Improving estimates of roughness length in a road weather prediction model using airborne LIDAR data

D. S. Hammond, L. Chapman and J. E. Thornes
School of Geography, Earth and Environmental Sciences, University of Birmingham, Edgbaston, Birmingham, B15 2TT, UK

Abstract

Changes in the aerodynamic characteristics of a site can have a major influence on the wind regime at the surface/air interface along a road which in turn has a local effect on road surface temperatures. Traditionally a parameter known as roughness length (Z_0) is used as the primary measure of the aerodynamic roughness of a surface, but Z_0 is notoriously difficult to estimate. This study takes a new approach to the estimation of Z_0 for a route-based road weather prediction model, using high resolution LIDAR data coupled with spatial processing techniques to provide estimates of effective roughness length (Z_0^{eff}) which take into account both the prevailing wind direction and the height of the surface elements (e.g. buildings, trees) within the upwind fetch of the forecast points. The range of roughness values obtained using this new technique are consistent with published values obtained from detailed boundary layer experiements, and are shown to distinguish between a variety of land use categories around a mixed urban and rural study route, thus giving confidence in the new technique.

Keywords: *Route based forecasting, roughness length, LIDAR*

1. Introduction

Obtaining local values of surface roughness for application in a road weather prediction model can be problematic. Typically the roughness length (Z_0) is used, which is a measure of the aerodynamic roughness of a surface affecting the height at which the neutral wind profile near to the ground extrapolates to zero (Oke, 1992). The length Z_0 is related, but not equal to, the height of the surface elements and is also a function of the shape and density of the elements. As such, Z_0 is notoriously difficult to calculate, and practical estimation of Z_0 at a particular locality is often based on published values for roughness of similar terrain elsewhere (Wieringa *et al*, 2001). A detailed review of roughness data from boundary-layer experiments conducted in the 1970s and 1980s was undertaken by Wieringa (1993), who found that the 1960 Davenport classification of effective terrain roughness (Davenport, 1960) most reliably described the effective roughness of realistic landscape types. The original Davenport classification has since been updated at both ends of the classification scale (Wieringa, 1992; Wieringa *et al*, 2001), providing arguably the best field-validated roughness classification to date (Table. 1).

In the following, a new method for parameterising surface roughness in a route based road weather prediction model (*ENTICE*) using high resolution LIDAR data obtained from airborne surveys is proposed. The range of roughness values obtained using the proposed method are compared to published roughness values for similar terrain based on the updated Davenport classification of effective terrain roughness (Table. 1). Statistical comparisons are then undertaken to assess whether the new roughness values distinguish between various land use classes, using the current *ENTICE* land use dataset and a more comprehensive land-cover dataset developed by Owen *et al* (2006). Finally, statistically modelling is used to assess the potential influence of the newly derived surface roughness data on the prediction of road surface temperatures.

Table. 1. Davenport classification of effective terrain roughness (Wieringa *et al*, 2001)

Z_0 (m)	Landscape Description
1. 0.0002 "*Sea*"	Open sea or lake (irrespective of wave size), tidal flat, snow-covered flat plain, featureless desert, tarmac and concrete, with a free fetch of several kilometres.
2. 0.005 "*Smooth*"	Featureless land surface without any noticeable obstacles and with negligible vegetation; e.g. beaches, pack ice without large ridges, marsh and snow-covered or fallow open country.
3. 0.03 "*Open*"	Level country with low vegetation (e.g. grass) and isolated obstacles with separations of at least 50 obstacle heights; e.g. grazing land without wind breaks, heather, moor and tundra, runway area of airports. Ice with ridges across-wind.
4. 0.10 "*Roughly Open*"	Cultivated or natural area with low crops or plant covers, or moderately open country with occasional obstacles (e.g. low hedges, isolated low buildings or trees) at relative horizontal distances of at least 20 obstacle heights.
5. 0.25 "*Rough*"	Cultivated or natural area with high crops or crops of varying height, and scattered obstacles at relative distances of 12 to 15 obstacle heights for porous objects (e.g. shelterbelts) or 8 to 12 obstacle heights for low solid objects (e.g. buildings).
6. 0.5 "*Very Rough*"	Intensively cultivated landscape with many rather large obstacle groups (large farms, clumps of forest) separated by open spaces of about 8 obstacle heights. Low densely-planted major vegetation like bush land, orchards, young forest. Also, area moderately covered by low buildings with interspaces of 3 to 7 building heights and no high trees.
7. 1.0 "*Skimming*"	Landscape regularly covered with similar-size large obstacles, with open spaces of the same order of magnitude as obstacle heights; e.g. mature regular forests, densely built-up area without much building height variation.
8. ≥ 2.0 "*Chaotic*"	City centres with mixture of low-rise and high-rise buildings, or large forests of irregular height with many clearings.

2. Re-parameterising effective roughness length for a route-based forecast model

2.1. Methods for calculating effective roughness length

In the *ENTICE* road weather prediction model, Z_0 is currently parameterised with respect to the ordinal land use and road type classifications at each forecast point using a look-up table of Z_0 values assimilated from various scientific literature. These values are a major oversimplification since they fail to account for variations in the surface elements within classes, and they take no account of wind direction and the associated surface elements within the upwind fetch. A simple rule of thumb for estimating Z_0 (Oke, 1992; Grimmond and Oke, 1999) which ignores the shape and spacing of the elements holds that, to a first order, Z_0 is related to the height of the surface elements (Z_H) by the empirical coefficient f_0 derived from observation, whereby:

$$Z_0 = f_0\overline{Z_H} \tag{1}$$

Both Garratt (1992) and Hanna & Chang (1992) estimate the value of f_0 to be ~ 0.1, which is a commonly quoted value for surfaces in general (Grimmond and Oke, 1999). Such a simple rule of thumb ignores the fact that Z_0 should intuitively show maximum values at intermediate densities of surface elements due to the smothering of surface roughness at high densities. This smothering effect causes an increase in the zero-plane displacement length (Z_d)

until the surface elements are so densely packed that they merge to form a new surface (i.e., $Z_H = Z_d$) with Z_0 returning to its background value. Thus, the expected form of Z_0/Z_H, with a peak at intermediate densities, means that this simple rule of thumb increasingly overestimates Z_0 at very high and very low densities and fails to identify the roughness peak, but across the range it does yield reasonable values for Z_0 (Grimmond and Oke, 1999). Z_0, however, is a local value and well defined only for homogenous terrain. In the case of heterogeneous terrain, such as road environments where surface roughness varies over short distances due to the varying height and spacing of surface elements, it is more appropriate to calculate an effective roughness length (Z_0^{eff}) from the distribution of local Z_0 values (Vihma & Savijärvi, 1991). The simplest way of calculating Z_0^{eff} is to take the areal average (denoted $\langle\ \rangle$) of the available local Z_0 values within a defined area, i.e.

$$Z_0^{eff} = \langle Z_0 \rangle \tag{2}$$

Under normal circumstances the logarithmic wind profile would typically be incorporated into such analyses by taking the logarithmic average of the roughness lengths within the defined area (Vihma & Savijärvi, 1991). However, using the natural logarithm of height in Eq. (2) would naturally lessen the influence of taller surface elements and weight the calculated Z_0^{eff} values towards the lower end of the roughness scale. Given the significant control that urban areas have on road surface temperatures due to factors such as sky view factor (Bärring *et al*, 1985; Eliasson, 1996; Chapman *et al*, 2001), screening (Bogren *et al*, 2000), increased traffic (Chapman & Thornes, 2005) and the urban heat island effect (Bradley *et al*, 2002), the authors, in wanting to maintain rather than reduce the disparity between urban and rural areas, have opted to use the arithmetic average of local Z_0 values as shown in Eq. (2).

2.2. Using LIDAR data to estimate Z_0^{eff}

The simple height-based rule of thumb outlined in Eq. (1) was applied to a LIDAR dataset of the West Midlands, UK, to provide local estimations of Z_0 at every forecast point along a mixed urban and rural study route that traverses through Birmingham city centre before passing through the south-west Birmingham suburbs and north Worcestershire countryside. The LIDAR dataset consisted of a 2m resolution Digital Terrain Model (DTM) giving elevation measurements of the natural terrain features, and a 2m resolution Digital Surface Model (DSM) which together with the natural terrain features included additional features such as buildings, vegetation and roads. Hence, subtracting the DTM from the DSM produces a dataset containing height measurements of all surface objects, which can be utilised within the simple height-based Z_0 calculation in Eq. (1) to provide local Z_0 estimations. To account for the prevailing wind direction and the effect of upstream surface elements on the surface roughness at each forecast point, Z_0^{eff} values for each forecast point were calculated by taking the areal average of all local Z_0 estimations (Eq. (2)) contained within wedge shaped areas spanning away from each forecast point. The wedges were calculated in ArcMap for various lengths of upwind fetch (100, 150, 200, 250 and 500 metres) using a 45° focal mean wedge neighbourhood function covering an approach angle from 247.5-292.5° to account for a prevailing westerly wind direction. To overcome a combination of intensive processing requirements and the limitation of single core processing on individual ArcMap tasks, buffers with distances equal to the fetch requirements were created around each of the forecast points and used as an analysis mask on the LIDAR dataset, from which the required LIDAR data within the buffer mask could be extracted and used to calculate the Z_0^{eff} values.

3. Comparison with published values for similar terrain

The newly calculated Z_0^{eff} values at each forecast point were compared against the Davenport classification of effective terrain roughness to assess whether the roughness values obtained using LIDAR data are typical of the values we would expect based on good quality observational data. Fig. (1) shows the percentage distribution of Z_0^{eff} values over the study route, revealing how the roughness values are positively skewed towards the lower end of the roughness scale as we might expect given the predominantly rural to suburban nature of the route. Maximum roughness values occur with an upwind fetch of 100 metres (Fig. 2) and are mainly located in the urbanised city centre where Z_0^{eff} values up to 3.1 metres are found. This compares well with the Davenport classification for “chaotic” terrain such as city centres containing a large mixture of low and high-rise buildings, where a Z_0 value $\geq$2.0m would be expected. When the distance of upwind fetch increases, the range of roughness values around the route decreases (Fig. 2), most likely due to the dampening of average surface element heights by an increasing proportion of low-rise surface elements within the defined neighbourhood area over larger fetches. With a fetch of 500 metres the range of roughness values along the route decreases by approximately 55% to a peak value of 1.38m in the city centre, which are still realistic values for terrain roughness in a densely built up area.

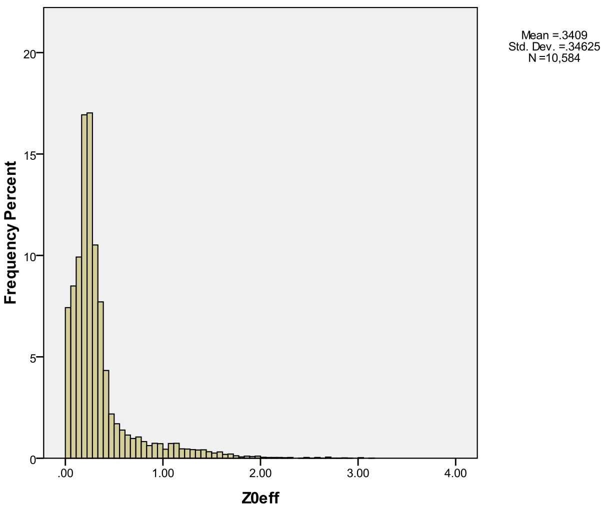

Fig. 1. Histogram showing the percentage frequency distribution of Z_0^{eff} values over the five distances of westerly upwind fetch used in the analysis.

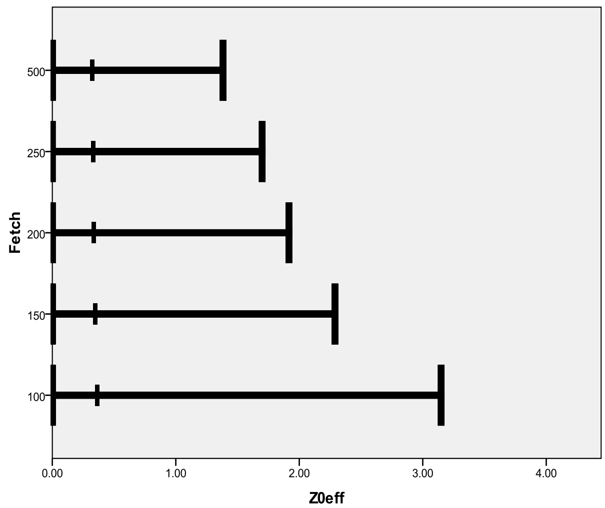

Fig. 2. Hi-Low plots showing the range of Z_0^{eff} values over the five distances of upwind fetch.

At the opposite end of the roughness scale, a few Z_0^{eff} values as low as 0.0004m are found on the westerly rural side of the route that fall within the “*smooth*” category of the Davenport classification, typical of a featureless land surface without any noticeable obstacles and negligible vegetation, such as beaches or fallow open country (Wieringa *et al*, 2001). Z_0^{eff} values as low as these are particularly low but are also plausible given their location on the rural section of the route within the open Worcestershire countryside. Also, the influence of the local road environment cannot be overlooked since roads by their very nature are smooth surface which undoubtedly have a dampening effect on the average surface element heights calculated within a defined neighbourhood area. Hence, one could argue that roughness values within a road environment are likely to be somewhat lower than might otherwise be expected for the surrounding terrain roughness. The vast majority of the rural and semi-rural forecast points, however, have roughness values that place them firmly within the “*Open*”, “*Roughly Open*” or “*Rough*” categories of the Davenport classification scale, with roughness values ranging from approximately 0.03m up to around 0.25m (Fig. 3). Likewise, most of the forecast points located within the suburban and urban areas of the route have roughness values of between 0.25m and 0.5m (Fig. 3), placing them within the “*Rough*” and “*Very*

Rough" categories of the Davenport roughness scale. Thus, the overall range of roughness values seems typical of the values we would expect for the general land use classes around the route.

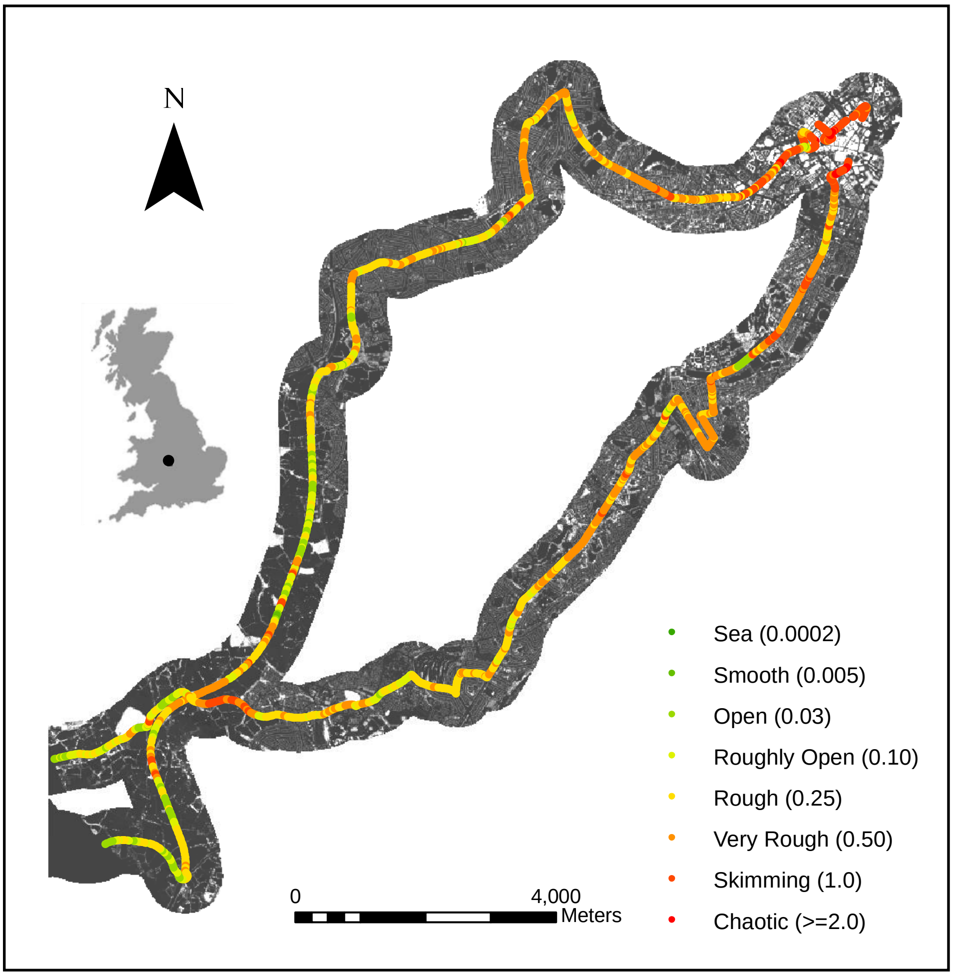

Fig. 3. Z_0^{eff} values along the study route based on an upwind fetch of 100 metres, categorised using the Davenport roughness classification. LIDAR data © 2009 Landmap.

4. Ratio versus ordinal dataset

The primary benefit of the newly calculated Z_0^{eff} values is the ratio scale of the roughness dataset, which provides measures of surface roughness at a much greater resolution than the previous ordinal dataset. For example, the forecast points shown in Fig. (4a) are all located in a rural/semi-rural section of the study route according to the *ENTICE* land use dataset, some along a minor country road and some on the M5 motorway as marked in Fig. (4a). From the existing look-up table of Z_0 values, all the forecast points along the M5 motorway would be assigned a Z_0 value of 0.50m by default, and all the points along the minor road a value of either 0.25m or 0.50m dependent on the land use class assigned to each point. However, with the new LIDAR based technique any variations in the height and spacing of the surface elements within the upwind fetch influences the roughness values calculated at each individual forecast point. Fig. (4b) displays the same set of forecast points as Fig. (4a) with the newly assigned roughness values, and clearly shows variations in surface roughness along both the motorway and the minor road due to variations in the upwind surface elements (e.g. trees, hedges, buildings). Previously the forecast points along this part of the route were assigned roughness values based on an ordinal classification, but now surface roughness is calculated on a quantitative ratio scale, enabling each forecast point to be assigned a unique Z_0^{eff} value that better represents the roughness characteristics at that particular point along the route. For the stretch of motorway shown in Fig. (4b), Z_0^{eff} values range between 0.1m and

0.4m, and between 0.08m and 1.40m along the minor road as a result of the road passing through a small forested area which is visible from the LIDAR data in Fig. (4b). Such a contrast in surface roughness over relatively short distances is impossible to identify using an ordinal classification of surface roughness, revealing the potential value that LIDAR data can bring to the parameterisation of Z_0^{eff} in a road weather prediction model.

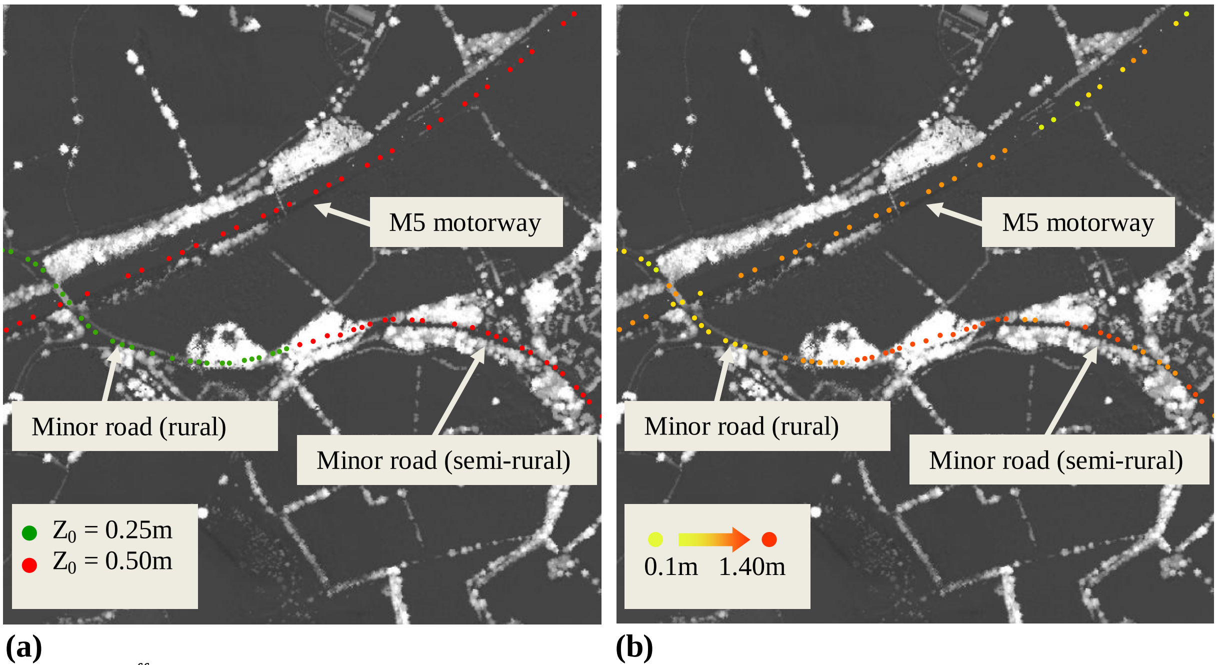

Fig. 4. Z_0^{eff} values for forecast points passing through a rural and semi-rural section of the study route, estimated using (a) the original *ENTICE* look-up table and (b) the new LIDAR spatial processing method. LIDAR data © 2009 Landmap.

5. Statistical analysis

To test for significant differences in the newly calculated Z_0^{eff} values between the existing land use categories used in the *ENTICE* model, Kruskal-Wallis rank-order tests were performed on the Z_0^{eff} values calculated for the five distances of upwind fetch. Kruskal-Wallis is the non-parametric equivalent of a one-way analysis of variance (ANOVA) and is used when a dataset violates the ANOVA assumptions about normality and homogeneity of variance. The same statistical analysis was then repeated using the urban land-cover classification derived by Owen *et al* (2006) (*OWEN*) for the UK West Midland metropolitan area in place of the *ENTICE* land use categories. The *OWEN* land-cover dataset consists of eight land-cover classes at 1 km^2 resolution (*villages/farms*, *suburban*, *light suburban*, *dense suburban*, *urban/transport*, *urban*, *light urban/open water* and *woodland/open land*) derived from dimensionality reduction of 25 spatial land-cover attributes using principal components analysis. In comparison, the *ENTICE* dataset consists of 5 proxy land use classes (*rural*, *semi-rural*, *suburban*, *urban* and *city centre*) derived via a spatial density analysis of vector road data using the method described by Chapman & Thornes (2006) to locate dense areas of the road network. This assumes that more heavily urbanised areas have a denser road network than suburban and rural areas, and takes no account of spatial land-cover attributes.

The results from the Kruskal-Wallis analyses were highly significant ($p < 0.001$) over all five distances of fetch for both the *ENTICE* and *OWEN* land-cover classifications. This indicates that significant differences exist in the Z_0^{eff} values between at least two of the land-cover classes in each classification, but does not reveal where these differences occur. Hence, post-hoc Wilcoxon rank-sum tests were performed on the Z_0^{eff} values within each independent land-cover class, comparing each class against each other to reveal where the significant differences occur. Table. (2) displays a Wilcoxon *p*-values matrix for the *ENTICE* land use classification.

Table. 2. *P*-values matrices for Wilcoxon rank-sum tests comparing Z_0^{eff} values between each land use class in the *ENTICE* land use classification.

	ENTICE 100m					ENTICE 150m					ENTICE 200m					ENTICE 250m					ENTICE 500m				
Land Use	**1**	**2**	**3**	**4**	**5**	**1**	**2**	**3**	**4**	**5**	**1**	**2**	**3**	**4**	**5**	**1**	**2**	**3**	**4**	**5**	**1**	**2**	**3**	**4**	**5**
1		0.027	0.000	0.000	0.000		0.415	0.000	0.000	0.000		0.637	0.000	0.000	0.000		0.715	0.000	0.000	0.000		0.001	0.000	0.000	0.000
2	0.027		0.003	0.000	0.000	0.415		0.000	0.000	0.000	0.637		0.000	0.000	0.000	0.715		0.000	0.000	0.000	0.001		0.000	0.000	0.000
3	0.000	0.003		0.000	0.000	0.000	0.000		0.104	0.000	0.000	0.000		0.989	0.000	0.000	0.000		0.711	0.000	0.000	0.000		0.297	0.000
4	0.000	0.000	0.000		0.000	0.000	0.000	0.104		0.000	0.000	0.000	0.989		0.000	0.000	0.000	0.711		0.000	0.000	0.000	0.297		0.000
5	0.000	0.000	0.000	0.000		0.000	0.000	0.000	0.000		0.000	0.000	0.000	0.000		0.000	0.000	0.000	0.000		0.000	0.000	0.000	0.000	

The Wilcoxon *p*-values for the *ENTICE* classification (Table. 2a) reveal that up to 90% of the land use comparisons are statistically significant at the 95% level using a Bonferroni corrected significance level of 0.005 on each comparison. This indicates that significant differences exist in the Z_0^{eff} values between the majority of the land use comparisons over all 5 distances of upwind fetch. The Wilcoxon *p*-values for the more extensive *OWEN* classification revealed a similar trend, with up to 97% of the land use comparisons statistically significant at the 95% level using a Bonferroni corrected significance level of 0.002 on the individual comparisons. A noticeable finding was the change in significance values between some land-cover comparisons as the distance of upwind fetch used in the analysis changes. For example, differences in the Z_0^{eff} values between the suburban (3) and urban (4) *ENTICE* land use classes are highly significant (*p*-value $<$ 0.001) when calculated over a fetch of just 100m (Table. 2), but statistically non-significant (*p*- value $\geq$ 0.104) over greater distances of upwind fetch. Hence, the distance of upwind fetch used to calculate surface roughness is shown to have a significant effect on the resulting roughness values, which supports previous findings in the literature and increases confidence in the proposed LIDAR based technique.

To assess the potential influence of the new LIDAR based Z_0^{eff} values on model performance, regression analyses were performed on 20 nights thermal mapping data for the study route (dependent variable) using parameters from the *ENTICE* Geographical Parameter Database (Chapman *et al*, 2001) as independent variables, one of which included surface roughness. When the original ordinal Z_0 values were replaced with the newly calculated Z_0^{eff} values obtained from LIDAR data, statistical prediction of road surface temperatures improved on all but one of the 20 nights (Fig. 5)

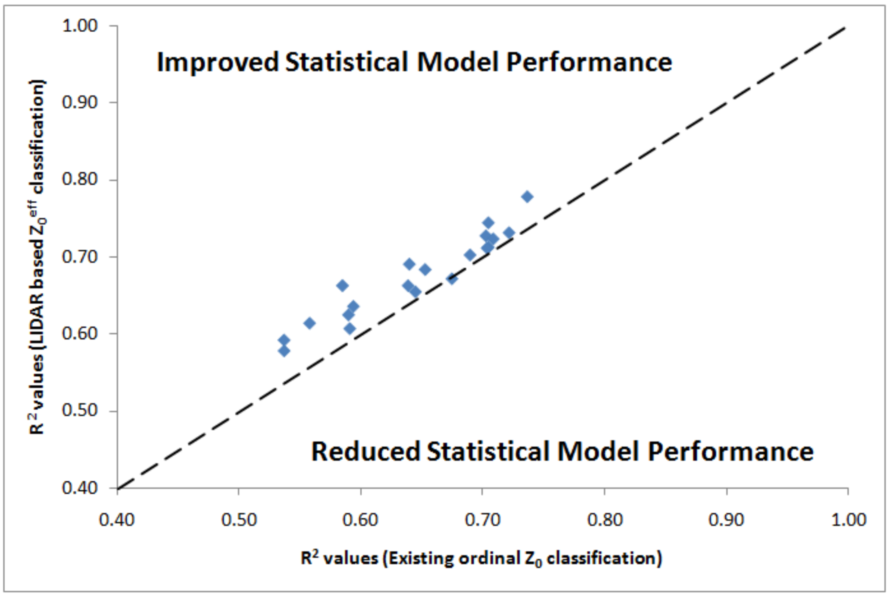

Fig. 5. Improvements in statistical model performance using LIDAR based Z_0^{eff} values.

Summary and Conclusions

A new method for parameterising surface roughness in a road weather prediction model using high resolution LIDAR data coupled with spatial processing techniques has been presented. The range of Z_0^{eff} values this method produces is consistent with published values for similar terrain based on good quality observational data from detailed boundary layer experiments. A major benefit of this new technique is the ability to calculate estimates of surface roughness on a quantitative ratio scale, enabling the roughness characteristics at every forecast point to be uniquely modelled based on the height and spacing of surface elements within the prevailing upwind fetch. Both the *ENTICE* and *OWEN* land-cover datasets have revealed significant differences in Z_0^{eff} values between land use groups, giving confidence not only in the technique itself but also to the validity of the land-cover datasets. Clearly the *OWEN* dataset provides a more comprehensive measure of land use, which is reflected in the statistical results where up to 97% of the Z_0^{eff} comparisons between land use groups are statistically significant. The most appropriate distance of upwind fetch to use is somewhat debatable, particularly for city centres which typically display greater spatial variability in surface character. Most recommendations in the literature suggest the fetch requirement to be a function of obstacle height (Wieringa, 1993; Bottema & Mestayer, 1998; Grimmond & Oke, 1999), which is a potential future improvement to the technique. Similarly, the new technique could be used to assimilate a lookup table of Z_0^{eff} values for various directions of upwind fetch, with the values selected based on the forecast wind direction. It is also acknowledged that the proposed technique assumes a constant direction of upwind flow, considering each portion of the upstream surface being modelled as an equal contributor to the aerodynamic character at a given forecast point, when in reality certain patches within this upstream area will be greater source contributors, and others less so, due to variations in the height and spacing of the surface elements. Finally, it should be recognised that the proposed technique fails to account for the problem of moving surface elements, most notably vehicle traffic. A potential solution could involve the weighting of Z_0^{eff} values based either on road type classification, or preferably daily traffic densities from loop detection systems where data is available. Despite these acknowledged limitations however, this newly proposed technique represents a significant improvement in the parameterisation of surface roughness for route-based road weather prediction models, and the quantitative dataset it provides should facilitate improvements to a recently developed methodology for verifying route based road weather forecasts (Hammond *et al*, 2010), which is the focus of ongoing research.

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