# UAS Ground Risk Model Summary

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This chapter describes the methodology of estimating travel time, energy consumption and emitted emissions for land logistics. Our definition of land logistics encompasses diesel vans, electric vans and bikes.

This document summarises the approaches and methods for quantification and mapping of third party risk (TPR) posed by Uncrewed Aerial Systems (UAS) to uninvolved persons on the ground, in the vicinity of overflight. The model is fully parameterised and applicable to a wide variety of aircraft. The approach encompasses all four relevant dimensions, that is three spatial and a temporal dimension, therefore is highly specific to the operation at hand, aiming to provide the most accurate representation of ground risk.

There are several steps involved in the procedure.

## 1 Spatiotemporal Population Mapping

This work estimates actual population distributions from the highest resolution authoritative data source available, namely census data. Whilst this is likely better than a uniform value being set for population density over large areas, this approach can still result in overestimation of the risk posed in urban areas due to the loss of resolution caused by using real data. The approach presented here is therefore more suited to longer BVLOS operations outside and around urban areas. The decision to use generic national data sources instead of attempting to concatenate many local datasets, which may have offered finer detail, was made to allow the approach to have a wide spatial applicability.

Estimates for dynamic populations derive from daily workflows segregated by demographic categories, for example school children or the elderly, which are mapped to their expected spatial locations for a given time. In this case, data from the census detailing the residential population is assumed to form 100% of the available population and is constant for a given area. The population categories are mapped to locations from human activity pattern studies to find the proportions of the population located in each of 10 different locations at a given time of day. The temporal populations proportions must then be located spatially; this requires combination with geospatial geometries appropriate to the activity.

The residential population in a given area is an estimate from a combination of censual , OSM and NHAPS data.

The population density of each census area is found from the census data, as shown in Figure 1. The population density value for each area is then scaled by the proportion of the population that is located in residential locations for a given time of day. This ensures the population spatial distribution remains the same compared to the census data.

There is no generally available counterpart to the census for non-residential areas that could be used to determine population densities for such areas on a large scale. Whilst it is possible to find building maximum occupancy data for a smaller collection of buildings, this approach does not scale well to larger or different areas, requiring a large amount of manual data input and subsequent updating.

Firstly, the total population must be found. As previously discussed, taking the census data to form the total population is suitable. Secondly, the total population value is scaled by the proportions of the population for each location, to find the absolute values for the population in each of the locations. Next, the geospatial geometries of each location are found using data from OSM. The area for each of these geometries is calculated and summed together for all geometries associated with a given location. This is repeated for each location. The population and spatial data is then combined to a population density by dividing the absolute population value for each location by the total area for that location.

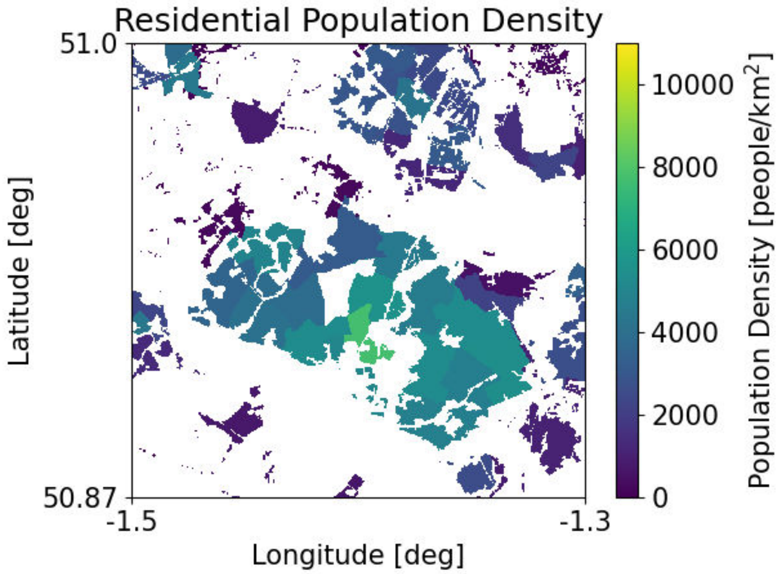


Figure 1: Residential Population map for the Southampton area. This shows the maximum density each residential area can have.

The road traffic population is derived from historical road traffic and vehicle occupancy estimates. It is used in combination with assumptions about the road geometry to derive the density of people located on any given location along a road. Historical road traffic is derived from open governmental data provided by the United Kingdom Department for Transport in the form of Annual Average Daily Flow (AADF) tables. AADF tables are produced by a combination of automatic traffic counters and manual enumeration of vehicles at a given point of on the road network. The data used in this work uses the amalgamated traffic direction version, with counts categorized by vehicular type. AADF values are scaled by similarly provided values corresponding to hours of the day in order to obtain estimates for traffic flow for an average day in the year.

Algorithm 1 is based on the projection of each road geometry to a single dimension, followed by the superposition of traffic counter locations on the line according to distance along the road. The counter values are then interpolated between and projected back onto the original road geometry. This is used to generate a population density value for each section of road considered.

Figure 4 demonstrates the large temporal variation in road population density for the same area at different times. This is calculated using Algorithm 1.

# 2 Flight Path Ground Risk Analysis

The probabilistic approach taken to analyse the risk posed to people on the ground by a UAS is widely used in previous work. It is based on the sequential occurrence of independent events, each with associated probabilities. The events, in order of occurrence, are:

1. Loss of Control (LoC) event that results in the UAS impacting the ground
2. Striking a person(s) as a result of the uncontrolled descent
3. The struck person(s) being fatally injured as a result

We extend previous models with the addition of time based quantities

$$P_{\text{casualty}}(x, y, t) = P_{\text{LoC}} \cdot P_{\text{strike}}(x, y, t) \cdot P_{\text{fatality}}(x, y) \tag{1}$$

where $x, y$ refer to the spatial dimensions, $t$ is hour of the day. The hour of the day $t$ is used to as input to the spatiotemporal population density model.

**Input:** unique road identifiers $\boldsymbol{L}$; road geometry line segments $\boldsymbol{S}$; traffic counter populations $\boldsymbol{T}$; interpolation resolution $r$;
**Result:** a set of 2-tuples of georeferenced polygons and associated population density values $\mathbf{P}$

**for** $\forall l \in \boldsymbol{L}$ **do**
    $\boldsymbol{S_l} \leftarrow$ GetSegmentsForRoad$(\boldsymbol{S}, l)$;
    $\boldsymbol{T_l} \leftarrow$ GetCountersForRoad$(\boldsymbol{T}, l)$;
    $\boldsymbol{O} \leftarrow \emptyset$;
    **for** $\forall s \in \boldsymbol{S_l}$ **do**
        $\boldsymbol{T_s} \leftarrow$ GetCountersOnSegment$(\boldsymbol{T}_l, s)$;
        $carriedLength := 0$;
        **if** $\boldsymbol{T_s} \neq \emptyset$ **then**
            $\boldsymbol{O} \leftarrow \boldsymbol{O} \prec (\text{Length}(s) + carriedLength)$;
            $carriedLength := 0$;
        **else**
            $carriedLength + = \text{length}(s)$;
        **end**
    **end**
    $nPoints \leftarrow \lfloor \text{Max}(\boldsymbol{O})/r \rfloor$;
    $\boldsymbol{M_l} \leftarrow \text{Interpolate}(\boldsymbol{O}, \boldsymbol{T}_l, nPoints)$ ;
    $w \leftarrow$ GetRoadWidth$(l)$;
    $\boldsymbol{R_l} \leftarrow$ Buffer$(\boldsymbol{S}_l, w)$;
    **for** $\forall i \in \{0, 1, 2..., nPoints\}$ **do**
        $clippedPolygon \leftarrow \text{Buffer}(\text{GetLatLng}(O_i), r/2) \cap \boldsymbol{R_l}$;
        $\boldsymbol{P} \leftarrow \boldsymbol{P} \prec \{clippedPolygon, M_{l,i}/\text{Area}(clippedPolygon)\}$;
    **end**
**end**

**Algorithm 1:** Interpolation of road traffic counts

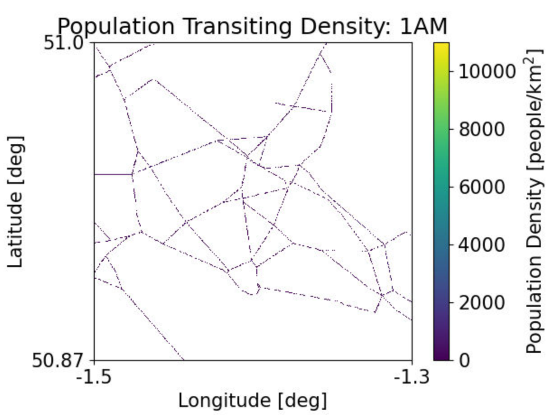


Figure 2: 1am

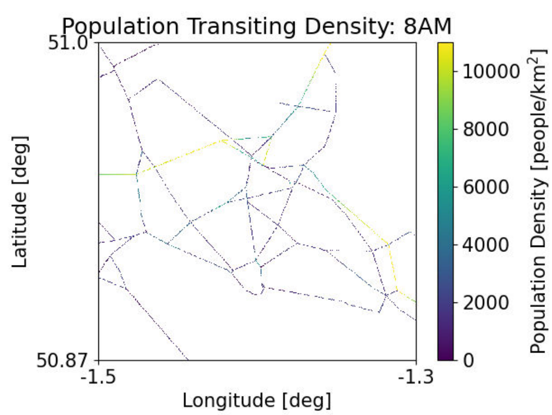


Figure 3: 8am

Figure 4: Roads population density at around Southampton, UK. left is a quiet period during the night, right is a "rush hour" traffic period.

### 2.1 Probability of Striking Persons

The probability of striking a person, $P_{strike}$, given an the impact of a UAS at a position $x, y$ and time $t$ is

$$P_{\text{strike}}(x, y, t) = \sum_{x,y} PDF \cdot \rho(x, y, t) \cdot A_{exp}(\theta) \tag{2}$$

where $\sum_{x,y} PDF$ is the sum of ground impact probability density functions for the given position

$x, y$; $\rho$ is the population density; $A_{exp}$ is the lethal area for the impact angle $\theta$. The lethal area is found by:

$$A_{exp} = \frac{2h_{\text{person}}(r_{\text{person}} + r_{\text{uas}})}{\tan\theta} + \pi(r_{\text{person}} + r_{\text{uas}})^2 \tag{3}$$

Where the height of a person, $h_{\text{person}}$, is assumed to be 1.8m, the radius of a human, $r_{\text{person}}$ is assumed to be 1.0m and the aircraft radius, $r_{\text{uas}}$, is set to half the maximum dimension of the aircraft considered.

## 2.2 Probability of Fatality

The fatality model used here was proposed by Dalamagkidis et al. and is based upon a logistic growth model as shown in Figure 5. The curve is defined by

$$P_{\text{fatality}}(x, y) = \frac{1}{1 + \sqrt{\frac{\alpha}{\beta}}\left[\frac{\beta}{E_K^{imp}(x,y)}\right]^{\frac{1}{S(x,y)}}} \tag{4}$$

where $E_K^{imp}(x, y)$ is the impact kinetic energy, $\alpha$ is the impact energy required for 50% probability of fatality at a shelter factor $S = 0.5$ and $\beta$ is minimum impact energy to cause a fatality with no shelter ($S \to 0$). The shelter factor $S(x, y)$ is in the interval $[0, 1]$ and encompasses shelter effects that obstacles in the vicinity of the impact have both in terms of blocking the path of the UAS, resulting in it not striking a person and absorbing impact energy. In this work, the sheltering factor is set to 0.3 as a conservative average value with more detailed sheltering maps left to future work.

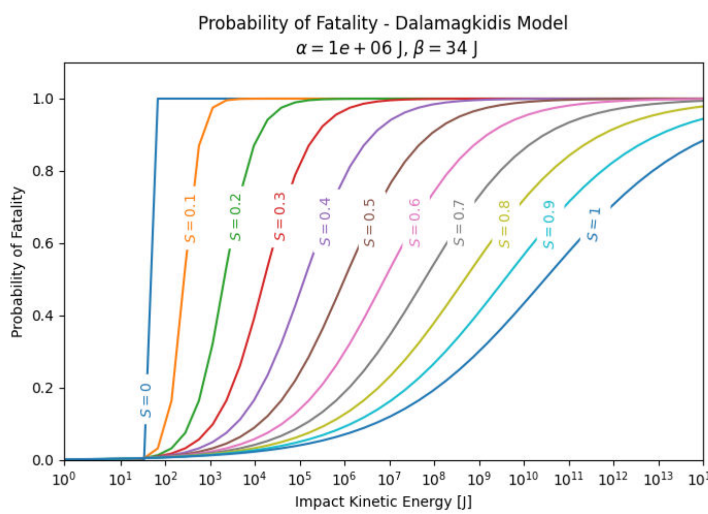


Figure 5: Fatality Curves created from the model by Dalamagkidis et al.

# 3 Mapping of Ground Risk

A region encompassing Southampton, UK is used as a example; a satellite view of the region is seen in Figure 6. The upper right of this view also shows Southampton Airport which is only considered later through the addition of the corresponding Flight Restriction Zone for UAS around it.

The population density maps generated demonstrate a marked redistribution of population throughout the day with residential areas almost regaining their full populations as defined in the census data during night time hours, shown in Figure 1. Daylight hours demonstrate a shift toward industrial, commercial, public and retail areas as people relocate to workplaces and engage in commerce. These effects are seen in Figure 11.


Figure 6: Southampton region used throughout this paper for demonstration.

The final ground risk maps can be seen at various times of the day for the same region as the population maps. Figure 16 and Figure 21 show the strike and fatality risk respectively for the Swoop Aero aircraft at 120m above ground.

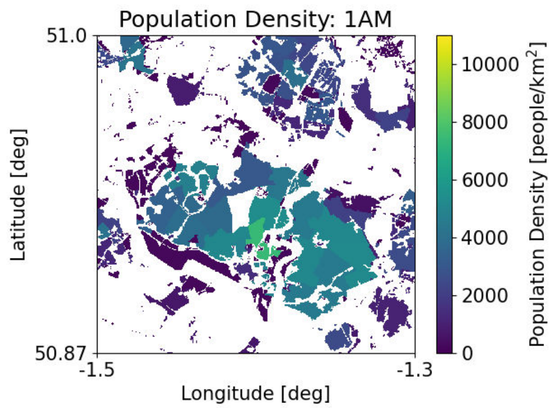


Figure 7: *
a) 1am

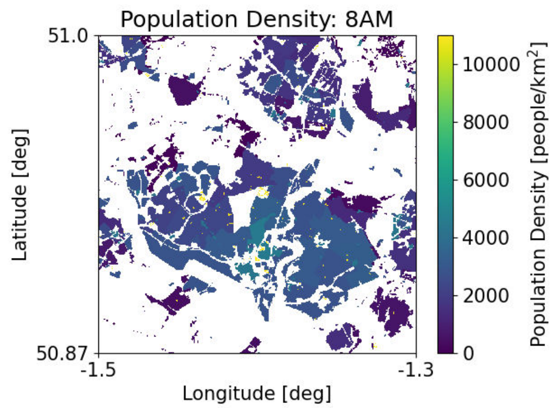


Figure 9: *
b) 8am

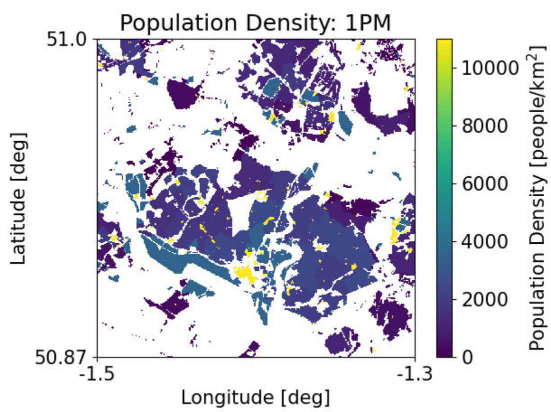


Figure 8: *
c) 1pm

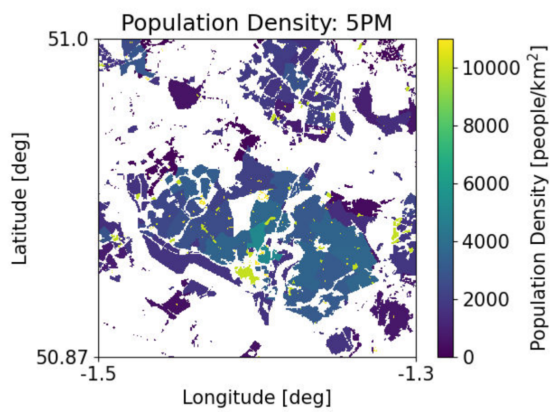


Figure 10: *
d) 5pm

Figure 11: Comparison of population densities at different times of the day around Southampton, UK.

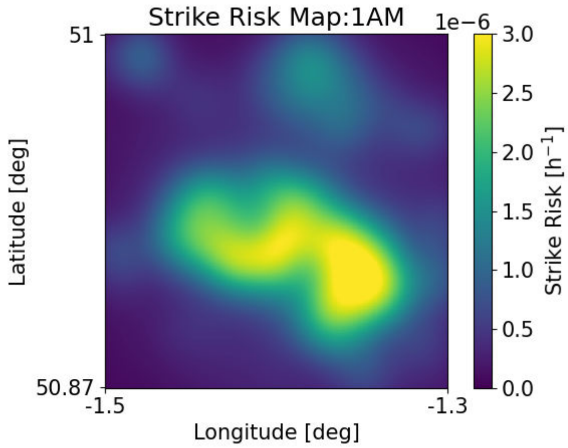


Figure 12: *
a) 1am

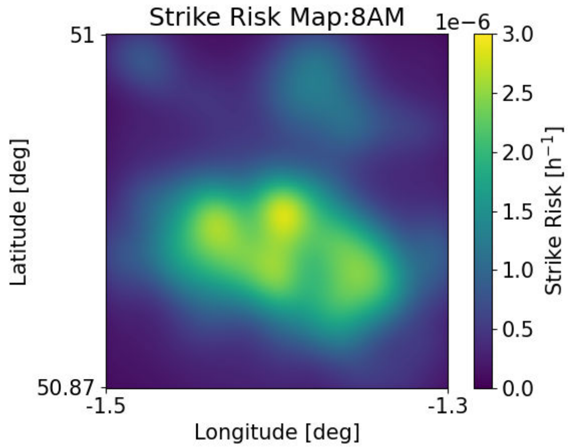


Figure 14: *
b) 8am

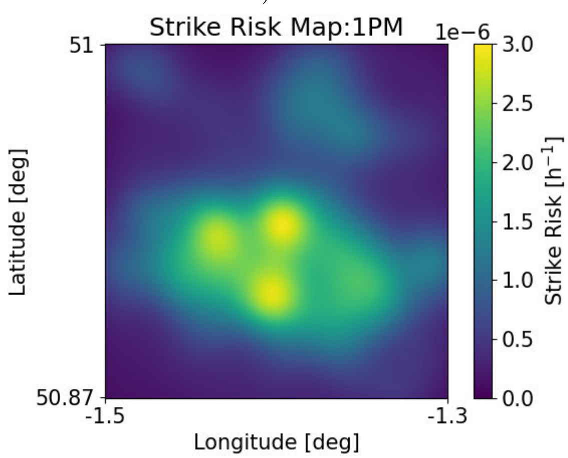


Figure 13: *
c) 1pm

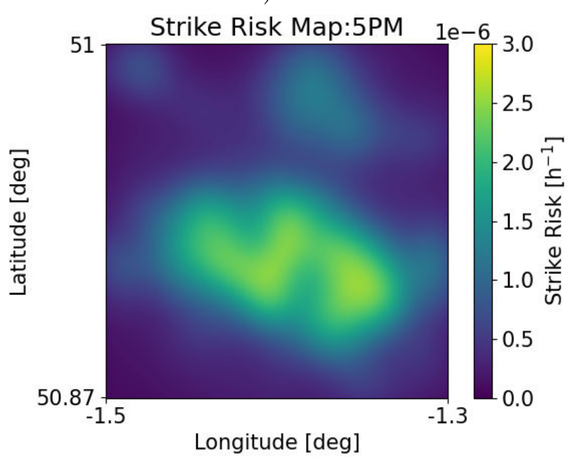


Figure 15: *
d) 5pm

Figure 16: Comparison of strike risk maps at different times of the day around Southampton, UK. Swoop Aero aircraft used at a height of 120m.

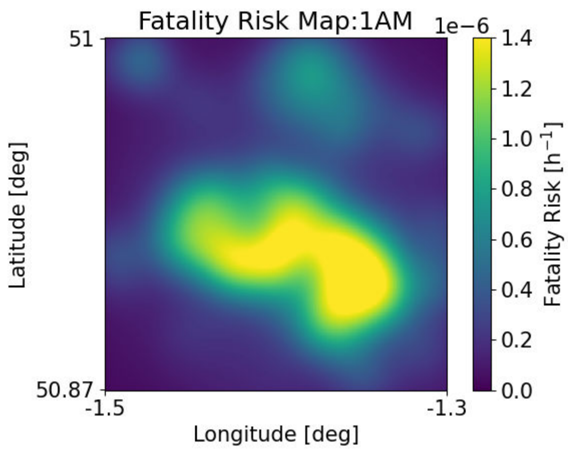


Figure 17: *
a) 1am

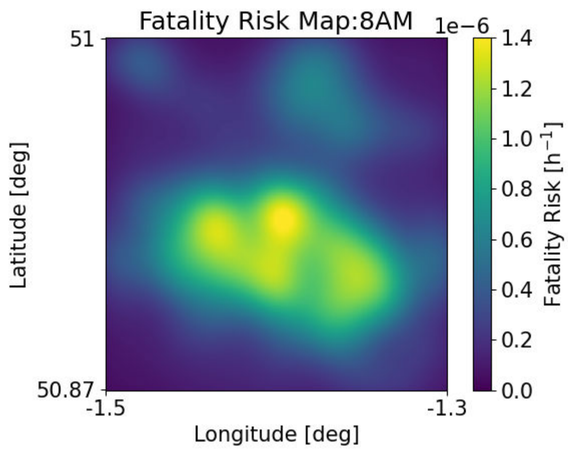


Figure 19: *
b) 8am

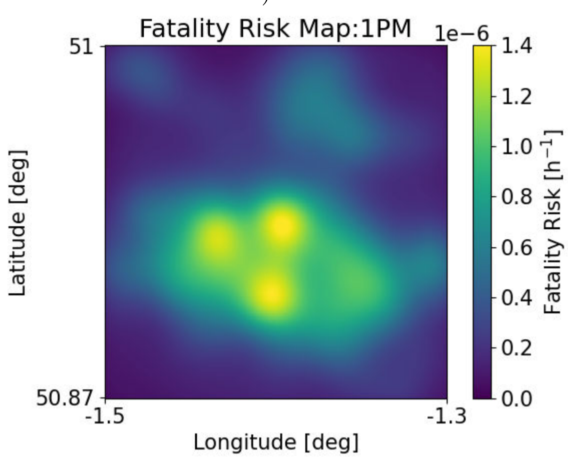


Figure 18: *
c) 1pm

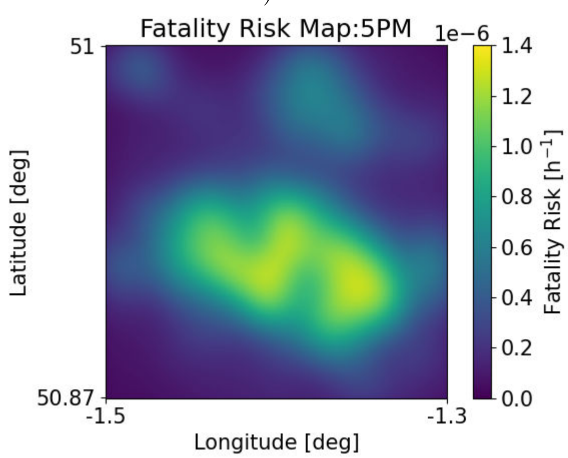


Figure 20: *
d) 5pm

Figure 21: Comparison of fatality risk maps at different times of the day around Southampton, UK. Swoop Aero aircraft used at a height of 120m.