EuroSun2026

A SOLAR SEPARATION MODEL INCLUDING CLOUD ENHANCEMENT – A NOVEL COMPOSITE APPROACH

Summary

When constructing a model to predict the diffuse component of solar irradiation from the global horizontal irradiation (GHI) for high frequency data, the cloud enhancement phenomenon must be catered for. There have been several research works on this topic, but in general they comprise two components to the model, one for low values of the clearness index, and a separate one for the higher values. This paper describes a process whereby the model is given a composite representation.

Keywords: Diffuse solar irradiation, separation models, cloud enhancement

Field of application for the findings: Solar Separation Models

Addressed audience: Solar Resources and Energy Meteorology

1. Introduction

In many instances, global horizontal irradiation (GHI) is the only component of irradiation either measured or inferred from some model output. The diffuse and direct irradiation is much more involved and potentially expensive to measure. If one needs to estimate the global irradiation on a tilted surface from knowledge of the GHI, the algorithm follows a two-step procedure, first separation into diffuse and direct components and then transposition to the tilted surface (Furtado et al. 2026). There have been several models developed to deal with the separation problem that include the cloud enhancement component – for example Bright and Engerer (2019), yang and Boland (2019), Starke et al. (2021) among others. All of these approaches have had to employ a two-part model, capturing one method to encapsulate the decaying logistic form for low and medium values of the clearness index, and a separate feature to capture the kick up of the diffuse fraction for high values of the diffuse. See fig. 1 for an example of this kick up of the diffuse fraction.

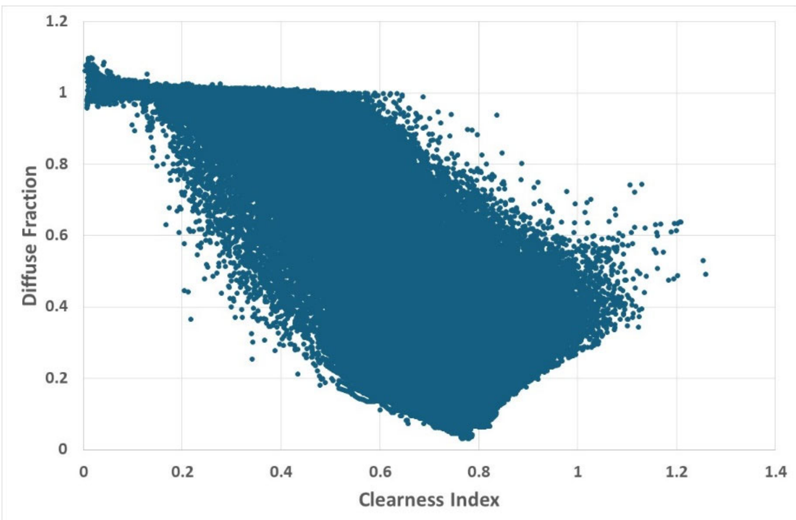

Fig. 1: Example of minute diffuse fraction versus clearness index for minute data

2. Methodology

Data sets from five sites were selected for training and testing the composite model. Note that at this stage, no formulas for the model will be described until the procedure has been submitted for publication. The first step was to fit the composite model to each site separately to ensure that it was a viable procedure. Next, random samples were selected from each site and the data pooled. The pooled data was separated into three quarters training and one quarter testing sets. The error metrics used in the study were Mean Bias Error (MBE), Mean Absolute Error (MAE) and Root Mean Square error (RMSE). The values for the metrics for the training and testing sets were almost the same, as shown in Table 1, where the values are given to three decimal places. Subsequently, the model with the parameter estimates from the training set were applied to the data from the original five sites. The error metrics for this comparison are given in Table 2. In this table, the designation Pooled means the model trained on the sampled data and the designation Original means the fit for all the site data.

Tab. 1: The error metrics for the training and testing sets for the pooled data

Error metrics	Training Set	Testing Set
MBE	0.000	0.002
MAE	0.053	0.053
RMSE	0.093	0.093

The results using the sampled data would not be expected to behave as well as the models tuned specifically for each site but the performance is sufficiently close, one could argue. This conclusion is backed up by comparing the results pictorially. Compare Figures 2 and 3, where the former depicts the fit with the locally optimised parameter estimates, while the latter shows the fit with the pooled estimates.

Tab. 2: The error metrics for the original sites

Locations		MBE	MAE	RMSE
Site 1	Pooled	0.005	0.066	0.106
	Original	0.000	0.062	0.102
Site 2	Pooled	-0.027	0.050	0.085
	Original	0.000	0.043	0.076
Site 3	Pooled	0.043	0.064	0.120
	Original	0.000	0.063	0.106
Site 4	Pooled	0.012	0.057	0.100
	Original	0.009	0.054	0.098
Site 5	Pooled	-0.006	0.033	0.061
	Original	0.000	0.025	0.058

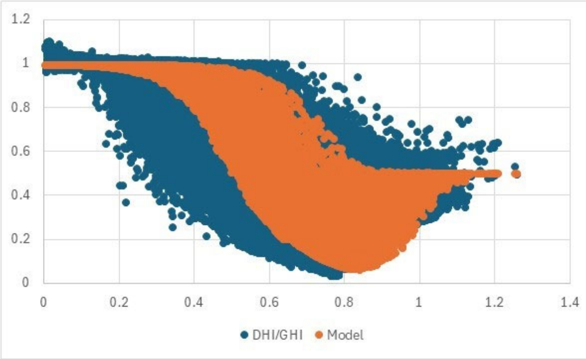

Fig. 2: Model fit with locally optimised parameter estimates

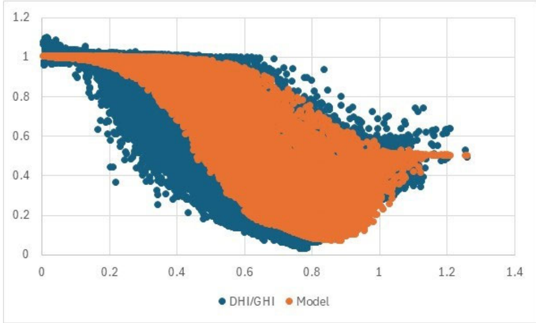

Fig. 2: Model fit with parameter estimates from pooled data

3. Discussion and further work

This preliminary study demonstrates the viability of the novel composite approach to dealing with the separation model for high frequency GHI data. The next phase of the research will focus on evaluating the potential for linking the estimates of the parameters of the model to climate characteristics to improve the model fit.

References:

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