SPECIAL PROJECT PROGRESS REPORT

Reporting year	2021/22			
Project Title:	Mining 5th generation reanalysis data for changes in the global energy cycle and for estimation of forecast uncertainty growth with generative adversarial networks			
Computer Project Account:	spatlh00			
Principal Investigator(s):	Leopold Haimberger, Alexander Bihlo			
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Name of ECMWF scientist(s) collaborating to the project (if applicable)	Hans Hersbach, M. Balmaseda			
Start date of the project:	1.1.2021			
Expected end date:	31.12.2023			

Computer resources allocated/used for the current year and the previous one

		Previous year		Current year	
		Allocated	Used	Allocated	Used
High Performance Computing Facility	(units)	10000	0.0	10000	0.0
Data storage capacity	(Gbytes)	1000	32	1000	32

Summary of project objectives

The special project focuses on detecting and estimating changes in the coupled oceanic/atmospheric water and energy cycles. Its second focus, also employing reanalysis data, are novel methods for describing forecast uncertainty growth.

Summary of problems encountered (if any)

Summary of results of the current year (from July of previous year to June of current year)

This year we continued our work on evaluating coupled energy and water budgets from ERA5 but also ocean reanalyses. The quality of indirectly estimated energy fluxes was determined by comparison with buoy and satellite data. Results are published in J. Climate (Mayer J et al. 2021) Improved energy flux divergence and surface energy and water balance estimates have been published in the Copernicus Climate Data Store (<u>https://cds.climate.copernicus.eu/cdsapp#!/dataset/derived-reanalysis-energy-moisture-budget?tab=overview</u>).

We are working on an update of the energy flow analysis of (von Schuckmann et al. 2021). We also started to analyse the flux trends over selected regions in the North Atlantic. One example is shown in Fig. 1, which indicates weakening latent heat flux over the Eastern North Atlantic, while there is strengthening over the Gulf Stream region. More detailed analysis of the region southeast of Greenland (upper right green square) indicates that decreasing surface humidity (decreasing temperature) is the main reason there. Over the Gulf Stream region, there is increasing surface temperature, consistent with latent heat increase, but the attribution is less clear (not shown).



Fig. 1: Trends in annual mean latent heat flux 2001-2020 over the North Atlantic. Positive trends means that the latent heat flux weakened over this period, Upper right panel shows time series of latent and sensible heat flux Southeast of Greenland, lower panels show which trends of the input quantities (10m wind, humidity or temperature of the lowermost model level or the skin humidity (qsfc) or skin temperature (skt)) contributed most to the trend.

Detailed studies of the flows to Arctic gateways led to improved estimates of lateral transports. Some technical difficulties with the complex ORCA grid used in most ocean reanalyses and some CMIP6 climate models could be overcome, they can be calculated now highly accurately with two different methods (projection onto lines and line integrals). Next step will be to set these transport in context with the AMOC and also to compare the meridional transports with those in CMIP6 models.



Fig. 2: Cross-channel volume water fluxes through Makassar strait, estimated from moorings (OBS) and 6 different contemporary ocean reanalyses with a resolution of $\frac{1}{4}$ degrees, except GLORYS12, where it is 1/12 degrees.

Additional work went into a careful analysis of the water flow through the Indonesian Throughflow (ITF) regions. Observations from moorings were thoroughly compared with contemporary ocean reanalyses. Results show good overall performance of ocean reanalyses, so that the relations of ITF volume fluxes to e.g. the ENSO cycle or the Southeast Asian Monsoon can be quantitatively evaluated. One notable difference is an apparent time lag of 1 month in reanalysis fluxes compared to fluxes from moorings, at least for the Makassar strait (2S, 118E). This can be seen Fig. 2), and it is also evident when looking at lagged correlation. Correlations at lag 1 (month) are between 0.75 and 0.8, whereas the lag0 correlations, shown in the figure legend, are only 0.5-0.6.

We have shown that it is possible to use deep neural networks to directly learn the spread from a deterministic weather forecast, thereby possibly alleviating the need for costly numerical ensemble prediction models. We have illustrated this idea by predicting the 500 hPa geopotential height, a measure of pressure in the middle of the troposphere. While still a rather stark simplification of the full three-dimensional structure of the atmosphere, prediction of the 500 hPa geopotential has been routinely considered as a first step in the history of weather forecasting.

In the Figure below we present an example of the results obtainable from a three-dimensional conditional generative adversarial network (pix2pix3D) to forecast the ensemble spread on March 31, 2020. The model has been trained on the ECMWF IFS data from 2010-2018, and is evaluated for the year 2020. We compare our model (third row), the climatological spread (first row) and persistence spread (second row) against the ground truth, i.e. the true ensemble spread as obtained from the IFS (last row) for forecast hours 18, 42, 66 and 90 (left to right). The titles show the associated structural similarity index measure (SSIM) values (best is 1) and RMSE (lower is better) of all models compared to the ground truth. This figure shows a quite substantial improvement of the deep learning based model compared to the climatology and persistence baselines.



Fig. 3: Ensemble spread forecast of geopotential as described in text

For the same day we show the ensemble plumes for randomly selected cities in the plot below. The three-dimensional generative adversarial network substantially outperforms the baseline models, and

gives a both qualitatively and quantitatively meaningful ensemble spread obtained from the deterministic control run only.



Fig. 4:Ensemble spread forecast up to hour 96 for selected sites. Blue: ground truth from ECMWF IFS ensemble, ochre: pix2pix3D forecast.

A verification over the test dataset (the year 2020) is depicted in the Figure below. This figure again illustrates the improvement of the deep learning based model in comparison with the climatological and persistence models. Note that here we have further improved upon our vanilla pix2pix3D model upon adding layer dropout and a multi-model pix2pix3D ensemble, which yield both lower RMSE and higher SSIM values.



Fig. 5:RMSE, SSIM and integral spread from ensemble forecasts. For details see Brecht and Bihlo(2022).

List of publications/reports from the project with complete references

R. Brecht and A. Bihlo, 2022: Computing the ensemble spread from deterministic weather predictions using conditional generative adversarial networks. Submitted to NeurIPS, arXiv:2205.09182

Mayer, J., Mayer, M., Haimberger, L., 2022: Comparison of Surface Energy Fluxes from Global to Local Scale. J. Climate **34**, 4551–4569, <u>https://doi.org/10.1175/JCLI-D-21-0598.1</u>

von Schuckmann, et al. 2021: Heat stored in the Earth system: Where does the energy go? The GCOS Earth heat inventory team, Earth Syst. Sci. Data, 12, 2013–2041, 2020, https://doi.org/10.5194/essd-12-2013-2020

Summary of plans for the continuation of the project

The next focus for energy budget evaluations will be the quantification of changes in the Western Boundary Currents. For this we try to figure out which input data in the IFS surface parameterization scheme over Ocean contribute most to the calculated trends of latent and sensible heat fluxes.

A bid for continuation of the Copernicus C3S-311c Lot2 service with CNR as lead contractor was successful, so that the work on improvement of radiosonde data can continue.

We plan to continue the development of differential equations-based machine learning models for global weather forecasting.