

Objectives

Earth's skin temperature (T_{skin}), or the combination of land and sea surface temperatures (LST and SST), is an essential climate variable that can be measured by remote sensors on board different satellites. The Geostationary Interferometric Infrared Sounder (GIIRS) on board FengYun-4 series satellites is the world's first geostationary hyperspectral infrared sounder. Its main goal is the provision of temperature and humidity profiles for improving weather forecasts. No official skin temperature product exists to date from GIIRS, and scientific literature relies on surface skin temperature from ERA5 hourly data.

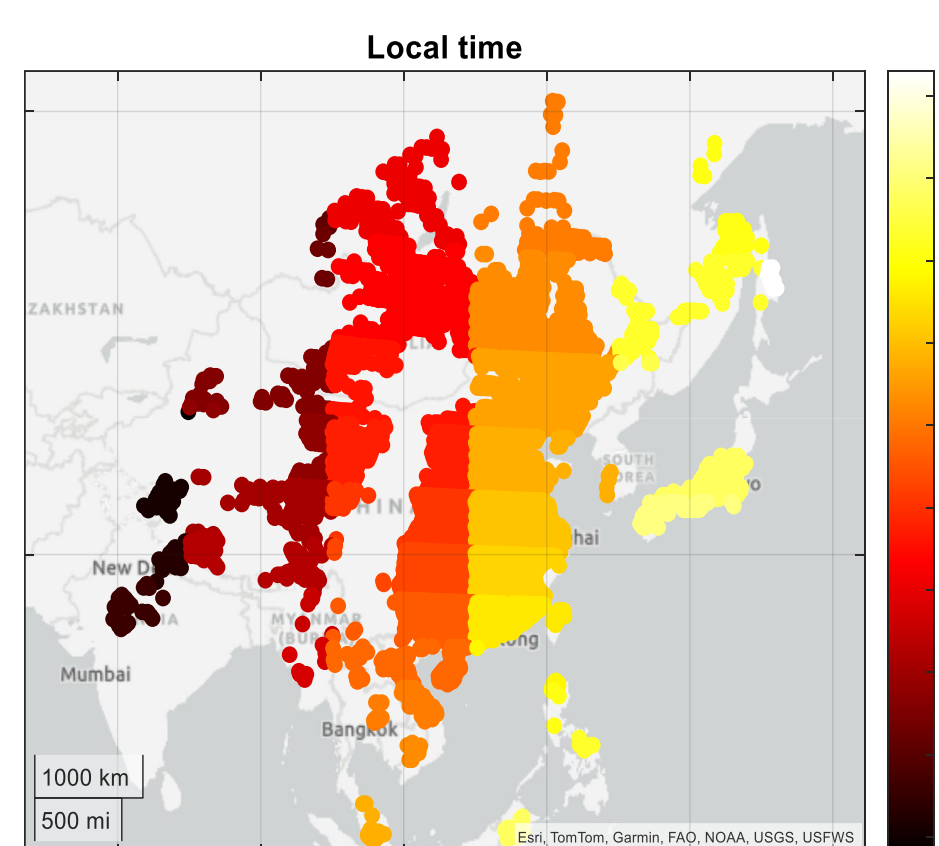
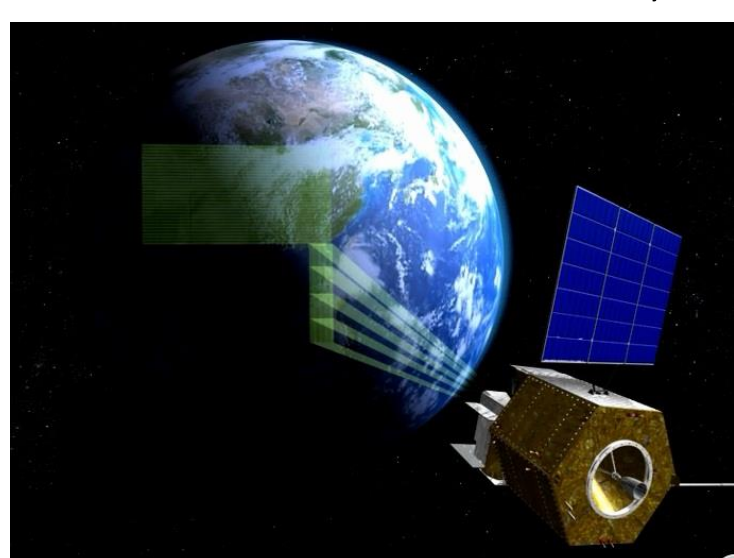


Fig 1. GIIRS area of sounding and hour of observation in local time for one measurement. 12 observations are made every day.



In this study, we focus on GIIRS mounted on FY-4B, the second satellite in the FY-4 series, which was launched in June 2021. The observation domain of FY-4B/GIIRS is mostly over eastern Asia, with a focus on China (Fig. 1). We present a fast method for retrieving land and sea surface temperatures from GIIRS based on convolutional and recurrent artificial neural networks from a set of spectral channels selected from GIIRS that are sensitive to T_{skin}. The neural networks are trained with skin temperatures from the Infrared Atmospheric Sounding Interferometer (IASI) official EUMETSAT T_{skin} product.

Neural Network Training

Our dataset for the neural network training is constructed out of 207232 (for land) and 134645 (for sea) GIIRS observations from the year 2023. The IASI clear sky T_{skin} corresponding to each spectra is used as target.

We limit our training to longitudes > 90°E in order to remove the errors at large viewing angles at the edges of the FY-4B scanning disk.

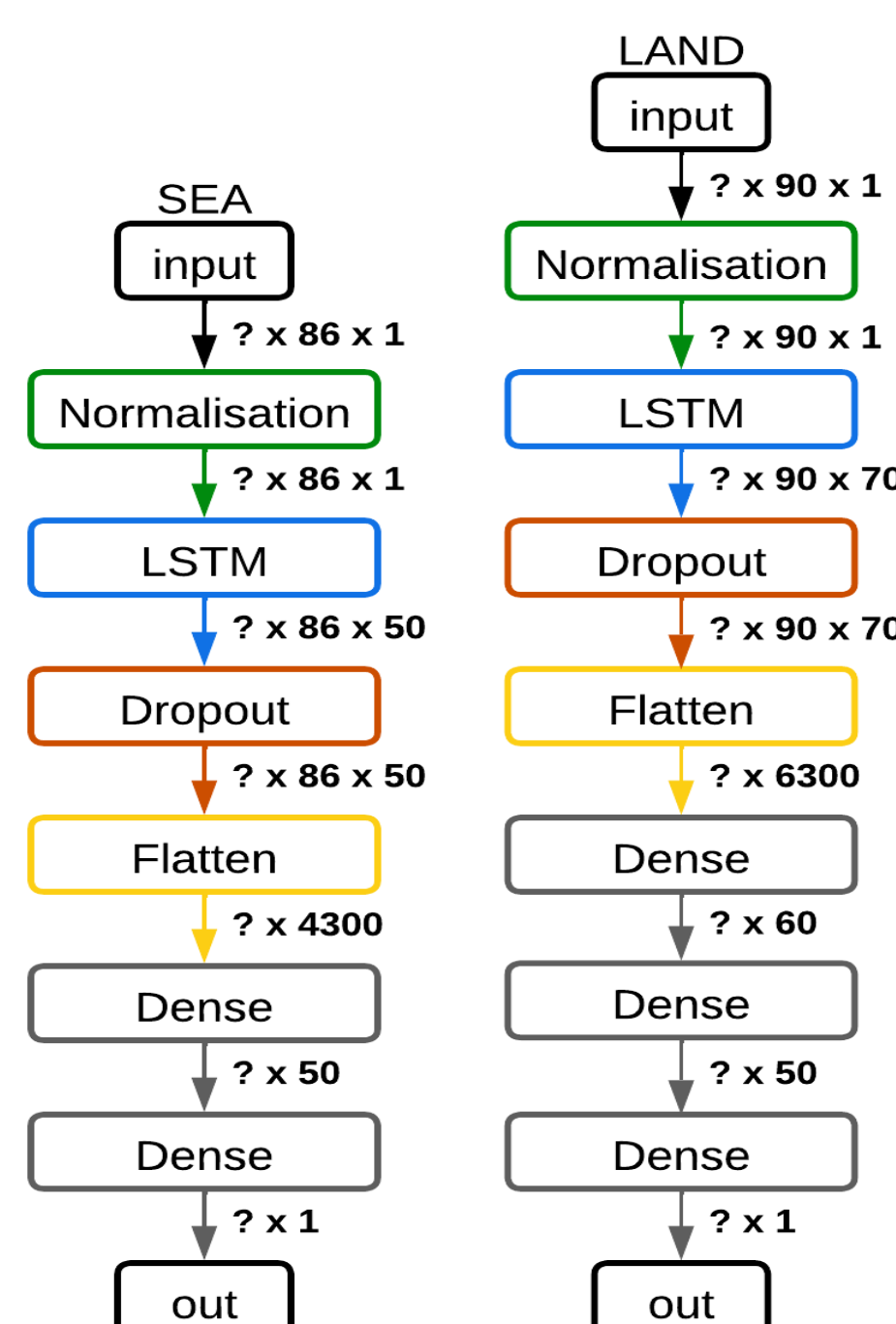


Fig 6. Neural network model architectures used to retrieve T_{skin} over the sea (left) and land (right)

For the land and sea datasets, two types of models were primarily tested: CNN (Convolutional Neural Network) and RNN (Recurrent Neural Network). Before starting model training, the data was first normalized. To do this, we tested three methods: MinMaxScaler and StandardScaler from scikit-learn, and finally a Normalization layer from TensorFlow at the beginning of the model. The third solution was chosen as it is simpler to implement when applying the final model. The training of several models for the LAND and SEA data led to retaining only the RNN models, which provide better results on average. The model for the LAND data is, however, slightly more complex, as the number of parameters is larger as the Fig. 6 shows.

IASI and GIIRS comparison

GIIRS spectral and spatial resolution are very close to those from IASI as Table 1 and Fig. 2 show

Table 1. Specifications of the IASI and GIIRS instruments

Instrument	IASI	GIIRS
Satellite	Metop	FY-4B
Date of launch	2006, 2012, 2018	2021
Coverage	Global, 9:30 AM/PM	China 12 obs/day
Spectral Resolution	0.5 cm ⁻¹	0.8 cm ⁻¹
Spatial footprint @ nadir	12 km	12 km

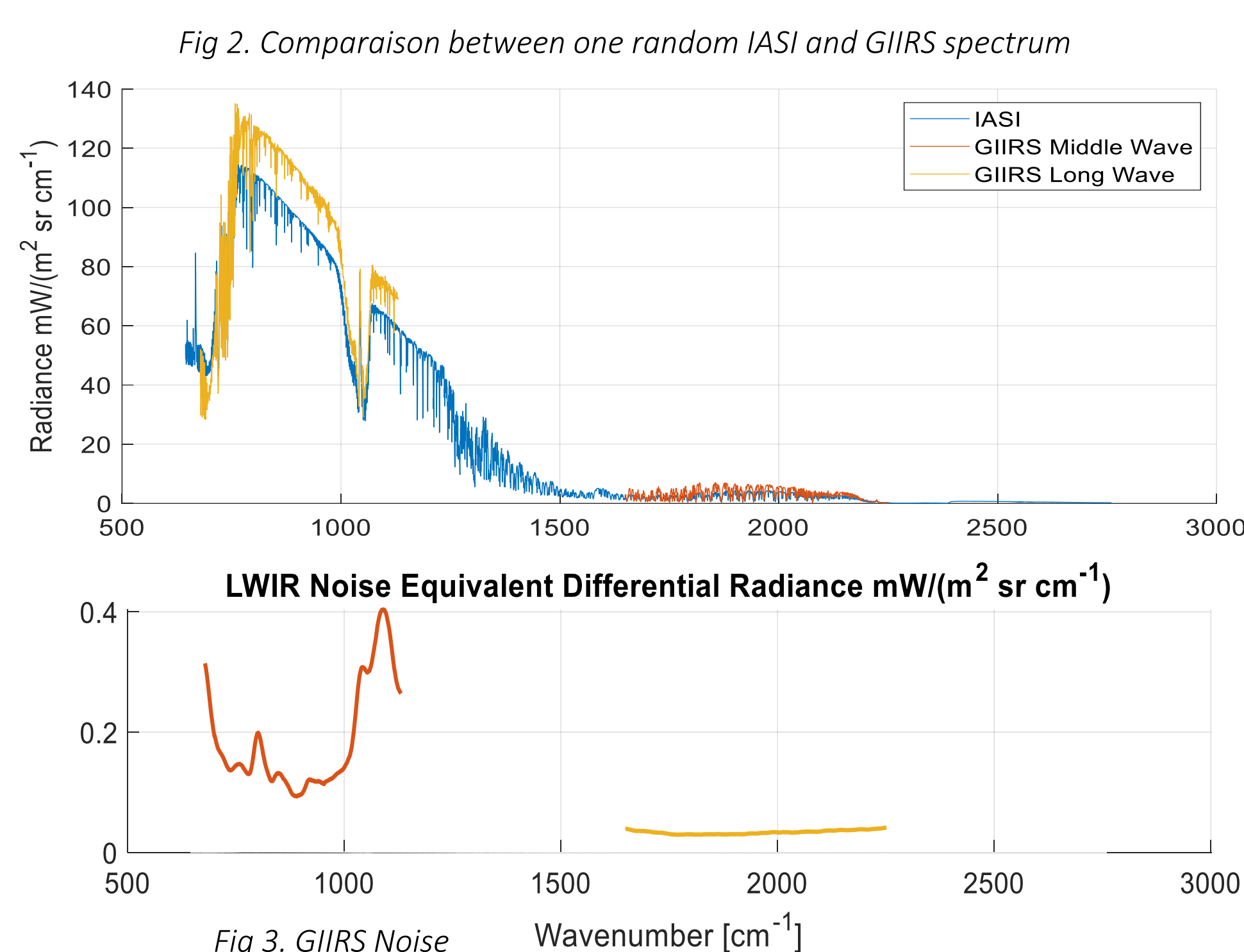


Fig 3. GIIRS Noise

Tskin channel selection

To start, a selection of 84 channels sensitive to T_{skin} within the GIIRS spectra are chosen, based on a previous work done for IASI by Safieddine et al., 2020¹. For IASI, 87 channels are selected that are sensitive to T_{skin}. Since the spectral resolution of GIIRS (Table 1) is slightly coarser, the GIIRS selection is made out of the closest IASI channel used to retrieve T_{skin}, which amount for 84 total channels. The IASI and GIIRS selection are shown on Fig. 4.

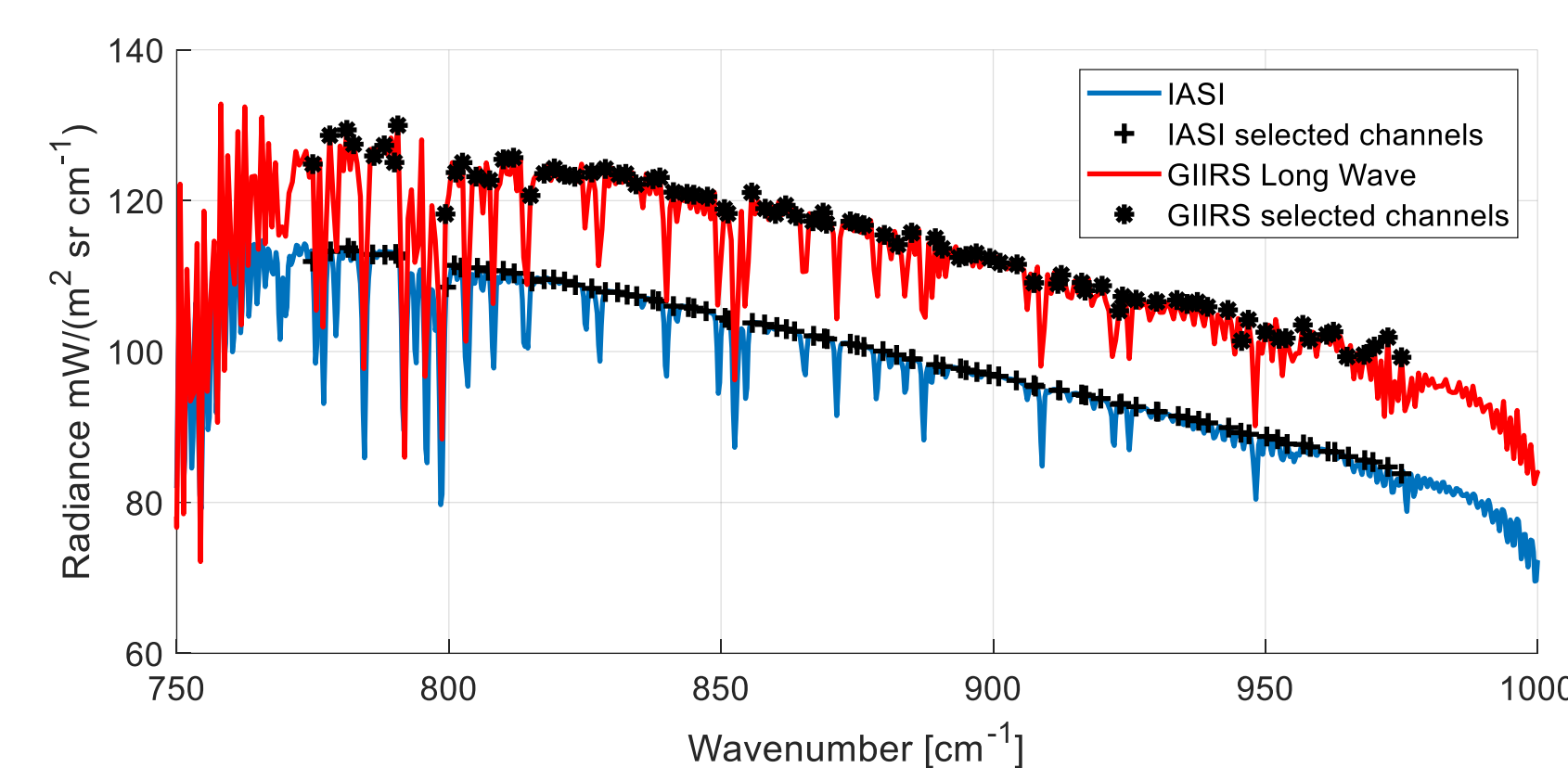


Fig 4. Selected channels to retrieve T_{skin} within the IASI and GIIRS spectrum

We then separate our dataset between land and sea. The land dataset includes four emissivity channels² within the same range as the channels used for radiances as shown on Fig. 4. A simple schematic of our method is shown on Fig. 5

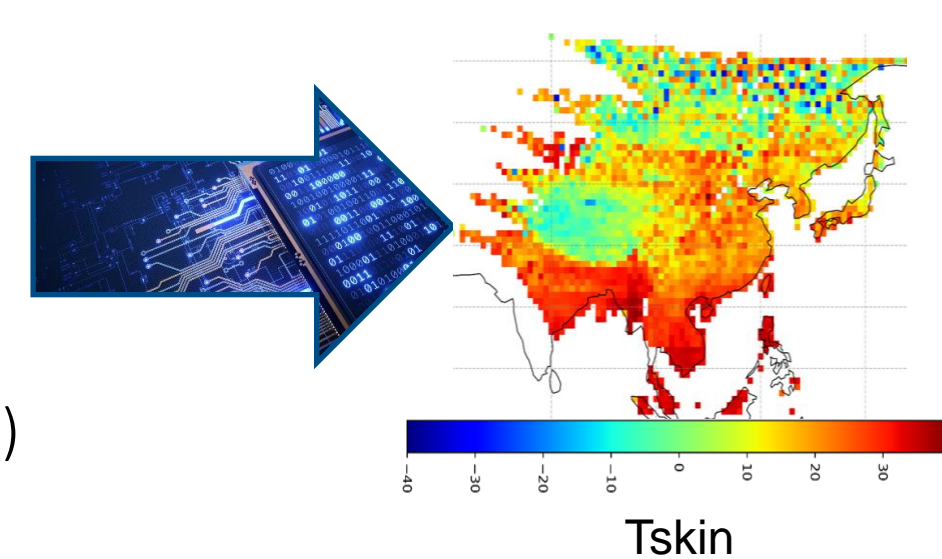
Fig 5. Schematic of our neural network model used to retrieve T_{skin}

Input/features

- 84 channels from GIIRS's spectra
- Longitude
- Latitude
- Emissivity (only over land)

Output/desired predictions

- T_{skin} EUMETSAT (clear sky)



Results and discussion

Over the sea

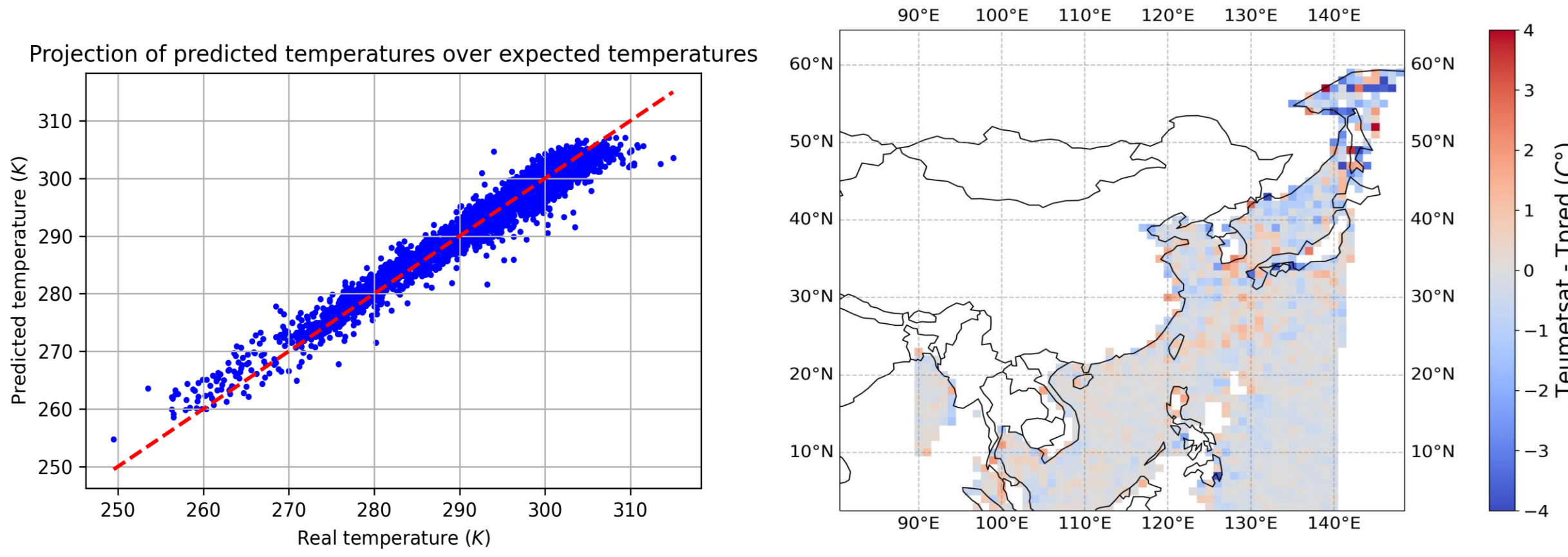


Fig 7. Performance of our neural network model used to retrieve T_{skin} over the sea

Over the sea, our first models are very good, with mean square error (mse) of 1.44. This is expected, as the sea T_{skin} (SST) is less complex (as the emissivity changes much less than that over land)

Over land

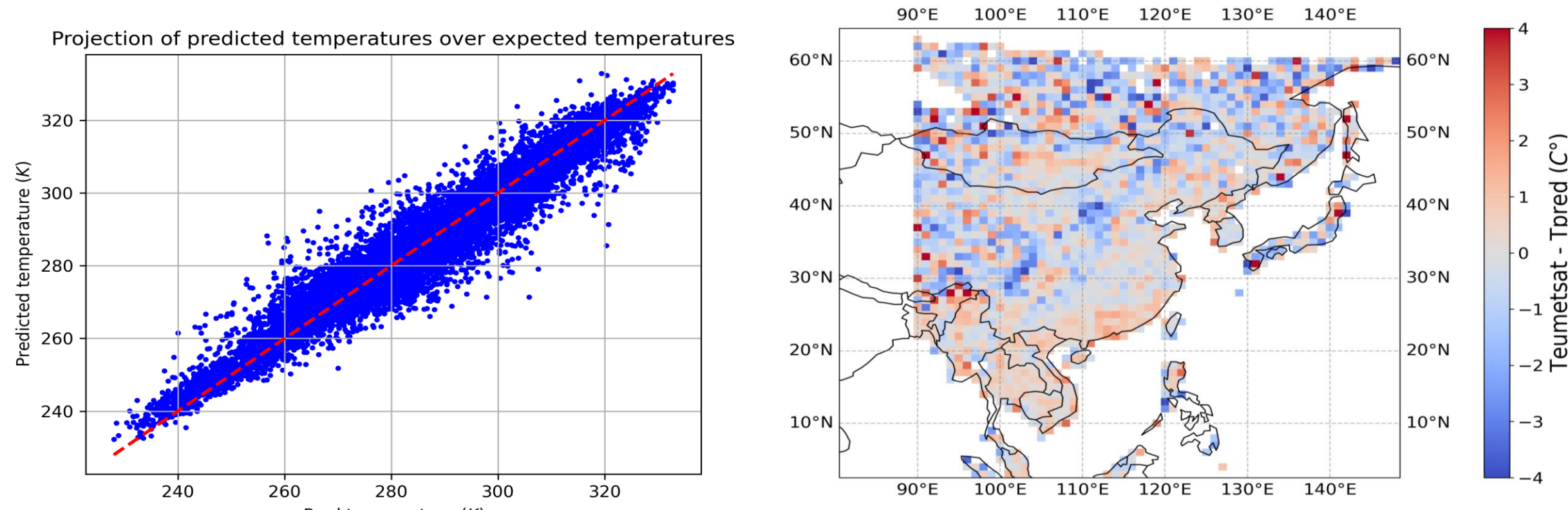


Fig 8. Performance of our neural network model used to retrieve T_{skin} over land

Over land, the problem is more complex (Fig 6); our first models are good, with mean square error (mse) of 14.8. We look at improving these models with more complex architectures or adding more auxiliary input data into our model (viewing angle, pressure at the surface, etc).

Future work

With this new T_{skin} product, we will be able to study the diurnal evolution of T_{skin} and the urban heat islands phenomenon over the GIIRS sounding area.



In preparation to the future launch of the Infrared Sounder (IRS), we will have the framework needed to have a T_{skin} product in near real time for IRS.

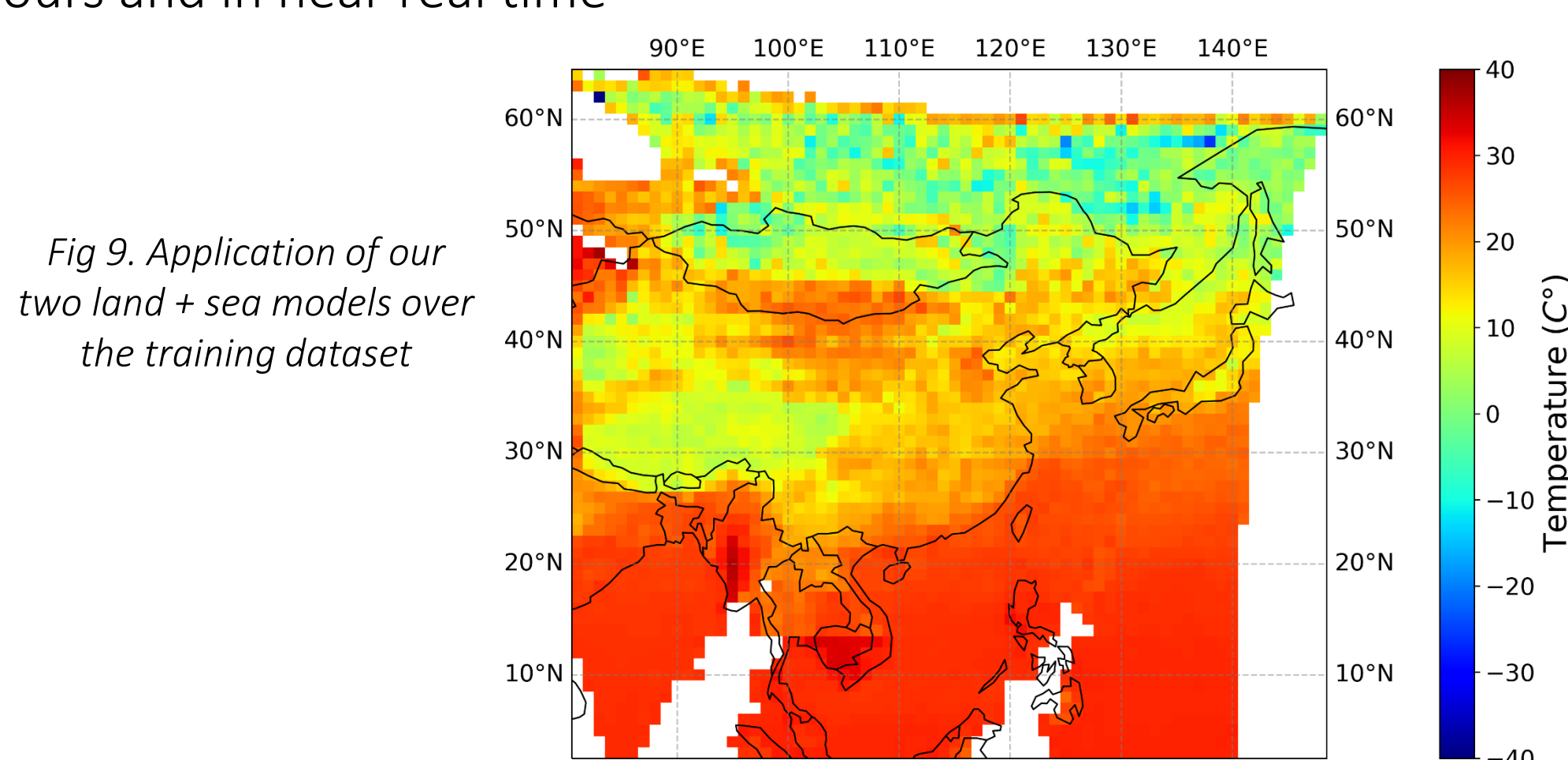


Fig 9. Application of our two land + sea models over the training dataset

The neural network model will be applied over land and sea as shown in Fig. 9 in order to produce a similar T_{skin} maps every two hours and in near real time