Conversion of the Knutson et al. Tropical Cyclone Frequency Projections to North Atlantic Landfall

STEPHEN JEWSON[a]

[a] *Lambda Climate Research, London, United Kingdom*

(Manuscript received 15 April 2022, in final form 14 June 2022)

ABSTRACT: A 2020 metastudy by Knutson et al. gave distributions for possible changes in the frequency and intensity of tropical cyclones under climate change. The results form a great resource for those who model the impacts of tropical cyclones. However, a number of steps of processing may be required to use the results in practice. These include interpolation in time, distribution fitting, and reverse engineering of correlations. In this paper we study another processing step that may be required, which is adjusting the frequency change results so that they apply to landfalling frequencies. An adjustment is required because the metastudy results give frequency adjustments as a function of storm lifetime maximum intensity rather than landfall intensity. Increases in the frequency of category-4 and category-5 storms, by lifetime maximum intensity, then contribute to increases in the frequencies of storms of all intensities at landfall. We consider North Atlantic Ocean storms and use historical storm information to quantify this effect as a function of landfall intensity and region. Whereas the original metastudy results suggest that the mean frequency of category-3 storms will decrease, our analysis suggests that the mean frequency of landfalling category-3 storms will increase. Our results are highly uncertain, particularly because we assume that tracks and genesis locations of storms will not change, even though some recent climate model results suggest otherwise. However, making the adjustments we describe is likely to be a better way to model future landfall risk than applying the original metastudy frequency changes directly at landfall.

SIGNIFICANCE STATEMENT: A recent metastudy gave distributions for possible changes in the frequency and intensity of tropical cyclones under climate change. For the North Atlantic Ocean, we show how to convert these results to changes at landfall. This conversion increases the changes in the frequencies of storms in intensity categories 0–3, and, in particular, the mean frequency change of storms in category 3 flips from decreasing to increasing in most regions.

KEYWORDS: North America; Hurricanes/typhoons; Tropical cyclones; Climate change; Probability forecasts/models/distribution; Risk assessment

1. Introduction

Tropical cyclones (TCs) cause great amounts of damage and disruption, and this has led to the development of risk models that can be used to calculate distributions that quantify their possible impacts (Friedman 1972; Vickery et al. 2000; James and Mason 2005; Emanuel et al. 2006; Hall and Jewson 2007; Yonekura and Hall 2011; Grieser and Jewson 2012; Lee et al. 2018; Sobel et al. 2019; Bloemendaal et al. 2020; Arthur 2021). These types of models are widely used in insurance and reinsurance for understanding TC risks (Friedman 1972; Grossi and Kunreuther 2005; Mitchell-Wallace et al. 2017; Michel 2018).

Climate change may now be changing the characteristics of TC behavior, and many studies have used numerical climate models to attempt to understand these possible changes: see recent reviews by Walsh et al. (2015), Knutson et al. (2019), and Knutson et al. (2020) and other recent studies by Bhatia et al. (2019), Murakami et al. (2020), Zhang et al. (2020), Yamaguchi et al. (2020), and Emanuel (2020). The estimates of the possible changes in TC behavior vary from study to study. They are therefore best represented as distributions that capture the range of different results from the different studies. Knutson et al. (2020, hereinafter K2020) took this approach and created distributions by standardizing results from studies by multiple different authors. They considered four TC variables: the frequency of storms in categories 0–5 [cat05; reported maximum wind speed greater than 33 kt ($1\ \text{kt} \approx 0.51\ \text{m s}^{-1}$)], the frequency of storms in categories 4 and 5 (cat45; reported maximum wind speed greater than 113 kt), the mean intensity of storms in categories 0–5, and rainfall rate.

Many of the risk models used to estimate the possible impacts due to TCs do not directly include climate change, and hence it is of interest to try and use the results from numerical modeling studies to adjust the risk models. However, there are a number of technical challenges that arise when trying to do so. Using the K2020 projections, we have attempted to understand and resolve some of these challenges in a recent series of studies. We have focused on the frequency and intensity changes only. To provide a relatively complete account of the issues involved in using the K2020 projections, we will now review each of these studies briefly. We will then introduce the topic of the present study, which is how to adjust the K2020 results so that they can be applied at landfall.

a. *Processing the K2020 results for use in TC impacts modeling*

The first challenge we have addressed arises because the K2020 projections describe changes in TC behavior relative to

Corresponding author: Stephen Jewson, stephen.jewson@gmail.com

DOI: 10.1175/JAMC-D-22-0056.1

a 2°C increase in global mean surface temperature (GMST). This is a concise way to combine results from different studies. Risk modelers, however, typically need to understand the possible change in TC behavior between specific time periods, rather than as a function of GMST. As a result, the K2020 results need interpolation and extrapolation using past and projected GMSTs. We have described a way to do this interpolation and extrapolation using a linear model applied to the logarithm of frequency, intensity, or rainfall (Jewson 2021a). Logarithms are required because these variables cannot take negative values.

The second challenge relates to the question of how to account for the correlations between the different variables presented in K2020. The K2020 distributions of changes in frequency, intensity and rainfall are specified using quantiles. A natural way to incorporate the changes into a risk model would be to simulate from distributions fitted to the quantiles. However, fitting distributions is not entirely straightforward in this case. This is because if the distributions and the correlations between the distributions are not fitted appropriately the distributions for the different variables may not be mutually consistent. We know a priori that the distributions are likely to be correlated with each other in some way: cat45 storms are a subset of cat05 storms, and changes in the frequency of cat45 storms will affect mean intensity. The correlations are not provided by K2020 and need to be estimated or derived. One approach to estimating the correlations would be to calculate them directly from the underlying modeling studies considered by K2020, but this would be difficult since the distributions for the different variables were based on different studies. In Jewson (2021b, hereinafter J2021) we took the alternative approach of reverse engineering correlation values that are consistent with the K2020 distributions for changes in frequency and intensity. Using these consistent correlation values, we were able to show that the mean intensity changes can be derived from the frequency changes. Risk models can therefore be adjusted using only the frequency changes, and the mean intensity in the risk model will change in accordance with the K2020 mean intensity changes as a consequence of the changes in the frequencies. We were also able to derive consistent changes in the frequency of storms in categories 0–3 (cat03) from the cat05 and cat45 frequency changes, by taking into account the relative frequencies of storms of different intensities in the historical record.

The third challenge is that the K2020 results provide frequency changes for the cat05 and cat45 intensity ranges. However, they give no information about what variations in the frequency changes might occur within the cat05 and cat45 ranges. As a result, when we derive cat03 changes from the cat05 and cat45 changes, we also cannot derive information about the changes within the cat03 range. In reality, the frequencies of different intensities of storms within the cat03 and cat45 ranges may change differently under climate change. For instance, the frequency of category-3 (cat3) storms may increase while the frequency of cat0 storms may decrease. This would be relevant to subsequent estimates of changes in the risk. In Jewson (2022b), we investigated whether the K2020 distributions can be modeled more accurately by using an assumption that the percentage changes in frequencies vary within the cat03 and cat45 ranges. We modeled the frequency changes as a linear function of intensity and compared the goodness of fit from that assumption with the goodness of fit for a model in which the frequency changes are constant within the cat03 and cat45 ranges. The linear function allows different changes within the cat03 and cat45 ranges, and also eliminates the somewhat implausible jump in the frequency changes between cat3 and cat4. For 4 out of 6 of the global TC basins we considered we found that the linear frequency change model fitted the K2020 distributions more accurately. For the southwest Pacific Ocean, the model based on constant changes failed to capture the K2020 changes at all, while the linear model worked reasonably well. However, for the North Atlantic Ocean we found that the model with constant changes fitted the K2020 distributions more accurately than the linear model.

The fourth challenge we have addressed is to derive ways to apply changes in TC frequencies to risk models. Risk modelers commonly adjust their models by making frequency changes, but those changes are typically given as point values, rather than as distributions. To adjust models using the K2020 results, adjustment methodologies that incorporate distributions are required. We have introduced and compared various methods for making such adjustments in Jewson (2022a).

b. *Landfall frequencies*

These various studies bring us closer to the point where it will be possible to use the K2020 frequency and intensity change results to adjust risk models in a well-justified way. In this paper we will address the main remaining issue, which is how to convert the K2020 frequency changes to appropriate frequency changes at landfall. We will focus on the North Atlantic.

How climate change may affect landfalling TC frequencies has been studied by a number of authors (Murakami and Wang 2010; Colbert et al. 2013; Wright et al. 2015; Liu et al. 2018; Levin and Murakami 2019; Ting et al. 2019; Knutson et al. 2022). Based on these studies, it seems likely that climate change may lead to changes in landfall frequencies via a number of mechanisms, including changes in genesis regions, tracks, frequency, and intensity. There have been many studies that have considered possible changes in frequency and intensity, and many of them are summarized in the K2020 results. However, the number of studies of possible changes in genesis regions and tracks is relatively small, and this makes it difficult to form any consensus about the changes or the uncertainty range of possible changes. Whether or not uncertain scientific results based on single studies or on a small number of studies that give different results should be included in impacts estimates is a complex question that should be evaluated on a case-by-case basis. Our particular goal in the present study is to create estimates of the impacts of climate change that are based on relatively well-established results derived from a large number of studies. As a result, we will not attempt to incorporate any of the results related to changes in genesis locations and tracks into our calculations at this point, even though these changes are potentially very important. The Knutson et al. (2022) study, in particular, suggests that changes in genesis regions and tracks may cause very large increases in the landfalling frequencies for cat45 storms, greatly in excess of the size of the changes that we will discuss below due to basin frequency changes. The effect of climate change on genesis and tracks is clearly an area where further research is required.

Given the above discussion, we will assume that there will be no change in the behavior of storms other than changes in frequency of storms of different intensity. Nevertheless, even under this assumption, the K2020 frequency changes should not be applied directly to landfalling storms, based on their intensity at landfall, for the following reason. K2020 present their frequency change results as changes in the frequencies of cat05 and cat45 storms, where cat05 and cat45 are defined using the lifetime maximum intensity. From those results, J2021 then derived frequency change results for cat03 storms, where cat03 is also defined using the lifetime maximum intensity. By these definitions of cat03 and cat45, a cat03 storm, if it makes landfall, can only make landfall with cat03 intensity or weaker. It can never make landfall with cat45 intensity, since then it would be redefined as a cat45 storm. A cat45 storm, however, can make landfall with either cat45 intensity, cat03 intensity, or weaker than cat03 intensity. An increase in the frequency of cat45 storms can therefore lead to an increase in the frequency of storms making landfall with cat03 intensity. We will refer to this as the cat45 splitting effect. To apply the K2020 results at landfall, this effect has to be accounted for. Since cat45 storms show an on-average increase in frequency in the K2020 North Atlantic results, we would expect that incorporating this effect into the analysis of landfall frequencies would lead to an on-average increase in the change of the frequency of storms making landfall as cat03, relative to the unadjusted K2020 frequency changes.

c. *Applying frequency adjustments to risk models*

How the K2020 results are best applied to a risk model depends on how the risk model is constructed. Some TC risk models attempt to simulate the entire life cycle of TCs, while others focus on simulating storms at landfall. For models that simulate the entire life cycle of TCs, each simulated storm has its own simulated lifetime maximum intensity. In this case, it would be possible in principle to apply the K2020 frequency change results directly to the risk model without explicitly accounting for cat45 splitting. This could be done by adjusting the frequency of each simulated storm so that the changes in the distribution of frequencies of storms with different simulated lifetime maximum intensities in the risk model match the changes in frequencies provided by K2020. If the model is realistic, then the proportions of cat45 storms that make landfall with cat45 intensity, with cat03 intensity, and with intensity lower than cat03, will be accurate. The simulation model will account for the cat45 splitting effect implicitly in the simulated storm set. The drawback of using this approach to apply the K2020 results is that TC risk models may not simulate storm life cycles realistically enough that the splitting effect is well captured. There are two particular reasons why risk models may not simulate the cat45 splitting effect well enough. First, building TC risk models that give realistic simulations of TC behavior across the entire TC life cycle is extremely difficult. Second, risk models are generally judged on how well they simulate landfall, and as a result risk modelers tend to focus most of their attention on ensuring that the landfall part of the model performs well, rather than on improving the simulation of the entire life cycle. For instance, simulating accurate landfall statistics, but not realistic TC life cycles, is required by the Florida commission on hurricane loss projection methodology (Florida State Board of Administration 2022).

For models that do not simulate the entire life cycle of TCs or do not simulate it sufficiently accurately, there is an alternative approach for applying the K2020 frequency changes. This alternative approach is to use historical TC information, and certain assumptions, to make adjustments to the K2020 basin frequency changes so that they can be applied directly to landfall frequencies, incorporating cat45 splitting. These adjusted frequency changes can then be used to adjust risk models so that the change in the landfalling characteristics of storms in the model matches the adjusted K2020 frequency changes. We will explore how to calculate these landfall frequency adjustments for the K2020 results in this article.

In section 2 we discuss the data we use for this study and review the frequency changes from K2020. In section 3 we present some simple conceptual models for the relationship between TC lifetime maximum intensity and intensity at landfall. In section 4 we show results based on the first three of these models. In section 5 we show results based on the fourth of these models. In section 6 we summarize and conclude.

2. Data

a. *K2020 results*

The K2020 projections for the North Atlantic consist of projected changes in TC behavior, under a 2°C increase in GMST. We will consider two of the four variables given in K2020: 1) the change in frequency of TCs in categories 0–5, that is, storms with reported maximum wind speeds above 33 kt (cat05 storms), and 2) the change in frequency of very intense TCs, in categories 4 or 5, that is, storms with reported maximum wind speeds above 113 kt (cat45 storms). In our analysis we will also consider category-0 (cat0) storms (reported maximum wind speeds in the range 33–63 kt), category-1 (cat1) storms (64–82 kt), category-2 (cat2) storms (83–95 kt), cat3 storms (96–112 kt), and cat03 storms. We will write the frequencies of cat03, cat45, and cat05 storms as F03, F45, and F05. K2020 presented their results using the median and six other quantiles. The median for the F05 change given by K2020 was −14.4%, with an interquartile range of 27.9%. The median for the F45 change was 11.3%, with an interquartile range of 60.6%. In both cases, the distributions overlap significantly with zero change.

The distributions defined by the K2020 results give the distribution of projections from studies by many different authors. The widths of the distributions can be considered as giving estimates of the uncertainty. However, the distributions are themselves uncertain. In particular, many of the studies from which the distributions were constructed are several years old and are not based on the latest generation of climate models. These distributions are perhaps the best estimates we have for the distribution of likely changes in hurricane frequencies at this point in time, but they are certainly not definitive. As a result, future climate may fall in the tails of these distributions, and new studies based on more recent climate models will likely give different results.

b. HURDAT2

HURDAT2 is a dataset of historical observations of North Atlantic TCs (Landsea and Franklin 2013). The same data are also available as part of the IBTrACS dataset (Knapp et al. 2010). We use these data to understand the dependencies between lifetime maximum intensity and intensity at landfall, which we will then use to adjust the K2020 results. Because observations of North Atlantic storms prior to 1950 may be less complete and less accurate, we extract and use a subset of HURDAT2 that extends from 1950 to 2021. This 72-yr dataset, which we will refer to simply as HURDAT2, contains 338 landfalling cat05 storms, of which 70 had lifetime maximum intensity in the cat45 range, and 268 had lifetime maximum intensity in the cat03 range. We only include landfalls west of 30°W. Intensities of each storm are recorded in knots, rounded to multiples of 5 kt. The cat03 intensity band therefore contains 16 different possible storm intensities.

c. Consistent distribution fitting to the K2020 results

J2021 discussed how to fit distributions to the K2020 frequency change quantiles. Their fitting procedure involved iterating over parameters to find the minimum of a cost function that measured the distance between the K2020 and fitted quantiles. The procedure simultaneously fitted distributions to the F05, F45, and mean intensity change distributions using a single cost function. Every iteration of the minimization process tested different values for the parameters of lognormal distributions being used to model the F05 and F45 changes. Also at every iteration, the mean intensity change distribution was derived from the F05 and F45 distributions using historical frequencies of storms of different intensities from HURDAT2. This process resulted in distributions that fitted the K2020 quantiles reasonably well. The resulting fitted distributions are not necessarily the same as the best fit distributions that would result from fitting distributions to F05, F45, and mean intensity separately. However, because they were fitted simultaneously, they have the advantage that they are mutually consistent. The fitted distributions and the HURDAT2 data can then be used to derive a distribution for changes in F03 that is also consistent.

The fitted median, mean, and standard deviation of the changes in F05, F03, and F45 from J2021 are given in Table 1. We can see from these results that the fitted medians are similar to but not exactly the same as the original K2020 medians given above. This is because the fitting process is fitting four parameters to 15 quantiles and can only achieve a compromise. The means of the fitted distributions are all higher than the medians, especially for F45. This is because the distributions of change are positively skewed, as can be seen in the original K2020 results. The skew arises partly because frequency changes cannot go below −100% and so are inherently skewed. The mean of the frequency distribution, and the mean change, are in some ways more useful indicators than the median and the median change. The mean and the mean change combine to give the new mean, while the same is not true for the median. Also, it is the mean of the frequency distribution that determines the conditional probabilities of storms of different intensities, and it is the mean change in F45 and not the median change that determines the change in the annual probability of occurrence for the most extreme storms. Since the J2021 mean change in F45 is 19.1%, the change in the annual probability of occurrence for the most extreme storms is also 19.1%. We will focus our initial analysis on the mean changes in landfall frequency, and then extend the analysis to consider the distribution around the mean.

TABLE 1. The frequency changes for North Atlantic Ocean tropical cyclones given in J2021, for cat05 storms (F05), cat03 storms (F03), and cat45 storms (F45). All changes correspond to a 2°C increase in GMST.

	F05	F03	F45
Median change	−13.6%	−17%	9.6%
Mean change	−11.2%	−15.5%	19.1%
Std dev change	20.4%	16.3%	49.2%

3. Conceptual models

In this section we discuss four simple conceptual models for the relationship between storm lifetime maximum intensity and landfall intensity. We will apply these models in sections 4 and 5 below. We start by discussing a number of features that are common to all 4 models.

First, we only consider storms that make landfall, and that have intensities at cat0 or above at landfall. Second, given our assumption that climate change will cause nothing but the frequencies of storms of different intensities to change, we conclude that the statistical relationships between basin and landfall storms also do not change. So, for instance, we will assume that the proportion of cat45 storms that make landfall with cat45 intensity remains constant. The limitations of this assumption were discussed above.

Third, since the K2020 frequency changes relate to storm maximum intensity, and we have assumed in the second point above that the proportion of cat45 storms that make landfall at cat45 intensity remains constant, we conclude that the percentage changes in F45 from K2020 can be applied directly to the frequency of storms that make landfall at cat45 intensity. In other words, for cat45 the landfall frequency changes are the same as the basin frequency changes. As a result, we conclude that the mean frequency of cat45 landfalls will increase by 19.1% everywhere. The 19.1% increase does not vary

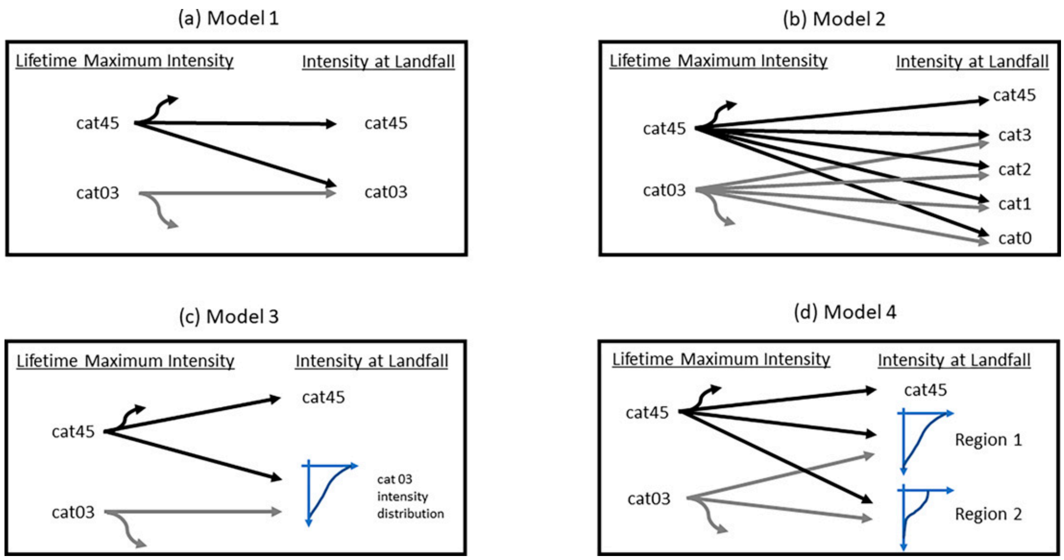

FIG. 1. The four conceptual models we use in this study. The straight arrows indicate the intensity at landfall of storms with a lifetime maximum intensity of cat03 or cat45. The curved arrows indicate storms that do not make landfall, or make landfall weaker than cat0 intensity. Shown are models that (a) consider 2 possible intensities for landfalling storms, (b) consider 5 possible landfall intensities, (c) consider 17 possible landfall intensities (16 corresponding to the 16 intensity bins in the cat03 range, along with cat45), and (d) consider landfall in two different regions.

regionally, although how many actual cat45 storms per year on average it translates into will vary regionally because of regional variations in the underlying frequency of cat45 landfalls. One implication is that regions that are currently modeled as not experiencing cat45 storms at all will still not experience cat45 storms. This could be considered a limitation, since it is possible that climate change will lead to cat45 storms at landfall in regions where they have never occurred before. However, a good risk model would extrapolate the historical record, and would give a nonzero frequency to cat45 storms making landfall in regions where they have not occurred in history but may occur in the future. That extrapolated frequency of cat45 storms would then be increased by 19.1%.

Fourth, the change in the frequency of storms that are cat03 intensity at landfall depends on both the changes in F45 and F03, because of cat45 splitting into cat45, cat03, or weaker at landfall, as described in the introduction. This makes calculating the changes in the frequency of storms with cat03 intensity at landfall more difficult. The change in frequency of storms with cat03 at landfall is not necessarily equal to the change in the frequency of cat03 storms in the basin but will be the same or higher because of the additional contribution due to the cat45 storms that make landfall at cat03 intensity. Deriving reasonable estimates for the change in the frequency of storms with cat03 intensity at landfall, and how they are affected by landfall intensity and region, is the main topic of this article.

a. *Model 1: Basic cat45 splitting model*

The first conceptual model that we consider is illustrated in Fig. 1a and reflects the discussion on cat45 splitting given in the introduction and above. This model is not a serious suggestion as a model for quantifying landfall frequency changes but is useful to help introduce the concepts. The shortcomings of the model will be addressed in the subsequent models. Figure 1a illustrates that cat03 storms can either make landfall at an intensity also in the cat03 range, or they may drop from our analysis by not making landfall or by making landfall at an intensity weaker than cat0. What they cannot do is make landfall at cat45 intensity. Figure 1a also illustrates that cat45 storms may make landfall at cat45 intensity, or at cat03 intensity, or drop from our analysis by not making landfall at all or by making landfall at an intensity weaker than cat0.

This model motivates the need to estimate the probability that a storm that makes landfall at cat03 intensity was previously cat45 intensity. We will write proportions and probabilities that quantify whether a storm that makes landfall at cat03 intensity was previously cat45 as p_{was45}. It is perhaps helpful to note that p_{was45} is related to the probability that a cat45 storm that makes landfall does so at cat03 intensity. It is also related to the probabilities that any landfalling storm is cat45 at some point in its lifetime, and that any landfalling storm is cat03 at landfall. All these probabilities can be estimated from the historical data, and the relationship between them is discussed in the appendix but is not used in our analysis.

b. *Model 2: Cat45 splitting by category*

The second conceptual model that we consider is illustrated in Fig. 1b and is slightly more complex than the first model. In this model, we consider that a cat03 storm can make landfall with any intensity from cat0 to cat3, or drop from our analysis, but once again cannot make landfall with cat45 intensity. A cat45 storm can make landfall with any intensity from cat0 to cat5 or drop from our analysis. This model allows us to consider the possibility that p_{was45} may depend on the intensity category at landfall. Intuitively it might be expected that p_{was45} will be higher for storms that are cat3 at landfall than for storms that are cat0 at landfall because the intensity change from the maximum intensity is less. This is investigated using the HURDAT2 data in the next section.

c. Model 3: Cat45 splitting by intensity

The third conceptual model that we consider is illustrated in Fig. 1c and is again slightly more complex. In this model, we consider that a cat45 storm that makes landfall as cat03 can make landfall with any of the 16 possible intensities within the cat03 range. Relative to the second model, we no longer restrict the quantification of the intensities to just the four category bins 0, 1, 2, and 3. This model allows for slightly more subtle application of the K2020 changes in cat45 frequencies, by allowing p_{was45} to depend on the landfall intensity in knots.

d. Model 4: Cat45 splitting by intensity and region

The fourth conceptual model that we consider is illustrated in Fig. 1d and is more complex again. In this model, we consider that a cat45 storm that makes landfall as cat03 can make landfall with any intensity within the cat03 range, and in one of two different regions. The values of p_{was45} for the different intensities within those regions may be different. This leads to values of p_{was45} that vary by both landfall intensity and region. This model can then be extended to a larger number of regions.

4. Results for models 1, 2, and 3

We now apply the first three conceptual models using HURDAT2 data.

a. Model 1

Figure 2 shows every landfall at cat03 intensity in our subset of the HURDAT2 data. Storms are marked differently to show whether their lifetime maximum intensity was cat03 or cat45. Of the 318 cat03 landfalls, 50 (15.7%) had a lifetime maximum intensity of cat45 and 268 (84.3%) had a lifetime maximum intensity of cat03. The value of p_{was45} is therefore 15.7%. We can use this proportion, along with the first conceptual model, to calculate the implied changes in the frequency of cat03 at landfall. There are two contributions to the mean change in the frequency of storms with cat03 intensity at landfall: one from cat03 storms and one from cat45 storms, as follows:

$$\begin{aligned}
&\text{Change in mean frequency of cat03 at landfall}\\
&\quad = \text{change in mean frequency of cat03 from J2021}\\
&\qquad \times (1 - p_{was45}) + \text{change in mean frequency of cat45}\\
&\qquad \text{from J2021} \times (p_{was45})\\
&\quad = (-15.5\%) \times (84.3\%) + (19.1\%) \times (15.7\%)\\
&\quad = -13\% + 3\% = -10\%. \qquad (1)
\end{aligned}$$

The result is a net decrease of −10% in the mean frequency of storms with cat03 intensity at landfall. Because this model does not distinguish between different intensities within the cat03 band, nor between different regions, this −10% change applies equally to all storms with cat03 intensity at landfall in all regions. This is less of a decrease than the original J2021 decrease of −15.5% for cat03 storms in general. The Akaike information criterion (AIC) score of this model is 279: we discuss AIC scores and how to interpret them below. The mean frequency changes at landfall from this model, by intensity category at landfall, are given in Fig. 3a.

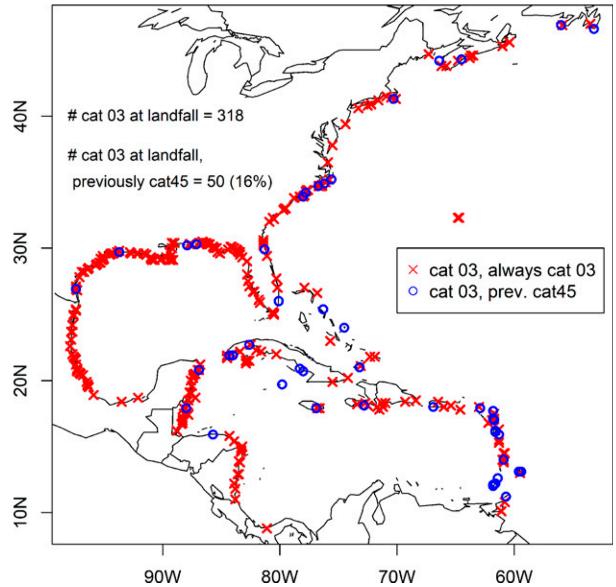

FIG. 2. Storms from HURDAT2 during the period 1950–2021 that make landfall with cat03 intensity. Red crosses indicate storms that have a lifetime maximum intensity of cat03, and blue circles indicate storms that have a lifetime maximum intensity of cat45.

b. Model 2

Figure 4 investigates the second conceptual model, in which we consider p_{was45} to be a function of landfall intensity by category. Figure 4a shows all the storms with cat0 intensity at landfall, marked differently to show whether their maximum intensity was cat03 or cat45. Of the 192 cat0 landfalls, only 12 ($p_{was45} = 6.3\%$) had a maximum intensity in the cat45 range. Figures 4b–d show the same but for storms with cat1, cat2, and cat3 intensity at landfall, respectively. Of the 72 cat 1 landfalls, 15 ($p_{was45} = 20.8\%$) had a maximum intensity in the cat45 range. Of the 34 cat2 landfalls, 10 ($p_{was45} = 29.4\%$) had a maximum intensity in the cat45 range. Of the 20 cat3 landfalls, 13 ($p_{was45} = 65\%$) had a maximum intensity in the cat45 range. From these p_{was45} values we see that the more intense the storm at landfall, the greater the chance that it had a maximum intensity in the cat45 range. This is not surprising. We apply these values to the J2021 mean changes in F45 and F03 using Eq. (1). We find that the net changes in frequency for storms with intensities of cat0, cat1, cat2 and cat3 at landfall are given by −13.3%, −8.3%, −5.3%, and 7.0%. These are illustrated in Fig. 3b. Storms with cat3 intensity at landfall now show an *increase* in mean frequency, rather than a decrease.

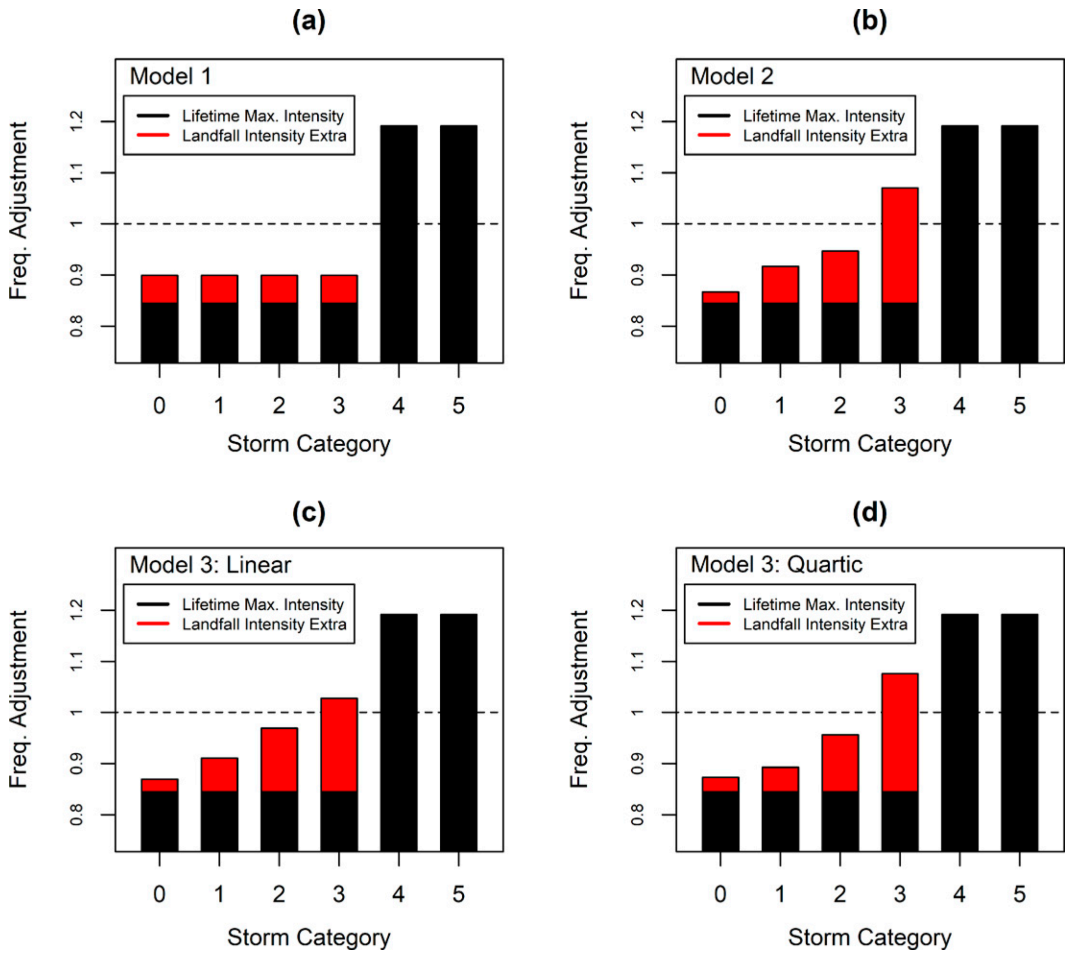

FIG. 3. Projections of mean changes in storm frequencies by intensity category, based on J2021, K2020, and the landfall frequency adjustments derived in this study. Results are shown for (a) model 1, (b) model 2, (c) model 3 with a linear function of intensity, and (d) model 3 with a quartic function of intensity. Changes in frequency as a function of lifetime maximum intensity are shown in black. Changes in frequency as a function of landfall intensity are shown in red and black.

This is because the majority of them were previously cat45 intensity. The AIC score for this model is 239.

We can ask how robust these results are. Our goal in this study is not to accept or reject hypotheses, and so we do not do any statistical testing. Our goal, instead, is to build a good predictive model for landfall risk. A standard way to ascertain which of a set of mathematical models is the best predictive model (i.e., is likely to give the best predictions or projections) is to compare their AIC scores (Burnham and Anderson 2002; Claeskens and Hjort 2008). The AIC score takes into account how well the models fit the data being modeled, and also whether they may be overfitting the data by using too many parameters. A lower AIC score indicates a better predictive model. A comparison of our first and second models shows that the first model has just a single parameter whereas the second model has four parameters. The second model will definitely fit the data more closely, by using more parameters, but could be overfitted. In fact, a comparison of the AIC scores (279 for the first model and 239 for the second) suggests that the second model is a better predictive model and is not overfitted. This suggests that the use of extra parameters has led to the modeling of a genuine effect, which is the variation of p_{was45} by landfall intensity category.

c. Model 3

We now apply the third conceptual model, in which we consider p_{was45} to be a function of landfall intensity in knots. The landfalling data is too sparse to allow us to estimate p_{was45} in each of the 16 cat03 intensity bins separately. As an alternative, we will use a statistical model that fits a smooth curve to p_{was45} as a function of landfall intensity. We use logistic regression to fit this curve. Logistic regression is a form of generalized linear model that allows the modeling of a probability or proportion as a function of a continuous variable (Wasserman 2004; Wilks 2011). Figure 5a shows p_{was45} in each category bin, for storms with landfall intensity of cat0, cat1, cat2, and cat3, estimated directly from the observations. These are the same as the p_{was45} values from model 2. It also

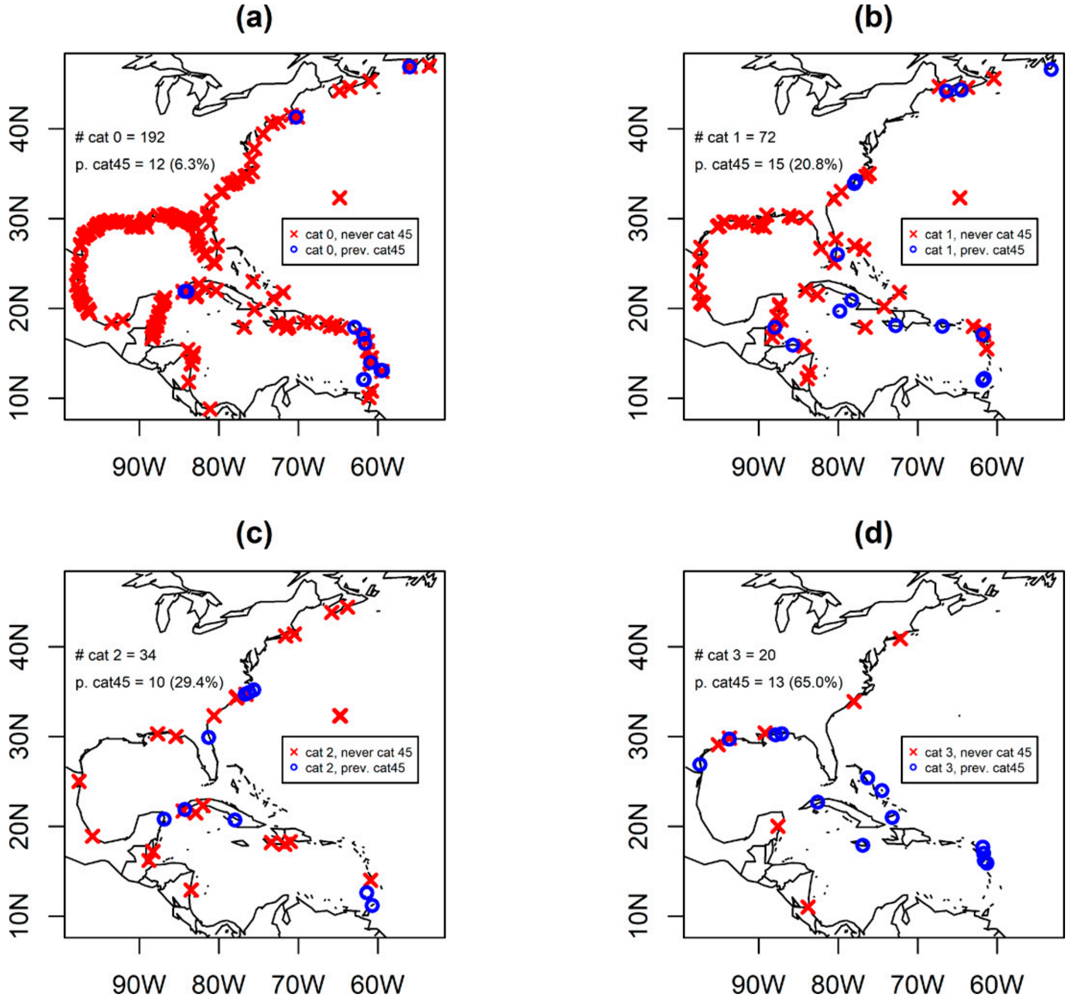

FIG. 4. Storms from HURDAT2 during the period 1950–2021 that make landfall with (a) cat0, (b) cat1, (c) cat2, and (d) cat3 intensities. Red crosses indicate storms that have a lifetime maximum intensity of cat03, and blue circles indicate storms that have a lifetime maximum intensity of cat45.

shows the logistic regression line, using landfall intensity as the predictor in the logistic model, and p_{was45} in each category bin derived from the logistic model. Based on Fig. 5a, the logistic model gives a somewhat reasonable, although not highly accurate, fit to the observed proportions in each bin. This model has an AIC score of 241, which is slightly higher than that for model 2. The higher AIC score implies that model 2 would give slightly better predictions than model 3, suggesting that model 3 is perhaps not a useful one. Also, the logistic fit gives a distinctly lower proportion in the cat3 bin than in the observations. The poor fit to the observed cat3 proportion is unfortunate, since cat3 landfalling storms are more important for society, on average, than weaker storms. It would be preferable if the model would fit the observed data better for cat3 storms, even if at the expense of fitting less well for the weaker storms. To achieve this, we have experimented with the formulation of the logistic regression model, by testing different powers of landfall intensity as the predictor. Increasing the power of intensity increases the curvature of the fitted curve. Figure 4b shows results from using a fourth power (quartic) on intensity. This gives a better fit to the cat3 storm proportion, which we find more appropriate, given the emphasis we wish to place on cat3 storms. This model has an AIC score of 236, which is now lower than the score for model 2. If we treat the power of intensity as an additional fitted parameter, as we should, then the AIC score increases to 238. This is still slightly lower than the AIC score for model 2, and so model 3, quartic version, is the best model so far in terms of AIC.

In Figs. 3c and 3d we show the application of the results from the linear and quartic logistic regression models to the J2021 frequency changes. The effect of these models is similar to the second model. The mean changes in the frequencies of cat0, cat1, and cat2 storms increase, but are still negative. The mean change in the frequency of cat3 storms switches to positive. The quartic model gives a slightly greater increase in the frequency of cat3s, as a consequence of the higher values in the fitted regression curve for cat3s. The logistic regression

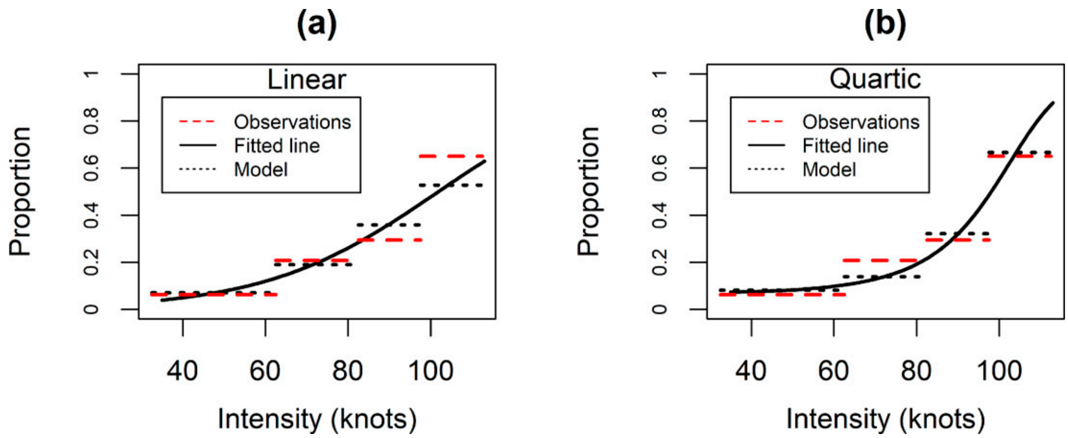

FIG. 5. Considering only storms that landfall at cat03 intensity, variations in the proportion of storms that were previously cat45 as a function of landfall intensity in knots: modeled results (a) for logistic regression as a function of intensity and (b) for logistic regression as a function of intensity to the fourth power. Observed proportions by Saffir–Simpson category for categories 0, 1, 2, and 3 are shown as a red dashed line, modeled proportions by intensity (kt) are shown as a black solid line, and modeled proportions by Saffir–Simpson category are shown as a black dotted line.

models have the slight advantage that they vary p_{was45} within the categories and avoid large jumps between categories.

5. Regionalization

We now apply the fourth conceptual model, in which we consider p_{was45} to be a function of both landfall intensity in knots, and region. This model is motivated by Fig. 2, which gives the impression that the proportion of landfalling cat03 storms that were previously cat45 may vary by region. For instance, in the southeast of the region (the Lesser Antilles), there would seem to be a higher proportion, while along the Gulf Coast there would seem to be a lower proportion. Such variations are not surprising, given the very different origins and life cycles of storms making landfall in these different regions. To reflect these variations, we now define four regions, as shown in Fig. 6. The definitions of the regions are subjective but are designed to reflect (i) what Fig. 1 suggests as to how p_{was45} varies in space; and (ii) some intuition, based on the tracks of historical storms, as to which storms might be considered likely to exhibit similar behavior. We have chosen 4 regions as a subjective compromise between the desire to resolve more regional information, balanced by the need not to split the data too thinly in each region.

We then fit logistic curves to the data for each region, and the results are shown in Fig. 7. The sparsity of the data can now be seen to be affecting the observed p_{was45} proportions by category. For instance, in region 2, the observed p_{was45} proportion is higher for cat2 than it is for cat3, which is the opposite of what one might expect from intuition. Similarly in region 4, the observed p_{was45} proportions for cat2 and cat3 are equal, which also does not correspond well to intuition. The logistic curves can be seen as a way to smooth over these irregularities to give plausible functional dependence. We have used different powers of intensity in each case (cubic, quartic, cubic, and linear, respectively) in an attempt to improve the fit for the cat3 observations. This has not been entirely successful, and the cat3 observations are not fitted well in each case. It is difficult to know whether the poor fit to the cat3 observations is because the statistical model is incorrect or because of data sparsity.

This model has an AIC score of 203, which makes it clearly the lowest of the AIC scores. This AIC score should, however, be considered artificially low, since we have chosen the regions based on examination of the data, which would tend to increase the goodness of fit, and could lead to overfitting. Nevertheless, this low AIC score gives support to the idea that by dividing into four regions we are able to model genuine spatial variation, which should lead to better projections. We do not divide the data any further, given the sparsity of the data.

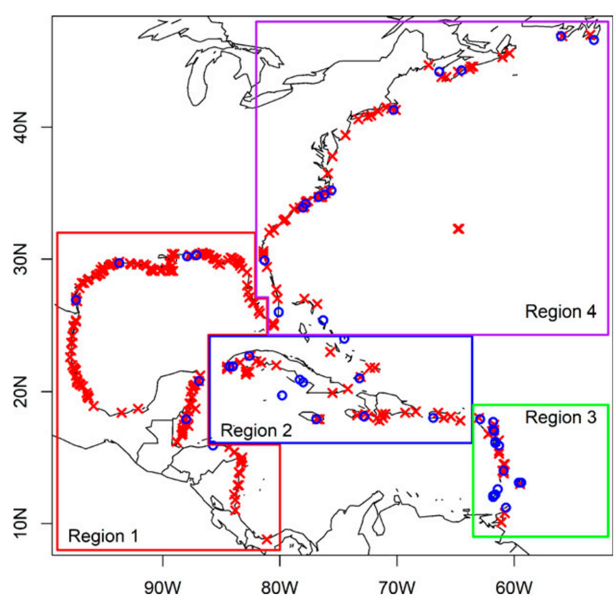

FIG. 6. As Fig. 2, but also showing four regions defined to allow the study of the regionalization of the proportion of cat03 landfalling storms that were previously cat45.

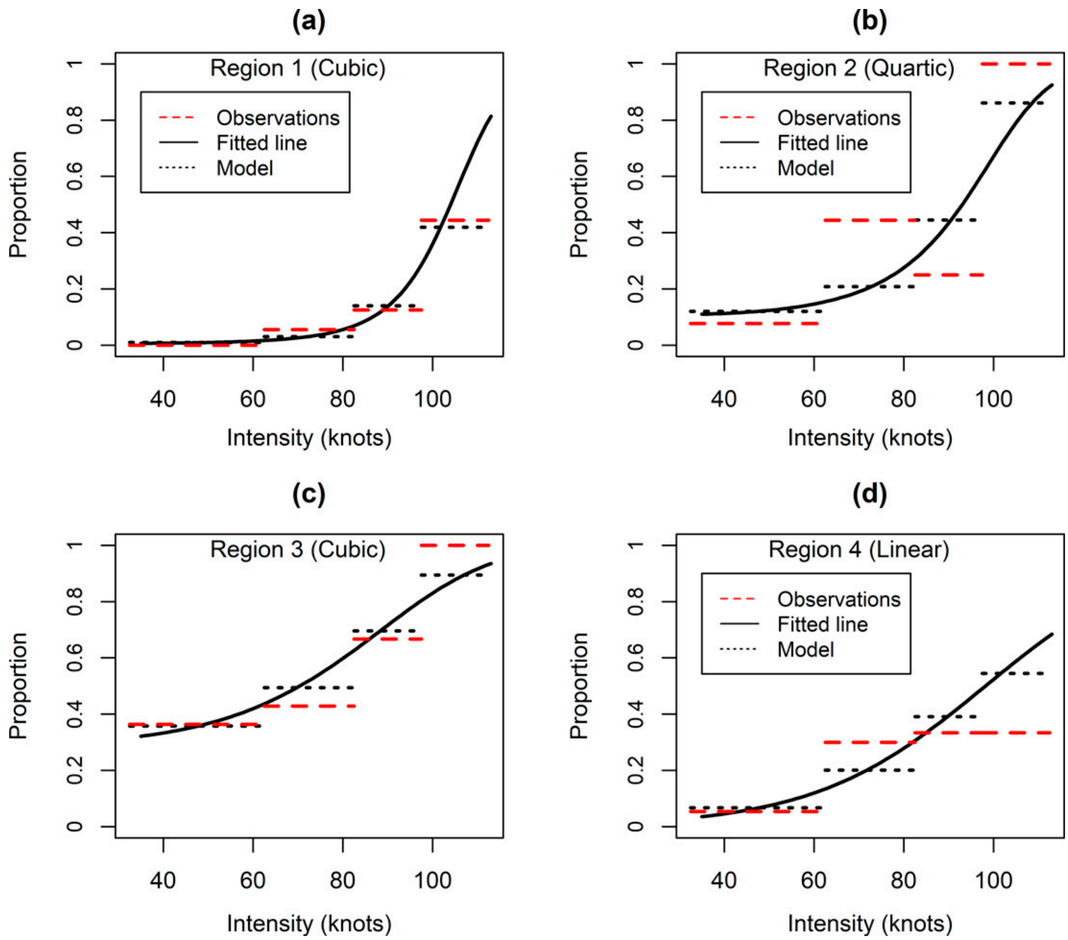

FIG. 7. As Fig. 5, but now showing results for the four regions in Fig. 6: logistic regression as a function of (a) intensity cubed, (b) intensity to the fourth power, (c) intensity cubed, and (d) intensity.

The impacts of these regional logistic regression models on projected changes in landfall frequencies for the different regions are given in Fig. 8. In region 1, changes relative to the J2021 changes are the smallest, reflecting that most historical storms that have cat03 intensity at landfall in this region had not previously been more intense than cat03. Region 3 shows the largest changes relative to the J2021 changes, reflecting that many historical storms that have cat03 intensity at landfall in this region had been more intense earlier in their lifetime. In each of regions 2, 3, and 4 we see that the storms with cat3 intensity at landfall show increasing, rather than decreasing mean frequencies. In region 3, storms with cat1 and cat2 intensity at landfall also show increasing, rather than decreasing mean frequencies.

Uncertainty

Figures 3 and 8 show the mean change in frequency by intensity category. The whole distribution of frequency changes can also be calculated by applying the landfall adjustments discussed above to every sample from the distributions fitted in J2021. Consideration of the whole distribution of frequency changes is required for accurate risk modeling, as shown in J2021. In Fig. 9 we illustrate the whole distribution of changes in frequency by category, for model 4, regions 1–4. In comparing the means and medians, we see that the mean changes are always larger than the medians, which is because the distributions are positively skewed. In region 4, for cat3, the mean change shows an increase, while the median change shows a decrease. The range of uncertainty is wide: this is a direct consequence of the large ranges of uncertainty in the K2020 results, arising from the very different results given in the different underlying climate modeling studies.

6. Conclusions

Anyone with an interest in the impacts of tropical cyclones should consider whether climate change may be affecting those impacts. Many estimates of the possible changes in TC behavior due to climate change have been published in the scientific literature. In a recent metastudy, K2020 combined a large number of those estimates to create distributions. These distributions form a convenient summary of much of the previous work and are a great resource for TC impacts modelers. However, there are a number of steps of processing that may

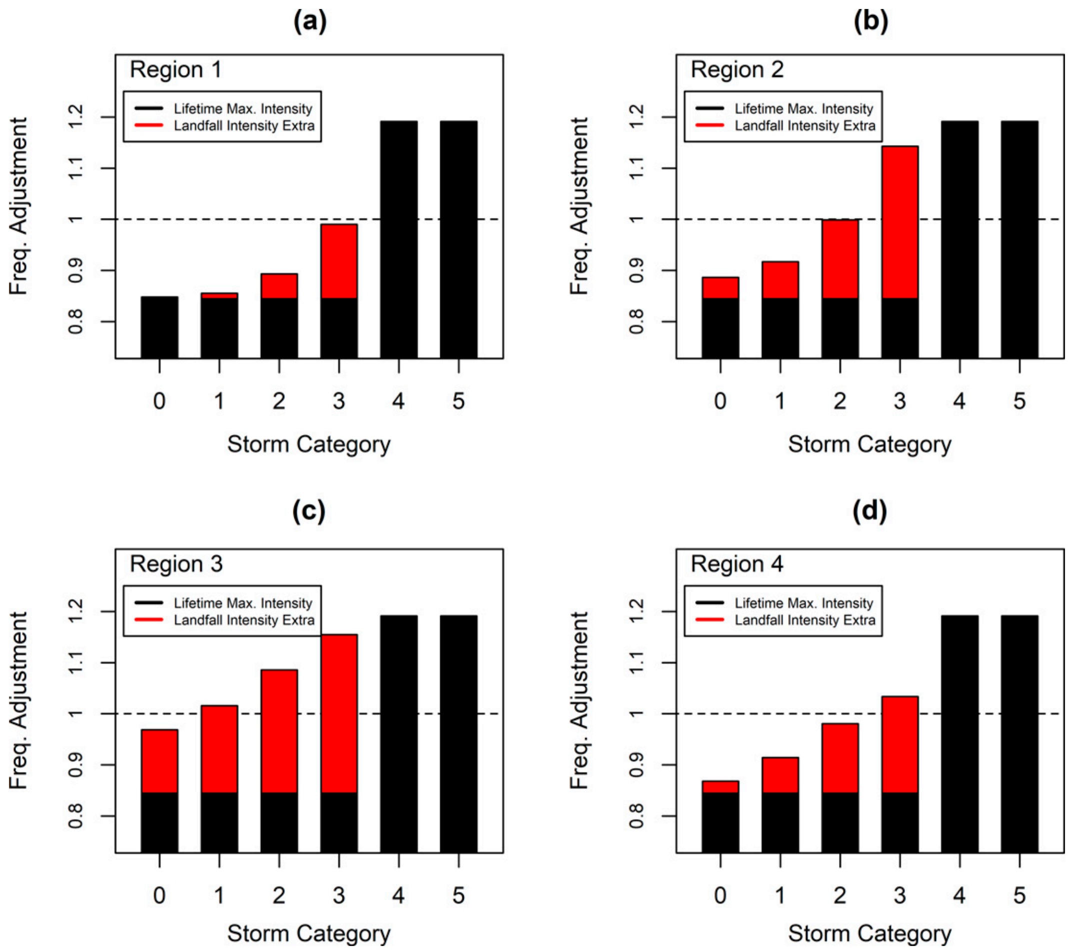

FIG. 8. As Fig. 3, but now for the four regions used in model 4, as shown in Fig. 6.

need to be applied to the K2020 results before they can be used in impacts models. They may need to be interpolated appropriately so that they represent changes over the required time period (Jewson 2021a). Distributions may need to be fitted to the K2020 quantiles, simultaneously for the different variables, in such a way as to capture the correct correlations between the variables and to ensure consistency between the changes in frequency and mean intensity (J2021). Consideration may need to be given as to whether to model variations in the frequency changes within the different intensities inside the cat03 and cat45 intensity ranges (Jewson 2022b). In addition, novel methods for making changes to impacts models may be needed, in order to account for the uncertainty in the K2020 results (Jewson 2022a).

In this study we consider another aspect of the interpretation of the K2020 results, which is how to convert them so that they can be applied at landfall. This conversion is a little complex, because cat45s may make landfall with either cat03 or cat45 intensity. Also, the proportion of storms that make landfall at cat03 intensity, but that were previously cat45 intensity (p_{was45}) appears to vary by intensity and by region. Modeling p_{was45} then leads to a method for estimating the projected changes in frequency at landfall.

We have considered a hierarchy of models for estimating landfall frequency changes, from a simple model that ignores the possibility of variation in p_{was45}, to a relatively complex model that attempts to model the variations in p_{was45} by intensity and by region. All the models show that the changes in frequencies of storms with cat03 intensity at landfall are larger than the changes given for cat03 storms by K2020. In the most complex of the models we consider, the mean frequency of cat3 storms at landfall actually increases in 3 out of 4 regions, rather than decreasing, as implied by the K2020 results. We compare our models using AIC and find that the most complex model achieves the lowest AIC score, and hence would be expected to give the best projections.

There are many uncertainties and assumptions in this work. All the climate models used in the K2020 study show biases relative to real climate, and in addition many are likely less realistic than the latest climate models. It is possible that none of the models correctly capture the physical processes that will determine how hurricanes respond to climate change. The K2020 study itself involved processing the individual model results into a single format, which involved approximations. Our study also involves making various assumptions, including (i) that the proportion of storms making landfall, by intensity,

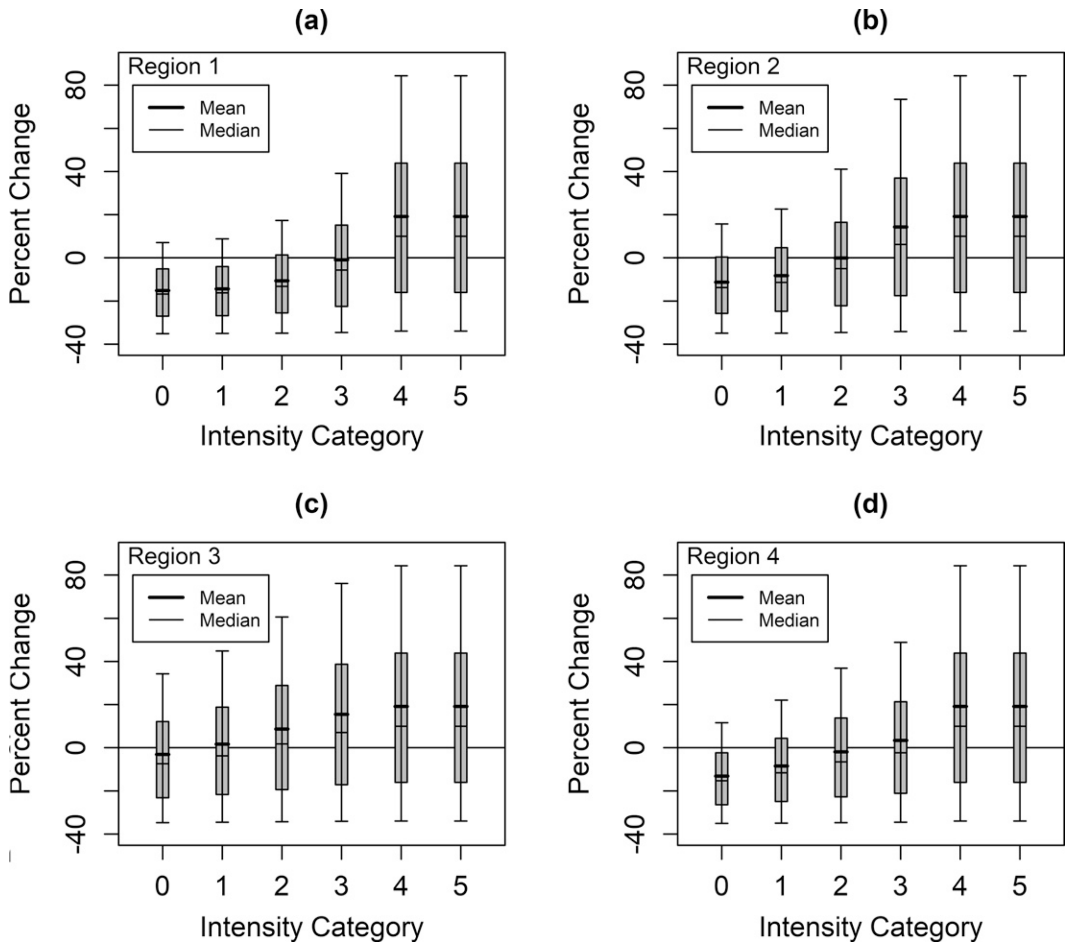

FIG. 9. Distributions of changes in frequency of landfalling storms for model 4 for regions 1–4. For each landfall category, we show the mean change, the median change, the 25% and 75% quantiles, and the 10% and 90% quantiles.

will not change because of climate change; (ii) that the proportion of cat03 storms at landfall that were previously cat45 storms can be modeled reasonably as a function of intensity using logistic regression; and (iii) that the proportion of cat03 storms at landfall that were previously cat45 storms can be modeled regionally using the sparse historical data we have available. The first of these assumptions may be quite inaccurate, as suggested by a recent climate modeling study (Knutson et al. 2022).

Given all these assumptions and approximations, our results should be considered approximate, and certainly not definitive. However, we would argue that making the adjustments we describe in this paper is likely to be a better way to model future landfall risk than by directly interpreting the K2020 frequency changes as landfall changes. Directly interpreting the K2020 frequency changes as landfall frequency changes would ignore that many storms with cat03 intensity at landfall were previously cat45 and that such storms would be expected to increase in mean frequency, based on the K2020 results.

Over the next few years and decades, we hope many of the uncertainties with regard to our understanding of tropical cyclones and climate change will be reduced. For instance, we hope numerical modeling studies will be able to distinguish the impacts of climate change at finer gradations of intensity, regionally, and at landfall. We also hope they will be used to quantify the correlations between changes at different intensities. The various steps that we have developed to process the K2020 results may then no longer be necessary.

Acknowledgments. Many thanks are given to Tom Knutson for discussions on this topic, to the editor and three anonymous reviewers, and to the companies that funded this research. The author owns Lambda Climate Research, a company set up to publish climate research of direct relevance to society.

Data availability statement. The data from K2020 are available online (https://doi.org/10.5281/zenodo.4757343).

APPENDIX

Relationships between Different Probabilities

Applying Bayes's theorem to the set of storms that landfall at cat03 or cat45 intensity gives

$$p(\text{a storm was cat 45}|\text{the storm is cat03 at landfall}) = \frac{p(\text{a storm is cat03 at landfall}|\text{the storm was cat45}) \times p(\text{a storm is cat45})}{p(\text{a storm is cat03 at landfall})}.$$

To estimate these probabilities from historical data, we define the following variables: a = the number of cat45 storms that make landfall as cat45, b = the number of cat45 storms that make landfall as cat03, and c = the number of cat03 storms that make landfall as cat03. The total number of storms that landfall at cat03 and cat45 intensity is given by $a + b + c$.

We can then estimate the four probabilities as follows:

$$p(\text{a storm was cat 45}|\text{the storm is cat03 at landfall}) = b/(b + c),$$

$$p(\text{a storm is cat03 at landfall}|\text{the storm was cat45}) = b/(a + b),$$

$$p(\text{a storm was cat45}) = (a + b)/(a + b + c), \quad \text{and}$$

$$p(\text{a storm was cat03 at landfall}) = (b + c)/(a + b + c).$$

These four estimates can easily be shown to obey Bayes's rule given in the equation above.

REFERENCES

Arthur, W., 2021: A statistical–parametric model of tropical cyclones for hazard assessment. *Nat. Hazards Earth Syst. Sci.*, **21**, 893–916, https://doi.org/10.5194/nhess-21-893-2021.

Bhatia, K., G. A. Vecchi, T. R. Knutson, H. Murakami, J. Kossin, K. W. Dixon, and C. E. Whitlock, 2019: Recent increases in tropical cyclone intensification rates. *Nat. Commun.*, **10**, 3942, https://doi.org/10.1038/s41467-019-11922-2.

Bloemendaal, N., I. D. Haigh, H. de Moel, S. Muis, R. J. Haarsma, and J. C. J. H. Aerts, 2020: Generation of a global synthetic tropical cyclone hazard dataset using STORM. *Sci. Data*, **7**, 40, https://doi.org/10.1038/s41597-020-0381-2.

Burnham, K., and D. Anderson, 2002: *Model Selection and Multimodel Inference.* Springer-Verlag, 488 pp.

Claeskens, G., and N. Hjort, 2008: *Model Selection and Model Averaging.* Cambridge University Press, 312 pp.

Colbert, A., B. Soden, G. Vecchi, and B. Kirtman, 2013: The impact of anthropogenic climate change on North Atlantic tropical cyclone tracks. *J. Climate*, **26**, 4088–4095, https://doi.org/10.1175/JCLI-D-12-00342.1.

Emanuel, K., 2020: Response of global tropical cyclone activity to increasing CO_2: Results from downscaling CMIP6 models. *J. Climate*, **34**, 57–70, https://doi.org/10.1175/JCLI-D-20-0367.1.

——, S. Ravela, E. Vivant, and C. Risi, 2006: A statistical deterministic approach to hurricane risk assessment. *Bull. Amer. Meteor. Soc.*, **87**, 299–314, https://doi.org/10.1175/BAMS-87-3-299.

Florida State Board of Administration, 2022: Florida commission on hurricane loss projection methodology. Accessed 4 April 2022, https://www.sbafla.com/method/Home.aspx.

Friedman, D., 1972: Insurance and the natural hazards. *ASTIN Bull.*, **7**, 4–58, https://doi.org/10.1017/S0515036100005699.

Grieser, J., and S. Jewson, 2012: The RMS TC-rain model. *Meteor. Z.*, **21**, 79–88, https://doi.org/10.1127/0941-2948/2012/0265.

Grossi, P., and H. Kunreuther, 2005: *Catastrophe Modeling: A New Approach to Managing Risk.* Springer, 252 pp.

Hall, T., and S. Jewson, 2007: Statistical modeling of North Atlantic tropical cyclone tracks. *Tellus*, **59A**, 486–498, https://doi.org/10.1111/j.1600-0870.2007.00240.x.

James, M., and L. Mason, 2005: Synthetic tropical cyclone database. *J. Waterw. Port Coastal Ocean Eng.*, **131**, 181–192, https://doi.org/10.1061/(ASCE)0733-950X(2005)131:4(181).

Jewson, S., 2021a: Conversion of the Knutson et al. tropical cyclone climate change projections to risk model baselines. *J. Appl. Meteor. Climatol.*, 60, 1517–1530, https://doi.org/10.1175/JAMC-D-21-0102.1.

——, 2021b: Interpretation of the Knutson et al. (2020) hurricane projections, the impact on annual maximum wind-speed, and the role of uncertainty. *Stochastic Environ. Res. Risk Assess.*, **36**, 1885–1901, https://doi.org/10.1007/s00477-021-02142-6.

——, 2022a: Application of uncertain hurricane climate change projections to catastrophe risk models. *Stochastic Environ. Res. Risk Assess.*, https://doi.org/10.1007/s00477-022-02198-y, in press.

——, 2022b: The interpretation and implications of the Knutson et al. 2020 projections of changes in the frequency and intensity of tropical cyclones under climate change. *Quart. J. Roy. Meteor. Soc.*, 148, 2219–2242, https://doi.org/10.1002/qj.4299.

Knapp, K., M. C. Kruk, D. H. Levinson, H. J. Diamond, and C. J. Neumann, 2010: The International Best Track Archive for Climate Stewardship (IBTrACS): Unifying tropical cyclone best track data. *Bull. Amer. Meteor. Soc.*, **91**, 363–376, https://doi.org/10.1175/2009BAMS2755.1.

Knutson, T., and Coauthors, 2019: Tropical cyclones and climate change assessment. Part I: Detection and attribution. *Bull. Amer. Meteor. Soc.*, **100**, 1987–2007, https://doi.org/10.1175/BAMS-D-18-0189.1.

——, and Coauthors, 2020: Tropical cyclones and climate change assessment. Part II: Projected response to anthropogenic warming. *Bull. Amer. Meteor. Soc.*, **101**, E303–E322, https://doi.org/10.1175/BAMS-D-18-0194.1.

——, J. J. Sirutis, M. A. Bender, R. E. Tuleya, and B. A. Schenkel, 2022: Dynamical downscaling projections of late twenty-first-century U.S. landfalling hurricane activity. *Climatic Change*, **171**, 28, https://doi.org/10.1007/s10584-022-03346-7.

Landsea, C., and J. Franklin, 2013: Atlantic hurricane database uncertainty and presentation of a new database format. *Mon. Wea. Rev.*, **141**, 3576–3592, https://doi.org/10.1175/MWR-D-12-00254.1.

Lee, C., M. Tippett, A. Sobel, and S. Camargo, 2018: An environmentally forced tropical cyclone hazard model. *J. Adv. Model. Earth Syst.*, **10**, 223–241, https://doi.org/10.1002/2017MS001186.

Levin, E., and H. Murakami, 2019: Impact of anthropogenic climate change on United States major hurricane landfalling frequency. *J. Mar. Sci. Eng.*, **7**, 135, https://doi.org/10.3390/jmse7050135.

Liu, M., G. Vecchi, J. Smith, and H. Murakami, 2018: Projection of landfalling tropical cyclone rainfall in the eastern United

States under anthropogenic warming. *J. Climate*, **31**, 7269–7286, https://doi.org/10.1175/JCLI-D-17-0747.1.

Michel, G., 2018: *Risk Modeling for Hazards and Disasters.* Elsevier, 338 pp.

Mitchell-Wallace, K., M. Jones, J. Hillier, and M. Foote, 2017: *Natural Catastrophe Risk Management and Modelling: A Practitioner's Guide.* Wiley Blackwell, 544 pp.

Murakami, H., and B. Wang, 2010: Future change of North Atlantic tropical cyclone tracks: Projection by a 20-km-mesh global atmospheric model. *J. Climate*, **23**, 2699–2721, https://doi.org/10.1175/2010JCLI3338.1.

——, T. L. Delworth, W. F. Cooke, M. Zhao, B. Xiang, and P.-C. Hsu, 2020: Detected climatic change in global distribution of tropical cyclones. *Proc. Natl. Acad. Sci. USA*, **117**, 10 706–10 714, https://doi.org/10.1073/pnas.1922500117.

Sobel, A., C.-Y. Lee, S. J. Camargo, K. T. Mandli, K. A. Emanuel, P. Mukhopadhyay, and M. Mahakur, 2019: Tropical cyclone hazard to Mumbai in the recent historical climate. *Mon. Wea. Rev.*, **147**, 2355–2366, https://doi.org/10.1175/MWR-D-18-0419.1.

Ting, M., J. Kossin, and S. Camargo, 2019: Past and future hurricane intensity change along the U.S. East Coast. *Sci. Rep.*, **9**, 7795, https://doi.org/10.1038/s41598-019-44252-w.

Vickery, P., P. Skerlj, and L. Twisdale, 2000: Simulation of hurricane risk in the US using empirical track model. *J. Struct. Eng.*, **126**, 1222–1237, https://doi.org/10.1061/(ASCE)0733-9445(2000)126:10(1222).

Walsh, K., and Coauthors, 2015: Tropical cyclones and climate change. *Wiley Interdiscip. Rev.: Climate Change*, **7**, 65–89, https://doi.org/10.1002/wcc.371.

Wasserman, L., 2004: *All of Statistics.* Springer, 442 pp.

Wilks, D., 2011: *Statistical Methods in the Atmospheric Sciences.* 3rd ed. Elsevier, 676 pp.

Wright, D., T. Knutson, and J. Smith, 2015: Regional climate model projections of rainfall from U.S. landfalling tropical cyclones. *Climate Dyn.*, **45**, 3365–3379, https://doi.org/10.1007/s00382-015-2544-y.

Yamaguchi, M., J. C. L. Chan, I.-J. Moon, K. Yoshida, and R. Mizuta, 2020: Global warming changes tropical cyclone translation speed. *Nat. Commun.*, **11**, 47, https://doi.org/10.1038/s41467-019-13902-y.

Yonekura, E., and T. Hall, 2011: A statistical model of tropical cyclone tracks in the western North Pacific with ENSO-dependent cyclogenesis. *J. Appl. Meteor. Climatol.*, **50**, 1725–1739, https://doi.org/10.1175/2011JAMC2617.1.

Zhang, G., H. Murakami, T. Knutson, and K. Yoshida, 2020: Tropical cyclone motion in a changing climate. *Sci. Adv.*, **6**, eaaz7610, https://doi.org/10.1126/sciadv.aaz7610.