Project: **1466**

Project title: **IOW-ESM — A regional earth system model for the Baltic Sea region**

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Report period: **2024-11-01 to 2025-10-31**

Developing and applying the model tuning library `tunelib`

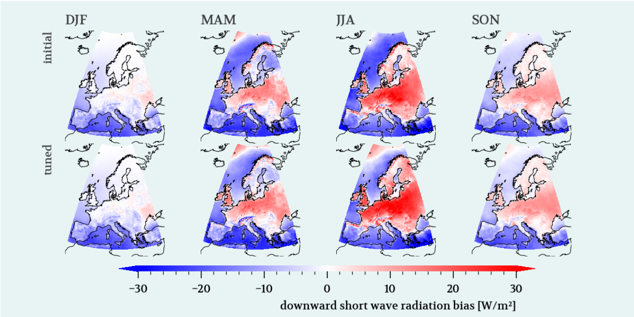

Fig. 1: Seasonal biases in the downward shortwave radiation before (upper row) and after (lower row) the objective tuning with a GPR-surrogate model. The initially existing biases over the Baltic Sea are visibly reduced. The analysis, however, also reveals unresolved model shortcomings in the rest of the domain.

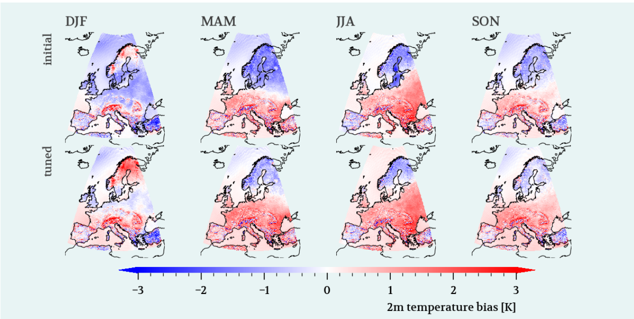

Fig. 2: As Fig. 1 but for the 2 meter temperature. The biases over the Baltic Sea are much reduced after the model tuning.

One of the critical tasks when implementing a novel or modified climate model, regional or global alike, is the calibration of the model setup and the quantification of setup-related uncertainties. Model statistics related to initial and boundary conditions in combination with the chaotic behavior of the climate system, often called internal or natural variability, are often characterized in model ensembles. However, uncertainties related to the choices for free parameters are rarely studied (e.g. Hourdin et al. 2017). It therefore often remains unclear whether model biases are related to insufficiently represented physics or a selectively chosen parameter set (Hourdin et al. 2023). As an example, our coupled regional climate model for the Baltic Sea region, the IOW-ESM, exhibited a cold bias in the SST throughout the spring and summer months (not shown). Analysis indicated that the bias was partially caused by a bias in cloud cover, leading to a biased shortwave radiation at the ocean surface. To tackle this issue, we employed the method of Perturbed Parameter Ensembles (PPEs, e.g. Bellprat et al. 2012; Williamson et al. 2017; Russo et al. 2020; Hourdin et al. 2023). To enable parallel work on the implementation of the ICOsahedral Non-hydrostatic general circulation model (ICON), the methods were first applied to the atmospheric component of the IOW-ESM version 1, COSMO-CLM. In an ensemble of 150 members forced by the ERA5 reanalysis, a total set of 12 parameters, related to the turbulent surface boundary layer and the cloud cover parameterizations, were randomly varied using a Latin hypercube. Each member was integrated for the years 1980 and 1981, amounting to a total of 300 years of integration.

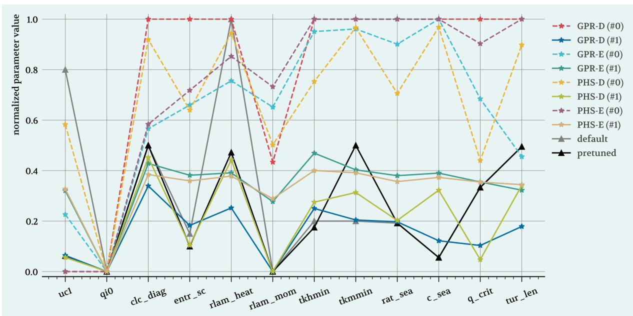

Fig. 3: Optimal parameter vectors found with four different surrogate models: Polyharmonic spline (PHS) fits and Gaussian Process Regressors (GPR) for the difference w.r.to the reference (-D), and the resulting RMSE (-E).

Using this ensemble, a range of metrics related to the cloud cover, 2-meter temperature, 10-meter winds, and the 500 hPa geopotential over the Baltic Sea were computed to set up surrogate models to optimize the parameter set with respect to the set of metrics. For comparison, we employ four different types of surrogate models and seek a single best estimate through global minimization algorithms. This procedure yielded three major conclusions. First, we find that all surrogate models exhibit two regions with minimum errors/maximum performance. The global optimization therefore leads to two optimal parameter vector candidates, clustered around the two optimal regions (c.f. Fig. 3). Furthermore, there are similarities depending on the two classes of surrogate models, emulating time series of the metrics or the respective root mean square errors. Third and most importantly, we find that both the inversion of the ensemble results (surrogate model fit) and the global optimization themselves exhibit large uncertainties. As a consequence, robust statistics are needed to both generate robust surrogate models and understand the uncertainty inherent to the methods applied. In reverse, one single inversion and optimization proved insufficient. Obeying these findings, we were able to significantly reduce the bias in downward shortwave radiation and 2-meter temperature over the Baltic Sea (c.f. Figs. 1 and 2). Preparing for the planned calibration of the IOW-ESM, version 2, the GPR-D type surrogate model was successfully tested in a history matching procedure (not shown). A flexible Python library implementing the tuning methods is publicly available (Karsten et al. 2025), and a manuscript reporting the above findings is currently in preparation.

Introducing ICON-A into the IOW-ESM infrastructure

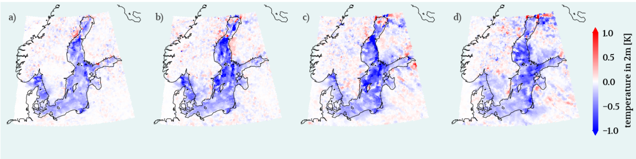

Fig. 4: Difference in 2 meter temperature between a coupled and an uncoupled simulation of ICON-A with MOM6. Columns show the forecast times 6 h (a), 12 h (b), 18 h (c), and 24 h (d).

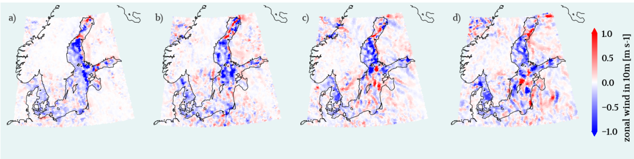

Fig. 5: As Fig. 4 but for the 10 meter zonal wind.

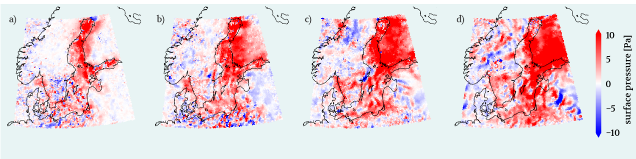

Fig. 6: As Fig. 4 but for the surface pressure.

Recently, the ICON model (Pham et al. 2021) was introduced as an atmospheric component (ICON-A) to the IOW-ESM. Similar to the coupling in the IOW-ESM, version 1.0.4, the coupling of fluxes between the model components is handled through a flux calculator operating on an exchange grid as described by Karsten et al. 2024. To facilitate the communication with the flux calculator, a coupling interface using the OASIS3-MCT coupler (Craig et al. 2017) was introduced. Preliminary analyses show that simulations with initial and boundary conditions derived from the ERA5 analysis for forecast times within the predictability limit are characterized by differences over the coupling area (i.e. the Baltic Sea) due to the momentum and heat transfer between the two model components. Within the first 24 hours, we find a cooler 2 meter temperature (Fig. 4), an inhomogeneously modified 10 meter zonal wind (Fig. 5), and a small and spatially variable difference in the surface pressure (Fig. 6). As one may expect, these model differences then propagate over the model domain and finally lead to modifications in the temporal mean state of the atmosphere, even within the predictability limit (not shown). With the technical implementation working, our work will now proceed with testing and the calibration of the coupled setup as demostrated above.

References

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