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Key Points:

- Urban land cover (ULC) and anthropogenic heat (AH), respectively, decreased and increased precipitation in the Yangtze River Delta
- Both the ULC and AH effects on precipitation were more pronounced during afternoon and during heavy precipitation events
- Relative contributions of various dynamical and thermodynamic processes to the temporal variation of precipitation responses were quantified

Supporting Information:

Supporting Information may be found in the online version of this article.

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Contrasting Effects of Urban Land Cover Change and Anthropogenic Heat on Summer Precipitation Over the Yangtze River Delta of China: Analyses From an Atmospheric Moisture Budget Perspective

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Abstract Both urban land cover (ULC) change and anthropogenic heat (AH) emission are important causes of urban heat island, but their relative contributions to the changes in urban precipitation and the related mechanism remain unclear. Based on numerical simulations utilizing the latest realistic urban fraction and AH data over the Yangtze River Delta urban agglomeration, we found that ULC and AH resulted in nearly opposite effects on precipitation. Various dynamical and thermodynamic processes were involved according to the atmospheric moisture budget analyses. AH increased precipitation particularly during afternoon, and the increases were stronger during heavy precipitation events because of the enhanced moisture convergence effect together with the release of moisture storage previously accumulated in the atmosphere. Differently, ULC reduced mean precipitation mainly due to suppressed evaporation. During weak precipitation events, the suppressed evaporation was largely balanced by the intensified moisture convergence, but during heavy events, ULC caused more pronounced precipitation reduction because the moisture convergence response disappeared and failed to offset the evaporation effect. The relative contributions of different dynamical and thermodynamic processes such as those related to circulation, moisture gradient, and background moisture availability to the temporal variation in the total moisture convergence were further quantified. Overall, our results help better understand the relative roles of different aspects of urbanization on precipitation, and suggest that compared to ULC, reduction in AH emission that is tightly related to the energy consumption structure could be more efficient for mitigating the risk of extreme precipitation.

Plain Language Summary Urban land cover (ULC) change and anthropogenic heat (AH) emission are two main causes of urban heat island, but how they would modify urban precipitation are still unclear. Here, based on numerical simulations utilizing the latest urban fraction and AH data over the Yangtze River Delta urban agglomeration, we found that ULC and AH can result in nearly opposite effects on precipitation. AH increased precipitation via intensifying moisture convergence, which was more pronounced during heavy precipitation events. Differently, ULC caused reduction in the mean precipitation due to the limitation in surface evaporation, but the disappeared moisture convergence response that failed to offset the suppressed evaporation was the main reason for the stronger ULC effect on precipitation during heavy precipitation events. Our findings help better understand the relative roles of different aspects of urbanization on precipitation and provide useful information to support the mitigation of the risk associated with extreme precipitation.

1. Introduction

With the progress of urbanization, both the urban land proportion and urban population have been steadily increasing during the past several decades (Angel et al., 2011). Urbanization has been found to significantly modify local and even regional climate, such as causing urban heat island (UHI) phenomenon via raising near-surface temperature, drying the urban planetary boundary layer, and modulating local circulations (Conlon et al., 2016; Fallmann et al., 2016; Li et al., 2018; Lin et al., 2016; Rozoff et al., 2003; Yang et al., 2017). Urbanization can also lead to significant rises in thermal discomfort hours and mortality (Kalkstein et al., 2008; Wong et al., 2013; Yang et al., 2019). Compared to other variables, the urbanization-induced changes in precipitation, which involve many dynamical and thermodynamic processes and interactions, are much more uncertain (Qian et al., 2022). Both

observational and modeling studies have demonstrated that urbanization has pronounced impacts on precipitation. For example, urbanization has been found to increase precipitation downwind of major cities (Changnon, 1968; Horton, 1921; Huff & Vogel, 1978; Li & Liu, 2021; Lin et al., 2021; Mukherjee et al., 2018), which is attributed to the UHI circulation (Han & Baik, 2008). Meanwhile, the UHI effect coupled with the intricate urban landscape may attract convective storms towards the urban (Ganeshan & Murtugudde, 2015). In addition, urban land cover may lead to the breaking of the squall line into individual convective cells over the urban area (Miao et al., 2011). Furthermore, the increased surface roughness resulting from urbanization can change wind speed, which further affects the magnitude and distribution of precipitation (Rozoff et al., 2003; Thielen et al., 2000).

China has experienced rapid urbanization since the end of last century. The proportion of the urban population has increased from 26.44% in 1990 to 62.51% in 2021 and exceeded the world average in 2013 (World Bank, 2022). In China, the Yangtze River Delta (YRD) is one of the fastest-growing urbanized regions, where both observational data and numerical simulations have shown that the urbanization has caused remarkable influences on the regional climate (Chen et al., 2014, 2016; Yang et al., 2019). For instance, Huang and Lu (2015) analyzed the observations from 41 stations in YRD and found there were significant positive correlations between the degree of urbanization (e.g., urbanization increased population and built-up area) and the warming rates. In addition to the changes in temperature, Yang et al. (2014) found that the annual-mean precipitation in the Taihu Lake Basin had a clear upward trend as the urbanization level rose, while the urbanization of Shanghai tended to increase the frequency and intensity of heavy precipitation in urban areas (Liang & Ding, 2017). The impact of urbanization on precipitation is not limited to local areas. For instance, Wan et al. (2015) suggested that the urban underlying surface has caused increased precipitation downwind of the YRD urban agglomeration. Urban land cover (ULC) change and anthropogenic heat (AH) emission are the two main aspects of urbanization, both of which can strongly contribute to the UHI phenomenon and increased level of thermal discomfort. However, the relative impacts of ULC and AH on precipitation are more complex and can be different across climate regimes. Numerical simulations over Tokyo showed that both AH and ULC increased precipitation in extreme rainfall events, with ULC exhibiting a more pronounced effect (Souma et al., 2013). With a relatively coarse resolution (i.e., 30 km) model, Feng et al. (2012) suggested that in China, both ULC and AH can lead to increased summer precipitation over the Beijing–Tianjin–Hebei region. However, convection permitting model (CPM) simulations by Wang et al. (2018) found that the summer-mean precipitation over the Beijing Region was increased by AH and decreased by ULC. For the city of Hangzhou over YRD, Chen et al. (2016) suggested that AH increased precipitation in the urban area, while ULC increased precipitation in the downwind region. Using CPM with idealized ULC distribution and AH emission, Hu et al. (2021) found the AH effect on precipitation was much stronger than that of ULC during twenty-six extreme rainfall days over the Pearl River Delta region. Marelle et al. (2020) performed simulations for multiple cities, including Shanghai, Tokyo, Paris, and New York, revealing a significant increase in the frequency of extreme precipitation events over urban areas, with AH playing a substantial role.

Most of the above studies about the individual effects of ULC and AH mainly focused on climatological mean results or particular precipitation events. However, Yang et al. (2019) revealed that the relative contributions of ULC and AH to the changes in surface energy budgets and local thermal conditions were subject to meteorological background and time of day, implying that their impacts on precipitation might also be highly case-dependent. Meanwhile, the physical mechanisms responsible for the different effects of ULC and AH, as well as their dependence on synoptic backgrounds still remain unclear. In this study, the impacts of ULC and AH on precipitation are studied based on the Weather Research and Forecasting (WRF) model coupled with a single-layer urban canopy model (SLUCM) (Chen et al., 2011; Kusaka et al., 2001), into which we incorporated the realistic spatial distributions of urban fraction (in 2020) and AH emission (in 2019) over China. We aim to investigate the different roles of ULC and AH, as well as their temporal variations across precipitation cases and time of day from an atmospheric moisture budget perspective. In the following, Section 2 shows the model and experimental configurations. The individual impacts of ULC and AH on precipitation and the associated moisture budget characteristics are presented in Section 3. Conclusion and discussions are given in Section 4.

2. Methodology and Data

2.1. Model Configuration

The Version 4.0 of WRF was applied in this study. Two one-way nested domains were configured (Figure 1a). The horizontal resolutions of the outer and inner domains were 12 km and 4 km, respectively, with the inner

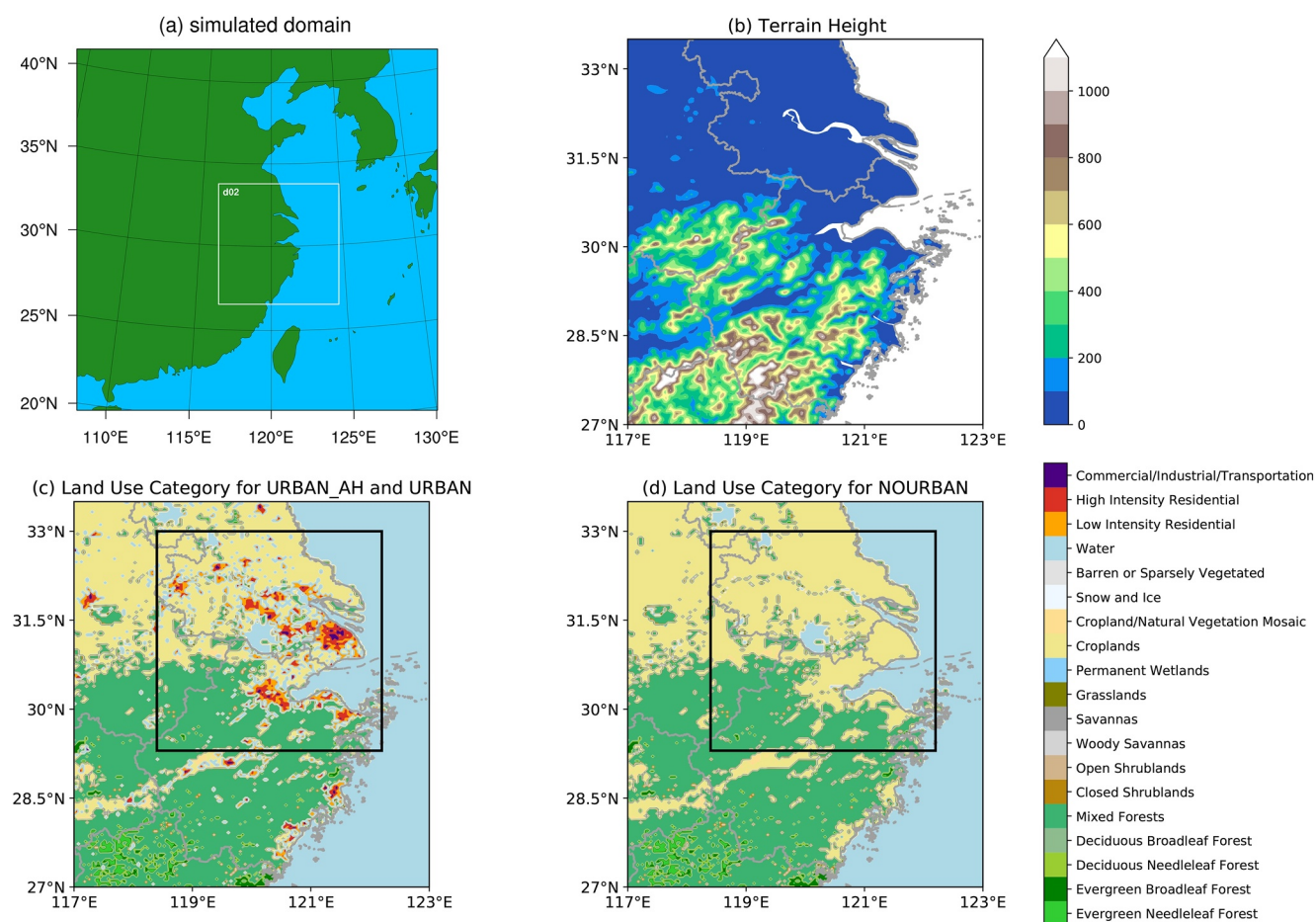


Figure 1. (a) WRF domain configuration, (b) terrain height, (c and d) Land-use categories in the inner domain for the experiments of (c) URBAN_AH/ URBAN and (d) NOURBAN. The black rectangle in (c, d) denotes the main study region.

domain covering the entire urban agglomeration in YRD (Figure 1a). There were 33 vertical layers from the surface to 50 hPa. The 6-hourly FNL (Final) Operational Global Analysis data of National Centers for Environmental Prediction (NCEP) ($1^\circ \times 1^\circ$ resolution; <https://rda.ucar.edu/datasets/ds083.2/>) was used to derive the initial and boundary conditions. Nudging was switched on for the outer domain, so as to provide more accurate boundary conditions for the inner domain simulations. The time interval of model output was 1 hr.

The SLUCM scheme was used to represent various urban processes. The additional physical processes applied in WRF included the Thompson aerosol-aware microphysics scheme (Thompson & Eidhammer, 2014), the Rapid Radiative Transfer Model for GCMs (RRTMG) longwave radiation scheme, the RRTMG shortwave radiation scheme (Iacono et al., 2008), the Mellor-Yamada-Janjić Planetary boundary layer scheme (Janjić, 1994, 2001), the Eta similarity surface layer (Janjić, 1994), and the Noah Land Surface scheme (Tewari et al., 2004).

2.2. ULC and AH Data

The Moderate Resolution Imaging Spectroradiometer (MODIS) 20 category land cover types of 2001 was used in WRF by default. To represent the realistic urban scenario, we updated the urban fraction at each WRF grid point based on the underlying surface types (at 30 m resolution) in the version 2020 of GlobeLand30 (<http://www.globallandcover.com>). The urban fraction was calculated by dividing the number of artificial surface pixels (at 30 m resolution from GlobeLand30) by the total number of pixels within each $1 \text{ km} \times 1 \text{ km}$ grid using the Geographic Information System software and then re-gridded to the model grid points using the bilinear interpolation procedure. In WRF/SLUCM, the urban type surface has three categories, i.e., low-intensity residential (LIR), high-intensity residential (HIR), and commercial/industrial/transportation (CIT), with urban fractions of

Table 1
Experiments and Corresponded LU and AH Information

Experiments	Land use	Anthropologic heat
URBAN_AH	MODIS + LIR + HIR + CIT	Yes
URBAN	MODIS + LIR + HIR + CIT	No
NOURBAN	MODIS + Croplands	No

50%, 90%, and 95%, respectively. Therefore, we divided all the model grid points into four groups based on specified thresholds of urban fraction. The thresholds of urban fraction for the classification were gradually tuned, in order to make the mean urban fractions in the first three groups equal to 95% (CIT), 90% (HDI), and 50% (LIR), respectively. The remaining group corresponded to non-artificial surface, where the default land cover types from the MODIS 20 category dataset of 2001 were used.

The gridded AH data (at 1 km resolution) in the Chinese mainland of 2019 was used to replace the WRF's default values estimated from emissions in 44 U.S. cities in 2000 (Ching et al., 2009). The gridded AH data consists of energy consumptions from building, human metabolism, industry, and transportation (Qian et al., 2023) generated by using the energy consumption inventory method and the Cubist machine learning model (Chen et al., 2020). We simply used the annual-mean AH data in 2019 for all the 10-year simulations, so there was no day-to-day or year-to-year variations. Firstly, we calculated the mean magnitude of AH for each urban type as defined above. Then, using the diurnal cycle of AH specified in the parameter input file (URBPARM), the daily-mean values of AH emission were converted to daily-maximum values, that is, 66.8 W/m² for LIR, 140.5 W/m² for HIR, and 181.7 W/m² for CIT, which were needed by WRF/SLUCM. Finally, the AH value at each urban grid point and each hour can be obtained based on the daily-maximum values and diurnal cycle of AH specified in the URBPARM file.

2.3. Experimental Design

Three sensitivity experiments were conducted (Table 1), which only differed from one another in the underlying surface type and AH emission within the inner domain. The three experiments over the inner domain were driven by identical boundary conditions from the outer domain simulations. The control experiment URBAN_AH represented the realistic urban scenario (Figure 1c), which used ULC and AH data as described in Section 2.2. The experiment URBAN used the same underlying surface distribution as URBAN_AH but with AH emission set to zero. Our statistical analysis indicated that cropland accounted for a very high proportion (about 69%) of non-urban grids in the adjacent areas of urban in our main study region (black box in Figure 1c). Therefore, all the urban grid points were set to cropland with AH emission equal to zero in the experiment NOURBAN. For non-urban areas, SLUCM was switched off and a plane model was used to calculate the thermal and dynamical effects of underlying surfaces.

All the experiments were integrated for 10 summers (15 May to 1 September) from 2011 to 2020. The period from 15 May to 30 May in each year was used for spinning up, and the results from 1 June to 31 August were for the analyses. The AH effect, ULC effect, and their joint effect were estimated as the results of URBAN_AH minus URBAN, URBAN minus NOURBAN, and URBAN_AH minus NOURBAN, respectively. However, both the case of NOURBAN_AH minus NOURBAN and the case of URBAN_AH minus URBAN can be referred to as the "AH effect". The two cases might be different because the AH effect can be modulated by the underlying surface. It should be noted that we only considered the AH effect over urban areas in the current study because in WRF the calculation of AH is handled by SLUCM. Moreover, although urbanization involves various aspects such as the horizontal or vertical expansion of cities, we simply focused on quantifying the impacts of the presence of ULC (i.e., urban area) and AH in this study.

2.4. Observational Data

The satellite precipitation data produced by the Climate Prediction Center Morphing Technique (CMORPH) (8 km × 8 km, 30 min) (<https://www.ncei.noaa.gov/products/climate-data-records/precipitation-cmorph>) was used for model evaluation. In CMORPH, motion vectors derived from geostationary satellite infrared data were used to propagate the high-quality precipitation estimates derived from passive microwave data (Joyce et al., 2004). To evaluate the simulated near-surface temperature and relative humidity, we used the gridded daily dataset CN05.1 (0.25° × 0.25°), which was constructed based on observations from 2416 surface stations in China with topographic correction (Wu et al., 2017; Wu & Gao, 2013; Xu et al., 2009). Hourly heavy precipitation was defined as those with precipitation intensity exceeding 7.6 mm/h (<https://glossary.ametsoc.org/wiki/Rain>).

2.5. Atmospheric Moisture Budget

For a specific region, precipitation is balanced by local surface evaporation, column-integrated moisture convergence, and change in the atmospheric moisture storage as follows (Tan et al., 2022):

$$\bar{P} - \bar{E} + \overline{PW} = -\frac{1}{g} \cdot \overline{\nabla \cdot \int_{p_t}^{p_s} (q \cdot \vec{V}) dp}, \quad (1)$$

where P is precipitation (i.e., temporal change of RAINNC in WRF), E is surface evaporation (i.e., QFX in WRF), q is specific humidity (i.e., QVAPOR in WRF), $\vec{V}$ is horizontal velocity (i.e., U and V in WRF), and p_s and p_t are the pressures at surface and model top, respectively (i.e., calculated from P and PB in WRF). PW represents the change in the atmospheric moisture storage that is the vertical integral of atmospheric moisture, and $-\nabla \cdot \int_{p_t}^{p_s} (q \cdot \vec{V}) dp$ is the vertical integral of moisture convergence throughout the entire atmosphere (Li et al., 2013; Wang et al., 2017).

q and $\vec{V}$ in URBAN or NOURBAN experiment can be expressed as $q_c - \Delta q$ and $\vec{V}_c - \Delta \vec{V}$, respectively, in which q_c and $\vec{V}_c$ correspond to the fields in the control experiment URBAN_AH, and Δq and $\Delta \vec{V}$ are the responses due to the changes in ULC or AH.

Hence, in the URBAN_AH experiment, the integral of moisture convergence is:

$$-\nabla \cdot \int_{p_t}^{p_s} (q \cdot \vec{V}) dp = -\nabla \cdot \int_{p_t}^{p_s} (q_c \cdot \vec{V}_c) dp, \quad (2)$$

while in URBAN or NOURBAN, the integral becomes:

$$\begin{aligned} -\nabla \cdot \int_{p_t}^{p_s} (q \cdot \vec{V}) dp &= -\nabla \cdot \int_{p_t}^{p_s} ((q_c - \Delta q)(\vec{V}_c - \Delta \vec{V})) dp \\ &= -\nabla \cdot \int_{p_t}^{p_s} (q_c \cdot \vec{V}_c) dp + \nabla \cdot \int_{p_t}^{p_s} (\Delta q \cdot \vec{V}_c) dp + \nabla \cdot \int_{p_t}^{p_s} (q_c \cdot \Delta \vec{V}) dp - \nabla \cdot \int_{p_t}^{p_s} (\Delta q \cdot \Delta \vec{V}) dp, \end{aligned} \quad (3)$$

where $\nabla \cdot \int_{p_t}^{p_s} (\Delta q \cdot \Delta \vec{V}) dp$ can be neglected.

Based on the equation above, the urban effect on precipitation becomes:

$$\begin{aligned} \Delta P &= \Delta E - \Delta PW - \Delta \left(\frac{1}{g} \cdot \overline{\nabla \cdot \int_{p_t}^{p_s} (q \cdot \vec{V}) dp} \right) \\ &\approx \Delta E - \Delta PW - \frac{1}{g} \left(\nabla \cdot \int_{p_t}^{p_s} (q_c \cdot \Delta \vec{V}) dp + \nabla \cdot \int_{p_t}^{p_s} (\Delta q \cdot \vec{V}_c) dp \right) \\ &\approx \Delta E - \Delta PW \\ &\quad - \frac{1}{g} \left(\int_{p_t}^{p_s} (q_c \cdot \nabla \cdot (\Delta \vec{V})) dp + \int_{p_t}^{p_s} (\Delta \vec{V} \cdot \nabla q_c) dp + \int_{p_t}^{p_s} (\Delta q \cdot \nabla \cdot \vec{V}_c) dp + \int_{p_t}^{p_s} (\vec{V}_c \cdot \nabla (\Delta q)) dp \right). \end{aligned} \quad (4)$$

The urban effect on moisture convergence can be divided into the last four items on the right side of Equation 4, which are related to the changes in wind convergence, mean wind, mean moisture, and moisture gradient, respectively.

3. Results

3.1. Model Evaluation

In this section, the model outputs in the control experiment URBAN_AH were evaluated against various observational datasets. To align with observation, the WRF outputs at 0200, 0800, 1400, and 2000 LST were first averaged to obtain daily-mean 2-m temperature and relative humidity and then re-gridded to match the grid spacing in observation using the bilinear interpolation procedure. Compared with CN05.1, WRF produced positive biases in near-surface temperature over urban areas. Specifically, the mean bias and root mean square error (RMSE) in the main study area (black box in Figure 1c) were 0.50°C and 1.28°C, respectively. Meanwhile, WRF underestimated near-surface relative humidity, with the mean bias and RMSE of −0.61% and 5.52%, respectively. These biases in WRF might be attributed partly to the fact that the locations of meteorological stations were weighted towards suburban rather than highly urbanized areas (Shi et al., 2015). In addition, there were still large uncertainties in the urban canopy parameters (UCPs) in WRF (He et al., 2019; Monaghan et al., 2014; Sun et al., 2021). We also calculated the temporal correlation coefficients between observations and simulations in the main study area, which were 0.92 and 0.79 for temperature and relative humidity, respectively. The comparison of the 850 hPa wind field from WRF and from the FNL reanalysis data suggests that WRF can well reproduce the low-level circulation (Figures 2e and 2f).

Then, we evaluated the simulated precipitation in URBAN_AH using the CMORPH data. The WRF outputs were interpolated into the CMORPH grids before the comparison. In terms of summer-mean results, WRF can reasonably reproduce the basic characteristics of the precipitation spatial distribution (Figures 3a and 3b), although the precipitation magnitude was overestimated especially over high terrain areas in Zhejiang province. The overestimation may be related to the fact that CMORPH tends to underestimate the precipitation in south-eastern China (Huang et al., 2016). The spatial correlation of summer-mean precipitation between CMORPH and the simulated results was 0.70. The overestimation of the total precipitation amount was partly contributed by the overestimated hourly heavy precipitation (Figures 3e and 3f).

We further compared the simulated diurnal cycles of precipitation over the main study area against the CMORPH data (Figure 4). In CMORPH (red lines in Figure 4), both the total precipitation amount and hourly heavy precipitation frequency were larger during daytime than during nighttime and reached their maximums at afternoon. The peak time of the heavy precipitation frequency was 17 LST, about 2 or 3 hours later than that of the total precipitation amount. The diurnal cycles of precipitation in WRF (blue lines in Figure 4) resembled that in CMORPH, but with some overestimation during afternoon. The peak time of the diurnal cycle was well simulated in terms of the heavy precipitation but was a bit later for the total precipitation compared to CMORPH. Changing the microphysics (MP) scheme had a minor impact on the diurnal variation (Figure S1 in Supporting Information S1). This suggests that the grid-spacing (4-km) applied here might still be too coarse to resolve small-scale updrafts at early stages of convection (Fosser et al., 2020).

Above analyses have suggested that, although with some model biases, WRF can generally well simulate the precipitation features in terms of mean magnitude, heavy precipitation frequencies, and their diurnal variations. WRF can also well reproduce the large-scale patterns of near-surface meteorological variables (i.e., temperature and relative humidity) and 850 hPa wind field. Hence, in the following sections we mainly use the WRF results to investigate the effects of ULC and AH on precipitation.

3.2. Individual Impacts of ULC and AH on Precipitation

The comparisons between different sensitivity experiments (Figure 5) show that the changes in the summer-mean precipitation amount and hourly heavy precipitation frequency induced by ULC were quite different from that induced by AH. AH increased precipitation (Figure 5b), whereas ULC had an opposite but relatively weaker effect (Figure 5a). Therefore, the joint effect of ULC and AH resulted in an overall increase in the total precipitation amount (Figure 5c) in the urban agglomeration areas of YRD, consistent with previous observational studies (Liang & Ding, 2017; Yang et al., 2014). The response of the hourly heavy precipitation frequency to ULC or AH (Figures 5d and 5e) was generally consistent with that of the total precipitation amount.

Here, all grid points in the main study area (black box in Figure 1c) were used to analyze the urban impacts on the diurnal variation of the total precipitation amount and hourly heavy precipitation frequency (Figure 6). For the total precipitation amount, the effects of both ULC (blue lines in Figure 6) and AH (green lines in Figure 6) were

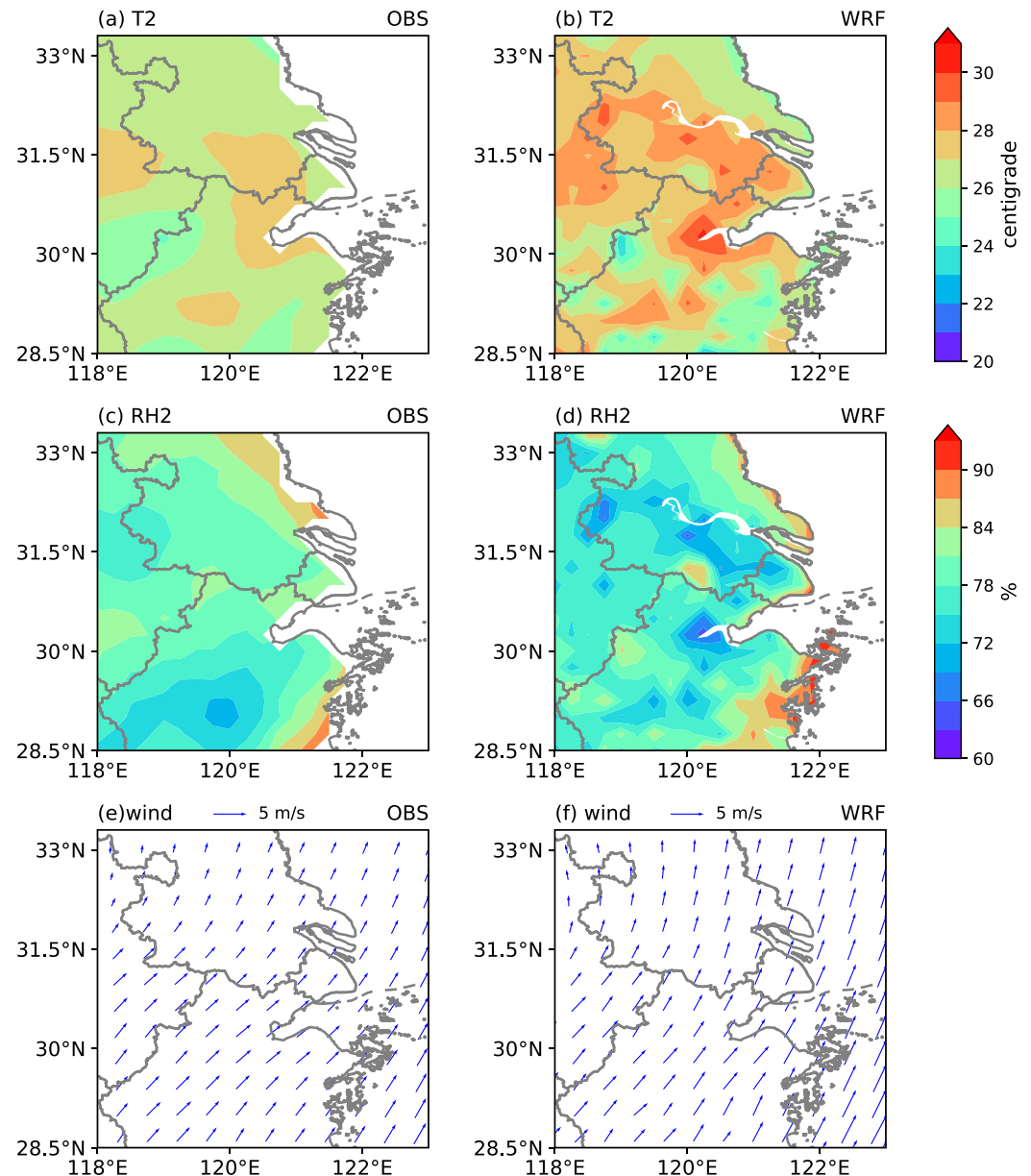


Figure 2. Spatial distributions of (a and b) 2-m temperature, (c and d) 2-m relative humidity and (e and f) 850 hPa wind filed averaged for the 10 summers from 2011 to 2020 in (a, c, f) observations and (b, d, and f) the URBAN_AH experiment.

obvious at afternoon and dusk (12~21 LST). ULC decreased while AH increased mean precipitation, with their maximum effects occurring at around 16 LST. Similarly, their effects on hourly heavy precipitation frequency were the most pronounced at afternoon and dusk (12~21 LST). The AH-induced increase and ULC-induced decrease in precipitation existed every year (Figure 6), suggesting the robustness of these two effects in our model results. Because of the opposite effects, the precipitation response to the joint effect of ULC and AH (pink lines in Figure 6) was relatively weak, with a large spread across different years.

Yang et al. (2019) found that the thermal effects of ULC and AH can be modulated by meteorological background, implying that the urbanization effects on precipitation could also be case-dependent. Therefore, we used the daily-mean precipitation from URBAN_AH averaged in the main study area to represent rainfall cases with different intensities. Days with precipitation rate less than 0.2 mm/day were excluded first. Then, all the cases were classified into several groups, with the weak and heavy groups corresponding to days when precipitation rates were in the ranges of 0–25th percentile and 75–100th percentile, respectively. The sample size was 181 days

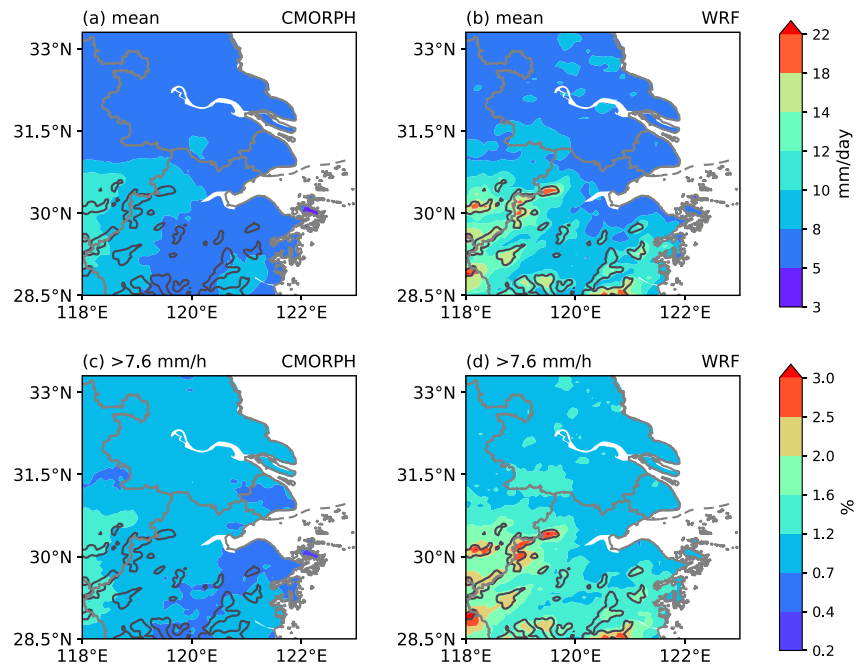


Figure 3. Spatial distributions of (a and b) precipitation amount and (c and d) frequency of hourly heavy precipitation (i.e., >7.6 mm/h) averaged for the 10 summers from 2011 to 2020 in (a and c) CMORPH and (b and d) the URBAN_AH experiment. Terrain height above 500 m is denoted by black lines.

for both the weak and heavy precipitation groups. The weak precipitation events mainly occurred during weak wind conditions at 850 hPa and contributed approximately 2.1% to the total precipitation (Figure S2 in Supporting Information S1). By contrast, strong southwest wind prevailed during heavy precipitation events that contributed 64.4% to the total precipitation.

Composite analysis was conducted by comparing the urban effects on precipitation between the weak and heavy groups, which helped reduce the impact of natural variability in the model. Figure 7 shows the warming effects induced by ULC and AH, which were quantified as the differences in 2-m temperature between different sensitivity experiments (see Section 2.3). On average, both ULC and AH induced noticeable warming near the surface, with the mean 2-m temperature increased by 0.29°C and 0.20°C in the main study area, respectively (Figures 7a and 7b). As precipitation intensity increased, there was a reduction of about 0.10°C in the warming effect of ULC, while the warming effect induced by AH remained relatively stable (Figures 7d and 7e). We

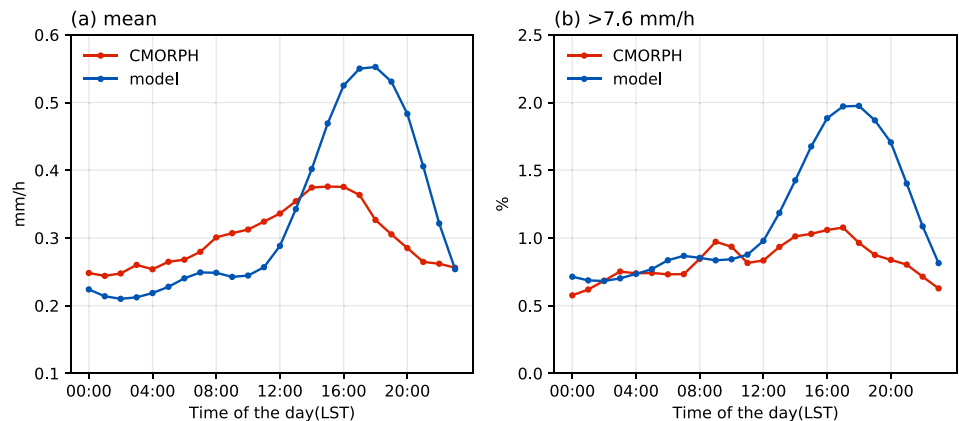


Figure 4. Diurnal variations of (a) precipitation amount and (b) frequency of hourly heavy precipitation (i.e., >7.6 mm/h) averaged for the 10 summers from 2011 to 2020 in CMORPH and in the URBAN_AH experiment over the areas in the black rectangle of Figure 1c.

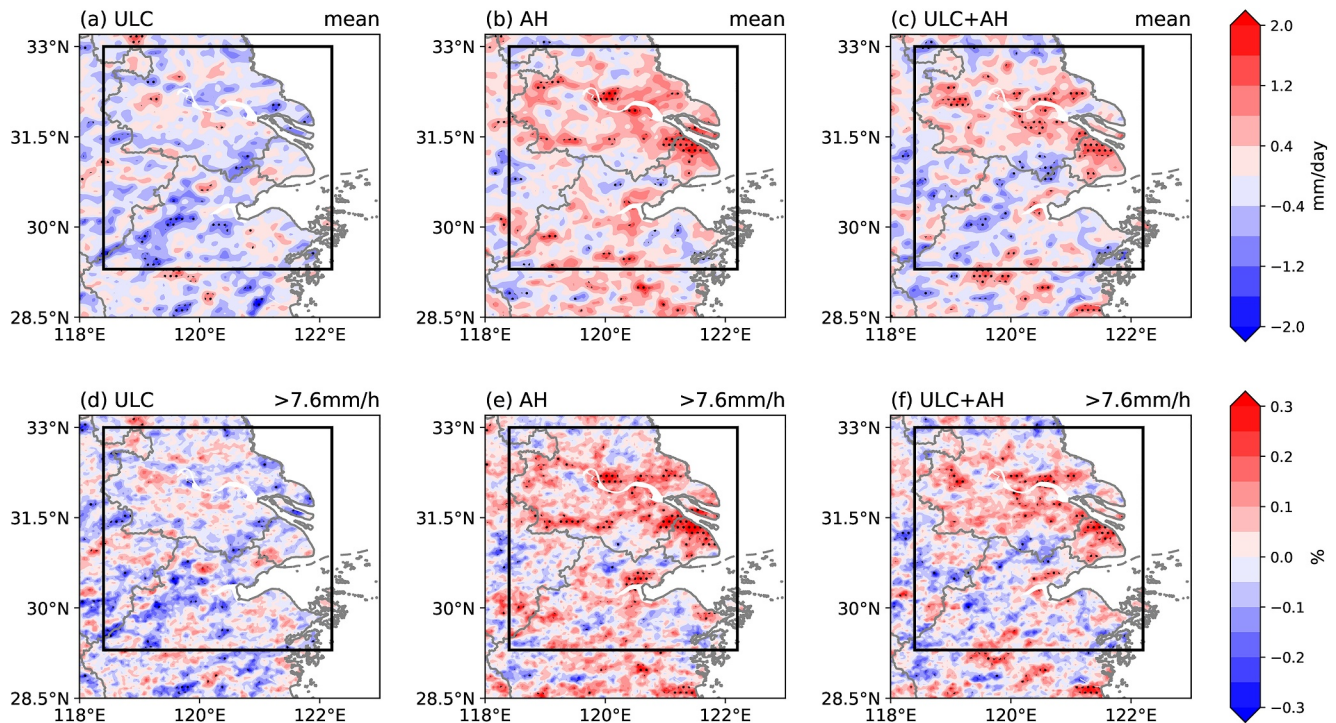


Figure 5. The spatial distribution of the changes in (a–c) precipitation amount and (d–f) hourly heavy precipitation frequency induced by the (a, d) ULC effect, (b, e) AH effect, and (c, f) their joint effect in the Yangtze River Delta during the 10 summers from 2011 to 2020. The dotted areas indicate where the changes are statistically significant at 95% confidence level.

further compared the precipitation responses under different background conditions. Consistent with the climatic mean results (Figure 5), ULC (AH) decreased (increased) precipitation for both the weak and heavy groups (Figure 8). Meanwhile, the contrasting effects of ULC and AH were more pronounced for the heavy group, which was partly related to the changes in the warming effect and will be discussed later. Similar results were found when using different thresholds from 0 and 0.35 mm/day for precipitation rate (Figure S3 in Supporting Information S1).

3.3. Characteristics of Atmospheric Moisture Budget

This section quantifies the individual effects of ULC and AH on precipitation from the perspective of the atmospheric moisture budget, in which precipitation is balanced by surface evaporation, moisture convergence, and moisture storage tendency in the atmosphere (Equation 1).

The diurnal variations of the responses in the above three moisture budget terms are presented in Figure 9. When AH was released to the atmosphere (green lines in Figure 9), the change in moisture convergence (Figure 9a) was much larger than that in evaporation (Figure 9b) and in moisture storage tendency (Figure 9c), suggesting that the precipitation response due to AH was almost entirely balanced by moisture convergence. There was a slight increase in evaporation, which was caused by the higher temperature but lower relative humidity (Figure S4 in Supporting Information S1) in the boundary layer that enhanced the moisture deficit near the surface, consistent with the findings revealed by Yang et al. (2019). The changes of evaporation in urban areas were because in each urban grid point, the fraction of artificial surface was below 100% (i.e., 95% for CIT, 90% for HDI, and 50% for LIR) and the rest part was covered by non-artificial surface type such as vegetation. Compared to AH, ULC caused quite different responses in the moisture budget features (blue lines in Figure 9). All the moisture budget terms were markedly modified due to ULC but exhibited different diurnal variations from one another. Moisture convergence decreased from 12 LST to 18 LST and increased after 19 LST. Evaporation began to decrease at sunrise (around 06 LST). However, precipitation at that time did not decrease immediately, which was at the expense of the reduced moisture storage tendency. After sunset, the response of evaporation gradually disappeared and the changes in moisture storage tendency became positive that acted to balance the enhanced

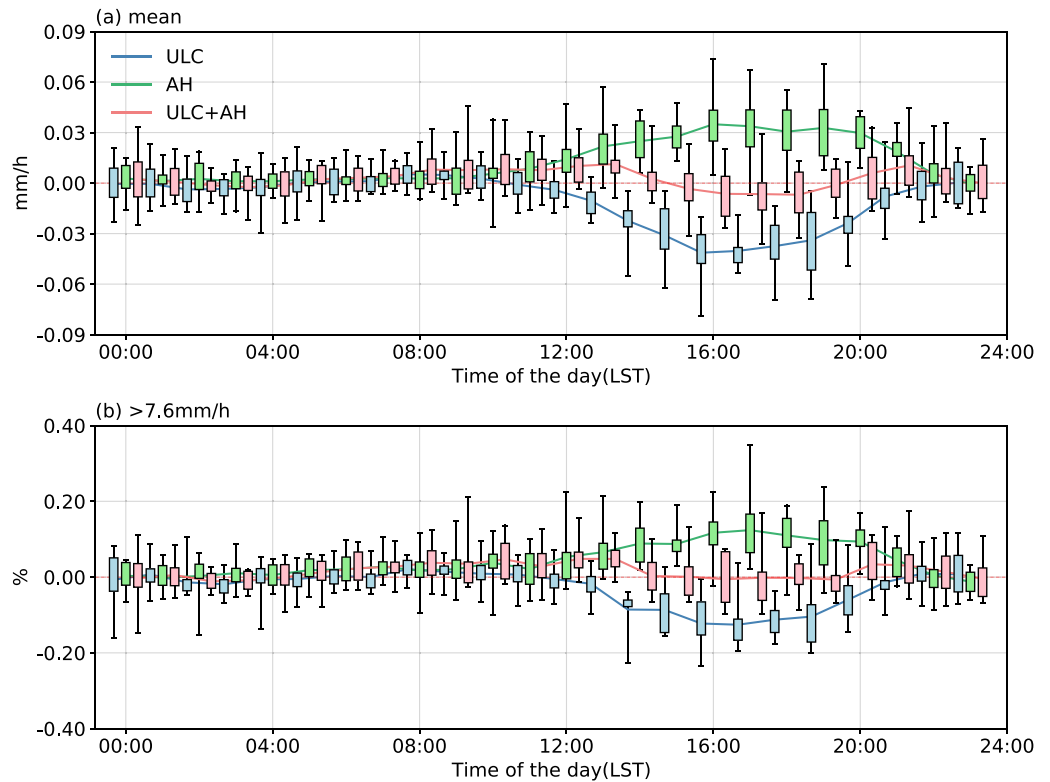


Figure 6. The effect on diurnal variation of (a) total precipitation (mm/h), and (b) hourly heavy precipitation frequency (%) (averaged in the black rectangle of Figure 1c) during the 10 summers from 2011 to 2020. The solid line represents the 10-summer mean values, the boxes represent the range of 25–75th percentile, and the whiskers represent the maximum (upper) and minimum (lower) values.

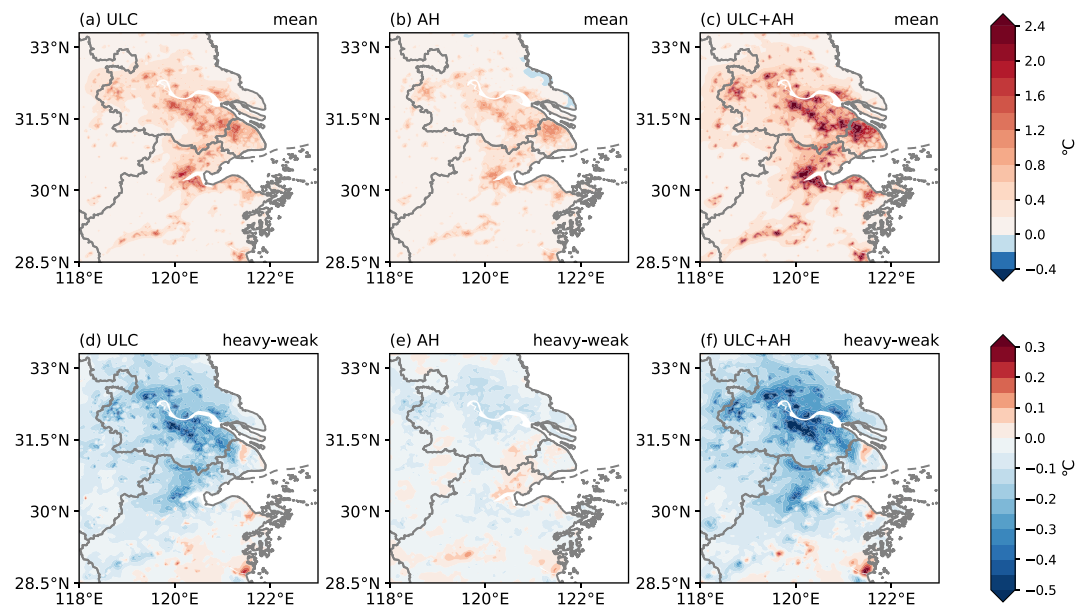


Figure 7. The spatial distribution of the change in 2-m temperature induced by the (a, d) ULC effect, (b, e) AH effect, and (c, f) their joint effect for (a–c) the mean results based on all precipitation cases and (d–f) the difference between the heavy and weak groups during the 10 summers from 2011 to 2020.

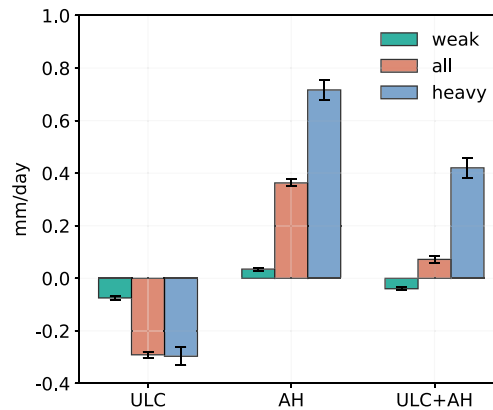


Figure 8. The responses of precipitation (averaged in the black rectangle of Figure 1c) induced by ULC change, AH emission, and their joint effect (corresponding to ULC, AH, and ULC+AH along the X-axis, respectively) under conditions with different precipitation intensities during the 10 summers from 2011 to 2020. The whiskers denote means $\pm 2\sigma$, where σ is the standard deviation of the urbanization effects for all selected cases in each group.

moisture convergence. Overall, the modulation effect of moisture storage played a more important role in the precipitation response to ULC than that to AH on diurnal timescale.

Above results have shown that both ULC and AH can affect precipitation via altering moisture convergence. Hence, we further decomposed the changes of moisture convergence into four terms (Equation 4), whose diurnal variations are presented in Figure 10. For the AH effect, the changes in moisture convergence were mainly contributed by the first term $\left(-\frac{1}{g} \int_{p_t}^{p_s} (q_c \cdot \nabla \cdot (\Delta \vec{V})) dp\right)$ and the fourth term $\left(-\frac{1}{g} \int_{p_t}^{p_s} (\vec{V}_c \cdot \nabla (\Delta q)) dp\right)$, which are related to the change in wind convergence and the change in moisture gradient, respectively. The change in wind convergence played a dominant role in the afternoon, whose effect was partly offset by that of moisture gradient.

For the ULC effect, the changes in moisture convergence were mainly contributed by the third term $\left(-\frac{1}{g} \int_{p_t}^{p_s} (\Delta q \cdot \nabla \cdot \vec{V}_c) dp\right)$; i.e., changes in mean moisture) and the fourth term $\left(-\frac{1}{g} \int_{p_t}^{p_s} (\vec{V}_c \cdot \nabla (\Delta q)) dp\right)$. Therefore, moisture convergence responded to ULC mainly through thermodynamic processes on diurnal timescale, which implies that the circulation effects on precipitation from increased surface roughness and warming might offset each other to a large degree. Apparently, the reduced moisture convergence in the afternoon can be explained by the decrease in mean moisture, while the intensified moisture convergence after sunset was explained by the change in moisture gradient.

Similar moisture budget analyses were also performed for daily rainfall events with different precipitation intensities (Figure 11). As mentioned above, the impacts of both AH and ULC became stronger with increased precipitation intensities. For the ULC effect, moisture convergence (red lines in Figure 11) increased and offset the effect of reduced evaporation (blue lines in Figure 11) during the weak rainfall cases (green bars in Figure 11), but was negligible during the heavy rainfall cases (blue bars in Figure 11). Hence, the dependence of the ULC effect on background precipitation intensity was mostly attributed to the variations of the changes in moisture convergence, although evaporation was more important in terms of summer mean (red bars in Figure 11).

For the AH effect, moisture convergence was the most important in terms of both summer-mean and case-to-case variation. In addition, moisture storage (green lines in Figure 11) also played a considerable role, which tended to absorb water vapor during the weak cases and release it during the heavy cases.

Moisture convergence was further decomposed into different dynamical and thermodynamic terms (Figure 12) given its dominant roles in the case-to-case variations of precipitation response. The change in wind convergence $\left(-\frac{1}{g} \int_{p_t}^{p_s} (q_c \cdot \nabla \cdot (\Delta \vec{V})) dp\right)$, blue bars in Figure 12) was the most important in terms of summer mean (Figure 12a).

However, both wind convergence and moisture gradient $\left(-\frac{1}{g} \int_{p_t}^{p_s} (\vec{V}_c \cdot \nabla (\Delta q)) dp\right)$, red bars in Figure 12) were important regarding the difference between the heavy and weak cases (Figure 12b). For the AH effect, the change in wind convergence was responsible for the increased moisture convergence while the change in moisture

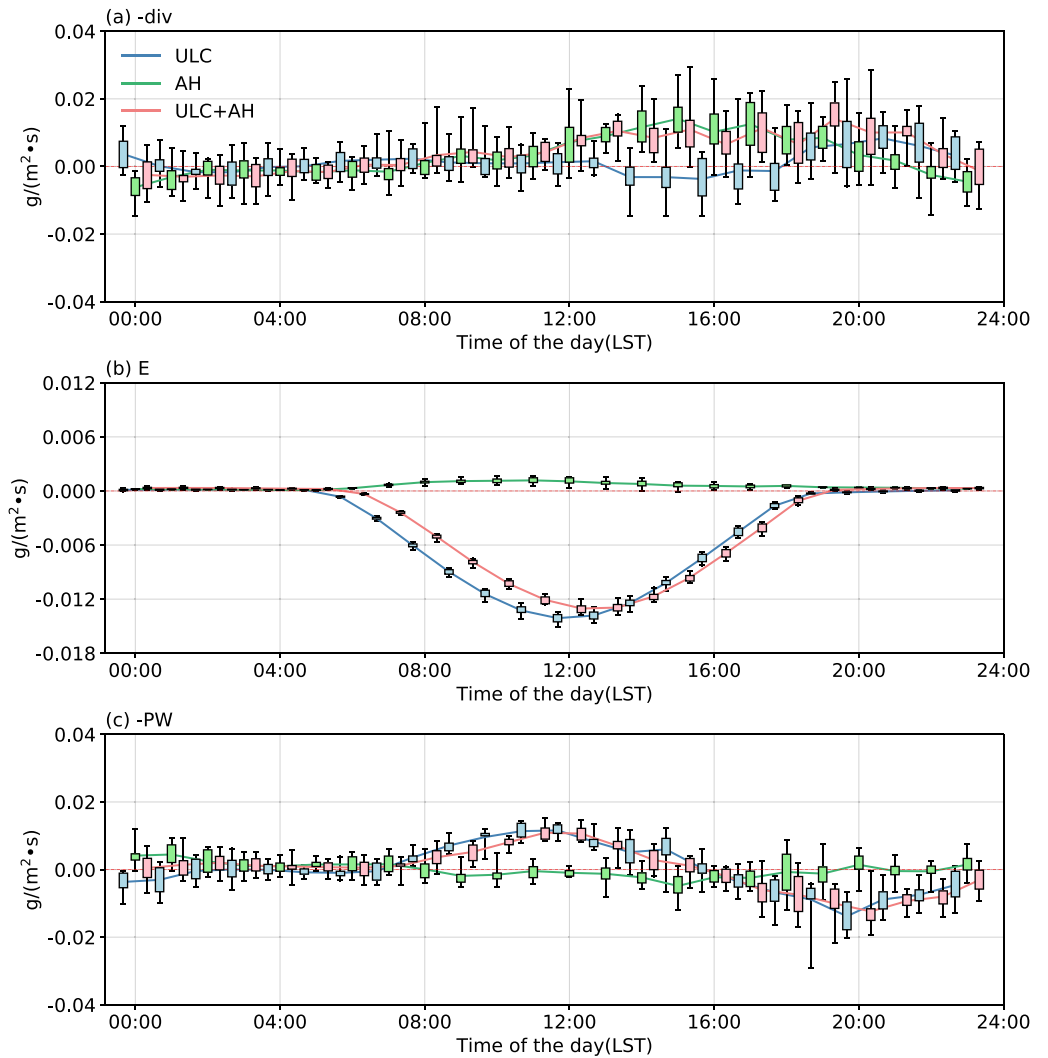


Figure 9. The effect on the diurnal variation of (a) $-\frac{1}{g} \nabla \cdot \int_{p_t}^{p_s} (q \cdot \vec{\nabla}) dp$, (b) E and (c) $-PW$ (averaged in the black rectangle of Figure 1c) during the 10 summers from 2011 to 2020. The meanings of the boxes and the whiskers are the same as those in Figure 6.

gradient caused an opposite effect. For the ULC effect, the change in wind convergence and moisture gradient jointly contributed to the decreased moisture convergence during the heavy cases, with the change in wind convergence playing a more important role. The effect of moisture gradient change was mainly located in the low-layer atmosphere (Figure 13), which was related to the weakened drying effect of ULC during heavy precipitation events (Figure S5 in Supporting Information S1).

Both the changes in circulation response ($\nabla \cdot (\Delta \vec{V})$) and moisture background (q_c) might be the reason for the different wind convergence effects (i.e., $-\frac{1}{g} \int_{p_t}^{p_s} (q_c \cdot \nabla \cdot (\Delta \vec{V})) dp$) between the heavy and weak cases. Therefore, we repeated the calculations of the difference in $-\frac{1}{g} \int_{p_t}^{p_s} (q_c \cdot \nabla \cdot (\Delta \vec{V})) dp$ but replaced $\Delta \vec{V}$ or q_c with the mean values in the heavy cases, so as to quantify the relative importance of $\nabla \cdot (\Delta \vec{V})$ and q_c (Figure 14).

Basically, the case-dependence of $-\frac{1}{g} \int_{p_t}^{p_s} (q_c \cdot \nabla \cdot (\Delta \vec{V})) dp$ was mainly contributed by the case-to-case variation in circulation response (blue bars in Figure 14). For the ULC effect, the variation in circulation response can be

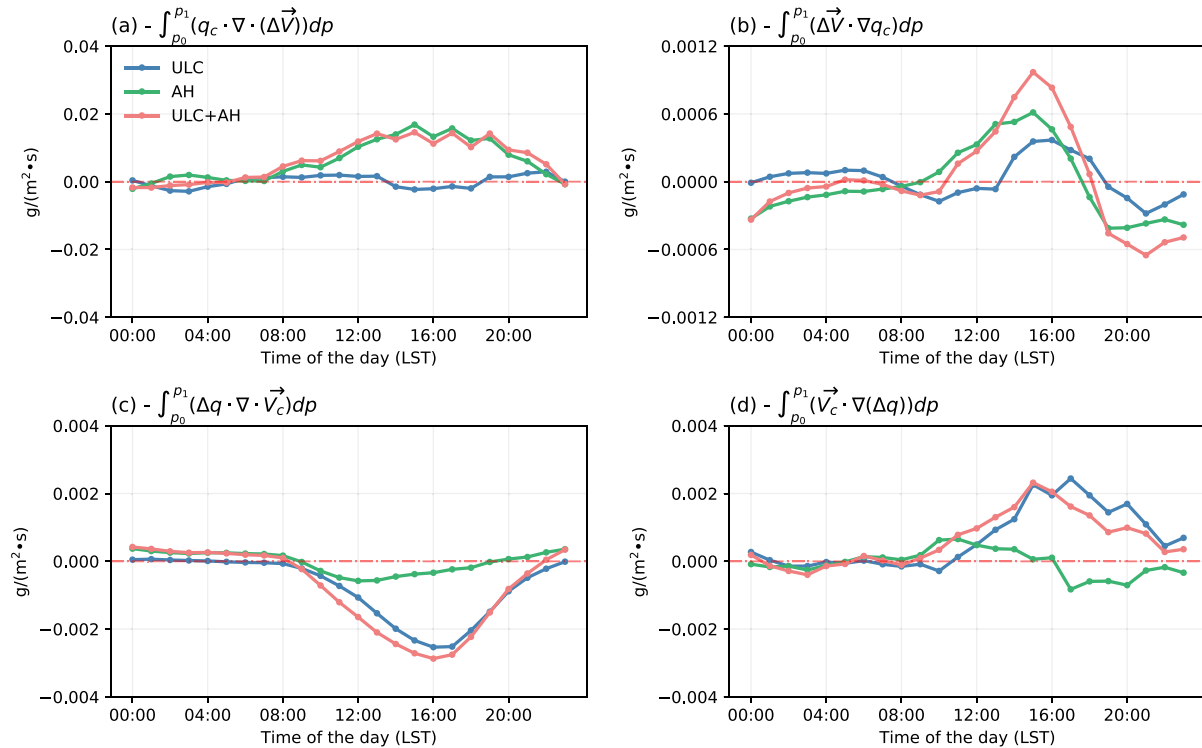


Figure 10. The diurnal variation of the responses in (a) $-\frac{1}{g} \int_{p_0}^{p_1} (q_c \cdot \nabla \cdot (\Delta \vec{V})) dp$, (b) $-\frac{1}{g} \int_{p_0}^{p_1} (\Delta \vec{V} \cdot \nabla q_c) dp$, (c) $-\frac{1}{g} \int_{p_0}^{p_1} (\Delta q \cdot \nabla \cdot \vec{V}_c) dp$, and (d) $-\frac{1}{g} \int_{p_0}^{p_1} (\vec{V}_c \cdot \nabla (\Delta q)) dp$, induced by ULC change, AH emission, and their joint effect averaged in the black rectangle of Figure 1c during the 10 summers from 2011 to 2020.

explained by the weaker warming but enhanced blocking effect during heavy cases. As precipitation intensity increased, the ULC-induced warming decreased (Figure 7d), which was responsible for the weakening of the wind convergence effect in the lower-layer atmosphere (Figure S6 in Supporting Information S1). Contrastingly, as precipitation intensity increased, the warming effect due to AH emission remained relatively stable (Figure 7e). However, the wind convergence effect was intensified throughout the low- and mid-troposphere (between 950 hPa and 400 hPa) (Figure S6 in Supporting Information S1). To understand this phenomenon, we further quantified the relative contributions of background specific humidity (q_c) and circulation changes $\nabla \cdot (\Delta \vec{V})$ at

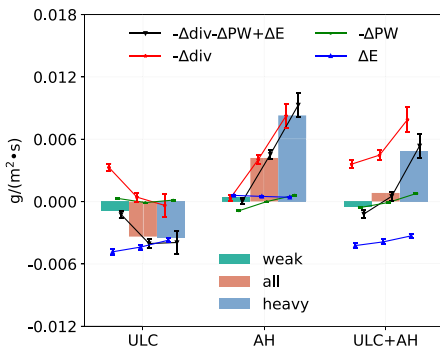


Figure 11. The responses of different atmospheric moisture budget terms (averaged in the black rectangle of Figure 1c) induced by ULC change, AH emission, and their joint effect (corresponding to ULC, AH, and ULC+AH along the X-axis, respectively) under conditions with different precipitation intensities during the 10 summers from 2011 to 2020. The meaning of the whiskers is the same as that in Figure 8.

different atmospheric levels to the enhanced wind convergence effect (Figure 15) and found that both background specific humidity (green line in Figure 15a) and circulation changes (green line in Figure 15b) were important throughout the atmosphere. Given the weak variation in the AH-induced warming, the enhanced effect due to circulation was likely a feedback to the changes in precipitation which was primarily caused by the variation in background specific humidity (orange bars in Figure 14) (Norris et al., 2019), which deserves further investigations and is beyond the scope of this study.

4. Conclusion and Discussion

Based on the WRF/SLUCM simulations utilizing the latest realistic urban fraction and AH data, this study investigated the individual effects of ULC and AH on precipitation over the YRD urban agglomeration. Meanwhile, atmospheric moisture budget analyses were performed to quantify the relative importance of various dynamical and thermodynamic processes. The results showed that, ULC and AH had nearly opposite effects on precipitation. AH can result in significant increases in the summer-mean precipitation and

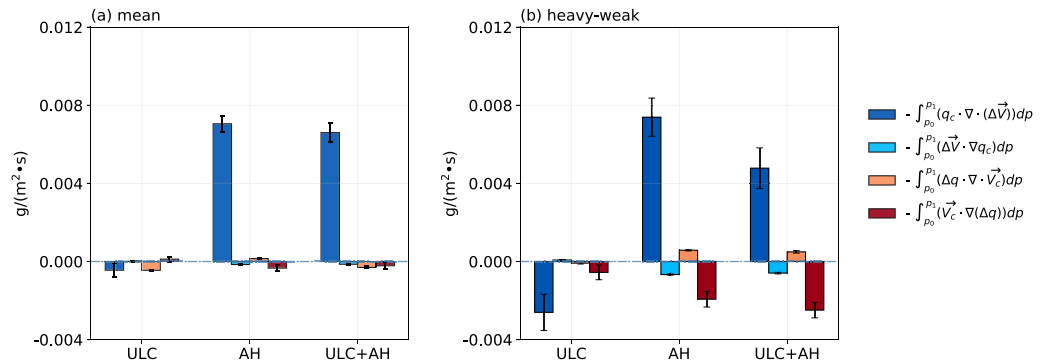


Figure 12. The responses of $-\frac{1}{g} \int_{p_1}^{p_0} (q_c \cdot \nabla \cdot (\Delta \vec{V})) dp$, $-\frac{1}{g} \int_{p_1}^{p_0} (\Delta \vec{V} \cdot \nabla q_c) dp$, $-\frac{1}{g} \int_{p_1}^{p_0} (\Delta q \cdot \nabla \cdot \vec{V}_c) dp$, and $-\frac{1}{g} \int_{p_1}^{p_0} (\vec{V}_c \cdot \nabla (\Delta q)) dp$ (averaged in the black rectangle of Figure 1c) induced by ULC change, AH emission, and their joint effect for (a) the mean results based on all precipitation cases and (b) the difference between the heavy and weak groups during the 10 summers from 2011 to 2020. The meaning of the whiskers is the same as that in Figure 8.

hourly heavy precipitation frequency, which were mainly attributed to the increased precipitation during afternoon. By contrast, ULC led to a considerable reduction in precipitation. Results from moisture budget analyses indicated that the precipitation response to AH was almost entirely balanced by the change in moisture convergence on diurnal timescale. Differently, the response to ULC was jointly determined by multiple factors. In specific, the changes in moisture storage tendency tended to balance the suppressed evaporation and enhanced moisture convergence after sunrise and sunset, respectively. As a result, the reduction in precipitation mainly occurred during afternoon.

We then compared the precipitation responses under conditions with weak and heavy rainfall based on daily-mean precipitation intensity. We found that both the AH and ULC effects became stronger during the heavy cases mainly because of the enhanced moisture convergence effect. The release of moisture storage previously accumulated in the atmosphere was also partly responsible for the stronger AH effect. Further analyses indicated that the case-dependence of the moisture convergence was mainly contributed by the variation in circulation response, but the related mechanisms associated with ULC and AH were different.

Overall, our results help better understand the relative roles of different aspects of urbanization on precipitation, suggesting that compared to ULC, reduction in AH that is tightly related to the transition of energy consumption structure could be more efficient for mitigating the risk of extreme precipitation. Note that in this study we treated all AH as additional sensible heat flux released into the atmosphere. In the future, we are planning to investigate the individual impacts of different AH types, i.e., latent versus sensible heat, on

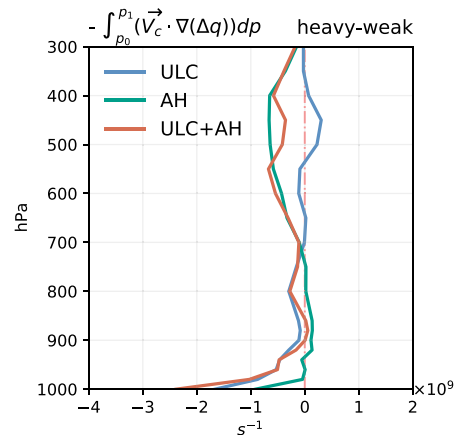


Figure 13. The vertical distribution of $-\frac{1}{g} \int_{p_1}^{p_0} (\vec{V}_c \cdot \nabla (\Delta q)) dp$ for the difference between the heavy and weak groups during the 10 summers from 2011 to 2020.

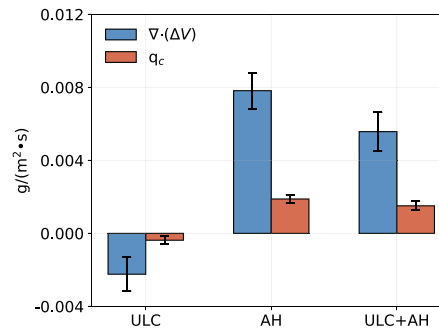


Figure 14. The contributions of circulation response (i.e., $\nabla \cdot (\Delta \vec{V})$) and background specific humidity (i.e., q_c) to the difference in $-\frac{1}{g} \int_{p_t}^{p_s} (q_c \cdot \nabla \cdot (\Delta \vec{V})) dp$ between the heavy and weak groups. The meaning of the whiskers is the same as that in Figure 8.

precipitation (Mishra et al., 2022), and consider the year-to-year variation of AH. Meanwhile, the configuration for land use distributions was simplified in this study. During the past decade, the Local Climate Zones (LCZ) scheme has been developed to classify a city and its surrounding area into 10 built types and seven natural types (Brousse et al., 2016; Ren et al., 2019; Ribeiro et al., 2021; Stewart & Oke, 2012; Yang et al., 2022). The National Urban Database and Assess Portal Tool (NUDAPT) and the World Urban Database and Access Portal Tool (WUDAPT) have also been developed to provide gridded UCP datasets for various cities (Brousse et al., 2016; Ching et al., 2009; He et al., 2019; Khanh et al., 2023; Ren et al., 2019; Sun et al., 2021; Varquez et al., 2021; Zonato et al., 2020). Furthermore, the classification of precipitation cases was simply based on precipitation intensity. How the effects of ULC and AH would vary across precipitation conditions with different cloud and convection characteristics, such as those associated with mesoscale convective system, isolated deep convection, and non-convective processes (Li et al., 2022) needs further investigations. In addition, there are large uncertainties in the model physics. Future study should examine the urban effects on precipitation using different physical parameterizations, such as the multi-layer urban canopy model (Martilli et al., 2002; Salamanca & Martilli, 2010), which is more sophisticated compared to SLUCM.

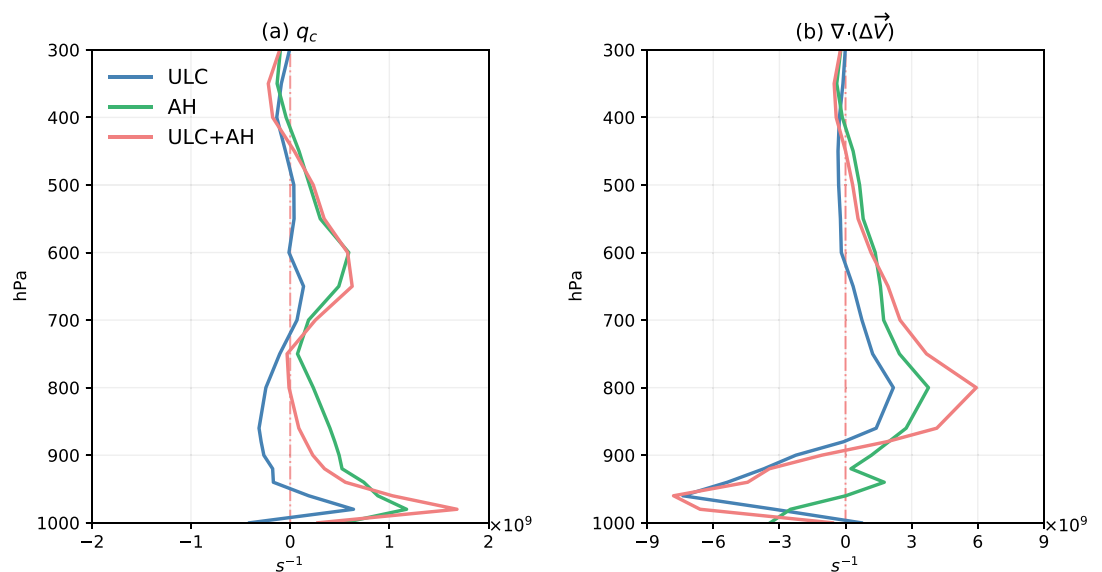


Figure 15. The vertical distribution of contributions from circulation response (i.e., $\nabla \cdot (\Delta \vec{V})$) and background specific humidity (i.e., q_c) to the difference in $-\frac{1}{g} \int_{p_t}^{p_s} (q_c \cdot \nabla \cdot (\Delta \vec{V})) dp$ between the heavy and weak groups.

Data Availability Statement

The 30-m resolution artificial surface in the version 2020 of GlobeLand30 is available on the National Geomatics Center of China (Chen et al., 2015; Chen et al., 2021) online (<http://www.globallandcover.com>). The satellite data from Climate Prediction Center Morphing Technique (CMORPH) is available on National Centers for Environment Information (Joyce et al., 2004; Xie et al., 2019). The CN05.1 dataset can be obtained from Climate Change Research Center, Chinese Academy of Sciences (Wu et al., 2017; Wu & Gao, 2013). The anthropogenic heat data in Chinese mainland of 2019 was publicly released by Qian et al. (2023). The initial and lateral boundary conditions for the WRF model were derived from the final analysis developed at the National Centers for Environmental Prediction (NECP FNL, 2000). The model outputs used in this study has been uploaded to repository for archive (Ma, 2023).

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