Meteorological

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## A tornado daily impacts simulator for the central and southern United States

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#### Abstract

In an average year (1979–2016), the United States experiences nearly 1,100 tornadoes, which cause a total of 68 fatalities. Annual fatality rates have decreased since the peak in the 1920s, but there is a concern that they could start to rise again with increases in vulnerable populations and the impacts of climate change. It is possible to assess the risk of tornado fatalities using the historical record. However, the rarity of tornadoes and the short period of record may not capture the true risk. One way around this problem is to simulate thousands of years' worth of tornadoes to obtain a broader picture of risk. Previous tornado risk models have distributed tornadoes randomly or used climatology to generate realistic tornado patterns on an annual (or longer) time scale. From an operational standpoint, it would be useful to have a model that distributes tornadoes on a daily time step to enable the forecasting of potential tornado impacts on a given day. The present study introduces one such model that distributes tornadoes using information about the favourability of the atmospheric environment for tornado development: The Tornado Daily Impacts Simulator (TorDIS). The paper demonstrates model utility through 1,000 year simulations over several metropolitan areas and with a comparison between modelled and observed impacts for several high-impact tornado days. Forecasting potential tornado impacts on a daily time step could allow emergency managers to plan ahead for high-risk days to prioritize their resources and save lives.

#### **KEYWORDS**

daily impacts, risk, spatial model, tornado, tornado favourable environment

#### **1** | INTRODUCTION

Since the early 1950s, the United States has experienced a steady increase in economic losses due to weather-related hazards (Bouwer, 2011; Field *et al.*, 2012; Sander *et al.*, 2013; Smith and Katz, 2013). The exact cause of this increase is unclear; however, it is likely caused by some combination of changing patterns in urban development

(Ashley *et al.*, 2014; Ashley and Strader, 2016) and changes in the environmental conditions that favour the formation of weather-related hazards (Strader *et al.*, 2017). These changes are likely to continue into the future as the United States continues to become increasingly urban (Alig *et al.*, 2004; EPA, 2009; Bierwagen *et al.*, 2010) and as climate change causes an increase in the number of days favouring severe weather events

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(Trapp *et al.*, 2007; Diffenbaugh *et al.*, 2013; Gensini and Mote, 2015).

The focus here is on one particular hazard: the tornado. The paper defines tornado hazard as the probability of the occurrence of a tornado at a given time and place. Tornado exposure is defined as the number of persons or housing units residing in the direct path of the tornado (Strader *et al.*, 2016); and tornado risk as the intersection of a tornado hazard and societal exposure (Field *et al.*, 2012). The exact effect that climate change has on tornadoes is unknown, but there have already been changes in interannual variability and the spatiotemporal clustering of tornadoes (Brooks *et al.*, 2014; Elsner *et al.*, 2015) as well as shifts in regional climatology (Agee *et al.*, 2016; Moore, 2017; Gensini and Brooks, 2018).

Advances in computational resources and software have enabled researchers to model the impact of hazards on people and property over large spatial domains and time periods (Burton, 2010; Ashley et al., 2014). Much of the modelling research has focused on the impacts of hurricanes (Pinelli et al., 2004; Peduzzi et al., 2012), floods (Remo et al., 2012) and earthquakes (Remo and Pinter, 2012; Dell'Acqua et al., 2013). Research on tornado impacts has mostly focused on scenario work involving transposing historical or synthetic tornado footprints (the area impacted by individual tornadoes) over heavily populated areas to identify worst-case scenario events (Rae and Stefkovich, 2000; Wurman et al., 2007; Ashley et al., 2014). For example, Hatzis et al. (2019) focused on replicating historical violent tornadoes to determine the likelihood of a violent tornado hitting or narrowly missing a heavily populated area; while Elsner et al. (2018b) used historical footprints to estimate property losses in Florida. Another modelling approach is to use spatial statistical models to project tornado hazards as a function of climatology, population density or teleconnections (e.g. El Niño Southern Oscillation (ENSO); Elsner et al., 2013b, 2016). This methodology allows for the assessment of tornado hazards, but does not address tornado impacts. Other statistical models have linked tornado casualties to factors such as tornado kinetic energy, population density, number of mobile homes and time of day (Elsner et al., 2018a; Fricker and Elsner, 2019); however, these models are incapable of directly addressing future changes in tornado impacts. A final statistical model uses neural networks to predict property damage from tornadoes (Diaz and Joseph, 2019); however, this approach does not explicitly assess impacts over the whole tornado footprint.

Other recent tornado modelling research has employed Monte Carlo methods, a technique that uses repeated random sampling to ascertain the probability distribution for some unknown quantity (Mooney, 1997) to understand better the probabilistic impacts of tornadoes (Meyer *et al.*, 2002; Daneshvaran and Morden, 2007). One model, in particular, the Tornado Impact Monte Carlo (TorMC) model, developed by Strader *et al.* (2016), is unique in its examination of the dynamic interaction between tornado risk, severity and exposure. This model was also used to study the impact of urbanization and climate change on future tornado exposure (Strader *et al.*, 2017).

The TorMC model represents an important step in the simulation of the dynamic relationship between tornado risk, severity and vulnerability over time and space by assessing tornado impacts on an annual time scale. However, from an operational standpoint, it would be useful to have a model capable of simulating tornado impacts on shorter time scales (Karstens et al., 2015; Smith et al., 2015). A daily impacts model would allow a user to determine how the impact of an observed tornado footprint compares with the potential impacts that could have occurred under the same atmospheric environment (i.e. how many more people could have potentially been exposed to the tornado). Such a model would rely on information regarding the favourability of the atmospheric environment for the production of tornadoes (Sobash et al., 2011; Nowotarski and Jensen, 2013; Karstens et al., 2015). Sources of such information could be atmospheric reanalysis data (Brooks et al., 2003b; Trapp et al., 2007; Gensini and Ashley, 2011), probabilistic outlooks from the Storm Prediction Center (SPC) (Hitchens et al., 2013; Herman et al., 2018) and numerical weather prediction model output (Schwartz et al., 2015; Powers et al., 2017). Environmental data could also be used to constrain tornado parameters such as magnitude (Colquhoun and Riley, 1996; Naylor and Gilmore, 2012) or even the number of tornadoes occurring on a given day (Thompson and Edwards, 2000; Corfidi et al., 2010). Additionally, climate projections for variables related to the atmospheric environment (e.g. shear and convective available potential energy (CAPE)) would allow for a spatially explicit approach to estimating future tornado impacts under climate change (Trapp et al., 2007; Diffenbaugh et al., 2013; Gensini et al., 2014b). By using projected atmospheric environments, it may be possible to estimate the location of future changes in tornado occurrence and severity as well as the magnitude of those changes (Diffenbaugh et al., 2008; Tippett et al., 2015).

No current published modelling approach simulates tornado impacts at the daily time scale. Hence, the objective of the present research is to present a proof of concept for one such daily impacts model: the Tornado Daily Impacts Simulator (TorDIS). Like the TorMC model, the TorDIS overlays tornado footprints upon cost surfaces such as population or housing units. However, in the TorDIS, all aspects of the tornado footprint (i.e. location, size, magnitude, direction) are constrained by the environment in which it forms. The following sections describe the TorDIS approach, validate the model's deterministic components through a global sensitivity analysis (global here implies that sensitivity is tested for all variables simultaneously instead of one at a time; Saltelli *et al.*, 2008) and showcase the model's utility through applications at the daily and annual time scales over the central and southern United States.

## 2 | TORDIS DEVELOPMENT

The TorDIS was developed as an extension of the work of Strader *et al.* (2016) to link tornado distribution and characteristics to daily atmospheric environments instead of basing them on climatology. Like the TorMC, the TorDIS is limited by the accuracy and scope of the historical data used by the model (Brooks *et al.*, 2003a; Verbout *et al.*, 2006; Doswell, 2007). It is important to note that the historical data used by the TorDIS only represent a fraction of all possible atmospheric environments and tornado characteristics. Tornado counts and characteristics may exhibit long-term patterns that are not evident in the short, observed record with extreme values that are greater or more likely (Meyer *et al.*, 2002; Doswell, 2007). As such, Monte Carlo simulations using these data cannot create a more accurate picture of tornado risk; however, they do provide a larger window of potential outcomes for analysis (Strader *et al.*, 2016). The primary objective of the present study is to expand upon the





methods of Strader *et al.* (2016) to work towards simulating tornado impacts at time scale suitable for operational use.

The TorDIS has five process steps (Figure 1): (1) study area selection; (2) production of a tornado probability field and determination of whether the day is favourable for tornado development; (3) selection of tornado parameters and creation of footprints (rectangular polygons with the selected lengths and widths, representing the area covered by tornadic winds); (4) extraction of cost information across the footprint; and (5) production of model output. Like the TorMC model, the TorDIS is modular in nature with many user-defined parameters to allow the user to control model output.

### 2.1 | Model input

#### 2.1.1 | Tornado record

The TorDIS simulates tornadoes by sampling various tornado parameters from the historical tornado distribution or theoretical distributions based on the historical record. The model requires a tornado database, in shapefile format, containing tornado locations, path lengths, widths, magnitudes and dates, as lines. By default, the TorDIS uses the SVRGIS tornado database (USA) from the SPC for the period 1979-2016 (https://www.spc.noaa.gov/gis/ svrgis/). However, the model can also be adjusted to use other databases such as the US Significant Tornado data set (Grazulis, 1993, 1997) or the European Severe Weather Database (https://www.essl.org/cms/europeansevere-weather-database/). The SVRGIS tornado database has many known flaws that have been reported elsewhere, including, but not limited to: population bias, reporting frequency (fewer weak tornadoes were observed early in the record), questions of accuracy (due to amateur reports), changes in reporting methodologies (e.g. reporting mean path width versus maximum path width) and concerns regarding using damage assessments to determine tornado magnitude (Verbout et al., 2006; Elsner et al., 2013a; Ashley et al., 2014; Strader et al., 2015). However, it was selected for use in the model since it is still the best record available (Strader et al., 2016).

### 2.1.2 | Atmospheric environmental data

An important aspect of the TorDIS is the linkage between tornado occurrence and magnitude and the atmospheric environment in which the tornado forms. Tornadoes require certain key ingredients to form, including a moist, unstable atmosphere, a source of lift, rotation and low cloud bases (Brooks *et al.*, 2003b; Ashley and Strader, 2016). These ingredients can be represented by certain severe weather diagnostic parameters, such as CAPE, storm relative helicity (SRH) and vertical wind shear (VWS). These parameters can be derived from reanalysis data (Brooks *et al.*, 2003b; Gensini and Ashley, 2011; Gensini *et al.*, 2014b) or model output (Gensini *et al.*, 2014b; Powers *et al.*, 2017). The Tor-DIS uses both gridded diagnostic parameters and proximity soundings (reanalysis-based atmospheric profiles at the closest points in space and time to the occurrence of tornadoes) to determine the favourability of the environment for tornado formation and the magnitude of a tornado should one occur, respectively.

By default, the TorDIS uses reanalysis data from the period 1979-2016 from the North American Regional Reanalysis (NARR) project for the central and southern United States (Figure 2). The NARR is an extension of the National Centers for Environmental Prediction (NCEP) Global Reanalysis project and uses the high-resolution Eta model (with 32 km horizontal resolution and 45 sigma levels) combined with the Regional Data Assimilation System (RDAS) to generate high-resolution atmospheric field variables (Gensini and Ashley, 2011). The fields are available eight times daily from the period 1979-2016, and all vertical fields are available at 29 pressure levels. Mesinger et al. (2006) evaluated the quality of the NARR data and found it to be a major improvement in both accuracy and resolution over previous global reanalysis efforts. This data set is chosen because of its high resolution over North America. There are caveats with the data: small biases have been documented in temperature and precipitation fields (Gensini and Ashley, 2011) and a lower vertical resolution in the lowest layers (as compared with radiosonde observations) can cause biases for some thermodynamic parameters that require vertical integration (e.g. CAPE) when compared with collocated observations (Gensini et al., 2014a). All gridded reanalysis data were collected only once per day (at 0000 UTC, the peak time for severe weather activity in the central United States; Brooks et al., 2003b; Gensini and Ashley, 2011), while proximity sounding data were collected at the time closest to the tornado report (Lee, 2002). The NARR data are processed using the Sounding/Hodograph Analysis Research Program in Python (Halbert et al., 2015) to obtain the severe weather diagnostic parameters used by the model.

The TorDIS can also be calibrated to use other reanalysis data sets, such as the NCEP Reanalysis-2 (Kanamitsu *et al.*, 2002) as well as numerical weather prediction model output (e.g. the Weather Research and Forecasting (WRF) model; Powers *et al.*, 2017) or future atmospheric environments from climate models, such as the North American Regional Climate Change Assessment Program (Mearns *et al.*, 2013) as long as they are available at a daily time scale. If the atmospheric data **FIGURE 2** Populations for major cities within the model domain. The dashed line refers to the maximum study area for a model run assuming a 50 km buffer to reduce edge effects



used are from future climate projections, the model can then project the average impact over that future time period taking into account changes in the atmospheric environment.

## 2.2 | Model mode and study area selection

The TorDIS has two modes in which it can be run: daily impact (DI) or annual impact (AI). Like the TorMC, the TorDIS is a stochastic model that relies on Monte Carlo simulations to estimate tornado impacts. In DI mode, the TorDIS is run many times (e.g. 10,000) using the atmospheric environment of one specific day (e.g. April 27, 2011) to constrain tornado production, distribution and characteristics. This mode can be used to assess the likelihood of population exposure exceeding that of a particularly impactful tornado on the day (e.g. the violent (rated four or higher on the Enhanced Fujita (EF) scale) tornado that hit Tuscaloosa and Birmingham, Alabama, on April 27, 2011; Doswell et al., 2012). In AI mode, the user specifies the number of years of simulations to run (e.g. 1,000). For each of these simulation years, a random year of environmental data are selected from the list of available years (e.g. 2005-2016). The TorDIS then proceeds to simulate tornadoes for each tornado favourable day during the randomly selected year. A random draw will not simulate the interannual variability of tornado hazards correctly (e.g. the ENSO is known to be linked to tornado activity; Cook and Schaefer, 2008; Allen et al., 2015). However, since the objective is to assess the longterm risk of tornado impacts and not the impacts for a specific year, this methodology was considered to be acceptable. This mode can be used to assess the long-term risk of population exposures exceeding 5,000 persons in a given area (Hatzis *et al.*, 2019). The objective in both modes is to determine the statistical distribution of potential tornado impacts over the period from which the atmospheric environmental data are drawn (i.e. one day or many years), through repeated sampling.

In addition to selecting a mode and the number of simulations, the user also must select a study area over which to run the model. The study area must be at least  $5,000 \text{ km}^2$  (roughly the area corresponding to a 40 km radius surrounding a given point; as used by the SPC to represent proximity; Hitchens *et al.*, 2013) and be within the model's spatial domain (Figure 2). The maximum study area size is limited by both the size of the domain and the buffer size used to reduce edge effects (Strader *et al.*, 2016). Figure 2 shows the maximum study area size for a 50 km buffer as a dashed line.

## 2.3 | Tornado probability field and daily tornado count

### 2.3.1 | Tornado probability regression model specification and sensitivity analysis

Tornado distribution in the model begins with a decision of whether or not the atmospheric environment is favourable for tornado development on a given day of the simulation. Several methods have been suggested for defining environmental favourability, within both atmospheric and health sciences, including linear discriminant analysis (Lee, 2002; Brooks et al., 2003b; Gensini and Ashley, 2011), geographically weighted regression (GWR; Nakaya et al., 2005; Ivajnšič et al., 2014) and logistic regression (Billet et al., 1997). The TorDIS makes use of logistic regression as most atmospheric variables do not follow a normal distribution (days with a high CAPE and/or a high VWS are rare; Brooks et al., 2003b; Gensini and Ashley, 2011), one of the assumptions of linear discriminant analysis (Pohar et al., 2004). Additionally, GWR has a high computational cost (Ali et al., 2007) and so it is not uncommon for large-scale studies on severe weather favourability to opt for non-geographically weighted methods (e.g. Brooks et al., 2003b; Gensini and Ashley, 2011; Diffenbaugh et al., 2013). The TorDIS uses four logistic regression equations to determine tornado favourability: severe weather probability in a low CAPE environment (svrlow); tornado probability given severe weather in a low CAPE environment (torn<sub>low</sub>); severe weather probability in a moderate to high CAPE environment (svr<sub>mod</sub>); and tornado probability given severe weather in a moderate to high CAPE environment (torn<sub>mod</sub>). All regression equations are additive; the coefficients are listed in Table S2 in the additional supporting information. A global sensitivity analysis was conducted to ensure that only important variables were included in the regression equations (the contribution of each variable to the total variance in tornado occurrence is shown in Figure S1 in the additional supporting information). The details regarding the regression model development and validation are presented in the tornado forecast model selection and validation section in the additional supporting information.

#### 2.3.2 | Daily tornado production

The process of determining whether a simulated day will have tornadoes starts with the creation of a tornado probability field for that day. The tornado probability fields are created by applying the regression equations (see Table S2 in the additional supporting information) to the gridded environmental data. First, the CAPE status (low or moderate to high) is assessed for each grid cell to determine which set of regression equations to use on that grid cell. The severe weather probability is then calculated using the relevant equation. Following the SPC's practice of not including severe weather probabilities < 2% (Hitchens *et al.*, 2013), if the cell has a severe weather probability of < 2%, the tornado probability is set to 0. Otherwise, the tornado probability is calculated using the relevant equation. Finally, all grid cells with tornado probabilities < 2% are set to 0.

Days are considered to be favourable for tornado production when the favourable area (area with  $\geq 2\%$ probability) covers at least 5,000 km<sup>2</sup>. Since daily tornado production is highly variable (Elsner et al., 2014; Tippett and Cohen, 2016) and not all days that are considered favourable produce tornadoes (Trapp et al., 2007; Lock, 2012), daily tornado counts are randomly drawn from the historical record for the study area. Tornado production is linked to lower lifted condensation levels (LCLs), with higher LCLs corresponding to increased outflow and a reduced likelihood of tornado formation (Rasmussen and Blanchard, 1998). Tornado outbreaks also tend to be the largest in the spring and fall (Brooks et al., 2003a; Doswell et al., 2006). To account for these patterns, daily tornado counts are broken down into eight categories based on season and the fifth percentile daily LCL height over the domain, and a daily tornado count is randomly drawn from the relevant category based on the atmospheric conditions of the day for each day considered favourable for tornado production. The fifth percentile was arbitrarily chosen to represent the lowest LCL that has significant areal coverage. Once the tornado probability field has been created and a daily tornado count has been selected, tornado touchdown points are distributed across the model domain using a weighted random distribution based on the tornado probability field.

#### 2.4 | Tornado magnitude

Tornado magnitude is measured on the EF scale and is related to 0-3 km storm relative helicity (SRH3), with stronger tornadoes more common in the high helicity environments more conducive of supercell production (Colquhoun and Riley, 1996; Rasmussen and Blanchard, 1998). The literature suggests multiple SRH3 thresholds for supercell production and thus stronger tornadoes, including 150 and 250 m<sup>2</sup>·s<sup>-2</sup> (Droegemeier et al., 1993; Moller et al., 1994; Colquhoun and Riley, 1996). A preliminary investigation of proximity sounding data for tornadoes in the SVRGIS database showed a clear distinction between magnitudes for tornadoes with SRH3 in the following categories: low (SRH3 < 150  $m^2 \cdot s^{-2}$ ), moderate  $(150 \text{ m}^2 \cdot \text{s}^{-2} \le \text{SRH3} < 250 \text{ m}^2 \cdot \text{s}^{-2})$  and high (SRH3  $\geq 250 \text{ m}^2 \cdot \text{s}^{-2}$ ). All the tornado magnitudes in the SVRGIS database are separated into groups based on the SRH3 category. Once a tornado is placed, the SRH3 value for that location is extracted and a tornado magnitude is randomly drawn from the relevant group.

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## 2.5 | Path length and width

Brooks (2004) showed that, when separated by magnitude class, both tornado path lengths and widths were well approximated by Weibull distributions due to their non-negative and positively skewed nature. Tornado path lengths and widths are randomly drawn from magnitudespecific Weibull distributions fitted to the observed path width and length data. Before fitting the Weibull distributions, both path length and width values in the SVRGIS database were adjusted to account for non-meteorological trends in their values (Strader et al., 2015, 2016). Jumps in the mean annual path width were found in 1995 (when path width reporting switched from mean width to maximum width; Agee and Childs, 2014; Ashley et al., 2014) and 2007 (with the switch from the F to the EF scale for measuring tornado magnitude; Strader et al., 2016), while a jump in the mean annual path length was only evident in 2007. Following the method of Agee and Childs (2014), path widths are detrended by determining the difference between the lower threshold of the mean annual path widths during the periods 1979-1994 (1995-2006) and 2007-2016 and adding that difference (61.2 and 51.5 m, respectively) to the path widths during the earlier two periods. Path lengths are similarly detrended by adding the difference between the lower threshold of the mean annual path length during the periods 1979-2006 and 2007-2016 (1.04 km) to each of the path lengths during the earlier period. The exact reason for the increase in path widths and lengths after 2006 is unknown (Strader et al., 2016). However, possible reasons include improvements to damage assessment methods (Agee and Childs, 2014) and the addition of non-structural damage indicators to the EF scale that allowed previously undetectable wind damage to be identified (Doswell et al., 2009; Edwards et al., 2013; Hatzis et al., 2019). Owing to the improvements in damage assessment introduced in the EF scale, the TorDIS considers the 2007-2016 length and width data the most accurate. Once a tornado's magnitude is set, path width and length are randomly selected from the appropriate Weibull distribution. Alternatively, if the user specifies, the path width and length can be randomly selected from the adjusted historical data based on the magnitude.

## 2.6 | Tornado direction

Tornado direction is closely linked to the 500 mb wind direction, which acts to steer the storm systems that generate tornadoes (Notis and Stanford, 1973; Suckling and Ashley, 2006). For each tornado touchdown point, the 500 mb wind direction is extracted (as a bearing). This bearing is assigned as the tornado's direction. After the direction has been assigned, a tornado footprint is created by using the direction and path length and width. For the results of the validation of this method, see the predicting tornado direction section in the additional supporting information.

### 2.7 | Cost extraction

Cost extraction, the determination of the impact of a given tornado, for the TorDIS, begins, as with the TorMC model, with the clipping of all tornado footprints to the specified study area. Once the clipping is complete an area-weighted sum (Ashley et al., 2014; Strader et al., 2016) is performed on all cost units intersected by the clipped footprints to determine the total cost over each footprint. First, the intersection of the footprint and the cost surface breaks the footprint apart into small sections corresponding to parts of the cost units. Each section is then allocated a cost based on the proportion of a cost unit it comprises (e.g. a section that occupies 25% of a 1,000 person unit would have 250 persons). The total cost for the footprint is calculated as the sum of the cost of all the sections. By default, the cost surface used by the Tor-DIS is the US Population Grids for 2010 (Summary File 1) from the Socioeconomic Data and Applications Center (SEDAC) (2010). However, any raster (e.g. gridded housing unit data) or polygon-based cost surface (e.g. per cent population in poverty at the census block level in Oklahoma) can be used by the model.

## 2.8 | Model output

The final output of the TorDIS includes shapefiles (containing the simulated tornado footprints with cost data, as well as tracks and touchdown points) and commaseparated value files containing the attribute data of the simulated tornadoes. The model also produces probability of exceedance curves for the tornado costs.

## 3 | MODEL APPLICATION

### 3.1 | Model performance

To demonstrate the TorDIS's ability to estimate probability distributions for tornado exposures given atmospheric environmental information, a simulation of 1,000 years (in AI mode) was run over the maximum study area size assuming a 50 km buffer. The number of simulations was limited to 1,000 compared with the 10,000 recommended RMetS

by Strader *et al.* (2016) due to computational restraints. Tornado path lengths and widths were randomly selected from Weibull distributions. The environmental data were derived from the NARR for 2005 to 2016, while the tornado database used was from the SVRGIS for 1979–2016 (the period when the NARR was available for proximity soundings). Only tornadoes that impacted the contiguous United States and did not occur entirely over one of the Great Lakes or the ocean were considered in the analysis. The cost surface used was the default 2010 population counts on a 1 km resolution grid from the SEDAC. For comparability, the following section emulates the structure used by Strader *et al.* (2016).

Over a 1,000 year simulation, the TorDIS generated 1,266,109 tornadoes over the study area with 46.8% EF0, 35.4% EF1, 12.8% EF2, 4.0% EF3, 0.9% EF4 and 0.1% EF5 (Table 1). The model magnitude distribution was similar to the observed magnitude distribution from 1979-2016 (46.4% EF0, 35.6% EF1, 12.9% EF2, 4.1% EF3, 0.9% EF4 and 0.1% EF5). Overall the model showed a bias towards the overproduction of tornadoes. The mean annual number of simulated tornadoes was  $1,266 \pm 412$  (95% confidence interval from 1,000 bootstrap samples of 38 each) compared with a mean annual observed total of 649 observed. The variance in annual tornado counts was similar to the observed counts during the 2005-2016 period (approximately 41,000 tornadoes). The mean annual simulated tornado day count was 201.0 compared with a mean of 98.8 days per year observed over the study area. The model's seasonal tornado production mirrors the observed production with a maximum in spring and a minimum in winter (Tippett et al., 2012). However, tornado production is slightly underestimated in spring and overestimated in all other seasons. The general overproduction of tornadoes is due to the model's high falsealarm rate at predicting tornado days (see Table S2 in the additional supporting information). The simulation does yield a similar number of consecutive runs of tornado days to what was observed (259 *versus* 243, respectively). However, the mean length of these consecutive runs was much shorter for observed tornado days (three) than for simulated tornado days (10). Additionally, the maximum length of a run of tornado days for the simulation was 136, while the longest observed run was 15 days.

Spatially, the model showed a bias towards the overproduction of tornadoes in areas not experiencing tornadoes during the 2005-2016 study period, while simultaneously underproducing tornadoes in areas with high tornado activity (Figure 3). This is likely due to the fact that the areas favourable for tornado development are often large (e.g. convective outlook areas), while tornado activity tends to be clustered (Doswell et al., 2006). This spatial bias was similar for all tornado magnitudes (Figure 3). The weighted random distribution method employed in the TorDIS tends to spread tornado activity throughout the favourable areas creating fewer clusters than would be observed in an actual storm system (Galway, 1977).

For further comparison with the observed record over the study area, a random sample of 38 years of violent (EF4+) tornadoes was chosen from the 1,000 year simulation to match the 1979–2016 observed period. The sample shows a similar distribution across the study area to what was observed (Figure 4), but a greater number of tornadoes (494 *versus* 218). The random sample also revealed a higher mean (13) tornado count when compared with the observed record (5.8).

The 1,000 year simulation over the study area yielded a mean tornado length and width of 7.7 km and 240.8 m, respectively (Table 1). The modelled lengths and widths increased as the tornado magnitude increased similar to the findings of Strader *et al.* (2016), with lengths ranging from 2.9 km (EF0) to 61.6 km (EF5) and widths ranging from 90.2 m (EF0) to 1,699.4 m (EF5). The mean lengths

Magnitude	Count	Mean length (km)	Mean width (m)	Mean direction (•)
EF0	592,064	2.9	90.2	84.6
EF1	448,380	7.9	239.2	83.7
EF2	161,737	15.6	478.3	83.3
EF3	51,132	28.1	968.1	83.4
EF4	11,651	39.5	1,320.2	82.0
EF5	1,145	61.6	1,699.4	86.0
All	1,266,109	7.7	240.8	84.0
Significant (EF2+)	225,665	19.9	638.9	83.3
Violent (EF4+)	12,796	41.5	1,354.1	82.3

TABLE 1 Tornado attributes from a 1,000 year Tornado Daily Impacts Simulator (TorDIS) simulation over the study area

Note: Attributes presented include tornado magnitude (Enhanced Fujita (EF) scale), count, mean length, mean width and mean direction.



**FIGURE 3** Spatial bias in tornado counts for all (a), significant (b) and violent (c) tornadoes. Bias is calculated as the difference between the mean annual simulated and observed tornado counts

for each magnitude class are within 1 km of the mean for the respective Weibull distribution, while the mean widths are within 12 m. Maximum modelled widths and lengths were mostly overestimated when compared with the observed maxima over the study area (e.g. maximum width (length) for simulated EF2 tornadoes was 4,060.4 m (137.9 km) compared with an observed maximum of 2,945.3 m (126.0 km)). This is likely due to the tendency of the Weibull distribution to over- or underestimate the tail ends of the distribution (Brooks, 2004). The mean modelled direction for all tornadoes over the study area was 74.9° (roughly westsouthwest to eastnortheast), which matches the findings of Suckling and Ashley (2006) for the South Central region.



EF4+ SVRGIS footprints 1979–2016

(a)

(b)



TorDIS random 38 years of EF4+ footprints



N

(c) TorDIS 38 most impactful years of EF4+ footprints



**FIGURE 4** (a) Observed violent (EF4+) tornado footprints for 1979–2016 from the SVRGIS over gridded 2010 population counts from the Socioeconomic Data and Applications Center (SEDAC) for the study area; (b) as for (a), but for a random sample of 38 years of simulated violent tornado footprints; and (c) as for (a), but for all violent tornado footprints from the 38 most impactful years over the study area (in terms of total persons exposed to tornado winds *per* year). Sample sizes were chosen to be over 38 years since this period matches the 1979–2016 observed period. Source: modelled after Strader *et al.* (2016, Fig. 4)

Based on the 2010 SEDAC population grids, the mean (median) number of persons impacted by a tornado footprint was 80 (1) (Table 2). Mean impacts (persons exposed) *per* footprint increase with increasing tornado magnitude from 6 (EF0) to 2,034 (EF5). The mean annual numbers of persons impacted by tornadoes peaked at the EF2–EF3 magnitude range due to the small number of higher magnitude tornadoes (only 1.0% (Table 1) of the simulated tornadoes had magnitudes of EF4+). One interesting finding was that among the top 10 most impactful (in terms of persons exposed) simulated tornadoes over the study area, two were EF2s. Lower magnitude tornadoes tend to have smaller footprints and would thus be expected to be less impactful (Brooks, 2004; Strader *et al.*, 2015). However, the tendency for maximum tornado lengths and widths to be overestimated lead to the possibility of a high-impact EF2 tornado.

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A significant difference between the TorMC model and TorDIS is in the ability to assess daily and seasonal differences in tornado impacts. From the 1,000 year simulation over the study area, the most active months for significant tornadoes were April-May (Figure 5a). This mirrors the observed record, which indicates peak significant tornado activity in spring (SPC, 2017). Median annual impacts (persons exposed) for significant tornadoes over each month of the simulation show a pattern that matches that of the significant tornado counts with a peak in April-May (Figure 5b). The correlation between the median annual impacts and the tornado counts results from the fact that tornado impacts are a function of both tornado footprint area and the environment in which they hit (Ashley et al., 2014; Ashley and Strader, 2016; Strader et al., 2018).

## 3.2 | Comparison of tornado risk across major metropolitan statistical areas

To show how the TorDIS can be used to study spatial variations in tornado impacts, the 1,000 year annual simulation was subset to focus on six metropolitan statistical areas (MSAs): Oklahoma City (Oklahoma), Dallas/Fort Worth (Texas), Chicago (Illinois), Birmingham (Alabama), Omaha (Nebraska) and St. Louis (Missouri), hereafter references to the city name refer to the MSA. These MSAs were chosen for their size (from < 1 million persons in Omaha to > 9 million persons in Chicago; US Census Bureau, 2010), distribution throughout the model domain and varying levels of tornado hazards (tornado hazards are most common in an "L"-shaped pattern



**FIGURE 5** Monthly variation in median significant tornado counts (a) and median annual persons exposed to significant tornado winds (b) over the study area for a 1,000 year simulation

Magnitude	Annual occurrence probability	Return period (years)	Mean tornado impact (persons)	Mean annual impact (persons)
EF0	592.064	0.002	6	3,680
EF1	448.380	0.002	45	20,219
EF2	161.737	0.006	177	28,555
EF3	51.132	0.020	618	31,588
EF4	11.651	0.086	1,225	14,269
EF5	1.145	0.873	2034	2,329
All	1,266.109	0.001	79	100,640
Significant (EF2+)	225.665	0.004	340	76,741
Violent (EF4+)	12.796	0.078	1,297	16,598

 TABLE 2
 Impact analysis from a 1,000 year Tornado Daily Impacts Simulator (TorDIS) simulation over the study area

Note: Results are organized by tornado magnitude and include annual occurrence probability, return period, mean number of persons impacted by an individual tornado and mean number of persons impacted *per* year.

**TABLE 3** Annual number of persons impacted by significant tornado winds *per* 1,000 km<sup>2</sup> over select metropolitan statistical areas (MSAs) during a 1,000 year Tornado Daily Impacts Simulator (TorDIS) simulation using the 2010 Socioeconomic Data and Applications Center (SEDAC) gridded population counts

Metropolitan statistical area	Normalized count	Mean	Median	Maximum	Standard deviation
Oklahoma City, OK	103	134	13	3,439	358
Dallas/Fort Worth, TX	108	399	52	8,365	819
Chicago, IL	103	476	79	13,992	1,103
Birmingham, AL	112	110	18	2,994	291
Omaha, NE	93	104	6	2,759	334
St. Louis, MO	82	142	16	3,002	373

Note: Summary statistics include the normalized count of significant tornadoes, mean, median, maximum and standard deviation of annual persons impacted.

between Nebraska, Texas and Alabama, and they drop off further towards the northeast; Concannon *et al.*, 2000; Ashley, 2007; Hatzis *et al.*, 2019).

The normalized significant tornado count was highest over Birmingham (112) and lowest over St. Louis (82) (Table 3). Chicago had the highest mean, median and maximum annual impact *per* 1,000 km<sup>2</sup> (476, 79 and 13,992 persons exposed, respectively). Omaha had the lowest mean (104), median (6) and maximum (2759) annual persons exposed *per* 1,000 km<sup>2</sup> (Table 3). A probability of exceedance curve for annual persons exposed (per 1,000 km<sup>2</sup>) to significant (Figure 6) tornado footprints shows how the combined factors of footprint area and population density affect the annual impact. The greatest impacts are in the MSAs with the greatest population density (Chicago and Dallas/Fort Worth; US Census Bureau, 2010).

Meanwhile, MSAs such as Oklahoma City and St. Louis tend to experience reduced impacts due to the sprawling nature of their population distributions (Rosencrants and Ashley, 2015). The annual impacts are greater in Birmingham at lower thresholds due to the higher rural density (Ashley, 2007), while the annual impacts are greater in Omaha at slightly higher thresholds because most of the population in Omaha is confined to the centre (US Census Bureau, 2010). This implies that tornadoes are unlikely to impact many people, but when they do, the totals will be higher (Hatzis et al., 2019). In fact, despite being the least populous MSA in the present study, significant tornadoes impacting Omaha nearly had the same probability of impacting 20,000 persons as in Oklahoma City, which had nearly 400,000 more people in 2010 (Table 3).

The most impactful tornado from any of the simulations was a 2.1 km wide and 85.0 km long EF4 tornado that was simulated to hit Chicago and impact 265,674 persons. For comparison, from 1979–2016, the widest tornado, which impacted Chicago, was 1.2 km and the longest tornado was 49.3 km (SPC, 2017). Five tornadoes



**FIGURE 6** (a) Probability that a significant tornado would impact more persons than a set threshold for a 1,000 year simulation over the Birmingham, Dallas/Fort Worth, Omaha, Chicago, Oklahoma City and St. Louis metropolitan statistical areas (MSAs); and (b) as for (a), but only zoomed in to the lower thresholds

impacted > 100,000 persons, all of which impacted either Chicago or Dallas/Fort Worth. Among the 25 most impactful tornadoes, all but one hit either Chicago or Dallas/Fort Worth. Twelve were EF4 or EF5 tornadoes, with the rest mostly being EF3 and three anomalously wide (> 1.5 km) EF2 tornadoes. Meteorologica

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# 3.3 | Tornado impacts on a daily time scale

A unique use of the TorDIS's daily time step is to determine how the impact of an observed tornado footprint compares with the potential impacts that could have occurred under that same atmospheric environment. As an example of this sort of analysis, a 10,000 year simulation was run, in DI mode, for four significant tornado outbreak days: February 5, 2008, April 27, 2011, May 22, 2011, and May 20, 2013 and one favourable day that was a "bust" (April 6, 2010) with no tornadoes occurring. These runs were conducted over the maximum study area size assuming a 50 km buffer (Figure 2). All other model settings and data sets were the same as for the annual run. Additionally, observed tornado footprints (damage path polygons) were collected from the National Weather Service for three high-impact violent tornadoes (an EF4 at Tuscaloosa-Birmingham, Alabama (April 27, 2011; Doswell et al., 2012); an EF5 at Joplin, Missouri (May 22, 2011; Paul and Stimers, 2012); and an EF5 at Moore, Oklahoma (May 20, 2013; Kurdzo et al., 2015)) and the total number of persons exposed (using the 2010 SEDAC population grids) to each footprint was calculated.

On February 5, 2008, a large weather system moved over the southeastern United States, producing 87 tornadoes and causing 57 fatalities (Chaney and Weaver, 2010). During this event, one tornadic supercell passed over Nashville, Tennessee, producing tornadoes to the southwest and northeast of the city, but not downtown (Hatzis *et al.*, 2019). The 10,000 year simulations of this environment yielded a mean of three significant tornadoes and a maximum of 24. These significant tornadoes impacted a mean of 1,178 persons *per* day and a maximum of 231,398 (Table 4), with the most impactful footprint exposing 129,185 persons to tornado winds. For comparison, the observed impact over the day was 9,096 persons, with the most impactful tornado footprint having an exposure of 2,327 persons. The observed impact was high, with only a 2.2% chance that it would have been exceeded on that day.

April 6, 2010, was a favourable day for tornado development with a 10% chance of tornadoes over northwest Missouri and southeast Iowa. However, while the day did produce severe weather (hail and wind), no tornadoes were observed (SPC, 2017). A 10,000 year simulation of this day produced a mean of three significant tornadoes and a maximum of 28 with a mean exposure of 1,862 persons and maximum exposure of 185,763 persons.

For the high-impact tornadoes, the probability that the exposure of a simulated violent tornado would be higher than observed, on the date of the event, was 1.5%, 3.6% and 2.7% for Tuscaloosa-Birmingham, Joplin and Moore, respectively. Given that all three tornadoes impacted > 5,000 persons, it is not surprising that these

TABLE 4	Tornado Daily Impacts Simulator (TorDIS) model results from a 10,000 year simulation of all tornadoes over the study area
on the specifie	d days

		Tornado count			Persons exposed		
Date	Magnitude	Median	Mean	Maximum	Median	Mean	Maximum
February 5, 2008	All	4	10	72	56	877	237,745
	Significant (EF2+)	2	3	24	168	1,178	231,398
	Violent (EF4+)	1	1	4	354	1,525	61,755
April 6, 2010	All	4	10	72	45	1,315	186,875
	Significant (EF2+)	2	3	28	148	1862	185,763
	Violent (EF4+)	1	1	5	401	2,856	102,806
April 27, 2011	All	4	10	72	82	914	102,831
	Significant (EF2+)	2	3	24	249	1,212	99,727
	Violent (EF4+)	1	1	5	506	1,663	66,562
May 22, 2011	All	2	4	67	15	438	148,670
	Significant (EF2+)	1	2	24	83	839	121,901
	Violent (EF4+)	1	1	3	340	2,375	90,100
May 20, 2013	All	4	10	72	39	788	162,916
	Significant (EF2+)	2	3	19	133	1,103	158,470
	Violent (EF4+)	1	1	4	304	1,449	116,848

Note: Summary statistics include the mean, median and maximum values for both tornado count (by magnitude) and persons exposed per tornado.

exposures are not very likely to be exceeded (Hatzis *et al.*, 2019).

## 3.4 | Limitations and future developments of the TorDIS

The TorDIS performs well (with a mean bias of 0.2 tornadoes per year and 85% of the study area experiencing a bias of  $\leq 0.5$  tornadoes *per* year) at simulating the spatial distribution of tornadoes. However, its performance is weaker at predicting whether or not a day is a tornado day. Storm initiation is often one of the biggest uncertainties for tornado forecasting in environments with sufficient instability and VWS (Lock, 2012; Schultz et al., 2014). The current version of the model tends to overpredict the likelihood of storm initiation resulting in nearly double the observed number of tornado days and a resultant bias towards more tornadoes overall. Another model limitation is the bias towards underproducing tornadoes, where they occur most frequently. Future model runs will increase the temporal resolution for the gridded environmental data (beyond one time step per day) to ensure that the environment varies throughout the day to represent real tornado production more accurately. Future runs will also introduce tornado-producing storms that can produce multiple tornadoes in close spatial proximity, more accurately replicating tornado outbreaks (Galway, 1977). These two additions should help reduce the spread of the simulated tornadoes to match more accurately the observed spatial clustering of tornadoes. A final limitation is that the model is currently unable to distinguish between tornado outbreaks of different sizes with similar environmental characteristics. Average Tor-DIS simulations for February 5, 2008, April 27, 2011, and May 20, 2013, yielded 10 tornadoes each over the study area (Table 4), while the observed counts were 60, 133 and 35, respectively (SPC, 2017). This limitation is due to the current methodology of randomly selecting daily tornado counts from the historical data based on the season and the LCL. Under this methodology, two events with a similar LCL occurring in the same season might have the same number of simulated tornadoes, even though the observed counts were very different. Future versions of the TorDIS will attempt to correct for this by employing regression analysis to select the daily number of tornadoes to simulate.

The next step in model development is implementing multiple footprints for each tornado to represent the wind field. Tornadoes are given magnitude ratings based on the maximum amount of damage over their footprints, with much of the footprint area covered by less intense winds (Fricker and Elsner, 2015; Strader *et al.*, Meteorological Applications

2015). Currently, the TorDIS creates only one footprint for each tornado (representing the EF0 wind field). However, future versions will add footprints for each magnitude class so that it is possible to know how many persons or buildings are actually experiencing significant  $(49.2 \text{ m} \cdot \text{s}^{-1})$  or violent  $(74.2 \text{ m} \cdot \text{s}^{-1})$  tornado winds (McDonald and Mehta, 2006). By intersecting these wind fields over building data, it would be possible to know whether a particular type of building in the footprint might be destroyed, increasing the likelihood of fatalities for anyone inside (Wurman et al., 2007; Brooks et al., 2008). Future work using the TorDIS will also seek to estimate potential fatalities in the path of individual tornadoes using such building-based estimates of fatalities and/or regressions taking into account components of vulnerability such as awareness (e.g. off-season or nocturnal tornado), access to shelter, mobility and risk perception (Simmons and Sutter, 2011; Klockow et al., 2014; Paul et al., 2015).

### 4 | CONCLUSIONS

The present study introduces the Tornado Daily Impacts Simulator (TorDIS), a Monte Carlo simulation-based tornado impacts model that distributes tornadoes based on the favourability of the atmospheric environment on a given day. The daily time step is useful because it allows for the prediction of the potential tornado exposures on any day as well as the analysis of the severity of a historical day's tornado exposures (i.e. how many more people might have been impacted by tornadoes on that day). The TorDIS builds on the work of Strader et al. (2016) by linking tornado distribution and parameters to the environment in which they form, allowing for daily and annual assessments of tornado impacts. Stochastic models such as the TorDIS and the Tornado Impact Monte Carlo (TorMC) (Strader et al., 2016), enable users to understand better the true risk posed by tornadoes through the use of repetition. They can also be combined with spatially explicit simulations of urbanization (e.g. Chaudhuri and Clarke, 2013; Koch et al., 2019) to analyse the potential future tornado exposure under scenarios of population growth and urban expansion.

To the authors' knowledge, the TorDIS is the first spatial tornado impact model to link tornado distribution and parameters to the atmospheric environment in order to enable daily tornado impact analysis. They hope the study can be used as a first step towards research-tooperations for daily impact analysis. The future addition of a fatality estimation module will also hopefully aid in the Federal Emergency Management Agency's goal of projecting casualties on high-risk severe weather days.

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Knowledge of potential casualty estimates could allow emergency managers to plan ahead for these high-risk days in order to prioritize their resources and save lives.

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#### SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of this article.

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