

Remote Sensing Applications for Land/ Atmosphere Interactions: Surface Net Radiation

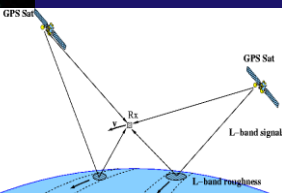
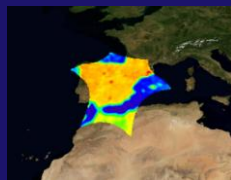
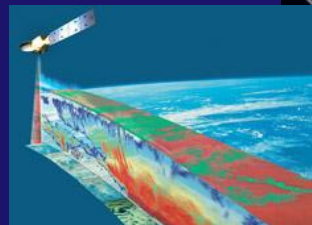
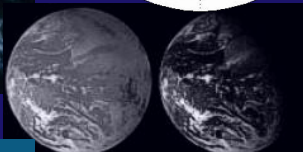
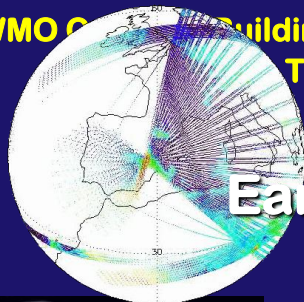
- Introduction
- Our Objective: Deriving Surface Energy Balance Fluxes from Net Radiation Measurements
- Estimation of Surface Net Radiation from Operational Meteorological Measurements
- Derivation of surface net radiation from top of the atmosphere GERB fluxes by means of linear models and neural networks
- Using the synergy GERB/SEVIRI and micrometeorological data to study the relationship between surface net radiation and soil heat flux

Ernesto López Baeza (Ernesto.Lopez@uv.es)
& Climatology from Satellites Group
University of Valencia. Faculty of Physics
Dept of Earth Physics & Thermodynamics

Climatology from Satellites Group

Earth Observation Missions Where we are Involved

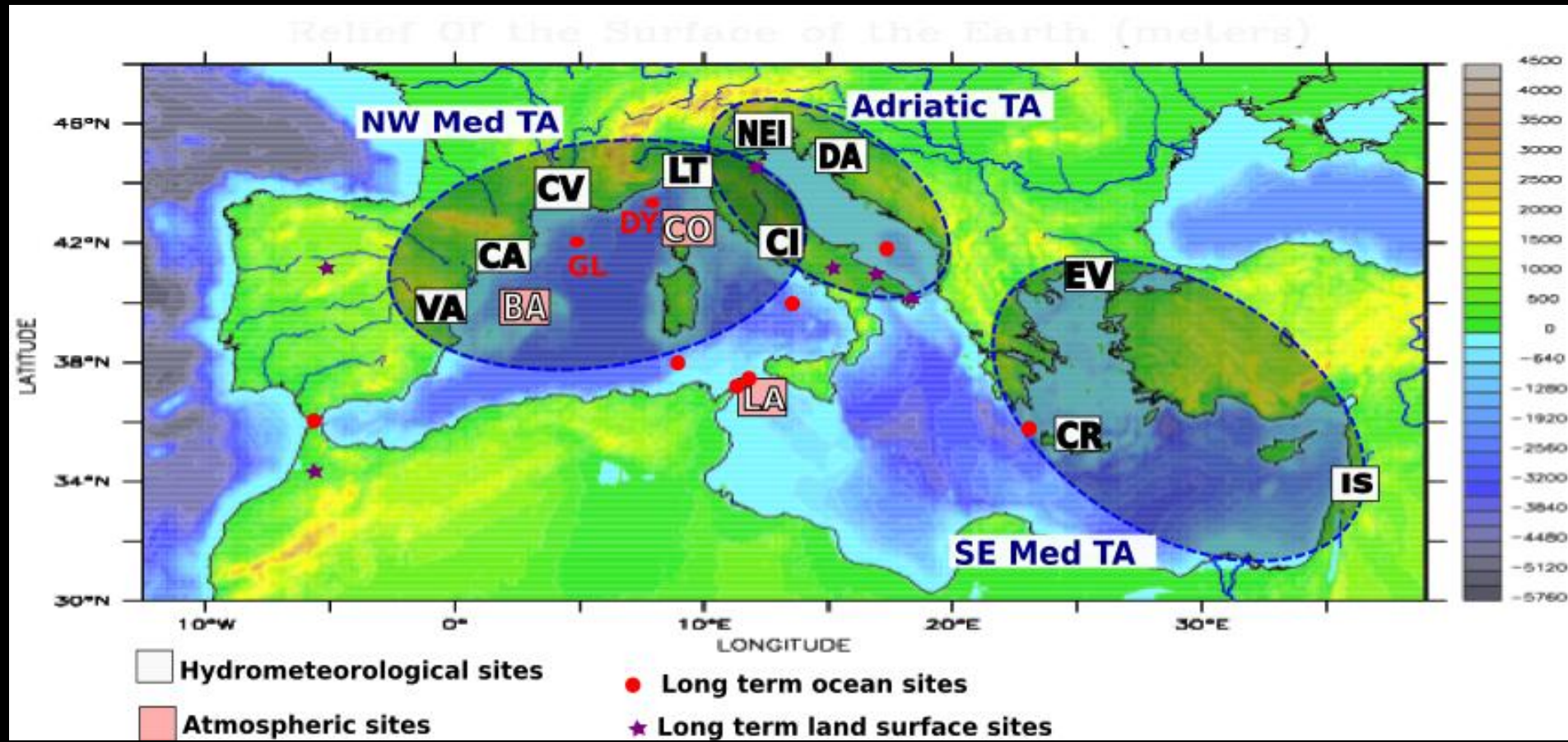
- **CERES** (*Clouds and the Earth's Radiant Energy System*) NASA
- **GERB** (*Geostationary Earth radiation Budget*) EUMETSAT
- **EarthCARE** (*Earth Clouds, Aerosols and Radiation Explorer*) ESA/JAXA
- **SMOS** (*Soil Moisture and Ocean Salinity*) ESA
- **SMAP** (*Soil Moisture Active and Passive*) NASA
- **SENTINEL-3** ESA
- **EPS/MetOp** (*EUMETSAT Polar System*) EUMETSAT/ESA
- **PARIS** (*Passive Reflectometry and Interferometry System*). Now **GEROS GNSS-R** (*Global Navigation Satellite System - Reflectometry*) ESA



HyMeX

Hydrological Cycle in Mediterranean Experiment for us

Definition of an Experimental Observatory of the Water Cycle



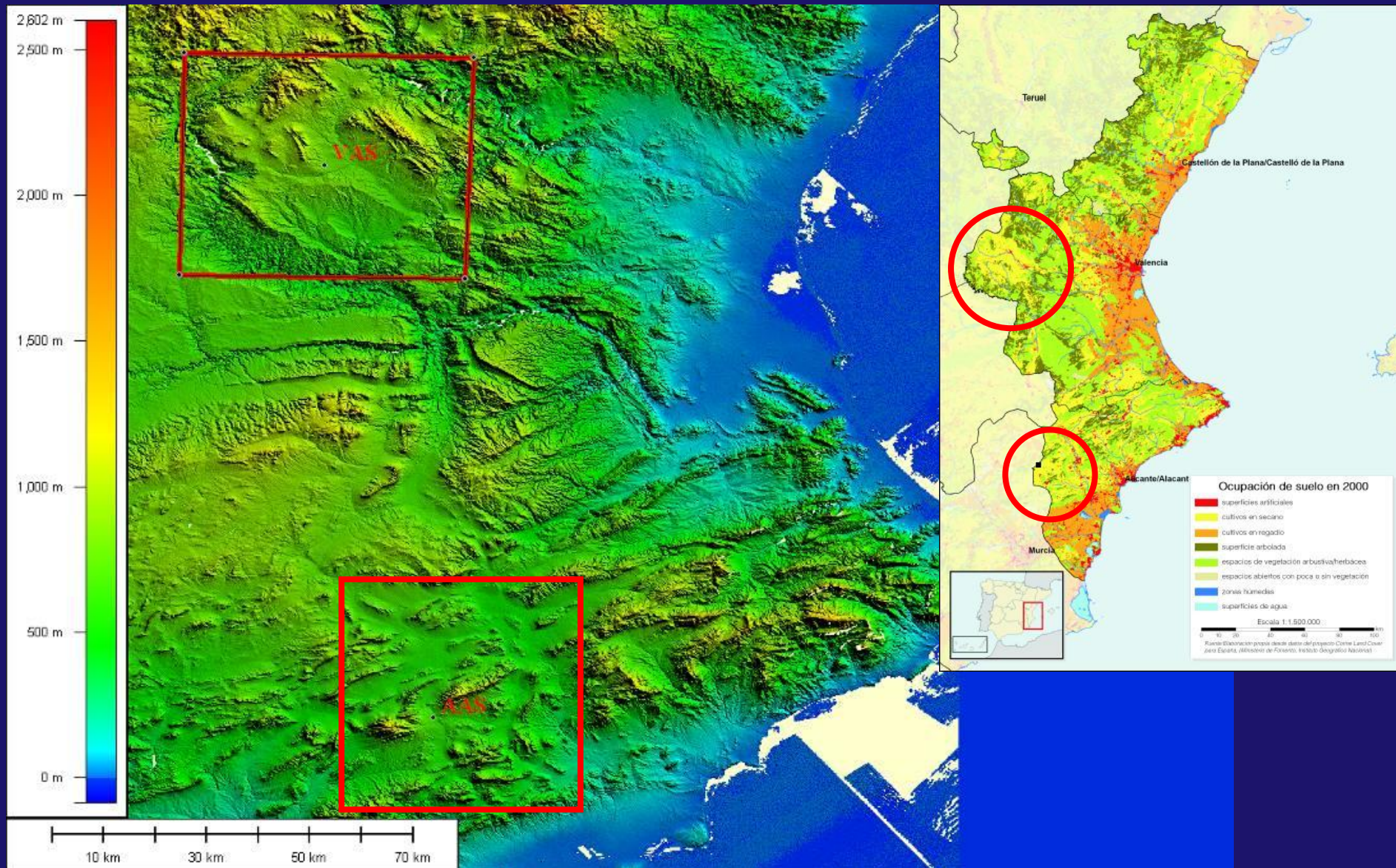
Valencia & Alacant Anchor Stations

(Most?) suitable area in Europe
for validation of low spatial
resolution remote sensing data
and products



HR MERIS, 23 March 2002





**GERB/CERES Ground Validation
Campaign June 2003** →



**GERB/CERES Ground Validation
Campaign February 2004** →





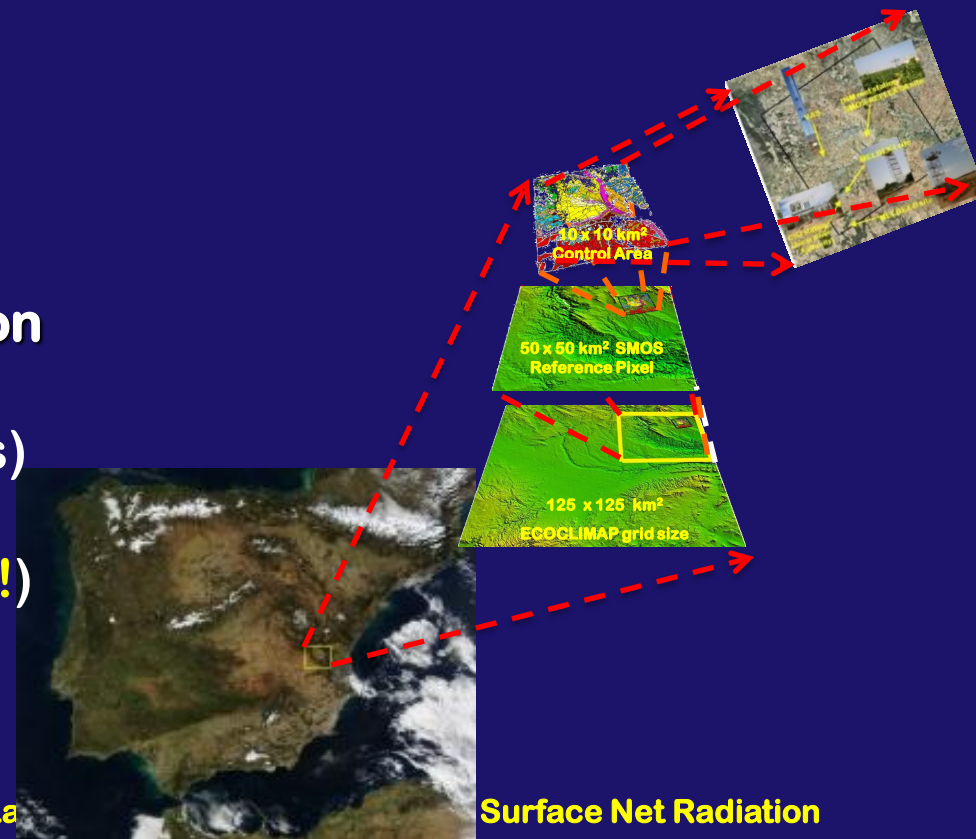
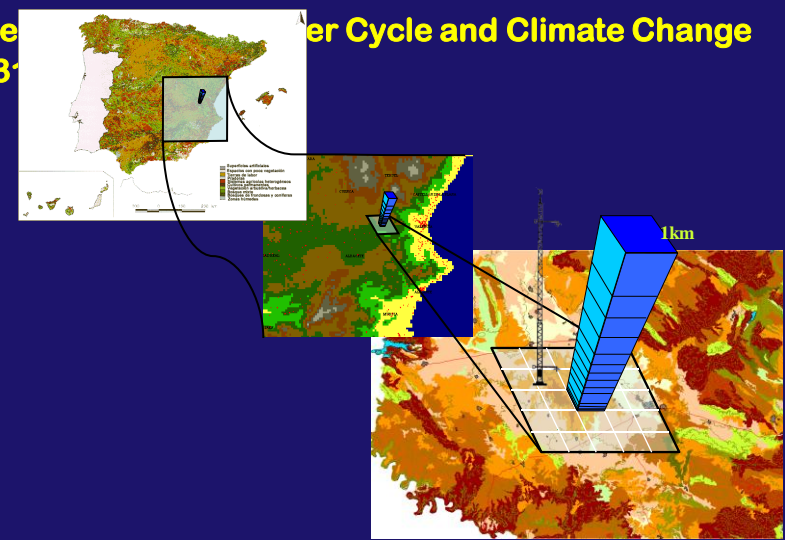
accounting for non-homogeneities of the area



Research Lines

Validation of Low Spatial Resolution Remote Sensing Data and Products (or *Making Sense of Satellite Data*)

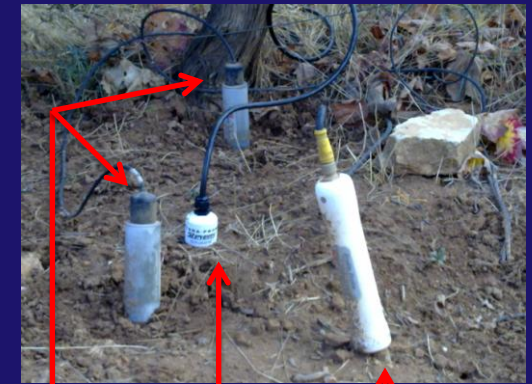
- Validation Sites Characterization
 - Valencia Anchor Station
 - Alacant Anchor Station
- Use of Meteorological Models
- Development of Validation Methodologies
 - Radiation (Clouds & Aerosols)
 - Soil Moisture
 - Biophysical Products (**NEW!!!**)
 - GNSS-R (**NEW**)



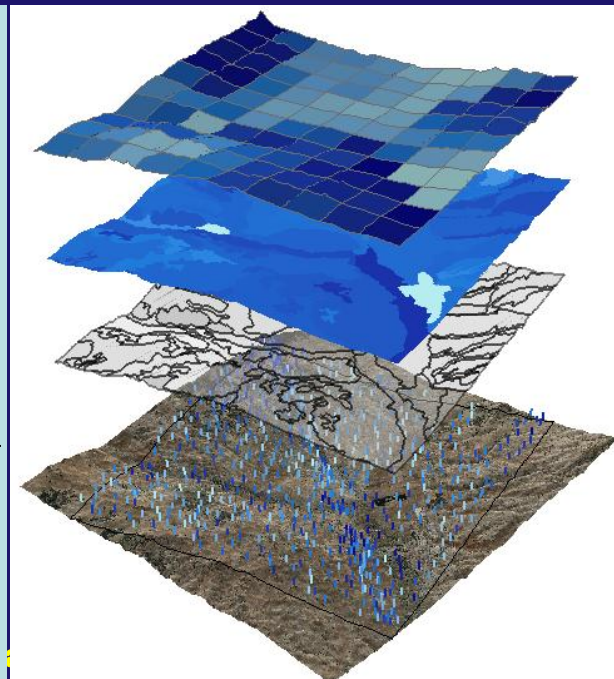
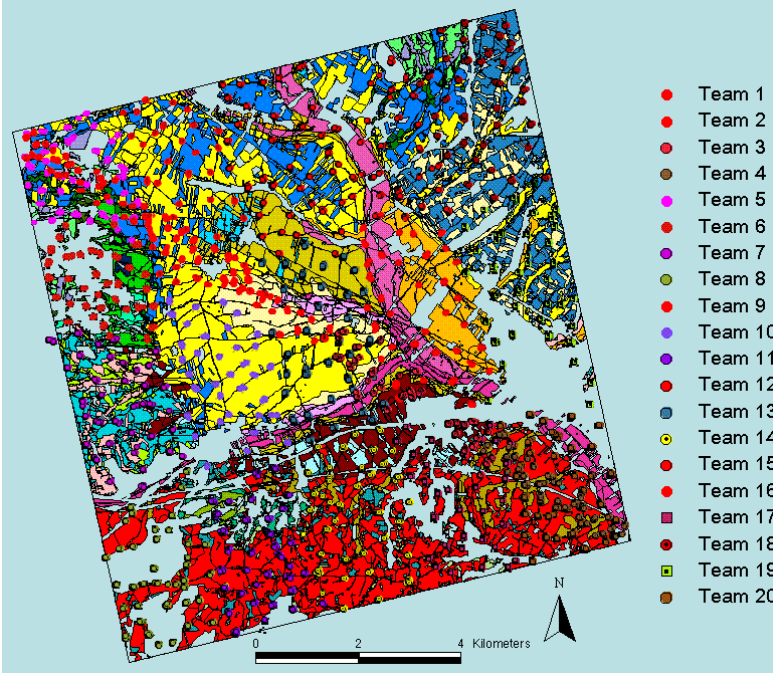
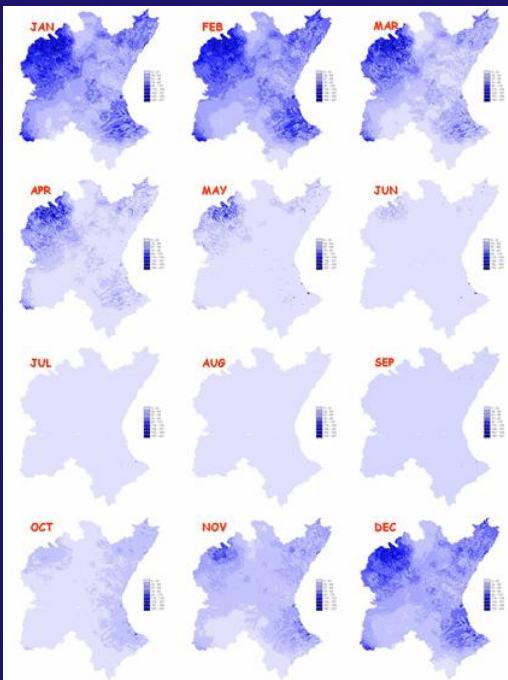
Research Lines

Soil Moisture from Passive Microwaves (*Estimation of Soil Moisture from Space*)

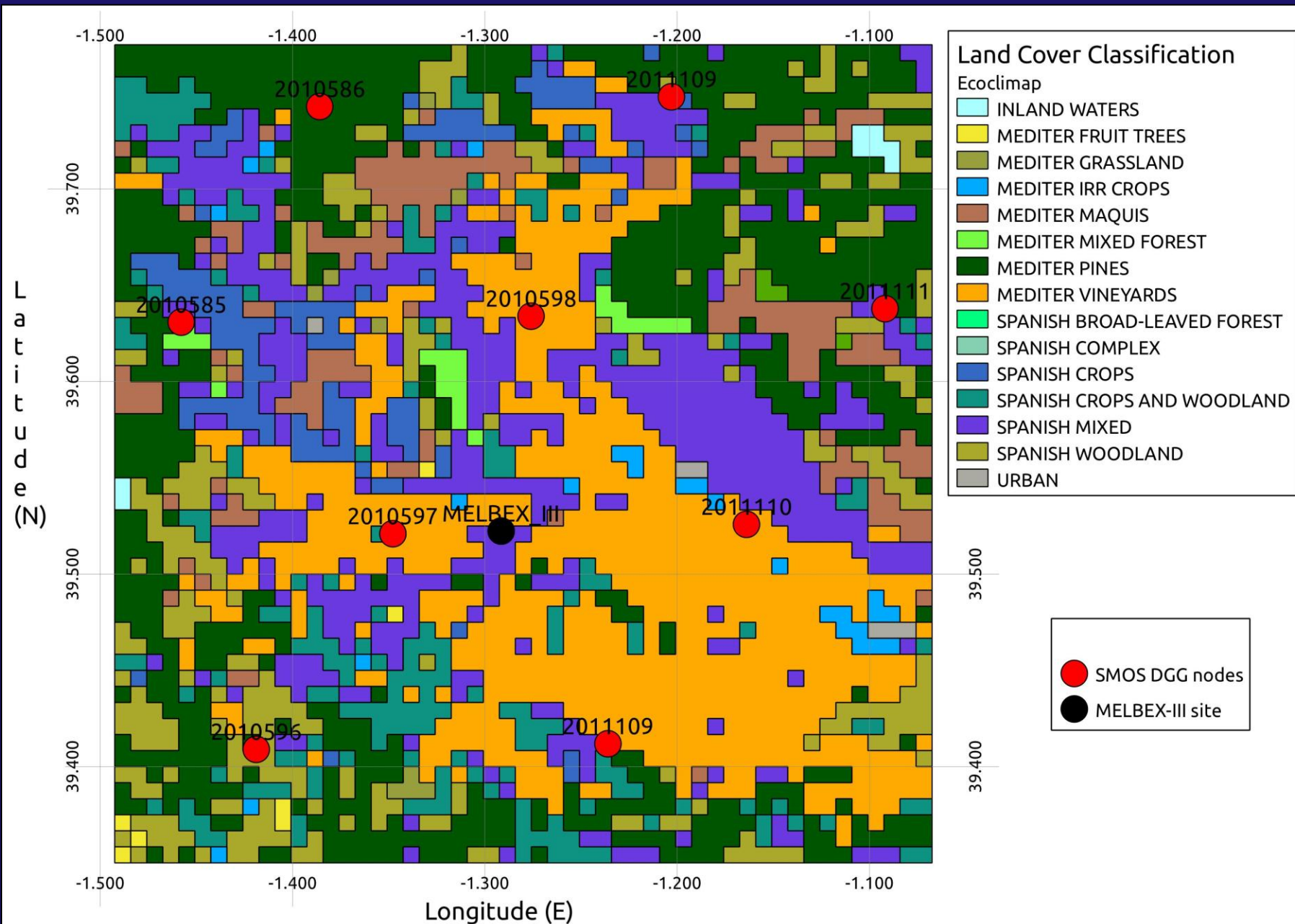
- MELBEX (*Mediterranean Ecosystem L-Band Characterization Experiment*)
 - Matorral & Shrubs
 - Vineyards
- Eddy-Covariance Methods
- Network of Soil Moisture Measurements
- Testbed for Soil Moisture Measuring Instruments Intercomparison



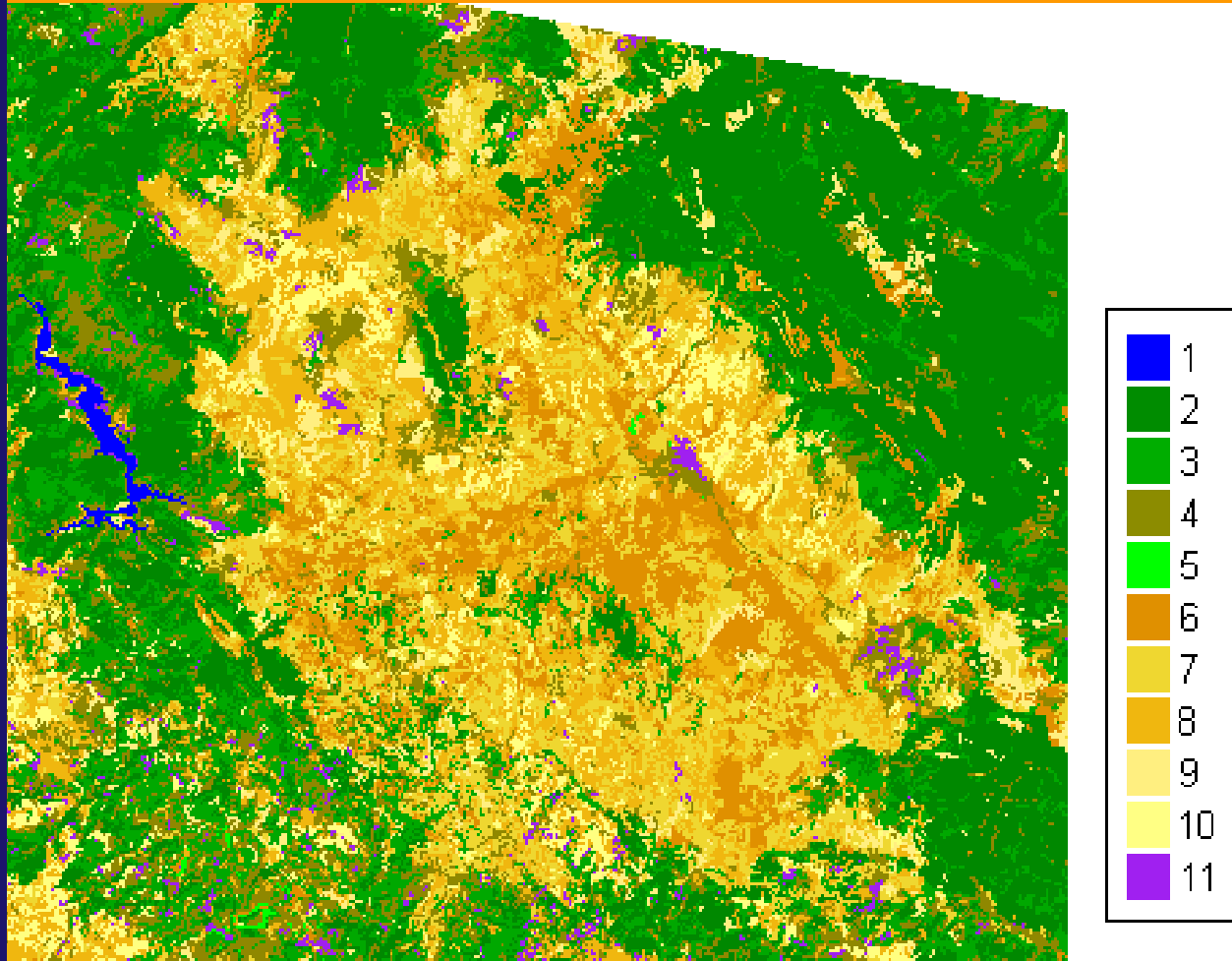
ThetaProbe – Delta-T
HydraProbe – Stefens
ProfileProbe – Delta-T



ECOCCLIMAP Land Use Map



Classified LANDSAT image (5th July 2003): 11 categories for the Valencia *Anchor Station* area (50 x 50 km²)

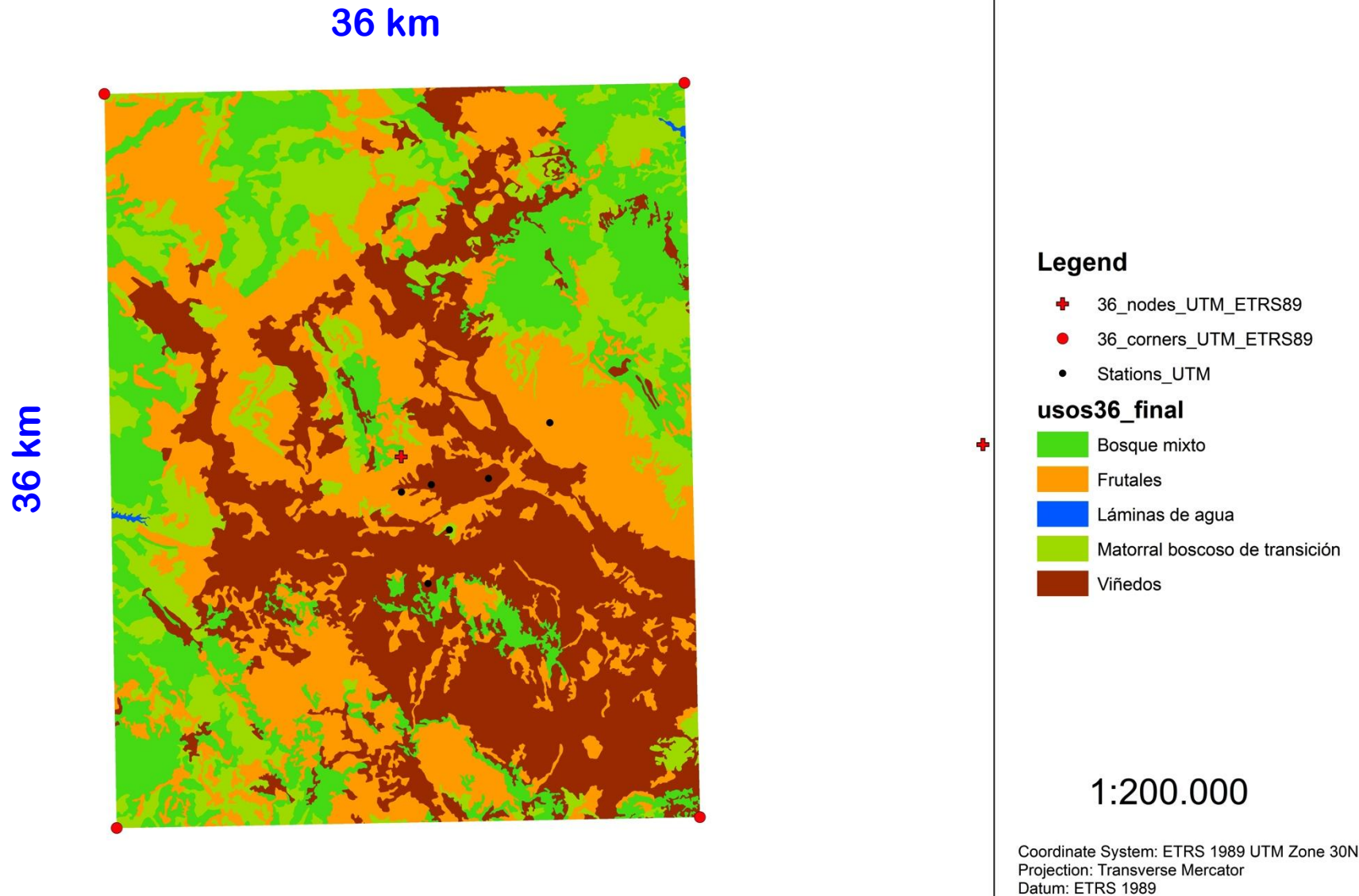


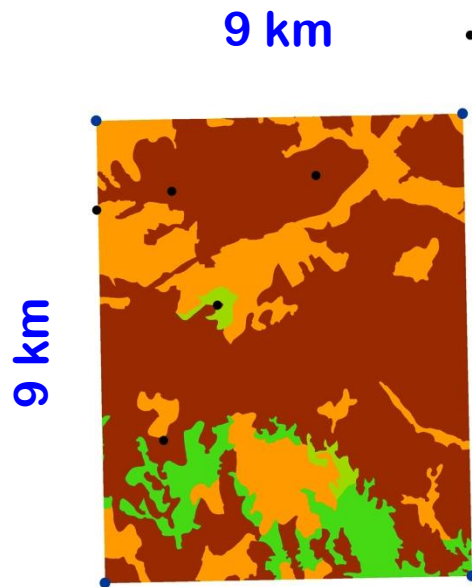
1: Water, 2: Pine trees, 3: Low-density Pine trees, 4: Shrubs, 5: Irrigated, 6: Vineyard, 7: Low-density vineyard, 8: Very low density, 9: Dry crops, 10: Bare soil, 11: Degraded



almond-, pine-, olive-tree areas







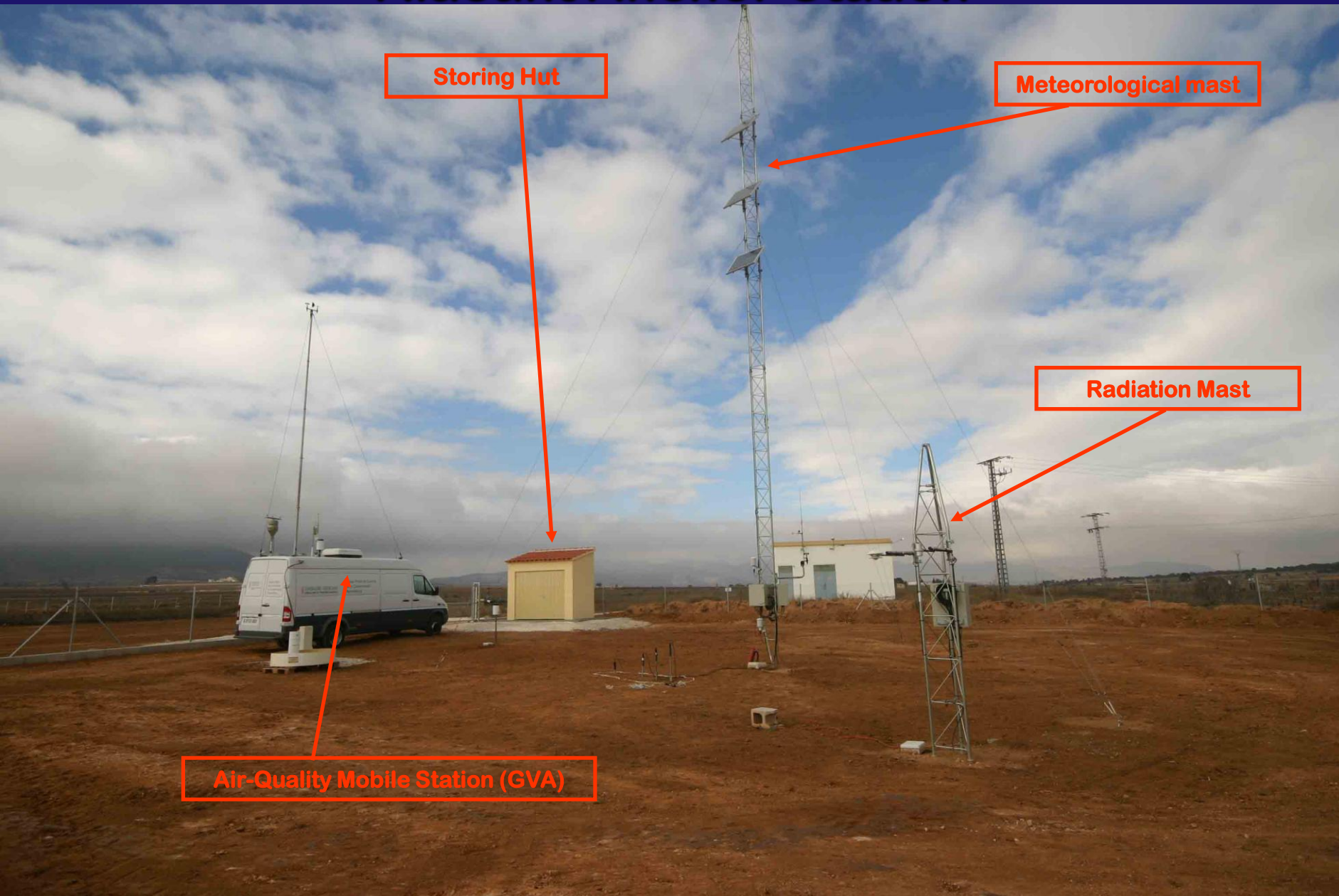
Legend

- 09_corners_UTM_ETRS89
- Stations_UTM
- Bosque mixto
- Frutales
- Láminas de agua
- Matorral boscoso de transición
- Viñedos

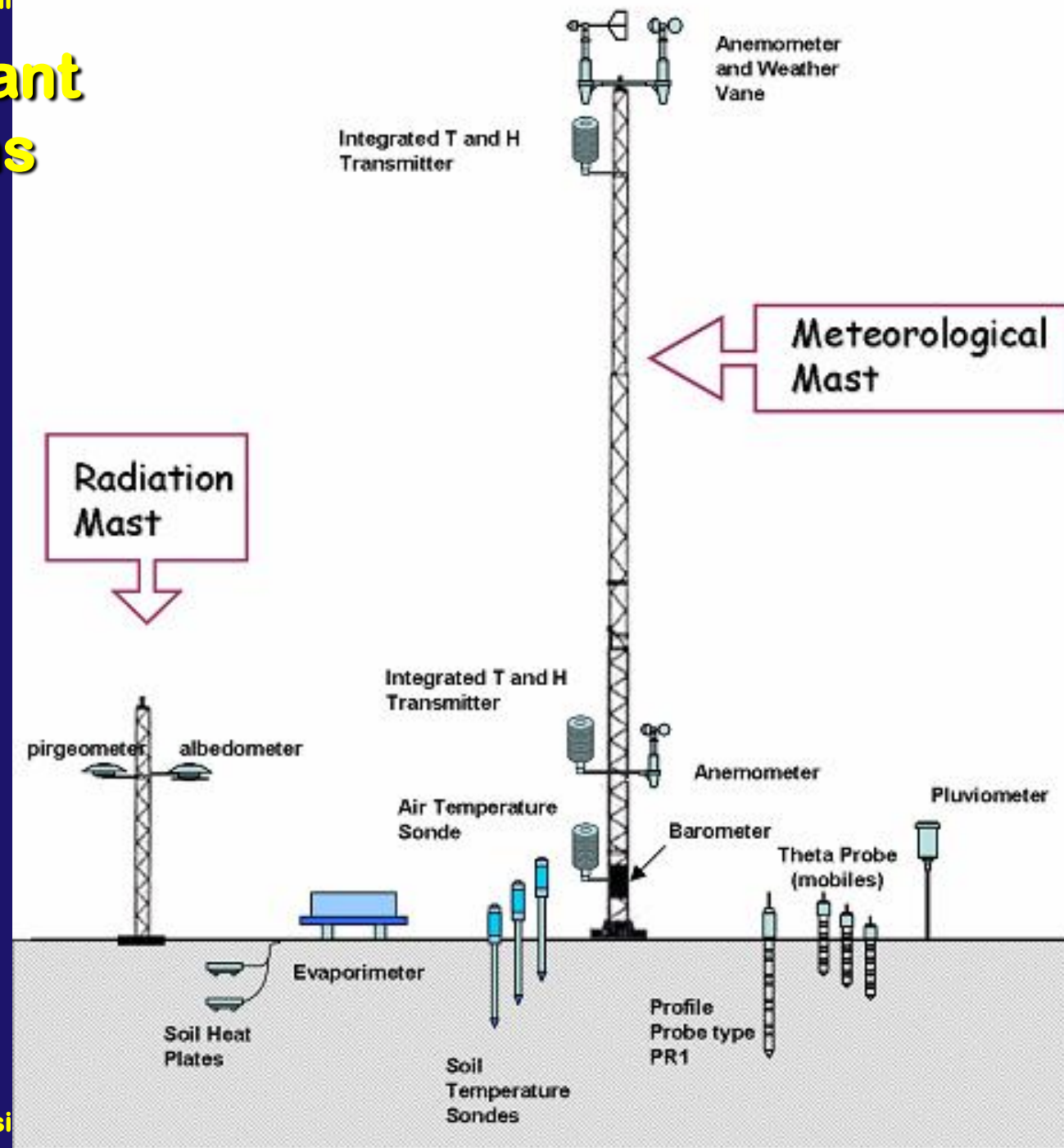
1:100.000

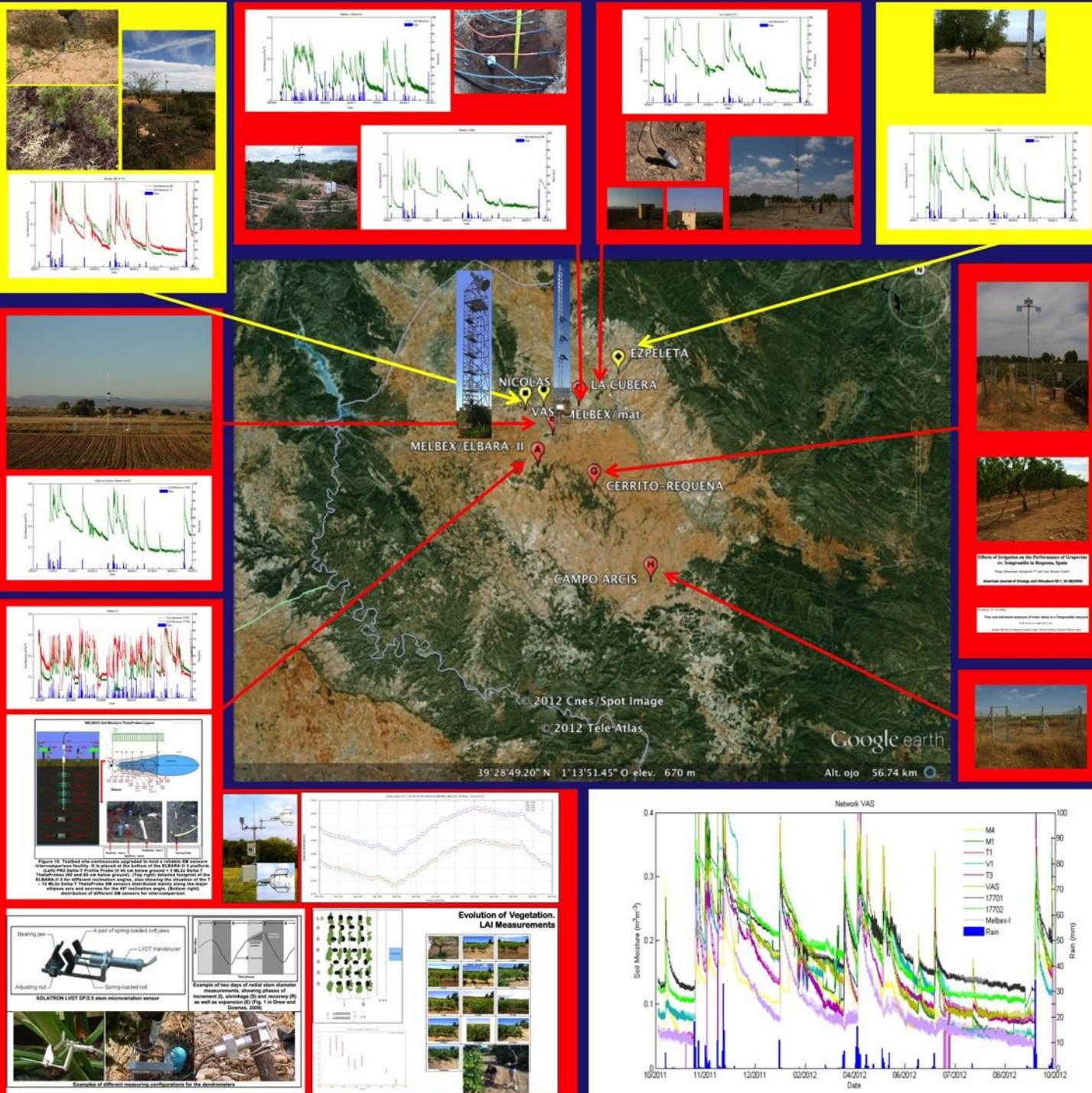
Coordinate System: ETRS 1989 UTM Zone 30N
Projection: Transverse Mercator
Datum: ETRS 1989

Alacant Anchor Station



Valencia & Alacant Anchor Stations



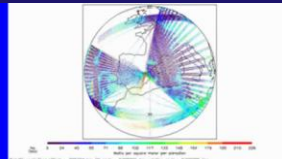


Acknowledgment

- Spanish Research Programme on Space, Ministry for Education & Science
- General Directorate for Climate Change, Dept. for Environment. Regional Gov. of the Valencian Autonomous Community
- European Space Agency (ESA) (SMOS)
- (NASA) (SMAP)
- CNES (Centre National des Etudes Spatiales) – TOSCA Program
- Irrigation Technology Service, Valencian Institute for Agricultural Research
- Jucar River Basin Authority. Office for Hydrological Planning
- Meteorological State Agency of Spain (AEMet)
- Bodegas IRANZO, Caudete de las Fuentes
- Bodegas y Viñedos de Utiel
- Bodega “La Cubera”, Utiel
- Mr Nicolas Guaita and Rafael Giménez, Caudete de las Fuentes



Climatology from Satellites Group
University of Valencia, Spain



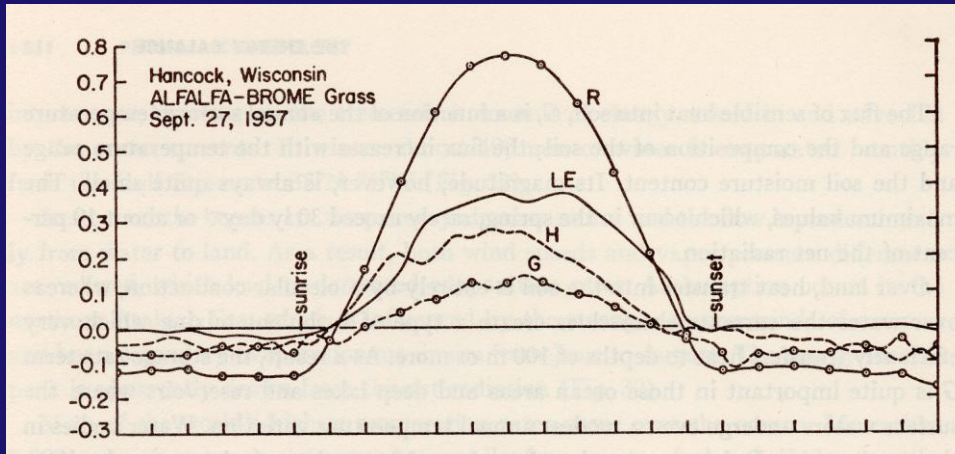
Remote Sensing Applications for Land/Atmosphere Interactions: Surface Net Radiation

Our Objective:

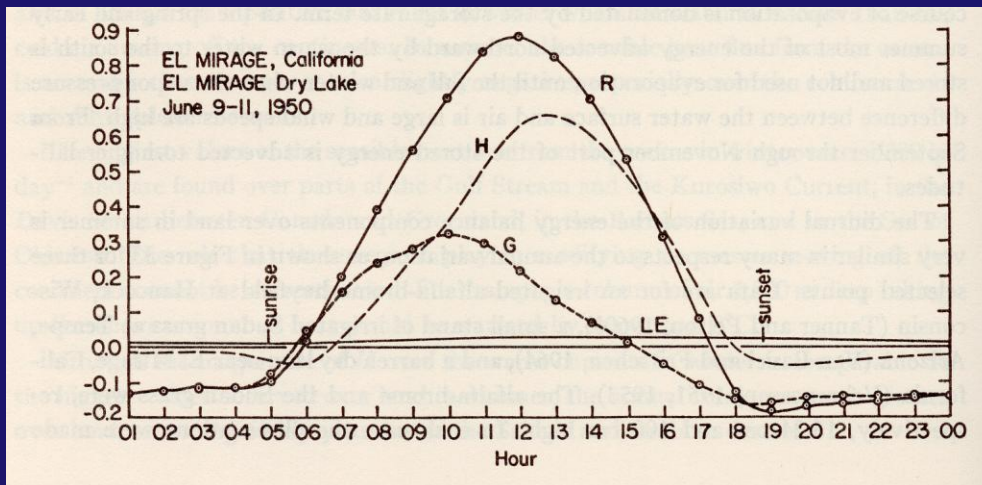
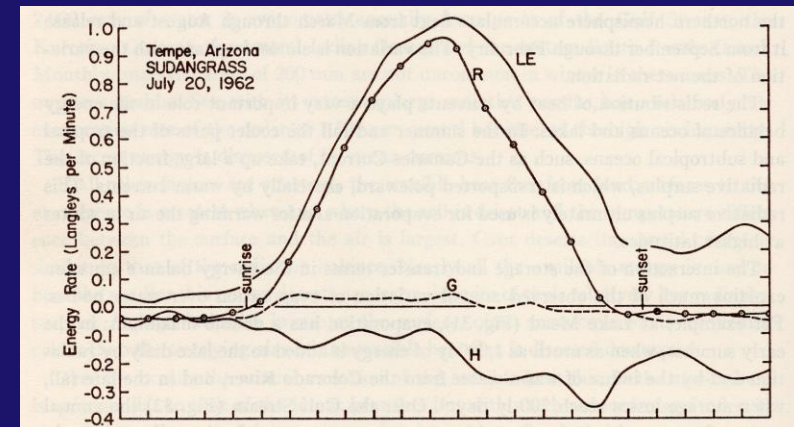
Deriving

**Surface Energy Balance Fluxes from
Net Radiation Measurements**

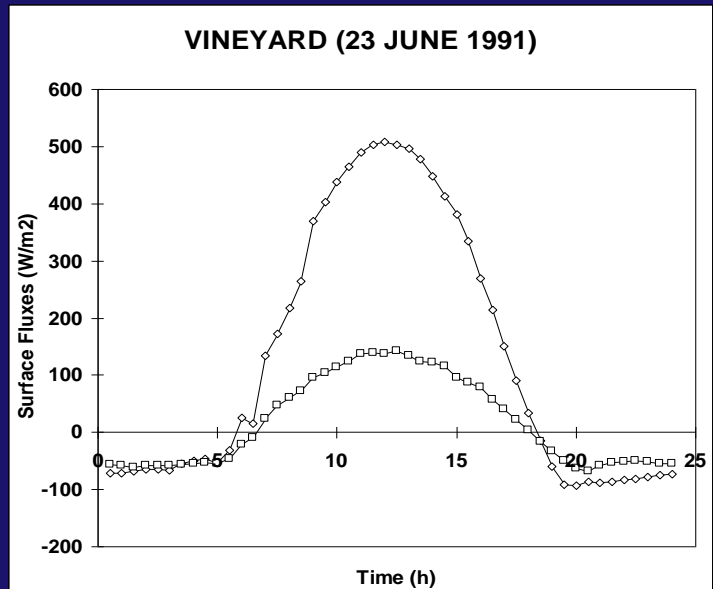
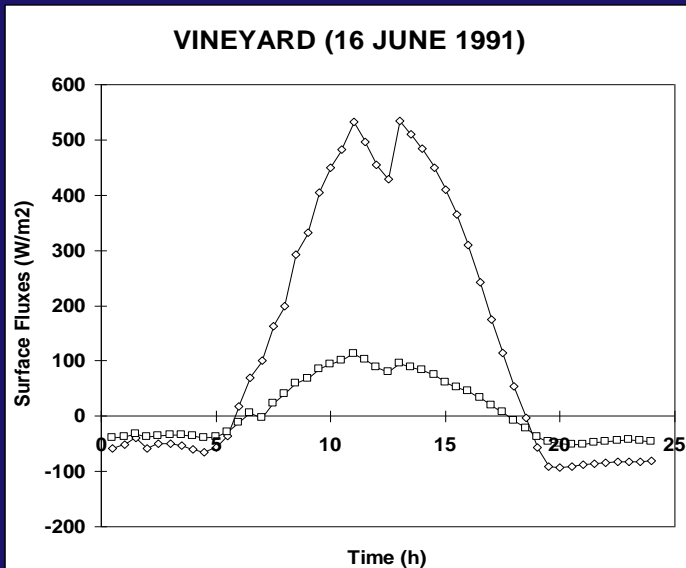
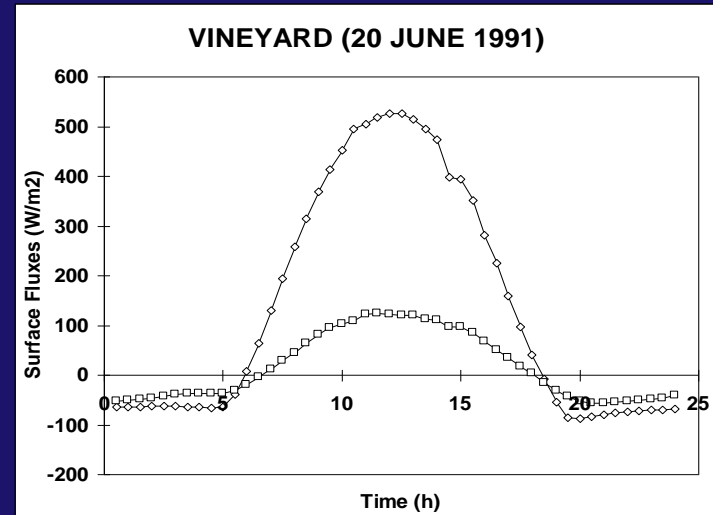
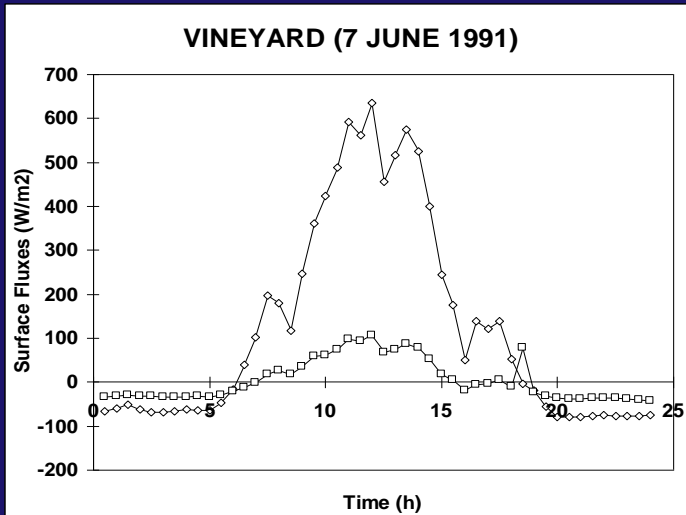
Examples of Average Diurnal Variations of the Surface Energy Balance. (Sellers, 1965)



$$R_n = H + \lambda E + G$$

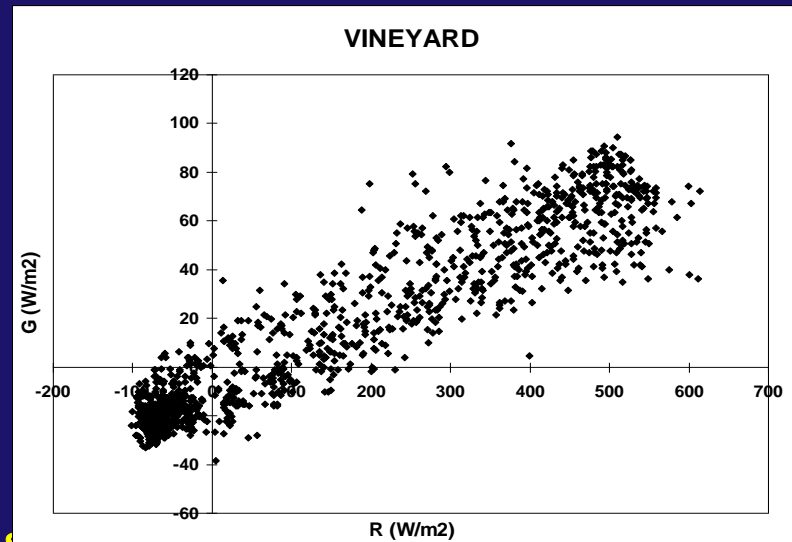
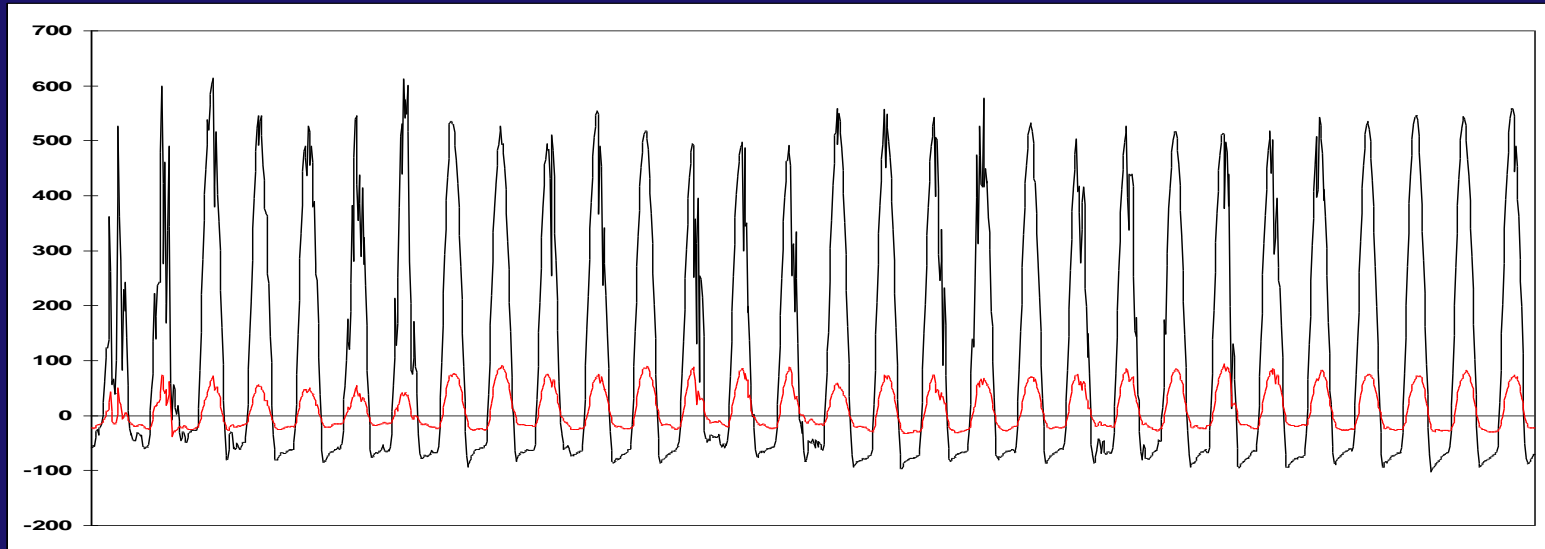


Examples of Diurnal Variations of Surface Net Radiation and Soil Heat Flux. (EFEDA data base)



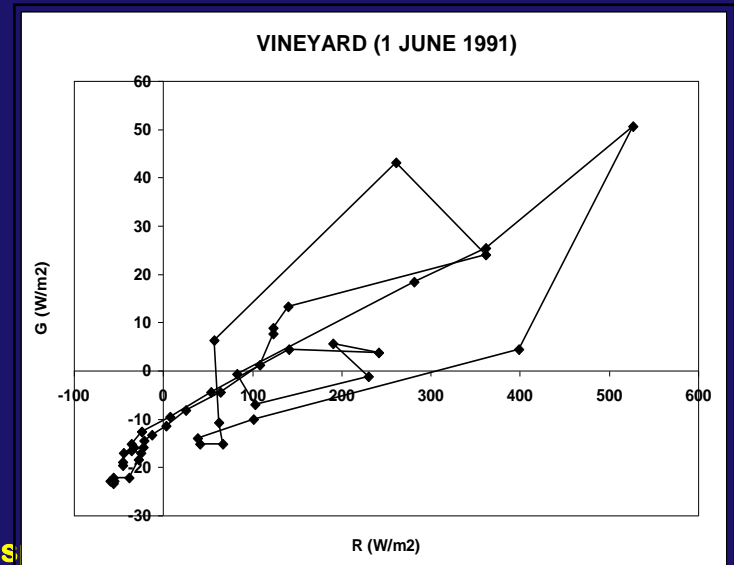
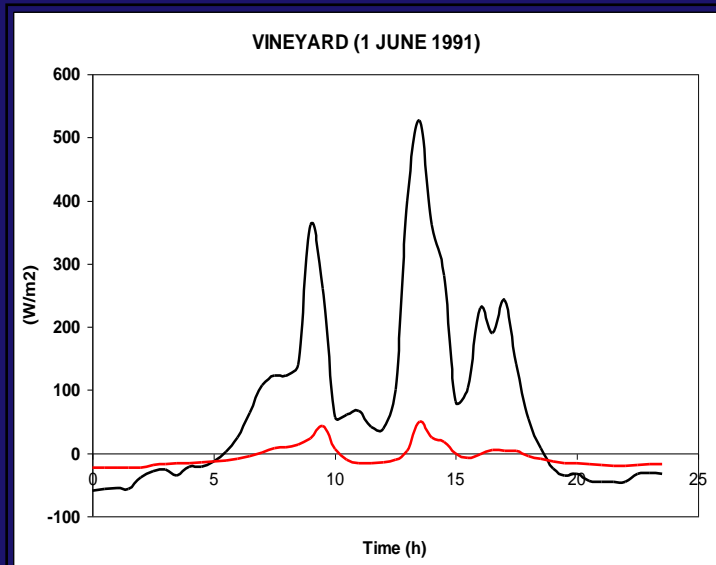
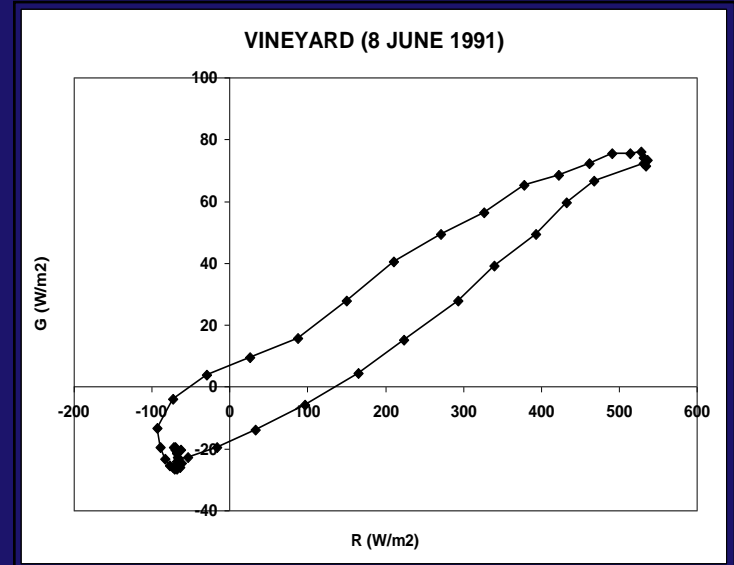
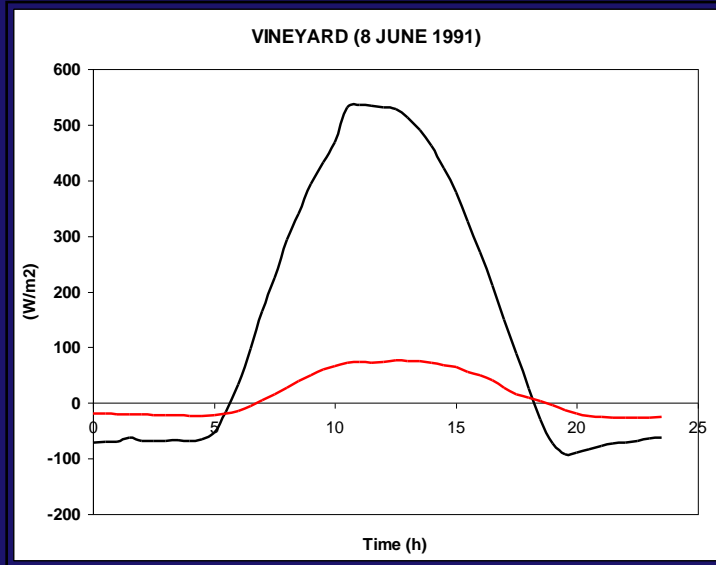
Surface Net Radiation and Soil Heat Flux

1 – 30 June 1991 (EFEDA data base)



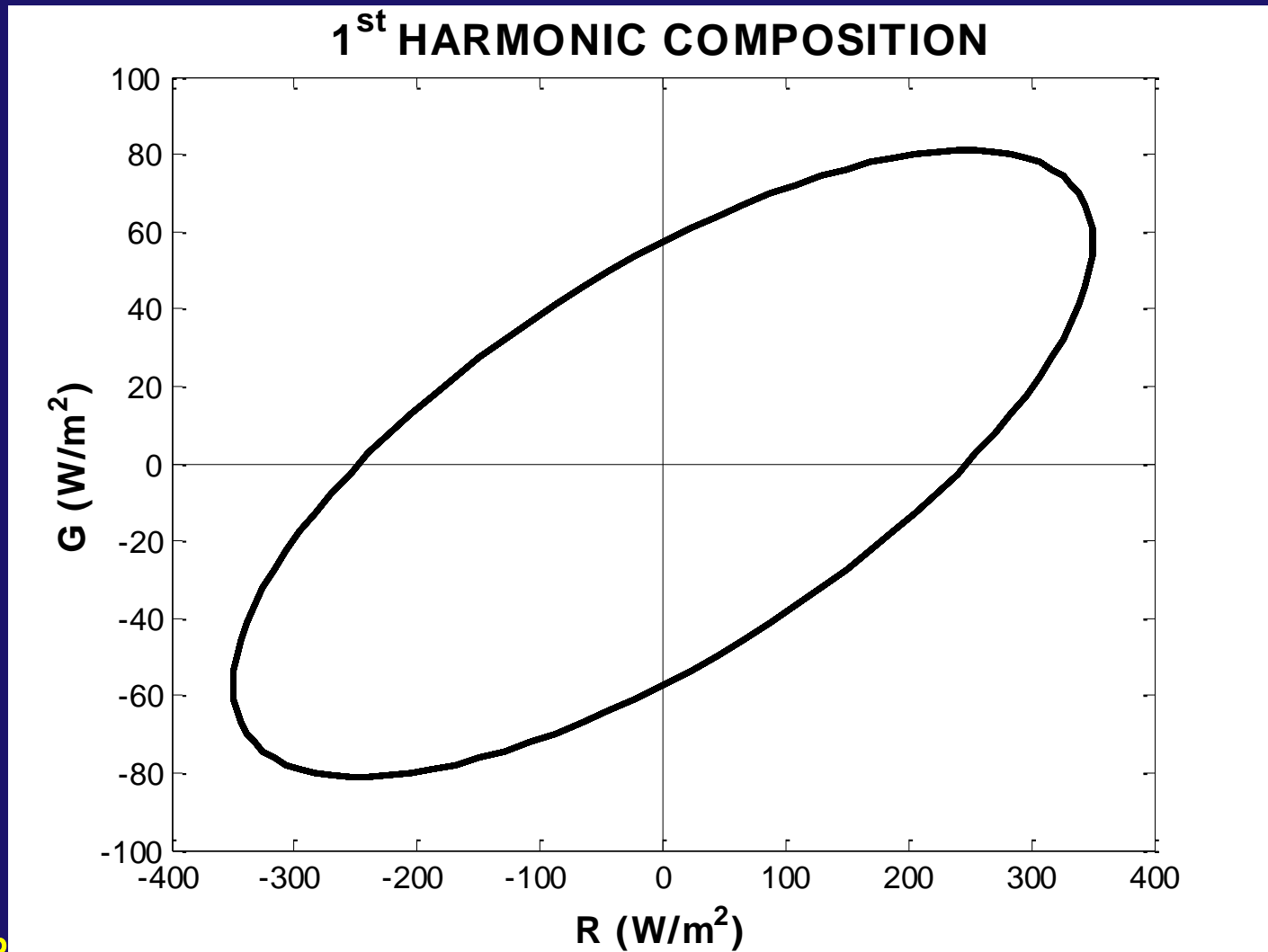
Surface Net Radiation and Soil Heat Flux

(two very different days June 1991). (EFEDA data base)



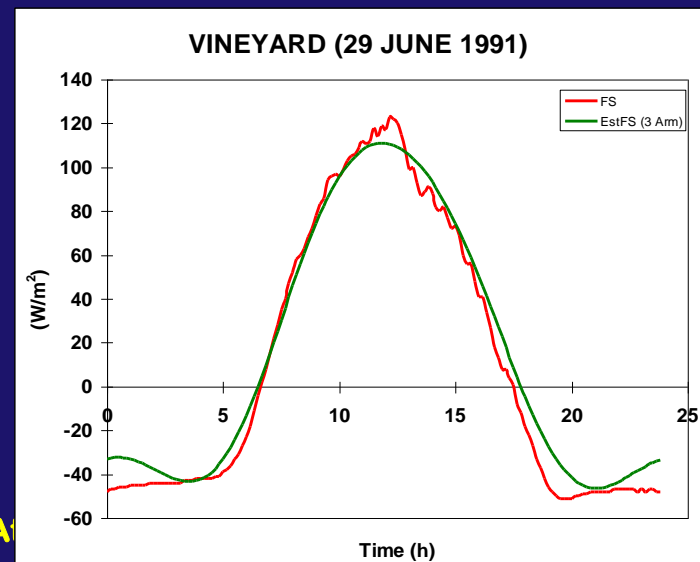
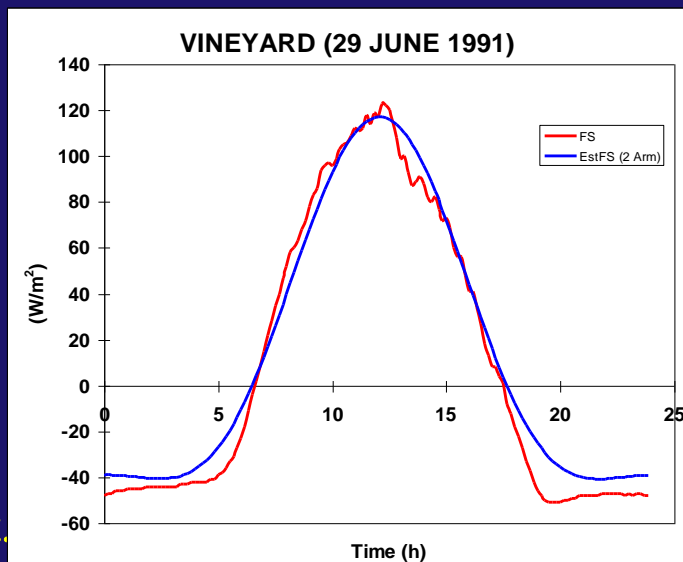
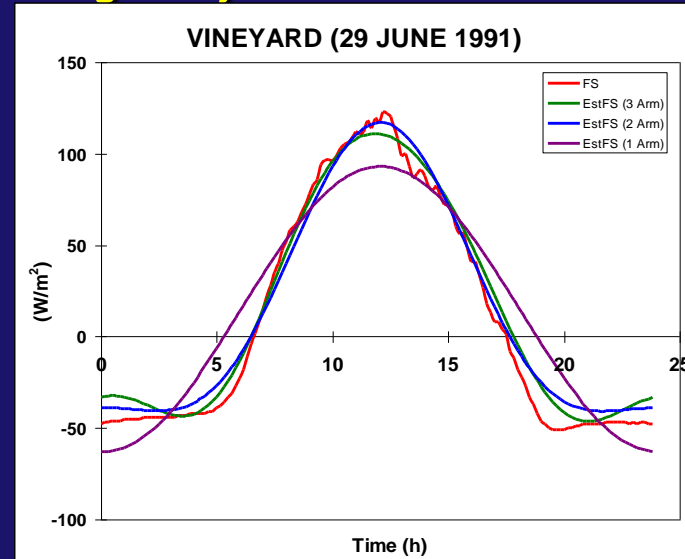
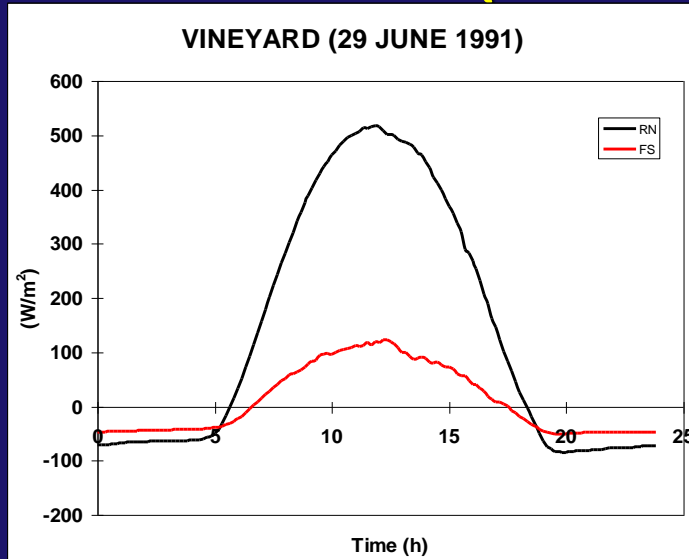
Surface Net Radiation and Soil Heat Flux

(a generic behaviour, June 1991). Basic Physics!!!

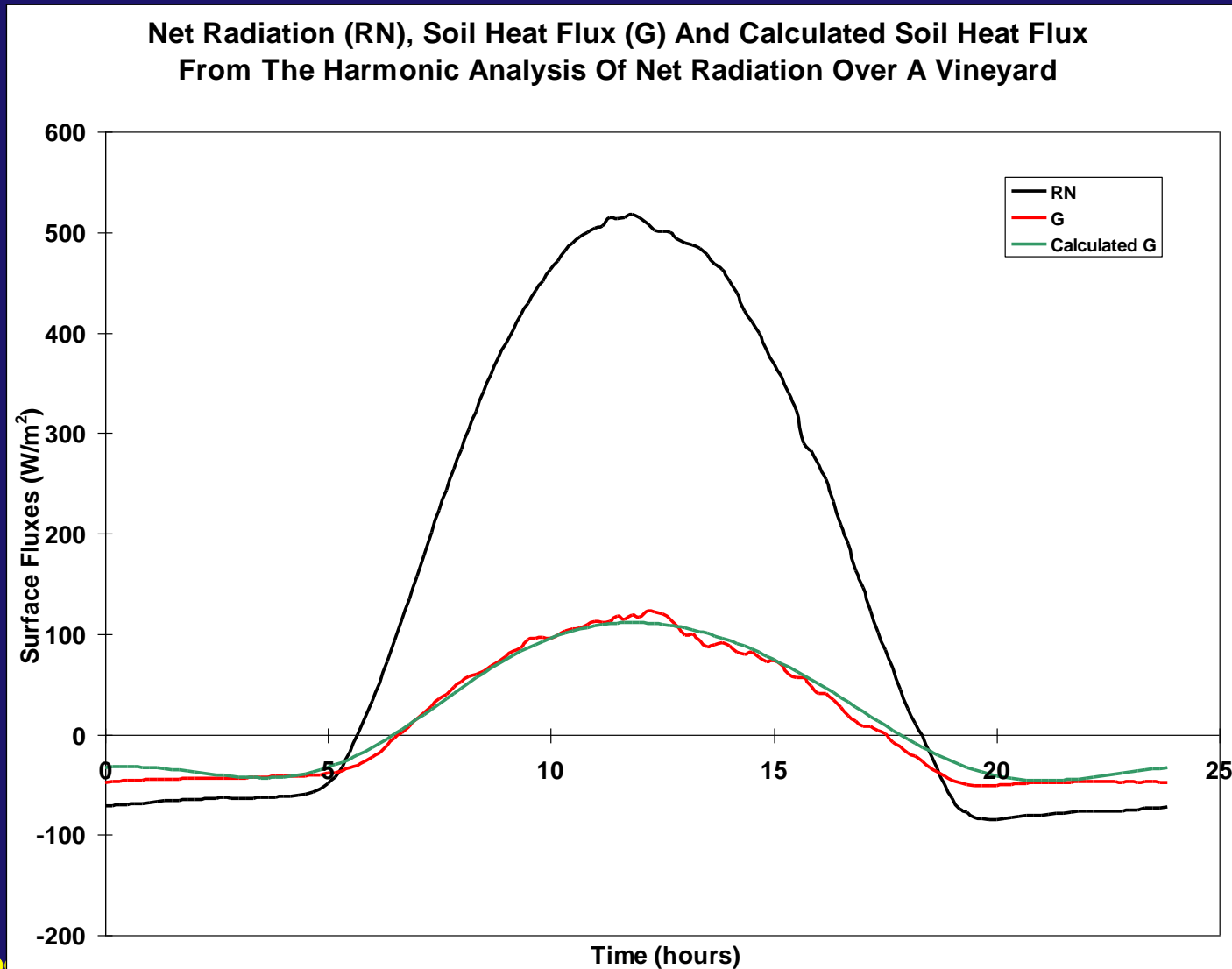


Surface Net Radiation and Soil Heat Flux

(Harmonic Analysis)



Deriving Soil Heat Flux from Surface Net Radiation



Extrapolation and Generalisation

- From point measurements to **GERB** net radiation data
- Parameterisation of surface type
 - Scene identification from **SEVIRI**
- Influence of soil moisture
 - Synergy with **SMOS**
- Extend to the other surface energy fluxes
 - Latent heat flux
 - Sensible heat flux
- Necessity of a suitable validation site
 - For example, the ***Valencia Anchor Station*** Site

Estimation of Surface Net Radiation from Operational Meteorological Measurements

Why obtain surface net radiation

The knowledge of net radiation at the surface is of fundamental importance because it defines the total amount of energy available for the physical and biological processes that take place at the surface, such as evapotranspiration, air and soil warming ...

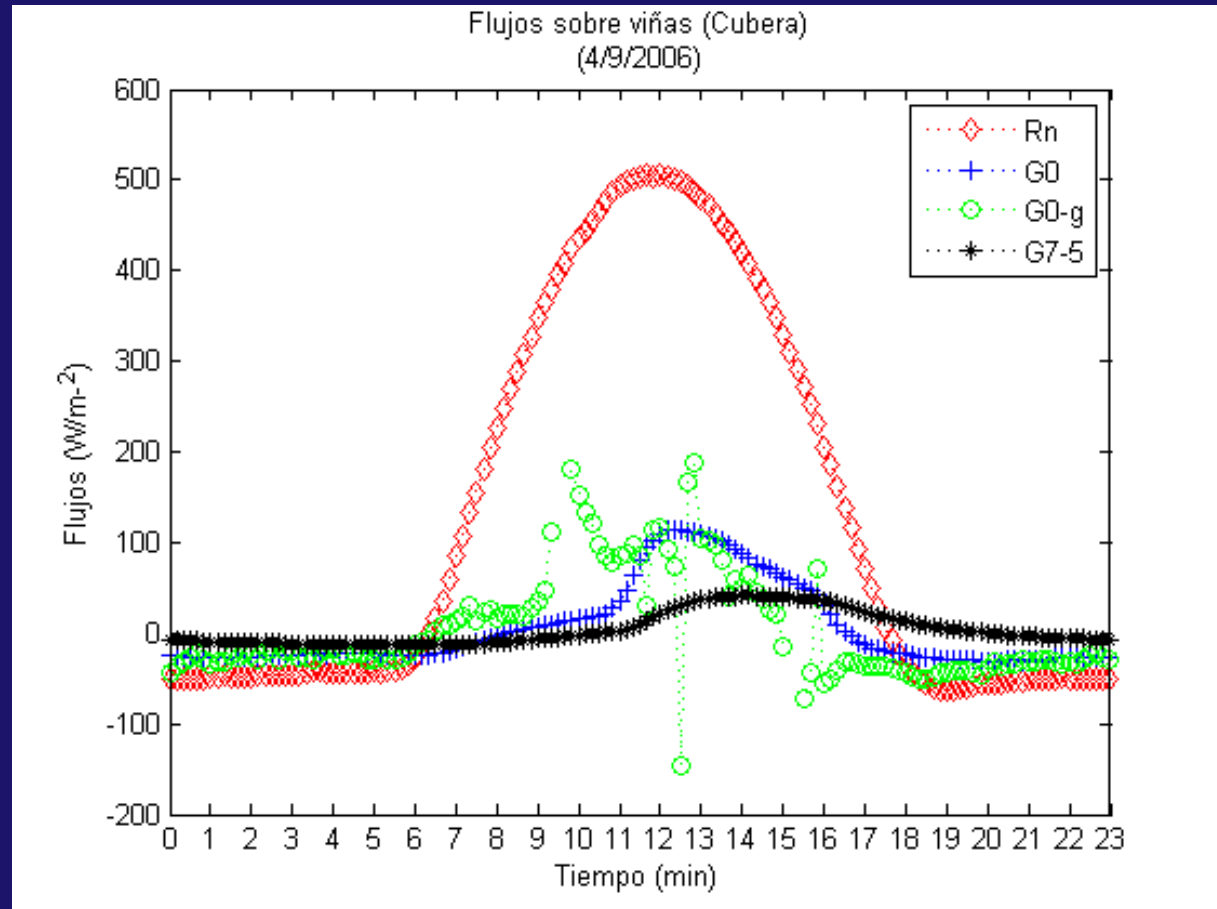
Usually, it is measured with net radiometers but they are expensive instruments, difficult to handle, require constant care and also involve periodic (and difficult???) calibration.



Develop a suitable methodology to estimate R_n at the surface using meteorological variables operationally measured at conventional meteorological stations

Using artificial neural networks

- input parameters meteorological quantities
- output parameter “*in situ*” R_n measurements from pyrrometers



Field Campaigns and Data Sets

vineyards & bare soil

Data set 1 (FESEBAV 2007) (Field Experiment on Surface Energy Balance Aspects over the Valencia Anchor Station area)

- 19th June to 18th September, 2007

- Mobile met station in a field of vines

- Lat 39° 31' 23'' N Lon 1° 17' 22'' W, altitude of 796 m asl



Field Campaigns and Data Sets

matorral

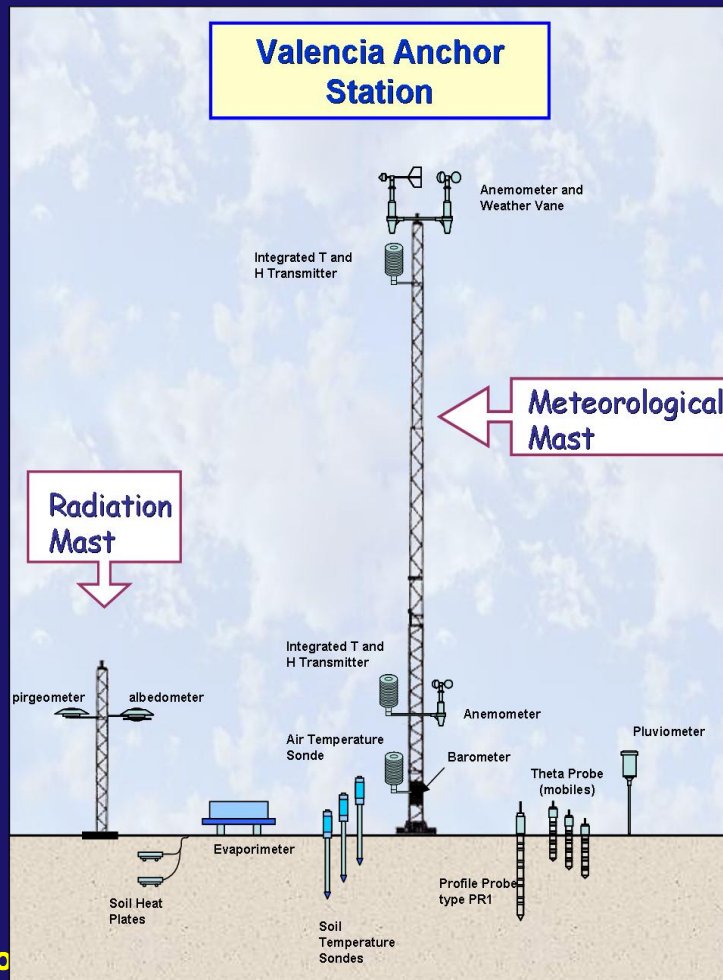


Field Campaigns and Data Sets

vineyards & bare soil

Data set 2 (VAS) Valencia Anchor Station

- Lat 39° 34' 15" N Lon 1° 17' 18" W, altitude of 813 m asl



Estima
using a
approa

Antoni
Olivas,
Ernesto

Table 3 Statistical values of the 10-min meteorological parameters utilized as input parameters in the ANN models for the training and validation set

Meteorological parameters	Statistics			
	Min	Max	Mean	Std
Wind velocity (m s^{-1})	0.0	5.05	1.22	0.73
Wind direction (deg)	0.0	359.90	158.98	92.81
Air temperature ($^{\circ}\text{C}$)	8.81	39.92	21.83	6.45
Surface temperature ($^{\circ}\text{C}$)	10.63	61.91	28.85	13.12
Soil temperature at 5 cm depth ($^{\circ}\text{C}$)	14.16	41.70	25.84	6.12
Relative humidity (%)	6.89	99.30	54.74	25.87
Soil moisture at 5 cm depth ($\text{m}^3 \text{m}^{-3}$)	0.07	0.29	0.09	0.03
Soil heat flux at depth of 7.5 cm (W m^{-2})	-22.54	50.68	-8.49	18.46
Net radiation ^a (W m^{-2})	-73.33	741.30	144.94	231.24

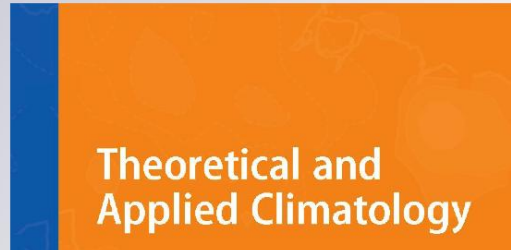
Min minimum, Max maximum, Std standard deviation

^a Net radiation was considered as output parameter in the ANN models

Theoretical and Applied
Climatology

ISSN 0177-798X

Theor Appl Climatol
DOI 10.1007/
s00704-011-0488-7



WS: Wind speed; AT: air temperature;
RH: relative humidity; RN: net radiation.

AP (mb) RH (%) RN (W/m^2)

Expert Systems with Applications 38 (2011) 14190–14195



Contents lists available at ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa



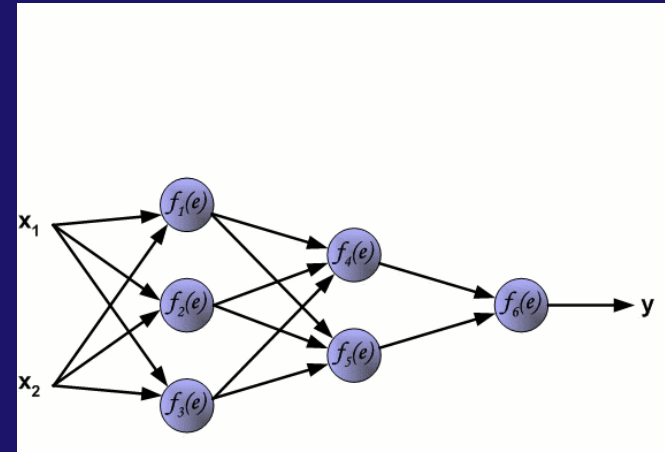
Modelling net radiation at surface using “*in situ*” netpyrradiometer measurements with artificial neural networks [☆]

Antonio Geraldo-Ferreira ^{a,b}, Emilio Soria-Olivas ^c, Juan Gómez-Sanchis ^{c,*}, Antonio José Serrano-López ^c, Almudena Velázquez-Blázquez ^d, Ernesto López-Baeza ^b

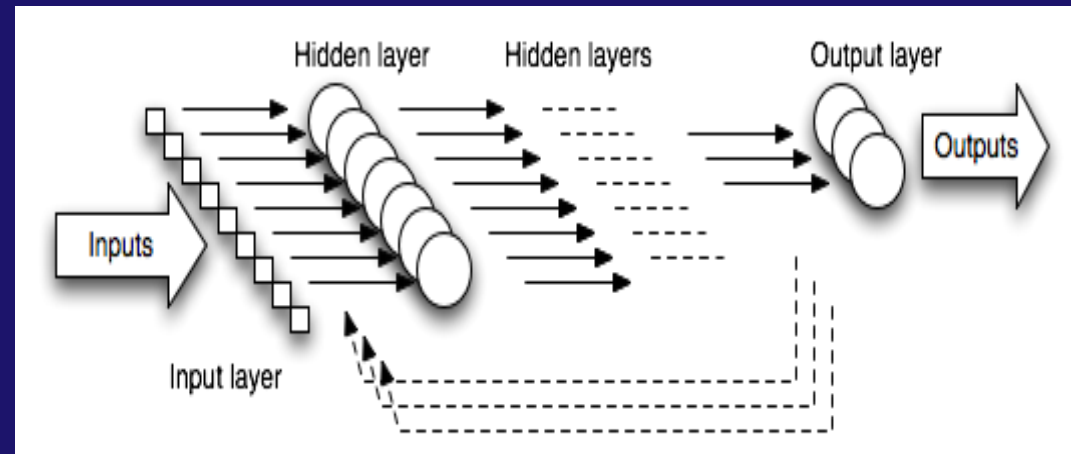
Methodology

The neural network used in this work is the **Multi-Layer Perceptron (MLP)**

A layered arrangement of individual computation units known as artificial neurons. Neurons from a specific network are grouped together in layers that form a fully connected network. The first layer contains the input nodes, which are usually fully connected to hidden neurons and these are, in turn, connected to the output layer.



Scheme of a fully-connected multilayer perceptron. *In our case, only one output neuron is necessary, since only one variable (net radiation) is predicted at each time.*



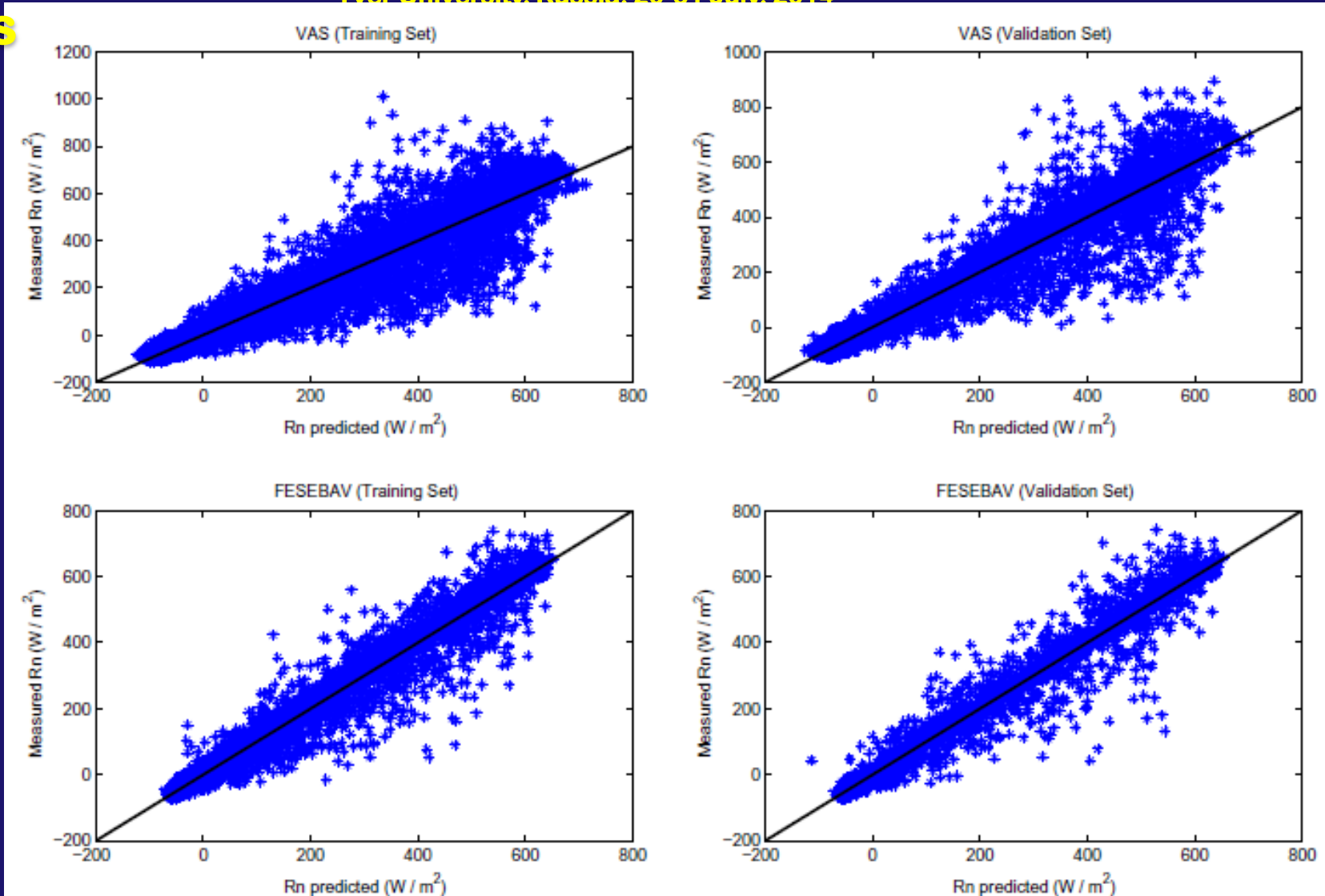
Input variables

- wind speed
- air temperature
- atmospheric pressure
- relative humidity

Output variable

- net radiation measured at the surface

Results



Linear regression between net radiation predicted by the neural network model vs actual measured values of surface net radiation

Results

Table 2

Performance indices for FESEBAV data set.

FESEBAV data set	MAE (W/m^2)	RMSE (W/m^2)	ME (W/m^2)	a	b
Training set $N = 8832$	19.46	35.56	-0.38	0.97	3.73
Validation set $N = 4416$	21.65	39.88	0.027	0.97	4.46

Table 3

Performance indices for VAS data set.

VAS data set	MAE (W/m^2)	RMSE (W/m^2)	ME (W/m^2)	a	b
Training set $N = 15,744$	34.55	61.36	0.65	1.00	0.30
Validation set $N = 7872$	36.47	65.07	-0.26	0.99	0.46

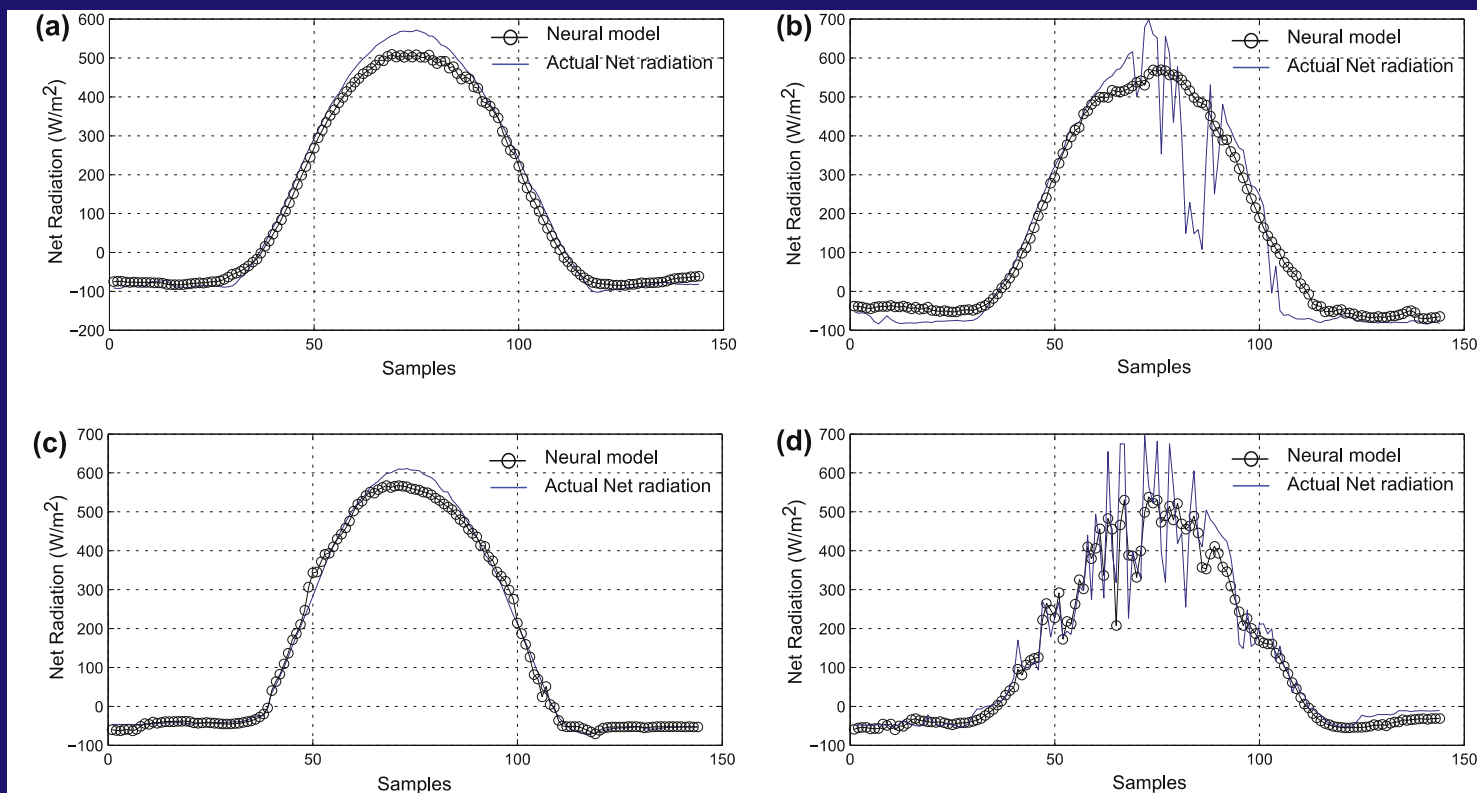


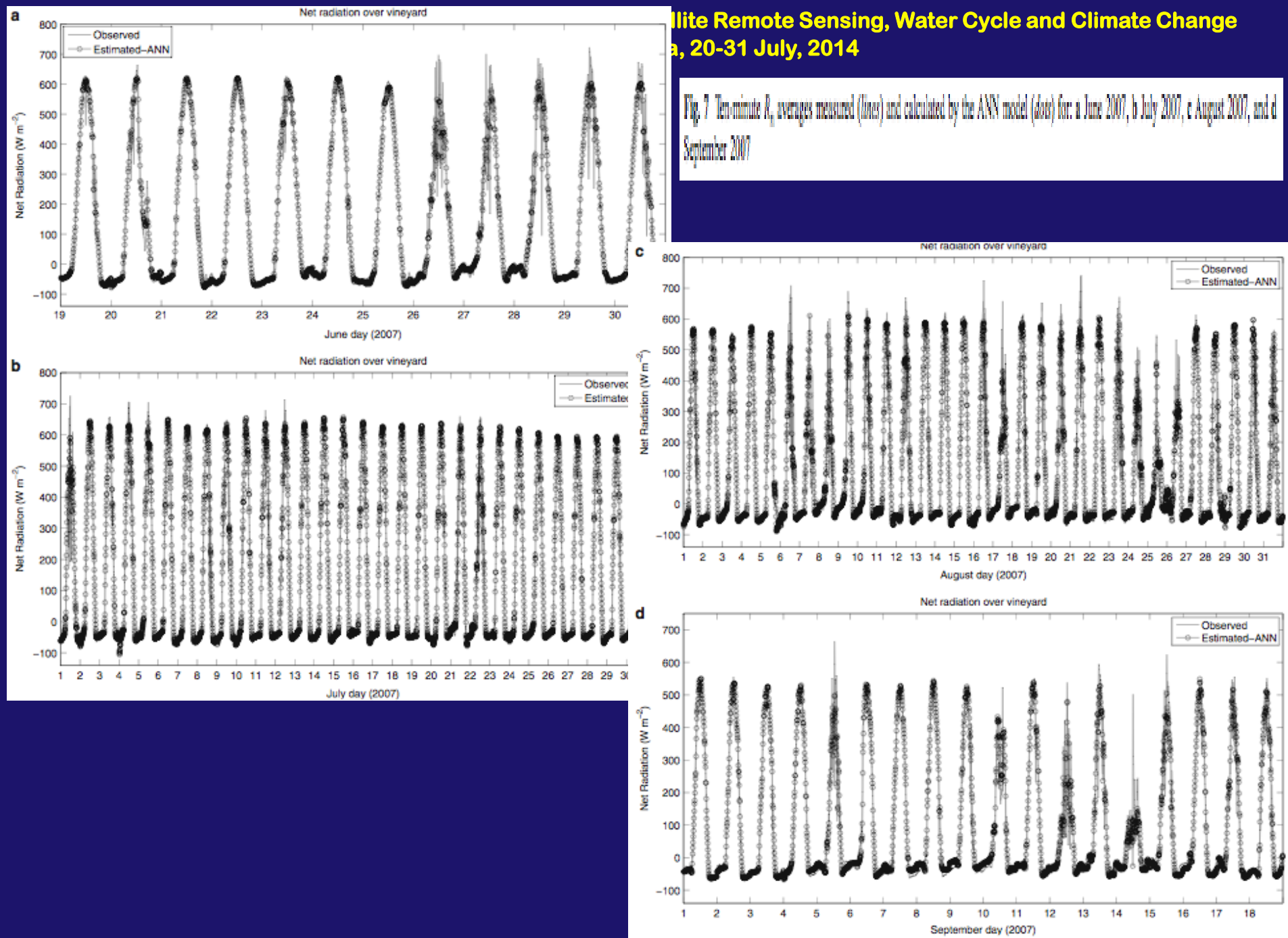
Fig. 5. Measured R_n values (···) and neural model prediction (—○—) for: (a) cloudy free-day, 2-7-2007, VAS data set; (b) cloudy day, 21-5-2007, VAS data set; (c) cloudy free-day, 15-8-2007, FESEBAV data set; (d) cloudy day, 26-6-2007, FESEBAV data set.

Results

Performance indices in sunny/cloudy days.

	MAE (W/m^2)	RMSE (W/m^2)	ME (W/m^2)
<i>FESEBAV data set</i>			
Cloudy days $N = 8784$	24.74	43.85	0.44
Sunny days $N = 4464$	11.41	17.21	-1.17
<i>VAS data set</i>			
Cloudy days $N = 17,712$	41.64	71.46	-0.34
Sunny days $N = 5904$	15.84	22.38	2.41

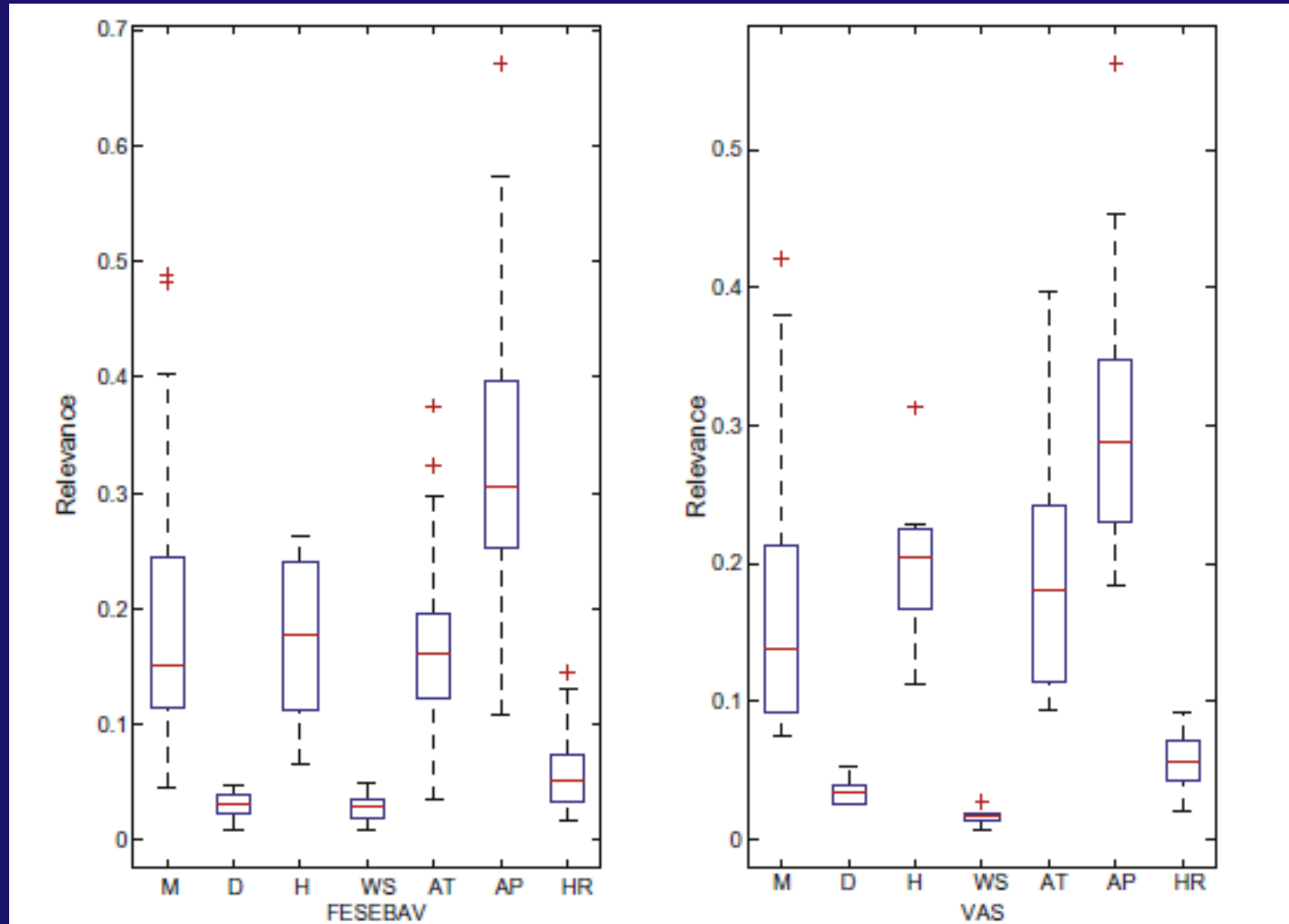
Fig. 7 Ten-minute R_n averages measured (lines) and calculated by the ANN model (dots) for: a June 2007, b July 2007, c August 2007, and d September 2007



Results

Sensitivity Analysis

Relevance of input variables. The inputs are: Month (M), Day (D), Hour (H), wind speed, air temperature, **atmospheric pressure** and relative humidity.



Partial conclusions

- Ability of neural models to replace (to an acceptable error) the use of radiometers for the measurement of surface net radiation, from **conventional operational met parameters**
(earlier we had tried with more variables)
- A sensitivity analysis shows the relevance of the input variables
atmospheric pressure being more relevant
- Need to be done for other surface types

Derivation of surface net radiation from top of the atmosphere GERSB fluxes by means of linear models and neural networks

Motivation

Provide an improved method for estimating R_N at surface, covering totally the diurnal cycle of R_N , with high temporal resolution (15 min)

Data used

Input variables

- GERB (Geostationary Earth Radiation Budget) TOA fluxes
 - TOT Channel [0.32 μm - 100.0 μm]
 - SW Channel [0.32 μm to 4.0 μm])
- $\text{LW} = \text{TOT} - \text{SW}$

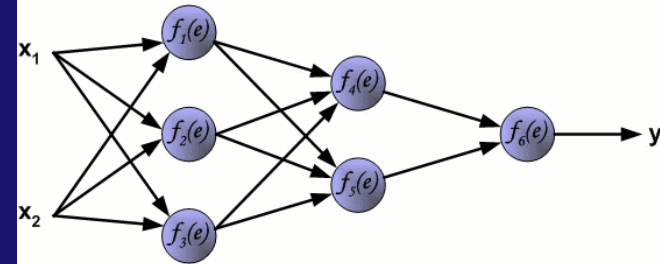
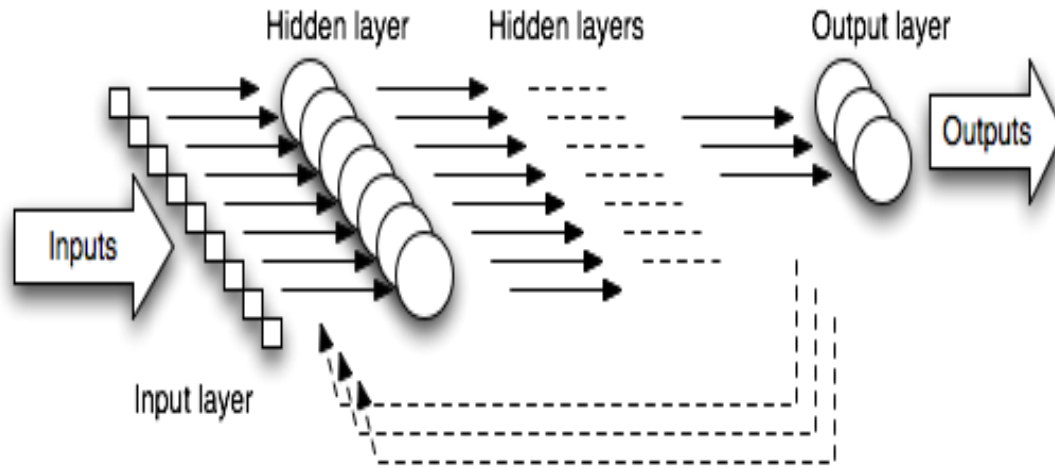
Output variable

- net radiation measured at the surface
 - Valencia Anchor Station (bare soil)
 - 31st July – 6th August, 2006 & 19th June – 18th August 2007
 - FESEBAV
 - matorral
 - 31th July - 5th August, 2006
 - vineyard
 - 19th June - 18th September, 2007

In order to have the same temporal resolution, in situ measurements (10 min frequency) were linearly interpolated to the hour of the satellite image acquisition (15 min frequency)

Methodology

The neural network used in this work is also the **Multi-Layer Perceptron (MLP)**.



Scheme of a fully-connected multilayer perceptron. *In our case, only one output neuron is necessary, since only one variable (net radiation) is predicted at each time.*

All sky conditions -both cloudy days and cloudy free-days- were considered in the analysis. Three input variables were selected for the neural network model (solar zenith angle (SZA), TOA shortwave and longwave fluxes). The objective or output variable was Net Radiation measured at surface.

Input variables

- SZA, TOA SW & LW fluxes

Output variable

- net radiation measured at the surface

From the GERB-1 and VAS data set, independent parts are used to train and validate the AAN model, and a **Multivariate Linear Regression (MLR)** model used as reference for comparison with the AAN model

Results

Statistical values of the input parameters to the ANN and MLR models for the training / validation set

Parameters	Basic Statistics for VAS data set				
	Minimum	Maximum	Mean	Std	N
Shortwave flux at TOA (W m^{-2})	0	715.81	103.70	117.22	6399
Longwave flux at TOA (W m^{-2})	125.56	350.69	284.85	26.14	6399
Net radiation at surface (W m^{-2})	-113.0	713.50	117.58	224.08	6399

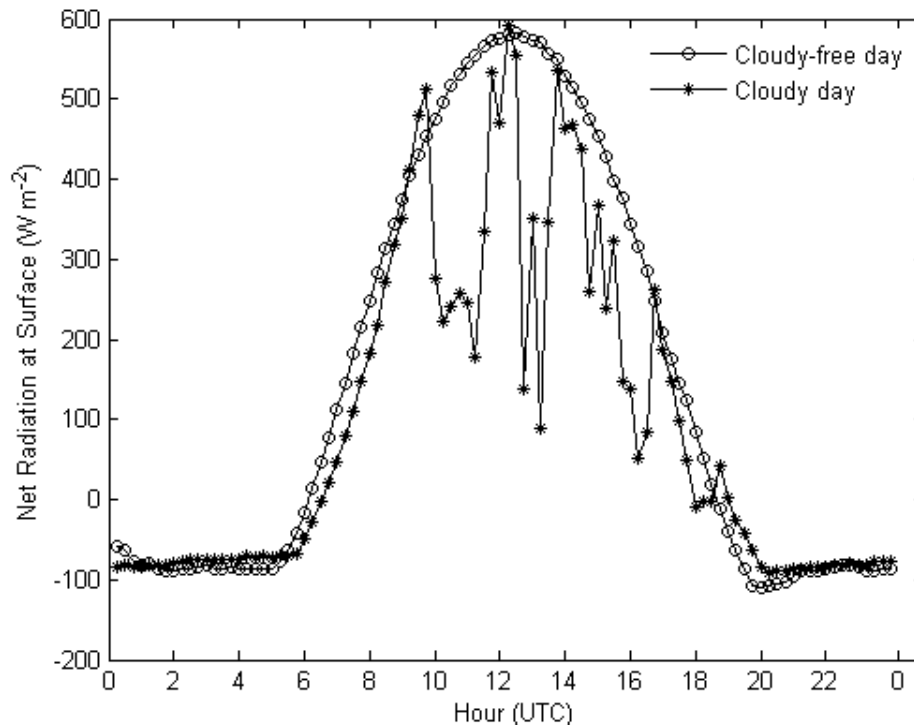


Figure shows the diurnal course of R_N for two typical days with and without clouds. The diurnal cycle of R_N in cloudy-free days shows a regular form but it is irregular in cloudy days.

Observed diurnal course of net radiation at VAS for two different days: 22nd July (cloudy day) and 12th August, 2007 (cloudy-free day)

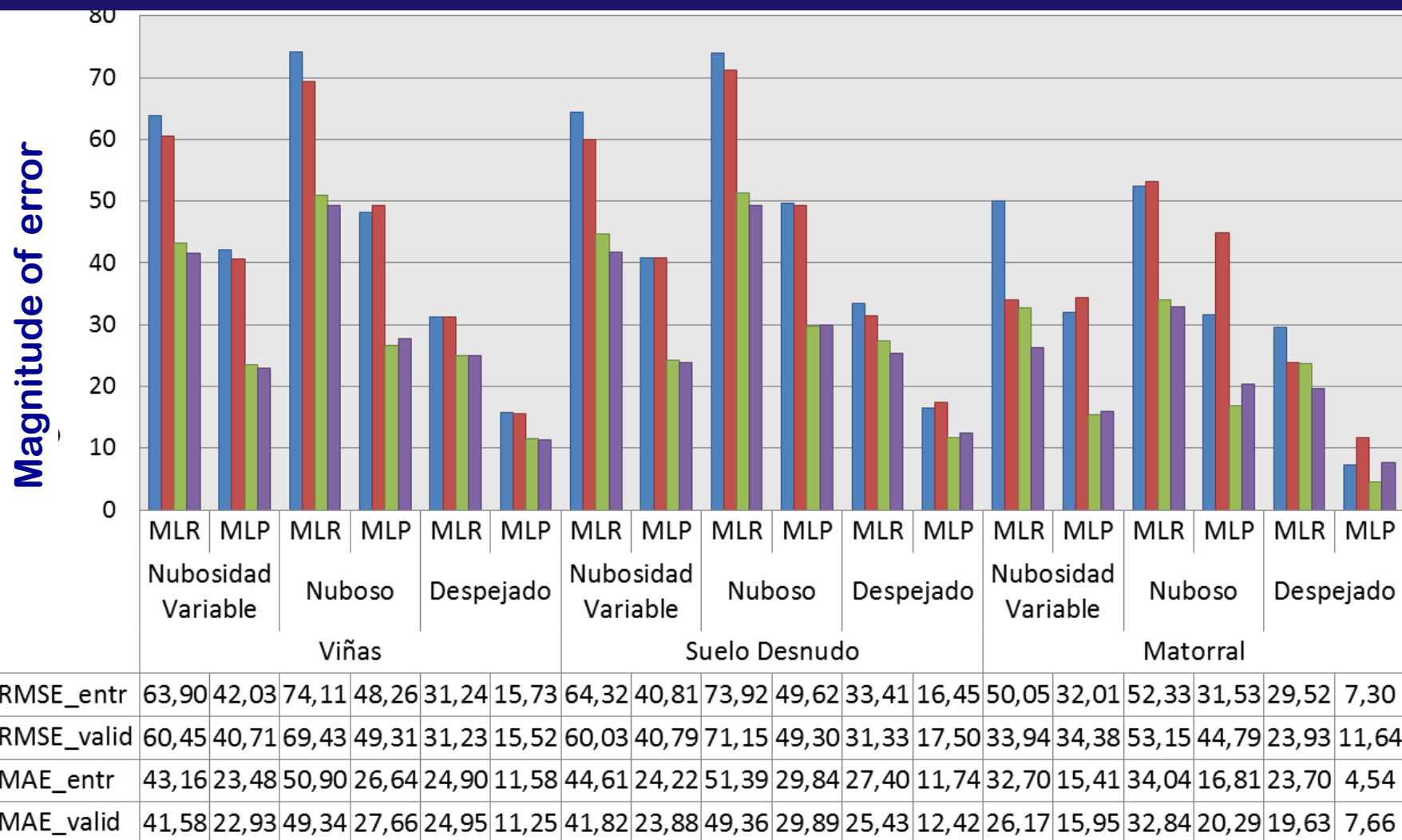
Results

MLR: Multivariate Linear Regression Model

Land uses	Sky conditions	$R_n = \beta_0 + \beta_1 SZA + \beta_2 SW + \beta_3 LW$				Statistical	N
		β_0	β_1	β_2	β_3	R^2	
VINEYARDS	Overall Conditions	344,46	-210,27	-42,88	16,37	0,89	5735
	Cloudy days	335,79	-202,79	-46,33	20,52	0,86	3862
	Cloudless days	367,61	-137,12	62,19	-3,96	0,97	1873
BARE SOIL	Overall Conditions	295,46	-196,19	-51,64	2,67	0,87	6399
	Cloudy days	288,20	-200,12	-57,65	0,78	0,84	4245
	Cloudless days	307,79	-154,98	9,16	7,29	0,96	2154
SCRUB	Overall Conditions	367,39	-126,37	18,79	91,75	0.93	472
	Cloudy days	350,19	-106,74	25,66	112,69	0.93	288
	Cloudless days	410,71	64,61	213,14	39,72	0.98	184

Results

Error indices -both for MLP and MLR- as well as the standard deviation of the models results for the training and validation data sets



The neural models performance is better than that obtained for the linear models

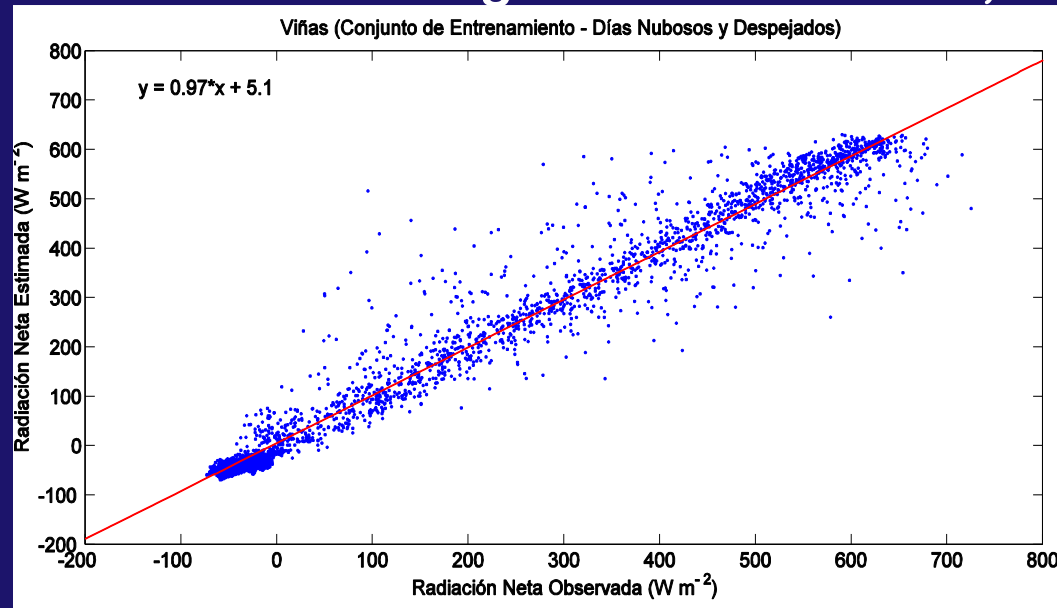
RMSE: Root mean square error; MAE: Mean Absolute Error; ME: Mean Error

Results

Scatter plots between R_N estimated by MLP and R_N measured in situ for training and validation set, considering:

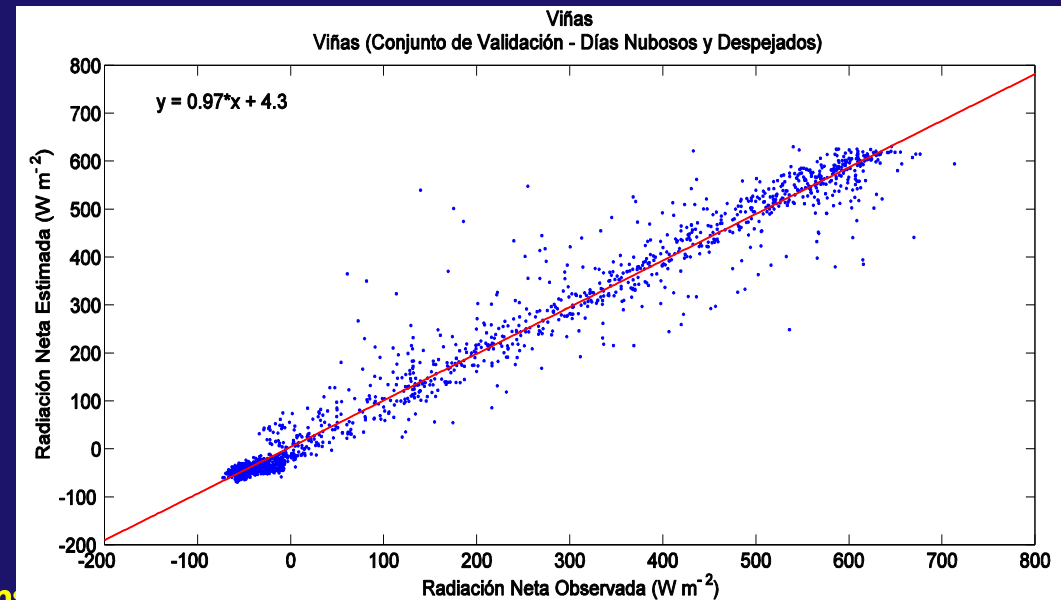
Land use:
Vineyards

All-sky
conditions



Training set

Validation set

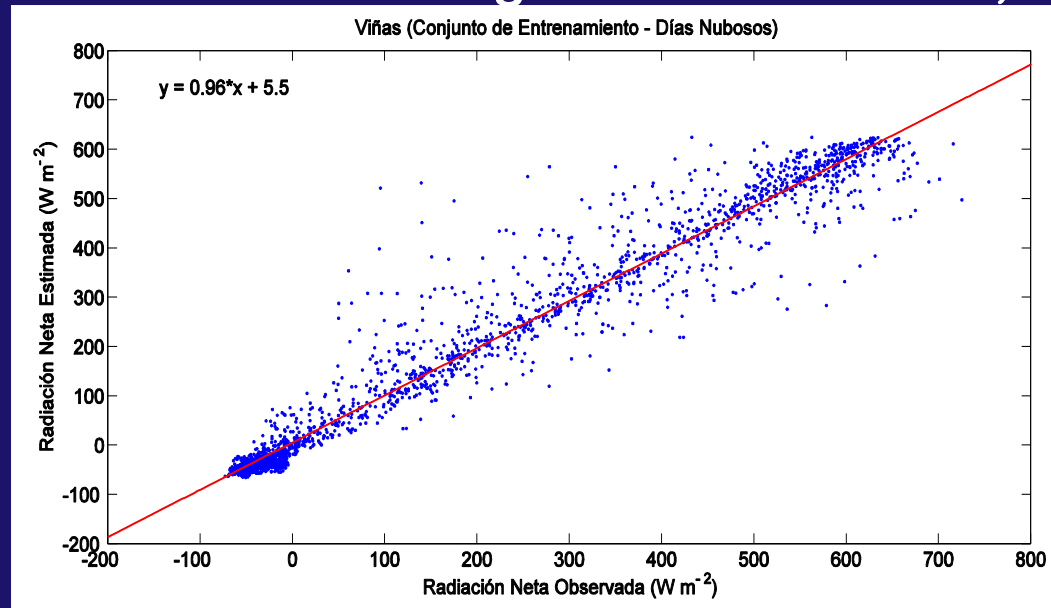


Results

Scatter plots between R_N estimated by MLP and R_N measured in situ for training and validation set, considering:

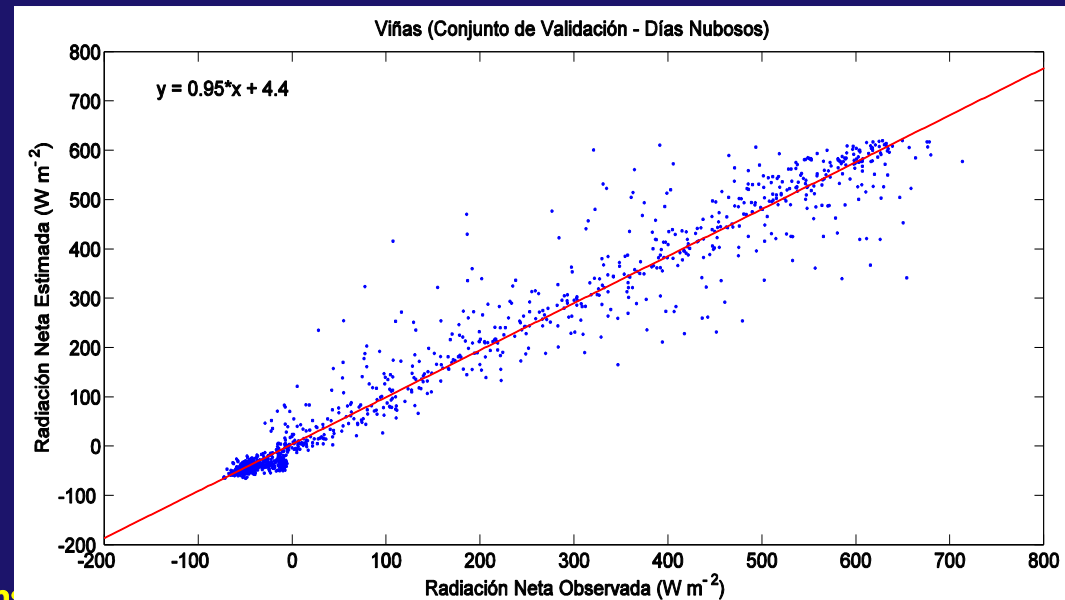
Land use:
Vineyards

Cloudy
conditions



Training set

Validation set

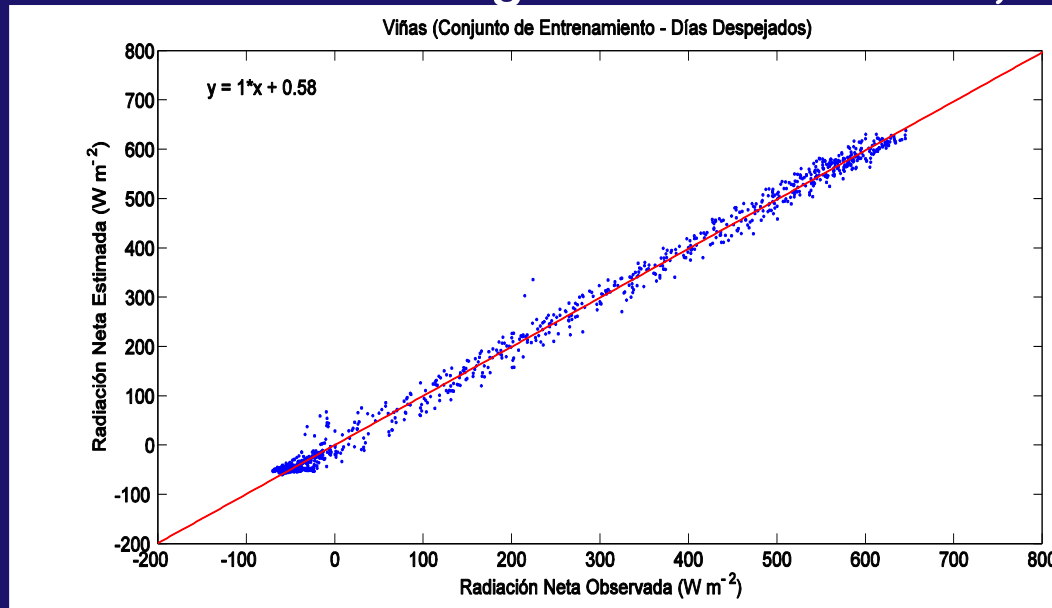


Results

Scatter plots between R_N estimated by MLP and R_N measured in situ for training and validation set, considering:

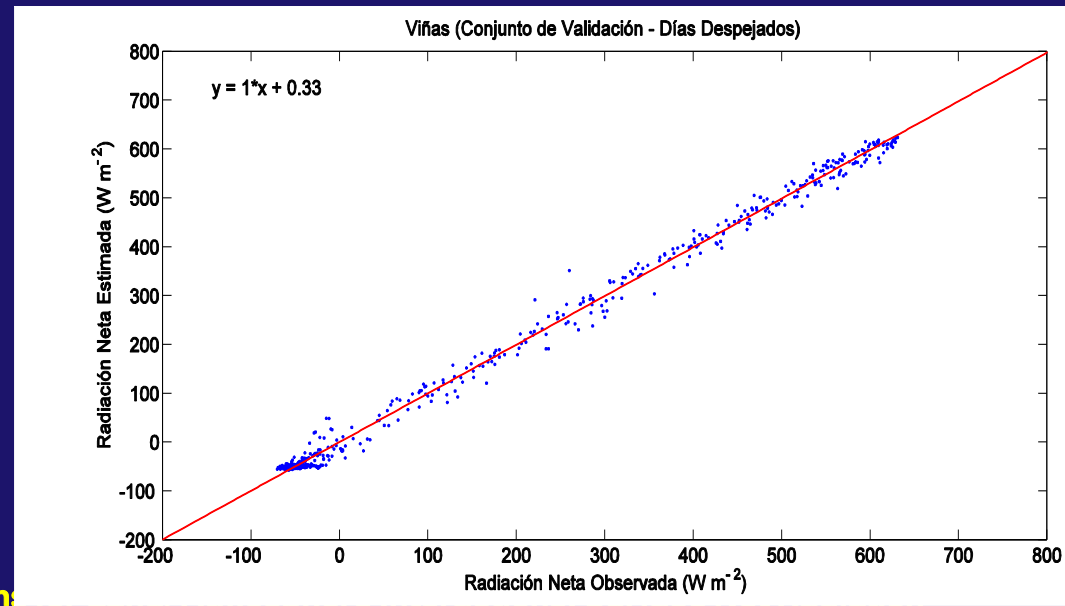
Land use:
Vineyards

Clear-sky
conditions



Training set

Validation set

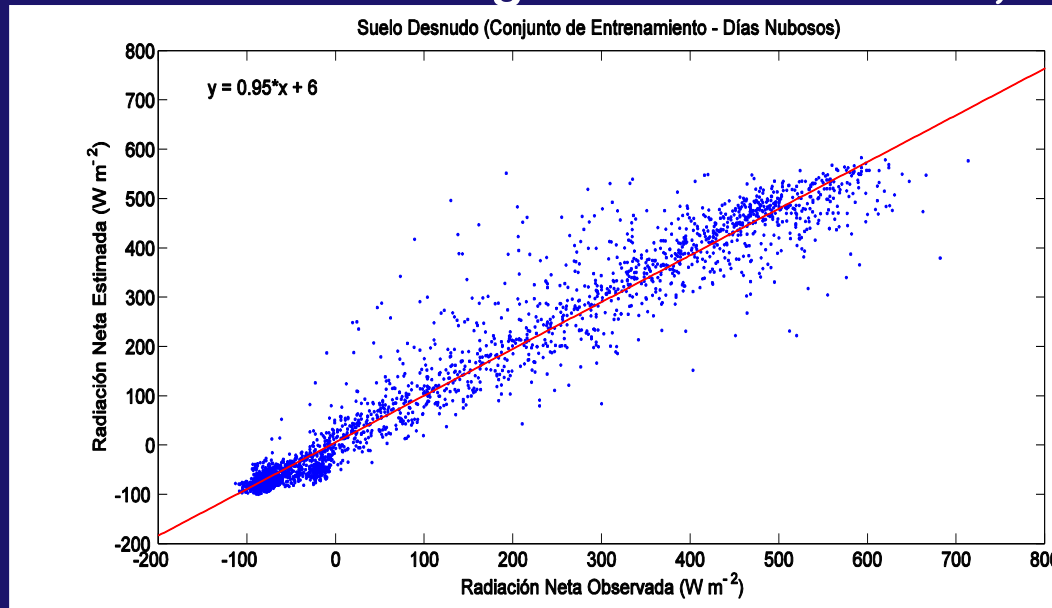


Results

Scatter plots between R_N estimated by MLP and R_N measured in situ for training and validation set, considering:

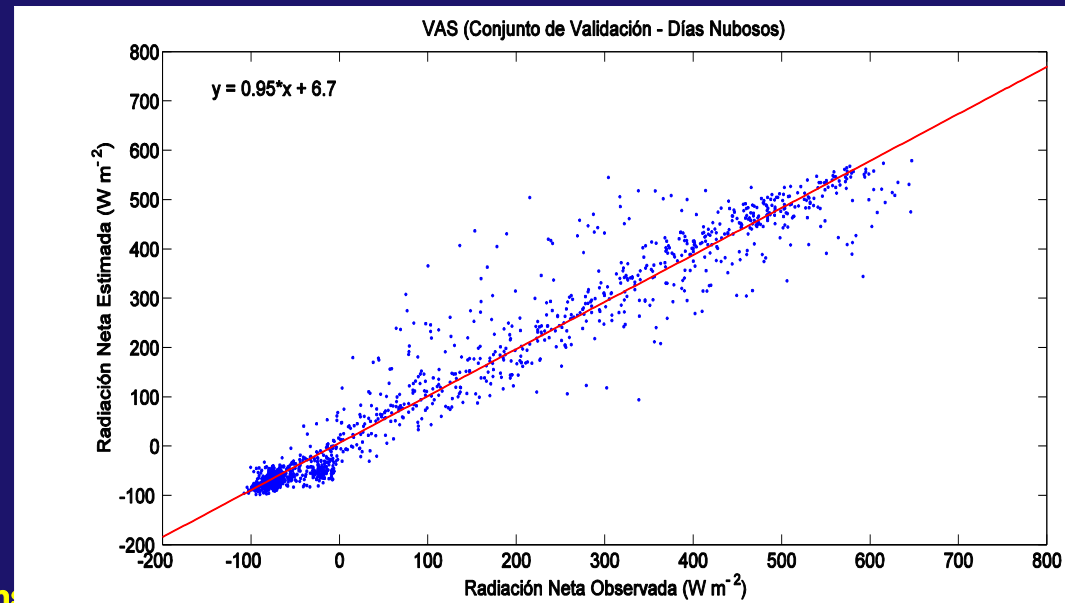
Land use:
Bare soil

All-sky
conditions



Training set

Validation set

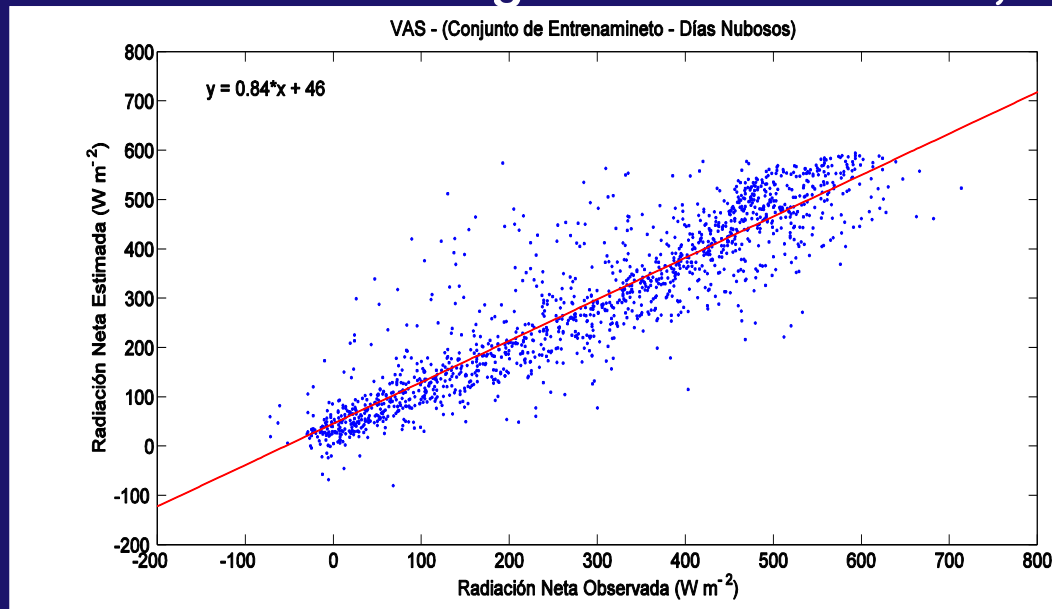


Results

Scatter plots between R_N estimated by MLP and R_N measured in situ for training and validation set, considering:

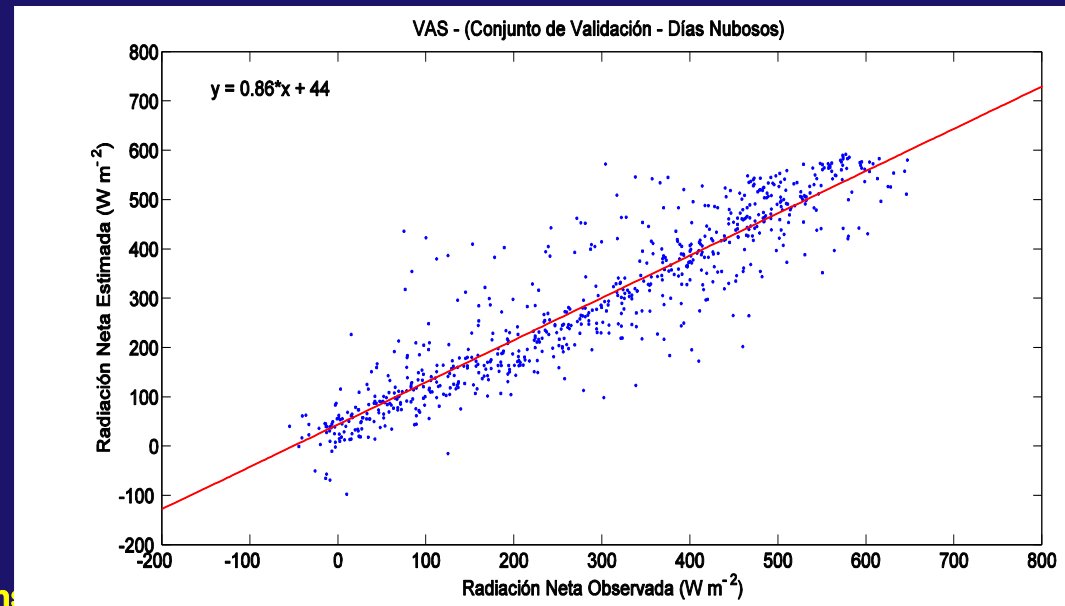
Land use:
Bare soil

Cloudy
conditions



Training set

Validation set

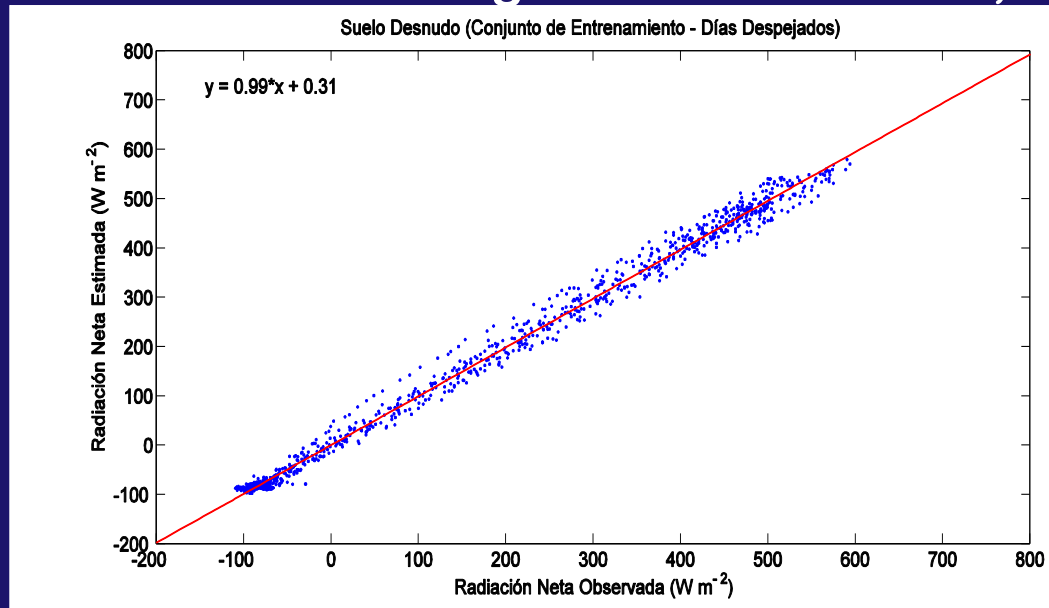


Results

Scatter plots between R_N estimated by MLP and R_N measured in situ for training and validation set, considering:

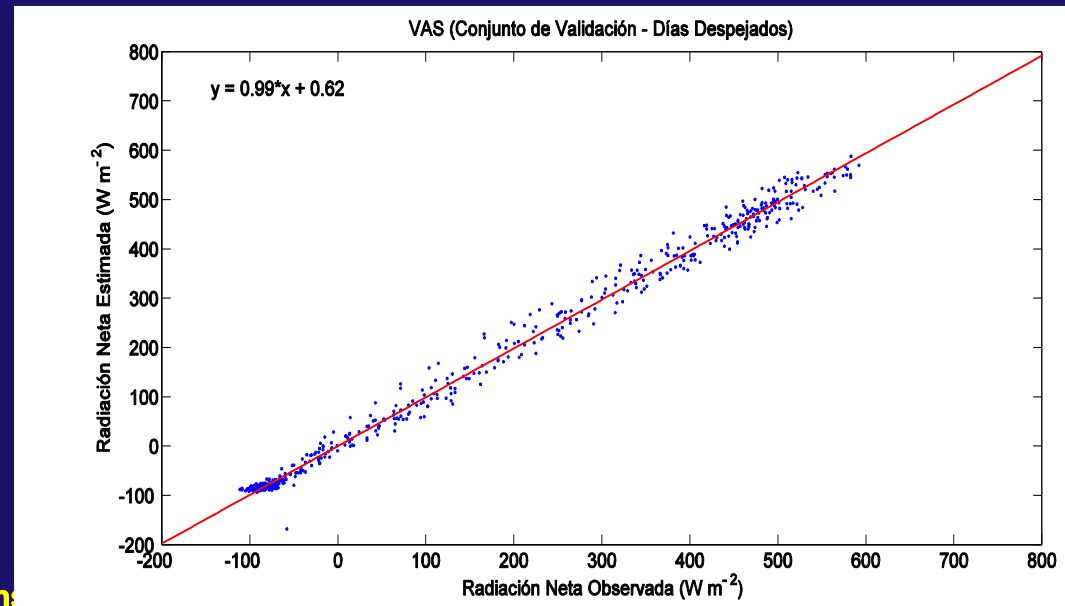
Land use:
Bare soil

Clear-sky
conditions



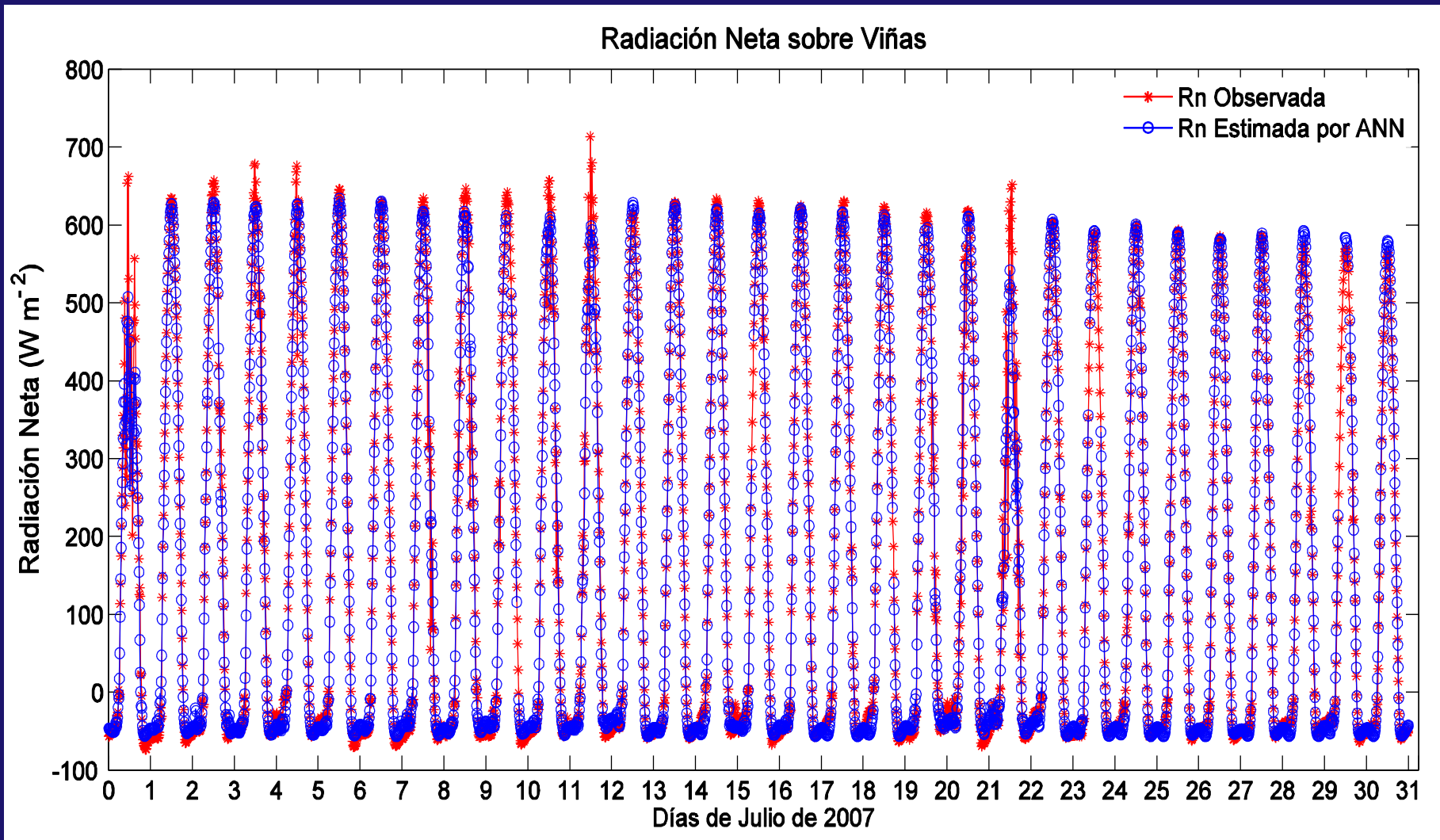
Training set

Validation set



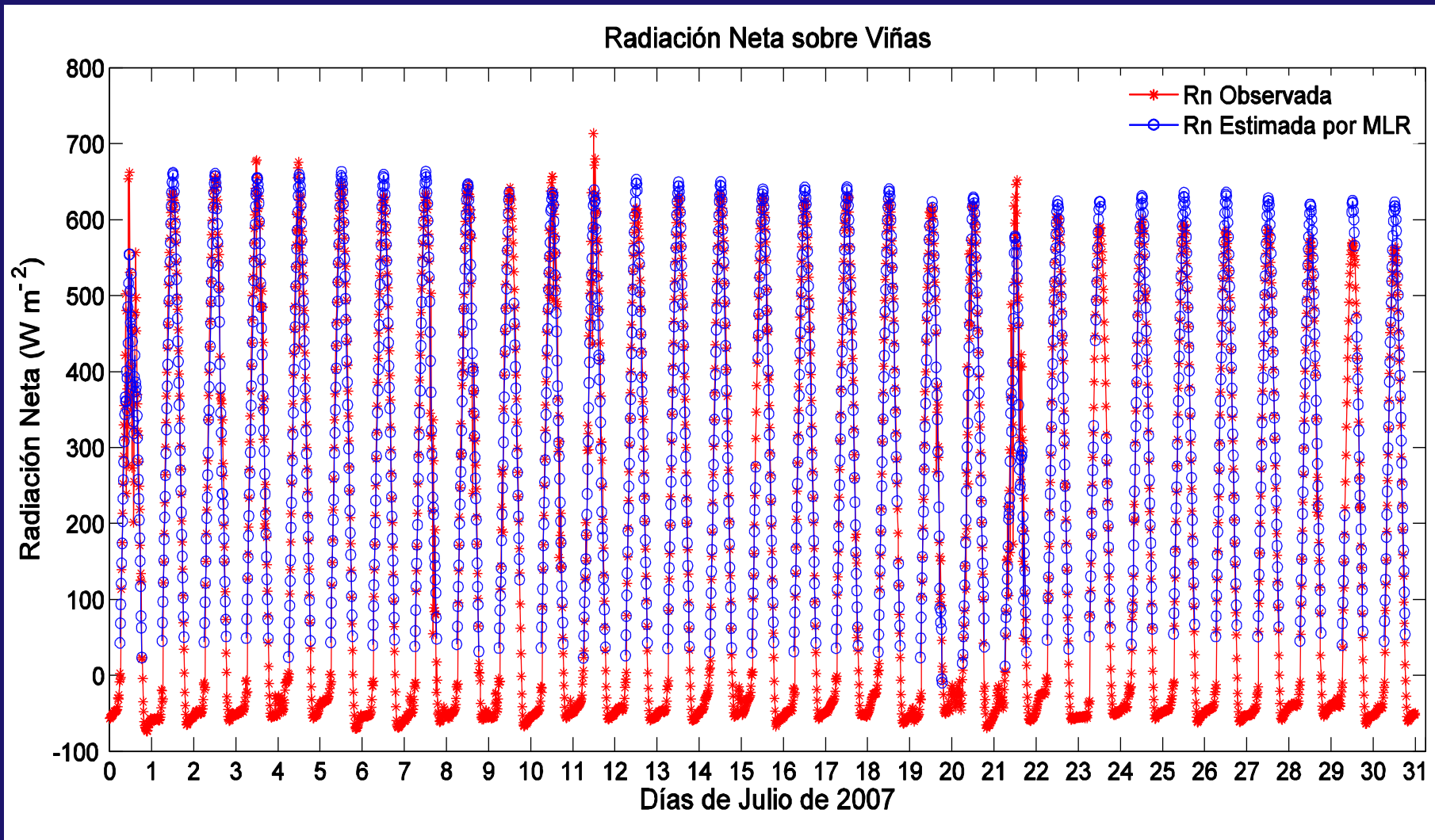
Results

Diurnal course of the desired signal, net radiation at the surface (red line), and the values provided by the neural network (MLP) (blue line) for all-sky conditions.



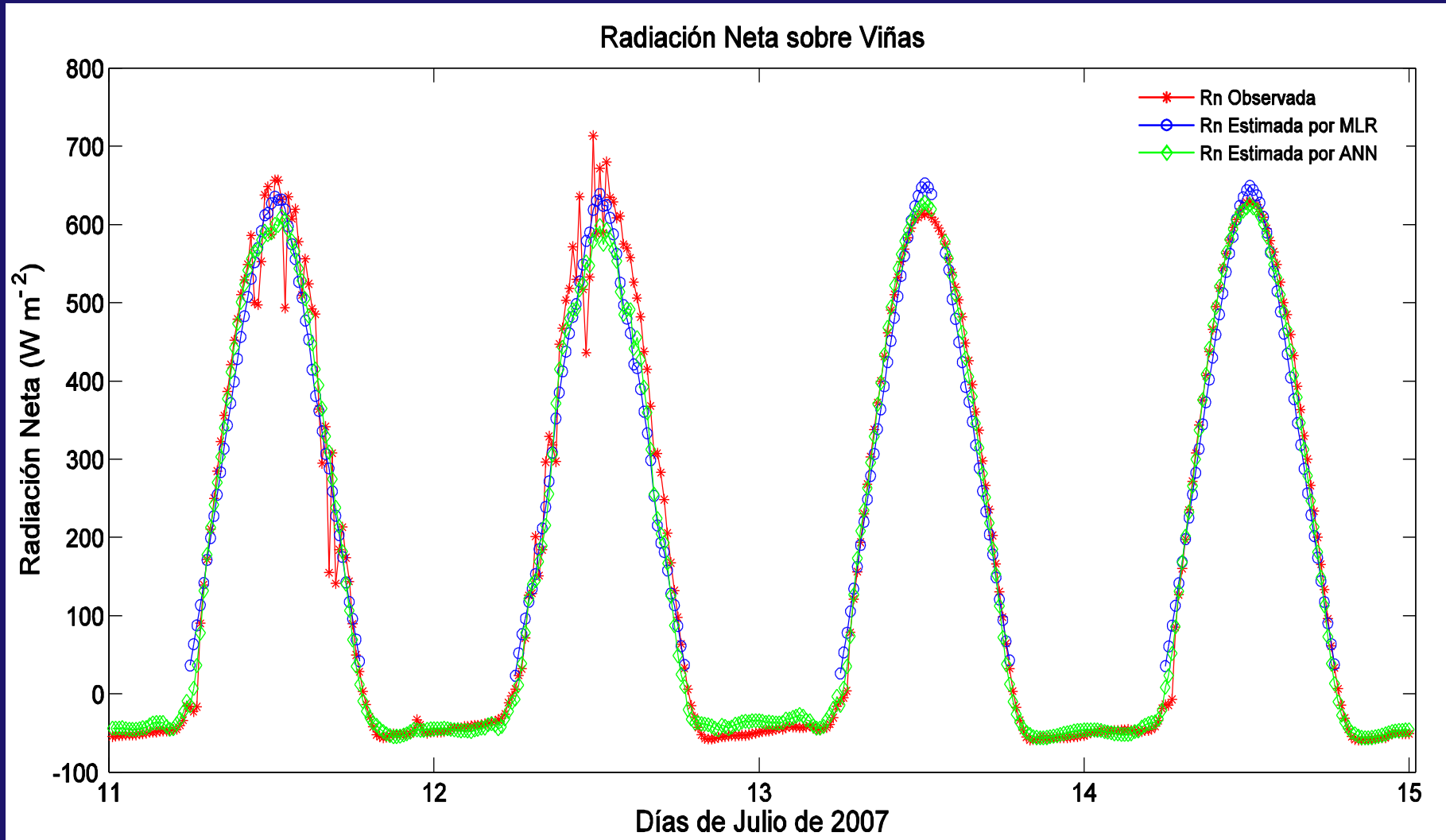
Results

Diurnal course of the desired signal, net radiation at the surface (red line), and the values provided by the multiple linear regression model (MLR) (blue line) for all-sky conditions.



Results

Diurnal course of the desired signal, net radiation at the surface (red line), and the values provided by the multiple linear regression model (blue line), and by the neural model (green line) for all-sky conditions



Partial conclusions

Artificial neural model proposed to model net radiation at the surface, from satellite measurements at the TOA

Good performance for both cloudy and clear-sky conditions as well as for all-sky conditions, for different land uses

Better performance than a multivariate linear model

Possibility of directly obtaining surface net radiation from TOA satellite flux measurements

Using the synergy GERB/SEVIRI and micrometeorological data to study the relationship between surface net radiation and soil heat flux

Methodology

Relationship between R_n and G according to Santanello and Friedl (2002)

$$\frac{G}{R_n} = (0.0074 \Delta T + 0.088) \cos \left(\frac{2\pi (t + 10800)}{B} \right)$$

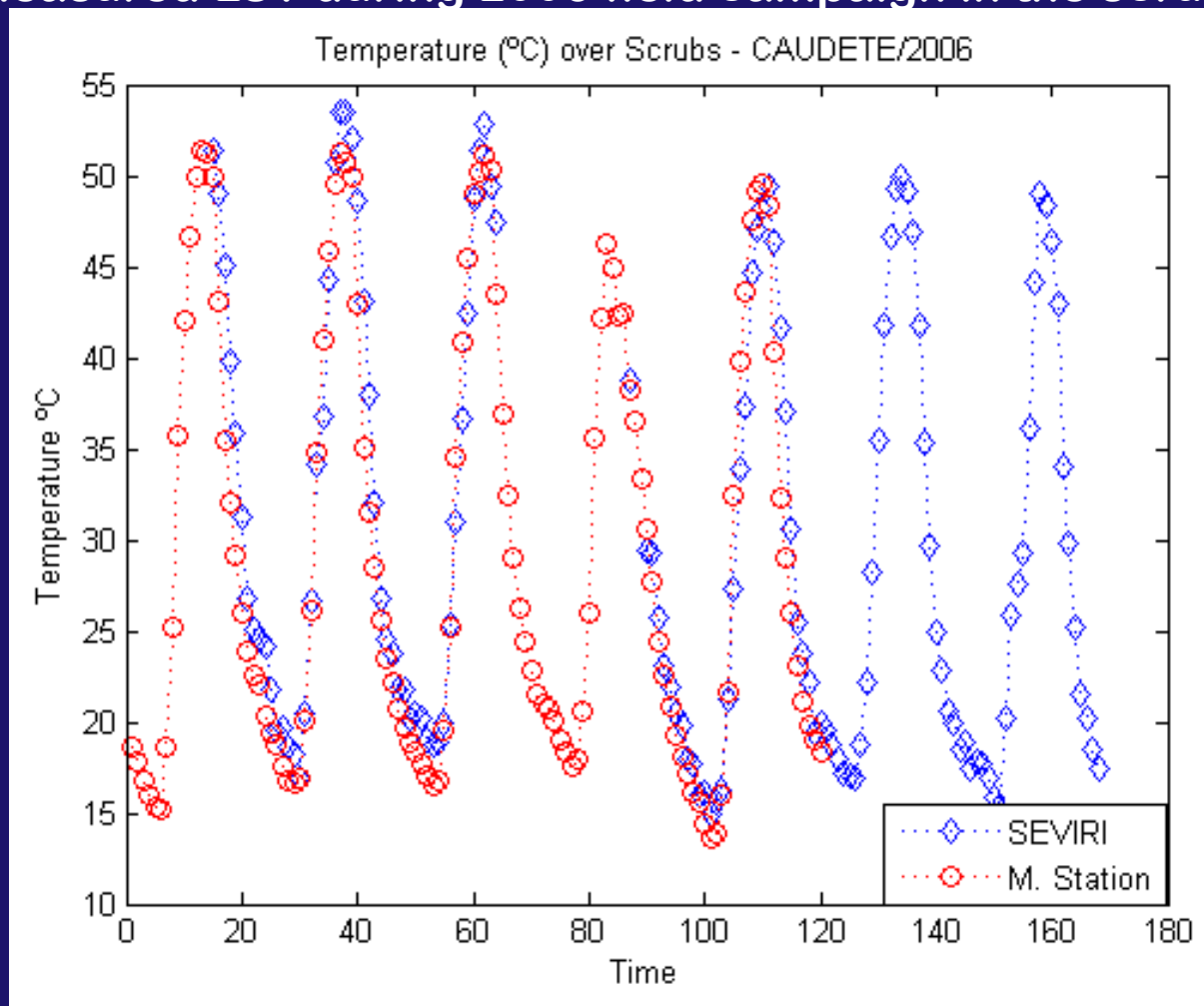
$B = (1729 * \Delta T) + 65013$ is a variable that depends on ΔT (Temp Max – Temp Min) and t is time (s)

B is assigned based on knowledge of soil type, moisture regimes, and seasonal dynamics in LAI.

Land surface temperature (LST) from SEVIRI and ground surface temperature from *Valencia Anchor Station* and micrometeorological station were used

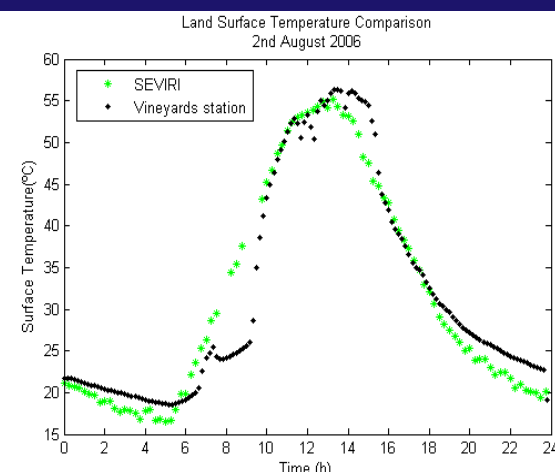
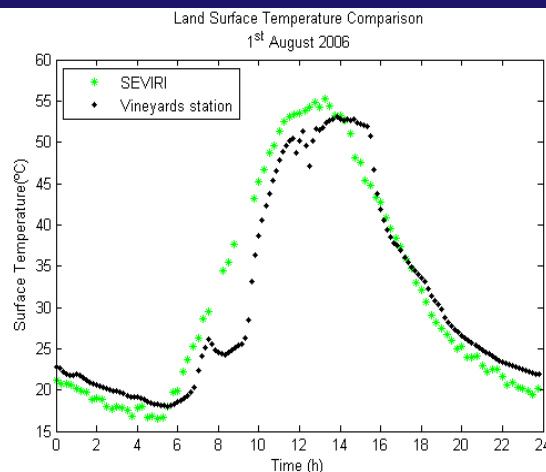
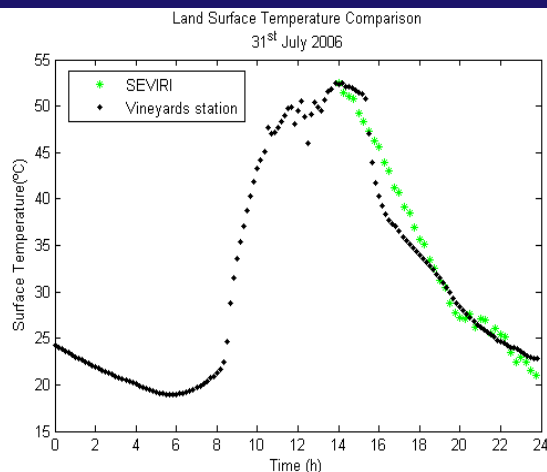
Results

Land surface temperature (LST) comparisons between SEVIRI and measured LST during 2006 field campaign in the scrubland



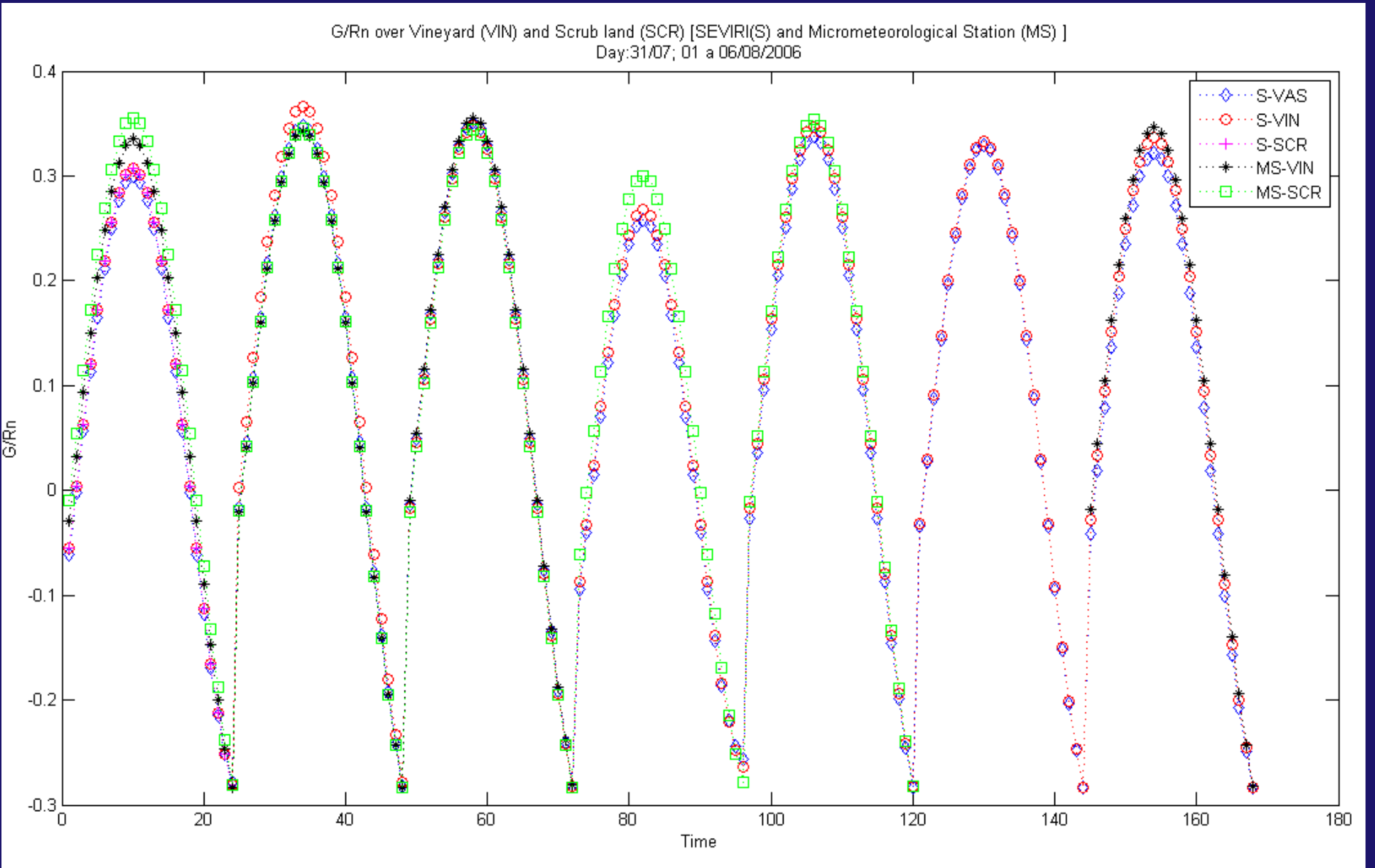
	August 01, 2006	August 04, 2006
avg	31.9 °C (S) / 30.2 °C (MS)	28.7 °C (S) / 27.8 °C (MS)
std	12.9 (S) / 12.5 (MS)	12.2 (S) / 12.8 (MS)
rmse	2.9 °C	3.8 °C

Land surface temperature (LST) comparisons between SEVIRI and measured LST in vineyards (2006)



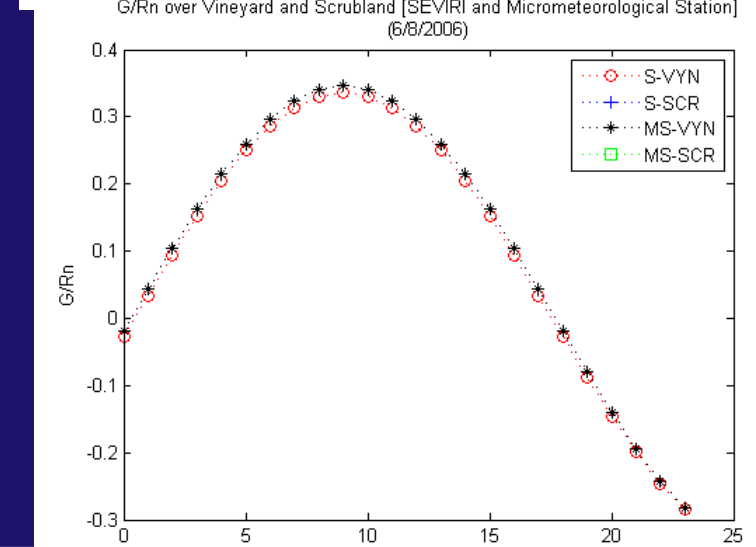
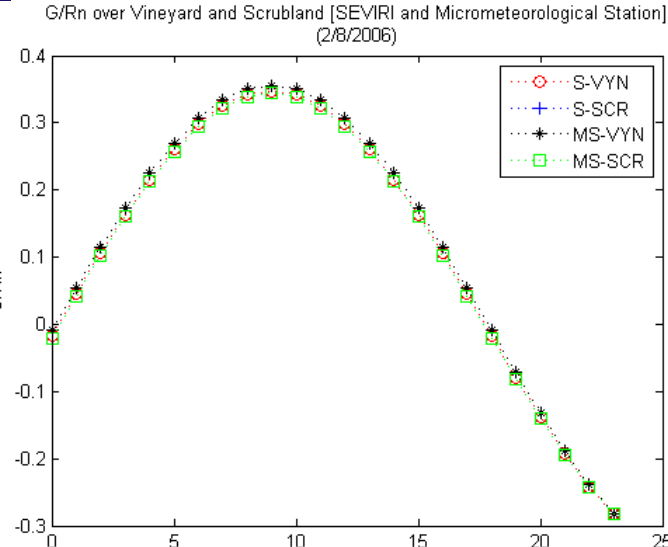
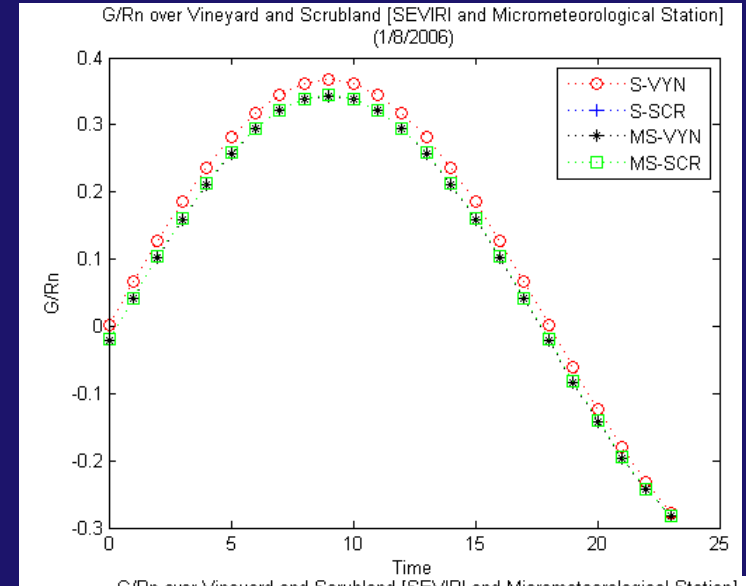
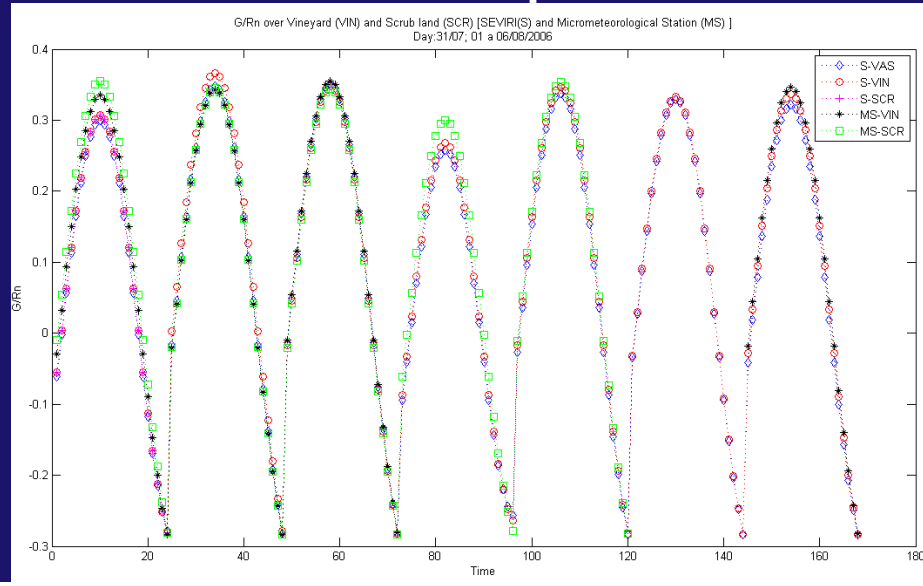
	31 th July 2006	1 st August 2006	2 nd August 2006
RMSE (°C)	2	3	3

G/Rn comparisons between SEVIRI and measured LST



RESULTS

G/Rn comparisons between SEVIRI and measured LST



	August 01, 2006	August 02, 2006
avg	0.14 (S) / 0.12 (MS)	0.12 (S) / 0.12 (MS)
std	0.2 (S) / 0.2 (MS)	0.2 (S) / 0.2 (MS)
rmse	0.02	0.008

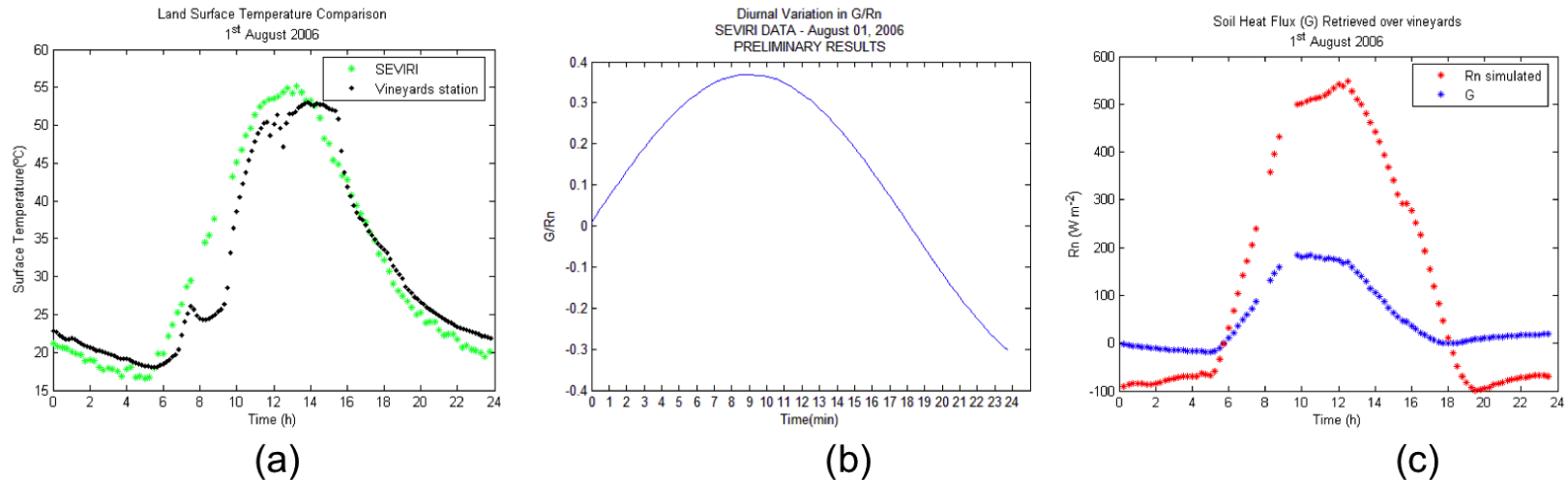
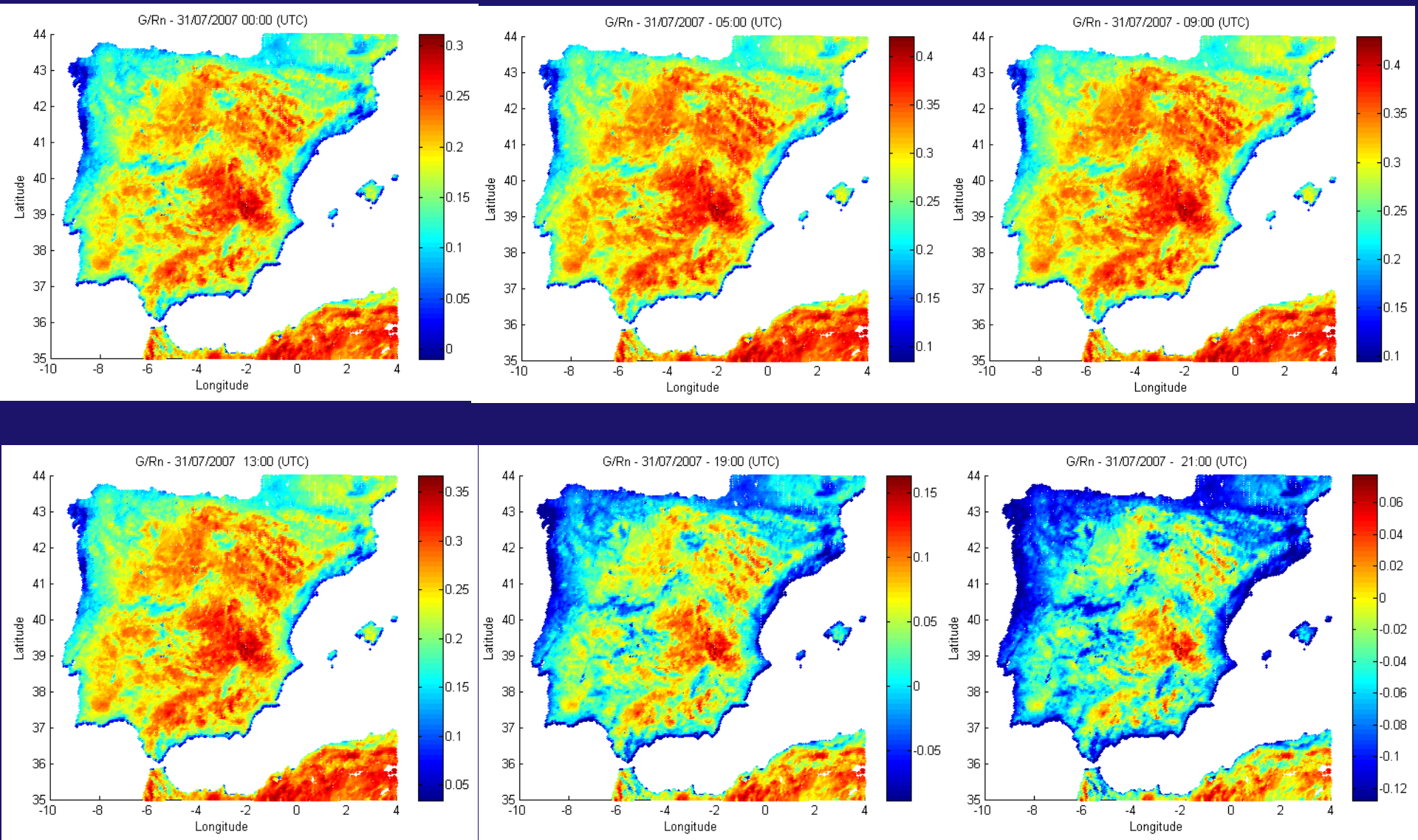


Figura 3. (a) Comparación entre la LST de SEVIRI y la de la estación micrometeorológica para el día 01/08/2006, (b) G/Rn simulado utilizando LST de SEVIRI, y (c), G estimado utilizando GERB_Rn simulado.

G/Rn from SEVIRI



CONCLUSIONS AND FUTURE WORK

- ◆ For the studied cases (July 31, August 1 and 2, 2006) the LST comparison between SEVIRI and ground measurements, over a vineyard, show a good agreement (RMSE = 2, 3 and 3 °C, respectively).
- ◆ From this preliminary study it is possible to visualize the possibility to use the synergy between GERB and SEVIRI in order to derive R_n , and consequently G at local or regional scales.

FUTURE WORK

Use of LST from SEVIRI in the simulations to extend the methodology to wider areas .

We try now to extend and extrapolate these G estimations to larger areas, at satellite observation scales, to provide reliable estimations of G , directly derived from net radiation measurements, at adequate regional scales.

This extension of the methodology to remote sensing data is being carried out through the application of the synergy between GERB (Geostationary Earth Radiation Budget) and SEVIRI (Spinning Enhanced Visible and Infrared Imager) data to provide estimates of net radiation and surface temperature with a frequency of 15 min intervals