SPECIAL PROJECT FINAL REPORT

All the following mandatory information needs to be provided.

Project Title:	BONSAI (Boosting eNsemble Size for Advanced Insights into climate predictability)
Computer Project Account:	spitbeal
Start Year - End Year :	2022 - 2025
Principal Investigator(s)	Alessio Bellucci
Affiliation/Address:	Consiglio Nazionale delle Ricerche, Istituto di Scienze dell'Atmosfera e del Clima (CNR-ISAC), Via Gobetti 101, Bologna, Italy
Other Researchers (Name/Affiliation):	Paolo Ruggieri (University of Bologna), Fred Kucharski (ICTP), Muhammad Adnan Abid (ICTP), Danila Volpi (CNR-ISAC), Susanna Corti (CNR-ISAC)

The following should cover the entire project duration.

Summary of project objectives

(10 lines max)

BONSAI aims at exploring the limit of very large ensembles of climate prediction, by designing a prototype decadal prediction system based on a reduced complexity model. Reducing the model complexity (including spatial resolution) while retaining the essential elements needed to reproduce the basic features of the observed climate and its variability, allows a one order of magnitude increase in the size of the forecast ensembles, compared to standard resolution/complexity decadal prediction. Moving from O(10) to O(100s) ensemble members allows a better sampling of the uncertainty affecting the initial conditions, and a more effective suppression of the unpredictable noise, to the benefits of the predictable fraction of the signal and the forecast skill. In order to grant a fair comparison with previous decadal forecast efforts, the experimental setup adopted in BONSAI follows the protocol established for the Decadal Climate Prediction Project (DCPP) in the context of the 6th Phase Coupled Model Intercomparison Project (CMIP6).

Summary of problems encountered

(If you encountered any problems of a more technical nature, please describe them here.)

The implemented procedures to create the restart files for the model initialization (requiring the re-gridding of ocean and sea-ice reanalysis fields from ORCA1 to ORCA2 grid, using SOSIE interpolation tool), the generation of ensemble members through perturbation of the SPEEDY model, and the overall set-up of the BONSAI decadal prediction system (including the design of bash scripts to automatize the launch of hundreds ensemble members and the post-processing of model output) were highly time consuming activities that required no usage of the HPC resources, during the first stage of the project. It was only in the second half of the 2nd reporting year that the production of BONSAI decadal hindcasts could start. This is reflected in the overall underuse of the allocated HPC resources.

Experience with the Special Project framework

(Please let us know about your experience with administrative aspects like the application procedure, progress reporting etc.)

The administrative procedures, including the application process, progress reporting, and overall communication, were smooth and straightforward. I encountered no major issues, and the support provided was timely and efficient throughout the duration of the project.

Summary of results

(This section should comprise up to 10 pages, reflecting the complexity and duration of the project, and can be replaced by a short summary plus an existing scientific report on the project.)

1. Introduction

The present document is a synthesis report on the activities performed as part of the BONSAI Special Project. These activities essentially focused on the development of the “BONSAI” Decadal Prediction System (hereafter BONSAI DPS) based on the SPEEDY-NEMO intermediate complexity model (Ruggieri et al., 2023) and on the performance and analysis of a set of 100-member ensembles of initialized decadal hindcasts, conducted for a range of yearly start-dates covering the 1980-2007 period.

2. Development of BONSAI Decadal Prediction System

BONSAI DPS consists of: 1) a dynamical model; 2) an initialization strategy; 3) an ensemble generation methodology. In the following sections, each of these components will be described.

2.1 The dynamical model.

BONSAI DPS relies on the fully coupled, intermediate complexity SPEEDY-NEMO model. SPEEDY-NEMO is based on a T30L8 configuration of the SPEEDY model for the atmosphere (Molteni, 2003), coupled to a 2-degree configuration of the NEMO v3.0 ocean model (Madec et al., 2008) and LIM2 sea-ice model (Fichefet et al., 1999). The formulation, climatology and variability of SPEEDY-NEMO, can be found in Ruggieri et al. (2023).

Prior to the implementation of the BONSAI DPS, several tests were conducted on the scaling properties of the SPEEDY-NEMO code when run on the ATOS HPC facility. Different model configurations were tested, using alternative partitions of the NEMO ocean model domain (the only model component benefitting from parallelization). After several tests, it was found that the model rapidly reaches a scaling “plateau” for larger than 8x4 NEMO domain decompositions (see Table 1). The “8x4” partition was therefore selected as the optimal configuration to perform the whole set of BONSAI hindcasts.

Experiment	**NPROCX*NPROCY (no. of cores)**	**SYPD**
Test 1	**8x2**	272
Test 2	**8x4**	326
Test 3	**8x6**	326

Table 1. Scaling analysis for SPEEDY-NEMO on ATOS HPC. On the mid column, the NEMO domain partition (corresponding to the number of cores) is reported in terms of zonal (NPROCX) and meridional (NPROCY) sub-domains. The right column shows the number of simulated years per day (SYPD) corresponding to each domain decomposition.

2.2 Model initialization: observational constraints and initialization strategy.

Given the primary role played by oceans and cryosphere in governing the global climate variability and predictability over the decadal range (Kushnir et al., 2019), for the first stream of planned decadal hindcasts only NEMO and LIM components were initialized with observational estimates, while a motionless atmosphere with standard temperature and moisture conditions was used to initialize SPEEDY.

The ocean initial conditions were taken from the 3D-var 5-member ocean reanalysis NEMOVAR-ORAS4 (Balmaseda et al., 2012), while for the sea-ice, an historical reconstruction of sea-ice conditions for the 1958-2012 period was used (Guemas et al. 2012, for details; hereafter G12). These two products represent some of the best available observational surrogates for the global ocean and sea-ice, and guarantee an accurate and realistic constrain of the initial state assigned to the forecast model, in line with the recommendations contained in the CMIP6 DCPP experimental protocol (Boer et al. 2016). One additional practical advantage in using these observationally-constrained products is the consistency of their underlying ocean-sea ice model components (NEMO-LIM) with the counterparts used in the SPEEDY-NEMO forecast model.

Since ORAS4 and G12 are provided on their native 1-degree (ORCA1) model configuration, while SPEEDY-NEMO runs on a coarser 2-degree (ORCA2) grid (Ruggieri et al., 2023), ocean and sea-ice fields had to be interpolated from the source (reanalyses) grid on the forecast model target grid, in order to generate the restart files to initialize the decadal hindcasts with the “observed” conditions. The re-gridding of the initial conditions was performed using the SOSIE open source software (https://brodeau.github.io/sosie/). SOSIE is a fortran90-coded algorithm, that was specifically designed to interpolate geophysical fields onto the ORCA family of tri-polar grids, over which the NEMO global ocean general circulation model and the embedded LIM sea-ice model are run. For this reason, SOSIE represented the most suitable tool to perform the interpolation of reanalysis fields.

In BONSAI, a full-value (FV) initialization strategy is adopted (Magnusson et al., 2012). Following this procedure, full values of 3D scalar (temperature and salinity) and vector (zonal and meridional velocities) ocean fields corresponding to November of a given initialization year are interpolated from the ORAS4 1-degree (ORCA1) grid to the nominal 2-degree (ORCA2) NEMO grid using, a bilinear scheme. The same procedure is applied to sea-ice variables (also on ORCA1 grid) from the G12 reconstruction. These include ice cover (lead fraction), ice thickness, snow depth and ice temperature.

The design of a set of bash scripts to automatize as much as possible the procedure for re-gridding ocean and sea-ice reanalyses fields on ORCA2 grid (using SOSIE), and for generating the restart files to initialize the forecast model was the first building block of the BONSAI DPS.

2.3 Ensemble generation

The approach followed to generate large-size ensembles of decadal hindcasts is a key element of BONSAI DPS. First, the 5-member ensemble of ORAS4 ocean reanalyses provides a mean to sample uncertainties in the initial oceanic conditions. For each of these five alternative oceanic states, a 100-member sub-set can be obtained by perturbing the atmospheric initial conditions. This is achieved by using a built-in feature of the SPEEDY model, enabling the generation of stochastic perturbations applied to the diabatic forcing during the initial stages of the model run.

Specifically, there are two parameters controlling the random perturbation in SPEEDY: *i)* with the NSTRDF parameter, we set the time interval after initialization (i.e., the number of time-steps) over which the random perturbation is applied; *ii)* with the INDRDF parameter we change the *seed* of the random forcing generator. In BONSAI DPS, for a given ocean reanalysis member, we generate *N* members by assigning progressively increasing INDRDF values, while maintaining a fixed NSTRDF=20 value (mimicking a finite time-length perturbation acting continuously over a 20-time step interval after initialization). This way the ensemble member is anchored to the corresponding INDRDF random forcing seed (e.g., for a given start date and ORAS4 realization, the ensemble member 1 is obtained by setting INDRDF=1, etc.).

An alternative way to generate ensemble members is by changing NSTRDF, although this approach appears to be less practical since it determines progressively long time-windows for the applied random forcing when the ensemble member identifier reaches high values, substantially deviating from the “initial state perturbation” concept in climate and weather predictions. The methodology adopted to generate the ensembles in BONSAI is schematically illustrated in Fig. 1.

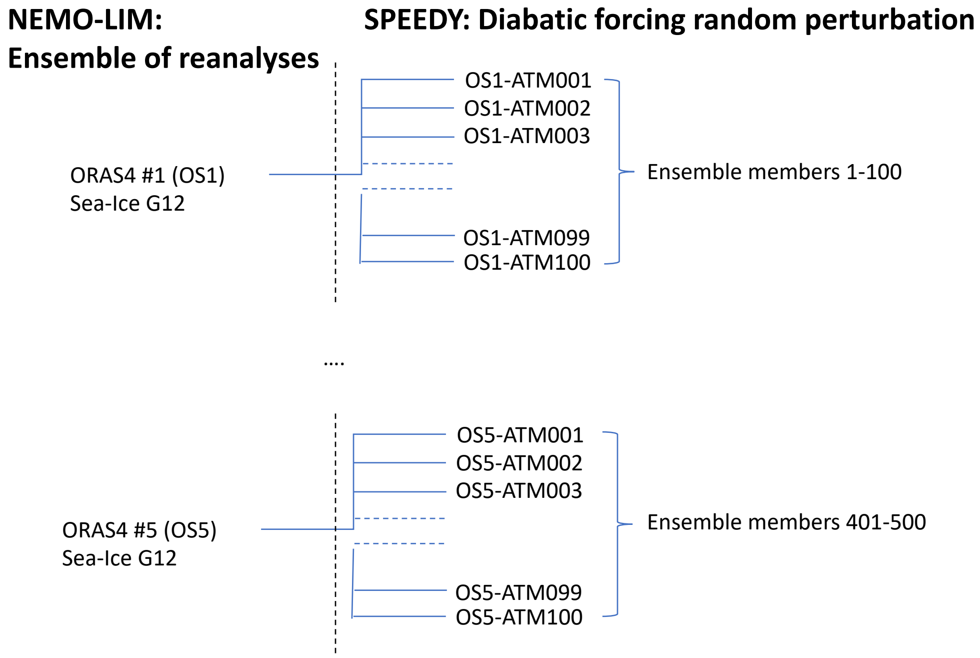

Fig. 1. Ensemble generation scheme used in BONSAI. The criterion followed to generate (potentially) 500 members for a generic start-date is illustrated. Note that for each ORAS4 ensemble member (5 in all), 100 members are generated by perturbing the initial state of the atmosphere, using a stochastic diabatic forcing (see text for details).

3. Bias assessment

During the project, 100-member ensembles of 10-year simulations were conducted for 28 yearly start-dates covering the 1980-2007period (totaling 28,000 simulated years), providing a solid basis for skill evaluation. After setting up the DPS system, a mandatory step was to assess the implemented strategies of model initialization and ensemble generation in BONSAI (described in Section 2). In particular, a major concern was to establish whether the ensemble generation methodology – relying on the perturbation of the atmospheric state – was functional to the generation of an adequate intra-member spread. Another, more practical aspect, regarded the initialization of the model, i.e., to verify whether the initial conditions from ORAS4 and G12 analyses were correctly assigned to the model through the interpolation procedure described in Section 2.2.

For illustrative purposes we show in Fig. 2 the global mean SST (GMSST) evolution for the 100-member reforecast ensemble initialized on November 1980 is shown, against the corresponding GMSST time series from ORAS4 member 1, here used as verification dataset. As expected, all ensemble members (color curves) detach from the common ORAS4 initial condition (solid black curve), consistent with the FV strategy adopted in BONSAI, providing indications that the interpolation from ORCA1 to ORCA2 performed with SOSIE did not introduce substantial distortions of the reanalysis fields, at the global scale.
Also evident is the large bias affecting the amplitude of the seasonal cycle in SPEEDY-NEMO, which appears to be largely dictated by the overly warm GMSST values during the extended boreal winter months, in contrast with the summer period characterized by a much closer agreement between predicted and observed conditions. After a closer inspection it emerged that the bias in the GMSST originates in the southern hemisphere, showing a ~5-6°C seasonal range, compared to the observed 4°C range, while tropics and extra-tropical Northern Hemisphere mean SSTs, on the other hand, show a considerably reduced bias (not shown).
Also visible in Fig. 2 is the intra-member dispersion, already manifest by the end of lead-year 1, although partly overshadowed by the strong locking exerted by the seasonal cycle.

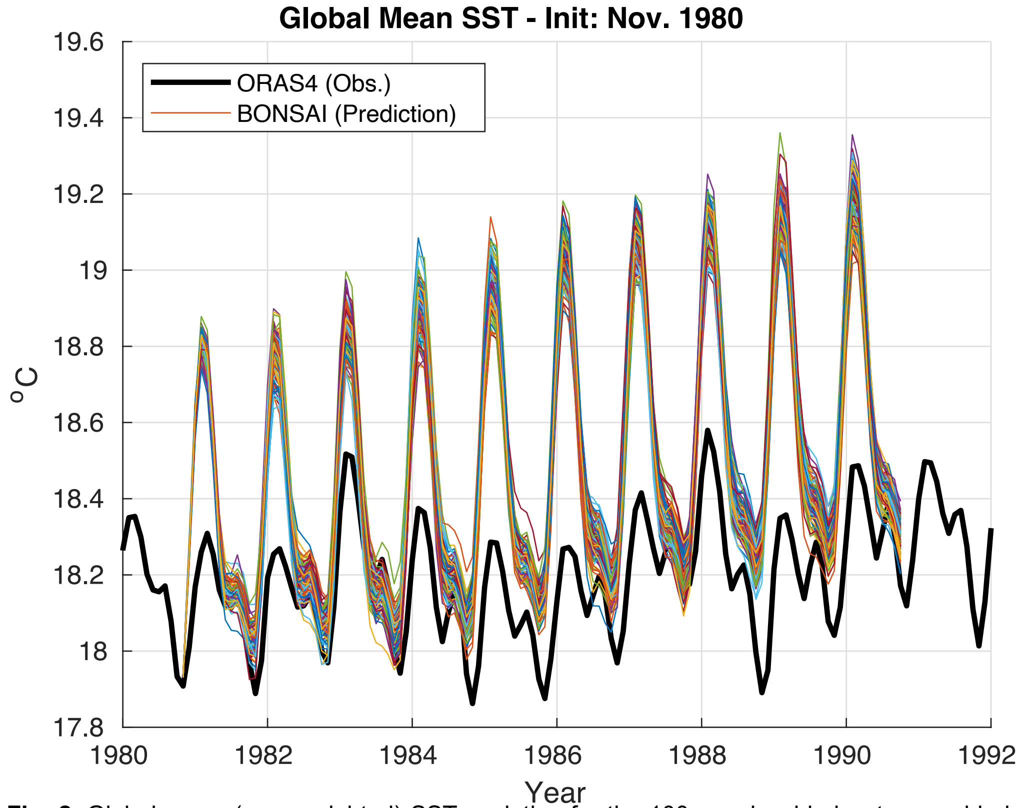

Fig. 2. Global mean (area-weighted) SST evolution for the 100-member hindcast ensemble initialized on November 1980 (color curves). The corresponding time series from ORAS4 reanalysis (member 1) is also shown (black solid curve).

4. Global skill evaluation

We now turn to the evaluation of the predictive skill of the BONSAI DPS. The analysis uses anomaly correlation coefficient (ACC) as the primary skill metric. ACC values are computed between simulated and observed sea surface temperatures for individual lead years as well as for aggregated lead-year intervals (2–5 and 6–10 years).

To account for the model's full-value initialization—which can lead to a long-term adjustment towards its own climatology—a drift correction is applied. This is done by subtracting the ensemble-mean forecast from each individual raw forecast, effectively removing spurious non-physical trends and enhancing the robustness of the skill assessment. The statistical significance of ACC values at the 95% confidence level is evaluated using a one-tailed Student's t-test. The Extended Reconstructed Sea Surface Temperature version 5 (ERSSTv5; Huang et al., 2020) dataset is used for verification.

The deterministic forecast skill of ensemble-mean SSTs, computed over the full set of start dates (1980–2007), is presented in Figure 3. The ACC patterns for individual lead years reveal a spatially heterogeneous picture, with regions of statistically significant skill interspersed with areas of weak or negligible skill. As expected, lead year 1 displays widespread significant ACC values across much of the global ocean, reflecting the strong positive impact of initialization on the near-term horizon.

Skill persists over the Atlantic sector in subsequent lead years, particularly over the Subpolar Gyre (see Section 5), while in the Pacific, ACC values decline markedly after lead year 1, with low skill persisting through lead year 5.

Interestingly, the evolution of skill over time lacks a clear monotonic trend. Several ocean sub-basins exhibit peaks in ACC at specific lead years, suggesting complex region- and time-dependent predictability. Notably, the Indo-Pacific region shows a resurgence of skill by lead year 10, with a pattern resembling the canonical ENSO structure.

A more stable and interpretable evaluation is obtained by aggregating ACC values across lead years 2–5 and 6–10. The resulting spatial patterns reveal a distinct asymmetry between the Atlantic and Pacific sectors: the Atlantic demonstrates higher skill in the near term (2–5 years), whereas the Pacific shows comparatively greater skill at longer lead times (6–10 years).

In summary, BONSAI DPS demonstrates substantial skill in the Subpolar Gyre, consistent with findings from other state-of-the-art decadal prediction systems. This encouraging result is explored in greater detail in the following section.

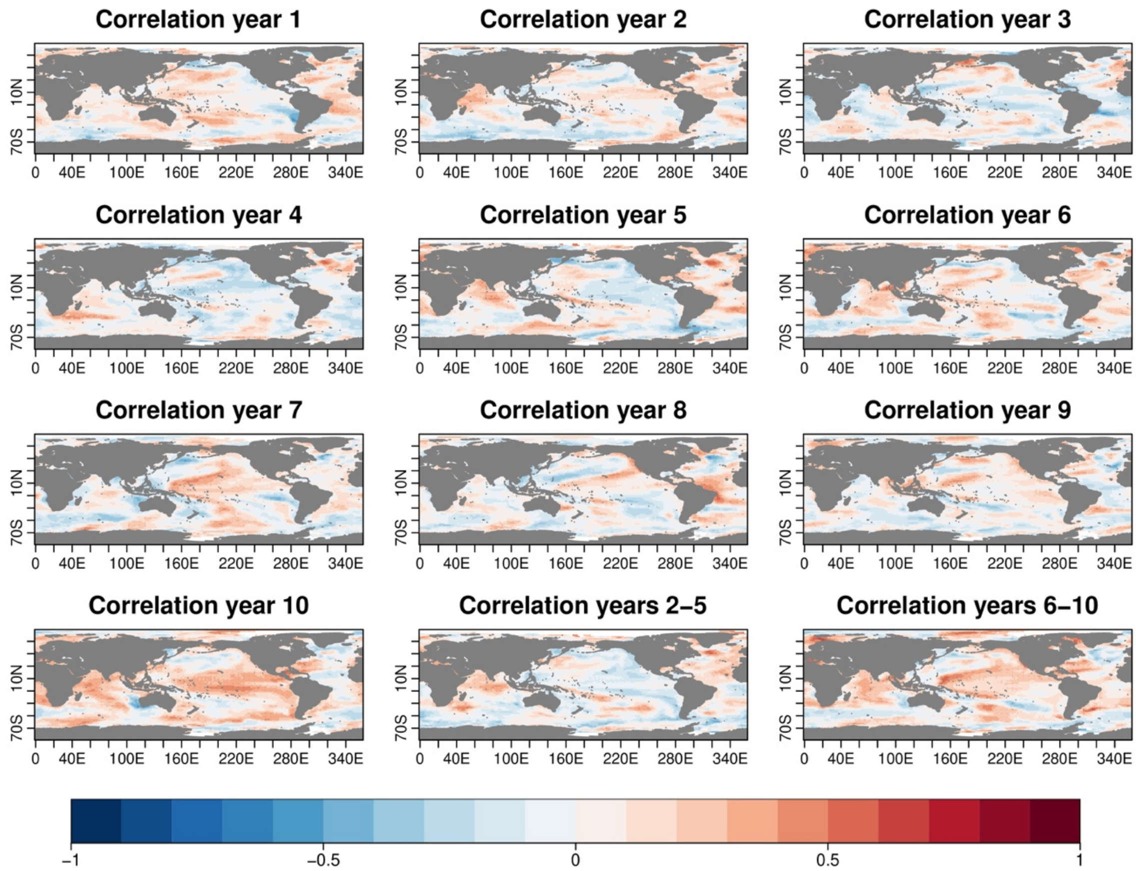

Fig. 3. Global patterns of anomaly correlation coefficient between predicted and observed SST for different lead-years as well as for lead-year intervals 2-5 and 6-10 (bottom row, mid and right panels, respectively).

5. Regional skill assessment: the North Atlantic Subpolar Gyre case

The North Atlantic Subpolar Gyre (SPG) is an area where initialized decadal hindcasts performed with state-of-the-art climate models generally reveal substantial predictive skill (Yeager et al., 2012; Msadek et al., 2014; Robson et al., 2018). This makes it a particularly suitable study area to test the predictive ability of BONSAI.

In this section, the system's skill in predicting the SPG SST evolution is evaluated, against the ORAS4 reanalysis as a verification data set. For this purpose, a simple index (hereafter SPGI) is defined as the basin mean SST computed over the [60°-10°W, 50°-60°N] longitude-latitude box, a broad area in the northern North Atlantic representative of the SPG region.

Figure 4 shows raw, annual mean SPGI values from a sub-set of the initialized hindcast ensembles (shown with alternating colors to facilitate readability; for each start date, the ensemble mean forecast is also shown, in white) and the corresponding evolution of the observational counterpart (in black). Note that all ensemble members display a transient response after the initialization, characterized by a rapid temperature increase, reaching a peak around lead-years 3-4, followed by a more gradual decline. This transient behavior is common to all starting dates and reflects the well-known spurious model adjustment triggered by the full-value initialization procedure, also referred to as "coupling shock" (Balmaseda et al., 2009).

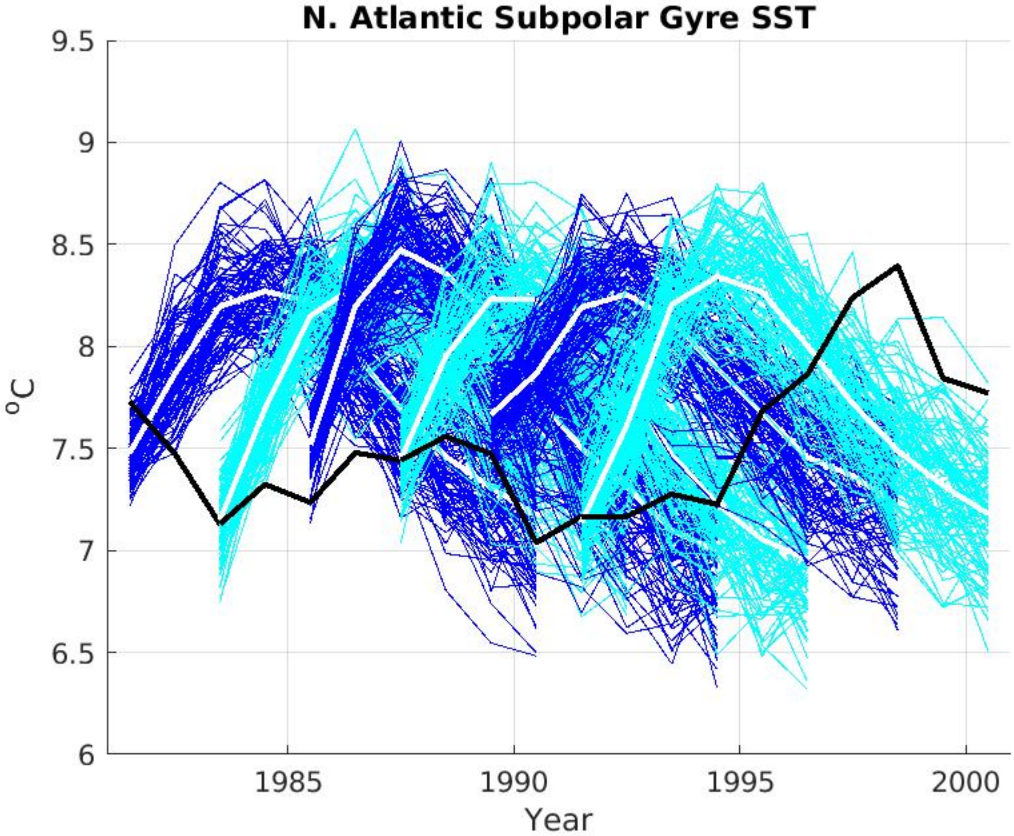

Fig. 4. Annual mean SST (°C) in the SPG box, for the raw 100-member decadal prediction ensembles (blue and cyan curves; alternating colors for clarity; ensemble mean in white) and ORAS4 reanalysis (thick black curve). Note that only a sub-selection of the full set of performed hindcasts is shown.

To remove this spurious signal, a mean drift is calculated by averaging over the full set of decadal hindcasts, and subtracted from each ensemble member to obtain calibrated SPGI anomalies. The mean drift provides a lead-year dependent climatology representative of the 1980-2000 period. The corresponding 1980-2000 climatology is subtracted from ORAS4 values to obtain consistent observed anomalies. The simulated and observed SPGI anomalies are then shown in Figure 5, for the full set of decadal hindcasts. For each starting date, the ensemble member anomalies are shown (in red) together with the ensemble mean (in white) and ORAS4 reanalysis (in black). After de-drifting, the magnitudes of predicted SPGI anomalies show a reasonable consistency with observations, with the latter mostly lying within the range of simulated values. The ensemble mean forecasts show smaller amplitude variability compared to reanalysis, with the observed extreme values occurred in the mid-to-late-90s only marginally captured by the initialized hindcasts. However, for a few start-dates, the ensemble mean fluctuations appear to be in phase with the observed signal (notably, 1985, and 1988-to-1990).

Next, the skill associated with individual ensemble members is assessed, by looking at the frequency distribution of correlation values between single member realizations and the observed trajectory. In Figure 6, the correlation frequency histograms corresponding to different ensemble forecasts are shown. These reveal variously shaped distributions, suggesting that the predictability over the study area is subject to a certain degree of non-stationarity. In this respect, the level of symmetry characterizing a given distribution is a particularly insightful parameter: start-dates (or, equivalently, climate states) featuring a high symmetry in the correlation value distribution, show an equal likelihood associated with the occurrence of “good” (positive, significant correlations) and “bad” predictions (negative correlations). Large deviations from symmetry, on the other hand, are indicative of climate states proving to be either particularly predictable (positively skewed distribution) or unpredictable (negatively skewed distribution).

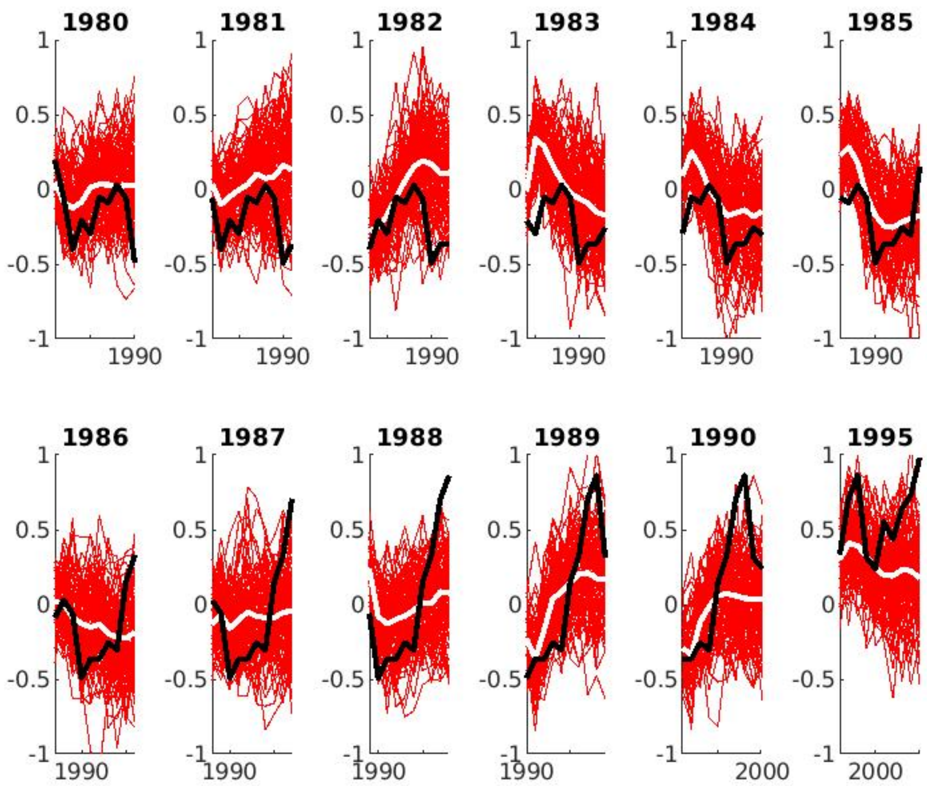

Fig. 5. Annual mean SST anomalies (°C) in the SPG box, for the drift-corrected decadal predictions (in red; ensemble mean in white) and ORAS4 reanalysis (thick black curve). The ORAS4 anomalies are computed relative to climatology over the reference period 1980–2000.

By scrutinizing the different start-dates in Fig. 6, it is evident the alternation between approximately symmetric and highly asymmetric (and positively skewed) distributions, while no occurrence of negatively skewed distribution is found. For example, correlations corresponding to start-dates 1980, 1981, 1982 and 1987 display a highly symmetric distribution, while start-dates 1983, 1985 and 1989 feature prominent modal peaks centered over correlation values exceeding 0.6-0.7, and relatively little or almost no occurrence of negative correlations. This result highlights the existence of “windows of opportunity” in decadal-scale climate predictability (Mariotti et al., 2020). According to this paradigm, there are specific epochs, and relative climate states, characterized by a higher degree of predictability, with a consistently larger occurrence of successful forecasts. In this specific SPG-based case study, early-80s appear to be a less predictable period, compared to late-80s/early-90s. It is worth noticing how this feature of the climate system can only be robustly assessed using BONSAI-like experimental settings, allowing to perform 100s-member ensembles of initialized reforecasts with the same climate model.

Based on the correlation distributions shown in Figure 6, it is possible to rank the individual ensemble members, and select the forecast sub-ensembles featuring the highest skill. In Figure 7, the mean forecast computed over the upper three, best ranking ensemble members are shown for each start-date. In line with what previously suggested, the largest discrepancies between predicted and observed SSTs occur during the early 80s, while there is a clear skill improvement emerging in the late 80s/early 90s, with most of the selected forecasts capturing years in advance the onset of the mid-90s rapid warming.
The analysis of SST prediction over the SPG in BONSAI DPS — which has a considerably lower resolution and degree of complexity than any model currently used in operational decadal predictions (Hermanson et al. 2022) — suggests that SST variability in the North Atlantic Ocean can be predicted years in advance provided that the ocean component is accurately represented and initialized, with a relatively marginal role for other components of the climate system.

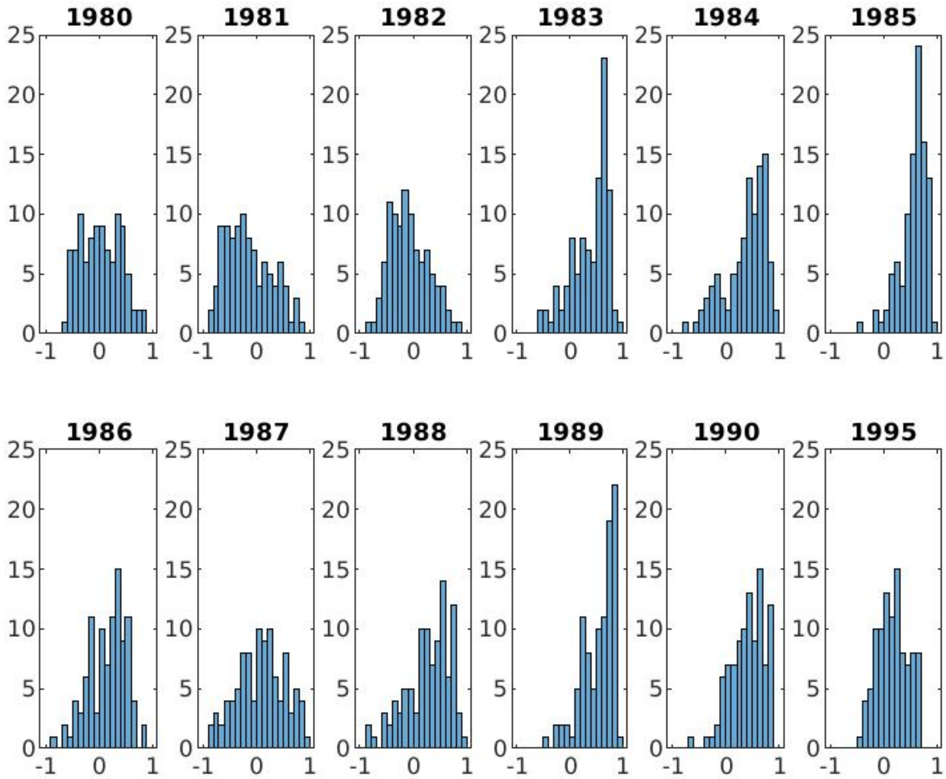

Fig. 6. Frequency distributions of Pearson correlation values between predicted and observed SST anomalies over the SPG box, for different start-dates. Correlation values in each histogram are binned into 0.1-wide intervals.

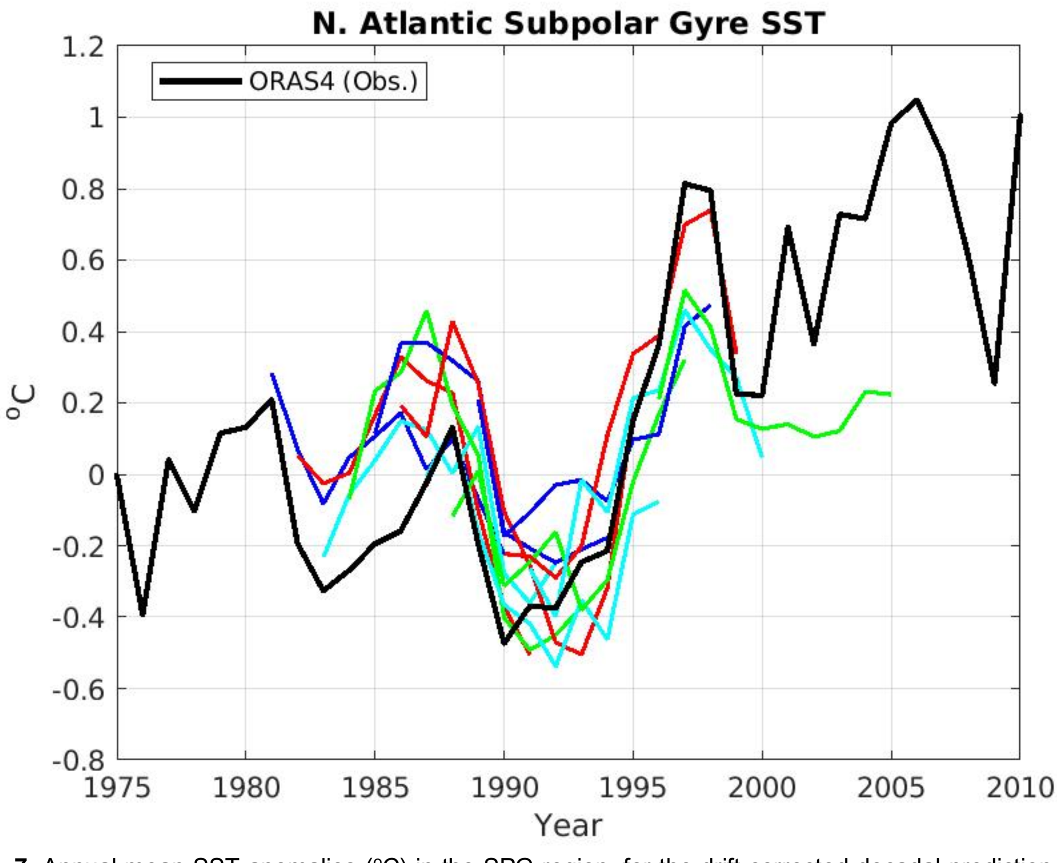

Fig. 7. Annual mean SST anomalies (°C) in the SPG region, for the drift-corrected decadal prediction (mean forecast over the upper-three best scoring ensemble members; alternating colors for clarity) and ORAS4 reanalysis (thick black curve). The ORAS4 anomalies are computed relative to climatology over the reference period 1980–2000.

6. Heat extremes in the Mediterranean.

The hindcasts produced in BONSAI were exploited in a study aiming at characterizing heat extremes over the Mediterranean region (Mele and Ruggieri, manuscript in preparation). The purpose of this study was to test the applicability of climate predictions to simulate plausible extreme events. As part of this effort the BONSAI hindcasts were used to compare temperature extremes in the Emilia-Romagna region in Italy (blue box in Fig. 8) simulated by the model with reanalysis data. Figure 8 provides an insight into the ability of the model to simulate the large-scale and synoptic conditions that led to observed extreme heat events in the target region encompassed by the blue box. The events on the right side of Figure 8 are identified as the most extreme cases in the ERA5 reanalysis (Hershbach et al., 2020), while those on the left side are chosen by defining extreme events in the hindcast (with a consistent definition) and by selecting those with a maximum correlation with the observed one in the Z500 field. This preliminary result reveals the ability of the model and the hindcasts to simulate realistic extreme events.

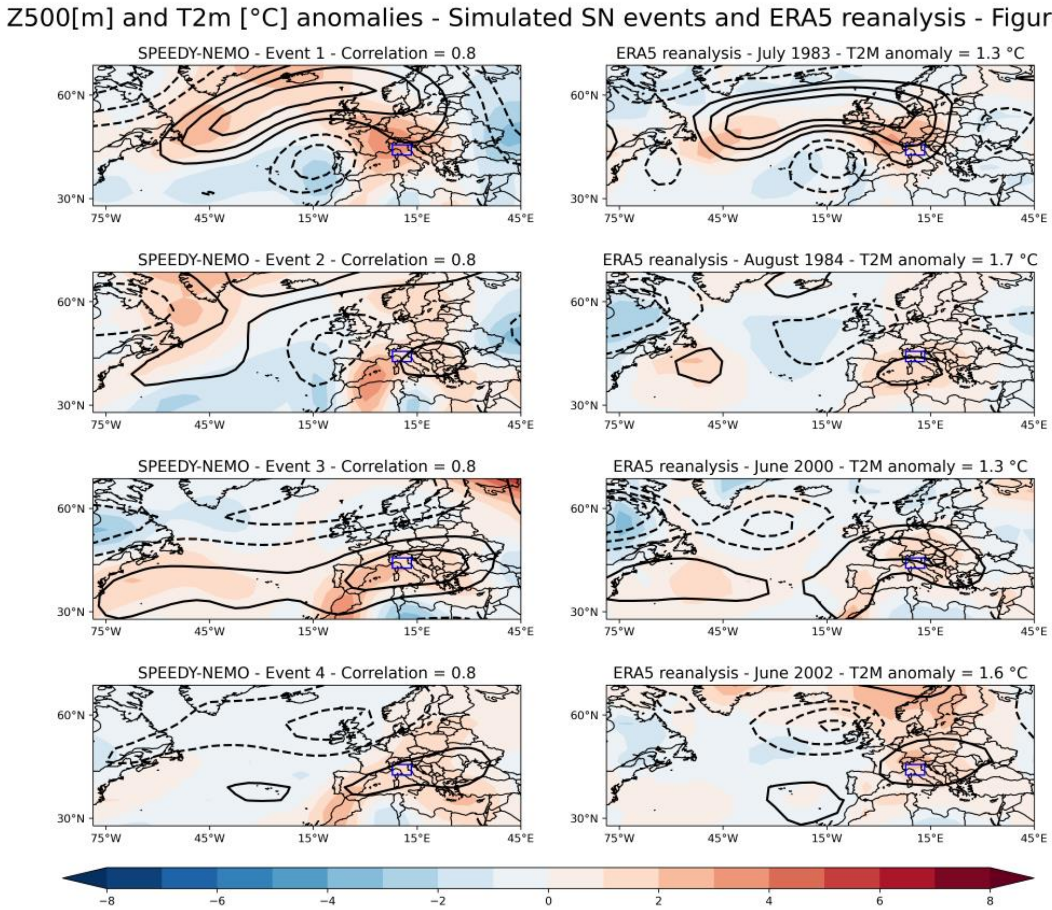

Figure 8. Contours of Z500 anomalies [m] and colormap of T2m anomalies [°C] in the clustering region: comparison between ERA5 reanalysis most severe events and SPEEDY-NEMO events with the highest Z500 anomaly correlation evaluated in this area. The 0 level Z500 anomaly contour has been omitted and the blue box shows the target region. Adapted from Mele and Ruggieri (in preparation).

7. Summary

With BONSAI, we developed a prototype for a low-complexity climate prediction system, specifically designed to leverage the potential of very-large ensemble forecasts—comprising hundreds of members, an order of magnitude larger than those used in typical current decadal prediction systems (DPS). This approach prioritizes ensemble size over model realism, relying on a simplified atmospheric component to reduce computational complexity.

Despite the limitations associated with this simplification—particularly in the atmospheric physics—the system demonstrated significant predictive skill, notably over the northern North Atlantic. This skill is comparable to that of more complex, state-of-the-art DPS, highlighting the importance of a well-represented ocean–sea ice component, combined with effective initialization and perturbation strategies, in compensating for simplifications elsewhere in the system.

To the best of our knowledge, BONSAI represents a unique approach within the current landscape of DPS. The resulting dataset, encompassing 28,000 simulated years, will serve as a valuable resource for future investigations into climate system predictability.

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Ruggieri, P., Abid, M.A., García-Serrano, J. et al. SPEEDY-NEMO: performance and applications of a fully-coupled intermediate-complexity climate model. Clim Dyn 62, 3763–3781 (2024). https://doi.org/10.1007/s00382-023-07097-8

Yeager, S., A. Karspeck, G. Danabasoglu, J. Tribbia, and H. Teng (2012) A Decadal Prediction Case Study: Late Twentieth-Century North Atlantic Ocean Heat Content. J. Climate, 25, 5173–5189. https://doi.org/10.1175/JCLI-D-11-00595.1.

List of publications/reports from the project with complete references

Ruggieri, P., Abid, M.A., García-Serrano, J. et al. SPEEDY-NEMO: performance and applications of a fully-coupled intermediate-complexity climate model. Clim Dyn 62, 3763–3781 (2024). https://doi.org/10.1007/s00382-023-07097-8

Bellucci, A., et al.: BONSAI: a low-complexity climate prediction system for very large ensembles of decadal forecasts, in preparation.

Mele L. and Ruggieri P., Advances in understanding extreme meteorological events: a review of the UNSEEN methodology and its applications, in preparation.

Future plans

(Please let us know of any imminent plans regarding a continuation of this research activity, in particular if they are linked to another/new Special Project.)

Currently, there is no follow-up Special Project linked to BONSAI. Next steps will be to further exploit the large data set created in BONSAI and to finalize the publications documenting the BONSAI Decadal Prediction System.