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Supplementary Information to: Predicting years with extremely low gross primary production from daily weather data using Convolutional Neural Networks

Aris Marcolongo[1,2*], Mykhailo Vladymyrov[1,3], Sebastian Lienert[2,4], Nadav Peleg[5], Sigve Haug[1] and Jakob Zscheischler[2,3,6]

[1]Mathematical Institute, University of Bern, Sidlerstrasse 5, 3012 Bern, Switzerland
[2]Climate and Environmental Physics, University of Bern, Sidlerstrasse 5, 3012 Bern, Switzerland
[3]Theodor Kocher Institute, University of Bern, Freiestrasse 1, 3012 Bern, Switzerland
[4]Oschger Centre for Climate Change Research, University of Bern, 3012 Bern, Switzerland
[5]Institute of Earth Surface Dynamics, University of Lausanne, 1015 Lausanne, Switzerland
[6]Department of Computational Hydrosystems, Helmholtz Centre for Environmental Research – UFZ, Permoserstr. 15, 04318 Leipzig, Germany
*Corresponding author. E-mail: aris.marcolongo@math.unibe.ch

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S1. Daily values of drivers and gross primary production

In Figs. S1, S2 and S3 we report the mean daily values of precipitation, temperature, radiation and gross primary production for each day of year. Shaded areas report plus/minus one standard deviation. Superposed also a typical daily evolution for one random year.

S2. Monthly predictions

We report the intermediate monthly predictions of the trained *CNN-M* models, when fitting monthly values in regression mode, in figures S4, S5 and S6 for temperate, boreal and tropical sites respectively. All plots report data of the test set.

S3. Training of CNN-M

In Figs. S7, S8 we report a description of the evolution of *CNN-M* during training, for $\alpha = \alpha_m = 0$ and $\alpha = \alpha_y = 1$. In the case of $\alpha = 1$, L2 regularization ($\lambda = 0.6$) was used for all weights. The metric reported is the Normalized Root Mean Squared Error (NRMSE) used in the main text and defined as:

$$NRMSE = \sqrt{\frac{1}{N_y}\sum_{i=1}^{N_y}\left(\frac{\hat{Y}_i^{GPP} - Y_i^{GPP}}{\sigma(Y^{GPP})}\right)^2}, \tag{S1}$$

where index i runs over N_y years and the notation introduced in the main text has been followed. The NRMSE is evaluated in Figs. S7, S8 for the validation set. The NRMSE is an aggregated metric

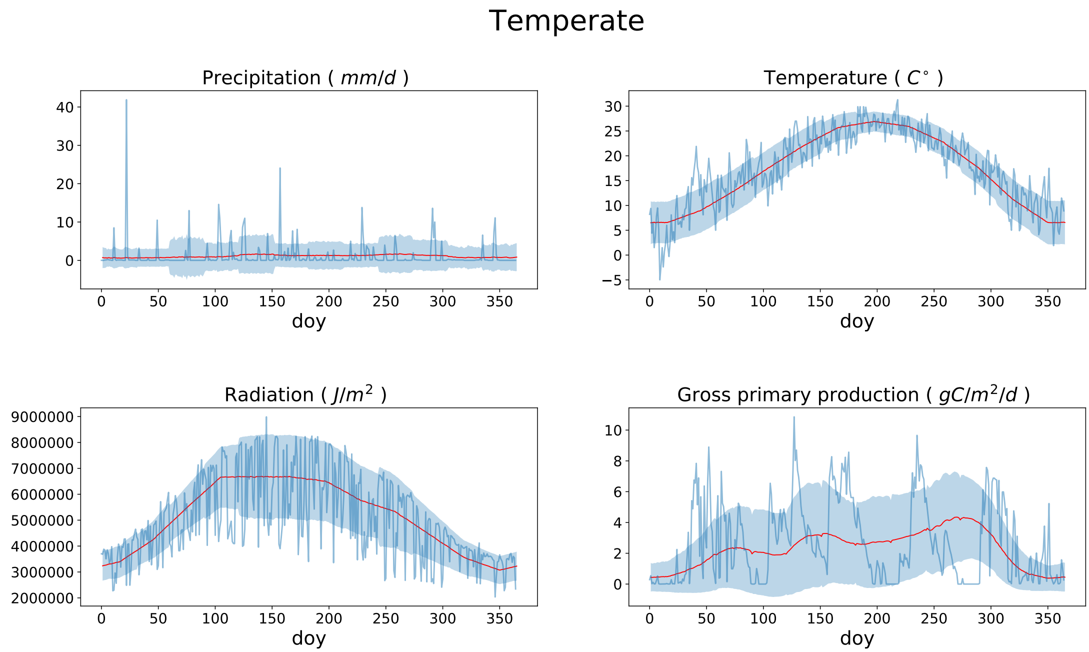

Figure S1. *Daily values of precipitation, temperature, radiation and gross primary production for each day of year and temperate site, reported with a red line. Blue shaded areas indicate plus/minus one standard deviation. Superposed with a blue light line a typical daily evolution for one random year.*

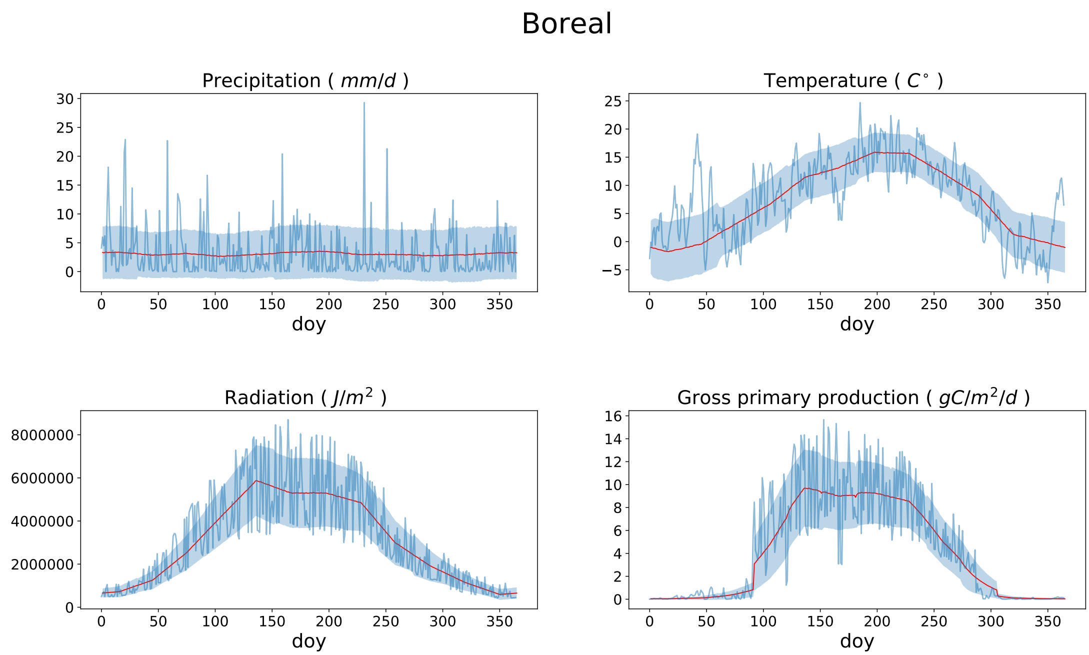

Figure S2. *As in Fig. S1, for site with boreal climate.*

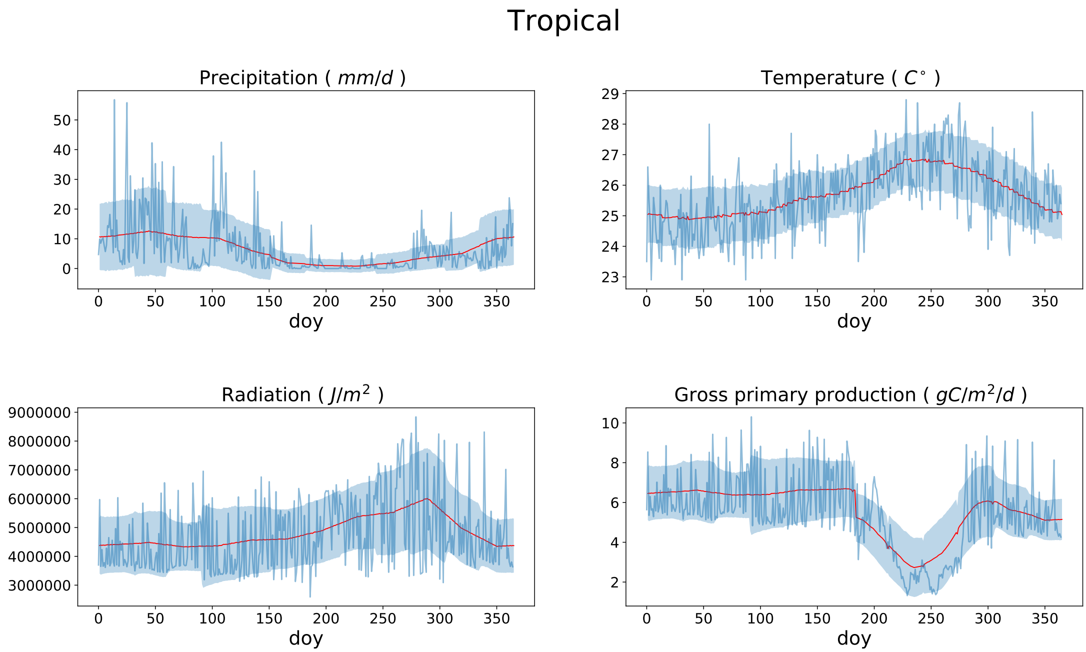

Figure S3. *As in Fig. S1, for tropical site.*

less informative than the entire distribution of residuals but is sensitive to outliers. A NRMSE of 1 corresponds to a model predicting for each year a constant equal to the mean value of the yearly GPP. Values much smaller than 1 are indication of a good model.
The learning rate scheduling is also reported in Fig. S7, S8. It start with a very low value for a few epochs, than it gradually achieves the highest value of 0.0005. Finally it becomes again gradually smaller to reach a good minimum.

S4. Training of CNN-D

In Fig.S9 and Fig.S10 we report the evolution during training of *CNN-D*. Accuracy is defined as in previous paragraph. In Fig.S10 we report instead the entire residuals distribution immediately before the loss function at the yearly scale is activated and at the end of the training.
The learning rate scheduling is also reported in Fig. S9 and behaves similar to the one used for *CNN-M*.

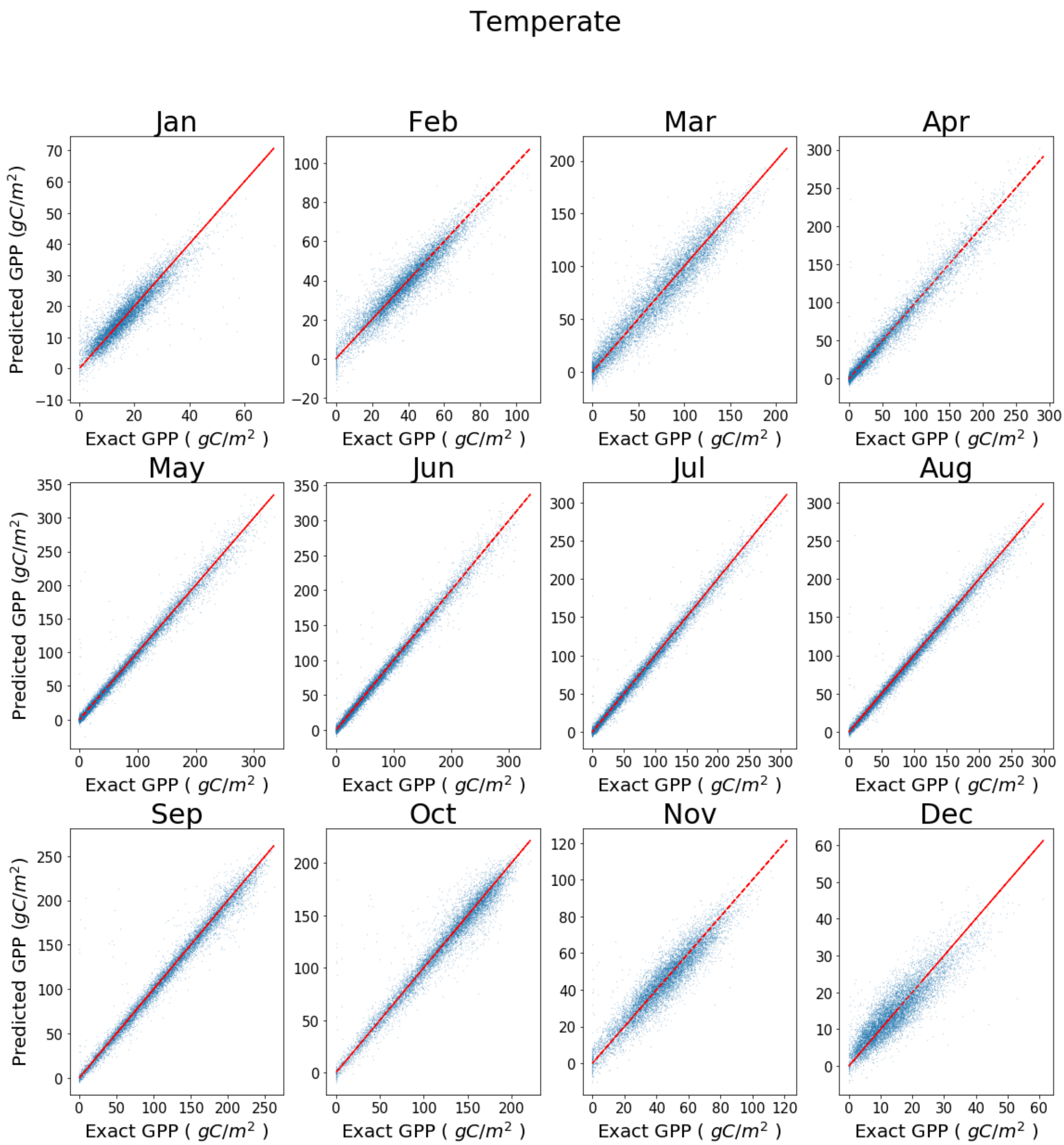

Figure S4. *Intermediate monthly predictions provided by* CNN-M *for temperate site. Red line corresponds to perfect prediction .*

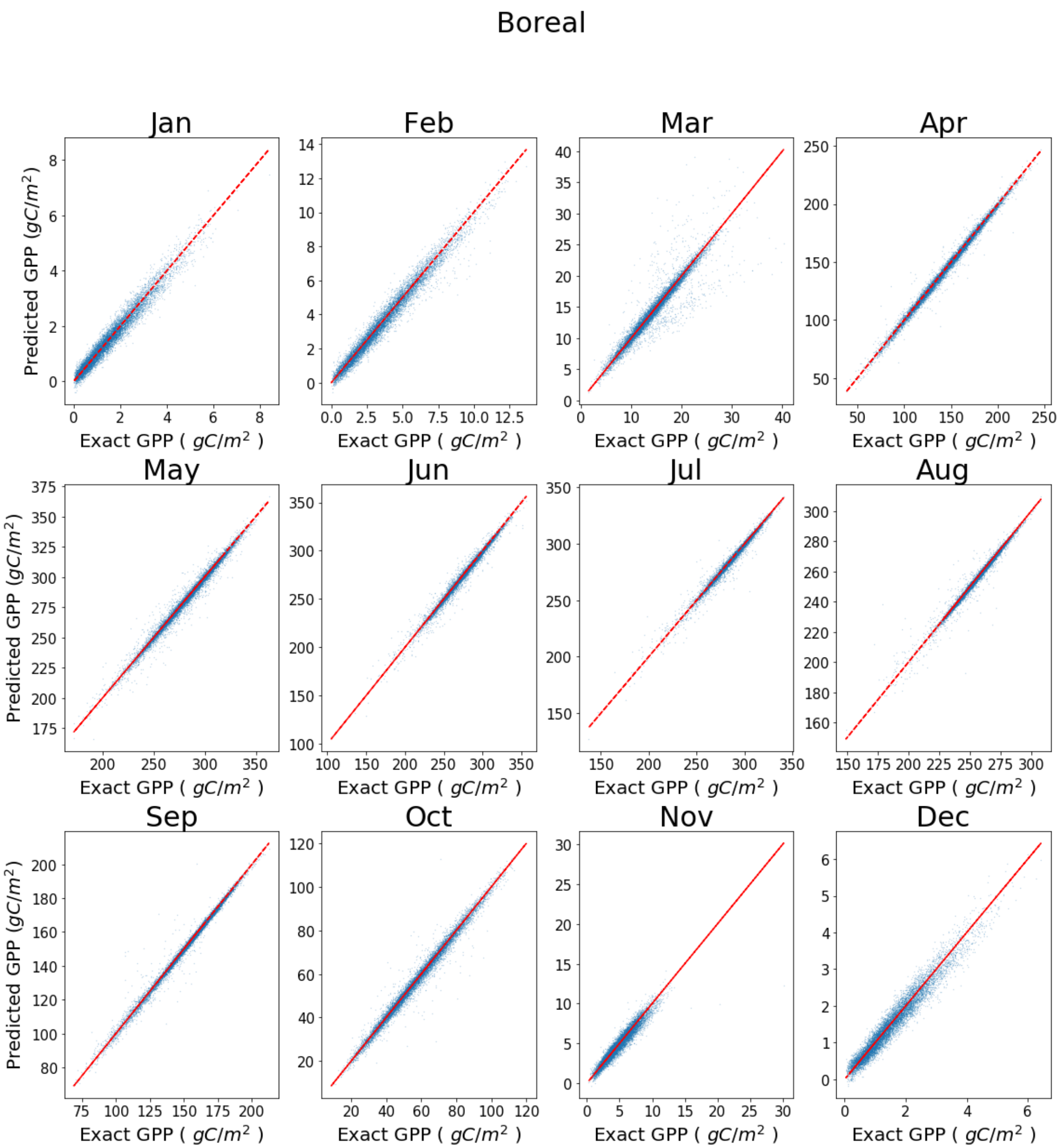

Figure S5. *Intermediate monthly predictions provided by* CNN-M *for boreal site. Red line corresponds to perfect prediction .*

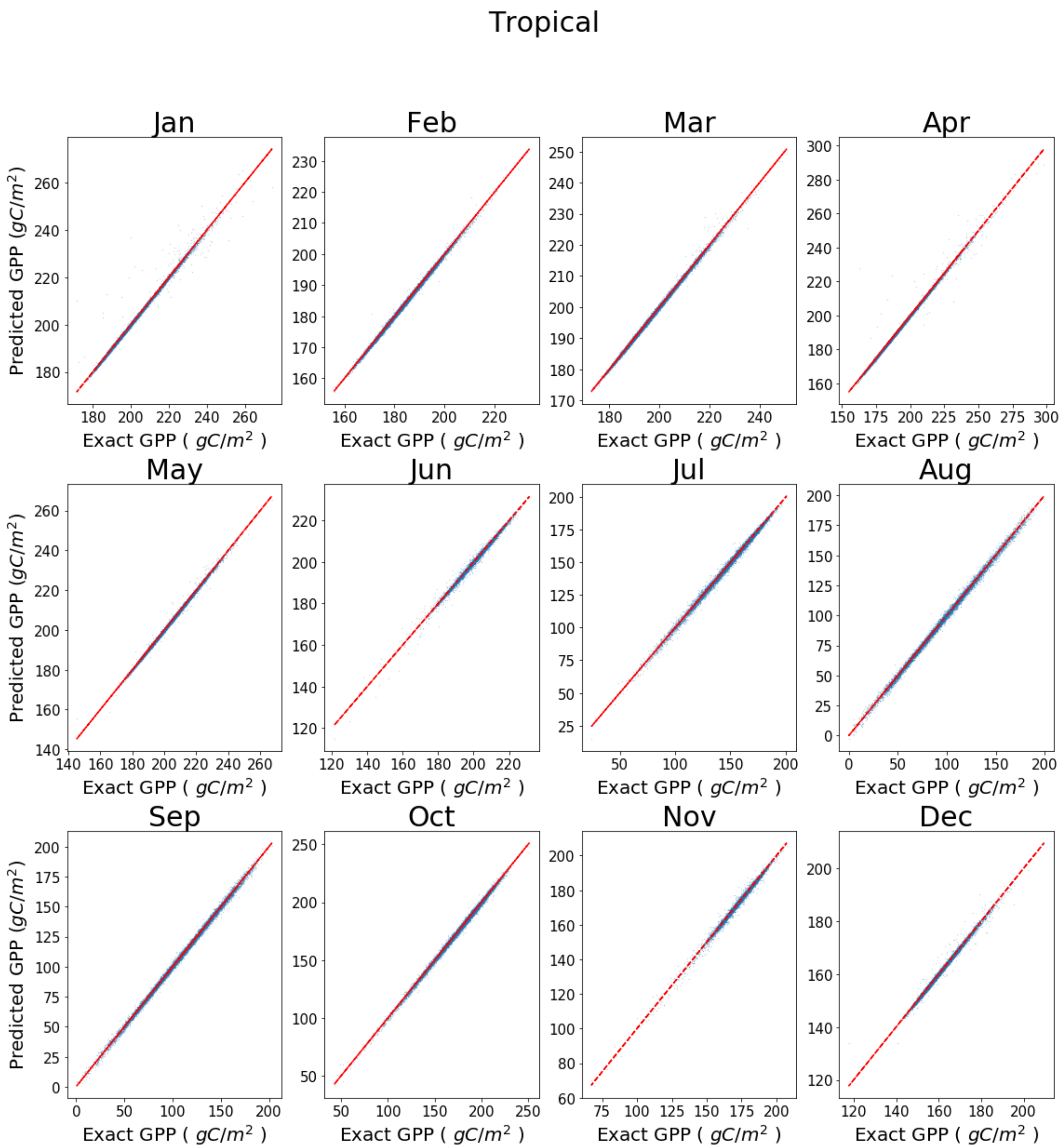

Figure S6. *Intermediate monthly predictions provided by* CNN-M *for tropical site. Red line corresponds to perfect prediction .*

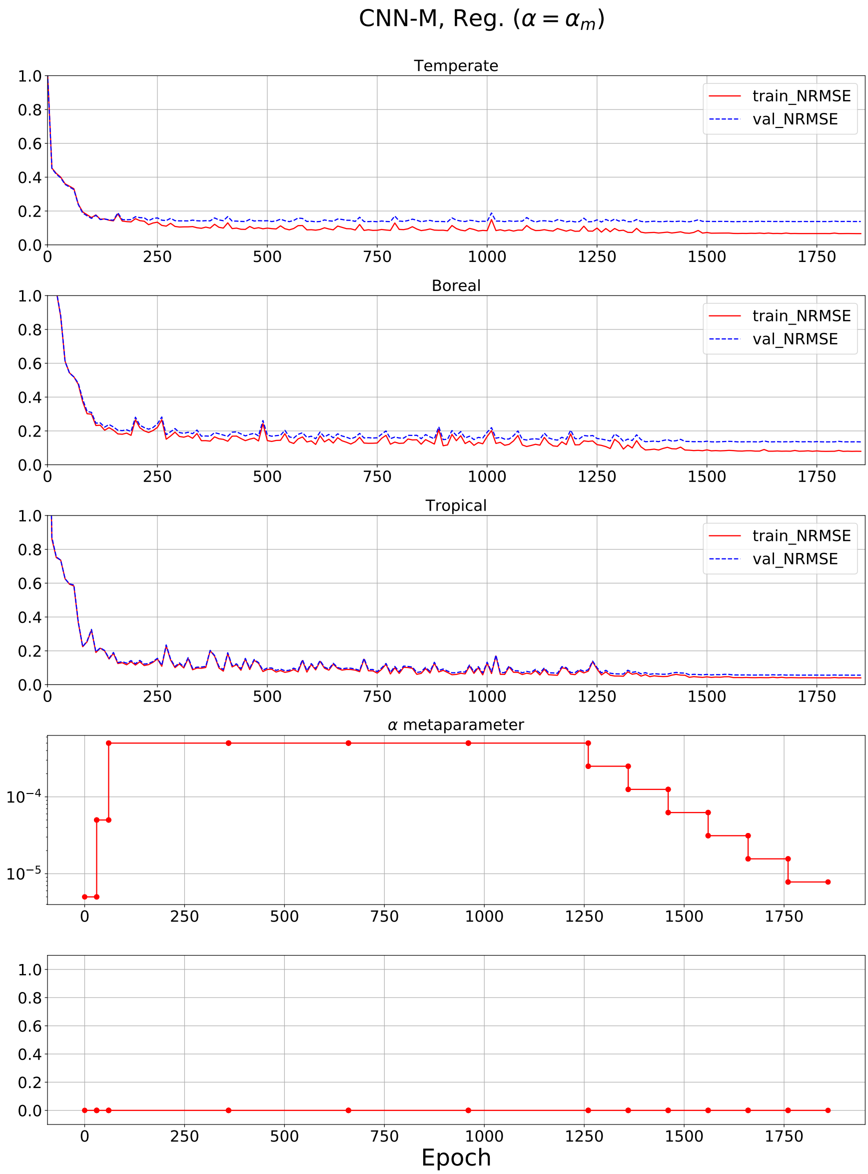

Figure S7. *Evolution of the accuracy of CNN-M with $\alpha = \alpha_m = 0$ during training evaluated in train and validation set.*

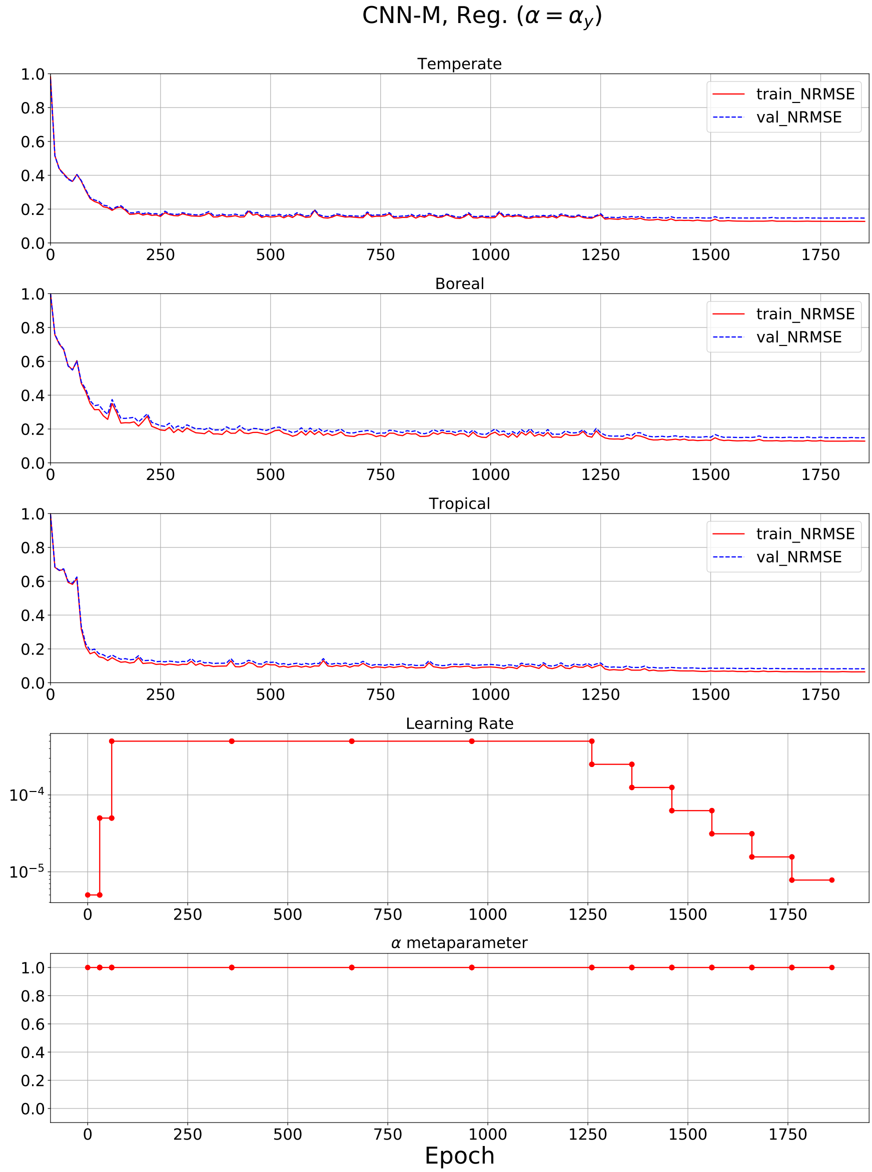

Figure S8. *Evolution of the accuracy of CNN-M with $\alpha = \alpha_y = 1$ during training evaluated in train and validation set. The smoother behavior with respect to* CNN-M *with $\alpha = 0$ (Fig. S7) is due to the fact that in this case L2 regularization needed to be used to avoid overfitting.*

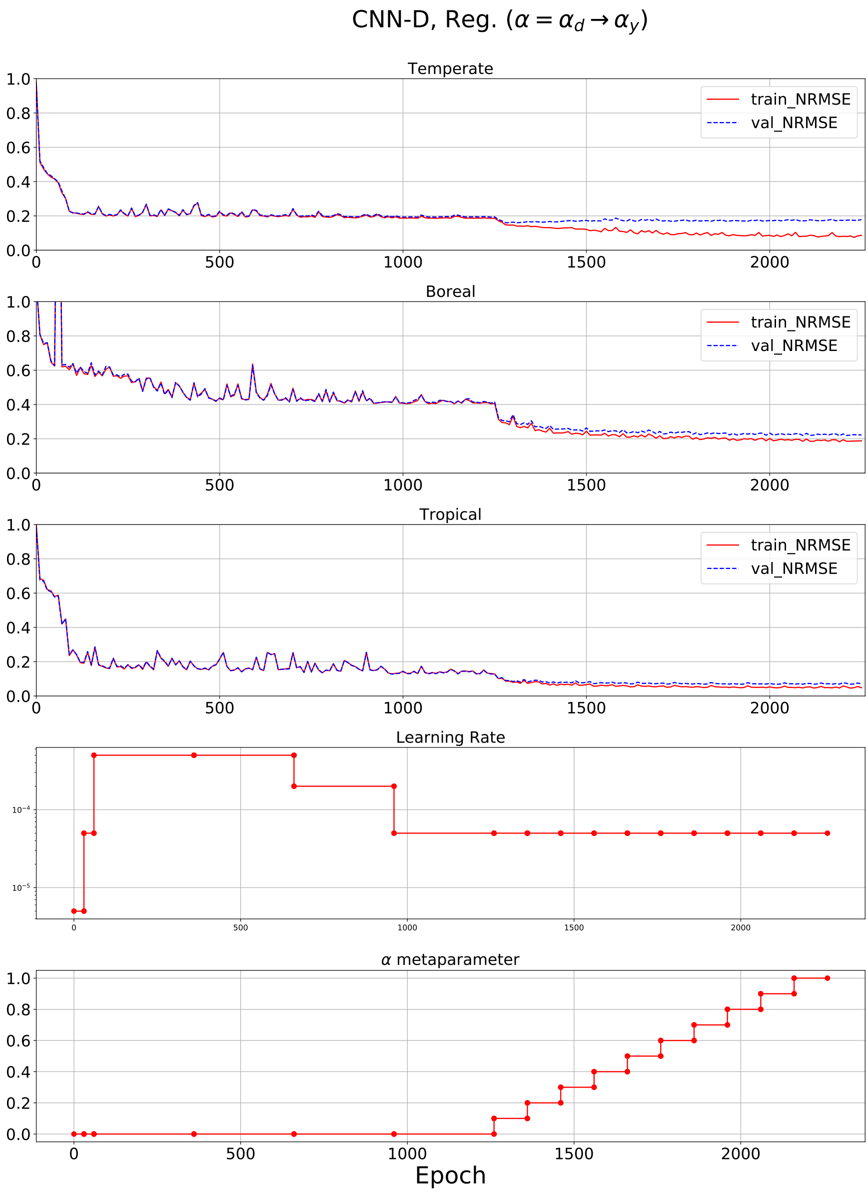

Figure S9. *Evolution of the accuracy of CNN-D during training evaluated in train and validation set. Compare also with the entire residual distribution in Fig. S10.*

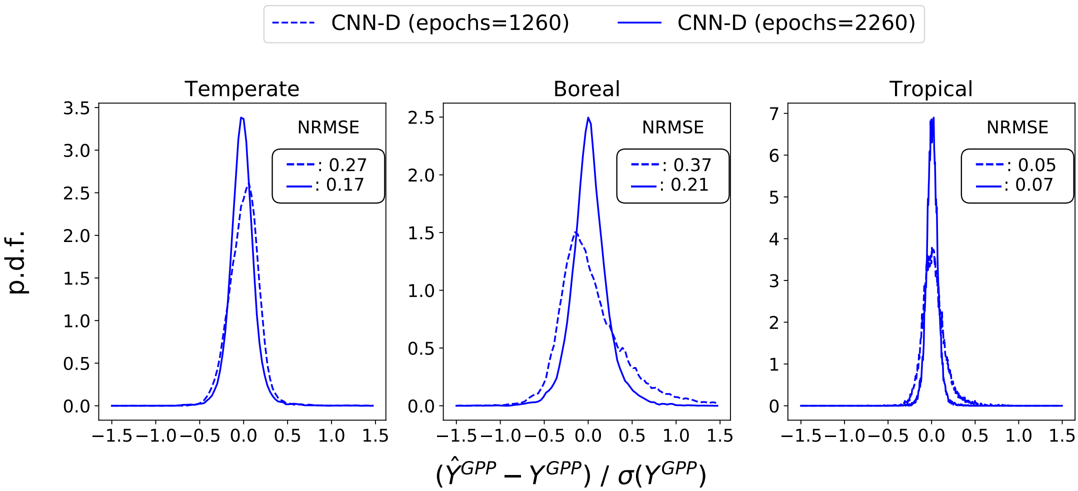

Figure S10. *Distribution of yearly residuals for CNN-D at different stages of the training. At epoch 1260 all the loss is at the daily scale. At epoch 2260, all the loss is at the yearly scale (see Fig.S9, last panel).*