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A Geodesign Method of Human-Energy-Water Interactive Systems for Urban Infrastructure Design: 10KM^2 Near-Zero District Project in Shanghai

Perry Pei-Ju Yang [a,b], Cheryl Shu-Fang Chi [c,*], Yihan Wu [a,b], Steven Jige Quan [a,b,d]

[a] Eco-Urban Lab, School of City and Regional Planning & School of Architecture, College of Design, Georgia Institute of Technology, Atlanta, GA 30332-0155, USA
[b] Eco-Urban Lab, College of Architecture and Urban Planning, Tongji University, Shanghai 200092, China
[c] Disney Research China, Shanghai 200021, China
[d] Graduate School of Environmental Studies, Seoul National University, Seoul 08826, Korea

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ABSTRACT

The grand challenges of climate change demand a new paradigm of urban design that takes the performance of urban systems into account, such as energy and water efficiency. Traditional urban design methods focus on the form-making process and lack performance dimensions. Geodesign is an emerging approach that emphasizes the links between systems thinking, digital technology, and geographic context. This paper presents the research results of the first phase of a larger research collaboration and proposes an extended geodesign method for a district-scale urban design to integrate systems of renewable energy production, energy consumption, and storm water management, as well as a measurement of human experiences in cities. The method incorporates geographic information system (GIS), parametric modeling techniques, and multidisciplinary design optimization (MDO) tools that enable collaborative design decision-making. The method is tested and refined in a test case with the objective of designing a near-zero-energy urban district. Our final method has three characteristics. ① Integrated geodesign and parametric design: It uses a parametric design approach to generate focal-scale district prototypes by means of a custom procedural algorithm, and applies geodesign to evaluate the performances of design proposals. ② A focus on design flow: It elaborates how to define problems, what information is selected, and what criteria are used in making design decisions. ③ Multi-objective optimization: The test case produces indicators from performance modeling and derives principles through a multi-objective computational experiment to inform how the design can be improved. This paper concludes with issues and next steps in modeling urban design and infrastructure systems based on MDO tools.

1. Introduction

The salient challenges of climate change and resource degradation necessitate urban design that integrates efficient energy and water infrastructure with compact urban forms and greater human experience. These requirements compound the complexity of urban systems and make it more urgent than ever for those within the discipline of urban design to work together with engineering designers in order to explore the potential synergistic effects of interrelated urban systems. A conventional urban design approach that relies on a designer's experience and heuristic judgments produces limited alternatives and risks leaving out resilient and energy-efficient options—a risk we can no longer afford.

Geodesign has emerged as a new design paradigm that infuses design and its ecological and social impacts with a blend of value-based and objective-oriented geospatial information in order to address cross-system design challenges. Geodesign is an iterative and dynamic process comprised of sets of concepts and methods that link systems thinking, digital technology, and geographic context [1]. It emphasizes collaboration across a wide range of disciplines with drastically different thinking logics (e.g., geographers, sociologists, architects, urban designers, civil engineers, and local residents). The geodesign framework comprises six sequential models: representation, process, evaluation, change, impact, and decision, as presented in Fig. 1 [1]. The first three models in this

* Corresponding author.
E-mail address: cheryl.chi@disney.com (C.S.-F. Chi).

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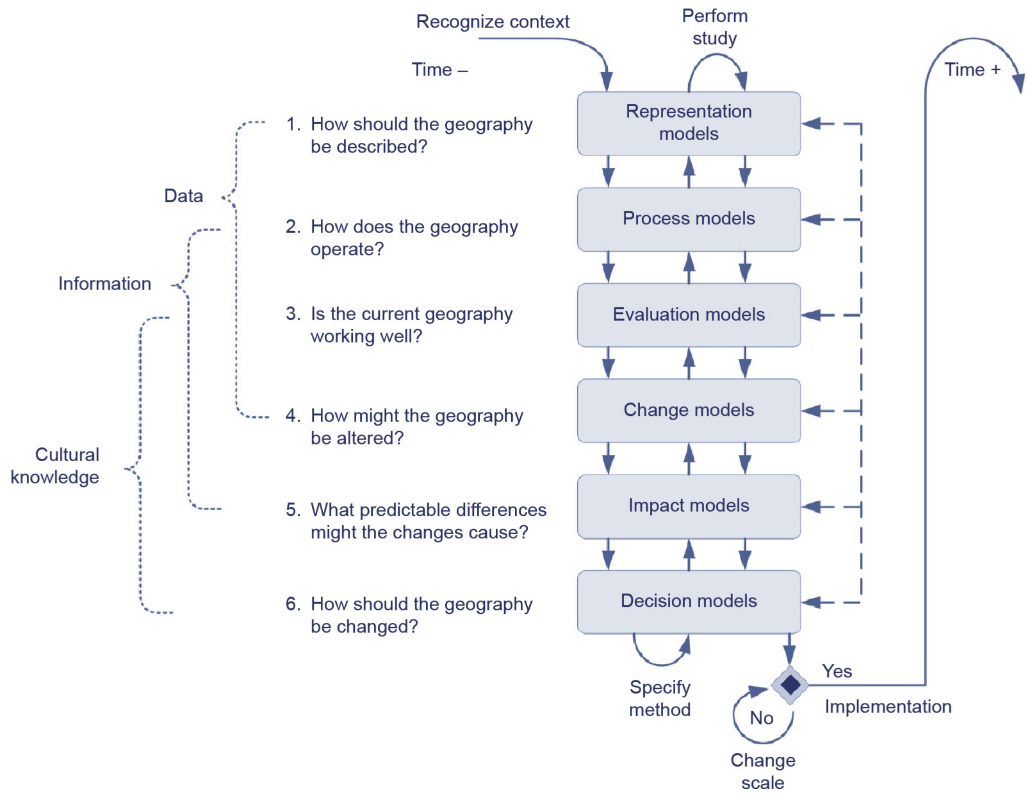

Fig. 1. A geodesign method by Steinitz [1].

framework define the description and scope of the site and evaluate the site's conditions and operation. The last three models address changes that can be made to the status quo through design and assess the potential impacts of these changes. Most importantly, the models answer six questions in three iterations in order to address the why, how, and what of a design. Specifically, the first iteration provides the design team with the basic knowledge and information needed to identify the mechanisms underlying the current situation and define the design problems. The second iteration answers the same six questions in a reverse order (i.e., from Question 6 to Question 1) and forms methodologies to address the defined problems. Lastly, the third iteration generates the final design proposals based on the data collected and the methodologies defined during the first two rounds of iteration.

Three major challenges must be faced when implementing geodesign into urban design: ① understanding the complex relationship and interdependence between design variables, components, and systems, and grasping the underlying mechanisms of change; ② defining the decision-making objectives and dealing with conflicts among the objectives of different stakeholders; and ③ coming up with a greater number of design options in order to make optimized decisions. In addition, when the geodesign framework was first developed, advanced computational and simulation tools that enable powerful analysis and information synthesis were not yet available. As a result, the question of how these tools enable the design process and help to address the contemporary challenges facing our cities is still underexplored.

Therefore, we propose an experimental and extended geodesign framework for a near-zero-energy district-scale urban design with an emphasis on how digital technologies, specifically, parametric modeling, the geographic information system (GIS), and multidisciplinary design optimization (MDO), enable the integration of urban engineering systems into urban design. This paper reports the results of the first phase of a larger research collaboration in which we developed and tested our framework using a test case. The paper concludes with a discussion of the identified issues and proposes a research agenda for advancing this effort. Ultimately, the proposed geodesign method enabled by digital technologies incorporates a human-centered urban design with a scientific-based engineering design, and thus is able to address the grand challenges of climate change more effectively.

2. The framework

2.1. An extension of Steinitz's geodesign framework

The geodesign framework proposed in this study extends Steinitz's geodesign framework, as presented in Fig. 2, to incorporate three core components that enable multidisciplinary collaborative design and the exploration of a large number of design options: MDO, parametric modeling, and urban performance-simulation tools (e.g., urban building energy modeling).

To enable designers to explore a large number of design alternatives, to make the greatest use of available knowledge, and to conceive design options that are outside of individual experience, we need a new approach and tool that exploit the strength of advanced computational and simulation technologies. MDO is one such approach.

MDO was developed to address design challenges and deal with the complexity and uncertainty of designing complex systems. This approach extracts and codes design rules and requirements into a set of algorithms and constraints for navigating a design space [2,3]. MDO was created in the 1980s; since then, it has progressed remarkably due to the increasing demand for high performance from complex engineering systems in areas such as reliability and robustness [2]. MDO is also called multi-objective design

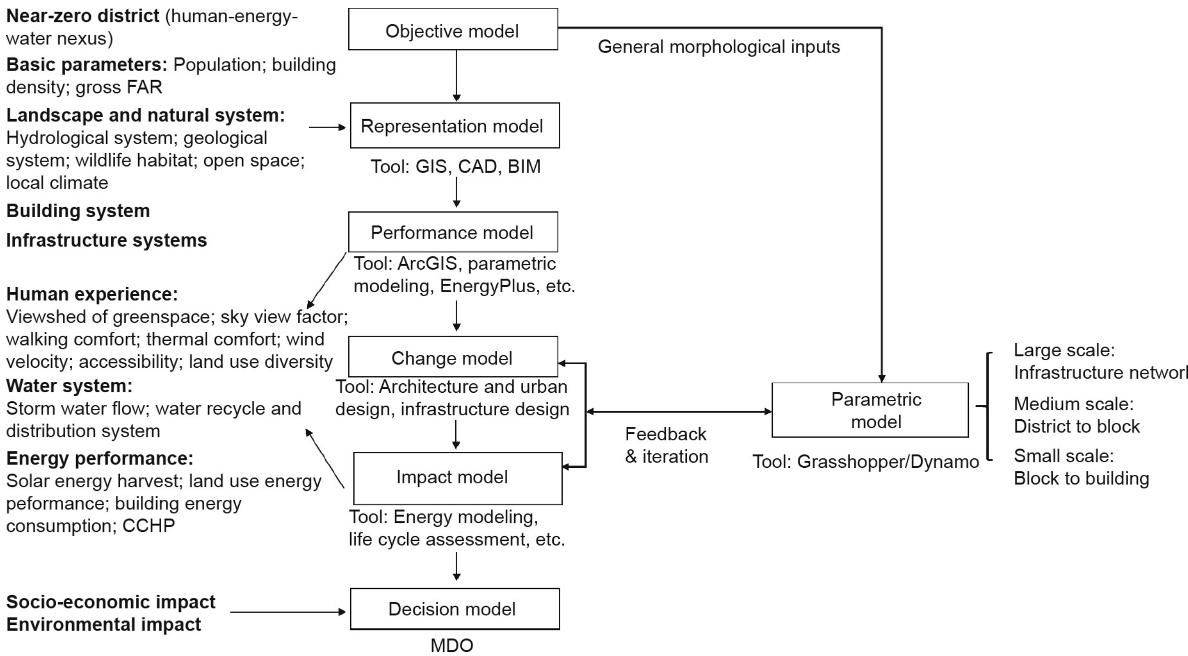

Fig. 2. An extended geodesign method for human-energy-water interactive urban systems. CCHP: combined cooling heating and power; FAR: floor area ratio.

optimization to highlight its capability to evaluate tradeoffs between multiple objectives.

With widely successful applications in designing advanced aircraft, vehicles, energy systems, and building systems, MDO appears to be a promising approach for addressing the emerging demands of the design of desirable future cities. In particular, many similarities exist between the MDO process that has been proposed for the conceptual design of distributed satellite systems [3] and the geodesign method [1], indicating the opportunity to apply MDO to urban design.

For example, the MDO approach requires the transformation of an urban design problem into a mathematical optimization problem, which comprises ① decision variables, ② objective functions, ③ constraint equations, and ④ decision variable bounds [3]. In the second iteration (i.e., the *how* questions) of the geodesign method [1], opportunities to use MDO can be identified. The questions regarding decision-making and impacts define design goals, objectives, and requirements. The question of evaluation defines performance metrics, along with other qualitative indicators.

However, although urban design deals with the physical and spatial forms of cities, urban design problems often involve emergent behaviors of urban systems, including the social and economic dimensions of a city. In the context of both complex engineered systems and urban systems, a system is defined as an integrated set of components that work together to achieve defined objectives. Optimal performance of a system often results from the synergies of its components rather than from the sum of the optimal performances of individual components.

As a result, the design goals of a city are often immeasurable and non-functional. Design requirements are often inferred from rules that are highly context dependent (e.g., zones and building typology) rather than being scientifically defined [4]. No quantifiable, clearly defined form-objective relationship exists, and the underlying mechanism between emergent behaviors and urban systems design is far from clear [5,6].

To address these challenges, performance-simulation tools and parametric modeling are crucial to connect design considerations at different system levels. A focal scale for design should be defined based on available computational and simulation tools [6], and the selected design parameters need to be quantifiable and have significant effects on design goals and metrics [5]. Performance-simulation models that capture the emergent behaviors of constituent systems of the design at the focal scale are needed in order to evaluate the synergetic performance by relating the input design to the output performance metrics (e.g., life-cycle cost, energy performance, and resilience metrics). At the same time, parametric modeling tools allow the configurations of physical objects at the lower scale of design to be varied and studied. Parametric modeling is a rule-based design approach in which the design intent is represented by geometric constraints and scripting that define the relationships among the parameters. With parametric modeling, designers are able to experiment with form design through a large number of iterations. Parametric modeling also enables designers to combine theories and practical problems by systematically exploring goal-form relationships [7].

For large complex systems, the next step is to partition and decompose the conceptual design problem and identify design modules in which the design parameters are highly interdependent and coupled [3]. For each module, systematic studies are performed by varying one design parameter in a baseline design framework and measuring how the resulting system attributes change. The resulting knowledge is then used to formulate MDO algorithms or to develop parametric models and an optimization workflow that defines the interface relationship among the modules in order to systematically and rapidly navigate a large number of possible design options.

In this way, modeling and simulation tools embody and store design rules and allow designers to move beyond the type of design that solely depends on designers' experience. Thus, the designers' creative work is built on a foundation of valid and tested scientific rules.

2.2. The near-zero district geodesign framework

In 2016, an urban design team from the Georgia Institute of Technology, Tongji University, and Disney Research China (DRC) conducted a workshop on a near-zero-energy district for a

2.7 km^2 site adjacent to Disneyland in Shanghai. The workshop discussed how to deliver an economically feasible, ecologically sensitive, and performance-driven design proposal that aims to create a sustainable, low-carbon, near-zero-energy district. Based on the framework presented in Fig. 2, the team subsequently performed the following work.

Step I—Objective model: The design objective was to explore a design proposal for the study site that addresses the unique human-energy-water nexus. The proposal should not only achieve the goal of near-zero carbon emissions, but also deliver efficient water management and human-centered values, such as visual experience and human comfort in an urban environment. The human-energy-water nexus is defined as the intrinsically interconnected relationships between energy, water systems, and human experience, and their interactions with urban forms that shape a city's resilience to climate change. The scope of the design work, required data, and performance-evaluation criteria were defined based on the objective. In particular, through site visits and interaction with stakeholders, including original site planners and members of DRC, the design team gained insights into the stakeholders' interests and local design norms and constraints, from which they further determined core design values that would be utilized to evaluate design scenarios.

Step II—Representation model: Performance-evaluation prerequisites and site information reflecting the design objectives were gathered in order to adequately depict the site details. A site inventory analysis was conducted to investigate the availability of geospatial data; the site information was then demonstrated using digital visualization tools.

Step III—Performance model: The design team, which comprised members from different disciplines, asked the question: What is meant by a good design? They then developed performance criteria for both human-centered values and infrastructure systems, including water and energy, based on the design objectives. Next, the team proposed and tested several advanced simulation tools (as listed in Fig. 2). It is notable that the selection of simulation tools must affect the evaluation criteria in order to produce quantifiable performance metrics that are meaningful to the design problem at hand. In this stage, the design team applied simulation tools, or design modules, to generate performance indicators to determine whether the site operates well under current conditions.

Step IV—Parametric model: Parametric modeling employs design parameters and procedural algorithms to develop a variety of theoretical district-scale urban morphological prototypes (1 km^2) in order to identify designs that perform well. City zoning laws and building construction standards and specifications usually constitute geometric primitives that govern the regeneration and new development of urban morphological forms. Important design parameters include the gross floor area ratio (FAR), road network pattern, building density distribution, block size, number of parcels, building cover ratio, building orientation, and building typology; the normative relationships and constraints of these parameters were utilized as formal rules in order to generate different urban design variations. The design team applied a parametrized, grid-based model to sketch urban forms and infrastructure, and determined factors such as site area (i.e., 960 m $\times$ 960 m), gross FAR (i.e., 0.8, 1, and 1.5), block size (i.e., 80 m $\times$ 80 m, 120 m $\times$ 120 m, and 240 m $\times$ 240 m), number of parcels within each block (i.e., 4, 8, and 12), and cover ratio (i.e., 0.3, 0.45, and 0.6), which are used as regulatory agents to control block configuration, building footprints, density, and heights. It is notable that density variations were also added to the model, in order to compare the differing impacts that centralized, decentralized, and linear morphological arrangements have on energy, water systems, and human experience, as presented in Fig. 3.

Step V—Generating guidelines: Next, parametric permutations were examined using simulation tools, and performance metrics were negotiated in order to render a range of design variations and to observe patterned relationships between design variation and performance outcomes. From the analytical results of systematic computational experimentation, the team then generated design guidelines and policy implications.

Step VI—Change model: The team proposed multiple design scenarios using a conventional design approach and applying specialized knowledge and skills from individual disciplines. The design guidelines derived from the focal-scale prototype designs were used as a learning and communicating tool among different disciplines.

Step VII—Impact model: The impact model uses the same agent-based toolkits that were applied in the performance model in order to systematically evaluate the performances of the design proposals. The goal is to be able to evaluate the performance of a design in a holistic way, in order to understand how focal-scale systems behave on a coarser scale. Due to the constraints of time and available data, as well as the experimental nature of the parametric modeling at this stage of research, the steps to develop the MDO algorithms needed to generate a large number of design options and navigate the options were not yet implemented in the workshop. MDO will be applied to evaluate multiple objectives and tradeoffs among different design options. If all the required algorithms are properly developed, design options coupled with development scenarios at different time frames can be generated quickly to evaluate the impacts of a design over time.

Step VIII—Decision model: The analytical results from the MDO model and other digital technologies will be utilized to inform quantified tradeoffs between different design objectives. This will allow decision-makers to weigh the pros and cons against their values and preferences before approaching final decisions.

3. Selection of design modules

Due to the degree of complexity in urban performance-evaluation modeling, a number of standardized simulation toolboxes should be built to support repeatable and transparent analysis and evaluations. The design modules are used to investigate the linkages between human-energy-water systems and urban form making, and thus help to generate design guidelines or explore design parameter tolerances in order to provide early-stage design support to designers.

3.1. Energy model

To create energy-efficient urban forms, one of the questions that should be answered is how much of a gap between energy consumption and onsite renewable energy production must be filled in order to achieve near-zero carbon emissions. Urban district energy consumption calculations and solar energy harvesting are correlated to urban morphological parameters such as building density, building volumes, and rooftop area; therefore, an energy-use design module can be applied to discover the optimized urban forms that achieve the greatest degree of energy balance.

3.1.1. Renewable energy production: Solar energy analysis

Numerous studies have found that it is extremely difficult to generate and collect onsite energy in a renewable way. The only feasible method that is ready for implementation is solar energy capture, which produces energy that can later be converted to electric power through solar panels. As an increasing number of LEED-certified buildings are being built worldwide, it has become

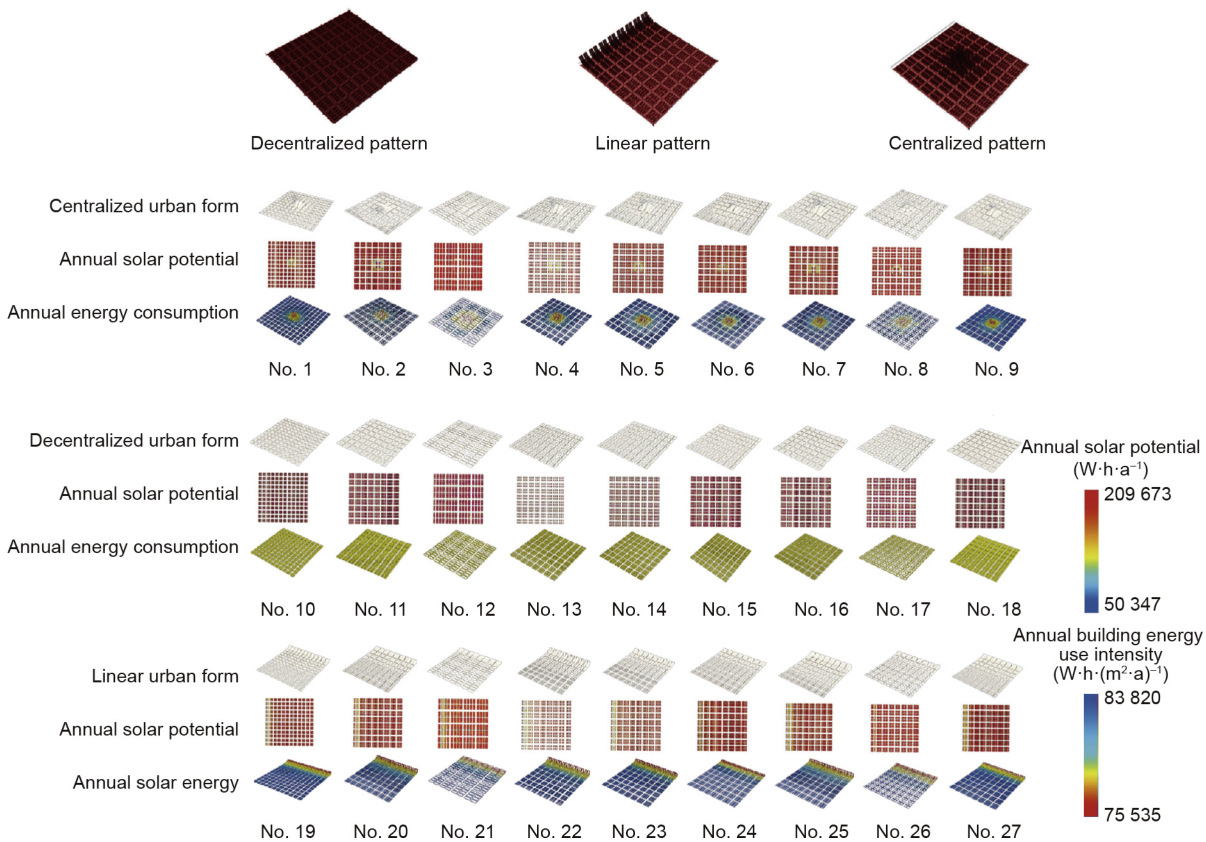

Fig. 3. Solar energy capture and energy consumption calculation based on different urban morphologies.

a general practice to install solar panels on building rooftops for solar energy harvesting. Our solar energy harvesting analysis uses the "Area Solar Radiation" tool in ArcGIS 10.3, and involves a number of parameters such as analysis duration (i.e., hours, day range, months, or years), spatial resolution (in this analysis, a 1 m × 1 m cell is used), and building rooftop geometry; the toolbox produces a radiation raster that gives solar power potentials in terms of watt hours per square meter per year. Compared with other solar power calculation tools, such as the EPC calculator, the "Area Solar Radiation" toolbox takes into account mutual shading factors that can significantly affect solar power potential on building rooftops [8].

3.1.2. Energy consumption

Energy consumption estimates have been intensively discovered and studied during the past few years. The majority of those involved in the discourse agree that energy consumption changes with fluctuations of local climate, and is closely associated with building use types, materials, and geometries [9]. In our study, a robust building energy consumption simulation software EnergyPlus is applied to calculate building heating and cooling loads and energy consumption using factors including weather profile, building geometry, building material, HVAC system, and occupancy rate.

3.2. Water model: Storm water management

In order to achieve water reuse efficiency, one of the objectives specified for the near-zero district is to maximize the collection and storage of storm water. A number of previous studies have explored the methodologies that simulate the storm water discharge process, thereby making it possible to estimate the amount of precipitation, infiltration, surface runoff, evapotranspiration, and lateral flow during a rainfall event. The capability of an urban area to capture storm water is highly dependent on local meteorological factors such as rainfall intensity, rainfall amount, and air temperature, in addition to geological conditions such as land cover type, soil moisture, and slope gradient.

In this study, a cell-based GIS hydrological simulation model is introduced, with the intention of converting the study site into a cell-based raster layer characterized by input parameters that include some meteorological factors and geological features [10].

The hydrological model is built on Thornthwaite's hydrological theory, which assumes that a water balance is achieved through precipitation, infiltration, and evapotranspiration processes; thus, by comparing the amounts of water inflow, water infiltration, and water outflow, the magnitude of water surplus and surface runoff can be determined [11]. Finally, the hydrological analysis tool provided by ArcGIS allows the user to compute the flow into each cell by accumulating the amount of precipitation that flows into each downslope cell. Thus, the stored water and surface water runoff on each cell can be calculated over the defined period of any rainfall event.

It should be noted that in order to obtain design principles from focal-scale parametric permutations, only factors such as local climate data, permeable surface areas, and impermeable surface areas were taken into account. A complete hydrological simulation process will be employed in the impact model after the design scenarios are formulated.

3.3. Human experience model: Accessibility analysis

In this study, accessibility was chosen as a measurement of human experience in order to investigate whether the built environment facilitates diverse attractions within a given walking distance. As Jacobs argues in her book *The Death and Life of Great American Cities* [12], vibrant urban life has always relied on walkability and a mixed use of land, and it is accessibility rather than car mobility that determines the success of a city. To reveal the complicated relationship between building density and accessibility, the design team selected measurement tools called "Reach" and "Straightness" to quantify the abstract concept of accessibility. A "Reach" analysis computes and summarizes the number of buildings that can be easily reached from each building within a given search radius, whereas a "Straightness" analysis identifies to what extent the shortest network distances between a building and other buildings resemble Euclidean distances [13]. The "Reach" index can be calculated using the following equation:

$$\mathrm{Reach}^{r}[i] = \sum_{j \in G - \{i\}; d[i,j] \le r} W[j] \tag{1}$$

where r is the search radius, i and j denote the location of buildings for someone in i to reach j, $d[i,j]$ is the shortest path distance between buildings i and j in network G, and $W[j]$ is the weight of destination j. The weight can be the building volume, number of job opportunities, and so forth. The "Straightness" index can be calculated using the following equation:

$$\mathrm{Straightness}[i]^{r} = \sum_{j \in G - \{i\}; d[i,j] \le r} \frac{\ddot{a}[i,j]}{d[i,j]} \cdot W[j] \tag{2}$$

where $\ddot{a}[i,j]$ is the geodesic distance between buildings i and j.

Increased building density generally implies better accessibility; however, the straightness factor should also be considered in order to determine whether a street network could potentially impair a person's capability to reach his or her destination due to an increasing number of turns. These two measurement tools thus need to be combined in order to test a community's livability in terms of accessibility.

4. Design guidelines

Using the design modules, the design team was able to produce water, energy, and human experience performance metrics for focal-scale parametric permutations (Table 1). For each performance indicator, there are patterned correlations among the parameters and performance metrics that inform certain optimized designs or design instructions. For example, in order to achieve the greatest energy-use balance, a decentralized parametric permutation in which building heights and density were evenly distributed was found to be an optimal configuration for urban design practice.

Nevertheless, it is commonly found in practice that design modules can inform distinct design guidelines; this finding highlights the challenge of urban design in balancing various decision criteria in term of human experience, efficient energy use, and water use. It also highlights the importance of understanding tradeoffs among various design decisions against multiple design objectives that are meaningful to human wellbeing and sustainability. Therefore, a multi-objective optimization analysis should be developed and conducted.

5. Discussion and conclusion

As conventional design methods are often based on individuals' experiences, thus inevitably leading to great deviance from scientific facts, an evidence-based design framework can serve as a unified means of connecting and merging the design results from multiple disciplines. This framework ensures that final design decisions are determined through rigorous, systematic, science-based iterations that take into account various environmental, social, and political facts.

To cope with the grand challenges of climate change and resource depletion, urban designers carry unprecedented social responsibilities and are compelled to change their design paradigm. As Batty [14] aptly points out, the core of geodesign is participation in the process of "science which is a prelude as well as an afterward to design when design is regarded as a constant, continuing process of reaching out for solutions or useful responses to urgent problems" (p. 2). Batty calls for "using science in design as well as design in science, building on new and powerful formalities as well as logical chains of reasoning, predictions, and prescription" (p. 2). This paper proposes a method of urban systems design that responds to Batty's call. The proposed method moves beyond using GIS as the central tool to manage design information in order to coordinate multiple advanced computational and simulation tools and address the interrelationship between urban forms and performance objectives. In addition, this method addresses the connection between the emergent behaviors of urban systems as a whole and the attributes of a single urban system or system components.

In the studio, we experimented with the proposed method with a multidisciplinary international design team, and identified the following next steps as a research agenda for developing the method into its full-fledged form.

(1) The knowledge system in the field of urban design needs integration. Most knowledge is embedded in and scattered across the experience of individual designers, who work on a limited number of projects in their career. To maximize the use of powerful digital technologies in this field, we need to systematically capture existing knowledge; variables, algorithms, and quantitative methods can then be developed based on this knowledge.

(2) MDO is a useful approach for extracting and accumulating design rules and criteria from experts' experience; it can also exploit and integrate advanced technologies in individual urban systems. However, collective efforts are needed to extract and transform the rules, criteria, and technologies into databases and algorithms.

(3) Current simulation and modeling tools only capture and quantify very limited emergent behaviors and attributes of complex urban systems. One of the reasons for this may be that current urban design research lacks systematic analysis and quantification, and relies heavily on an anticipatory approach. The integration of various case studies, interviews, and examinations of past designs is needed in order to understand the consequences of design decisions. Measures and metrics need to be developed and tested through empirical studies in a rigorous process.

(4) The iteration of a design across scales (or levels of design hierarchies) is critical in order to relate the attributes of individual design components and modules to the performance of a design at the focal scale. It is essential to note that ① the qualitative attributes of an urban design, such as quality of life, are equally important as the quantitative attributes; and ② simulations and models are representations and approximations of the design objectives and actual situations. Therefore, in the design process, professional judgments and designers' experience remain crucial. The question of how computational and simulation tools assist and interact with heuristic judgment in rapid iteration requires further study.

(5) The development of parametric modeling tools and performance-simulation tools has progressed significantly. However, the data that are available for validating these modules and simulation tools remain very limited. In addition, a simulation tool that produces high-quality output is often very data demanding. Collaboration between academia and professionals

Table 1
A comparison of water, energy, and human experience performance metrics of different urban morphologies.

Urban form typology[a]	Performance measures														
	η (m)	S_{ib} (m^2)	n_{blo}	CR_b	Gross FAR	n_{ppb}	S_{ibr} (m^2)	S_{tr} (m^2)	n_{bui}	EUI_{bui} ($W\cdot h\cdot(m^2\cdot a)^{-1}$)	E_{se} ($W\cdot h\cdot a^{-1}$)	E_{se}/S_{tr} ($W\cdot h\cdot(m^2\cdot a)^{-1}$)	w_{rw} (t)	Average AI	Average SI
Centralized	80	6 400	144	0.33	1.0	8	260	299 520	1 152	81 133	34 201 749 402	114 188.53	313 896.96	608	554
Centralized	120	14 400	64	0.42	1.0	8	756	387 072	512	79 908	44 380 833 224	114 657.82	405 651.46	224	198
Centralized	240	57 600	16	0.50	1.0	8	3 572	457 216	128	79 565	52 649 149 012	115 151.59	479 162.37	71	57
Centralized	120	14 400	64	0.20	1.0	8	360	184 320	512	79 782	21 047 904 549	114 192.19	193 167.36	224	198
Centralized	120	14 400	64	0.31	1.0	8	560	286 720	512	79 868	32 847 071 501	114 561.49	300 482.56	224	198
Centralized	120	14 400	64	0.42	0.8	8	756	387 072	512	80 893	44 446 987 156	114 828.73	405 651.46	224	198
Centralized	120	14 400	64	0.42	1.5	8	756	387 072	512	78 204	44 197 202 227	114 183.41	405 651.46	224	198
Centralized	120	14 400	64	0.41	1.0	4	1 482	379 392	256	80 023	43 582 753 860	114 875.26	397 602.82	134	112
Centralized	120	14 400	64	0.40	1.0	12	484	371 712	768	79 891	43 851 037 107	117 970.46	389 554.18	402	376
Decentralized	80	6 400	144	0.33	1.0	8	260	299 520	1 152	83 215	34 574 499 180	115 433.02	313 896.96	608	554
Decentralized	120	14 400	64	0.42	1.0	8	756	387 072	512	81 134	44 680 891 248	115 433.02	405 651.46	224	198
Decentralized	240	57 600	16	0.50	1.0	8	3 572	457 216	128	81 107	52 749 852 912	115 371.84	479 162.37	71	57
Decentralized	120	14 400	64	0.20	1.0	8	360	184 320	512	80 897	21 299 176 800	115 555.43	193 167.36	224	198
Decentralized	120	14 400	64	0.31	1.0	8	560	286 720	512	81 029	33 096 956 480	115 433.02	300 482.56	224	198
Decentralized	120	14 400	64	0.42	0.8	8	756	387 072	512	82 675	44 657 210 304	115 371.84	405 651.46	224	198
Decentralized	120	14 400	64	0.42	1.5	8	756	387 072	512	80 123	44 704 578 240	115 494.22	405 651.46	224	198
Decentralized	120	14 400	64	0.41	1.0	4	1 482	379 392	256	811 241	43 794 365 628	115 433.02	397 602.82	134	112
Decentralized	120	14 400	64	0.40	1.0	12	484	371 712	768	80 893	44 208 077 584	118 930.99	389 554.18	402	376
Linear	80	6 400	144	0.33	1.0	8	260	299 520	1 152	82 214	34 119 109 689	113 912.63	313 896.96	608	554
Linear	120	14 400	64	0.42	1.0	8	756	387 072	512	80 568	44 351 804 307	114 582.83	405 651.46	224	198
Linear	240	57 600	16	0.50	1.0	8	3 572	457 216	128	80 457	52 635 800 831	115 122.39	479 162.37	71	57
Linear	120	14 400	64	0.20	1.0	8	360	184 320	512	81 201	20 960 521 086	113 718.10	193 167.36	224	198
Linear	120	14 400	64	0.31	1.0	8	560	286 720	512	82 010	32 765 671 177	114 277.59	300 482.56	224	198
Linear	120	14 400	64	0.42	0.8	8	756	387 072	512	81 203	44 467 832 233	114 882.59	405 651.46	224	198
Linear	120	14 400	64	0.42	1.5	8	756	387 072	512	79 011	44 015 470 360	113 713.91	405 651.46	224	198
Linear	120	14 400	64	0.41	1.0	4	1 482	379 392	256	81 523	43 603 788 156	114 930.70	397 602.82	134	112
Linear	120	14 400	64	0.40	1.0	12	484	371 712	768	81 230	43 730 363 952	117 645.82	389 554.18	402	376

η: individual block proportion; S_{ib}: individual block area; n_{blo}: number of blocks; CR_b: coverage ratio per block; n_{ppb}: number of parcels per block; S_{ibr}: individual building roof area; S_{tr}: total roof area; n_{bui}: number of buildings; EUI_{bui}: energy-use intensity of buildings; E_{se}: annual total solar energy; w_{rw}: total weight of rain water collected from the roof; AI: accessibility index; SI: straightness index.

[a] Within a sample area of 1 km^2.

is needed in order to systematically collect, accumulate, and share data.

(6) As Steinitz [15] points out, multidisciplinary collaboration in the design process is challenging. Designers and engineers in different disciplines have difficulty understanding how their decisions impact other disciplines' design decisions. At the same time, designers and engineers who normally work at a lower level of design hierarchies (e.g., in detailed design or in the design of engineering components) often have difficulty seeing the "big picture." The interdependent relationships among disciplines and across design hierarchies still need to be clarified in order to devise mechanisms for collaboration and synthesis.

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Compliance with ethics guidelines

Perry Pei-Ju Yang, Cheryl Shu-Fang Chi, Yihan Wu, and Steven Jige Quan declare that they have no conflict of interest or financial conflicts to disclose.

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