SPECIAL PROJECT PROGRESS REPORT

All the following mandatory information needs to be provided. The length should *reflect the complexity and duration* of the project.

Reporting year	July 2022-June 2023
Project Title:	BONSAI (Boosting eNsemble Size for Advanced Insights into climate predictability)
Computer Project Account:	SPITBEAL
Principal Investigator(s):	Alessio Bellucci
Affiliation:	Consiglio Nazionale delle Ricerche, Istituto di Scienze dell'Atmosfera e del Clima (CNR-ISAC)
Name of ECMWF scientist(s) collaborating to the project (if applicable)	………………………………………………………………… …………………………………………………………………
Start date of the project:	15/02/2022
Expected end date:	31/12/2024

Computer resources allocated/used for the current year and the previous one
(if applicable)
Please answer for all project resources

		Previous year		Current year	
		Allocated	Used	Allocated	Used
High Performance Computing Facility	(SBU)	4 Millions	0	8 Millions	815068
Data storage capacity	(Gbytes)	16000	0	48000	274

Summary of project objectives (10 lines max)

Special Project BONSAI aims to push the boundaries of large climate prediction ensembles by developing a prototype decadal prediction system based on a simplified dynamical model. By reducing the complexity of the model, including while preserving the essential elements necessary to replicate the fundamental characteristics of the observed climate and its variability, we can significantly increase the size of the forecast ensembles. This advancement allows for an order of magnitude expansion, enabling us to transition from the current standard resolution/complexity decadal prediction's ensemble size of around 10 members to hundreds of members. This yields several benefits. Firstly, it enhances the sampling of uncertainty related to initial conditions, resulting in more reliable predictions. Secondly, it enables more effective suppression of unpredictable noise, thus improving the signal-to-noise ratio and enhancing forecast skill. Ultimately, this enhancement contributes to a better understanding of the predictable aspects of the climate system and improves our ability to make accurate long-term climate projections.

Summary of problems encountered (10 lines max)

The implemented procedures to create the restart files for the model initialization (regridding of ocean and sea-ice reanalyses 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, delivering a first set of 100-member ensembles for 4 different start-dates (in all, 400 10-year hindcasts; 4000 simulated years). This is reflected in the overall underuse of the allocated HPC resources.

Summary of plans for the continuation of the project (10 lines max)

Having finalized the set-up of the BONSAI decadal prediction system (DPS), the next stage of the project will focus on the production and analysis of decadal predictions for the entire set of planned start-dates. The unprecedented large number of ensemble members will require the design of diagnostic tools allowing an efficient handling of the large volumes of data. A thorough assessment of the DPS will be provided, with metrics and diagnostics outlining the skill of BONSAI in reproducing the observed past, and inspecting the added value associated with the use of very large forecast ensembles.

List of publications/reports from the project with complete references

Summary of results

1. Introduction

In the present document, we report on the advancements made during the second year of activities for the SP BONSAI. 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 release (and preliminary analysis) of 100-member ensembles of initialized decadal hindcasts, conducted for a selected set of start-dates.

2. The BONSAI Decadal Prediction System

The 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). A paper documenting the formulation, climatology and variability of SPEEDY-NEMO, authored by some of the BONSAI SP partners, has been recently submitted for publication on Climate Dynamics (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 climatological conditions were used for the atmosphere.
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 reanalyses 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. Following the original plan, we exploited the 5-member ensemble of ORAS4 ocean reanalyses to sample uncertainties in the initial oceanic conditions. For each of these five alternative oceanic states, a 100-member sub-set is then 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.

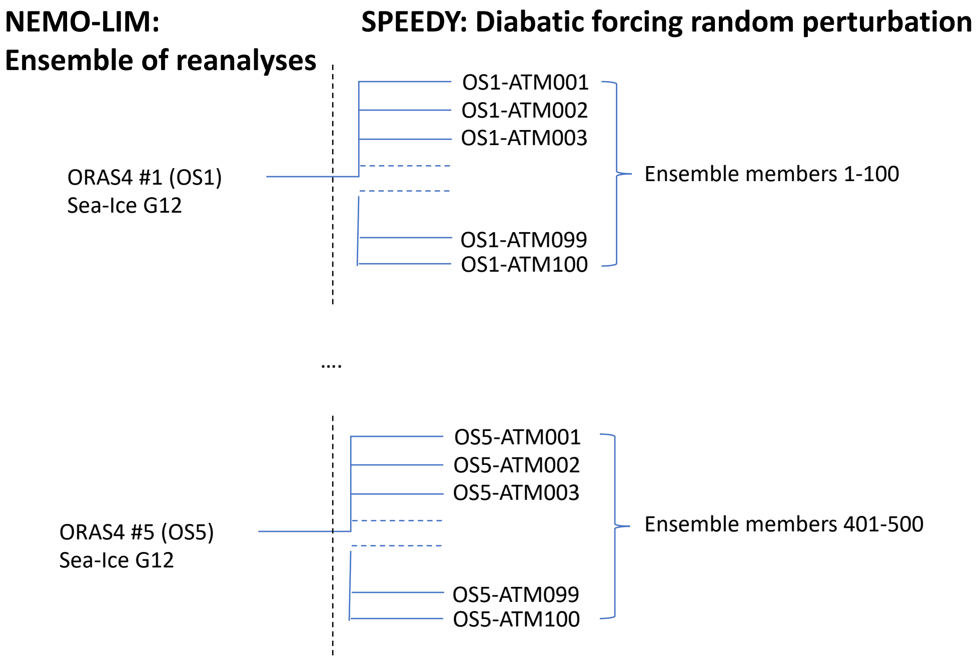

Fig. 1. Ensemble generation scheme used in BONSAI. The criterion followed to generate (potentially) 500 members for a generic start-date is illustrated. Note that for each ORAS4 ensemble member (5 in all), 100 members are generated by perturbing the initial state of the atmosphere, using a stochastic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

3. Decadal hindcasts

During this reporting period, 100-member ensemble simulations were conducted for a selection of start-dates, including years 1980, 1985, 1990 and 1995. A primary objective of this stream of simulations was to provide a first test-bed for the implemented strategies concerning 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.

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 (the same used to initialize the ensemble) as a 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. The origins of this bias need to be further inspected, although it must be considered that no flux corrections have been used in this configuration of SPEEDY-NEMO, an uncommon set-up for intermediate complexity models (Ruggieri et al., 2023; Kroger and Kucharski, 2010). Also visible 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.

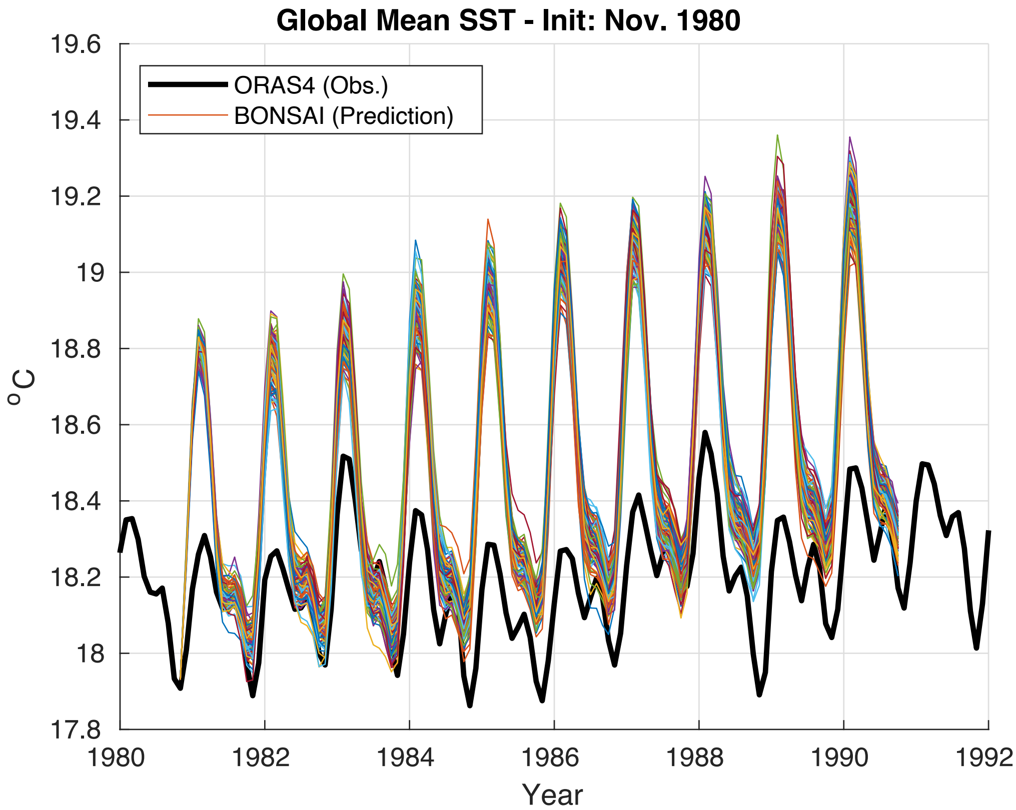

Fig. 2. Global mean (area-weighted) SST evolution for the 100-member hindcast ensemble initialized on November 1980 (color curves). The corresponding time series from ORAS4 reanalysis (member 1) is also shown (black solid curve).

In order to better characterize the ensemble spread, annual mean GMSSTs are shown for the four start dates completed so far (Fig. 3), together with the ORAS4 GMSST estimate (in black). The interannual evolution of decadal hindcasts highlights a strong spurious drift affecting all ensemble members, regardless of the specific start-date. This is an expected feature in initialized predictions relying on the FV methodology, as in this case. The origin of this drift can be traced back to the model adjusting towards its own climatology, following the initialization with an observed state which is far from the model's attractor (Bellucci et al., 2015). In this specific case, the model is clearly drfting away from the observed initial conditions towards a warmer (model) climate. By assuming stationarity in the model drift, the spurious adjustment is removed *a posteriori* by computing the mean drift over the whole set of hindcasts, and subtracting the obtained mean drift estimate from each individual hindcasts (ICPO, 2011).

The residual anomalies after drift removal are shown in Fig. 4 for every member in each individual start date. Note that, for consistency, ORAS4 time series have also been detrended, following an analogous procedure.

An emerging result is that the methodology for the ensemble generation succeeds in creating an adequate ensemble spread, despite the initial perturbations are only applied to the atmospheric component, while keeping the ocean-sea ice initial state identical in all members. The envelope of the ensemble predictions mostly encompasses the observed anomalies. Two notable exceptions are the large GMSST drop in the early 90s, associated with the global cooling following the Pinatubo eruption occurred in 1991, and the late 90s warm peak associated with the 1997/1998 ENSO event. The corresponding GMSST anomalies exceed the range of predicted anomalies (see in particular start-dates 1990 for the Pinatubo event and 1995 for ENSO, bottom-left and bottom-right panels in Fig 4, respectively). This Is not surprising since the forcing fields used in SPEED-NEMO do not account for the signature of the volcanic eruptions (consistent with a "no cheating" approach, since volcanic events are not predictable), while ENSO events are inherently unpredictable several years in advance.

For one of the start-dates (1985) we sampled the probabilistic dimension of BONSAI DPS, by identifying those ensemble members featuring a significantly high correlation (r>0.6) with the observations, for the specific 10-year window covered by the initialized ensemble. The identified members are highlighted in Fig. 4 (upper-right panel), showing the striking ability of some individual hindcasts in reproducing the internal multiannual variability in the observed GMSST. This simple test exemplifies the potential advantages of performing very large ensembles of decadal hindcasts, even under low-complexity model configurations.

Future efforts will be dedicated to extend and refine this kind of analysis, focusing on regional diagnostics, for a wider range of state variables and indices (including AMOC, precipitation, SLP, AMV/PDV), and specific temporal windows. This will possibly allow the identification of ensemble members subsets that maximize the predictive skill of BONSAI DPS, leveraging on the unprecedented large size of the ensembles.

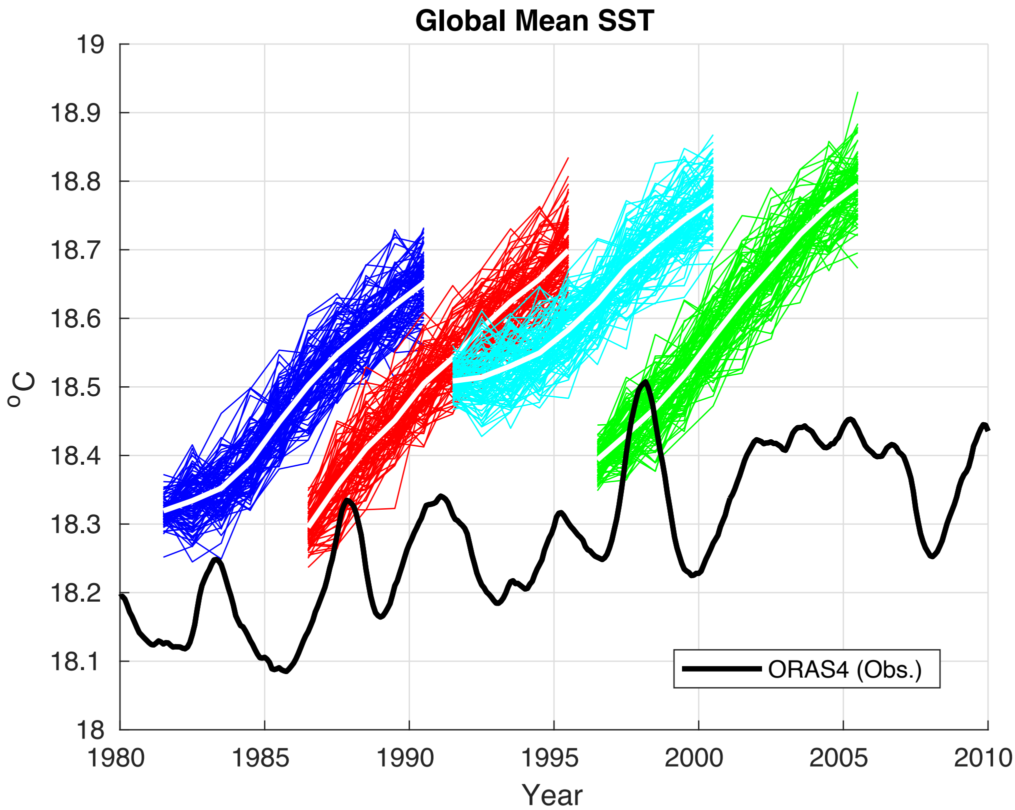

Fig. 3. Annual GMSST for start-dates 1980, 1985, 1990 and 1995 (color). For each start date, the corresponding ensemble mean is also shown (in white). ORAS4 observational estimate is shown in black.

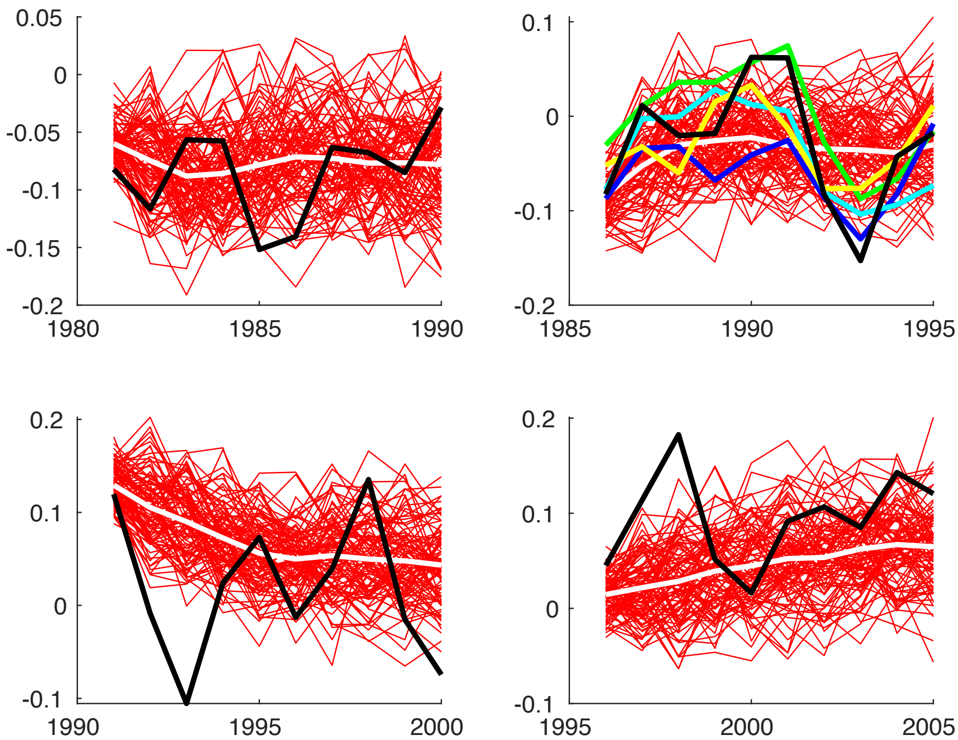

Fig. 4. GMSST anomalies after model de-drifting (red) for start-dates 1980 (top-left), 1985 (top-right), 1990 (bottom-left) and 1995 (bottom-right). The ensemble mean is indicated in white. Detrended anomalies from ORAS4 are shown in black. For start-date 1980 (top-right panel), individual ensemble members highlighted in yellow, cyan, green and blue identify members featuring a correlation with observations r>0.6.

4. References

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