Response to the comments of Reviewer 1, Reviewer 2 and the editor

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This document provides the detailed answers to the remarks and questions of the reviewers and the editor. The points of the Reviewer are italicized, and the (proposed) modifications in the text are in bold face. The pages and lines refer to the manuscript attached along with the response.

1 Reviewer 1

In this manuscript the authors investigate causal relationships, in monthly to inter-annual time scales, between the climate dynamics of three ocean-atmosphere basins (The North Atlantic, the North Pacific and the Tropical Pacific region) using three reanalyses datasets (ORA-20C, ORAS4 and ERA-20C). The applied methodology, Convergent Cross Mapping (CCM) has been applied to other systems, but has not yet been used (to the best of my knowledge) to investigate climate causal relationships. I found this study very interesting. As the authors acknowledge in the introduction, unveiling causal relations is a very challenging task, and different methods (also depending on the choice of variables), are likely to yield different results. Here the CCM method is well motivated and described, and also the datasets used for reconstructing three- dimensional attractors are well justified. The results obtained are sound. Therefore, I am happy to recommend the acceptance of this manuscript, after the authors have taken the following points.

We would like first to thank the reviewer for her/his positive support to this work. Below we answer her/his specific points.

1 By using three time series, the authors reconstruct three-dimensional attractors (instead of using one time series and Takens' delayed coordinates). Could the *authors discuss how important is the method used to reconstruct the attractor and the chosen attractor dimension? What could be expected if (i) two-dimensional attractors are reconstructed from two time series (instead of three, using, e.g., only the zonal velocity at either 200 or 500 hPa and the ocean temperature)? and (ii) three-dimensional attractors are reconstructed from one time series using Takens delayed coordinates?*

The motivation of this approach is to avoid the difficulties associated with the embedding and the delay. Now the choice of three variables for the Atlantic and Pacific is motivated by the results we have obtained in previous works on the low-dimensional modelling of the coupled ocean atmosphere system, in which we have found that these three variables dominates the dynamics (Vannitsem et al, 2015; Vannitsem, 2015). This 3D space constitutes a kind of projection of the full phase space. For the Tropical Pacific, the choice is motivated by the importance of the surface temperature and the zonal wind in the development of the coupled ocean-atmosphere dynamics. For the latter region we could indeed imagine to use only 2D maps.

(i) Using 2D maps, useful results can also be obtained. An example is given here for the influence of the Tropical time series on the North Atlantic in Figure 1. In the different results presented in this figure, the only influence which emerges is from the atmospheric Tropical observables to the 2D map defined by the Geopotential at 500 hPa and the Ocean Temperature. But the growth as a function of L is weaker than the one obtained when using the 3D map (Fig 3a of the manuscript). As mentioned by Sugihara et al (2012), the variation of ρ with L is faster before saturation when the strenght of coupling is higher. Here the coupling between the variables when a 2D map is used seems to be less important than when using the three variables, suggesting that the Tropical Pacific atmosphere indeed influence the coupled ocean-atmosphere system as defined by the three observables. In other words, the latter result suggests that the dependences between these regions is better elucidated based on the three dimensional space. Care should however be taken here drawing definitive conclusions on this comparison since the setup of the analysis has considerably changed with a change of phase space dimensionality and a reduction of the number of analogs used (only three in this case).

In the text, we add at page 11, line 19:
Note that the reduction of the state space coordinates associated with $\vec{X}$ from three to two also provides interesting results with a dominating influence from the atmospheric Tropical Pacific variables on the two-dimensional projection ($NA_{\Psi_{a,1}}, NA_{\theta_{o,2}}$). However the increase before saturation of $\rho(L)$ is much more limited than when using the three variables to build the North Atlantic projection of the attractor (not shown). The latter result suggests that the dependences between these regions is better elucidated based on the three dimensional space.

(ii) When building attractors using the Takens' theorem, one needs to define an embedding dimension and a delay τ. Estimating the embedding dimension based for instance on the estimates of the correlation dimension of the attractor is very challenging when the expected embedding dimension is high since the approach needs to select close analogs to work properly (e.g. Kantz and Schreiber, 1995).

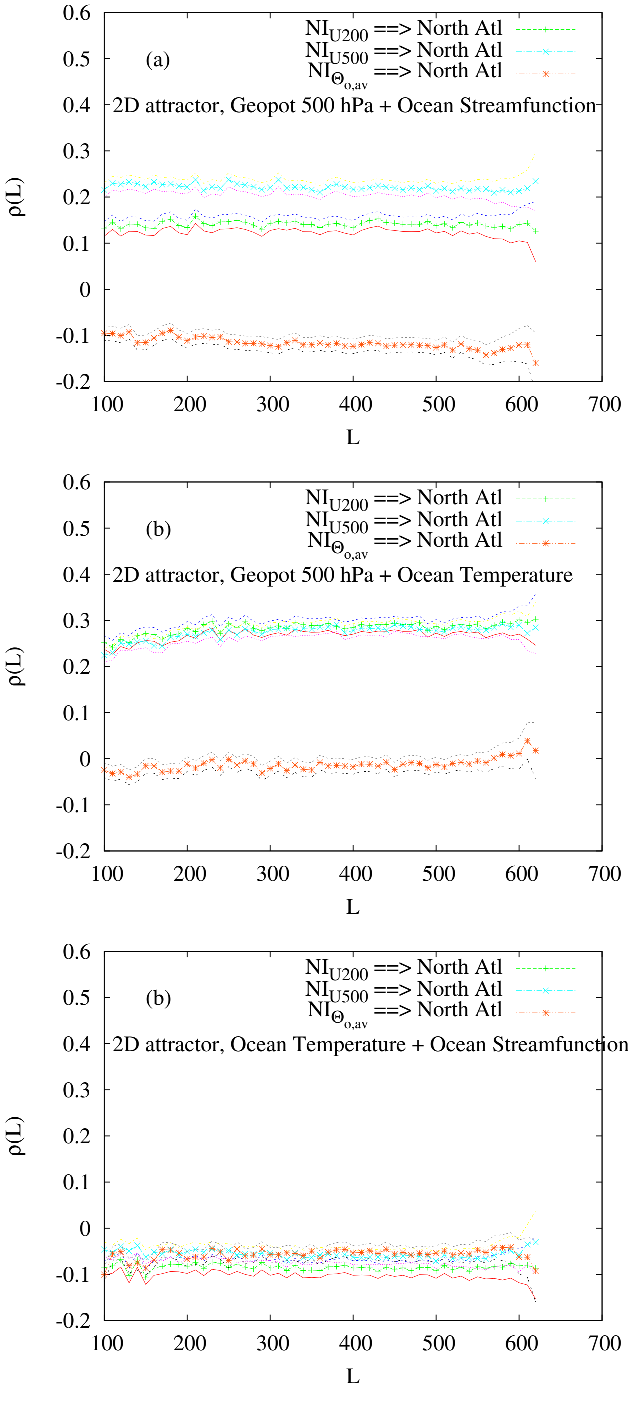

Figure 1: Example of CCM as a function of the length L of the samples, as obtained from the 2D maps for the reanalyses ERA-20C and ORA-20C. The influence investigated here is the one from the Tropical Pacific on the North Atlantic. Each line with symbols corresponds to the influence of one variable on a specific coupled ocean-atmosphere basin. The specific variables are denoted in the caption corresponding to each line in each Panel. The 2D maps used are (a) Geopotential at 500 hPa + Ocean Streamfunction, (b) the Geopotential at 500 hPa + Ocean Temperature and (c) the Ocean Temperature + Ocean Streamfunction.

It therefore needs very long time series that are usually not affordable (Van den Dool, 1994, Nicolis, 1998). So a way to overcome this problem is to increase progressively the embedding dimension and see whether the results are robust or not. For the delay τ, one usually uses a time period for which successive situations become sufficiently decorrelated, but not too much. Different methods are usually proposed to evaluate this delay, for instance based on decorrelation times, or simply by trial and error (e.g. Casdagli, 1991; Parker and Chua, 1989). In the present cases these delays should be relatively short for the atmosphere, but much longer for the ocean as it can be guessed by inspecting the time series of the right panels of Figures 1 and 2 of the manuscript. For the latter we are therefore facing an important problem since the decorrelation time (or delay) is not substantially smaller than the length of the time series. In the present context, we therefore opt for another approach based on selecting a subset of variables, a projection on a low-dimensional space.

We have modified the text after line 14 at page 5 to clarify point (ii):
Estimating the embedding dimension based for instance on the estimates of the correlation dimension is very challenging when the expected dimension is high since the approach needs to select close analogs to work properly (e.g. Kantz and Schreiber, 1995). It therefore needs very long time series that are usually not affordable (Van den Dool, 1994, Nicolis, 1998). So a way to overcome this problem is to increase progressively the embedding dimension and see whether the results are robust or not. For the delay τ, one usually uses a time period for which successive situations become sufficiently decorrelated, but not too much. Different methods are usually proposed to evaluate this delay, for instance based on decorrelation times, or simply by trial and error (e.g. Casdagli, 1991; Parker and Chua, 1989). In the present cases these delays should be relatively short for the atmosphere, but much longer for the ocean as it can be guessed by inspecting the time series of the right panels of Figures 1 and 2. For the latter we are therefore facing an important problem since the decorrelation time (or delay) is not substantially smaller than the length of the time series.

We also added a sentence explaining what information can be extracted from the growth of $\rho(L)$ at page 5, line 3.
Another important behavior of $\rho(L)$ as a function of L is that the rate of increase is related with the strength of coupling.

2) The authors state that "If there is a causality relation of Y on X, "ro" (Eq. 3) will increase with L". However, what this study uses (and I am not sure is always true) is the fact that "an increase of "ro" with L reveals/uncovers a causal relation of Y on X". Could the authors discuss the limits of validity of these two statements? I assume they hold if "L" is appropriated (not too small, and not too close to the length of the dataset). How about if X and Y are both driven by Z?

This point is one key element of the method. The main hypothesis behind these statements is that when extra information (larger L) is present, then one should expect to get better analogs around X and therefore to get better knowledge on the correct value of Y. This has been amply demonstrated on different simple systems by Sugihara et al (2012), and also by other authors. Note also that in an ideal context where the attractor can be reconstructed with precision and for L going to infinity, the correlation should converge to 1. In practical situations, this precision and the asymptotic limit are never reached. The convergence is then limited to a certain level by the presence of observational error, the approximation of the dynamics (like when a low-dimensional approximation is made of the full system) and the length of the series, L.

When a common driver Z is at play on X and Y, and that X and Y are independent, then the correlation between Y and $\hat{Y}$ is positive but it does not depend on the data set length L. So a constant value as a function of L is expected. This has also been shown in Sugihara et al (2012). So we added at line 6, page 5:

For instance, if a confounding factor Z affects both $\vec{X}$ and Y (that are otherwise independent of each other), they will contain a similar information, and the inference of $\hat{Y}$ based on $\vec{X}$ will display a correlation with Y, but which is independent of L (Sugihara et al, 2012).

To explain the behavior as a function of L, we also add at page 5, line 9:

Note also that in an ideal context where the attractor can be reconstructed with precision and for L going to infinity, the correlation should converge to 1. In practical situations, this precision and the asymptotic limit are never reached. The convergence is then limited to a certain level by the presence of observational error, the approximation of the dynamics (like when a low-dimensional approximation is made of the full system) and the length of the series, L.

Minor comments are

3) In the Introduction, the authors say "an important question nowadays is to know whether the Tropical Pacific system forces the dynamics of the climate system in the extratropics". In my view there is plenty of evidence (it is well known) that the Tropical Pacific system forces the dynamics of the climate system in the extratropics, and therefore, I suggest the authors to re-word this sentence.

Right. We reformulate the sentence as follows (page 2, line 4):

In particular, an important question that has attracted a lot of attention in the past decades is to know whether the Tropical Pacific system *forces* the dynamics of the climate system in the extratropics.

4) Regarding the link between galactic cosmic rays and global temperature variations, there is a discussion (Questionable dynamical evidence for causality between galactic cosmic rays and interannual variation in global temperature, doi: 10.1073/pnas.1510571112 and the reply, DOI: 10.1073/pnas.1511080112) that the authors, in my view, should also cite.

Thank you very much for these interesting references. These are incorporated in the new version of the manuscript.

5) Table 1 would be easier to read if there is a space between the numbers (i.e., instead of x—y, x — y), also the letters in the figures are too small.

Thank you very much for the suggestion. We did it.

2 Reviewer 2

1. There is a quickly growing literature on causal inference methods based in information theory. The authors provide one sentence on page 2 lines 21-23 on it, saying something like "finding a good estimator for analyzing real data is difficult". I have no idea what this is about, and see no reason why the information theoretic methods could not be used here, even with the time series used in this paper. Please provide a proper argument on why these methods cannot be used, and why the proposed CCm method is better/more suitable. My fear is there is no such argument.

One of the present authors used a technique developed by Liang (2014) to compute the dependences based on information flow. This technique has been built assuming that the system is linear, and Liang (2014) found experimentaly that this approach could work for nonlinear systems as well. The estimator in this case is a combination of correlations and derivatives of correlations. This approach has been extended by introducing a normalization (Liang, 2015). One problem pointed out by the Liang (2014) is the fact that several choices can be made for the discretization of the derivative. Another aspect is that one cannot have dependences without correlation. The latter situation seems surprising since some systems (like the one pointed out by the reviewer in his/her remark 6) can display dependences without correlation. In view of these difficulties, we decided to postpone the investigation based on these approaches to a future work.

We understand that our comment in the mansucript is not based on sufficiently firm grounds, so we modified it in the following way (page 2, line 28):
Alternative approaches based on the transfer of information are very appealing and a lot of progresses have been made in that direction (Liang and Kleeman, 2005, Runge t al, 2012, Liang, 2014, Liang, 2015). We however do not pursue in that direction and let the use of these techniques for a follow-up study.

2. section 2: The authors talk about phase space while they mean state space. A phase space is a position-velocity space, which is of interest when describing the motion of particles, but not for fluid dynamics, which is governed by first-order time derivatives. Please correct.

Well the phase space is a terminology which is not only valid for position-velocity space. It is used in general to describe the abstract space spanned by the coordinates which are the variables of the dynamical system themselves, and it is used interchangeably with the other terminology of "state space". I refer to classical books like Nicolis (1995) or Broer and Takens (2011). We do not see why we have to change the terminology, but we modified it under the insistence of the Editor.

3. The distance measure is a crucial ingredient in CCM as far as I understand it, yet no discussion is provided. Saying that typically the Euclidian distance is used is not useful, more discussion is needed. This is related to the next point.

We have modified the sentence by expliciting the distance used. Other distances can be used. The text added at page 3, line 33:

$d_i = \sqrt{\sum_j (X_j(t) - X_{j,i}(t))^2}$ **where $X_j(t)$ and $X_{j,i}(t)$ are the (delay) coordinates of the reference point and the ith analog, respectively. Other distances could be used.**

4. The weights in eq 2 seem to be completely arbitrary. First I assume that the authors use something like $exp(-d_j/d_min)$, otherwise the whole procedure doesn't seem to make sense. But that might be just a typo. More importantly is why this is a good weighting, also relation to Euclidian distances. As far as I can see this is completely ad hoc. At least a justification for this choice of weights needs to be given. Furthermore, the question immediately arises how sensitive the results are to form of the weights. This is not discussed. Please do!

You are right. Thank you very much for pointing out that. Now the weight given in Eq 2 is modified.

The development of this type of nonlinear forecasting traces back to several seminal papers, see for instance (Casdagli, 1991, Elsner and Tsonis, 1992) for a detailed discussion. In its original version, more general weights w_i were proposed that should be fitted through a least square approach (Casdagli, 1991). Sugihara and May (1990) proposed to simplify the approach by using a simpler variant based on exponential functions depending on the distance between the analogs and the reference point. This weighting penalizes analogs that are far from the reference point, and the normalization by the minimum distance allows for having weights based only on the relative distance. This technique works well as discussed in Sugihara and May (1990). Moreover it does not need any additional parameter, implying that the approach is parcimonious.

We have added in the manuscript at page 4, line 11:

The development of this type of nonlinear forecasting traces back to several seminal papers, see for instance Casdagli (1991) and Elsner and Tsonis (1992) for a detailed discussion. In their original versions, more general weights w_i were proposed that should be fitted through a least square approach (Casdagli, 1991). Sugihara and May (1990) proposed to simplify the approach by using a simpler variant based on exponential functions depending on the distance between the analogs and the reference point. This weighting penalizes analogs that are far from the reference point, and the normalization by the minimum distance allows for having weights based only on the relative distance. This technique works well as discussed in Sugihara and May (1990). Moreover it does not need any additional parameter, implying that the approach is parcimonious.

5. The prediction defined by eq 1 depends on which analogs have been used, so on the prior sample. How large is the sensitivity of the results to that?

This is true, and in order to evaluate the uncertainty associated with the choice of the sample L, we have performed a large number of other random sampling and provide the mean value and a standard deviation as a measure of uncertainty. We added a paragraph on that at the end of Section 2 (page 6, line 9):

Note that in order to evaluate the impact of the random sampling of L events in the datasets, we can repeat the sampling a certain number

of times and infer a mean (or a median when strong assymetries are present) and a standard deviation. In the experiments that will be described below, this approach is adopted and each correlation value is estimated over a large number of samples.

6. The CCM methods starts out strong with the embedding, but then falls back to correlations, with all weaknesses that the paper wants to avoid in the first place. For instance, if X(t) = sin(omega t) and y(t) = X(t - pi/(2 omega)) the relation between X and Y is circular, so the correlation in eq 3 is zero. This, however, would negate the existence of a very strong causal relation.

It seems that the reviewer is confusing the correlation between X and Y, and the correlation between $\hat{Y}$ and Y, where $\hat{Y}$ is the estimate based on the X attractor. This correlation is a measure of the quality of inference which has been used for a long time now, and which is still used to evaluate weather forecasts. This measure is related to the error between the inferred situation and the observed one.

Coming back to the example given by the reviewer, what is matter is the inference $\hat{Y}$ based on X and what we get with this circular solution is a correlation between $\hat{Y}$ and Y very close to 1 (and not equal to 0). So a kind of perfect inference. Now there is no increase as a function of L due to the fact the same source of information is present in both, the signal X.

7. As far as I can see, if the causal relation between X and Y peaks strongly at say 2 tau adding more elements in X will not increase the correlation, it might even make the correlation smaller. But the authors say differently in e.g. p4 lines 19-25. Please clarify.

Well it seems that the reviewer is confusing the approach based on delay embedding and the approach adopted here in which contemporary data are used. We add the term **contemporary** in the description of the approach at page 5, line 24.

8. section 3. The authors assume that the main ocean dynamics is governed by Sverdrup balance in mid latitudes. This might be true for the large-scale dynamics, but is not so for scales smaller than a few 100 km. Are the main conclusions of the paper justified when all dynamics of the ocean beyond Sverdrup are ignored? For instance, isn't is essential for the North Atlantic circulation and the interaction with the atmosphere, e.g. via the storm tracks, that the GulfStream extension is not zonal? I think the authors should at least justify much more strongly why they think they can use this simple mode structure to project the reanalyses data sets on.

Thank you very much for the comment. Indeed the projection used here is meant to investigate the large scale dynamics and the link between the different ocean basins. There is by no means any aim at providing or using information at smaller scales. We add a paragraph on that (page 7, line 13),

This approach of reducing the dynamics of the ocean and the atmosphere to a few spectral large-scale components may at first sight look arbitrary. However for the two midlatitudes basins these modes possess the largest amplitudes (Vannitsem and Ghil, 2017), and for the Tropical Pacific, it is known that these large scale flows are strongly affected by

the interaction between the ocean and the atmosphere. Moreover we are interested in the basin scale interaction between midlatitudes and the tropics. If such an interaction exists, we expect that these should be visible through the analysis of these large-scale fields. It is clear that these specific variables do not represent the full dynamics, and additional analyses with more modes is worthwile, in particular to see what is the role of the main currents present in the ocean like the Gulf Stream or the Kuroshio current.

9. The authors use the monthly fields for the analysis. Are these snapshots or monthly averages?

Yes it is monthly averages. We have clarified that at line 9, page 8, and in the caption of Figure 1.

10. What was dmin for each time series?

The value of d_{min} changes for each reference point (on the attractor projection) in the sample of size L, since it is the minimum distance among the analogs around the reference point. And of course it also changes with the sample chosen. There is no specific value of d_{min} for a series. To clarify that, we have modified the description at line 10 of page 4 as

The quantity $\min d_j$ denotes the minimum of d_j of the $j = 1, .., E+1$ analogs around the reference point $\vec{X}(t)$.

11. The authors calculate a CI, and there is a growing tendency in the science community to eradicate its use because of its arbitrariness, among other problems. Can the authors instead provide error estimates on their results?

This is what we have done by randomly selecting new samples of L events a certain number of time and applying the CCM algorithm again. This provides an error estimate of the possible values of $\rho(L)$. We translated that in a CI using the mean and the standard deviation. This is now explained at the end of section 2 (page 6, line 9):

Note that in order to evaluate the impact of the random sampling of L events in the datasets, we can repeat the sampling a certain number of times and infer a mean (or a median when strong assymetries are present) and a standard deviation (here using the Fisher Z test). In the experiments that will be described below, this approach is adopted and each correlation value is estimated over a large number of samples. The algorithm is sketched in Appendix A.

12. It is important that the analogs are independent from each other. How did the authors ensure that? Please at least discuss this.

We tested different period of exclusions when selecting the analogs. We chose 48, 24 and 12 months. Since there were no substantial differences in the results, we decided to keep a minimum of 12 months between analogs. A sentence has been added at page 11, line 8:

Note also that for this analysis, the analogs have been selected to be at least separated by a period of 12 months. Longer exclusion periods have been used without substantial differences.

13. Please make the legends of all figures larger, and the error estimate lines thicker.

We have increased the size of the legends.

14. Fig 3 (c) and (e) should be interchanged(?)

Thank you very much for pointing out this. No but the text should be corrected. We have done that at the beginning of page 13.

15. What happens for low time lags in fig 4f?

We have now represented the full curves.

16. Please describe the distribution of the random anomalies in page 13 line 15.

These random anomalies were simulated assuming a gaussian distribution around each monthly mean. The variance of the distribution is estimated from the anomalies of the corresponding month for all years in the datasets. the information has been incorporated at page 13, line 35:

These random anomalies were simulated assuming a gaussian distribution around each monthly mean. The variance of the distribution is estimated using the anomalies of the corresponding month for all years in the datasets.

17. page 13 lines 18-24. I don't necessarily agree with the authors' conclusion on the fact that the annual surrogates give the same correlations as the full time series. This does not mean that there is no underlying dynamical causal structure, only that the annual signal is dominant. One has to be careful, as the annual signal is very, very strong. While the authors argue that they don't want to try to remove the annual signal from the time series because of the issues with doing that, perhaps they have to do it this time, e.g. by using different methods and compare results.

Thank you very much for this interesting point. We have analyzed using the CCM the monthly anomalies discussed above. The results are displayed in Figs. 2 and 3. These results confirm what was said when analyzing the surrogates.

One very interesting result (corroborating what we said when looking at the surrogates) is the fact that there is no influence between the anomalies over the Tropical Pacific and the North Atlantic for both reanalysis datasets. See panels (a) and (c) of each figure.

These results are now incoporated in the text as follows.

In section 4.1, at page 15, line 17:

Finally to further test the robustness of these results a complementary way to clarify whether montlhy anomalies between different basins are indeed related to each other is to apply direcly CCM on these anomalies. The results are displayed in the Appendix C, Fig. C1. The same conclusions are reached with the absence of dependences between the variables over the North Atlantic basin and the Tropical Pacific,

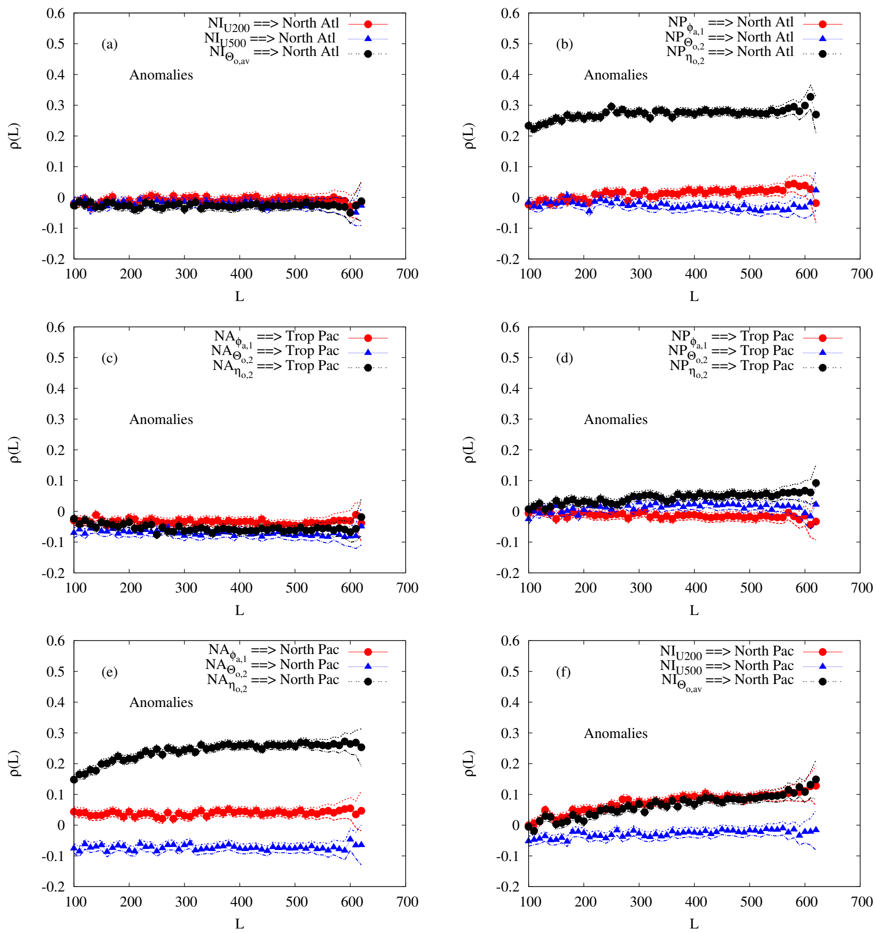

Figure 2: CCM as a function of the length L of the samples, as obtained from the anomaly of the monthly time series displayed in Fig. 1 for the reanalyses ERA-20C and ORA-20C. Each line with symbols corresponds to the influence of one variable on a specific coupled ocean-atmosphere basin. The specific variables are denoted in the labeling of each line in each Panel.

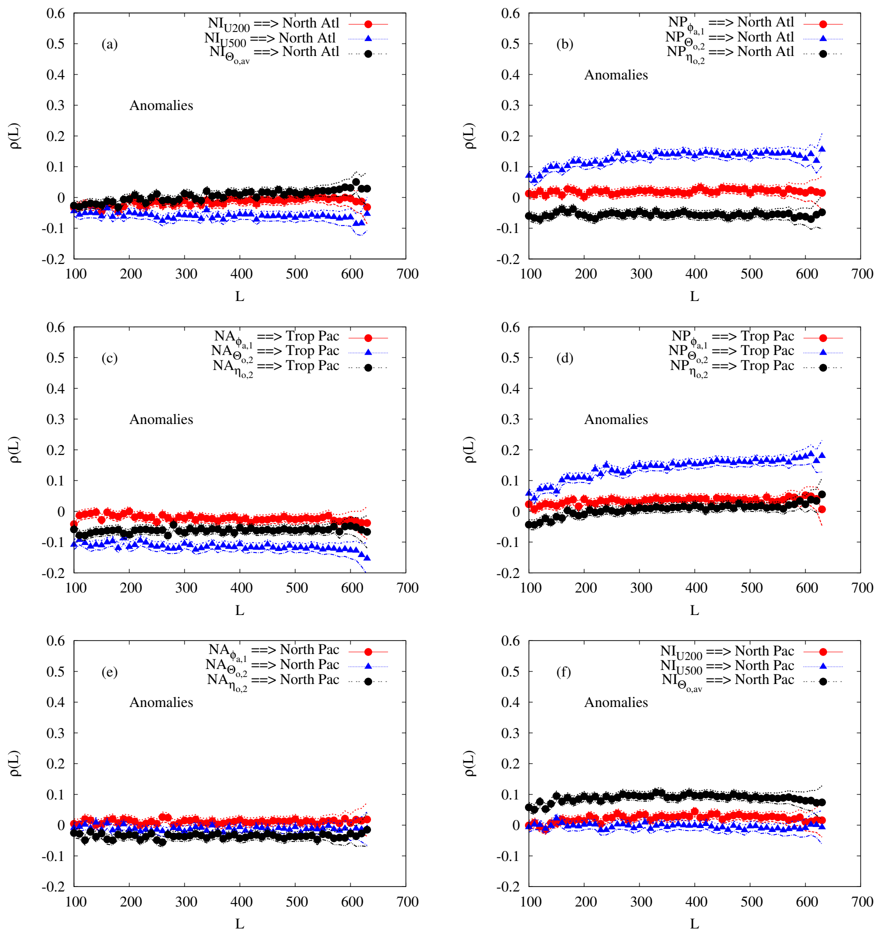

Figure 3: CCM as a function of the length L of the samples, as obtained from the anomaly of the monthly time series displayed in Fig. 2 for the reanalyses ERA-20C and ORAS4. Each line with symbols corresponds to the influence of one variable on a specific coupled ocean-atmosphere basin. The specific variables are denoted in the labeling of each line in each Panel.

and a strong mutual dependence between the ocean dynamics over the North Atlantic and the North Pacific.

And in section 4.2, at page 17, line 18:

Finally for the sake of completeness, the application of the CCM to the monthly anomalies is displayed in Fig. C2. Here as for the ERA-20C/ORA-20C dataset, no link between the anomalies of the Tropical Pacific and the North Atlantic is found (panels (a) and (c)). An important difference is however visible on the influence of the North Pacific ocean temperature on the North Atlantic and on the Tropical Pacific (panels (b) and (d)). Again, this contrasts with the results obtained with the other reanalysis dataset.

18. section 4.2. I'm not sure one can say that ORA-20C is more reliable than ORAS4. I understand from their description that both do not assimilate ocean variables, they only differ in their atmospheric forces. But the ocean circulation is not only determined by the surface forcing, but also, and perhaps to a much larger extend, on the initial condition and on model biases. How do the initial conditions differ between the two ocean products, and assuming they are both initialised from a smoothed observational data set of T and S observations, could it be the case that the ORA-20C run has a less realistic ocean vertical structure because ocean model biases have degraded that longer compared to ORAS4?

This paragraph has been modified (page 17, line 10) as,

We may conjecture that the ORA-20C reanalysis data set is more reliable since a more consistent atmospheric forcing has been applied and the ocean model has gotten more time to equilibrate around its climate. But care should be taken here is drawing definitive conclusions on that. A better approach to disentangle which of these reanalyses provide the correct answer is to investigate a full coupled ocean-atmosphere reanalysis obtained for the whole 20th Century.

19. The conclusions are too strong given the CCM method used, the high simplification of the Earth system dynamics to a few in my view quite unrealistic modes, apart from the other potential problems mentioned above. The first conclusion especially, see point 17 above, but also the 4th conclusion. The authors seem to miss the possibility that the atmospheric forcing needs some time to give visible changes in the ocean, e.g. the gyre circulation needs a few years to adapt to a change in the wind stress. It is not necessarily ocean only dynamics that sets time scales of over a year.

The conclusions have been amended. First a new item is introduced mentioning the different results for the coupling between the North Pacific and the other basins obtained with the two different ocean reanalyses (page 20, line 8),

The results presented here for the two ocean reanalysis datasets disagree on the nature of the dependence between the North Pacific basin and the other ones. The ORA-20C indicates a dynamical influence (transport), while the ORAS4 suggests more an influence dominated by the ocean temperature. This difference is probably related to the specific data assimilation setup used in each case. To clarify what is really at work here new reanalysis datasets are needed. We can conjecture that the most reliable one should be built by using a coupled

ocean-atmosphere data assimilation system running continuously on the longest period possible.

and also the last item has been modified as follows,

The inter-dependences between the North Atlantic and the North Pacific on longer time scales than a year seems to be important, and is probably related to the coupled ocean-atmosphere dynamics on long time scales. One could conjecture that the thermohaline circulation should play a role on this link. Additional analyses with longer data sets, with climate model runs, but also with the analysis of additional basins like the Tropical Atlantic or the Indian Monsoon region are necessary to clarify this role.

20. The fact that the CCM method is useful for the simplified model in the appendix does not provide a trong argument that it will work for the real ocean as the simplified model does indeed only have a few modes, while the real Earth system has many, with interactions that are much more complicated and more nonlinear. Please provide a stronger justification on why this experiment backs up the analysis on the far more complicated real system.

Well if it does not work in such a case then there is no reason to think that it will work on real data. This is why we did it, to get some confidence in the method. Now the application to more sophisticated systems is planned and we add a comment on that at page 6, line 4:

It provides some confidence in the CCM algorithm, but we should keep in mind that the system explored in Appendix B is relatively simple and the application of CCM on more sophisticated climate models is worth performing. This is left for a future study whose results will be compared with the ones of the present analysis.

3 Editor's comments

We thank the editor for his general comments that are italicised in the following. The modifications in the text are in blue in the attached manuscript.

1. Motivation and Scope

The manuscript Causal dependences between the coupled ocean-atmosphere dynamics over the Tropical Pacific, the North Pacific and the North Atlantic definitely addresses a pertinent problem of interest to Earth System Dynamics, and it does so with a technical treatment grounded on Applied Mathematics. Therefore, the rationale behind the contribution falls within the scope of the journal.

However, it should be noted that the manuscript actually tackles a form of dynamic codependence, which is not necessarily equivalent to causal dependence, as shall be explained throughout this document.

As a general response, we would like to indicate that we do not want to address the complicated problem of tackling the notion of "causality" in all its richness. Rather we adopt a dynamical system approach in which causality has a very precise meaning (see beginning of section 2). This working definition allows to get clear information on the link between variables (or observables), following the works done in the past on that topic, starting from the seminal work of Granger (e.g.

see his Nobel lecture or his seminal paper of 1969). And we believe that we do not have to modify the terminology in the present analysis of causality since there will be a very important risk to make the reader very much confused on the relation of the present work to the past ones.

Discussing the different notions of causality is certainly very interesting from a philosophical and epistemological point of view but is much beyond the scope of the present investigation. We address below all the specific points raised by the editor.

2. Methodological Core

The literature statement that observables are causally connected if belonging to the same dynamical sys- tem is devoid of physical grounds. A straightforward counter-example stems from fundamental Physics: in Hamiltonian systems there is no causal connection between the intervening variables, notwithstanding their membership to the same dynamical system.

The shared membership is solely a proof that the observables have a dynamic codependence, connected through the kinematic-geometry of the dynamical system. Any statements about causality are simply working assumptions guiding the scientific endeavour to formulate informed hypothesis about the system. This being said, the authors have made efforts to avoid the temptation to assign cause-effect relationships between variables belonging to the same dynamical system, i.e. to the same deterministic prescription of their time variation and state-geometric dependence. Rather, the authors address codependence, a legitimate concept when discussing Dynamical Systems, and which entails kinematic-geometric mutual information rather than causality.

In fact, the dependence is aptly described as being bilateral and fundamentally cross-inferential, in that knowledge gathered from one observable provides information about others living in the same system. Naturally, this is essentially the case for fully coupled dynamical systems where all variables are actually connected. However, not all dynamical systems are coupled, for which reason the readers should be further cautioned about the detailed assumptions of the methodological construct. A very good service was already done regarding the distinction between unforced and forced systems, so the authors shall easily complement their exposition with the aforementioned aspects.

The causal dependence which is discussed in the present manuscript is clearly stated at the beginning of section 2. Causal dependence is present provided that the variables share a common attractor manifold and reflects links between variables. This is fully in line with the typical definition one can find in common dictionaries.

We do not see to what the editor is referring to when mentioning the notion of 'causality', and which is probably related to another definition of causality (concept not explained by the editor). In all the papers on the development of CCM, the "co-dependence" (to use the words of the editor) is referred to as "causality" or "causation". See Sugihara et al (2012), Tsonis et al (2015)... If in the present manuscript we change the wording by using "codependence" it is even more confusing than using the concept of causality introduced previously in the literature, starting from the work of Granger (1969). Even if the words could be confusing, we build on past works, and clarifying that wording would need a deep work to understand what is "true causation" and in what context.

3. Dynamic Dependence vs. Causality

This being said, there is a significant risk that the readership will confuse the undeniable inferential power of dynamical system approaches with the concept of causality. For that reason, any statements about observables influencing each other should be avoided unless based on the authors physical interpretation of the specific systems being discussed from their background knowledge.

Providing information about (i.e. being a predictor of) something entails inferential power that may or may not be accompanied by a cause-effect relation. The authors do a good service in staying within the inferential view by saying that codependent variables living in the same dynamical system provide information about each other.

Traditional Dynamical System frameworks provide invaluable services to describe system dynamics un- der very specific assumptions stemming from analytical mechanics and kinematic geometry. The readers should be reminded of those assumptions, so that it becomes clear that Dynamical System based diag- nostics are fundamentally motion-descriptive. In this sense, a dynamic coupling between observables is fundamentally a local kinematic-geometric correlation among contemporaries. Therefore, no causality can be inferred from such diagnostic.

Overall, a diagnostic of null dynamic dependence does not necessarily preclude the existence of causal dependence. Likewise, the detection of dynamic dependence does not necessarily prove the existence of causality in the system.

Focus should be given on whether this particular method has detected or not dynamic codependence among the study data, for the set of conditions under which the method holds, and for the data features that have been actually captured. The causality considerations then come from the authors physical interpretation of the mechanisms at play, as the geometry of the method per se is inherently non-causal.

Again the concept of causality used here is well stated at the beginning of section 2 (the two first paragraphs) and what is said by the editor is probably related to another concept of causality that we are not addressing here. See also the response to comments 1 and 2.

4. CCM vs. Alternative Methods

The CCM method falls into the usual paradigms of inference from shared information, akin to the rationale behind the classical Mutual Information diagnostics in Information Theory (IT). Mutual In- formation in IT, as CCM, assesses non-directional similarity among observables, yielding positive results when they share information in the multivariate space spun by their dynamics, with the fundamental difference that in IT the treatment is made in the probabilistic space rather than the state space. Therefore, both Mutual Information and CCM fall onto the same paradigm of cross-inference that quantifies the ability to provide information about one observable from another, but contain no proof of causal relation between them.

It might then be wondered whether popular measures of directional information (e.g. Conditional Mutual Information, Transfer Entropy, Bayesian Approaches) then provide causal information. Transfer Entropy is by the way the non-Gaussian generalisation of Granger Causality. However, notwithstanding their clear directional inferential power, these are not causal either, as predictors are not necessarily causes and the physics are entirely lost in the statistical constructs undergone in the aforementioned methods. Overall, while comparison with a vast diversity of other methodologies alleging causal inference would be interesting, in reality none of the many published alternatives provides satisfactory treatment of causality either, *so this remains fundamentally an open problem. In that sense, despite being clear that this study it investigating dynamic dependence rather than actual causality, it adds to the crucial debate on these problems and should therefore not be lightly dismissed.*

I do agree that the notion of causality is a complicate matter to define as already stated previously. We do not make any claim that we solved that problem, but rather we work with a very practical way to clarify interdependences, referred to as causality or causation, as mentioned at points 1, 2 and 3.

5. Correlation vs. Dynamic Relation in Estimation Quality Assessment

The authors aptly acknowledge the limitations of the classical state space reconstruction, and wisely look for a methodological improvement to implement in their analysis. The adaptations made to CCM are well motivated and enrich the scientific discourse about such procedures. However, it is not devoid of caveats that need to be taken into consideration. The evaluation of the similarity between actual and estimated value of a variable is done in a statistical correlation-based diagnostic that raises serious questions as to whether the quality of the estimation is being properly evaluated in that manner.

In fact, contrary to what the reader is led to believe from the manuscript (page 4), a high Pearson correlation between actual and estimated values does not necessarily prove that the estimation is good. Likewise, a low (or even null) correlation is not indicative of fundamental dissimilarity between observa- tion and estimation. These caveats stem from that correlation measure being limited in its adequacy to linearly related, normally distributed data, being assessed for statistically aggregate relationships. In other words, statistical metrics such as Pearson Correlation do not provide the dynamical relation between variables mentioned in the manuscript (page 4). Rather, they provide a first-order linear sta- tistical relation between them, aggregated over the domain where the statistic has been drawn.

Well I disagree with this view. The correlation is very often used in evaluating forecasts at all lead times in order to check their skill. In fact this correlation is another way to evaluate the mean square error as the following relation holds in general

$$\rho(\hat{Y}, Y) = 1 - \frac{< (\hat{Y} - Y)^2 >}{2}$$

assuming that the variables are centered and standardized as it is the case here. So there is one-to-one correspondence between the two. So a high correlation is associated with a low value of the mean square error and vice versa. So it is a clear indication of the quality of an inference or a forecast.

Other scores could be used but the most natural ones are the mean square error or the Pearson correlation.

6. Prediction vs. Estimation

The methodology takes aim at analogs found around one variable X(t) to recover the value of another variable Y (t), contemporary to X(t) (page 4, second sentence). However, in the following sentence the authors mention prediction. Physically speaking, a prediction entails the estimation of a future state. Here, however, the reader is informed about an estimation of a contemporary variable, i.e. without lead time. Therefore, the action to predict should rather be phrased as to estimate.

OK. I do agree with this point. Historically, Granger (1969) was calling that predictions. We modify this terminology by "inference" or "estimate".

7. Metric for Analogs

According to page 3 (bottom), an Euclidean distance is mentioned for analog selection. In smooth flows living in symplectic manifolds that should work well, as there will be local homeomorphisms between the local attractor charts and an Euclidean tangent bundle. However, that is not necessarily the case for real-world applications where such smoothness no longer holds. Euclidean distances should thus be used only under thoroughly justified appropriate conditions.

Well in the (continuous) state space which is an Euclidean space, the analogs are in general selected based on a specific norm like the Euclidean distance, whatever the complicated manifold on which the system lives.

8. State vs. Phase Space

A State Space comprises the state variables participating in the system. A Phase Space comprises the state variables and the corresponding conjugated momenta. A system with N state variables has a N - dimensional state space, and a 2N -dimensional phase space. For instance, given a state space RN , the corresponding phase space is R2N = RN RN (which by the way is a symplectic manifold). Interchangeable use of state and phase space is thus prone to ambiguity and error: an unfortunate mis- take that has propagated across significant sectors of the scientific literature. With all due personal respect and consideration for illustrious past references from which we have learned so much, we must nevertheless exert objective criticism when something that they have written is unfortunately incorrect. Published mistakes should in no way be deemed correct when these concepts are rigorously defined in Physics, where each has their unique meaning as explained in the previous paragraph.

Therefore, for the sake of clarity, physical rigour, and to avoid any ambiguity and further propagation of misinformation, the term Phase Space needs to be reserved solely to the space spun by the state variables and their conjugate momenta. The state spun by the state variables of the system will have to read State Space. Caution must also be exerted when treating the state space per se, as not all observables involved in the dynamics are actually state variables. For instance, fluxes are not state variables despite being ob- servable quantities. The bottom line is that the state space is not necessarily the space spun by all the observables, but rather solely by the actual state variables. Again here, fundamental Physics informs on which variables of a dynamical system are state variables and which ones are not.

We disagree with the editor on that point. Phase space is used in both cases as already pointed out to reviewer 2 and links to the specific references. We are really reluctant to change the wording on that but we feel forced to do so by the editor. So we change it without any enthusiasm because there is no ”error” behind that choice provided the meaning is clear. Moreover the distinction made by the editor disappears when considering the embedding theorem since it is shown that there is an equivalence between the ”state” space representation of the dynamics and its representation based on the successive derivatives of the trajectory (Broer and Takens, 2011).

9. Geophysical Case Study

The geophysical case study discussed in the manuscript is very interesting and ensures the goodness of fit within the scope of Earth System Dynamics. Notwithstanding the existence of prior studies discussing the absence of causal relationships *across oceanic basins, the present study has the merit to explore dynamic codependence with a methodology that, despite its caveats, still provides insightful food for thought and discussion. Whether or not dynamic codependence is detectable with the used method depends on both the specific abilities of the method and on the nature of the relations being diagnosed. For that reason, it is wise to refer to what exactly is being diagnosed and what is being eluded i.e. not assessed by the method. In this sense, the authors have already undergone significant revision efforts in their author responses to the referee comments. With further reflection and discussion, the case study can be further strengthened, for which reason I encourage the authors to further contextualise their findings in the light of ocean-atmospheric physics, the methodological construct and practical workflow, the details of which should be further discussed as well (see point 10 below).*

OK. We have made considerably efforts (as already recognized by the editor) in improving the "workflow" of the presentation of the technique (see also Appendix A). We have further clarified the information provided by the technique based on a more detailed analysis of the simple coupled ocean-atmosphere system presented in Appendix B:

At page 5, lines 31-37, we have added

One important result is the ability of the method to isolate dominant links between the projected attractor (the target of the analysis) and specific variables. The nature of a link can sometimes be directly related to terms present in the dynamical equations but not always due to the multivariate construction of the analogs on the projected attractor. Likewise the absence of relationship inferred from the CCM in the present framework does not imply that there could not be some dependences when other projections of the full state space are used. The conclusions reached are therefore dependent on the specific configuration used and other experimental designs are necessary to corroborate the conclusions. This is planned for a future investigation.

At page 20, lines 27-29, we have added,

Finally it should be stressed that the specific design of the CCM approach adopted here based on a low-dimensional projection of the full atmosphere-ocean attractor does not allow to have a one-to-one correspondence of the influence of one variable on another. Moreover other subspaces could be used that can provide different results. More variables should be considered such as projections on additional Fourier modes, or by using projections on a few Empirical Orthogonal Functions. These analyses will allow to evaluate the robustness of the present results.

At page 24 (appendix B), lines 5-10:

Note that the angle of approach adopted in Section 2 by considering a low-order projection of the full state space as target does not allow to have a detailed information on the nature of the coupling between the variables since what is inferred is a global influence of a variable on a subset of other variables. The analysis also opens new questions on the role of the different variables in this low-order model and the dependences on the specific subspace selected as the target. This problem is out of the scope of the present work but is worth pursuing in the future. We can now proceed with this approach in the context of the datasets

presented in Section 3.

The algorithm of the CCM is also provided in the new Appendix A.

10. Reproducibility

The reproducibility of the study depends on the readers ability to read in between the lines. However, that should not be the case: the workflow should be fully explicit, otherwise a significant segment of the readership will be alienated. While I was personally able to attest the reproducibility in my own terms, I am skeptical about whether the general readership will. In fact, a thoroughly detailed workflow is still largely missing in the manuscript. A thoroughly detailed workflow with crucial mathematical and algorithmic details will strongly improve the reproducibility and soundness of the manuscript. Only then will be the appealing narrative and results be properly assimilated, and the actual meaning of the diagnostics being undertaken will be properly understood by the readers.

We have addressed this by revisiting the results of Appendix B and giving some caution at the end of section 2 and in the conclusion as indicated at comment 9 of the editor.

A workflow is also provided in a new Appendix A.

11. Overall Decision

All in all, the manuscript addresses dynamic codependence on the basis of shared attractor membership, rather than causal dependence. For that reason, the title and body should be adjusted accordingly, in order to avoid misinterpretation.

We will not change the title and the text along these lines since it will introduce additional confusions as discussed at points 1, 2 and 3 above. We hope that the editor will understand our position on that matter.

We have considerably clarified the technique and its limitations as requested by the editor and Reviewer 2.

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Causal dependences between the coupled ocean-atmosphere dynamics over the Tropical Pacific, the North Pacific and the North Atlantic

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Abstract.

The causal dependences between the dynamics of three different coupled ocean-atmosphere basins, The North Atlantic, the North Pacific and the Tropical Pacific region, NINO3.4, have been explored using data from three reanalyses datasets, namely the ORA-20C, the ORAS4 and the ERA-20C. The approach is based on the Convergent Cross Mapping (CCM) developed by Sugihara et al (2012) that allows for evaluating the dependences between variables beyond the classical teleconnection patterns based on correlations.

The use of CCM on these data mostly reveals that (i) the Tropical Pacific (NINO3.4 region) only influences the dynamics of the North Atlantic region through its annual climatological cycle; (ii) the atmosphere over the North Pacific is dynamically forcing the North Atlantic on a monthly basis; (iii) on longer time scales (interannual), the dynamics of the North Pacific and the North Atlantic are influencing each other through the ocean dynamics, suggesting a connection through the thermohaline circulation.

These findings shed a new light on the coupling between these three different important regions of the globe. In particular they call for a deep reassessment of the way teleconnections are interpreted, and for a more rigorous way to evaluate causality and dependences between the different components of the climate system.

1 Introduction

In environmental sciences, statistical quantities are essential tools to characterize the properties of a system, the most familiar of which are the mean, the variance, and the correlation in space or time. Correlations are very often associated with the notion of *dependences* in climate sciences, assuming that a certain variable is influencing the one to which it is correlated. Although it is true when dealing with a Gaussian linear system, the picture becomes far more complicated when dealing with a nonlinear system. In particular for nonlinear deterministic dynamical systems, the correlation between variables is neither sufficient nor necessary for causation or dependence between these variables, e.g. (Granger , 1969, 2003; Sugihara et al , 2012).

Teleconnections in the form of correlations between distant points in space are used in climate sciences in order to evaluate the link of a dynamical process in some part of the world with a distant target. In particular, an important question that has attracted a lot of attention in the past decades is to know whether the Tropical Pacific system *forces* the dynamics of the climate system in the extratropics. In this context, important teleconnections are found between events like El-niño or La-niña and the temperature and precipitation patterns allover the World, e.g. (Fraedrich and Müller , 1992; Brönnimann , 2007; Lau , 2016). The origin of these teleconnections for the North Atlantic and North Pacific is currently explained through the concept of *atmospheric bridge* that allows for the transfer of information from one basin to another, e.g. (Sardeshmukh and Hoskins , 1988; Alexander et al , 2002; Yu and Lin , 2016; Lau , 2016). This explanation assumes that there is a causality principle leading to these teleconnections, mostly going from the Tropical Pacific to the remote regions. This view originating from teleconnection patterns should however be taken with care, since co-variability does not imply causation or inter-dependences as already mentioned above. Another possible explanation of these teleconnections is the influence of an external driver on both variables that are correlated, even if they are dynamically independent.

How can we then measure this dependence? Answering this question is difficult as discussed by Clive Granger in his Nobel lecture in 2003 (Granger , 2003). One way proposed by Granger (1969) is to use the information on the predictability of the system with or without the influence of the variable expected to be the *cause*. In this context two forecasting models should be developed one with and the other without the variable investigated as predictor (Mosedale et al., 2006; Mokhov et al , 2011; Tirabassi et al , 2015). A drawback of the approach is precisely the necessity to build such a forecasting model. Moreover as discussed in details in the supplementary material of Sugihara et al (2012), the approach can lead to ambiguous results when applied to nonlinear deterministic dynamical systems.

A powerful method has been recently proposed by Sugihara et al (2012), known as Convergent Cross Mapping (CCM), which is a method suitable for nonlinear deterministic dynamical systems as it is based on analogs of the current state. This method has also been tested with success when nonlinear dynamical systems are affected by noise (Mønster et al , 2017), and in coupled dynamical systems in order to identify the leading element of the coupling (BozorgMagham et al , 2015). It has also been recently used to disentangle the link between galactic cosmic rays and the variations of the global temperature (Tsonis et al , 2015; Luo et al , 2915; Ye et al , 2015) or between environmental drivers and influenza (Deyle et al , 2016). This is the method that will be used in the present study. Alternative approaches based on the transfer of information are very appealing and a lot of progress have been made in that direction (Liang and Kleeman , 2005; Runge et al , 2012; Liang , 2014, 2015). We however do not pursue in that direction and let the use of these techniques for a follow-up study.

In the present work, we address the question of causality dependence between the Tropical Pacific, the North Atlantic and the North Pacific coupled ocean-atmosphere dynamics at monthly to interannual time scales, in order to clarify the remote role of these different climate sub-systems on the others. This will be done by first constructing low-order systems based on projections on a few Fourier modes that are assumed to dominate the dynamics in each of the basins. This projection has already been applied successfully in the context of the analysis of the coupling between the ocean and the atmosphere over the

North Atlantic (Vannitsem and Ghil , 2017). Once these projections are identified, the time series associated with each of these modes can be analyzed using the CCM approach. The specific choice of regions and Fourier modes, although reasonable, is however a little arbitrary. The current analysis is therefore a proof-of-concept on investigating the question of causality in the Earth System dynamics using the CCM approach, keeping in mind that an extension of the analysis to other regions and state (or phase) space representations should be explored.

Section 2 will introduce the technique of Convergent Cross Mapping (CCM). In Section 3, the datasets and the projections used are described. The datasets are coming from reanalyses performed at the European Center for Medium Range Weather Forecasts (ECMWF). The results on the application of CCM on these data are then presented in Section 4. The main conclusions and future works are outlined in Section 5.

2 Convergent Cross Mapping (CCM)

In the present work as in Sugihara et al (2012), two variables recorded as a function of time, say $X(t)$ and $Y(t)$, are said causally linked if they are coming from the same dynamical system. In this case a two-way *dependence* relation is present between them and the information gathered from one of the variables should, in principle, provide information on the other one. This type of dependence should not be confused with the case where a dynamical system is forced by an external driver, in which case there is a one-way dependence from the driver to the dynamical system. Disentangling the nature of this coupling is crucial in science when one is interested in describing the dynamics of the system under investigation. This is particularly true when the system is very complicated, as the Earth System is.

Several approaches have been developed in the recent past that allow for analyzing the dependences between time series. Granger Causality (GC) analysis is a celebrated approach based on the evaluation of the predictability of a variable in the absence or the presence of an hypothetical driver (Granger , 1969). As indicated in Sugihara et al (2012), its application is restricted to separable systems for which the driver can be effectively removed. In nonlinear deterministic dynamical systems in which all the variables are interconnected, the GC approach does not provide the desired answer on the effective link between the variables, see the examples given in Sugihara et al (2012). These authors therefore propose to approach the problem of causality in systems governed by deterministic dynamical systems by considering that the variables are indeed sharing the same attractor and that these variables can therefore provide information on each other. In addition, if an external driver is forcing the dynamical system under interest, the knowledge on the dynamics of the system can provide information on the driver, but not the opposite.

The original method proposed by Sugihara et al (2012) is based on the Takens' reconstruction theorem: Given a time delay τ, an embedding dimension E of an Euclidean space and the time series of a variable X, a reconstructed attractor, M_x, can be built. Each variable of that state space corresponds to a given delay, and each point of the reconstructed attractor is obtained from the time series as follows $\boldsymbol{X}(t) = X(t), X(t-\tau), X(t-2\tau), ..., X(t-(E-1)\tau)$. For each state space point, $\boldsymbol{X}(t)$, of the reconstructed attractor, a set of close points are selected, called analogs, based on a distance, typically the Euclidean distance $d_i = \sqrt{\sum_j (X_j(t) - X_{j,i}(t))^2}$ where $X_j(t)$ and $X_{j,i}(t)$ are the (delay) coordinates of the reference point and the ith analog, respectively. Other distances could be used. Since these are close to $\boldsymbol{X}(t)$, they should share some dynamical properties that can be exploited to make predictions starting from the current situation at time t. This set of analogs can also be used to recover the value of another variable, say $Y(t)$, contemporary to $\boldsymbol{X}(t)$. The idea is to use the analogs found around $\boldsymbol{X}(t)$, to *predict* the expected variable $Y(t)$, denoted $\hat{Y}(t)$, as

$$\hat{Y}(t) = \sum_{i=1}^{E+1} Y_i \times w_i \tag{1}$$

using weights defined as,

$$w_i = \frac{\exp(-\frac{d_i}{\min d_j})}{\sum_i \exp(-\frac{d_i}{\min d_j})} \tag{2}$$

where the distances d_i are associated with the $E+1$ analogs obtained for the variable $\boldsymbol{X}$ (Tsonis et al , 2015), and Y_i are the values of Y contemporary to the ith analog on M_x. The number of analogs, $E+1$, is chosen such that one can form a simplex around the point $\boldsymbol{X}(t)$. The quantity $\min d_j$ denotes the minimum of d_j of the $j = 1, .., E+1$ analogs around the reference point $\boldsymbol{X}(t)$. The development of this type of nonlinear forecasting traces back to several seminal papers, see for instance Casdagli (1991); Elsner and Tsonis (1992) for a detailed discussion. In their original versions, more general weights w_i were proposed that should be fitted through a least square approach Casdagli (1991). Sugihara and May (1990) proposed to simplify the approach by using a simpler variant based on exponential functions depending on the distance between the analogs and the reference point. This weighting penalizes analogs that are far from the reference point, and the normalization by the minimum distance allows for having weights based only on the relative distance. This technique works well as discussed in Sugihara and May (1990). Moreover it does not need any additional parameter, implying that the approach is parcimonious.

The dynamical relation between the variables $\boldsymbol{X}$ and Y can then be studied by comparing the actual value $Y(t)$ to the inferred value $\hat{Y}(t)$ obtained using analogs of $\boldsymbol{X}(t)$ on the M_x attractor. Repeting this method starting from different times t, the correlation coefficient between $Y(t)$ and $\hat{Y}(t)$ can be computed:

$$\rho = \frac{cov(Y, \hat{Y})}{\sigma_Y \sigma_{\hat{Y}}} \tag{3}$$

where $cov(.,.)$ denotes the covariance between the variables $Y(t)$ and $\hat{Y}(t)$, and σ_Y and $\sigma_{\hat{Y}}$ are their standard deviations. The values of ρ are thus lying between -1 and 1, and is also known as the Pearson correlation coefficient. High values of ρ indicate that the estimation of Y is good. However, this correlation does not necessarily mean that there is causality, as already emphasized in the Introduction. For instance, there could be a confounding factor Z that influences both X and Y in the same manner. In that case, X and Y would behave similarly, and therefore, there will be a correlation between σ_Y and $\sigma_{\hat{Y}}$ (Sugihara et al , 2012).

To solve that problem, the method as described above can be repeated for increasing sizes L of the samples. For each sample of size L, an attractor is build, from which analogs can be isolated and the correlation coefficient can be computed. Note that different ways to build these L-size libraries were proposed without substantial differences (Ye et al , 2015). We therefore adopt this approach proposed in Tsonis et al (2015) by randomly selecting a set of L events. If Y influences $\boldsymbol{X}$, the effect of

Y will be present in the reconstructed attractor M_x. By increasing the length L, more information on the time series of $\boldsymbol{X}$ are gathered, and therefore the selection of the analogs on the attractor is better. If there is a causality relation of Y on $\boldsymbol{X}$, ρ will increase with L. Another important behavior of $\rho(L)$ as a function of L is that the rate of increase is related with the strength of coupling.

On the contrary, if there is no causality, the added information on the variable X will not give any information regarding Y, and the correlation coefficient will not increase with L. For instance, if a confounding factor Z affects both $\boldsymbol{X}$ and Y (that are otherwise dynamically independent of each other), they will contain a similar information, and the inference of $\hat{Y}$ based on $\boldsymbol{X}$ will display a correlation with Y which is independent of L (Sugihara et al , 2012). This provides a criterion on the role of a variable Y on $\boldsymbol{X}$. Note also that in an ideal context where the attractor can be reconstructed with precision and for L going to infinity, the correlation should converge to 1. In practical situations, this precision and the asymptotic limit are never reached. The convergence is then limited to a certain level by the presence of observational error, the approximation of the dynamics (like when a low-dimensional approximation is made of the full system) and the length of the series, L.

The CCM method requires the knowledge of the embedding dimension E and the time delay necessary for reconstructing the attractor M_x from the time series. Estimating the embedding dimension based for instance on the estimates of the correlation dimension of the attractor is very challenging when the expected embedding dimension is high since the approach needs to select close analogs to work properly (e.g. Kantz and Schreiber , 1995). It therefore needs very long time series that are usually not affordable (Van den Dool , 1994; Nicolis , 1998). So a way to overcome this problem is to increase progressively the embedding dimension and see whether the results are robust or not. For the delay τ, one usually uses a time period for which successive situations become sufficiently decorrelated, but not too much. Different methods are usually proposed to evaluate this delay, for instance based on decorrelation times, or simply by trial and error (e.g. Casdagli , 1991; Parker and Chua , 1989). In the present cases these delays should be relatively short for the atmosphere, but much longer for the ocean as it can be guessed by inspecting the time series of the right panels of Figures 1 and 2. For the latter we are therefore facing an important problem since the decorrelation time (or delay) is not substantially smaller than the length of the time series.

A practical alternative is to build an attractor from a set of contemporary variables that are relevant to the dynamics from an expert evaluation. In such a case a set of $E = N$ variables at the same time t are used as entries of $\boldsymbol{X}$ to represent the attractor (in fact a projection of the full attractor in a subspace of N variables), and the analogs around a specific state space point $\boldsymbol{X}(t)$ can then be found in the same way as above. These analogs can be used to define the weights (2) that are in turn used to predict $Y(t)$. The influence of Y on $\boldsymbol{X}$ can then be inferred by computing Eq (1). In order to see what is the impact of the modification of the approach it has been applied in the context of a well known system, a coupled ocean atmosphere model of 36 ordinary differential equations developed in Vannitsem (2015), for which some results have been reported in Appendix B. One important result is the ability of the method to isolate dominant links between the projected attractor (the target of the analysis) and specific variables. The nature of a link can sometimes be directly related to terms present in the dynamical equations but not always due to the multivariate construction of the analogs on the projected attractor. Likewise the absence of relationship inferred from the CCM in the present framework does not imply that there could not be some dependences when other projections of the full state space are used. The conclusions reached are therefore dependent on the specific configuration used and other experimental designs are necessary to corroborate the conclusions. This is planned for a future investigation.

Overall this analysis demonstrates that the approach should be able to isolate important dependences between variables. It provides some confidence in the CCM algorithm, but we should keep in mind that the system explored in Appendix B is relatively simple and the application of CCM on more sophisticated climate models is worth performing. This is left for a future study whose results will be compared with the ones of the present analysis. Note also that when the series are much shorter than discussed in Appendix B, correlation can also be negative indicating that the total length of the series has an important impact.

The CCM method with this modification will be applied on the data presented in the next Section. Note that in order to evaluate the impact of the random sampling of L events in the datasets, we can repeat the sampling a certain number of times and infer a mean (or a median when strong assymetries are present) and a standard deviation (here using the Fisher Z test). In the experiments that will be described below, this approach is adopted and each correlation value is estimated over a large number of samples. The algorithm is sketched in Appendix A.

3 Time series based on reanalysis datasets

The dynamics of the coupled ocean-atmosphere system has been recently investigated by adopting a novel approach which finds its roots in the low-order modelling of such dynamical systems (Vannitsem , 2015; Vannitsem et al , 2015). It consists at projecting key fields of the large-scale dynamics of the system on a few sets of modes that are dominating its dynamics. In Vannitsem and Ghil (2017), the coupling between the ocean and the atmosphere over the Atlantic has been investigated by projection the geopotential at 500 hPa on the mode $F_1 = \sqrt{2}\cos(\pi y/L_y)$, and the ocean potential temperature field at a certain depth (close to the surface) and the sea surface height on the mode $\phi_2 = 2\sin(\pi x/L_x)\sin(2\pi y/L_y)$. Note the sea surface height is a proxy for the upper-layer ocean streamfunction field. F_1 is one of the largest-scale Fourier modes of the atmospheric field that is confined in an x-periodic β-channel with free-slip boundary conditions in the y-direction, while Φ_2 is one of the dominant Fourier modes compatible with free-slip boundary conditions in a rectangular, $L_x \times L_y$ closed basin. The latter mode corresponds to the typical structure of a double gyre in such a closed ocean basin. We thus expect the projection of the geopotential on $F_1(x,y)$ to provide information on the intensity of the large-scale eastward zonal transport in the atmosphere, while the projection of the temperature and streamfunction field in the ocean on $\phi_2(x,y)$ will allow us to evaluate the strength of the dominant component of the meridional gradient of temperature and the intensity of the double-gyre dynamics in the ocean, respectively. The domain chosen in terms of the spherical coordinates is 55°W $\leq \lambda \leq$ 15°W, 25°N $\leq \phi \leq$ 60°N, with $(x = \lambda - \lambda_0, y = \phi - \phi_0)$; here $(\lambda_0 = 305°, \phi_0 = 25°)$ and $(L_x = 40°, L_y = 35°)$. Note that the domain used here is the same as in Vannitsem and Ghil (2017) but a typographical error on the domain of projection is reported in the supplementary material of Vannitsem and Ghil (2017). The time series obtained for the North Atlantic will be denoted $NA_{\Psi_{a,1}}, NA_{\theta_{o,2}}, NA_{\eta_{o,2}}$ for the projection the geopotential at 500 hPa on the mode F_1, the ocean potential temperature field at 5 meter deep and the sea surface height on the mode ϕ_2, respectively.

A similar approach can be performed for the North Pacific, except that the domain is now larger in the zonal direction. In this case the spherical-rectangle domain is (165°E–225°E, 25°N–60°N). The series obtained for this domain will be denoted $NP_{\Psi_{a,1}}, NP_{\theta_{o,2}}, NP_{\eta_{o,2}}$ as for the North Atlantic. Note that for both basins the projected time series contains the dominant part of the variability. It however does not preclude that other important processes are missing in the description here. Further analysis with more modes are certainly worth doing in the future.

For the Tropical Pacific one can wonder what kind of variables should be considered. First a dominant variable in the Tropical Pacific is the mean temperature of the upper ocean layer, known to be associated with the dynamics of El-Niño. It is also known that the Walker circulation is considerably affected by the upper layer ocean temperature, and vice versa (Philander , 1990). Let us therefore consider for now the mean ocean potential temperature in the NINO3.4 region, known to have strong correlation with the variability in the North Atlantic region (Brönnimann , 2007). For the characterization of the Walker circulation, the zonal wind at 500 hPa and 200 hPa over the same domain are chosen. They provide some information on the position and the strenght of the Walker circulation over the NINO3.4 region. The series obtained will be denoted as $NI_{U200}, NI_{U500}, NI_{\theta_{o,av}}$.

This approach of reducing the dynamics of the ocean and the atmosphere to a few spectral large-scale components may at first sight look arbitrary. However for the two midlatitudes basins these modes possess the largest amplitudes (Vannitsem and Ghil , 2017), and for the Tropical Pacific, it is known that these large scale flows are strongly affected by the interaction between the ocean and the atmosphere. Moreover we are interested in the basin scale interaction between midlatitudes and the tropics. If such an interaction exists, we expect that these should be visible through the analysis of these large-scale fields. It is clear that these specific variables do not represent the full dynamics, and additional analyses with more modes is worthwile, in particular to see what is the role of the main currents present in the ocean like the Gulf Stream or the Kuroshio current.

Three different reanalyses datasets from the European Center for Medium-Range Weather Forecasting (ECMWF) are used. The ERA-20C dataset provides a continuous reanalysis for the atmosphere of the 20th century which assimilates observations from surface pressure and surface marine winds only. It is produced using the IFS model cycle Cy38r1 and detailed information can be found on the website of the ECMWF at https://www.ecmwf.int/en/forecasts/datasets/reanalysis-datasets/era-20c, see also the report on the quality of this reanalysis dataset (Poli et al , 2015). It covers the period 1900-2010.

The second dataset is the Ocean reanalysis ORAS4 obtained using the NEMO model. The ocean model is forced by the heat, momentum and fresh water fluxes at the upper surface, and ocean observations. For the upper surface fluxes, the ERA40 reanalysis dataset is used from September 1957 to December 1988, then the ERA-Interim from January 1989 to December 2009. In 2010, these fluxes are provided by the ECMWF operational analyses. For the SST and ice products, ERA40 (until December 1981) and Reynolds dataset are used. Finally observational data within the ocean are the temperature and salinity profiles from September 1957 to December 2010, and the sea level anomalies from November 1992 onward. More information on the datasets used and the model configuration can be found at tps://www.ecmwf.int/en/research/climate-reanalysis/ocean-reanalysis, and more information on the quality of this product can be found in Balmaseda et al. (2013). The period covered by the dataset used in the present study is fixed from January 1958 to December 2010.

Finally, the third reanalysis dataset used is the ORA-20C which is a 10-member ensemble of ocean reanalysis covering the 20th century using atmospheric forcing from ERA-20C. This dataset is more homogeneous than the ORAS4 since the atmospheric forcing is consistent during the whole 20th century. As pointed out in de Boisséson and Balmaseda (2016), the uncertainty is large during the first part of the century before the assimilation process constrains all the members of the ensemble to a state more consistent with other reanalysis products. One can suspect this dataset to be better than the ORAS4 for the dynamics of the ocean during the second part of the century since the state of the ocean has gotten some time to adjust toward a representative climatology during the first half. We will therefore use data from January 1958 consistently with the ORAS4 dataset to December 2009, the final date of data availability at the time when the present work has been conducted.

So the atmospheric data from the ERA-20C that will be used in the present work will cover the same periods as the ones fixed for the ORAS4 and the ORA-20C, respectively. All data used are monthly values.

The different monthly-averaged time series obtained by projecting the fields on the 2 Fourier modes are grouped by zones, 3 for the North Atlantic (containing one series for the atmosphere and two series for the ocean), three for the North Pacific (as for the North Atlantic), and three for the Tropical Pacific (two series for the atmosphere and one series for the ocean). The nine time series based on the reanalyses ERA-20C and ORA-20C are displayed in Fig. 1 for the three regions. The three series in each zone will constitute a 3-dimensional projection of the local coupled ocean-atmosphere dynamics. The same projections but using the ERA-20C and the ORAS4 are displayed in Fig. 2.

Let us first briefly investigate the covariance structure of these time series. Table 1 displays the covariances between the different time series of Figs. 1 and 2, with on the left side of each column the covariances for the series of Fig. 1, while on the right side, the ones corresponding to series of Fig. 2. There are a few remarkable correlations. First the ones between the atmospheric fields $NA_{\Psi_{a,1}}$, NI_{U200}, NI_{U500} and $NP_{\Psi_{a,1}}$, suggesting that some key variables of the global dynamics have been selected. The ocean temperature modes, $NA_{\theta_{o,2}}$, $NP_{\theta_{o,2}}$ and $NI_{\theta o,av}$ are also highly correlated. Interestingly the $NP_{\Psi_{o,2}}$ is anti-correlated with $NI_{\theta o,av}$. Another remarkable result is that the transport in the North Pacific, $NP_{\Psi_{o,2}}$, is highly correlated with the transport in the North Atlantic, $NA_{\Psi_{o,2}}$, although different amplitudes are found for the two ocean reanalysis datasets. Some other correlations are much less robust when one looks at the two different ocean datasets, in particular associated with the transport and the ocean temperature over the North Atlantic (second and third column in Table 1). These differences should be associated with the different approaches to force the ocean model, and reflect important uncertainties in reconstructing the past evolution of the Earth System.

Table 1. Correlation coefficients between the different variables for the two reanalysis datasets. On the left: ORAS4, ERA-20C; and on the right: ORA-20C, ERA-20.

	$NA_{\Psi_{a,1}}$	$NA_{\theta_{o,2}}$	$NA_{\eta_{o,2}}$	NI_{U200}	NI_{U500}	$NI_{\theta o,av}$	$NP_{\Psi_{a,1}}$	$NP_{\theta_{o,2}}$	$NP_{\eta_{o,2}}$
$NA_{\Psi_{a,1}}$	1	0.22 ∣ 0.12	0.12 ∣ 0.05	0.45 ∣ 0.45	0.45 ∣ 0.46	−0.10 ∣ −0.15	0.41 ∣ 0.41	−0.18 ∣ −0.14	0.02 ∣ −0.03
$NA_{\theta_{o,2}}$	0.22 ∣ 0.12	1	0.52 ∣ 0.41	−0.06 ∣ −0.20	−0.03 ∣ −0.17	−0.13 ∣ −0.10	0.07 ∣ −0.05	0.39 ∣ 0.42	0.28 ∣ 0.29
$NA_{\eta_{o,2}}$	0.12 ∣ 0.05	0.52 ∣ 0.41	1	−0.17 ∣ −0.06	−0.19 ∣ −0.13	0.07 ∣ 0.06	−0.09 ∣ −0.01	0.07 ∣ 0.10	0.25 ∣ 0.55
NI_{U200}	0.45 ∣ 0.45	−0.06 ∣ −0.20	−0.17 ∣ −0.06	1	0.82 ∣ 0.83	−0.48 ∣ −0.58	0.49 ∣ 0.50	−0.04 ∣ −0.04	0.07 ∣ 0.07
NI_{U500}	0.45 ∣ 0.46	−0.03 ∣ −0.17	−0.19 ∣ −0.12	0.82 ∣ 0.83	1	−0.40 ∣ −0.47	0.50 ∣ 0.51	−0.08 ∣ −0.07	−0.08 ∣ −0.04
$NI_{\theta_{o,av}}$	−0.10 ∣ −0.15	−0.13 ∣ −0.10	0.07 ∣ 0.06	−0.48 ∣ −0.58	−0.40 ∣ −0.47	1	−0.05 ∣ −0.12	−0.38 ∣ −0.40	−0.22 ∣ −0.21
$NP_{\Psi_{a,1}}$	0.41 ∣ 0.41	0.07 ∣ −0.5	−0.09 ∣ −0.01	0.49 ∣ 0.50	0.50 ∣ 0.51	−0.05 ∣ −0.12	1	−0.01 ∣ −0.01	0.25 ∣ 0.18
$NP_{\theta_{o,2}}$	−0.18 ∣ −0.14	0.39 ∣ 0.43	0.07 ∣ 0.10	−0.04 ∣ −0.04	−0.08 ∣ −0.07	−0.38 ∣ −0.40	−0.01 ∣ −0.01	1	0.57 ∣ 0.58
$NP_{\eta_{o,2}}$	0.02 ∣ −0.03	0.28 ∣ 0.29	0.25 ∣ 0.55	0.07 ∣ 0.07	−0.08 ∣ −0.04	−0.22 ∣ −0.21	0.25 ∣ 0.18	0.57 ∣ 0.58	1

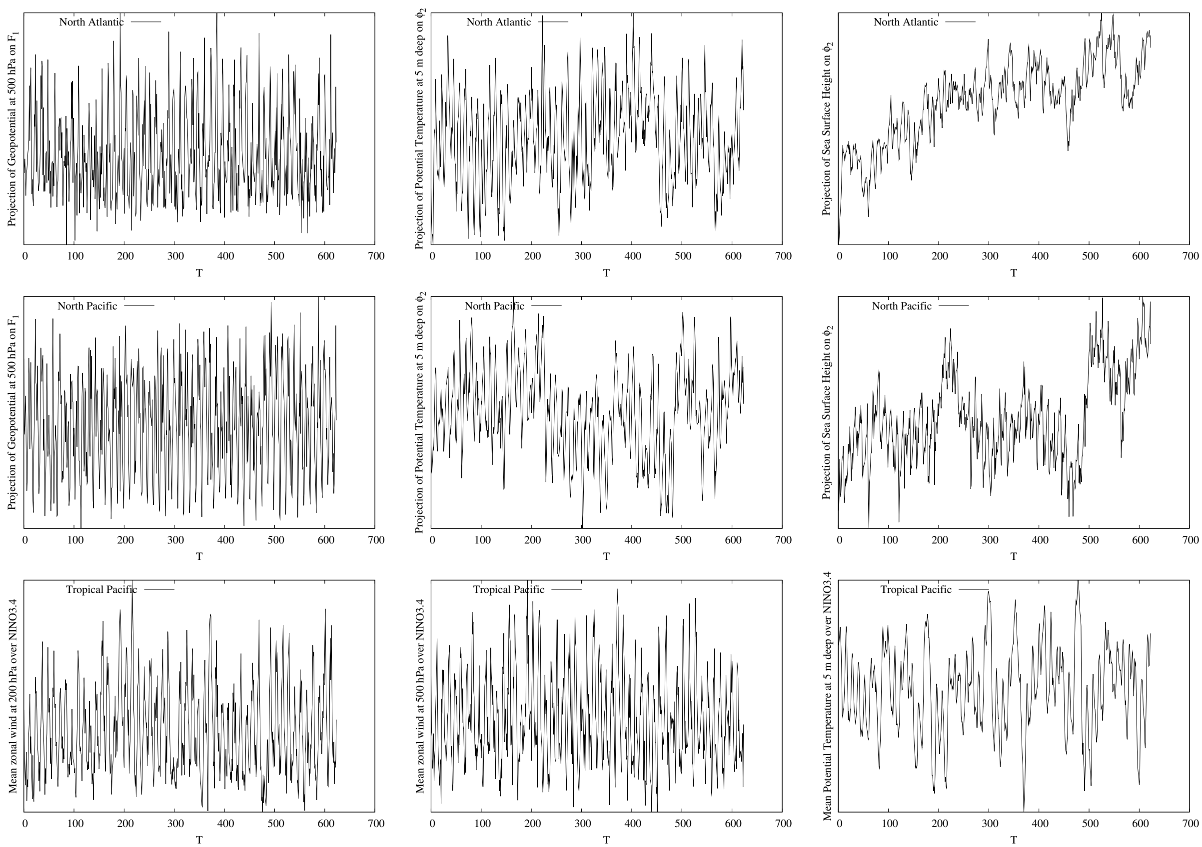

Figure 1. Monthly-averaged time series of the projections of the Atlantic, Pacific and Tropical fields on the dominant modes of the dynamics, as obtained from the ocean reanalysis ORA-20C and the ERA-20C atmosphere reanalysis. Top row from left to right, the geopotential at 500 hPa projected on F_1, the ocean temperature at 5 meters deep projected on ϕ_2, and the sea surface height projected on ϕ_2 for the Atlantic. Middle row, as for the top row but for the Pacific. Bottom row from left to right, zonal velocity at 200 hPa and 500 hPa, and the ocean temperature at 5 meters deep averaged over the NINO3.4 region. All time series are standardized (with a mean equal to 0 and a variance equal to 1).

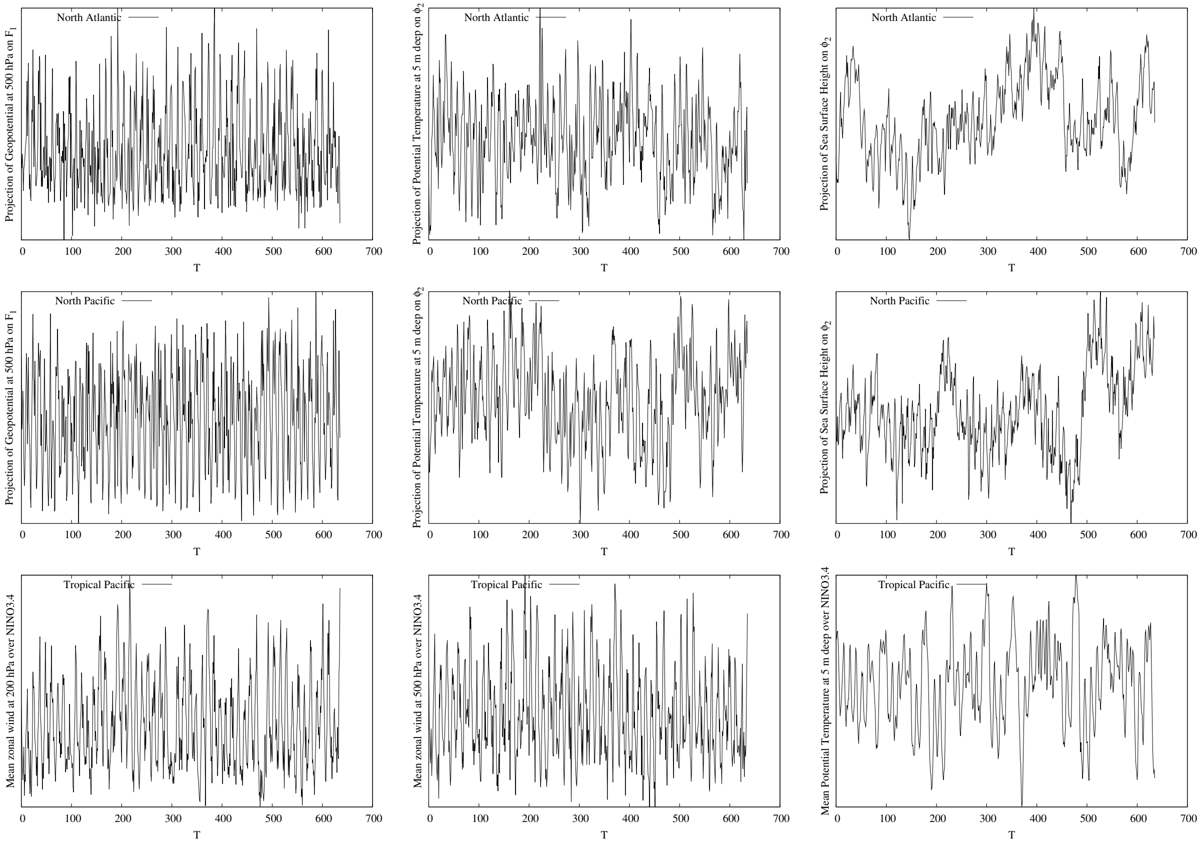

Figure 2. Monthly time series of the projections of the Atlantic, Pacific and Tropical fields on the dominant modes of the dynamics, as obtained from the ocean reanalysis ORAS4 and the ERA-20C atmosphere reanalysis. Top row from left to right, the geopotential at 500 hPa projected on F_1, the ocean temperature at 5 meters deep projected on ϕ_2, and the sea surface height projected on ϕ_2 for the Atlantic. Middle row, as for the top row but for the Pacific. Bottom row from left to right, zonal velocity at 200 hPa and 500 hPa, and the ocean temperature at 5 meters deep averaged over the NINO3.4 region. All time series are standardized.

Important correlations appear in the datasets explored, suggesting that common information are present in the different coupled ocean-atmosphere basins discussed here. These correlations are presumably highly dependent on the seasonal cycle affecting the Earth system. Further analysis by removing the seasonal signal could be done to clarify the correlations between the anomalies found in each basins. We will not, however, go in that direction in the present work since there are several ways to do it and since the seasonal signal is part of the dynamics itself. It suffices here to recognize that links exist between these basins, whose nature will be clarified by using the CCM algorithm discussed in Section 2. It will be shown that the annual cycle is also affecting the CCM results and two different ways to disentangling its role on the causality analysis will be proposed.

4 Results of the application of Convergent Cross Mapping

4.1 Reanalyses: ERA-20C/ORA-20C

Let us start the analysis by investigating the CCM for the series displayed in Fig. 1. In Panel (a) of Fig. 3, the correlation $\rho(L)$ of the inferred variable $\hat{Y}$ with the actual solution Y is shown for the three variables of the Tropical Pacific. These inferred variables are obtained by building analogs in the North Atlantic as described in Section 2. Note that a 95% confidence interval is provided based on the Fisher Z-transform test based on resampling a certain number of times the samples of length L, indicating that the influence of the two atmospheric Tropical series is significant. This confidence interval for large L is larger than for smaller values due to the fact that we are reaching the limit of the number of data points. Note also that for this analysis, the analogs have been selected to be at least separated by a period of 12 months. Longer exclusion periods have been used without substantial differences.

An increase of the correlation is found as a function of L, suggesting that the North Atlantic depends on the two large-scale atmospheric variables selected for the Tropical Pacific. The correlation for the ocean temperature of the Tropical region is however negative. As already mentioned previously this feature may occur when the time series is too short and when there is no significant coupling between the variables. This suggests that the prediction of the Tropical temperature based on analogs over the Atlantic are very poor, and therefore indicates the absence of influence of the Tropical ocean temperature. So the dominant influence is from the zonal flows in the atmosphere, associated with the dynamics of the Walker circulation.

The influence of the three variables of the North Pacific on the North Atlantic is very important as shown in Panel (b) with the three CCM increasing and significantly positive. The North Pacific ocean dynamics has a larger influence than the North Pacific ocean temperature on the Atlantic, as reflected by the larger amplitude of the CCM values. Note that the reduction of the state space coordinates associated with $\boldsymbol{X}$ from three to two also provides interesting results with a dominating influence from the atmospheric Tropical Pacific variables on the two-dimensional projection $(NA_{\Psi_{a,1}}, NA_{\theta_{o,2}})$. However the increase before saturation of $\rho(L)$ is much more limited than when using the three variables to build the North Atlantic projection of the attractor (not shown). The latter analysis suggests that the dependences between these regions is better elucidated based on the three dimensional space.

The impacts of the North Atlantic and of the North Pacific regions on the Tropical Pacific are displayed in Panels (c) and (d). All CCM values of Panel (c) are almost flat as a function of L suggesting that even when it is positive (very significant for the geopotential at 500 hPa), there is no dependence of the Tropical Pacific on the dynamics over the Atlantic. A slightly different picture emerges for the influence of the North Pacific on the Tropical Pacific, with a slightly increasing CCM for the Geopotential at 500 hPa over the North Pacific suggesting an influence of the upper-air dynamics over the North Pacific on the Tropical Pacific. Note that sometimes it is difficult to have a clearcut answer on the increase or not of a correlation as a function of L. There is a degree of arbitrariness that should be alleviated using other approaches as the ones that will be discussed later based on the temporal averaging or based on surrogates.

In Panels (e) and (f), the CCM values characterizing the influence of the North Atlantic (e) and Tropical Pacific (f) on the North Pacific, are displayed. A clear increase of CCM associated with the influence of the North Atlantic ocean dynamics

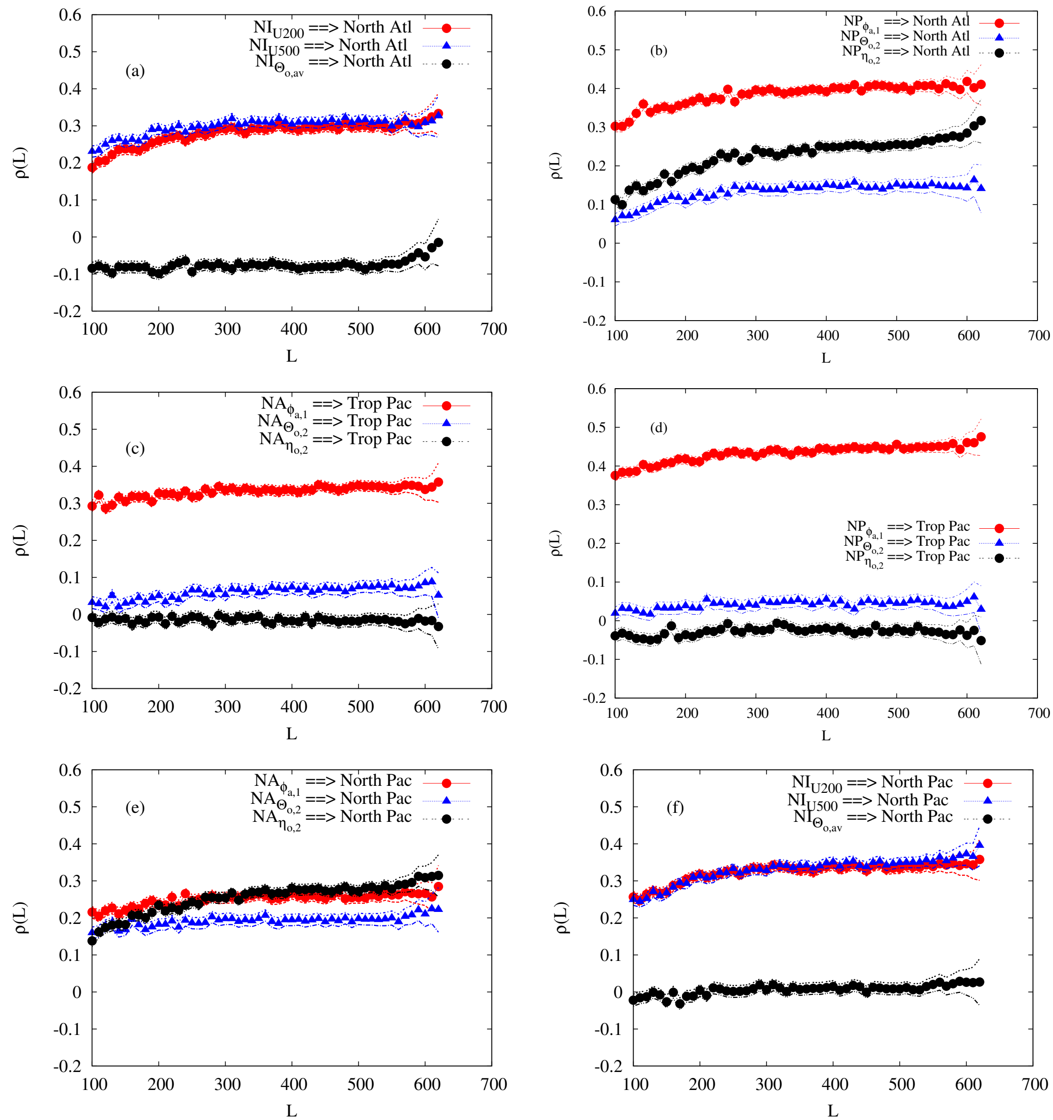

Figure 3. CCM as a function of the length L of the samples, as obtained from the monthly time series displayed in Fig. 1 for the reanalyses ERA-20C and ORA-20C. Each line with symbols corresponds to the influence of one variable on a specific coupled ocean-atmosphere basin. The specific variables are denoted in the caption corresponding to each line in each Panel.

on the North Pacific is found (Panel (e)). The CCM values for the two other variables are also slightly increasing with L, suggesting a dependence of these two variables on the North Pacific. Interestingly the influence of the Geopotential of the North Pacific on the North Atlantic (Panel (b)) is more important than the one from the North Atlantic to the North Pacific since the correlation is higher. This asymetry looks reasonable since the dominant flow is eastward in the Northern extratropics. Finally Panel (f) suggests that the atmospheric zonal flow over the Tropical Pacific influences the North Pacific dynamics, but not the ocean temperature.

To summarize, the analysis reveals that: (i) The upper-air Tropical Pacific dynamics and the North Pacific ocean and atmosphere dynamics influence the dynamics over the North Atlantic; (ii) the upper-air North Pacific dynamics influences the Tropical Pacific; and (iii) the North Atlantic ocean dynamics and the upper-air Tropical Pacific dynamics influence the dynamics over the North Pacific. These results seems to support the view of several authors, e.g. Sardeshmukh and Hoskins (1988); Alexander et al (2002); Lau (2016), that there is an *atmospheric bridge* dependence from the Tropical Pacific to the North Atlantic, via the North Pacific. Furthermore, a dependence between the North Pacific and the North Atlantic emerges, which is mostly oriented from the North Pacific to the North Atlantic since the correlations are larger in Panel (b) than in Panel (e) for the atmospheric variable, in line with the findings of Drouard et al (2015). But another very interesting dynamical signature emerges suggesting that the North Pacific and the North Atlantic ocean dynamics are dependent to each other. A possible candidate for this coupling is the thermohaline planetary circulation that affects both regions of the globe.

To disentangle the importance of the thermohaline circulation which displays a variability on very long time scales, one can investigate the dependence properties when longer time scales are considered. An average of the data set has been performed using a sliding window of 12 months. This approach allows for removing most of the impact of the annual signal, while keeping a number of data points large enough to perform the CCM analysis. Larger windows could be used but it will introduce very long time correlations that could penalize the selection of analogs since one needs analogs that are sufficiently uncorrelated in time. The results are displayed in Fig. 4. A first remarkable result is the fact that for a one-year average, the mutual dependence of the dynamics over the North Atlantic and Pacific is dominated by the ocean dynamics (see Panels (b) and (e)). The CCM values of the other variables in these two Panels are flat, and close or below 0. At the same time new dependences emerge between the North Pacific and the Tropical Pacific (Panel (d)), in particular for the ocean transport. This further supports the conjecture that the three regions are coupled via the large scale global ocean dynamics. This is presumably linked with the thermohaline circulation, but further analyses using additional variables and Tropical regions are needed in order to disentangle this point. This will be the subject of a future work.

Another very important finding in Fig. 4 is the fact that CCM values are now close to 0 (and do not display any dependence in L) for the influence of the Tropical Pacific on the North Atlantic, and vice versa (Panels (a) and (c)). It suggests that the dependence between these two regions is confined to time scales smaller than a year. One can therefore wonder whether this dependence is associated purely to the annual cycle or to some specific Tropical events like El-Niño or La-Niña, or in other words if it is mostly associated with the climatology of the Tropical Pacific or not.

To clarify this point, surrogate 3-dimensional attractors have been built by using the monthly means (averaged over the different years) on which random anomalies with the appropriate variance are superimposed. These random anomalies were

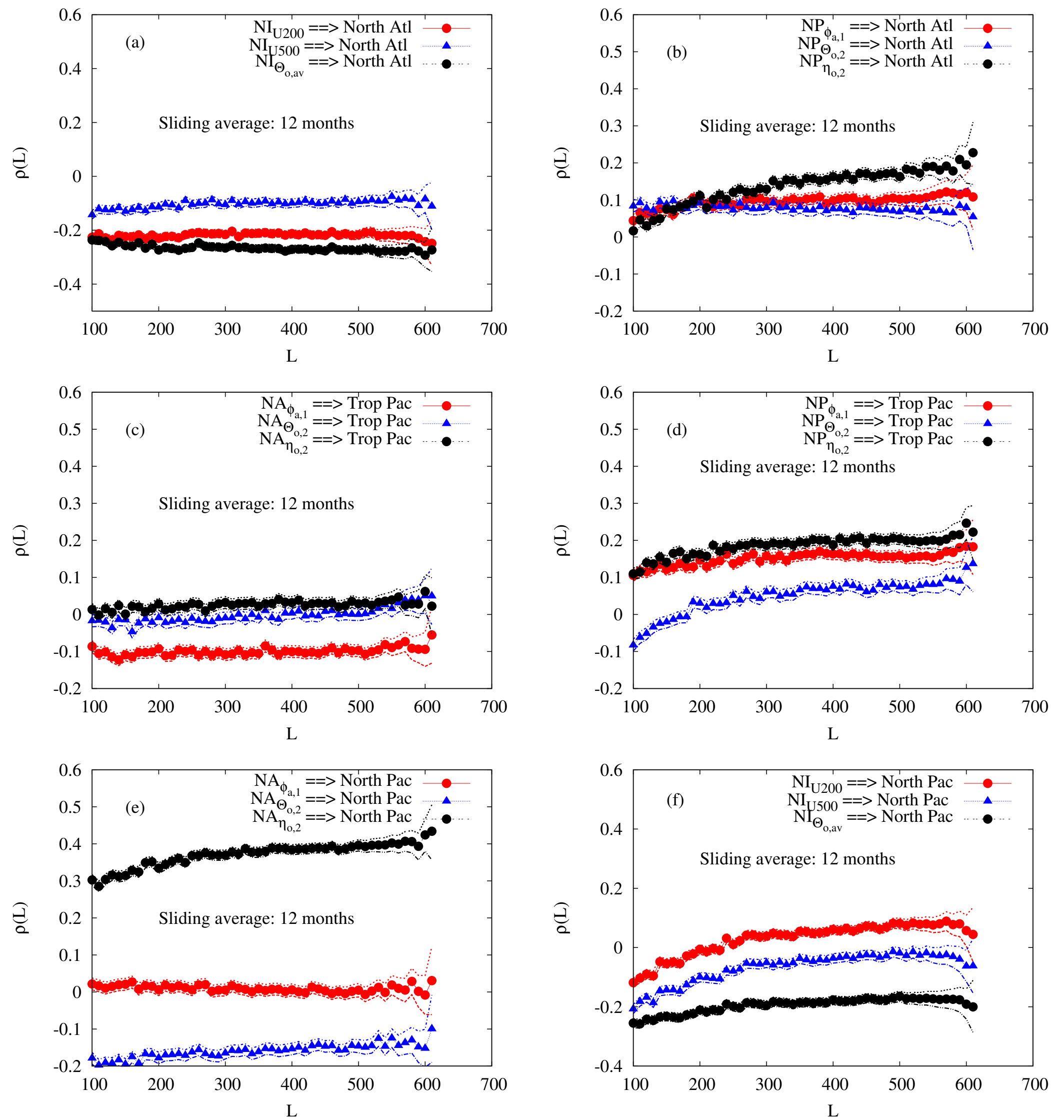

Figure 4. CCM as a function of the length L of the samples, as obtained from the series of Fig. 1 after averaging over a sliding window of 12 months for the reanalyses ERA-20C and ORA-20C. Each line with symbols corresponds to the influence of one variable on a specific coupled ocean-atmosphere basin. The specific variables are denoted in the caption corresponding to each line at each Panel.

simulated assuming a gaussian distribution around each monthly mean. The variance of the distribution is estimated using the anomalies of the corresponding month for all years in the datasets.

These new attractors are then used to predict the true variable of interest Y. Figure 5 displays the corresponding Panels that should be compared to Fig. 3. Two different random surrogates have been built, implying that two curves are displayed in each Panel for each variable, Y. The first remarkable result is that the CCM values of the ocean dynamics variables of Panels (b) and (e) are now flat and close to 0, suggesting that the CCM values for the transport in the two North ocean basins found in Fig. 3 are indeed indicating a dynamical coupling between the two basins beyond the annual climatological variations. Also in Panel (b), the CCM values for the influence of the North Pacific series (ocean temperature and Geopotential at 500 hPa) on the surrogate attractor of the Atlantic considerably decrease, suggesting the importance of the influence of the North Pacific on the North Atlantic beyond the annual climatological influence.

However when looking at the results in Panel (a), the CCM values based on the use of the surrogate attractors are very close to the one obtained with the actual attractors. This surprising feature suggests that there is no influence between the Tropical Pacific and the North Atlantic beyond the annual climatological variations. Or in other words that the Tropical Pacific variability does not influence the anomalies over the North Pacific. This has a very strong implication in the sense that there is no dynamical link between an event like El Niño or La Niña and the anomalies over the North Atlantic. A similar picture is found for the influence of the Tropical Pacific on the North Pacific as illustrated in Panel (f).

Finally to further test the robustness of these results a complementary way to clarify whether monthly anomalies between different basins are indeed related to each other is to apply direcly CCM on these anomalies. The results are displayed in the Appendix C, Fig. C1 The same conclusions are reached with the absence of dependences between the variables over the North Atlantic basin and the Tropical Pacific (panels (a) and (c)), and a strong mutual dependence between the ocean dynamics over the North Atlantic and the North Pacific (panels (b) and (e)).

In summary, in the limit of the data at our disposal, the analysis suggests that the anomalies associated with the dynamics over the North Atlantic and North Pacific cannot be inferred based on the variability of the variables we have used so far in the Tropical Pacific. Note that the previous analysis is made for all seasons and without distinctions between certain types of events, say strong El-Niño events, as it is usually done when analyzing the effect of ENSO over other regions of the globe, e.g. Brönnimann (2007). Such a split between seasons and/or events are worth performing, but the time series are already short and the selection of certain events will reduce considerably the statistics. The absence of link between the Tropical Pacific and the North Atlantic coupled dynamics could also reflect the non-stationary properties of the teleconnections between the North Atlantic and the Tropical Pacific as documented in López-Parages et al (2016); Johnson and Kosaka (2016); Goss and Feldstein (2017) and references therein. The analysis of long climate runs of state-of-the-art models with the approach used here would be very useful in that respect.

4.2 ERA-20C/ORAS4

Let us now consider the second ocean reanalysis, ORAS4, while keeping the same atmospheric reanalysis. This second investigation should allow us to clarify the robustness of our findings. Figure 6 shows the results of the computation of CCM that

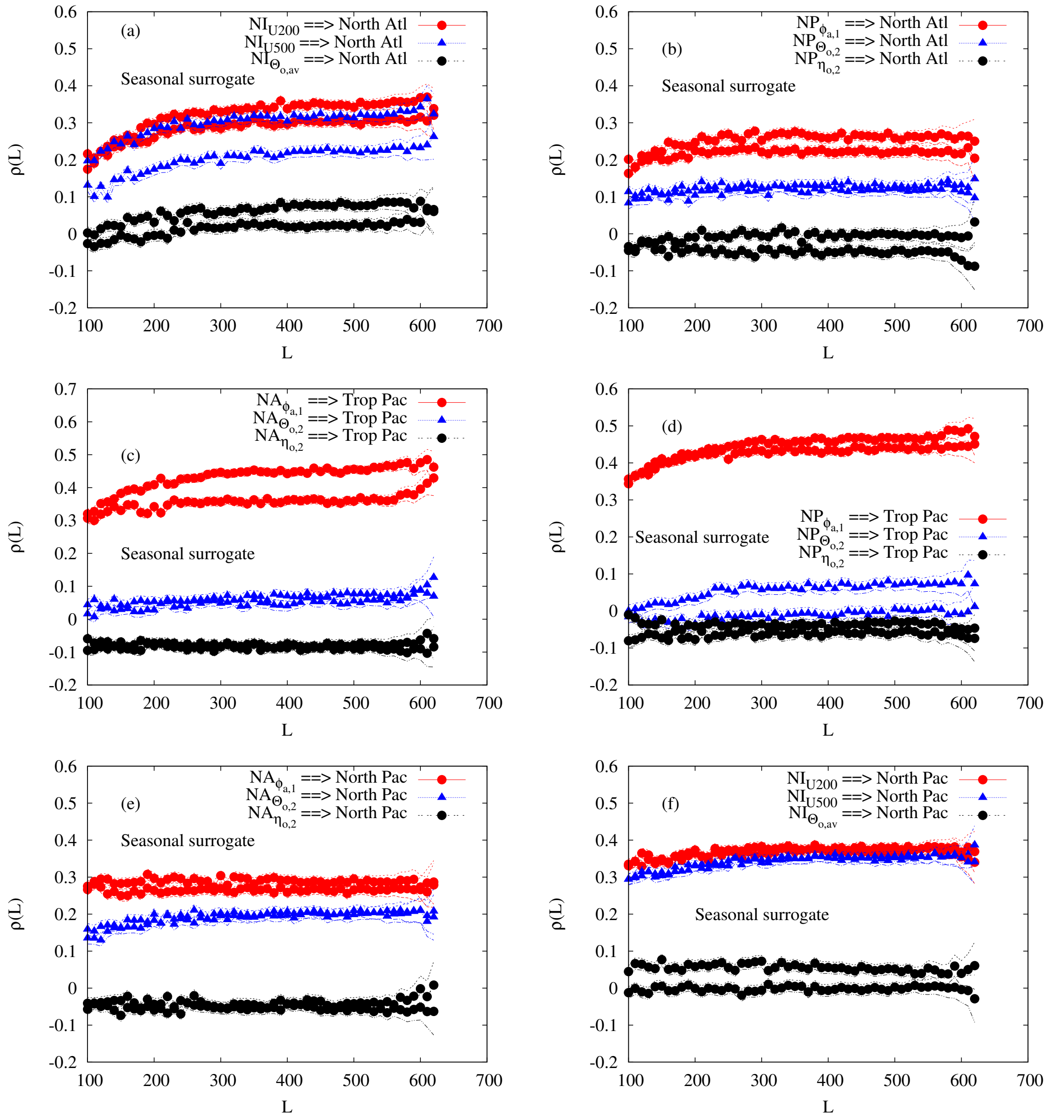

Figure 5. CCM as a function of the length L of the samples, as obtained from surrogate 3-dimensional attractors built by superimposing random anomalies to the annual climatological cycle, based on the data from Reanalysis ERA-20C and ORA-20C. Two different surrogates have been used. Each line with symbols corresponds to the influence of one actual variable (not a surrogate series) on a specific coupled ocean-atmosphere surrogate attractor. The specific variables are denoted in the caption corresponding to each line in each Panel.

should be compared with the results presented in Fig. 3. One remarkable feature is the absence of dependences between the North Atlantic and the North Pacific for the ocean dynamics, see black full circles in Panels (b) and (e). This result considerably differs from the one obtained with the ORA-20C. Another important difference is a larger amplitude of the influence of the Tropical Pacific ocean temperature on the North Pacific, and of the North Pacific variables on the North Atlantic. The other dependences are more robust.

These results suggest that the dynamics within the ocean differs considerably between ORAS4 and ORA-20C as already suggected by the covariances displayed in Table 1. These differences are probably due to (i) the fact that these reanalyses are obtained with different atmospheric forcing, specifically ORA-20C with ERA-20C and ORAS4 with different atmospheric reanalysis products and (ii) to the fact that for ORA-20C the ocean model started beginning of 1900 while for ORAS4 it started end of 1957. We may conjecture that the ORA-20C reanalysis data set is more reliable since a more consistent atmospheric forcing has been applied and the ocean model has got more time to equilibrate around its climate. But care should be taken here in drawing definitive conclusions on that. A better approach to disentangle which of these reanalyses provide the correct answer is to investigate a full coupled ocean-atmosphere reanalysis obtained for the whole 20th Century.

The investigation of the dependences for sliding averages over 12 months displayed at Fig. 7, also suggests a suppression of the dependences for most of the variables, at the exception of the one associated with the influence of the North Pacific ocean temperature on the Tropical Pacific (Panel (d)). It is also remarkable that a dependence emerges of the North Atlantic ocean dynamics on the North Pacific, but much weaker than for the other ocean reanalysis dataset.

Finally for the sake of completeness, the application of the CCM to the monthly anomalies is displayed in Fig. C2. Here as for the ERA-20C/ORA-20C dataset, no link between the anomalies of the Tropical Pacific and the North Atlantic is found (panels (a) and (c)). An important difference is however visible on the influence of the North Pacific ocean temperature on the North Atlantic and on the Tropical Pacific (panels (b) and (d)). Again, this contrasts with the results obtained with the other reanalysis dataset.

5 Conclusions

The causality between the dynamics of three different coupled ocean-atmosphere basins, The North Atlantic, the North Pacific and the Tropical Pacific region, NINO3.4, has been explored using data from three different reanalyses datasets, the ORA-20C, the ORAS4 and the ERA-20C. The approach used is the Convergent Cross Mapping developed by Sugihara et al (2012) which allows to go beyond the classical teleconnection patterns and which provides a clear signature of the inter-dependences between series or regions. The analysis reveals a few very important facts that should help in improving our understanding of the remote influence of large-scale dynamical processes, and in particular the impact of the Tropical Pacific coupled dynamics on the extratropics:

- The Tropical Pacific coupled ocean-atmosphere dynamics does not seem to have an impact on the extratropics beyond the annual climatological cycle. This very surprising result suggests that there is little hope to improve predictability in the extratropics based on information on the variability in the Tropical Pacific. This result needs however more attention and

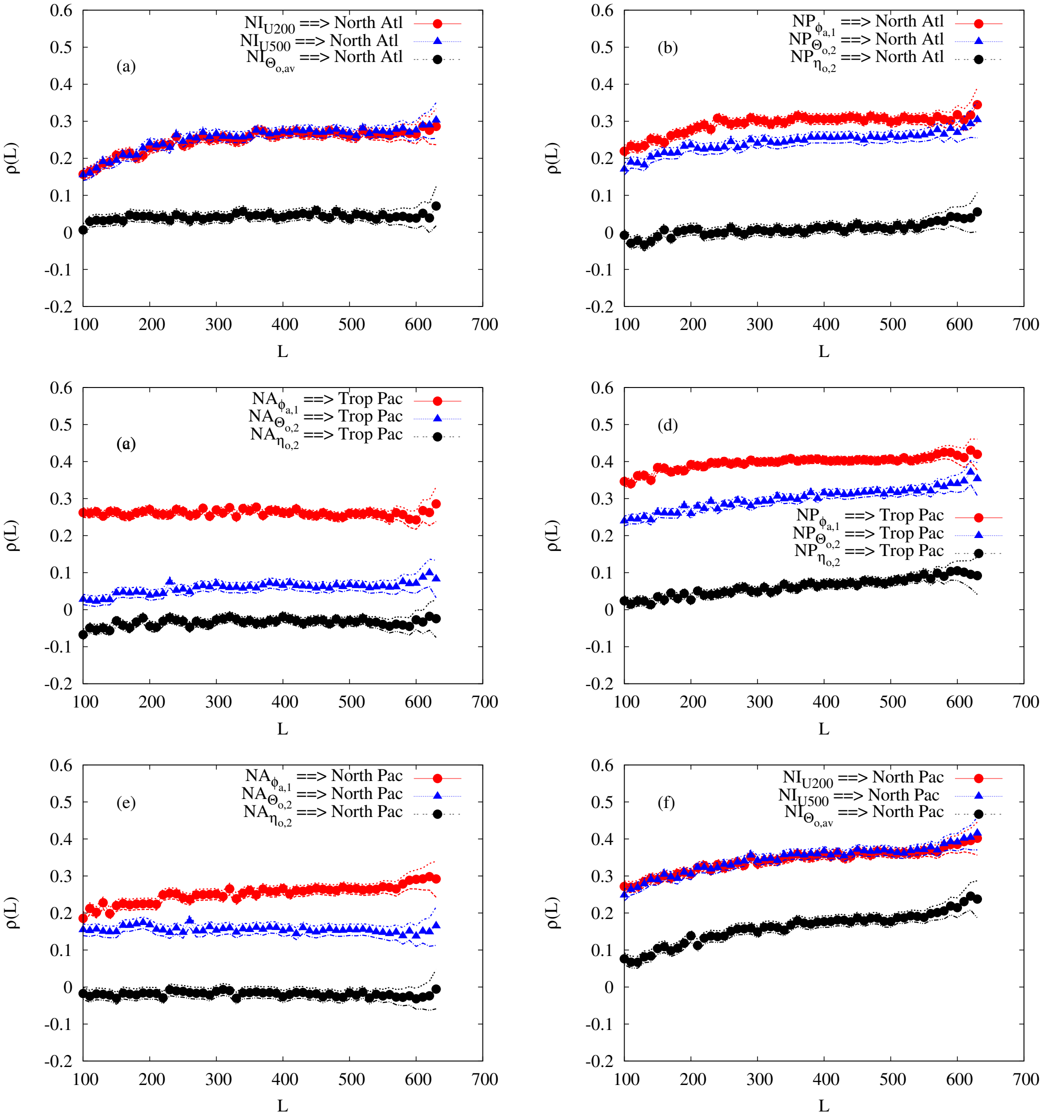

Figure 6. CCM as a function of the length L of the samples, as obtained from the monthly time series displayed in Fig. 2 for the reanalyses ERA-20C and ORAS4. Each line with symbols corresponds to the influence of one variable on a specific coupled ocean-atmosphere basin. The specific variables are denoted in the caption corresponding to each line in each Panel.

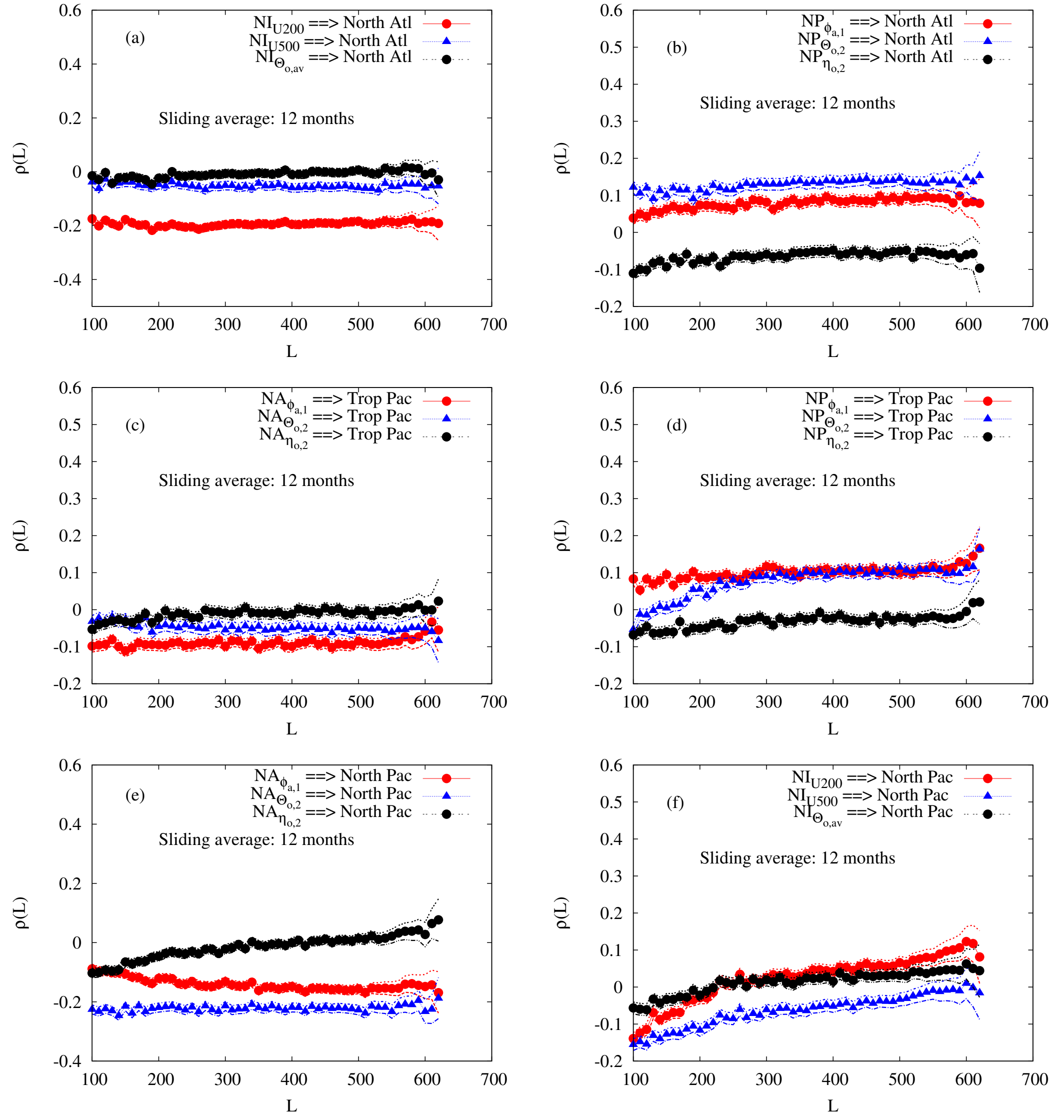

Figure 7. CCM as a function of the length L of the samples, as obtained from the series of Fig. 2 after averaging over a sliding window of 12 months for the reanalyses ERA-20C and ORAS4. Each line with symbols corresponds to the influence of one variable on a specific coupled ocean-atmosphere basin. The specific variables are denoted in the caption corresponding to each line in each Panel.

a thorough inspection of other datasets and long climate model runs in order to be confirmed. It is possible in particular that a more detailed analysis based on the selection of specific events, like strong El-niño or La-niña, will provide new information on the interactions between the Tropical Pacific and the rest of the world, beyond the climatological annual signal. But such an investigation needs considerably more data than the ones used in the present work and therefore calls for the development of even longer coupled reanalyses, or the use of long climate model runs.

– The atmosphere over the North Pacific considerably influences the North Atlantic (beyond the climatological annual signal), in agreement with the results found for instance in Drouard et al (2015).

– The results presented here for the two ocean reanalysis datasets disagree on the nature of the dependence between the North Pacific basin and the other ones. The ORA-20C indicates a dynamical influence (transport), while the ORAS4 suggests more an influence dominated by the ocean temperature. This difference is probably related to the specific data assimilation setup used in each case. To clarify what is really at work here new reanalysis datasets are needed. We can conjecture that the most reliable one should be built by using a coupled ocean-atmosphere data assimilation system running continuously on the longest period possible.

– The inter-dependences between the North Atlantic and the North Pacific on longer time scales than a year seems to be important, and is probably related to the coupled ocean-atmosphere dynamics on long time scales. One could conjecture that the thermohaline circulation should play a role on this link. Additional analyses with longer data sets, with climate model runs, but also with the analysis of additional basins like the Tropical Atlantic or the Indian Monsoon region are necessary to clarify this role.

The present work has demonstrated the urgent necessity to go beyond the teleconnection patterns for the investigation of the interaction between the different components of the climate system, using tools recently developed in the context of nonlinear sciences. Teleconnection patterns do provide information on a co-variability (which is an interesting information per se), but not of the influence of a region on another through a dynamical coupling. A common forcing can for instance induce a correlation between two variables even if these are perfectly independent in a dynamical sense.

New analyses will be performed along the lines drawn above, in particular in climate model runs. Several long control climate runs of CMIP5 models are available and can be analyzed in the same perspective as in the present work, in order in particular to evalute the impact of ENSO on the dynamics of the North Pacific and the North Atlantic.

Finally it should be stressed that the specific design of the CCM approach adopted here based on a low-dimensional projection of the full atmosphere-ocean attractor does not allow to have a one-to-one correspondence of the influence of one variable on another. Moreover other subspaces could be used that can provide different results. More variables should then be considered such as projections on additional Fourier modes, or by using projections on a few Empirical Orthogonal Functions. These analyses will allow to evaluate the robustness of the present results.

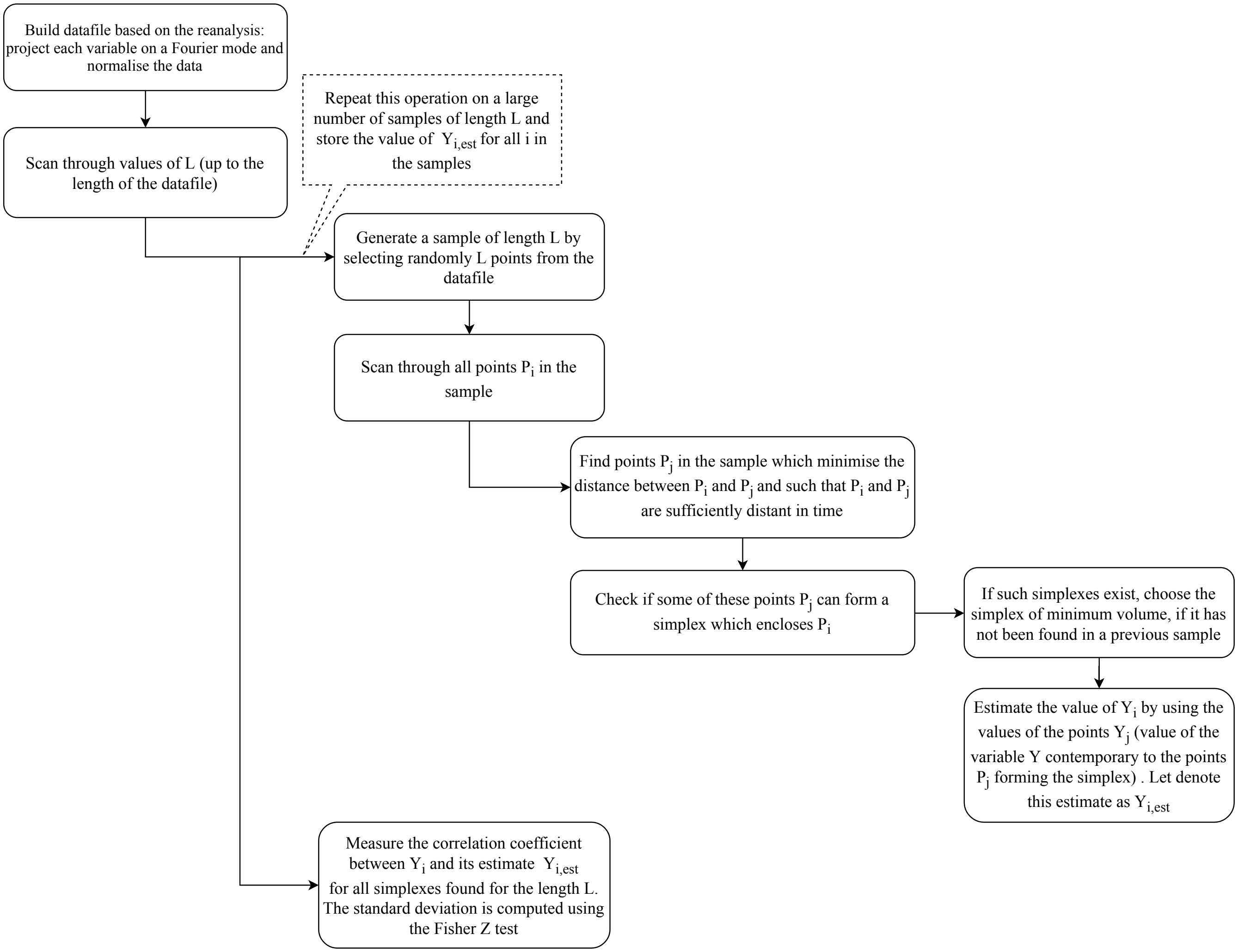

Figure A1. Algorithm used to compute the CCM presented in Section 2, based on the series discussed in Section 3.

Code and data availability. The code for CCM and the time series are available upon request to the authors. The data are made available on zenodo.org.

Appendix A: The CCM algorithm

The different steps of the CCM algorithm used to compute the correlation coefficient is detailed in Fig. A1.

Appendix B: CCM applied to an idealized model

To test the CCM technique described in Section 2, we use a dynamical system recently developed in Vannitsem (2015). It consists of a set of 36 ordinary differential equations representing the large scale dynamics of a coupled ocean-atmosphere system at midlatitudes. The equations are described in Vannitsem (2015) and in its supplementary material. The atmospheric model is based on the vorticity equations of a two-layer, quasi-geostrophic flow defined on a β-plane. The ocean dynamics is based on the reduced-gravity, quasi-geostrophic shallow-water model on a β-plane. For the ocean, it is assumed that temperature is a passive scalar transported by the ocean currents, but the oceanic temperature field displays strong interactions with the atmospheric temperature through radiative and heat exchanges.

All fields are developed in Fourier series on a β-plane as,

$$\delta T_o = \sum_{i=2(and \neq 5)}^{8} \Theta_{o,i}\phi_i, \quad \Psi_o = \sum_{i=1}^{8} \Psi_{o,i}\phi_i, \tag{B1}$$

$$\psi_a = \sum_{i=1}^{10} \Psi_{a,i}F_i, \quad \delta T_a = \sum_{i=1}^{10} \Theta_{a,i}F_i \tag{B2}$$

(B3)

where $\Theta_{a,i} = (\psi^1_{a,i} - \psi^3_{a,i})/2$ and $\Psi_{a,i} = (\psi^1_{a,i} + \psi^3_{a,i})/2$, with ψ^1 and ψ^3 the streamfunctions in the upper and lower layer of the atmosphere. Ψ_o is the streamfunction field in the ocean. δT_o and δT_a are temperature anomaly field with respect to spatially averaged reference temperatures. The modes ϕ_i used for the ocean are compatible with free-slip boundary conditions in a closed basin, while F_i are modes used for the atmospheric fields compatible with free-slip boundaries in the meridional direction and periodic boundaries in the zonal direction, see also the paper Vannitsem et al (2015).

The CCM analysis is performed on the solutions generated by the model with the same parameters as in Fig. 3 of Vannitsem (2015) with a surface friction coefficient $C = 0.006$ kg m^{-2} s^{-1}. The model is forced with seasonal variations of the solar input as discussed in Vannitsem (2015), and the solutions are averaged over one month (1/12 of the 365 days of the model year). The three variables used for building the attractor and the analogs are $(\Psi_{a,1}, \Theta_{o,2}, \Psi_{o,2})$ as for the North Atlantic and North Pacific datasets discussed in Section 3. Then several other variables are used to see if they have causality relations with the three variables used to build the attractor. The length of the time series is $L = 6000$ months.

The results are shown in Fig. B1 for different variables and also for a sliding window of 12 months at Panels (e) and (f). As it can be seen in Panels (a) and (b) the only atmospheric variable (explored so far) influencing the dynamics of $(\Psi_{a,1}, \Theta_{o,2}, \Psi_{o,2})$ is $\Theta_{a,1}$, since the correlation is high and increases as a function of L. This variable is strongly linked to the dynamics of $\Psi_{a,1}$ in the equations of the model, since it is the only one influencing (linearly) the evolution of $\Psi_{a,1}$. The others do not seem to have a strong influence. In Panels (c) and (d), the impact of some ocean variables is illustrated with no apparent influence of $\Psi_{o,5}$ and $\Theta_{o,3}$. But all other variables have different levels of influence with a clear increase of the correlation as a function of L.

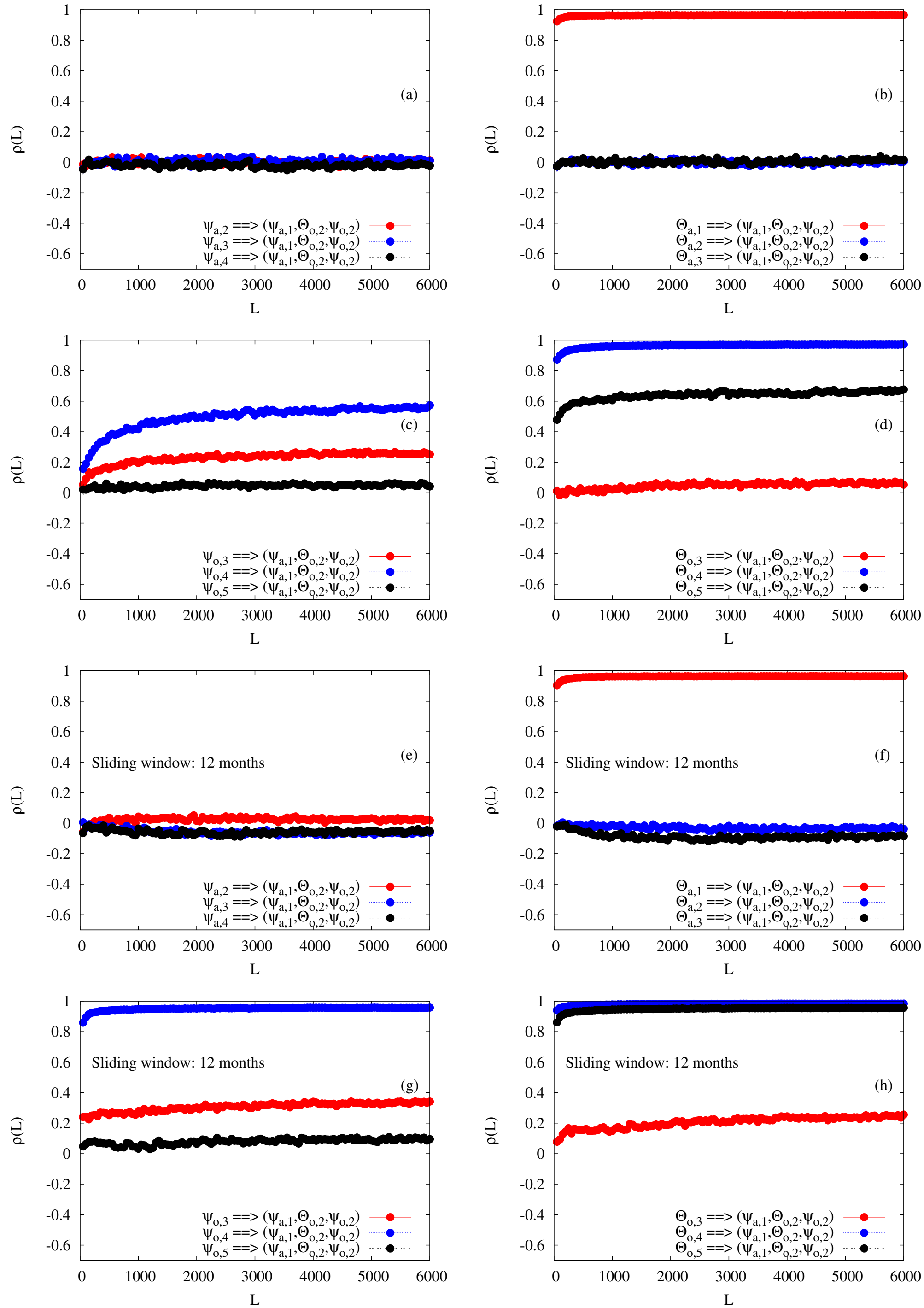

Figure B1. CCM as a function of the length L of the samples, as obtained from monthly time series of the low-order coupled ocean-atmosphere model integration. Panels (a) to (d) displays the values for the influence of a set of model variables on $(\Psi_{a,1}, \Theta_{o,2}, \Psi_{o,2})$ at monthly time scale. Panels (a) to (d) displays the values for the influence of a set of model variables on $(\Psi_{a,1}, \Theta_{o,2}, \Psi_{o,2})$ after the application of a sliding average over 12 months. Each line with symbols corresponds to the influence of one variable on $(\Psi_{a,1}, \Theta_{o,2}, \Psi_{o,2})$. The specific variables are denoted in the caption corresponding to each line in each Panel.

Finally, in Panels (e) to (h) the impact of using a sliding average is illustrated. First the CCM plotted in Panel (f) indicates that the influence of $\Theta_{a,1}$ is not removed, indicating its essential role on the dynamics at different time scales of motion. Second the influence of the ocean modes which were found to play a role at monthly time scales is further enhanced.

This brief analysis of a low-order system based on the CCM algorithm described in Section 2 indicates that it is a powerful tool to isolate the influence of certain variables on others in the system. Note that the angle of approach adopted in Section 2 by considering a low-order projection of the full state space as target does not allow to have a detailed information on the nature of the coupling between the variables since what is inferred is a global influence of a variable on a subset of other variables. The analysis also opens new questions on the role of the different variables in this low-order model and the dependences on the specific subspace selected as the target. This problem is out of the scope of the present work but is worth pursuing in the future. We can now proceed with this approach in the context of the datasets presented in Section 3.

Appendix C: Application of CCM to anomalies

The CCM is applied on the anomalies of the different time series displayed in Figs. 1 and 2. The anomalies are defined as $X(t,\tau) - \mu(\tau)$ where $\mu(\tau)$ is the average value over all years for month τ, and the argument t is the year for which the anomalies are computed. The analysis of these results is done in the core of the text.

Author contributions. TEXT

Competing interests. The authors declare no competing interest

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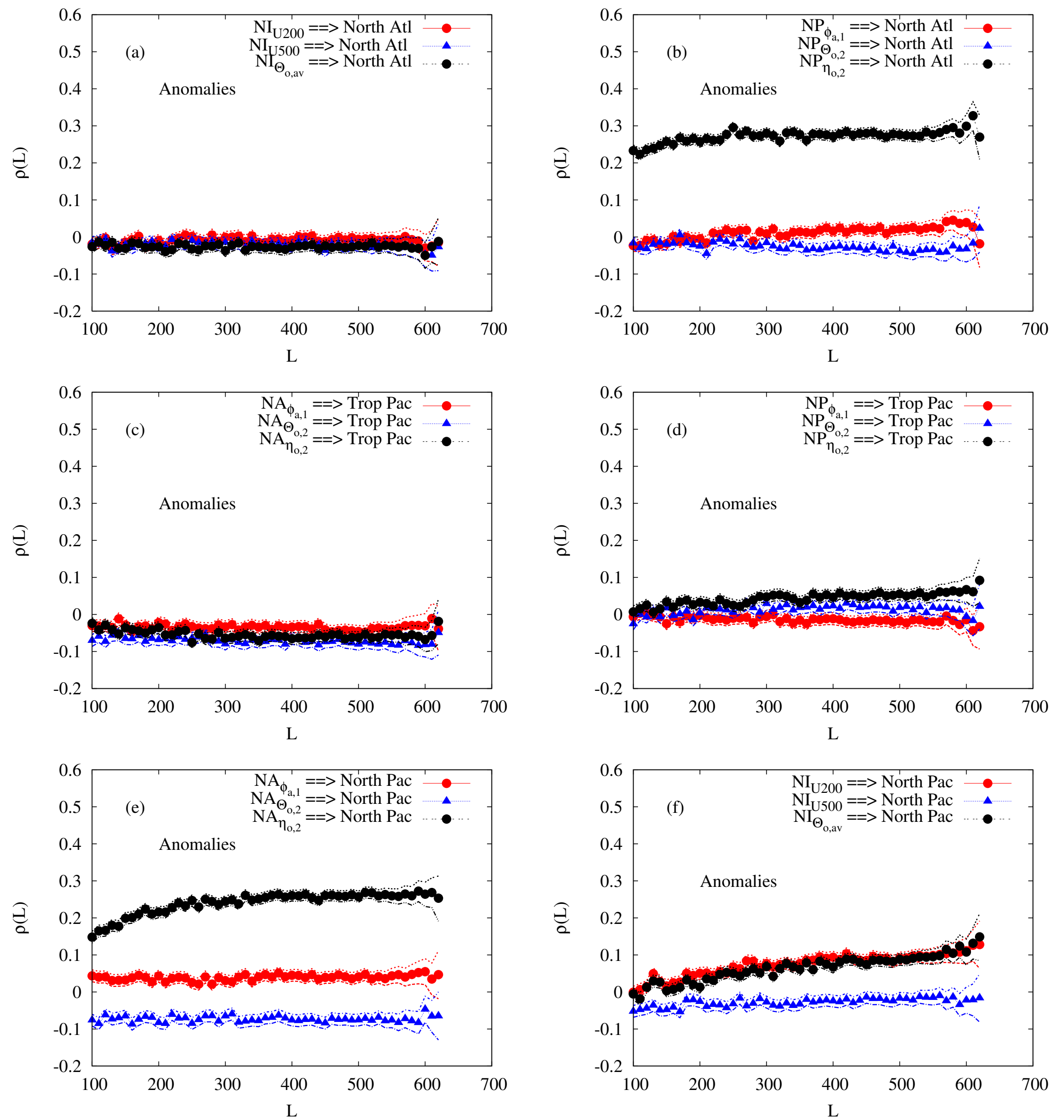

Figure C1. CCM as a function of the size L of the samples, as obtained from the anomaly of the monthly time series displayed in Fig. 1 for the reanalyses ERA-20C and ORA-20C. Each line with symbols corresponds to the influence of one variable on a specific coupled ocean-atmosphere basin. The specific variables are denoted in the caption corresponding to each line in each Panel.

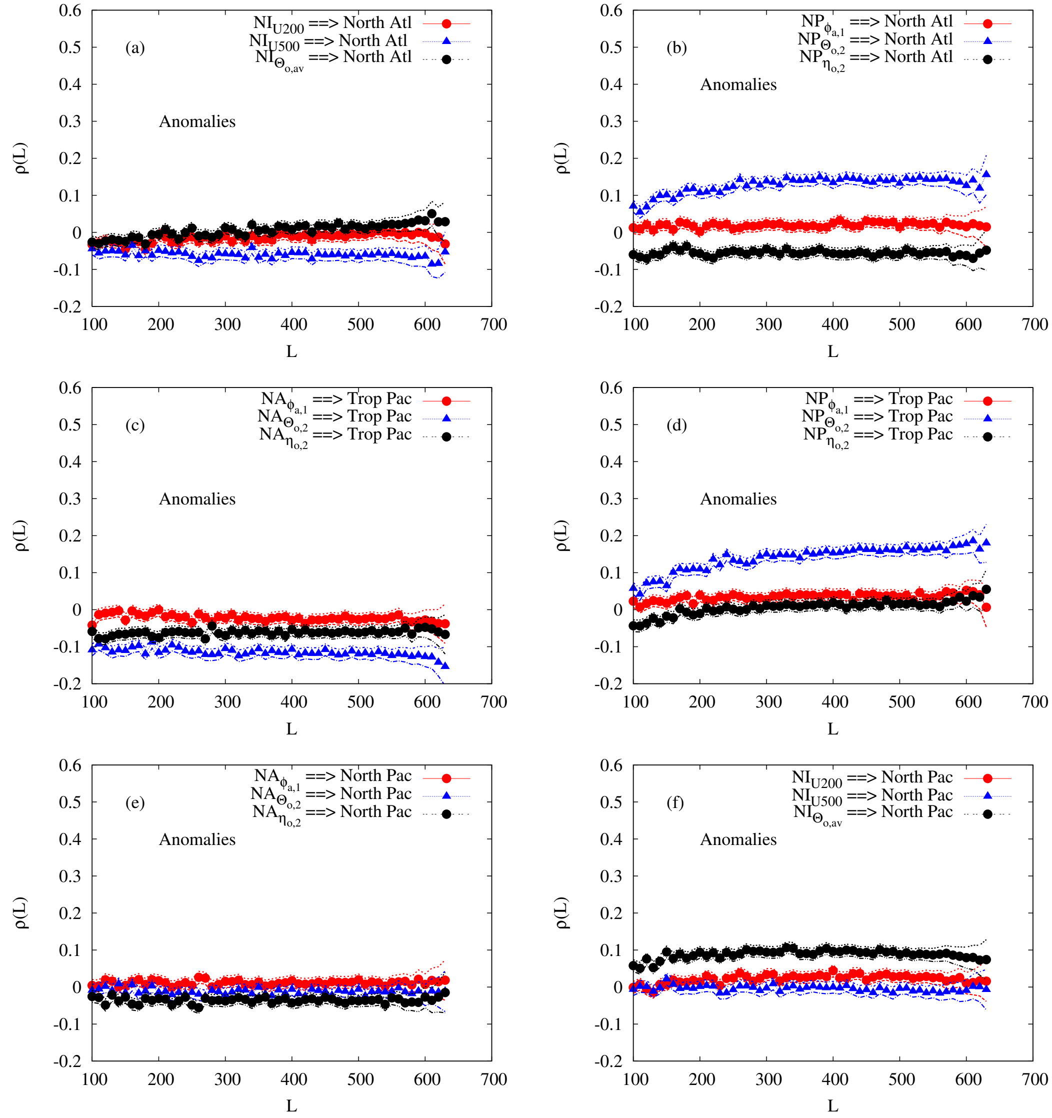

Figure C2. CCM as a function of the size L of the samples, as obtained from the anomaly of the monthly time series displayed in Fig. 2 for the reanalyses ERA-20C and ORAS4. Each line with symbols corresponds to the influence of one variable on a specific coupled ocean-atmosphere basin. The specific variables are denoted in the caption corresponding to each line in each Panel.

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