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Refining Assignment of Runoff Control Targets with a Landscape Statistical Model: A Case Study in the Beijing Urban Sub-Center, China

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Abstract: Rapid urbanization has triggered large changes to both the urban landscape and the yield and degree of confluence of runoff. The annual runoff volume control rate (ARVCR) is the key target identified in sponge city overall planning and is based on local natural and social conditions. However, the large impact that landscape patterns have on the runoff process causes the capacity to implement the targets to differ between those patterns. Refinement of ARVCR targets based on landscape pattern indices is therefore needed. This study identified statistical relationships between landscape indices and runoff control targets in the delta pilot region of the Beijing urban sub-center and extended the statistical model to the Beijing urban sub-center, an area almost 20 times larger than the pilot region. Landscape factors were quantified based on their area, shape, and distribution. In the delta pilot region, the runoff control volume for each block was obtained from a simulation using the SWMM model, and the correlation between landscape indices and runoff control volume capacity in different functional land-use blocks was identified by multiple linear stepwise regression. Because the distributions of landscape indices were similar in the pilot delta area and the Beijing urban sub-center, the model could be extended to the much larger study area. The statistical model provided a runoff control scheme that produced a refined assignment of the total annual runoff control target and provided guidance that could be implemented in land-use planning.

Keywords: runoff control target assignment; landscape pattern; land function; statistical model; downscaling

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1. Introduction

Rapid urbanization has brought great changes to the urban hydrological cycle [1,2]. In response to the associated environmental problems, China has proposed the concept of "natural storage, natural infiltration, and natural purification" for sponge cities [3,4]. The government has proposed that the annual runoff volume control rate (ARVCR) be the key target in the construction of sponge cities [5,6]. The requirements of the ARVCR are specified on a large (e.g., district) scale in accord with the overall plan for runoff control. In practice, however, the overall plan has been used only as an outline. Detailed construction plans are used to provide detailed guidance for urban management. Existing plans analyze and optimize the planning of urban sponge facilities mainly from the perspective of overall planning on city or district scales [4,7]. When runoff control measures are used to plan the details of construction, ARVCR targets must be feasible and are specified at the block scale for infrastructure and for on-site construction. The goals of runoff control are based on both scientific and practical considerations and take into account economic issues that constrain zoning and construction strategies.

The urban landscape is complex, and that complexity must be considered in assessing the impacts of runoff on urban bodies of water [8,9]. Some of the changes in the urban landscape provide evidence of the various hydrological impacts of the urbanization process. Scholars have used hydrological models such as SWMM (stormwater management model) and DHSVM (distributed hydrology soil vegetation model) to analyze the relationship between impervious surface and landscape patterns [10,11], and the results have shown that the increase in impervious surface area is one of the main reasons for the frequent occurrence of urban flooding. Urban morphology also influences the roughness of landcover edges and the connectivity of different landcover types and therefore disrupts the original yield and process of the runoff [12,13]. These studies have demonstrated that an isolated and fragmented landscape results in decreased runoff yield, but the relationship between landscape and runoff has not been quantified. This lack of quantification has made it difficult to relate landscape patterns to the control of runoff at a fine scale. Extant research on the relationship between urban landscape patterns and hydrological processes has therefore been largely confined to the overall planning level [8,12].

A few studies have been concerned with the decomposition of runoff volume control tasks at smaller scales [2,5], but because the applied methods have been based on runoff coefficients and have ignored the impacts of specific landscape features on runoff processes, the results have been too opaque to discern a clear explanation for the observed variability of runoff responses. Field-monitoring experiments have shown that in urban areas, runoff processes are significantly influenced by landscape patterns [8]. Research has indicated the synergistic, evolutionary relationship between landscape patterns and runoff processes and has demonstrated that landscape indices can be used to effectively predict runoff [14–16]. The indices of landscape pattern and landcover connectivity are critical to the runoff yield process, especially in urban drainage systems [9]. The fragmentation of blocks by roads and buildings results in a landscape pattern that differs from that of the continuous, natural site [17]. Representative factors or indices vary among different kinds of surface morphologies because of the inherently patchy fragmentation and heterogeneity of urban landscapes. The focus of the current study was an urban region with a flat topography. The landscape pattern was the most significant predictor of runoff response processes because the regional slope differences were small (<1‰), and the soil types were spatially homogeneous. In such cities, research on the relationship between landscape characteristics and runoff control requires consideration of the different types of land use and is thus consistent with the scheme to control runoff by regulating urban development.

To address this need, we developed a statistical model of the relationship between indices of surface landscape patterns and runoff control targets. Based on the results of the analysis of features identified via remote sensing, we developed a three-dimensional, quantitative description of the landscape based on area, shape, and distribution factors. We also identified a mechanism to translate the target for total annual runoff control from the overall planning stage to planning the details of proposed construction activities. FRAGSTATS software was used to quantify the landscape indices; runoff from the blocks in the pilot delta region was obtained from a simulation using the SWMM model; and the correlation between landscape characteristics and runoff from different functional land-use blocks was identified by multiple linear stepwise regression. Finally, the statistical model was extended to a large scale—almost 20 times the pilot area—to guide the delineation of runoff volume control tasks across the region.

2. Methodology and Data

2.1. Study Area

The study was conducted in the Beijing urban sub-center, China. Figure 1 shows the total area of 155 square kilometers. The climate is a typical northern temperate, semi-humid, continental monsoon climate with hot and rainy summers and cold and dry winters. The annual rainfall in 2019 was 506 mm. The percentage of green cover of the whole study region is 27%. The elevation of the study area is 8.2–30.0 m, and the average slope is 0.3–0.6‰. The pilot area of 8.8 km^2 was located in a delta region. There were 73 blocks in the pilot delta region, including 22 residential blocks, 13 commercial blocks, 14 public service blocks (such as hospitals and schools), and 24 plaza and green-space blocks (see Table 1). The whole study region has an ARVCR of 80%.

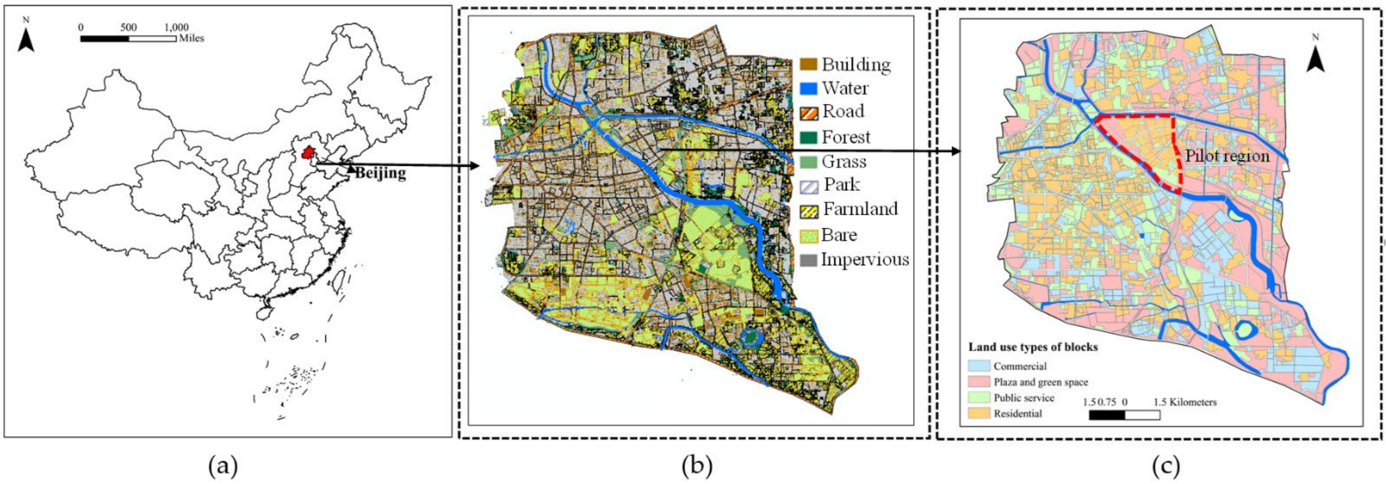

Figure 1. Study area for the ARVCR target in the built-up area of the Beijing urban sub-center. (**a**) Beijing, China; (**b**) Landcover of Beijing urban sub-center; (**c**) Land use types of blocks.

Table 1. Land cover by different types of land use in the whole study area.

Land-Use Type	Area (hm^2)	Impervious (%)	Vegetation (%)	Water (%)
Public service	28.8	67.4	31.4	1.2
Commercial	31.6	65.1	33.5	1.4
Plaza and green space	50.4	71.3	24.1	4.6
Residential	106.0	69.6	26.7	3.7

2.2. Quantification of Landscape Indices

Blocks were defined in city overall planning considering the land-use function types, such as residential, public service, commercial, and so on, as shown in Figure 1c. We used the indices of landscape patterns to characterize the patterns of blocks. The landscape indices shown in Table 2 were calculated at the block scale, and the explanation and equation used to calculate the index are shown in the Supplementary Information (SI) Table S1. We used FRAGSTATS software to quantify the landscape indices. FRAGSTATS was developed in 1995 with funding from the United States Department of Agriculture [18] and has been widely applied in land-use studies [19,20]. Calculation of the landscape indices consisted of the following steps: (1) acquiring high-resolution, remote-sensed data and pre-processing the data; (2) decoding the combination of remotely sensed data and urban construction land-use-planning data followed by resampling the decoded files and transforming them into raster data; and (3) cutting the data into raster data for each block based on the urban-planning data.

Table 2. Landscape indices.

Area Factors		Shape Factors		Distribution Factors	
Impervious ratio	IR	Shape Index	Shape	Contiguity Index	Contig
Green ratio	GR	Fractal Dimension Index	FRAC	Euclidean Nearest Neighbor Index	ENN
Average patch area	AREA	Landscape Shape Index	LSI	Contagion Index	CONTAG
Patch density	PD	Total Edge Contrast Index	TECI	Proportion of Like Adjacency	PLADJ
Total core area	TCA	Contrast-weighted Edge Density	CWED	Landscape Division Index	DIVISION
		Edge Contrast Index	ECON	Splitting Index	SPLIT
				Shannon Diversity Index	SHDI
				Aggregation Index	AI

We used remote sensing data for the identification of land cover and thus as a basis for the quantification of landscape indices. The remote sensing data used in this study were obtained from the WorldView-2 remote sensing satellite of the United States with a resolution of 0.5 m. The data covered east longitudes from 116°39′38″ to 116°43′8″ and north latitudes from 39°55′553″ to 39°53′169″. After performing a radiometric correction and geometric correction of the original remote sensing images, we manually sketched the land cover edge and determined the land cover type in relation to the actual site.

2.3. Runoff Simulated by Hydrological Model

We used the SWMM model to simulate the volume of runoff from the pilot area (as shown in Figure 2), and then we used Equation (1) to calculate the runoff control volume (RCV). We used actual runoff data from field monitoring for model calibration and validation to ensure reliability (see SI Figure S2). We then used a statistical model to calculate the correlation coefficient between landscape characteristics and runoff control volume. We used the Nash–Sutcliffe efficiency factor (NSE) to judge the accuracy of the model simulations. The range of the NSE is $(-\infty, 1]$ [14]. The better the fit of the model simulation, the closer the value of the NSE to 1. We required that the NSE exceed 0.5 for model validation. We used Equations (1) and (2) to calculate the NSE:

$$RCV_i = R^i_{on} - R^i_{off} \tag{1}$$

$$NSE = 1 - \frac{\sum_{t=1}^{T}\left(Q_0^t - Q_m^t\right)^2}{\sum_{t=1}^{T}\left(Q_0^t - \overline{Q_0}\right)^2} \tag{2}$$

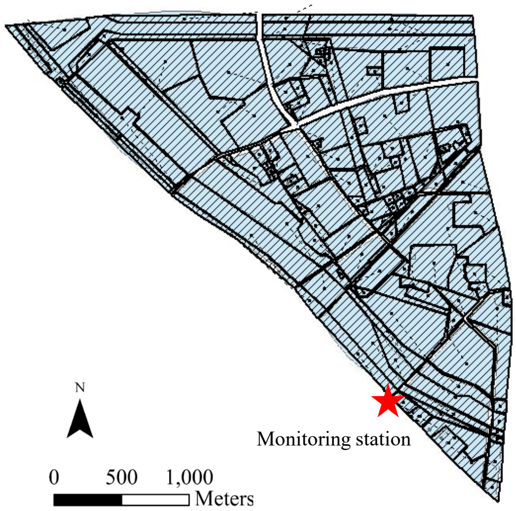

Figure 2. The delta pilot region simulated with the SWMM model.

In these equations, RCV_i was the runoff control volume in the ith block, R^i_{on} was the inflow to the ith block and included precipitation and inflow from upstream, R^i_{off} was the runoff from the ith block, NSE was the Nash efficiency coefficient, Q_0 was the measured flow rate, Q_m was the simulated flow rate, and $\overline{Q_0}$ was the average of the measured flow rates. The dummy variable t indicates the tth flow rate, and T is the total number of samples.

2.4. Assignment of the ARVCR Target

Statistical Model Development

We created a runoff control volume capacity indicator (s_i) to quantify the runoff retention and infiltration capacity of a specific block. The dependent variable of the regression was the runoff volume control capacity. The greater the runoff control volume capacity of an area, the higher the runoff control rate. Because blocks with a high runoff control volume capacity tended to be assigned a high ARVCR, there was a tendency for the s_i to be proportional to the runoff control rate (Equation (3)). The relationships between the s_i and landscape indices were obtained by developing statistical models using stepwise regression methods (as in Equation (4)). We used Equation (4) to calculate the runoff control volume of a specific block, and we used FRAGSTATS software to quantify landscape indices. It is noteworthy that in this study we performed the regressions of s_i versus landscape indices separately for different land uses. We could thus explore the impact of human activities on the runoff process. To ensure the reliability and reasonableness of the response relationship, we tested the goodness-of-fit and significance levels as follows:

$$s_i \propto R_i \tag{3}$$

$$s_i = a_1 x_1 + a_2 x_2 + \cdots + a_n x_n + b + \varepsilon \tag{4}$$

where s_i is the runoff control volume capacity indicator; R_i is the runoff volume control rate of the specific block; $x_1, x_2, \cdots x_n$ are the landscape indices of the specific block; a_1, a_2, $\cdots a_n$ are regression coefficients; b is a constant term; and ε is a random error that has an expectation value of zero and a variance $\sigma^2 > 0$. The error term ε accounts for the effects of random variables that were not taken into consideration.

We obtained the relationship between the runoff control rate target and the intensity of rainfall from the local, multi-year rainfall event statistics (Figure 3). We used this relationship to reassign the target of ARVCR into each block (Equation (5)) by regarding the s_i of each block to be a measure of runoff control capacity for that block. The product of the rainfall intensity corresponding to the overall ARVCR target (α_{total}) and the area of the whole region (A_{total}) equals the total runoff control volume requirement. We used the ratio of the s_i of a block to the s_i of the whole region to allocate the total runoff control demand among blocks. We calculated the rainfall intensity (P_i) of the assigned target by dividing the allocated control volume by the block area (A_i). We then used the curve in Figure 3 to convert the value of P_i to the ARVCR target for the block. The corresponding design rainfall corresponding to a total runoff control rate of 80% for the planning scenario was 26 mm.

$$P_i = \frac{\frac{s_i}{\sum_{i=1}^{n} s_i} * \alpha_{total} * A_{total}}{A_i} \tag{5}$$

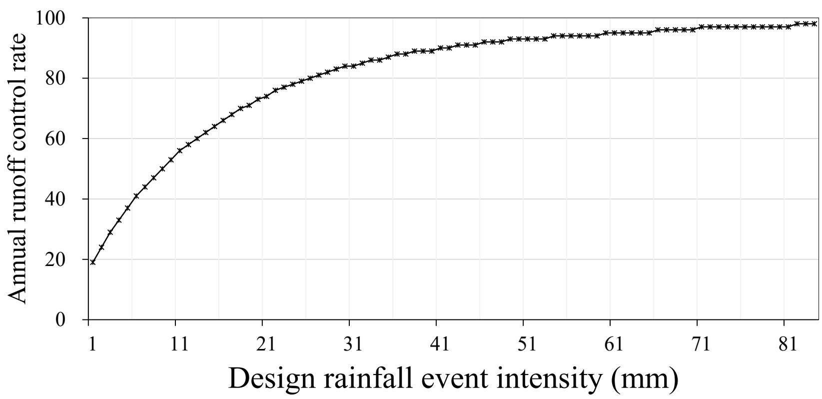

Figure 3. Relationship between ARVCR and design rainfall intensity.

3. Results and Discussion

3.1. Landscape Patterns of Different Land-Use Functions

Many studies have pointed out that among the landscape area factors, the percentages of impervious surface area (IR) and green area (GR) are the most important indices affecting the runoff infiltration and retention process [21,22]. In our study, the mean percentages of impervious surfaces and green areas were 69.4% and 30.6%, respectively, for residential functional blocks, 65.1% and 33.5%, respectively, for commercial functional blocks, 67.4% and 31.4%, respectively, for public service functional blocks, and 71.3% and 24.1%, respectively, for plaza and green space functional blocks (Figure 4). The ranges of the IR and GR indices for plaza and green space functional blocks were relatively wide, mainly because of the variable design pattern of the plaza and green space. The ranges of IR and GR were also relatively wide for residential land, mainly because of the differences of the patterns of anthropogenic land use at different stages of urban development. The GR indices of the different functional blocks were similar and averaged 30 ± 4%. This similarity was related to factors that constrained the percentage of urban space allocated to green areas during urban planning.

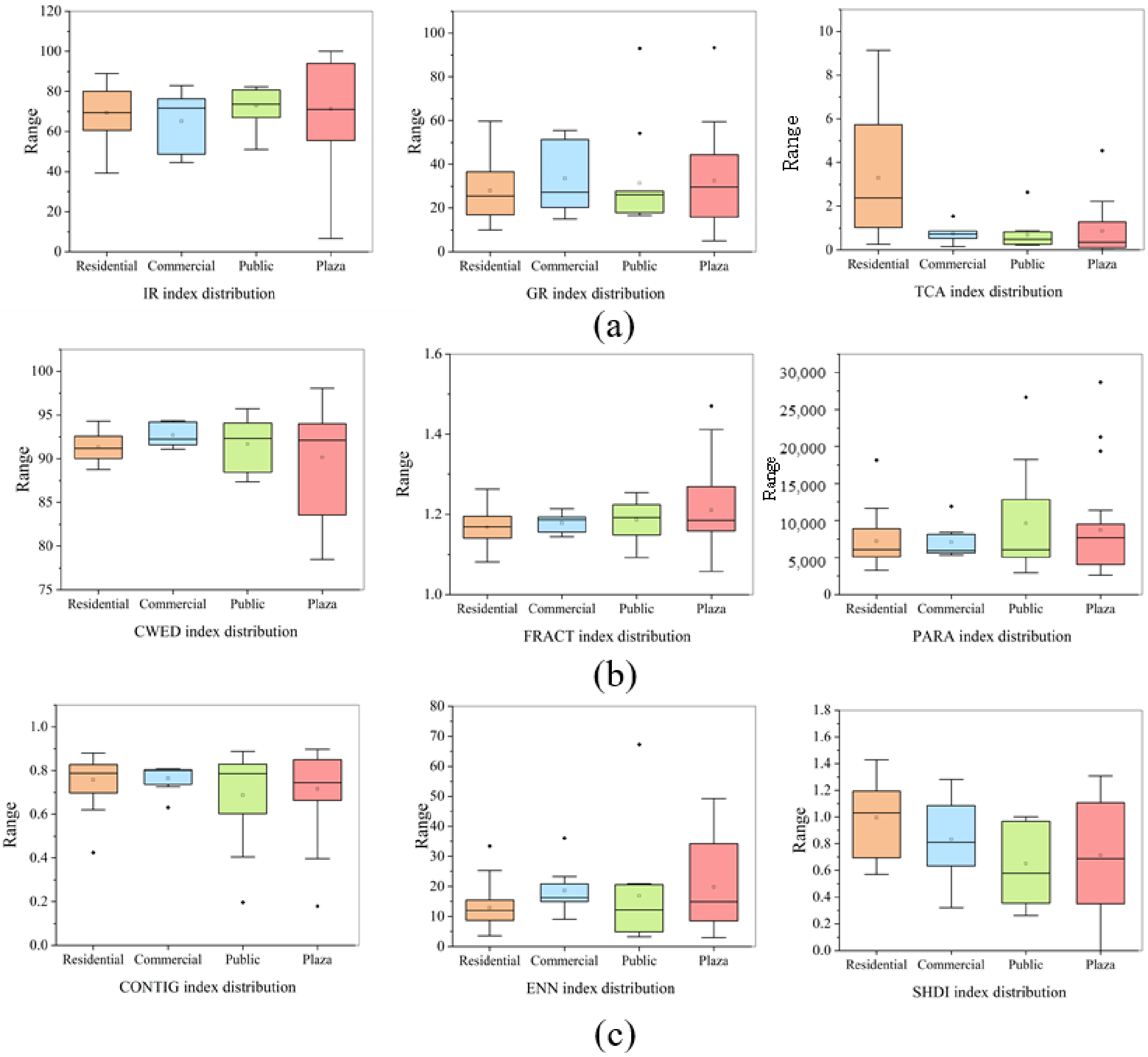

Figure 4. Landscape indices in different functional blocks for the pilot delta region. (**a**) Area factors; (**b**) Shape factors; (**c**) Distribution factors.

Among the various types of land use, the average value of the SHAPE factor ranged from 1.65 to 1.81. The SHAPE index value is independent of the area, with a value of one representing the most regular square and the larger the value the more complex the shape. The average values of SHAPE were similar for commercial land and public service land, 1.706 and 1.709, respectively. The ranges of SHAPE for plaza and green space were wider, mainly because impervious plazas were regularly shaped, whereas green spaces were fragmented. The edge/area ratios were similar for residential and commercial land;

the roughest landscape was land allocated to public services, for which the PARA was 9634. The edge/area ratios of plaza and green space were slightly higher than that of residential land.

The average value of the proximity index ranged from 0.689 to 0.815 in all types of land use (Figure 4). The average values of the SHAPE indices for residential and commercial land were similar, 0.758 and 0.765, respectively. The CONTIG index was highest for public service land and lowest for plaza and green space. The CONTIG index represents the adjacency to one another of different types of patches. The wide range of the distribution of plaza and green space within plaza and green space indicated that there were large differences in the uses of plaza and green space. The distributions of the CONTAG and CONTIG indices were similar. CONTAG indicates the degree of agglomeration or extension of patches. Smaller values indicate the presence of many small patches in the landscape; higher values indicate the presence of highly connected dominant patch types in the landscape. The mean values of the ENN index were similar in commercial and public service land, 18.65 and 16.87, respectively. The mean value of the ENN index was largest for plaza and green space. The area of blocks in the plaza and green space was large. The mean value of the SHDI index was large (0.995) in residential land and lowest in public services land (0.652). The mean value of the AI index exceeded 90 in all types of land use. The SHDI was evenly distributed within all types of land. The distribution of the AI was relatively wide in the plaza and green space.

Human activities affect the urban landscape. The zoning of the functions of land reflects, to some extent, how human activities change land use. The landscape and function of land interact to a certain extent. In previous studies, the urban landscape has been described mostly from a macroscopic perspective, and there has been no discussion of whether the urban landscape differs between different functional areas. This lack of specificity has made it difficult to extrapolate the relationships between regional surface indices and hydrological processes to other regions. This study provided a statistical analysis of the landscapes in different functional blocks and thus clarified the characteristics of landscape patterns in specific blocks. It provided a quantitative methodology that could be used to extend the study to other areas and provided a basis for analyzing hydrological processes specific to different functional areas.

3.2. Statistical Model for Quantifying Runoff Volume Control Capacity with Landscape Indices

This study assigned the runoff control target into specific blocks based on the management guidelines. Statistical models were developed in four typical land-use types: plaza and green space, residential, commercial, and public service.

The significance level of the regression model was less than 0.1 for all the block functions (Table 3). The simulated total annual runoff factor was therefore significantly correlated with the landscape indices. The fact that the Durbin–Watson statistic was close to two indicated that there was very little autocorrelation in the model. Table 4 shows the regression coefficient, standardized error, and statistical significance of the regression equations for the different functional blocks. The fact that the standard errors were all less than 0.3 indicated that the coefficients of the independent variables were reliable. The significance levels of the regression models were all less than 0.05; the models were therefore statistically significant.

Table 3. Statistical correlation models for different functional blocks.

Block Function	Statistical Model	R^2	Sig. F	Durbin–Watson
Plaza and green space	$s_1 = -0.063 \times \mathrm{IR} + 0.014 \times \mathrm{TECI} + 0.879$	0.812	0.009	1.557
Residential	$s_2 = -0.133 \times \mathrm{IR} + 0.095 \times \mathrm{CONTIG} + 0.028 \times \mathrm{SHDI} + 0.875$	0.580	0.003	1.820
Commercial	$s_3 = 0.284 \times \mathrm{CWED} - 0.072 \times \mathrm{IR} - 0.178 \times \mathrm{TECI} + 0.860$	0.883	0.002	2.313
Public	$s_4 = 0.263 \times \mathrm{GR} + 0.231 \times \mathrm{ENN} + 0.744$	0.610	0.039	1.928

where s_1, s_2, s_3, and s_4 are the runoff volume control capacity indicators of the four types of site, Sig. F denotes the value of statistical significance.

Table 4. Regression model reliability test.

Land Use	Parameters	Regression Coefficient	Standard Error	Sig. F
Plaza and green space	Constant	0.879	0.024	0.000
	IR	−0.063	0.033	0.030
	TECI	0.014	0.093	0.042
Residential	Constant	0.875	0.020	0.000
	IR	−0.133	0.070	0.009
	CONTIG	0.095	0.227	0.038
	SHDI	0.028	0.026	0.040
Commercial	Constant	0.860	0.019	0.000
	CWED	0.284	0.086	0.009
	IR	−0.072	0.016	0.002
	TECI	−0.178	0.070	0.032
Public	Constant	0.744	0.034	0.000
	GR	0.263	0.187	0.043
	ENN	0.231	0.137	0.046

where Sig. F denotes the value of statistical significance.

In the first statistical model, which described runoff from the plaza and green space, the most important indices were the IR and TECI. We attributed this result to the fact that green plazas often exhibit irregular edge patterns. Runoff control ability was negatively correlated with the impermeability of the block. In addition, the fact that runoff control volume capacity was positively correlated with edge characteristics indicated that runoff control capacity was enhanced when the edges of the green spaces exhibited a more complex, irregular morphology. In the statistical model of residential land use, the IR, CONTIG, and SHDI were the indices that mainly portrayed the runoff yield and degree of runoff confluence. The distribution of different blocks (e.g., sparsely or closely spaced) within the residential area was identified as a key index that influenced the regional runoff-generating capacity. The SHDI index describes the complexity of the different forms of landcover composition within the block, such as roads, grass, and roofs. High SHDI values indicate low landcover homogeneity. In the statistical model of the commercial functional blocks, the fact that the CWED, IR, and TECI were the main indices that influenced the runoff process indicated that the runoff control volume capacity was closely and positively related to the edge length of the blocks. This model showed that within the commercial area, blocks that were fragmented and had irregular edges were associated with a greater amount of runoff control capacity. The model for the public service type of land use showed that runoff control volume capacity could be rather well characterized by the ENN index; there was also a significant relationship between the runoff control volume capacity and the IR and GR indices. The implication was that increasing the patch distances within the public area would increase runoff control capacity.

An uneven distribution of land-use function and building forms results in a high degree of heterogeneity in the surface landscape [15,21]. In the process of urbanization, cities tend to spread from the center to the periphery and then form areas with relatively concentrated services such as commercial, residential, industrial, and plaza and green spaces [1]. Previous studies [23] have investigated the relationship between landscape indices and runoff yield and confluence without distinguishing between land-use functions. The fact that the model made distinctions between different functional areas improved the runoff simulation performance compared to previous models [14–16]. In this study, we distinguished land-use functions in order to explore the response relationship between runoff generation and landscape. This distinction greatly improved the validity of the model.

3.3. Assignment of the ARVCR Target with a Statistical Model That Considers Landscape

This study explored how consideration of the different functions of land use would affect the assignment of the ARVCR target. Relationships obtained from the statistical model of runoff and landscape for the pilot area were extended to the Beijing urban sub-center. Figure 5 shows that the distributions of landscape indices were similar in the pilot delta area and the Beijing urban sub-center. The model could therefore be extended to the much larger Beijing urban sub-center.

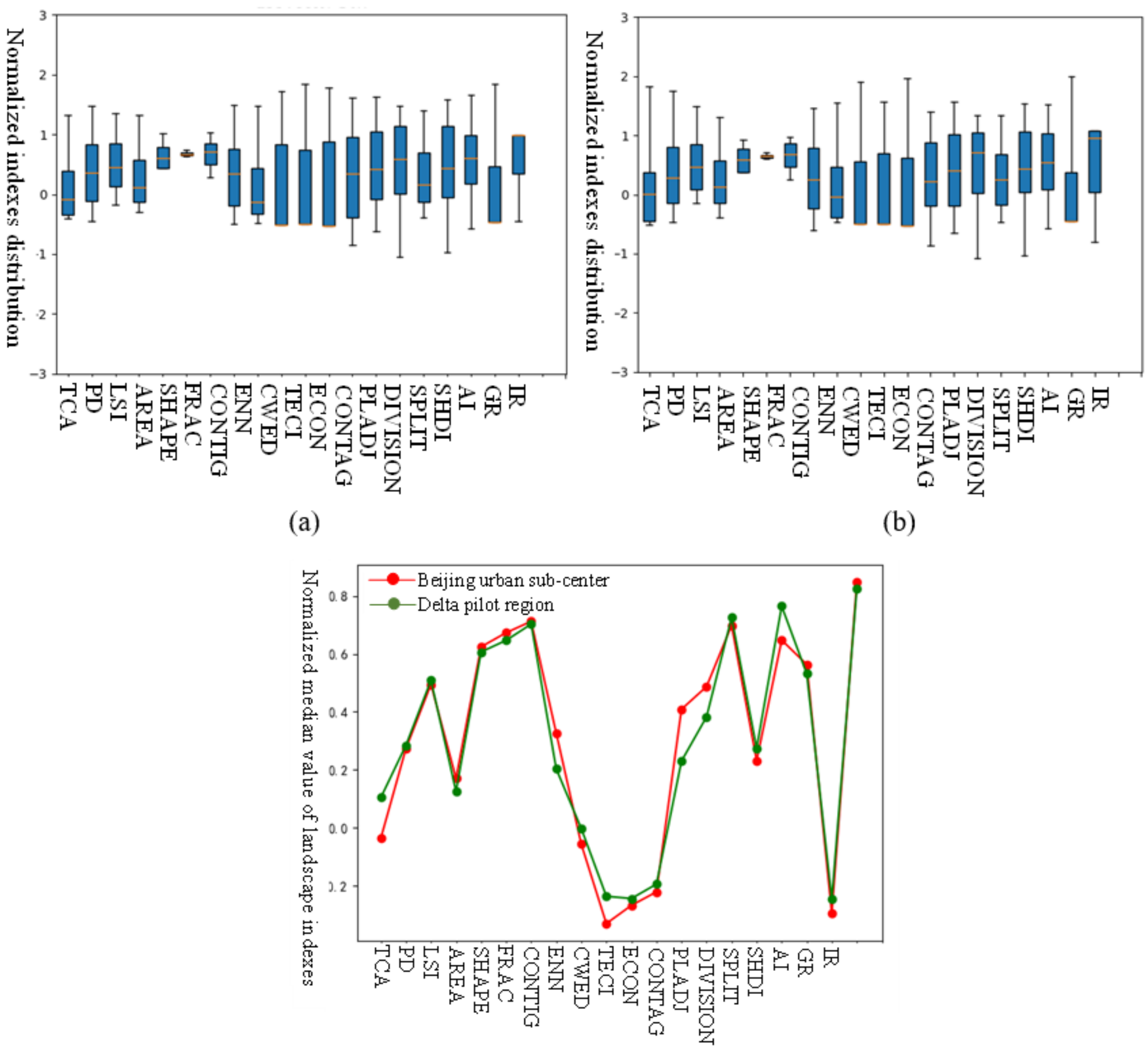

Figure 5. Comparison of landscape indices between the Beijing urban sub-center and the delta pi-lot region. (**a**) Beijing urban sub-center; (**b**) Delta pilot region; (**c**) Comparison of the normalized median values of the Beijing urban sub-center and the Delta pilot region.

The ARVCR of the Beijing urban sub-center was 80%. Figure 6a shows the results of the assignment of ARVCR planning values. In contrast to the underlying characteristics of the study area shown in Figure 1, the ARVCR of the region with a high percentage of impervious surfaces ranged from 40% to 95%, the ARVCR of the green areas was 90%, and the ARVCR of roads was 68.3%. The analysis of the results from Figure 6 showed that the method of assigning ARVCRs based on landscape indices facilitated the allocation of runoff control volumes to blocks.

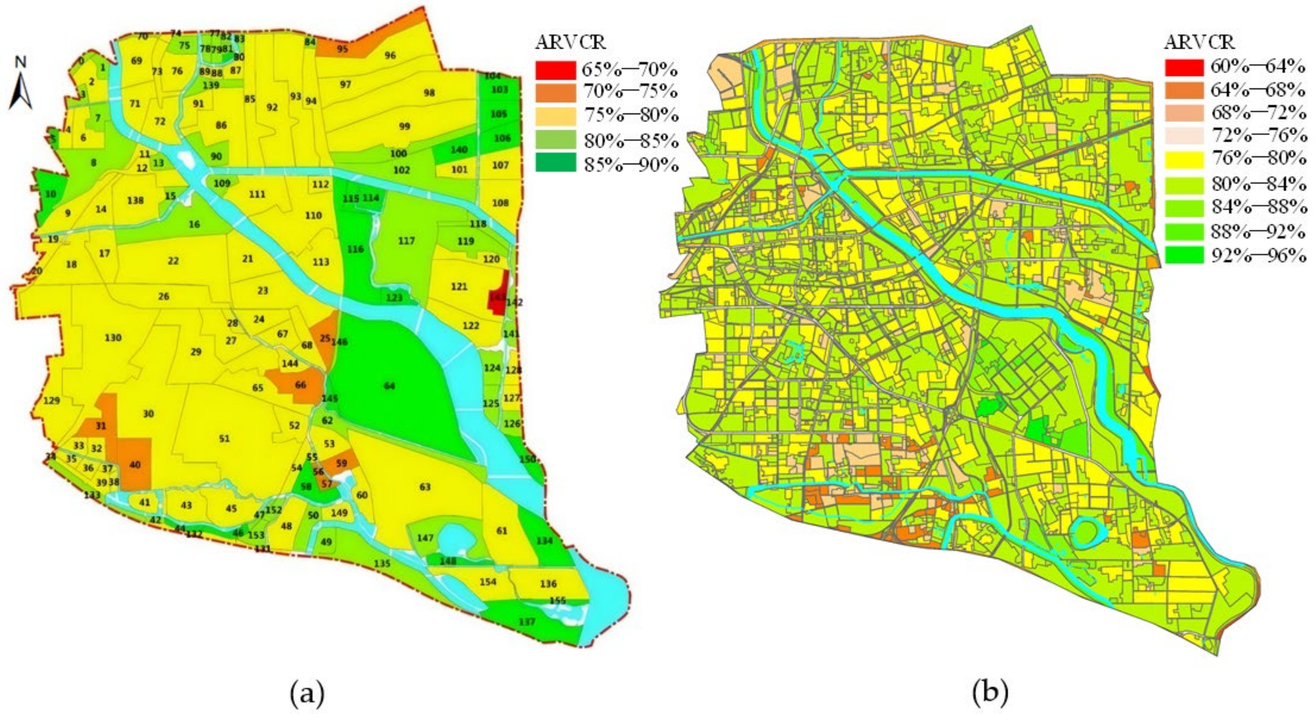

Figure 6. Comparison of the ARVCRs based on overall planning and the assignment via statistical methods. (**a**) ARVCR of overall planning; (**b**) ARVCR assigned by statistical model.

As illustrated in Figure 7, the blocks assigned an ARVCR target of 78–80% accounted for the largest percentage (36%) of the area of the Beijing urban sub-center. The blocks assigned an ARVCR target of 92–94% also accounted for a large area proportion (15%) of the area. Blocks assigned an ARVCR target of 86–88% accounted for the smallest proportion (2%) of the area. The study concluded that the larger runoff control targets were the areas where there were blocks with a wide range of percentages of green space and that those areas could provide greater runoff control. In contrast, the densely built areas included a high percentage of impervious surfaces and had a limited ability to control runoff. They were therefore assigned a smaller ARVCR target.

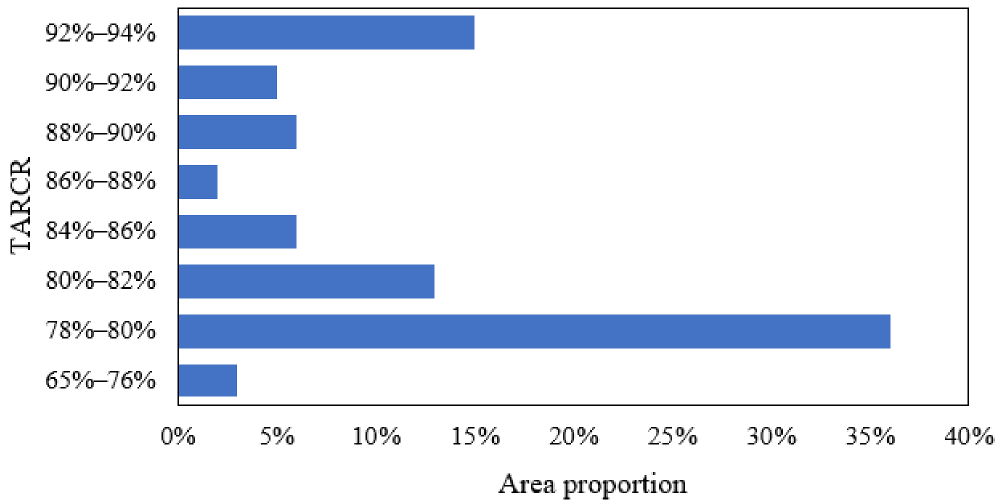

Figure 7. Percentages of area assigned the indicated ARVCRs.

The current method of assigning ARVCR targets uses only runoff coefficients as weighting factors and ignores the influence on runoff characteristics of different landscape-pattern indices. Instead, the current method is still at the stage of subjective and crude decomposition of runoff tasks [4,7]. This study considered the urban landscape characteristics and hydrological relationships on a block scale and quantitively extended relationships identified by the statistical models that were developed for different functional blocks. A realized assignment of ARVCR targets could be used to inform engineering practices related to urban runoff.

4. Conclusions

To identify a more informed and effective method for assigning targets to annual runoff volume control rates and to apply that methodology from the overall planning stages to the detailed construction planning stages, we developed a statistical model that described the relationship between landscape and runoff control targets in a pilot region, and we extended the model to a region almost 20 times larger than the pilot region. The results of this study showed that developing the relationship between landscape and runoff control targets by distinguishing site functions produced reliable results. The consistent distribution of indices in the delta and Beijing urban sub-center indicated that the statistical model could be quantitatively upscaled. The statistical model provided a runoff control scheme that produced a refined assignment of annual runoff volume control targets and provided guidance that could facilitate the planning of land use.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/w14091466/s1, Figure S1. SWMM model parameter calibration, Table S1. Definitions and methods of calculating the landscape pattern indexes, Table S2. Calibrated SWMM model hydrological parameters.

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