



Supplement of

Probabilistic end-to-end irradiance forecasting through pre-trained deep learning models using all-sky-images

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S1 Forecasts with image sequences

The scenarios presented include a range of conditions, selected at random for illustration purposes:

- 1. Clear-sky
- 5 2. Broken cloud
 - 3. Overcast
 - 4. Ramp-up
 - 5. Ramp-down

All eight models, across their four prediction horizons, are ¹⁰ presented. We also show the corresponding ASI images for t-n, t, t+n, with t being the current time-step and n the forecasting horizon.

While we were able to filter out most of the clear-sky conditions from the data set using the method proposed by

¹⁵ Reno and Hansen (2016), some periods still remain within the data set. This scarcity, however, did not impact the ability of the model to perform predictions in clear-sky conditions, as shown in the Fig. S1, S2, S3, and S4. The narrow probability distribution also shows, that the model has high confi-²⁰ dence while performing its prediction in these conditions.

During broken clouds, the models only show acceptable prediction patterns for the prediction horizons 5 and 10 minutes. For horizons above 10 minutes, the model behaves more or less like a persistence model. In these conditions, all mod-²⁵ els show lower confidence compared to the clear-sky condi-

tions, as shown in Fig. S5, S6, S7, and S8.

During overcast situations, the model behaves like a persistence forecast model, but maintains a low GHI expectation with high confidence. Fig. S9, S10, S11, and S12 illustrate ³⁰ the forecasts and their corresponding ASI images.

In events where a cloud unveils the sun, causing a rampup in GHI, the models can accurately predict this ramp-up event up to a prediction horizon of 20 minutes. At a prediction horizon of 30 minutes, the model is not able to predict

- ³⁵ the ramp event. From the input image sequence, it is evident that the model likely has no information within the images suggesting such a ramp event. The probabilistic models also show much lower confidence during the ramp event, showing that the situation is evaluated correctly to determine a proper
- ⁴⁰ probability distributions. These effects can be observed in Fig. S13, S14, S15, and S16.

In the ramp-down scenario, the models generally predict the timing correctly, evolving to a persistence behavior the longer the horizon is chosen. As evident in the observation

⁴⁵ time-series in Fig. S17, S18, S19, and S20, there is a higher variability compared to the ramp-up scenario. The model therefore chooses to be less confident about its predictions, until it reaches clear-sky conditions later on.

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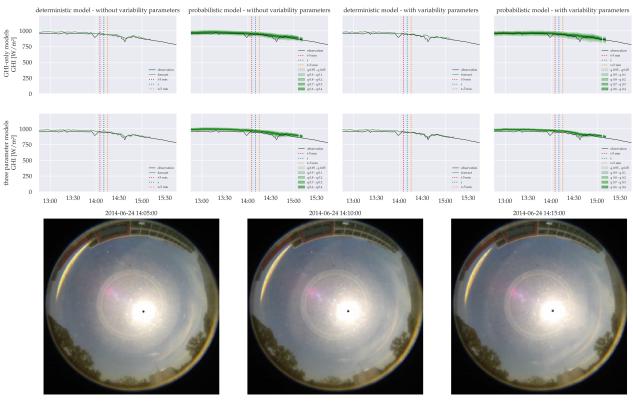


Figure S1. Image sequence with corresponding 5 minute forecast, with clear-sky images.

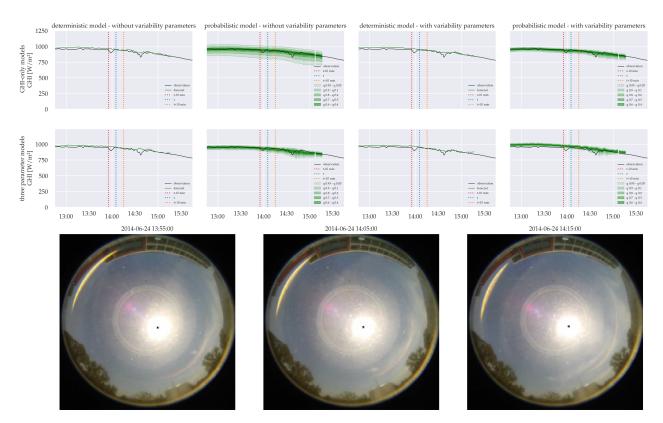


Figure S2. Image sequence with corresponding 10 minute forecast, with clear-sky images.

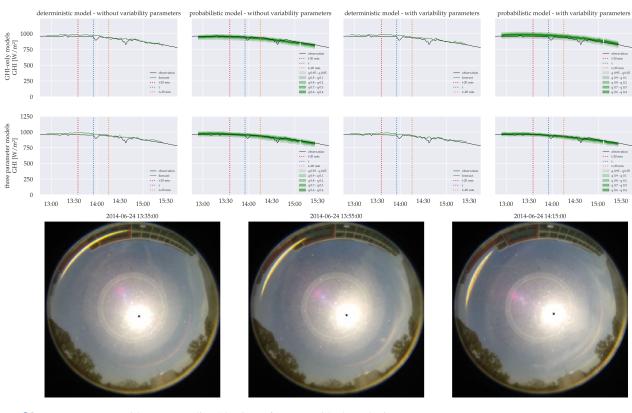


Figure S3. Image sequence with corresponding 20 minute forecast, with clear-sky images.

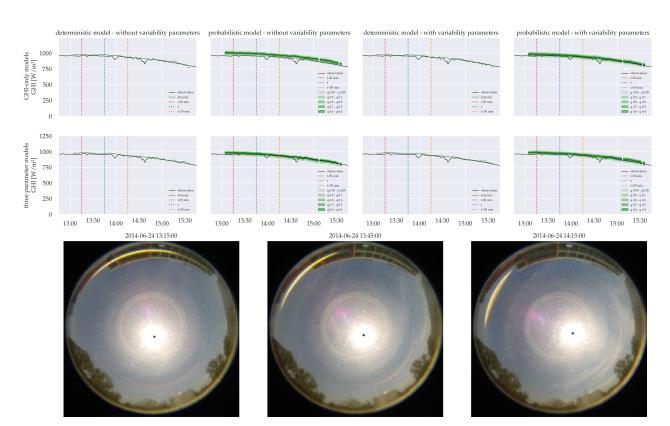


Figure S4. Image sequence with corresponding 30 minute forecast, with clear-sky images.

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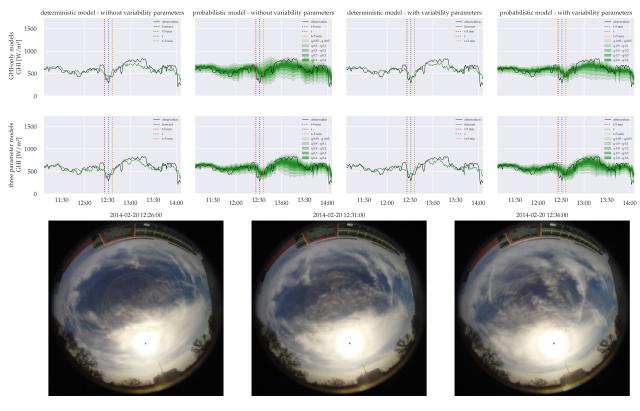


Figure S5. Image sequence with corresponding 5 minute forecast, with images of broken clouds.

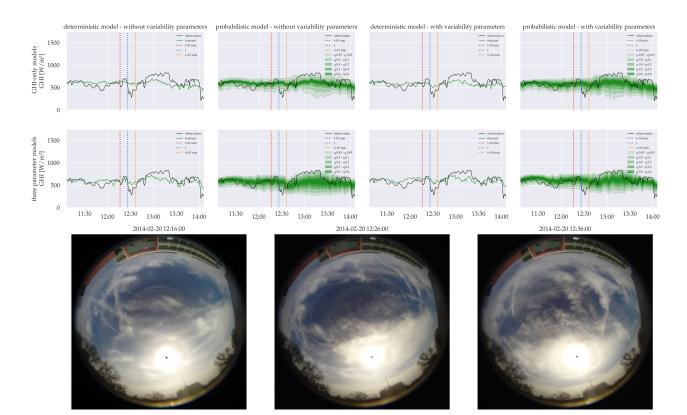


Figure S6. Image sequence with corresponding 10 minute forecast, with images of broken clouds.

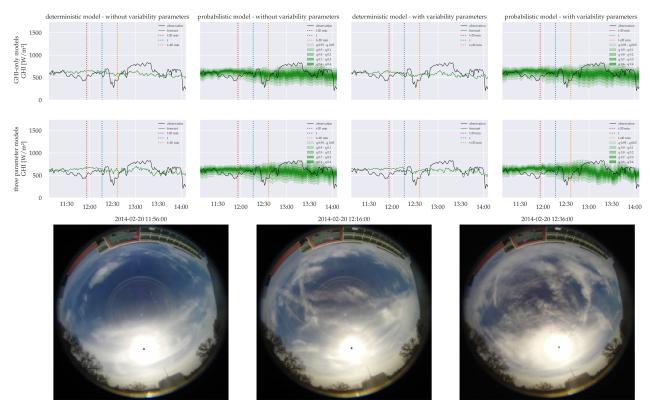


Figure S7. Image sequence with corresponding 20 minute forecast, with images of broken clouds.

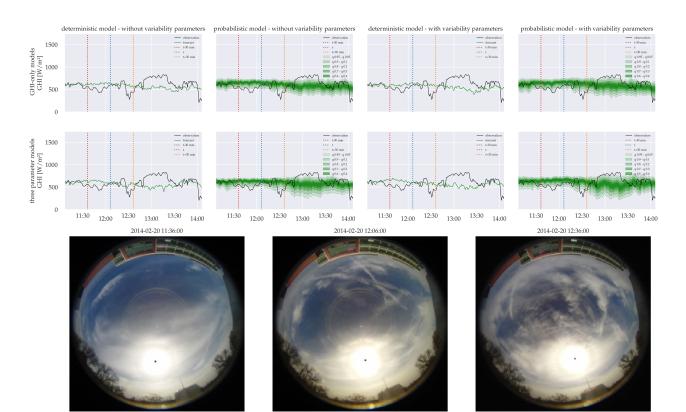


Figure S8. Image sequence with corresponding 30 minute forecast, with images of broken clouds.

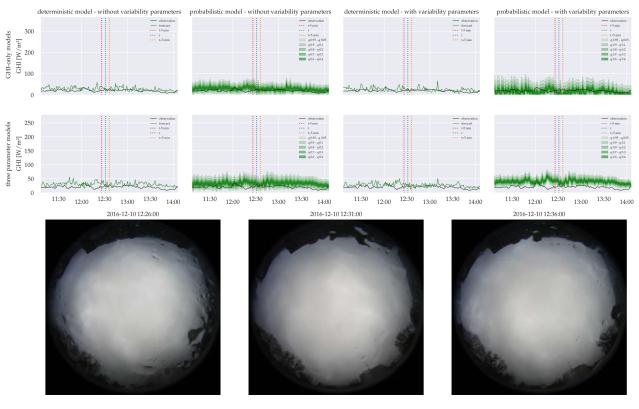


Figure S9. Image sequence with corresponding 5 minute forecast, in cloudy conditions.

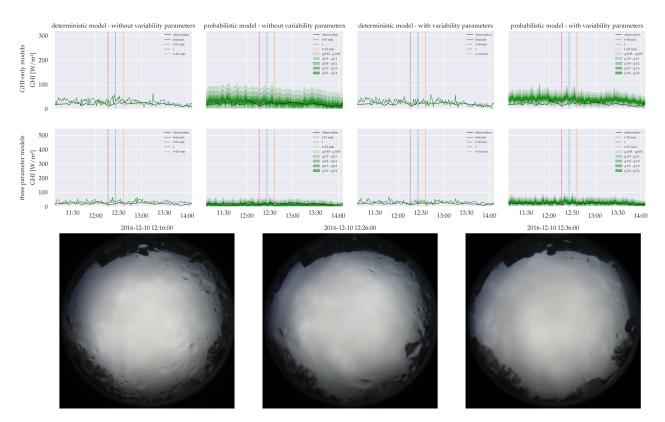


Figure S10. Image sequence with corresponding 10 minute forecast, in cloudy conditions.

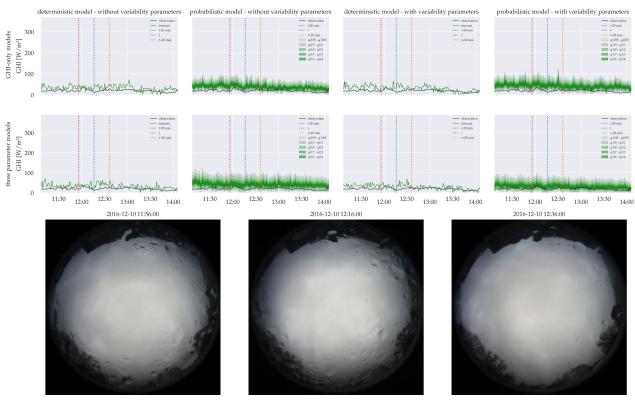


Figure S11. Image sequence with corresponding 20 minute forecast, in cloudy conditions.

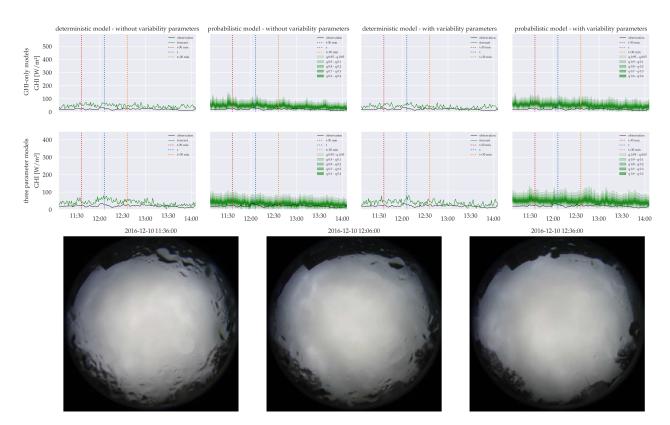


Figure S12. Image sequence with corresponding 30 minute forecast, in cloudy conditions.

1

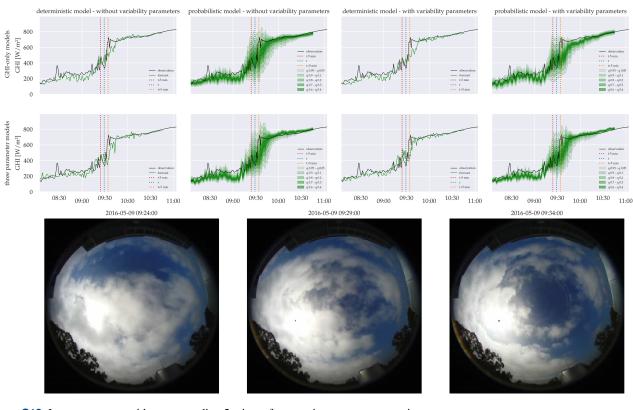


Figure S13. Image sequence with corresponding 5 minute forecast, in a ramp-up scenario.

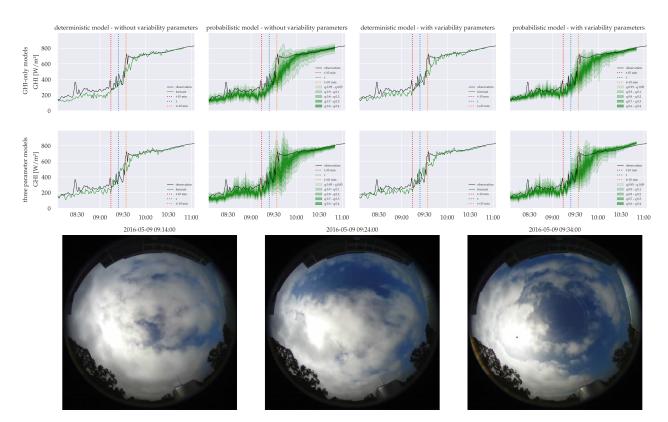


Figure S14. Image sequence with corresponding 10 minute forecast, in a ramp-up scenario.

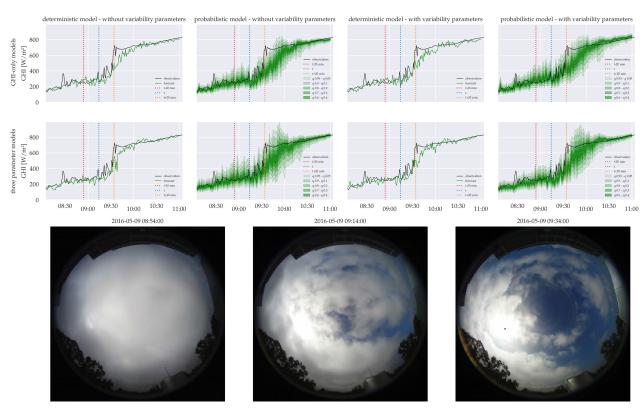


Figure S15. Image sequence with corresponding 20 minute forecast, in a ramp-up scenario.

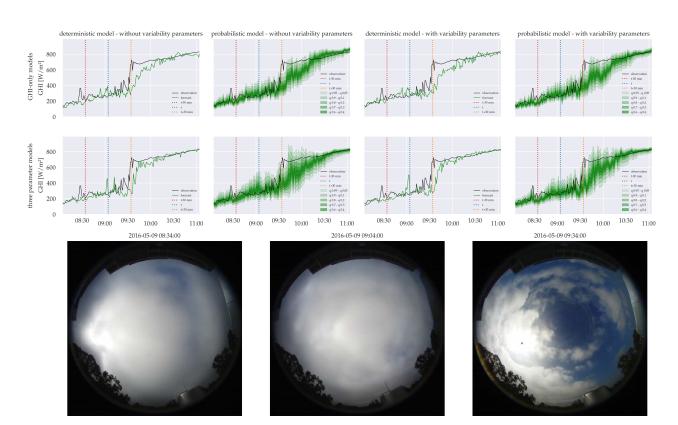


Figure S16. Image sequence with corresponding 30 minute forecast, in a ramp-up scenario.

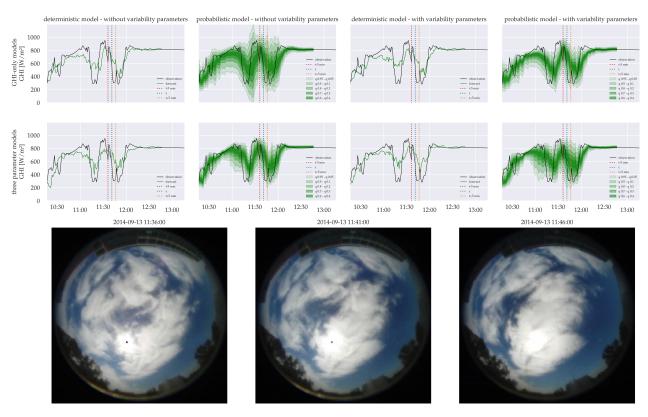


Figure S17. Image sequence with corresponding 5 minute forecast, in a ramp-down scenario.

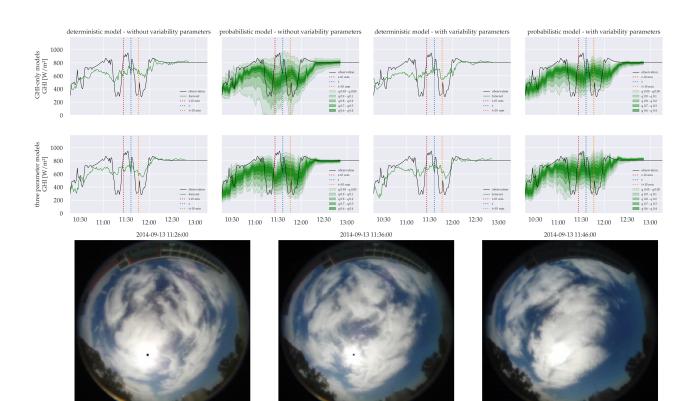


Figure S18. Image sequence with corresponding 10 minute forecast, in a ramp-down scenario.

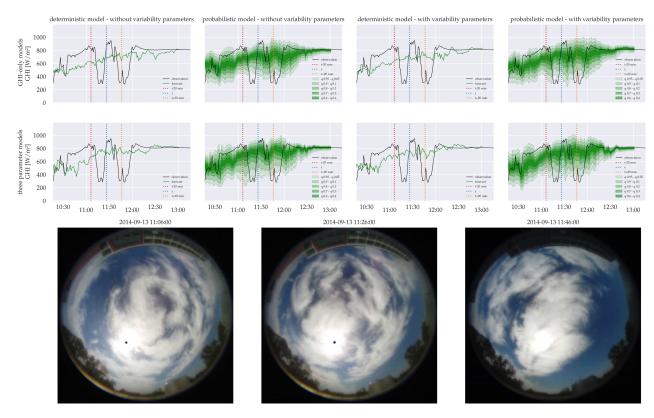
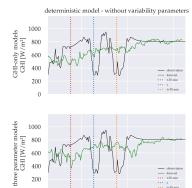


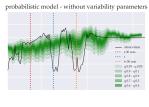
Figure S19. Image sequence with corresponding 20 minute forecast, in a ramp-down scenario.

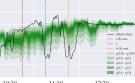


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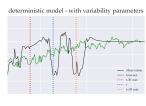
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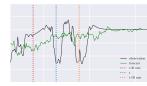
2014-09-13 10:46:00



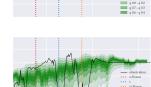


10:30 11:00 11:30 12:00 12:30 13:00 2014-09-13 11:16:00





 ${}^{10:30} \quad {}^{11:00} \quad {}^{11:30} \quad {}^{12:00} \quad {}^{12:30}$ 13:00



probabilistic model - with variability parameters

10:30 11:00 11:30 12:00 12:30 13:00 2014-09-13 11:46:00

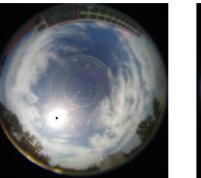






Figure S20. Image sequence with corresponding 30 minute forecast, in a ramp-down scenario.