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Urban surface cover determined with airborne lidar at 2 m resolution – Implications for surface energy balance modelling

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ABSTRACT

Urban surface cover largely determines surface–atmosphere interaction via turbulent fluxes, and its description is vital for several applications. Land-cover classification using lidar has been done for small urban areas (<10 km^2) whereas surface-cover maps in atmospheric modelling often have resolutions >10 m. We classified land cover of the urban/suburban area (54 km^2) of Helsinki into six classes based on airborne lidar data, and an algorithm for machine-learning classification trees. Individual lidar returns were classified (accuracy 91%) and further converted to 2-m-resolution grid (95% accuracy). Useful lidar data included: return height and intensity, returns-per-pulse and height difference between first and last returns.

The sensitivity of urban surface-energy-balance model, SUEWS, to simulate turbulent sensible and latent heat fluxes was examined. Model results were compared with eddy-covariance flux measurements in central Helsinki. An aggregation of the surface-cover map from 2 to 100 m reduced the fraction of vegetation by two thirds resulting in 16% increase in simulated sensible heat and 56% reduction in latent heat flux. Street trees became indistinguishable already at 10 m resolution causing 19% reduction

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in modelled latent heat flux. We thus recommend having surface-cover data with 2 m resolution over cities with street trees, or other patchy vegetation.

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1. Introduction

Urban surface cover is strongly interrelated with several surface properties and processes in the surface–atmosphere interaction of an urban area. The replacement of pervious surfaces and vegetation by impervious materials alters the surface energy balance: most notably, the available energy is used for the vertical turbulent sensible heat flux rather than evaporation (e.g. Grimmond and Oke, 1991; Nordbo et al., 2012a; Loridan and Grimmond, 2012) which leads to the intensification of the inadvertent urban heat island effect, observed in many cities (Arnfield, 2003). The reduced evaporation and percolation are accompanied by a larger runoff, and together they affect the water balance of a city and cause a higher flood risk (Xiao et al., 2007); though this could give rise to opportunities for improving the urban environment (Coutts et al., 2013). The lack of vegetation also minimizes carbon dioxide (CO_2) uptake via photosynthesis and reduces the buffering effect of air pollutants (Demuzere et al., 2014). Indeed, the fraction of natural area has been shown to be a very strong proxy for predicting CO_2 emissions from cities (84% explanation power, Nordbo et al., 2012b).

The exact determination of the fraction of vegetation has received a lot of attention due to links to urban-heat-island mitigation. The simulated urban heat island in Tokyo was shown to be up to 1.5 °C weaker when patchy vegetation was taken into account in a simulation (Hirano et al., 2004). By patchy vegetation, we mean small and isolated vegetation surrounded by impervious surfaces (one example is street trees). Vegetation has been concluded to have a cooling effect in an urban environment due to shadowing effects and evaporative cooling, especially in summer (Simpson, 2002; Bowler et al., 2010; Lindberg and Grimmond, 2011; Coutts et al., 2013). Thus, there is a clear need for land-cover classification that adequately resolves patchy vegetation.

Urban surface cover is commonly available only with a coarse resolution (10–50 m) and without building and tree height information. At such a resolution, patchy vegetation is almost entirely disregarded. Airborne Light Detection And Ranging (LiDAR, hereafter lidar) measurements are based on active remote-sensing technology where visible or near-infrared (NIR) light is sent and received in high-frequency pulses (Beraldin et al., 2010). Lidar technology provides a solution to the resolution problem: it allows detailed scanning of a 3D complex urban structure with a high horizontal and vertical accuracy with a relatively low cost. Furthermore, the intensity of returned lidar pulses is an indicator for the colour of the target hit, which improves the ability for land-cover determination. Generally, the determination of urban morphology is comparatively simpler since it relies only on the height information of the returned lidar pulse; whereas intensity information is additionally needed for surface-cover classification.

The use of the lidar scanning technique is increasing its popularity in the determination of urban land cover (Table 1). Classification has been mainly done using object-based approaches (Blaschke, 2010), where pixels are first divided into segments which are then classified into land-cover classes using different methods (Brennan and Webster, 2006; Im et al., 2008; Matikainen and Karila, 2011; Buján et al., 2012; Zhou, 2013; O'Neil-Dunne et al., 2013 in Table 1). Classification trees, a machine learning algorithm presented in Breiman et al. (1984), or other related approaches, have been used in many studies, and overall accuracies over 90% have been reached (e.g., Im et al., 2008; Mancini et al., 2009; Matikainen and Karila, 2011 in Table 1). The number of surface-cover classes ranges from 2 to 10 among the research done within a decade, and the most commonly used variables used for classification are: height above ground and intensity or/and a colour channels from an orthoimage (geometrically corrected aerial photograph, Table 1). Segmentation and classification have typically been carried out using rasterized data. This is the most straightforward approach when an orthoimage

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