Interactive comment on “Site specific parameterizations of longwave radiation” by G. Formetta et al.

Anonymous Referee #1

1Q) (4-100) remove, because the spectrum goes beyond 4 and is intersecting with the shortwave.

1A) We thank the reviewer for the suggestion and we fixed it.

2Q) across the USA: contiguous
2A) We thank the reviewer for the suggestion and we fixed it.
across the contiguous USA

3Q) the contiguous USA: contiguous
3A) We thank the reviewer for the suggestion and we fixed it.

4Q) Please add the following sentence: Longwave radiation was measured with Eppley Pyrgeometers with uncertainty of +/- 3 W/m-2.
4A) We thank the reviewer for the suggestion and we added it.

5Q) “where the ice plays a fundamental role”: Modify ice with snow and ice
5A) We thank the reviewer for the suggestion and we modified it:
“where snow and ice play a fundamental role”

6Q) Instead of Moreover specify: “Regarding longwave downwelling radiation the”
6A) We thank the reviewer for the suggestion and we modified the sencence accordinly.

7Q) ”model is able to provide higher performances”: higher than what?
7A)We thank the reviewer for the suggestion and we revised the sentence:

“model is able to provide on average the best performances with the regression model parameters independently of the latitude and longitude classes”

8Q) lower performances respect to the: use with respect to

8A) We thank the reviewer for the suggestion and we revised the sentence.

9Q) the effect different all-sky emissivity: the effect of

9A) We thank the reviewer for the suggestion and we revised the sentence.

10Q) the regression models for locations outside: use climates

10A) We thank the reviewer for the suggestion and we revised the sentence.

11Q) outside the USA: use contiguous

11A) We thank the reviewer for the suggestion and we revised the sentence.

Interactive comment on “Site specific parameterizations of longwave radiation” by G. Formetta et al.

Anonymous Referee #2

The organization of the paper has improved and the methods section is more comprehensive now.

We thank the reviewer for the comments that have improved again the quality of our paper. Below you can find the point-by-point answers to the questions-suggestions:

However, otherwise many of the issues in the first manuscript version still persist in the revised version, for example:

Q1) Unlike the authors answer (2nd reviewer, A3), Angstrom (1918) still does not appear in the reference list.

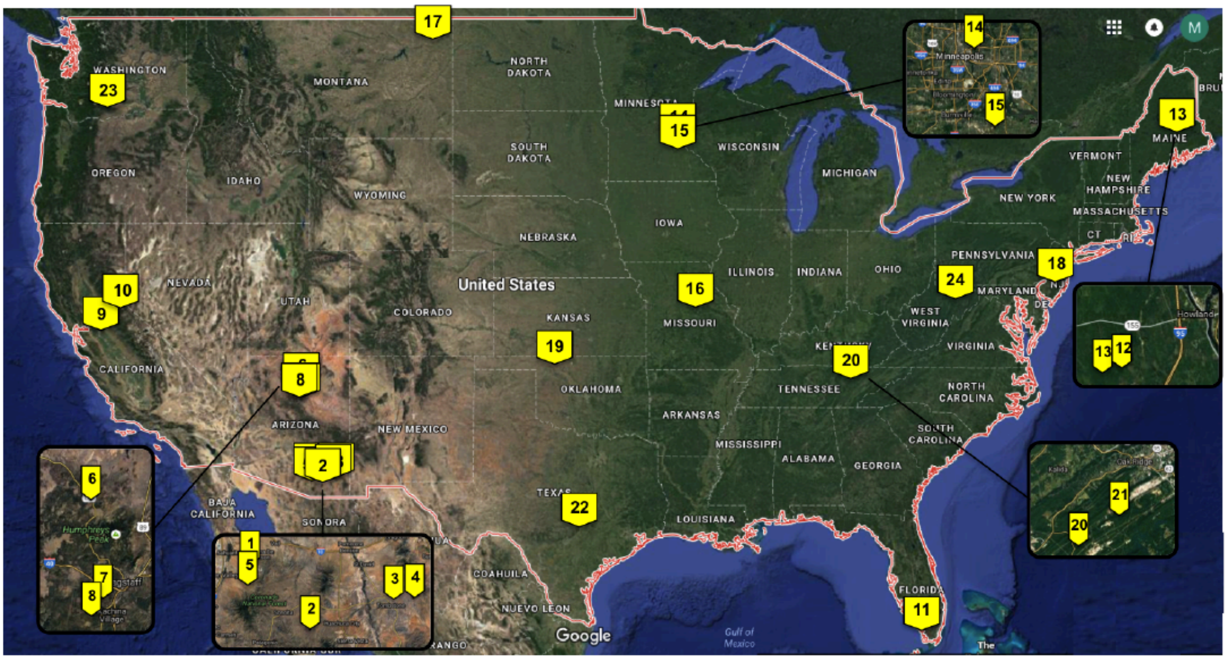
A1) We verified the reference and we have corrected it in the revised paper.

Q2) The mix of citation styles in both, the text and the reference list. The reference list is not sorted alphabetically*.*

A2) We verified and changed the style all the reference in the new version of the paper.

Q3) Unlike the authors answer (2nd reviewer, A27), Figure 2 still does not show the locations of the tests sites with the correct index. The numbers should be between 1 and 24, and all numbers should be visible.

A3) We modified the figure in order to make all the number visible. Below you can find the final figure:



Q4) ***Q31/A31: I really think the figures should be changed in order to allow the reader to (i) see the variability within the classes and (ii) compare the results of all three approaches (original parameters, fitted parameters, and parameters from regression analysis). These two things are essential for the message of the manuscript and currently not possible.***

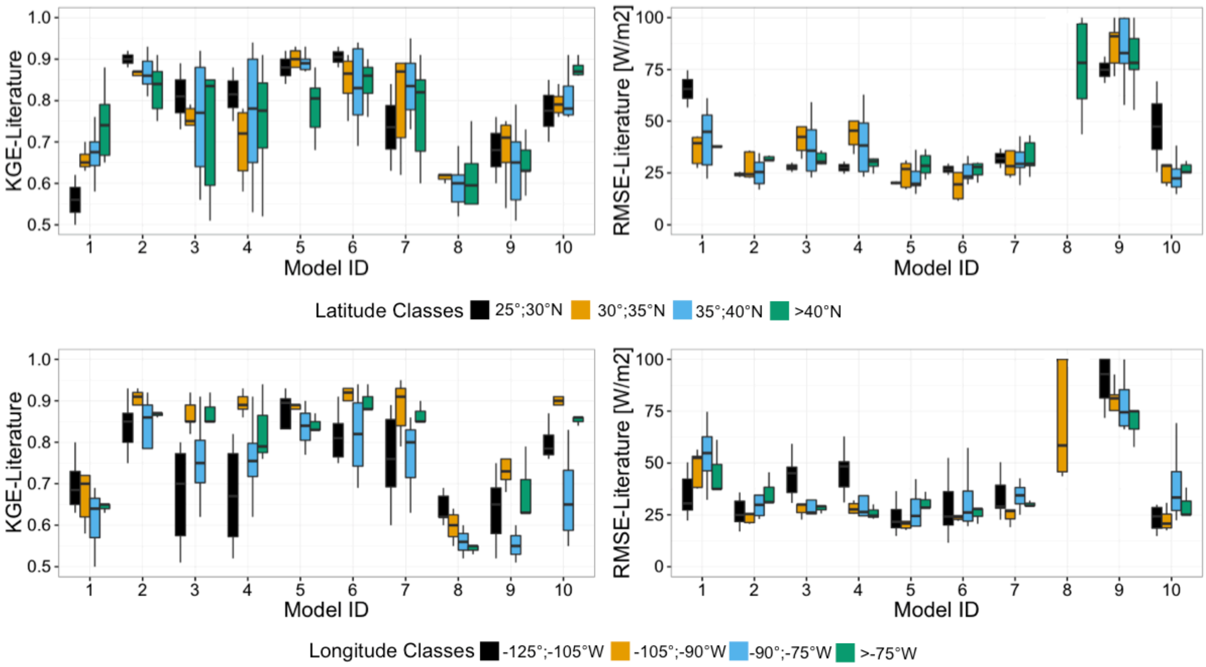
A4) Although we believe that the results are comparable even if we use the bar-plots, we revised the figure accepting part of the reviewer suggestion. On one side, in order to see the variability within the classes we used boxplots instead of bar-plots, as suggested by the reviewer. On the other side, we really would like to not reduce the number of figures from the current five to two. This is mainly for two reasons:

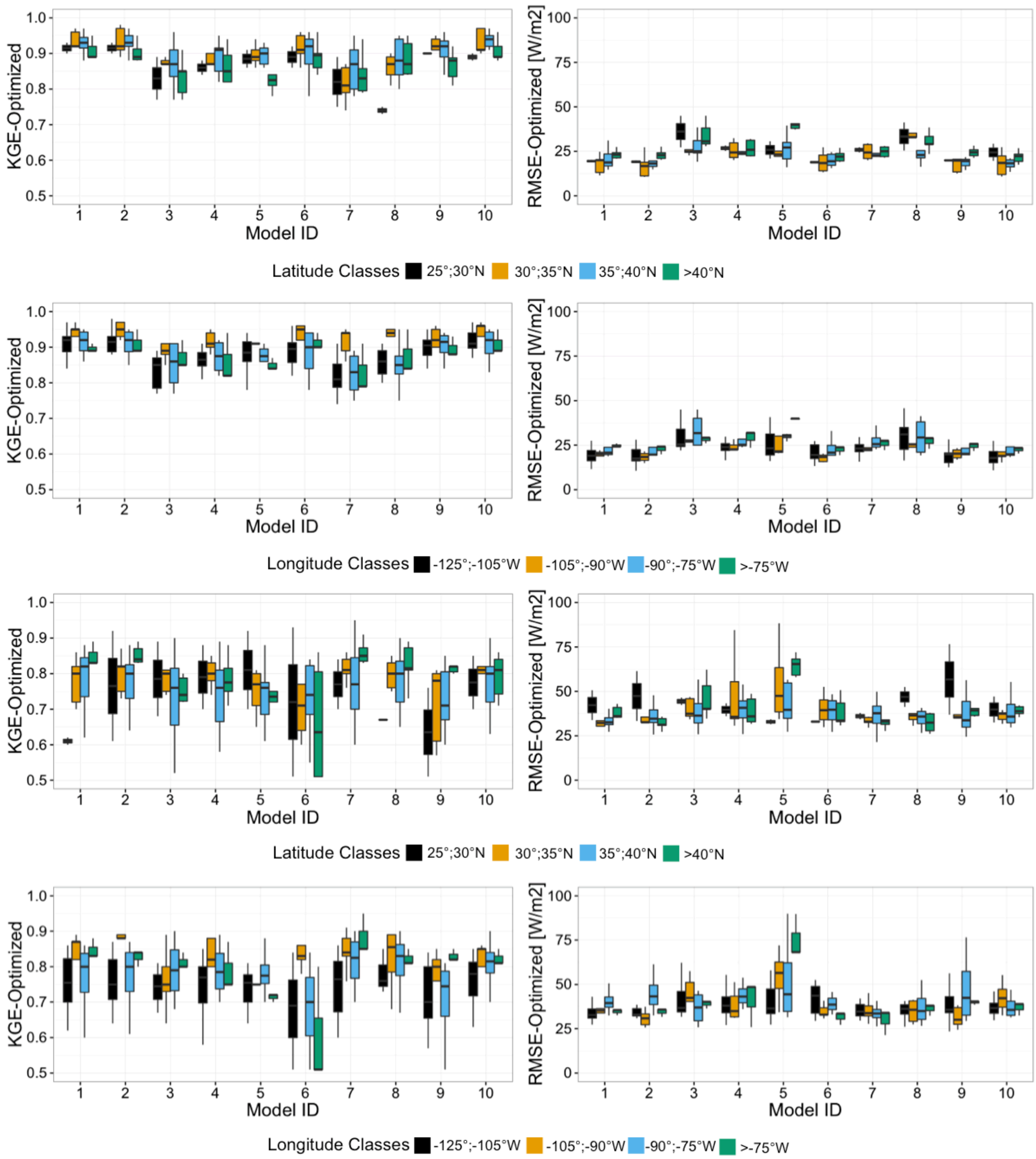
1) we really would like to facilitate the reader as we specified in the Q31/A31 answer of the previous round of revision: "We agree in part with him: we prefer to keep the plots as we made because it was an original idea of all the coauthors and the meaning of not reducing everything to 2 figures was because we wanted to facilitate the reader and his comprehension of the results. We believe that this configuration was a good compromise between

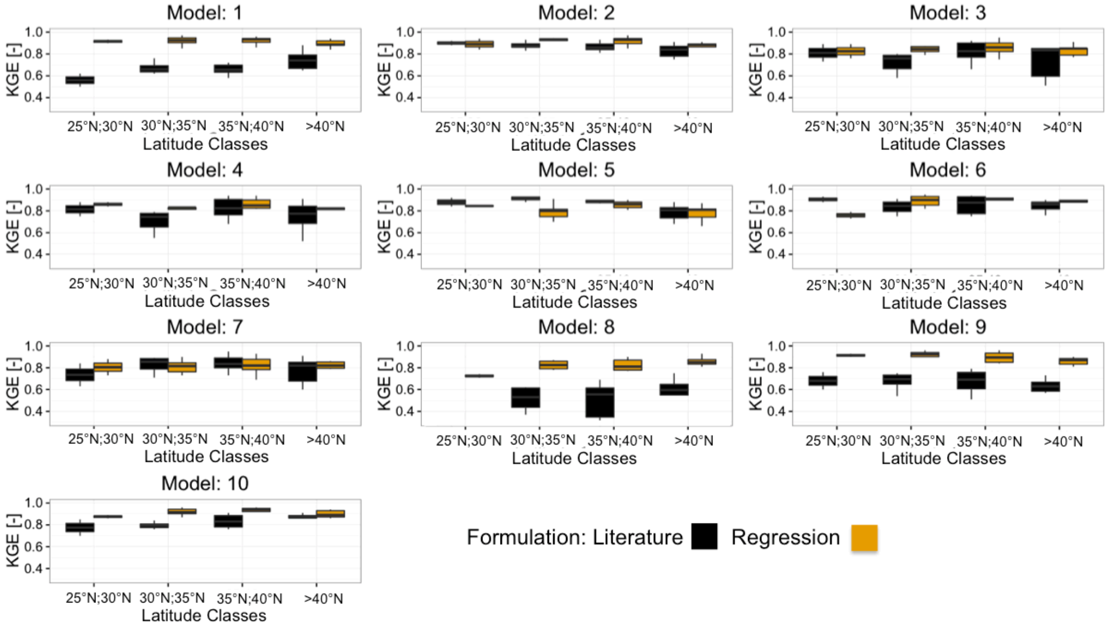
the amount of information for each plot and the possibility of a common reader to easily get the results";

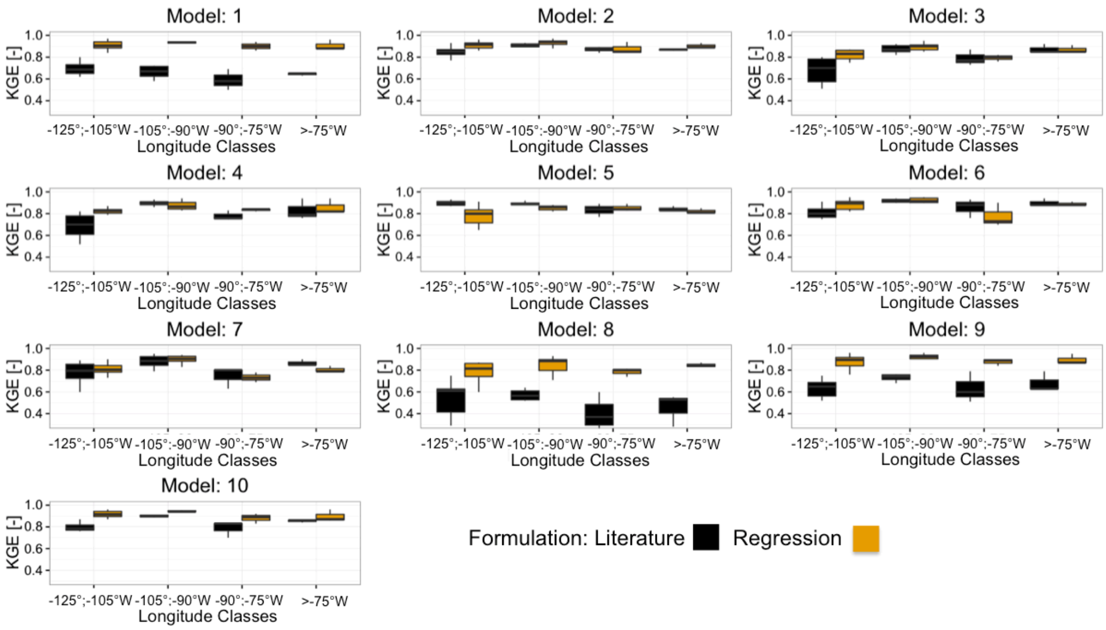
2) the modification would change the whole structure of the paper and even though this change could be made, the paper at that point would not reflect the original idea that the authors had of it. This idea was positively accepted by the reviewer n.1;

3) The comparison between results could be made by comparing the different figures between each other. The new figures are presented below:




KGE-Optimized
RMSE-Optimized [W/m2]
Model ID
1 2 3 4 5 6 7 8 9 10
Latitude Classes 25°;30°N 30°;35°N 35°;40°N >40°N
Longitude Classes -125°;-105°W -105°;-90°W -90°;-75°W >-75°W





Q5) Q33/A33: A discussion section would really be helpful

A5) The modification of the figures according the reviewer question Q4 allow us to add the following sentence about results discussion:

I -"In general all the models except the Model 8 (Konzelmann et al., 1994) provided values of KGE higher that 0.5 and RMSE lower that 100 [W m^{-2}] for all the latitude and longitude classes. Model 8 is the less performing model for many of the stations likely because the model parameters were estimated for the Greenland where the ice plays a fundamental role on the energy balance. Its KGE values range between 0.33 and 0.62 on average, while its RMSE values are higher than 100 [W m^{-2}] except for latitude classes >40°N and longitude classes >-70°W. Model 6 (Idso 1981) and Model 2 (Brunt 1932) provide the best results and the lower variability, independently of the latitude and longitude ranges where they are applied. Their average KGE values are between 0.75 and 0.92, while the RMSE has a maximum value of 39 [W m^{-2}]. Moreover, all the models except 2 and 6 show a high variability of the goodness of fit through the latitude and longitude classes."

II-"The calibration procedure reduces the RMSE values for all the models to below 45 [W m^{-2}], even for Model 8, which also in this case had the maximum improvement."

III-"Finally, the use of the parameters estimated by the regression model provides a reduction of the model performances variability for all the models except Model 5 and 8, for longitude class -125;-105°W and -105;-90°W respectively."

Q6) Q13/A13 (l59): The added value of this study is not clear to me, in particular point 1 ("i) developed a method to systematically compute the site-specific model parameters for location where measurements are available") is clearly wrong. This point should be removed as lots of studies systematically calibrate empirical models, e.g. Carmona et al. (2014) as the authors admit themselves, and also Juszak and Pellicciotti (2013).

A6) We removed the sentence according the reviewer suggestion. The new sentence is:

"However, none of the above studies have developed a method to systematically estimate site-specific model parameters for location where measurements are not available using basic site characteristics. Moreover, differently from other studies, all the tools used in this paper are open-source, well documented, and ready for practical use by other researchers and practitioners.”

Q7) Q5/Q6: The manuscript still does not contain information on which model is best. Furthermore, important results are moved to the supplementary material, which was not available for review. They should be checked carefully. The presence of the table mentioned ("Presenting in a table the value of the regression parameters for each model was not our focus but we added it in a supplementary material.") should be indicated in the text.

A7) We apologize for this mistake: we added in the text the reference to the table and we submitted the modified table. The new sentence in the revised paper is:
“Optimized model parameters for each model are reported in the supplementary material (Table S1)”
Secondly, we stated which are the best models:
1) In the abstract: “Also in this case Model 6 (Idso 1981) and Model 2 (Brunt 1932) SMs provided the best performances.”
2) In the section 4.1: “Model 6 (Idso 1981) and Model 2 (Brunt 1932) provide the best results and the lower variability, independently of the latitude and longitude ranges where they are applied.”
3) In section 4.2: “Model 6 (Idso 1981) and Model 2 (Brunt 1932) provide the best results on average for all the analyzed latitude and longitude classes.”

Q8) l92: What is an hour angle?
A8) We specified the definition of the hour angle. The new sentence is:
“…where w is the hour angle, i.e. is the angle between the observer meridian and the solar meridian. It is zero at noon and positive before noon”.

Q9): What do you mean by "and citation therein"?

A9) We mean references in that paper. To make it more understandable we modified "and citation therein" with "and references therein" in the revised paper.

Q9): Table 2: If you take the literature formulation as in Flerchinger et al., 2009 (mentioned in the answer A19), this should be cited in the table caption

A9) We added the following sentence in the table 2 caption:
" The models follow the formulations presented in Flerchinger et al., 2009"

Q10) l145: the sentence "which could be compensated by the optimization of the parameters a and b" is not based on an argument

A10) The discussion was related to the choice of the threshold and was clarified in the sentence before l145, after the previous revision. It says:
"On one side, a threshold of 0.6 to define the clear-sky conditions helps in the sense that allows to define time-series of measured clear-sky $L_\downarrow$ with comparable length in all the stations, which is useful for a reliable calibration process. On the other side, it introduces a small error in computing the emissivity in all-sky condition using equation 3."
In order to explain better we revised again the sentence specifying the fact that the calibration procedure could provide values to the parameter a and b that compensate that small error:
"Although the effects of this small error would need further investigations, they could be compensated by the optimization of the parameters a and b, that are non-linearly related to the emissivity in all-sky conditions"
Finally, in the conclusion we better clarify that (one limitation of the study and consequently) future work could involve the investigation of those effects of derived from these small error on the clear sky emissivity. The revised sentence is:
"Finally, the methodology proposed in this paper provides the basis for further developments such as the possibility to: i) investigate the effect of different all-

sky emissivity formulation and quantify the influence of the clearness index threshold”

Q11) Figure 4: The caption is wrong as now Model 8 is within the range for all but one case.

A11) We fixed the caption in the revised paper and we deleted the refuse in the previous revision. The new caption for figure 4 is:

“KGE and RMSE values for each clear-sky simulation using literature formulations, grouped by classes of latitude and longitude. Only values of KGE above 0.5 are shown. Only values of RMSE below 100 W/m^2 are shown.”

Q12) Figures 4,5,6,8,9: It would be better to rename the latitude and longitude classes, e.g. change 25;30 to 25-30°N

A12) We thank the reviewer for the suggestion. All the figures in the revised paper have the suggested notation.

Q13) l309: the latitude class name is not intuitive, do you mean between 25°N and 30°N?

A13) We revised according his/her suggestion. The new sentence is:

“…literature formulation for latitude between 25°N and 30°N.”

Q14) Figure 6: The caption does not mention which parameters were taken (original, fitted, or from regression analysis)

A14) We thank the reviewer for the suggestion and we revised the caption specifying that we used the optimized parameters:

Old caption: “KGE and RMSE values for each model in all-sky conditions grouped by classes of latitude and longitude. Only values of KGE above 0.5 are shown”

New caption: “KGE and RMSE values for each model in all-sky conditions with the optimized parameters; results are grouped by classes of latitude and longitude. Only values of KGE above 0.5 are shown”

Q15) Figures 8+9: The captions are equal, the figures are not, mention the difference in the captions

A15) We thank the reviewer for the suggestion. The caption are different: figure 8 say: “and results are grouped by latitude classes” and figure 9 say: “and results are grouped by longitude classes”

Q16) Units should not be in italics.

A16) We thank the reviewer for the suggestion and we modified all the units in the text in order to be not italics.

Q17) The English of the changed paragraphs needs proofreading.

A17) We thank the reviewer for the suggestion and we revised the new sentences we added.

Q18) Citation of tables and figures are not consistent: either "table 1" or "Table 1" and never "figure1"

A18) We revised using Figure and Table in a consistent way all over the paper.

Performances of site specific parameterizations of longwave radiation

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October 21, 2016

Abstract

In this work ten algorithms for estimating downwelling longwave atmospheric radiation ($L_\downarrow$) and one for upwelling longwave radiation ($L_\uparrow$) are integrated into the JGrass-NewAge modeling system. The algorithms are tested against energy flux measurements available for 24 sites in North America to assess their reliability. These new JGrass-NewAge model components are used i) to evaluate the performances of simplified models (SMs) of $L_\downarrow$, as presented in literature formulations, and ii) to determine by automatic calibration the site-specific parameter sets for $L_\downarrow$ in SMs. For locations where calibration is not possible because of a lack of measured data, we perform a multiple regression using on-site variables, i.e. mean annual air temperature, relative humidity, precipitation, and altitude. The regressions are verified through a leave-one-out cross validation, which also gathers information about the possible errors of estimation. Most of the SMs, when executed with parameters derived from the multiple regressions, give enhanced performances compared to the corresponding literature formulation. A sensitivity analysis is carried out for each SM to understand how small variations of a given parameter influence SM performance. Regarding the $L_\downarrow$ simulations, the Brunt (1932) and Idso (1981) SMs, in their literature formulations, provide the best performances in many of the sites. The site-specific parameter calibration improves SM performances compared to their literature formulations. Specifically, the root mean square error (RMSE) is almost halved and the Kling Gupta efficiency is improved at all sites. Also in this case Brunt (1932) and Idso (1981) SMs provided the best performances.

The $L_\uparrow$ SM is tested by using three different temperatures (surface soil temperature, air temperature at 2 m elevation, and soil temperature at 4 cm depth) and model performances are then assessed. Results show that the best performances are achieved using the surface soil temperature and the air temperature.

1 Introduction

Longwave radiation ~~(4-100 μm)~~ is an important component of the radiation balance on earth and it affects many phenomena, such as evapotranspiration, snow melt (Plüss and Ohmura, 1997), glacier evolution (MacDonell et al., 2013), vegetation dynamics (Rotenberg et al., 1998), plant respiration, and primary productivity (Leigh Jr, 1999). Longwave radiation is usually measured with pyrgeometers, but these are not normally available in basic meteorological stations, even though an increasing number of projects has been developed to fill the gap ~~(Augustine et al., 2000) , as seen in~~ Augustine et al. (2000) , Augustine et al. (2005) and Baldocchi et al. (2001). The use of satellite products to estimate longwave solar radiation is increasing (GEWEX, Global Energy and Water cycle Experiment, ISCCP the International Satellite Cloud Climatology Project) but they have too coarse a spatial resolution for many hydrological uses. Therefore, models have been developed to solve energy transfer equations and compute radiation at the surface (e.g. Key and Schweiger (1998), Kneizys et al. (1988)). These physically based and fully distributed models provide accurate estimates of the radiation components. However, they require input data and model parameters that are not easily available. To overcome this issue, simplified models (SM), which are based on empirical or physical conceptualizations, have been developed to relate longwave radiation to atmospheric proxy data such as air temperature, water vapor deficit, and shortwave radiation. They are widely used and provide clear sky (e.g. Ångström (1915); Brunt (1932); Idso and Jackson (1969)) and all-sky estimations of downwelling ($L_\downarrow$) and upwelling ($L_\uparrow$) longwave radioation(e.g. Brutsaert (1975); Iziomon et al. (2003a)).

SM performances have been assessed in many studies by comparing measured and modeled $L_\downarrow$ at hourly and daily time-steps (e.g. Sugita and Brutsaert (1993a); Iziomon et al. (2003b); Juszak and Pellicciotti (2013); MacDonell et al. (2013); Schmucki et al. (2014)). Hatfield et al. (1983) was among the first to present a comparison of the most used SMs in an evaluation of their accuracy. They tested seven clear-sky algorithms using atmospheric data from different stations in the United States. In order to validate the SMs under different climatic conditions, they performed linear regression analyses on the relationship between simulated and measured $L_\downarrow$ for each algorithm. The results of the study show that the best models were Brunt (1932), Brutsaert (1975) and Idso (1981). Flerchinger et al. (2009) made a similar comparison using more formulations (13) and a wider data-set from North America and China, considering all possible sky conditions. Finally, Carmona et al. (2014) evaluated the performance of six SMs, with both literature and site-specific formulations, under clear-sky conditions for the sub-humid Pampean region of Argentina.

However, none of the above studies have ~~: i)~~ developed a method to systematically ~~compute the~~ estimate site-specific model parameters for location where measurements are ~~available, and ii) provided their estimate for any location based on~~ not available using basic site characteristics. ~~Moreover, differently from other studies, all the tools used in this paper are open-source, well documented, and ready for practical use by other researchers and practitioners.~~

This paper introduces the LongWave Radiation Balance package (LWRB) of the JGrass-NewAGE modelling system Formetta et al. (2014a). LWRB implements 10 formulations for $L_\downarrow$ and one for $L_\uparrow$ longwave radiation.

The package was systematically tested against measured $L_\downarrow$ and $L_\uparrow$ longwave radiation data from 24 stations across the contiguous USA, chosen from the 65 stations of the AmeriFlux Network. Unlike all previous works, the LWRB component follows the specifications of the Object Modeling System (OMS) framework (David et al., 2013). Therefore, it can use all of the JGrass-NewAge tools for the automatic calibration algorithms, data management and GIS visualization, and it can be seamlessly integrated into various modeling solutions for the estimation of water budget fluxes (Formetta et al., 2014a). Moreover, differently from other studies, all the tools used in this paper are open-source, well documented, and ready for practical use by other researchers and practitioners.

2 Methodology

The SMs for $L_\uparrow$ [~~Wm~~W m^{-2}] and $L_\downarrow$ [~~Wm~~W m^{-2}] longwave radiation are based on the Stefan-Boltzmann equation:

$$L_\downarrow = \epsilon_{all-sky} \cdot \sigma \cdot T_a^4 \tag{1}$$

$$L_\uparrow = \epsilon_s \cdot \sigma \cdot T_s^4 \tag{2}$$

where $\sigma = 5.670 \cdot 10^{-8}$ [W m^{-2} K^{-4}] is the Stefan-Boltzmann constant, T_a [K] is the air temperature, $\epsilon_{all-sky}$ [-] is the effective atmospheric emissivity, ϵ_s [-] is the soil emissivity and T_s [K] is the surface soil temperature. To account for the increase of $L_\downarrow$ in cloudy conditions, $\epsilon_{all-sky}$ [-] is formulated according to eq. (3):

$$\epsilon_{all-sky} = \epsilon_{clear} \cdot (1 + a \cdot c^b) \tag{3}$$

where c [-] is the cloud cover fraction and a [-] and b [-] are two calibration coefficients. Site specific values of a and b are presented in Brutsaert (1975), (a=0.22 and b=1), Iziomon et al. (2003a) (a ranges between 0.25 and 0.4 and b=2) and Keding (1989) (a=0.183 and b=2.18). In our modeling system a and b are calibrated to fit measurement data under all-sky conditions. The cloud cover fraction, c, can be estimated from solar radiation measurements (Crawford and Duchon, 1999), from visual observations (Alados-Arboledas et al., 1995, Niemelä et al., 2001), and from satellite data (Sugita and Brutsaert, 1993b) or it can be modeled as well. In this study we use the formulation presented in Campbell (1985) and Flerchinger (2000), where c is related to the clearness index s [-], i.e. the ratio between the measured incoming solar radiation, I_m [~~Wm~~W m^{-2}], and the theoretical solar radiation computed at the top of the atmosphere, I_{top} [~~Wm~~W m^{-2}], according ~~the following relationship:~~ to $c = 1 - s$ (Crawford and Duchon, 1999). This type of formulation needs a shortwave radiation balance model to estimate I_{top} and meteorological stations to measure I_m; also, it cannot estimate c at night. In our application, the fact that the SMs are fully integrated into the JGrass-NewAge system allows us to use the shortwave radiation balance model (Formetta et al., 2013) to compute I_{top}. Night-time values of c are computed with a linear interpolation between its values at the last hour of daylight and the first hour of daylight on consecutive days. The computation of the first and last hour of the day is based on the model proposed in Formetta et al., 2013 that ~~follow~~ follows the approach proposed in Corripio (2002), equations (4.23~~-4.25~~)-(4.25). The sunrise occurs at $t = 12 \cdot (1 - \omega/\pi)$ and the sunset will be at $t = 12 \cdot (1 + \omega/\pi)$ where ω is the hour angle~~.~~ , i.e. the angle between the observer meridian and the solar meridian. It is zero at noon and positive before noon. Those equations are based on the assumption that sunrise and sunset occur at the time when the z coordinate of the sun vector equals zero.

The formulation presented in equation (3) was proposed by Bolz (1949) applied in other studies (Carmona et al. (2014), Maykut and Church (1973), Jacobs (1978), Niemelä et al. (2001)). Evaluating the effectiveness of different formulations respect to equation (3) is still an open question which is not object of the current paper. It has been investigated in several studies (i.e. Flerchinger et al. (2009), Juszak and Pellicciotti (2013), and ~~citation~~ references therein) and some of them recommended the one proposed by Unsworth and Monteith (1975).

Ten SMs from literature have been implemented for the computation of ϵ_{clear}. Table 1 specifies assigned component number, component name, defining equation, and reference to the paper from which it is derived. X, Y and Z are the parameters provided in literature for each model, listed in ~~table~~ Table 2.

ID	Name	Formulation	Reference
1	Angstrom	$\epsilon_{clear} = X - Y \cdot 10^{Ze}$	~~Angstrom (1918)~~Ångström (1915)
2	Brunt's	$\epsilon_{clear} = X + Y \cdot e^{0.5}$	~~Brunt's (1932)~~Brunt (1932)
3	Swinbank	$\epsilon_{clear} = (X \cdot 10^{-13} \cdot T_a^6)/(\sigma \cdot T_a^4)$	~~Swinbank (1963)~~Swinbank (1963)
4	Idso and Jackson	$\epsilon_{clear} = 1 - X \cdot exp(-Y \cdot 10^{-4} \cdot (273 - T_a)^2)$	~~Idso and Jackson (1969)~~Idso and Jackso
5	Brutsaert	$\epsilon_{clear} = X \cdot (e/T_a)^{1/Z}$	~~Brutsaert (1975)~~Brutsaert (1975)
6	Idso	$\epsilon_{clear} = X + Y \cdot 10^{-4} \cdot e \cdot exp(1500/T_a)$	~~Idso (1981)~~Idso (1981)
7	Monteith and Unsworth	$\epsilon_{clear} = X + Y \cdot \sigma \cdot T_a^4$	Monteith and Unsworth (1990)
8	Konzelmann	$\epsilon_{clear} = X + Y \cdot (e/T_a)^{1/8}$	~~Konzelmann et al (1994)~~Konzelmann et
9	Prata	$\epsilon_{clear} = [1 - (X + w) \cdot exp(-(Y + Z \cdot w)^{1/2})]$	~~Prata (1996)~~Prata (1996)
10	Dilley and O'Brien	$\epsilon_{clear} = (X + Y \cdot (T_a/273.16)^6 + Z \cdot (w/25)^{1/2})/(\sigma \cdot T_a^4)$	~~Dilley and O'Brien (1998)~~Dilley and O'I

Table 1: Clear sky emissivity formulations: T_a is the air temperatue [K], w [kg/m^2] is precipitable water = 4650 [e_0/T_a] and e [kPa] is screen-level water-vapour pressure. The models follow the formulations presented in used in Flerchinger (2000) . The Angstrom and Brunt model was presented as cited by Niemelä et al. (2001). Konzelmann uses water vapour pressure in [Pa] not [kPa].

The models presented in ~~table~~ Table 1 were proposed with coefficient values (X, Y, Z) strictly related to the location in which the authors applied the model and where measurements of $L_\downarrow$ radiation were collected. Coefficients reflect climatic, atmospheric and hydrological conditions of the sites, and are reported in Table 2.

The formulation of the $L_\uparrow$ requires the soil emissivity, which usually is a property of the nature of a surface, and the surface soil temperature. Table 3 shows the literature values (Brutsaert, 2005) of the soil emissivity for different surface types: ϵ_s varies from a minimum of 0.95 for bare soils to a maximum of 0.99 for fresh snow.

It is well known that surface soil temperature measurements are only available at a few measurement sites~~.~~ ~~Under~~ , therefore, under the hypothesis that difference between soil and air temperatures is not too big, it is possible to simulate $L_\uparrow$ using the air temperature (Park et al., 2008). In our approach three different types of temperature were used to simulate $L_\uparrow$, specifically: surface soil temperature (where available), air temperature at 2 m height, and soil temperature at 4 cm depth.

ID	Name	X	Y	Z
1	Angstrom	0.83	0.18	−0.07
2	Brunt	0.52	0.21	[−]
3	Swinbank	5.31	[−]	[−]
4	Idso and Jackson	0.26	−7.77	[−]
5	Brutsaert	1.72	7	[−]
6	Idso	0.70	5.95	[−]
7	Monteith and Unsworth	−119.00	1.06	[−]
8	Konzelmann et al	0.23	0.48	[−]
9	Prata	1.00	1.20	3.00
10	Dilley and O'brien	59.38	113.70	96.96

Table 2: Model parameter values as presented in their literature formulation.

Nature of surface	Emissivity
Bare soil (mineral)	0.95 − 0.97
Bare soil (organic)	0.97 − 0.98
Grassy vegetation	0.97 − 0.98
Tree vegetation	0.96 − 0.97
Snow (old)	0.97
Snow (fresh)	0.99

Table 3: Soil emissivity for surface types (Brutsaert, 2005).

The LWRB package (see flowchart in ~~figure~~Figure1) is part of the JGrass-NewAge system and was preliminary tested in Formetta et al. (2014b). Model inputs depend on the specific SM being implemented and the purpose of the run being performed (calibration, verification, simulation). The inputs are meteorological observations such as air temperature, relative humidity, incoming solar radiation, and sky clearness index. The LWRB is also fed by other JGrass-NewAGE components, such as the shortwave radiation balance (SWRB) (Formetta et al., 2013). To test model performances (i.e. verification), the LWRB can be connected to the system's Verification component; to execute the parameter calibration algorithm (Formetta et al., 2014a), it can be connected to the LUCA (Let Us CAlibrate) component. In turn, all these components can and/or need to be connected to other ones, as the problem under examination may require. Model outputs are $L_\downarrow$ and $L_\uparrow$. These can be provided in single points of specified coordinates or over a whole geographic area, represented as a raster map. For the latter case a digital elevation model (DEM) of the study area is necessary in input.

The subsection 2.1 and 2.2 respectively present the calibration and the verification procedure. Moreover a model sensitivity analysis procedure is presented in subsection 2.3 and a multi-regression model to relate optimal parameter set and easy available meteorological data is proposed in subsection 2.4.

2.1 Calibration of $L_\downarrow$ longwave radiation models

Model calibration estimates the site-specific parameters of $L_\downarrow$ models by tweaking them with a specific algorithm in order to best fit measured data. To this end, we use the LUCA calibration algorithm proposed in Hay et al. (2006), which is a part of the OMS core and is able to optimize parameters of any OMS component. LUCA is a multiple-objective, stepwise, and automated procedure. As with any automatic calibration algorithm, it is based on two elements: a global search algorithm; and the objective function(s) to evaluate model performance. In this case, the global search algorithm is the Shuffled Complex Evolution, which has been widely used and

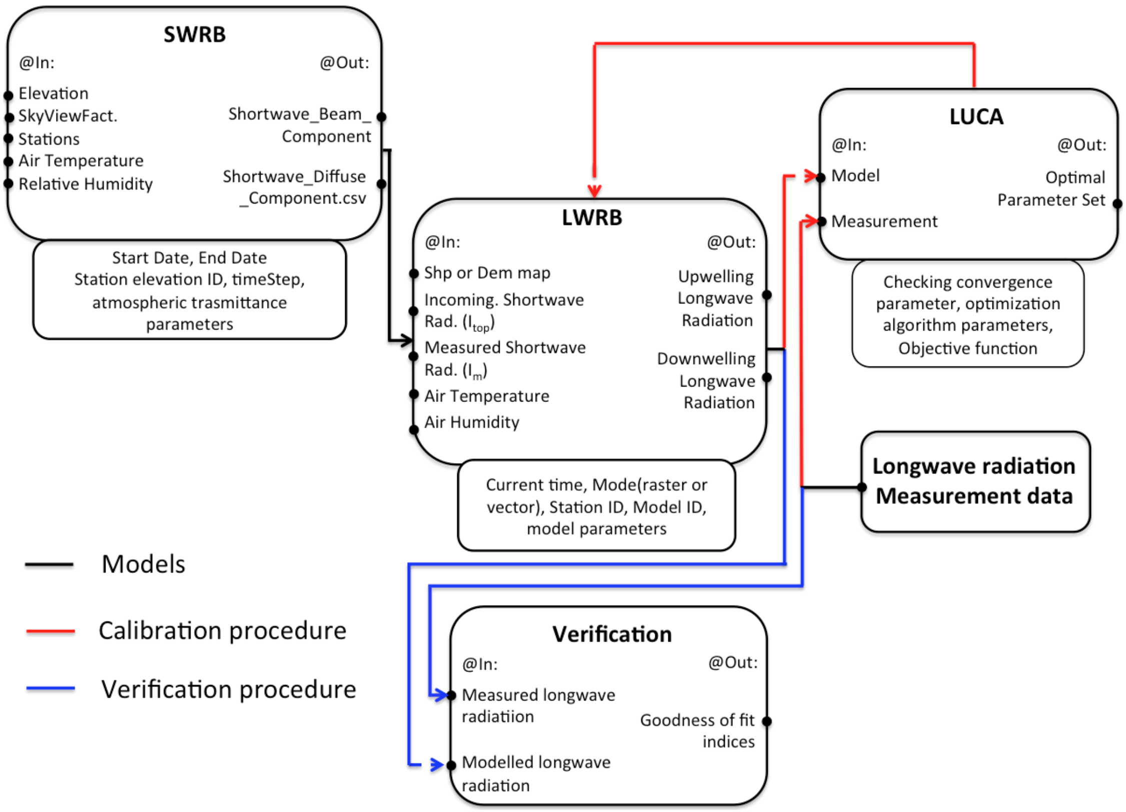

Figure 1: The LWRB component of JGrass-NewAge and the flowchart to model longwave radiation.

described in literature (e.g., Duan et al., 1993). As the objective function we use the Kling-Gupta Efficiency (KGE, Gupta et al. (2009)), which is described below, but LUCA could use other objective functions just as well.

The calibration procedure for $L_{\downarrow}$ follows these steps:

- The theoretical solar radiation at the top of the atmosphere (I_{top}) is computed using the SWRB (see Figure 1);
- The clearness index, c, is calculated as the ratio between the measured incoming solar radiation (I_m) and I_{top};
- Clear-sky and cloud-cover hours are detected by a threshold on the clearness index (equal to 0.6), providing two subsets of measured $L_{\downarrow}$, which are $L_{\downarrow clear}$ and $L_{\downarrow cloud}$. On one side, a threshold of 0.6 to define the clear-sky conditions helps in the sense that allow to define time-series of measured clear-sky $L_{\downarrow}$ with comparable length in all the stations, and this is useful for a reliable calibration process. On the other side, it introduces a small error in computing the emissivity in all-sky condition using equation (3~~which~~). Although the effects of this small error would need further investigations, they could be compensated by the optimization of the parameters a and b, that are non-linearly related to the emissivity in all-sky conditions;
- The parameters X, Y, and Z for the models in ~~table~~ Table 1 are optimised using the subset $L_{\downarrow clear}$ and setting a=0 in eq. 3;

- The parameters a and b for eq. 3 are optimized using the subset $L_{\downarrow cloud}$ and using the X, Y, and Z values computed in the previous step.

The calibration procedure provides the optimal set of parameters at a given location for each of the ten models.

As well as parameter calibration, we carry out a model parameter sensitivity analysis and we provide a linear regression model relating a set of site-specific optimal parameters with mean air temperature, relative humidity, precipitation, and altitude.

2.2 Verification of $L_{\downarrow}$ and $L_{\uparrow}$ longwave radiation models

As presented in previous applications (e.g. Hatfield et al. (1983), Flerchinger et al. (2009)), we use the SMs with the original coefficients from literature (i.e. the parameters of ~~table~~ Table 2) and compare the performances of the models against available measurements of $L_{\downarrow}$ and $L_{\uparrow}$ for each site. The goodness of fit is evaluated by using two goodness-of-fit estimators: the Kling-Gupta Efficiency (KGE) ~~presented in Gupta et al. (2009) ;~~ and the root mean square error (RMSE).

The KGE (eq. 4) is able to incorporate into one objective function three different statistical measures of the relation between measured (M) and simulated (S) data: (i) the correlation coefficient, r ; (ii) the variability error, $a = \sigma_S/\sigma_M$; and (iii) the bias error, b$=\mu_S/\mu_M$. In these definitions μ_S and μ_M are the mean values, while σ_S and σ_M are the standard deviations, of measured and simulated time series.

$$KGE = 1 - \sqrt{(r-1)^2 + (a-1)^2 + (b-1)^2} \tag{4}$$

The RMSE, on the other hand, is presented in eq. 5:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(M_i - S_i)^2} \tag{5}$$

where M and S represents the measured and simulated time-series respectively and N is their length.

2.3 Sensitivity analysis of $L_{\downarrow}$ models

For each $L_{\downarrow}$ model we carry out a model parameters sensitivity analysis to investigate the effects and significance of parameters on performance for different model structures (i.e. models with one, two, and three parameters). The analyses are structured according to the following steps:

- we start with the optimal parameter set, computed by the optimization process for the selected model;
- all parameters are kept constant and equal to the optimal parameter set, except for the parameter under analysis;
- 1000 random values of the analyzed parameter are picked from a uniform distribution centered on the optimal value with width equal to ± 30% of the optimal value; in this way 1000 model parameter sets

were defined and 1000 model runs were performed;

- 1000 values of KGE are computed by comparing the model outputs with measured time series.

The procedure was repeated for each parameter of each model and for each station of the analyzed dataset.

2.4 Regression model for parameters of $L_{\downarrow}$ models

The calibration procedure previously presented to estimate the site specific parameters for $L_{\downarrow}$ models requires measured downwelling longwave data. Because these measurements are rarely available, we implement a straightforward multivariate linear regression (Chambers et al., 1992; Wilkinson and Rogers, 1973) to relate the site-specific parameters X, Y and Z to a set of easily available site specific climatic variables, used as regressors r_i. To perform the regression we use the open-source R software (https://cran.r-project.org) and to select the best regressors we use algorithms known as "best subsets regression", which are available in all common statistical software packages. The regressors we have selected are: mean annual air temperature, relative humidity, precipitation, and altitude. The models that we use for the three parameters are presented in equations (6), (7), and (8):

$$X = i_X + \sum_{k=1}^{N} \alpha_k \cdot r_k + \epsilon_X \tag{6}$$

$$Y = i_Y + \sum_{k=1}^{N} \beta_k \cdot r_k + \epsilon_Y \tag{7}$$

$$Z = i_Z + \sum_{k=1}^{N} \gamma_k \cdot r_k + \epsilon_Z \tag{8}$$

where N=4 is the number of regressors (annual mean air temperature, relative humidity, precipitation, and altitude); r_k with k=1,.., 4 are the regressors; i_X, i_Y, and i_Z are the intercepts; α_k, β_k, and γ_k are the coefficients; and ϵ_X, ϵ_Y, and ϵ_Z are the normally distributed errors. Once the regression parameters are determined, the end-user can estimate site specific X, Y and Z parameter values for any location by simply substituting the values of the regressors in the model formulations.

3 The study area: the AmeriFlux Network

To test and calibrate the LWRB SMs we use 24 meteorological stations of the AmeriFlux Network (http://ameriflux.ornl.gov). AmeriFlux is a network of sites that measure water, energy, and CO2 ecosystem fluxes in North and South America. The dataset is well-known and used in several applications such as Xiao et al. (2010), Barr et al. (2012), and Kelliher et al. (2004). Data used in this study are the Level 2, 30-minute average data. Complete descriptions and downloads are available at the Web interface located at http://public.ornl.gov/ameriflux/.

We have chosen 24 sites that are representative of most of the contiguous USA and span a wide climatic range: going from the arid climate of Arizona, where the average air temperature is 16 °C and the annual precipitation is 350 mm, to the equatorial climate of Florida, where the average air temperature is 24 °C and the annual precipitation is 950 mm. Some general and climatic characteristics for each site are summarized in ~~table~~ Table 4, while ~~figure~~ Figure 2 shows their locations. The 30-minute average data have been cumulated to obtain continuous time series of averaged, hourly data for longwave radiation, air and soil temperature, relative humidity, precipitation, and soil water content. Longwave radiation was measured with Eppley Pyrgeometers with uncertainty of +/- 3 [W m^{-2}].

SiteID	State	Latitude	Longitude	Elevation (m)	Climate	T (^{o}C)	Data period
1	AZ	31.908	−110.840	991	semiarid	19	2008 – 2013
2	AZ	31.591	−110.509	1469	temperate,arid	16	2002 – 2011
3	AZ	31.744	−110.052	1372	temperate,semi-arid	17	2007 – 2013
4	AZ	31.737	−109.942	1531	temperate,semi-arid	17	2004 – 2013
5	AZ	31.821	−110.866	116	subtropical	19	2004 – 2014
6	AZ	35.445	−111.772	2270	warm temperate	9	2005 – 2010
7	AZ	35.143	−111.727	2160	warm temperate	9	2005 – 2010
8	AZ	35.089	−111.762	2180	warm temperate	8	2005 – 2010
9	CA	37.677	−121.530	323	mild	16	2010 – 2012
10	CA	38.407	−120.951	129	mediterranean	15	2000 – 2012
11	FL	25.365	−81.078	0	equatorial savannah	24	2004 – 2011
12	ME	45.207	−68.725	61	temperate continental	5	1996 – 2008
13	ME	45.204	−68.740	60	temperate continental	6	1996 – 2009
14	MN	44.995	−93.186	301	continental	6	2005 – 2009
15	MN	44.714	−93.090	260	snowy, humid summer	8	2003 – 2012
16	MO	38.744	−92.200	219	temperate continental	13	2004 – 2013
17	MT	48.308	−105.102	634	continental	5	2000 – 2008
18	NJ	39.914	−74.596	30	temperate	12	2005 – 2012
19	OK	36.427	−99.420	611	cool temperate	15	2009 – 2012
20	TN	35.931	−84.332	286	temperate continental	15	2005 – 2011
21	TN	35.959	−84.287	343	temperate	14	1994 – 2007
22	TX	29.940	−97.990	232	warm temperate	20	2004 – 2012
23	WA	45.821	−121.952	371	strongly seasonal	9	1998 – 2013
24	WV	39.063	−79.421	994	temperate	7	2004 – 2010

Table 4: Some general and climatic characteristics of the sites used for calibration: elevation is the site elevation above sea level, T is the annual average temperature, and data period refers to the period of available measurements.

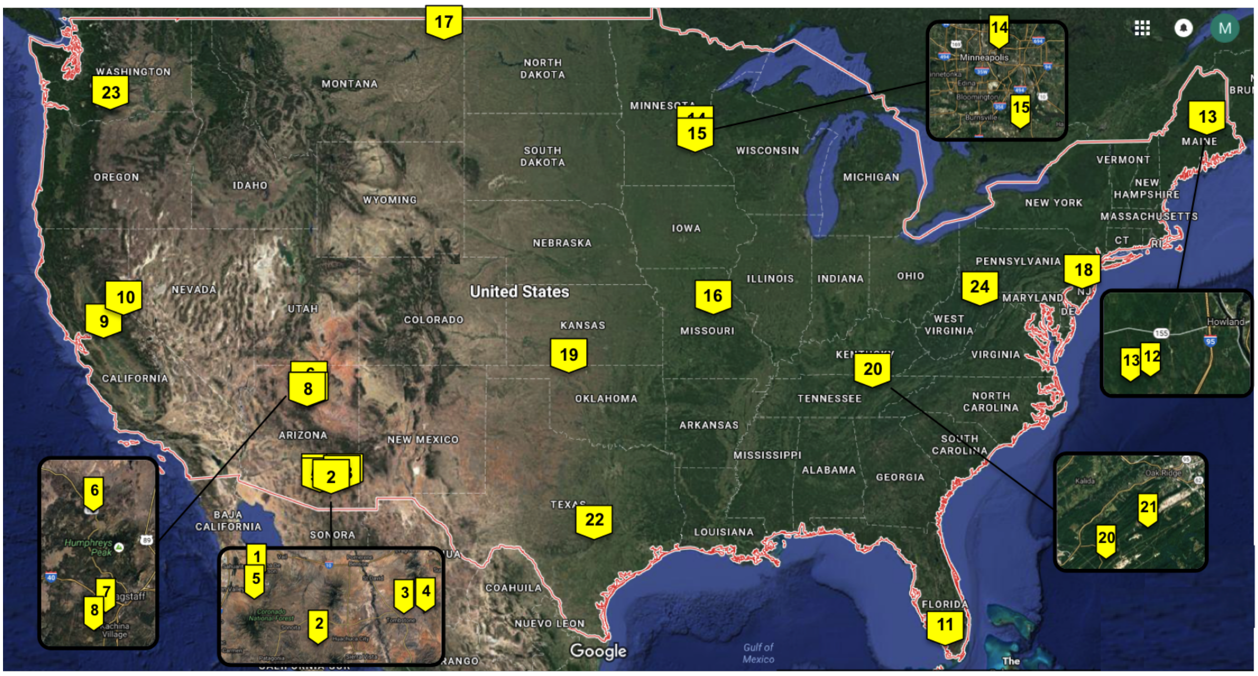

Figure 2: Test site locations in the United State of America.

4 Results

4.1 Verification of $L_{\downarrow}$ models with literature parameters

When implementing the ten $L_{\downarrow}$ SMs using the literature parameters, in many cases, they show a strong bias in reproducing measured data. A selection of representative cases is presented in Figure 3 ~~,~~ which shows scatterplots for four SMs in relation to one measurement station. The black points represent the hourly estimates of $L_{\downarrow}$ provided by literature formulations, while the solid red line represents the line of optimal predictions. Model 1 (Ångström (1915)) shows a tendency to lie below the 1:1 line, indicating a negative bias (percent bias of -9.8) and, therefore, an underestimation of $L_{\downarrow}$. In contrast, model 9 (Prata (1996)) shows an overestimation of $L_{\downarrow}$ with a percent bias value of 26.3.

Figure 4 presents the boxplot of KGE (first column) and RMSE (second column) obtained for each model under clear-sky conditions, grouped by classes of latitude and longitude. In general all the models except the Model 8 (Konzelmann et al. (1994)) ~~does not perform very well for~~ provided values of KGE higher than 0.5 and RMSE lower than 100 [W m^{-2}] for all the latitude and longitude classes. Model 8 is the less performing model for many of the stations likely because the model parameters were estimated for the Greenland where ~~the ice plays~~ snow and ice play a fundamental role on the energy balance. Its KGE values range between ~~0.16 and 0.41~~0.33 and 0.62 on average, while its RMSE values are higher than 100 ~~W/m^2, with a maximum of 200 W/m^2~~[W m^{-2}] except for latitude classes >40°N and longitude classes >-70°W. Model 6 (Idso (1981)) and ~~model~~ Model 2 (Brunt (1932)) provide the best results and the lower variability, independently of the latitude and longitude ranges where they are applied. Their average KGE values are between 0.75 and ~~0.94~~0.92, while the RMSE has a maximum value of 39 ~~W/m^2.~~ [W m^{-2}]. Moreover, all the models except 2 and 6 show a high variability of the goodness of fit through the latitude and longitude classes.

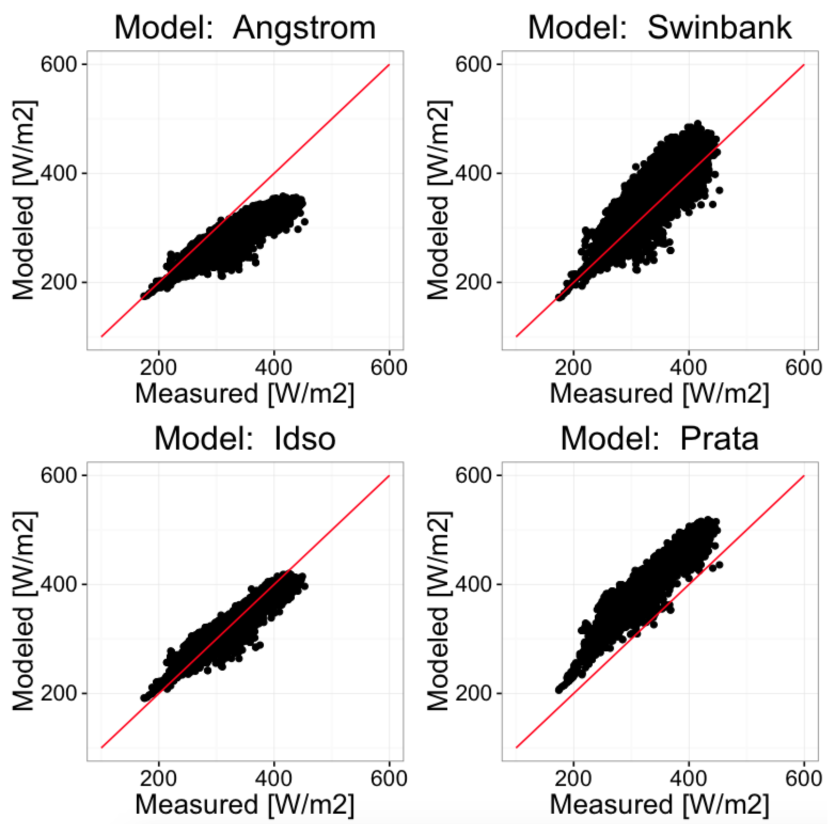

Figure 3: Results of the clear-sky simulation for four literature models using data from Howland Forest (Maine).

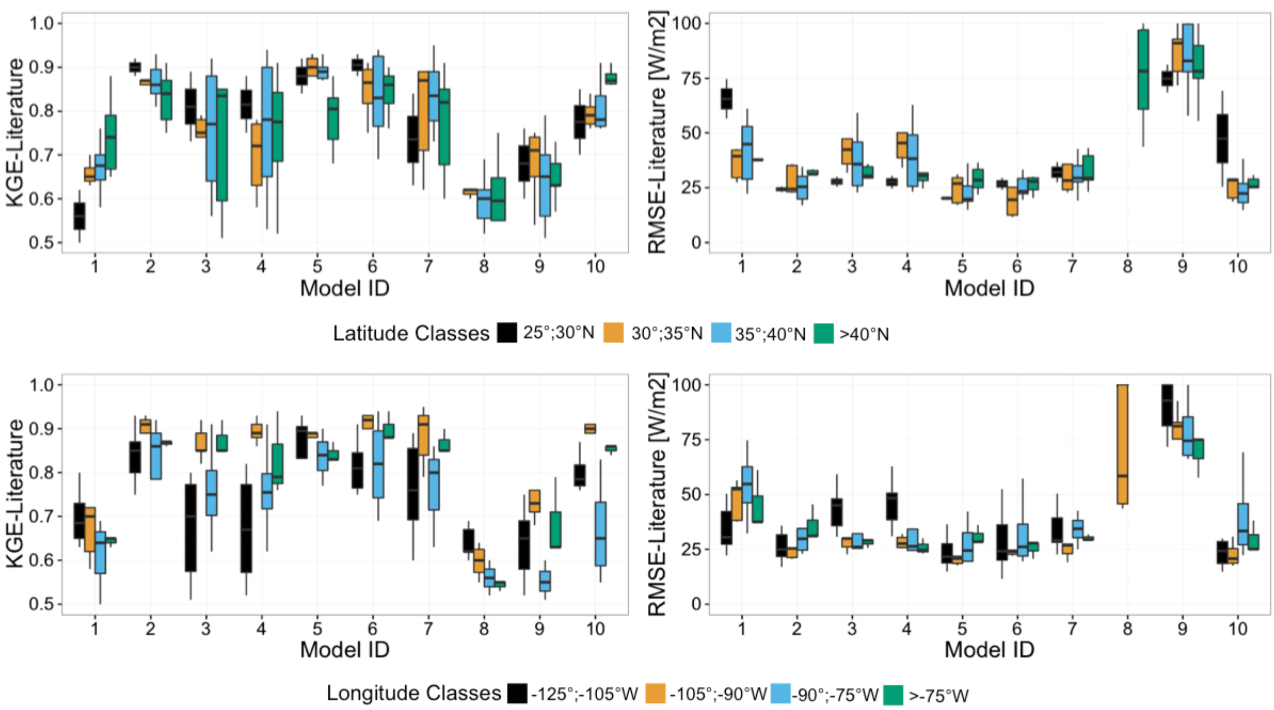

Figure 4: KGE and RMSE values for each clear-sky simulation using literature formulations, grouped by classes of latitude and longitude. ~~The~~ Only values of ~~the~~ KGE ~~shown are those~~ above 0.5 ~~: in this case, model 8 KGE values~~ are ~~not represented as they are between 0.16 and 0.41~~shown. ~~The range~~ Only values of RMSE ~~is 0-100 W/m^2~~below 100 [W m^{-2}] are shown.

4.2 $L_\downarrow$ models with site-specific parameters

The calibration procedure greatly improves the performances of all ten SMs. Optimized model parameters for each model are reported in the supplementary material (Table S1). Figure 5 presents the boxplots of KGE and RMSE values for clear-sky conditions grouped by classes of latitude and longitude. The percentage of KGE improvement ranges from its maximum value of ~~80% for model~~ 70% for Model 8 (which is not, however, representative of the mean behavior of the SMs) to less than 10% for ~~model~~ Model 6, with an average improvement of around 35%. Even though variations in model performances with longitude and latitude classes still exist when using optimized model parameters, the magnitude of these variations is reduced with respect to the use of literature formulations. The calibration procedure reduces the RMSE values for all the models to below ~~50 W/m^2, with the exception of model~~ 45 [W m^{-2}], even for Model 8, which ~~now has a maximum of 58 W/m^2.~~ also in this case had the maximum improvement. Model 6 (Idso (1981)) and Model 2 (Brunt (1932)) provide the best results on average for all the analyzed latitude and longitude classes.

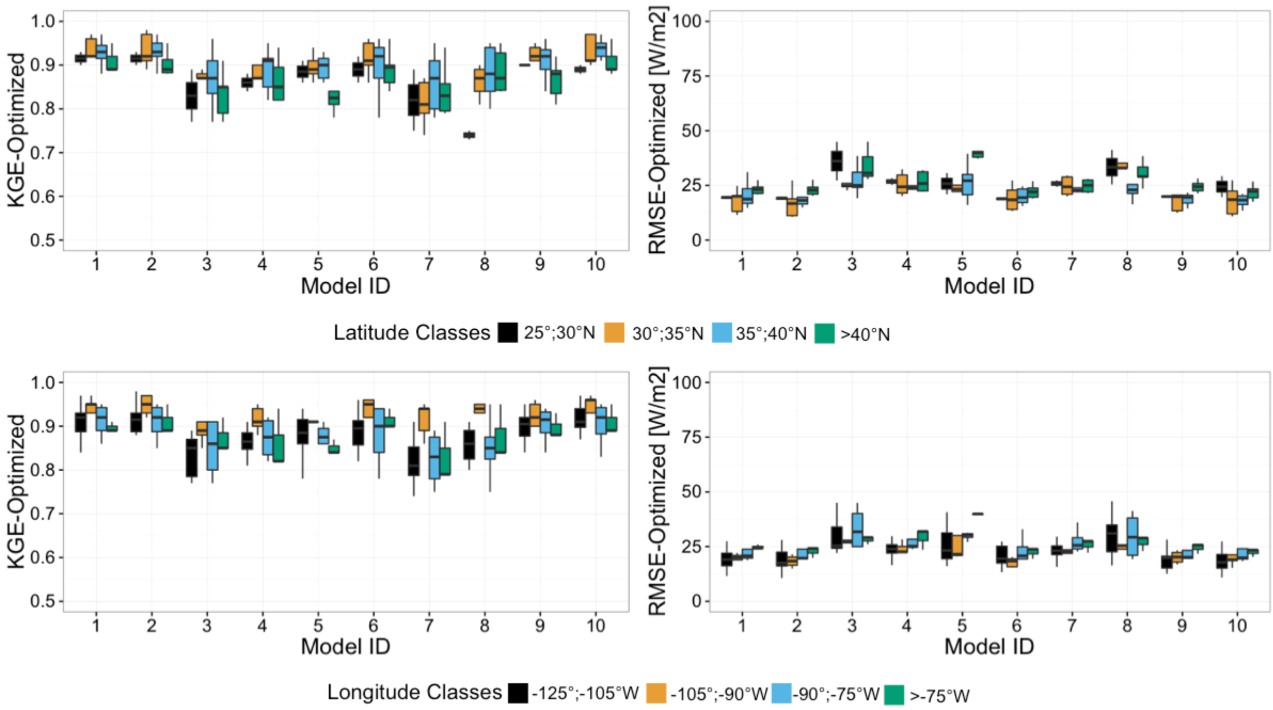

Figure 5: KGE (best is 1) and RMSE (best is 0) values for each optimized formulation in clear-sky conditions, grouped by classes of latitude and longitude. Only values of KGE above 0.5 are shown.

Figure 6 presents the boxplots of KGE and RMSE values for each model under all-sky conditions, grouped by latitude and longitude classes. In general, for all-sky conditions we observe a deterioration of KGE and RMSE values with respect to the clear-sky optimized case, with a decrease in KGE values up to a maximum of 25% ~~for model~~ on average for Model 10. This may be due to uncertainty incorporated in the formulation of the cloudy-sky correction model (eq. 3): it seems that sometimes the cloud effects are not accounted for appropriately. This, however, is in line with the findings of Carmona et al. (2014).

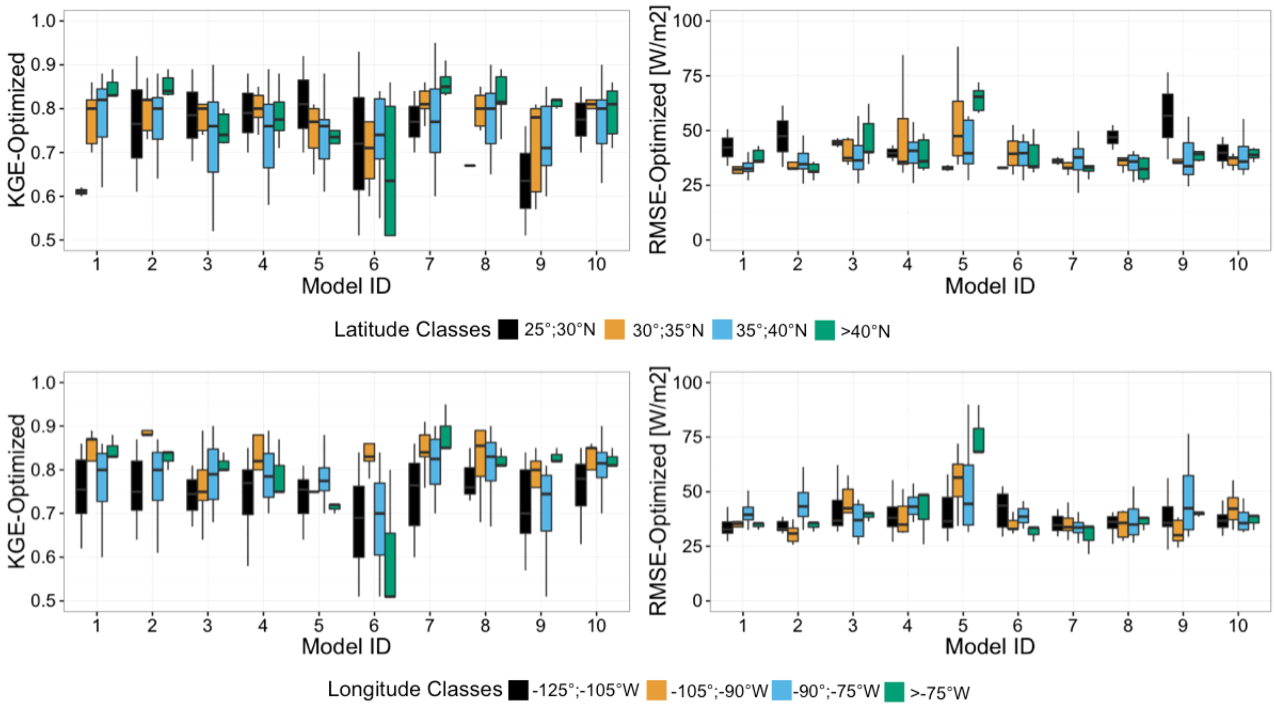

Figure 6: KGE and RMSE values for each model in all-sky conditions ~~,~~ with the optimized parameters; results are grouped by classes of latitude and longitude. Only values of KGE above 0.5 are shown.

4.3 Sensitivity analysis of $L_\downarrow$ models

The results of the models sensitivity analysis are summarized in Figures 7-a and 7-b for models 1 to 5 and models 6 to 10, respectively. Each figure presents three columns, one for each parameter. Considering model 1 and parameter X: the range of X is subdivided into ten equal-sized classes and for each class the corresponding KGE values are presented as a boxplot. A smooth blue line passing through the boxplot medians is added to highlight any possible pattern to parameter sensitivity. A flat line indicates that the model is not sensitive to parameter variation around optimal value. Results suggest that models with one and two parameters are all sensitive to parameter variation, presenting a peak in KGE in correspondence with their optimal values; this is more evident in models with two parameters. Models with three parameters tend to have at least one insensitive parameter, except for ~~model~~ Model 1, that could reveal a possible overparameterization of the modeling process.

4.4 Regression model for parameters of $L_\downarrow$ models

A multivariate linear regression model was estimated to relate the site-specific parameters X, Y and Z to mean annual air temperature, relative humidity, precipitation, and altitude. The script containing the regression model is available, ~~with the supplementary material, at the web page of this paper: https://github.com/geoframecomponents~~as specified in Reproducible Research section below.

The performances of the $L_\downarrow$ models using parameters assessed by linear regression are evaluated through the leave-one-out cross validation (Efron and Efron, 1982). We use 23 stations as training-sets for equations (6), (7), and (8) and we perform the model verification on the remaining station. The procedure is repeated for each of the 24 stations.

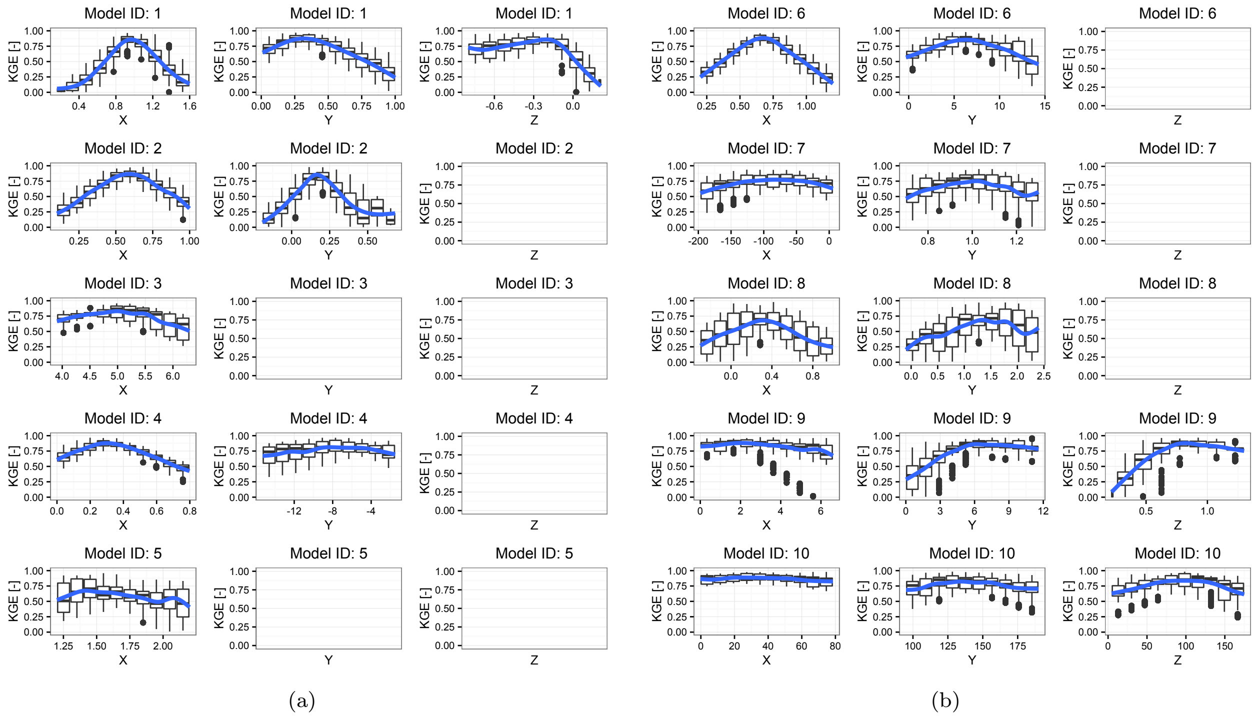

Figure 7: Results of the model parameters sensitivity analysis. It presents as boxplot the variation of the model performances due to a variation of one of the optimal parameter and assuming constant the others. The procedure is repeated for each model and the blue line represents the smooth line passing through the boxplot medians.

The cross validation results for all $L_{\downarrow}$ models and for all stations are presented in ~~figures~~ Figures (8) and (9), grouped by classes of latitude and longitude, respectively. They report the KGE comparison between the $L_{\downarrow}$ models with their original parameters (in ~~red~~black) and with the regression model parameters (in ~~blue~~black).

In general, the use of parameters estimated with regression model gives a good estimation of $L_{\downarrow}$, with KGE values of up to ~~0.97~~0.92. With respect to the classic formulation, model performance with regression parameters improved for all the models ~~, in particular for model~~ independently of the latitude and longitude classes. In particular for Model 8 ~~in which~~ the KGE improved from ~~a minimum of 0.16~~ 0.26 for the classic formulation to ~~a maximum of 0.97~~of 0.92, on average. Finally, the use of the parameters estimated by the regression model provides a reduction of the model performances variability for all the models except Model 5 and 8, for longitude class -125;-105°W and -105;-90°W respectively.

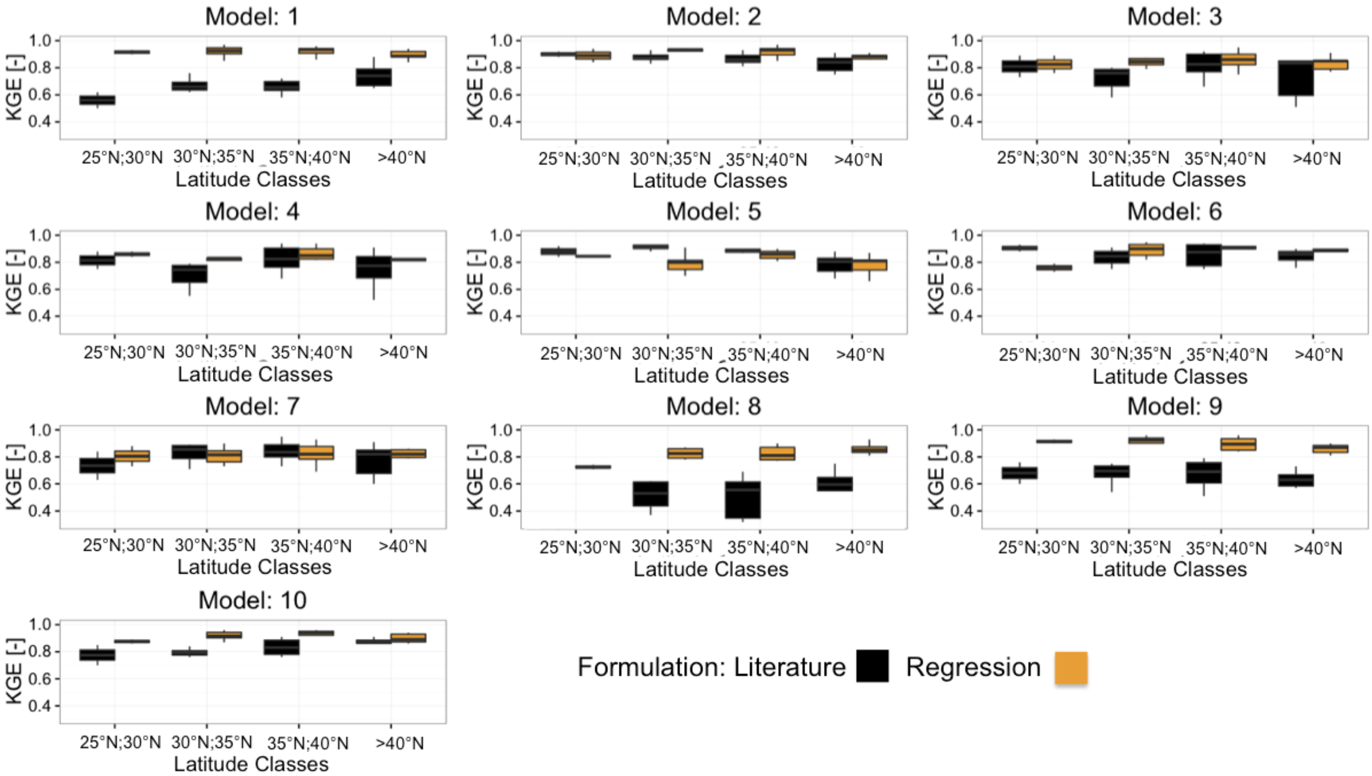

Figure 8: Comparison between model performances obtained with regression and classic parameters: the KGE values shown are those above ~~0.7~~ 0.3 and results are grouped by latitude classes.

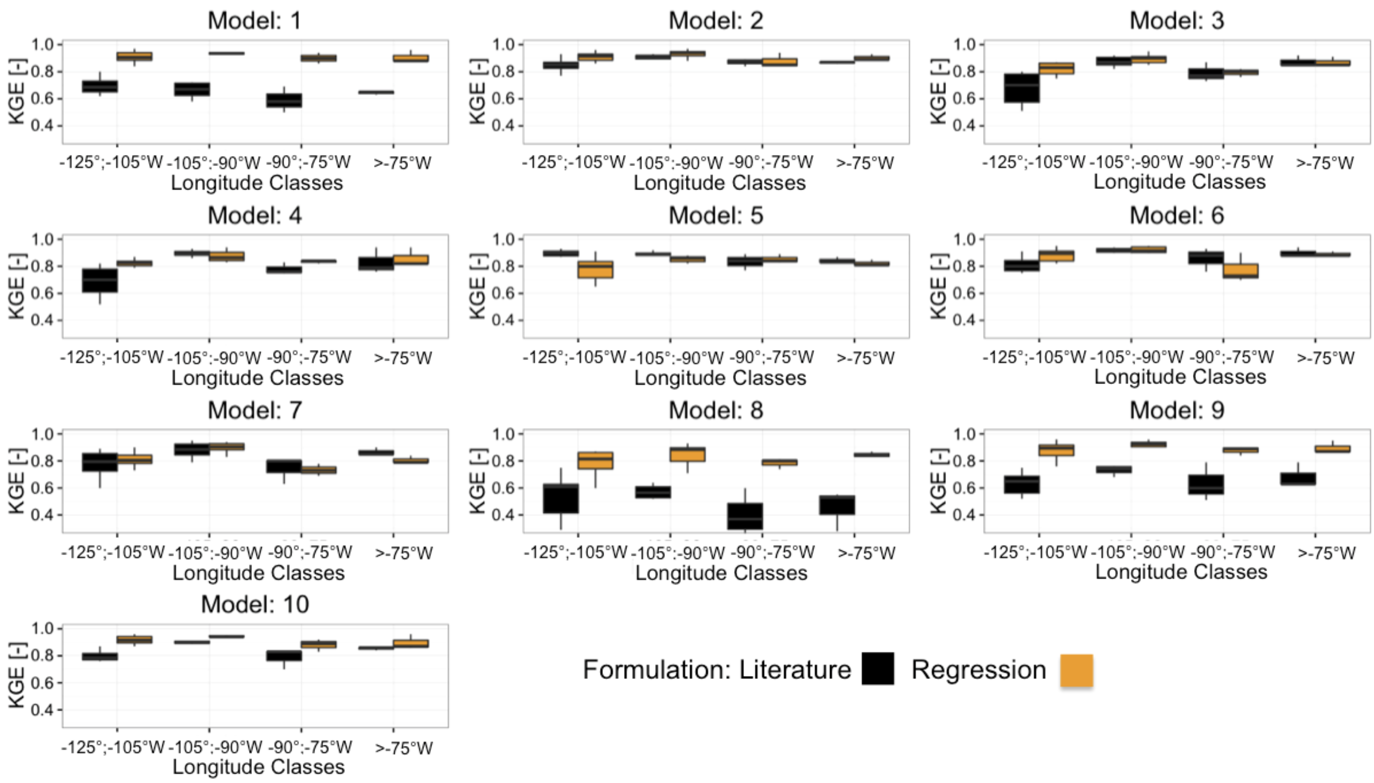

Figure 9: Comparison between model performances obtained with regression and classic parameters: the KGE values shown are those above ~~0.7~~ 0.3 and results are grouped by longitude classes.

4.5 Verification of the $L_\uparrow$ model

Figure 10 presents the results of the $L_\uparrow$ simulations obtained using the three different temperatures available at experimental sites: soil surface temperature (skin temperature), air temperature, and soil temperature (measured at 4 cm below the surface). The figure shows the performances of the $L_\uparrow$ model for the three different temperatures used in terms of KGE, grouping all the stations for the whole simulation period according to season. This highlights the different behaviors of the model for periods where the differences in the three temperatures are larger (winter) or negligible (summer). The values of soil emissivity are assigned according the soil surface type, according to Table 4 (Brutsaert, 2005). Although many studies investigated the influence of snow covered area on longwave energy balance (e.g. Plüss and Ohmura (1997); Sicart et al. (2006)), the SMs do not explicitly take into account of it. As presented in König-Langlo and Augstein (1994), the effect of snow could be implicitly taken into account by tuning the emissivity parameter.

The best fit between measured and simulated $L_\uparrow$ is obtained with the surface soil temperature, with an all-season average KGE of 0.80. Unfortunately, the soil surface temperature is not an easily available measurement. In fact, it is available only for 8 sites of the 24 in the study area. Very good results are also obtained using the air temperature, where the all-season average KGE is around 0.76. The results using air temperature present much more variance compared to those obtained with the soil surface temperature. However, air temperature (at 2 m height) is readily available measure, in fact it is available for all 24 sites.

The use soil temperature at 4 cm depth provides the least accurate results for our simulations, with an all-season average KGE of 0.46. In particular, the use of soil temperature at 4 cm depth during the winter is not able to capture the dynamics of $L_\uparrow$. It does, however, show a better fit during the other seasons. This could be because during the winter there is a substantial difference between the soil and skin temperatures, as also suggested in Park et al. (2008).

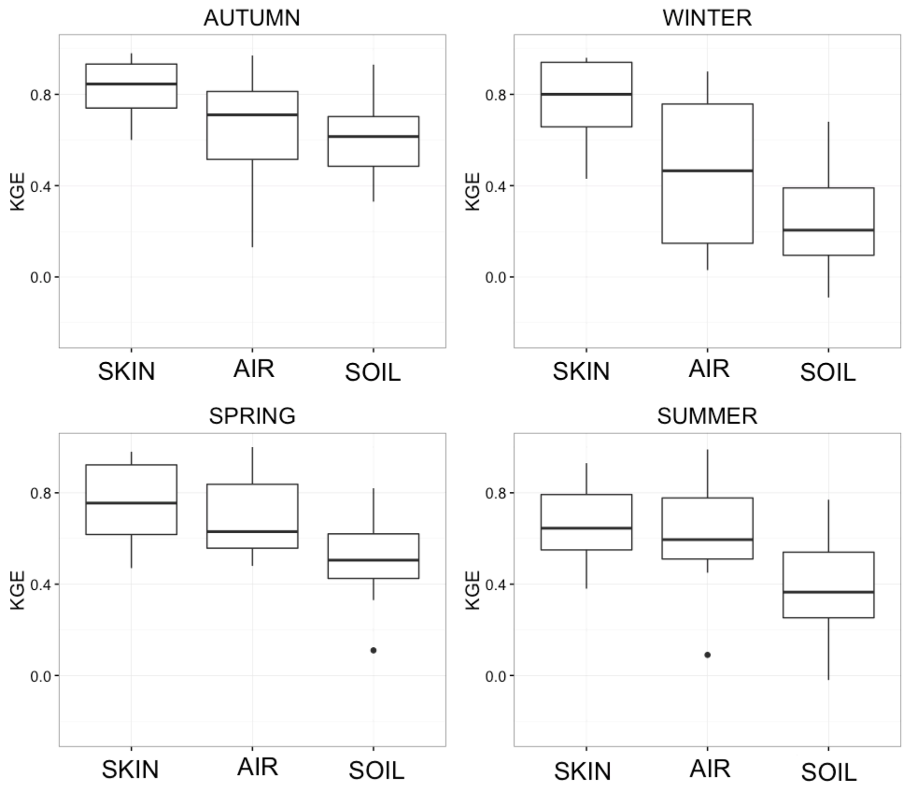

Figure 10: Boxplots of the KGE values obtained by comparing modeled upwelling longwave radiation, computed with different temperatures (soil surface temperature (SKIN), air temperature (AIR), and soil temperature (SOIL)), against measured data. Results are grouped by seasons.

5 Conclusions

This paper presents the LWRB package, a new modeling component integrated into the JGrass-NewAge system to model upwelling and downwelling longwave radiation. It includes ten parameterizations for the computation of $L_\downarrow$ longwave radiation and one for $L_\uparrow$. The package uses all the features offered by the JGrass-NewAge system, such as algorithms to estimate model parameters and tools for managing and visualizing data in GIS.

The LWRB is tested against measured $L_\downarrow$ and $L_\uparrow$ data from 24 AmeriFlux test-sites located all over ~~continental~~ contiguous USA. The application for $L_\downarrow$ longwave radiation involves model parameter calibration, model performance assessment, and parameters sensitivity analysis. Furthermore, we provide a regression model that estimates optimal parameter sets on the basis of local climatic variables, such as mean annual air temperature, relative humidity, and precipitation. The application for $L_\uparrow$ longwave radiation includes the evaluation of model performance using three different temperatures.

The main achievements of this work include: i) a broad assessment of the classic $L_\downarrow$ longwave radiation parameterizations, which clearly shows that the Idso (1981) and Brunt (1932) models are the more robust and reliable for all the test sites, confirming previous results (Carmona et al., 2014); ii) a site specific assessment of the $L_\downarrow$ longwave radiation model parameters for 24 AmeriFlux sites that improved the performances of all the models; iii) the set up of a regression model that provides an estimate of optimal parameter sets on the basis climatic data; iv) an assessment of $L_\uparrow$ model performances for different temperatures (skin temperature, air temperature, and soil temperature at 4 cm below surface), which shows that the skin and the air temperature are better proxy for the $L_\uparrow$ longwave radiation. ~~Moreover~~ Regarding longwave downwelling radiation the Brunt (1932) model is able to provide ~~higher~~ on average the best performances with the regression model parameters independently of the latitude and longitude classes. For the Idso (1981) model the formulation with regression parameter provided lower performances with respect to the literature formulation for latitude between ~~25-30~~25°N and 30°N.

The integration of the package into JGrass-NewAge will allow users to build complex modeling solutions for various hydrological scopes. In fact, future work will include the link of the LWRB package to the existing components of JGrass-NewAge to investigate $L_\downarrow$ and $L_\uparrow$ effects on evapotranspiration, snow melting, and glacier evolution. Finally, the methodology proposed in this paper provides the basis for further developments such as the possibility to: i) investigate the effect of different all-sky emissivity formulation ~~,~~ and quantify the influence of the clearness index threshold ii) verify the usefulness of the regression models for ~~locations outside the~~ climates outside the contiguous USA; iii) analyze in a systematic way the uncertainty due to the quality of meteorological input data on the longwave radiation balance in scarce instrumented areas.

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Replicable Research

The LWRB package has been implemented according to the object oriented paradigm, making them flexible, expendable for future improvements and maintenance. Thanks to Gradle Buid tool, an open source build automation system and Travis CI, a continuous integration service used to build and test software projects, the principle of the replicability of the research is fully satisfied. Researchers interested in replicating or extending our results are invited to download our codes at:

https://github.com/geoframecomponents.

Instructions for using the code can be found at:

http://geoframe.blogspot.co.uk/2016/04/lwrb-component-latest-documentation.html.

Regression of parameters were performed in R and are available at

https://github.com/GEOframeOMSProjects/OMS_Project_LWRB/blob/master/docs/Regression.R

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