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Key Points:

- A recently produced high-resolution GCM ensemble allows for the first time a systematic assessment of Genesis Potential Indices (GPIs) performance
- All the analyzed GPIs show poor skill in reproducing the interannual variability and future trends of modeled cyclones
- Possible ways forward include adding variables related to Tropical Cyclones small-scale dynamics, and using advanced statistical techniques based on Machine Learning

Supporting Information:

Supporting Information may be found in the online version of this article.

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Tropical Cyclone Genesis Potential Indices in a New High-Resolution Climate Models Ensemble: Limitations and Way Forward

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Abstract Genesis Potential Indices (GPIs) link the occurrence of Tropical Cyclones (TCs) to large-scale environmental conditions favorable for TC development. In the last few decades, they have been routinely used as a way to overcome the limitations of climate models (GCM), whose resolution is too coarse to produce realistic TCs. Recently, the first GCM ensemble with high enough horizontal resolution to realistically reproduce TCs was made available. Here, we address the questions of whether GPIs are still relevant in the era of TC-permitting climate model ensembles, and whether they have sufficient predictive skills. The predictive skills of GPIs are assessed against the TCs directly simulated in a climate model ensemble. We found that GPIs have poor skill in two key metrics: inter-annual variability and multi-decadal trends. We discuss possible ways to improve the understanding of the predictive skill of GPIs and therefore enhance their applicability in the era of TC-permitting GCMs.

Plain Language Summary Tropical Cyclones are extreme weather events which cause large damage when they hit inhabited areas. Understanding future cyclone activity in advance is very important to limit the damage. Until recently, climate models that scientists use to study future extremes where not able to reproduce realistic tropical cyclones because available computers were not powerful enough. Scientists used to look at indicators of cyclone activity -known as genesis potential indices—based on a number of quantities responsible for cyclone formation, rather than looking at cyclones themselves. Using cyclone data from a new set of climate model projections, we show that genesis potential indices are not always accurate in explaining future cyclone activity. We discuss how future research could help us improve the understanding of the drivers of tropical cyclone activity, and therefore the accuracy of genesis potential indices.

1. Introduction

Tropical cyclones (TC), synoptic scale vortices fueled by air-sea heat and moisture fluxes, form in the tropical latitudes belts in both hemispheres at a global rate of approximately 80–90 per year (K. J. Walsh et al., 2016). Landfalling TCs are among the natural disasters producing the largest economic losses (Mendelsohn et al., 2012), due to the associated strong winds (with gusts exceeding 300 km per hour in Category 5 TCs), heavy precipitation, and storm surges, leading to extensive flooding of coastal areas. Therefore, predicting the occurrence, intensity and trajectory of TCs is of crucial socio-economic importance. Short-term forecasts of tropical cyclones have shown a significant increase in accuracy over the last decades (Robertson et al., 2020) due to the improvement of Numerical Weather Prediction models and the availability of high-quality observational data of past events (Knapp et al., 2010). On the other hand, the skill of long-term climate predictions and projections has not yet exhibited a comparable improvement (Befort et al., 2022; Vecchi et al., 2014). This is primarily due to the large amount of computer resources needed to run climate models over extended time periods (Climate Projections), for a large number of ensemble members (Seasonal predictions), or a combination of both (Decadal predictions). Due to limitations of available computer power, global climate model ensembles, such as the ones produced for the various iterations of the Coupled Models Intercomparison Project (CMIP), have been until recently routinely run at horizontal resolutions of the order of 100 km, which is not fine enough to achieve a realistic representation of tropical cyclones (K. Walsh et al., 2013). Some studies have used high-resolution models to study the response of TCs to anthropogenic global warming (Murakami et al., 2012, 2015). Yet, single model analyses are not able to properly characterize the uncertainty that is intrinsically associated with such estimates (Villarini & Vecchi, 2012).

To overcome the lack of high-resolution models, a different approach has been developed to study the future occurrence of TCs. Numerical indices were introduced, linking the occurrence of TCs to the presence of large-scale environmental factors known to be conducive to TC development, for example, (K. Emanuel & Nolan, 2004; Gray, 1979). Such indices, collectively known as Genesis Potential Indices (GPIs), are statistical fits of observations and reanalysis fields, unlike other indicators of TC activity derived from theory, for example, potential intensity (K. A. Emanuel, 1988) or ventilation index (Tang & Emanuel, 2012). GPIs commonly take the form of a product (or, in some more complex relationship, a product of exponentials) of large-scale atmospheric or oceanic variables with numerical coefficients empirically determined from past TC observations. In principle, once the functional form of a GPI has been identified from past observations, under the assumption that the same relationship is valid for climate models, it can be applied to GCM output to infer future TC activity at inter-annual to multi-decadal scales. In practice, however, GPIs are hindered by poor skill in several metrics (Menkes et al., 2012). GPIs reproduce with high accuracy the spatial pattern and seasonal cycle of observed TCs, for which they were derived. Their accuracy is generally lower at inter-annual time scales. They are however able to reproduce the modulation of TCs by ENSO (S. J. Camargo et al., 2007; Patricola et al., 2014) and MJO (S. J. Camargo et al., 2009; Vitart, 2009). Moreover, the few studies analyzing GCM-simulated future TCs generally show a decreased frequency in projected TC activity, while GPIs generally predict an increase in TC frequency (S. J. Camargo et al., 2014). Moreover, (S. J. Camargo et al., 2020) showed that the discrepancy between model TCs and GPI is present not only in future trends but also in the climatology. While modified versions of the GPI have been proposed, partially addressing both shortcomings (lack of skill at inter-annual scales and inconsistent long-term trends), the question remains of whether GPI can be considered a reliable indicator of TC activity in climate projections.

The paradigm described above has changed recently since the first ensemble of high-resolution GCMs was produced within the 6th Climate Modeling Intercomparison Programme (CMIP6, Tebaldi et al., 2021). Such a high-resolution model ensemble (HIGHResMIP, High Resolution Model Intercomparison Project, Haarsma et al., 2016) allows for the first time the analysis of directly simulated future changes of TC activity and the estimate of the associated uncertainty. On the other hand, the availability of a high-resolution GCM ensemble such as HighResMIP provides the opportunity to robustly assess the skill of GPIs on an independent data set not used to determine the values of the parameters appearing in the indices. Though one could argue that TC-permitting GCM ensembles will soon make GPIs obsolete, the case for abandoning those indices is not necessarily straightforward. An example of application of GPIs which remains relevant in the high-resolution GCM era is the use in tropical cyclone risk models (Lee et al., 2020, 2022; Sobel et al., 2019). Moreover, using GPIs allows to produce an on-the-fly assessment of TC activity without the need to process a large amount of data at sub-daily frequency and without the additional complications of cyclone tracking. This approach still has added value in operational settings such as seasonal predictions. Moreover, for seasonal-to-decadal forecasts relying on a large ensemble of simulations, running the system at TC-permitting horizontal resolution is still a few years away. Therefore, we argue that the GPI approach can provide added value to these applications that still rely on coarse GCMs. However, such added value depends on the GPIs predictive skill in capturing TC inter-annual variability and future trends.

In this paper we provide an assessment of the GPI predictive skill by objectively and systematically comparing the TC activity predicted using the GPIs with directly simulated TCs in a high-resolution multi-model GCM ensemble. Our findings will provide indications to drive future research efforts for advancing the understanding of TC activity in projections and will provide guidance for the development of refined versions of GPI for example, based on machine learning.

The rest of the manuscript is organized as follows. In Section 2, the data sets and methods used in this study are described. In Section 3, the main results of the study are presented and discussed. Section 4 contains conclusive remarks and suggestions for future work.

2. Data and Methods

2.1. Climate Model Data

Model data is obtained from the HighResMIP ensemble (Haarsma et al., 2016). We use the five models in Table 1, for which tropical cyclone tracking has been performed and analyzed in the literature. HighResMIP is

Table 1
List of HighResMIP Models Employed in This Study: Model Name and Horizontal Resolution of the Atmospheric Component

Model	Resolution
CMCC-CM2-VHR4	~0.3°
CNRM-CM6-1-HR	~0.5°
EC-Earth3P-HR	~0.35°
HadGEM3-GC31-HM	~0.35°
MPI-ESM1-2-XR	~0.45°

an ensemble of high-resolution (0.5° or finer in the atmosphere, 0.25° in the ocean) climate model simulations. Given the substantial amount of computer power needed to run climate simulations at this resolution, the HighResMIP protocol is based on shorter simulations with respect to the CMIP standard: 1950–2014 for the historical simulations and 2015–2050 for climate projections. Moreover, a single future scenario is considered, using the same forcing as the high-end CMIP5 emissions scenario. To verify that the small size of the ensemble does not introduce additional bias in the variables of interest, we repeated the computation of one of the GPIs (EN-GPI) for the larger ScenarioMIP CMIP6 ensemble (O'Neill et al., 2016), including about 30 models with a lower spatial resolution (Table S1 Supporting Information S1). For the ScenarioMIP simulations, we consider the scenarios SSP5-8.5 and SSP1-2.6 over the period 2015–2100. Results for the ScenarioMIP simulations are reported in Supporting Information S1.

2.2. Genesis Potential Indices

Several formulations of the Genesis Potential Index have been proposed in the literature. In this work, we analyze three of the most widely used and/or most recently formulated, namely the GPI from K. Emanuel and Nolan (2004) (hereafter EN-GPI), the GPI from Tippett et al. (2011) (hereafter TC-GPI), and the Dynamical Genesis Potential Index from Wang and Murakami (2020) (hereafter WM-GPI). The EN-GPI is based on the following large-scale variables, known to be conducive to TC formation: the absolute vorticity at 850 hPa, the relative humidity at 600 hPa, the wind shear between 200 and 850 hPa, and the TC maximum potential intensity (MPI), a theoretical estimate of the maximum attainable TC wind speed in a given environment. The main difference of TC-GPI with respect to EN-GPI is the replacement of MPI with the relative sea surface temperature due to its more straightforward computation and interpretability (Ramsay & Sobel, 2011; Vecchi & Soden, 2007). The WM-GPI, on the other hand, replaces the thermodynamic variables (MPI and relative humidity) with additional dynamical variables to improve the year-to-year correlation among GPI and observed TC occurrence. The performance of the different GPIs on reanalysis data sets has been previously analyzed by Menkes et al. (2012) who found large differences among the climatology of genesis indices among different reanalyzes. Murakami and Wang (2022) analyzed WM-GPI in coarse-resolution GCM simulations while S. J. Camargo et al. (2014) analyzed a different version of TC-GPI.

2.3. Cyclone Tracks

Cyclone tracks were based on the publicly available tracking database produced in the PRIMAVERA project (Roberts et al., 2020a) using the tracking scheme TRACKS (Hodges, 1995) and described in detail in Roberts et al. (2020b). All models reasonably reproduce the spatial pattern and seasonality of cyclone genesis. There are significant biases in the total yearly number of detected TCs (Bourdin et al., 2022). However, that is not an issue for the sake of comparison with GPIs as those indices by construction only describe variations of cyclone number and not its absolute value. Therefore, GPIs are generally normalized so that their integral coincides with the observed number of TCs (Menkes et al., 2012). In this work, we performed such normalization for each of the climate models separately, using as a reference the historical TC climatology of the model. Such normalization does not affect interannual variability correlations shown in Section 3.1, but will facilitate the comparison between GPIs and TC trends across different climate models (Section 3.2). We repeated the analysis for one of the GPI formulations using a second cyclone tracking scheme also used in the PRIMAVERA project, TempestExtremes (Ullrich et al., 2021; Zarzycki & Ullrich, 2017). We found that the choice of the tracking scheme does not substantially affect the results of the analysis (Figures S6–S8 in Supporting Information S1).

3. Results

3.1. TC Interannual Variability

GPIs have been reported by several studies to have medium to poor skill in reproducing the observed annual year-by-year frequency of observed TC occurrence, with the index performance being strongly sensitive to the analyzed ocean basin (S. Camargo et al., 2007; Wang & Murakami, 2020). One of the three examined indices, the WM-GPI, was derived with the improvement of this metric as one of the main goals. The skill of the three GPIs in reproducing the TC interannual variability (Figure 1) consistently shows a major decrease when computed for the HighResMIP ensemble with respect to the reference values (the correlation between the annual time series of ERA5 GPI and IBTrACS TCs). The WM-GPI gives marginally better results than the other two indices on some basins but still shows a performance decline with respect to the GPI computed from reanalysis. A notable feature is that the skill decrease is larger in basins where the reference GPI produces the best results, such as the North Atlantic. This might indicate overfitting, possibly due to the different accuracy of historical observations in different basins. Another interesting feature is that, when comparing the TC interannual variability between historical (Figure 1) and future (Figure 2) simulations, the GPIs' skill consistently decreases in some basins (e.g., a further decrease in the North Atlantic), while it consistently increases in other basins (e.g., the East North Pacific). This could indicate that the common variables among the three GPIs play different roles in different ocean basins in modulating the TC interannual variability.

3.2. TC Future Changes and Multidecadal Trends

As a first step, we verify that GPI projections in HighResMIP are consistent with the larger CMIP6 GCM ensemble. The result is shown in Figure S2 of the Supporting Information S1 for the EN-GPI. For the period of overlap (2015–2050), and comparable emission scenarios (RCP8.5 and SSP5-8.5) the two ensembles produce similar results, increasing the confidence in the robustness of results obtained from the smaller HighResMIP ensemble. For the 2070–2100 period, the changes in GPI projected by the CMIP6 ensemble are similar in pattern to the mid-century projections but with larger magnitude (Figure S3 in Supporting Information S1).

A comparison of the maps of the ensemble mean changes projected by the HighResMIP models (Figure 3, individual models in Figures S7–S9 of the Supporting Information S1) shows that the three GPIs predict consistent global-scale patterns of change and comparable amplitudes. Minor differences appear at the regional scale, for example, the pattern and/or amplitude of the index increase is larger for TC-GPI and WM-GPI with respect to EN-GPI in the West North Pacific and East North Pacific Basins.

Previous studies showed a poor agreement between TCs detected in climate models and TCs predicted from GPIs calculated in the same models (S. J. Camargo, 2013; Wehner et al., 2015). The disagreement is often found even in the sign of the change, with model projections showing a decreasing TC frequency but an increasing GPI.

Analyzing the compared trends of detected TCs and GPI (Figure 4), disaggregated at both the model and basin level, a more complex picture emerges. For all three GPIs, the sign disagreement is found for a fraction of between half and two thirds of all model-basin pairs. The level of agreement is slightly better for EN-GPI compared to the other indices. The total mean square error is higher for TC-GPI, as this index projects GPI trends that are two-three times higher than for the two other indices. A notable feature is that no disagreements in the trend sign is found for positive TC trend pairs. When aggregating the results by ocean basin, there are very few instances across the three GPIs where more than three models agree on the trend sign. Similar results hold when aggregating the trends by model.

4. Discussion and Conclusions

We assessed the predictive skill at different time scales (interannual and multi-decadal) of three different widely used genesis potential indices in an ensemble of high-resolution climate simulations. The analysis revealed that all three GPIs generally have low skill in reproducing the occurrence of GCM-detected tropical cyclones according to two crucial metrics: interannual variability, and trends of future cyclone activities. When looking at the indices basin by basin, we found the lack of skill to be widespread with very few exceptions. Moreover, for the interannual variability, we found a substantial decrease in the index skill when calculated for climate models with respect to the reference values from reanalyzes.

Here, we discuss a critical review of possible causes of GPI failures and suggest future research directions to be explored to solve the issue. Possible reasons for the discrepancies between the activity of directly detected TCs and those predicted by the GPIs include the following:

1. The GCMs produce TCs at about the right locations and times for the wrong reasons.
2. GPIs do not include some essential physical variable linked to TC occurrence, for example, related to the occurrence of disturbances evolving into TCs (seeds).

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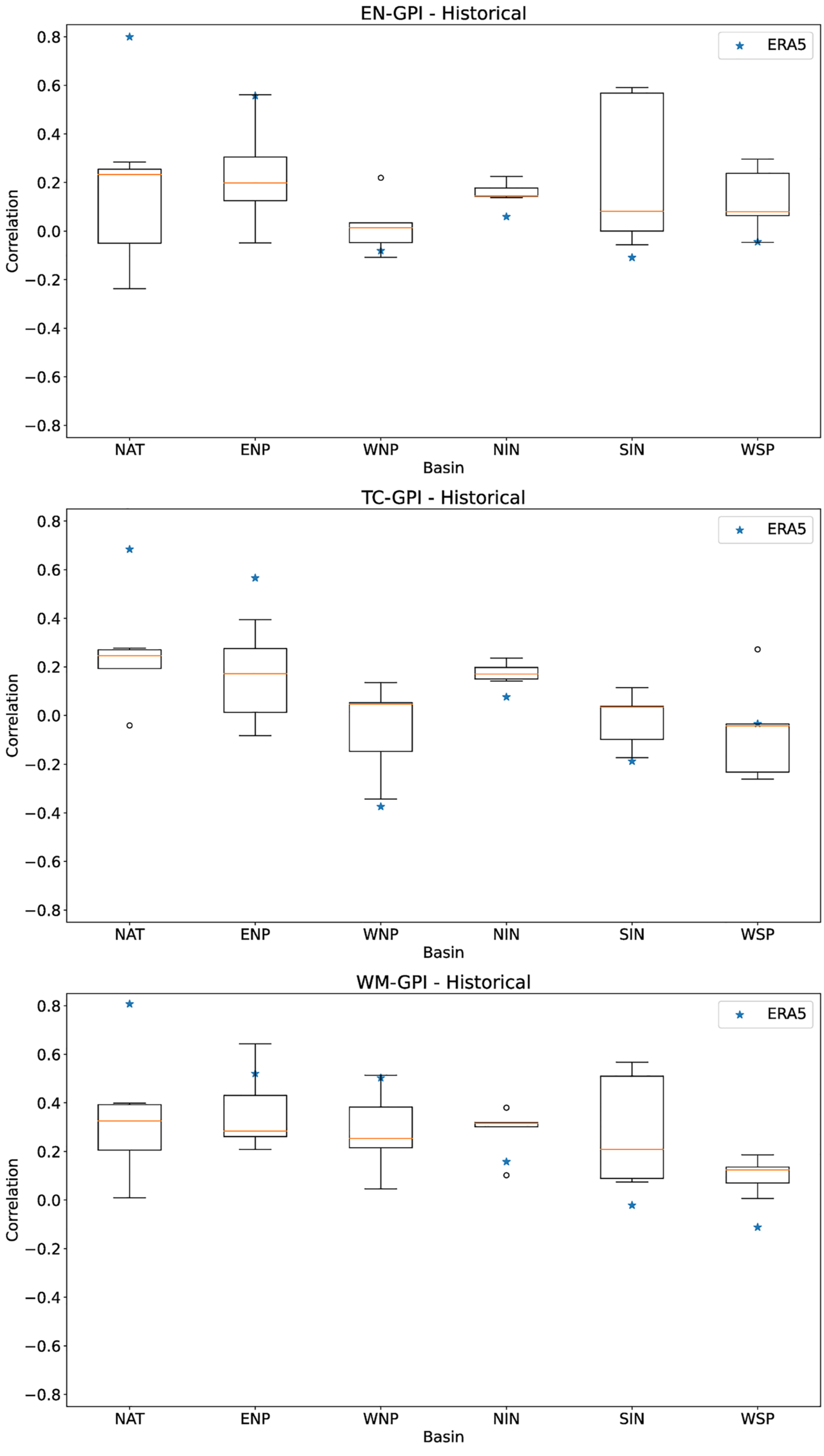

Figure 1. Boxplots showing the ensemble spread of the correlation between yearly time series of, respectively, the number of directly detected TCs and the TC number predicted through GPIs in the historical simulations: EN-GPI (top panel), TC-GPI (middle panel) and WM-GPI (bottom panel). The box and whiskers represents respectively the interquartile range (IQR) and the furthest data points within 1.5 times the IQR. Horizontal axis shows the different ocean basins: North Atlantic (NAT), East North Pacific (ENP), West North Pacific (WNP), Northern Indian (NIN), Southern Indian (SIN), and West South Pacific (WSP).

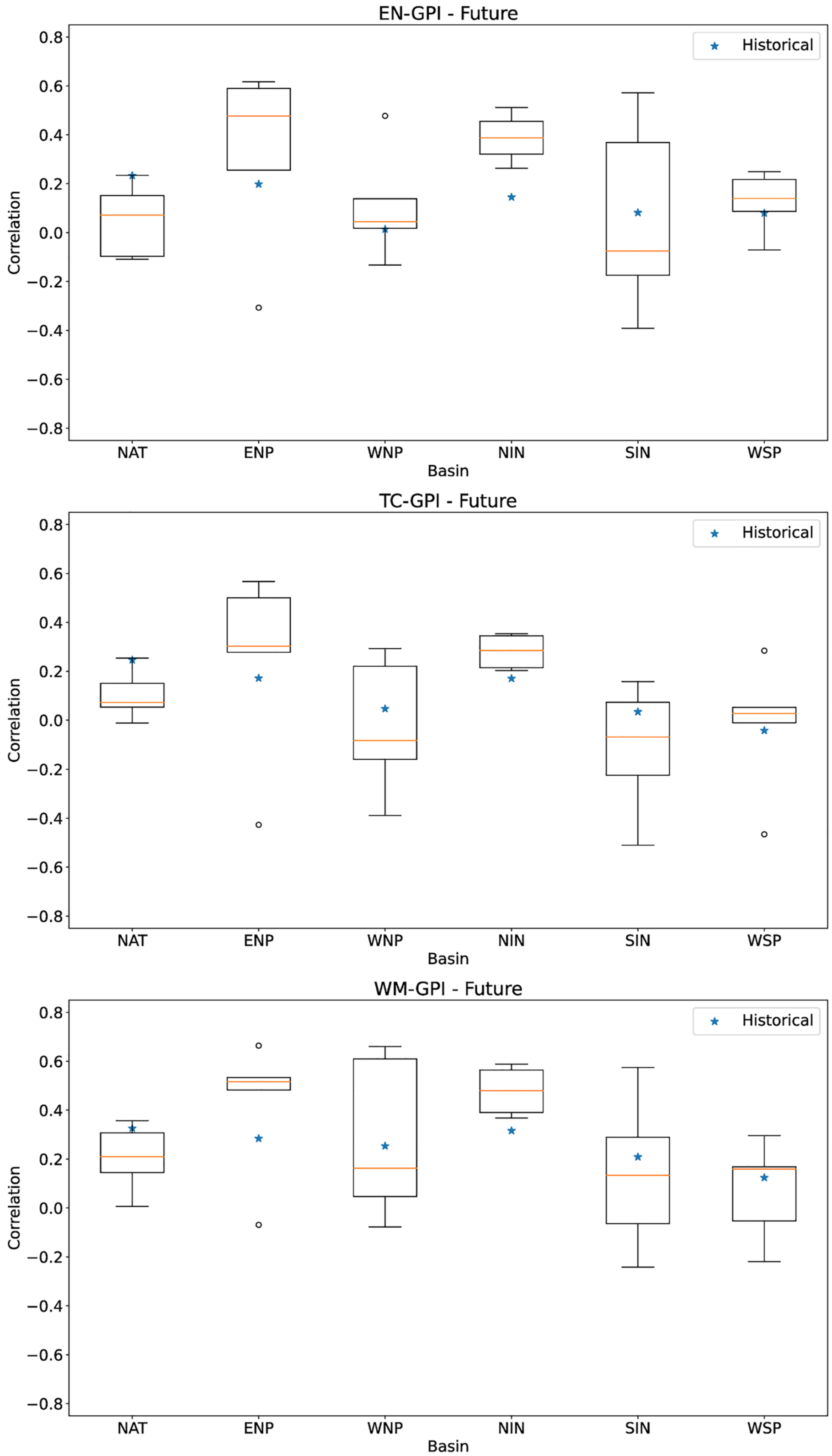

Figure 2. Same as Figure 1 for future projections.

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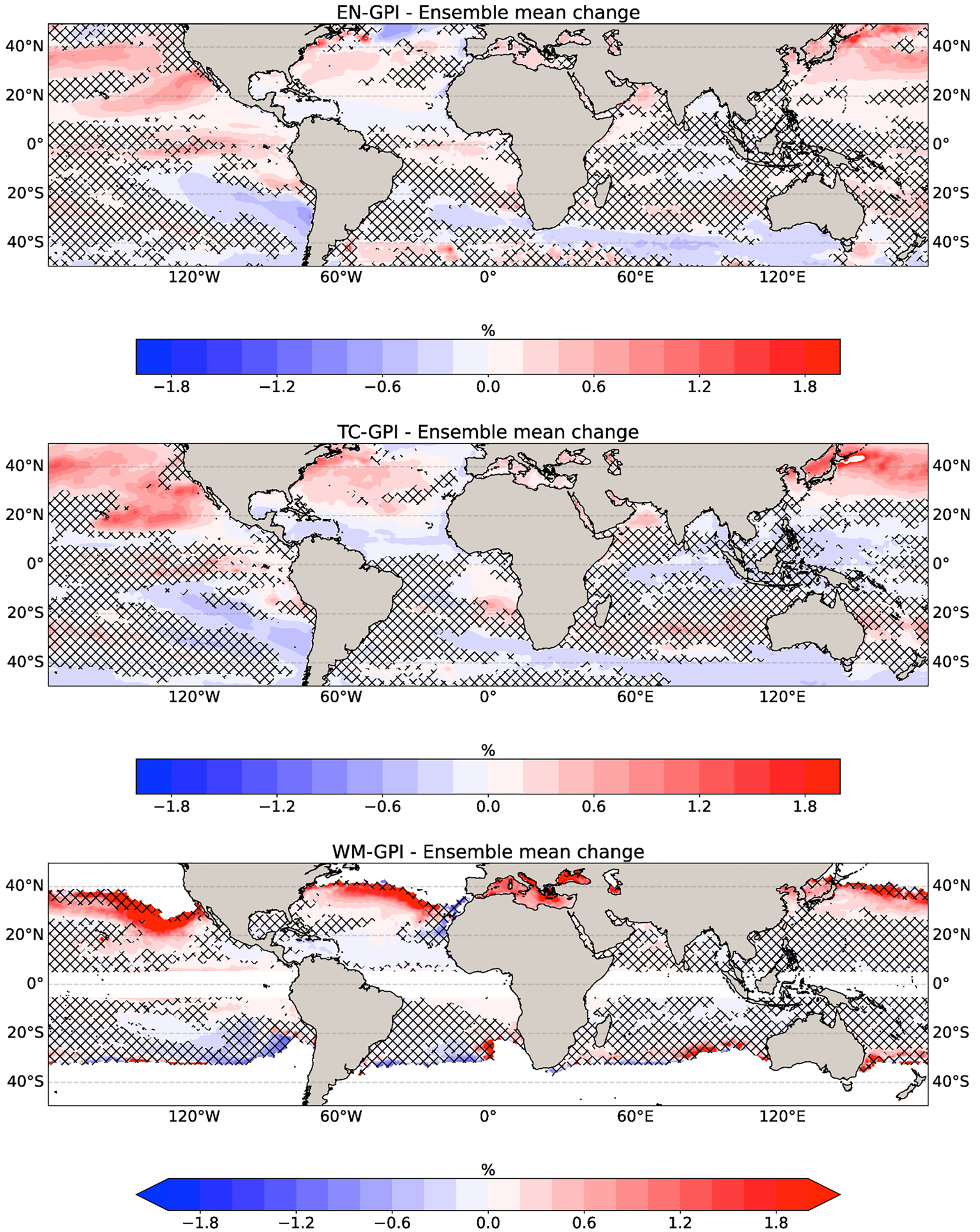

Figure 3. Ensemble mean change in highest-future with respect to hist-1950 simulations for: EN-GPI (top panel), TC-GPI (middle panel) and WM-GPI (bottom panel). Stippling indicates regions where the change is statistically significant (according to a two-tailed *t*-test) and of the same sign in at least three ensemble members.

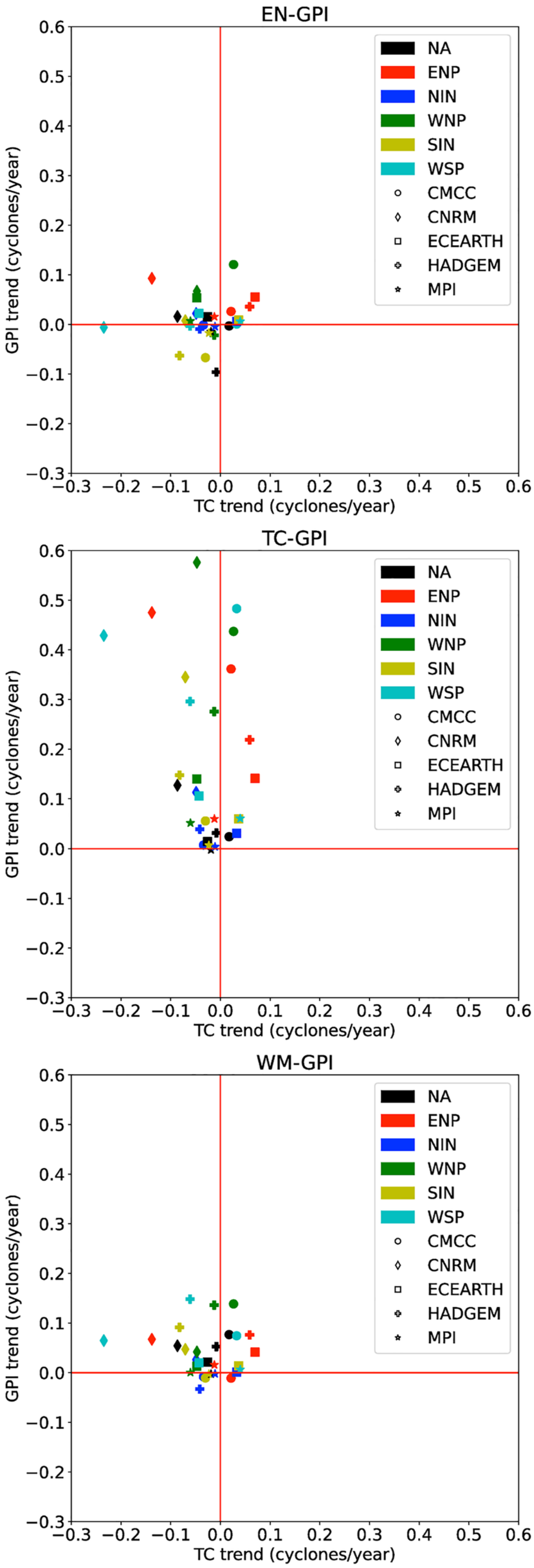

Figure 4. Future trends of directly detected TCs and the TC number predicted through GPIs: EN-GPI (top panel), TC-GPI (middle panel) and WM-GPI (bottom panel).

3. GPIs capture too much noise from the training data set to be able to make meaningful predictions (overfitting).
4. Different variables modulate TC activity differently in each ocean basin; therefore, it is impossible to construct a universal GPI with good skill globally.
5. Different variables modulate TC occurrence at different scales; therefore, it is impossible to construct a unique GPI with good skill for all the analyzed metrics.

More than one of the reasons outlined above may play a role simultaneously. However, each of the hypotheses in the list points to new possible research directions worth exploring.

1. The first hypothesis cannot be robustly ruled out until larger GCM ensembles are produced, with horizontal resolutions further increasing from TC-permitting to TC-resolving (Zhao & Held, 2012). However, model deficiencies likely result in failures representing the small-scale dynamics responsible for the initial formation of tropical disturbances rather than large errors in large-scale variables responsible for the evolution of the initial depression into a TC (Vidale et al., 2021; Yamada et al., 2021). Therefore, this issue is likely to be, to some extent, related to hypothesis number 2. Moreover, this relies on the assumption that statistical relationship derived from reanalysis are still valid in models.
2. This hypothesis is true to some extent, as, by design, GPIs only relate to the probability that a TC precursor evolves into a full TC given a favorable environment, but they do not take into account the likelihood of occurrence of such initial disturbances (generally referred to as seeds). The extent to which seeds, rather than large-scale conditions, modulate the variability of TC occurrence is currently unknown. Several studies have recently revived the debate around this topic by proposing new modelization of the occurrence of seeds (K. Emanuel, 2022; Hsieh et al., 2020; Ramsay et al., 2020; Sobel et al., 2021; Yang et al., 2021).
3. The hypothesis that GPIs are, at least to some extent, suffering from overfitting seems to be supported by the results of this work, in particular by the substantial decrease in the indices' skill when computed on a data set not related to the one used to fit its parameters, such as a climate model. Advanced statistical methodologies, particularly those based on machine learning (Chen et al., 2020; Yip & Yau, 2012), could help to address overfitting problems (given enough data to train the models).
4. Previous studies (Sharmila & Walsh, 2017) have shown that the interplay of a different group of variables appearing in GPIs, particularly thermodynamic and dynamic variables, in modulating TC variability varies depending on the considered ocean basins. If this is the case, a global GPI would necessarily be a trade-off between different optimal formulations in different basins. Basin-dependent tuning of GPIs could be a strategy worth exploring for some set of applications.
5. Similarly to hypothesis 4, it is possible that different predictors drive the variability of TC occurrence across different dimensions (i.e., time and space) and or different scales (e.g., interannual and multidecadal time scales). Again, indicators aiming at skilfully reproducing TC variability across all the dimensions and scales would necessarily be a trade-off between different metrics. Recent work from Ascenso et al. (2023) using advanced optimization techniques showed that this is indeed the case for TC interannual variability and spatial patterns. Moreover, they provide a framework to quantify and select the desired trade-off, depending on the desired application of the index.

We suggest two ways to address the limitations discussed in the manuscript. Statistical methodologies based on Machine Learning techniques (Chen et al., 2020) could help alleviate some of the mentioned problems (e.g., by applying regularization techniques or transfer learning). The results from the current work would provide in this framework a systematic and robust benchmark of current GPIs skills, against which newly developed ML-enhanced TC genesis indices can be effectively tested. On the other hand, progress in the theoretical understanding of tropical cyclone genesis would provide more robust indicators of TC activity.

Data Availability Statement

All the climate model data used to compute the GPIs are publicly available from https://esgf-node.llnl.gov/search/cmip6/. The Tropical Cyclone tracks for the HighResMIP models can be retrieved from https://catalogue.ceda.ac.uk/uuid/e82a62d926d7448696a2b60c1925f811.

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