

Determining Optimal Resolution for Urban Terrain Inputs to Microclimate Modeling

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Key Points:

- The resolution of the urban parameters in a numerical weather model make a difference to the output of the model.
- The differences are small but meaningful.
- Including urban development in weather modeling for the future will necessitate addition of the morphology of new neighborhoods to existing ones, and the capability for representing this growth at the resolution appropriate to the study is important.¹

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Abstract

As the numerical weather prediction community seeks deeper understanding of multi-scale interactions among the atmosphere, human systems and the overall earth system, more explicit representation of surface terrain in these models has become necessary. While a great body of work has examined the differences in error and uncertainty of simulations at various horizontal grid resolution, no studies have been performed that compare the results of running the models at the same horizontal grid resolution but with different resolutions of surface terrain. We examine the differences in meteorological output from the Weather Research and Forecasting (WRF) model run at 270m horizontal resolution using 10m resolution urban terrain (morphology) inputs and 100m resolution inputs. We find that differences in urban terrain resolution may amplify or dampen the representation of shortwave absorption by low albedo concrete and asphalt and the re-radiation of this energy as heat to the neighborhood.

Plain Language Summary

As cities continue to grow, scientists search for ways to describe accurately both the effect that urban growth has on climate and how cities might be vulnerable to climate change. In order to understand these interactions, scientists can use weather models to represent how certain characteristics of urban areas, such as building height, neighborhood density, and green space, might affect local weather. In this study, we use those urban characteristics at two different resolutions as urban terrain inputs to the Weather Research and Forecasting model for a Washington D.C. neighborhood. Higher resolution representations of the neighborhood provide a more precise characterization of the urban surface, but take more time and data to be processed than those at lower resolutions. We compare the results of the weather model when it is given a higher resolution (10 meter) and a lower resolution (100 meter) representation of the urban terrain of the Washington, D.C. Waterfront neighborhood. We find small but meaningful differences between the two model simulations, and our results show that researchers must make decisions about whether these differences are negligible for their studies or if they require the use of more detailed representation of urban characteristics.

1 Introduction

While it has long been known that the variety of surface roughness elements in a set of weather model parameters imparts mathematically the most critical effects on the generation of a system's vertical wind profile and mixing layer depth (Oke, 1988), only recently has the introduction of more granular distinctions in land use and land cover within physical models opened new research for including the communication of a neighborhood's urban morphology to the natural environment within which it exists (Ching et al., 2009; Oleson et al., 2010). Urban and non-urban areas have different sensitivities to weather and climate suggesting that the best estimate of a climate change signal within an urban area must be obtained through explicitly representing the urban areas within weather and climate simulations (Best, 2006). Certainly, as the need for greater spatial detail and fidelity of atmospheric flow fields in numerical weather prediction models increases, these models must account for the influence of buildings, trees, and other morphological features within the urban boundary layer. For example, the vertical walls of buildings affect overall thermal properties of an urban area because they reflect and absorb shortwave radiation. Additionally, losses of infrared energy at night over built areas are diminished due to the decreased sky view factor below the roof level of the buildings (Shahmohamadi et al., 2011). Representing these morphological characteristics of urban areas as inputs to weather models provides a way for weather models to incorporate the influence on the local atmosphere of the complexities of spatial distributions of

62 buildings of different shapes and sizes so that, for example, the impact of significant weather
63 events such as heat waves can be estimated at neighborhood resolution (Ching et al., 2009).

64 As urban areas grow, geography, topography, climate, history, technology, policy,
65 infrastructure, culture, and population demographics all influence growth and changes
66 in urban morphology (Oliveira, 2016). This growth can take forms such as edge expansion,
67 which occurs when a new urban patch appears on the contour of an existing neighborhood
68 or infilling, which occurs when gaps inside a neighborhood become partially or
69 totally filled with new growth (Sapena & Ruiz, 2015). These growth patterns, then, aggregate
70 in different ways to the overall densification or sprawl of a city and can affect
71 the local meteorology and the larger scale climate through changes in atmospheric patterns
72 (Allen-Dumas et al., 2020).

73 A variety of urban environment modeling studies have been conducted using urban
74 morphological representations at different scales. For example, Oleson et al. developed
75 an urban parameterization for the representation of urban expansion and its interaction
76 with the Earth system within the Community Land Model component of the Community
77 Climate System Model (Oleson et al., 2010). The urban parameters are rendered
78 in the model at $0.5^\circ \times 0.5^\circ$ horizontal resolution and include height to width ratio,
79 roof fraction, average building height, and pervious fraction of the urban canyon for each
80 four urban density classes (tall building, high, medium and low density districts). This
81 configuration of the Community Land Model has been used by numerous researchers for
82 many scientific investigations. In particular, (Li et al., 2016) ran simulations with the
83 model for the Continental United States to understand the impact of urban land use on
84 climate at that scale.

85 Ching et al. (Ching et al., 2009) developed a suite of urban parameter inputs called
86 the National Urban Database and Access Portal Tool (NUDAPT) at 1km horizontal resolution
87 for the higher resolution capability of the Weather Research and Forecasting (WRF)
88 model. The 132 parameters included account for physical quantities related to buildings
89 such as plan area, plan area density, frontal area index and height to width ratio for every
90 5m vertical layer in the model. Among the vast research conducted with the WRF
91 model using these parameters, Vahmani et al. (Vahmani et al., 2019) ran several urban
92 heat mitigation scenarios in this configuration at 1.5km resolution that evaluated exposure
93 to future heat extremes under differing future climate and population scenarios. With
94 buildings and additional landscape characteristics at one centimeter resolution, Reza (Reza,
95 2019) used the ENVI-met model to simulate microclimate changes due to changes in urban
96 structure, and evaluated the impact of a 1°C increase in ambient temperature on
97 the energy use in the buildings in the neighborhood. Each of these studies produced insight
98 into different scientific questions, and each used the models and the associated urban
99 morphological representations available to them.

100 However, none of these experiments evaluated the difference that the resolution of
101 the input morphology would make in the output that was achieved. This observation is
102 notable because there are numerous studies exploring the benefits and consequences of
103 various horizontal grid resolutions in micrometeorological simulations, and it is reasonable
104 to hypothesize that urban morphology resolution is equally important. For example,
105 it may be critical to know how much difference the resolution of the urban terrain
106 input makes for determining neighborhoods and households most at risk to heat extremes
107 (Ishigami et al., 2008) under a given micrometeorological simulation. Likewise, as cities
108 grow through expansion, infill and building higher, the resolution at which this change
109 can be represented to a weather model may be the key to understanding the impact of
110 this growth on the local and the broader environment.

111 In this paper we show, as an example, the differences in WRF simulation output
112 at 270m horizontal grid resolution between running the model with 10m neighborhood
113 morphological inputs and running it with 100m morphological inputs. This work con-

114 tributes to the important and growing literature on urban micrometeorological modeling
 115 by elucidating the trade-offs between modeling expenses such as compute time and data
 116 requirements and the fidelity and resolution of the resulting simulations. We find small
 117 but meaningful differences between the simulations. Most notably, we see contrasts in
 118 the spatial distribution of temperature, humidity and wind between the two simulations,
 119 which may be important to estimating the full contribution of urban parameters to the
 120 thermal characteristics of a neighborhood in a city (Lee, 1984).

121 2 Materials and Methods

122 Two 1-month, three-domain, nested meteorological simulations were run for the month
 123 of July, 2010 using North American Regional Reanalysis (NARR) data (Mesinger et al.,
 124 2006) as initial and boundary conditions over urban terrain inputs at each of 10m and
 125 100m resolution for the Washington, DC Waterfront neighborhood. The simulations used
 126 the Weather Research and Forecasting (WRF) model run on the Oak Ridge National
 127 Laboratory (ORNL) Summit and Cades supercomputers, respectively. The horizontal
 128 resolution for each of the model domains (from outermost to innermost) was 6750m (d01),
 129 1350m (d02) and 270m (d03), respectively; and each contained 29 vertical levels with
 130 the model top at 100 hPa as defined by the NARR input. The number of grid cells in
 131 each domain is given in Table 1.

132 The urban terrain inputs at 10m and 100m resolution were generated using shape-
 133 files of building footprints and corresponding building heights acquired from Open Data
 134 DC (OpenDataDC, 2021) for the year 2015. From these shapefiles, urban parameters
 135 were calculated following the methodology of the NUDAPT project (Ching et al., 2009).
 136 For this calculation, a tool was produced using the Python coding language, which out-
 137 put files for the urban topography at both 10m and 100m resolution as WRF-readable
 138 binary files integrable with WRF using the established NUDAPT paths in the WRF sim-
 139 ulation environment.

140 Landcover characteristics used were those obtained from the US Geological Sur-
 141 vey National Land Cover Database (NLCD) (Homer et al., 2012) at 30 m resolution and
 142 included in the WRF pre-processing geography input package. The NLCD provides ur-
 143 ban land classifications such as percentage impervious surface, percentage of tree canopy
 144 cover and percentage of coverage of constructed materials.

145 The timestep used for the outermost (6750 m) domain was 10 seconds. The timestep
 146 for each nested grid was in the same ratio to the outer domain as was its spatial dimen-
 147 sion. Nesting ratios for the simulations were 5:1. This ratio is based on recommenda-
 148 tions from Werner (Werner, 2017) to align U and V velocities calculated at the edges of
 149 the parent-to-child Arakawa C-grids with mass quantities calculated at the centers of these
 150 cells. The simulations were run from June 30 through July 21, 2010, and each included
 151 a 24-hour model spinup before the 10-day period evaluated here.

152 Physics packages for WRF were chosen based on optimum packages for urban scenar-
 153 ios. The most significant packages are shown in Table 2. WRF output was postpro-
 154 cessed so that its Coordinated Universal (UTC) timestamps aligned with local Eastern
 155 Daylight time for comparison with observations at local time from the archives accessed
 156 for both the Weather Underground data reported for the Reagan National Airport (DCA)
 157 (Weather Underground, 2010) and the National Centers for Environmental Information
 158 archives (Menne et al., 2012) for the National Arboretum. Additionally, 10m windspeed
 159 and direction were derived from U and V, and relative humidity was calculated using
 160 2m temperature, surface pressure and 2m water vapor mixing ratio inputs to the NCAR
 161 Command Language (NCL) relhum function based on (Murray, 1966) and the SH2RH
 162 function provided by the R "humidity" package (Cai, 2019).

Table 1. Numbers of grid cells for simulations' nested domains. Two simulations were run. The first used urban terrain at 10m resolution in the d03 domain; the second used urban terrain at 100m in the d03 domain.

d01	d02	d03	d03
99x93	145x135	100x120	100x120

Table 2. Physics packages for WRF simulation

Domain	Microphysics	Radiation	Cloud Fraction	Cumulus	Surface Physics	Land	PBL	Urban Params
d01	Single Moment 3-class	New Goddard	Xu-Randall	Kain-Fritsch	Monin-Obukhov	Noah	BouLac	Urban Canopy
d02	Single Moment 3-class	New Goddard	Xu-Randall	Kain-Fritsch	Monin-Obukhov	Noah	BouLac	Urban Canopy
d03	Single Moment 3-class	New Goddard	Xu-Randall	Betts-Miller-Janjic	Monin-Obukhov	Noah	BouLac	10m morphs
d03	Single Moment 3-class	New Goddard	Xu-Randall	Betts-Miller-Janjic	Monin-Obukhov	Noah	BouLac	100m morphs

163 It is known that numerical weather prediction models contain inherent biases. When
 164 these models are used for official forecasts, the biases must be removed before the fore-
 165 casts can be distributed (Davis, 2004). For experimentation to evaluate differences in
 166 output due to changes in parameters, as we have done here, it is enough to know how
 167 the model output compares to measurements so that the output is referenced with re-
 168 gard to an actual weather event. To acknowledge the bias of the simulated data we present
 169 with respect to measurements, spatial averages of temperature, humidity and wind for
 170 July 1-10, 2010 over the 2015 Waterfront neighborhood were compared to those mea-
 171 sured at the Reagan National Airport (DCA), which is located across the Potomac and
 172 southwest of the neighborhood. Additionally, the temperature spatial averages were com-
 173 pared to those recorded at the National Arboretum located to the northeast of the neigh-
 174 borhood. Figures 1, 2 and 3 show that daily maximum, minimum and average temper-
 175 atures track below the DCA measurements by about 10°F or more and lead the obser-
 176 vations by about a day in trend. Maximum and average temperatures track more closely
 177 with the National Arboretum values, while minimum temperature values are farther be-
 178 low those measured at the National Arboretum. Simulated relative humidity is overes-
 179 timated in each case as compared to the DCA measurements and by as much as 40% for
 180 the minimum. Some of the bias, such as systematic cold bias and overestimation of hu-
 181 midity during the summer and high bias of wind speed (Figure 5) over all seasons, is gen-
 182 erally characteristic of the WRF model (García-Díez et al., 2013; Pan et al., 2018; Bughici
 183 et al., 2019). Some of the additional bias may be due to the sensitivity of the model to
 184 the difference in the urban terrain between that which would have been present in 2010
 185 and that which was used (2015) in the model simulation (Wang et al., 2011). Neverthe-
 186 less, the difference in the spatially averaged model results from the simulations run with
 187 the two resolutions of the urban terrain showed much less difference from each other and
 188 demonstrated that the simulation results were likely not significantly affected by initial
 189 conditions.

190 Spatially averaged planetary boundary layer height ranged from a lowest minimum
 191 of 50m to a highest maximum of 1750m throughout the 10-day study period, a range sim-
 192 ilar to that shown in the average July, 2011 (a month with related record temperatures
 193 to those of July, 2010) observations over the Baltimore-Washington area during the D.C.
 194 DISCOVER-AQ campaign (Hegarty et al., 2018). Differences in the maxima and min-
 195 ima of the simulations with each resolution morphology were nearly 375 meters at the
 196 maximum on July 8 (10m terrain showing the highest level) and 50 meters for the min-
 197 imum on July 7 (100m terrain with higher boundary layer), respectively. The largest dif-
 198 ference in maximum temperature between the two simulations occurs on July 8 (10m
 199 simulation warmer) as well, which corresponds to the large difference in the boundary
 200 layer on that day. Other small differences between the boundary layer simulation out-
 201 puts are shown throughout the 10-day period, but are less drastic.

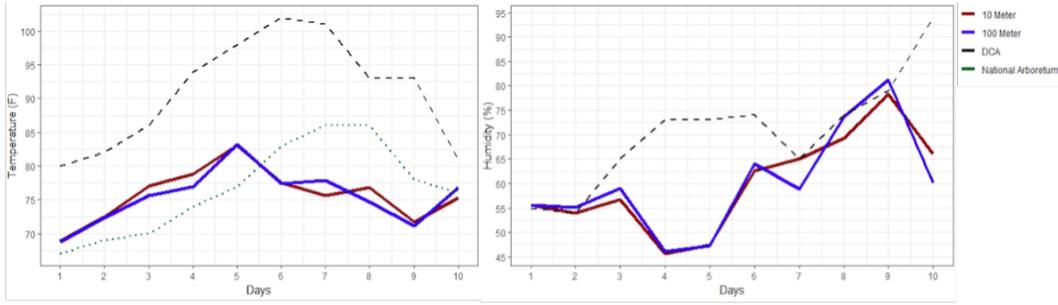


Figure 1. Maximum temperature and humidity, spatial averages over 10m (red line) and 100m (blue line) morphologies for Washington, DC Waterfront neighborhood run with July 1-10, 2010 meteorological initial and boundary conditions. Observations from the Reagan National Airport (DCA) are shown in black (dashed line) and observations from the National Arboretum are shown in green (dotted line) for comparison.

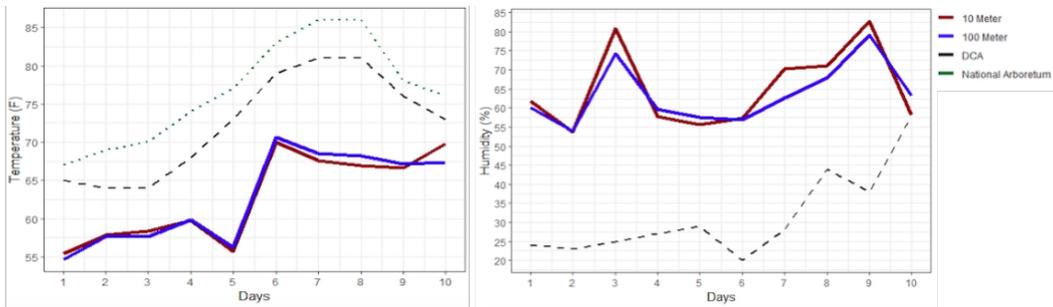


Figure 2. Minimum temperature and humidity, spatial averages over 10m (red line) and 100m (blue line) morphologies for Washington, DC Waterfront neighborhood run with July 1-10, 2010 meteorological initial and boundary conditions. Observations from the Reagan National Airport (DCA) are shown in black (dashed line) and observations from the National Arboretum are shown in green (dotted line) for comparison.

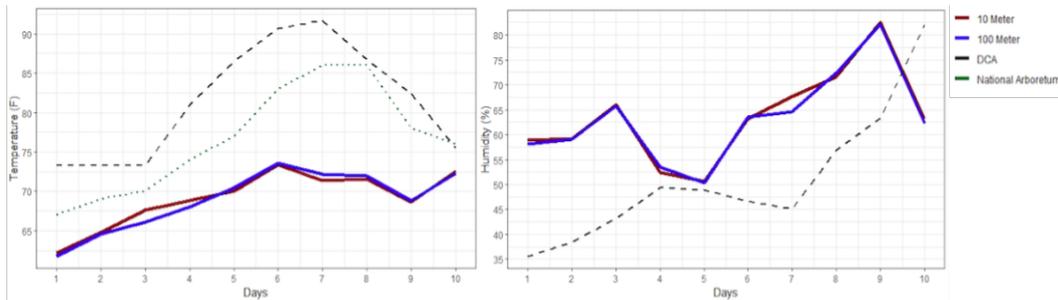


Figure 3. Average temperature and humidity, spatial averages over 10m (red line) and 100m (blue line) morphologies for Washington, DC Waterfront neighborhood run with July 1-10, 2010 meteorological initial and boundary conditions. Observations from the Reagan National Airport (DCA) are shown in black (dashed line). Observations from the National Arboretum in this case are for observations that occurred sometime during each day between the minimum and maximum temperatures, but are not necessarily averages. These values are shown in green (dotted line).

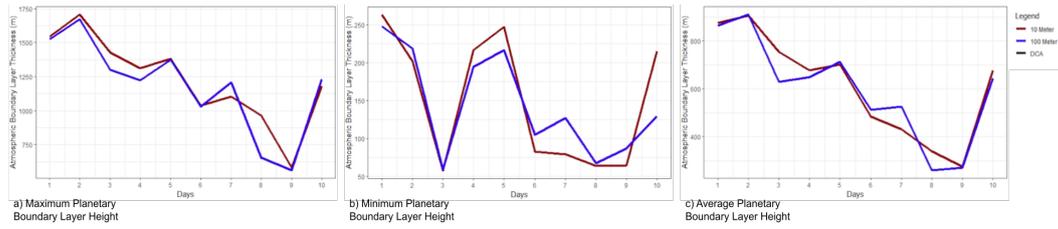


Figure 4. Spatially averaged planetary boundary layer (PBL) heights over 10m and 100m morphologies for Washington, DC Waterfront neighborhoods run with July 1-10, 2010 meteorological initial and boundary conditions

202 Wind pattern comparisons (Figure 5) show that for simulations run with both 10m
 203 and 100m urban terrain, the wind direction is fairly consistent from the west southwest
 204 direction. Variation in wind speed counts occur mostly in the middle of the range of the
 205 wind speed data. DCA measured data shows more variability in wind direction with most
 206 of the wind coming from directly south and directly north. Wind speeds from DCA are
 207 also much slower compared to those simulated over each urban terrain input. Differences
 208 between the simulated and the observed wind speed and direction may be due in part
 209 to the distance between DCA and the Waterfront neighborhood, and to the difference
 210 in respective fetch (Fagherazzi & Wiberg, 2009).

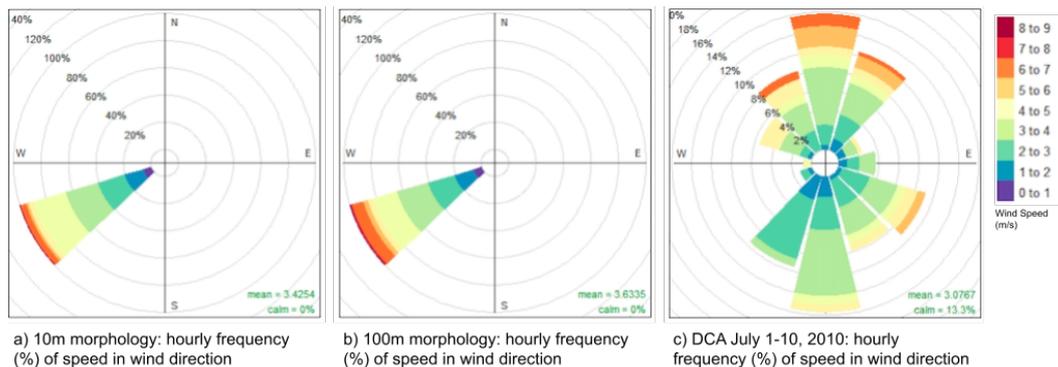


Figure 5. Hourly wind over 10m and 100m morphologies for Washington, DC Waterfront neighborhood run with July 1-10, 2010 meteorological initial and boundary conditions

211 **3 Results and Discussion**

212 Records beginning in the late 1800s for Washington, DC show that its population
 213 has grown continuously, and its land surface radius has expanded with greater heat-absorbing
 214 paved and built area leading to increasing heat records within the city and intensifying
 215 its urban heat island effect (Samenow, 2012). During the summer of 2010, Washington,
 216 DC recorded temperatures that surpassed 98°F (37°C) on 11 days, reaching a peak of
 217 102°F (39°C) on July 6 and 7. July 6 of that year broke two records: the earliest 100° reading
 218 in a day, occurring before noon, and the longest uninterrupted stretch of temperatures
 219 above 100°F (7 hours).

220 Figure 6 shows the spatial distribution over the Washington, DC Waterfront neigh-
 221 borhood of the averaged daily maximum temperature over the ten days of the 2010 heat-

222 wave using urban terrain inputs at each of 10m and 100m. While the temperature dis-
 223 tribution over the neighborhood looks similar for the a) 10m and the b) 100m render-
 224 ings, the difference plot shows locations up to 0.59°F cooler in the 100m result as com-
 225 pared to the 10m result. In the simulation result using the 10m terrain, the largest area
 226 over the built section shows the highest temperatures. In the result simulated with the
 227 100m terrain, none of the area reaches the highest temperature. A possible explanation
 228 for this difference is that the higher resolution building inputs allowed the darkly-colored
 229 and highly heat absorbent impervious surfaces to be exposed to the model, feeding the
 230 radiation from these surfaces back into the overall system (Lee, 1984).

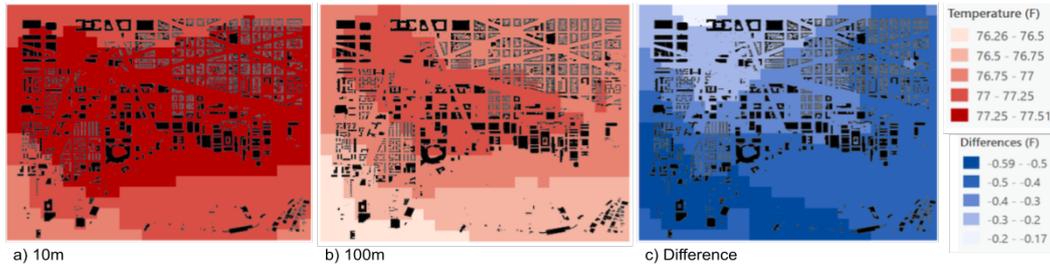


Figure 6. Time-averaged maximum temperature over a) 10m and b) 100m morphologies for the Washington, DC Waterfront neighborhood run with July 1-10, 2010 meteorological initial and boundary conditions. The c) difference panel is the result of subtracting the values produced by the simulation run with the 10m morphology from the values produced by the simulation run with the 100m morphology.

231 However, the urban heat island effect has its greatest impact on night time tem-
 232 peratures, as heat is essentially trapped in the urban core during the day rather than
 233 escaping into space (Samenow, 2012). The 2010 and 2011 heatwaves in Washington, DC
 234 were recorded as having both the most and the second most nights above 80° (7 in 2011
 235 and 4 in 2010). Figure 7 shows the time-averaged minimum temperature over the Wa-
 236 terfront neighborhood for the 10 day heatwave. The largest differences between the re-
 237 sults appears in the northern portion (up to 0.16° warmer for the 100m simulation) of
 238 the neighborhood, and in the southern portion (as much as .018° cooler in the 100m sim-
 239 ulation). The highest minimum temperatures for both simulations are over the water-
 240 ways in the southwest corner of the neighborhood, a result that agrees with (Mikolaskova,
 241 2009) and (Scheitlin, 2013), who demonstrated that land locations experience higher max-
 242 imum temperatures and lower minimum temperatures than locations over water.

243 Average daily temperatures averaged over the 10 day heat wave show variation as
 244 well across the Waterfront neighborhood (Figure 8). The most obvious difference between
 245 the results of using the two different morphology resolutions is the extent of the salmon
 246 colored region shown in panel a) (10m resolution morphology), which covers most of the
 247 built area of the neighborhood. In the result that used the 100m morphology, this tem-
 248 perature range covers only an area centered on the Nationals stadium (circular build-
 249 ing near the Anacostia River), potentially indicating that, as with the maximum tem-
 250 perature result, the higher resolution morphology exposed more heat-absorbent land area
 251 that, on average, maintains a higher temperature than the remaining northeast part of
 252 the neighborhood. Nevertheless, the differences observed in the spatial distribution of
 253 maximum, minimum and average temperature over the Waterfront neighborhood rep-
 254 resented at the two different resolutions are at most 0.25° to 0.6°F. Thus, temperature
 255 dependent planning choices that can be made within this margin of error may best be
 256 modeled using the more quickly generated urban terrain inputs at the coarser resolution.

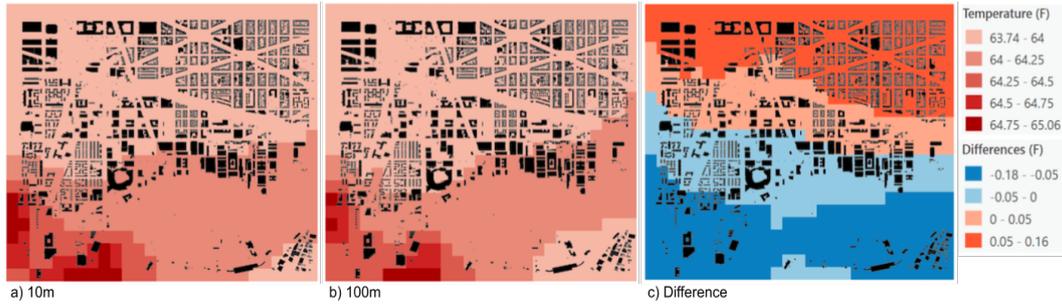


Figure 7. Time-averaged minimum temperature over a) 10m and b) 100m morphologies for the Washington, DC Waterfront neighborhood run with July 1-10, 2010 meteorological initial and boundary conditions. The c) difference panel is the result of subtracting the values produced by the simulation run with the 10m morphology from the values produced by the simulation run with the 100m morphology.

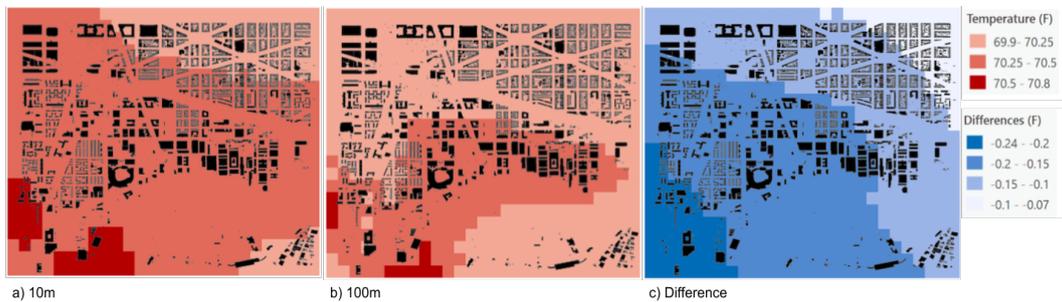


Figure 8. Time-averaged average temperature over a) 10m and b) 100m morphologies for the Washington, DC Waterfront neighborhood run with July 1-10, 2010 meteorological initial and boundary conditions. The c) difference panel is the result of subtracting the values produced by the simulation run with the 10m morphology from the values produced by the simulation run with the 100m morphology.

257 Spatial variability for relative humidity (Figure 9) across the Waterfront neighbor-
 258 hood ranged from 57.09% to 59.68% in both the 10m and the 100m resolution terrain
 259 simulations. The largest difference between the simulations was 0.53%, with the 100m
 260 simulation showing the higher humidity on the western side of the neighborhood along
 261 the Washington Channel. The simulated northwest area of the neighborhood at 100m
 262 was drier by 0.21% than that of the simulated area with 10m resolution terrain.

263 Wind direction over both the 10m and the 100m resolution urban terrain is gener-
 264 ally from the west southwest as was seen in the wind rose comparison (Figure 5) in sec-
 265 tion 2. However, slight differences in the time averaged maximum wind speeds and di-
 266 rection over the two different terrain resolutions shown in Figure 10 indicate a shift from
 267 mostly west to more northwest originating wind, especially as the air exits the urban area
 268 and flows over the Anacostia River. Wind speed in both simulations is slower over the
 269 built area and faster over the water, a result that concurs with the tendency of warm
 270 air to stagnate in urban canyons and speed up over areas that are less built up (Shahmohamadi
 271 et al., 2011). The largest differences in wind speed between the two simulations occur
 272 over the northwestern portion of the Waterfront neighborhood, at which the 100m res-
 273 olution terrain simulation produces the slower of the two maximum speeds in that area.

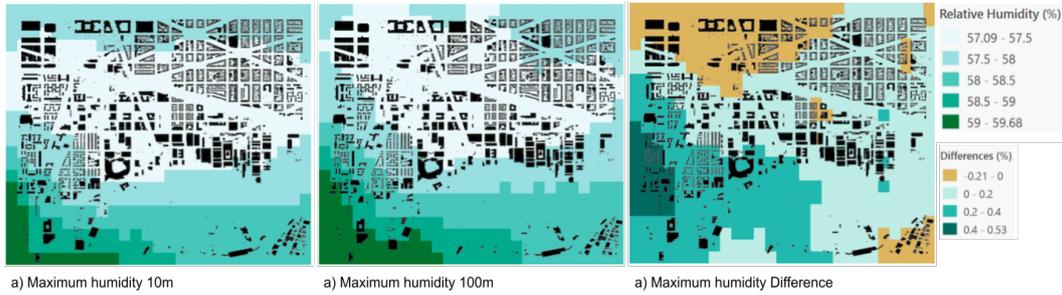


Figure 9. Time averaged maximum relative humidity over a) 10m and b) 100m morphologies for the Washington, DC Waterfront neighborhoods run with July 1-10, 2010 meteorological initial and boundary conditions. The c) difference panel is the result of subtracting the values produced by the simulation run with the 10m morphology from the values produced by the simulation run with the 100m morphology.

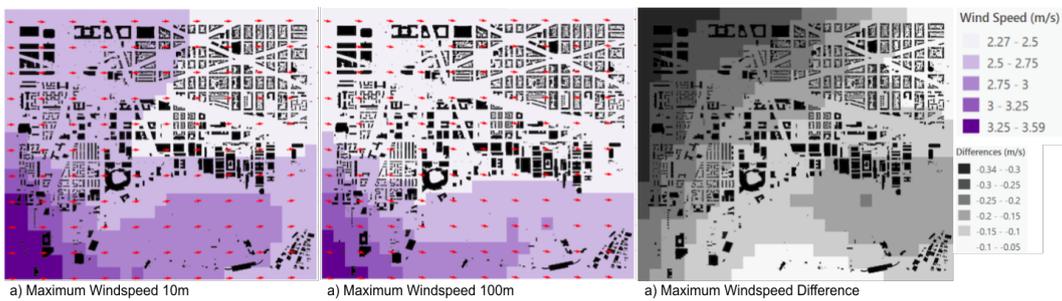


Figure 10. Time averaged maximum windspeed and direction over 10m and 100m morphologies for Washington, DC Waterfront neighborhoods run with July 1-10, 2010 meteorological initial and boundary conditions

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4 Conclusions and Future Work

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We have shown that for simulations at 270m horizontal grid resolution over a neighborhood in Washington, DC, the spatial variability in temperature, humidity and wind speed and direction across the neighborhood changes with the resolution of the urban morphology used, and that the simulated results show different areas of the neighborhood up to 0.6°F warmer or cooler, 0.5% wetter or drier, and 0.3m/s windier or calmer depending on the resolution of the morphology used in the simulation. These differences may be negligible for the pursuit of some types of knowledge, but may be very meaningful for others. One possible explanation for the spatial patterns we saw with this experiment was that dark impervious surfaces such as asphalt were revealed between the buildings at 10m resolution whereas those areas may have been represented to the model as built (and lighter colored) areas at 100m resolution. Thus, for including new morphology scenarios in such models that build on modeling growth in impervious surfaces in response to population shift scenarios (Brelsford et al., 2020), or the impact of building regulations and codes on the dimensions of buildings, their geometrical form and arrangement and their energy efficiency (Asimakopoulos, 2001), possibly higher morphological resolution is necessary. Contrastingly, for understanding the ways in which a neighborhood's demography may affect the type of buildings that make up a new neighborhood and their packing density within it (Oke, 1988), 100m may be sufficient.

293 Researchers and urban planners have begun to develop future scenarios, pathways
 294 and plans, and to implement projects that improve urban sustainability and urban re-
 295 siliency (McPhearson et al., 2016). Understanding the resolution at which urban terrain
 296 inputs to weather models makes a difference in those scenarios and pathways will help
 297 planners choose modeling approaches that provide the most useful and time-efficient in-
 298 formation for the solutions that are needed.

299 In conclusion, we show that horizontal resolution differences in terrain inputs to
 300 numerical weather models do result in differences, especially in the spatial variability of
 301 micrometeorological parameters. However, the study did not investigate the appropri-
 302 ateness of the numerical techniques applied the (sub-kilometer) horizontal grid resolu-
 303 tion at which the simulations were performed, and thus, the results still carry some un-
 304 certainty (Wedi, 2014). Nevertheless, the results presented here pose interesting new ques-
 305 tions about the required resolution of the model's surface terrain, especially with regard
 306 to urban interactions with the local to regional atmosphere.

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 314 form the experiments reported here. WRF-generated data from each of the simulations
 315 will be available through data DOI at Zenodo.

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