Developing a hazard-impact model to support impact-based forecasts and warnings: The Vehicle OverTurning (VOT) Model

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Abstract
Impact-based weather warnings have been issued by the Met Office since 2011. The National Severe Weather Warning Service (NSWWS) uses a risk matrix combining the level of impacts the weather may cause and the likelihood of those impacts occurring to define a warning level. The impact assessment can be considered subjective being predominantly based on meteorologist expertise and experience of past high-impact weather events and discussions with local advisors. The Vehicle OverTurning (VOT) model is a prototype Hazard Impact Model developed to test the hypothesis that risk models can be run in real time for short-term weather-related hazards. The method intends to provide an objective, consistent assessment of potential risk to road users in Great Britain during high-wind events. It aims to support the production of NSWWS wind warnings by highlighting areas of the road network that are at risk of disruption due to vehicles overturning. The VOT model does this by combining probabilistic hazard information with vulnerability and exposure data to produce a risk of vehicle overturning forecast. The model is being demonstrated with operational meteorologists at the Met Office. Initial reviews of the model’s output indicate that the scientific approach used in this prototype can identify routes with a higher risk of vehicle overturning, associated with strong wind events. Ad hoc feedback from forecasters support the authors’ belief that the risk modelling approach is useful to operational meteorologists when issuing weather warnings.

KEYWORDS
ensemble forecasts, exposure, hazard, impact-based forecasting, risk, severe weather warnings, vehicle overturning, vulnerability

1 | INTRODUCTION

Weather can affect all areas of society from transport (e.g. Kulesa, 2002; Koetse and Rietveld, 2009) to infrastructure (e.g. Hor et al., 2005), to health (e.g. Goldman et al., 2014) and the economy (e.g. Smith, 1993; Subak et al., 2000). It is essential to effectively communicate the possible occurrence of future uncertain weather events so that users of weather information can prepare for and mitigate against the potential impacts, to reduce losses and ensure their safety and well-being. There is increasing
recognition that traditional forecasts and warnings, that are solely hazard focused, can be difficult for users to relate to and take action upon (Demuth et al., 2012), and that including impact information can add value and improve their meaningfulness to users (Harrowsmith, 2015; WMO, 2015).

To address this, the Met Office introduced impact-based warnings in 2011 as part of the National Severe Weather Warning Service (NSWWS) (Met Office, 2018). NSWWS warnings are issued when severe weather has the potential to bring impacts to the UK. Warnings are based on a combination of the severity of potential impacts and the likelihood of those impacts occurring. A risk matrix (Figure 1) is used to determine the appropriate warning level (yellow, amber or red) for dissemination to the public and responder communities. Potential impacts are assessed using NSWWS impact tables, which provide a qualitative indication of the types (e.g. transport and utility disruption and building damage) of impacts expected for each weather type and impact level (Met Office, 2017). Operational meteorologists use these tables in conjunction with their own experience and other factors, such as time of day, location and antecedent conditions, along with discussions with civil contingency advisors to decide which level of potential impact is most appropriate. The hazard likelihood for NSWWS warnings is assessed by reviewing a range of weather model outputs, including ensemble prediction systems, to understand the temporal, spatial and intensity uncertainties of the severe weather and therefore the likelihood of the impacts occurring. This combination of factors determines the most probable scenario and therefore the warning level within the matrix and the spatial extent of the warning.

This methodology, especially the impact assessment, is subjective and may give way to inconsistencies as different meteorologists on multiple shifts can issue and update NSWWS warnings during a single event. One method to help reduce this subjectivity is to use Hazard Impact Models (HIMs) to support meteorologists in their warning issuance. This involves understanding how a specific hazard (e.g. strong winds) interacts with an asset(s) (e.g. road networks) and its users (e.g. road vehicles and drivers) and the resulting impacts that occur. Within the meteorological community, the term “risk” has frequently been used synonymously with hazard “likelihood”. However, the idea of combining hazard and impact information to evaluate risk is not a new concept. The insurance and reinsurance sectors have used catastrophe models to model losses associated with hazardous events for the last 25 years (Lloyds, 2014). Catastrophe models require numerous inputs including hazard, vulnerability, exposure and financial datasets to calculate losses and anticipated risk. Risk simulations are run to assess likely hazardous events and calculate their impacts based on the exposure and vulnerability of assets included within an insurer’s portfolio. The widespread use of catastrophe models and the developments in risk research has led to a growing understanding of risk-based approaches and their pertinence for a range of weather-related application areas, for example, aviation (Steiner et al., 2009), urban drainage (Coudent et al., 2015) and flood risk (Balica et al., 2012; Dale et al., 2014).

However, pull through from research to operational forecasting and warnings remains relatively limited. The Met Office, through the NSWWS risk matrix and products such as Ensemble Prediction System First Guess Warnings (EPS-W) (Neal et al., 2014), is one National Meteorological and Hydrological Service (NMHS) using these approaches in operational warnings. China is also using impact-based warnings for typhoons, through its Shanghai Meteorological Service, as well as for specific user-orientated sectors such as aviation, wind energy and winter road maintenance (Tang et al., 2012). Their approaches align closely with the framework used by the insurance and reinsurance sectors. Many other NMHSs have begun exploring impact-based forecasting and warnings using World Meteorological Organisation (WMO) Guidelines on Multi-hazard Impact-based Forecast and Warning Services (WMO, 2015).

It was theorized that a catastrophe modelling framework (Ewing, 2011) could be adapted to develop real-time, hazard impact forecasting tools that communicate the risk of uncertain future events in the short range (adapting approaches from the insurance sector, which do not typically run at short time scales). The focus of this initial work, and this paper, was to test this hypothesis by setting up a prototype HIM that could routinely calculate future potential risk by combining hazard forecast information with vulnerability and exposure data. Impacts related to storms, including extreme wind events, cost more than any other type of weather-related disaster between 1995 and 2015 (UNISDR and CRED, 2015). In the UK, wind-related domestic property damage exceeds £340 million.
annually, with on average over 200,000 properties being damaged (Association of British Insurers, 2005). However, a single windstorm event can cost the insurance industry more than this value on a single day. The St Jude’s Day Storm in October 2013 was reported to cost the insurance industry between £300 and £500 million in the UK alone, with a total European loss of £1.3 billion (Willis Re, 2014). The transport sector is particularly affected by wind hazards and individual storms can result in high numbers of road vehicle accidents, injuries and fatalities. A storm on January 25, 1990, which brought extreme wind speeds with a return period of around 200 years, resulted in 300 road accidents that resulted in injuries and/or fatalities (McCallum, 1990; Baker and Reynolds, 1992). These accidents were directly attributed to the high wind conditions. Even in less extreme storms, such as October 28, 2002, which had a return period of only one or two years, there were numerous reports of vehicle-overturning incidents (Baker et al., 2008). With the road transportation network being a key enabler of the UK economy (Eddington, 2006) and a system running close to capacity, the impacts of these types of meteorological hazards can be severe and costly.

This paper describes the Met Office’s prototype Vehicle OverTurning (VOT) model, which is a key part of the Natural Hazards Partnership’s (NHP) Hazard Impact Modelling project (Hemingway and Gunawan, 2018). The model aims to forecast objectively the risk of vehicle overturning associated with strong winds along the major trunk road network in Britain. It combines probabilistic weather forecast data from the UK configuration of the Met Office Global and Regional Ensemble Prediction System (MOGREPS-UK) (Bowler et al., 2008), with vulnerability and exposure data to provide an objective and routine assessment of potential risk to the road network and road users during high-wind events. The outputs from this model are an additional tool for forecasters to use. They are designed to improve understanding and subsequent communication of future potential risk of vehicle overturning during high-wind events and support operational meteorologists in issuing impact-based warnings at a national scale.

2 | TERMINOLOGY

The terminology used throughout this paper follows UNISDR terminology, as outlined below. Definitions of these terms, as applied to the VOT model, are provided for clarity:

- Hazard: A process, phenomenon or human activity that may cause loss of life, injury or other health impacts, property damage, social and economic disruption or environmental degradation (UNISDR, 2017).
- Vulnerability: The conditions determined by physical, social, economic and environmental factors or processes that increase the susceptibility of an individual, a community, assets or systems to the impacts of hazards (UNISDR, 2017). Within the VOT model, vulnerability is a composite of multiple indicators used to describe the susceptibility of the road network (the asset).
- Exposure: The situation of people, infrastructure, housing, production capacities and other tangible human assets located in hazard-prone areas (UNISDR, 2017). In the context of the VOT model, road network exposure quantifies the road users (i.e. the type and number of vehicles).
- Risk: The potential loss of life, injury, or destroyed or damaged assets that could occur to a system, society or community in a specific period of time, determined probabilistically as a function of hazard, exposure, vulnerability and capacity (UNISDR, 2017). The VOT model aims to forecast the risk of vehicle overturning, rather than a complete impact assessment of associated disruption linked to a vehicle overturning event. However, recognizing the uncertainties and limitations of this initial prototype (discussed below) the term “risk of disruption” is used as a means of communicating parts of the network that are more or less likely to experience vehicle overturning incidents.

3 | VOT MODEL DESIGN

The VOT model is probabilistic, using the high-resolution MOGREPS-UK and used to forecast probabilities of wind gust and wind direction. MOGREPS-UK is a convection-permitting, 12-member ensemble that has been operational since 2013 (Mylne, 2013; Tennant, 2015) and provides hourly, 2 km gridded maximum wind gust in the last hour and hourly instantaneous wind direction fields, which are updated every 6 hr. With a lead time out to 7 + 36 hr (1.5 days), the VOT model uses these forecasts to estimate the probability that a hazardous event will occur and integrates this information with road network vulnerability and exposure data to produce risk of disruption values that can identify parts of the network that are more or less likely to experience vehicle-overturning incidents. The risk of disruption is computed for lengths of road up to 2 km using the Integrated Transport Network (ITN) trunk road network data from Ordnance Survey (OS) MasterMap. This dataset consists of approximately 72,000 road sections covering all trunk routes (motorways and major A-roads) in Great Britain. Sections 3.1–3.3 describe the methods used to produce the hazard, vulnerability and exposure fields in the VOT model. Section 3.4 describes how these data are integrated to produce a risk of disruption index. The risk maps described in Section 3.4 are the only outputs to be shared with forecasters in the Met Office operations centre. Upstream data (hazard, vulnerability and exposure) used to calculate the risk of disruption
index are not output as map products for forecasters to review, but are shown here in Figures 2–4 for clarity.

3.1 VOT model: Defining the hazard

A range of approaches can be used to identify meteorological hazards, including: (1) operational techniques looking at the physical meteorology and raw model output, (2) statistical methods based on event frequency and past data (WMO, 1999), (3) climatologically based thresholds (e.g. Zhang et al., 2011) and (4) impact-based thresholds. Climatologically based thresholds have been widely used to provide an indication of the likely impacts associated with severe weather events. Such thresholds are pseudo-impact based, as they assume that regions with different climatologies will have adapted infrastructure and utilities, resilient to their climate (i.e. the effects of 50 mph winds in Scotland will be less damaging than the same magnitude of winds in South East England). This differs from an impact-based threshold that determines, given a certain magnitude of hazard, the impact upon a specific asset, for example, a vehicle or road, buildings, or health services. Impact-based thresholds have been used to develop the VOT model, leading on from collaborative work with the Transport Research Group at Birmingham University in 2008 (Baker et al., 2008).

Several authors have assessed weather-related road accidents across the UK (Andrey and Olley, 1990; Palutikof, 1991), aiming to identify spatial (Edwards, 1996) and temporal (Edwards, 1999) correlations between weather types, accident frequency and accident severity (Edwards, 1998). The influence of strong winds upon a vehicle and its steering geometry has received significant interest. Edwards (1994) showed that increases in wind speed lead to increases in accident risk, but also that this relationship is complicated by factors such as vehicle geometry, road type and road orientation to the prevailing wind. Reviews of accidents that occurred during the Burns’ Day (January 25, 1990) storm indicated that wind speeds of 20 m/s (49.2 mph) were sufficient to lead to vehicle accidents (Baker and Reynolds, 1992), while the British Transport and Road Research Laboratory (TRRL) (1975) suggest

**FIGURE 2** Calculating the hazard component. Raw wind gust data (a) from 12 Met Office Global and Regional Ensemble Prediction System UK (MOGREPS-UK) members (only member 3 is shown) is converted into a weighted wind gust field (b) through the application of the wind gust thresholds (Table 1). Hazard probability, based on the number of MOGREPS-UK members exceeding thresholds for each wind gust threshold, is applied to the road network (c). The example is from December 5, 2013, 10:00 UTC; the MOGREPS-UK run time was December 4, 2013, 15:00 UTC; the lead time of the data is \( T + 19 \) hr.
that wind speeds of 15 m/s (33.6 mph) pose a danger to road vehicles. Of those accidents recorded during the Burns’ Day storm, 66% involved high-sided vehicles and light goods vehicles, while 27% involved cars (Baker and Reynolds, 1992). These findings support the consensus that high-sided vehicles are more vulnerable to strong winds than other vehicle types (Baker, 1988; Perry and Symons, 1994). This is due to the force exerted on a vehicle by the wind, which is proportional to the square of the wind speed and area of vehicle presented to the wind. This becomes an increasingly complicated issue when the vehicle is in motion as the overturning moment, oscillatory factors and low-level turbulence additionally influence vehicle stability (Perry and Symons, 1994).

The Transport Research Group at Birmingham University used a simple mechanical model (Baker et al., 2008) to calculate a set of accident gust speeds for different vehicle types (Table 1). In brief, the model calculates characteristic wind speed curves for vehicles with specific aerodynamic parameters (vehicle weight, area and height of the broadside of the vehicle) and velocities, together with aspects of the road structure (camber, curvature). Using the rolling moment coefficient and the yaw angle, calculated from the velocity wind vector, the wind-induced vehicle overturning moment is determined. Based on the characteristic wind speed curves, worst-case scenario wind gust accident thresholds were identified for each vehicle type: (1) unloaded Heavy Goods Vehicle (UHGV), (2) loaded HGV (LHGV), (3) unloaded Light Goods Vehicle (LGV) and (4) cars. Loaded LGV’s were not considered as Department of Transport statistics on vehicles with gross weights > 2,500 kg and < 15,000 kg are limited and would have resulted in an incomplete exposure dataset.

The VOT model uses the rounded, minimum accident wind gust speeds (Table 1) to determine the wind gust values required to overturn each of the four vehicle types (Baker et al., 2008). These are relative to vehicles travelling above approximately 25 m/s, or 56 mph. The hazard forecast probability for each vehicle type and forecast lead time is estimated by the number of MOGREPS-UK ensemble members that exceed each wind-gust threshold. Probabilities range linearly between 0 and 1, where 0 indicates that no members have wind gust values that pass a particular threshold, and 1 indicates that all 12 members have wind gust values that exceed the vehicle-specific threshold for that particular road section (Figure 2).

### 3.2 VOT model: Quantifying vulnerability

To generate the vulnerability index used within the VOT model, characteristics of the road network that make it susceptible to wind-induced vehicle overturning need to be identified. Measures of vulnerability for road networks fall into three categories: structure-related, nature-related and traffic-related (Husdal, 2004). In order to test the risk framework and reduce complexity this initial research focuses on structure- and nature-related vulnerability, as these are easiest to quantify based on available data. Vehicle vulnerability is partially captured by the use of vehicle specific thresholds to define the wind gust hazard, which account for the aerodynamic differences between vehicles, making some more vulnerable than others to high winds. Traffic-related vulnerability, which in Husdal’s (2004) framework quantifies traffic flow, is captured in the exposure field, conforming more naturally to the definitions described in Section 2.

Structure-related (physical) vulnerability describes the way the road was built, while nature-related vulnerability pertains to the environment, topography and terrain a road traverses (Husdal, 2004). Owing to the variety of vulnerability indicators that can be collated to derive an overall vulnerability score for the road network, indices are used (Cutter et al., 2003; Peduzzi et al., 2009). This standardizes the scoring to resolve issues such as numerically formatted (e.g. altitude of the road section) versus text-based (e.g. infrastructure attributes) variables and differences in variable units in the case of numeric factors (e.g. altitude of the road section and number of lanes). It also allows the vulnerability indicators to be combined mathematically (Balica et al., 2012). Within the VOT model, a scale between 0 (least vulnerable) and 1 (most vulnerable) is used for each vulnerability indicator calculated using Equation (1) (Balica et al., 2012):

\[
\delta = \frac{d - d_{\text{min}}}{d_{\text{max}} - d_{\text{min}}} \tag{1}
\]

where \(d\) is the element value; \(d_{\text{min}}\) is the minimum element value over all road sections; and \(d_{\text{max}}\) is the maximum element value over all road sections.

An additive model, with no a priori assumption of the importance of the factors, is then applied. This means that each vulnerability indicator has an equal contribution to the overall model vulnerability. This was considered the best option, given the absence of a defensible method for assigning weights (Cutter et al., 2003). The vulnerability analysis is kept simple, using only four vulnerability indicators. The choice of indicators, including the number used, were guided by the work of Husdal (2004), the availability and quality of vulnerability data and the resolution of the MOGREPS-UK forecast information which is used to define the hazard footprint. The four vulnerability indicators used in the VOT model are described below.

#### 3.2.1 Vulnerability indicator 1: Altitude of road section

The mean altitude of each road section is derived from a 90 m digital elevation model (DEM). It is recognized that higher altitude sections are more likely to experience higher wind gusts...
than those at lower altitude (TRRL, 1975). Each ensemble member provides a forecast of wind gust speed on a 2 × 2 km grid and therefore cannot accurately represent the wind gusts that would likely be observed along a specific section of road. The addition of this index allows each road segment, within the forecast grid cells, to be allocated higher or lower vulnerability based on the section’s specific mean altitude. Mean altitude values are normalized using Equation (1) to generate an index between 0 and 1 (enhanced vulnerability over elevated terrain).

3.2.2 | Vulnerability indicator 2: Number of lanes

The number of lanes per road section is used as a proxy for carriageway width, providing an indication of the road segment’s resilience (ability to resist, absorb, accommodate, adapt to, transform and recover from the effects of a hazard; UNISDR, 2017) to a vehicle overturning incident. This indicator assumes that single-lane carriageways are less able to absorb the effects of an overturned vehicle causing increased disruption to the wider network. By contrast, routes with higher numbers of lanes (e.g. sections of the M25 motorway around London that have six lanes) can absorb the impact of an overturned vehicle by closing certain lanes but allowing traffic to continue using the route, reducing the disruption on the surrounding network (Omer et al., 2013; Ganin et al., 2017). Therefore, single-lane carriageways are considered most vulnerable to disruption (value of 1) while the largest carriageways are considered the least vulnerable (value of 0).

3.2.3 | Vulnerability indicator 3: Infrastructure attributes

This indicator provides additional information on which roads have an enhanced susceptibility to high winds. Data from the OS 1:250,000 scale OS Travel Map and ITN layers highlight whether a road section has a tunnel, bridge, slip road or roundabout within it. Information from the Highways Agency (known as Highways England since 2015) on “Locations with Very High Blow-Over Risk” (Highways Agency, 2013, personal communication) identify locations prone to incidents associated with strong winds. Road sections that are part of a bridge/viaduct or are identified as “Locations with Very High Blow-Over Risk” are considered the most vulnerable and are assigned a vulnerability value of 1. Tunnel sections are allocated a vulnerability value of 0 (least vulnerable) as the tunnel shields the road from the wind preventing vehicle overturning incidents. Road sections that are slip roads and/or roundabouts are given a vulnerability value of 0.2. These sections are considered less vulnerable to vehicle overturning incidents because vehicle velocities tend to fall below the 25 m/s (55.9 mph) threshold corresponding to the minimum accident wind gust threshold (Table 1) for each vehicle type. This is particularly true for shorter, traffic managed and ramp metered slip roads (Hegyi et al., 2005). All other road sections are assigned a vulnerability value of 0.6 or moderately vulnerable. This is due to the speed with which vehicles typically travel along motorways, dual carriageways and single-carriageway routes (83% of cars travel at speeds > 60 mph on motorways, 81% on dual carriageways and 11% on single carriageways; Department of Transport, 2017a). The index values used have been subjectively determined based on an understanding of the road networks being modelled (i.e. number of motorways, dual and single-carriageway routes) and how wind gusts are likely to interact with the network and vehicles.

3.2.4 | Vulnerability indicator 4: Road orientation

Both wind gust speed and road orientation, relative to wind direction, are critical to induce a vehicle overturning incident. All minimum accident wind speeds for the different vehicle types (except cars) occur with a wind direction of 70° to the road orientation or vehicle travelling direction (Table 1). A vehicle is most susceptible to overturning when the wind is both sufficiently strong and interacts with the broadside of the vehicle at this angle. A buffer zone of 30° is applied either side of this critical overturning angle to capture model limitations in resolving wind direction. This range also captures the majority of accident gust speeds that lie within 1 SD (standard deviation) of the vehicle-specific thresholds, used to determine the wind gust hazard (Table 1), and align with the findings of Snæbjörnsson et al. (2007).

For each road section, the mean orientation of the road was determined allowing the critical overturning angle and buffer zone to be calculated. These values are determined for wind directions at both 70 and 250° to the road orientation to take account of traffic flow in both directions. Adding the buffer zone to the critical overturning angle generates four thresholds (T1–T4) known as critical angles. These determine the outer limits of the wind direction range for both sides of the carriageway. As gust direction is not currently available in MOGREPS-UK, 10 m wind direction is used as a proxy. The forecast wind direction for each ensemble member is assessed to determine whether it is within these critical angles (value of 1) or not (value of 0) along each road section.

3.2.5 | Total vulnerability

In order to generate a single vulnerability index, which describes the road networks’ vulnerability to wind-induced vehicle overturning, the individual vulnerability indicators are summed and then normalized using Equation (1). This
FIGURE 3 Total vulnerability value maps and frequency distributions for Great Britain for the Vehicle OverTurning (VOT) model: (a) map and vulnerability values used when the wind direction is not within the critical overturning angles; and (b) map and vulnerability values used when wind direction is within the critical overturning angles.

FIGURE 4 Exposure fields (a) EXP1, (b) EXP2 and (c) EXP3 (Table 2) for the trunk road network based on statistically forced annual average daily flow (AADF) data (Department of Transport, 2013, 2017b).
 producers a total vulnerability score, between 0 (low vulnerability) and 1 (high vulnerability), for each road section in the trunk road network throughout Great Britain. This results in two road network vulnerability maps (Figure 3). Vulnerability indicators 1–3 are static, whereas indicator 4 (road orientation relative to wind direction) varies depending on each ensemble member’s wind direction forecast at each model lead-time. Where different members of the same model run do not agree on whether the wind direction falls within the critical angles, values from both maps are taken in proportion.

### 3.3 VOT model: Quantifying exposure

The VOT model primarily aims to indicate the potential for vehicles to be overturned during strong winds. As such, the exposed elements are the vehicles using the road network as they are the element directly affected by the hazard and have the potential to be overturned. Real-time data feeds of traffic flow have not been used for this conceptual prototype. Instead, freely available Department of Transport annual average daily flows (AADFs) from count points on the roads are used (Department of Transport, 2013) to derive exposure scores which vary according to each vehicle-specific wind gust threshold. AADF figures indicate the number of vehicles using a stretch of road on an average day of the year, in units of numbers of vehicles per day. These are available for each junction-to-junction link on the major road network and provide average daily flow information for each road and vehicle type. Major roads within the traffic census are defined as motorways and all A-roads, inclusive of trunk roads, non-trunk roads and principal roads, resulting in a total geographical distribution of count points which far exceed those required for the VOT model. Using spatial software each road section in the VOT model was attributed to a representative AADF count point, based on location and road name, and assigned the associated vehicle count data.

Vehicle overturning is a function of gust speed (addressed in Section 3.1), wind direction, vehicle speed (addressed in vulnerability, Section 3.2) and the aerodynamic parameters of the vehicle. The latter is addressed by the use of vehicle-specific wind gust thresholds, which define the hazard, but also here to describe the variability in the exposed vehicle population as the hazard severity increases. In order to estimate the likelihood of a vehicle being overturned on a route it is important to recognize that not all vehicles are equally exposed to the hazard as defined by the vehicle-specific thresholds (Table 1). Therefore, an additive approach is used whereby the population of vehicles exposed (and are capable of being overturned) align and increase with corresponding increases in the hazard magnitude. This allows the model to differentiate between routes with more or less road freight and therefore are at greater or lesser risk of experiencing a vehicle overturning incident.

To conform to the time-steps used in the VOT model, AADF vehicles per day were converted to mean numbers of vehicles/hr, using Department for Transport (2013) statistics. The statistics were used to force temporal variability in the hourly traffic flows of the different vehicle types, based on their different hourly flow distributions (i.e. car traffic has a bimodal temporal distribution due to morning and evening rush hours, which see peak traffic flows, while HGV’s tend to have a flatter temporal distribution in their traffic flows). Initial calculations were completed for only the car, LGV and HGV vehicle types, as a breakdown of UHGVs and LHGVs by time of day was not available in the TRA0308 (Department for Transport, 2013) table. However, HGV

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**TABLE 1** Accident wind gust speeds (m/s) for vehicles with different aerodynamic parameters at different vehicle speeds and wind directions, adapted from Baker et al. (2008). Minimum accident gust thresholds, shown in bold, are rounded and used in the Vehicle OverTurning model.

| Vehicle speed (m/s) | Wind direction (°) |
|--------------------|-------------------|
|                    | 30 | 40 | 50 | 60 | 70 | 80 | 90 | 100 | 110 | 120 |
| Unloaded heavy goods vehicle (UHGV) (mass = 7,500 kg, area = 50 m², height = 3.5 m) | 5  | 39.1 | 34.5 | 31.8 | 30.0 | 29.0 | 28.9 | 29.1 | 29.5 | 30.9 | 32.8 |
|                    | 15 | 35.1 | 30.8 | 28.1 | 26.8 | 26.2 | 26.6 | 27.2 | 29.0 | 31.1 | 33.8 |
|                    | 25 | 31.4 | 27.1 | 24.8 | 23.4 | 23.1 | 23.2 | 24.1 | 26.2 | 29.1 | 32.2 |
| Loaded HGV (LHGV) (mass = 15,000 kg, area = 50 m², height = 3.5 m) | 5  | 45.0 | 43.1 | 41.8 | 41.2 | 41.2 | 42.0 | 43.1 | 44.1 | 44.1 | 44.1 |
|                    | 15 | 42.0 | 40.1 | 39.2 | 39.1 | 40.1 | 41.7 | 44.1 | 44.1 | 44.1 | 44.1 |
|                    | 25 | 42.1 | 38.5 | 37.0 | 36.0 | 36.2 | 37.7 | 40.1 | 40.1 | 40.1 | 40.1 |
| Unloaded light goods vehicle (LGV) (mass = 2,500 kg, area = 20 m², height = 2.5 m) | 5  | 41.5 | 37.2 | 24.5 | 32.8 | 31.5 | 31.2 | 32.1 | 33.4 | 33.5 | 35.2 |
|                    | 15 | 38.3 | 34.1 | 30.8 | 29.3 | 29.1 | 29.1 | 29.8 | 31.2 | 33.5 | 36.5 |
|                    | 25 | 34.8 | 30.1 | 27.2 | 26.1 | 25.5 | 26.1 | 27.2 | 31.1 | 32.1 | 36.1 |
| Car or small van All speeds | 35.0 | 35.0 |

Note: Minimum accident gust thresholds, shown in bold, are rounded and used in the Vehicle OverTurning (VOT) model. Values highlighted with grey represent those accident gust speeds which are within 1 standard deviation of the minimum accident gust speed.

Source: Adapted from Baker et al. (2008).
traffic by axle configuration were available (TRA3105: Department for Transport, 2013). Using these statistics, the number of rigid HGVs with gross weights up to 7.5 t, coinciding with the aerodynamic parameters used to derive the UHGV wind gust threshold, and rigid HGVs with gross weights between 7.5 and 15 t, coinciding with the aerodynamic parameters used to derive the LHGV threshold, were calculated. Within the HGV population, approximately 35% of vehicles are associated with the aerodynamic characteristics of UHGVs, while approximately 7% of vehicles are associated with the aerodynamic characteristics of LHGVs. Using these percentages, the mean number of UHGVs and LHGVs/hr are calculated from the total HGV population.

Three exposure scores were produced using the mean numbers of vehicle/hr (Figure 4). Exposure score 1 (EXP1) describes the spatial and temporal variability of the UHGV population across the network and is used where the gust speed exceeds the UHGV accident gust speed threshold (23 m/s), but are less than the LGV accident gust speed threshold (26 m/s). As the hazard severity increases, additional vehicle-type populations are added to the exposure to represent the growing population of vehicles at risk of being overturned by the strengthening gust speeds. The data used for each exposure field and its application in the VOT model are shown in Table 2.

EXP3 (Table 2) includes all vehicle types, including cars and LHGVs. Owing to the large number of cars making up the total vehicle population, including the relatively small number of LHGVs as a separate exposure field would lead to negligible differences between the two exposure scenarios. In addition, the wind gust thresholds used to determine hazard situations for cars and LHGVs are very similar (35 and 36 m/s, respectively) so combining them within a single exposure field is appropriate for this initial methodology.

### 3.4 | VOT model: Calculating the risk of vehicle overturning

The three components of the VOT model (hazard probability, vulnerability and exposure) are equally weighted, as no evidence exists to support unequal weighting (Cutter et al., 2003). The three components are multiplied together to produce a risk score between 0 and 1 (Figure 5). This value allows road sections that have a greater relative risk due to vehicle overturning incidents, compared with other road sections, to be highlighted and endeavours to communicate the potential for vehicle overturning related disruption that could occur on the network. Given the uncertainties associated with forecasting the risk of vehicle overturning, the term “risk of disruption” is used when communicating the resultant risk output. High-risk road sections are generally those likely to experience high wind gusts, and which have a high vulnerability and large traffic volumes (i.e. high exposure). Note that if wind gust speeds do not exceed any of the vehicle overturning thresholds the forecast risk value will be 0.

Four risk of disruption network maps are produced, each representing one of the four VOT thresholds (Table 1), for each hourly time-step out to $T + 36$ hr. This results in a total of 144 risk-of-disruption maps. To reduce time and potential confusion for operational meteorologists, a single network map showing the maximum risk of disruption value across all vehicle categories, for each road section and model time-step is made available via a webpage. The risk of disruption values are grouped into risk categories described as low risk, low to medium risk, medium to high risk, and high risk, with corresponding colour attributes (green, yellow, amber and red, respectively). As the aim is to provide an overview of vehicle overturning risk at the national scale, and as a result of the normalized vulnerability and exposure values, the risk values produced are relative to other road sections. The implication of this is that some road sections will never exceed certain colour categories due to very low exposure values, as seen for some roads in the Scottish Highlands that will never exceed the green (low risk) colour category. This is appropriate when reviewing the risk of disruption at the national scale, as the impacts of strong winds on roads in the Scottish Highlands may be locally problematic but insufficient to warrant a large-scale response.

The maximum risk of disruption maps for each time step are available via a Web Map Service (WMS) allowing forecasters to pick the hour of the risk of disruption forecast they would like.

| Field          | Exposure data used                                      | Application in the Vehicle OverTurning (VOT) model                                      |
|----------------|---------------------------------------------------------|-----------------------------------------------------------------------------------------|
| EXP1 (Figure 4a) | Mean number of UHGVs/hr                                 | Used when the UHGV (23 m/s) gust threshold is exceeded                                  |
| EXP2 (Figure 4b) | Mean number of UHGVs + LGVs/hr                         | Used when the LGV (26 m/s) gust threshold is exceeded                                  |
| EXP3 (Figure 4c) | Mean number of UHGVs + LGVs + cars + LHGVs/hr          | Used when the car (35 m/s) and/or LHGV (36 m/s) gust thresholds are exceeded           |
to see and zoom in to road sections which are of interest to them. No upstream data (i.e. separate hazard, vulnerability or exposure data) are currently available for forecasters to view on the webpage. This was a conscious decision, so as not to increase substantially the volume of data that forecasters needed to review in order to make appropriate impact-based warning decisions.

4 | APPLICATION OF THE VOT MODEL IN WARNING ISSUANCE: A CASE STUDY FROM JANUARY 9, 2015

On January 6, 2015, a NSWWS wind warning was issued for much of Scotland and northern parts of Northern Ireland. A vigorous depression was expected to develop over the Atlantic during January 8 associated with a strong jet stream. The depression was forecast to run rapidly eastnortheast, passing northern Scotland early on January 9 bringing with it very strong winds of 60–70 mph (27–31 m/s) (NSWWS, 2015, unpublished data). The storm’s progress was monitored, and an amber wind warning was issued on January 7, valid for January 9, covering northern Scotland and the Orkneys (Figure 6a).

On the morning of January 8, the VOT model’s lead time was sufficient to cover the warning period. It showed medium to high risk of disruption (amber and red road sections) in the Central Belt of Scotland (Figure 6b). The VOT model was used as evidence in Met Office guidance documents (Met Office, 2015, unpublished data) to modify and issue NSWWS warnings valid for the morning of January 9. An amber wind warning was issued in the Central Belt of Scotland and the yellow wind warning was extended to cover northern England (Figure 6c).

During January 9, numerous impacts were experienced within the NSWWS warning areas. A van overturned on the Forth Road Bridge (BBC, 2015) and a HGV on the M74, southwest Scotland (Metro, 2015). Other impacts included thousands without power, train service disruption, school closures, multiple trees down, and building and caravan damage (BBC, 2015).
Evaluating the performance of an HIM, such as the VOT model, is challenging because of (1) the lack of a single source of weather- and transport-related impact data, (2) the difficulty attributing impacts to specific weather events and (3) the subjectivity, lack of standardization or detail and slow acquisition times of many sources of impact information.

To validate the VOT model for this case study a range of impact information sources were reviewed. News media and Twitter from January 9 were scoured to identify reports of vehicle overturning events. An agreement with Highways England provided locations for vehicle overturning incidents that had been reported to them by local authorities. The Met Office Weather Observation Website (WOW) (2018) was also reviewed for content as it has a weather impact reporting function, where reports are categorized by impact type including travel disruption. While this does not explicitly refer to vehicle overturning incidents, it does give some insight into disruption potentially caused by high winds and provides additional data points with which to verify the VOT model forecasts.

The quality of validation data varies. News media and Twitter usually lack useful detail on time, location and vehicle type and are generally subjective; there are also large data volumes to sort; however, useful images are commonly included. Highways England data are more detailed on vehicle type, disruption caused and location but are only available, with significant lag, after the event. WOW data are the most subjective, lack the required detail and commonly misrepresent the impact with a biased assessment of severity. Impact data collection for HIM validation is challenging but useful information can be acquired where multiple and varied data sources are available (Robbins and Titley, 2018).

For this case, the VOT model performs well (Figure 7) in capturing the areas that observed vehicle overturning events. Most disruption occurred on routes where a medium to high risk of disruption (amber) was forecast. One Highways Agency report and two WOW travel disruption reports are outside of the forecasted risk areas. As previously mentioned, attribution of impacts to specific weather events is difficult. Furthermore, vehicle overturning events can result from other factors other than strong wind. It is possible, therefore, that the Highways Agency event and those recorded via the WOW were either not directly related to vehicle-overturning events or were circumstantially attributed to the wind hazard due to the media coverage of the event.

5 | DISCUSSION

The prototype VOT model aims to test the hypothesis that risk models can be developed and run in real-time to support the issuing of NSWWS warnings. It provides a quantifiable
methodology for the identification of roads with a heightened risk of vehicle-overturning incidents, induced by strong winds. The case study presented above demonstrates that the model is capable of providing risk information in a useful and usable way to operational meteorologists. To ensure that the VOT model produces a consistent, clear and robust assessment of risk, several assumptions were made during the model’s design. These, together with their implications for warning issuance, are discussed below.

5.1 Challenges for hazard identification

The VOT model uses gridded, 2 km wind gust forecasts to determine the probability of exceeding a vehicle-specific threshold. This forecast resolution can resolve lee wave gust features around the Pennines, but precludes the accurate modelling of local-level turbulence (induced by variable surface roughness and local-level topography, e.g. embankments and tree lining) or the specific interaction of gusts upon individual vehicles traversing a route. Although it would have been desirable to correct 10 m wind gust forecasts to 3 m to resolve some of this local-level turbulent flow (Baker et al., 2008), this was not feasible within the proof-of-concept stage. Vulnerability data provide additional detail to downscale the hazard and capture how gusts might interact with specific sections of road by accounting for road attributes (e.g. tunnel, bridge, slip-road). Furthermore, such detailed modelling of the hazard is not required to achieve the VOT model’s purpose, which is to provide forecasts indicating heightened levels of relative risk in support of national-scale warnings. It is, however, important that the best available 2 km wind gust forecasts are used because these forecasts define the hazard footprint in space and time, which in turn determines whether vehicles using a specific route are exposed and vulnerable. Therefore, an investigation was carried out to evaluate which model fields from MOGREPS-UK were most appropriate for use (Rourke, 2014, unpublished data). For practical reasons, the initial wind gust input field used was the instantaneous wind gust on the hour. This was deemed inappropriate as it missed strong gusts that were simulated over the intervening hour. Therefore, a new field forecasting the 10 m maximum wind gust in the last hour was produced from MOGREPS-UK. This field better represents the changes in wind gusts over time resulting in more accurate probabilities of gusts exceeding vehicle overturning thresholds.

5.2 Assumptions and constraints in quantifying vulnerability and exposure

As highlighted in Section 3.2, there are numerous ways to consider road network vulnerability for vehicle overturning during strong wind events. For this model, the focus has been on quantifying a metric that captures structure- and nature-related vulnerability for each ≤ 2 km section of the road network. The choice of variables included in the vulnerability index was based on the availability of data at the time of design, the resolution of the modelling approach and the purpose of the forecasts (i.e. to forecast the risk of vehicle overturning incidents and support NSWWS). This means that some aspects of vulnerability, which could contribute to a heightened risk of vehicle overturning, were not included. Local-level features such as road camber/cant and radius of curvature were not included, as these tend to vary significantly across a 2 km segment of road meaning resolutions of sub-100 m would have been required (Baker et al., 2008). Such detailed local-level asset mapping was out of scope for the proof-of-concept design. However, in future model developments vulnerability indicator 1 (Section 3.2.1) could be modified to take account of routes with or without shielding (e.g. from trees, embankments, adjacent topography), which effect how exposed a route is to strong winds. Of course, it is not only the road asset that can be vulnerable. Other vulnerabilities such as driver behaviour, skill, age and adaptability to the hazard (Baker, 1988; Petridou and
Moustaki, 2000; Kilpeläinen and Summala, 2007; Zicat et al., 2018), as well as time of day, light conditions (Plainis et al., 2006) and driver tiredness (Williamson et al., 2014) can also play a role and contribute to the risk of a vehicle overturning incident. Asset-user vulnerability was not included in the vulnerability assessment due to the difficulty of acquiring data and the significant challenges associated with modelling human behaviour (Toledo, 2007). Although these additional vulnerability factors are not included in the VOT model, the positive performance of the model in the above case study and subsequent evaluation work (Hemingway and Crocker, 2018, unpublished data) suggests that the four vulnerability indicators (altitude, number of lanes, road section attributes and orientation) are successful at distinguishing differences in risk associated with strong wind events. Once a suitably long archive of events is available, sensitivity analysis can be completed to assess the sensitivity of the indicators that make up the vulnerability index. This would involve assessing the indicators used, the method of integration and the scale at which the index is applied.

It is also recognized that there are assumptions and constraints in the development of the exposure fields used in the VOT model, which have implications for the risk forecast. It is not necessary to use live traffic flow data in the model, so statistically forced AADF data are used (Section 3.3) to represent anticipated traffic flow at a specific time of day and day of the week. However, changes in traffic flow associated with bank holidays, rerouting due to scheduled and/or prolonged road works or changes in traffic flow associated with the opening of new routes are not captured due to the update frequency of the underlying information. A more robust methodology, scheduled to be implemented in the next model version, is to use vehicle flow count data from the Highway Agency Traffic Information System Traffic Flow Data System (Highways England, 2016). This data contains hourly traffic flow data, including vehicle length, as a proxy for vehicle type, from 1,500 roadside inductive loops. The hourly traffic flow data can be processed to account for weekdays, weekends and bank holidays providing a better representation of traffic flow expected on an hourly basis.

The exposure field also does not differentiate between vehicles that are travelling at a speed conducive to vehicle overturning (approximately 25 m/s or 55.9 mph; Table 1). This is partially captured by vulnerability indicator 3 (Section 3.2.3) where road attributes are used as a proxy to indicate potential changes in traffic flow. However, no robust assessment of vehicle travelling speed is currently implemented in the prototype. This could suggest that the exposure information overestimates the number of vehicles that could actually be at risk of overturning. However, the speed limit for cars and LGVs on single-carriageway routes is 60 mph, while on motorways the limit is 70 mph and approximately 50% of these vehicles exceed this limit (Department for Transport, 2017a). Therefore, there is confidence that vehicle exposure for these vehicle types is representative. For HGVs, speed limits were increased in 2015 to 50 mph for single-carriageway routes and 60 mph for dual and motorway routes. Some improvement could be made to allow for differentiation of HGV speeds by route. Other factors that affect speed, particularly for HGVs, is their weight and the steepness of the road section, which could be additional indicators to the vulnerability metric.

### 5.3 Visualizing vehicle overturning risk

Green, yellow, amber and red colours are used to visualize the risk forecast, representing low, low-medium, medium-high and high risk of vehicle overturning respectively. These colours and risk categories loosely align with NSWWS impact categories used in the risk matrix (Met Office, 2017) (Figure 1). There are quantitative risk values behind the colour categorization that result from the risk algorithm calculation in the VOT model. The quantitative bins for each colour were chosen based on a rank percentile analysis of the maximum risk value each road section can achieve. Case studies have validated the current colour categorizations and the VOT model has been described by an operational meteorologist as a “great example of how an impacts model can assist” (Page, 2017, personal communication) impact-based warning issuance. Such feedback indicates that the model meets its aim to support operational meteorologists in the issuance of national severe weather warnings.

The current methodology displays relative risk across the road network in Britain. This is due to vulnerability and exposure being normalized over all road network sections. Some A-roads in the Highlands of Scotland have exceptionally low exposure compared with sections of the M25 motorway, while other road sections lie in tunnels and are therefore not vulnerable to strong winds. This means that some sections of the network will never exceed a low or low-medium categorization when assessed at the national scale. This is desirable for national-level warning, where the main aim is to identify large-scale disruptive events that could require significant response actions. This is not to suggest that disruption induced by an overturned vehicle in the Highlands of Scotland would not be significant to those affected. It is simply that the numbers of disrupted vehicles would be significantly less in this instance than if a similar event were to occur along a route with higher exposure, leading to increased response needs. However, an alternative approach that moves away from a relative risk score could be achieved by using a long archive of VOT model forecasts or reforecasts. From such an archive a risk “climatology” map for the road network could be produced that identifies the prevalence of each risk
category at each section. It would then be possible to use this risk climatology to determine the extent to which real-time VOT risk of disruption forecasts deviate from this average (i.e. a risk anomaly map). This would highlight to operational meteorologists events where the risk of disruption were heightened compared with climatology.

The VOT model produces risk of disruption output for each of the four VOT thresholds (Table 1 and Section 3.4); however, for convenience and simplicity a maximum risk of disruption for each road section and time step is calculated and visualized for operational meteorologists. This is not ideal as some users may find information about low risk of disruption values for the higher vehicle overturning thresholds (i.e. cars and LHGV) additionally informative and useful when communicating the risk associated with different severities of impact. Innovative WMS output along with user consultation could provide an improved and more informative visualization system.

5.4 | Future work

The application of a risk framework for real-time, impact-based forecasting remains a relatively new area in the meteorological community and there are, therefore, several avenues for further research. Some of these have been highlighted above. However, two fundamental questions that need to be addressed are: How does one evaluate the VOT model’s performance?; How does one assess its benefit? The case study (Section 4) demonstrates that impact data can be collected and successfully used to validate the VOT model. However, the process of impact data collection, evaluation and validation against the model is manual, complex and time consuming. Other challenges include incomplete reporting of impacts (i.e. lack of impact reports does not mean a lack of impact), inaccurate attribution of impacts, and the challenge of accounting for mitigating action taken to reduce potential future impacts based on the forecast. Effective mitigation should reduce weather-related impacts and, indeed, this is a desired outcome for impact-based forecasts and warnings, but how does one account for this in validation approaches? There is ongoing research in the impact data collection and attribution area that, it is hoped, will lead to the development of new methods for more time-effective validation (Papagiannaki et al., 2013; Robbins and Titley, 2018). Assessing the benefit of the VOT model, and other future HIMs, is also challenging. This, however, is a growing area of study and key research area for the WMO and the World Weather Research Programme’s High Impact Weather Project (HIWeather, 2018).

The methodology described here has the potential to be used for a range of other hazards and assets. Under the NHP there is ongoing work by the Centre for Ecology and Hydrology, Health and Safety Executive, Met Office and Flood Forecasting Centre to develop a Surface Water Flooding HIM (Aldridge et al., 2016), while the British Geological Survey is progressing a Landslide HIM. In each case, the hazards, vulnerabilities and exposure data differ and the processes for data integration vary, but the underlying risk-based framework and outputs based around the warning risk matrix are consistent. The development of additional HIMs offers great prospects for future multi-hazard forecasting and warning, as well as improved communication to users as to the potential future impacts associated with a range of hazards.

6 | SUMMARY AND CONCLUSIONS

This paper describes the Vehicle OverTurning (VOT) model, a prototype probabilistic Hazard Impact Model (HIM) that combines hazard, vulnerability and exposure data to forecast the risk of vehicle overturning incidents, induced by strong winds. The methodological approach, caveats and assumptions used and the model’s application in support of national severe weather warning issuance are described. The complexities associated with defining and applying impact-based thresholds, the assumptions used to develop vulnerability and exposure metrics specific to the road network in Great Britain, and the challenges for integrating and visualizing the real-time risk forecast in a usable and useful way are discussed. The VOT model has successfully demonstrated that risk models, adapted from approaches developed in the insurance sector, can be developed and run in real-time to provide risk assessments across weather-related time scales. Initial feedback and case study evaluation indicate that the model can effectively identify parts of the network that are more or less likely to experience vehicle overturning incidents during strong wind events. These findings also indicate that the method used offers real benefit in the communication of future risks associated with specific types of weather hazards. It is recognized that there are several areas for improvement, further assessment and extension (i.e. sensitivity analysis of vulnerability indices and risk components) and, that there are challenges that need to be addressed (e.g. data availability, evaluation/validation, user engagement and education) to ensure user understanding and uptake. Despite these considerations, the VOT model has been received positively by operational meteorologists in the Met Office and it is seen as useful tool to assist the issuance of national severe weather warnings.

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**How to cite this article**: Hemingway R, Robbins J. Developing a hazard-impact model to support impact-based forecasts and warnings: The Vehicle OverTurning (VOT) Model. *Meteorol Appl*. 2020;27:e1819. [https://doi.org/10.1002/met.1819](https://doi.org/10.1002/met.1819)