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Estimation of solar radiation and its application to crop simulation models in Greece

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ABSTRACT: Lack of data on site-specific daily solar radiation (R_g) is a significant impediment for most crop modeling applications. For this reason, 5 methods for estimating R_g were tested: the Ångström-Prescott equation (AP), the Supit - van Kappel formula (SK) and 3 temperature-based methods: Campbell-Donatelli model, Hargreaves equation, and piecewise multiple linear regressions with a breakpoint (PLR). To overcome the lack of long and continuous time series of R_g measurements at multiple sites, satellite-derived R_g from the HelioClim-1 database were tested against observations from 2 stations, and then interpolated for 12 additional stations. When sunshine duration data were available, the AP equation was best, because it (1) produced intercepts and slopes closest to zero and unity, respectively and (2) had the lowest relative RMSE (9 to 18.6%). When cloud cover observations and data on maximum and minimum temperatures were available, the SK equation was equally effective as AP in most assessment metrics. When the only data for a site were daily maximum and minimum temperatures, the PLR approach with a breakpoint, which reflects the value at which the response of daily R_g changes as a function of the extraterrestrial solar radiation R_A and the diurnal temperature range, performed best. The mean relative RMSE of the PLR approach was <3.7% higher than that of AP. The SK equation provided the most suitable simulation of measured R_g for the CERES-Wheat crop model, while among the temperature-based methods PLR produced the smallest yield errors. Future validation efforts should explore the validity of the PLR model in other regions and under regimes with greater availability of R_g data

KEY WORDS: Solar radiation estimation · Crop simulation models · Piecewise multiple linear regression · Greece

1. INTRODUCTION

Global solar radiation (R_g) reaching the earth's surface is the energy source for photosynthesis and evapotranspiration (Podestá et al. 2004), and an important input parameter for crop growth simulation models used in decision making. In most countries, including Greece, long and continuous records of daily R_g are scarce because of the cost of the measuring instruments required, as well as their difficult maintenance and calibration (Hunt et al. 1998). Most first-order weather stations in Greece (~40) measure temperature and rainfall, but only 2 of them have long and reliable daily records of R_g.

Various approaches have been developed to estimate R_g at instrumented sites where R_g is not measured: use of stochastic weather generators (e.g. Mavromatis & Hansen 2001), linear interpolation techniques (Grant et al. 2004, Soltani et al. 2004), higher order statistics (Safi et al. 2002), neural networks (Reddy & Ranjan 2003), and empirical approaches (e.g. Mavromatis & Jagtap 2005). Stochastic weather generators can be used for risk analysis, but not for crop model validation and simulation for a specific period, as the weather generators cannot generate data to match the actual weather at a particular time of interest (e.g. Mavromatis & Hansen 2001). Linearly interpolated R_g data may be a good substitute for a few missing values at a particular site, but they cannot be applied to stations without R_g measurements (Trnka et al. 2005). The use of neural networks is limited by the

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nature of the method, which requires a relatively high number of input variables and sufficient testing prior to their application to a site that is distant from the region where the relationships were originally established (Trnka et al. 2005). Therefore, much effort has been directed to empirical methods relying on the association between solar radiation and weather variables such as sunshine duration (Ångström 1924, modified by Prescott 1940, Rivington et al. 2005), temperature (e.g. Bristow & Campbell 1984, Hargreaves et al. 1985), temperature in combination with cloud cover (Supit & van Kappel 1998), or daily precipitation (e.g. Hunt et al. 1998, Weiss et al. 2001, Weiss & Hays 2004).

Remote sensing data on R_g play an increasingly important role as an alternative to *in situ* observations (Lefèvre et al. 2007). The main advantage is the availability of spatially continuous (grid) data with consistent accuracy, measured by satellite at frequent and regular time intervals. Furthermore, satellite assessments are spatially more stable and less biased than interpolations from ground station data (Šúri 2007). The HelioClim-1 database of the Ecole des Mines de Paris contains daily R_g data for Europe, Africa and the Atlantic Ocean from 1985 onward (Cros et al. 2004a).

The main objectives of this study were to evaluate (1) the accuracy of several empirical models widely used for estimating daily R_g versus a piecewise linear regression model, a technique not reported to date for R_g modelling, for 3 different data availability scenarios at 12 observation sites across Greece for the period 1985–1989 and for the parameters sunshine duration, cloud cover + temperature, and temperature only; (2) the effects of measured and estimated R_g on durum wheat *Triticum durum* production, as simulated with the CERES-Wheat crop model. The results of this analysis could also serve as a basis for selecting a suitable method for estimating missing radiation data.

2. MATERIALS AND METHODS

2.1. Data

2.1.1. Remotely sensed solar radiation

HelioClim-1 (HC1) is an integrated information system that contains a database of global irradiation data processed with the Heliosat-2 algorithm from a time series of Meteosat-4 to Meteosat-7 images at reduced (sampled) B2 resolution (grid cell of about 30 × 30 km at the equator). The HC1 dataset covers Europe, Africa and the Atlantic Ocean and is available from 1985 onwards through the SoDa website (www.soda-is.com) (Cros et al. 2004a). However, free access is provided to only 5 yr of daily data (1985–1989), and therefore this period was chosen for the present study. Heliosat-2 converts satellite data into assessments of the daily mean R_g at ground level for each day (Rigollier et al. 2004). It is based on the principle that 'the attenuation of the downwelling shortwave radiation by the atmosphere over a pixel is determined by the magnitude of change between the reflectance that should be observed under a very clear sky and that currently observed' (Lefèvre et al. 2007, p 243). The web-server performs an on-line spatial linear interpolation to deliver a daily time-series of R_g for any given location (Lefèvre et al. 2007).

The quality of HC1 data have been assessed by several comparisons between daily ground measurements and satellite-derived solar radiation (Cros et al. 2004a, Rigollier et al. 2004, Lefèvre et al. 2007). A relative accuracy of <20% in relative root mean squared error (RMSE) was found in these comparisons. To overcome the limited availability of long and reliable daily R_g measurements in Greece, the suitability of HC1 data was tested against the observations from 2 stations (Fig. 1) for 1985–1989.

2.1.2. Station data

The study included 12 representative sites from 35° to 41° N latitude and 20° to 28° E longitude (Fig. 1). Mean daily maximum and minimum air temperature, sunshine duration and cloud cover for these sites ranged from 19.2 to 22.9°C, 7.2 to 16.6°C, 5.8 to 8.1 h,

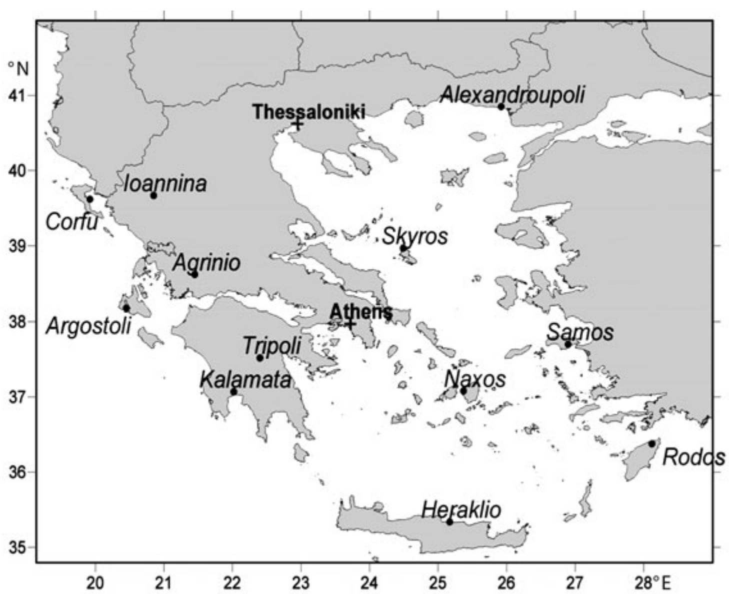

Fig. 1. Meteorological stations in Greece used for the evaluation of (•) solar radiation estimation methods and (+) HelioClim-1 versus observed radiation data

Table 1. Stations used for the evaluation of solar radiation estimation methods. Data shown are mean for 1985–1989. Alt.: altitude, R_g: global solar radiation, T_{max} and T_{min}: maximum and minimum temperature, respectively

Station	Lat. (°N)	Long. (°E)	Alt. (m)	R_g (MJ m^{-2} d^{-1})	T_{max} (°C)	T_{min} (°C)	Sunshine duration (h)	Cloud cover (octas)
Alexandroupoli	40.85	25.92	4	12.9	19.2	8.9	6.3	3.3
Ioannina	39.67	20.85	484	13.8	19.8	7.5	5.8	3.3
Corfu	39.62	19.92	4	15.0	22.5	12.0	7.1	3.1
Skyros	38.97	24.49	48	15.5	19.3	14.1	7.0	3.3
Agrinio	38.62	21.45	46	14.3	22.9	9.6	7.1	3.1
Argostoli	38.11	20.29	5	16.0	21.5	14.3	7.7	3.0
Samos	37.70	26.90	3	16.1	22.2	13.5	8.1	2.6
Tripoli	37.52	22.40	663	15.0	20.1	7.2	7.2	3.9
Naxos	37.08	25.37	3	16.8	20.4	15.3	7.4	2.7
Kalamata	37.07	22.02	7	15.4	22.4	11.2	7.6	3.1
Rodos	36.38	28.12	11	19.1	22.0	16.6	8.1	2.3
Heraklio	35.34	25.17	39	17.5	21.8	15.0	7.5	3.2

and 2.3 to 3.9 octas, respectively (Table 1). Sunshine duration was measured by Campbell-Stokes sunshine recorders. There were no missing data in the weather records of the stations with the exception of sunshine duration data. At 9 stations, gaps in sunshine data were <3% of the total days, and at 3 stations (Skyros, Agrinio and Rodos), the gaps were approximately 10%. These sunshine duration time series were not excluded from the analysis, since no years with >31 consecutive days of missing data or with >50 missing days in total were identified. Mean daily values of the satellite-derived radiation varied from 12.9 MJ m^{-2} d^{-1} in Alexandroupoli to 19.1 MJ m^{-2} d^{-1} in Rodos. The first 3 yr of data were used for fitting model parameters, and the last 2 yr were used for model evaluation.

2.2. Estimation of solar radiation

2.2.1. Estimation using sunshine duration (AP model)

The equation postulated by Ångström (1924) and improved by Prescott (1940) was:

$$R_g = R_A\left(\alpha_A + b_A \frac{n}{N}\right) \qquad (1)$$

where R_A is the extraterrestrial solar radiation, α_A and b_A are site specific empirical coefficients, and n and N are the actual and astronomical sunshine duration, respectively. N was calculated as a function of latitude and day of the year according to Allen et al. (1998).

2.2.2. Estimation using cloud cover (SK model)

Non-linear relationships between daily R_g and cloud cover observations were first suggested in the 1960s. The formula proposed by Supit & van Kappel (1998) was applied as:

$$R_g = R_A\left[a_S\sqrt{T_{max} - T_{min}}\,\right] + b_S\sqrt{\left(\frac{C_W}{8}\right)} + c_S \qquad (2)$$

where: a_S, b_S and c_S are site specific empirical constants, T_{max} and T_{min} are the maximum and minimum daily temperatures, and C_W is the mean total cloud cover during daytime observations (in octas).

2.2.3. Estimation using temperature data (CD, H and PLR models)

The central assumption in most temperature-based methods is that, on clear days associated with high transmittance and radiation, strong diurnal warming and nocturnal cooling leads to a large daily temperature range (T_{max} – T_{min}). On overcast or rainy days, cloudiness reduces incoming radiation during daytime and outgoing radiation at night (Podestá et al. 2004). Donatelli & Campbell (1998) developed an approach which estimates R_g on any given Day i as the product between R_A and a clear sky transmissivity coefficient τ:

$$R_{g,i} = \qquad (3)$$
$$\tau R_{A,i}\left[1 - \exp\left(-b\{0.017\exp[\exp(-0.053 + T_{avg,i})]\}\Delta T_i^2[f(T_{min,i})]\right)\right]$$

where ΔT_i is the daily air temperature range [$\Delta T_i = T_{max,i} - 0.5(T_{min,i} + T_{min,i} + 1)$], $T_{avg,i}$ is the average air temperature of Day i and $f(T_{min,i})$ is a function of T_{min} on Day i: $f(T_{min}) = \exp(T_{min,i}/T_{nc})$, and T_{nc} is the summer night air temperature factor. Thus, the Campbell-Donatelli model (CD model) requires 3 site-specific empirical parameters: τ, b and T_{nc}.

A relatively simple method of relating R_g to daily temperature range was proposed by Hargreaves et al. (1985) (H model):

$$R_g = R_A a_H\sqrt{(T_{max} - T_{min})} + b_H \qquad (4)$$

where a_H and b_H are site-specific empirical constants.

Non-linear models have also been proposed for estimating daily R_g from common meteorological variables. A generalized additive model (GAM) linking proxies of cloudiness and atmospheric humidity to R_g was proposed by Podestá et al. (2004). It is not uncommon that the nature of the relationship between one or more independent variables and a dependent variable changes over the range of the independent variables. Several studies conditioned τ on either (1) the wet/dry status of the current and/or previous day or (2) the precipitation amount or (3) the range in daily temperature extremes (ΔT) (Acock & Pachepsky 2000, Winslow et al. 2001, Spokas & Forcella 2006), based on the assumption that ΔT is an important factor in determining the presence or absence of clouds (Mahmood & Hubbard 2002), along with precipitation. A piecewise multiple linear regression (PLR) model with 2 separate regression equations was tested: one for R_g values that are less than or equal to a breakpoint c and one for $R_g > c$:

$$\begin{aligned} R_g &= b_{01} + b_{11}R_A + b_{21}\Delta T \quad \text{if } R_g \le c \\ R_g &= b_{02} + b_{12}R_A + b_{22}\Delta T \quad \text{if } R_g > c \end{aligned} \tag{5}$$

where b_{11}, b_{21}, b_{12} and b_{22} are the 4 different intercepts, and b_{01} and b_{02} refer to the slopes of the 2 regression lines below and above the breakpoint c, respectively.

The empirical coefficients of the 5 R_g estimation models, including breakpoint c, were estimated with a nonlinear least squares regression (Statsoft 2004). This procedure aims at minimizing the loss function, which is the sum of squared deviations of the dependent variable from those predicted by the 5 models. To find the best fitting set of parameters for each equation, the efficient Levenberg-Marquardt algorithm was employed. The preset by the software defaults of the parameter start values, step sizes and convergence criteria, required by the estimation procedure, were used. The mean of the dependent variable at each site (see Table 1) was used by the least squares estimation algorithm as the start value of breakpoint c.

R_A was calculated as a function of latitude, day of the year, solar angle and solar constant according to Allen et al. (1998).

2.3. Crop simulations

The CERES-Wheat crop model (Ritchie & Otter 1985) simulates daily wheat crop growth, development and yield dynamically as a function of weather (T_{max}, T_{min}, precipitation and R_g), planting date, N fertilizer management, cultivar and soil characteristics (Soltani et al. 2004). It accurately simulates grain yields in various climates (e.g. Pecetti & Hollington 1997, Timsina & Humphreys 2006). To overcome the inadequate length (5 yr) of HC1 data, WGEN was used to provide long term weather series for use with CERES-Wheat; WGEN (Richardson & Wright 1984) is a widely used stochastic weather generator that requires mean monthly weather data of T_{max} and T_{min}, precipitation and R_g to generate daily weather at a site. There are no significant differences between crop simulation output obtained with WGEN generated and actual weather data (Soltani et al. 2000, Hartkamp et al. 2003); the latter study also demonstrated the suitability of WGEN for generating adequate long-term time series even when model parameters were derived from relatively short-term (<10 yr) daily weather data.

A standardized scenario for a durum wheat crop simulation was created within CERES-Wheat using the same cultivar (SIMETO), planting date (25 October) and soil profile at each location. With HC1 and the daily R_g estimated with the 5 models during 1985–1989, 6 sets of 5 yr daily weather data were available for each site. Parameters for WGEN were then calculated for each data set/location combination. Sufficient weather data were next generated to simulate 99 wheat–fallow runs for each site. To consider the weather effect during the fallow period on the following wheat season, the 'sequence' option of the model, allowing carrying over of soil water between seasons, was employed. The Ritchie modification of the Priestley-Taylor approach was used for estimating potential evapotranspiration (ET). Simulation of nitrogen was deactivated for these runs. We decided to focus on simulated grain yield, crop biomass and growing season ET output.

2.4. Model evaluation

To evaluate the model performance, regression- and difference-based analyses were conducted. These included the calculation of the mean bias error (MBE) and root mean squared error (RMSE).

$$\text{MBE} = \sum_{i=1}^{n} \frac{E_i - O_i}{n} \tag{6}$$

$$\text{RMSE} = \left(\frac{\sum_{i=1}^{n} (E_i - O_i)^2}{n} \right)^{1/2} \tag{7}$$

where n is the number of observations, E_i is the model prediction and O_i is the observed value for Day i. The reduced major axis method for slope and intercepts estimates was preferred to the more frequently used ordinary least squares approach (Ricker 1984). The data analysis tool IRENE (www.isci.it/tools) was used for statistical analysis. The applicability of the estimated R_g to CERES-Wheat was evaluated by comparing the median, and lower and upper quartiles of the crop simulation output distributions derived with HC1, and estimated radiation values. The non-parametric Mann-Whitney *U*-test was used to assess whether crop model output with various R_g inputs came from the same distribution (5% level of significance).

3. RESULTS AND DISCUSSION

3.1. Evaluation of HelioClim-1

A better agreement was found between the monthly course of HC1 values and the ground measurements for Athens than for Thessaloniki (Fig. 2). The average bias was negative (underestimation) for the former site (–8.5%) and positive (overestimation) for the latter (+16.7%). This bias varied from one year to another and its timing was not consistent among sites.

On daily basis, the relative MBE in Athens (data not shown) varied from 3.8% in July to 16.4% in March. Larger errors were estimated for Thessaloniki, ranging from 6.8% in May to 28.9% in January. For 6 months, the relative RMSE for Thessaloniki (data not shown) was >20% (the acceptable deviation between daily measured and calculated irradiation: Cros et al. 2004a,b). RMSE in Athens remained within the accepted range for all months and ranged from 4% in July to 16.4% in March. Errors were smaller in spring and summer, when clear skies prevail, and greater with overcast skies during autumn and winter. Similar trends and comparable ranges of errors were reported by Rigollier et al. (2004) and Lefèvre et al. (2007). The consistent overestimation of actual daily measurements in Thessaloniki (Fig. 2), a site located by the sea, is related to (1) spatial sampling and filtering of satellite data that may include measurements over the sea (a cloud index lower than measured over land is expected, since there are generally fewer clouds over sea than over land) and (2) the very high value of the cloud reflectivity within the Heliosat-2 algorithm (Dagestad 2005).

The overestimation and underestimation of the measured R_g in Thessaloniki and Athens, respectively, resulted in a corresponding increase by 6.8% and a decrease by 2.7% in the median values of the simulated yields (Table 2). These discrepancies, however, were not statistically significant according to the p values of the Mann-Whitney *U*-test. The upper quartiles presented similar trends in the deviations of simulated yields and the lower quartiles had the opposite trend. The median values of simulated biomass produced with HC1 data, significantly overpredicted and underpredicted the yield obtained with on-site radiation data from Thessaloniki and Athens by 14.8 and 7.6%, respectively (Table 2). The *U*-test did not identify any significant deviations in the median values of modeled ET obtained with the 2 sources of R_g.

Table 2. CERES-Wheat yield (at 0% moisture), evapotranspiration (ET) and total biomass simulated on the basis of solar radiation data for Thessaloniki and Athens. Obs: with actual data; Sat: with satellite-derived data. Q50: median; Q25 and Q75: quartiles. p: significance (Mann-Whitney *U*-test)

	Yield (kg/ha)		ET (mm)		Biomass (kg/ha)	
	Obs	Sat	Obs	Sat	Obs	Sat
Thessaloniki						
Q50	3303	3527	275	288	7355	8446
p	0.228		0.054		≤0.001	
Q25	2576	2171	255	260	5928	6404
Q75	3765	4248	297	314	8123	9479
Athens						
Q50	2814	2714	255	248	6996	6467
p	0.385		0.166		0.040	
Q25	2064	2137	227	228	4898	4527
Q75	3638	3270	283	269	8348	7361

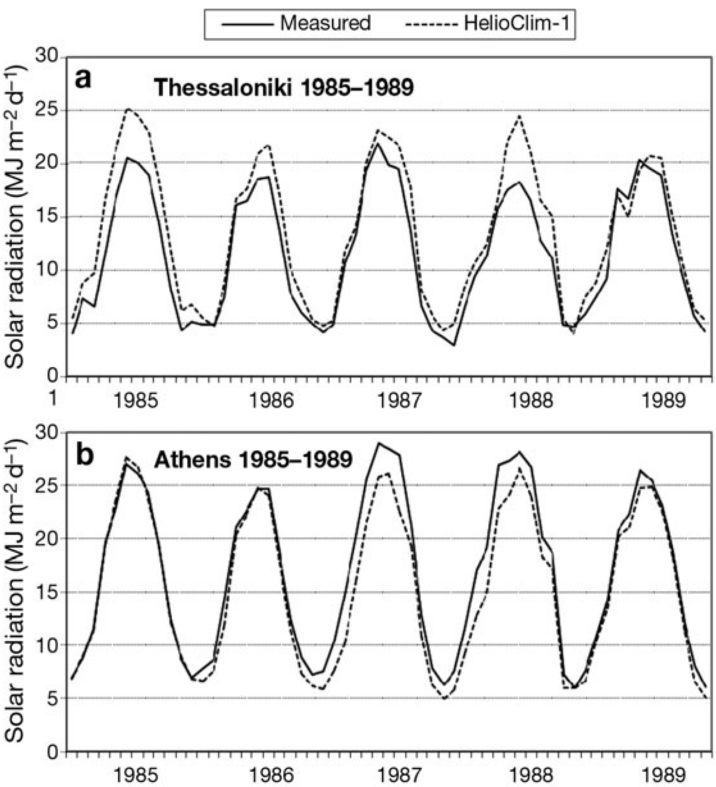

Fig. 2. Actual versus HelioClim-1 derived solar radiation for (a) Thessaloniki and (b) Athens during 1985–1989 (n = 5 × 12)

The above-mentioned results lead us to conclude that (1) since the majority of deviations between historical and estimated R_g were within the accepted range, HC1 data are a useful alternative to *in situ* radiation observations, and (2) at sites where only temperature and precipitation data are available, daily solar radiation data derived from Meteosat images can be used as input in the CERES-Wheat model, at least for wheat yield and ET (on which we focus below).

3.2. Solar radiation estimation methods

3.2.1. Regression-based evaluation

The regression-based statistics for the calibration and the independent datasets are summarized in Table 3. Of the 5 R_g estimation methods, the AP approach ranked first, because it had the intercepts and slopes closest to zero and unity, respectively. The SK equation was also efficient and ranked second. Of the 3 temperature-based models, PLR significantly outperformed the CD and H models. PLR using only daily extreme temperatures presented similar or better regression line slopes and intercept values than the SK equation, which requires additional cloud information. The H equation was the least successful for estimating daily solar radiation. These results generally agree with previous studies, which also recognized the superiority of approaches based on the sunshine duration, despite the need for site-specific parameterization for deriving the empirical coefficients α_A and b_A of the AP equation.

All 5 radiation models overestimated low R_g values (overcast skies) and underestimated the middle and high range of observed radiation (clear skies), as indicated by the positive slopes and the negative intercepts of the regression analysis results. Similar trends for these models were reported by Trnka et al. (2005) in central European lowlands. Forcing factors that were not included in the models but may be associated with daily radiation forcing are probably responsible for the systematic biases at the extremes of the observed R_g distribution. For example, large-scale advection, dust storms, seasonal burning, grassland fires, and pollution from fires may significantly influence recorded radiation (e.g. Thornton & Running 1999). In addition, and with regards to cloud

Table 3. Regression-based evaluation of 5 methods for estimation of solar radiation, for the calibration (1985–1987) and validation (1988–1989) periods. Int.: intercept (MJ m^{-2} d^{-1}). PLR: Piecewise linear regression

	Ångström-Prescott (Eq. 1)		Supit-van Kappel (Eq. 2)		Hargreaves (Eq. 4)		Campbell-Donatelli (Eq. 3)		PLR (Eq. 5)	
	Int.	Slope	Int.	Slope	Int.	Slope	Int.	Slope	Int.	Slope
Calibration										
Alexandroupoli	–0.77	1.06	–0.69	1.05	–1.45	1.11	–0.98	1.08	–0.85	1.06
Ioannina	–0.49	1.04	–0.54	1.04	–1.08	1.08	0.38	0.99	–0.69	1.05
Corfu	0.47	0.97	–0.48	1.03	–1.28	1.08	–0.85	1.06	–0.66	1.04
Skyros	–1.10	1.06	–0.63	1.04	–3.40	1.22	–1.82	1.12	–0.95	1.06
Agrinio	–1.04	1.06	–0.48	1.03	–1.07	1.07	–1.18	1.08	–0.61	1.04
Argostoli	–1.16	1.06	–0.60	1.04	–1.78	1.11	–2.05	1.12	–0.77	1.05
Samos	–0.50	1.03	–0.63	1.04	–2.12	1.13	–1.49	1.10	–1.12	1.07
Tripoli	–1.38	1.08	–0.70	1.05	–1.33	1.09	0.54	0.99	–0.75	1.05
Naxos	–0.48	1.03	–0.59	1.03	–6.40	1.38	–4.42	1.24	–1.04	1.06
Kalamata	–0.87	1.05	–0.58	1.04	–1.49	1.10	–1.30	1.08	–0.77	1.05
Rodos	–0.12	1.01	–0.65	1.03	–2.93	1.15	–2.81	1.14	–1.19	1.06
Heraklio	–0.59	1.03	–0.97	1.06	–4.15	1.24	–2.16	1.13	–1.05	1.06
All stations	–0.70	1.04	–0.63	1.04	–2.37	1.15	–1.51	1.09	–0.87	1.05
Validation										
Alexandroupoli	–1.16	1.04	–1.42	1.03	–3.43	1.19	–1.75	1.06	–1.15	1.05
Ioannina	–0.55	0.99	–1.37	1.05	–1.84	1.09	–1.22	1.04	–1.82	1.10
Corfu	–1.61	1.05	–1.42	1.05	2.07	0.90	–2.40	1.10	–1.64	1.07
Skyros	–1.20	1.09	–1.95	1.10	–4.05	1.24	–2.75	1.15	–1.23	1.06
Agrinio	–1.39	1.03	–1.09	1.04	–1.98	1.09	–2.62	1.11	–1.58	1.07
Argostoli	–1.91	1.06	–1.41	1.06	–1.65	1.09	–2.39	1.12	–1.11	1.05
Samos	–1.70	1.05	–2.08	1.06	–2.99	1.11	–2.97	1.12	–1.72	1.07
Tripoli	–1.79	1.07	–1.69	1.07	–1.62	1.08	–0.08	0.99	–0.99	1.04
Naxos	–1.41	1.05	–1.51	1.06	–6.46	1.34	–5.26	1.27	–1.74	1.08
Kalamata	–1.67	1.06	–1.81	1.06	–1.83	1.09	–1.67	1.07	–1.02	1.05
Rodos	–0.65	1.00	–0.83	1.04	–2.49	1.17	–1.76	1.10	–0.39	1.02
Heraklio	–1.13	1.05	–2.24	1.09	–4.09	1.21	–1.89	1.10	–1.29	1.06
All stations	–1.35	1.05	–1.57	1.06	–2.53	1.13	–2.23	1.10	–1.31	1.06

observations required by the SK formula, observers have a tendency to underestimate low and overestimate high overcast conditions (Brinsfield et al. 1984). The same authors also noted that underlying surface conditions can potentially introduce errors in the estimates. Furthermore, various other atmospheric constituents such as O_2, CO_2, O_3, CH_4, and anthropogenic gases also influence the amount of incident radiation, and thus affect the performance of this type of model.

3.2.2. Difference-based evaluation

All models consistently presented positive MBE errors (Table 4), probably for the reasons reported in Section 3.2.1. The methods using temperature data only, outperformed the AP and SK equations. PLR was the best approach for the independent dataset, as it had the lowest MBE. The relative value of MBE for all stations combined was 2.5%, ranging from –0.3% (underestimation) for Rodos to 4.1% (overestimation) for Samos. The average relative MBE for the AP and SK models were higher than the MBE found by Trnka et al. (2005) for the lowlands in central Europe — 4.2 and 3.9% (see Table 4) versus 1.1 and 1.7%). Supit & van Kappel (1998) also reported a lower relative MBE for the AP model (3.6%) but an identical one for SK. CD model performed better in central Europe (Trnka et al. 2005), showing a lower value for relative MBE (2.9 vs. 3.8% in Table 4). The opposite was true for H (6.3 vs. 3.5% in Table 4).

The accuracy of the models expressed in terms of the RMSE is consistent with the results obtained with the regression-based analysis. Comparing model performance for all stations combined, there was an increase by 1.3% or less in average relative RMSE by employing SK instead of AP, and by 3.7% or less by selecting PLR (Table 5). The corresponding errors were much larger with the H and CD formulas. In comparison with AP, H increased the relative RMSE by 13.4% for the calibration and by 12.8% for the validation period. The respective metrics for CD relative to AP were 8.8 and 8.7%. The average error of AP expressed in terms of relative RMSE was similar to that in central Europe (13.8 and 15.4% [see Table 5] versus 14.5%) (Trnka et al. 2005) and lower than the 17.2% reported by Supit & van Kappel (1998). SK performed much better with regard to relative RMSE in this study compared with Trnka et al. (2005) and Supit & van Kappel (1998) — 15.1 and 16.4% (see Table 5) versus 24.7% in the first study and 22.6% in the latter. The RMSE values produced with CD were well within the range of 2.5 to 5.0 MJ m^{-2} d^{-1} reported by Donatelli & Campbell (1998) from 11 stations all over the world, and the mean relative RMSE value of 32% reported by Trnka et al. (2005) overestimated the respective error statistics, compared to those in Table 5. The H model also performed better under Mediterranean conditions than in central Europe (26.6 and 28.8% in this study versus 32% in Trnka et al. [2005]).

3.2.3. Spatial structure of empirical model parameters

The empirical coefficients of the AP, SK, CD and H models, estimated with the nonlinear least squares estimation methodology summarized in Section 2.2.3, are presented in Table 6. Only the empirical parameters from the AP equation showed a relatively strong linear association with latitude. The site specific parameter α_A decreased linearly with increasing lati-

Table 4. Difference-based evaluation of 5 methods for estimation of solar radiation, for the validation period (1988–1989); actual mean bias error (MBE) (MJ m^{-2} d^{-1}) and relative MBE (MBE / mean × 100). PLR: Piecewise linear regression

	Ångström-Prescott (Eq. 1)		Supit-van Kappel (Eq. 2)		Hargreaves (Eq. 4)		Campbell-Donatelli (Eq. 3)		PLR (Eq. 5)	
	Actual	Relative	Actual	Relative	Actual	Relative	Actual	Relative	Actual	Relative
Alexandroupoli	0.70	5.8	0.97	7.7	0.92	7.3	0.99	7.9	0.49	3.9
Ioannina	0.63	4.5	0.59	4.3	0.52	3.8	0.62	4.5	0.41	3.0
Corfu	0.75	5.0	0.66	4.4	–0.50	–3.4	0.82	5.5	0.50	3.4
Skyros	–0.23	–1.4	0.31	2.0	0.30	1.9	0.37	2.4	0.22	1.4
Agrinio	0.87	5.9	0.49	3.5	0.63	4.5	0.94	6.6	0.55	3.9
Argostoli	0.82	5.1	0.46	2.9	0.19	1.2	0.37	2.3	0.37	2.3
Samos	0.82	5.2	1.10	7.0	1.13	7.2	1.00	6.4	0.65	4.1
Tripoli	0.71	4.7	0.58	3.8	0.32	2.1	0.18	1.2	0.32	2.1
Naxos	0.48	2.9	0.46	2.7	0.59	3.5	0.60	3.6	0.30	1.8
Kalamata	0.72	4.7	0.80	5.3	0.36	2.4	0.51	3.4	0.30	2.0
Rodos	0.66	3.5	0.02	0.1	–0.66	–3.5	–0.09	–0.5	–0.06	–0.3
Heraklio	0.31	1.8	0.59	3.4	0.27	1.5	0.13	0.7	0.22	1.3
All stations	0.64	4.2	0.59	3.9	0.53	3.5	0.55	3.8	0.37	2.5

Table 5. Difference-based evaluation of 5 methods for estimation of solar radiation for the calibration (1985–1987) and evaluation (1988–1989) periods; actual root mean squared error (RMSE) and relative RMSE (RMSE / mean × 100). PLR: Piecewise linear regression

	Ångström-Prescott (Eq. 1)		Supit-van Kappel (Eq. 2)		Hargreaves (Eq. 4)		Campbell-Donatelli (Eq. 3)		PLR (Eq. 5)	
	Actual	Relative	Actual	Relative	Actual	Relative	Actual	Relative	Actual	Relative
Calibration										
Alexandroupoli	3.00	19.2	3.16	19.8	5.31	28.4	4.16	27.7	2.99	22.0
Ioannina	2.15	19.3	2.15	20.4	3.02	28.6	2.78	27.6	2.42	21.8
Corfu	1.90	12.6	2.10	13.9	3.38	22.4	3.00	19.9	2.44	16.2
Skyros	2.45	14.7	2.51	16.2	5.56	36.0	4.23	27.4	3.07	19.9
Agrinio	1.96	13.6	2.10	14.6	3.10	21.6	2.82	19.6	2.34	16.3
Argostoli	2.10	13.1	2.30	14.4	3.90	24.4	3.45	21.6	2.62	16.4
Samos	2.01	12.5	2.19	13.5	3.93	24.2	3.78	23.2	2.90	17.8
Tripoli	2.39	16.0	2.46	16.4	3.35	22.4	3.22	21.5	2.51	16.8
Naxos	1.84	10.9	2.12	12.5	6.39	37.8	4.20	24.8	2.78	16.4
Kalamata	1.99	12.6	2.17	14.0	3.42	22.1	3.01	19.5	2.49	16.1
Rodos	1.74	9.0	2.11	11.1	4.34	22.8	3.62	19.0	2.81	14.8
Heraklio	2.09	11.9	2.55	14.6	5.05	28.8	3.43	19.6	2.67	15.2
All stations	2.14	13.8	2.33	15.1	4.23	26.6	3.48	22.6	2.67	17.5
Evaluation										
Alexandroupoli	2.50	24.7	2.60	25.2	3.73	42.3	3.64	33.1	2.88	23.8
Ioannina	2.68	15.7	2.79	15.6	3.91	21.9	3.77	20.1	2.98	17.5
Corfu	2.54	16.8	2.41	16.2	3.57	23.9	3.61	24.2	2.67	17.9
Skyros	2.99	18.6	2.79	18.0	5.65	36.5	4.30	27.8	3.11	20.1
Agrinio	2.29	15.4	2.36	16.7	3.30	23.3	2.99	21.1	2.46	17.4
Argostoli	2.16	13.5	2.58	16.1	4.77	29.8	4.37	27.3	2.91	18.2
Samos	2.50	15.9	2.62	16.6	4.38	27.8	4.15	26.4	3.04	19.3
Tripoli	2.34	15.5	2.50	16.6	3.42	22.7	3.16	21.0	2.56	17.0
Naxos	2.02	12.0	2.38	14.2	6.51	38.8	4.47	26.7	2.90	17.3
Kalamata	2.11	13.9	2.43	16.0	3.69	24.3	3.35	22.0	2.42	15.9
Rodos	2.04	10.7	2.22	11.6	4.50	23.5	3.58	18.7	2.79	14.6
Heraklio	2.12	12.1	2.51	14.3	5.37	30.6	3.63	20.7	2.73	15.6
All stations	2.36	15.4	2.52	16.4	4.40	28.8	3.75	24.1	2.79	17.9

Table 6. Empirical coefficients of Eqs. (1) to (4) estimated for the calibration period (1985–1987)

	Ångström-Prescott (Eq. 1)		Supit-van Kappel (Eq. 2)			Campbell-Donatelli (Eq. 3)			Hargreaves (Eq. 4)	
	α_A	b_A	a_S	b_S	c_S	τ	b	T_{nc}	a_H	b_H
Alexandroupoli	0.19	0.52	0.05	0.46	−1.03	0.72	0.34	68.4	0.17	−1.92
Ioannina	0.25	0.49	0.06	0.38	−0.07	0.65	0.31	51.5	0.15	−0.82
Corfu	0.24	0.50	0.05	0.53	−0.31	0.67	0.35	18.1	0.19	−1.90
Skyros	0.26	0.50	0.04	0.56	1.10	0.62	0.72	6.3	0.24	0.41
Agrinio	0.20	0.52	0.05	0.50	−1.85	0.68	0.23	29.3	0.17	−3.04
Argostoli	0.24	0.50	0.06	0.53	−0.24	0.66	0.76	15.2	0.22	−1.22
Samos	0.25	0.46	0.05	0.48	1.16	0.64	0.90	29.2	0.19	0.43
Tripoli	0.22	0.51	0.07	0.41	0.12	0.64	0.29	19.1	0.15	−0.47
Naxos	0.28	0.48	0.03	0.61	0.80	0.62	0.52	4.1	0.20	3.95
Kalamata	0.23	0.49	0.06	0.46	−0.67	0.69	0.28	20.5	0.19	−2.62
Rodos	0.33	0.47	0.06	0.56	1.45	0.69	1.89	15.4	0.25	1.39
Heraklio	0.34	0.40	0.05	0.50	2.45	0.64	0.41	6.2	0.21	2.01

tude ($\alpha_A = -0.022\text{Lat} + 1.085$, $r^2 = 0.53$, where r^2 is the coefficient of determination) and ranged from 0.19 in Alexandroupoli to 0.34 in Heraklio (Table 6). The opposite trend was found for parameter b_A ($b_A = 0.016\text{Lat} - 0.103$, $r^2 = 0.52$). No latitudinal linear trend was found for the empirical coefficients of SK, CD and H models.

The estimated empirical parameters of the PLR model for $R_g \leq c$ were compared with those obtained for $R_g > c$ against latitude in Fig. 3. The average R_g at each site (see Table 1) was assigned by the least squares estimation algorithm as the most appropriate for breakpoint c. The increased parameter b_{12} (the coefficient of R_A) has greater influence on the estima-

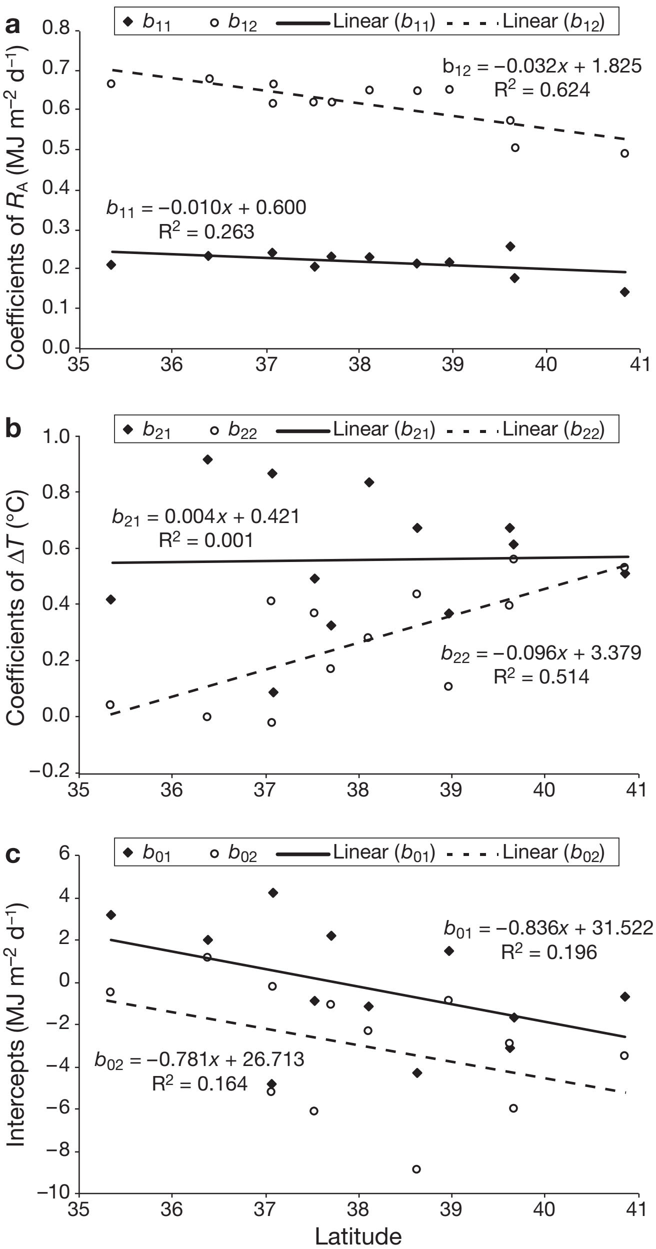

Fig. 3. Empirical coefficients of (a) extraterrestrial solar radiation (R_A), (b) diurnal temperature range (ΔT) and (c) intercepts of Eq. (5) against latitude for $R_g \leq c$ (◆) and for $R_g > c$ (○)

tion of solar radiation when $R_g > c$ than when $R_g \leq c$. This is because both b_{22} and b_{02} (the coefficient for ΔT and the intercept, respectively; see Eq. 5) present lower values under higher radiation. The coefficients of R_A decreased linearly with increasing latitude (Fig. 3a), more than when $R_g > c$ ($r^2 = 0.62$). The difference in the coefficient of ΔT on either side of the breakpoint c declined as latitude increased (Fig. 3b), but with generally higher values when $R_g \leq c$. The intercept values with $R_g > c$ were much lower compared to those under low radiation and both showed a weak relationship with latitude (Fig. 3c).

Although the use of HC1 data appeared to be adequate for the purpose of this work, the site specific empirical coefficients of the 5 R_g models in Table 6 and Fig. 3 should be used with caution elsewhere, since their estimates using the satellite-derived and actual radiation may be different in other geographical areas.

3.2.4. Crop simulations

The relative differences (%), in the median (Q50), lower and upper quartiles (Q25 and Q75) of wheat yield and ET simulated with HC1 and estimated with the 5 solar radiation models, are compared in Table 7. In agreement with Trnka et al. (2007), even the approaches that showed the lowest bias in R_g estimates, i.e. the AP and SK models, led to significant distortions of crop model output. Across all sites, each model was able to produce solar radiation data that resulted in either closely matching or largely different yield estimates for all quartiles. The CD, H and PLR approaches tended to underestimate the quartiles of yield across most geographical locations. AP and SK, on the other hand, overestimated the yield quartiles in most locations, showing lower yield discrepancies. When comparing the average of the absolute values for each of the 3 quartiles at all sites, SK provided the best results, and AP ranked second (Table 7). Rivington et al. (2006) and Trnka et al. (2007), on the other hand, found the AP model to be the most suitable source of R_g for crop growth models in the UK and central Europe, respectively. Among the temperature-based models, PLR produced the smallest and H the largest errors. The Mann-Whitney *U*-test identified 2 sites (Corfu and Argostoli) with statistically significant deviations in the distributions of simulated yield using R_g estimated with SK, and 3 sites with equally significantly deviations when PLR was employed.

All models resulted in lower estimates of relative quartile errors for ET than for yield (Table 7). Furthermore, all methods tended to overpredict the quartiles of ET for most sites; the H model had the largest deviations. As for yield, when SK was compared with AP, it produced slightly lower average discrepancies for the 50th and 75th percentiles. Among the temperature-based models, CD marginally outperformed PLR in terms of the upper and lower quartiles, while H was the poorest performer. The superiority of CD over 2 other temperature-based models (not used in this study) was reported by Bellocchi et al. (2003). These authors recommended the use of a radiation model that accounts for seasonality (such as CD) as a radiation source for crop models.

Table 7. Comparison of the relative differences (%) between solar radiation values derived from HelioClim-1 data and estimates with Eqs. (1) to (5); median (Q50) and lower and upper quartiles (Q25 and Q75) of simulated wheat yield and evapotranspiration. *Significant differences (Mann-Whitney *U*-test, 5% level). PLR: Piecewise linear regression

	Ångström-Prescott (Eq. 1)			Supit-van Kappel (Eq. 2)			Hargreaves (Eq. 4)			Campbell-Donatelli (Eq. 3)			PLR (Eq. 5)		
	Q25	Q50	Q75	Q25	Q50	Q75	Q25	Q50	Q75	Q25	Q50	Q75	Q25	Q50	Q75
Wheat yield															
Alexandroupoli	−2.4	−0.4	−1.2	−1.0	0.3	1.4	−7.9	−4.7	−4.7	−1.5	−0.8	0.4	−2.0	1.1	−1.5
Ioannina	2.8	3.5	3.2	4.0	3.0	2.7	6.6	7.5*	8.3	1.2	2.7	3.7	2.6	1.9	2.1
Corfu	7.8	4.6*	4.0	10.0	5.1*	3.7	9.8	4.2*	3.1	3.9	−0.3	−1.4	6.0	0.9	−0.7
Skyros	−2.9	2.3	1.3	−4.0	2.5	−4.0	−44.9	−18.4	−21.5	−22.2	−0.9	−10.8	−8.7	−0.6	0.2
Agrinio	8.8	4.4*	2.9	0.5	−1.9	−0.9	2.3	−2.6	−0.7	5.2	1.6	0.4	2.1	−5.1	−7.3
Argostoli	2.5	3.3*	2.5	−4.6	−4.8*	−5.0	0.2	−0.1	−1.8	−3.6	−3.5*	−4.6	−10.8	−11.9*	−13.3
Samos	−6.7	−5.9	−4.3	5.2	3.0	2.8	15.4	11.9*	11.7	3.7	1.8	2.7	6.5	2.0	−0.7
Tripoli	3.7	4.3	4.7	−0.3	−0.7	−0.9	0.5	1.8	2.2	−2.1	−4.4*	−6.7	1.6	−2.2	−1.2
Naxos	−7.6	−5.7	2.6	−6.4	−11.3	0.3	−51.3	−47.4*	−25.1	−35.4	−32.4	−6.7	−18.2	−14.8	2.2
Kalamata	10.9	9.2*	7.5	3.6	2.5	2.3	−0.1	−1.0	−0.8	−3.5	−4.5*	−5.3	−3.3	−5.1*	−6.3
Rodos	2.9	1.6	0.9	4.0	3.2	1.4	12.7	9.9*	8.3	6.0	4.4*	2.9	−1.4	−3.9*	−5.5
Heraklio	−9.3	2.6	0.0	−11.9	4.5	4.9	−30.2	−6.7	10.8	−12.0	1.3	−0.2	−8.7	1.8	−3.0
All stations	5.7	4.0	2.9	4.6	3.6	2.5	15.2	9.7	8.3	8.4	4.9	3.8	6.0	4.3	3.7
Evapotranspiration															
Alexandroupoli	2.0	1.1	1.0	0.8	0.4	0.3	0.4	1.1	0.0	0.8	1.1	0.0	2.0	2.0	1.3
Ioannina	1.0	0.7	1.2	1.6	1.3	1.2	1.6	1.3	2.8	−1.0	−1.2	0.0	1.6	1.2	1.4
Corfu	4.6	5.4*	4.1	4.2	4.8*	3.3	6.4	6.1*	4.4	3.9	4.8*	2.2	6.0	6.3*	4.1
Skyros	−1.5	2.1	2.0	−4.4	−0.3	1.5	−0.7	2.1	4.1	−1.5	1.2	1.5	0.7	0.6	1.0
Agrinio	3.9	3.5*	3.2	0.6	0.6	0.6	0.6	1.2	1.2	3.2	3.6*	3.2	2.9	2.3	1.2
Argostoli	0.3	0.5	−0.3	−3.9	−3.8*	−3.9	−0.3	−0.6	−0.6	−1.3	−1.9	−1.8	−3.6	−3.8*	−3.
Samos	1.4	1.0	1.2	5.3	3.9*	3.7	11.3	10.4*	10.3	6.7	5.7*	6.5	8.1	6.2*	5.9
Tripoli	3.0	3.4*	3.6	0.5	0.6	1.0	0.5	1.0	1.0	−4.0	−5.3*	−4.4	−0.3	0.5	0.2
Naxos	0.0	−0.2	1.9	0.5	0.4	2.6	−2.4	−1.7	3.4	0.0	−0.8	2.3	−0.5	−0.8	3.0
Kalamata	5.1	5.9*	5.0	2.2	3.0*	2.1	2.6	3.3*	2.7	0.0	0.9	0.3	1.6	2.3*	1.8
Rodos	1.3	0.9	0.9	1.6	1.5	1.7	7.6	7.0*	7.5	4.1	4.0*	4.6	3.5	3.1*	3.8
Heraklio	−0.4	0.5	1.5	0.4	1.6	3.1	−3.2	1.6	4.0	−1.4	0.8	1.5	0.7	1.0	1.8
All stations	2.0	2.1	2.2	2.2	1.9	2.1	3.1	3.1	3.5	2.3	2.6	2.4	2.6	2.5	2.5

4. CONCLUSIONS

Five methods for estimating daily global radiation were tested in Greece to determine the most appropriate source of daily solar radiation data when direct measurements are not available. Three different scenarios were investigated. When sunshine duration data was available at a site, the AP model is the best choice according to the (1) regression-based statistics, and (2) lowest relative RMSE (average values across sites were 13.8 and 15.4% for the calibration and independent periods, respectively). When the locations of interest do not have sunshine duration records, but reliable cloud cover observations and daily extreme temperature data, the SK model was as efficient as AP in most assessment metrics. When only daily T_{max} and T_{min} are measured on-site, the PLR approach with a breakpoint (Eq. 5), which reflects the value at which the behavior of daily R_g changes as a function of the extraterrestrial solar radiation (R_A) and the diurnal temperature range (ΔT), was best. Compared with the AP equation, the PLR approach increased mean relative RMSE by <3.7%. The H equation was the least successful for estimating solar radiation, confirming the conclusions of Choisnel et al. (1992) regarding its limited applicability in Europe, due to its low accuracy.

This study, in agreement with the concluding remarks of Rivington et al. (2006), also demonstrated a substantial range in model performance across different assessment metrics (i.e, regression-based versus difference-based metrics). For example, AP ranked first according to RMSE values and regression-based statistics, but had the highest mean MBE error. Therefore, as Rivington et al. (2006) recommended: (1) practitioners need to be aware of the variation in the model's performance based on different assessment statistics and (2) applying multiple different metrics for assessment of introduced uncertainty is suggested.

Even the models yielding the lowest errors in R_g estimates significantly distorted the crop simulation output. The SK model was the most suitable, and the AP model ranked second, as substitutes for measured solar radiation, with regard to reducing the amount of uncertainty in estimates of yield (simulated with CERES-Wheat), and of ET for the crop scenario considered. Among the methods using temperature data only, PLR produced the smallest and the H the largest yield errors.

Extensive validation of the models tested in this study is constrained by the limited availability of radiation observations in Greece. This limitation implies that the present results should be used with caution elsewhere. The performance of PLR should be investigated in other regions/regimes with greater availability of actual R_g data. Furthermore, the presence of a seasonal cycle in the observed (satellite) and modeled radiation and its effect on variability complicates the interpretation of the results. For comparability we adopted the same methodology as other studies in Europe (e.g. Supit & van Kappel 1998, Trnka et al. 2005), and we developed the models using the raw R_g series rather their anomalies from the mean. Nevertheless, *a priori* there is no reason to assume that model performance depends on the seasonal cycle.

Other approaches such as (1) generalized linear/non-linear models (including the GAM approach proposed by Podestá et al. 2004) and multiple regressions linking proxies of cloudiness and atmospheric humidity to daily R_g, and (2) the empirical formula developed by Winslow et al. (2001), which requires also daily precipitation data in addition to extreme temperatures, have also been investigated without showing any improvement in solar radiation prediction. We present only those models for estimating daily R_g that are fairly easy to implement and are not too complex or data intensive. For this reason, we think that the differences in model performance reported in this study, as in similar studies (Trnka et al. 2005, 2007), cannot be attributed to the differences in their complexity, but rather to the fact that some weather parameters are better predictors of daily R_g than others (e.g. sunshine duration versus air temperature), since they are better proxies for the amount of cloudiness and humidity and thus atmospheric transmittance.

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