Supporting Information

Climate-Conscious Urban Growth Mitigates Urban Warming:
Evidence from Shenzhen, China

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Section S1: Materials and Methods

S1.1: Experimental Design

Figure S1 The experimental design to investigate the effectiveness of the CUGP. LU, land use; SMOLA, spatial multi-objective land use allocation.

S1.2: Land Use Map Pre-processing

First, to simplify the case, some of the minor land use types are merged into more general classes (Table S1). Then, using a pixel-level ISA map estimated using a building footprint data retrieved from Tianditu (http://www.tianditu.cn) and a road network data provided by the Shenzhen government, the urban land type was reclassified into high-density (ISA≥80%), mid-density (80%>ISA≥50%), and low-density (50%>ISA≥20%) urban lands. To better reflect the meteorological characteristics of urban lands, the classification scheme from recommendations from the National Center of Atmospheric Research was adopted, which is consistent with the classification scheme used in the WRF/Noah/LSM model1.

Table S1 Generalization of land use/cover types, and preliminary statistics.

| OID | Original Types   | General Types         | NID | Area (Km2) | Percentage |
|-----|------------------|-----------------------|-----|------------|------------|
| 1   | Forest           | Forest                | L4  | 585.0      | 28.23%     |
| 2   | Other forest     |                       |     |            |            |
| 3   | Urban            | High-density urban    | L1  | 539.5      | 26.03%     |
|     |                  | Mid-density urban     | L2  | 315.0      | 15.20%     |
|     |                  | Low-density urban     | L3  | 46.8       | 2.26%      |
| 4   | Orchard          | Garden land           | L5  | 267.5      | 12.91%     |
| 5   | Tea garden       |                       |     |            |            |
| 6   | Other garden     |                       |     |            |            |
| 7   | River            | Water                 | L6  | 80.3       | 3.87%      |
| 8   | Pond             |                       |     |            |            |
Section 1.3: NSGA-II based SMOLA Model

Figure S2 shows the flowchart of the NSGA-II-based SMOLA model in this paper, including its four main modules: initialization, evaluation, elitism, and evolution. The evaluation module, containing objectives and constraints of the SMOLA model, has been explained in Section 2.3. For technical details of the optimization model, please refer to the supplementary material.

Initialization: random boundary-based urban growth

We initiated the first generation by iteratively applying a random boundary-based urban growth operator to the status quo until the required generation size was met. The first generation was then fed to the SMOLA model as the start of the optimization process.

Elitism: fast non-dominated sorting

We applied the fast non-dominated sorting (Deb et al., 2002) as the elitism operator, which helps in achieving better convergence in SMOLA. In non-dominated sorting, solution A dominates Solution B when and only when one of the objectives of Solution A gets better than Solution B without degrading some of the other objectives. In this way, the arbitrary process of weight assignment in classical multi-objective methods is avoided. Moreover, the solutions are sorted into multiple fronts containing solutions that are equally good without additional subjective preference, which provides decision make with more options. The crowding distance \(^3\) is used to encourage the diversity of solutions on each front.

Evolution: sectional crossover and point-based mutation

The land use plans in the optimization process are evolved using a combination of bio-inspired
evolutionary operators, such as crossover and mutation, where a pair of parents is selected from the previous generation for producing a child. In the selection of parents, preference is given to elite individuals; the less-fit solutions are also possible to be selected to ensure genetic diversity. Generation by generation, the solutions evolve towards the Pareto-optimal front, where no solution can be further improved in any one of the objectives without degrading the others. In this paper, the sectional crossover operator, rather than point-based crossover, was used to achieve faster convergence and generate less dispersed land use plans. The point-based mutation operator was utilized to increase the genetic diversity of the generations to avoid premature convergence. The parameters of genetic algorithm, such as the population size $N$, the selection rate $\alpha$, the mutation rate $\beta$, are established after intensive experiments using the parameter tuning method of Coy et al. (2001). The optimal combination of parameters is as follows:

- population size ($N$): 800
- crossover rate: 0.9
- mutation probability: 0.1
- number of iterations: 2000

Figure S2 Flowchart of the non-dominated sorting genetic algorithm (NSGA-II) implemented in this paper.

Section S2: Results and Discussion
S2.1: Modeling Results of LST-Land Use Relationship
Here’re the modeling results for both the spatially fixed modeling and the spatially explicit modeling. GWR is found to be a more appropriate analytical framework in conducting research involving multiple spatial data with autocorrelated structures. The fixed Gaussian kernel is used as the samples are evenly distributed, and the optimal kernel size is selected by minimizing AICc. Geographic variability tests are also implemented to verify the improvement in modeling performance by incorporating spatial-varying coefficients.

Table S2 Estimated spatially fixed and spatially explicit models of both daytime and nighttime LST. For local variables in the spatial-explicit model, the minimum, median and maximum of the estimated coefficients are listed, while their spatial distribution is illustrated in Figure S3.

| Land use/Cover     | Spatially fixed Model (OLS) | Spatially explicit Model (sGWR) |
|-------------------|-----------------------------|--------------------------------|
|                   | Day                         | Night                         |
|                   | beta | beta | Min. | Median | Max. | Min. | Median | Max. |
| Urban (high-density) | 3.769 | 0.517 | 0.859 | 3.110  | 5.806 | -1.195 | 0.322 | 1.971 |
| Urban (mid-density) | 2.938 | Excluded € | -0.114 | 2.392  | 5.587 | Excluded € | 0.140† |
| Urban (low-density) | Excluded € | 0.364 | 3.273 | -0.548 | 1.053 | -2.123 | -0.599 | -0.011 |
| Forest            | -1.625 | -1.028 | -3.273 | -0.548 | 1.053 | -2.123 | -0.599 | -0.011 |
| Waterbody         | Excluded € | 0.261 | Excluded € | 0.100† |
| Mudflat           | -4.548 | -1.803 | 0.003† | -0.282† |
| Shrub land        | -3.012 | -1.517 | -1.559† | -0.827† |
| Intercept         | 34.503 | 24.543 | 29.159 | 34.983 | 39.143 | 21.567 | 24.552 | 26.275 |
| R²                | 0.537 | 0.275 | 0.810 | 0.725 |

€ Excluded in both OLS and GWR models based on the statistical significance test using bootstrap confidence interval at the 99.5% confidence level
† Spatially fixed coefficients in the spatial-explicit model.

Figure S3 illustrates the spatially varying coefficients estimated for the major land use types, including high-density urban land, mid-density urban land, and forest land. High-density urban lands increase both $LST_d$ and $LST_n$, for most areas. Mid-density urban lands also significantly increase daytime surface temperature, but less than in the high-density urban lands. Meanwhile, there are also some areas in Shenzhen, e.g. the peninsula in the southeast corner, where the $LST_n$ decreases with intense urban development. We will explain this in the discussion section.

Diurnally, daytime and nighttime warming responses to land use share many similarities but also have significant differences. Both $LST_d$ and $LST_n$ respond positively to urban lands. Forest land, mudflats, and shrublands are found to be the major cooling sources for both $LST_d$ and $LST_n$. However, changes in $LST_d$ and $LST_n$ are significantly attributable to different sets of land use factors. For example, the effects of waterbody are found insignificant during the daytime, but positively significant during the nighttime. Also, $LST_d$ and $LST_n$ respond differently to some of the land use factors that exist in both models, e.g. high-density urban land. The warming/cooling responses during the daytime are stronger. Due to the significant spatial variances and diurnal differences in the warming responses, a certain land use change may lead to conflicting effects...
between $LST_d$ and $LST_n$, a trade-off situation (Zhang et al., 2017). Climate responses to urban land uses significantly depend on the configuration of urban lands, such as the development density, since the estimated coefficients for high-density, mid-density, and low-density urban land are significantly different.

![Figure S3: The spatially varying coefficients for the LST-land use relationship estimated by spatially explicit modeling, which varies not only spatially but also diurnally and configurationally.](image)

**S2.2: Optimization Results**

**S2.2.1: Effectiveness and Cost**

Figure S4 shows the improvement of objectives throughout the 2000 iterations. Since it is impossible to fit all four objectives in a 3-D visualization, we integrated the climate objectives with the changing cost to generate a combined measure, i.e., LST change per land unit change (LCPC), which reflects the efficiency of the optimized changes. The NSGA-II-based optimizer simultaneously improves not only the climate objectives but also the changing cost and land use compatibility.

Such cooling benefits are achieved with a small number of changes. Land use plans in the Pareto-
optimal front require an average of 432.0 land units, i.e., 5.2% of all land units, to be changed, which includes the 4.4% of all land units required as necessary urban growth. So, only 0.8% of extra land units need to be changed to achieve the significant cooling benefit.

Figure S4 Improvement of objectives in the optimization process. LCPC_d and LCPC_n are respectively the daytime and nighttime LST change per land use change. Formulation of the compatibility measure can be found in Section 2.3.

S2.2.2: Parameter Sensitivity Analysis

To test the sensitivity of model results based on model parameters, the growth rate and the elevation constraint of urban lands, we repeated the CUGP model for 12 times using different parameter combinations. Table S3 shows the average land surface temperature of the unplanned and planned urban growth for both daytime and nighttime. The comparisons between the warming impacts of the unplanned and planned urban growth were examined using T-tests. Mitigation effects in the 12 experiments are statistically significant (p<0.005). Results from the sensitivity analysis confirmed that the CUGP significantly mitigates urban warming brought by urban growth in Shenzhen.
Table S3. Average land surface temperature during daytime and nighttime using different growth rate and elevation threshold values.

| Temp. (°C) | Growth Rate | Elevation Threshold | 80m Unplanned | Planned | Diff. | 120m Unplanned | Planned | Diff. |
|------------|-------------|---------------------|----------------|---------|-------|----------------|---------|-------|
|            |             |                     | Unplanned | Planned | Diff. | Unplanned | Planned | Diff. |
| Day        | 10%         |                     | 36.33      | 36.26   | -0.07 | 36.35      | 36.25   | -0.10 |
|            | 20%         |                     | 36.55      | 36.46   | -0.09 | 36.57      | 36.46   | -0.11 |
|            | 30%         |                     | 36.76      | 36.71   | -0.05 | 36.79      | 36.68   | -0.11 |
| Night      | 10%         |                     | 23.50      | 23.47   | -0.03 | 23.50      | 23.47   | -0.03 |
|            | 20%         |                     | 23.54      | 23.51   | -0.03 | 23.54      | 23.50   | -0.04 |
|            | 30%         |                     | 23.58      | 23.56   | -0.02 | 23.58      | 23.55   | -0.03 |

* All differences are statistically significant (p<0.005).

We have also observed that using 120m, the 99th percentile of the elevation values of existing urban lands, as the elevation constraint increased the mitigation effects of the CUGP since it enlarged the solution space of urban growth and increased the variances in the first generation of genetic operation. In the experiments using 80m as the elevation constraint, the mitigation effects decreased with the increased urban growth rate, because the solution space of urban growth plan became smaller due to large urban growth demand and small land resources available. While in the experiments using 120m as the elevation constraint, the mitigation effects increased with the increased urban growth rate since more lands were available for urban development and could still provide a larger enough solution space even when the urban growth rate reached 30%. Similar trends were observed in daytime and nighttime temperatures.

S2.2.3: Optimized Changes

We further reclassified these changes (Table S4) to highlight the change in urban development density and to differentiate urban expansion and urban redevelopment.

Table S4 Classification scheme of urban changes

| Category           | Urban Expansion | Urban Redevelopment |
|--------------------|-----------------|---------------------|
|                    | From            | To                  | From             | To                  |
| Urban intensification III | Non-urban       | HDU                 | -                 | -                   |
| Urban intensification II | Non-urban       | MDU                 | LDU               | HDU                 |
| Urban intensification I   | Non-urban       | LDU                 | LDU               | MDU                 |
| Urban deintensification I | -                | MDU                 | HDU               | -                   |
| Urban deintensification II | -               | HDU                 | MDU               | -                   |
|                      |                 |                     |                   |                     |

* HDU, high-density urban land; MDU, mid-density urban land; LDU, low-density urban land.

We aggregated the gravity centers, i.e., geometric-median centers, of the proposed changes for each
generation generated in the optimization process to visualize the overall spatial shift as the optimization proceeds (Figure S5). While calculating the gravity centers, each urban change is weighted with its change in development intensity. Starting from the gravity centers of the random boundary-based urban growth in the first generation, the optimized gravity centers gradually moves towards the east.

Figure S5 The spatial distribution of the gravity centers of the optimized urban growth plans in the 1st, 500th, 1000th and the last generation. As the generations evolve iteratively, the gravity centers of urban growth gradually move towards the east half of Shenzhen.

Table S5 Percentages of forest land and waterbody within specific radiuses to urban lands for the status quo, baseline urban growth plans, and optimized urban growth plans.

| Types of urban lands | Radius (km) | The Status quo | Baseline urban growth plans | Optimized urban growth plans |
|----------------------|------------|----------------|-----------------------------|-----------------------------|
| High-density         | 0.5        | 3.9%           | 5.9%                        | 6.6% (+0.7%)                |
|                      | 2          | 12.9%          | 11.3%                       | 12.3% (+1.0%)               |
|                      | 5          | 19.4%          | 14.8%                       | 15.8% (+1.0%)               |
| Mid-density          | 0.5        | 9.5%           | 7.1%                        | 7.0% (-0.1%)                |
|                      | 2          | 16.9%          | 13.0%                       | 13.2% (+0.2%)               |
|                      | 5          | 20.6%          | 16.3%                       | 16.6% (+0.3%)               |
| Low-density          | 0.5        | 15.8%          | 10.2%                       | 9.2% (-0.1%)                |
|                      | 2          | 17.9%          | 14.0%                       | 12.7% (-1.3%)               |
|                      | 5          | 18.9%          | 16.4%                       | 14.8% (-1.6%)               |

S2.3 Probability distribution of unplanned urban growth
Since we have 800 land use plans after unplanned urban growth, we focused on urban lands, and assigned weights to different urban land use types. We assign 0 for non-urban lands, and 1, 2, 3 respectively for low-, mid-, and high-density urban lands. Then,
we aggregate the 800 plans by taking the average at each cell location.

Figure S6 shows the distribution of existing urban lands. Figure S7 shows the probability distribution of new urban lands of unplanned urban growth. We can see that new urban developments are relatively evenly distributed before the optimization. Figure 5 in the manuscript shows the distribution of urban changes optimized by the CUGP.

S2.4 Discussion: using empirical models for evolutionary optimization
We have adopted one of the top-down empirical approaches, sGWR (Eq. 2), to model the temperature-land use relationship used in the evolutionary optimization process. As an alternative, regional climate models such as WRF/urban could probably provide better climate simulation results than empirical models if calibrated correctly.

First, we argue that empirical approaches with acceptable accuracy is more suitable for evolutionary optimizations compared with climate simulations considering calculation efficiency and the fact that the climate models do not necessarily provide more reliable climate predictions. Since the evolutionary process is an intensively iterative process,
that is, for every one of the 800 chromosomes (proposed land use plans) in every one of the 1000 generations, we need to evaluate its climate effects. Clearly, climate models require longer calculations due to its much higher computational complexity compared to land use regression approaches, especially when the required spatial resolution is as high as 500m. Simulating 800,000 land use plans for a period of one year using regional climate models at high spatial resolution is not feasible in practice. Moreover, we agree that climate models could probably provide better climate simulation results than empirical models if calibrated correctly. In order to achieve high accuracy, climate models also need to be validated using ground measurements. Since climate factors can contain significant spatial variances, such a validation can be partial since the ground measurement are point-based, can be affected by local environment, and limited in sample size. Therefore, the climate models do not necessarily provide more accurate climate predictions compared with empirical models.

Second, instead of the inaccurate global modeling approaches (Eq.1), we used sGWR (Eq.2), one of the local regression approaches that consider spatial heterogeneity in the temperature-land use relationship due to the inherent complexity of the city-atmosphere system. To further improve the prediction accuracy of the model, we re-classified urban lands into high-density, mid-density, and low-density categories to consider their different contributions to temperature and built prediction models for the daytime and nighttime temperature respectively. By doing so, we achieved acceptable prediction accuracies for both daytime ($R^2=0.810$) and nighttime ($R^2=0.725$) by using the sGWR instead of global regression approaches (see Table S2 for detailed results).

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