observations in the Visible - Near-Infrared (VNIR) and Shortwave-Infrared (SWIR) parts of the electromagnetic spectrum.

The Sentinel satellite constellation is able to provide both TIR and VNIR-SWIR observations but not always at the required spatial resolution. In particular, a TIR sensor (Sea and Land Surface Temperature Radiometer - SLSTR) is present only on the Sentinel-3 (S3) satellite and has a spatial resolution of around 1 km. On the other hand, the VNIR-SWIR observations are available from sensors on both Sentinel-2 (S2) and S3 satellites and at resolutions ranging from 10 m to 500 m. Therefore, a study was recently conducted that assessed the use of combined S3 and S2 data to estimate ET at 20 m scale [2]. The study relied on machine learning algorithm to establish a complex relationship which is present between TIR and VNIR-SWIR observations when limited in both space and time, to downscale (sharpen) LST to tens of meters resolution and then used that LST as input to an ET model. In that study, the methodology was evaluated by using Landsat satellites as proxy of S2 and Terra satellite as proxy of S3 and comparing the accuracy of ET estimated with sharpened LST and ET estimated with LST based on high-resolution Landsat TIR observations. The conclusion was that the methodology allows for estimation of high-resolution (30 m) ET with good accuracy, although with reduced dynamic range when compared to ET derived with the actual high-resolution LST observations [2].

In this paper, we further validate the approach by, for the first time, using only S3 TIR and S2 VNIR-SWIR observations (apart from ancillary inputs such as meteorological data and land cover map). Furthermore, the validation is performed against measurements from a flux tower located in a semi-arid savannah ecosystem where heat and mass exchanges come from three different sources: a sparse tree cover with two underlying continuous layers composed of annual herbaceous species and soil.

2. METHODOLOGY

One of the major approaches for modelling actual ET with the use of satellite based observations of LST and vegetation parameters is the Two-Source Energy Balance (TSEB) modelling scheme [3, 4]. In comparison with other ET models, it has the advantage of being the more physically based and of being able to accommodate varying fractions of vegetation cover. In the TSEB scheme, the energy balance is enforced through four major land-surface energy fluxes with minor fluxes (such as photosynthesis) being ignored:

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

In the above equation left side represents the energy available for driving the land-surface processes, and is composed of net radiation (R_n - the balance of incoming and outgoing long-wave and short-wave radiation) minus the ground heat flux (G). On the right side are the sensible heat flux (H - heat transfer between surface and lower atmosphere) and the latent heat flux (LE - energy used for water evapotranspiration). In the model, H is driven by the temperature difference between the surface and the air and modulated by a series of resistances, representing the micrometeorological conditions impacting the heat transfer (e.g. wind speed or surface roughness). LE is typically estimated as the residual of the other fluxes. In the TSEB scheme the fluxes originating from soil and vegetation are estimated separately before being combined to obtain bulk fluxes. The Python implementation of TSEB model, as used in this study, is described in [2] and available online from https://github.com/hectornieto/pyTSEB (last accessed 01.12.2017).

To model H, LST and air temperature (T_a) observations are required. While T_a can be considered to vary rather smoothly at regional scales, especially if it is assumed to be measured above the air blending height, LST spatial behaviour is very dynamic. Therefore, high-resolution LST is required to accurately model H, and therefore LE, at the appropriate landscape scale. In [2] the fine-scale LST was derived by using a machine learning approach to sharpen coarse-scale LST from Terra satellite TIR observations with fine-scale VNIR observations obtained by Landsat satellite. In this study, the same approach is applied to coarse-scale LST from S3 and fine-scale VNIR-SWIR observations from S2. The machine learning algorithm is based on an ensemble of regression trees which are first trained with coarse-scale LST and fine-scale optical observations aggregated to the same coarse-scale [5]. The trained model is then applied to fine-scale image to derive the corresponding fine-scale LST. In the current study, a digital terrain model and related terrain slope and aspect maps are used during the training and application of the sharpening model in addition to the VNIR-SWIR observations. Various enhancements of the regression tree approach (such as moving window and global applications or linear regressions fitted to data within each tree leaf) are described in [2], while the Python source code is available online (https://github.com/radosuav/pyDMS - last accessed 01.12.2017).

A step which was found to significantly enhance the accuracy of the fluxes derived with sharpened LST, was to use a "disaggregation" approach [6] to ensure spatial consistency between fluxes at fine and coarse spatial scales [2]. In that approach, the fluxes are first estimated at the coarse scale at which the thermal observations were acquired. Afterwards, all the high-resolution flux pixels falling within one low-resolution flux pixel are adjusted (by varying the low-resolution air temperature) until there is a consistency between the two scales. This is done under the assumption that the coarse-scale estimates are more accurate since they are obtained from LST at the original spatial resolution.

3. DATA

3.1. Model data

The LST and emissivity were derived based on [7], using brightness temperatures of SLSTR bands S8 and S9. The atmospheric correction of S2 VNIR reflectances was performed in Sen2Cor at 20 m resolution. Afterwards, vegetation indices were calculated from bottom of atmosphere (BOA) reflectances while leaf area index and fractions of vegetation cover and absorbed photosynthetically active radiation were derived using a neural network which is available as part of the SNAP software (step.esa.int - last accessed 01.12.2017). Broadband near-infrared and visible albedos were estimated using parameterisation which was previously derived for Landsat 7 spectral bands [8], under the assumption that the location of spectral bands between S2 and Landsat 7 is broadly similar. For low-resolution model runs the S2 derived parameters were resampled (using averaging) to the LST spatial resolution, while for the high-resolution runs the LST was sharpened to 20 m using the approach outlined in previous section.

There were 18 dates from November 2016 till November 2017 on which it was possible to estimate fluxes. On certain dates on which a S2 overpass was present there was no S3 overpass. In those cases, the closest S3 overpass date was found (with a limit of 3 days from S2 overpass date) and fluxes were estimated on that date with the assumptions that the vegetation conditions observed by S2 would not have significantly changed during this period.

Ancillary data required for the TSEB model include meteorological forcing (T_a, wind speed, pressure, relative humidity and incoming solar radiation) which were obtained from the ECMWF ERA5 reanalysis data [9]. The only exception is the incoming solar radiation which was estimated based on the simple model of Ineichen [10] and ECMWF aerosol optical thickness forecast [11]. The other ancillary dataset is landcover map which is used to set certain model parameters (e.g. vegetation height). The map was based on Corine landcover from 2012, resampled to the required resolution and reclassified into simpler land cover classes.

3.2. Validation data

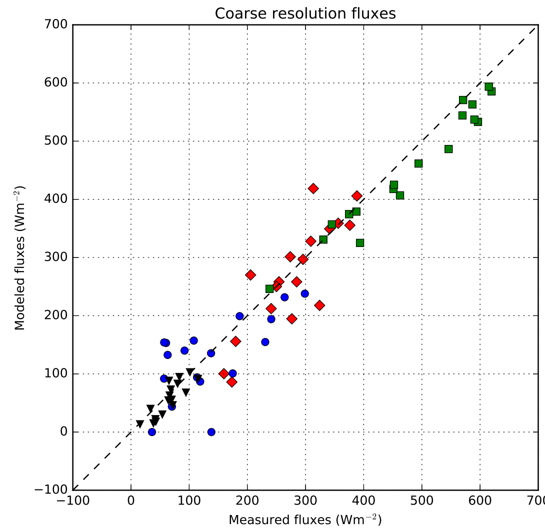
The study site is located at Majadas de Tiétar, Cáceres (Spain) FLUXNET site (http://www.fluxdata.org:8080/sitepages/siteInfo.aspx LMa, last accessed 04.01.2018). The site is a Mediterranean savannah (dehesa) with an overstory dominated by holm oak and understory mainly composed of short herbaceous species. It experiences hot and dry summers, with 30 °C daily average temperature and only individual rain events, and is characterized by by mean annual temperature of 16.7 °C and precipitation of around 650 mm.

The EC system consists of a three-dimensional sonic anemometer and an infrared gas analyzer to measure dry mixing ratios of CO_2 and H_2O. The measurement height was 15 m above the ground and 7 m above the mean canopy height. Based on the findings of a previous study utilising the same measurements [12], the energy closure gap was distributed between measured H and LE using the Bowen ratio before comparing the estimated fluxes against those measurements. In addition, flux measurement footprints were estimated and used when validating the fine resolution flux estimates. Short-wave and long-wave incoming/outgoing radiation are measured with a net radiometer at 15 m above the ground.

4. RESULTS

The accuracy statistics of both coarse and fine scale model runs are shown in Table 1, with the scatterplots of the modelled versus measured fluxes presented in Figure 1. The coarse resolution sensible heat flux is estimated with a good accuracy, with Root Mean Square Error (RMSE) representing 19% of the average measured value and correlation of 0.85. The RMSE of latent heat flux is of larger magnitude to that of H and (also due to lower measured LE values) it corresponds 46% relative error. The correlation of the LE estimate is also lower, at 0.64. The net radiation has very high correlation (0.98) but it also has a significant underestimation bias of close to 30 W/m^2.

The accuracy statistics of fine resolution flux estimates look very similar. The RMSE of H decreases slightly compared to the coarse estimates and the high correlation remains almost unchanged. The situation is similar in case of LE with RMSE decreasing slightly but this time the increase of correlation is more significant. On the other hand, the fine scale R_n estimate has larger RMSE then the coarse scale estimate.



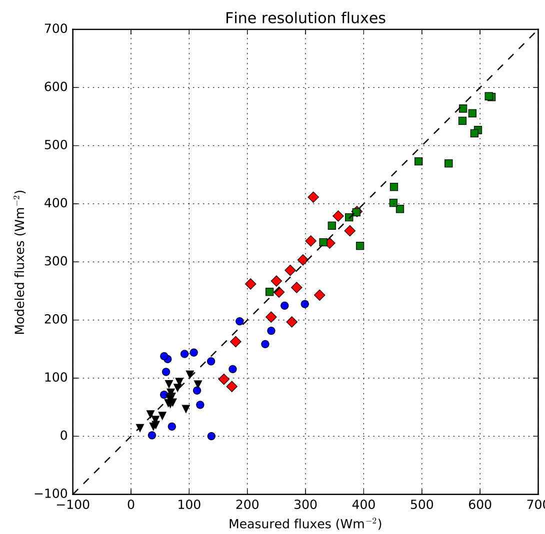


Fig. 1. Instantaneous land surface energy fluxes derived at coarse (top) and fine (bottom) resolutions. Green squares represent net radiation, red diamonds represent sensible heat flux, blue circles represent latent heat flux and black triangles represent ground heat flux.

5. DISCUSSION AND CONCLUSIONS

The flux tower is located in a savannah landscape, which is uniform at kilometer scale while being heterogeneous at tens of meters scale (due to consisting of isolated trees surrounded by grassland). Therefore, it is difficult to illustrate the benefit of modelling the fluxes at 20 m spatial resolution,

Table 1. Accuracy statistics of instantenous land-surface energy fluxes modelled with TSEB at coarse and fine spatial resolutions. Root Mean Square Error (RMSE) and Bias (modelled minus measured values) are in W/m^2, coefficient of variation (CV - RSME divided by the mean of the measured values) and correlation (r) are unitless.

	H				LE				Rn				G			
Resolution	RMSE	Bias	CV	r	RMSE	Bias	CV	r	RMSE	Bias	CV	r	RMSE	Bias	CV	r
Coarse	52	-10	0.19	0.85	62	-8	0.46	0.64	37	-27	0.08	0.98	17	-9	0.26	0.86
Fine	48	-11	0.17	0.86	60	-18	0.44	0.69	43	-30	0.09	0.97	18	-7	0.27	0.83

as compared to 1 km resolution, when validating the estimates against the tower measurements. On the other hand, the fluxes derived using the sharpened LST and the disaggregation approach are of slightly higher accuracy than those derived using the original resolution LST. This is despite the increased landscape complexity at the tens of meters scale. This illustrates the robustness of the proposed approach and demonstrates that with a proper treatment it is possible to combine S2 and S3 measurements to derive ET with acceptable accuracy and high spatial resolution.

The true benefit of obtaining higher resolution estimates becomes apparent in the irrigated fields located north of the measurement site (Fig 2). While no fields can be distinguished in the coarse-scale map, when sharpened LST is used to derived the fluxes the evapotranspiration of the individual fields (and other landscape features) can be clearly separated. This allows, for example, the estimation of the amount of water used during a growing season on one field, when combined with temporal extrapolation (from instantaneous to daily estimates) and interpolation (between the dates with valid model runs).

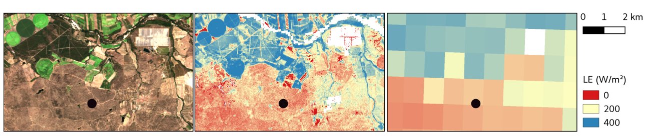


Fig. 2. Maps of the area surrounding the flux tower, indicated as black dot. Left panel shows Sentinel-2 true colour composite on 24.09.2017, while middle and right panels shows respectively fine scale and coarse scale instantaneous latent heat flux estimates obtained during Sentinel-3 overpass on 23.09.2017.

The current study has demonstrated that it is feasible to estimate land surface energy fluxes using S2 and S3 observations at both coarse (kilometer) and fine (tens of meters) scales. As part of Sentinels for Evapotranspiration project (http://esa-sen4et.org/ - last accessed 09.04.2018) the robustness of the fine scale ET modelling methodology will be further developed and validated in other landscapes (croplands, grasslands, coniferous and broadleaf forests) and climatic zones (semi-arid and temperate). In addition, an impact of different meteorological inputs and ET modelling approaches (one-source, two-source and contextual) on the accuracy of the modelled fluxes will be investigated. Finally, evaluation of ET partitioning between grass, soil and oaks will be undertaken as part of a separate study.

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