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# Monitoring Evapotranspiration over the Alpilles Test Site by Introducing Remote Sensing Data at Various Spatial Resolutions into a Dynamic SVAT Model

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**Abstract.** Remote sensing estimation of evapotranspiration (ET) was done by combining remote sensing data and the ISBA soil-vegetation-atmosphere transfer model over the Alpilles test site. We tested the possible use of low resolution data (~1km) to derive leaf area index (LAI) at the field scale using a disaggregation method. Disaggregated LAI were then used as inputs of ISBA for monitoring ET for 9 months. Estimation of LAI and ET were first performed at high resolution for being used as reference for evaluating the use of low resolution data. Estimations of LAI at high spatial resolution using an artificial neural network (ANN) algorithm were in very good agreement with ground measurements. At low resolution, we found that it was possible to estimate accurately LAI for the most frequent types of vegetation cover, wheat and sunflower, but not for the other types. However, the estimation of ET from disaggregated low resolution data was found to be quite accurate for any type of vegetation cover (the comparison to high resolution estimation was good). ISBA simulations were eventually compared to independent estimates of ET using thermal infrared and a simplified energy balance equation showing large discrepancies in some areas or for some crop types: these corresponded to area with soil characteristics being different from those used in the simulation and to crops which were irrigated (irrigation inputs were not accounted in the simulations). This study enlightened the possible use of low resolution data for monitoring crop evapotranspiration at the field scale and the possibility of identifying areas with soil having contrasted water behaviour and irrigated crops.

**Keywords:** Remote sensing, Soil-Vegetation-Atmosphere Transfer model, Energy balance, Evapotranspiration, crop water availability, spatial resolution, scaling.

## INTRODUCTION

The estimation of crop evapotranspiration (ET) is a crucial step toward a rational use of water at the field scale as well as the regional scale (e.g. irrigation district). This requires the integration of various types of information (land use, soil maps, meteorological data, remote sensing data...) together with simulation models. Detailed maps of crop development and evapotranspiration may be computed from high spatial resolution data provided by Earth observation satellites such as LANDSAT (TM or ETM+ sensors), TERRA (ASTER sensor) or SPOT-HRV sensor (without thermal infrared). However, routine (i.e., daily to weekly) monitoring of plant development and evapotranspiration, is not feasible at this high spatial resolution because of the low frequency of satellite coverage over the region of interest (i.e., approximately every 2 weeks). Cloud cover further reduces the number of useable observations resulting in high-resolution satellite imagery of a region typically being available once a month, which is not very useful for routine and operational ET monitoring. In this study, we tried to overcome such difficulties by combining two techniques which made it possible to increase the available information: *-i*) a dynamic Soil-Vegetation-Atmosphere Transfer (SVAT) model was used in order to simulate evapotranspiration between remote sensing data acquisitions [1, 2], and *-ii*) an unmixing method was tested that made it possible to use low spatial resolution data (~1km) for monitoring vegetation at the field scale [3].

## METHODS, EXPERIMENTAL DATA AND SVAT MODEL

In this study, evapotranspiration was monitored over the Alpilles test site [4-6] for 9 months by using the ISBA SVAT model [7] in combination with high and low spatial resolution remote sensing data (as low resolution data were not available, they were actually reconstructed from high resolution data). The model was **first** fed by high resolution maps of leaf area index (LAI) obtained from SPOT and airborne POLDER data, and run to provide hourly and daily ET maps at a 20 meter spatial resolution. These maps were used in the following as a **reference** set of data for evaluating estimation of LAI and ET from low resolution data. In a **second step**, synthetic data at 1 km spatial resolution were built by aggregating reflectances measured at high resolution by the airborne POLDER sensor. In a **third step**, the disaggregation method developed by [3] was used for deriving LAI at the field scale, or for each crop type, from the synthetic low spatial resolution data. These LAI were inputted in ISBA in order to compute ET along the crop season for each crop types in each 1 km pixel. In a **fourth step**, ET maps from low resolution data were compared to the high resolution simulations and to independent ET maps obtained by [8] using thermal infrared data and a simplified surface energy balance equation.

The Alpilles-ReSeDA experiment included field measurements, aircraft and satellite data acquisitions, covering the whole growing season of winter and summer crops (October 1996 to November 1997). The site had an area of 4 km by 5 km and was located 20 km South of Avignon in France. The main crops were wheat (30 % of the area), sunflower (20 %), orchards (15%), vegetables and forage. The various ground data collected were described in detail by [4]. Among the available remote

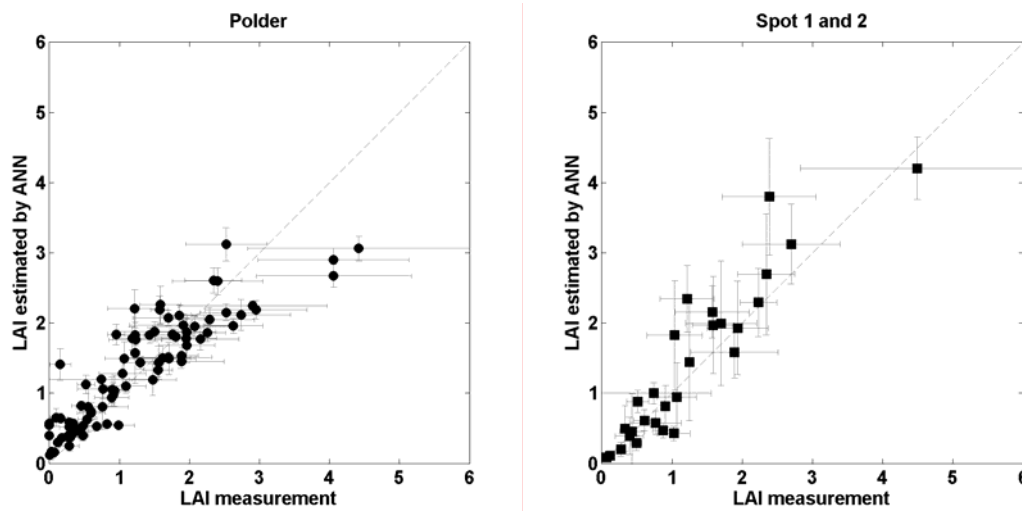
sensing data, we used in this study data from SPOT-HRV (4 dates), the airborne visible and near-infrared multiangular radiometer POLDER (16 dates) and an airborne thermal infrared camera INFRAMETRICS 760 (18 dates), all of them ground registered with a 20 m spatial resolution. A detailed description of airborne remote sensing data acquisition and processing was given by [5, 6].

The **ISBA** model (Interactions between Soil, Biosphere and Atmosphere, [7]) solved the surface energy balance and the soil water balance with a five minute time step and simulated surface temperature, soil moisture in the root zone, surface soil moisture and energy fluxes. ISBA required various inputs: meteorological variables (hourly time step), albedo, emissivity, LAI, fraction of vegetation cover and vegetation height (daily time step), minimum stomatal resistance and maximum root depth (crop characteristics), soil characteristics such as texture, wilting point and field capacity. In this work, meteorological variables were measured at the center of the Alpillles test site. LAI was derived from POLDER and SPOT-HRV data (see below), interpolated in time between the available images, and then used for computing fraction of vegetation cover, albedo and emissivity. Vegetation height, minimum stomatal resistance, wilting point and field capacity were derived from ground information (measurements in some fields, land use map, soil map). A description of the use of ISBA over wheat in the frame of the ReSeDA SVAT model intercomparison exercise was given in [9].

The simplified surface energy balance equation (**SSEBE**) was derived by [8] as an improvement of the simplified relationship from [10]. This model was used to compute daily ET from reflectances and thermal infrared brightness temperature maps acquired near midday. The required parameters, albedo, emissivity, momentum and thermal roughness, were derived from reflectances using algorithms developed by [11, 12, 13, 14].

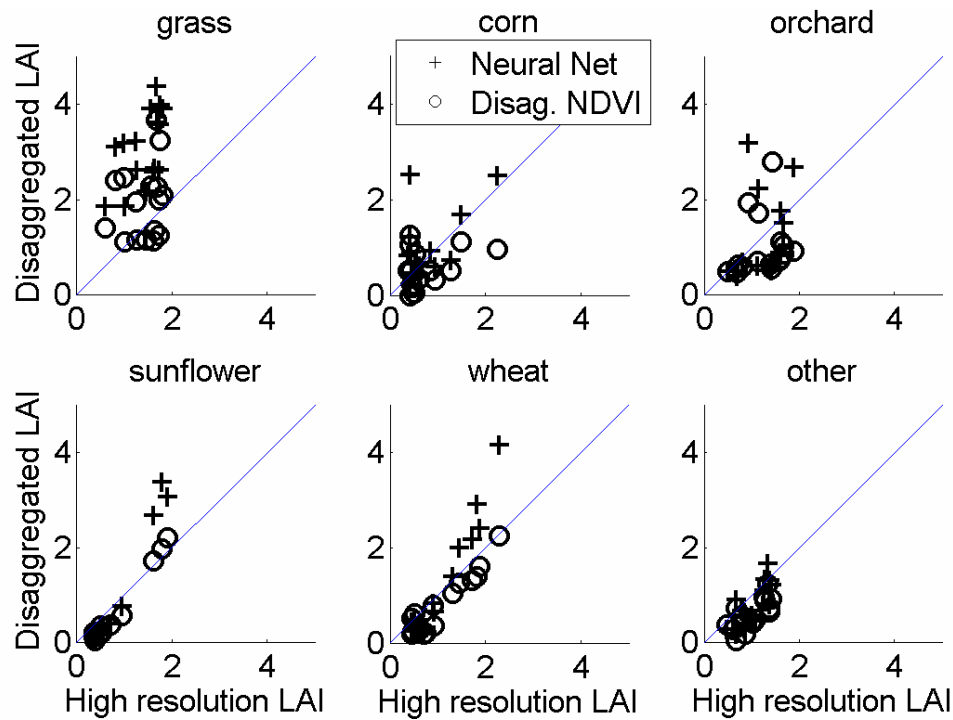
## **LEAF AREA INDEX ESTIMATION FROM HIGH AND LOW RESOLUTION DATA**

**High resolution.** LAI was estimated using Artificial Neural Networks (ANN) trained over a synthetic database built using the SAIL canopy radiative transfer model [15] and the PROSPECT leaf radiative transfer model [16]. The procedure implemented by [17] was adapted to the use of reflectances obtained from various sensors. Here, it was applied to green, red and near infrared nadir reflectance measurements by the airborne POLDER sensor and the HRV sensors on board of SPOT 1 and 2. We obtained very good results for both types of sensors as shown in Figure 1. The evaluation was done against ground measurements of LAI on wheat, sunflower and alfalfa crops (28 ground data for SPOT and 85 for POLDER). Estimations were almost unbiased with root mean square errors of 0.46 in both cases. It was however important to notice that LAI was almost always lower than 4, which was a favorable situation for estimating LAI.



**FIGURE 1.** Estimation of LAI from POLDER and SPOT-HRV nadir measurements compared to LAI ground measurements over wheat, sunflower and alfalfa (bars represents the spatial variability of LAI in the investigated fields).

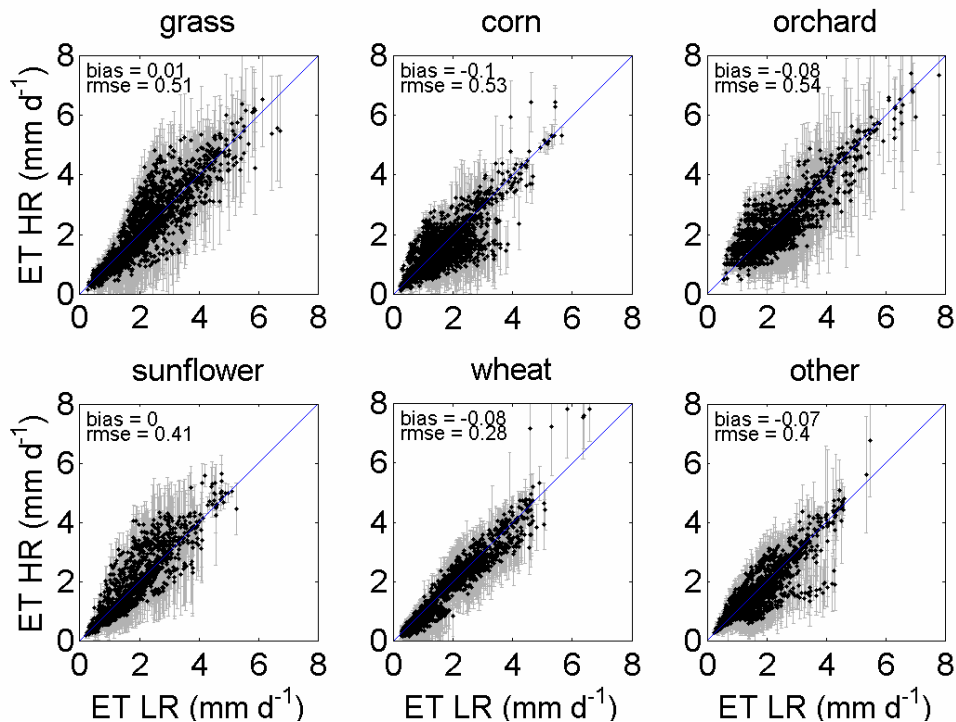
**Low resolution.** In this study, low resolution remote sensing data were built from high resolution images by simply averaging reflectances over 1 km pixel (50 by 50 pixels at 20 m resolution). The resulting images contained 5 by 4 pixels in green, red and near infrared wavebands. The disaggregation method developed by [3] on the basis of the Best Linear Unbiased Predictor was then used for deriving reflectance at the level of each land use class in each 1 km pixel (the land use of each kilometric pixel being known). The disaggregation was performed independently for each day images were available. The disaggregated reflectances were used for estimating LAI using the same ANN algorithm as above. The results were not satisfactory, the method being not only unable to catch the high inter-pixel variability of LAI for each land use class (not shown), but also not able to estimate the mean behaviour of LAI for each land use class over the whole images (Figure 2). Three main factors explained these problems: *-i*) the area was small and the number of kilometric pixels was low limiting the available information for the disaggregation algorithm, *-ii*) the reflectance variability in each land use class was very large making difficult to distinguish classes, *-iii*) the disaggregation was performed in each waveband independently leading to inconsistencies when combining wavebands for estimating LAI using the ANN. In order to overcome this last point, we tried to estimate LAI from NDVI (Normalised Difference Vegetation Index built from red and near infrared reflectances) using a standard LAI-NDVI equation [17]. NDVI was computed at the kilometric scale and then disaggregated, which was theoretically incorrect since NDVI should not be spatially averaged. However, this was correct in practice since we were able to confirm that, over our area, the average of high resolution NDVI was almost identical to NDVI computed from kilometric pixels. LAI estimated from disaggregated NDVI were compared to the reference data when considering the mean LAI for each class over the whole area in Figure 2. Good results were obtained for wheat and sunflower but not for the other land use classes. As when using ANN, the variability of LAI from one kilometric pixel to another was not estimated (not shown).



**FIGURE 2.** Estimation of mean LAI for each land use class over the whole area from 1 km resolution data using either the ANN (+ = Neural Net) algorithm directly applied to the disaggregated reflectances, or the LAI-NDVI model ( o = Disag. NDVI) applied to disaggregated LAI.

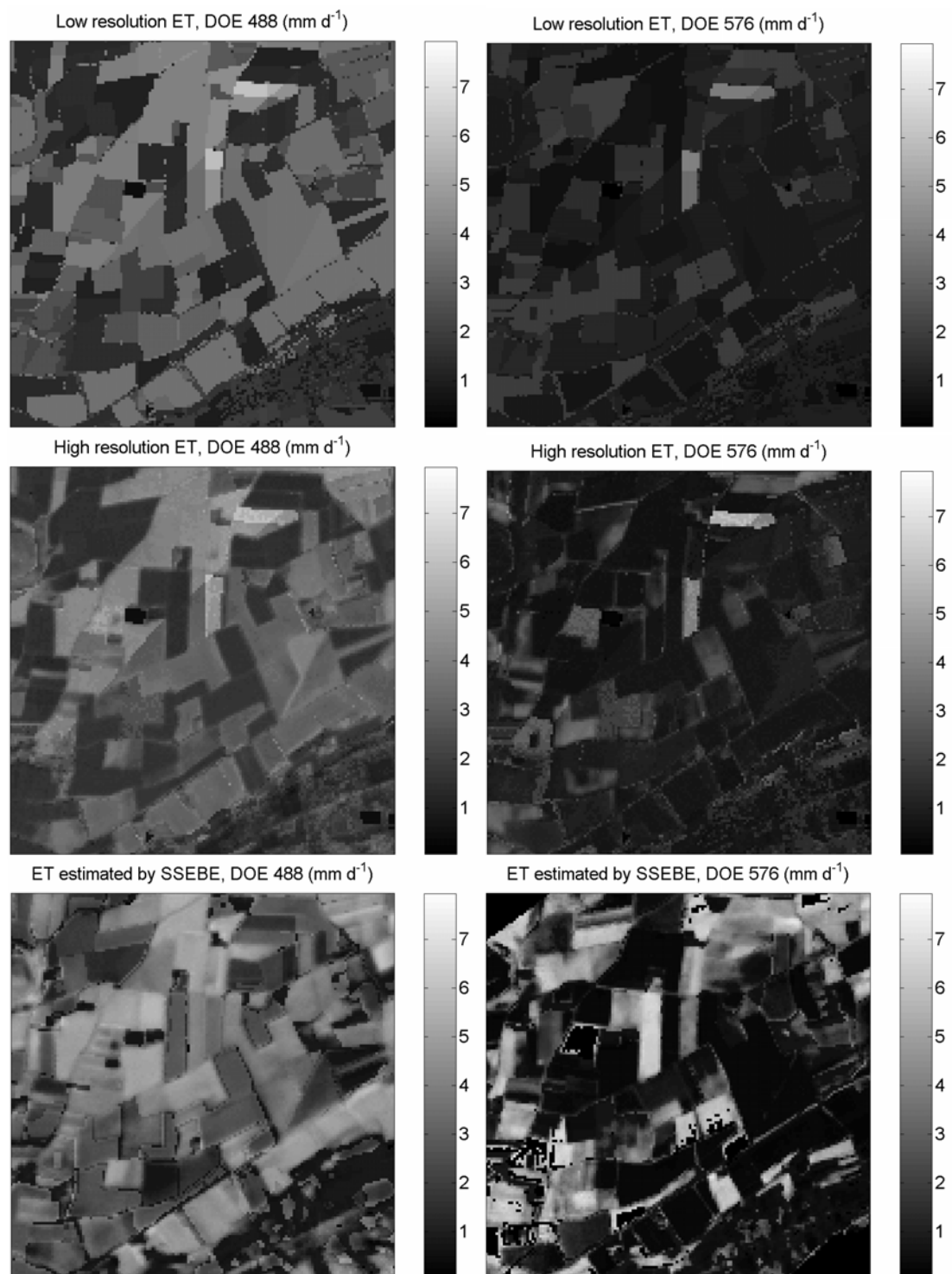
## ESTIMATION OF EVAPOTRANSPIRATION

Simulation of evapotranspiration using ISBA were performed from land use and soil map information and remote sensing estimation of LAI (at low resolution we used the LAI-NDVI derivation). The model was started January 1<sup>st</sup>, 1997, assuming that soil moisture was field capacity (which was realistic since December was very rainy [4]). LAI was linearly interpolated between remote sensing data acquisition and the model was run for 9 months. Figure 3 presents the comparison between ET simulated from low and high resolution remote sensing data for each land use class (each point corresponds to one simulated day and one kilometric pixel). Root Mean Square Errors (RMSE) were always lower than  $0.6 \text{ mm d}^{-1}$  and mean bias lower than  $0.1 \text{ mm d}^{-1}$  showing a good agreement between the two resolutions. The agreement was very good for wheat and at a lesser extent for sunflower (the two crops with the best estimates of LAI at low resolution). It was interesting to notice that the errors in LAI estimations (presented in Figure 2) had not a very large effect on ET simulations as shown by the low level of bias (in particular for grass, corn and orchard). This may be linked to a low overall sensitivity of the model to LAI when considering the whole crop season, the water use being regulated by soil water holding capacity and the distribution of rainy events. It must also be noticed that the level of RMSE was mostly linked to the difficulties of the disaggregation method to catch the inter-pixel variability. An indication of spatial variability is given by the intra-pixel standard deviation bars displayed in Figure 3.



**FIGURE 3.** Comparison of ET simulated by ISBA from low resolution data (ET LR) to simulations from high resolution data (ET HR). Each point corresponded to the values for one simulated day, one pixel and one land use class. The vertical bars corresponded to the standard deviation of high resolution ET for each day, each pixel and each land use class.

Figure 4 presents ET maps obtained from ISBA simulations using low and high resolution data and ET maps obtained by using thermal infrared and the Simplified Surface Energy Balance Equation. Two days are displayed, one in spring at the time of full development of wheat crops (May 2<sup>nd</sup>, Day of Experiment DOE 488) and one in summer at the time of full development of sunflower crops (July 29<sup>th</sup>, DOE 576). It illustrates the general agreement between ET simulated from low and high resolutions data. It also illustrates that the disaggregation method was not able to catch some aspects of the spatial variability of ET, not only inside of a kilometric pixel (by construction, the method cannot provide intra-pixel variability), but also from one area of the images to another (inter-pixel variability). However, the variability linked to the variations in soil types was still visible. Maps of ET obtained from thermal infrared and the SSEBE on DOE 488 also exhibited a general agreement with the maps simulated by ISBA. However significant differences were noticed in some wheat fields. Larger differences existed for DOE 576. They may be attributed to differences in crop water status, either because crops were irrigated while irrigation supplies were not accounted for in the simulations, or because soil water holding capacity was different than the value prescribed in the model. In this last case, differences may originated from differences in root depth, field capacity or wilting point. [2] provided an analysis of the problem for wheat crops (see maps for DOE 488), showing that it was possible to detect irrigated fields by analysing thermal infrared data (~10 % of



**FIGURE 4.** Maps of ET obtained by ISBA simulations from low and high spatial resolution data and by SSEBE using thermal infrared data for two days: DOE 488 = May 2<sup>nd</sup> and DOE 576 = July 29<sup>th</sup>. The mapped area was 3 km by 3 km representing the 9 central kilometeric pixels of the Alpillles test site.

wheat fields were actually irrigated) and that variations in wilting point in the southern area of the image might be responsible for increasing wheat ET. In summer (DOE



576), simulated ET was in general very low unless for two alfalfa fields for which a large root depth was prescribed. Conversely, the SSEBE map displayed a large number of fields with very high evapotranspiration. They corresponded to corn, tomato, orchard and grass fields which were irrigated (sunflower was not usually irrigated).

## SUMMARY

In this study, we tried to monitor evapotranspiration from remote sensing data. In order to provide ET estimates all along the crop season, a SVAT model was used which allowed continuous simulations. The possible use of low spatial resolution remote sensing data was investigated with success by implementing a disaggregation method that allowed to estimate LAI of the major crops in the area. The comparison to independent estimations of ET from thermal infrared showed that the question of assessing soil water characteristics and irrigation supplies was more significant than the question of using low spatial resolution data instead of high resolution data.

## ACKNOWLEDGMENTS

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