Climate Change Initiative
Living Planet Fellowship

2014

Omar Bellprat

Barcelona Supercomputer Centre

4000114580/15/I-SB0

STANDARD COVER PAGE FOR ESA STUDY CONTRACT REPORTS

ESA STUDY CONTRACT REPORT

ESA Contract No: 4000114580/15/I-SBo	SUBJECT: Living Planet fellowship "Verification High resolution climate forecast on Intra-seasonal-to-annual Timescales with Advance satellite datasets of the Climate Change Initiative"	CONTRACTOR: Barcelona Supercomputing Center (BSC)
ESA CR( )No: 4000114580/15/I-SBo	No. of Volumes:.1 This is Volume No:.1	CONTRACTOR'S REFERENCE: 1000004688

ABSTRACT:

The European Space Agency (ESA) funded as part of the Climate Change Initiative (CCI) post-doctoral fellowships to exploit the newly derived Essential Climate Variables in contemporary climate research. VERITAS-CCI: "VERification of high-resolution climate forecasts on Intraseasonal-to-interannual Timescales with Advanced Satellite datasets of the Climate Change Initiative" belonged to one of these projects. Its principal goal has been to use the CCI observational references (ORs) as an independent source of forecast verification in ongoing efforts to improve near-term (seasonal-to-decadal) climate prediction.

The project has achieved numerous advances in climate prediction in collaboration with other research projects (SPECS1, CMUG2). It has demonstrated long-lead (up to four month) increased predictability obtained from initialisation of the land surface (Prodhomme et al., 2016a) and sea-ice (Guemas et al., 2016) as well as benefits from increasing the horizontal resolution of global seasonal forecasts (Prodhomme et al., 2016). In order to detect these improvements new statistical approaches have been developed that advance current practice in comparing competing prediction systems (Siegert et al., 2017). Acknowledging observational uncertainty in the verification process has led to new ways on how to formulate the verification question, adopting the paradigm to verify observational references instead of climate models (Massonnet et al., 2016) as well as systematically accounting observational uncertainty in verification (Bellprat et al, 2017).

The work described in this report was done under ESA Contract. Responsibility for the contents resides in the names of the authors.

Names of authors:
Dr. Omar Bellprat

NAME OF ESA STUDY MANAGER: Dr Stephen Plummer DIV: EOP-SC DIRECTORATE: EOP	ESA BUDGET HEADING:

“Using satellite remote sensed observations of the ESA Climate Change Initiative (CCI) for verification of climate prediction: A summary of the VERITAS-CCI ESA project”

Omar Bellprat
Living Planet Fellowship
Barcelona, 12th March 2017

Summary

The European Space Agency (ESA) funded, as part of the Climate Change Initiative (CCI), post-doctoral fellowships to exploit the newly derived Essential Climate Variables in contemporary climate research. VERITAS-CCI: "VERification of high-resolution climate forecasts on Intraseasonal-to-interannual Timescales with Advanced Satellite datasets of the Climate Change Initiative" was one of these projects. Its principal goal has been to use the CCI observational references (ORs) as an independent source of forecast verification in ongoing efforts to improve near-term (seasonal-to-decadal) climate prediction.

The verification of seasonal-to-decadal predictions (also known as forecast quality assessment) is a fundamental aspect in climate prediction research. Climate predictions are only useful if their ability to predict future climate is demonstrated (Doblas-Reyes, 2013) and they can even be harmful through erroneous decisions otherwise (Weisheimer and Palmer, 2014). Demonstrating prediction skill requires the simulation of initialized ensemble predictions using an Earth system model for a past period for which the observed outcome is already available. The ORs used to compare the predictions should ideally be independent from the data used to initialize or to tune the model. The CCI datasets greatly contribute to this challenge by providing observational references which are (1) largely independent from the data used in climate prediction, (2) of high quality accompanied with an estimate of observational uncertainty, and (3) of high-resolution required to cope with ongoing research in high-resolution climate modelling.

VERITAS-CCI explored the benefits from initializing sea-ice and land-surface conditions (e.g. soil moisture, snow) from re-analysis datasets and from increasing the horizontal resolution in seasonal prediction hindcasts with the EC-Earth3 Earth system model (Hazeleger, 2014). Current operational seasonal prediction centres generally do not account for the potential predictability originating from these observations. Neither do they generally run at cutting edge global high-resolution (25 km). This research project therefore contributes to the future of operational climate prediction centres. VERITAS-CCI further placed a special focus on the use of observational uncertainties provided by the CCI products. ORs are as climate models an approximation of the true climate and thus they come with associated uncertainties which have to be taken into account. However, the model community is currently usually ignoring these, partly because of the lack of formal concepts on how to consider the uncertainties in model verification.

The project has achieved numerous advances in climate prediction in collaboration with other research projects (SPECS1[1], CMUG2[2]). It has demonstrated long-lead (up to four month) increased predictability obtained from initialisation of the land surface (Prodhomme et al., 2016a) and sea-ice (Guemas et al., 2016) as well as benefits from increasing the horizontal resolution of global seasonal forecasts (Prodhomme et al., 2016b). In order to detect these improvements new statistical approaches have been developed that advance current practice in comparing competing prediction systems (Siegert et al., 2017). Acknowledging observational uncertainty in the verification process has led to new ways on how to formulate the verification question, adopting the paradigm to verify observational

[1] Seasonal-to-decadal Prediction for the improvement of European Climate Services (SPECS), FP7
[2] Climate Modelling User Group (CMUG) of the Climate Change Initiative (CC)

references instead of climate models (Massonnet et al., 2016) as well as systematically accounting observational uncertainty in verification (Bellprat et al, 2017).

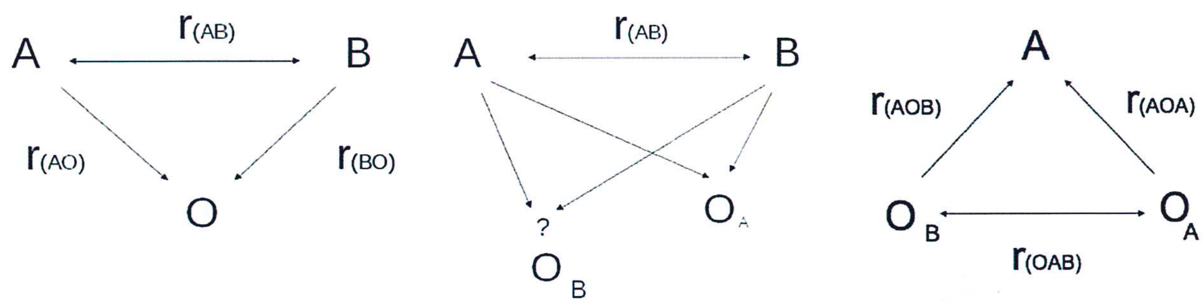
The following report provides an overview of the work conducted in VERITAS-CCI. It highlights individual results obtained in the publications listed above and presents scope for future research in exploiting the CCI and CCI+ datasets in climate prediction.

1. Methods and research questions

(a) Metrics and context

Seasonal forecast quality can be measured in numerous ways (Doblas-Reyes et al., 2013). One widely adopted measure is the Pearson correlation between the ensemble mean seasonal prediction and the observed anomalies of seasonal means. It measures whether predicted anomalous seasons correspond (linearly) with the observed anomalies (e.g. warm summers) over the hindcast period. The correlation skill has the advantage that it is easy to communicate and that it relates directly to other scores (Siegert et al., 2017). The work carried out in VERITAS-CCI uses essentially the correlation skill ("r") as a verification metrics, but the results are robust also when using other metrics as presented in the publications.

Different ways how to frame the verification question have been developed during the VERITAS project as illustrated in figure 1. Panel (a) denotes the traditional verification question in "Is the new forecast B better than the former forecast A?" i.e. is $r_{BO} > r_{AO}$? In Siegert et al. (2017), we demonstrate that in order to answer this question, it is fundamental to take into account the mutual correlation between system A and B (r_{AB}) which allows to increase the power to detect a significant difference. Almost exclusively all studies neglect this aspect currently. Panel (b) asks the question of how the correlation depends on the choice of observational reference. This is rarely done in this community and will provide evidence of how strongly the CCI datasets differ from previously developed products of the same ECVs. The last question in panel (c) reverses the verification question, is the alternative observational dataset correlating more with the forecast system A? In Massonnet et al. (2017) we show that this question is not only justified but provides useful insights on the quality of observational references.



(a) Best model *(b) Observational uncertainty* *(c) Best observation*

Figure 1: Verification approaches adopted in this study to compare model A and B and observation O_A and O_B. (a) Classical comparison for two competing experiments with a single observation which requires the consideration of correlation between the two models currently often neglected. (b) Uncertainty in the comparison of two experiments if using a single observation: how much is the skill affected by the choice of the observational reference? (c) Verification of different observations when comparing to a single model: which observation leads to the highest correlation skill?

(b) Seasonal prediction hindcasts

Five sets of seasonal prediction hindcasts were carried out using EC-Earth version 3.1 (Hazeleger, 2014). These hindcasts evaluate the added-value of increasing the horizontal resolution (from T255-ORCA1 to T511-ORCA025, approximately from 80 km to 40 km in the atmosphere and 100 km to 25 km in the ocean, Prodhomme et al. 2016), of initializing the predictions with observed land-surface parameters (which includes soil moisture or snow) instead of using a climatology (Siegert et al., 2017), and of initializing predictions with observed sea-ice instead of using climatological conditions (Guemas et al., 2016). The experiments carried out within VERITAS are listed in Table 1.

Table 1: EC-Earth hindcasts to study the effects of horizontal resolution and initialisation of land surface (subscript 1) and sea ice (subscript 2)

Resolution | Initialisation	Realistic Init	Clim. land-surface init	Clim. sea-ice init
Low resolution (T255ORCA1)	$x_{1,2}$	X_1	X_2
High-resolution (T511ORCA025)	X_1	X_1	

Additional seasonal prediction hindcasts were included in the analysis exploring observational uncertainty. These are hindcasts carried out within the framework of the SPECS project, the North American Multi-model Ensemble (NMME, http://www.cpc.ncep.noaa.gov/products/NMME/), and the European Centre for Medium Range Weather Forecasts System 4 (ECMWF S4). VERITAS-CCI focuses on the prediction of summer (JJA) and winter (DJF) conditions which are initialized in May and November, respectively. The number of ensemble members analyzed is 10 in each set of hindcasts even in cases where more members would be available. The hindcast period was restricted to the years 1993 to 2009 which coincides with the availability of the CCI datasets

(c) Observational datasets

Three types of ECVs for which CCI has developed new observational references were considered in this project: sea-surface temperature (SST), soil moisture (SM) and sea-ice extent (SIE). The datasets are complemented with observational references for the same variables but from different institutions. Observations for other variables that are fundamental for climate prediction verification such as 2m temperature (T2M) and precipitation (PR) are considered as well. The observations used in the entire project are summarized in the table below, while the results highlighted in section 2 will refer to the analysis of a subset of these observations only.

Table 1: Summary of observational references used in VERITAS-CCI.

Variable	***Dataset s***	***References***
Sea-surface temperature (**SST**)	CCI Analysed v1.0, HadISST v.1.1, ERA-Interim, ERSST v.3b, ERSST v.4	*Merchant et al., 2014, Rayner et al., 2003, Dee et al., 2011, Xue et al., 2003,Liu et al., 2014*
Sea-ice concentration (**SIC**)	CCI SSM/I, HadISST v.1.1, OSI-SAF, COBE2, NSIDC	*Ivanova et al., 2014, Rayner et al., 2003, Eastwood et al., 2011, Hirahara et al., 2014, Fetterer et al., 2016*
Soil moisture (**SM**)	CCI Combined v.2.1, ERA-Land	*Liu et al., 2012, Balsamo et al., 2015*
2 m Temperature (**T2M**) Precipitation (**PR**)	ERA-Interim	*Dee et al, (2011)*

2. Highlighted research results

(a) Improving seasonal forecasting systems

The prediction of the Earth's climate into one season ahead is possible thanks to slow modes of variability that play major role in the climate system. The El Niño Southern Oscillation (ENSO, Trenberth, 1999) is the most important mode at the seasonal time-scale. ENSO is an equatorial Pacific interannual variability mode that has a strong impact on the seasonal climate over many regions due to teleconnections pathways across the globe. The success of seasonal predictions has predominantly been relying on the prediction of ENSO up-to-date which can be forecasted for summer and winter conditions a few seasons in advance. Many regions, particularly over land, are, however, weakly affected by ENSO such as for example Europe. The seasonal prediction skill over Europe is therefore marginal and large efforts are being conducted in order to find additional driving factors which are predictable into one season ahead or more.

One well known factor with long-term memory that impacts summer-time conditions over Europe is soil moisture. The soil moisture content conditions the surface energy budget in summer and can therefore impact also local precipitation patterns (see a review in Seneviratne et al., 2013). Soil moisture undergoes intra-seasonal-to-interannual variability and hence potentially holds predictive capacity at the seasonal time-scale, an source of predictability which current operational seasonal forecasting centres are not necessarily accounting for. Figure 2 shows the impact from initializing land-surface conditions from re-analysis data (ERA-Land, Balsamo et al., 2015, see Table 1). The map shows the difference in correlation skill between the hindcast using observed conditions of the land-surface minus the one using climatological conditions ($r_{BO} > r_{AO}$, Fig.1a) using two different tests to detect significant correlation changes. A large increase in summer correlation skill over Europe is achieved from initializing the land-surface, particularly over the Eastern and North-Eastern part of the continent. Many of these regional improvements are found to be statistically significant, particularly when adopting the statistical test developed within VERITAS as we presented in Siegert et al., (2017), which leads to twice the amount of grid-points where significant improvements were detected.

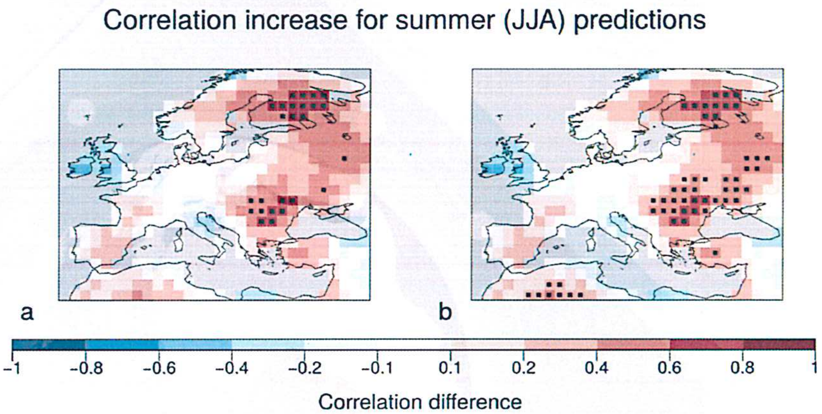


Figure 2: Benefits from initializing land-surface conditions to predict mean summer (JJA) conditions over Europe illustrated as the difference in ensemble mean correlation between the initialized hindcast minus the hindcast using climatological conditions of the land-surface. Stippling denotes significant improvements of correlation at the 5% significance level using commonly applied tests in the forecast community (left panel) and newly derived tests within VERITAS (Siegert et al., 2017) which doubles the amount of significant changes.

In VERITAS-CCI, we have also worked on further improving the current prediction skill of ENSO in EC-Earth3. Shaffrey et al. (2009) reported large improvements of the ENSO variability obtained by increasing the horizontal resolution of HadGEM3. This result was confirmed by the high-resolution experiments carried out with EC-Earth within VERITAS as illustrated in figure 3 for the summer prediction skill of ENSO (as well as for winter predictions – not shown). Simulations initialized in May predict the evolution of summer ENSO significantly better at a 1% significance level (panel b using ESA CCI as a reference, Bellprat et al., 2015). This improvement is consistent across different datasets, yet the observational uncertainty projects on an uncertainty in the correlation skill that has about the same magnitude as the improvement thanks to increased resolution (see panel a). Both results obtained via initializing the land-surface and increasing the horizontal resolution, but also thanks initializing the sea-ice conditions as discussed in Guemas et al. (2016) point towards promising paths for future operational seasonal predictions systems.

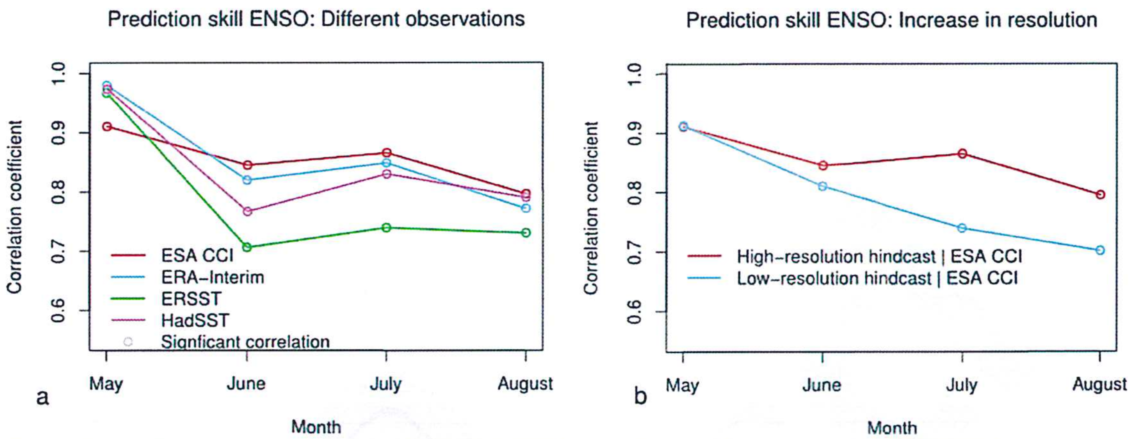


Figure 3: (a) Temporal correlation of Niño 3.4 SSTs over the hindcast period (1993-2009) for each forecast month of the high-resolution hindcasts started in May. The correlation coefficients are shown for four different observational datasets and circles denote correlations that are significant at the 5% significance level. (b) Comparison of changes in the horizontal resolution using the high-resolution (red) and low-resolution (blue) hindcast for the same correlation analysis using only the ESA CCI observations as reference. The differences in the correlation in panel (b) are significant at the 1% confidence level for June, July, and August.

(b) Evaluating observational references using climate models

A striking feature of the analysis using different observational references presented in figure 3 is that different datasets systematically increase or lower the correlation skill of the forecasting system after the first month of the initialization (note that ESA CCI agrees the least for the month of initialization, May, presumably due to its independence to the re-analysis and observations used to initialize the models). This behaviour can be explained by adopting the notion of uncertain observations. Both model and observations represent the true variability of ENSO with a model or an observational error respectively, assuming a noise plus truth paradigm (Sanderson and Knutti, 2012). The correlation between models and observations increases or decreases as a consequence with increasing or decreasing noise in either of the two covariates (model and observations). Different levels of correlation skill across different observational references therefore point to different levels of observational noise in the datasets.

We explored this idea in Massonnet et al., (2016). Figure 4 shows a central finding of the study expanding the analysis of figure 3 to a large number of seasonal forecasting systems carried out in SPECS and the NMME. The figure strikingly confirms the hypothesis: almost exclusively all models and members of these (colored dots) obtain higher correlation skill with the newly developed CCI SST product in comparison to ERSST4 relying on in-situ data alone. This is particularly striking since the CCI SST product was developed after the production of these hindcasts and thus more independent from these than ERSST4. The result essentially justifies the reversal of the verification question as illustrated in figure 1c and hence demonstrates that climate models can be used to evaluate the quality of global observational datasets.

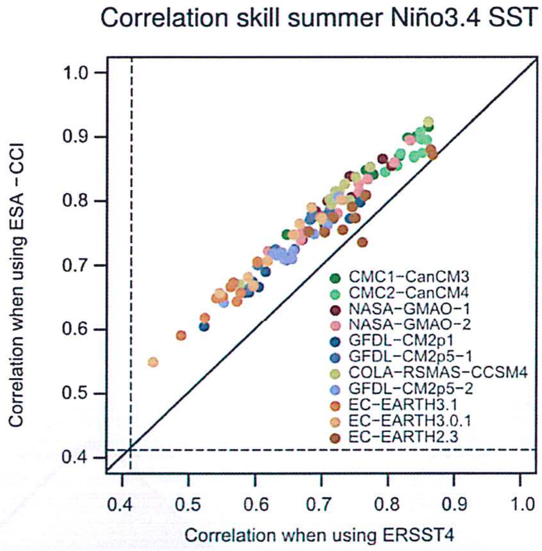


Figure 4: Temporal correlation of Niño 3.4 SSTs over the hindcast period (1993-2009) for each forecast systems and each forecast month of the NMME and SPECS ensemble predictions started in summer.

(c) The role of observational uncertainty in forecast verification

Observational uncertainty clearly plays a role when verifying ENSO predictions. But how important is the uncertainty elsewhere and how does it compare to other verification uncertainties? Uncertainties in seasonal forecast skill have been examined thoroughly in the community but mainly those resulting from limited sampling (see for instance Ferro, 2014). Predictions scores are subject to two main sample uncertainties, the size of the ensemble used to compute the ensemble mean signal and the length of the hindcast (number of retrospective predictions). The correlation skill obtained with a specific set of hindcasts is therefore only a sample of the true correlation skill with an underlying confidence bound. In Bellprat et al., (2017) we compared the observational uncertainty as an additional source of uncertainty to these sample uncertainties. An example of this analysis is presented in figure 5. The figure illustrates which source of uncertainty dominates the overall correlation uncertainty over different regions.

The analysis reveals interesting patterns. The observational uncertainty of SST dominates the two other sources of uncertainty over many regions of the globe, particularly those with known low number of in-situ observations such as the polar region. Over regions with higher observational measurement density such as the North Atlantic and the North Pacific (due to shipping routes) the largest uncertainty results from the length of the hindcast period used to compute the correlation. However, over some regions of the North Atlantic and Pacific the ensemble size dominates the overall uncertainty. This is because in the mid-latitudes, SSTs are predominantly forced by the atmosphere which in these regions is weakly constrained by the initial conditions (regions of strong unpredictable internal variability) and thus a large ensemble size is required to efficiently sample the internal variability.

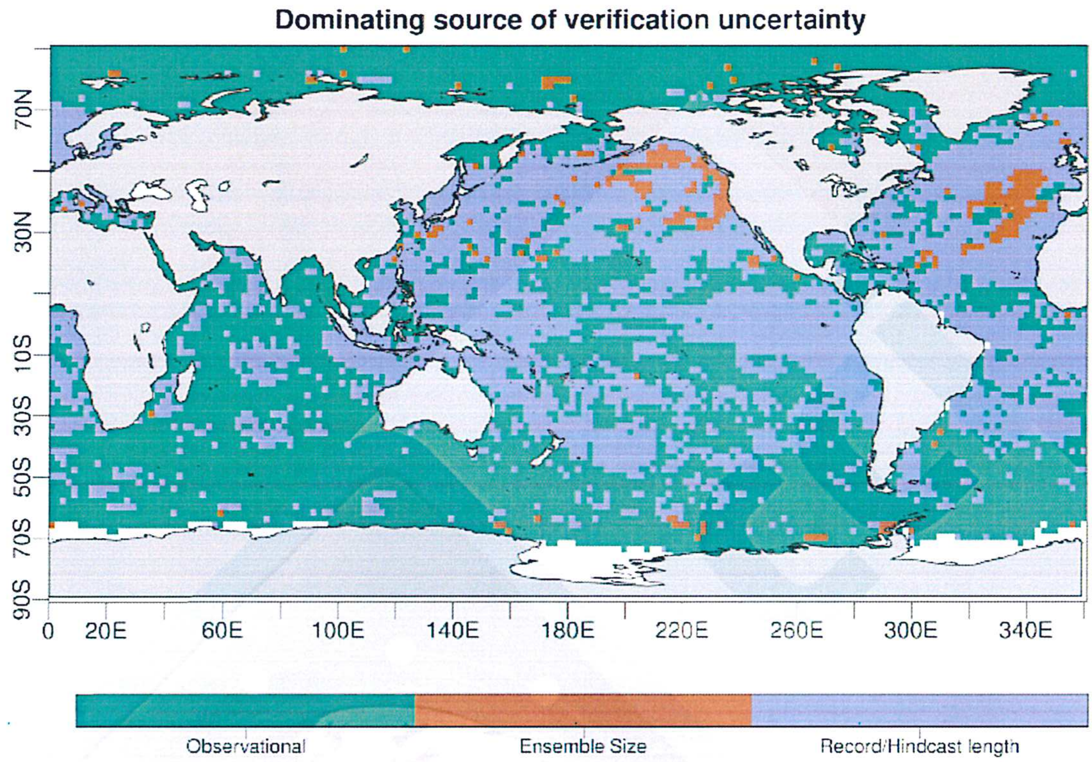


Figure 5: Dominant source of verification uncertainty when computing ensemble mean correlation skill for summer predictions of SSTs over each grid-point. The dominant source is determined by resampling different observational references (observational uncertainty), different retrospective predictions with replacement (hindcast length uncertainty) and different ensemble members with replacement (ensemble size uncertainty). The resampled component that induces the largest uncertainty in the correlation is shown in the map. This analysis is done using ECMWF S4 for the hindcast period 1981 - 2010.

3. Conclusions and Outlook

VERITAS-CCI contributed, in collaboration with other climate prediction research projects, to the amelioration of seasonal forecasting systems. The experiments carried out in VERITAS-CCI demonstrate that a significant amount of additional forecast skill can be obtained by initializing the land-surface and partly also sea-ice conditions, as well as by increasing the horizontal resolution of global climate models. These results will be fundamental in designing future operational systems and defining research themes for future research on seasonal forecasting. One lesson learnt is that while initializing the land-surface or sea-ice regionally increase the prediction skill, some regions sees a deterioration in prediction skill. This points toward remaining methodological challenges in the initialization of the model, uncertainties in the re-analysis products used to initialize the model, and also structural deficiencies of the model physics that drifts away from the initialization state.

A key contribution of the project has been the adoption of uncertain observations in the verification process of climate predictions or simulations in general. Observational uncertainty remains an aspect that is weakly acknowledged and VERITAS-CCI demonstrated some examples from seasonal forecasting that could be further explored in future research towards a joint uncertainty assessment of models and observations. However, bringing together model and observational uncertainties revealed many challenges that lie ahead. Many observational datasets do not provide uncertainty estimates and if they do, it remains unclear how these can be propagated to model scales. Further work is also required to establish how to use observational uncertainty estimates in verification metrics. Should the future rely on the provision of observational ensembles that facilitates these aspects? It is evident that a substantial amount of additional work is to be done in this area, work which is highly relevant for the provision of climate information as they are in preparation world-wide.

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Bellprat, O., Massonnet, F., Siegert, S., Prodhomme C., Macias-Gomez, D., Guemas, V., Doblas-Reyes, F. 2016: Exploring observational uncertainty for verification of climate predictions. *Remote Sensing of the Environment, CCI special issue*

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