Assessing the effect of spatial resolution on energy flux estimates using the SPARSE two-source energy balance model

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1. INTRODUCTION

In a climatic context increasingly affected by the impacts of climate change, such as water scarcity, droughts, and floods, environmental monitoring plays a fundamental role in understanding which actions can mitigate these impacts on agriculture. Indeed, accurate estimates of crop water requirements (CWRs) are becoming increasingly necessary to a proper use of the water resources. The literature is rich of surface energy balance (SEB) applications in several environmental contexts and with data from multiple sources. Data acquired from multi-platform remote sensors have encouraged the use of SEB models to monitor large areas and to provide satisfactory estimates of CWRs. In particular, the two-source energy balance (TSEB) model proposed by Norman et al. [1] was employed to estimate actual evapotranspiration (ET_a) using land surface temperature (LST) acquired from remote sensing (RS) platform as Landsat and Modis [2]. However, traditional satellite RS approach shows some limitations, including coarse spatial resolution (~30 m), infrequent revisit times (~15 days) and data gaps due to meteorological conditions (*e.g.*, cloud cover).

In the context of precision agriculture, the use of unmanned aerial vehicles (UAVs) may provide a solution to overcome the limitations of conventional RS supports. Although these systems require specialized operator skills (*e.g.,* pilot licensing), dedicated post-processing software, and high-performance computing resources, environmental monitoring using UAVs has seen widespread adoption in recent years. As an example, some authors demonstrated that UAV equipped with multispectral and thermal cameras are the most frequently employed tools in precision agriculture for monitoring crop health and water stress [3]. Gómez-Candón et al. [4], in a typical Mediterranean environment, studied the reliability of the TSEB model to estimate effective ET_a in 19 wheat fields characterized by different irrigation strategies. The results obtained showed that the TSEB model together with high-resolution images can be a promising tool for estimating ET_a obtaining route mean square error (RMSE) equal to 0.24 mm h^{-1}. The objective of this study is to analyze how the performance of a TSEB model (named SPARSE) changes with the progressive degradation of input data spatial resolution.

2. MATERIALS AND METHODS

The experiment was carried out in a commercial citrus orchard located in the Northwest of Sicily, Italy. Main meteorological variables are measured by a standard weather station. Surface energy balance components are monitored by an eddy covariance (EC) flux tower, more details regarding the experimental layout are available in De Caro et al. [5].

Optical and thermal high-resolution images were acquired in April 2025, 23rd at noon using two different UAVs platforms. The first platform was a DJI Mavic 3M equipped with a multispectral camera characterized by a field of view (FOV) of 73,91°; this camera is capable of acquiring four spectral bands at 560 ± 16 nm (green), 650 ± 16 nm (red), 730 ± 16 nm (red edge) and, at 860 ± 16 nm (near infrared). The second was a DJI Mavic 3T equipped with a thermal camera (in the range of 8 – 14 µm) with a resolution of 640×512 pixels, with a FOV 41,2°. The UAV flew over at a height of 45 m a.g.l., collecting images with at 0.02x0.02 and 0.06x0.06 m per pixel for the multispectral and thermal camera, respectively. Flight planning had 80/70 frontal and side overlaps, respectively.

In this study the Soil Plant Atmosphere and Remote Sensing Evapotranspiration (SPARSE) model was employed. From theoretical point of view, SPARSE is a two-source energy balence model implemented using a parallel soil-plant resistance network scheme [6]. This model relies on meteorological data, as well as the Normalized Difference Vegetation Index (NDVI), Land Surface Temperature (LST), albedo (α), and Leaf Area Index (LAI). Using these inputs, it enables the estimation of instantaneous energy fluxes from both soil and vegetation. Initially, the spatial resolution of NDVI was aggregated at the same spatial resolution of the thermal image (*i.e.*, 0.06x0.06 m). SPARSE was applied to this spatial resolution up to the spatial resolution of Landsat-8 (*i.e.*, 30x30 m) by aggregating NDVI and LST employing four different spatial odd kernels (11x11 ~0.60 m; 101x101 ~6 m; 301x301 ~18 m and 501x501 ~30 m). The four components of the surface energy model simulated by SPARSE were compared to those monitored by the EC (*i.e.*, solar net radiation (R_n), latent heat flux (LE), sensible heat flux (H) and soil heat flux (G_o)). For the comparison, the SPARSE outputs were averaged over the EC footprint [7].

3. Results and discussion

Figure 1 shows the value of the four components retrieved by applying the SPARSE model at different spatial resolutions resulting in the four considered kernels.

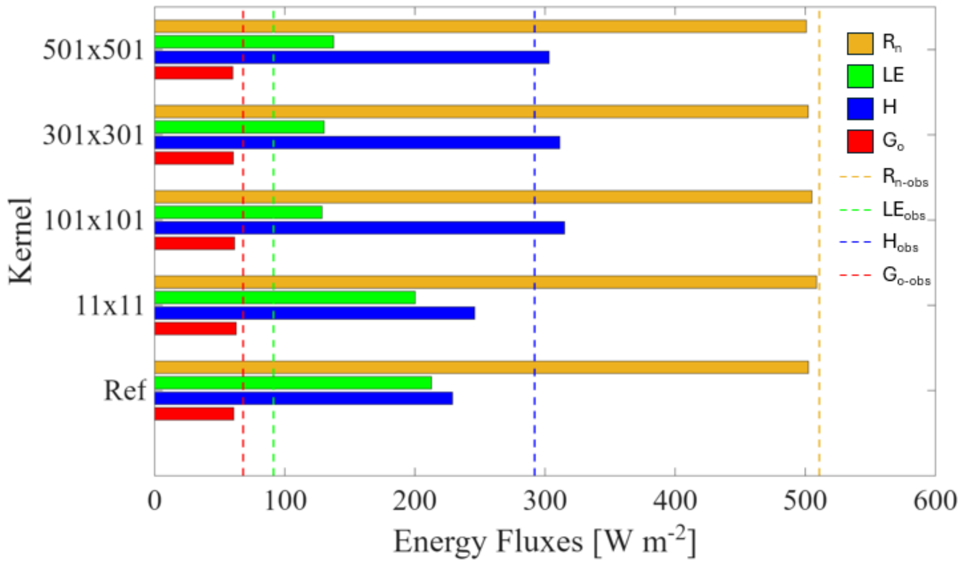

Fig. 1. Comparison between simulated energy fluxes components solar net radiation R_n (orange bar), latent heat flux, LE (green bar) sensible heat flux, H (blue bar), soil heat flux (G_o) (red bar) end measured fluxes (vertical dashed line).

Results shown in fig. 1 indicate that G_o and R_n are not significantly affected by changes in spatial resolution. In contrast, H and LE appear to be sensitive to resolution changes. Specifically, at a spatial resolution of ~6 m (101 × 101), the differences between the estimated and measured LE and H were equal to 37 Wm^{-2} and 23 Wm^{-2}, respectively; these are also better than that obtained at the reference spatial resolution (121 Wm^{-2} and 63 Wm^{-2}, respectively). These preliminary results suggest that the model performs better when the pixel is not homogeneous (*i.e.*, completely vegetated). These results are consistent with the ones found by of Neely et al. [8], who demonstrated that, in a cotton field, the progressive aggregation of TSEB model raster inputs leads to increasingly reliable estimates of LE, with mean absolute error values of about 7%. This confirms that the flux estimations based on two-source model are more reliable when the assumption of mixed pixels (vegetation + soil) is satisfied.

4. Conclusion

Results of the SPARSE model applied with high resolution UAV images demonstrate that the model well perform when the spatial resolution decreases. As expected, these results confirm that the TSEB approach is capable to retrieve satisfactory results on mixed pixels. Further analyses will be conducted exploring several kernels, to identify the pixels aggregations effects on the estimates. Also, further investigations under different vegetation cover conditions will help to better understand how sensitive the model is to variations in land cover. Finally, it will be important to investigate the model response following precipitation or irrigation events in order to assess how the response changes in terms of LE and H.

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