Flux.Land: A Data-driven Toolkit for Urban Flood Adaptation

Isaac Seah[1], Fadi Masoud[2], Fabio Dias[2], Aditya Barve[3], Mayank Ojha[3], Miho Mazereeuw[3]

[1]University of Toronto, Centre for Landscape Research, Ontario/Canada ·
isaac.seah@mail.utoronto.ca
[2]University of Toronto, Centre for Landscape Research, Ontario/Canada
[3]Massachusetts Institute of Technology, Urban Risk Lab, Massachusetts/USA

Abstract: Climate-change-induced hazards are causing large scale displacements of communities, destruction of property, and disruption of critical infrastructure. These increasingly unpredictable climate events result in complex and cascading impacts, emphasizing the need for comprehensive, data-driven, multidisciplinary design and planning toolkits. To effectively adapt to such unpredictability, these toolkits must consider a complex network of interdependencies – a range of interconnected factors, datasets, and stakeholders – that influence the planning process. With the emergence of powerful and accessible web-based computational capabilities, there is an opportunity to enhance risk management tools and allow for data-driven planning and design scenarios to support adaptive infrastructure provisions and retrofits. This paper shares the development of Flux.Land, an accessible and collaborative spatial decision support system (SDSS), allows community and planning agencies to visualize climate impacts and take collective action. In the context of flood-prone Broward County, Florida, this paper showcases how a large corpus of data-driven design and planning scenarios can be generated through the systematic definition of quantifiable design goals, evaluation metrics, and curation of computationally derived design recommendations. Through Flux.Land, we illustrate how data-driven, collaborative, web-based toolkits can be harnessed for data-driven planning and decision making across geographical, social, and environmental scales.

Keywords: Climate change, urban flooding, risk management toolkits

1 Introduction

Many cities around the world are experiencing more frequent rainfall events, storm surge, saltwater intrusion, and an increased risk of urban flooding due to climate change (HETTIARACHCHI et al. 2018). The intensification of unpredictable weather events results in significant impacts at the environmental, geographical, and social levels (DOOCY et al. 2013). As cities attempt to prevent and reduce the negative impacts of climate change, critical urban issues related to these impacts are often treated independently (BETTENCOURT & GEOFFREY 2010). This lack of cross-sectoral collaboration can result in ineffective policy-making and urban planning, sometimes leading to unfortunate and "disastrous unintended consequences" (JABAREEN 2013). For instance, design of hard and mechanical infrastructures such as levees or seawalls that are not sensitive to future cascading impacts can prove to be inadequate to future climatic conditions, either because of their limited assumed variability (MILLY et al. 2008), or inaccurate climate projections (JOHN & WICKEL 2009). Some of these consequences result in increasing socio-economic vulnerability of many low-lying coastal cities by precipitating adverse impacts of disasters such as flooding. Some projections depict that the cost of future flood losses in South Florida could be over US$ 50 billion (€ 41.4 billion) by 2050 (HALLEGATTE et al. 2013); while others indicate a 1.8m sea-level rise by 2100 would displace over two million people (OPPENHEIMER et al. 2019). To avoid such consequences,

planners and stakeholders should not only consider physical vulnerabilities, but also socio-economic and environmental aspects (TINGSANCHALI 2012).

With difficult-to-quantify social, environmental, and economic dimensions involved in climate change adaptation, one strategy devised to address the 'ill-structured' problem domain is the utility of spatial decision support systems (SDSS) and visualization tools for adaptation planning (LIESKE 2015). Referencing Goudine's Climate Visualizations for Adaptations Products (CVAP) framework, existing SDSS and visualization tools can be categorized into the spectrum of "Inform", "Consult", "Involve", and "Partner" themes (GOUDINE et al. 2020). As SDSS and visualization tools move from "Inform" to "Partner" engagement themes, they become increasingly interactive, realistic, and suitable for high-risk decision making.

Within the "Inform" engagement theme, SDSS and visualization tools are often used to support decisions associated with lower risk in terms of outcomes and impacts; most often used to present, rather than produce research findings (GOUDINE et al. 2020). Examples include SimilarityExplorer, a visual inter-comparison tool that allows for filtering and cross-comparison of climate level data but does not reflect a high accuracy of data related to vital public infrastructure or demographic data (POCO et al. 2014). On the other end of the spectrum, the "Partner" theme in the CVAP's framework describes realistic SDSS and visualization tools that allow for interactivity, communication and fostering 'partner-like' relationships between decision-makers and stakeholders, facilitating decision making processes with a high level of inherent risk. Examples of such tools include the Mobile Augmented Reality (MAR) app, where a user is allowed to track an unspecified location, populate it with geometry, and visualize an augmented reality flooding of that environment (HAYNES et al. 2018).

The research team from the University of Toronto's Centre for Landscape Research (CLR) and MIT's Urban Risk Lab (URL) has developed *Flux.Land* to address the increasingly complex problem domain in climate change adaptation. *Flux.Land* is a web-based SDSS that extends the functions described in CVAP's "Partner" engagement theme to facilitate discussions in situations where solutions to climate-driven urban planning problems are not apparent (GOUDINE et al. 2020), but involve a high level of inherent risk. *Flux.Land* aims to facilitate these discussions through the three following approaches:

1. Developing data visualization features on *Flux.Land* to visualize precise geospatial data sets
2. Implementing data clustering algorithms and tools on *Flux.Land* for rapid analysis of hidden relationships across social, environmental, and economic dimensions
3. Introduce an integrated, data-driven design and scenario planning methodology, allowing stored data points on *Flux.Land* to be used to generate data-driven recommendations, enabling use cases such as rapid prototyping of land use intents

By combining visualization and analytical capabilities with the latest data-driven design methodologies, *Flux.Land* is able to foster greater interactivity and understanding of the intertwining relationships that exist between climate change, environment, social and economic factors.

2   Methods: Integrating Data Visualization, Data Analytics, and Data-driven Design

Using Broward County's urban-flooding vulnerability as the subject of study, *Flux.Land* focuses on the environment, infrastructure, and demographic datasets of the region. This data was collected from Broward County's open-source data platforms (BROWARD COUNTY GOVERNMENT 2019), cross-referenced with land-parcel data, and further hosted on cloud-based database servers. The data was then processed for visualization through each of *Flux.Land*'s different modules. These modules include data visualization and querying, clustering presets, and data-driven design examples.

2.1   Data Visualization Capabilities

For *Flux.Land*'s data visualization capabilities, we developed two main interfaces: a 3D/ orthographic map view and a sectional tool that correlates elevational information of streets, water bodies, and future sea-level rise impacts on groundwater tables. *Flux.Land*'s 3D/orthographic map view allows for layered visualization and analysis of geospatial data (Figure 1). A user can use this view to identify relationships across a diverse set of factors such as income, elevation saltwater intrusion areas, and flood risk zones. *Flux.Land*'s sectional tool allows for the visualization of above and below ground data, highlighting the relationship between groundwater and surface elevation considering sea-level rise (Figure 2). Emphasis was placed on the platform's simple navigation and design aimed at stakeholders from varying degrees of expertise – from the general public to planners. These visualization approaches were adopted as they have shown to be effective in the exchange of views on spatial decision problems (ANDRIENKO et al. 2007). In addition, collaborators using a shared map interface often experienced a heightened awareness of different scopes relevant to other collaborators, allowing for more efficient inter-disciplinary discussions (ARCINIEGAS & JANSSEN 2012).
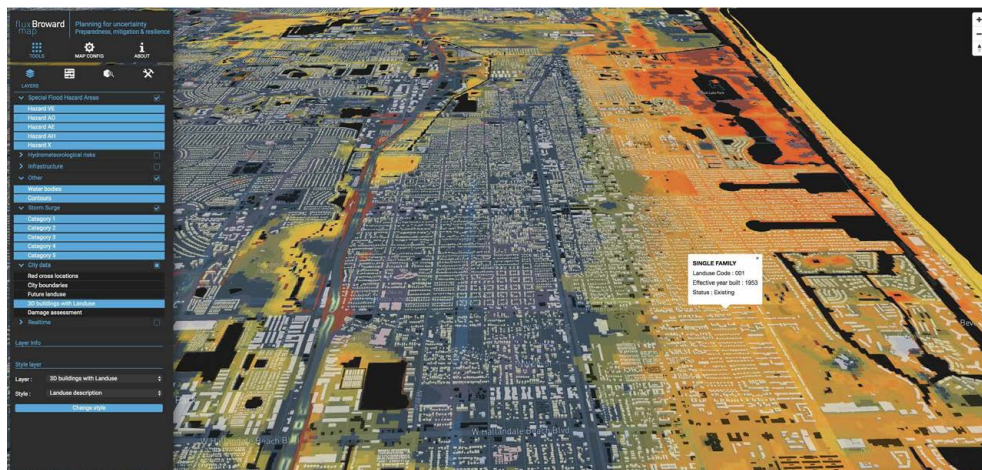

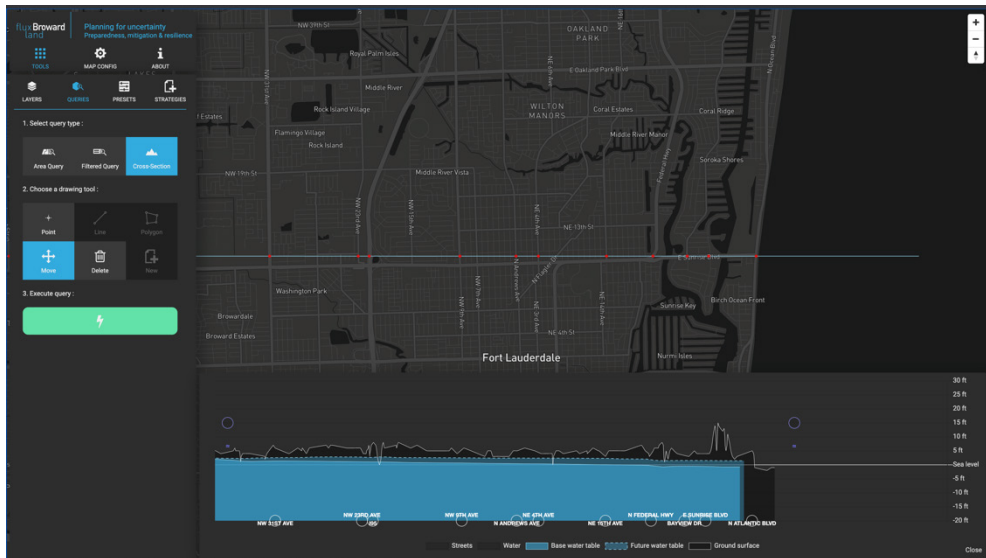**Fig. 1:**   Flux.Land's 3D orthographic map view

Fig. 2: Sectional tool depicting relationship between groundwater, surface elevation and water bodies

2.2 Hierarchical Clustering: Identifying Latent Relationships

While planning processes are often constrained within the administrative boundaries, the impacts of climate change and climate disasters are not (YOO et al. 2011). A hierarchical data clustering feature was developed in order to elicit these underlying similarities and differences within areas of interest beyond simple visualization of datasets across administrative boundaries. Contrary to conventional tapestry segmentation where a model of social classifications is created with segments of neighbourhood derived addresses (ESRI 2020), *Flux.Land*'s hierarchical clustering allows segments to form from a confluence of geospatial, social and environmental data that are often not bounded by administrative boundaries. By visualizing geographical clusters with similar properties, identified through a hierarchy-based relationship tree (algorithm 1), *Flux.Land* can highlight latent relationships across social, economic, and environmental factors and provide impetus to collaborate across administrative divisions to overcome these issues. Here, the clustering feature identifies different non-administratively bounded regions that have shared characteristics, enabling policymakers and stakeholders to effectively deploy different climate adaptation strategies based on different vulnerability patterns that transcend physical factors.

On *Flux.Land*, a set of parcel-level features for clustering were selected via working sessions with government officials from Broward County's Environmental Planning and Community Resilience Division. In order to represent three general areas of interrelated impacts – age and affordance of the built fabric, latent socio-economic factors, and future forecasts, clusters were generated based on selected features that include building age, land value, base flood elevation, median income, percentage of minorities, homeownership rate and residential building usage. Once the features for clustering were identified, the overall clustering approach can be broken into 3 main steps: (1) generation of clusters based on input geospatial,

parcel-level data, (2) creation of a cost layer to present relationships between identified clusters and (3) visualization and analysis of resulting clusters (Figure 3).
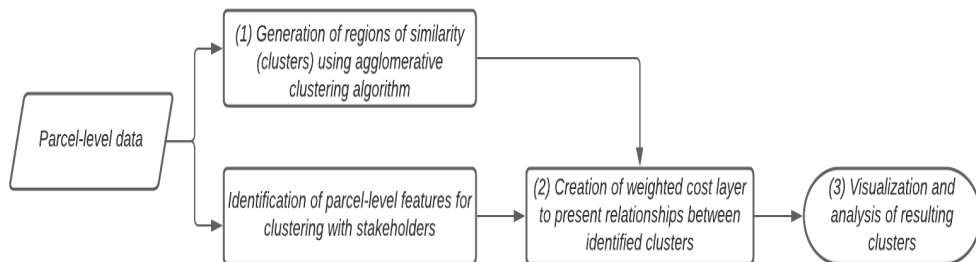

Fig. 3:   Workflow to create clusters that have shared characteristics

Using parcel-level data, neighbourhoods and regions of similarity were generated using an agglomerative clustering algorithm (algorithm 1). We first identified the distribution of each parcel-level feature across Broward County. Then, we implemented a distance function to derive a relationship tree based on the variance between each feature in a group of parcels, relative to each parcel's feature's position in the overall distribution (DIAS & SILVER 2018).

Algorithm 1:   Hierarchical Agglomerative Clustering (DIAS & SILVER 2018)

1:	Input: Parcel data $\{X_N\}_{N=1}^N$, group-wise distance $Dist(G, G)$	
2:	$A \leftarrow \emptyset$	> There are 0 clusters in the *Active Set* at the start
3:	**for** $n < 1 \dots N$ **do**	
4:	$A \leftarrow A \cup \{\{x_n\}\}$	> Each parcel is added as a cluster to the *Active Set*
5:	$T \leftarrow A$	> Create a tree containing every cluster generated
6:	**while** $|A| > 1$ **do**	> Loop until all parcels are in a single cluster
7:	$G_1^*, G_2^* \leftarrow minimum\ Dist(G_1, G_2)$	> group parcels with the smallest distance
8:	$A \leftarrow (A \setminus \{G_1^*\}) \setminus \{G_2^*\}$	> remove individual cluster/parcels from Active Set
9:	$A \leftarrow A \cup \{G_1^* \cup G_2^*\}$	> add resulting cluster into Active Set
10:	$T \leftarrow T \cup \{G_1^* \cup G_2^*\}$	> add resulting cluster into tree
11:	**end while**	

The resulting clusters of similarity were then joined against a cost layer that was developed based on a heuristic equation derived from the normalized values of the factors of interest, highlighting the hierarchical relationships between each cluster. In the current implementation, the weights for each factor of interest are identified and refined via working sessions with stakeholders, where factors of greater importance to existing planning problems are given higher weights.

Cost Layer Equation

$$c_{region} = \alpha \frac{(F1 - F1_{min})}{(F1_{max} - F1_{min})} + \beta \frac{(F2 - F2_{min})}{(F2_{max} - F2_{min})} + \gamma \frac{(F3 - F3_{min})}{(F3_{max} - F3_{min})}$$

c_{region} = cost of region

F1, F2, F3 = values of factors

α, β, γ = pre-defined weights

The resulting clusters were then uploaded onto *Flux.Land,* enabling users to examine latent relationships across geographical areas and interdisciplinary factors.

2.3   Data-driven Design Methodology

Building on the data points and clusters embedded on *Flux.Land,* we further propose an integrated data-driven design and scenario planning methodology, where government officials, planners, or individuals are able to use the data points stored on the platform to generate a set of data-driven recommendations. Using contextual-specific data points and clusters generated on the platform, a practitioner can leverage the platform's information database to make better design decisions. The integrated data-driven design methodology can be summarized in three key steps: (1) defining design priorities and goals, (2) quantifying evaluation metrics and design parameters, (3) design discovery, optimization, and curation of design recommendations.

In the first step, two key design goals were established for this initial study in the context of South Florida by reducing flood risk for 2.5 million residents by generating interconnected open-space networks of floodable low-lying parcels, and increasing land values and the municipal tax-base by maximizing developable, infrastructurally connected parcels on high-ground.
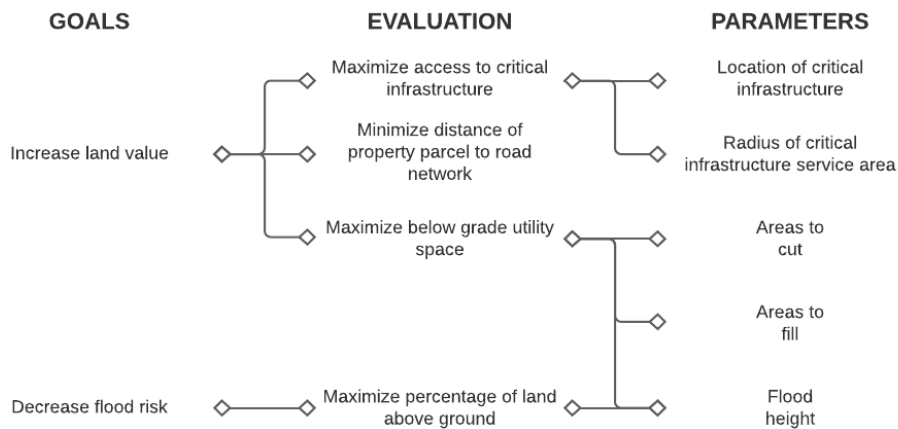

Fig. 4:   Goals, evaluation metrics and design parameters designed to reduce flood risk and increase land value

The second step of the data-driven design methodology further distills each design goal into evaluation metrics and the urban morphology into constituent design parameters through an iterative design process. For *Flux.Land*'s initial proof-of-concept, land value was evaluated by a combination of coverage by critical infrastructure, the distance of property parcel to transportation networks, and below-grade utility space. To evaluate flood risk, the amount of percentage of land above ground was calculated. These evaluation metrics were then further broken down into design parameters, including the location of critical infrastructure, the radius of critical infrastructure coverage, areas for cut and fill process, and sea-level rise scenarios (Figure 4).

Finally, in the third step, these design parameters and evaluation metrics were processed with the Galapagos library (RUTTEN 2013), a suite of evolutionary algorithms via Rhino3D. The algorithm iterates through permutations of defined parameters, producing recommendations that are performed based on the defined evaluation metrics. These recommendations would then serve as a starting point for further in-depth design ideation, or land-use zoning reconsiderations.

For our study with Broward County, using the goals, evaluation metrics and defined parameters (Fig. 4), a series of conceptual urban landscape configurations were parametrically generated using simulated 'cut and fill' processes, in tandem with rising sea levels. By simplifying a digital elevation surface model of the existing urban landscape into a grid of 3D elevation points and evaluating the gradient between each point, the availability of land above water, and the area of a given radius around each point, we were able to identify which point on the surface was the most optimal for cut-and-fill processes at each increment in sea level rise. By simulating the sea level rise of 0.25, 0.5, and 0.75 metres, we were able to observe how sea-level rise affects the generated urban landscape configurations.

3   Results and Discussion

To test the implementation of *Flux.Land,* review sessions were held with Broward County's Environmental Planning and Community Resilience Division on the 10th of July 2019 and 18th February 2020. Feedback was provided for our implementations of data visualization, clustering, and data-driven design methodology on the *Flux.Land* platform.

On *Flux.Land*'s data visualization capabilities, reviewers found its 3D/orthographic map view (Fig. 1) to be intuitive, especially users who had prior experiences in GIS technologies. Reviewers also found the sectional tool (Fig. 2) to be very useful in capturing quick snapshots of the water table in geographically sensitive locations like airports for preliminary planning discussions. In time-sensitive situations, *Flux.Land* provides a more accessible method to quickly retrieve analytical data, as compared to requiring specialized GIS software and data science teams to access and analyze similar data. However, as the platform is not currently equipped with a self-serve data upload capability, reviewers voiced the need for SDSS platforms like *Flux.Land* to be equipped with data management features that allow for new geospatial datasets to be uploaded, removed, and managed easily. This would allow the platform to be updated based on the evolving needs of the users.

Using the parcel-level features and weights defined by stakeholders from Broward County, reviewers were also presented with the results of *Flux.Land*'s data clustering feature. For each combination of factors, the primary factor of interest was assigned a weight of 0.4, and

secondary factors were assigned a weight of 0.3 each in the cost layer which was used to derive the relationships between each cluster. The reviewers' observations of the clusters presented are as follows:

Table 1: Observations of cluster results

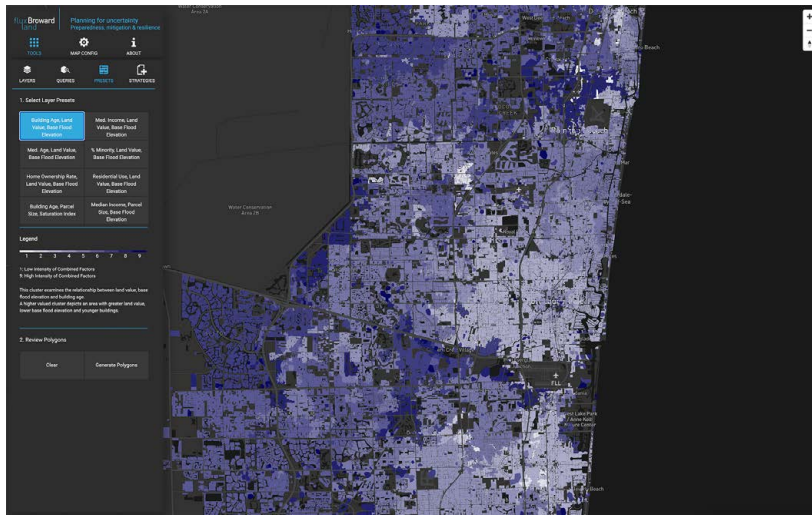| No.	Factors	Cluster Description	Reviewer's Observations
1	Building age, land value, base flood elevation	The resultant clusters examine the relationship between land value, base flood elevation, and building age. A higher-valued cluster depicts an area with greater land value, lower base flood elevation and younger buildings.	Reviewers identified that areas with greater land value, lower base flood elevation and younger buildings were deeper inland, whereas regions close to the downtown core were most vulnerable to urban flooding and had older buildings (Figure 5).
2	Median income, land value, base flood elevation	The resultant clusters examine the relationship between median income, parcel size and base flood elevation. A higher-valued cluster depicts an area with lower median income, higher base flood elevation and higher land value.	Reviewers identified that the median income was lower in the downtown core, where communities were more susceptible to flood risk due to higher base flood elevation (Figure 6).
3	Median age, land value, base flood elevation	The resultant clusters examine the relationship between land value, base flood elevation and median income. A higher-valued cluster depicts an area with greater land value, higher base flood elevation and higher median age.	Reviewers identified that populations with higher median age and a higher risk of displacement due to flood vulnerability were more likely to be located along the coastal areas.
4	Percentage of minorities, land value, base flood elevation	The resultant clusters examine the relationship between land value, base flood elevation and percentage of minorities. A higher-valued cluster depicts an area with greater land value, higher base flood elevation and higher percentage of minorities.	Reviewers identified that the percentage of minorities was higher in the downtown core, where base flood elevation was higher, resulting in higher flood vulnerability.

Fig. 5: Cluster indicating the relationship between building age, land value, base flood elevation. Darker colored clusters depict areas with greater land value, lower base flood elevation, and younger buildings.
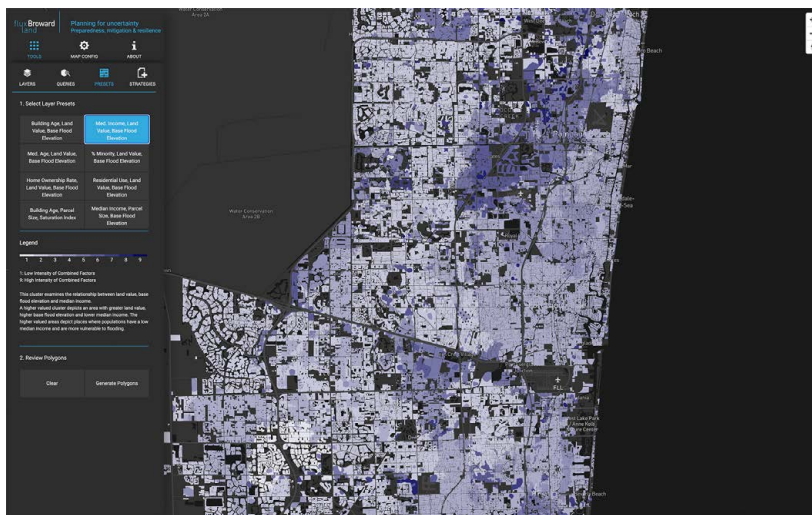

Fig. 6: Cluster indicating the relationship between median income, land value, base flood elevation. Darker colored clusters depict areas with lower median income, higher base flood elevation, and higher land value.

Using the resultant clusters, the team further tested the proposed data-driven design methodology and produced a series of landscape configurations based on the parameters defined (Fig. 4). The blue areas on the plotted areas in Figure 7 indicate water bodies, and the white lines indicate the topographical contour of the site of study. The two configurations depict how the contours of the area of study could change as more cut-and-fill operations are applied as sea level rises. The left diagram depicts conditions before cut and fill operations and sea-

level rise, while the right diagram depicts conditions at 0.75m sea-level rise. These configurations were then consequently evaluated against the expanded evaluation metrics (Figure 8).
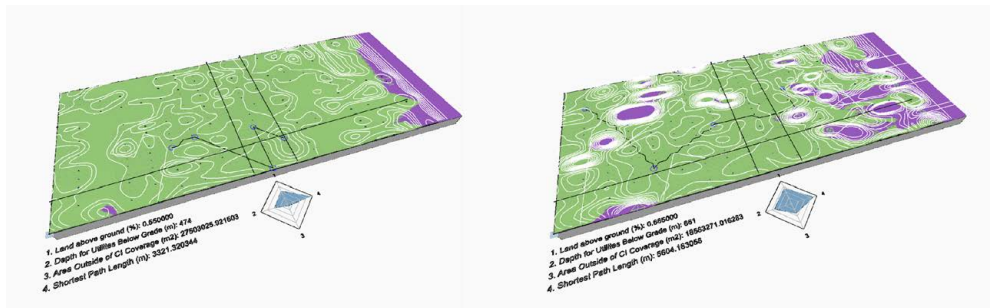

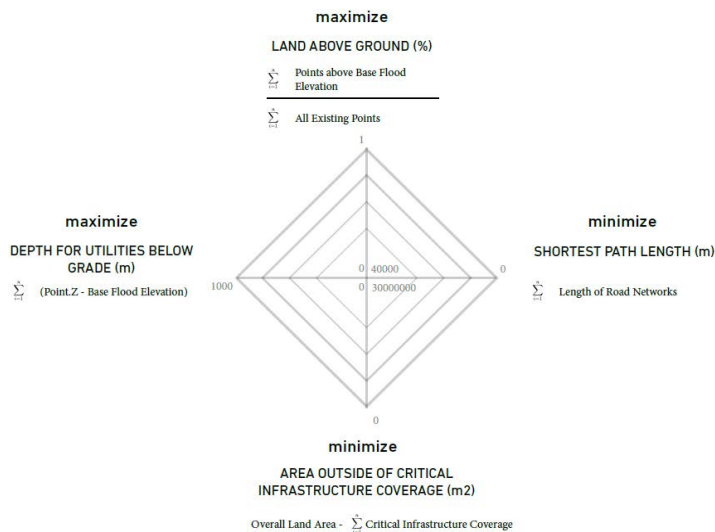**Fig. 7:** Parametrically derived landscape studies

Fig. 8: Expanded evaluation metrics illustrated as a spider chart

The resulting configurations exemplify how our data-driven design methodology can be applied to data points on SDSS like *Flux.Land*, and be used to parametrically generate planning configurations, while allowing practitioners to measure the performance of the configurations using the defined evaluation metrics.

4   Next Steps

While the processes and features highlighted above have been contextualized for Broward County, this approach can easily be extended for other jurisdictions as well. The feedback retrieved from reviewers of the platform will continue to shape future iterations of *Flux.Land* and other similar types of SDSS. In future deployments of *Flux.Land*, an API first approach will be taken when integrating data sets onto the platform, so that organizations can continue

to visualize updated data in a self-serve manner. We also plan to add more features to enhance the usability of the platform – for example providing customizable topographic representational options like colours and annotation tools for greater interactivity with geospatial datasets. We are also in the process of conducting a formal usability evaluation of the platform to understand how it has impacted users, ranging from urban planning practitioners to school students.

The current versions of the parametrically generated designs for Broward County have also demonstrated that the platform can facilitate smarter decision making within the defined constraints. With these results, we intend to further refine the robustness of the clustering algorithm and extend the application of the data-driven design methodology in more complex urban scenarios through continued collaboration with different agencies that can benefit from *Flux.Land*.

5   Conclusion

With increasing complexity in the problem space of climate resilience and adaptation, there is a pressing need for more interactive and collaborative tools so that cross-disciplinary collaboration can happen more effectively. Through *Flux.Land*'s visualization, analytics, data-driven design, and planning features, we illustrate how SDSS and visualization tools can be extended to become participatory design tools. As computing power continues to increase, analytical tools will become more sophisticated in describing the complex social, environmental, and economic factors that determine the form and function of urban landscapes. As such, tools like *Flux.Land* have the potential to become more assistive in the design and management of climate-informed adaptation planning. As seen in the context of Broward County, *Flux.Land* is a nascent example of how data-driven, collaborative, web-based toolkits can be harnessed for data-driven planning and decision-making across scales. Here, *Flux.Land* enabled human decision-makers to experiment and understand the nuanced relationship between geographical, social, and environmental context through customizable datasets; advancing the efficiency and robustness of design-based decisions in the face of highly complex planning scenarios. By enhancing access to the underlying data and presenting it in an easily digestible manner to a wider audience, tools like *Flux.Land* will also help make the resilience planning processes become more participatory and equitable. The development of Flux.Land was carried out with an understanding that vulnerability to disasters and climate change is underpinned by complex socio-political processes, and by providing a way to visualize some of these complexities, SDSS tools may help in mitigating the impacts of changing climate.

References

ANDRIENKO, G., ANDRIENKO, N., JANKOWSKI, P., KEIM, D., KRAAK, M.-J., MACEACHREN, A. & WROBEL, S. (2007), Geovisual analytics for spatial decision support: Setting the research agenda. International Journal of Geographical Information Science, 21 (8), 839-857.

ARCINIEGAS, G. & JANSSEN, R. (2012), Spatial decision support for collaborative land use planning workshops. Landscape and Urban Planning, 107 (3), 332-342.

BETTENCOURT, L. & GEOFFREY, W. (2010), A unified theory of urban living. Nature, 467, 912-913.

BROWARD COUNTY GOVERNMENT (2019), Broward County Geohub.
    https://geohub-bcgis.opendata.arcgis.com/.

DIAS, F. & SILVER, D. (2018), Visualizing demographic evolution using geographically inconsistent census data. UT Sociology Working Paper No. 2018-03.
    http://sociology.utoronto.ca/wp-content/uploads/2018/04/Working-Paper-2018-03.pdf.

DOOCY, S., DANIELS, A., MURRAY, S. & KIRSCH, T. D. (2013), The human impact of floods: a historical review of events 1980-2009 and systematic literature review. PLoS currents, 5, ecurrents.dis.f4deb457904936b07c09daa98ee8171a.
    doi:10.1371/currents.dis.f4deb457904936b07c09daa98ee8171a.

ESRI (2020), Methodology Statement: 2020 Esri Tapestry Segmentation.
    https://downloads.esri.com/esri_content_doc/dbl/us/J9941_Tapestry_Segmentation_Met
    hodology_2020_r.pdf.

GOUDINE, A., NEWELL, R. & BONE, C. (2020), Seeing Climate Change: A Framework for Understanding Visualizations for Climate Adaptation. ISPRS International Journal of Geo-Information, 9 (11).

HALLEGATTE, S., GREEN, C., NICHOLLS, R. J. & CORFEE-MORLOT, J. (2013), Future flood losses in major coastal cities. Nature Climate Change, 3 (9), 802-806.

HAYNES, P., HEHL-LANGE, S. & LANGE, E. (2018), Mobile Augmented Reality for Flood Visualisation. Environmental Modelling & Software, 109, 380-389.

HETTIARACHCHI, S., WASKO, C. & SHARMA, A. (2018), Increase in flood risk resulting from climate change in a developed urban watershed – the role of storm temporal patterns. Hydrology and Earth System Sciences, 22 (3), 2041-2056.

JABAREEN Y. (2013), Planning the resilient city: Concepts and strategies for coping with climate change and environmental risk. riskCities, 31, 220-229.

JOHN H. M. & WICKEL, A. J. (2009), Embracing uncertainty in freshwater climate change adaptation: A natural history approach. Climate and Development, 1 (3), 269-279.

LIESKE, D. J. (2015), Coping with climate change: The role of spatial decision support tools in facilitating community adaptation. Environmental Modelling & Software, 68, 98-109.

MILLY, P. C., BETANCOURT, J., FALKENMARK, M., HIRSCH, R. M., KUNDZEWICZ, Z. W., LETTENMAIER, D. P. & STOUFFER, R. J. (2008), Climate change. Stationarity is dead: whither water management? Science, 319 (5863), 573-574. doi:10.1126/science.1151915.

OPPENHEIMER, M., GLAVOVIC, B., HINKEL, J., WAL, R., MAGNAN, A., ABD-ELGAWAD, A., CAI, R., CIFUENTES-JARA, M., DECONTO, R. & GHOSH, T. (2019), Sea level rise and implications for low lying islands, coasts and communities. The Intergovernmental Panel on Climate Change.

POCO, J., DASGUPTA, A., WEI, Y., HARGROVE, W., SCHWALM, C., COOK, R., BERTINI, E. & SILVA, C. (2014), SimilarityExplorer: A Visual Inter-Comparison Tool for Multifaceted Climate Data. In: Computer Graphics Forum, 341-350.

RUTTEN, D. (2013), Galapagos: On the Logic and Limitations of Generic Solvers. Architectural Design, 83, 132-135. https://doi.org/10.1002/ad.1568.

TINGSANCHALI, T. (2012), Urban flood disaster management. Procedia Engineering, 32, 25-37.

YOO, G., HWANG, J. H. & CHOI, C. (2011), Development and application of a methodology for vulnerability assessment of climate change in coastal cities. Ocean & Coastal Management, 54 (7), 524-534.