Response to Anonymous Referee #1

The study introduces a statistical forecast model of the July-October North Atlantic accumulated cyclone energy (ACE) wherein the causal effect network (CEN) approach is used to identify relevant precursors of the seasonal tropical cyclone (TC) activity in late and early spring of the same year. In the current version, I see the paper largely as a demonstration of the CEN method. There is not much value in other results. In the case of May forecasts, the robust precursors are well known. Results of the March forecasts are more interesting. However, it is not clear what physical mechanisms are at play, and whether the reported results will hold if a longer observational record is used.

> *We thank the reviewer for her/his useful comments. We agree that in the first version of the manuscript the discussion of the March precursors lacked some depth. As discussed below in more detail, we therefore added some analysis according to the reviewer`s suggestions.*

To improve the manuscript, I suggest the following:

a) Provide more discussion of the physical relevance of the March precursors.

> *In the new version of the manuscript, (see Fig. 10 and lines 268-282) we now hypothesize on the mechanism connecting the detected dipole precursor pattern in March to enhanced VWS in July-August. More precisely, we speculate that a high-pressure anomaly in the southern Indian Ocean and a low-pressure anomaly in the western South Pacific could weaken the trade winds in the western Pacific which is favorable for El Niño formation (which in turn is known to have an enhancing influence on VWS in the Atlantic).*
> *We test this hypothesis by constructing a causal effect network that shows the links between SSTs in the El Niño 3.4 region, trade winds in the western Pacific and the strength of the identified MSLP dipole. This analysis supports our hypothesis. Note, however, that more research is needed to confirm the robustness of this linkage, something we also clearly state in the paper.*

Incidentally, does the MSLP dipole pattern also exhibit a trend?

> *We use detrended time series to identify precursors and therefore do not expect the link between precursors and predictands to rely on such trends. The reviewer is right, however, that the skill in our final forecast model could depend on trends in the precursors and we thank him/her for pointing this out. We have, therefore, additionally analyzed the linear trends in three regions that have been identified as robust precursors in most training sets (see Figure S3).*
>
> *For the two identified MSLP precursors, no significant trend is detected (p-values 0.16 for the western Pacific precursor and 0.67 for the Indian Ocean precursor). Also, the trend in the Atlantic SST precursor is insignificant (p-value=0.25). While we cannot rule out that (insignificant) trends maybe contribute to the prediction skill, we conclude that they cannot fully explain the relationships identified and are thus not primary responsible for our model skill.*
>
> *We added a discussion about the potential influence of trends in line 293-296.*

b) Build a forecasting model based on March reanalysis data using a longer observational record. At least JRA55 data is available since 1958. This would allow to assess the robustness of the presented results and perhaps provide more insight into the physical mechanisms.

> *We thank the reviewer for this suggestion. In the modified version of the manuscript, we now test the skill of a prediction model (that is trained over the period 1980-2018) to the earlier period of JRA55 (1958-1978). The skill of our model is reduced in the pre-1979 period which is mainly due to a systematic overestimation in hurricane activity.*
> *We hypothesize that this overestimation could be explained by the influence of anthropogenic aerosols on hurricane activity that is not captured in our model. In the period 1950-1980 high aerosol emissions lead to tropical cyclone suppression in the Atlantic. Regulations in the late 1970s lead to fewer emissions weakening the tropical cyclone suppression* (Dunstone et al. 2013)*.*
> *We also think that the quality of reanalysis products before the use of satellites before 1979 introduce systematic uncertainties which make it extremely difficult to further investigate the robustness of the our results (compare* Tennant 2004)*. We nevertheless included this sensitivity test into the SI (Fig. S8) and discuss it in line 308-319 of the manuscript.*

Minor Comments:

1. Line 30: I suggest replacing “regional” with “global and regional”.

> *We thank the reviewer for spotting this error in the manuscript and we now changed “regional” to “global”.*

2. Line 65: What time period reanalyses data do you use?

> *We added the periods used for both datasets in the manuscript (line 67 and 69-70).*

3. Line 90: Please clarify why for the seasonal forecasting case potentially existing common drivers do not represent a problem.

> *We agree with the reviewer that this part was not clear enough. We reformulated this paragraph and only explain the shortcomings of our application (line 89-95). We also discuss these shortcomings again in the discussion section (line 347-352).*

4. Line 105: Maybe “for seasonal hurricane activity of the same year”?

> *We modified the manuscript accordingly.*

5. Line 110: I suggest providing more background why SST and MSLP are used to find precursors of VWS.

> *We agree with the reviewer, that in the initial version of the manuscript an explanation was lacking. We added a sentence motivating the choice of these variables in line 115-117.*

6. Line 230: “(Fig. 7c)” instead of “(Fig. 7b)”.

Done

7. Line 235: “(see Figs. 7b and d)” instead of “(see Fig. 7c and d)”.

Done

8. Line 290: Please clarify why it may be challenging to incorporate other favorable conditions into your framework.

We agree with the reviewer that this statement should be better explained. Although relative humidity is an important variable for the analysis of tropical cyclone formation it varies on shorter time scales and seasonal averages of relative humidity might not be insightful. SSTs and VWS are both to some extent modulated by ENSO and seasonal averages can therefore differ substantially. We added an explaining sentence in line 343-346.

References

Dunstone NJ, Smith DM, Booth BBB, et al (2013) Anthropogenic aerosol forcing of Atlantic tropical storms. Nat Geosci 6:534–539. doi: 10.1038/ngeo1854

Tennant W (2004) Considerations when using pre-1979 NCEP/NCAR reanalyses in the southern hemisphere. Geophys Res Lett 31:n/a-n/a. doi: 10.1029/2004GL019751

Response to Anonymous Referee #2

General comments

The authors are using a causal effect network to forecast Atlantic tropical cyclone activity (July-October) as presented by accumulated cyclone energy (ACE). They developed two models, using ERA5 and JRA-55 data, for the months of March and May. Analysing the deterministic and probabilistic skill of their models, they find that it is competitive with other seasonal forecasts currently available.

The technique used here identifies predictors that have already been recognized in previous studies. So in that sense, the manuscript doesn't lead to new insights into the drivers of Atlantic cyclone activity. However, the objective of the paper is more to showcase this new method and the fact that it recovers the known drivers lends credibility to the results. I would encourage the authors to apply this technique for basins which have received less attention and for which the current forecast systems have more difficulty (e.g. Australian basin).

> *We thank the reviewer for this useful suggestion. We think that for the present manuscript it makes sense to keep the focus on the Atlantic basin, exactly because the involved mechanisms are relatively well documented. Thus, our study should serve as a proof of concept of the method and we intend to apply it to other basins in a follow up study (see line 358-359). We have modified the framing of the manuscript accordingly.*

As I mention in my comments below, the authors identify regions of mlsp in the southern hemisphere In March as robust predictors of vertical wind shear during the hurricane season. Given the limited amount of observations that go into constructing the reanalyses over that region, I was wondering whether the authors thought this link was real or an artifact of the lack of observations. The authors should provide a comment to that effect in the manuscript.

> *We share the concern raised by the reviewer and we are aware of the possibility of detecting artifacts of the reanalysis as precursors for our model. In the revised manuscript we therefore discuss a potential mechanism that could explain the influence of the identified MSLP dipole in March on VWS in the hurricane season (see Fig. 10 and lines 268-281).*
>
> *We speculate that a high-pressure anomaly in the southern Indian Ocean and a low-pressure anomaly in the western South Pacific could weaken the trade winds in the western Pacific which is favorable for El Nino formation (which in turn is known to have an enhancing influence on VWS in the Atlantic).*
> *We test this hypothesis by constructing a causal effect network that shows the links between SSTs in the El Nino3.4 region, trade winds in the western Pacific and the strength of the identified MSLP dipole. This analysis supports our hypothesis. Note, however, that more research is needed to confirm the robustness of this linkage, something we also clearly state in the paper.*
>
> *Furthermore, we extended the sensitivity tests adding a trend analysis for the identified precursors (see Fig. S3, line 293-296) and an application of a forecast model trained on the period of 1980-2018 to an earlier test period (1958-1978) using the JRA55 reanalysis (see Fig. S8, line 308-319 and the response to reviewer 1).*

Given the limited available datasets, we cannot fully rule out the eventuality of detecting artifacts as precursors. However, our sensitivity tests suggest that the identified MSLP precursors have a physical link to VWS in during the hurricane season.

Finally, the text is well written and easy to follow. I recommend it for publication after the minor points below have been addressed.

We thank the reviewer for this overall positive feedback.

Specific comments

Line 18: "Earlier seasonal hurricane forecasting provides a multi-month lead time to implement more effective disaster risk reduction measures."

I'm not aware of any organization or government using seasonal forecasts for disaster risk reduction. Are the authors aware of any? If not, I would recommend removing this sentence from the abstract.

With this statement we wanted to refer to long term planning of governments and financial institutions. As we don't have a specific reference outlining how seasonal forecasts are used in this context we removed the sentence.

Line 26: "Preparedness for the secondary impacts can however be improved if reliable forecasts for the potential risks of the upcoming hurricane season are available (Martinez 2018)."

Does this refer to seasonal forecast? If so, it might be worth adding a sentence explaining how these forecasts are used in that context.

We thank the reviewer for this comment. Martinez 2018 indeed refers to forecasts on shorter time scales. We now reference (Murphy et al. 2001) *that discusses the use of seasonal forecasts more generally. We think that for secondary impacts the statements of this study are also applicable to seasonal hurricane forecasts.*

Line 156: "The color of the nodes indicates the strength of the auto dependence,"

auto dependence has not been defined. Can the authors explain what it means? And how is the strength of the link defined?

We thank the reviewer for this comment. We used the term "auto-dependence" to differentiate it from "auto-correlation". Thus, it refers to how much the past of a process influences the next time-step. Both auto-dependence and link strength are calculated using partial correlations as described in Runge et al. (2019).
We only use the link strength to identify robust precursors. The final forecast model is based on a simple regression which is why we do not think that in depth discussion of the interpretation of link strengths is necessary.
In the revised manuscript we shortly explain the meaning of auto-dependence and link strength in the caption of Fig. 3 (line 162-165).

Line 182: “our cross-validated forecast seems competitive with operational forecasts”. Could the authors be more precise? Which operational forecasts are they referring to?

We were referring to Fig. 1 from Klotzbach et al. 2019 in which the skill of seasonal April forecasts of ACE provided by CSU, TSR and NOAA is presented. We added the abbreviations of these institutes to the manuscript and specifically mention Fig. 1 in the citation (line 191-192).

Line 199: “deficit to predict some of the most active seasons might be due to missing relevant predictors”

There is also a stochastic component to TC formation. Two different years with similar large-scale fields conditions would/could lead to a different numbers of cyclones.

We thank the reviewer for this comment. We added the following sentence to the manuscript (line 212-213):
“Furthermore, it has to be noted that there is some stochastic component to TC formation which systematically limits the skill of our empirical forecast model that is based on favorable conditions for TC formation.”

Line 231: “As robust precursors, a high-pressure system over the southern Indian Ocean and a low-pressure system eastward of New Zealand are identified in nearly all training sets”

Is this a true feature or possibly a feature of the reanalysis, which have very little observation over the southern ocean?

We fully understand the concern of the reviewer. Please find our answer to this question below general remarks of the reviewer.

Line 262: “Overall these precursors seem less robust in JRA55 and thereby the forecast skill is also slightly reduced”

The Spearman correlation is higher using JRA-55 in March actually.

We thank the reviewer for pointing this out. We think, however, that there has been some confusion. The Spearman correlation in March is 0.22 for JRA55 and 0.27 for ERA5.

Technical corrections

Line 21: “Tropical cyclones (TCs) are among the most damaging weather events in many tropical and subtropical regions.”

This statement should be referenced.

We included a reference to the MunichRe natural hazard database (Munich Re 2020)*: https://natcatservice.munichre.com/*

Line 28: Klotzbach (2019) should be Klotzbach et al. 2019

Klotzbach, P. J., E. S. Blake, J. Camp, L.-P. Caron, J. Chan, N. Kang, Y. Kuleshov, S.-M. Lee, H. Murakami, M. Saunders, Y. Takaya, F. Vitart, and R. Zhan, 2019: Seasonal tropical cyclone forecasting. Tropical Cyclone Research and Review, 8, 134-149, doi: 10.6057/2019TCRR03.03.

Done

Line 30: “A whole variety of forecasting methods are applied ranging from purely statistical forecasts to forecasts based on regional climate model simulations and hybrid approaches.”

I’m not familiar with the methodology of every group, but nowadays global climate models are used instead of regional climate models.

We thank the reviewer for correcting this statement. We changed “regional” to “global”.

Line 32: “Their skill depends on their ability to represent TC genesis and development and their capacity to forecast the large-scale circulation over the Atlantic main development region (MDR).”

As well as their ability to adequately represent the interaction between the two.

We fully agree with the reviewer and added the sentence (line 37).

Line 35: “With increasing spatial resolution their representation of TCs improves.” I would add a reference here.

We added the following reference (Roberts et al. 2020)*:*
1. Roberts, M. J. et al. Impact of model resolution on tropical cyclone simulation using the HighResMIP-PRIMAVERA multimodel ensemble. J. Clim. 33, 2557–2583 (2020).

Line 61: “official WMO agencies”

Done

Line 64: “We use the monthly reanalysis data provided on a regular 1-degree grid.”

Aren’t the ERA5 data at 35 km resolution?

ERA5 is indeed available on a higher resolution. We are using the 1-degree grid (which is also provided on the website). We hope that removing the word “provided” clarifies this.

Line 88: “As such, we cannot exclude potential common drivers on longer, e.g. annual time scales”

Do you mean multi-annual or decadal time scales?

We meant multi-annual up to multi-decadal time scales. Based on a comment of reviewer 1, we rewrote this paragraph also specifying these time scales (line 89-95).

Line 99: “A statistical model is built”

Thanks

Line 126: “we will still refer to our cross-validated predictions as “forecasts””

I would recommend using hindcast, to avoid confusion.

We agree with the reviewer and write about “hindcasts” throughout the revised manuscript.

Line 199: hypothise -> hypothesize

Done

Line 202: “as a predictor”

Done

Line 219: “(BSS) is indicated in the lower right corner of each panel.”

Done

Line 294: “causal effect network rather helps to identify “the least spuriously link”

Done

Line 297: “The detected causal links might not be stationary over time”

Nonstationarity in the climate influence on TC activity has been pointed out by:

Fink AH, Schrage JM, Kotthaus S (2010) On the potential causes of the nonstationary correlations between West African precipitation and Atlantic Hurricane activity. J Clim 23(20):5437–5456

Caron, L-P, M Boudreault and C Bruyère (2015) Changes in large-scale controls of Atlantic tropical cyclone activity with the phases of the Atlantic Multidecadal Oscillation. Climate Dynamics, 44, 1801-1821. doi:10.1007/s00382-014-2186-5.

We thank the reviewer for suggesting these references (that we now included in line 93, 354). Following the suggestion of reviewer 1, we also included a test using the earlier period (1958-1978) of JRA55 (see Fig. S8). Since the data quality of the reanalysis before the satellite era (before 1979) seems questionable in the southern hemispheric oceans (Tennant 2004) *we still cannot fully investigate potential non-stationarities in our precursors. See line 308-319. Nevertheless, we have added a sentence discussing this possibility.*

Figure 1: I would like to thank the authors for taking the time to produce this figure. It helped a lot in understanding the methodology.

We would like to thank the author for this nice comment. We are very glad to hear that this figure is helpful.

References

Munich Re (2020) Natural catastrophe know-how for risk management and research. https://natcatservice.munichre.com. Accessed 19 May 2020

Murphy SJ, Washington R, Downing TE, et al (2001) Seasonal forecasting for climate hazards: Prospects and responses. Nat Hazards 23:171–196. doi: 10.1023/A:1011160904414

Roberts MJ, Camp J, Seddon J, et al (2020) Impact of model resolution on tropical cyclone simulation using the HighResMIP-PRIMAVERA multimodel ensemble. J Clim 33:2557–2583. doi: 10.1175/JCLI-D-19-0639.1

Runge J, Nowack P, Kretschmer M, et al (2019) Detecting and quantifying causal associations in large nonlinear time series datasets. Sci Adv 5:eaau4996. doi: 10.1126/sciadv.aau4996

Tennant W (2004) Considerations when using pre-1979 NCEP/NCAR reanalyses in the southern hemisphere. Geophys Res Lett 31:n/a-n/a. doi: 10.1029/2004GL019751

Robust Predictors for Seasonal Atlantic Hurricane Activity Identified with Causal Effect Networks

Peter Pfleiderer[1,2,3*], Carl-Friedrich Schleussner[1,2,3], Tobias Geiger[3,4], Marlene Kretschmer[5]

[1] Climate Analytics, Berlin, Germany
[2] IRI THESys, Humboldt Universität Berlin, Berlin, Germany
[3] Potsdam Institute for Climate Impact Research, Potsdam, Germany
[4] German Meteorological Service, Climate and Environment Consultancy, Stahnsdorf, Germany
[5] University of Reading, Department of Meteorology, Reading, UK

Correspondence to: Peter Pfleiderer (peter.pfleiderer@climateanalytics.org)

Abstract. Atlantic hurricane activity varies substantially from year to year and so do the associated damages. Longer-term forecasting of hurricane risks is a key element to reduce damages and societal vulnerabilities by enabling targeted disaster preparedness and risk reduction measures. While the immediate synoptic drivers of tropical cyclone formation and intensification are increasingly well understood, precursors of hurricane activity on longer time-horizons are still not well established. Here we use a causal network-based algorithm to identify physically interpretable late-spring precursors of seasonal Atlantic hurricane activity. Based on these precursors we construct statistical seasonal forecast models with competitive skill compared to operational forecasts. In particular, we present a skillful prediction model to forecast July to October tropical cyclone activity at the beginning of April. Our approach highlights the potential of applying causal effect network analysis to identify sources of predictability on seasonal time-scales.

1 Introduction

Tropical cyclones (TCs) are among the most damaging weather events in many tropical and subtropical regions (Munich Re 2020). The compound nature of tropical cyclone hazards combining heavy winds, extreme precipitation and coastal flooding contributes to their severity (Ye and Fang 2018), directly impacting societies. Furthermore, a range of secondary impacts in the aftermaths of cyclones such as displacement, loss in livelihoods or income, and health impacts are being reported (Camargo and Hsiang 2014). Applying risk reduction measures to the direct damages of TCs is challenging and is expected to become even more so with global warming and sea level rise (Woodruff et al. 2013). Preparedness for the secondary impacts could, however, be improved if reliable forecasts of the potential risks of the upcoming hurricane season are available (Murphy et al. 2001).

Several academic institutes provide seasonal hurricane forecasts for the Atlantic basin (Klotzbach et al. 2019). The Colorado state university was one of the first, already issuing seasonal forecasts in 1984 (Gray 1984a, b). Since then, a variety of forecasting methods are applied, ranging from purely statistical forecasts to forecasts based on numerical global climate model

Deleted: motivated

Deleted: We

Deleted: Earlier seasonal hurricane forecasting provides a multi-month lead time to implement more effective disaster risk reduction measures.

Deleted: also

Deleted: effects

Deleted: in

Deleted: forecasting

Deleted: Tropical cyclones (TCs) are among the most damaging weather events in many tropical and subtropical regions. The compound nature of tropical cyclone hazards combining heavy winds, extreme precipitation and coastal flooding contributes to their severity (Ye and Fang 2018), directly impacting societies. Furthermore, a range of secondary impacts in the aftermaths of cyclones such as displacement, loss in livelihoods or income, and health impacts are being reported (Camargo and Hsiang 2014). Applying risk reduction measures to the direct damages of TCs is challenging and is expected to become even more so with global warming and sea level rise (Woodruff et al. 2013). Preparedness for the secondary impacts can however be improved if reliable forecasts for the potential risks of the upcoming hurricane season are available (Martinez 2018). ¶
Several institutes provide seasonal hurricane forecasts for the Atlantic basin (Klotzbach 2019). The Colorado state university was one of the first institutes already issuing seasonal forecasts in 1984 (Gray 1984a, b). A whole variety of forecasting methods are applied ranging from purely statistical forecasts to forecasts based on regional climate model simulations and hybrid approaches (Klotzbach et al. 2017; Klotzbach 2019).¶
Dynamical forecast models are based on global or regional circulation models that simulate the climate including tropical cyclone occurrences (Vitart and Stockdale 2001; Vecchi et al. 2014; Manganello et al. 2017). Their skill depends on their ability to represent TC genesis and development and their capacity to forecast the large-scale circulation over the Atlantic main development region (MDR). With increasing spatial resolution their representation of TCs improves. Their ability to predict the large-scale circulation and low frequency variability can, however, remain a limiting factor for seasonal forecasts (Manganello et al. 2017).¶
Statistical forecast models are usually based on favorable climatic conditions in the region of TC formation and established teleconnections affecting cyclone activity on the basins scale (Klotzbach et al. 2017). Besides warm sea surface temperatures (SST), both the formation and intensification of TCs critically depend on low vertical wind shear (VWS) over the tropical Atlantic (Frank and Ritchie 2001; Emanuel et al. 2004). Furthermore, dry air intrusion and anticyclonic wave breaking can hamper TC formation (Hankes and Marinaro 2016). Finally, a lack of easterly African waves can lead to lower TC activity (Dieng et al. 2017; Patricola et al. 2018).¶
Classical

simulations and hybrid approaches (Klotzbach et al. 2017, 2019). The Barcelona Super Computing Center each year collects and publishes seasonal forecasts from universities, private entities and government agencies[1].

Dynamical forecasts are based on global circulation models that simulate the climate system including tropical cyclone occurrences (Vitart and Stockdale 2001; Vecchi et al. 2014; Manganello et al. 2017). Their skill depends on their ability to represent TC genesis and development, and their capacity to forecast the large-scale circulation over the Atlantic main development region (MDR) as well as their ability to adequately represent the interaction between the two. With increasing spatial resolution, their representation of TCs improves (Roberts et al. 2020). Their ability to predict the large-scale circulation and low frequency variability can, however, remain a limiting factor for seasonal forecasts (Manganello et al. 2017).

Statistical forecast models, in contrast, are usually based on favorable climatic conditions in the region of TC formation and established teleconnections affecting cyclone activity on the basins scale (Klotzbach et al. 2017). Besides warm sea surface temperatures (SST), both the formation and intensification of TCs critically depend on low vertical wind shear (VWS) over the tropical Atlantic (Frank and Ritchie 2001; Emanuel et al. 2004). Furthermore, dry air intrusion and anticyclonic wave breaking can hamper TC formation (Hankes and Marinaro 2016). Finally, a lack of easterly African waves can lead to lower TC activity (Dieng et al. 2017; Patricola et al. 2018).

The included predictors of a statistical forecast model are often chosen based on correlation analysis and expert judgement. One major challenge in statistical forecasting is yet to select a set of skillful predictors without running into overfitting issues, implying dropping skill when applied to independent test data (Hawkins 2004).

Recently, a novel statistical forecast approach based on causal effect networks (CEN) was proposed (Kretschmer et al. 2017). In such a network, causal links between the predictand and a set of potential predictors are identified by iteratively testing for conditionally independent relationships, thereby removing spurious correlations (Runge et al. 2019). First applications have shown that statistical forecast models based on causal precursors can result in skillful forecasts as they identify relevant predictors without overfitting (Kretschmer et al. 2017; Di Capua et al. 2019; Saggioro and Shepherd 2019; Lehmann et al. 2020).

Here we apply this approach to detect remote predictors in spring of hurricane activity in the Atlantic basin from July to October. We first demonstrate the applicability of the method by constructing a forecast for the July-October accumulated cyclone energy (ACE) based on May precursors using reanalysis data. The identified precursors are well-documented drivers of hurricane activity in the Atlantic, indicating the usefulness of our approach. To increase forecast lead time, we then apply the same method to construct a forecast based on March reanalysis and obtain competitive forecast skill based on these predictors.

[1] https://seasonalhurricanepredictions.bsc.es/predictions

Deleted: models

Deleted: with regard to the inclusion of potential predictors in the model

Deleted: resulting in

Field Code Changed

Deleted: Recently, a novel statistical forecast approach based on causal effect networks (CEN) emerged (Kretschmer et al. 2017; Di Capua et al. 2019; Saggioro and Shepherd 2019). In such a network, including the predictand and a set of potential predictors detected from gridded climate data, causal links are identified by iteratively testing for conditionally independent relationships, thereby removing spurious correlations (Runge et al. 2019b). First applications have shown that statistical forecast models based on causal precursors result in skillful forecasts as they identify relevant predictors without overfitting (Kretschmer et al. 2017; Di Capua et al. 2019).¶

Deleted: explore

Deleted: climate

Deleted:

Deleted: novel

2 Methods

2.1 Data

We use tropical cyclone locations and maximum sustained wind speeds from the official WMO agencies from the IBTrACS database (Knapp et al. 2010, 2018). Our main analysis is based on the fifth generation of ECMWF atmospheric reanalyses (ERA5) (Copernicus Climate Change Service (C3S) 2017). We use the monthly reanalysis data on a regular 1-degree grid for the period 1979-2018. For sensitivity testing, we also use the Japanese 55-year reanalysis (JRA55) on monthly time-scale and provided on a regular 1.25-degree grid (The Japan Meteorological Agency (JMA) 2013). As data in the pre-satellite era are less reliable (Tennant 2004), we focus on the period from 1979-2018, but we also perform sensitivity tests using the full range of the JRA55 dataset ranging from 1958-2018.

2.2 Accumulated Cyclone Energy (ACE)

Following Waple et al. (2002), we calculate accumulated cyclone energy (ACE) as an indicator for seasonal tropical cyclone activity:

$$ACE = 10^{-4} \sum_{all\ days} v_{max}^2 ,$$

ACE is accumulated for TCs within the Atlantic basin with maximal sustained wind speeds above 34 knots over all days from July-October.

2.3 Causal effect networks (CEN)

Causal effect networks have been introduced to statistically analyze and visualize causal relationships between different climatic processes, referred to as "actors". Specifically, spurious correlations due to indirect links, common drivers or autocorrelation effects are identified as such and removed from the network structure (Kretschmer et al. 2016; Runge et al. 2019). The remaining links can then be interpreted in a more causal way within the set of considered variables.

Here we use a two-step approach to construct causal effect networks consisting of a condition selection algorithm (PC-algorithm) and a momentary conditional independence (MCI) test. This so called PCMCI algorithm was introduced by Runge te al. (2019) and a python implementation is openly available on github.com/jakobrunge/tigramite (Runge 2014). The properties of the PCMCI algorithm including mathematical proofs and numerical tests are documented and discussed in Runge et al. (2019).

Note that this algorithm relies on several assumptions, which in real-world scenarios are likely never fully fulfilled (Runge 2018). Specifically, it requires a comprehensive sampling of potentially relevant climate signals as well as sufficient temporal coverage to ensure full representation of multi-annual to multi-decadal modes. As we are particularly restricted by the relatively short reanalysis record, we cannot exclude potential state-dependencies, e.g. on annual time scales as well as non-stationarities (Fink et al. 2010; Caron et al. 2015). As this represents a divergence from the theoretical methodological approach of causal

Deleted: Tropical cyclone locations and maximum sustained wind speeds from the official WMO agency are taken from the IBTrACS database (Knapp et al. 2010, 2018).¶
The main analysis is based on the fifth generation of ECMWF atmospheric reanalyses (ERA5) (Copernicus Climate Change Service (C3S) 2017). We use the monthly reanalysis data provided on a regular 1-degree grid. For sensitivity testing, we also use the Japanese 55-year reanalysis (JRA55) provided on monthly time-scale and on a regular 1.25-degree grid (The Japan Meteorological Agency (JMA) 2013).¶

Field Code Changed

Deleted: →→→→→→→→→→(1)

Formatted: Centered

Deleted: 34knots and

Deleted: in

Deleted: ¶
2.3 Causal effect networks (CEN)¶
Causal effect networks have been introduced to statistically analyze and visualize causal relationships between different climatic processes, referred to as "actors". Specifically, spurious correlations due to indirect links, common drivers or autocorrelation effects are identified as such and removed from the network structure (Kretschmer et al. 2016; Runge et al. 2019b). The remaining links can then be interpreted in a more causal way within the set of considered variables. ¶
Here we use a two-step approach to construct causal effect networks consisting of a condition selection algorithm (PC-algorithm) and a momentary conditional independence (MCI) test. This so called PCMCI algorithm was implemented by Jakob Runge and is openly available on github.com/jakobrunge/tigramite (Runge 2014). The properties of the PCMCI algorithm are documented and discussed in Runge et al. (2019). ¶
Note that this algorithm requires several preconditions to be met (Runge 2018). Specifically, it requires a comprehensive sampling of potentially relevant climate signals as well as sufficient temporal coverage to ensure full representation of multi-annual to multi-decadal modes. Only such a comprehensive coverage can allow for the identification of all spurious links and causal pathways. The condition of full climate signal coverage is not strictly fulfilled in our application of seasonal forecasting as we only select climate variables within a fixed time lag. As such, we cannot exclude potential common drivers on longer, e.g. annual time scales. For our application in seasonal forecasting, potentially existing common drivers do not represent a problem. However, this represents a divergence from the original methodological approach of causal precursor analysis. Therefore, we will refer to the results of the CEN analysis as "robust precursors" acknowledging that we cannot assure *full true* causality here. ¶
¶
¶
... [1]

precursor analysis, we will therefore refer to the results of the CEN analysis as "robust precursors" acknowledging that we cannot assure *true* causality.

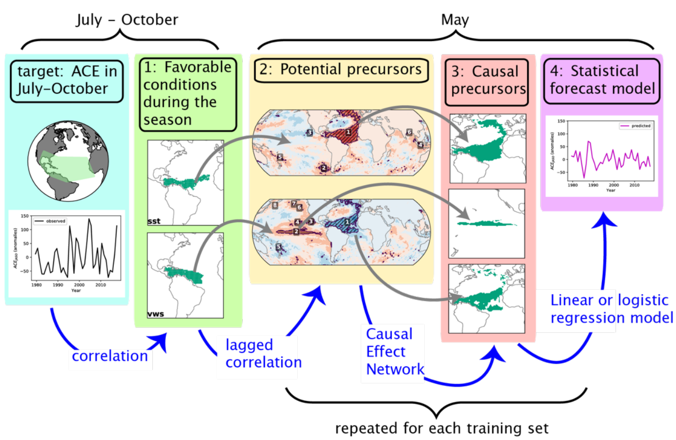


Figure 1: Schematic overview of the four steps to build a forecast model for ACE in July-October (left): 1) The regions of interest for two favourable conditions of hurricane activity (SST and VWS) are identified. 2) For each of the favourable conditions of 1) potential precursors in May are identified by clustering the most significantly correlated grid cells within SST data. 3) Causal effect networks are used to select a sub-set of robust precursors. 4) A statistical model is built based on the identified robust precursors of 3). Steps 2)-4) are repeated for the different training sets leading to a different forecast model for each hindcasted year.

2.4 Using CEN as a robust precursor selection tool to construct a statistical forecast model

We apply a CEN approach to identify robust precursors in May (and in March) of seasonal hurricane activity of the same year. Similar to Kretschmer et al. (2017), our methodology consists of 4 steps (see schematic overview in Fig. 1):

1. We first identify regions where **favorable conditions for TC** formation and intensification are most relevant. Here we use SSTs and VWS fields as established favorable conditions but without prescribing spatial patterns a priori. We then identify the regions in the tropical Atlantic that are correlated with ACE in our target region during the hurricane season (July to October).
2. We search for ***potential* precursors of the favorable conditions** identified in step 1. To do this, we calculate lagged point correlation maps of gridded SST, and mean sea level pressure (MSLP) data and cluster the most significantly correlated points into potential precursor regions. We use SSTs and MSLP as they are commonly used to describe the forcing on the atmosphere and the current location of pressure systems which in turn gives insights on the atmospheric circulation in general.
3. We identify ***robust* precursors** amongst all potential precursor regions identified in step 2 by constructing a causal effect network (CEN) using the so-called PCMCI algorithm.

Deleted: Forecast model construction. Four

Deleted: are performed

Deleted: Regions

Deleted: small

Deleted: build

Deleted: predicted

Deleted: in

Deleted: We apply a CEN approach to identify robust precursors in May (and in March) for hurricane season activity the same year. Similar to Kretschmer et al. (2017), our methodology consists of 4 steps (visualized in Fig. 1):¶

Deleted:) (see Fig. 2

Deleted: For

Deleted: with

Deleted: or

Deleted: applying

Deleted: CEN

Deleted: PCMCI

4. We construct a **statistical forecast model** based on the robust precursors identified in step 3 using linear regression and logistic regression. While for the detection of potential and robust precursors (step 2 & 3) detrended anomalies of climate variables are used, the final forecast models are constructed with the raw reanalysis data.

More details including all relevant free parameters of our approach (such as significance thresholds and clustering parameters) are listed and discussed in the SI.

2.5 Forecast model evaluation

We evaluate the skill of our model by performing a cross-validation hindcast: For each hindcasted year, we construct a new statistical model using all years but the year we aim to hindcast as well as the two preceding years of that year. Specifically, steps 2-4 are iteratively performed for each hindcasted year (see Fig. 1). By excluding the two preceding years from the training set, we assure that autocorrelations of up to 3 years do not leak information from the training data into the testing data. Note that despite a clear separation between training and testing data such cross-validation tests cannot guarantee reproducibility of the forecast skill in a real forecasting setting (Li et al. 2020).

3 Results

3.1 Favorable conditions for active hurricane seasons

Favorable conditions for active hurricane seasons are (among others) warm SSTs and low VWS over the western tropical North Atlantic (Fig. 2). We identify the regions where the association of SSTs and VWS on basin wide ACE is strongest by clustering most strongly correlated grid-cells (see SI for more information). These regions cover large parts of the main development region (MDR) and we call them SST_{MDR} and VWS_{MDR}. The relationships between these variables and TC formation as well as TC intensification are well documented (Frank and Ritchie 2001).

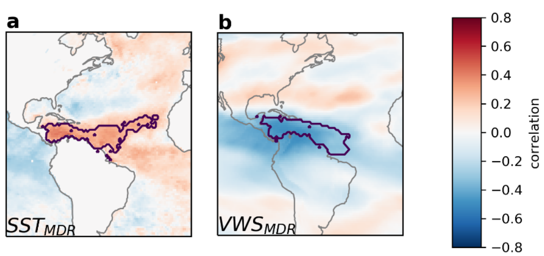


Figure 2: Favorable conditions for high ACE in July-October. a) Point correlation between SST and basin wide mean ACE in July-October. The contour line indicates the identified region in the Atlantic basin, which consist of a cluster

Deleted: forecast

Deleted: prediction

Deleted: predicted

Deleted: forecast

Deleted: want

Deleted: predict

Deleted: .

Deleted: predicted

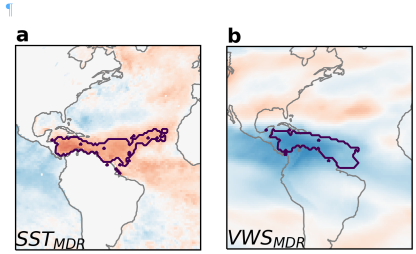
Deleted: ¶
As recently discusses by Li et al. (2020),

Deleted: do not assure the

Deleted: the

Deleted: world. For the sake of readability, we will still refer to our cross-validated predictions as "forecasts". And in distinction to that we will refer to forecasts that have been tested in the real world as "operational forecasts".

Deleted: **Favorable conditions** for active hurricane seasons are (among others) warm SSTs and low VWS over the western tropical North Atlantic (Fig. 2). We identify the regions where the association of SSTs and VWS on basin wide ACE is strongest by clustering most strongly correlated grid-cells (see SI for more information). These regions cover large parts of the main development region (MDR) and we call them SST_{MDR} and VWS_{MDR}. The relationships between these variables and TC formation as well as TC intensification are well documented (Frank and Ritchie 2001). ¶
¶



Deleted: :

Deleted: **. b: As (a) but for VWS.**

of the 5% most significantly correlated grid-cells. Details on the definition of the region are described in the supplementary information. b) As (a) but for VWS.

To identify **potential precursors** (step 2 in Fig. 1) of SST_{MDR} and VWS_{MDR} we next calculate lagged point correlation maps using the regional averages of VWS_{MDR} (SST_{MDR}) and gridded SST data. VWS_{MDR} in July-October is strongly correlated with SSTs in May in several locations. Potential precursor regions are found in the tropical Atlantic and Pacific, in the northern North Atlantic and in the northeastern Pacific (see Fig. 3a).

We then construct a **causal effect network** (step 3 in Fig. 1) with all identified potential precursors. We find that warm SSTs in the tropical Pacific and cold SSTs in the subtropical North Atlantic are *robust* precursors of strong VWS_{MDR} (Fig. 3b). The signal from the Pacific resembles the Nino3.4 region and thus reflects the El Niño Southern Oscillation (ENSO) which is a well-known driver of variations in hurricane activity (Gray 1984a; Tang and Neelin 2004; Kim et al. 2009). In combination, the difference between tropical Atlantic SSTs and tropical Pacific SSTs is consistent with the hypothesis that Atlantic hurricane activity mainly depends on the temperature of Atlantic SSTs relative to the other basins (Vecchi and Soden 2007; Murakami et al. 2018).

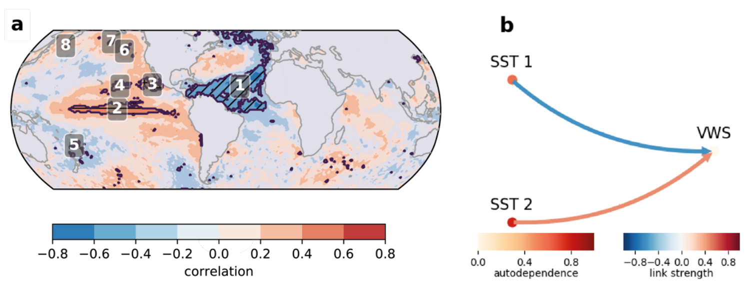


Figure 3: Precursors of VWS_{MDR} in a training set containing the years 1979-2015: a) Pointwise correlation between SSTs in May and VWS_{MDR} averaged over July-October. Labels indicate clustered regions that are treated as potential precursors. b) Robust precursors of VWS_{MDR} as detected by our method. The color of the arrows indicates the link strength and the color of the nodes indicates the strength of auto-dependence. The link strength (including auto-dependence of variables) is calculated following Runge et al. (2019) using partial correlations. This was shown to give a normalized measure of causal strength ranging between -1 and 1. For visualization purposes only ingoing links of VWS_{MDR} are shown here, the full network is shown in Fig. S1.

Deleted: between

Deleted: (Gray 1984a; Tang and Neelin 2004; Kim et al. 2009). In combination, the difference between tropical Atlantic SSTs and

Field Code Changed

Formatted: German

Deleted: :

Deleted: b: Detected robust

Deleted: .

Deleted: the

Deleted:

Deleted: , the color of the arrows indicates the link strength. Only

The correlation maps vary for the different training sets, partly leading to different potential precursors of VWS_{MDR} (Fig. 4a). For instance, some regions are only identified as potential precursors in some training sets (lighter shading). Nevertheless, throughout all different training sets, SSTs in the Atlantic and in the Niño3.4 region are consistently identified as robust precursors of VWS_{MDR} (Fig. 4c).

A robust precursor for warm SST_{MDR} in July-October is a large SST region in the North Atlantic (Fig. 4d). This region extends to the north-eastern Atlantic. The strong link of this precursor to SST_{MDR} is a result of the high autocorrelation of SSTs. Furthermore it is likely, that water from north of the MDR would be advected into it during the following months (Klotzbach et al. 2019). The identified SST signals north in the subpolar Atlantic and Arctic ocean may not have a direct impact on the cyclone activity, but could also be the result of the presence of a common driver of multi-month/annual SST in the North Atlantic that cannot be resolved by our temporally limited application of the CEN method for forecasting purposes. This does not mean that the SST signal in the region does not have skill as a robust precursor, but only that no direct 'causal' pathway might be at play here.

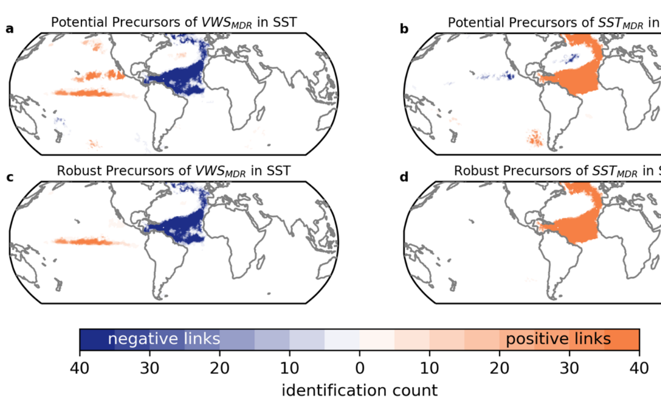


Figure 4: Potential and robust precursors of VWS_{MDR} (a and c) and SST_{MDR} (b and d) in May. Number of training sets in which a grid-cell is part of a potential (a-b) and robust (c-d) precursor region. The maximum number is 40 - the number of different training sets considered.

Deleted: -b

Deleted: a few

Deleted: not

Deleted: all

Deleted: (Klotzbach 2019).

Formatted: German

3.2 Forecast model based on May precursors

We next hindcast each years' ACE in July-October with a linear regression model (step 4 in fig. 1) based on the absolute values of the robust precursors identified in May for the training set (containing again all years but the hindcasted year and the two preceding years) (see Fig. 5). With a Pearson correlation coefficient of $\rho = 0.47$ (and a Spearman rank correlation coefficient of $\rho_{rank} = 0.53$), our cross-validated hindcast seems competitive with operational forecasts (from CSU, TSR and NOAA) which have $\rho < 0.4$ (see Fig. 1 in Klotzbach et al. 2019).

Our model skillfully discriminates between above and below median seasonal activity (Fig. 5b). However, the intensity of most extreme hurricane seasons is underestimated in our linear forecast model (e.g. years 1995, 2004, 2005, 2017 in Fig. 5a). Figure 5b shows that despite this lack in sensitivity of the linear model, it can still deliver valuable information on the occurrence of above 66th percentile seasons.

As an addition to the linear model, we next use a logistic regression classifier to construct probabilistic forecast models. We focus on predicting the most active (above 66th percentile) and least active (below 33th percentile) seasons using the same predictors as for the linear model (Fig. 6b-c). For each year this model gives a probability of having an above 66th (below 33rd) percentile season. As it does not assume a linear relationship between predictors and predictands it might be better suited for the prediction of extreme seasons.

We evaluate the performance of the model using the Brier skill score (BSS) (Brier 1950). With a positive BSS, the result of the forecast model that gives the probability of finding an above 66th percentile season (Fig. 6c) is slightly superior to a climatological forecast, which would be forecasting above 66th percentile seasons with a probability of 33% in each year. The reliability curve flattens out for high forecast probabilities indicating that the usefulness of this forecast is however limited. For instance, the false positive rate is 50% for seasons which are hindcasted to be an above 66th percentile season with a probability of 60%. Yet, seasons that are very unlikely to become particularly active are hindcasted with high confidence.

We hypothesize that the deficit to hindcast some of the most active seasons might be due to missing relevant predictors. For example, Klotzbach et al. (2018) argued that the extreme TC activity in 2017 was due to an enhanced Pacific Walker circulation during near neutral ENSO conditions. The Pacific Walker circulation and ENSO are strongly correlated, but in 2017, forecast models using ENSO as a predictor (rather than the Walker circulation) heavily underestimated the seasonal activity (Klotzbach et al. 2018). Furthermore, it has to be noted that there is some stochastic component to TC formation which systematically limits the skill of our empirical forecast model that is based on favorable conditions for TC formation.

Deleted: 1

Deleted: predict

Deleted: that is

Deleted: predicted

Deleted: forecast seems competitive with operational forecasts which have $\rho < 0.4$ (Klotzbach 2019).

Deleted: prediction

Deleted: more

Deleted: (Brier 1950).

Deleted: The usefulness of this forecast is however limited as the

Deleted: .

Deleted: even when

Deleted: model predicts

Deleted: active

Deleted: higher than 60%, roughly half

Deleted: these seasons will be false positives. It rather predicts

Deleted: We hypothise that the deficit to predict some of the most active seasons (e.g. 1995, 2004, 2005 and 2017 compare Fig. 5a) might be due to missing relevant predictors. Klotzbach et al. (2018) argue that the extreme TC activity in 2017 was due to an enhanced Pacific Walker circulation during near neutral ENSO conditions. The Pacific Walker circulation and ENSO are strongly correlated, but in 2017 forecast models using ENSO as an predictor (rather than the Walker circulation) heavily underestimated the seasonal activity (Klotzbach et al. 2018).¶

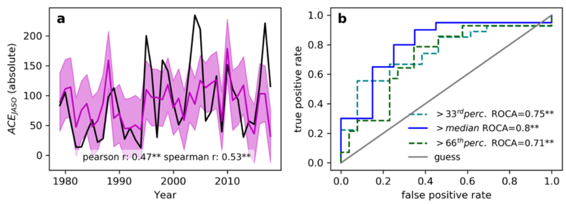


Figure 5: Hindcast skill based on May reanalysis. a: ACE yearly aggregated over July-October (black) and based on our linear forecast model using precursors identified for the month of May (magenta). The shading corresponds to a 66% confidence interval based on the standard deviation of the model over the training periods. b: Receiver operating characteristic (ROC) curve (see SI) for different seasonal activities: above (the long-term) median seasons in blue, above the 33rd percentile in cyan and above the 66th percentile in green. The area under the ROC curve (ROCA) is indicated in the legend with significance levels (- alpha=0.05, * - alpha=0.1).**

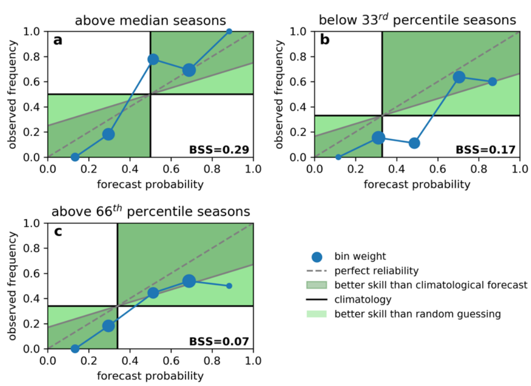


Figure 6: Reliability diagrams for a logistic regression model on May precursors and for three types of seasonal activities: above median (a), below 33rd percentile (b), above 66th percentile (c) seasons. Dots show the mean hindcasted probability versus the observed frequency of a (seasonal) event. The size of the dots indicates the relative amount of data points that contributed to a bin. A perfectly reliable forecast would lie on the diagonal (dashed gray line). Dots within the dark-green area contribute to a forecast skill improvement compared to the climatology while dots within the light-green area contribute to a forecast skill improvement compared to random guessing. The Brier Skill Score (BSS) is indicated in the lower right corner of each panel.

Formatted: German

Deleted: Forecast

Deleted: period

Formatted: German

Deleted: reanalysis

Deleted: predicted

Deleted: left

3.3 Forecasting at longer lead times

So far, the robust precursors we detected with our data-driven approach are already well documented in the literature, providing us with confidence in the approach. We next apply the same methods to construct a forecast model based on reanalysis data in March, where existing operational forecasts show little skill (Klotzbach et al. 2017, 2019). At the end of March, it is difficult to forecast the state of ENSO for the upcoming hurricane season due to the ENSO predictability barrier (Torrence and Webster 1998; Hendon et al. 2009). Indeed, in March, the El Niño region is not identified as a robust precursor of VWS_{MDR} in July-October (see Fig. S2).

We further search for robust precursors in mean sea level pressure data (MSLP). To avoid spurious effects at this long-time lag on atmospheric time scales, we adjust our criteria to yield large-scale precursors and cluster the 7.5% most significantly correlated grid cells (instead of 5% elsewhere) into large-scale precursor regions (see SI for more details).

We identify potential precursor regions in both hemispheres (Fig 7a). As robust precursors, a high-pressure system over the southern Indian Ocean and a low-pressure system eastward of New Zealand are identified in nearly all training sets (Fig 7c). For SST_{MDR}, autocorrelation still plays an important role and, as for the May forecast, a larger area in the North Atlantic remains a robust predictor (see Fig 7 d).

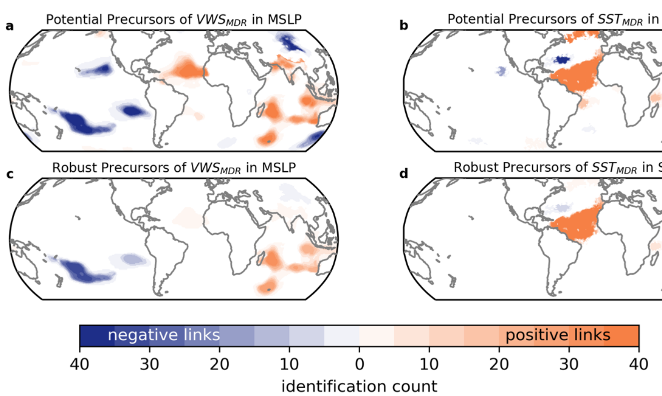


Figure 7: Potential and robust precursors of VWS_{MDR} and SST_{MDR} in March. As Figure 4 but in March and with MSLP precursors for VWS_{MDR}.

Deleted: 2

Deleted: We next apply the same methods to construct a forecast model based on ***March*** reanalysis data, where existing operational forecasts show little skill (Klotzbach et al. 2017; Klotzbach 2019). Here we find different precursors for VWS_{MDR}. At the end of March, it is difficult to forecast the state of ENSO for the upcoming hurricane season due to the ENSO predictability barrier (Torrence and Webster 1998; Hendon et al. 2009). Indeed, in March, the El Niño region is not identified as a robust precursor of VWS_{MDR} in July-October (see Fig. S2).¶

Deleted: therefore

Deleted: for this atmospheric variable. We therefore

Deleted: broader

Deleted: all clustering parameters are listed in the

Deleted: Potential

Deleted: are identified all over the globe

Deleted: 7b

Formatted: Subscript

Deleted: 7c and

Formatted: German

As expected, the overall skill of a hindcast based on these March precursors is lower than for the May hindcast but still considerable with a spearman rank correlation of 0.27 between the observed and the hindcasted ACE (Fig. 8). Despite being relatively low, this correlation is promising since this correlation is near zero in most operational forecast models (compare Klotzbach et al. 2017; Klotzbach 2019).

The linear model shows skill in hindcasting above median as well as extremely active seasons (Fig. 8b). For instance, an above 66th percentile season can be hindcasted with a true positive rate of 65% and a false positive rate of only 27%. The hindcasts of the logistic regression model for above 66th percentile seasons has skill over a climatological forecast ($BSS = 0.11$). The reliability diagram (Fig. 9c) shows a rather flat curve with few data points with high observed frequencies. This means that when the model predicts high probabilites for above 66th percentile seasons a relatively high number of these events are false positives. For above median TC activity the reliability curve is substantially closer to the diagonal and the skill over a climatological forecast is higher ($BSS = 0.17$ Fig. 9a).

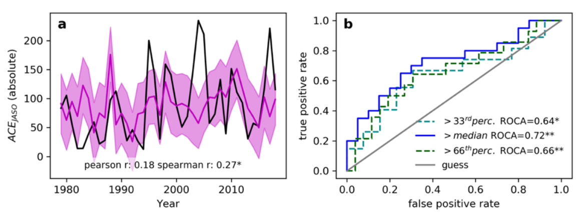
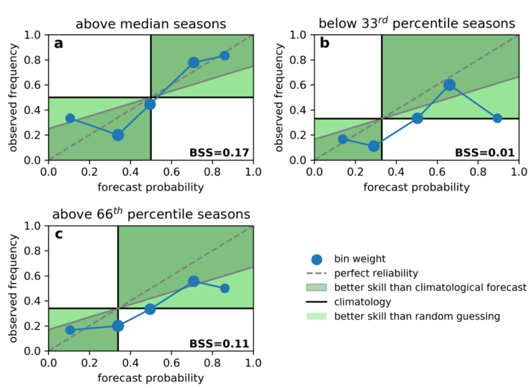


Figure 8: Hindcast skill based on March reanalysis. As Figure 5 but for March.



Deleted: As expected, the overall skill of a forecast based on these March precursors is lower than for the May forecast but still considerable with a spearman rank correlation of 0.27 between the observed and the predicted ACE (Fig. 8). Although relatively low, this correlation is promising since this correlation is near zero in most operational forecast models (compare Klotzbach et al. 2017; Klotzbach 2019).
The linear model shows skill in forecasting

Deleted: forecasted

Deleted: forecasts

Deleted: The skill of the March forecast significantly drops when detrended ACE anomalies are predicted using detrended precursor anomalies (see Fig. S3). This suggests that the skill of the March forecast model is partly due to the increase in ACE and the increase in Atlantic SSTs over the period 1979-2018.

Formatted: German

Deleted: Forecast

Deleted: as

Moved (insertion) [1]

Formatted: German

Figure 9: Reliability diagrams for a logistic regression model on March precursors. As Figure 6 but for March.

Our results suggest that the identified dipole pattern in MSLP in the southern Indian Ocean and the western south Pacific enhances VWS in the tropical Atlantic 4-6 months later (see Fig. 7c for the dipole) but the underlying mechanism is not obvious. We hypothesize that this dipole weakens the trade winds in the western Pacific, thereby favoring the formation of El Niño events. This would sub-sequentially lead to strong VWS in the Atlantic (during the main hurricane season).

We test this hypothesis by constructing a causal effect network. As input data we include time-series constructed as the MSLP difference between the southern Indian Ocean and the western south Pacific (“Delta MSLP”), the strength of the trade winds in the western Pacific (“Trade winds 850 hPa”) and SSTs in the Niño 3.4 region (“SST Niño 3.4”) (all regions are displayed in Figure 10a). The CEN is then calculated for the months of February to July which is roughly the period for which we want to test the hypothesis.

The detected causal links between the actors are shown in a Figure 10b. Indeed, weak trade winds in the western Pacific are suggested to favor the formation of El Niño events in the next month. Further, a strong pressure gradient towards the Indian Ocean weakens the trade winds (on a time scale of two months). At the same time, strong trade winds increase the pressure difference between Indian Ocean and Pacific. Overall, although a more detailed analysis is needed, our analysis suggests that the identified March dipole, might indeed be physically linked to the upcoming Atlantic hurricane activity.

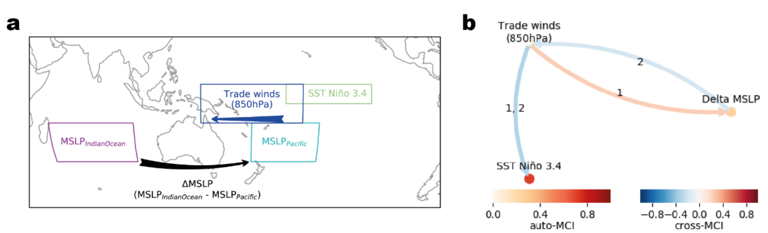


Figure 10: Causal effect network (CEN) to test if the detected robust precursor in March affects ENSO variability. a) Regions included to construct the time-series that enter the CEN. To describe the robust precursors, we include the MSLP difference between the southern Indian Ocean (magenta box) and the western South Pacific (cyan box). We further include an index of western Pacific trade winds at 850hPa (blue box) and SSTs in the Nino3.4 region (green box). b) Resulting CEN of the time-series calculated over the regions as shown in a). For the CEN calculation only the months February to July and time lags of 1 to 4 months are considered. The color of the arrows indicates the link strengths, with the color of the nodes indicating the strength of the auto-dependence.

Deleted: Since

Moved (insertion) [2]

Formatted: Font: Bold

Deleted: theoretical explanation of

Deleted: MSLP

Deleted: available as yet, we assessed the relevance of its contribution

Deleted: model solely based on

Deleted: Atlantic. This model, however, has no skill (see Fig. S4). Therefore,

Deleted: can conclude that

We also test whether the skill of our forecast model could be the result of linear trends in precursors. As shown in figure S3, the trends of March precursors are small compared to the interannual variability and are not statistically significant (p-values > 0.15 according to a two-sided Student´s t-test). We therefore conclude that the skill of our March forecast relies on the year to year variability of the identified precursors VWS_{MDR} and SST_{MDR} and does indeed include some useful information.

Note that the identified robust precursors of strong VWS_{MDR} over the southern hemispheric oceans might suffer from quality deficits of the reanalysis product, as only relatively few observations of SSTs and MSLP are available in these regions. We therefore perform a number of sensitivity tests to investigate how robust this signal is and whether it could be an artefact of the used ERA5 reanalysis data. To do this, we conduct the same analysis using JRA55 reanalysis and obtain similar precursors in May and March (Fig. S4 & Fig. S6). Overall these precursors are yet less robust in JRA55 and the forecast skill is slightly reduced (Fig. S5 & Fig. S7).

The reason for this difference might also lie in the method applied to identify potential precursors (step 2 in Fig. 1). Applying the same clustering algorithm with the same parameters on a dataset with a different grid size leads to a minimally different clustering behavior and might therefore affect the whole model building approach. The strong influence of the clustering step on the identified potential precursors and all the subsequent steps in the analysis could thus partially explains the differences between the results obtained with JRA55 and ERA5.

Finally, we test whether our model has skill outside of the period used for the main analysis (1979-2018) by applying a forecast model trained on 1980-2018 to the early period of JRA55 (1958-1978). In the pre-1979 period, our model captures main features as a reduced hurricane activity in the 1970s after higher activity in the 1960s (see Fig. S8). It, however, systematically overestimates hurricane activity and the skill is lower than in the cross-validated hindcast of the period 1979-2018.

The reduced skill in the pre-1979 period could be a result of non-stationarities in precursors of Atlantic hurricane activity. For instance, changes in anthropogenic aerosol emissions lead to a suppression of tropical cyclone activity in the period 1950-1980 (Dunstone et al. 2013). This could explain the systematic overestimation of hurricane activity in our model as it does not capture the effect of aerosols.

It has to be noted as well that reanalysis for time periods before the use of satellites (before 1979) are subject to considerable uncertainties especially in the southern hemisphere (Tennant 2004). It therefore remains difficult to investigate whether the identified relationship between March precursors and hurricane activity is robust under different climate states with the available datasets.

In summary, the identified MSLP precursors in March appear to be less robust than the well-documented May precursors. However, as far as it can be assessed with the given reanalysis datasets, sensitivity tests suggest that the identified March precursors indeed contain useful information contributing to a skillful seasonal forecasts of ACE.

Deleted: combination of warm SSTs in the Atlantic and the identified MSLP dipole pattern between the south Indian Ocean and the south Pacific underscoring the relevance of this potential mechanism

Deleted: The results of our forecast models are to some extend sensitive to

Deleted: Applying

Deleted: method to the

Deleted: results in

Deleted: S5-6

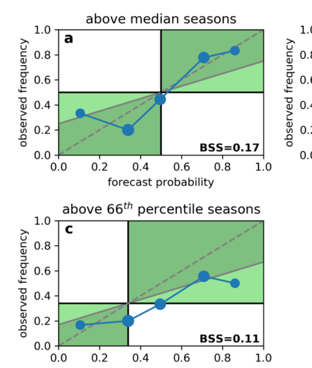
Deleted: seem

Deleted: thereby

Deleted: also

Deleted: -8

Deleted: ¶



Moved up [1]: **Figure 9: Reliability diagrams for**

Formatted: German

Deleted: **a logistic regression model on March reanalysis.**

Moved up [2]: **As Figure 6 but for March.**¶

¶

Deleted: ¶

Deleted: This highlights a potential caveat of the method: the

Deleted: .

4 Discussion

A crucial component of statistical forecasting is the selection of meaningful predictors. Because too many included features quickly lead to overfitting, methods are required to sub-select relevant predictors from a large set of potential predictors (Hawkins 2004). Here we showed that causal effect networks (CEN), a data-driven method based on causal inference techniques, can be used to identify robust predictors of a variable of interest.

Using CEN, we identified warm SSTs in the Atlantic and La Niña conditions in May as robust precursors of an active hurricane seasons in July-October. These precursors are consistent with the prevailing literature and thus show the usefulness of our approach. We performed hindcasts based on these precursors and showed that the skill of our forecast model compares well with operational forecast models (Klotzbach et al. 2019), although, the real forecasting skill of our model can only be evaluated in the coming years.

At longer lead times, the skill of operational forecast models issued at the beginning of April is limited (Klotzbach et al. 2019). Here we also identified robust precursors in March including a region of Atlantic SSTs and two regions of mean sea level pressure anomalies in the southern Indian Ocean and east of New Zealand. A model based on these precursors provides valuable hindcasts of above median and above 66th percentile seasonal activity. We speculate on the involved mechanism at play, and suggest that a strong pressure gradient in that region weakens the trade winds in the western Pacific, which would favor the formation of El Niño events, which in turn are associated with reduced hurricane activity. We provided some evidence for this hypothesis by applying a simple CEN on the involved actors, but more research is needed to show the robustness of this link.

In this study we searched for robust precursors of two well-known favorable conditions for TC formation and intensification, that is, warm SSTs and low VWS in the Atlantic main development region. Including more variables to the characterization of favorable conditions, such as relative humidity or upper troposphere temperatures could further increase the skill. It might, however, be challenging to incorporate these conditions in our current framework which was constructed using seasonally aggregated data. For relative humidity in particular, variability on shorter time scales than SSTs or VWS might be relevant in this context.

Here we constructed causal effect networks for favorable conditions in the hurricane season and their potential precursors in SSTs or MSLP at a fixed time lag of two or four months. Yet, mechanisms on different time-scales and lags might also play a role and might further affect our results (Runge 2018). Overall, we cannot guarantee that the identified links are "truly causal". The causal effect network approach rather helps to identify "the least spurious links" and therefore most robust precursors or most skillful predictors. We stress that physical knowledge of the underlying mechanisms are essential to ensure a meaningful interpretation of our data-centric approach.

A challenge that we did not address here are potential non-stationarities regarding the detected robust precursors (as discussed in Fink et al. 2010; Caron et al. 2015). Such non-stationarities could lead to varying forecast skill. Given the limited time span

Deleted: would

Deleted: (Hawkins 2004)

Deleted: show

Deleted: a core set of

Deleted: Warm SSTs in the Atlantic and La Niña conditions in May are identified as robust precursors of active hurricane seasons in July-October. The skill of our forecast model compares well to operational forecast models (Klotzbach 2019), although, the real forecasting skill of our model can only be evaluated in the coming years.
At longer lead times, the skill of operational forecast models issued at the beginning of April is limited (Klotzbach 2019). Our model based on Atlantic SSTs and two mean sea level pressure regions in the southern Indian Ocean and east of New Zealand in March seems to overcome this forecast barrier and provides valuable predictions of above median and above 66th percentile seasonal activity. This forecast seems not to rely on the ENSO signal but on a teleconnection between the identified pressure regions and vertical wind shear (4 months before the season) in the Atlantic that has not been documented so far. Incorporating this new signal into statistical forecasts that use ENSO projections could therefore lead to an improved skill.

Deleted: :

Deleted: vertical wind shear

Deleted: that works on seasonal time scales.

Deleted: We constructed causal effect networks for favorable conditions in the hurricane season and their potential precursors in SSTs or MSLP at a fixed time lag of 2 or 4 months. In our application, the underlying assumptions of the causal effect network algorithm are not strictly fulfilled (Runge 2018) and thus we cannot guarantee that the identified links are "truly causal". The causal effect network rather helps to identify "the least spuriously link" and therefore most robust precursors or most skillful predictors.
A challenge that we did not address here are potential non-stationarities in the climate system. The detected causal links might not be stationary over time, which could lead to varying forecast skill. Unfortunately, the time span for which reliable reanalysis datasets exists is limited which makes further investigation of this problem challenging. One way to deal with this is to apply this approach to climate simulations for which longer time series are available.
The forecast model construction

for which reliable reanalysis datasets exist, this issue remains difficult. Applying our approach to climate simulations for which longer time series are available is therefore a logical next step.

Our here proposed technique to construct statistical forecasting models is generic and can easily be applied for other meteorological phenomena. It could for instance be applied to forecast seasonal hurricane activity in other basins for which fewer forecasts exist.

From a methodological viewpoint, the most sensitive step in the approach seems to be the identification of potential precursors (step 2 in Fig. 1). Depending on the choice of the free parameters of the clustering algorithm and significance threshold for correlated grid-cells, the detected potential precursor regions can vary and subsequently affect the causal network. Improving the robustness of this step or finding alternative ways of defining these potential precursors would further enhance the applicability of the method. Given the recent advances in novel machine learning techniques we are confident that this method can be further improved.

Deleted: developed in this study is highly automated

Deleted: seasonal forecasts of

Deleted: In our view

Deleted: critical

Deleted: is

Deleted: fig

4 Conclusions

Using a causal effect network approach, we identified skillful spring predictors of seasonal Atlantic hurricane activity from July to October. For shorter lead times of two months, the identified precursor regions represent well-documented physical drivers. Statistical forecast models based on these drivers yield considerable prediction skill, demonstrating the potential of our method. For longer lead times of up to four months, our method suggests a pressure dipole between the southern Indian Ocean and the western South Pacific as a predictor of hurricane activity in the following season. A prediction model based on these March precursors still shows skill, but challenges in predicting in particular highly active hurricane seasons remain.

We see different entry points for our findings to be incorporated into applied seasonal hurricane forecasts. Besides a direct application of our early April forecast model, we encourage other statistical forecasting groups to investigate whether our newly identified predictors can help to improve their statistical forecast models. Furthermore, the causal links identified here could form the basis for hybrid forecasting techniques where a dynamical forecast ensemble is constrained by selecting only members that adequately reproduce the causal links as demonstrated by Dobrynin et al. (2018).

Improved seasonal forecasting with long lead-times can support seasonal planning of disaster risk reduction measures, particularly also related to disaster relief and emergency aid provision. While basin scale dissipated energy does not directly provide risk profiles for individual countries, it allows to inform decision making on the regional level, including on financial support needs pooled e.g. in the Caribbean Catastrophe Risk Insurance Facility serving Caribbean islands states (CCRIF). As such, improved seasonal forecasting can provide essential information to ensure hurricane preparedness in affected countries.

Deleted: We applied

Deleted: networks to identify

Deleted: for

Deleted: forecasts.

Deleted: we identify

Deleted: known precursors while for

Deleted: we find novel predictors from which a competitive early April forecast model can be constructed. Our model shows competitive skill in forecasting seasonal

Deleted: , although some

Deleted: the representation of the most

Deleted: be a

Deleted: (2018)

Deleted: however

Deleted: .

Code availability

All python scripts required to reproduce the analysis are available under: github.com/peterpeterp/atlantic_ace_seasonal_forecast

Author contributions

All authors conceived the study. P.P. did the analysis and wrote the manuscript with contributions from all authors.

Deleted: P.P., C.-F.S., T.G. and M.K.

Deleted: created all figures. P.P.

Competing interests

The authors declare no competing interests.

Acknowledgements

We acknowledge the openly available TIGRAMITE tool developed by Jakob Runge (github.com/jakobrunge/tigramite). We also acknowledge the IBTrACS dataset (ncdc.noaa.gov/ibtracs), fifth generation of ECMWF atmospheric reanalyses (ecmwf.int/en/forecasts/datasets/reanalysis-datasets/era5) and the Japanese 55-year reanalysis (jra.kishou.go.jp/JRA-55). P.P. and C.-F.S. acknowledge support by the German Federal Ministry of Education and Research (01LN1711A). T.G. acknowledges from the German Federal Ministry of Education and Research (BMBF) under the research project SLICE (01LA1829A). M.K. was supported by the ERC Advanced Grant "ACRCC" (Grant 339390) and received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement (No 841902).

References

Brier GW (1950) Verification of forecasts expressed in terms of probability. Mon Weather Rev 78:1–3

Camargo SJ, Hsiang SM (2014) Tropical Cyclones: From the Influence of Climate to their Socio-Economic Impacts. Extrem Events Obs Model Econ 73:90. doi: 10.1002/9781119157052.ch18

Caron L-P, Boudreault M, Bruyère CL (2015) Changes in large-scale controls of Atlantic tropical cyclone activity with the phases of the Atlantic multidecadal oscillation. Clim Dyn 44:1801–1821. doi: 10.1007/s00382-014-2186-5

CCRIF The Caribbean Catastrophe Risk Insurance Facility. https://www.ccrif.org. Accessed 28 May 2020

Copernicus Climate Change Service (C3S) (2017) ERA5: Fifth generation of ECMWF atmospheric reanalyses of the global climate. In: Copernicus Clim. Chang. Serv. Clim. Data Store. https://cds.climate.copernicus.eu/cdsapp#!/home. Accessed 12 Nov 2019

Di Capua G, Kretschmer M, Runge J, et al (2019) Long-lead statistical forecasts of the indian summer monsoon rainfall based on causal precursors. Weather Forecast 34:1377–1394. doi: 10.1175/WAF-D-19-0002.1

Dieng AL, Sall SM, Eymard L, et al (2017) Trains of African Easterly Waves and Their Relationship to Tropical Cyclone Genesis in the Eastern Atlantic. Mon Weather Rev 145:599–616. doi: 10.1175/MWR-D-15-0277.1

Dobrynin M, Domeisen DI V., Müller WA, et al (2018) Improved Teleconnection-Based Dynamical Seasonal Predictions of Boreal Winter. Geophys Res Lett 45:3605–3614. doi: 10.1002/2018GL077209

Dunstone NJ, Smith DM, Booth BBB, et al (2013) Anthropogenic aerosol forcing of Atlantic tropical storms. Nat Geosci 6:534–539. doi: 10.1038/ngeo1854

Emanuel K, DesAutels C, Holloway C, Korty R (2004) Environmental Control of Tropical Cyclone Intensity. J Atmos Sci 61:843–858. doi: 10.1175/1520-0469(2004)061<0843:ECOTCI>2.0.CO;2

Fink AH, Schrage JM, Kotthaus S (2010) On the Potential Causes of the Nonstationary Correlations between West African Precipitation and Atlantic Hurricane Activity. J Clim 23:5437–5456. doi: 10.1175/2010JCLI3356.1

Frank WM, Ritchie EA (2001) Effects of vertical wind shear on the intensity and structure of numerically simulated hurricanes. Mon Weather Rev 129:2249–2269. doi: 10.1175/1520-0493(2001)129<2249:EOVWSO>2.0.CO;2

Gray WM (1984a) Atlantic Seasonal Hurricane Frequency. Part I: El Niño and 30 mb Quasi-Biennial Oscillation Influences. Mon Weather Rev 112:1649–1668. doi: 10.1175/1520-0493(1984)112<1649:ASHFPI>2.0.CO;2

Gray WM (1984b) Atlantic Seasonal Hurricane Frequency. Part II: Forecasting its Variability. Mon Weather Rev 112:1669–1683. doi: 10.1175/1520-0493(1984)112<1669:ASHFPI>2.0.CO;2

Hankes I, Marinaro A (2016) The impacts of column water vapour variability on Atlantic basin tropical cyclone activity. Q J R Meteorol Soc 142:3026–3035. doi: 10.1002/qj.2886

Hawkins DM (2004) The Problem of Overfitting. J. Chem. Inf. Comput. Sci. 44:1–12

Hendon HH, Lim E, Wang G, et al (2009) Prospects for predicting two flavors of El Niño. Geophys Res Lett 36:L19713. doi: 10.1029/2009GL040100

Kim H-M, Webster, PJ, Curry JA (2009) Impact of Shifting Patterns of Pacific Ocean Warming on North Atlantic Tropical Cyclones. Science (80-) 325:77–80. doi: 10.1126/science.1174062

Klotzbach P, Blake E, Camp J, et al (2019) Seasonal Tropical Cyclone Forecasting. Trop Cyclone Res Rev 8:134–149. doi: 10.1016/j.tcrr.2019.10.003

Klotzbach PJ, Saunders MA, Bell GD, Blake ES (2017) North Atlantic Seasonal Hurricane Prediction. pp 315–328

Klotzbach PJ, Schreck CJ, Collins JM, et al (2018) The extremely active 2017 North Atlantic hurricane season. Mon Weather Rev 146:3425–3443. doi: 10.1175/MWR-D-18-0078.1

Knapp KR, Diamond HJ, Kossin JP, et al (2018) International Best Track Archive for Climate Stewardship (IBTrACS) Project, Version 4. In: NOAA Natl. Centers Environ. Information. https://doi.org/10.25921/82ty-9e16. Accessed 26 Sep 2019

Knapp KR, Kruk MC, Levinson DH, et al (2010) The international best track archive for climate stewardship (IBTrACS). Bull Am Meteorol Soc 91:363–376. doi: 10.1175/2009BAMS2755.1

Kretschmer M, Coumou D, Donges JF, Runge J (2016) Using Causal Effect Networks to analyze different Arctic drivers of mid-latitude winter circulation. J Clim 160303130523003. doi: 10.1175/JCLI-D-15-0654.1

Kretschmer M, Runge J, Coumou D (2017) Early prediction of extreme stratospheric polar vortex states based on causal precursors. Geophys Res Lett 44:8592–8600. doi: 10.1002/2017GL074696

Lehmann J, Kretschmer M, Schauberger B, Wechsung F (2020) Potential for early forecast of Moroccan wheat yields based on climatic drivers. Geophys Res Lett 0–3. doi: 10.1029/2020GL087516

Li J, Liu L, Le TD, Liu J (2020) Accurate data-driven prediction does not mean high reproducibility. Nat Mach Intell 2:13–15. doi: 10.1038/s42256-019-0140-2

Manganello J V., Cash BA, Hodges KI, Kinter JL (2017) Seasonal forecasts of North Atlantic tropical cyclone activity in the North American Multi-Model Ensemble. Clim Dyn 0:1–16. doi: 10.1007/s00382-017-3670-5

Munich Re (2020) Natural catastrophe know-how for risk management and research. https://natcatservice.munichre.com. Accessed 19 May 2020

Murakami H, Levin E, Delworth TL, et al (2018) Dominant effect of relative tropical Atlantic warming on major hurricane occurrence. Science (80-) 6711:eaat6711. doi: 10.1126/science.aat6711

Murphy SJ, Washington R, Downing TE, et al (2001) Seasonal forecasting for climate hazards: Prospects and responses. Nat Hazards 23:171–196. doi: 10.1023/A:1011160904414

Patricola CM, Saravanan R, Chang P (2018) The Response of Atlantic Tropical Cyclones to Suppression of African Easterly Waves. Geophys Res Lett 45:471–479. doi: 10.1002/2017GL076081

Roberts MJ, Camp J, Seddon J, et al (2020) Impact of model resolution on tropical cyclone simulation using the HighResMIP-PRIMAVERA multimodel ensemble. J Clim 33:2557–2583. doi: 10.1175/JCLI-D-19-0639.1

Runge J (2018) Causal network reconstruction from time series: From theoretical assumptions to practical estimation. Chaos 28:. doi: 10.1063/1.5025050

Runge J (2014) TIGRAMITE – Causal discovery for time series datasets. GitHub Repos.

Deleted: PJ

Deleted: 6057/2019TCRR03.03

Deleted: Martinez AB (2018) A false sense of security: The impact of forecast uncertainty on hurricane damages. Univ Oxford, Dep Econ Discuss Pap 831:. doi: 10.2139/ssrn.3070154

Runge J, Nowack P, Kretschmer M, et al (2019) Detecting and quantifying causal associations in large nonlinear time series datasets. Sci Adv 5:eaau4996. doi: 10.1126/sciadv.aau4996

Saggioro E, Shepherd TG (2019) Quantifying the timescale and strength of Southern Hemisphere intra-seasonal stratosphere-troposphere coupling. Geophys Res Lett. doi: 10.1029/2019gl084763

Tang BH, Neelin JD (2004) ENSO Influence on Atlantic hurricanes via tropospheric warming. Geophys Res Lett 31:L24204. doi: 10.1029/2004GL021072

Tennant W (2004) Considerations when using pre-1979 NCEP/NCAR reanalyses in the southern hemisphere. Geophys Res Lett 31:n/a-n/a. doi: 10.1029/2004GL019751

The Japan Meteorological Agency (JMA) (2013) JRA-55: Japanese 55-year Reanalysis, Daily 3-Hourly and 6-Hourly Data

Torrence C, Webster PJ (1998) The annual cycle of persistence in the El Nino/Southern Oscillation. Q J R Meteorol Soc 124:1985–2004. doi: 10.1256/smsqj.55009

Vecchi GA, Delworth T, Gudgel R, et al (2014) On the seasonal forecasting of regional tropical cyclone activity. J Clim 27:7994–8016. doi: 10.1175/JCLI-D-14-00158.1

Vecchi GA, Soden BJ (2007) Effect of remote sea surface temperature change on tropical cyclone potential intensity. Nature 450:1066–1070. doi: 10.1038/nature06423

Vitart F, Stockdale TN (2001) Seasonal forecasting of tropical storms using coupled GCM integrations. Mon Weather Rev 129:2521–2537. doi: 10.1175/1520-0493(2001)129<2521:SFOTSU>2.0.CO;2

Waple AM, Lawrimore JH, Halpert MS, et al (2002) CLIMATE ASSESSMENT FOR 2001. Bull Am Meteorol Soc 83:S1--S62

Woodruff JD, Irish JL, Camargo SJ (2013) Coastal flooding by tropical cyclones and sea-level rise. Nature 504:44–52. doi: 10.1038/nature12855

Ye Y, Fang W (2018) Estimation of the compound hazard severity of tropical cyclones over coastal China during 1949–2011 with copula function. Nat Hazards 93:887–903. doi: 10.1007/s11069-018-3329-5

Deleted: Bathiany S, Bollt E, et al (2019a) Inferring causation from time series in Earth system sciences. Nat Commun 10:2553. doi: 10.1038/s41467-019-10105-3¶
Runge J,

Deleted: 2019b

Formatted: Indent: Left: 0 cm, Hanging: 0,85 cm

Deleted: ¶

Page 3: [1] Deleted	Peter Pfleiderer	5/28/20 10:38:00 AM