<u>LATE</u> REQUEST FOR A SPECIAL PROJECT 2022–2024

MEMBER STATE: Italy

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Project Title: BONSAI

If this is a continuation of an existing project, please state the computer project account assigned previously.	**SP** __________________	
Starting year: (A project can have a duration of up to 3 years, agreed at the beginning of the project.)	2022	
Would you accept support for 1 year only, if necessary?	YES ☐	NO X

Computer resources required for the years: (To make changes to an existing project please submit an amended version of the original form.)		**2022**	**2023**	**2024**
High Performance Computing Facility	(SBU)	4 Millions	8 Millions	7 Millions
Accumulated data storage (total archive volume)[2]	(GB)	16000	48000	80000

Continue overleaf

[1] The Principal Investigator will act as contact person for this Special Project and, in particular, will be asked to register the project, provide an annual progress report of the project's activities, etc.
[2] If e.g. you archive x GB in year one and y GB in year two and don't delete anything you need to request x + y GB for the second project year.

Principal Investigator: Alessio Bellucci

Project Title: BONSAI (**BO**osting e**N**semble **S**ize for **A**dvanced **I**nsights into climate predictability)

Extended abstract

The completed form should be submitted/uploaded at https://www.ecmwf.int/en/research/special-projects/special-project-application/special-project-request-submission.

All Special Project requests should provide an abstract/project description including a scientific plan, a justification of the computer resources requested and the technical characteristics of the code to be used.

Requests asking for 1,000,000 SBUs or more should be more detailed (3-5 pages).

Following submission by the relevant Member State the Special Project requests the evaluation will be based on the following criteria: Relevance to ECMWF's objectives, scientific and technical quality,and justification of the resources requested. Previous Special Project reports and the use of ECMWF software and data infrastructure will also be considered in the evaluation process.

All accepted project requests will be published on the ECMWF website.

1. Project overview and objectives

Predicting climate fluctuations from one decade to the next is a major challenge in climate sciences and at the same time responds to the needs of many planners who are interested in reliable climate information over the near-term temporal horizon. This demand fostered pioneering efforts aimed at exploiting the predictive ability of global climate models beyond the seasonal range (Smith et al., 2007; Keenlyside et al., 2008; Pohlmann et al., 2009). Decadal predictions (DP) are now a well-established and consolidated activity, carried forward by several groups worldwide, and officially endorsed and supported by the World Meteorological Organization through the Lead Centre for Annual to Decadal Climate Prediction (Kushnir et al., 2019).

The theoretical foundations of decadal predictions rely on the multi-annual scale predictability inherent to the slowly evolving components in the climate system. These include primarily the oceans, through the slow evolution of the large-scale current systems and heat content, but other nonoceanic components (including land surface, sea-ice and stratosphere) may also contribute to climate predictability beyond the seasonal range (see Bellucci et al., 2015b for a review). In addition to these internal variability drivers, predictability also stems from externally-induced variability dictated by changes in the radiative forcing of anthropogenic (green-house gases, aerosols, ozone) and natural (volcanoes, solar variability) agents. In standard century-scale climate change projections (for a long time the only available product used to inform decision makers on future climate-related risks) time-varying external forcings are the only source of predictability. Compared to climate projections, decadal predictions have the ambition of supplying additional skill by synchronizing simulated and observed climate fluctuations through the initialization of a dynamical model using the best available observational estimate of the climate system (Meehl et al., 2009). Through model initialization, the projected state draws skill not only from the boundary-value predictability associated with changes in the external forcing, but also from the initial-value predictability inherent to the processes driving the internal variability of the climate system.

After around 15 years of activity, a considerable amount of evidence has been found showing the potential benefits of DP as a reliable source of climate information over the decadal temporal horizon (Smith et al., 2020). At the same time, there has been a growing awareness that the predictable fraction of simulated signals is relatively low in climate models, and skilful predictions can only be achieved provided that a sufficiently large number of forecast realizations are conducted, in order to efficiently suppress the unpredictable noise (arising from model imperfections and uncertainty in the initial conditions) through ensemble averaging (Scaife and Smith, 2018; Smith et al., 2019). The need for very large ensembles, however, clashes with the heavy computational burden of running multiple retrospective forecasts with an adequate sampling of the most recent past, for verification and anomaly calibration purposes. For this reason, with a few exceptions, groups performing DP usually run O(10)-member ensembles. This is also done in compliance with the CMIP6 DCPP-A protocol (Boer et al., 2016), recommending 10-member ensembles of 5-year hindcasts with yearly start-dates covering the 1960-present period, totalling ~3000 years in all. While this is considered the absolute minimum set for DP, running 3000 years simulations is still, for many groups, a difficult goal to achieve even with a standard (1^{o}) resolution model configuration.

A possible, still unexplored, strategy to reconcile the need for large-sized forecast ensembles using a reasonable amount of computational resources is to trade the number of ensemble members with the resolution and/or level of complexity of the forecast model. Reducing the resolution/complexity of the model determines a consistent reduction in the computational resources requested for running a standard set of DCPP-like decadal hindcasts, disclosing the possibility of drastically increasing the number of ensemble members. Reasons for giving priority to ensemble size instead of model resolution reside in the relatively large scale characterizing the processes that are expected to be predictable over the targeted time horizon. For instance, predicting low-frequency changes in the strength of the AMOC, in turn modulating basin-wide SST and atmospheric circulation patterns, may not require highly-resolved model grids, since the role of smaller scales on the decadal predictability of these processes is yet to be established.

Within BONSAI we aim 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, will allow a one order of magnitude increase in the size of the forecast ensembles, compared to what is currently used in standard resolution/complexity decadal prediction. Moving from O(10) to O(100s) ensemble members will allow 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. Ensemble simulations will be performed using a coupled ocean-atmosphere global climate model based on a T30L8 configuration of the Simplified Parametrizations primitivE-Equation Dynamics (SPEEDY; Molteni et al., 2003) model for the atmosphere, coupled to a 2-degree configuration of the Nucleus for European Modelling of the Ocean (NEMO) ocean model (Madec et al., 2008) and using LIM2 (Fichefet, 2009) for sea-ice. In order to grant a fair comparison with previously released, standard resolution/ensemble size efforts, the experimental setup adopted in BONSAI will follow the protocol established for the Decadal Climate Prediction Project (DCPP) in the context of the 6^{th} Phase Coupled Model Intercomparison Project (CMIP6).

BONSAI will take advantage of the unprecedentedly large number of the ensemble members to assess the multi-annual predictability of the leading climate variability modes, for the first time in a single-model framework. Special emphasis will be given to those climate signals that suffer from a low signal-to-noise ratio, for which there are indications of potential skill improvements by substantially increasing the number of ensemble realizations. These will include (among others) typical mid-latitude atmospheric variability modes, such as the North Atlantic Oscillation/Arctic Oscillation (NAO/AO), or more ocean-grounded processes such as the Pacific Decadal Variability (PDV) in the extra-tropical North Pacific.

The predictability of specific decadal-scale transients/shifts occurred in the recent past will be investigated, such as the mid-90s warming in North Atlantic Subpolar Gyre (Yeager et al., 2012) or the early 2000s hiatus in the global warming trend and its connection with a phase change in the Inter-decadal Pacific Oscillation (Kosaka and Xie, 2013). These specific events will provide "windows of opportunity" to test the benefits of very large ensembles. For the start-dates nearby the inception of these specific events, the number of ensemble members will be further increased (up to ~1000) compared to the other start-dates. This tailored increase in the ensemble size will be a useful testbed to further advance our physical understanding of predictability aspects so far only hinted at by standard, O(10)-member, decadal prediction systems.

The envisaged step-change in the forecast ensemble dimension will also disclose the possibility of investigating so far unexplored aspects in DP concerning the role of initialization associated with individual components of the climate system. Alternative observational estimates for the ocean, land and cryosphere (see-ice cover) will be considered as a way to sample the uncertainty in the initial state of the climate system. Having O(100s) ensemble members will give the possibility of robustly estimating the impact of the initialization of specific components of the Earth system. Besides the skill of the ensemble mean, the predictive skill associated with specific sub-ensembles constituted by members featuring common characteristics (e.g., common ocean state estimate yielded by the use of a certain ocean reanalysis) will be also evaluated. Comparing the skill of different sub-ensembles (e.g., skill of "ocean A" vs "ocean B", etc.) will make it possible to establish the relative merits of specific observational datasets, using the forecast quality as an *a posteriori* evaluation metric. A comprehensive mapping of the roles of ocean, ice, and land initialization on the overall skill of the prediction system will be a major outcome of BONSAI.

2. Methodology

2.1 Experimental setup

BONSAI will broadly follow the experimental protocol designed for the initialized decadal hindcasts contributed to CMIP6 by the Decadal Climate Prediction Project (DCPP) and documented in Boer et al. (2016). The main features of the protocol are schematically recapped below:

- Coupled integrations initialized with observational estimates
- 10-year hindcasts initialized every year on the 1st November from 1980 to 2014 (i.e., 1981 is the first full hindcast year)
- 500-member ensembles, except for a few specific case studies corresponding to particularly relevant climate events/transients where up to 1000 ensemble members will be run (see "Windows of opportunity" section)
- Prescribed forcings based on CMIP6 historical values of atmospheric composition

A major discrepancy with DCPP protocol is that the former covers the longer 1960-present period, whereas in BONSAI only start dates for the 1980-present period will be considered. This choice is meant to exclude the (pre-satellite era) 1960-1980 interval, for which less reliable observational products are available.

2.2 Initialization and ensemble generation

In BONSAI a full-value (FV) initialization strategy will be adopted (Magnusson et al., 2012). In FV the model is initialized with an analysis representing the best available estimate of the "real world" (observed) state. After initialization, the model will drift from the approximately "true" state towards its (biased) climate, producing a spurious adjustment which will be removed through an a posteriori bias correction technique (ICPO, 2011).

ERA5 reanalysis will be used for initializing the atmosphere, while different members of ORAS5 and/or ORAS4 ocean reanalysis will be used for the ocean-sea ice system. Similarly, alternative land surface analyses will be considered for constraining the land component.

Large (500-member) ensembles will be generated for each start date, using different sources of information to initialize the forecast model. The primary mean to generate the large number of ensemble members will be via perturbations of the atmospheric state. The latter will be obtained using a built-in feature of the SPEEDY model, enabling the generation of stochastic perturbations applied to the initial conditions of different atmospheric state variables.

2.3 Additional simulations: Windows of Opportunity (WoP) and Historical simulations (HIST)

On top of the above described set, additional reforecasts will be run addressing specific climate shifts/transients occurred in the recent decades, and having a particularly high relevance for the global and regional climates. Two specific events will be selected, namely the mid-90s warming in the North Atlantic Subpolar Gyre (Yeager et al., 2012) and the so called global warming *hiatus* occurred in the first decade of the present century (Kosaka and Xie, 2013). For the start dates nearing the inception of these events, the original number of 500 members will be doubled. This local-in-time ensemble size increment is equivalent to the addition of two more start dates.

Finally, an ensemble of 500 uninitialized simulations for the historical period will be run for the 1980-2023 period under the same forcing conditions used in the initialized hindcasts. The ensemble will be generated perturbing the final state of a single 1870-1980 simulation, using the built-in stochastic perturbation device in the SPEEDY model. This set will be used to evaluate the added value of the initialization, comparing the predictive ability of BONSAI against the uninitialized HIST set, using standard deterministic and probabilistic metrics for skill evaluation (e.g., anomaly correlation coefficient, mean squared skill score, ROC score, etc.).

In terms of computational resources, the additional WoP and HIST runs are equivalent to 3 more 500-member start dates (see *Resources and Technical implementation* section). Thus, the total number of effective start dates will be 35 (the reforecasts for the 1980-2014 period), plus 3 more (counting WoP and HIST) totalling 38 in all.

3. Workflow

The full set of simulations performed within BONSAI (including both initialized predictions and un-initialized projections) is schematically divided in two streams, described below.

Stream 1: A sub-set of 100 members reforecast for the 1980-2023 period and a twin set of as many HIST simulations, to be completed by the end of Month 12.

Stream 2: Extend Stream 1 up to 500 members; complete WoP and remaining HIST simulations.

The work plan is schematically provided below:

- Month 1-6: Setup of the decadal prediction system on the Atos HPC, including the preparation of the initial conditions
- Month 7-12: Run Stream 1 simulations
- Month 13-36: Based on Stream 1 results, revise experimental setup if needed (e.g., initialization strategy, use of flux correction to mitigate possible strong model biases, etc.). Run Stream 2 experiments.

4. Resources and technical implementation

The project relies on an intermediate complexity model, 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). It is important to stress that, while the atmospheric component is based on a set of simplified physical parameterizations that considerably lower its degree of complexity, the ocean component has a more standard configuration in terms of spatial resolution and physical parametrizations and has been previously used in the context of CMIP5 near-term prediction activities (Bellucci et al., 2013; 2015). Given the prominence of ocean-based processes in decadal predictions, using a model with a standard (i.e., not overly simplified) ocean general circulation model will bring added value to BONSAI experiments.

Currently, SPEEDY-NEMO model is technically running on the HPC facility at the University of Bologna. Using this computational resource, with 18 cores SPEEDY-NEMO runs 1 model year in 0.29 hours (equivalent to ~82 simulated years per day) corresponding to 5.29 core hours. Considering a total amount of simulated years of (500 members)*(10 year)*(38 start dates) = 190000 years, the requested computational resources for running BONSAI is ~1 million core hours. Based on these estimates (and assuming equivalence with ECMWF Atos HPC), the requested computing resources for BONSAI are 19 million SBUs.

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