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# Assessment of inner-outer interactions in the urban boundary layer using a predictive model

Karin Blackman, Laurent Perret, Romain Mathis

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Urban-type rough-wall boundary layers developing over staggered cube arrays with plan area packing density,  $\lambda_p$ , of 6.25%, 25% or 44.4% have been studied at two Reynolds numbers within a wind tunnel using hot-wire anemometry (HWA). A fixed HWA probe is used to capture the outer-layer flow while a second moving probe is used to capture the inner-layer flow at 13 wall-normal positions between  $1.25h$  and  $4h$  where  $h$  is the height of the roughness elements. The synchronized two-point HWA measurements are used to extract the near-canopy large-scale signal using spectral linear stochastic estimation and a predictive model is calibrated in each of the six measurement configurations. Analysis of the predictive model coefficients demonstrates that the canopy geometry has a significant influence on both the superposition and amplitude modulation. The universal signal, the signal that exists in the absence of any large-scale influence, is also modified as a result of local canopy geometry suggesting that although the non-linear interactions within urban-type rough-wall boundary layers can be modelled using the predictive model as proposed by Mathis et al. (2011a), the model must be however calibrated for each type of canopy flow regime. The Reynolds number does not significantly affect any of the model coefficients, at least over the limited range of Reynolds numbers studied here. Finally, the predictive model is validated using a prediction of the near-canopy signal at a higher Reynolds number and a prediction using reference signals measured in different canopy geometries to run the model. Statistics up to the 4<sup>th</sup> order and spectra are accurately reproduced demonstrating the capability of the predictive model in an urban-type rough-wall boundary layer.

## 1. Introduction

As urbanization continues to advance, our cities are faced with significant challenges related to air quality. These challenges are exacerbated by the complexity of the urban geometry and the dynamic processes that take place within the urban canopy and above within the atmospheric boundary layer. The urban boundary layer contains coherent structures such as large-scale turbulent organized structures of either high or low momentum that form above the roughness in the inertial layer from groups of hairpin vortices (Adrian et al. 2000). Within the roughness sublayer, shear layers form along the top of the upstream roughness elements and contain small-scale structures induced by the presence of the roughness (Coceal et al. 2007). These turbulent structures and the intermittent exchanges they produce govern the transport of heat, momentum and pollution in the urban canopy and understanding these turbulent structures and how they interact is crucial to addressing the challenges facing our cities today.

In smooth-wall boundary layers, in addition to the superposition mechanism of the large scales onto the near-wall flow (Townsend 1976), a non-linear mechanism of amplitude modulation has been recently shown to exist between the large-scale structures

43 in the inertial layer and the small scales close to the wall (Hutchins and Marusic 2007;  
 44 Mathis et al. 2009, 2011b,c; Marusic et al. 2011; Inoue et al. 2012). As large-scale regions  
 45 of high (low) momentum pass over the small scales close to the wall the small scales are  
 46 amplified (suppressed) (Mathis et al. 2009). This mechanism was first observed experi-  
 47 mentally by Rao et al. (1971) who noted a strong non-linear coupling between the inner  
 48 and outer layer in the smooth-wall boundary layer. More recently, amplitude modulation  
 49 has been shown to increase with increasing Reynolds number as large-scale structures be-  
 50 come more intense thereby contributing more to the turbulent interactions (Mathis et al.  
 51 2009). Furthermore, all three components of velocity have been shown to be modulated  
 52 by the large scales in a similar manner (Talluru et al. 2014). The near-wall evolution  
 53 of the amplitude modulation has been found to show strong similarities with the skew-  
 54 ness profile of the streamwise velocity component (Mathis et al. 2009). This resemblance  
 55 was found to be due to one component of the scale-decomposed skewness (see §4.3 for  
 56 more details), which proved to be a good diagnostic quantity to study the presence of  
 57 amplitude modulation (Mathis et al. 2011c; Duvvuri and McKeon 2015). It should be  
 58 noted that strong correlation between large-scale structures and small-scale amplification  
 59 or suppression does not imply that the large-scales actively modulate the small scales.  
 60 However, some recent studies, such as Duvvuri and McKeon (2015), have found evidence  
 61 that support this causality.

62 Amplitude modulation has also been confirmed to exist using DNS in a d-type 2D bar-  
 63 roughened wall with plan area packing density  $\lambda_p = 12.5\%$  (the ratio between the area of  
 64 the surface occupied by the roughness elements and the total surface area) (Nadeem et al.  
 65 2015), using LES of a staggered cube array with  $\lambda_p = 25\%$  and homogenous roughness  
 66 (Anderson 2016) and experimentally in a sand-roughened wall (Squire et al. 2016) and  
 67 rod-roughened wall (Talluru et al. 2014). In each of these cases the amplitude modulation  
 68 was modified compared to the smooth-wall flow configuration, but the nature of the  
 69 mechanism remained the same. The amplitude modulation was shown to be stronger in  
 70 rough-wall flows compared to smooth-wall boundary layers, the presence of the roughness  
 71 causing a wall-normal shift of the peak spectral energy of the near-wall small scales  
 72 resulting in a modification of the amplitude modulation behaviour in both the near-  
 73 wall and outer-wall regions (Anderson 2016; Talluru et al. 2014). This modification was  
 74 shown to cause the large-scale structures of the outer layer to interact with both the  
 75 near-wall small scales and small scales away from the wall (Nadeem et al. 2015). When  
 76 investigating the influence of buoyancy effect using LES Salesky and Anderson (2018)  
 77 found that an increase in convection resulted in an increase in the angle of inclination  
 78 of near-surface large-scale structures. This in turn causes a shift in the location of the  
 79 outer peak of the streamwise velocity spectra until the energy is concentrated in a single  
 80 peak. Although the modulation is shown to decrease as the large-scale structures change  
 81 from streamwise to vertically dominated the modulation is still present over all cases  
 82 studied. Awasthi and Anderson (2018), who studied amplitude modulation in the flow  
 83 over roughness with spanwise heterogeneity, found that the outer peak was present in  
 84 upwelling zones but not present in downwelling zones where structures were steeper and  
 85 shorter.

86 Evidence from experiments performed in a boundary layer developing over a rough  
 87 wall consisting of staggered cubes with  $\lambda_p = 25\%$  confirmed the existence of a non-linear  
 88 interaction between the most energetic large-scale structures present above the canopy  
 89 and the small-scale structures induced by the presence of the roughness (Blackman and  
 90 Perret 2016). The analysis of the spatio-temporal modulation coefficient confirmed the  
 91 existence of a mechanism similar to amplitude modulation and demonstrated that the  
 92 large-scale momentum regions influence the small scales within the roughness sublayer

93 after a time delay, agreeing with the results of Anderson (2016). Further evidence of  
 94 amplitude modulation within this staggered cube roughness configuration was found  
 95 by Basley et al. (2018) through investigation of the characteristics of the amplitude  
 96 modulation coefficient of the three velocity components and the turbulent kinetic energy  
 97 in a wall-parallel plane located in the roughness sublayer (*i.e.* just above the top of the  
 98 roughness elements). Recently, using triple decomposition of the kinetic energy budget  
 99 in a boundary layer developing over staggered cubes with  $\lambda_p = 25\%$  this non-linear  
 100 relationship was linked to an instantaneous exchange of energy between the large-scale  
 101 momentum regions and the small scales close to the roughness (Blackman et al. 2018).  
 102 Finally, investigation of this non-linear relationship has been expanded to the study of  
 103 street canyon flows using six rough-wall boundary layer configurations consisting of three  
 104 upstream roughness geometries (cubes or 2D bars with different streamwise spacing) and  
 105 two street canyon aspect ratios (Blackman et al. 2017). Although a modification of the  
 106 non-linear relationship exists close to the top of the roughness elements between 3D and  
 107 2D roughness, the non-linear mechanism similar to amplitude modulation was confirmed  
 108 to exist in all of the configurations.

109 The study of amplitude modulation in the smooth-wall boundary layer has led to  
 110 the development of a predictive model for the near-wall fluctuations using a large-scale  
 111 boundary layer signal (Mathis et al. 2011a). The application of this predictive model  
 112 has been expanded to a rough wall consisting of sand-roughness (Squire et al. 2016) and  
 113 has recently been improved using Spectral Linear Stochastic Estimation (SLSE) (Baars  
 114 et al. 2016a). Compared to the smooth-wall boundary layer, the linear interaction or  
 115 superposition mechanism in the rough wall was found to be weaker while the amplitude  
 116 modulation was found to be stronger. This suggests that roughness elements generate  
 117 small scales that contribute significantly to the amplitude modulation (Squire et al. 2016)  
 118 agreeing with the results of Anderson (2016) and Talluru et al. (2014).

119 In the context of atmospheric flows developing over the urban canopies, the effect of  
 120 the roughness configuration used to generate a rough-wall boundary layer on the mean  
 121 flow characteristics and turbulence statistics has been studied extensively (Macdonald  
 122 et al. 1998; Cheng and Castro 2002; Takimoto et al. 2013; Blackman et al. 2015). Other  
 123 work has used two-point statistics and correlations to investigate the characteristics of  
 124 turbulent events such as sweeps and ejections that occur within the shear layer (Takimoto  
 125 et al. 2013). Recently, Perret et al. (2019) studied the influence of canopy flow regime and  
 126 Reynolds number on the characteristics of the scale-decomposed velocity fluctuations us-  
 127 ing staggered cube arrays with  $\lambda_p = 6.25\%$ ,  $25\%$  and  $44.4\%$ . The roughness configurations  
 128 were classified using the flow regimes identified by Grimmond and Oke (1999) as isolated  
 129 wake flow ( $6.25\%$ ), wake interference flow ( $25\%$ ) and skimming flow ( $44.4\%$ ). Through  
 130 spectral analysis and scale-decomposition dynamical similarities were found between the  
 131 canopy configurations. The Reynolds number was shown to have a negligible effect on  
 132 the characteristics of the large-scale fluctuations. However, the skimming flow regime  
 133 was shown to result in near-canopy large scales that contributed more to the variance  
 134 suggesting that a stronger correlation exists between the inertial layer and the roughness  
 135 sublayer as the canopy flow becomes less important. The above classification has recently  
 136 been investigated by Basley et al. (2019) who performed a PIV-based investigation of  
 137 the same three canopy configurations as Perret et al. (2019). Using data acquired in two  
 138 horizontal planes, they focused on the characteristics of the coherent structures existing  
 139 in the roughness sublayer and the logarithmic region. They evidenced that, closer to the  
 140 canopy, the features of those participating to wall-normal exchange of momentum were  
 141 dependent on the roughness array configuration. They appeared to be more or less free  
 142 to develop for the sparsest configurations while constrained in the densest case. It was

143 shown that this apparent confinement of the flow is not gradual with  $\lambda_p$ . Their results  
 144 indeed suggest that there exists a threshold in  $\lambda_p$  above which the canopy-generated  
 145 shear layers cannot develop freely (*i.e.* in the skimming flow regime).

146 The present work focuses on the interaction between the most energetic scales pop-  
 147 ulating the outer layer and those from the roughness sublayer, just above the top of  
 148 the canopy. A predictive model similar to that developed by Mathis et al. (2011a) for  
 149 smooth-wall flows is employed to enable the quantification of both the superimposition  
 150 and the modulation mechanisms when the wall geometry is strongly modified. Although  
 151 this type of model has been applied successfully in boundary layers over smooth walls and  
 152 homogeneous rough walls, it has not yet been applied to an urban-type rough-wall bound-  
 153 ary layer. Furthermore, previous work has shown a non-negligible influence of the canopy  
 154 configuration on the non-linear interactions (Blackman et al. 2017) and the characteris-  
 155 tics of the near-canopy large scales (Perret et al. 2019). Here, three rough-wall boundary  
 156 layers developing over arrays of cubical roughness elements with  $\lambda_p = 6.25\%$ ,  $25\%$  and  
 157  $44.4\%$  will be used to investigate (*i*) through scale decomposition of the streamwise ve-  
 158 locity component the influence of the canopy flow regime on the interaction between the  
 159 most energetic scales existing in the outer layer and near the canopy, (*ii*) the impact of  
 160 varying both the Reynolds number and the canopy configuration on the predictive model  
 161 characteristics and (*iii*) whether the predictive model in its current form can be used in  
 162 an urban-type boundary layer.

163 The following sections outline the methodologies used in the present work including  
 164 the predictive model (§2) and experimental details (§3). The results and discussion,  
 165 including the influence of both the plan area packing density and the Reynolds number  
 166 on the characteristics of the model coefficients and universal signal, which is the signal  
 167 that exists in the absence of large-scale influence, are presented in §4. A validation of the  
 168 predictive model is also presented using combinations of data from the six configurations.  
 169 The last section (§5) is devoted to the conclusions.

## 170 2. The Predictive Model

171 The predictive model, developed by Mathis et al. (2011a) and shown in Eq 2.1, has  
 172 the ability to predict the statistics of the fluctuating streamwise velocity component  
 173 in the inner region from an outer region input. Here,  $u_p^+$  is the predicted statistically  
 174 representative streamwise fluctuating velocity signal and  $u_{oL}^+$  is the filtered outer-layer  
 175 large-scale streamwise fluctuating velocity signal and the only input into the model. The  
 176 signal  $u^*$  is the universal time series that corresponds to a small-scale signal that would  
 177 exist if there were no large-scale influence. The superscript  $+$  denotes normalizations of  
 178 the velocity fluctuations using the friction velocity  $u_\tau$ , the distance using  $\nu/u_\tau$ , and the  
 179 time using  $\nu/u_\tau^2$ . The universal signal,  $u^*$ , and coefficients  $\beta$ ,  $\alpha$  and  $\theta_L$  are determined  
 180 using a calibration method involving two-point measurements of the streamwise velocity  
 181 fluctuations. The predicted signal,  $u_p^+$ , the large-scale outer-layer signal,  $u_{oL}^+$ , and the  
 182 universal signal,  $u^*$ , are all time series as a function of  $z^+$  while coefficients  $\beta$ ,  $\alpha$  and  $\theta_L$   
 183 are all functions of  $z^+$ .

$$u_p^+(z^+) = u^*(1 + \beta u_{oL}^+(z_o^+, \theta_L)) + \alpha u_{oL}^+(z_o^+, \theta_L). \quad (2.1)$$

184 The model consists of two parts. The first term of the right-hand side of Eq. 2.1 describes  
 185 the amplitude modulation by the large-scale outer layer structures on the small scales  
 186 close to the roughness, while the second term models the superposition of these large-scale  
 187 structures. To account for the inclination angle of the large-scale structures ( $\theta_L$ ) a time  
 188 lag, which corresponds to the shift in the maximum correlation between the outer- and

189 inner-layer large-scale signals, is used. For further information regarding this model the  
 190 reader is referred to the work of Mathis et al. (2009) and Mathis et al. (2011a). Recently,  
 191 an alternative approach to this model has been proposed by Baars et al. (2016a) who  
 192 rewrite the model as

$$u_p^+ = u^*(1 + \Gamma u_L^+) + u_L^+, \quad (2.2)$$

193 where the coefficient  $\Gamma = \beta/\alpha$  and  $u_L^+ = \alpha u_{oL}^+(z_o^+, \theta_L)$  represents the superposition effect  
 194 of the outer large-scales felt at a wall-normal location  $z^+$  within the near-canopy. Baars  
 195 et al. (2016a) propose a refined procedure for obtaining this superposition component,  $u_L^+$ ,  
 196 based on a SLSE, which is applied here. A brief explanation of the method is presented  
 197 below and the reader is referred to Baars et al. (2016a) and Perret et al. (2019) for further  
 198 information.

199 The present two-point measurements are first used to determine the linear coherent  
 200 spectrum (LCS) between an outer layer signal and an inner layer signal (Eq 2.3), which  
 201 represents the maximum correlation coefficient for each Fourier scale.

$$\gamma^2(f^+) = \frac{\|\langle U_o(f^+) \overline{U(f^+)} \rangle\|^2}{\langle \|U_o(f^+)\|^2 \rangle \langle \|U(f^+)\|^2 \rangle}. \quad (2.3)$$

202  $U(f^+)$  is the Fourier transform of  $u$  at frequency  $f^+$ ,  $U_o(f^+)$  is the Fourier transform of  
 203 the outer layer signal  $u_o$ ,  $\| \|$  denotes the modulus,  $\langle \rangle$  denotes ensemble averaging and  
 204  $\overline{(\ )}$  denotes the complex conjugate. Thus, the LCS represents the correlation between  
 205 streamwise velocity components at two wall-normal locations for a particular frequency.  
 206 The spectral coherence obtained for each of the six configurations studied here are shown  
 207 in Fig. 9 of Perret et al. (2019).

208 As in Baars et al. (2016a) the existence of a non-negligible coherence between veloc-  
 209 ities at two different wall-normal locations at certain frequencies allows for the scale  
 210 decomposition of the velocity signal into  $u_L^+$  which is the portion of the signal correlated  
 211 with the outer-layer signal (large scales) and  $u_S^+$  which is the portion uncorrelated with  
 212 the outer-layer signal (small scales). A spectral linear stochastic estimation based on the  
 213 cross-spectrum between the outer-layer signal,  $u_o^+$ , and  $u^+$  is used to derive a transfer  
 214 function that is then used to extract  $u_L^+$  from  $u_o^+$  (Baars et al. 2016a):

$$U_L(f^+) = H_L(f^+) U_o(f^+) \quad (2.4)$$

215 where  $H_L$  is the transfer kernel which accounts for the correlation between  $u^+$  and  $u_o^+$   
 216 at each frequency. This transfer function kernel is computed by using the synchronized  
 217 inner-layer and outer-layer data and Eq 2.5.

$$H_L(f^+) = \frac{\langle U(f^+) \overline{U_o(f^+)} \rangle}{\langle U_o(f^+) \overline{U_o(f^+)} \rangle} \quad (2.5)$$

218 The transfer kernel is therefore the ratio between the cross-spectrum of  $u^+$  and  $u_o^+$  and  
 219 the auto-spectrum of  $u_o^+$ . For further details see Perret et al. (2019). Beyond a certain  
 220 frequency,  $f_{th}^+$ , coherence will no longer exist between the two signals. However, due to  
 221 the presence of noise a non-physical but non-negligible value of  $\|H_L(f^+)\|$  at frequencies  
 222 greater than  $f_{th}^+$  can exist. To avoid errors in the estimated signal,  $u_L^+$ , from these non-  
 223 physical values the transfer function is set to zero at frequencies above  $f_{th}^+$ . As in Baars  
 224 et al. (2016a) the frequency threshold  $f_{th}^+$  is determined as the frequency at which the  
 225 coherence  $\gamma^2(f^+)$  falls below 0.05. The transfer kernel is also smoothed to avoid further

226 errors from noise. The transfer kernel is then applied to  $u_o^+$  in the spectral domain using  
 227 Eq 2.4. The inverse Fourier transform of the  $U_L(f^+)$  signal then gives  $u_L^+(t^+)$ .

228 Applying the SLSE method described above to each of the wall-normal locations ( $z$ ),  
 229 the new model becomes

$$u_p^+(z^+, t^+) = u^*(z^+, t^+) (1 + \Gamma(z^+) u_L^+(z^+, t^+ - \tau_a)) + u_L^+(z^+, t^+), \quad (2.6)$$

230 where  $u_L^+(z^+, t^+)$  is obtained using

$$u_L^+(z^+, t^+) = \mathcal{F}^{-1} [H_L(z^+, f^+) \mathcal{F}(u_o^+(z_o^+, t^+))], \quad (2.7)$$

231 where  $\mathcal{F}$  and  $\mathcal{F}^{-1}$  denote the direct and inverse Fourier transform operators, respectively.  
 232 The model input is a measurement of the streamwise velocity fluctuations from the outer  
 233 layer,  $u_o^+(z_o^+, t^+)$ , and a kernel  $H_L(z^+, f^+)$ . Once  $u_L^+$  has been determined the model  
 234 shown in Eq 2.6 is used to obtain the predicted signal. For this, a universal signal,  $u^*$ ,  
 235 and a coefficient,  $\Gamma$ , both location-dependent, are required. A phase-shift between the  
 236 local large scales  $u_L^+(z^+, t^+)$  and the large-scale envelope of the amplitude modulated  
 237 small scales ( $(u_S^+(z^+, t^+))^2$  in the present case) has been evidenced both in smooth-  
 238 (Guala et al. 2011; Baars et al. 2015) and rough-wall boundary layers (Basley et al. 2018;  
 239 Pathikonda and Christensen 2017). To account for that effect, a time shift  $\tau_a$  is introduced  
 240 to the new model. Its inclusion results in a refined estimation of  $u^*$  and therefore a refined  
 241 predicted signal,  $u_p^+$  (Baars et al. 2016a). The model parameter  $\alpha(z^+)$  is chosen to be  
 242 equal to the maximum of from the temporal cross-correlation between the outer-layer  
 243 signal,  $u_o^+$ , and the large-scale signal produced from the SLSE method,  $u_L^+(z^+)$  (Mathis  
 244 et al. 2011a). The model calibration is conducted using the synchronized two-point hot-  
 245 wire measurements described in §3 at each wall-normal location of measurement. To  
 246 derive  $u^*$  and  $\Gamma$  the small-scale signal of the inner layer is obtained using

$$u_S^+(z^+, t^+) = u^+(z^+, t^+) - u_L^+(z^+, t^+). \quad (2.8)$$

247 This signal represents the fluctuations that are uncorrelated with the large-scale struc-  
 248 tures in the outer layer. For the calibration  $u^+(z^+, t^+)$  is equivalent to the predicted  
 249 signal giving

$$u_S^+(z^+, t^+) = u^*(z^+, t^+) (1 + \Gamma(z^+) u_L^+(z^+, t^+ - \tau_a)) \quad (2.9)$$

250 where  $u^*$  and  $\Gamma$  are unknown. As discussed, the universal signal is the signal that exists in  
 251 the absence of any influence of the large scales in the outer layer. As described by Mathis  
 252 et al. (2009) and Mathis et al. (2011a)  $u_S^+$  does not include any superposition effect, but  
 253 does include amplitude modulation effects. Therefore, to find  $u^*$  Eq 2.10 is used where  
 254  $\Gamma$  is solved for iteratively such that  $u^*$  does not show any amplitude modulation. Here,  
 255 the absence of amplitude modulation is defined using the scale-decomposed skewness as  
 256 it has been previously shown by Blackman and Perret (2016) that the non-linear term  
 257  $\overline{u_L^+ u_S^{+2}}$  is directly related to amplitude modulation. Therefore  $u^*$  constitutes no amplitude  
 258 modulation when

$$\overline{u_L^+(z^+, t^+ - \tau_a) u^{*2}} = \overline{u_L^+(z^+, t^+ - \tau_a) \left( \frac{u_S^+(z^+, t^+)}{1 + \Gamma(z^+) u_L^+(z^+, t^+ - \tau_a)} \right)^2} = 0. \quad (2.10)$$

259 For every wall-normal measurement location, Eq 2.10 is solved iteratively to obtain  $\Gamma(z^+)$   
 260 where  $u^*$  is minimally modulated by  $u_L^+(z^+, t^+ - \tau_a)$ . The signal  $u^*$  is then computed  
 261 using the coefficient  $\Gamma$ , and  $\beta$  is determined from the relation  $\Gamma = \beta/\alpha$ . Finally, the  
 262 predicted signal,  $u_p^+$ , is estimated using Eq 2.6. For further details, the reader is referred  
 263 to Mathis et al. (2009), Mathis et al. (2011a) and Baars et al. (2016a).



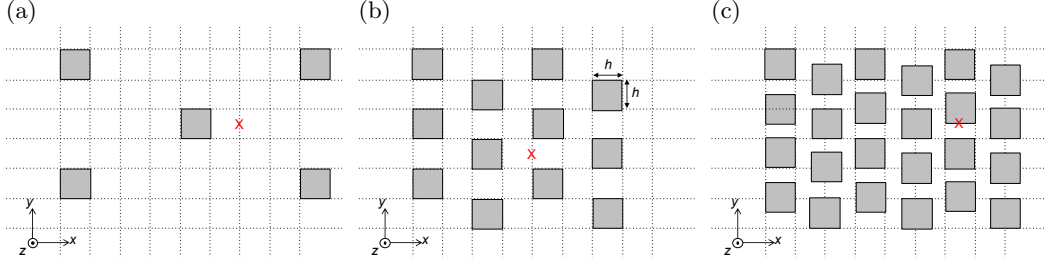


FIGURE 1. Investigated canopy configurations with a)  $\lambda_p = 6.25\%$ , b)  $\lambda_p = 25\%$  and c)  $\lambda_p = 44.4\%$  where the red cross ( $\times$ ) is the hot-wire measurement location.

### 264 3. Experimental details

265 The experiments were conducted in a boundary layer wind tunnel with working section  
 266 dimensions of 2 m (width)  $\times$  2 m (height)  $\times$  24 m (length) and a 5:1 inlet ratio contraction  
 267 in the *Laboratoire de recherche en Hydrodynamique, Energétique et Environnement*  
 268 *Atmosphérique* at Ecole Centrale de Nantes. The empty wind tunnel has a freestream  
 269 turbulence intensity of 0.5% with spanwise uniformity to within  $\pm 5\%$  (Savory et al.  
 270 2013). To reproduce the lower-part of the atmospheric boundary layer five 800 mm vertical  
 271 tapered spires were used immediately downstream of the contraction to initiate the  
 272 boundary layer development and were followed by a 200 mm high solid fence located 750  
 273 mm downstream of the spires. These turbulence generators were then followed by a 22  
 274 m fetch of staggered cube roughness elements with height of  $h = 50$  mm. For further  
 275 details related to the wind tunnel facility and set-up the reader is referred to Perret et al.  
 276 (2019). Three different staggered cube configurations were studied consisting of plan area  
 277 packing densities,  $\lambda_p$ , of 6.25%, 25% or 44.4% (Fig. 1). Finally, the experiments were per-  
 278 formed at two nominal freestream velocities  $U_e$  of 5.7 and 8.8 m/s, resulting in a total of  
 279 six flow configurations.

280 Flow measurements were conducted 19.5 m downstream of the wind tunnel inlet along  
 281 a wall-normal profile across the boundary layer using hot-wire anemometers (HWA). Two  
 282 HWA probes were used simultaneously in order to investigate the relationship between  
 283 the lower part of the boundary layer and the logarithmic region (Fig. 2). The first was a  
 284 fixed HWA probe at a wall-normal location of  $z/h = 5$  (*i.e.* within the inertial layer) while  
 285 the second probe was positioned at 13 different wall-normal locations in the lower part  
 286 of the boundary layer between  $z/h = 1.25$  and  $z/h = 4$ . The wall-normal location of the  
 287 reference probe at  $z/h = 5$  has been chosen based on previous studies (Perret and Rivet  
 288 2013; Blackman and Perret 2016; Basley et al. 2018), performed in the  $\lambda_p = 25\%$  cube  
 289 array, in which the focus was to analyse scale interactions between the canopy flow and  
 290 the overlying boundary layer in order to highlight the existence of a non-linear amplitude  
 291 modulation mechanism as previously evidenced by Mathis et al. (2009) in smooth-wall  
 292 boundary layers. It has been shown that the amplitude modulation mechanism is effec-  
 293 tively detected in urban surface layer with a reference point located in the range  $3h - 5h$ .  
 294 This ensures that the reference point is out of the RSL (the targeted flow) and well within  
 295 the logarithmic layer (in the constant flux region). This mild sensitivity regarding the  
 296 choice of the reference wall-normal location is in agreement with the findings of Mathis  
 297 et al. (2009). Accuracy of the single hot-wire measurements in this region of the flow was  
 298 assessed by Perret and Rivet (2018) using a combination of stereoscopic PIV and the con-  
 299 cept of convective cooling velocities. Measurements of the streamwise velocity component  
 300 using a single hot wire showed good accuracy with a relative error of the variance always  
 301 below 5%. This was further confirmed by the comparison between results obtained via

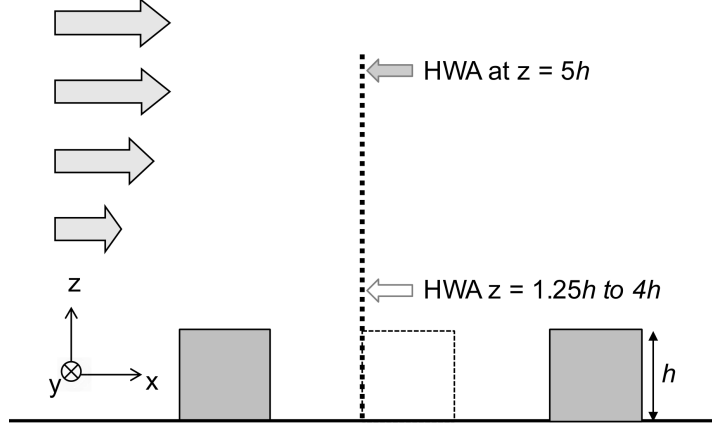


FIGURE 2. HWA measurement set-up showing the two-probe arrangement.

302 Laser Doppler anemometry (LDA) and HWA performed by Herpin et al. (2018). Two  
 303 Disa 55M01 electronics associated to Dantec 55P11  $5\ \mu\text{m}$  single HWA probes with a wire  
 304 length of  $1.25\ \text{mm}$  were used with overheat ratio set to 1.8. The HWA measurements  
 305 were conducted at a frequency of  $10\ \text{kHz}$  for a period of  $24\ 000\ \delta/U_e$ . The signals were  
 306 treated with an 8<sup>th</sup> order anti-aliasing linear phase elliptic low-pass filter prior to digiti-  
 307 zation. Calibration was performed at the beginning of each measurement set by placing  
 308 the probes in the free-stream flow. The calibration procedure is based on King's law and  
 309 accounts for temperature correction using the method proposed by Hultmark and Smits  
 310 (2010). For further details including the relative error of the mean, variance, 3<sup>rd</sup> order  
 311 and 4<sup>th</sup> order statistics, as well as the statistical error of convergence, refer to Perret  
 312 et al. (2019). A detailed comparison between the present  $\lambda_p = 25\%$  flow configuration  
 313 and similar configurations from the literature was completed by Perret and Rivet (2018),  
 314 including a comparison of the standard deviation of the three velocity components and  
 315 Reynolds shear stress from Reynolds and Castro (2008). They also compared the wall-  
 316 normal distribution of Q1, Q2, Q3 and Q4 events to the DNS of Coceal et al. (2007),  
 317 confirming that the present flow shows the correct flow structure. Further comparison  
 318 between the literature and measurements performed via PIV, HWA and LDA can be  
 319 found in Herpin et al. (2018).

## 320 4. Results

321

### 4.1. Boundary layer characteristics

322 Table 1 lists the main characteristics of the investigated boundary layers. The logarithmic-  
 323 law parameter aerodynamic roughness length,  $z_0$ , was determined by fitting the vertical  
 324 streamwise velocity profile to the logarithmic law (Perret et al. 2019). As described by  
 325 Perret et al. (2019) the zero-plane displacement height,  $d$ , is estimated directly from the  
 326 calculation of the moment of pressure forces on the roughness elements while the fric-  
 327 tion velocity,  $u_\tau$ , is also estimated from the measured form drag. The independence of  
 328  $u_\tau/U_e$  and  $z_0/h$  from the Reynolds number  $Re_\tau$  indicates that the three flow configu-  
 329 rations are in the fully rough regime. The boundary layer thickness,  $\delta$ , shown in Table  
 330 1 defines the wall-normal location at which the mean velocity is equal to 99% of the  
 331 free-stream velocity  $U_e$ . In the measurement cross-section, for all the configurations, the  
 332 non-dimensional pressure gradient  $K = (\nu/\rho U_e^3)dP/dx$  along the wind tunnel was found

---

Symbols	$\lambda_p$ (%)	$U_e$ (m/s)	$u_\tau/U_e$	$\delta/h$	$Re_\tau$	$h^+$	$d/h$	$z_0/h$	$K \times 10^8$	$(h-d)/\delta$	$z_{RSL}/h$
○	6.25	5.65	0.070	22.4	29 700	1330	0.52	0.08	-2.48	0.021	3.6
●	6.25	8.80	0.072	21.5	45 500	2110	0.52	0.09	-1.29	0.022	3.8
△	25	5.77	0.074	22.7	32 400	1430	0.59	0.11	-2.89	0.018	3.6
▲	25	8.93	0.076	22.1	49 900	2260	0.59	0.12	-2.28	0.018	4.0
□	44.4	5.62	0.063	23.2	27 300	1170	0.77	0.04	-2.65	0.010	2.2
■	44.4	8.74	0.063	22.1	40 700	1840	0.77	0.04	-2.12	0.010	2.4

---

TABLE 1. Scaling parameters. The coloured symbols chart will be used in all the following figures.

333 to be below  $-2.9 \times 10^{-8}$ . The aerodynamic parameters  $d$  and  $z_0$  can be used to classify  
334 the roughness flow regime with the model derived by Macdonald et al. (1998) or the data  
335 compiled by Grimmond and Oke (1999). The three canopies studied here represent the  
336 three near-wall flow regimes as defined by Grimmond and Oke (1999) where the  $\lambda_p =$   
337 6.25% represents isolated wake flow,  $\lambda_p = 25\%$  represents wake-interference flow and  $\lambda_p =$   
338 44.4% represents skimming flow (see Fig. 3 of Perret et al. 2019). For further details  
339 the reader is referred to Perret et al. (2019).

340 Fig. 3 shows the wall-normal profiles of the main statistical characteristics of the  
341 streamwise velocity component including mean velocity, variance, skewness and kurtosis  
342 for the six cases shown in Table 1. Scaling using the roughness length and displacement  
343 height results in a collapse of the mean streamwise velocity component in regard to both  
344 canopy geometry and Reynolds number. The remaining statistics show agreement within  
345 the outer layer scaling using the displacement height and boundary layer thickness. How-  
346 ever, both the variance and skewness are influenced by the canopy geometry within the  
347 inner layer close to the roughness. Perret et al. (2019) conducted detailed scaling analy-  
348 sis for these six cases, but were unable to find a scaling that collapses the variance and  
349 skewness close to the wall. One salient feature of the present flow configurations put  
350 forward by these authors is the variation of the wall-normal extent of the roughness sub-  
351 layer as a function of  $\lambda_p$ . While classically defined as the region where the flow statistics  
352 are non-homogeneous in the horizontal plane, Squire et al. (2016) recently proposed to  
353 define its upper limit  $z_{RSL}$  as the lower limit of the inertial region in which the velocity  
354 variance follows a logarithmic law. Following this approach and based on the data shown  
355 in Fig. 3(b), Perret et al. (2019) found that  $z_{RSL}$  varies with the roughness configuration  
356 and Reynolds number (Table 1). This suggests that the densest canopy configuration  
357 prevents the canopy-induced coherent structures from developing in the wall-normal di-  
358 rection. This matches well with the well-recognized picture of the skimming flow regime  
359 in which a thin shear-layer develops at the canopy top with very limited penetration  
360 of the flow within the canopy and is consistent with the recent results of Basley et al.  
361 (2019).

#### 362 4.2. Scale Decomposition

363 In the case of the atmospheric surface layer developing over large roughness elements, the  
364 outer and inner peaks in the energy spectrum are rarely separated. The cubical obstacles  
365 induce energetic structures with typical frequencies smaller than that of the near-smooth  
366 wall turbulence in a range closer to those attributed to the large-scale structures devel-  
367 oping in the logarithmic and outer region. It should also be pointed out that although  
368 the outer peak is not clearly visible this does not mean that large-scale influence does  
369 not exist, but rather that scale separation is not clear and significant overlapping ex-

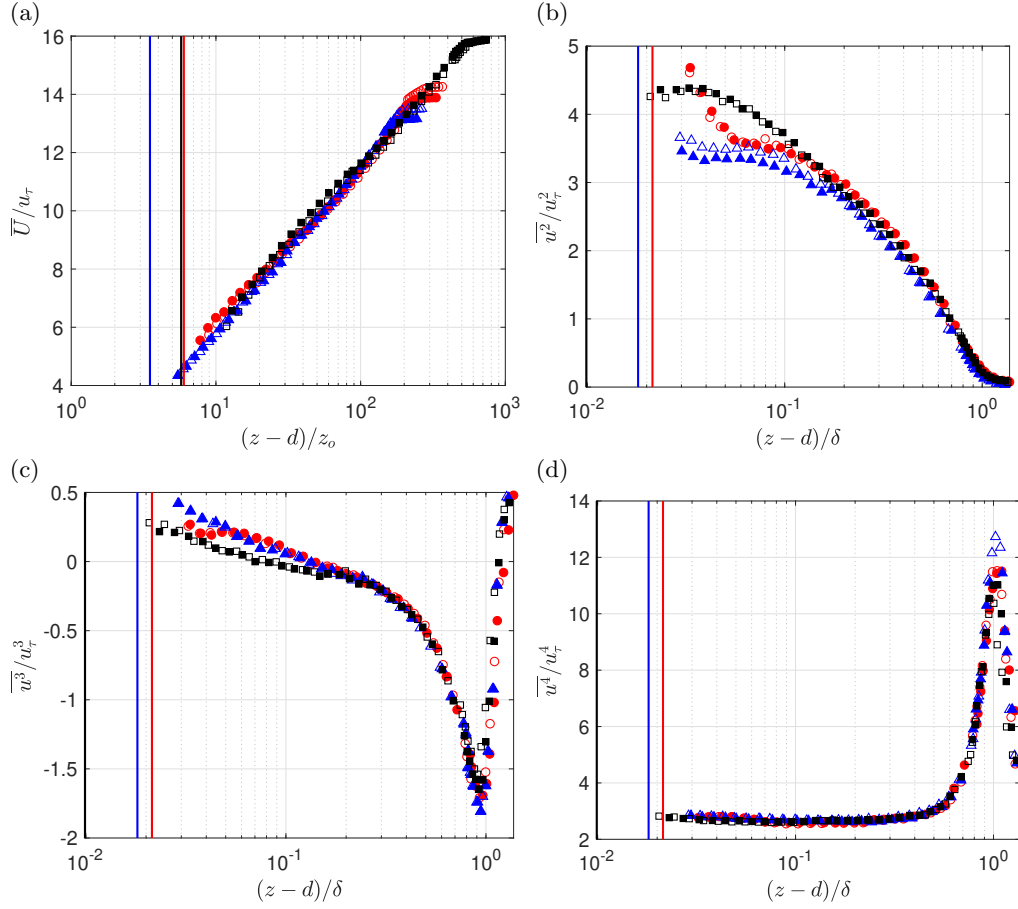


FIGURE 3. Wall-normal profiles of the a) mean b) variance, c) skewness and d) kurtosis of the streamwise velocity component. Vertical solid lines show the wall-normal location of the canopy top  $z = h$  for the three roughness configurations (being negligible when normalizing by  $\delta$ , variation of  $(h - d)/\delta$  with  $Re_\tau$  is not shown).

370 istants between the different coherent structures interacting with each other. This has been  
 371 shown by Perret et al. (2019) and is the reason why the scale-separation method based  
 372 on a two-point measurement approach is favoured here (Baars et al. 2016b; Pathikonda  
 373 and Christensen 2017). Using the method described in §2 the large-scale signal,  $u_L^+$ , is  
 374 extracted from the raw near-wall velocity signal,  $u_{NW}^+$ , at each of the moving HWA probe  
 375 wall-normal locations in each of the six cases using a transfer function. The modulus and  
 376 phase of the transfer function for the moving probe location of  $z/h = 1.25$  in each of  
 377 the six cases are shown in Fig. 4 where it is clear that the modulus and phase of the  
 378 transfer function depend on the canopy geometry, but not on the Reynolds number. In  
 379 this section, the focus is on the main statistical characteristics of  $u_L$  and  $u_S$  and their  
 380 contribution to the skewness, which is an indicator of the existence of amplitude modu-  
 381 lation (Duvvuri and McKeon 2015). A thorough analysis of the spectral content of the  
 382 flow and of its large- and small-scale components has been performed by Perret et al.  
 383 (2019) and Basley et al. (2019) in the same flow configurations as here. These authors  
 384 demonstrated the co-existence of VLSMs, LSMs and canopy-generated coherent struc-

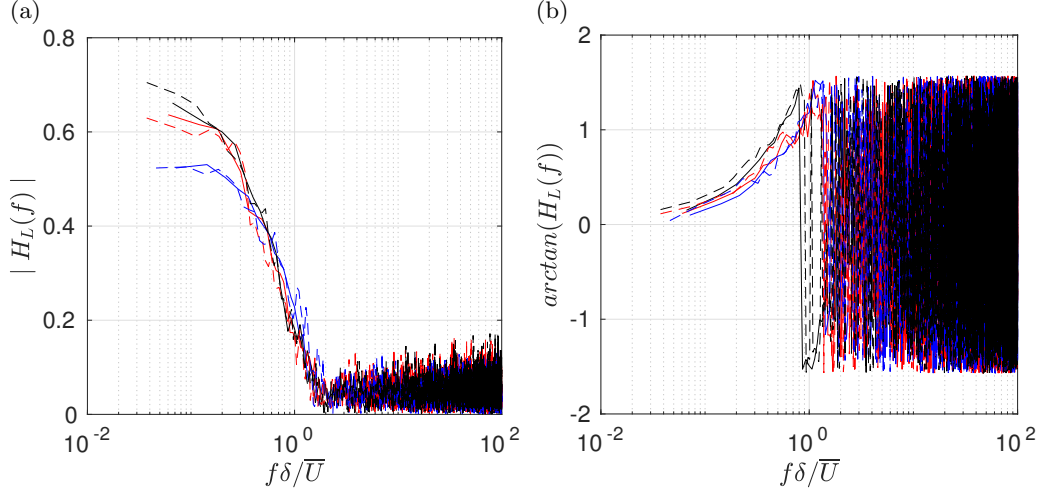


FIGURE 4. a) Modulus and b) phase of the transfer kernel  $|H_L|$  at  $z/h = 1.25$  for configurations with  $\lambda_p = 6.25\%$ ,  $25\%$  and  $44.4\%$  at  $Re_\tau = 32\,400$  and  $49\,900$ . The colour chart is as per Table 1 for canopy configurations, solid and dashed lines correspond respectively to the low and the high Reynolds numbers.

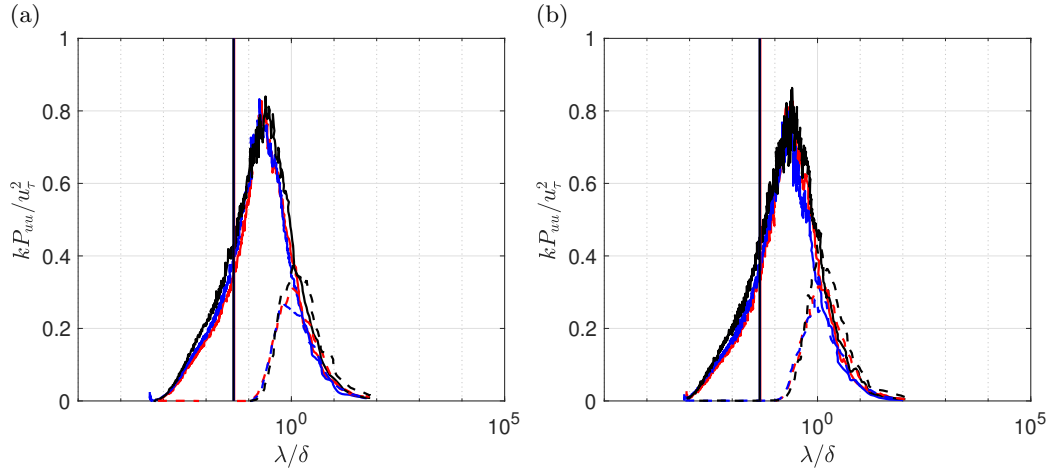


FIGURE 5. Spectra of  $u^*$  (solid line) and  $u_L^+$  (dashed line) for configurations with  $\lambda_p = 6.25\%$ ,  $25\%$  and  $44.4\%$  at a)  $Re_\tau = 32\,400$  and b)  $49\,900$  at  $z/h = 2.1$ . Vertical solid lines show the streamwise wavelength corresponding to the obstacle height  $\lambda = h$ .

385 tures whose characteristics obey different scaling laws. For the sake of conciseness, these  
 386 results are not recalled here, the reader being referred to these studies.

387 Once  $u_L^+$  is extracted using triple decomposition† the small-scale signal,  $u_S^+$ , can be  
 388 computed. Finally,  $u^*$  is computed using the method described in §2. The spectra of the  
 389 universal and large-scale signal (Fig. 5) of the six cases show the differences in energy  
 390 content of the two signals. No significant change occurs in the energy distribution between  
 391 the different canopies and different Reynolds numbers. Finally, an increase in Reynolds  
 392 number does not affect the magnitude of energy contained in the universal and large-

† Triple decomposition was first introduced by Hussain (1983) to decompose the instantaneous velocity field into mean, large-scale and small-scale components.

393 scale signals. This last point may be tempered by the narrow range of Reynolds number  
 394 used here, as it has been shown previously that the large-scale content increases as the  
 395 Reynolds number increases (see Mathis et al. 2009, 2011a among others). The statistics  
 396 of the  $u^*$  signal including variance, skewness and kurtosis are compared in Fig. 6 with the  
 397 statistics of the raw near-wall velocity signal  $u_{NW}^+$ ,  $u_L^+$  and  $u_S^+$  showing only the  $\lambda_p = 25\%$   
 398 case as an example. In all six cases (not shown here)  $u_S^+$  captures the majority of the  
 399 variance in the inner layer while the large-scale contribution becomes important only in  
 400 the outer layer. The skewness is shown to be almost completely captured by  $u_S^+$  with the  
 401 contribution from  $u_L^+$  close to zero. The kurtosis of the raw signal is shown to be a result  
 402 of both  $u_L^+$  and  $u_S^+$  with the contribution of  $u_S^+$  increasing with wall-normal distance in  
 403 the outer layer. Mathis et al. (2011a) noted that the universal signal is the signal that  
 404 exists in the absence of the influence of large-scale structures while  $u_S^+$  is the signal that  
 405 exists in the absence of any superposition. Therefore a comparison between the  $u_S^+$  and  
 406  $u^*$  signals provides insight into the influence of the amplitude modulation on the  $u_S^+$   
 407 structures. The presence of amplitude modulation causes no influence in the variance or  
 408 kurtosis as  $u_S^+$  and  $u^*$  have similar profiles. In the absence of amplitude modulation the  
 409 magnitude of skewness of  $u^*$  is significantly lower throughout the boundary layer. These  
 410 trends are true for each of the six configurations except in the case of the skewness of  $u^*$ .  
 411 The wall-normal location at which the profile of the skewness of  $u^*$  crosses the profile  
 412 of the skewness of  $u_L^+$  changes depending on the roughness configuration. In roughness  
 413 configurations with  $\lambda_p = 6.25\%$  or  $25\%$  the  $u^*$  profile crosses the  $u_L^+$  profile at a wall-  
 414 normal distance of approximately  $(z - d)/\delta = 0.09$  while in roughness configurations  
 415 with  $\lambda_p = 44.4\%$  this crossing occurs at  $(z - d)/\delta = 0.05$ . As  $u^*$  is the signal that  
 416 exists in the absence of influence of the large scales it should correspond to a signal  
 417 from a low Reynolds number flow where large-scale influence is weak. The decrease of  
 418 contribution of  $u^*$  to the skewness in the configuration with  $\lambda_p = 44.4\%$  is a result of  
 419 increased large-scale activity. No significant differences are found between cases when  
 420 varying Reynolds number as both Reynolds numbers are sufficient to generate significant  
 421 large-scale activity and differ by less than a factor of two.

#### 4.3. Influence of canopy geometry and Reynolds number

422 Skewness decomposition as shown in Eq. 4.1 has been used to investigate the non-linear  
 423 interactions between large- and small-scale structures in turbulent flows (Blackman and  
 424 Perret 2016).  
 425

$$\overline{u^{+3}} = \overline{u_S^{+3}} + \overline{u_L^{+3}} + 3\overline{u_L^+ u_S^{+2}} + 3\overline{u_L^{+2} u_S^+} \quad (4.1)$$

426 Here it is used to determine the influence of the canopy geometry and Reynolds number  
 427 on these non-linear interactions. Figure 7 shows the small-scale skewness, large-scale  
 428 skewness and two scale-interaction terms. The influence of the canopy geometry is par-  
 429 ticularly apparent in the contribution of the small scales close to the canopy where there  
 430 is a clear separation between the cases (Fig. 7a). This separation is a result of the distinct  
 431 canopy flow regimes in each of the cases. As mentioned, within the skimming flow regime  
 432 ( $\lambda_p = 44.4\%$ ) there is a thinner shear layer (or roughness sublayer) whereas in the iso-  
 433 lated wake ( $\lambda_p = 6.25\%$ ) and wake-interference ( $\lambda_p = 25\%$ ) flow regimes the shear layer  
 434 wall-normal extent is larger increasing the importance of the small scales. Away from  
 435 the canopy, in the outer-layer, the influence of the canopy geometry or flow regime is not  
 436 significant. Moreover, throughout the boundary layer the canopy geometry does not sig-  
 437 nificantly influence the large-scale contribution or the contribution of the non-linear term  
 438  $\overline{u_L^{+2} u_S^+}$ , which represents the influence of the small scales onto the large scales. However,

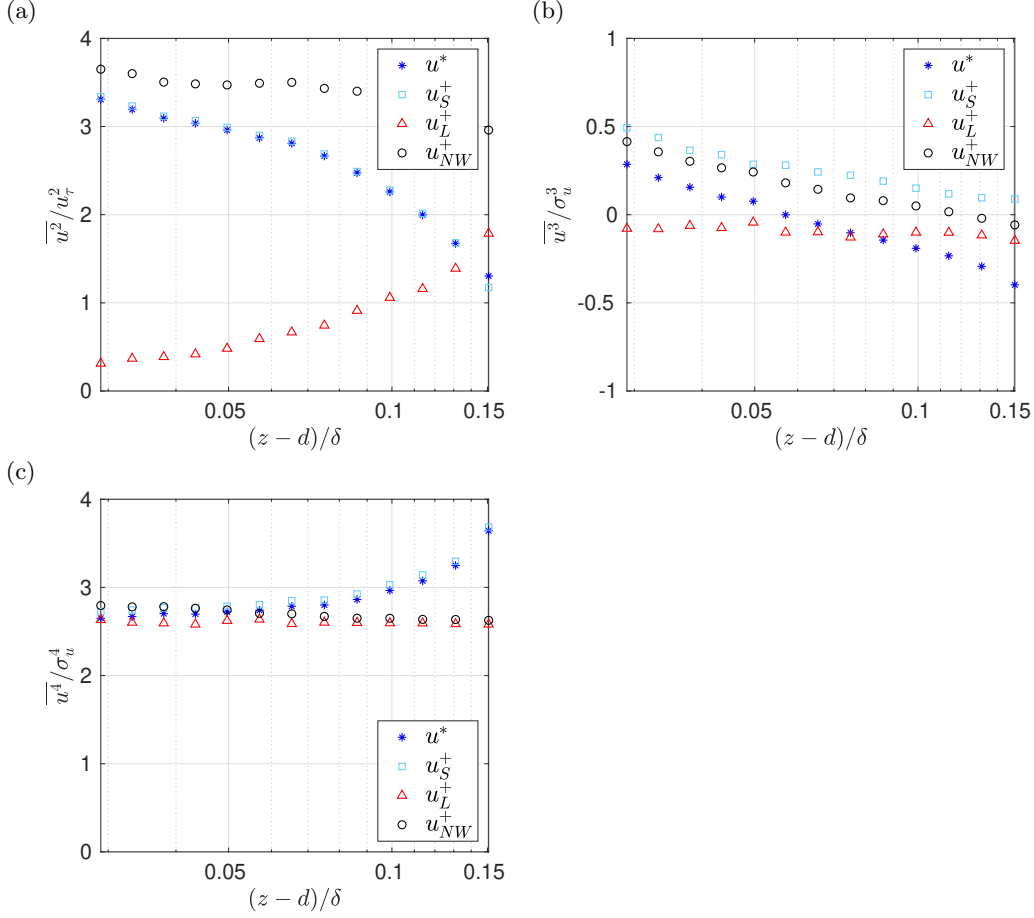


FIGURE 6. Comparison of  $u^*$ ,  $u_L^+$ ,  $u_S^+$  and  $u_{NW}^+$  statistics a) variance, b) skewness and c) kurtosis for configuration with  $\lambda_p = 25\%$  at  $Re_\tau = 32\,400$ .

439 an increase in Reynolds number increases the contribution of this non-linear term within  
 440 the outer-layer (Fig. 7d). Finally, the non-linear term  $\overline{u_L^+ u_S^{+2}}$  has been shown to represent  
 441 the amplitude modulation (Mathis et al. 2011c; Duvvuri and McKeon 2015). Here, it is  
 442 clear that although the canopies with  $\lambda_p = 6.25\%$  and  $25\%$  display similar amplitude  
 443 modulation, the amplitude modulation of the canopy with  $\lambda_p = 44.4\%$  is significantly  
 444 modified at both Reynolds numbers (Fig. 7c). Throughout the boundary layer, except  
 445 close to the canopy, the amplitude modulation is weaker in the  $\lambda_p = 44.4\%$  canopy. As  
 446 mentioned in section 4.1, this flow configuration has the finest roughness sublayer. This  
 447 is confirmed if one considers the wall-normal location of the zero-crossing of the skewness  
 448 of the streamwise velocity component as the upper limit of the roughness sublayer  
 449 (Fig. 7a). It is also where the small-scale component  $u_S$  is the least energetic relative to  
 450 the large scales (Perret et al. 2019). In this flow configuration, the small scales are less  
 451 energetic and more confined to near the canopy top, the amplitude modulation imprint  
 452 is therefore weaker than the two other cases.

453 The coefficients  $\alpha$  and  $\beta$  of the predictive model computed for each of the cases listed  
 454 in Table 1 using the method in §2 are shown in Fig. 8 along with the coefficient  $\Gamma$ . The  
 455 roughness configuration affects the superposition coefficient,  $\alpha$ , close to the roughness

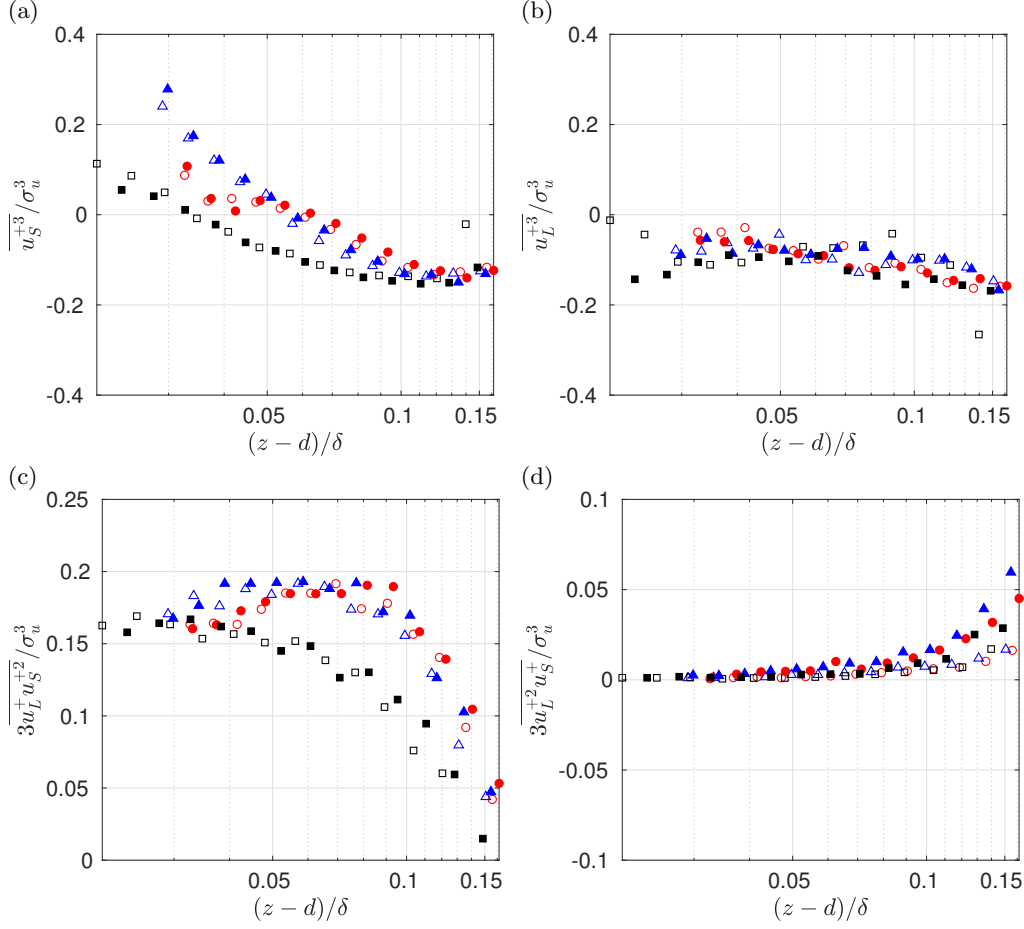


FIGURE 7. Triple decomposition of the skewness of the streamwise velocity component including a)  $\overline{u_S^{+3}}$ , b)  $\overline{u_L^{+3}}$ , c)  $\overline{3u_L^+ u_S^{+2}}$  and d)  $\overline{3u_L^{+2} u_S^+}$ .

456 in the inner layer where differences in the flow regimes are important. However, in the  
 457 outer layer the superposition is consistent in all roughness configurations. In the outer  
 458 layer the influence of the roughness flow regime disappears and the large-scale structures  
 459 become similar thereby resulting in similar superposition. The amplitude modulation  
 460 coefficient,  $\beta$ , depends on roughness configuration in the inner layer, but in the case of  
 461 the roughness configuration with  $\lambda_p = 44.4\%$  the amplitude modulation is decreased both  
 462 in the inner layer and the outer layer. This is consistent with the non-linear term  $\overline{u_L^+ u_S^{+2}}$   
 463 which shows lower magnitudes of amplitude modulation in the  $\lambda_p = 44.4\%$  configuration.  
 464 As discussed, the characteristics of the shear layer in the skimming flow regime change  
 465 the characteristics of the small-scale structures and their interactions with the large-scale  
 466 structures in the outer layer above. The dependence of the superposition and amplitude  
 467 modulation on the roughness configuration close to the roughness is a result of changes  
 468 to the dynamics of the shear layers that develop at the top of the roughness elements  
 469 in the different flow regimes. Within the skimming flow regime the shear layer does not  
 470 penetrate the roughness elements resulting in a thin, but strong shear layer, whereas  
 471 the spacing between roughness elements in the isolated and wake-interference regimes  
 472 result in a shear layer that penetrates the canopy layer increasing the vertical transfer



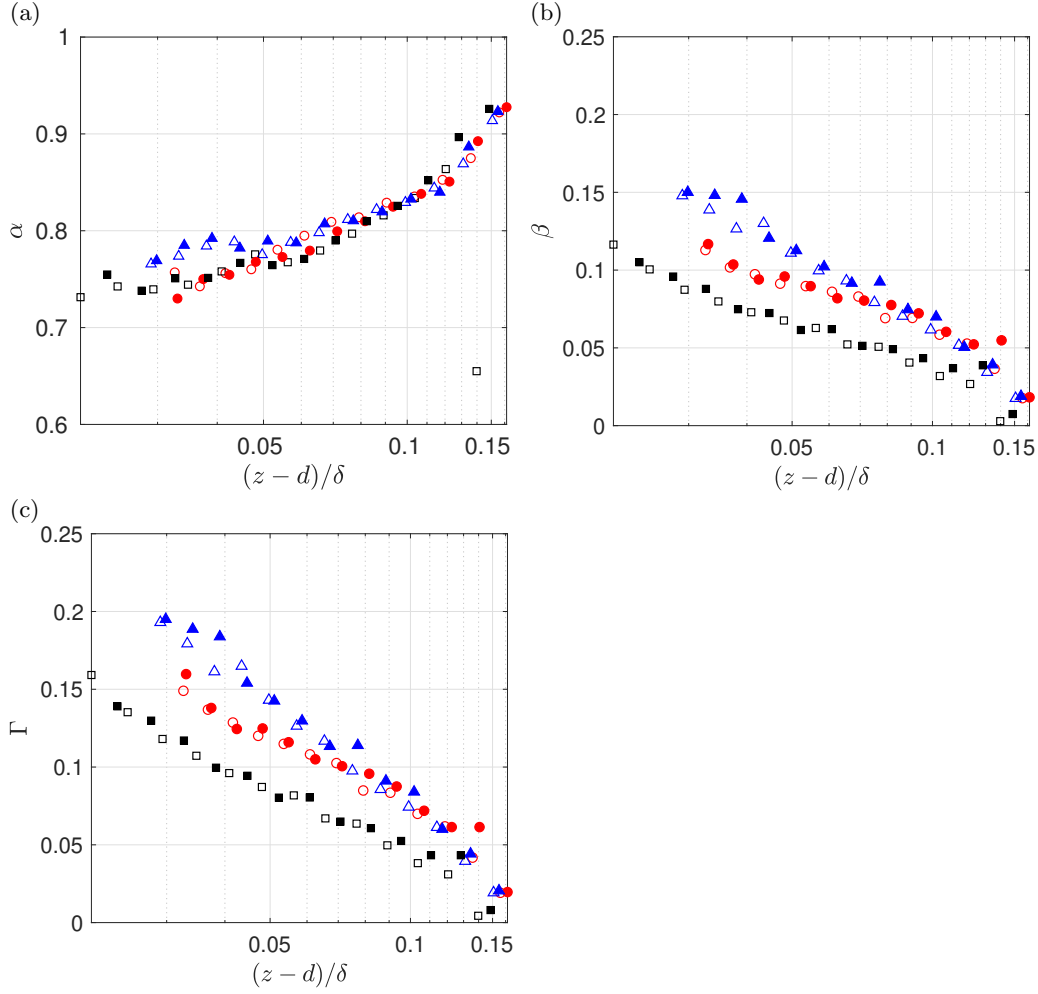


FIGURE 8. Predictive model coefficients a)  $\alpha$ , b)  $\beta$  and c)  $\Gamma$  for configurations with  $\lambda_p = 6.25\%$ ,  $25\%$  and  $44.4\%$  at  $Re_\tau = 32\,400$  and  $49\,900$ .

473 of momentum of small-scale structures in this region (Basley et al. 2019). The shear  
 474 layer in the wake-interference flow regime also experiences a strong flapping phenomenon  
 475 that promotes the transfer of momentum between the canopy layer (small scales) and  
 476 outer layer (large scales). The results show that an increase in Reynolds number does not  
 477 increase the superposition or the amplitude modulation in contradiction to Mathis et al.  
 478 (2011a) who found that increased Reynolds number increases the large-scale activity in  
 479 the outer layer thereby increasing the amplitude modulation. These results should be  
 480 tempered by the fact that the Reynolds numbers used here are not sufficiently separated  
 481 to significantly affect the large scales and therefore the scale interactions.

482 The variance, skewness and kurtosis of the universal signal,  $u^*$ , and  $u_L^+$  in each of the  
 483 six cases are presented in Fig. 9. The influence of the roughness configuration can be seen  
 484 in the profiles of variance and skewness in the inner-layer close to the roughness, whereas  
 485 this influence becomes negligible in the profile of kurtosis. The changes in variance and  
 486 skewness are a result of changes to the small-scale structures produced by the roughness.  
 487 Small scales in the wake-interference flow regime have larger magnitudes of skewness

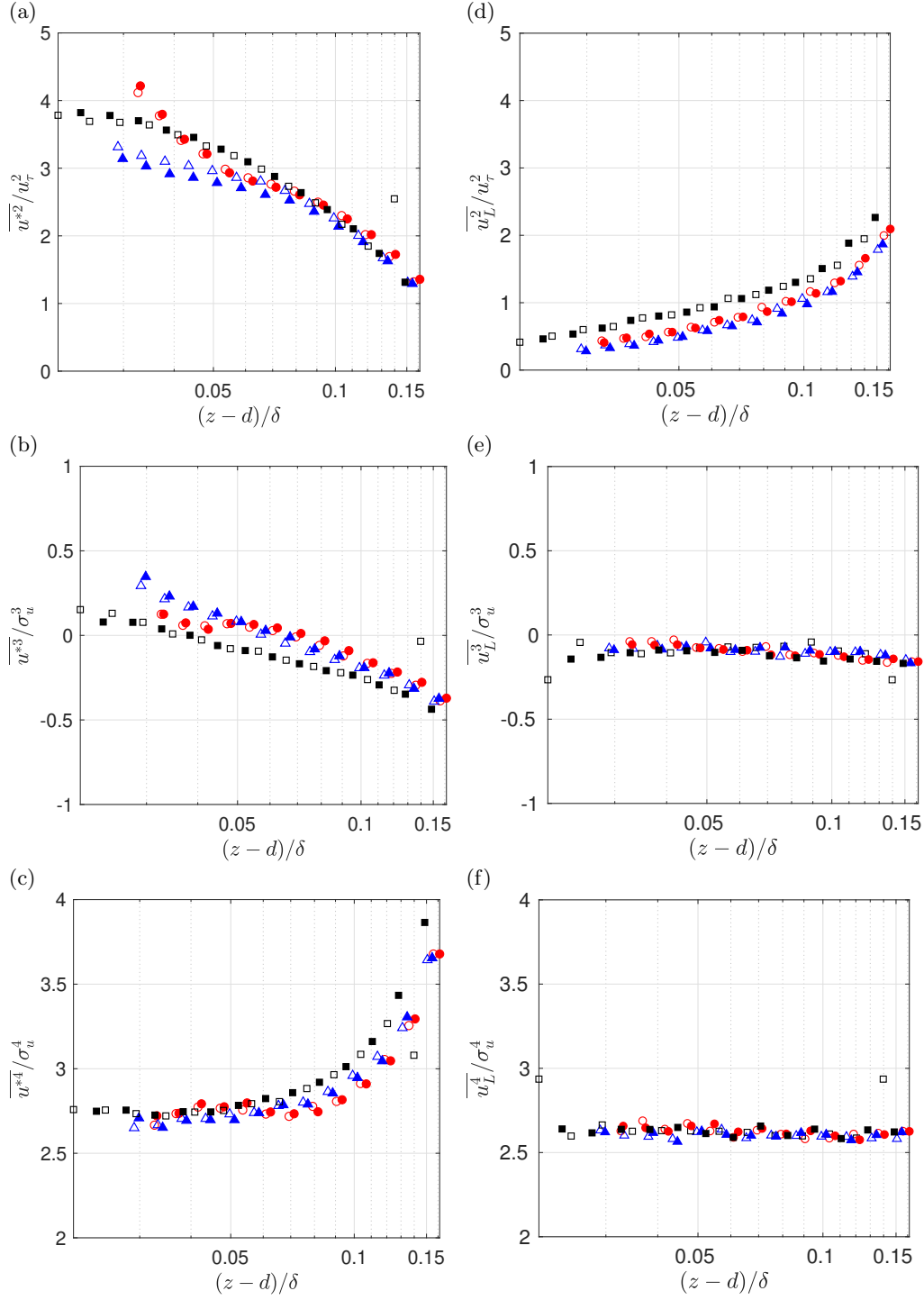


FIGURE 9. Comparison of  $u^*$  statistics a) variance, b) skewness and c) kurtosis and  $u_L^+$  statistics d) variance, e) skewness and f) kurtosis for configurations with  $\lambda_p = 6.25\%$ ,  $25\%$  and  $44.4\%$  at  $Re_\tau = 32\,400$  and  $49\,900$ .

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	Test 1		Test 2		Test 3	
	$\lambda_p$ (%)	$Re_\tau$	$\lambda_p$ (%)	$Re_\tau$	$\lambda_p$ (%)	$Re_\tau$
Calibration	25	32 400	25	32 400	44.4	32 400
Large-scale	25	49 900	6.25 or 44.4	32 400	25	49 900
Prediction	25	49 900	25	32 400	44.4	49 900

---

TABLE 2. Characteristics of the input (calibration parameters and large-scale signal) and output of the predictive model used for testing and validating the prediction capabilities of the model.

---

488 and smaller magnitudes of turbulence intensity compared to the skimming flow regime.  
489 Although there is an increase in magnitude of variance of the large-scale structures in the  
490 44.4% configuration these changes are not limited to the region close to the roughness  
491 as in the  $u^*$  profile (Fig. 9d). Excluding this slight increase in the variance the similarity  
492 of the other  $u_L^+$  profiles suggests that the very-large-scale structures in each of the cases  
493 have similar characteristics. Using the outer-layer scaling a change in Reynolds number  
494 does not affect the statistics of the universal or large-scale signals. These results have  
495 shown that the model coefficients and universal signal are significantly influenced by the  
496 canopy geometry or canopy flow regime while the large-scale structures have been shown  
497 to be similar in each of the cases. Therefore, the universal signal is not universal for all  
498 rough-wall boundary layers and the predictive model must be calibrated for each of the  
499 roughness flow regimes.

#### 500 4.4. Prediction and Validation

501 Model coefficients provided by the calibration allow for the prediction of a statistically  
502 representative signal,  $u_p^+$ , that hypothetically can be reconstructed at any Reynolds num-  
503 ber, where the only required input is the large-scale reference signal,  $u_L^+$ . In this section,  
504 a series of tests are performed in order to assess whether the above assumption, which  
505 works well in smooth-wall boundary layer, still holds in an atmospheric boundary layer  
506 over an urban canopy. To do so, a series of tests is performed to validate and assess  
507 the capabilities of the model, in which canopy configuration and Reynolds numbers are  
508 mixed, as seen in Table 2.

509 The capabilities of the predictive model, which has been calibrated for  $\lambda_p = 25\%$   
510 and  $Re_\tau = 32\,400$ , is first tested by predicting the near-canopy signal for the same  
511 plan density at the higher Reynolds number  $Re_\tau = 49\,900$  (Test 1). To do this a large-  
512 scale reference signal measured at  $Re_\tau = 49\,900$  is used to run the predictive model  
513 where the universal signal and model coefficients were determined from a calibration at  
514  $Re_\tau = 32\,400$ . Additionally, the large-scale reference signal must be interpolated onto  
515 the non-dimensional time-scale  $t^+$  of the universal signal so that the time sampling of  
516 both signals is consistent. In addition, the two signals must have the same length, by  
517 clipping the longest of the two. Figure 10 shows the characteristics of the predicted  
518 signal (blue stars) compared with the characteristics of the measured near-canopy signal  
519 (black circles) up to the 4<sup>th</sup> order. Although there is some slight discrepancy between  
520 the prediction and the near-canopy signal, it is clear that the predictive model calibrated  
521 at a lower Reynolds number is able to reproduce the characteristics of the near-canopy  
522 signal at a higher Reynolds number. Finally, the spectra of the predicted signal are  
523 similar to the spectra of the measured signal as shown in Fig. 11. There is a slight shift  
524 in the wavelength of the spectra of the predicted signal that becomes more significant  
525 closer to the roughness. This might be due to the application of Taylor’s hypothesis  
526 which has questionable suitability close to the roughness. However, the similarity of the

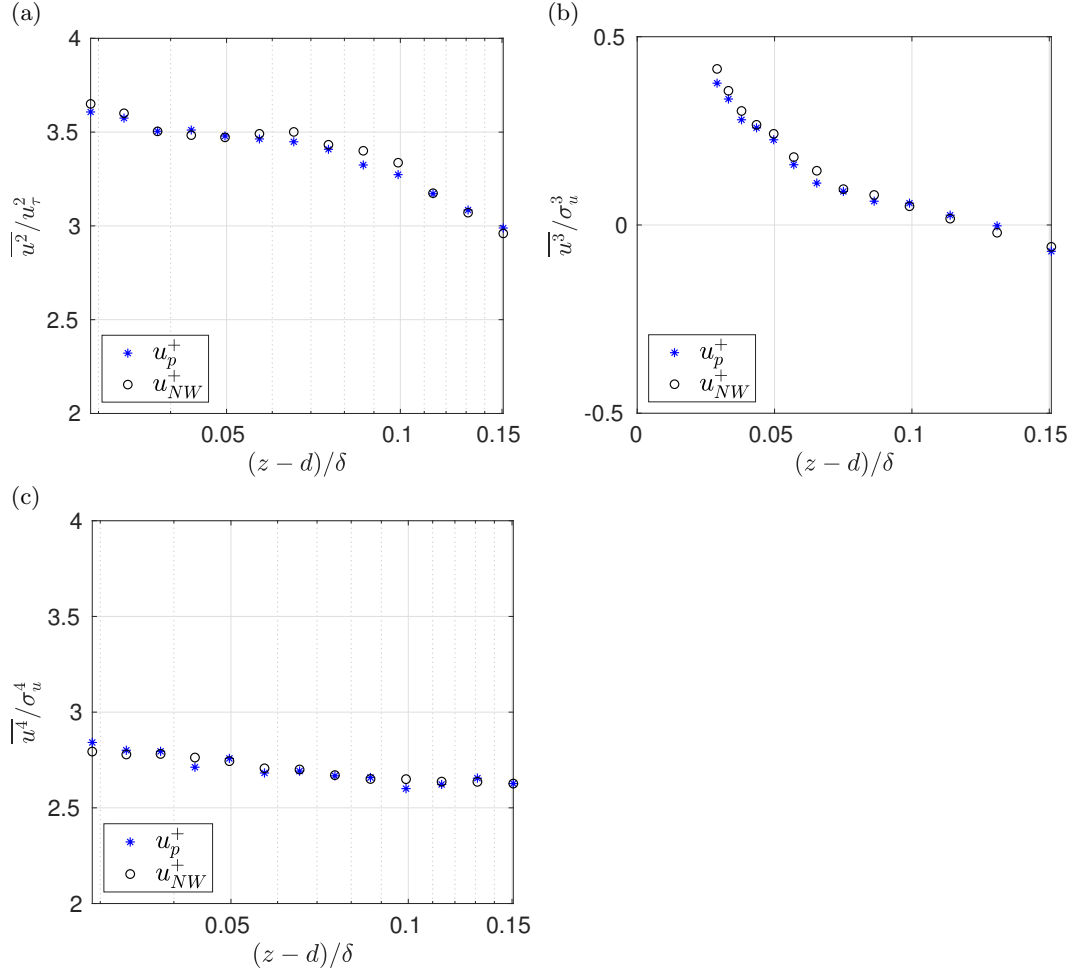


FIGURE 10. Comparison of  $u_{NW}^+$  and  $u_p^+$  statistics a) variance, b) skewness and c) kurtosis for  $\lambda_p = 25\%$  and  $Re_\tau = 49900$  where  $u_p^+$  is determined using model coefficients calibrated at  $Re_\tau = 32400$  and  $u_L^+$  at  $Re_\tau = 49900$  (Test 1).

527 spectra further validates the model and suggests that the model can be calibrated at any  
 528 arbitrary Reynolds number.

529 Another crucial question in making a predictive model for urban canopy flow, is to  
 530 what extent the calibration is dependent on the plan area packing density at which the  
 531 calibration is performed. Indeed, the previous section clearly evidenced that the universal  
 532 signal and model coefficients are canopy dependent. In an attempt to shed light on this,  
 533 the near-canopy signal is predicted for the  $\lambda_p = 25\%$  at  $Re_\tau = 32400$  configuration using  
 534 large-scale reference signals from the datasets of the  $\lambda_p = 6.25\%$  and  $44.4\%$  configurations  
 535 at the same Reynolds number (Test 2). To perform these predictions the calibrated model  
 536 for the  $\lambda_p = 25\%$  configuration is used along with a large-scale reference signal from a  
 537 configuration with a different  $\lambda_p$ . As above, the large-scale reference signal from either  
 538 the  $\lambda_p = 6.25\%$  or  $44.4\%$  configuration is interpolated onto the non-dimensional time-  
 539 scale of the universal signal calibrated for the  $\lambda_p = 25\%$  configuration. Fig. 12 shows  
 540 the characteristics of the predicted signal using a large-scale reference from the  $\lambda_p =$   
 541  $6.25\%$  configuration (blue triangles),  $\lambda_p = 44.4\%$  configuration (red squares) and the

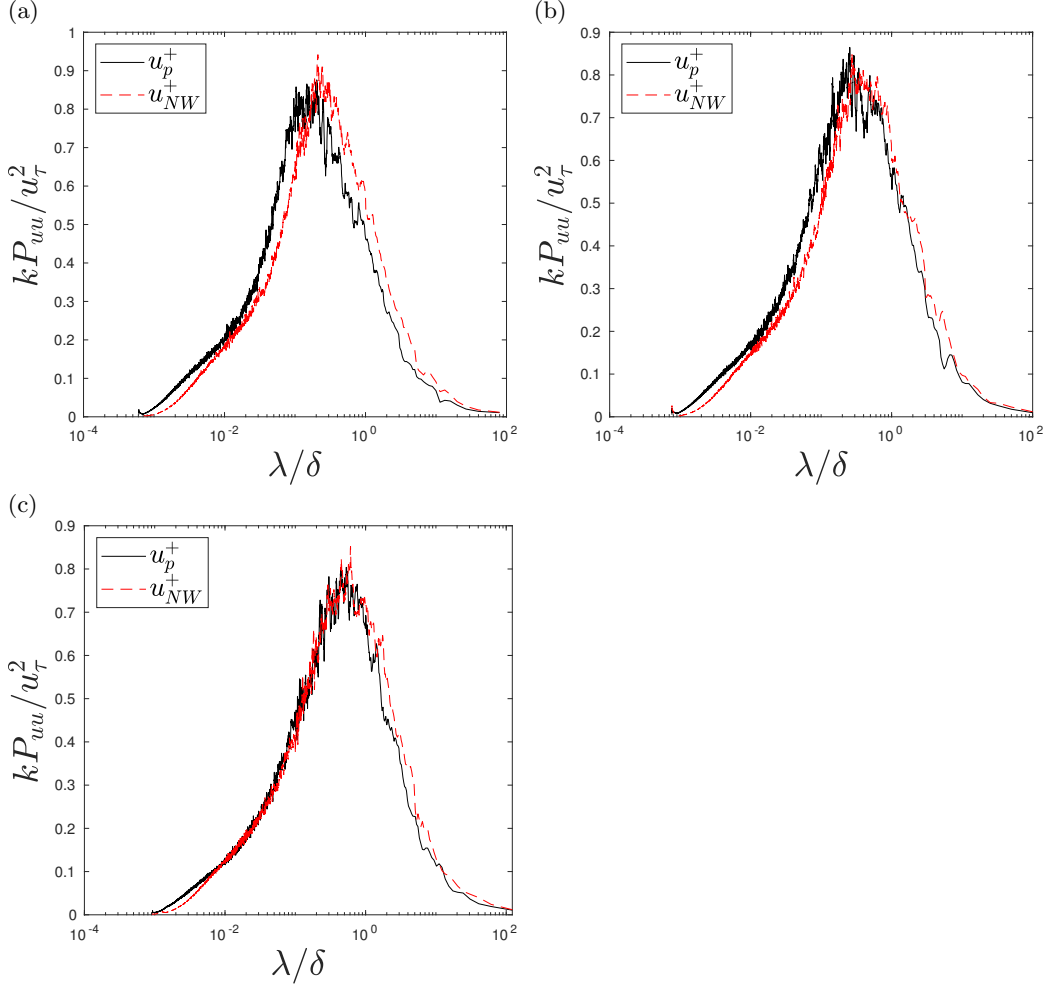


FIGURE 11. Spectra of  $u_{NW}^+$  and  $u_p^+$  at a)  $z/h = 1.25$ , b)  $z/h = 2.1$  and c)  $z/h = 3.2$  for  $\lambda_p = 25\%$  and  $Re_\tau = 49\,900$  where  $u_p^+$  is determined using model coefficients calibrated at  $Re_\tau = 32\,400$  and  $u_L^+$  at  $Re_\tau = 49\,900$  (Test 1).

542 measured near-canopy signal of the  $\lambda_p = 25\%$  configuration (black circles). The spectra  
 543 of the predicted signals and measured near-canopy signal are shown at several wall-  
 544 normal locations in Fig. 13. There is excellent agreement between the predicted signals  
 545 and the near-canopy signal for the statistics up to the 4<sup>th</sup> order and the spectra in both  
 546 prediction cases.

547 To determine the error associated with these predictions the near-canopy signal was  
 548 predicted within each canopy using a large-scale reference signal from each of the other  
 549 canopy configurations for the lowest wall-normal location of  $z/h = 1.25$  as a test. The  
 550 error for the statistics up to the 4<sup>th</sup> order was computed for each prediction using Eq. 4.2  
 551 where  $\phi_m$  and  $\phi_p$  are any statistics of the original measured and predicted signals, re-  
 552 spectively.

$$error = (\phi_m - \phi_p) / \phi_m \quad (4.2)$$

553 Fig. 14 shows the error averaged over the two predictions for each canopy configura-

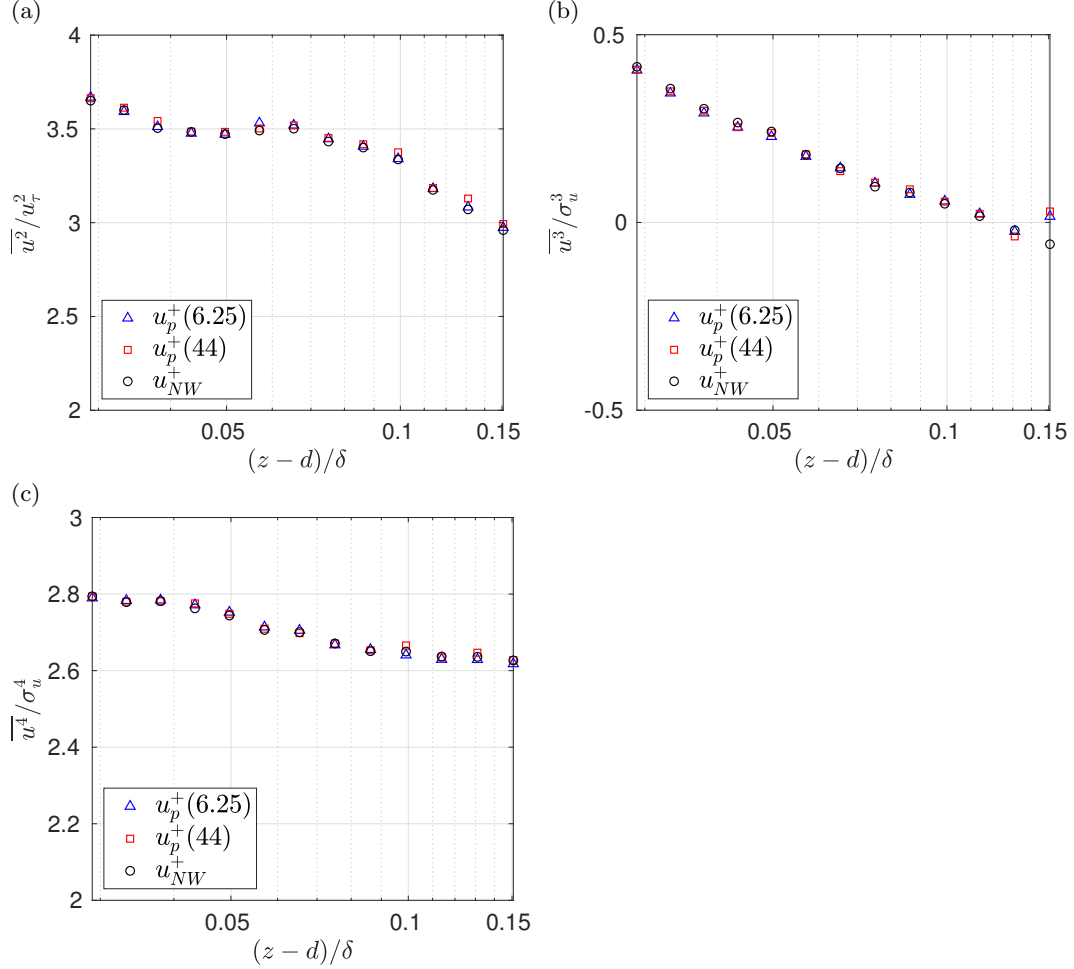


FIGURE 12. Comparison of  $u_{NW}^+$  and  $u_p^+$  statistics a) variance, b) skewness and c) kurtosis for  $\lambda_p = 25\%$  and  $Re_\tau = 32\,400$  where  $u_p^+$  is determined using model coefficients calibrated for  $\lambda_p = 25\%$  and  $u_L^+$  from  $\lambda_p = 6.25\%$  or  $44.4\%$  (Test 2).

554 tion. The error is less than 3% for all statistics and in all canopies with the largest error  
 555 of 3% for the kurtosis of the  $\lambda_p = 25\%$  configuration. This confirms that a calibrated pre-  
 556 dictive model can be used to predict the near-canopy signal using a large-scale reference  
 557 signal measured in any other canopy configuration.

558 The final validation of the model combines both the Reynolds number and  $\lambda_p$  validation  
 559 by predicting a near-canopy signal within the  $\lambda_p = 44.4\%$  configuration at  $Re_\tau = 49\,900$   
 560 using the calibrated model at  $Re_\tau = 32\,400$  and a large-scale reference signal from the  
 561  $\lambda_p = 25\%$  configuration at  $Re_\tau = 49\,900$  (Test 3). As in the previous validation the  
 562 model is able to accurately reproduce the spectra of the near-canopy signal as well as  
 563 the statistics up to the 4<sup>th</sup> order (Fig. 15). The model is able to accurately reproduce  
 564 these statistics because, as has been shown here, the characteristics of the large scales  
 565 in each of the canopies are similar. However, the differences in the characteristics of the  
 566 universal signal and the predictive model coefficients prevent the application of a  
 567 calibrated model at one  $\lambda_p$  to a prediction at another  $\lambda_p$ . The model must be calibrated  
 568 using measurements from a canopy with the same configuration as the targeted one.

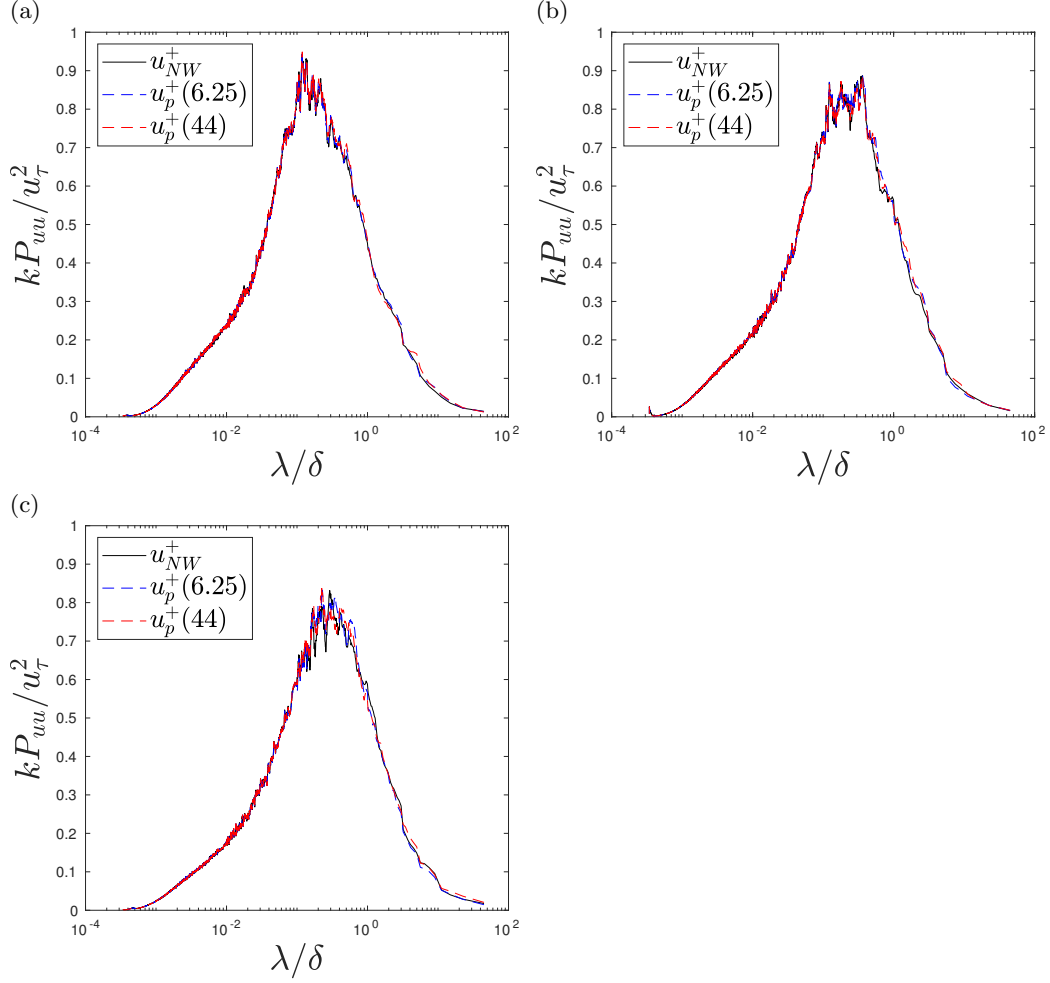


FIGURE 13. Spectra of  $u_{NW}^+$  and  $u_p^+$  at a)  $z/h = 1.25$ , b)  $z/h = 2.1$  and c)  $z/h = 3.2$  for  $\lambda_p = 25\%$  and  $Re_\tau = 32\,400$  where  $u_p^+$  is determined using model coefficients calibrated for  $\lambda_p = 25\%$  and  $u_L^+$  from  $\lambda_p = 6.25\%$  or  $44.4\%$  (Test 2).

569 In the smooth wall special attention has been paid to conserving the phase between  
 570 the universal signal and large-scale signal used to run the predictive model (Mathis et al.  
 571 2011a). In these cases the large-scale reference signal used to run the predictive model  
 572 was adjusted to retain the Fourier phase information of the large-scale signal used to  
 573 build the universal signal. The phase information of the original large-scale signal is  
 574 extracted using a Fourier transform and applied to the new large-scale reference signal.  
 575 This process essentially re-synchronizes the new large-scale reference with the universal  
 576 signal,  $u^*$  (Mathis et al. 2011c). Here, this process was applied before performing the  
 577 predictions detailed above. To determine influence of the phase shift on a prediction  
 578 a test is performed using the large-scale reference signal used to build the predictive  
 579 model. This signal is shifted out of phase with the universal signal and a prediction of  
 580 the statistics made at each time-shift (Fig 16). As the phase shift increases the estimation  
 581 of the variance, skewness and kurtosis worsen until they reach a plateau. The effect of the  
 582 phase shift increases with increasing order of the statistic with the kurtosis showing the

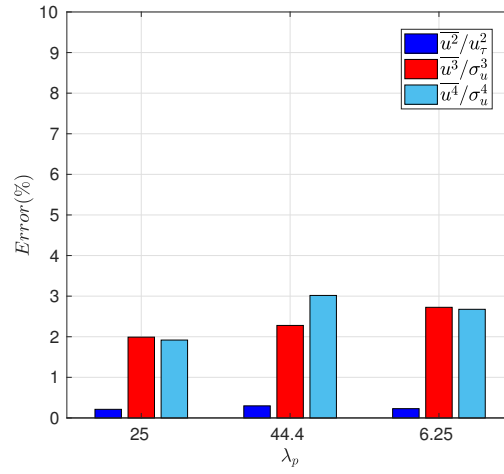


FIGURE 14. Error of  $u_p^+$  statistics variance, skewness and kurtosis where  $u_p^+$  is determined using model coefficients calibrated at a certain  $\lambda_p$  and  $u_L^+$  at a different  $\lambda_p$  both at  $Re_\tau = 32\ 400$ .

583 largest discrepancy. This suggests that conserving the phase information of the large-scale  
 584 signal used to calibrate the model is important to the prediction.



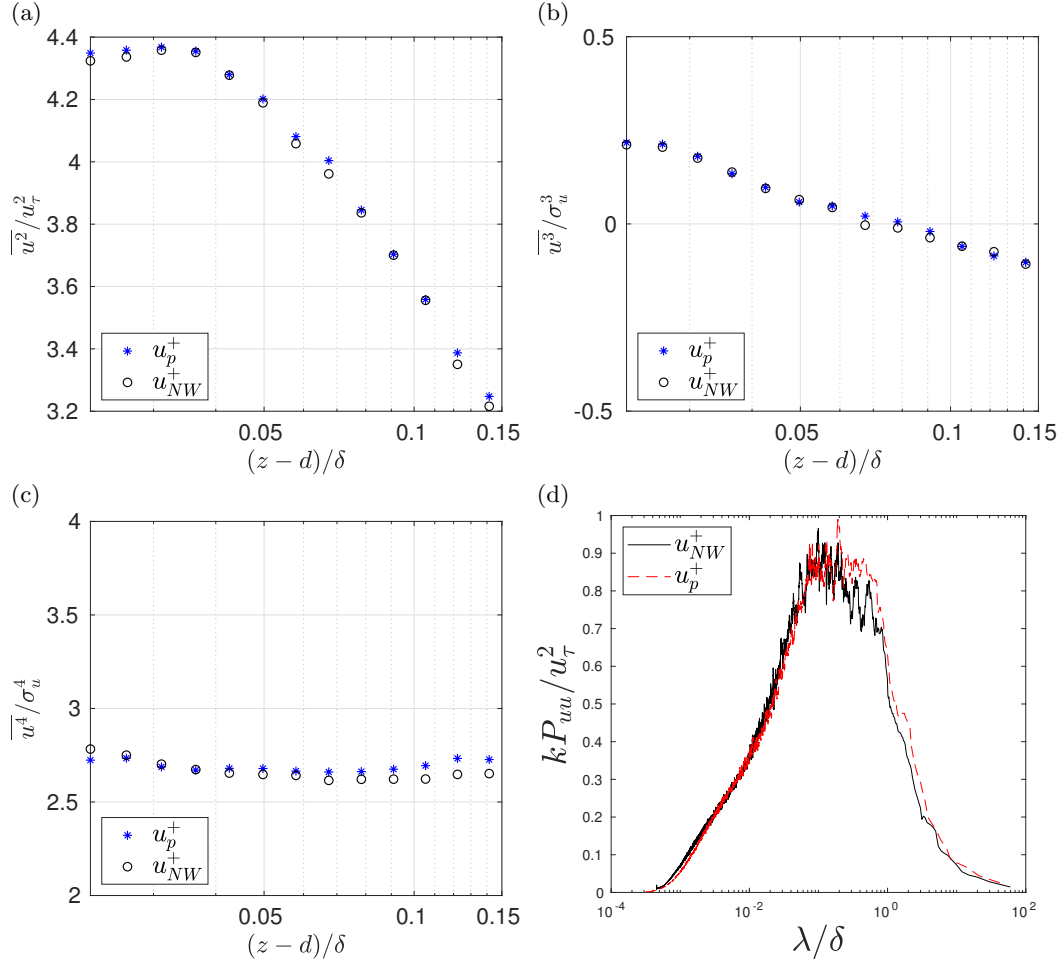


FIGURE 15. Comparison of  $u_{NW}^+$  and  $u_p^+$  statistics a) variance, b) skewness and c) kurtosis and d) spectra at  $z/h = 1.5$  for  $\lambda_p = 44.4\%$  and  $Re_\tau = 49\,900$  where  $u_p^+$  is determined using model coefficients calibrated for  $\lambda_p = 44.4\%$  and  $Re_\tau = 32\,400$  and  $u_L^+$  from  $\lambda_p = 25\%$  and  $Re_\tau = 49\,900$  (Test 3).

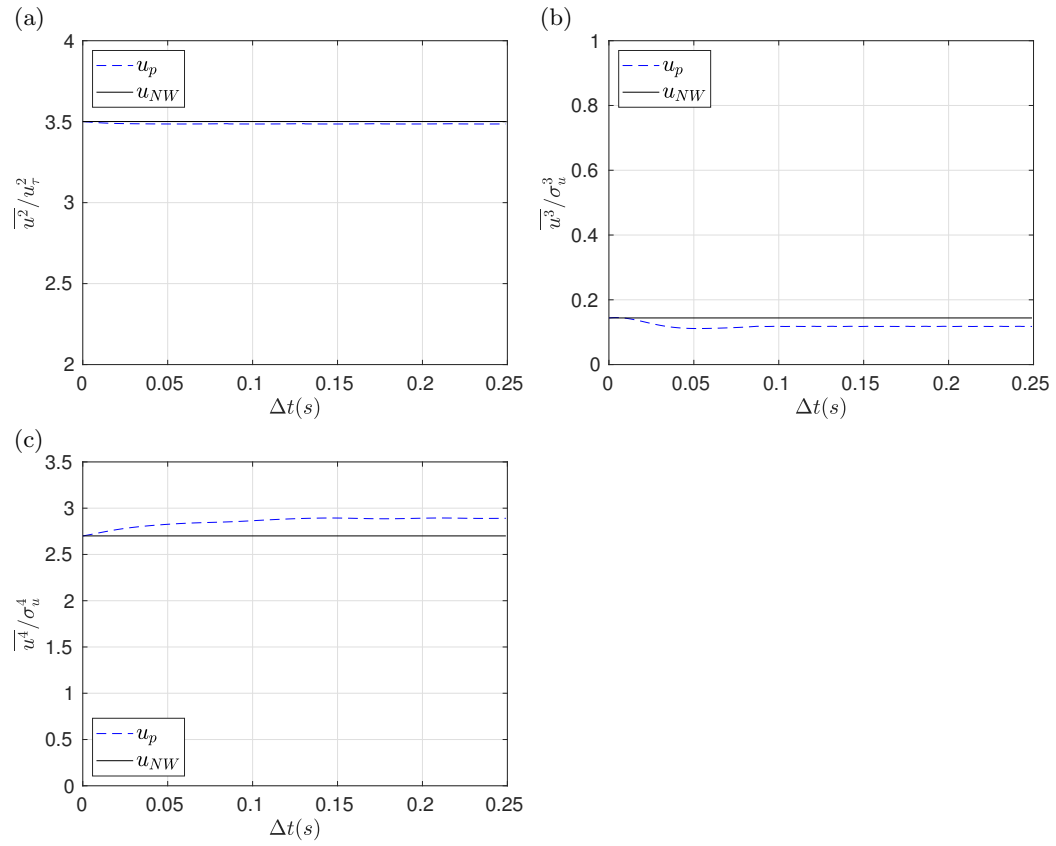


FIGURE 16. a) Variance, b) skewness and c) kurtosis of  $u_p^+$  and  $u_{NW}^+$  for configuration with  $\lambda_p = 25\%$  at  $Re_\tau = 32\ 400$  using phase shifted large-scale reference signal at  $z/h = 2.1$  ( $(z-d)/\delta = 0.066$ ).

585 **5. Conclusion**

586 A predictive model of the same form as that originally introduced by Mathis et al.  
587 (2011a) for the smooth-wall boundary layer has been derived to investigate the scale-  
588 interaction mechanisms known to exist in the near-canopy region of boundary-layer flows  
589 developing over large roughness elements. This modeling approach allows for the identi-  
590 fication and quantification of both the superimposition of the most energetic (large)  
591 scales from the outer layer onto the near-canopy (smaller-scale) turbulence and the ampli-  
592 tude modulation of the near-canopy flow by the outer-layer flow. It also enables the  
593 extraction of the portion of the near-canopy velocity that is free from any influence of  
594 the large scales. Three roughness arrays consisting of cubical roughness elements with  
595 plan area packing densities of 6.25%, 25% and 44.4% (corresponding to the three flow  
596 regimes identified in such flows, Grimmond and Oke 1999; Perret et al. 2019) were stud-  
597 ied at two freestream velocities and used to determine the influence of both the canopy  
598 geometry and Reynolds number on the interaction between the most energetic scales  
599 from the outer layer and those in the roughness sublayer. Through analysis of the pre-  
600 dictive model coefficients it was shown that the canopy geometry has a non-negligible  
601 influence on the scale interactions. The superposition, represented by the coefficient  $\alpha$ ,  
602 was modified in the inner layer close to the canopy top as a result of a change in the local  
603 flow regime. Furthermore, the skimming flow regime,  $\lambda_p = 44.4\%$ , showed lower levels of  
604 amplitude modulation (given by the model parameter  $\beta$ ), both in the inner and outer  
605 layers when compared to configurations of isolated and wake interference flow regime.  
606 These patterns were also visible in the statistics of the universal signal,  $u^*$ , where the  
607 variance was modified close to the roughness as a result of local canopy geometry. For  
608 the densest canopy, both the variance and skewness had lower magnitudes throughout  
609 the roughness sublayer. Investigation of the model coefficients  $\alpha$  and  $\beta$  and statistics  
610 of  $u^*$  demonstrated that the Reynolds number does not significantly influence the su-  
611 perposition or amplitude modulation contradicting previous results in the smooth-wall  
612 boundary layer (Mathis et al. 2011a). However, this is likely a result of the limited range  
613 of Reynolds numbers used here and therefore requires further investigation.

614 The capacity of the derived models to serve as predictive tools to model near-canopy  
615 turbulence and to generate synthetic signals which have the same statistical character-  
616 istics of the targeted flows has also been investigated. Model validation was performed  
617 in three steps. The first, consisted of a prediction of the streamwise velocity component  
618 within the roughness sublayer of the  $\lambda_p = 25\%$  configuration at the highest Reynolds  
619 number,  $Re_\tau = 49\,900$ , using the model parameters calibrated at  $Re_\tau = 32\,400$  (Test  
620 1). The second validation consisted of a prediction of the streamwise velocity component  
621 within the roughness sublayer of the  $\lambda_p = 25\%$  configuration using its model parameters  
622 combined with a large-scale signal from the  $\lambda_p = 6.25\%$  or  $44.4\%$  configurations (Test  
623 2). Finally, the third validation consisted of a prediction of the streamwise velocity com-  
624 ponent within the roughness sublayer of the  $\lambda_p = 44.4\%$  configuration at the highest  
625 Reynolds number,  $Re_\tau = 49\,900$ , using the model parameters calibrated at  $Re_\tau = 32\,400$   
626 and a large-scale signal from the  $\lambda_p = 25\%$  configuration (Test 3). Each of the model  
627 validations demonstrated the suitability of the predictive model within the urban-type  
628 rough-wall boundary layer. The statistics up to the 4<sup>th</sup> order were accurately reproduced  
629 as well as the spectra. Finally, analysis of the phase between  $u^*$  and  $u_L^+$  suggests that it is  
630 important to preserve the phase between the two signals particularly in the case of higher  
631 order statistics. It should be however emphasised that the model must be calibrated for  
632 each type of canopy flow regime.

633 Through this work it has been demonstrated that the non-linear interactions within the

roughness sublayer of urban-type rough-wall boundary layers can be modelled using the predictive model as proposed by Mathis et al. (2011a). Although the Reynolds number was shown to have a negligible influence on the model parameters data should be obtained from higher Reynolds number rough-wall flows to expand the range studied. Another point of importance, not addressed in the present study, is the strong spatial heterogeneity of the flow within the roughness sublayer and inside the canopy. The recent experimental study by Herpin et al. (2018) on the scale superimposition in these regions has shown the spatial heterogeneity, both in the wall-normal direction and in the horizontal plane, of this mechanism. These results combined with those obtained here call for a more sophisticated model capable of accounting for the spatial heterogeneity of the flow over large roughness elements. In its present form, the statistical predictive model is a powerful tool, but the dynamic nature of the urban boundary layer and the complexity of the transport processes in the urban canopy limit the capabilities of a statistical model. Future efforts should concentrate on developing a dynamic predictive model, which would have significant potential for the urban boundary layer. Finally, urban canopies with uniform height, such as those studied here, have been shown to have characteristics that are common to other obstructed shear flow canopies (Ghisalberti 2009). These canopies range from terrestrial vegetative canopies to submerged aquatic canopies such as coral and all have an inflection point in the profile of the shear stress. This commonality points to the need for more general approaches to the investigation of amplitude modulation in canopies.

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