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| **Deliverable title** | **Derive observable ocean climate indicators from seasonal forecast** |
| **Description** | Derive the user-relevant indicators defined in Milestone MS7 from the ensemble of ECMWF and CMCC seasonal forecasts systems contributing to C3S |
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# Executive summary

A set of 43 area-averaged indicators of ocean variables for monitoring and forecasting was defined earlier in the project (Milestone 7). These indicators target five sectorial applications: i) seasonal forecasts of weather statistics (SF); ii) Climate Variability and Change (CVC); ii) Coastal Sea Level Rise (CSL); iv) Marine Health (MH) and v) Marine Productivity (MP).

The 43 EuroSea indicators have been derived from state-of-the-art datasets of Essential Ocean/Climate Variables (EOVs/ECVs). These are monthly sea surface temperature (SST) and sea level anomaly (SLA) from the Copernicus Climate Chance Service (C3S) and upper 300m ocean heat content (OHC) from Copernicus Marine Environmental Service (CMEMS) Global ocean Reanalysis Ensemble Products (GREP). The EOVs/ECVs indicators show potential for climate monitoring of changes in upwelling areas and regional sea level rise. Indicators such as these are also used to verify the skill of seasonal forecasts.

The ensemble of ECMWF and CMCC seasonal forecasts contributing C3S has been used to derive probabilistic forecasts of these indicators up to 6 months ahead. The seasonal forecast indicator dataset consists of 43 areas for SST, SSH and OHC. For each variable, there are 48 seasonal reforecasts, initialized over the period 1993-2016 (24 years), twice a year (May and November starts). For each initial date during this period there is a 25-member ensemble forecast of the following 6 months. The indicator dataset has been exchanged on an agreed data format in netcdf.

This report describes the indicator dataset, and provides some example illustrating the information content of seasonal forecasts. Preliminary results show that in most instances the seasonal forecasts of SST beat the persistence forecasts, and that uncertainty in OHC initial conditions in upwelling region limits the assessment of forecast skill. Results also highlight the importance of representing the decadal variability and trends in ocean heat content and sea level. More detailed analysis and interpretation of results will continue during the upcoming months, and they will be reported in due time via the scheduled deliverables.

# 1. Context within EuroSea: Quality assessment of ocean variables from C3S seasonal forecasts.

This deliverable is a contribution from Task 4.6, which deals with the quality assessment of ocean variables from the C3S seasonal. This task is part of EuroSea WP4 on Data integration, Assimilation, and Forecasting.

Knowledge of forecast skill is a prerequisite for utilizing forecast information. Assessing the skill of ocean variables from seasonal forecast has remained elusive due to the lack of verifying ocean datasets of sufficient quality and length. In this task we aim at observable essential ocean climate variables (EOVs/ECVs) to verify seasonal forecasts from two seasonal forecasts systems (CMCC and ECMWF) contributing to the C3S seasonal multi-model product. The EOVs/ECVs are Ocean Heat Content (OHC) from the CMEMS GREP ensemble of ocean reanalyses, the SLA ECV distributed by the Copernicus Climate Change Service (C3S), and the new SST records from ESA-CCI, also distributed by C3S. This task evaluates the spatial distribution of skill in these variables, with a particular focus on the skill for user-relevant indicators. The deliverable reported here deals with preparations of data and software for the demonstrators of seasonal forecast of user-relevant ocean indicators.

# 2. Data

## 2.1. Selection of Essential Ocean/Climate Variables

### ESA CCI Sea Surface Temperature

The ESA SST CCI (Climate Change Initiative) and [C3S global Sea Surface Temperature Reprocessed product] provide gap-free maps of daily average SST at 20 cm depth at 0.05deg. x 0.05deg. horizontal grid resolution, using satellite data from the (A)ATSRs, SLSTR and the AVHRR series of sensors (Merchant et al., 2019). The ESA SST CCI and C3S level 4 analyses were produced by running the Operational Sea Surface Temperature and Sea Ice Analysis (OSTIA) system (Good et al., 2020) to provide a high resolution (1/20deg. - approx. 5km grid resolution) daily analysis of the daily average sea surface temperature (SST) at 20 cm depth for the global ocean. Only (A)ATSR, SLSTR and AVHRR satellite data processed by the ESA SST CCI and C3S projects were used, giving a stable product. The record covers the period 1982-2019.

### Global ocean Reanalysis Ensemble Product (GREP)

GREP is an ensemble of four global 3D ocean reanalysis products: C-GLORS v7 (CMCC: Storto and Masina, 2016), FOAM (Met Office UK: Blockley et al., 2014), GLORYS2V4 (Mercator: Garric et al., 2017) and ORAS5 (ECMWF: Zuo et al., 2019). All products are built on version 3 of NEMO and are provided from 1993 to 2019 on the native ORCA025 tri-polar curvilinear grid. There are 75 depth levels, 34 of which are shallower than 300 m. All use the same fluxes (CORE) and atmospheric forcing (ERA-I) (with the subtle exception being ORAS5, which also includes wave effects). All products assimilate similar data streams, typically ARGO, XBT temperature profiles and AVISO Sea Level Anomaly. However, the products all have diverse assimilation schemes, observation quality control, model parameters, spin-up and surface constraints (Storto et al., 2019). The GREP covers the period 1993-2018.

Ocean reanalyses are the unique choice for the task of global heat content validation because the ocean variables have coverage in space and time that is not matched by observations (Riser et al., 2016). Besides, ocean reanalyses integrate the observational information with that of atmospheric reanalyses via a physical ocean model (Balmaseda et al., 2013). An ensemble of ocean reanalyses, such as GREP, is more powerful than a single standalone reanalysis; the ensemble product accounts for a range of uncertainties represented by the diverse inputs and methods used in each member. Storto et al. (2019) found the ensemble mean was a significant improvement on previous single-member versions of reanalyses, across a range of marine variables.

The correlation between individual GREP products and the ensemble mean[1] is a way of estimating the robustness of the interannual variability in the GREP (Figure 1). Over most parts of the ocean tropics there is strong degree of consistency among the members of the GREP, with correlation values exceeding .9. The correlation is lowest over western boundary currents, Atlantic upwelling areas, and Southern Ocean. Given

[1] The figure shows the average of the correlation of the individual ensembles with the ensemble mean.

the relatively large disagreement in the reanalyses in these regions, the forecast validation may be less reliable.

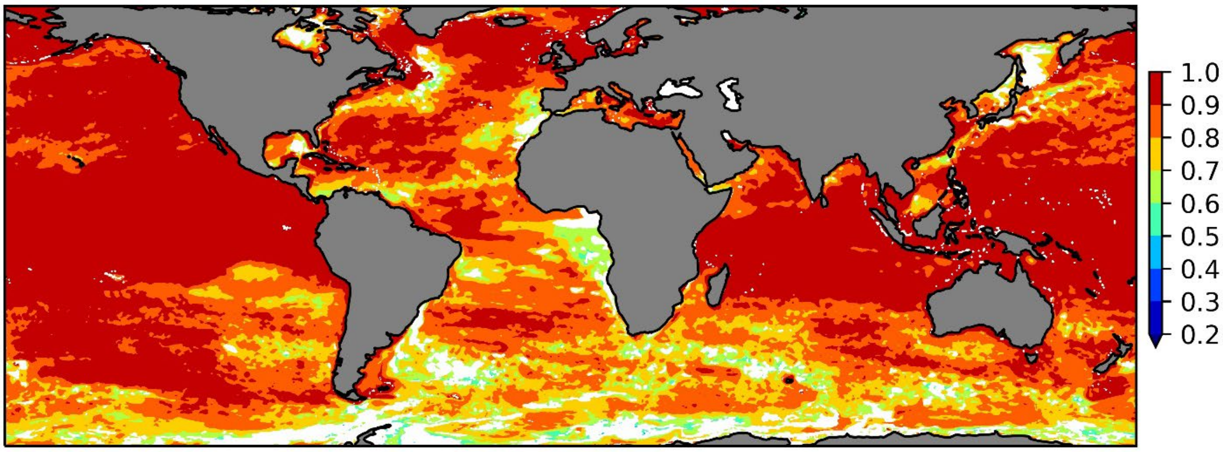


*Figure 1. GREP Temporal Correlation. Average correlation between the Ocean Heat Content 0-300 m of the GREP ensemble members and the GREP ensemble mean. Statistics are for the 1993-2016 period. From McAdam et al., 2021, submitted to Clim Dyn.*

From here on, the term "GREP" will refer to the reanalyses' ensemble mean. As our forecast systems are initialised with either ORAS5 or C-GLORS, the OHC0-300 m validation dataset is not truly independent. However, as for the ESA CCI SST, the spatial and temporal coverage is unparalleled and necessary for a comparison of long-term data.

### Sea Level Anomaly ESA-CCI

The sea level data set used here is based on the sea level Ocean Monitoring Indicators, produced by CMEMS, for which the C3S products are used as input data. These C3S products are derived from the DUACS delayed-time altimeter gridded maps of sea level anomalies based on a stable number of altimeters (two) in the satellite constellation. The altimeter satellite multi-mission gridded sea surface heights and derived variables are computed with respect to a twenty-year mean reference period (1993-2012). Up-to-date altimeter standards are used to estimate the sea level anomalies. Contrary to near-real-time sea-level products, the stability and accuracy of the delayed-time products make them adapted to climate applications and ocean monitoring indicators. Details on the altimeter and processing algorithms are available in Pujol et al. (2016) and Taburet et al. (2019). The record covers the period 1993-2019.

## 2.2. Ocean output from seasonal forecasts

The two forecast systems used here are the Seasonal Prediction System Version 3 from the Centro Euro-Mediterraneo sui Cambiamenti Climatici (CMCC-SPS3), and the fifth generation Seasonal Forecasting System from the European Centre for Medium-Range Weather Forecasts (ECMWF-SEAS5). Since 2018 both systems have been contributing to the Copernicus Climate Change Service (C3S), which makes seasonal forecasts of atmosphere and surface variables (precipitation, 2m-temperature) freely available online. These systems produce forecast of ocean variables other than SST, but these are not yet publicly available, since they have not yet been verified. This is the gap that the current EuroSea activity tries to fill.

The model components of each system are detailed in Table 1. Both systems base their ocean model component on the eddy-permitting version 3.4 of NEMO, which has a horizontal resolution of 25 km at the equator. The ocean model grid is tripolar, introducing grid cell anisotropy north of 20°N towards the artificial poles over Canada and Siberia. The vertical resolution in ECMWF-SEAS5 is higher than in CMCC-SPS3; in the upper 300 m, there are 35 and 29 vertical levels in ECMWF-SEAS5 and CMCC-SPS3 respectively.

*Table 1. Component, resolution and initialisation details for CMCC-SPS3 and ECMWF-SEAS5 coupled forecast system*

| | ECMWF-SEAS5 | CMCC-SPS3 |
|---|---|---|
| Ensemble | 51 | 40 |
| Coupler | Single-Executable | CPL7 |
| **Atmosphere** | | |
| Model | IFS | CAM |
| Horizontal Resolution | 36km | 1° |
| Vertical Resolution (top) | 91 levels (0.01 hPa) | 45 levels (0.3 hPa) |
| Initialisation | ERA-Interim | ERA-Interim |
| **Ocean** | | |
| Model | NEMO v.3.4 | NEMO v3.4 |
| Horizontal Resolution | 0.25° tripolar grid | 0.25° tripolar grid |
| Vertical Resolution | 75 levels | 50 levels |
| Initialisation | ORAS5 | C-GLORS |
| **Sea Ice** | LIM2 | CICE4 |
| **Waves** | 0.5° | N/A |
| **Land** | Embedded within IFS | CLM 4.5 1° |
| **Rivers** | N/A | River Transport Model (RTM) |

Both systems use versions of their respective ocean reanalysis to create initial conditions. In CMCC-SPS3, the initial conditions are based on C-GLORS (Storto and Masina, 2016), while in ECMWF-SEAS5 they are based on ECMWF ORAS5 (Zuo et al., 2019). Both reanalyses use identical horizontal resolutions (0.25°), while the number of vertical levels is 75 and 50 for ECMWF-SEAS5 and CMCC-SPS3 respectively. The model for sea-ice is also different (see Table 1). Both use atmospheric forcing from ERA-Interim until 2016, and ECMWF's NWP analysis thereafter. Both systems used a variant of the CORE bulk formulation, although ORAS5 also includes wave forcing. Both systems assimilate temperature and salinity profiles, and altimeter derived sea-level anomalies, but the assimilation methods and observational datasets also differ. C-GLORS uses the 3D-variational data assimilation scheme OceanVar (Dobricic and Pinardi, 2008; Storto and Masina, 2016), while

ORAS5 uses NEMOVAR. Thus, within the ocean component alone there are several factors which may contribute to differences in forecast output between the two systems.

The atmospheric model components have in common only the initial conditions (Table 1). The configuration of IFS in ECMWF-SEAS5 provides higher vertical and horizontal resolution than CAM in SPS3. CMCC-SPS3 uses the CPL7 coupler from the Community Earth System Model (CESM, Craig et al., 2012), while ECMWF-SEAS5 uses a single-executable (Mogensen et al., 2012). The coupling occurs every 90 minutes in CMCC-SPS3, every 60 minutes for ECMWF-SEAS5, with both capturing diurnal cycles. In both, ocean and sea-ice models are tightly coupled (i.e. they share a horizontal grid). Meanwhile, the atmosphere and wave models provide fluxes of heat, momentum, freshwater and turbulent kinetic energy to the ocean and sea ice components, while the ocean and sea-ice models provide SST, surface currents and sea-ice concentration in return.

Both ECMWF-SEAS5 and CMCC-SPS3 ensembles sample the uncertainty in the initial conditions of the land, ocean and atmosphere (Table 1). The size of the ensemble (50 for ECMWF-SEAS5 and 40 for CMCC-SPS3) ensures a high signal-to-noise ratio in the ensemble mean. In CMCC-SPS3, the ensemble is made by combining various perturbations in each initial condition set: 10 perturbations of the atmospheric component, 4 of the ocean component and 3 of the land-surface component. Then, 40 scenarios are picked from the possible 120. ECMWF-SEAS5 samples initial uncertainty in the ocean via the 5-member ensemble of ORAS5, and in the atmosphere via initial perturbations from the Ensemble of Data Assimilation (EDA) and singular vectors. It also applies stochastic physics perturbations to represent uncertainty arising from missing sub-scale processes. Further details of the ensemble generation are given in Johnson et al. (2019) and Sanna et al. (2017) for ECMWF-SEAS5 and CMCC-SPS3 respectively.

## 2.3. Indicators

The information content of seasonal forecasts is not always easy to communicate. The forecasting systems are complex, the numerical output needs calibration, and more importantly, the forecasts are of probabilistic nature. After several years of engagement with users, there are now an important number of applications based on atmospheric variables from seasonal forecasts, such as energy production, water management, agriculture and insurance. The time is ripe to reach out further afield and attempt to extract value of the seasonal forecasts for marine applications.

The use of indicators aims at making the output of seasonal forecasts more accessible to users, and to communicate ideas behind probabilistic forecasts in terms of skill and uncertainty. The approach followed here is relatively simple: To define a series of area-averaged indices, which can be easily verifiable targeting a reduced number of sectorial applications. The choice of sectorial applications was largely influenced by the legacy of previous EU projects MyOcean and MyOcean2, with updates on perceived needs for seasonal forecast information for marine applications. A joint workshop with EuroSea WP7, with representation of CMEMS and C3S, identified the following sectorial applications:

- Seasonal Forecasts of atmospheric variables. (**SF**)
- Climate Variability and Change: changes in circulation, heat absorption, sea level change. (**CVC**)
- Coastal Sea Level Change (**CSL**)
- Marine Health: large scale conditioner for Marine heat waves (**MH**)
- Marine Productivity: upwelling regions (**MP**)

The indicators have been grouped by basins (Atlantic, Pacific, Indian Ocean) and latitudinal bands. As an example, Table 2 below lists EuroSea indicators proposed for seasonal forecast verification over the Atlantic and Mediterranean basins. The table includes the short and long names of indicator, the short name being the label to find the coordinate in table A1 (Appendix). Some indicators are defined as linear combinations of individual boxes (e.g., the Atlantic Subpolar Gyre Index). The table also specifies the corresponding sectorial application and specific comments. The indicators for other basins and latitude bands are given in separate tables A2-5 in the appendix.

*Table 2. Definition of Seasonal Forecast Indicators for the Atlantic-Mediterranean basins.*

| Atlantic and Mediterranean Basin Indicators | | | |
|---|---|---|---|
| **Index Short Name** | **Index Long Name** | **Sectorial Application** | **Relevance** |
| CANARYC | Canary Current | MP, MH | Major upwelling region |
| BENGUELA | Benguela | MP, MH, SF, CVC | Major upwelling region |
| GMEX | Gulf of Mexico | MH, SF, CVC | Warm pool region relevant for tropical cyclones with vulnerable marine ecosystem. |
| CARIB | Caribbean | MH, SF, CVC | Warm pool region relevant for tropical cyclones with vulnerable marine ecosystem. |
| WMEDI | Western Mediterranean | MH, SF | Vulnerable marine ecosystems |
| EMEDI | Eastern Mediterranean | MH, SF | Vulnerable marine ecosystems. |
| MDR | Mean Development Region for Tropical Cyclones | SF | Mean area of Tropical Cyclogenesis. |
| NSEAS | Northern European Seas | CSL, SF, MH, MP | Relevant for marine ecosystems, sea level raise, fisheries and marine ecosystems. |
| ATLSPG | Atlantic Subpolar Gyre. Defined as difference between boxes: ATL60NA-ATL40N | SF, CVC | Proxy for AMOC and decadal variability. Possible application to heat heaves. |
| NATL | North Atlantic | SF, CVC | Monitor ocean heat content and sea level change in latitudinal bands. Influences atmospheric circulation. |
| NEATL | North East Atlantic | CVC, CSL, MH | SST relevance for heat waves affecting Europe. Climate indicator for circulation. Sea Level rise in Western Europe. |
| NWATL | North West Atlantic | SF, CVC | Affected by Gulf Stream. Climate indicator for |

| Atlantic and Mediterranean Basin Indicators | | | |
|---|---|---|---|
| | | | circulation. Influences atmospheric circulation. |
| TRATL | Tropical Atlantic | SF, CVC | Climate indicator of heat absorption and circulation. Influences atmospheric circulation. |
| NSTRATL | North Subtropical Atlantic | SF, CVC | Influence on hurricane season, atmospheric circulation, Atlantic ITCZ (Africa and Brazil climate). |
| SSTRATL | South Subtropical Atlantic | SF, CVC | Large influence on atmospheric circulation, Atlantic ITCZ (African Monsoon, Brazil). |
| DTRATL | Tropical Atlantic Dipole NSTRATL-SSTRATL | SF, CVC | Atlantic Meridional model climate indicator. Influences atmospheric circulation (Atlantic ITCZ, African Monsoon). |
| EQATL | Equatorial Atlantic | SF, CVC | Climate and seasonal indicator. |
| ATL3 | Atlantic El Nino Index | SF, CVC | Climate and seasonal indicator. Ocean variability. |
| ATL2 | Gulf of Guinea | SF, CVC, MP | Upwelling. Climate and seasonal indicator. |
| SATL | South Atlantic | CVC | Climate indicator. |

An example of the timeseries of these indicators is provided in Figure 2, which shows the monthly mean anomalies of SST (top), OHC (middle) and SLA (bottom) over the CANARYC region from the verifying ECVs. The OHC indicator shows the individual GREP products as well as the ensemble mean in black. All of them show coherent interannual variability, which is more visible in SST. Superimposed on this variability are decadal modulations in the OHC, and a clear upward trend in the SLA.

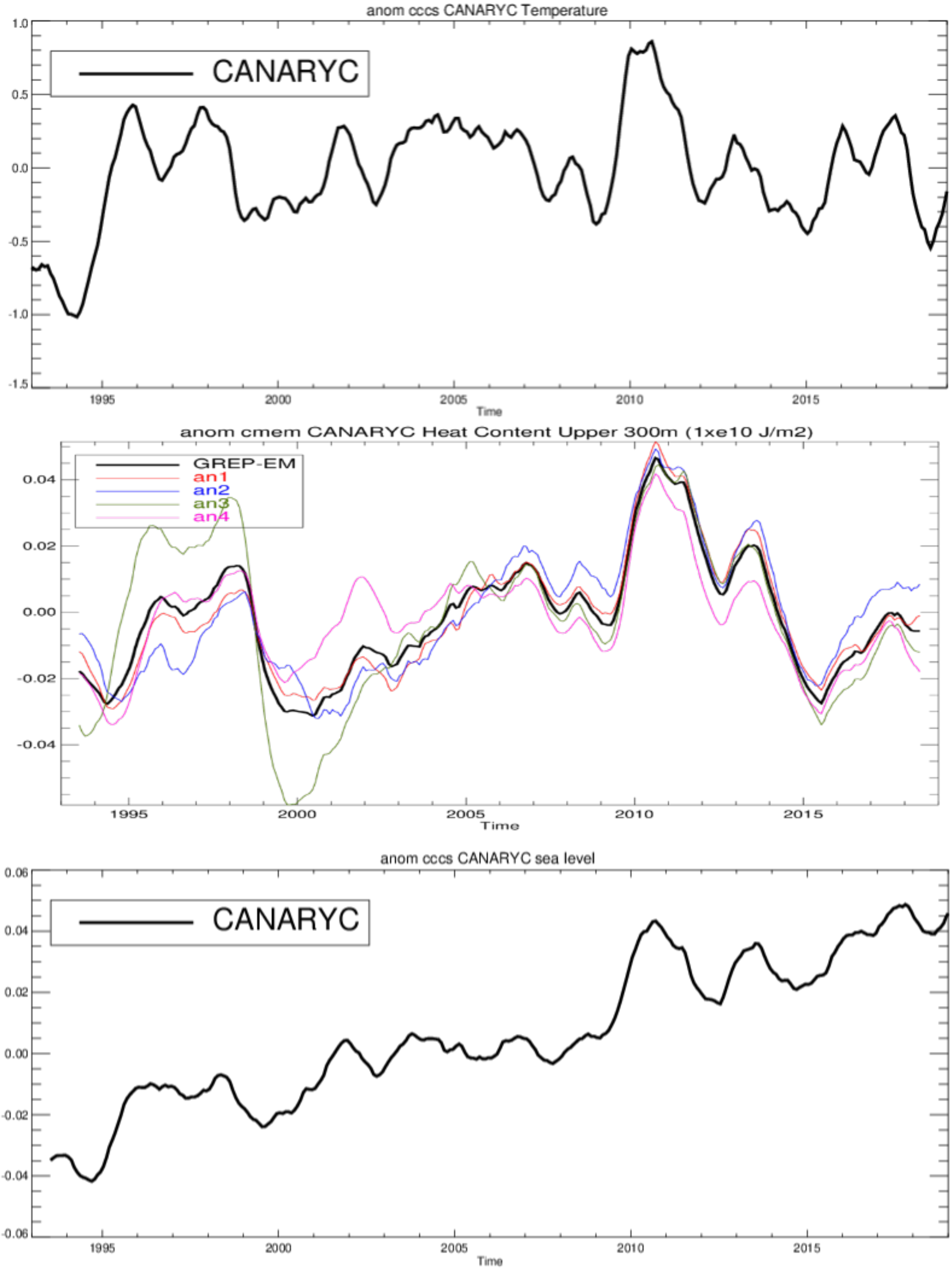


*Figure 2. Timeseries of SST (top), OHC (middle) and SLA (bottom) anomalies over the CANARYC region from the verifying ECVs. The OHC indicator shows the four individual GREP products as well as the ensemble mean in black. All of them show coherent interannual variability, which is more visible in SST. Superimposed on this variability are decadal modulations in the OHC, and a clear upward trend in the SLA. The anomalies are with respect the 1993-2016 climate and are smoothed with a 12-month running mean. Units are degrees Centigrads for SST, $10^{10}$ Jules/m2 for OHC and meters for SLA.*

The indicators are monthly means of area-averaged variables, with a temporal evolution that the seasonal forecasts are trying to forecast in a probabilistic way (via ensemble forecasting) up-to 6 months ahead. The forecasts are available every month, but here we focus only on those starting in May and November. As an example, Figure 3 shows the forecast plumes for the CANARYC SST anomaly indicator from the two seasonal forecast systems (25 ensemble members each) initialized in November 1997 and May 1998. The forecasts initialized in November 1997 were able to predict the rapid warming during the boreal winter and spring of 1998; those initialized in May 1998 captured the decline of the warm anomaly during summer 1998. The spread in the prediction, which is an indication of the uncertainty, was relatively large; this is an important piece of information to convey since it affects decision making.

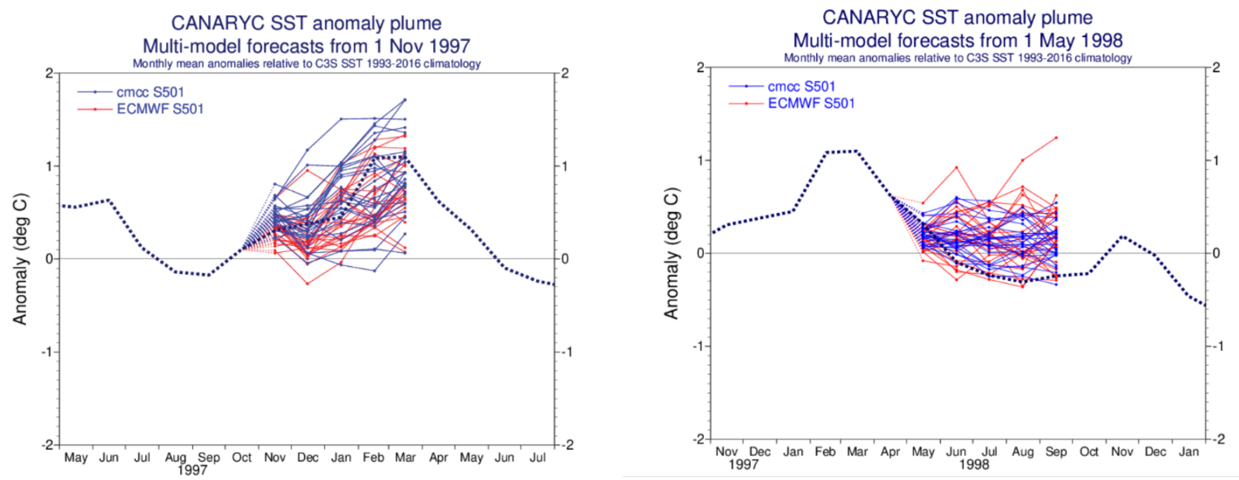


*Figure 3. Forecast plumes of SST anomaly over the Canary upwelling region, as represented by the CANARYC indicator. Shown are the ensemble seasonal forecasts from ECMWF (red) and CMCC (blue) initialized in November 1997 (left) and May 1998 (right). The dotted line is the observational indicator.*

## 3. Calibrating the Seasonal Forecast Indicators

To process the seasonal forecasts indicators, we have gathered a set of retrospective seasonal forecasts (re-forecasts) of the 43 indicators from the two models, for each of three variables. The reforecast dataset comprises 48 independent initial dates, spanning the 1993-2016 period with semi-annual sampling (May and November starts). This 1993-2016 period was chosen, so it is the same as that used for the C3S seasonal multi-model. The forecast range is 6 months. For an individual date, the forecast from each system comprises 25 ensemble members. The reforecast data set is necessary for the calibration and skill assessment, essential steps for the usability of seasonal forecasts. In this deliverable we describe the calibration procedure. The skill assessment will be the subject of subsequent deliverables.

The first order correction to the seasonal forecast model output is the correction of the mean. The seasonal forecast mean state is estimated as the average of all the ensemble forecasts starting in a given calendar month (e.g., all forecasts initialized on the first of May of the different years comprised in the reforecast period). The model climate depends then on the calendar month in which the forecasts were initialized, and changes with lead time. As an example, Figure 4 shows the forecast mean state from the two seasonal forecasting systems for November and May starts for the Canary Current (CANARYC), Caribbean (CARIB) and Western Mediterranean (WMEDI) indicators, for SST (left) and OHC (right). For reference, the mean seasonal cycle of the verification datasets is also shown. Typically, the SST forecast mean state drifts slowly from the observations. The degree of drift depends on the model, region and calendar month. In the examples shown in Figure 4, the drift is larger for May than for November starts. In contrast to the monotonic drift in SST, the OHC shows an abrupt initial jump, after which the values change very slowly. This is symptomatic of errors in the initial conditions, and consistent with the uncertainty in the OHC shown in Figure 1.

The relationship between SST and OHC mean errors in a given model is not always straight forward. Over the Canary Current area, the sign of the drift is the same in OHC and SST, but this is not the case for other regions (e.g., Caribbean), an indication that the reasons for the SST errors are not always related to the errors in the local subsurface. However, there is some indication that if a model has relatively higher mean OHC than the other, the mean SST will also be warmer.

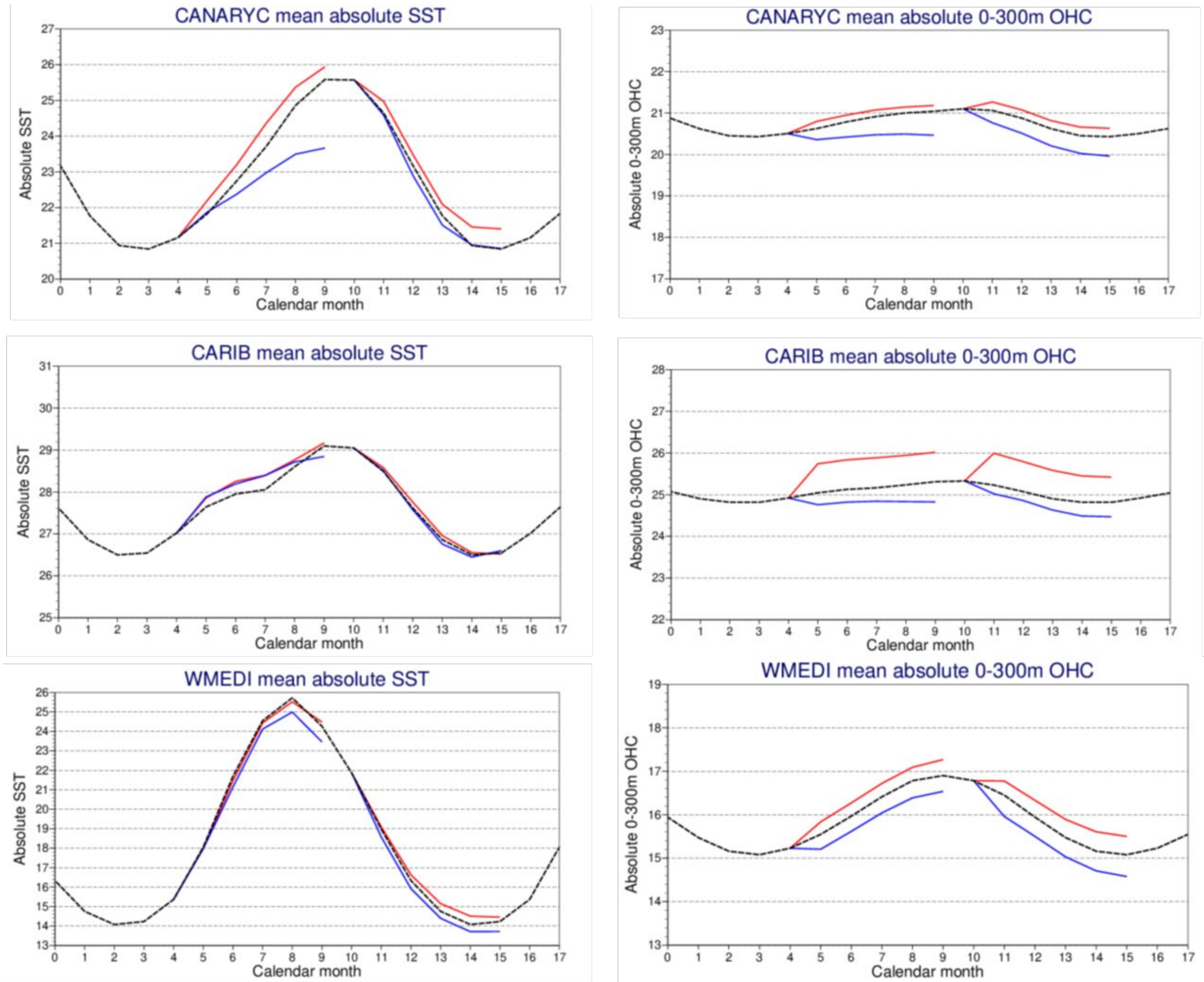


*Figure 4. Mean seasonal cycle of SST (left) and OHC (right) over the Canary Current (top), Caribbean (middle) and Western Mediterranean (bottom). The red and blue lines are for the each of the seasonal forecasting systems, showing the mean evolution of forecasts initialized in May and November. The dashed black line shows the verification. The differences in OHC are visible in the first*

*month, and remain relatively stable after that. This is a clear indication of discrepancies already in the initial conditions. In contrast, the forecast drift is SST evolves slowly over time.*

The forecasts anomalies, as those shown in Figure 3 above, are calculated by removing the model climatology for a given initial calendar month and lead time from the ensemble of forecasts. Figure 3 showed the ensemble anomalies for a specific date.

# 4. Interpreting the Seasonal Forecast Indicators

The use of timeseries indicators allows to inspect the performance of the forecasts over the different dates of historical periods covered by the reforecasts, as shown in the top panels of Figure 5. In this instance the SST anomaly of the ensemble mean of the two seasonal forecasting systems (red and blue) are compared with the verifying timeseries (black) over the CANARYC and CARIB regions. As well as many successful forecasts, there are also some striking forecast failures - so called forecast busts. For instance, in the CANARYC region both seasonal forecasts failed to maintain the cold anomalies before 1995. The reason for this failure is unknown and deserves further investigation. The first step would be to characterize the mechanisms for the observed SST anomalous cold and long-lasting anomaly during the 1993-1995 period.

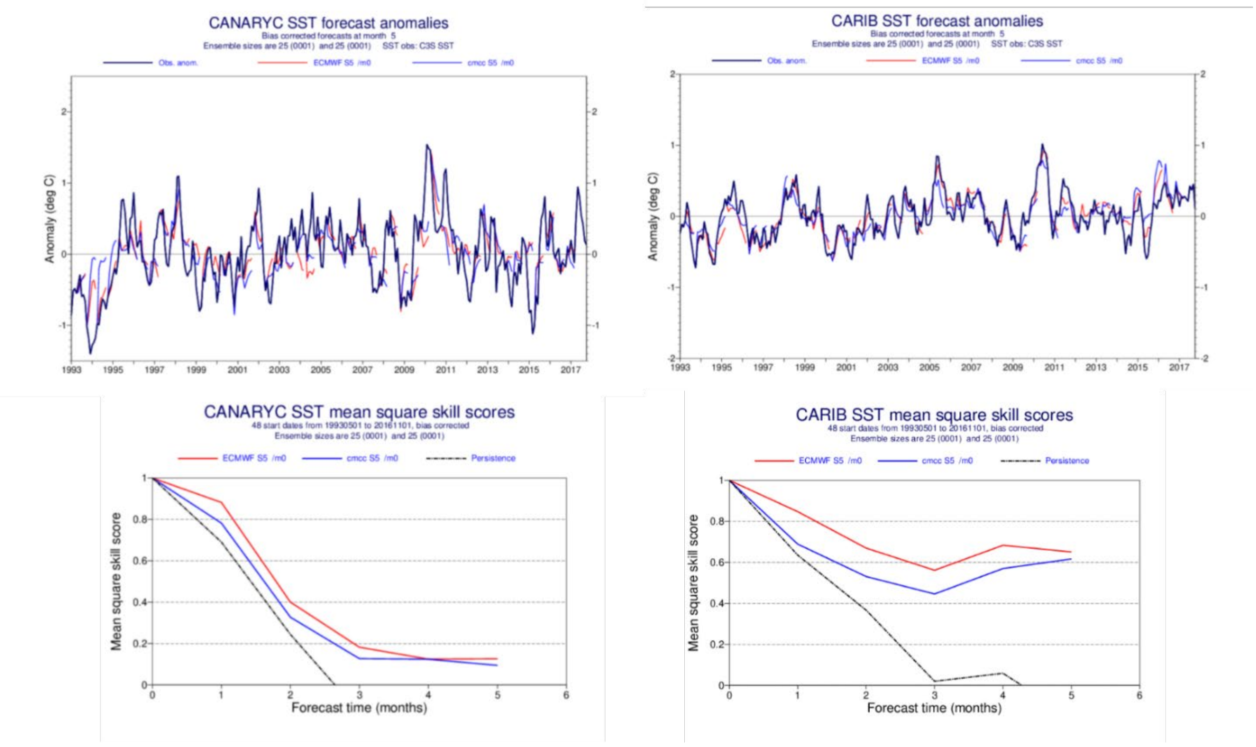


*Figure 5. Top) Time series of SST anomalies in the CANARYC (left) and CARIB (right), indicators from the verification data set (black) and the anomalies from the ensemble mean of the two seasonal forecasting systems (red and blue) initialized in May and November. The anomalies are calculated with respect the 1993-2016 climatology. The seasonal forecasts anomalies have been computed by removing the model climatological values in Figure 4, which depend on forecast lead times. Bottom) Seasonal skill quantification in terms of Mean Skill Square Score (MSSS; MSSS>0 if skill is better than climatology) for the two seasonal forecasting systems (red and blue) and for persistence (black dotted). Both seasonal forecasts systems beat persistence and climatology.*

A further step is to quantify the skill of the forecast ensemble mean, as shown in the lower panels of Figure 5. The skill is measured using to deterministic Mean Square Skill Score (MSSS) defined as:

$$MSSS \quad = 1 - \frac{RMSE_{fc}}{RMSE_{clim}}$$

The MSSS is a normalized score that compares the root mean square error (RMSE) of the anomalies from the forecast ensemble with that of the climatological forecast. A perfect forecast will have MSSS=1. ($RMSE_{fc}$=0). A forecast with no value over the climatology will have MSSS=0. For the two indicators shown in Figure 5, the seasonal forecasts add information over the climatology, with positive values for all lead times. The seasonal forecasts also beat the persistence forecasts (black dotted line). Other forecasts scores such as RMSE and anomaly correlation coefficient (ACC) have been computed for different regions and variables, and the results will be reported in the future.

A summary of the different aspects of the seasonal forecasts is illustrated in Figure 6 for the predictions of SST anomalies for the Western Mediterranean (WMEDI indicator). The figure shows timeseries of the indicator and the ensemble mean forecasts (top left). The timeseries show short lived duration of the anomalies, with the occasional occurrence of extremes, such as the warm event in summer of 2003, which the forecast ensemble mean fails to capture. The ensemble mean skill is better than the persistence forecasts, an indication of the rapid onset of Western Mediterranean anomalies, with higher values of the MSSS (top right). The forecasts are also better than climatology over the first 2-3 months, but beyond that, there is no apparent value on the seasonal forecast information over climatology. The bottom panels of Figure 6 illustrate the performance of the ensembles in forecasts initiated in November 2002 and May 2003. The spread is much larger in the later, an indication of the unpredictability of the summer 2003 conditions. On this occasion, one of the ensemble members showed extreme warm values, suggesting that the forecasts might have suggested probability of extremes. Better quantification of the reliability of the ensemble for prediction of extremes is needed, using specific probabilistic scores. Comparison of ensemble spread of the forecasts initialized in November and May over the reforecast record indicate that the spread is smaller for the former than for the later (not shown), suggesting that summer conditions are less predictable at the seasonal time scale.

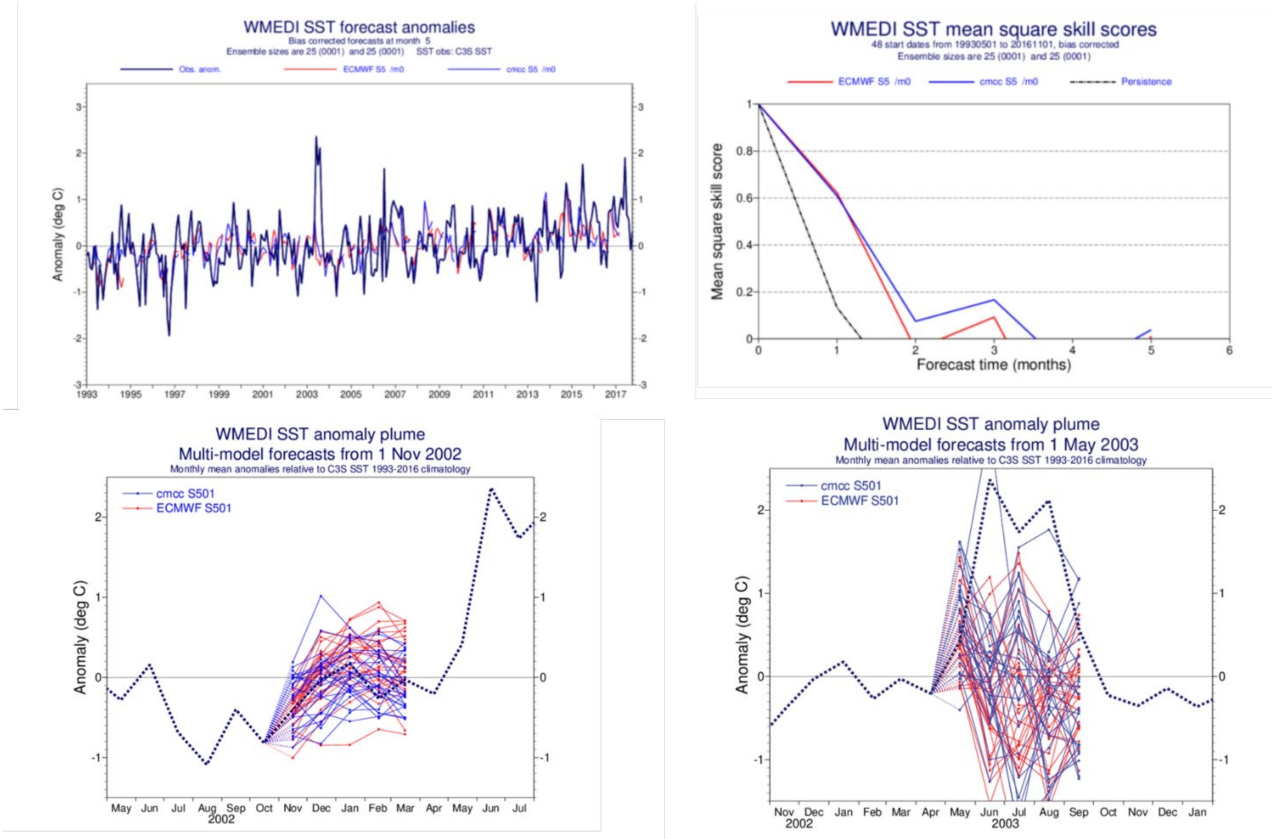


*Figure 6. Performance of the seasonal forecasts over the Western Mediterranean region (WMEDI) indicator. The overall performance of the ensemble mean can be seen in the top panels, which show the timeseries (left) and the MSSS skill (right). The bottom panels zoom on the visualization of the ensemble forecasts initialized in November 2002 and May 2003, with the observations shown as black dotted line. The latter shows a large spread, indicating the little predictability – in the deterministic sense – of the extreme warm event in summer 2003, although, some ensemble members reach extreme anomaly values.*

The analyses of seasonal forecasts of ocean heat content and sea level provides new insights into the characteristics of seasonal forecasts. Given that the visible decadal variability and trends dominate many of these indicators (as shown in Figure 2), the seasonal forecasts performance will be affected by the ability of initial ocean conditions and coupled models to represent and maintain these signals. This is an emerging challenge for seasonal forecasts, which up-to now have been more focused on the representation of interannual variability (Tietsche et al., 2020).

Analysis of the OHC indicators shows a diverse behaviour. While over the tropical open oceans predictions of OHC are better than persistence and comparable to those of SST, closer to the coasts and over Southern Ocean the skill suffers, and it is much dependent on the forecasting system. For instance, the ECMWF SEAS5 struggles to predict the OHC decadal variability associated with the Atlantic Meridional Overturning Circulation (AMOC), in agreement with the findings reported by Tietsche et al., 2020, while the CMCC system has difficulties over the Southern Ocean. A comparative analysis of seasonal skill in the OHC versus SST is provided in McAdam et al., 2021, and it will be included in the next report.

Long-term trends dominate the sea level variability over most of the ocean, except for the Equatorial regions. Therefore, it is expected that persistence will be a good predictor for sea level variations at seasonal time scales. Beating persistence is thus a non-negligible challenge for seasonal prediction systems of SLA. Figure 7 illustrates this idea over the Caribbean region (CARIB indicator). Both seasonal forecasting systems struggle to represent and predict the observed trends in sea level (top left panel). The CMCC system (blue) underestimates the rising SLA trend from the first month. The ECMWF system seems to overestimate the trend, by producing lower sea level before 2000. This is believed to be related with the overestimation of the decadal variability of the AMOC in the ECMWF ocean initial conditions reported by Tietsche et al., 2020.

To test the impact of the trend on this indicator, a simple linear trend correction has been applied to the forecasts, as a function of lead time. The trend correction clearly improves the behaviour of the CMCC forecasts through the reforecast record (Figure 7, top right). The linear trend correction improves the ECMWF values before 2000, at expense of slightly degrading the last part of the record. The scores for the forecasts before and after trend correction appear in the lower panels of Figure 7 (left and right respectively), confirming the importance of capturing the linear trends on the seasonal forecasts. After trend corrections, the CMCC seasonal forecast beats persistence after month 2. None of the models are able to beat persistence at month 1, suggesting that further improvements in the ocean initialization are needed.

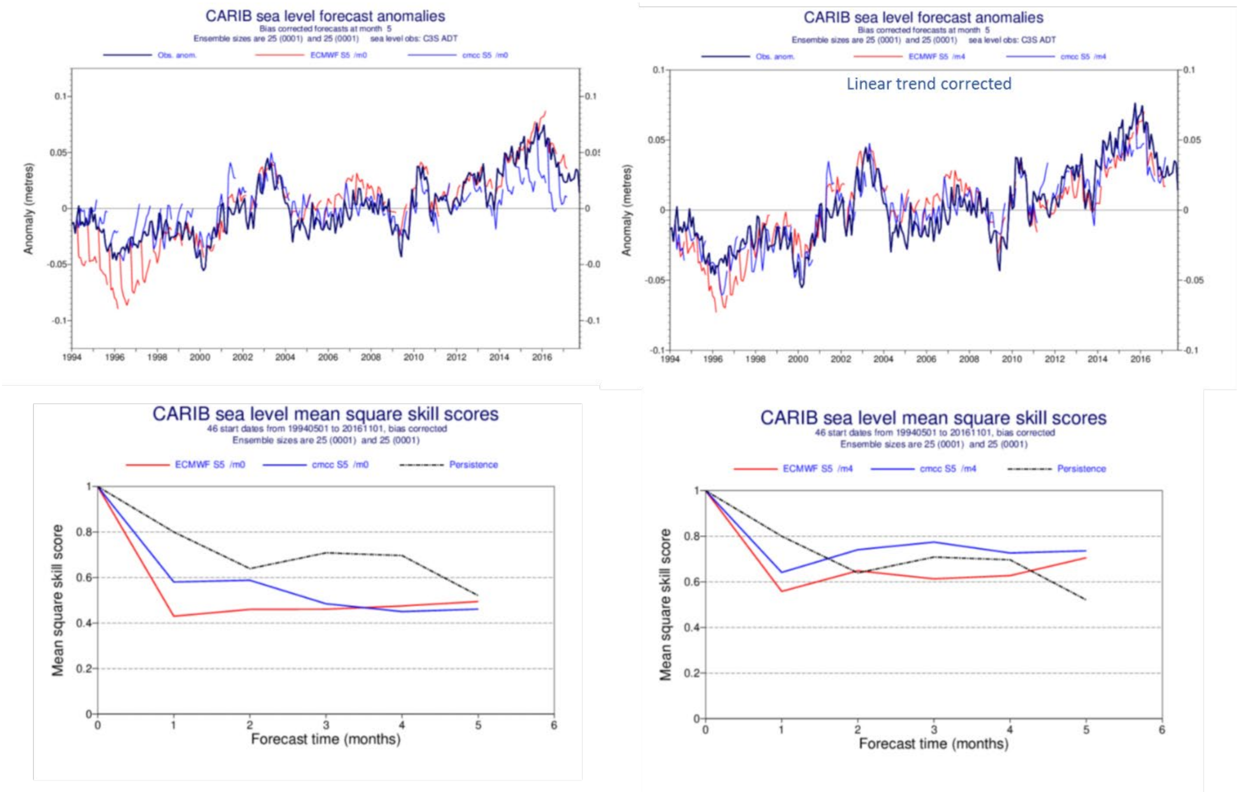


*Figure 7. Time series of SLA over the Caribbean indicator from the verification data set (black) and the from the ensemble mean of the two seasonal forecasting systems (red and blue) initialized in May and November (top left). The corresponding timeseries after the forecasts have been corrected for linear trend and appear in the top right panel. The lower panels show the MSSS for the seasonal forecasts and persistence (black dotted line) before and after linear trend correction (left and right).*

# 5. Conclusions

A set of observable ocean indicators for monitoring and forecasting was defined. These indicators target five sectorial applications: i) seasonal forecasts of weather statistics (SF); ii) Climate Variability and Change (CVC); ii) Coastal Sea Level Rise (CSL); iv) Marine Health (MH) and v) Marine Productivity (MP).

The indicators are area-averaged timeseries of monthly means over 43 different regions, and their reference values have been derived from state-of-the-art datasets of Essential Ocean/Climate Variables (EOVs/ECVs). These are monthly SST and SLA from the Copernicus Climate Chance Service (C3S) and OHC from Copernicus Marine Environmental Service (CMEMS) Global Ensemble of ocean Reanalyses Products(GREP). The indicators show potential for climate monitoring of changes in upwelling areas and regional sea level rise. Indicators such as these are also used to verify the skill of seasonal forecasts.

The indicators have also been derived from the ensemble of ECMWF and CMCC seasonal forecasts contributing to C3S. These are probabilistic forecasts of indicators up to 6 months ahead. The seasonal forecast indicator dataset consists of 43 areas, in which SST, SSH and OHC are validated. For each variable, there are 48 seasonal reforecasts, initialized over the period 1993-2016 (24 years), twice a year (May and November starts). For each initial date during this period there is a 25-member ensemble forecast of the following 6 months. The indicator dataset has been exchanged on an agreed data format in netcdf. The reforecasts have been used to estimate the mean model climate as a function of lead time and initial date, which allows the calibration of the forecast anomalies. The reforecasts are also used for skill assessment, a necessary step for the usability of forecast information.

We have presented some examples of the calibration of the indicators, which include correction of mean bias and linear trend. Preliminary results show that in most instances the seasonal forecasts of SST beat the persistence forecasts, and that uncertainty in OHC initial conditions in the upwelling region limits the assessment of forecast skill. Results also highlight the importance of representing the decadal variability and trends in ocean heat content and sea level in the initial conditions. This is a non-negligible challenge for the ocean data assimilation systems used in the production of ocean initial conditions. The representation of decadal variability and trends is essential for decadal forecasts and climate projections. Therefore, the results from the seasonal forecasts are also very relevant for the efforts on decadal variability and climate projections.

This preliminary analysis of the seasonal forecasts indicators points to the need of probabilistic scores to evaluate the ability of seasonal forecasts to represent short lived extreme events, such as the extreme warm event in the Western Mediterranean during the summer 2003. We have also shown that there is need to better understand and characterize the variability of the upwelling areas, specifically, the long-lasting cold period over the Canary Upwelling region during 1993-1994 with cold anomalies that have not been seen since then. The prediction of this event can be considered a seasonal forecast bust, with both seasonal forecasts systems consistently failing to predict the cold conditions for three consecutive initialization dates during this period (May 1993, Nov 1993, May 1994). Understanding this important error should lead to improvement of forecasting systems. It is also important to gain understanding, in relation to the forecast performance among the different ocean variables. Work will continue along these lines, and the results will be reported in the next deliverable.

# Appendix

*Table A1: Coordinates of the EuroSea Indicators for Seasonal Forecasts*

| Short Name | Long Name | Longitudes (°East ) | Latitude (°North) |
|---|---|---|---|
| nino12 | Nino 1+2 | 270.,280. | -10., 0. |
| nino34 | Nino 3.4 | 190., 240. | -5., 5. |
| atl3 | Atlantic 3 | 340., 360. | -3., 3. |
| atl2 | Atlantic 2 | 0. ,10. | -3.,3. |
| ATL60NA | Subpolar Gyre North | 260., 9.13 | 59., 61. |
| ATL40NA | Subpolar Gyre South | 260., 358. | 39., 41. |
| NATL | North Atlantic | 290., 15. | 30., 70. |
| NEATL | North East Atlantic | 320., 15. | 30., 70. |
| NWATL | North West Atlantic | 260., 320. | 30., 70. |
| TRATL | Tropical Atlantic | 280., 20. | -20., 30. |
| NSTRATL | North Subtropical Atlantic | 280., 20. | 5., 28. |
| SSTRATL | South Subtropical Atlantic | 300., 20. | -20., 5. |
| EQATL | Equatorial Atlantic | 290., 30. | -5., 5. |
| SATL | South Atlantic | 290., 20. | -70., -30. |
| NPAC | North Pacific | 100., 260. | 30., 70. |
| NEPAC | North East Pacific | 210., 260. | 30., 70. |
| NWPAC | North West Pacific | 100., 210. | 30., 70. |
| TRPAC | Tropical Pacific | 125., 280. | -30., 30. |
| NSTRPAC | North Southtropical Pacific | 105., 270. | 10., 30. |
| SSTRPAC | South Southtropical Pacific | 105., 270. | -30., -10. |
| TREPAC | Tropical East Pacific | 210., 270 | . -30., 30. |
| TRWPAC | Tropical West Pacific | 100., 210 | . -30., 30. |

| | | | |
|---|---|---|---|
| EQPAC | Equatorial Pacific | 130., 280. | -5., 5. |
| SPAC | South Pacific | 150., 290. | -70., -30. |
| IND1 | W. Indian Ocean Dipole | 50., 70. | -10., 10. |
| IND2 | Eastern Indian Ocean Dipole | 90., 110. | -10., 0. |
| EQIND | Equatorial Indian Ocean | 40., 120. | -5., 5. |
| TRIND | Tropical Indian Ocean | 40., 120. | -30., 30. |
| SIND | Southern Indian Ocean | 20., 150. | -70., -30. |
| NXTRP | Northern Extratropics | 0., 360. | 30., 70. |
| TROP | Tropics | 0., 360. | -30., 30. |
| SXTRP | Southern Extratropics | 0., 360. | -70., -30. |
| CANARYC | Canary Current | 330., 350. | 11., 31. |
| BENGUELA | Benguela | -35., -15. | 5., 20. |
| HUMBOLDT | Humboldt | 275., 290. | -40., -5 |
| NCALIFC | Northern California | 225., 240. | 34., 45. |
| SCALIFC | Southern California | 235., 250. | 22., 34. |
| MDR | Mean Development Region (tropical cyclones) | 275., 340. | 10., 20. |
| CARIB | Caribbean | 275., 300. | 10., 20. |
| GMEX | Gulf of Mexico | 260., 280. | 20., 30. |
| WMEDI | Western Mediterranean | 0., 15. | 35., 44. |
| EMEDI | Eastern Mediterranean | 15., 30. | 30., 40. |
| NSEA | Northern European Seas | -3., 8. | 51., 61. |

*Table A2: Stage Indicators for the Pacific Ocean Basin*

| Pacific Ocean Indicators | | | |
|---|---|---|---|
| **Index Short Name** | **Index Long Name** | **Sectorial Application** | **Relevance** |
| HUMBOLDT | Humboldt Upwelling Area | MP, MH | Major upwelling area. |
| NCALIFC | Northern California Upwelling Area | MP, MH, SF, CVC | Major upwelling area. |
| SCALIFC | Southern California Upwelling Area | MP, MH, SF, CVC | Major upwelling area. |
| NPAC | North Pacific | CVC | Climate indicator. |
| NEPAC | North Eastern Pacific | SF, CVC, MP, MH | Relevant for Marine heat waves. Marine Productivity. Climate variability and change. PDO. |
| NWPAC | North Western Pacific | CVC, MP | Relevant for Marine productivity. Climate variability and change. |
| TROP | Tropical Pacific | SF, CVC | Climate indicator. Affect worldwide atmospheric circulation. Heat uptake and distribution. |
| NSTRPAC | North Subtropical Pacific | SF, CVC | Climate indicator for the Pacific Meridional Mode. Affects ocean and atmosphere climate circulation. |
| SSTRPAC | South Subtropical Pacific | SF, CVC | Climate indicator for the Pacific Meridional Mode. Affects ocean and atmosphere climate circulation. |
| TREPAC | Tropical Eastern Pacific | SF, CVC | Eastern Part of Pacific Zonal Mode. Key component for heat exchange between West-East. Decadal and Interannual atmospheric variability. Link with the Atlantic variability. |
| TRWPAC | Tropical Western Pacific | SF, CVC, CSL | Western Part of Pacific Zonal Mode. Key component for heat exchange between West-East. Decadal and Interannual variability. Links with Indian Ocean. Sea level change. |
| EQPAC | Equatorial Pacific | SF, CVC | Relevant to ENSO and ocean circulation |
| NINO3.4 | ENSO index | SF, CVC, MP, MH | ENSO affects atmospheric climate, but also marine health and productivity via remote impacts. |
| NINO1.2 | Coastal ENSO index | SF, CVC, MP, MH | Marine productivity and upwelling area. Climate variability. Atmospheric Impact. |
| SPAC | South Pacific | CVC | Climate indicator. |

*Table A3: Indicators for the Indian Ocean basin*

| Indian Ocean Basin Indicators | | | |
|---|---|---|---|
| **Index Short Name** | **Index Long Name** | **Sectorial Application** | **Relevance** |
| IND1 | Eastern Node of the Indian Ocean Dipole | SF, CVC, CSL | Atmospheric Circulation. Climate Indicator. Coastal Sea Level. |
| IND2 (SETIO) | Western Node of Indian Ocean Dipole | SF, CVC, MP, CSL | Marine Productivity. Atmospheric circulation. Climate indicator. Coastal Sea Level. |
| INDPL | Indian Ocean Dipole IND1-IND2 | SF, CVC | Atmospheric circulation. Climate variability. |
| EQIND | Equatorial Indian Ocean | SF, CVC | |
| TRIND | Tropical Indian Ocean | SF, CVC | Atmospheric circulation. Climate variability. Heat absorption and sea level change. |
| TRWIND | West Tropical Indian Ocean | SF, CVC | Related to the interannual and decadal changes in the ocean-atmosphere coupled system. |
| TREIND | East Tropical Indian Ocean | SF, CVC | Related to interannual and decadal changes in the ocean-atmosphere coupled system. |
| SIND | Southern Indian Ocean | CVC | Interbasin connection. It helps to monitor how the Southern ocean affects other basins. |

*Table A4: Latitudinal band indicators*

| Latitudinal Bands Indicators | | | |
|---|---|---|---|
| **Index Short Name** | **Index Long Name** | **Sectorial Application** | **Relevance** |
| NXTRP | Northern Extratropics | CVC | Climate change indicator. Complements NPAC, NATL. |
| TROP | Tropics | CVC | Climate indicator of variability and change. Complements TRIND, TRATL, TRPAC. |
| SXTRP | Southern Extratropics | CVC | Complements SPAC, SIND, SATL. |

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