Remote Sensing Applications for Land/Atmosphere: Earth Radiation Balance

- Introduction
- 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)

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& Climatology from Satellites Group (http://nimbus.uv.es)

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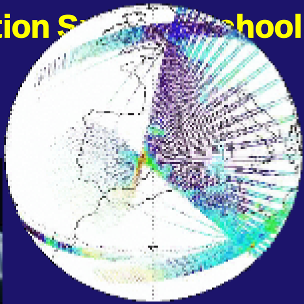
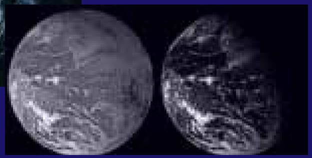
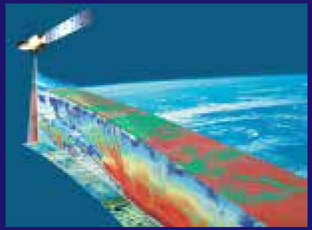
Dept of Earth Physics & Thermodynamics

Space Missions where we are implied

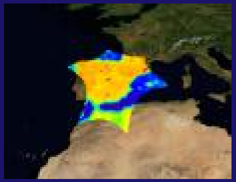




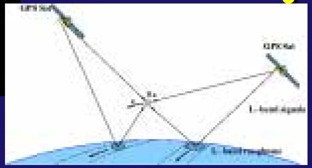
- **CERES (*Clouds and the Earth's Radiant Energy System*) NASA**
- **GERB (*Geostationary Earth radiation Budget*) EUMETSAT**



- **EarthCARE (*Earth Clouds, Aerosols and Radiation Explorer*) ESA/JAXA**



- **SMOS (*Soil Moisture and Ocean Salinity*) ESA**
- **SMAP (*Soil Moisture Active and Passive*) NASA**



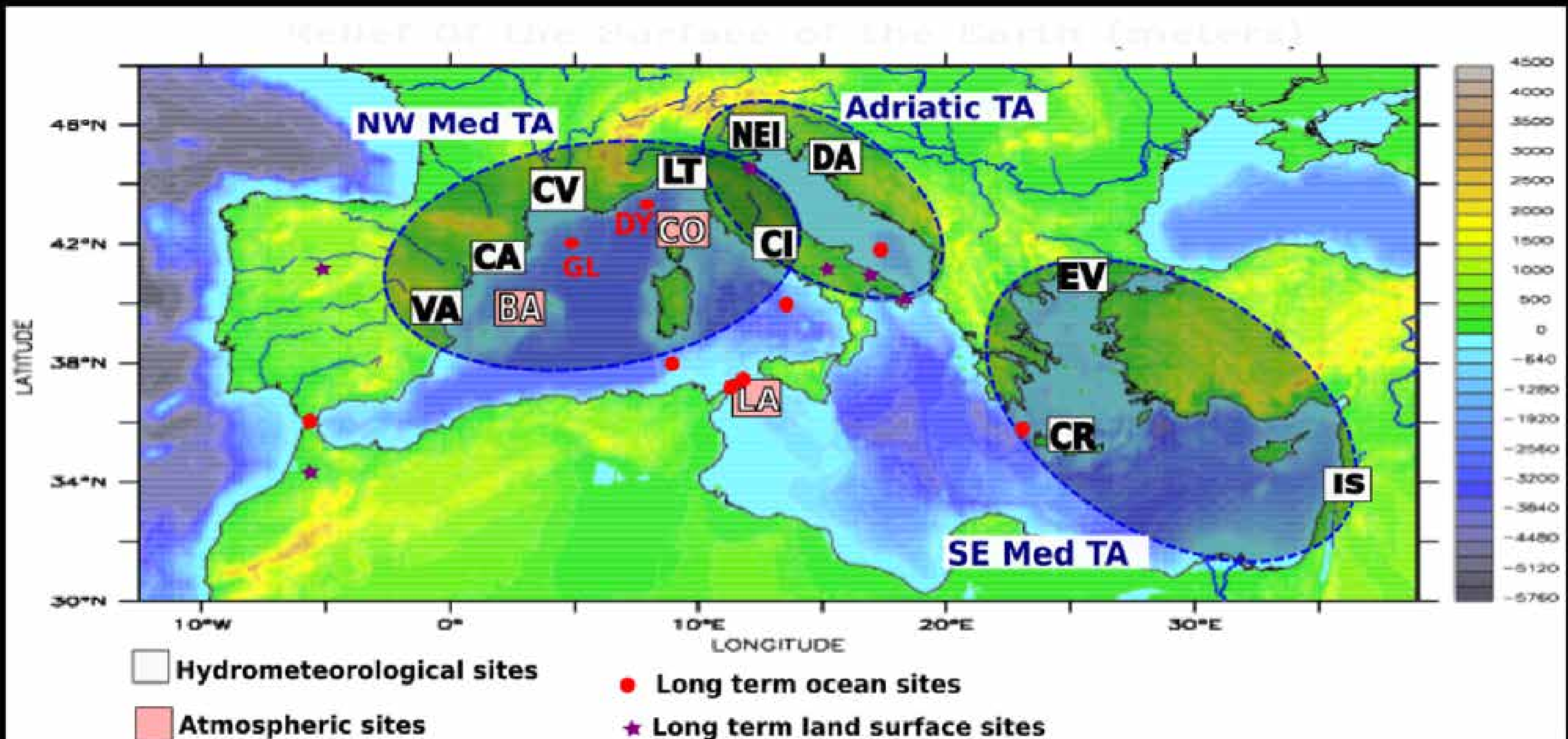
- **EPS/MetOp (*EUMETSAT Polar System*) EUMETSAT/ESA**
- **PARIS (*Passive Reflectometry and Interferometry System*) GNSS-R (*Global Navigation Satellite System - Reflectometry*) ESA**

HyMeX

Hydrological Cycle in Mediterranean Experiment

for us

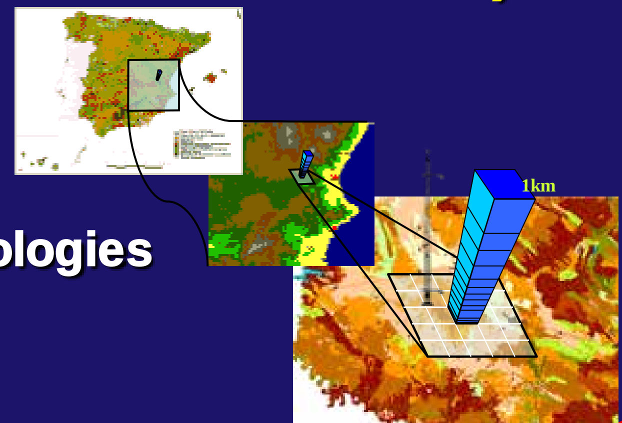
Definition of an Experimental Observatory of the Water Cycle



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!!!)



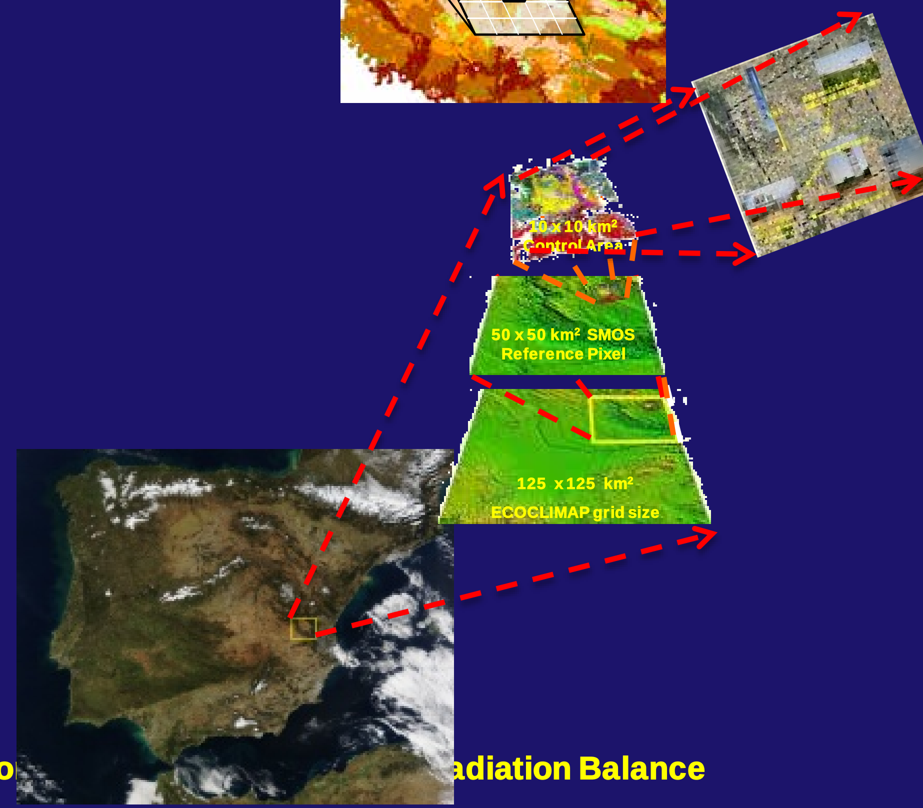
23 March 2002

The VALENCIA & ALACANT *ANCHOR STATIONS*

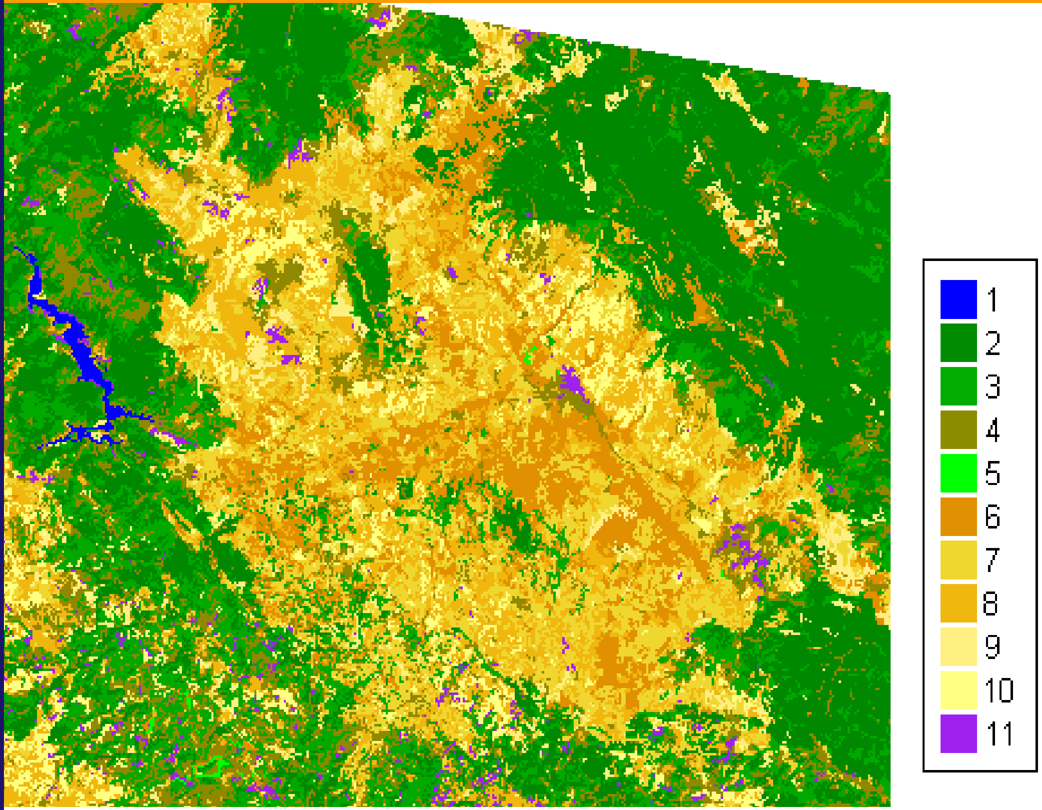
High Resolution MERIS Image.

Most suitable area in Europe

for validation of low-resolution sensors



Classified LANDSAT image (5th July 2003): 11 categories for the Valencia *Anchor Station* area (50 x 50 km^2)



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

Our Objective:

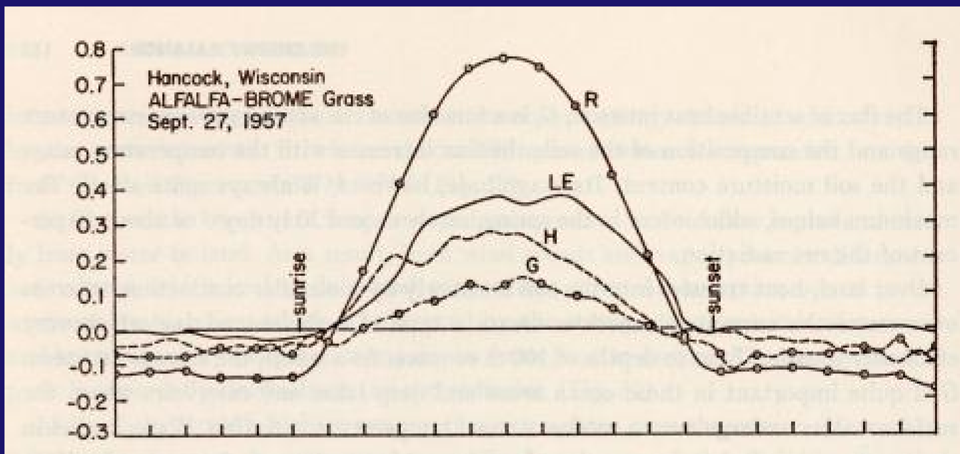
Deriving

Surface Energy Balance Fluxes

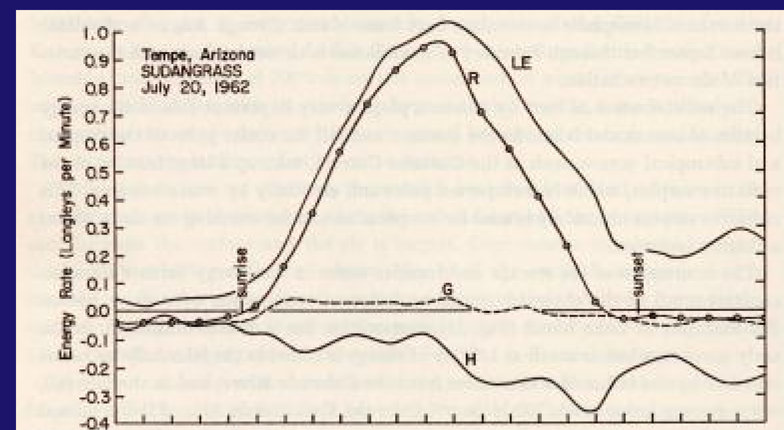
from

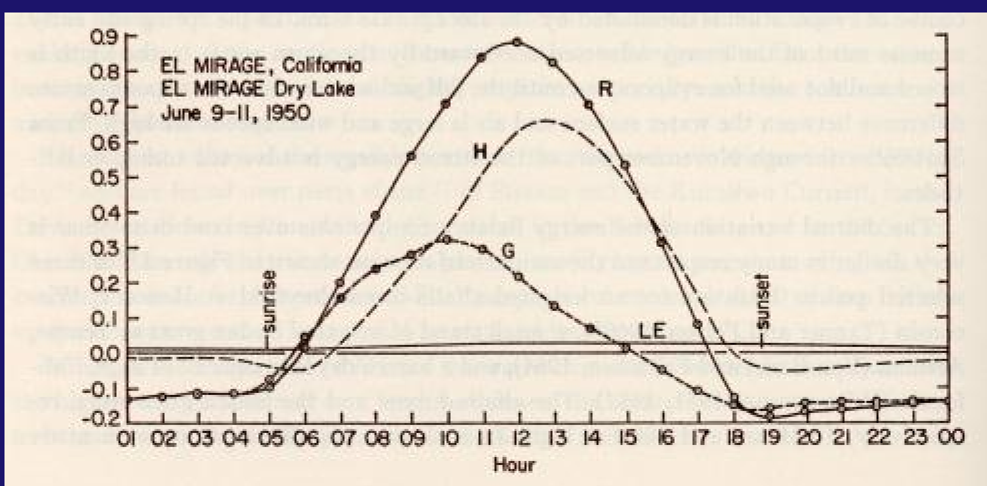
Net Radiation Measurements

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

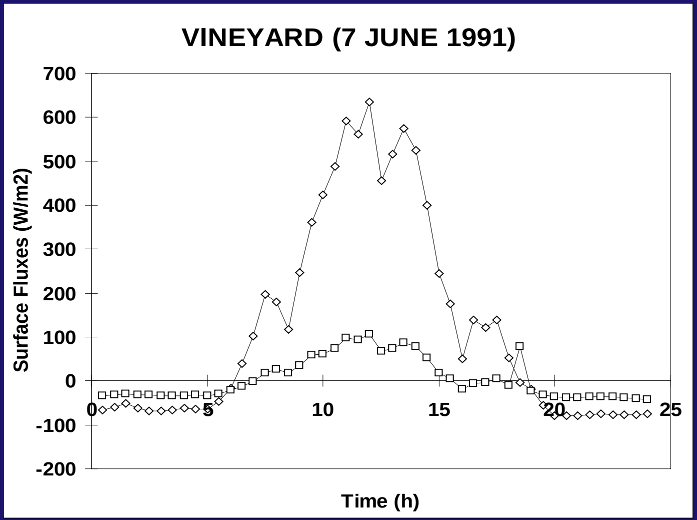


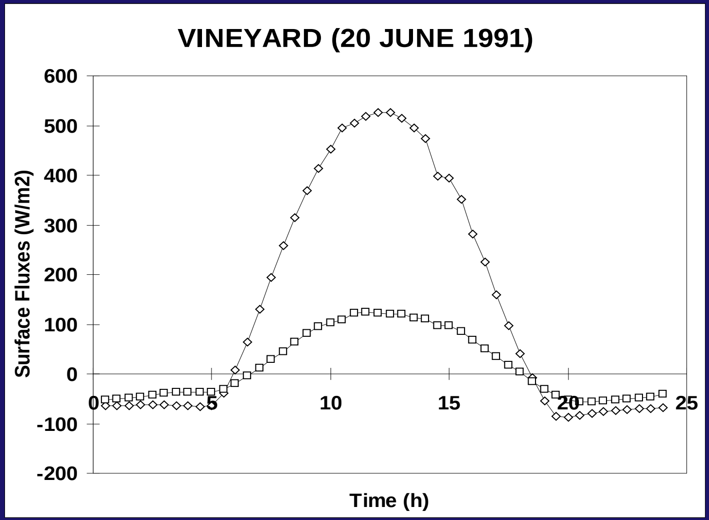
Rn = H + l E + G

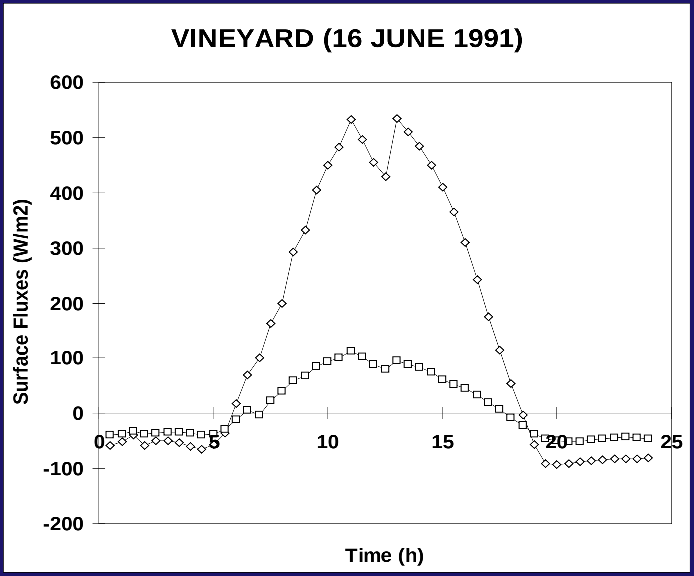


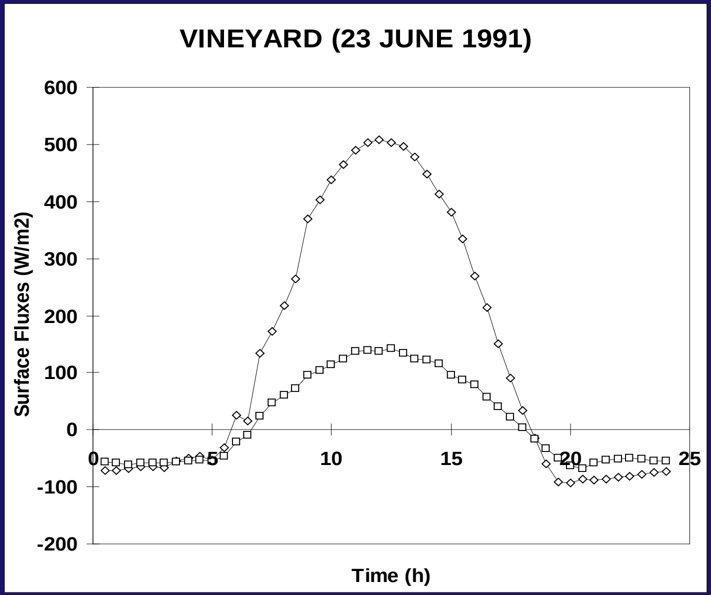


Examples of diurnal variations of Surface Net Radiation and Soil Heat Flux. (EFEDA data base)



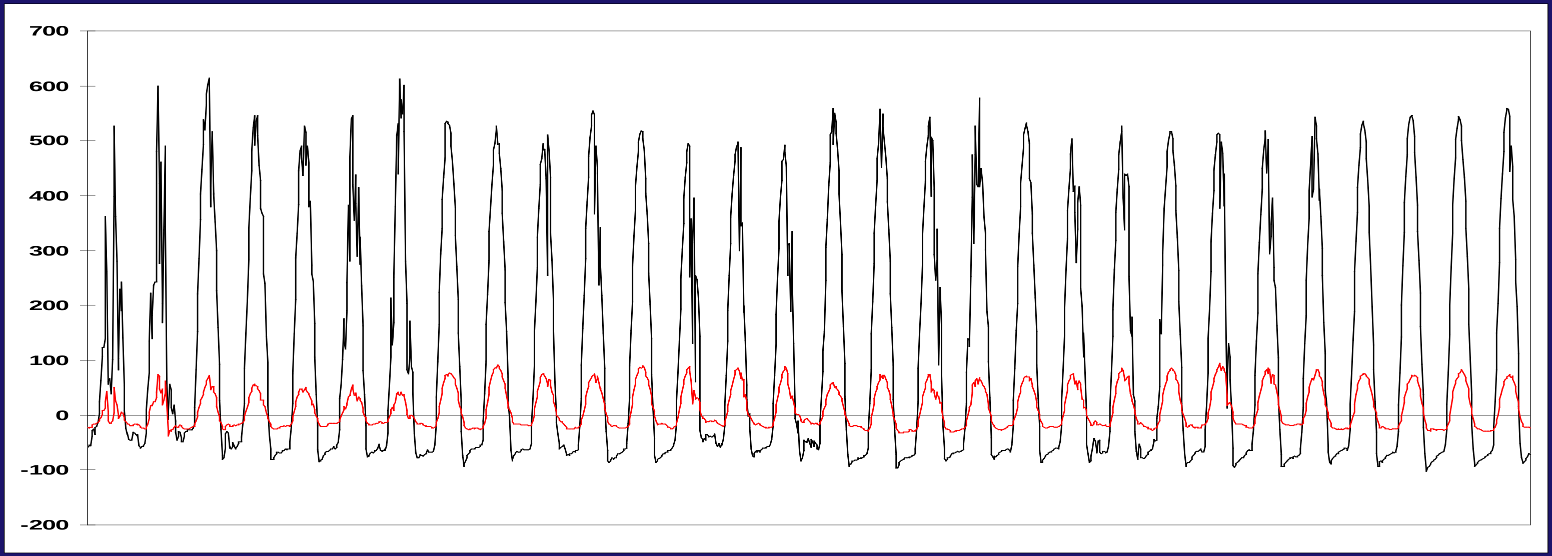


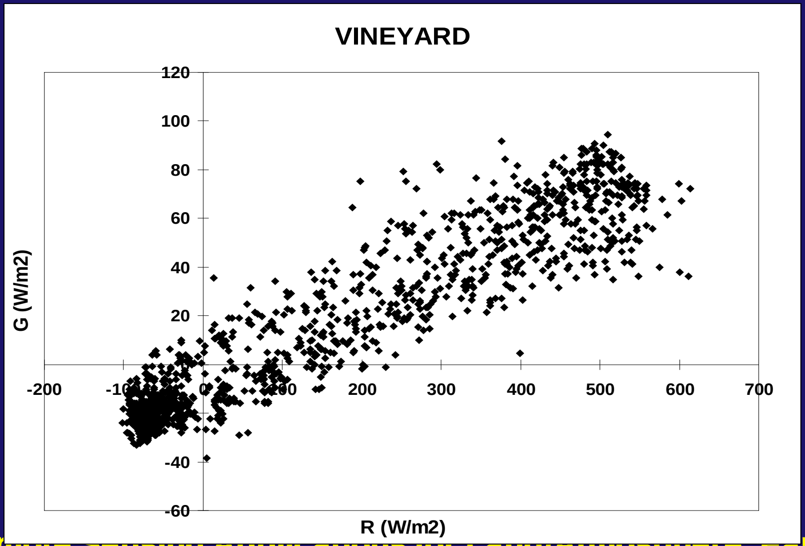




Surface Net Radiation and Soil Heat Flux

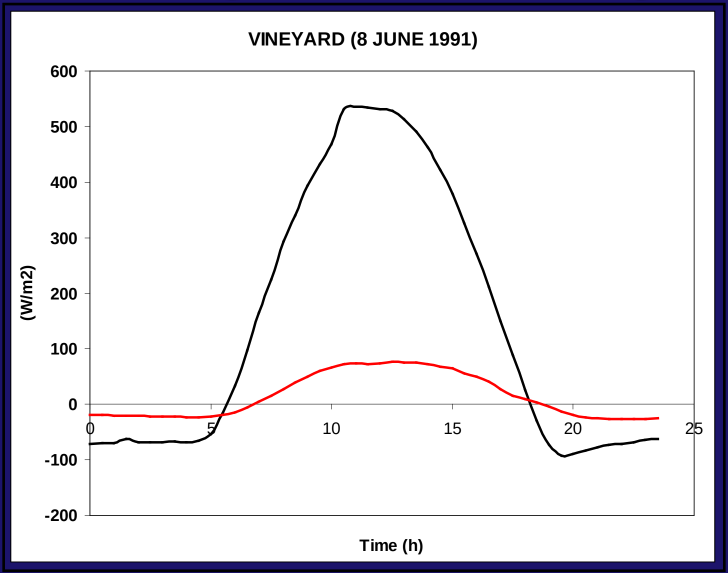
1 – 30 June 1991 (EFEDA data base)

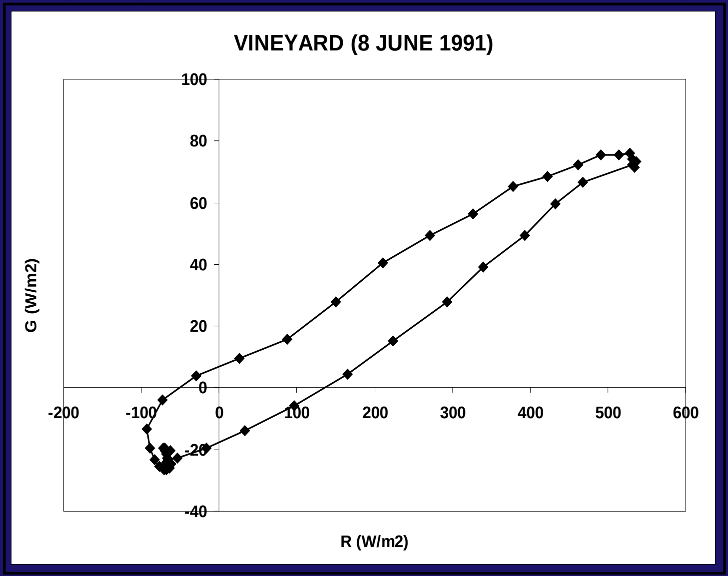


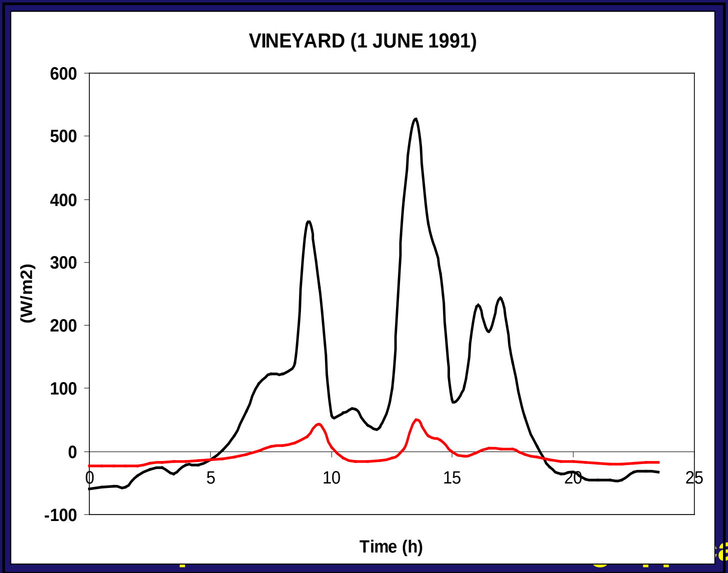


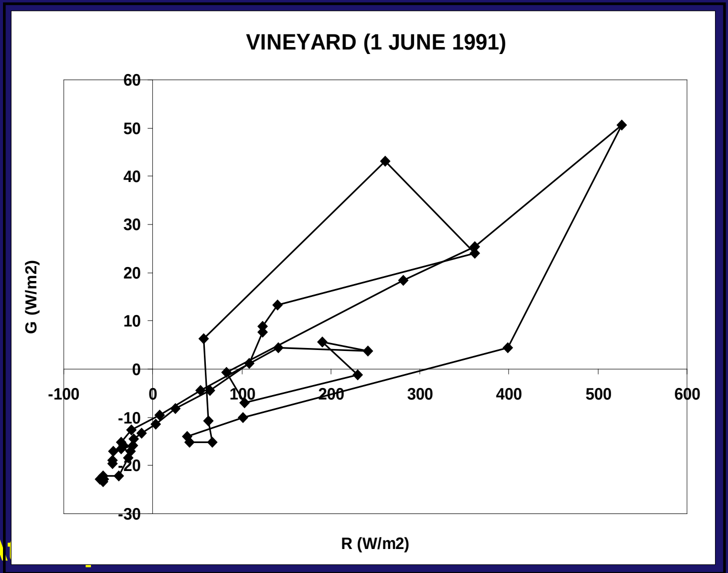
Surface Net Radiation and Soil Heat Flux

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



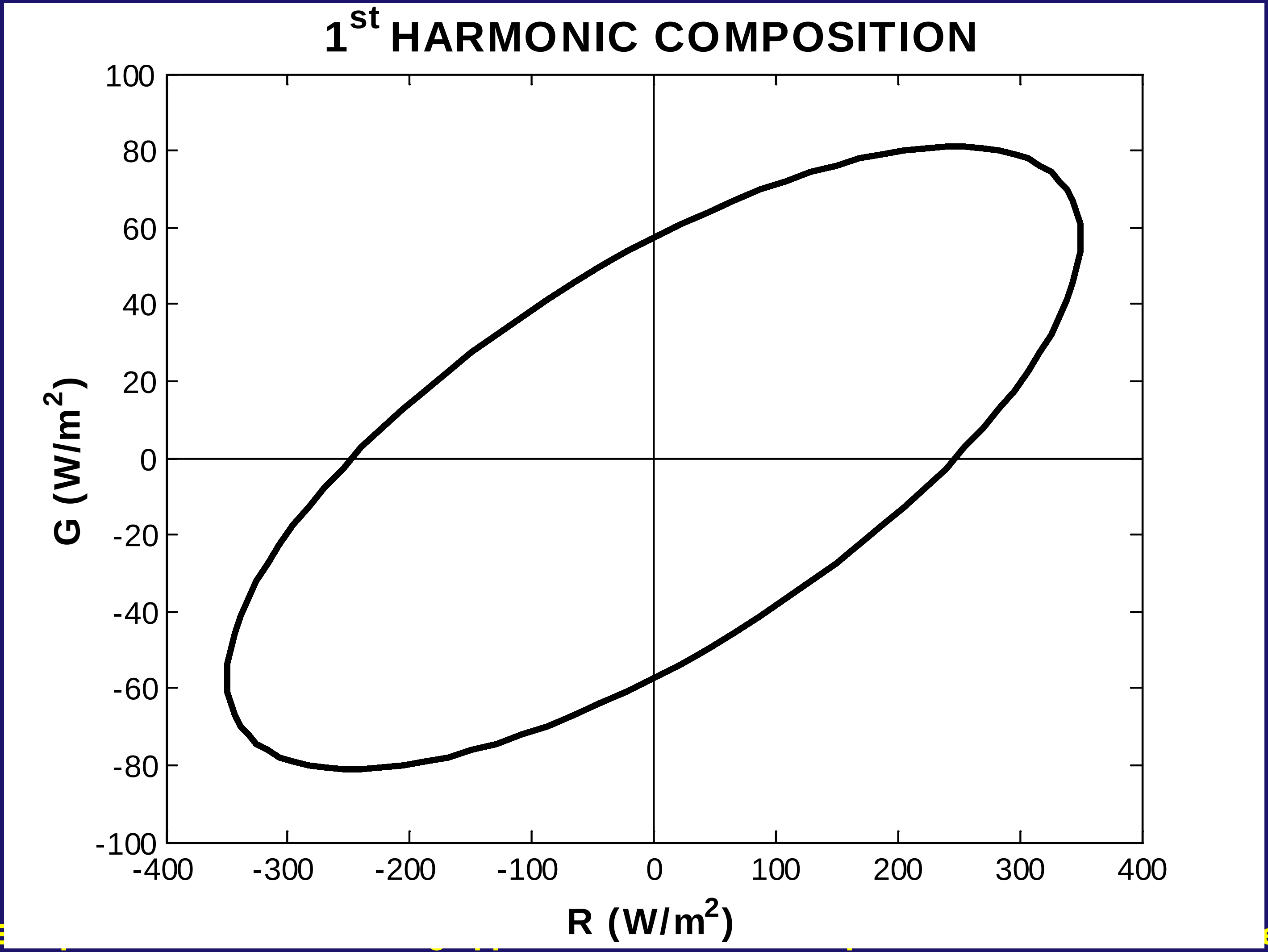






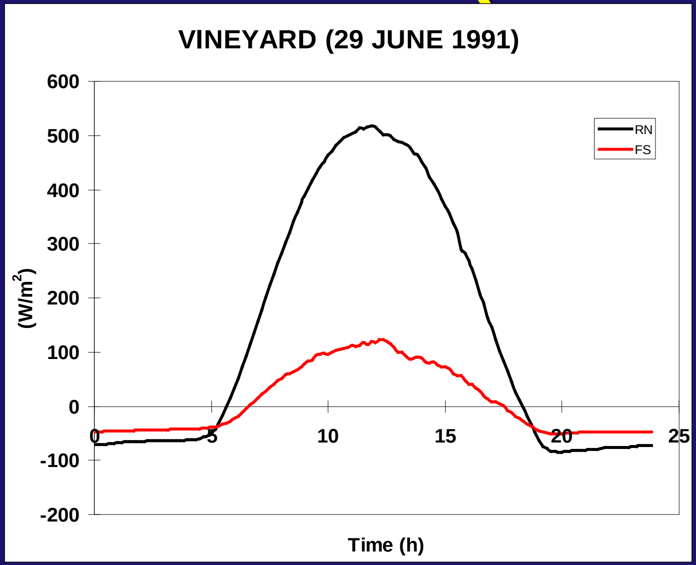
Surface Net Radiation and Soil Heat Flux

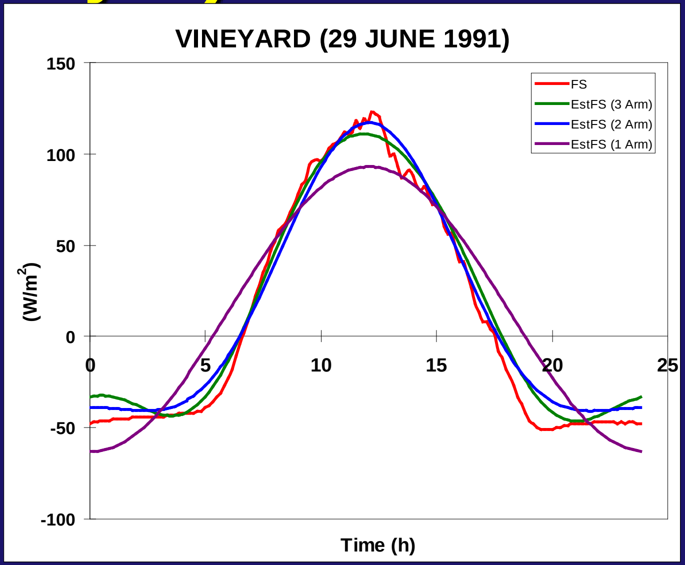
(a generic behaviour, June 1991). Basic Physics!!!

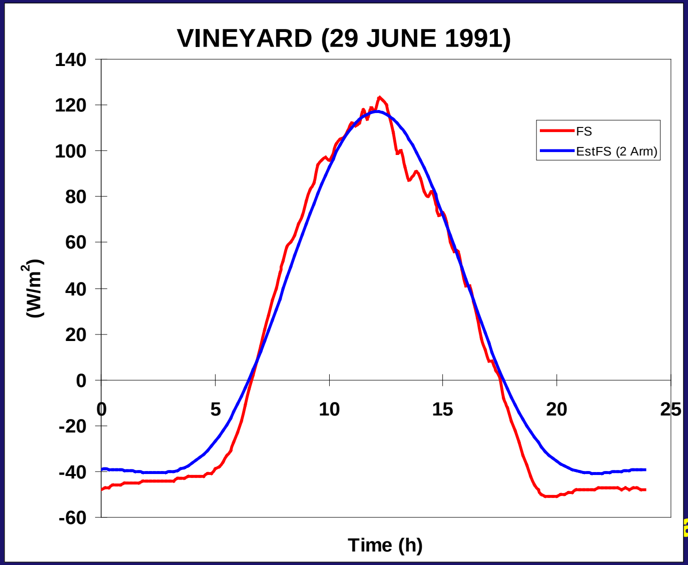


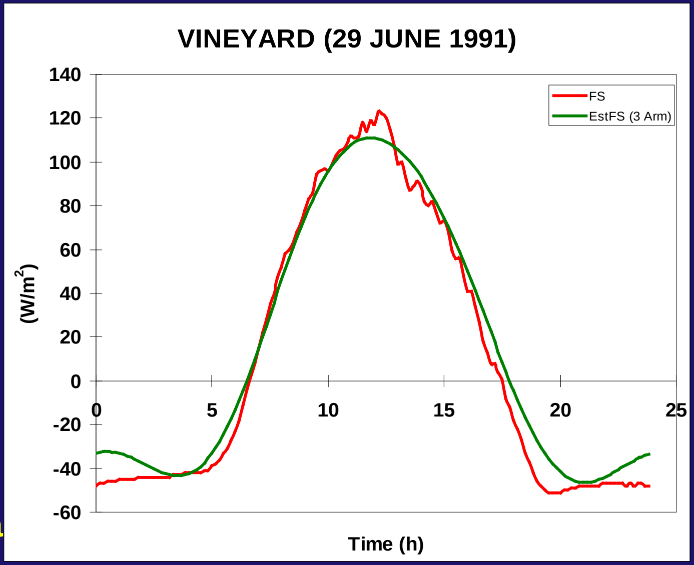
Surface Net Radiation and Soil Heat Flux

(Harmonic Analysis)









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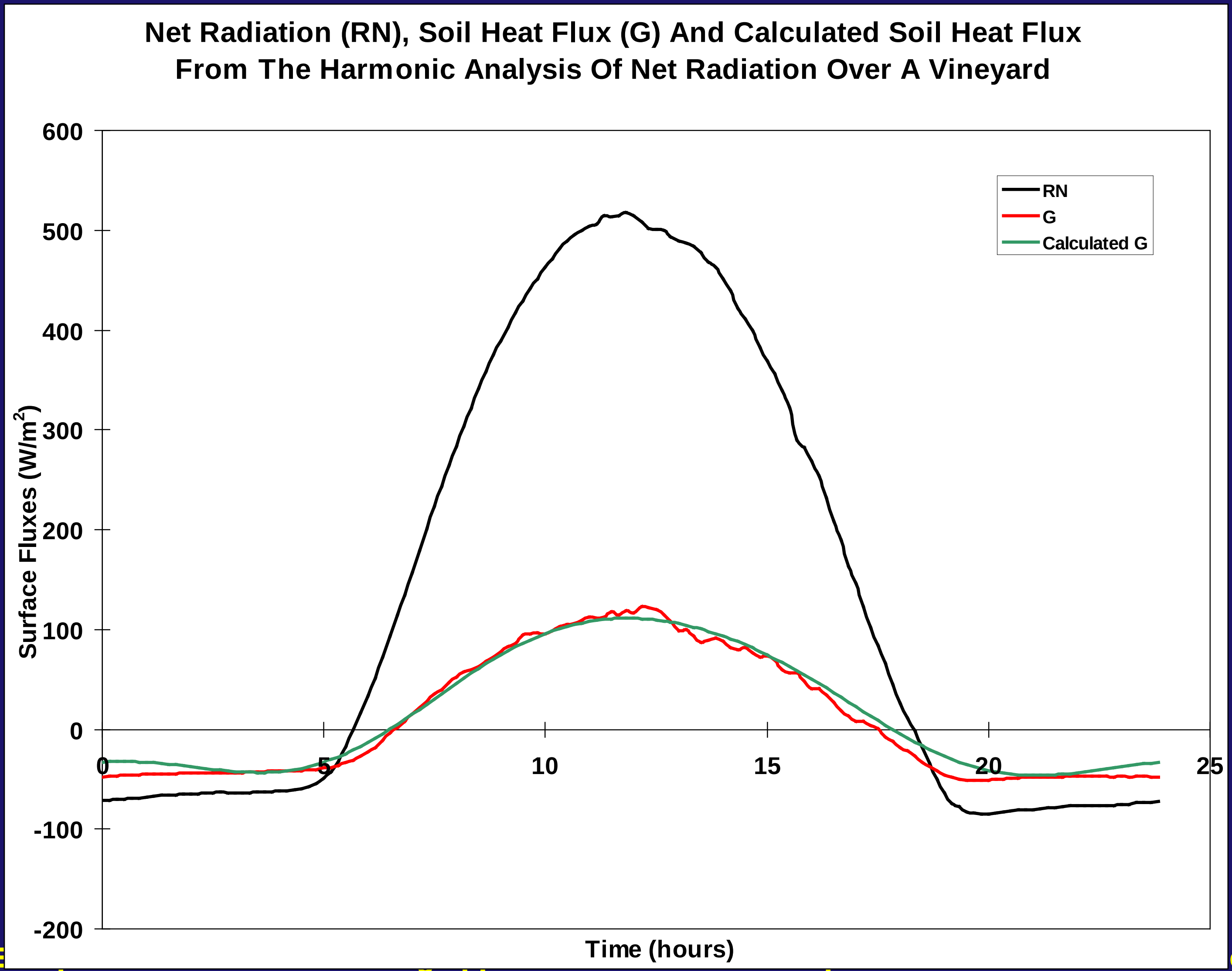
Deriving Soil Heat Flux from Surface Net Radiation



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

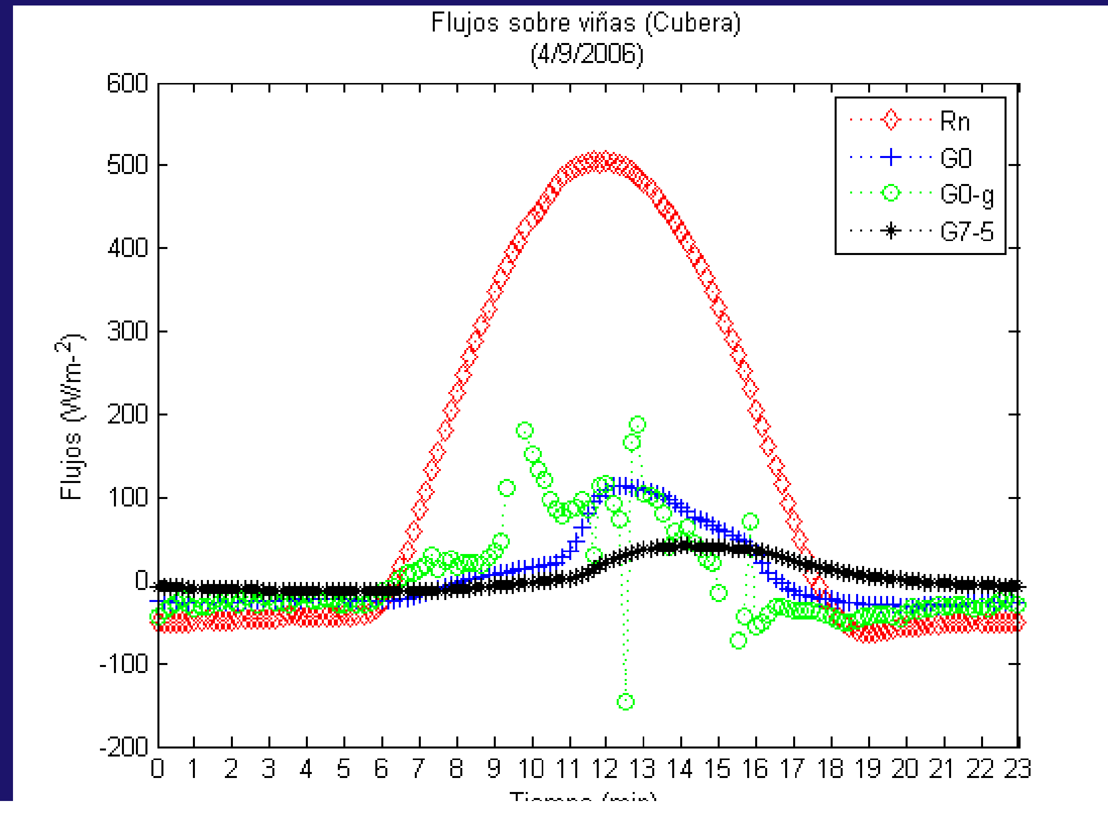
Estimation of Surface Net Radiation from Operational Meteorological Measurements

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 *Rn* at the surface using meteorological variables operationally measured at conventional meteorological stations



Using artificial neural networks

- **input parameters meteorological quantities**
- **output parameter "*in situ*" *Rn* measurements from pyrradiometers**

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ORIGINAL PAPER

Estimating net radiation at surface using artificial neural networks: a new approach

Antonio Geraldo Ferreira & Emilio Soria-Olivas &
Antonio José Serrano López & Ernesto Lopez-Baeza

Field Campaigns and Data Sets

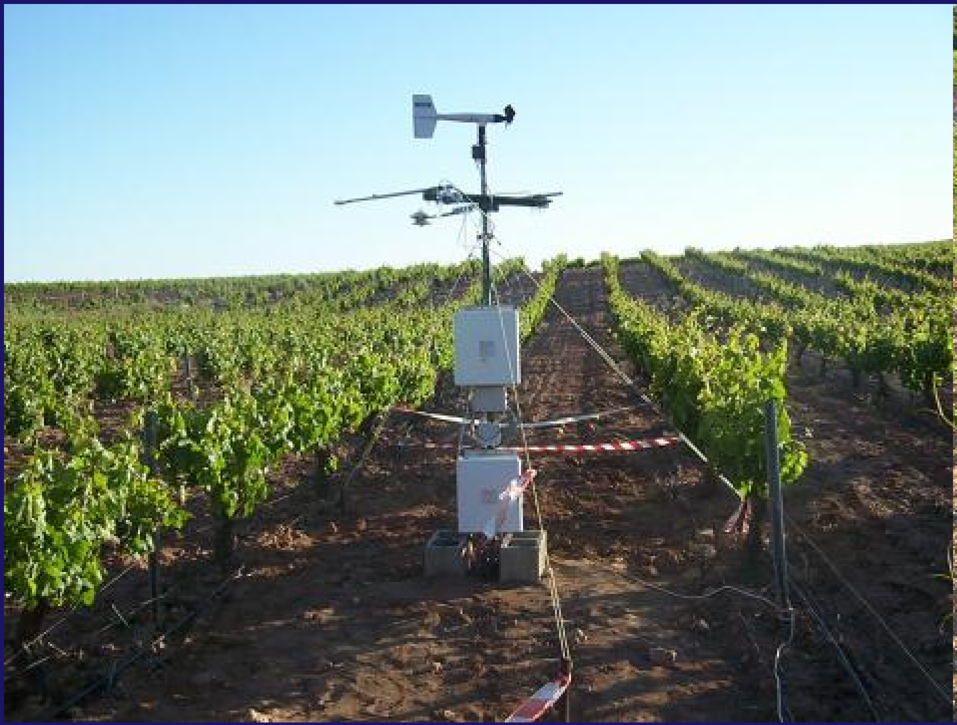
vineyards & bare soil

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

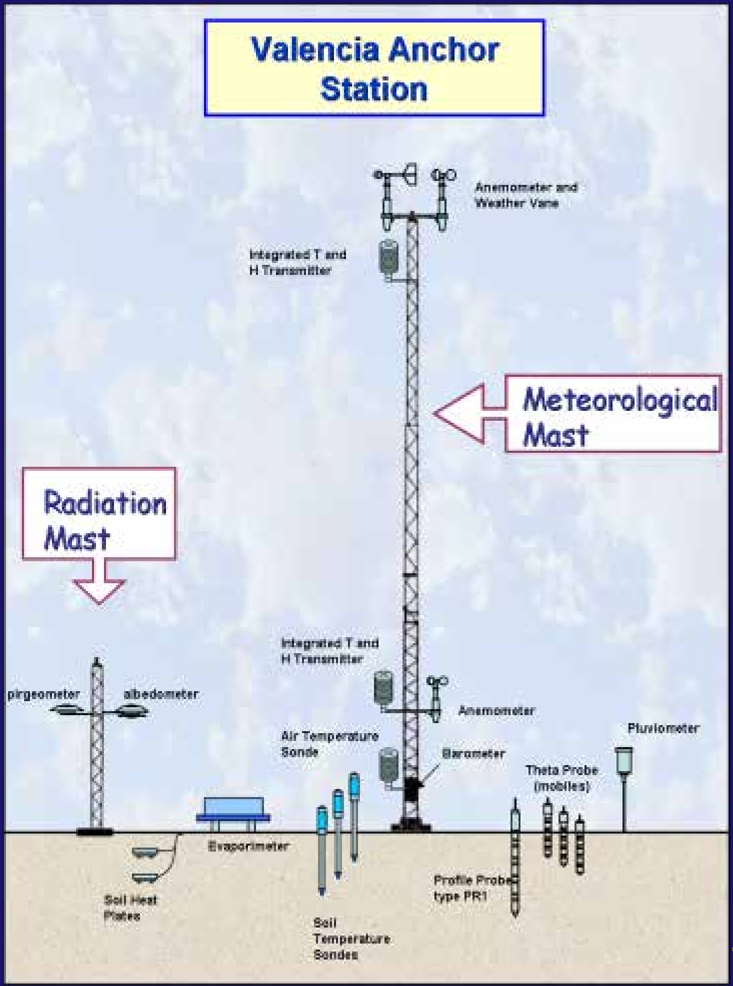
matorral

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**



for L

Table 1

Basic statistic of FESEBAV and VAS data sets. WS: Wind speed; AT: air temperature; AP: atmospheric pressure; RH: relative humidity; RN: net radiation.

	WS (m/s)	AT (°C)	AP (mb)	RH (%)	RN (W/m^2)
FESEBAV (N = 13,248)					
Maximum	5.05	40.05	937.00	99.30	741.30
Minimum	0.00	8.82	916.00	6.89	−73.30
Mean	1.21	21.99	926.12	54.74	144.94
Standard deviation	0.73	6.57	3.77	25.8	213.24
VAS (N = 23,616)					
Maximum	8.30	36.50	938.00	95.00	1011.15
Minimum	0.00	4.00	914.00	8.00	−114.2
Mean	1.90	19.50	925.44	53.89	136.36
Standard deviation	1.42	6.07	4.06	21.78	244.34

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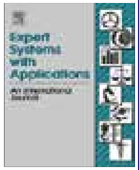


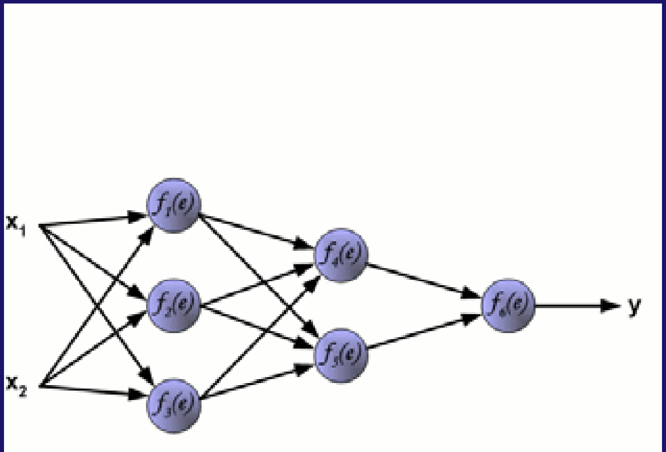
Modelling net radiation at surface using "*in situ*" netpyrradiometer measurements with artificial neural networks ☆

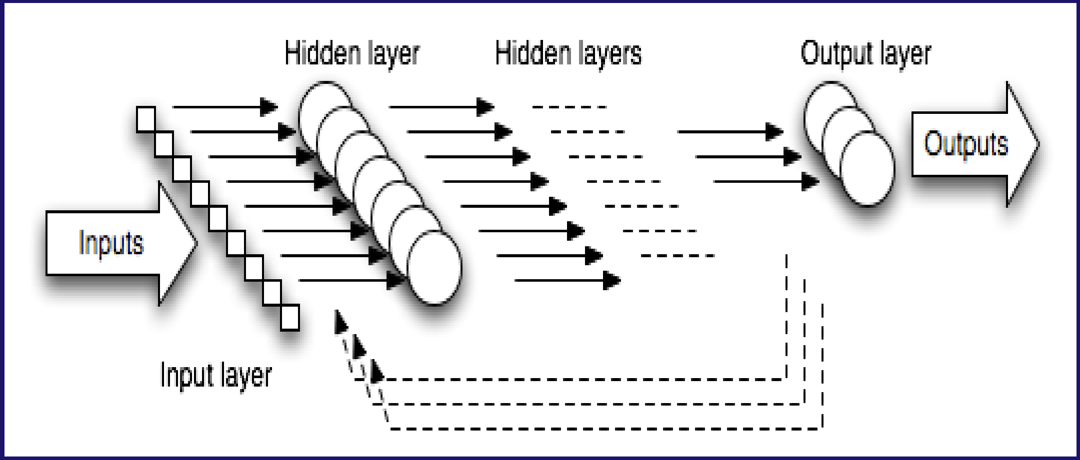
Antonio Geraldo-Ferreira [a,b], Emilio Soria-Olivas [c], Juan Gómez-Sanchis [c,*], Antonio José Serrano-López [c], Almudena Velázquez-Blazquez [d], Ernesto López-Baeza [b]

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.*

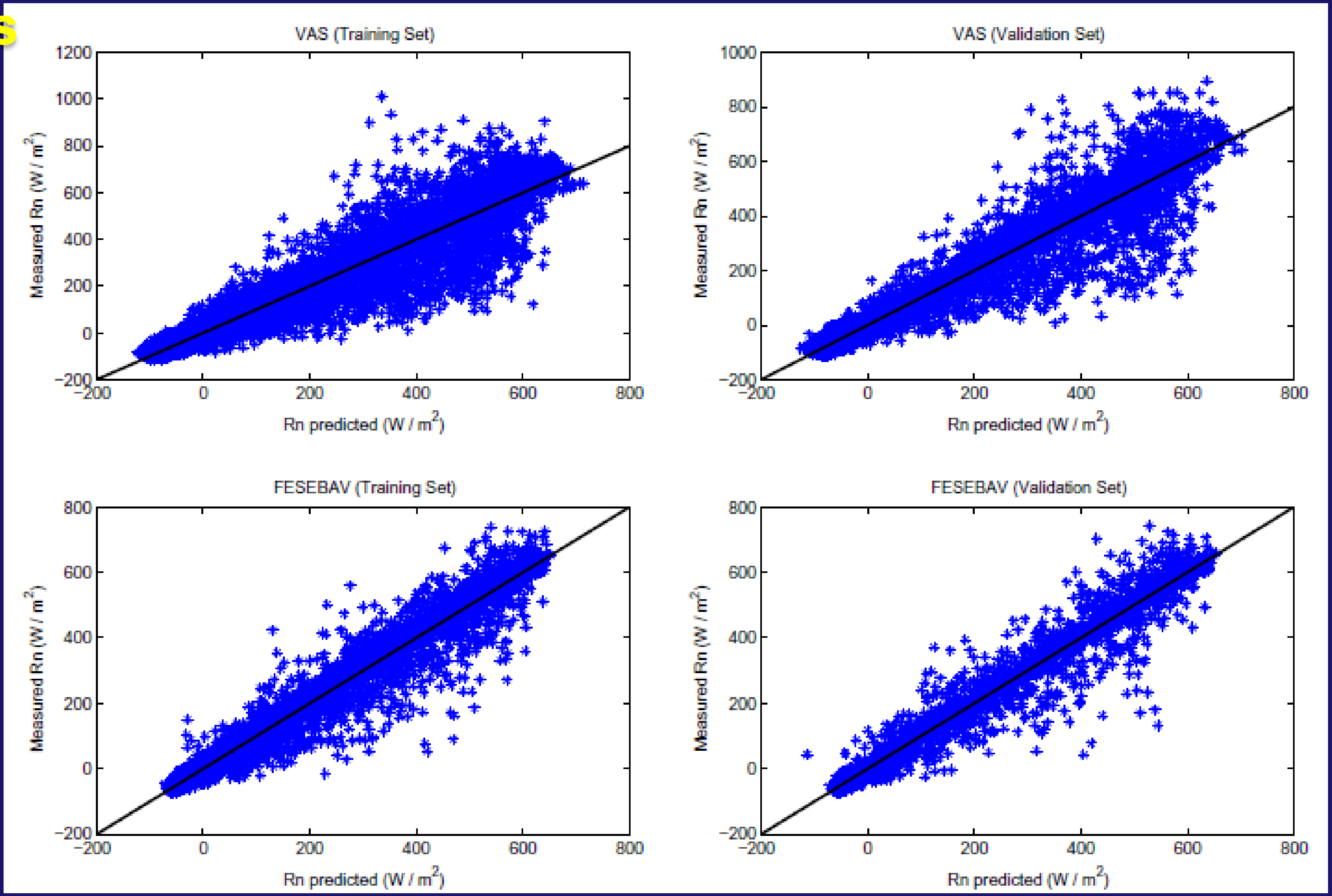
Input variables

- 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

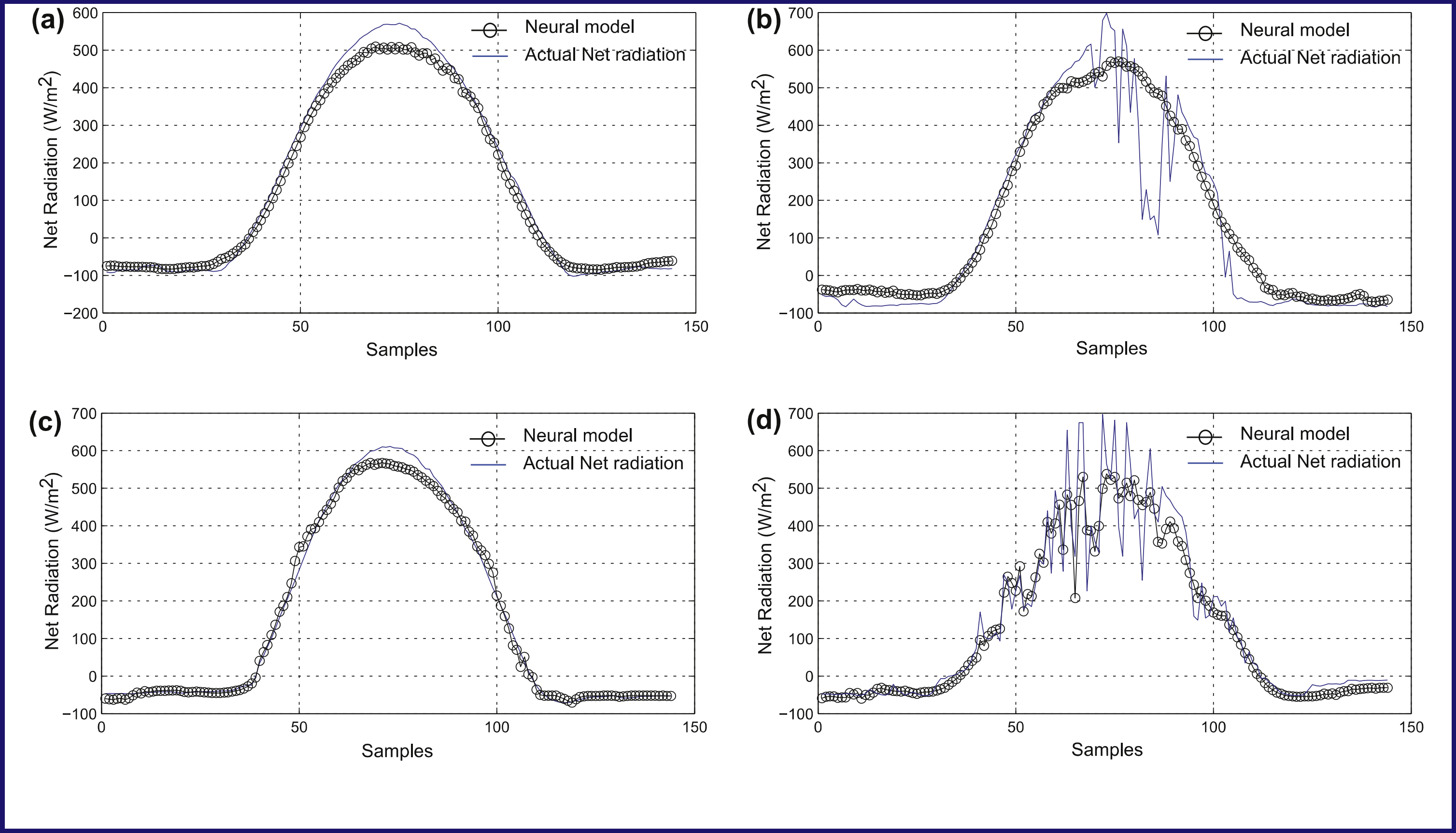
Results

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



Results

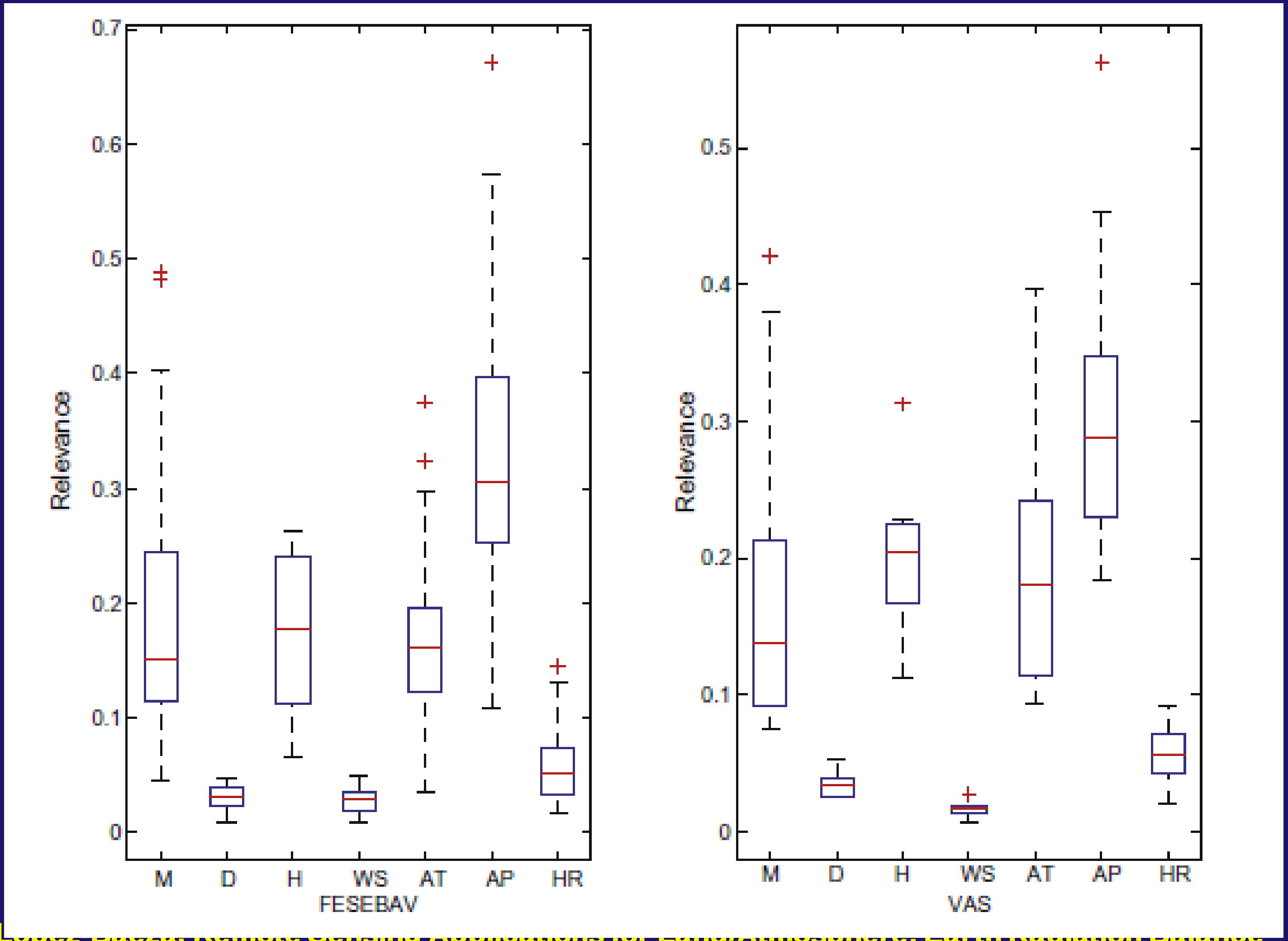
Performance indices in sunny/cloudy days.

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

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 GERB 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)

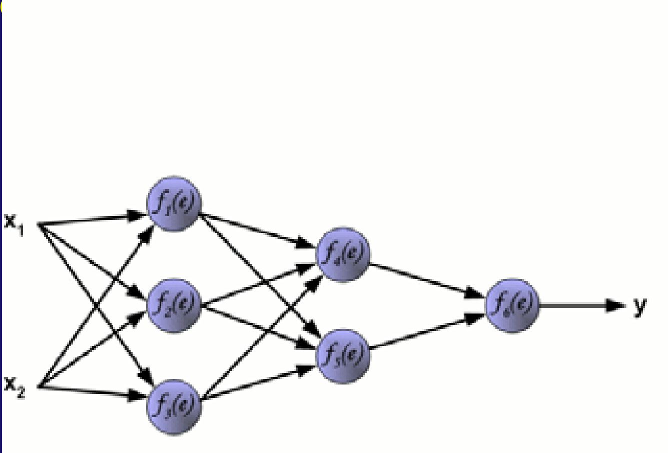
Data used

Input variables	Output variable

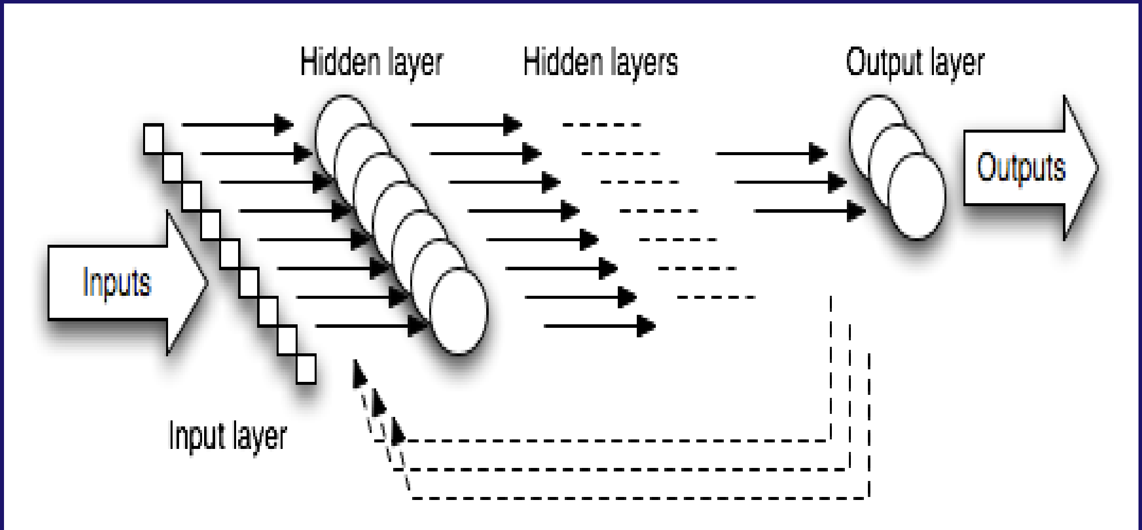
• GERB (Geostationary Earth Radiation Budget) TOA fluxes
  • TOT Channel [0.32 μm - 100.0 μm]
  • SW Channel [0.32 μm to 4.0 μm])
  • LW = TOT – SW
	• **net radiation** measured at the surface
	  • Valencia Anchor Station (bare soil)
	    • 31st July – 6th August, 2006 & 19th June – 18th August 2007
	  • 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

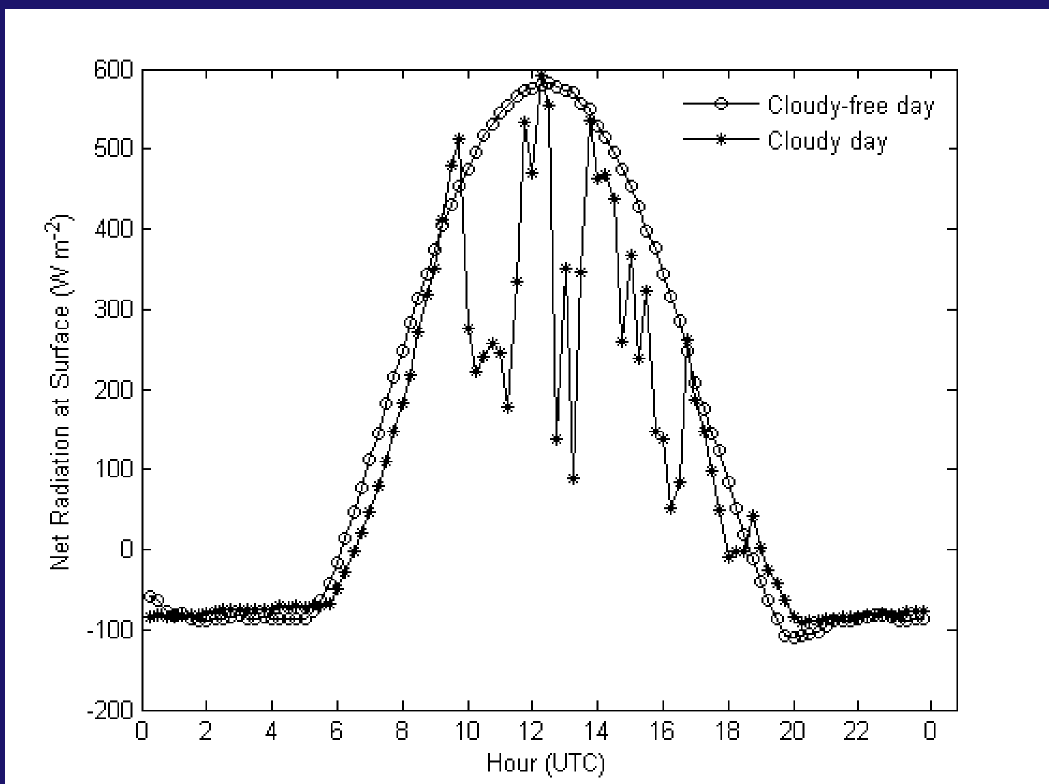


Figure shows the diurnal course of R_N for two typical days with and without clouds. The diurnal cycle of R_N in cloudy-free days shows a regular form but it is irregular in cloudy days.

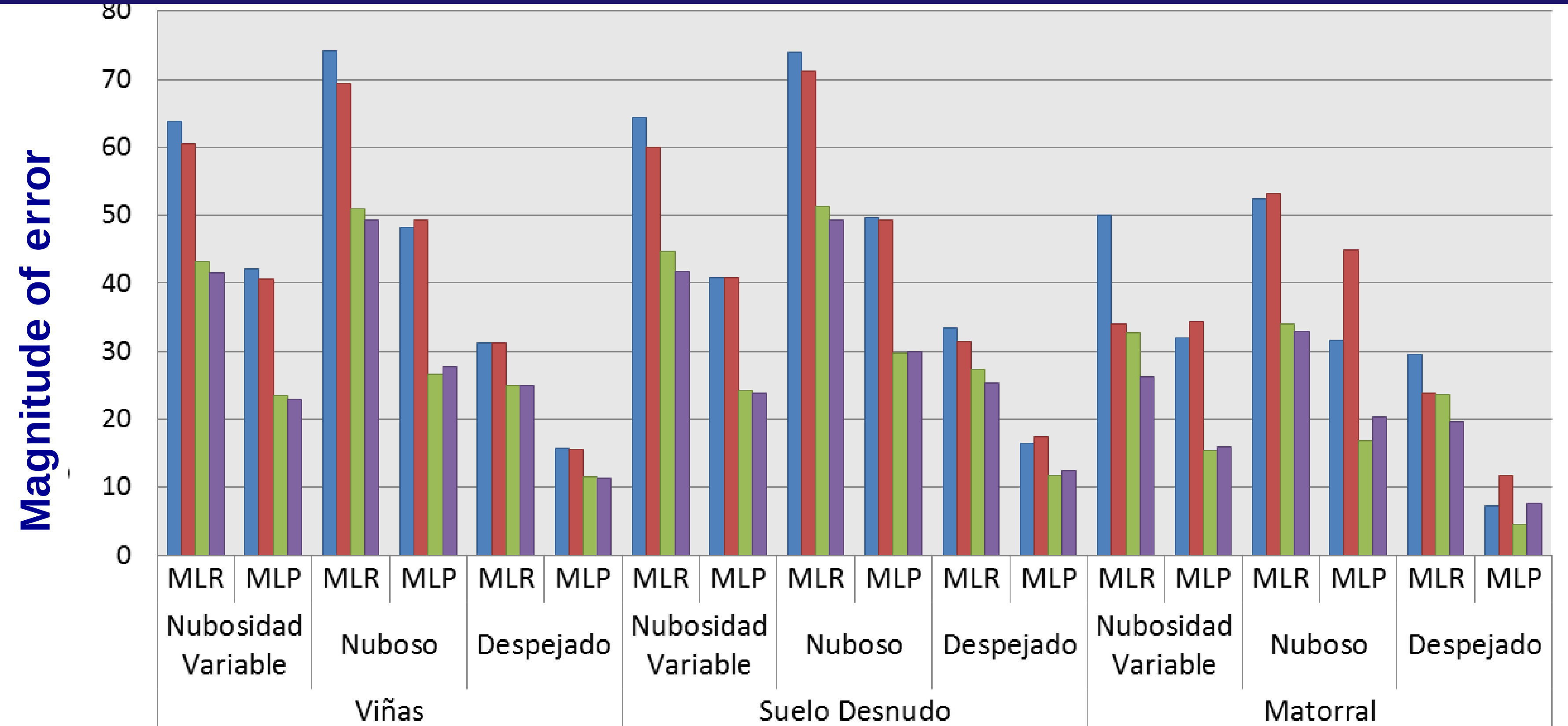
Observed diurnal course of net radiation at VAS for two different days: 22nd July (cloudy day) and 12th August,2007 (cloudy-free day)

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
SCRURB	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



	Viñas						Suelo Desnudo						Matorral					
	Nubosidad Variable		Nuboso		Despejado		Nubosidad Variable		Nuboso		Despejado		Nubosidad Variable		Nuboso		Despejado	
	MLR	MLP	MLR	MLP	MLR	MLP	MLR	MLP	MLR	MLP	MLR	MLP	MLR	MLP	MLR	MLP	MLR	MLP
RMSE_entr	63,90	42,03	74,11	48,26	31,24	15,73	64,32	40,81	73,92	49,62	33,41	16,45	50,05	32,01	52,33	31,53	29,52	7,30
RMSE_valid	60,45	40,71	69,43	49,31	31,23	15,52	60,03	40,79	71,15	49,30	31,33	17,50	33,94	34,38	53,15	44,79	23,93	11,64
MAE_entr	43,16	23,48	50,90	26,64	24,90	11,58	44,61	24,22	51,39	29,84	27,40	11,74	32,70	15,41	34,04	16,81	23,70	4,54
MAE_valid	41,58	22,93	49,34	27,66	24,95	11,25	41,82	23,88	49,36	29,89	25,43	12,42	26,17	15,95	32,84	20,29	19,63	7,66

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

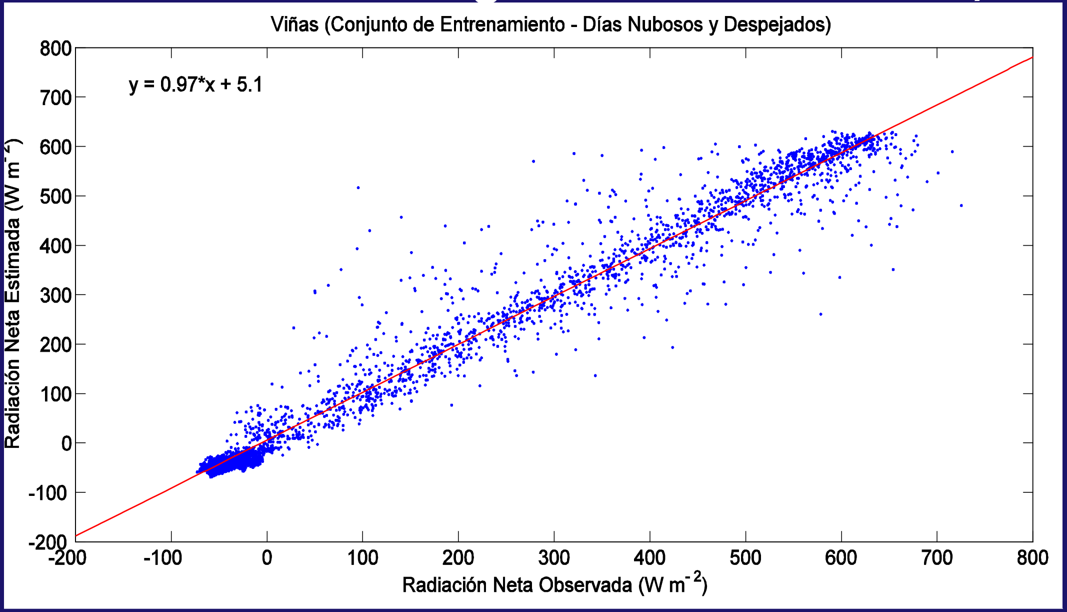
RMSE: Root mean square error; MAE: Mean Absolute Error; ME: Mean Error

Results

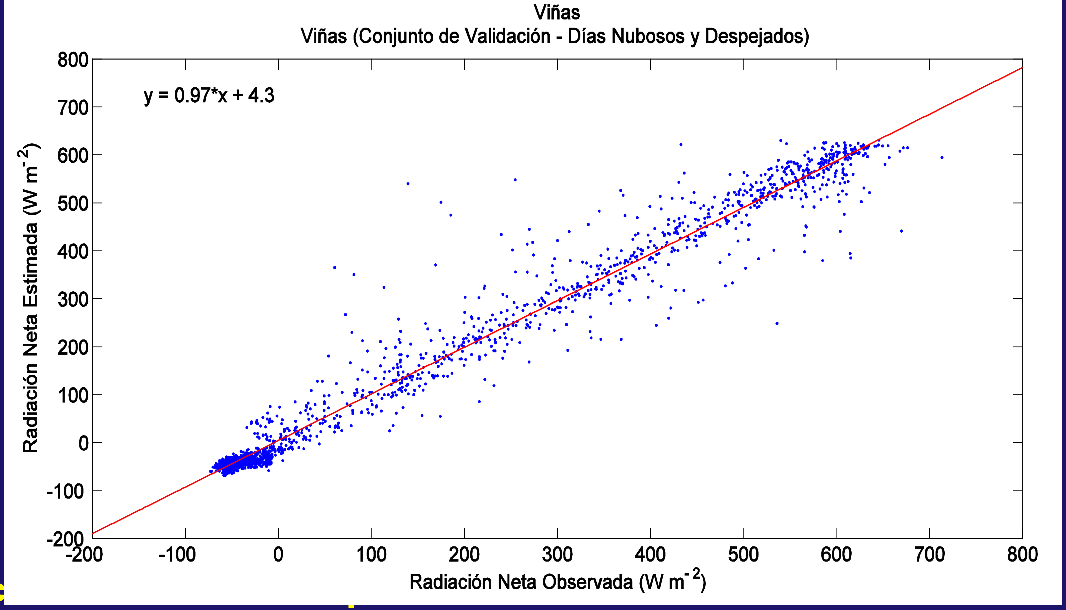
Scatter plots between R_N estimated by MLP and R_N measured in situ for training and validation set, considering:

Land use: Vineyards

All-sky conditions



Training set



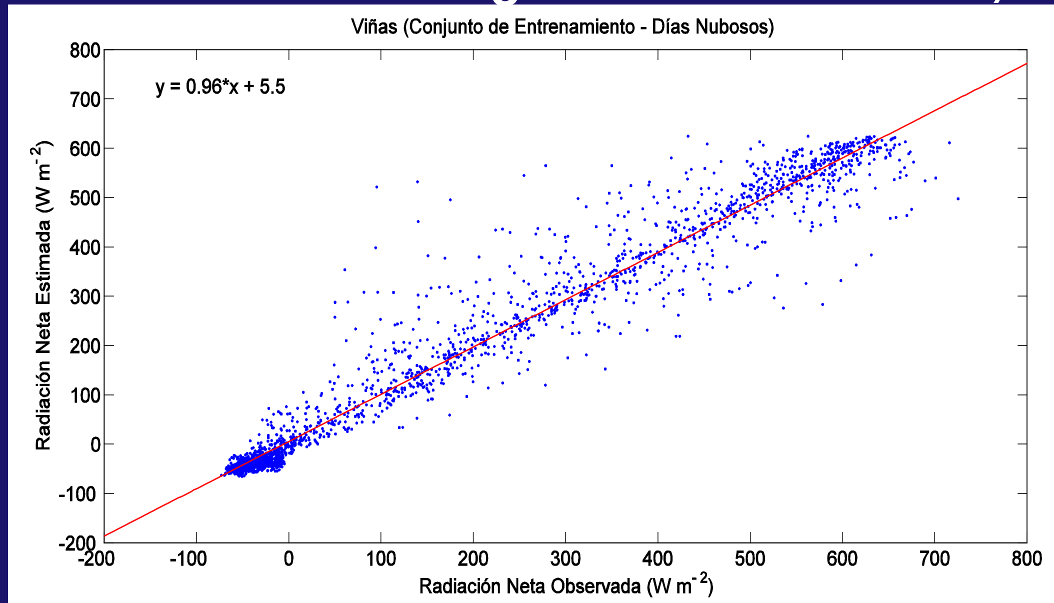
Validation set

Results

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

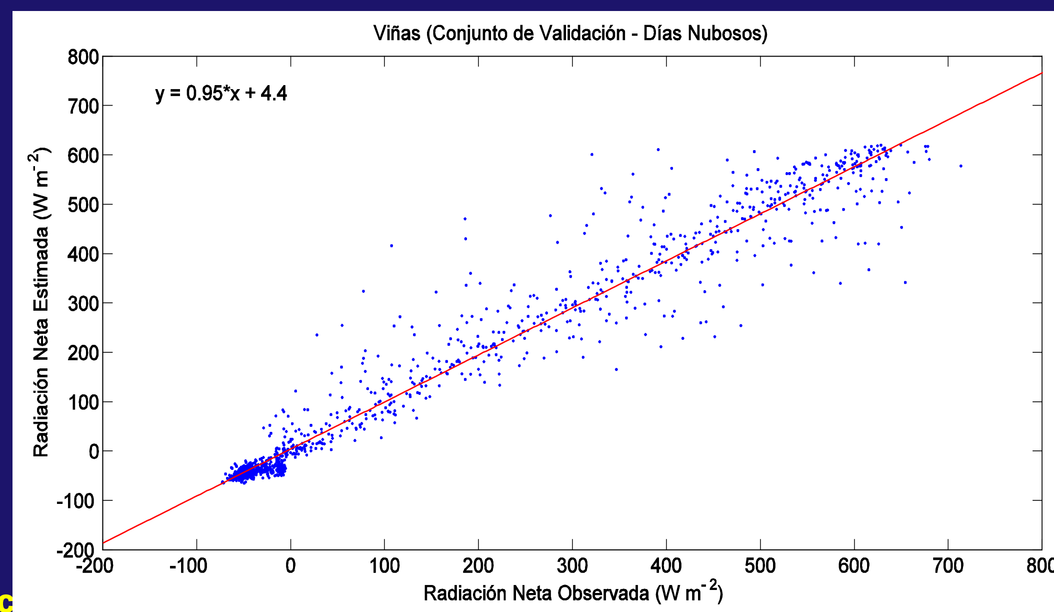
Land use: Vineyards

Cloudy conditions



Training set

Validation set

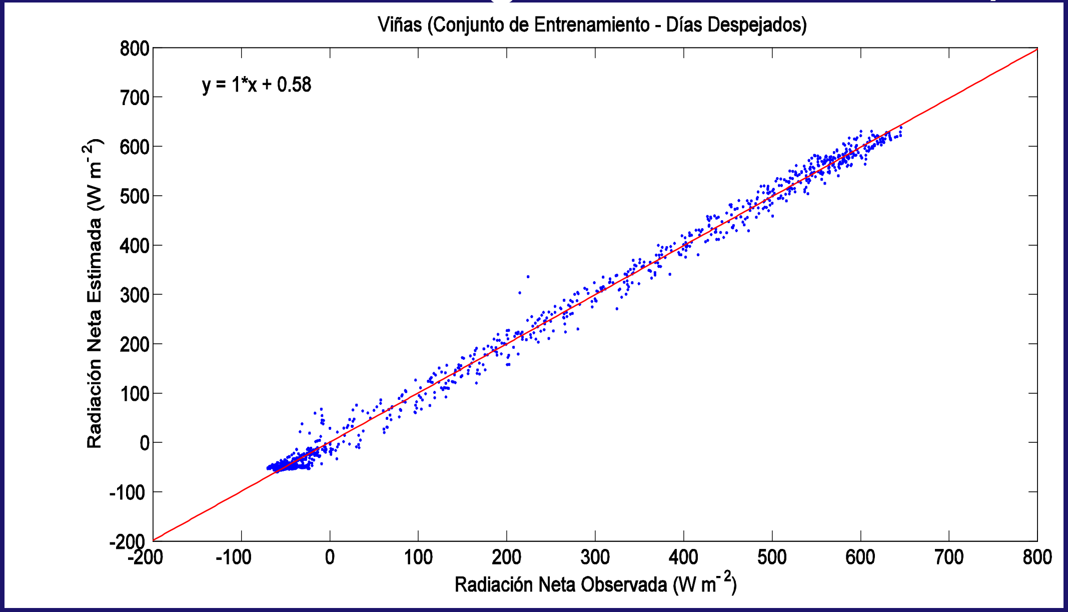


Results

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

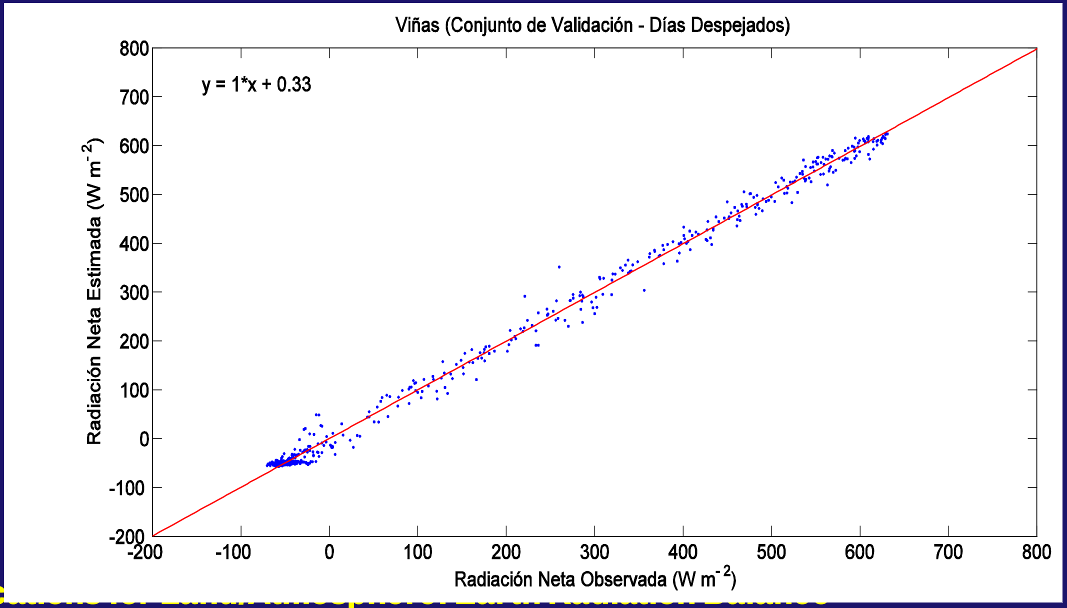
Land use: Vineyards

Clear-sky conditions



Training set

Validation set

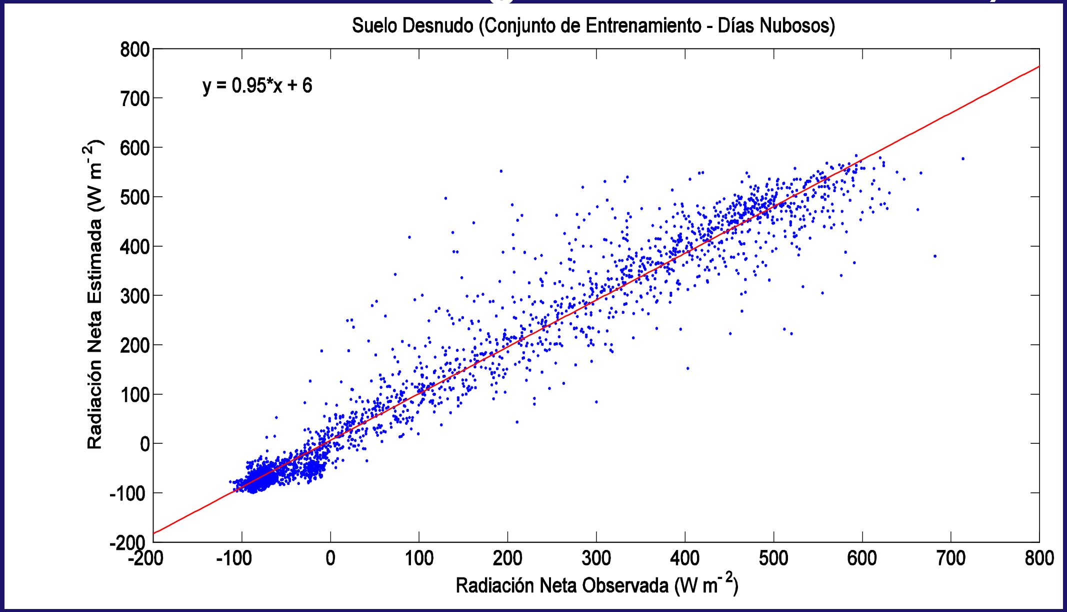


Results

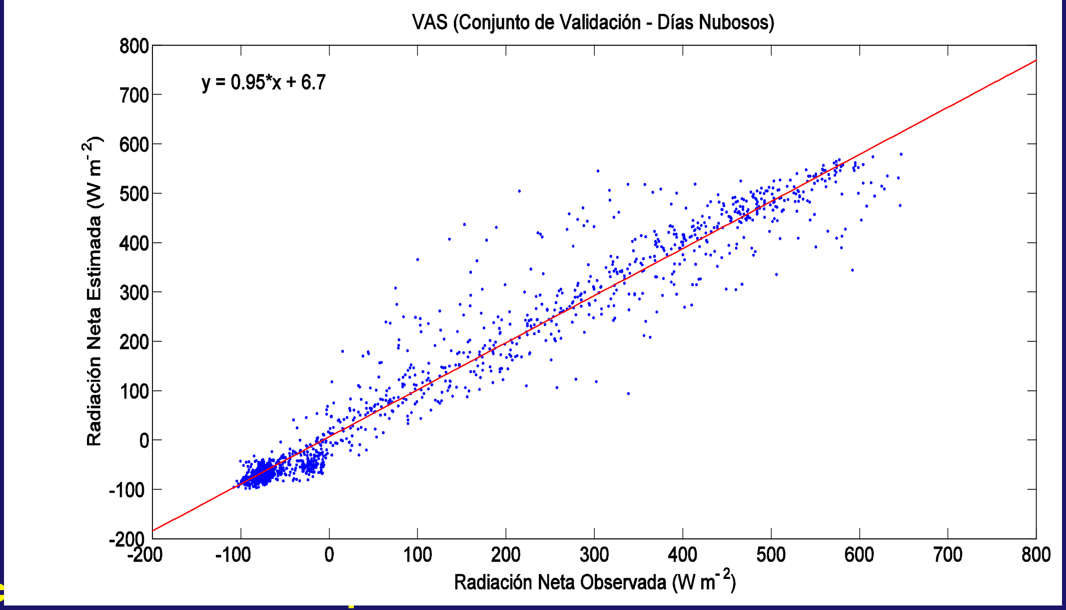
Scatter plots between R_N estimated by MLP and R_N measured in situ for training and validation set, considering:

Land use: Bare soil

All-sky conditions



Training set



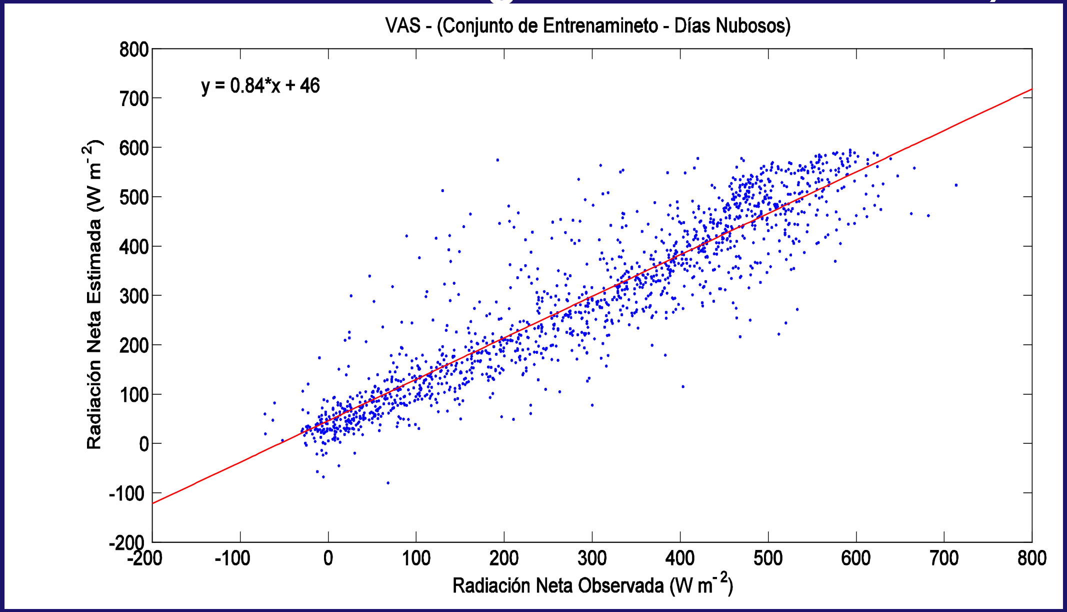
Validation set

Results

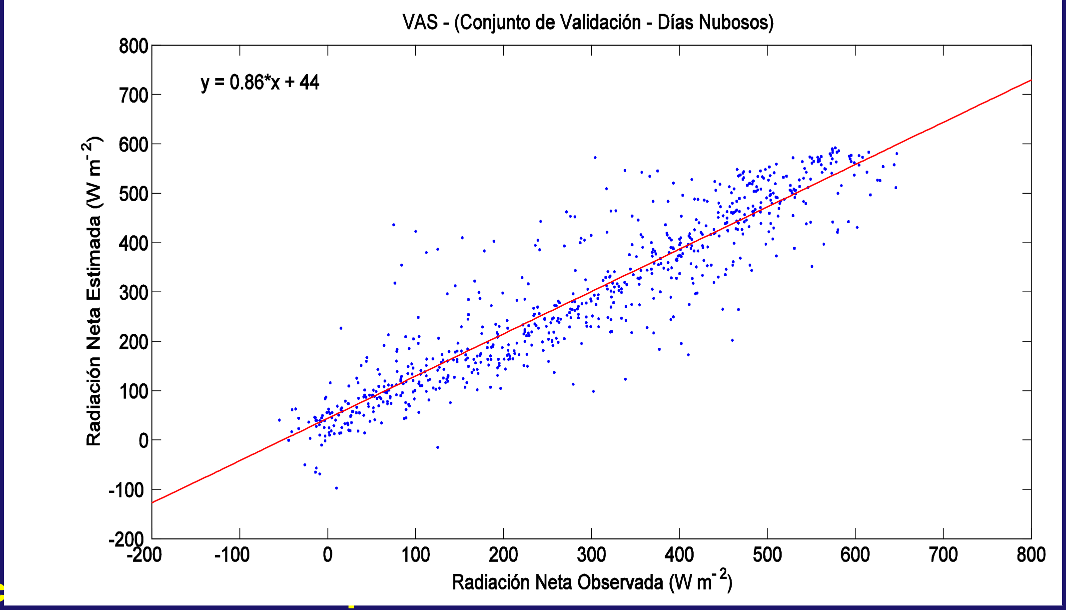
Scatter plots between R_N estimated by MLP and R_N measured in situ for training and validation set, considering:

Land use: Bare soil

Cloudy conditions



Training set



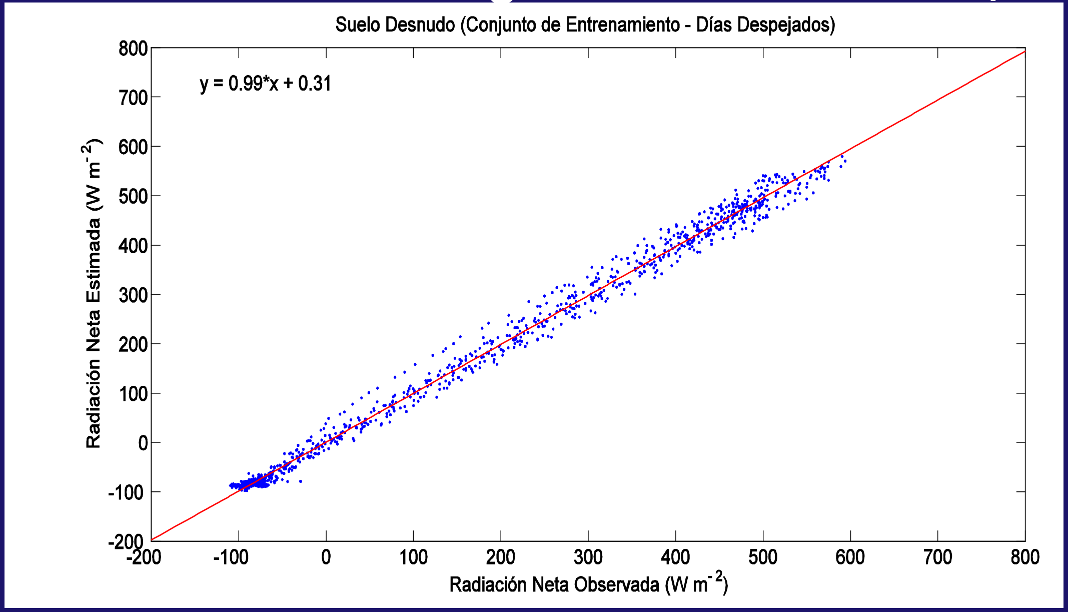
Validation set

Results

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

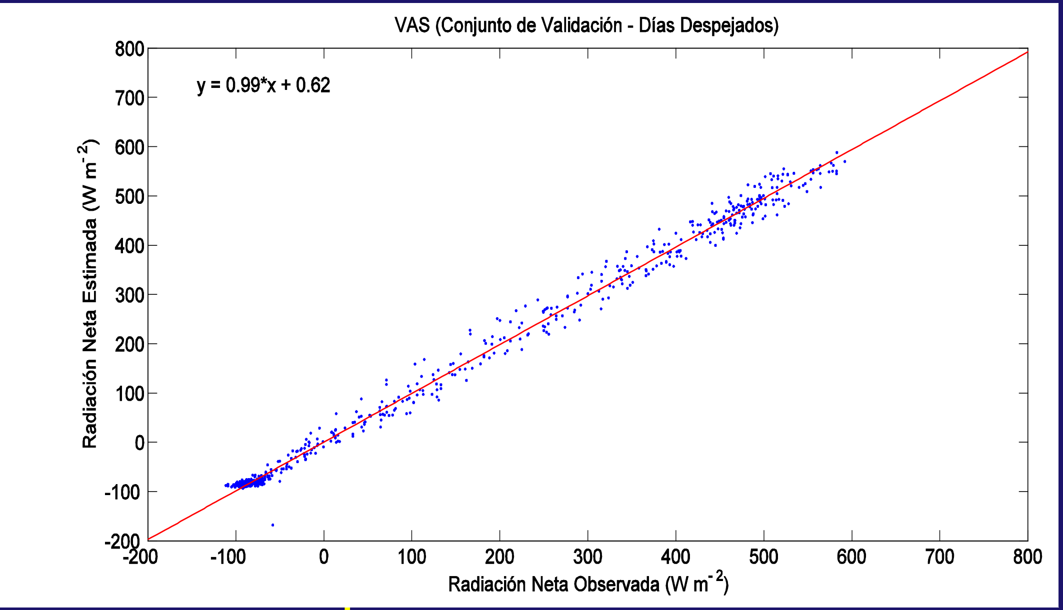
Land use: Bare soil

Clear-sky conditions



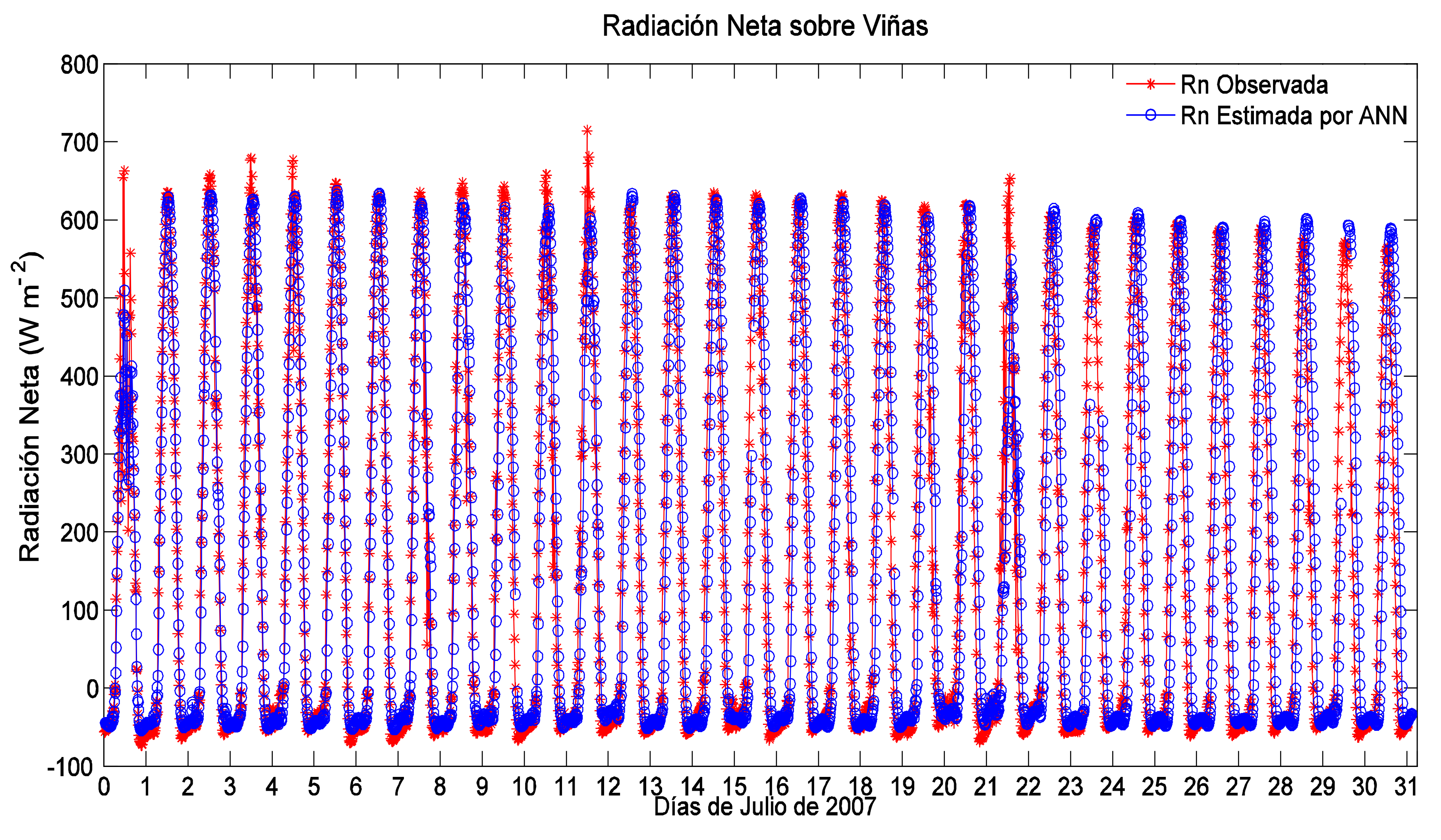
Training set

Validation set



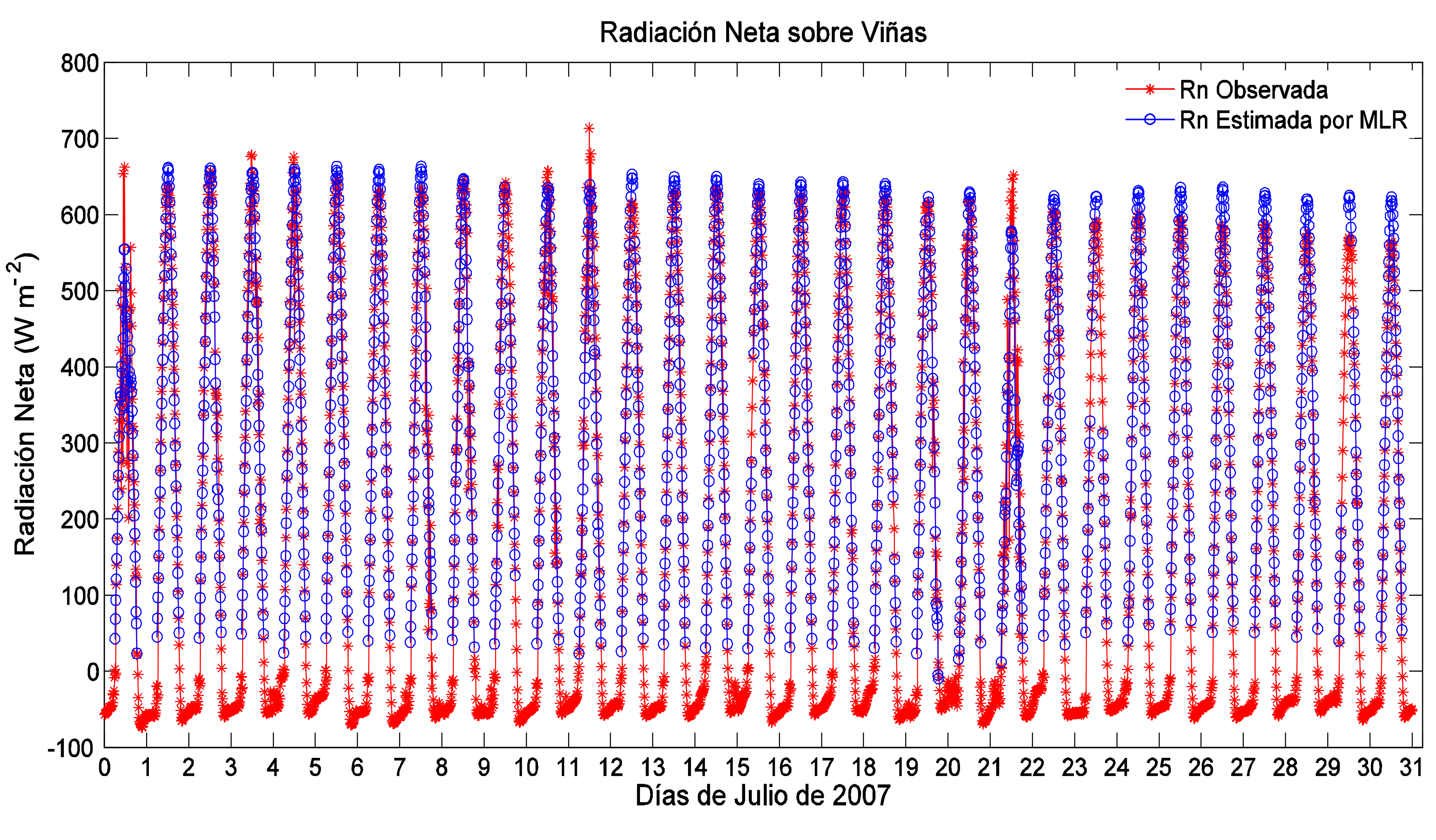
Results

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.



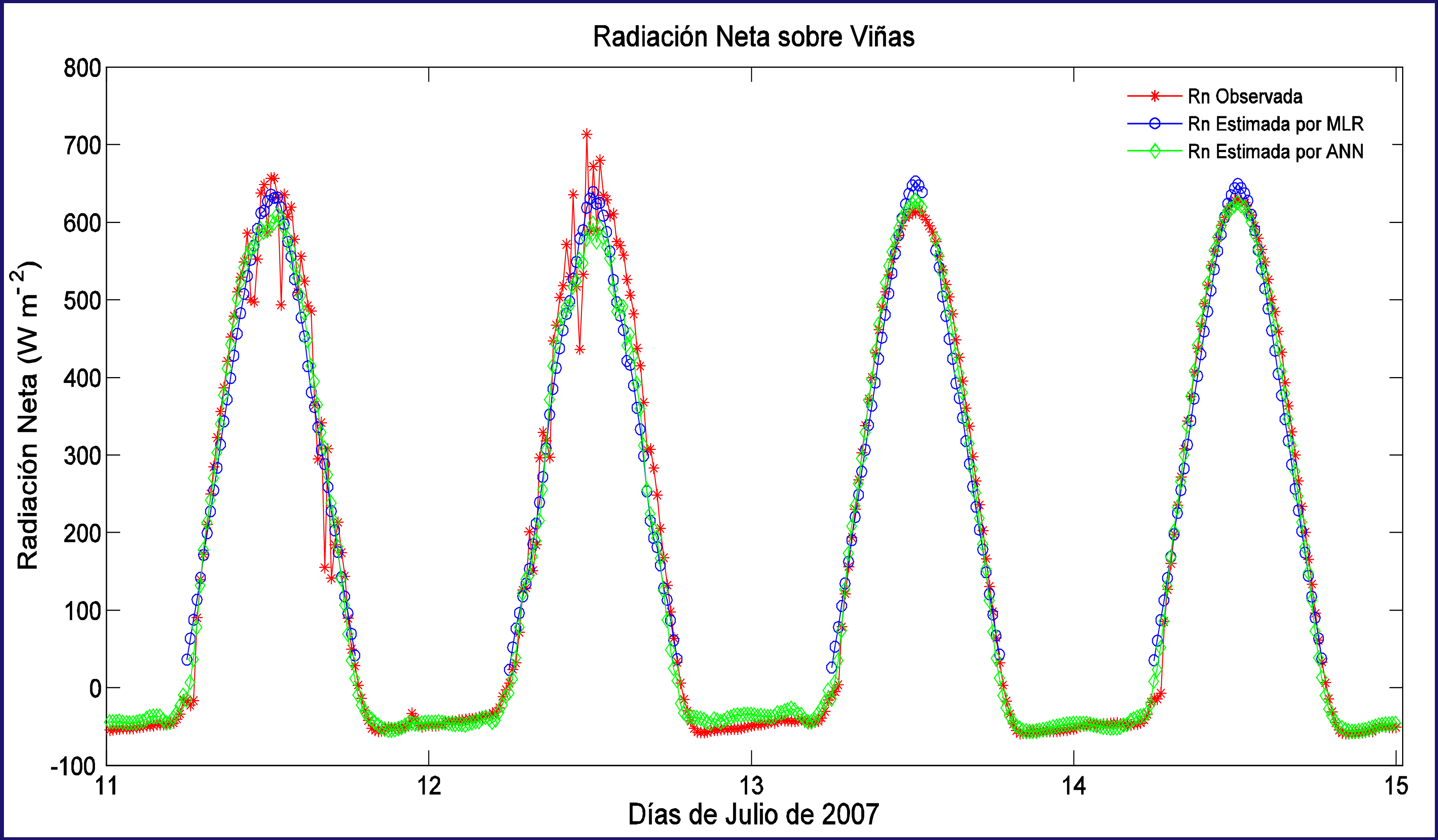
Results

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 Rn and G according to Santanello and Friedl (2002)

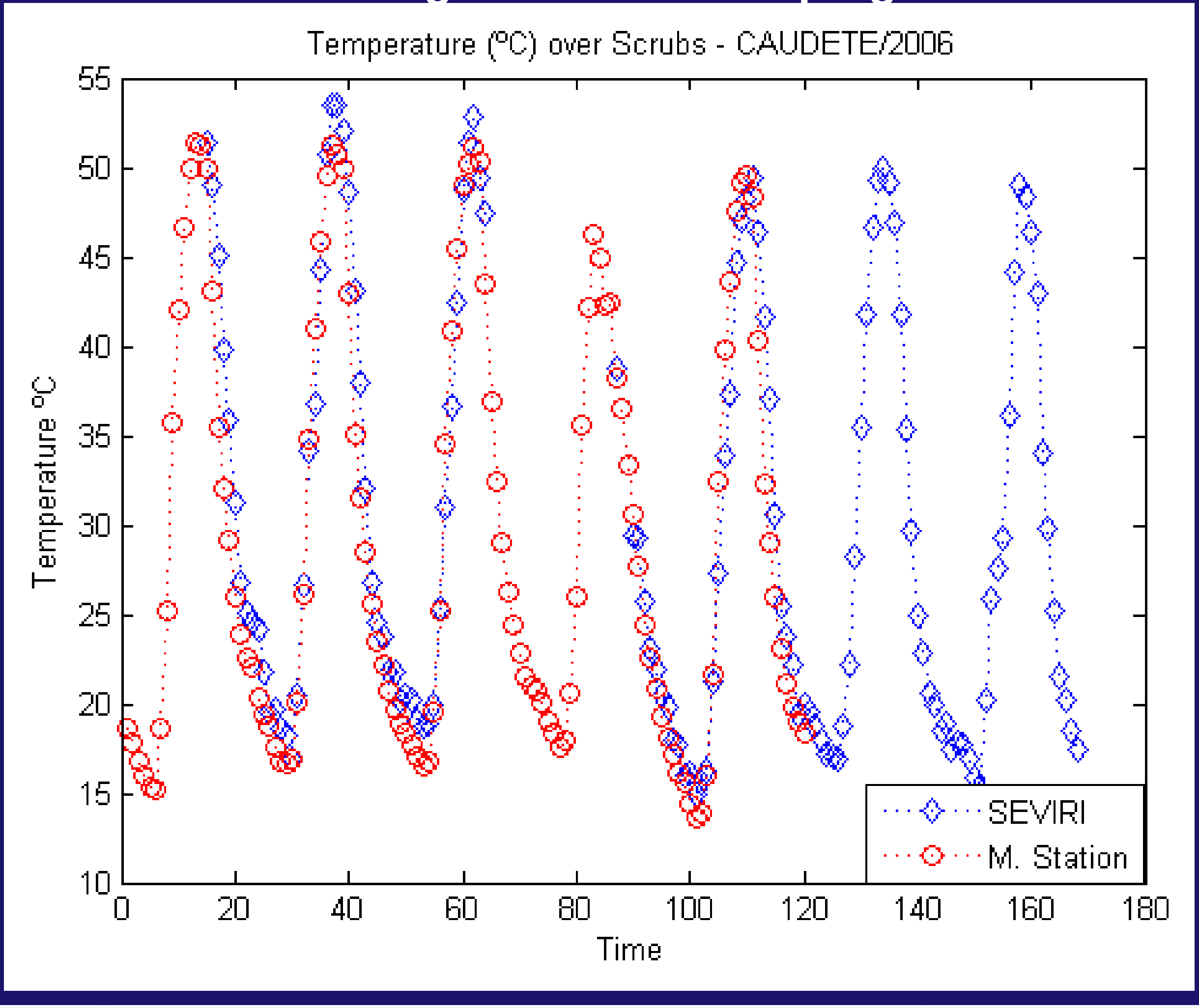
$$\frac{G}{Rn} = (0.0074\,\Delta T + 0.088)\cos\left(\frac{2\pi(t+10800)}{B}\right)$$

B = (1729 * ΔT) + 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

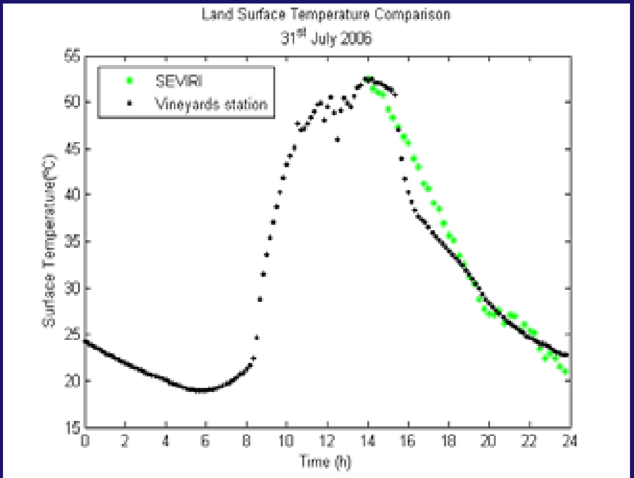
Land surface temperature (LST) comparisons between SEVIRI and measured LST during 2006 field campaign in the scrubland

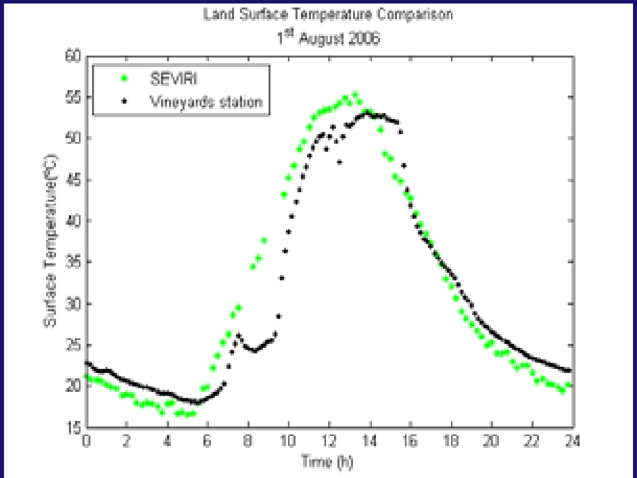


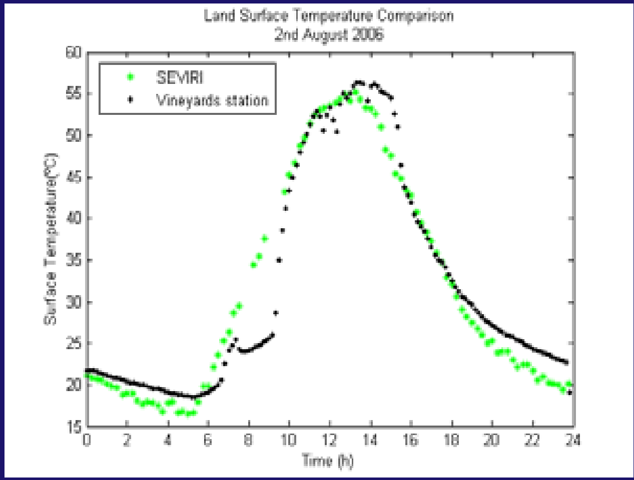
	August 01, 2006	August 04, 2006
avg	31.9 ^{0}C (S) / 30.2 ^{0}C (MS)	28.7 ^{0}C (S) / 27.8 ^{0}C (MS)
std	12.9 (S) / 12.5 (MS)	12.2 (S) / 12.8 (MS)
rmse	2.9 ^{0}C	3.8 ^{0}C

Results

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



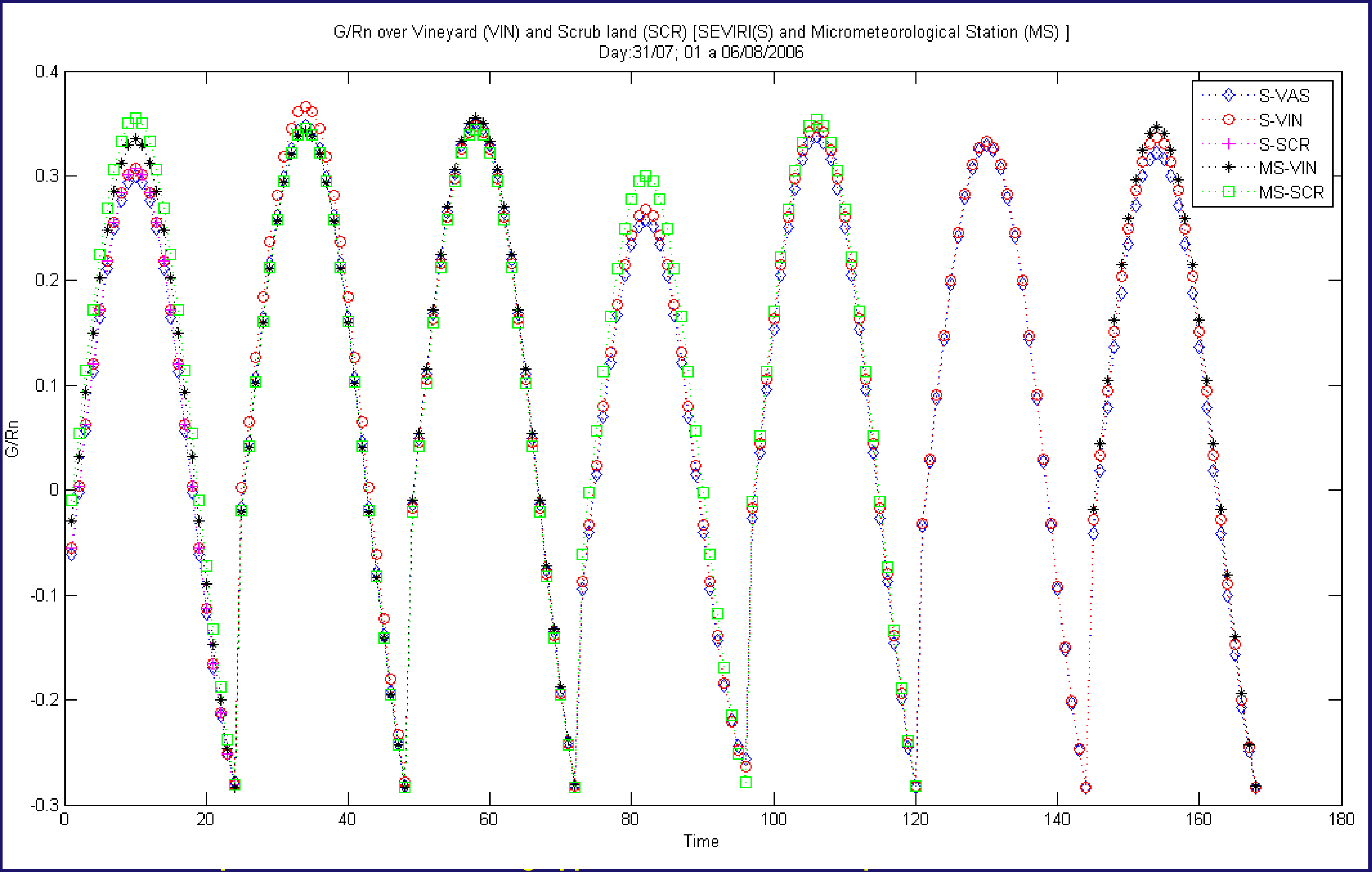




	31th July 2006	1st August 2006	2nd August 2006
RMSE (ºC)	2	3	3

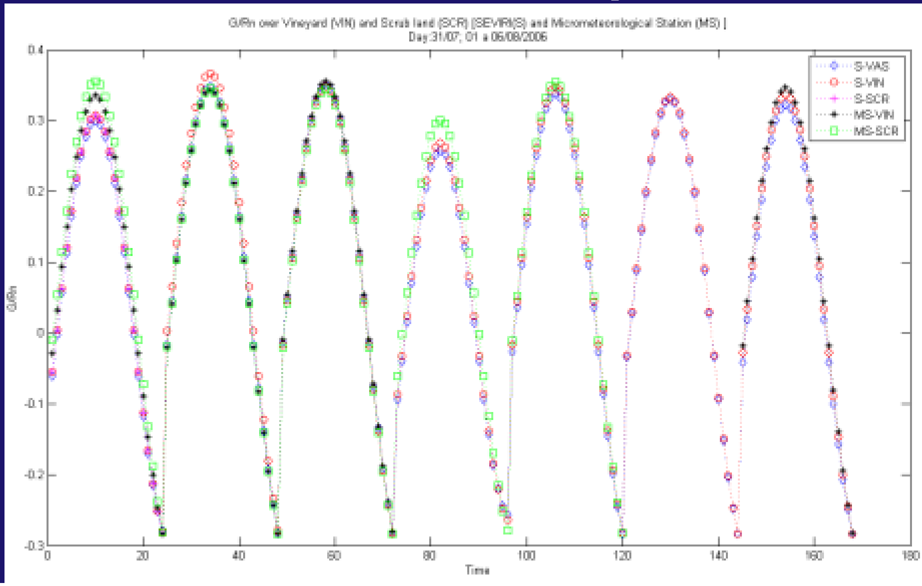
Results

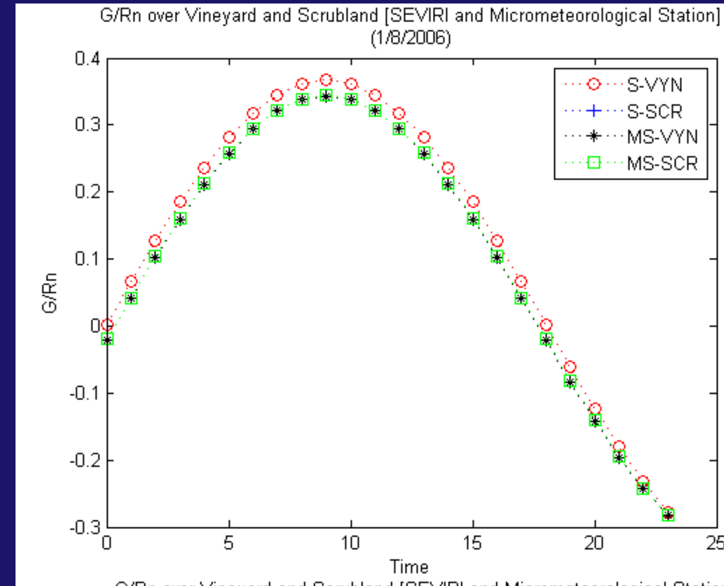
G/Rn comparisons between SEVIRI and measured LST

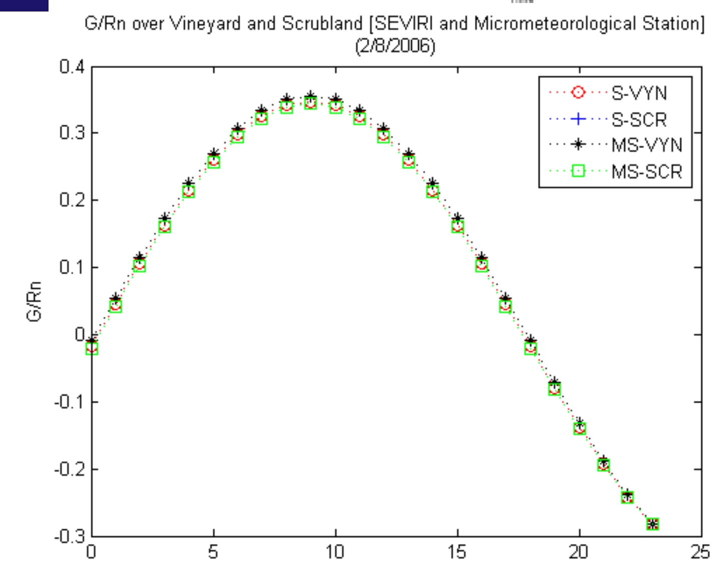


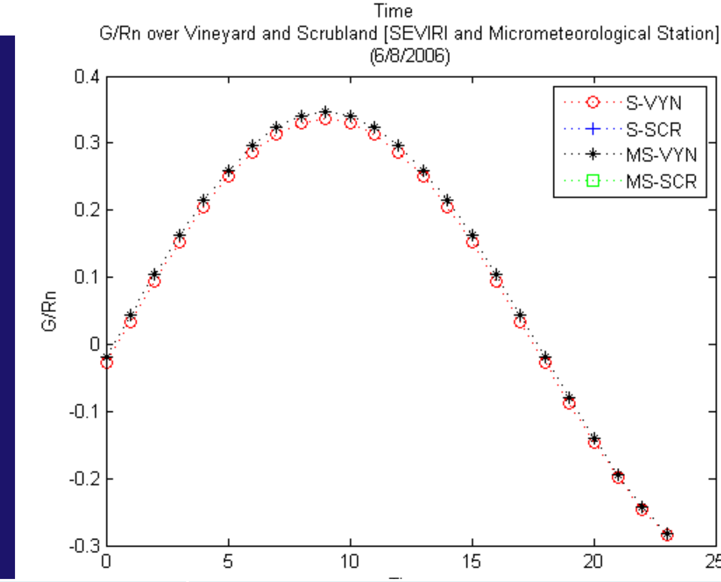
Results

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

Results

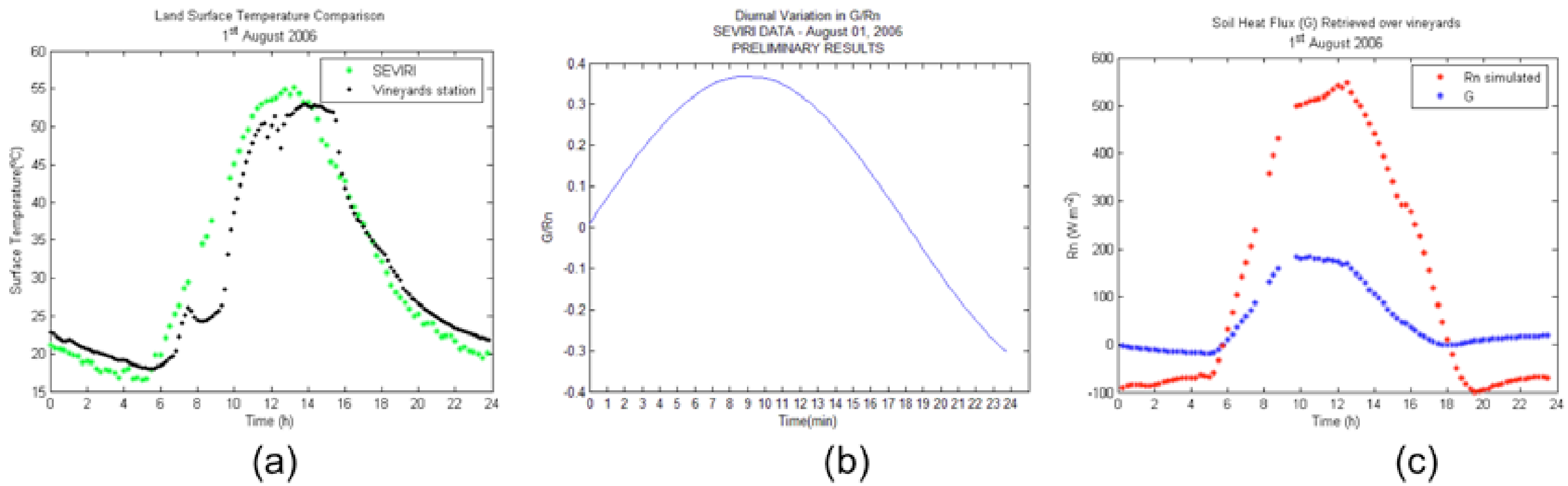


Figura 3. (a) Comparación entre la LST de SEVIRI y la de la estación micrometeorológica para el día 01/08/2006, (b) G/Rn simulado utilizando LST de SEVIRI,y (c), G estimado utilizando GERB_Rn simulado.

Results

G/Rn from SEVIRI