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A generative AI decision-making tool for interactive greenspace design using a Pollinator Habitat Indicator

Abstract

Generative artificial intelligence (AI) is increasingly used in landscape architecture to accelerate design development and enhance stakeholder engagement. This study presents a new landscape concept design tool to support collaborative greenspace problem-solving by integrating rapid scenario generation with a Pollinator Habitat Indicator (PHI). We define this as the PHI-AI Landscape Design Tool. The model combines text-to-image generative workflows with an ecological scoring system that ranks AI-generated design scenarios based on the proportional composition and spatial configuration of habitat-supportive landscape elements. The PHI-AI Landscape Design Tool demonstrates a strong capacity to interpret spatial landscape geometry and circulation logic. The model generates layout variations that reflect coherent planting configurations, and practical circulation connections for user functionality. This enables the rapid production of multiple greenspace design alternatives that remain legible, adaptable, and flexible to human-controlled decision-making processes.

We present an experimental design to illustrate how AI-generated design scenarios can be collaboratively evaluated using aesthetic preference ranking, PHI scores, and complementary landscape metrics. The system is designed to function as a human-in-the-loop decision workflow, allowing users to mutually modify prompts, spatial targets, and design elements to refine outcomes in response to project-specific objectives and stakeholder feedback. By accelerating the efficiency of greenspace layout variations while preserving flexibility for collaborative refinement, the PHI-AI Landscape Design Tool advances AI-assisted landscape planning beyond visualization toward an interactive, evidence-based design decision-making process. The framework offers a scalable approach for integrating nature-based solutions, ecological quality, and the planning phase of landscape design.

Keywords: Generative artificial intelligence, landscape architecture, nature-based solutions, greenspace design, pollinator habitat, collaborative decision-making, participatory landscape planning

Highlights

- A new generative AI tool for interactive greenspace concept design decision-making
- Pollinator habitat indicator integrated into AI-assisted design workflows
- Enables human-in-the-loop evaluation of aesthetic and ecological trade-offs
- Efficiently generates greenspace design variations of feasible spatial geometries
- Accelerates collaborative landscape planning in early design phases

1. Introduction

Generative artificial intelligence (AI) technologies are advancing at an unprecedented pace, rapidly reshaping how professionals seek to address complex sustainability problems through nature-based solutions, climate-adaptive planning, and ecological restoration (Wang et al., 2025a). Landscape architects and planners are particularly skilled at balancing multidisciplinary project objectives by bridging scientific investigations with socially responsive nature-based design solutions to enhance stakeholder engagement (Albert et al., 2021). Early generative AI applications for landscape design have primarily focused on enhancing visualizations, where photo-realistic perspective images to improve visual communication (Li & Amoroso, 2023). The quality of AI images has significantly improved in recent years, substantially enhancing the efficiency of community engagement opportunities beyond hand-sketching or conventional software tools (Awashra et al., 2025). Text-to-image models and hybrid workflows that integrate AI with traditional drawings and GIS metrics are also increasingly recognized as valuable tools for landscape design (Chen et al., 2024; Schroth and Maier, 2025). The capacity of tailored AI tools that support planting design efficiency has been demonstrated in recent studies (Liu et al., 2024; Ashari and Shafaghati, 2025), along with algorithmic open-space configuration (Serdar and Kaya, 2019), and the emergence of workflows for generating complex conceptual urban layouts through text-to-image models like Stable Diffusion and ControlNet (Ye et al., 2025).

Here, we present a new generative AI tool for improving collaborative greenspace concept design that balances automation, aesthetic preference, and cultural ecosystem services by incorporating an interactive, flexible, and measurable decision-making framework. Our AI tool was modelled to accelerate the generation of conceptual landscape plan drawings derived from descriptive prompts aiming to enhance pollinator habitats through greenspace design variations. We integrated a Pollinator Habitat Indicator (PHI) scoring systems into the conceptualization process, where AI-generated design scenarios correspond to resulting PHI scores while supporting user-defined aesthetic preferences with collaborative editing features. We refer to this model as the PHI-AI Landscape Design Tool.

Generated greenspace design scenarios are then customizable to project-specific objectives and aesthetic preferences, allowing users to visually compare greenspace variation in a flexible and collaborative decision-making process. By integrating PHI scores into the generative workflow, the tool supports evidence-based, ecologically informed processing during early stages of landscape concept design. This combines social-ecological capabilities that offer new opportunities for aligning nature-based solutions, public aesthetic preference, and design feasibility within an interactive digital planning interface.

1.1 Background

Generative AI use in landscape architecture fits in a broader AI-generated content (AIGC) framework where models can directly support landscape analysis, design, and assessment techniques (Xing et al., 2025). Landscape planning requires analysis of existing site conditions within greater spatial and geographic contexts. LaDeco is one tool that uses deep learning to segment photographs into core landscape elements and measured visual components. The tool allows for the replication of visual landscape character assessments. This is fundamental workflow in landscape analysis and enhances the efficiency of assessing alternative design proposals (Ho, 2023). Similar workflows use remote sensing within greenspace generative adversarial network (GAN) applications to automate the extraction of environmental contexts, generating design techniques that can respond to urban geometry, land cover types, and hardscape features. This moves beyond thinking of landscapes as blank canvases towards a more-detailed representation of existing landscape characteristics (Chen et al., 2025). Geodesign is another approach that incorporates existing spatial components within collaborative design simulations. This workflow improves nature-based solutions by using tools to co-create landscapes that support planning strategies for assessing ecological and social trade-offs (Esmail et al., 2025).

Public participation often benefits from highly visual, easily interpretable representations of proposed greenspace designs, where preference can be ranked to advance landscape architectural decision-making (Cai et al., 2022). However, producing multiple conceptual layout scenarios is traditionally time-consuming and resource intensive (Ye et al., 2025). AI tools can reduce these constraints by generating diverse, presentation-ready drawings in seconds, enabling rapid iteration and responsive dialogue with community members, partners, and multidisciplinary teams (Awashra et al., 2025). Chen et al. (2023) proposed a workflow for generating greenspace design layouts quickly with GAN-based plan development through optimized training. Text-to-image diffusion models can support conceptual landscape design layouts by refining design scenarios to effectively enhance stakeholder engagement and the collaborative design decision-making process (Ye et al., 2025). CBS3-LandGen is also a new multi-modal system that integrates text, image, and generative optimization under an architectural framework to accelerate collaborative design and landscape plan generation (Lu & Shi, 2025).

Landscape design projects aimed at nature-based solutions commonly strive for ecosystem services by evaluating the performance of restoration efforts towards balancing social-ecological objectives. Wang and Zhang (2026) recently proposed a Deep Neural Network-based Green Space Design Optimization Framework (DNN-GSOF) that couples convolutional neural network based landscape layouts with neural indicators to optimize urban greenspace configuration for linking social, ecological, and economic components relating to planning regulations. Dong et al. (2026) proposed another deep learning optimization workflow using UNet surrogates to enhance the efficiency of design decision-making by linking ecosystem services and human comfort (e.g., habitat and cooling) in the planning phase. Similar work in the field of river restoration has shown that it is possible to improve public perceptions of naturalized riverscapes by leveraging AI to improve ecosystem services (Poledniková and Galia, 2021) and work by Kupferschmidt et al. (2024) demonstrated that through careful analysis of biases, generative AI models can reproduce many domain-specific environmental and landscape characteristics. These advancements reflect a growing professional trend, where landscape architects and planners are adopting AI strategies not as a replacement for design and creative expertise, but as complementary models that accelerate creative exploration, production of deliverables, and enhance inclusive communication venues with collaborators (Braiden et al., 2025).

1.2 Study Purpose

Multidisciplinary landscape design projects that must simultaneously meet ecological and aesthetic values can run into tensions in balancing seemingly oppositional endpoints. These tensions are common in restoration projects and foundational to concepts like ‘cues to care’ (Nassauer, 1995; Li and Nassauer, 2020), where public acceptance of designed landscapes is often tied to the perception of ecological health (Nassauer et al., 2009; Yang et al., 2021). The naturalness of greenspaces is generally preferred over engineered hardscapes (Hoyle et al., 2019) and percieved ecological value is a driving force for landscape preference (Ode et al., 2009). Simultaneously, public preferences for orderly naturalness tend to involve more tidy aesthetic objectives with stronger cohesive design elements that are recognized as cared for in some way (Khachatryan et al., 2020). Most developed AI tools remain specialized in either the optimization of ecosystem services or visual and functional qualities, with some singular interpretive models that integrate ecological and experimental dimensions (e.g., Dong et al., 2026). The acceleration of diffusion-based design concept models (e.g., Lu and Shi, 2025) highlight new opportunities for human involvement in the planning process, however, the flexibility required for true design collaboration throughout the planning process remains limited.

The subjective preference for a certain landscape design is often intangible, from an aesthetic perspective, and collaborative design frameworks would benefit from AI tools that offer a preliminary indicator value of model outputs while allowing freedom for post-generative revisions to support dynamic preference engagements (Wang et al., 2025b). A model that can generate an array of potential design solutions with accompanying measures of ecological quality could provide useful starting points to bridging diverse project objectives through a highly visual and easily communicated medium. While landscape architects and the public are not generally trained in scientific analysis or interpretation of complex generative AI outputs, tools used to augment landscape design conceptualization should be trained by scientific experts so that rendered designs can be visually and scientifically compared, but customizable for public users.

Our PHI-AI Landscape Design Tool was developed by a multidisciplinary team of experts in landscape architecture, ecology, and engineering. AI-generated landscape imagery has shown to influence public perceptions of environmental interventions and support more accessible communication of design possibilities and intentions (e.g., Chen et al., 2023). Because bias will fundamentally exist within AI design models trained by human inputs (Alkhateeb et al., 2025; Ashari & Shafaghati, 2025), we suggest transparency of project-focused design objectives is a benefit for landscape design decision-making, rather than viewing human-control as a limitation of machine learning. By boosting the efficiency and quality of early-phase concept designs, the PHI-AI Landscape Design Tool can enable a more interactive, participatory, and transparent planning framework that complements geodesign approaches (e.g., Esmail et al., 2025) while supporting cues to care with multidisciplinary inputs and output revision opportunities.

2. Methods

2.1 AI Model Conceptualization

The conceptualization of our PHI-AI Landscape Design Tool aimed to leverage the production efficiency of generative AI while offering post-production collaborative flexibility for users. Three design objectives were defined for modelling the PHI-AI Landscape Design Tool, including the development of a platform that was 1) rooted in ecosystem services with pollinator-focused habitat indicators, 2) interactive in its approach to aesthetic preferences, and 3) visually communicable to enhance stakeholder engagement. The output graphics of gendered design scenarios were intended to be relatively simplistic. These graphics represent a concept design ‘style’ that signals an outcome for collaborative revision and decision-making rather than a photo-realistic image illustrating a finalized product.

Generative AI-derived greenspace designs then offer measurable outputs for user-defined analysis with complementary metrics applied to raster-based imagery data. These evidence-based concepts build a foundation for advancing landscape architectural design practices, where formal construction drawings can follow with detailed plant types, surface materials, and installation specifications. Ashari and Shafaghati (2025) recently found that AI-derived meadow landscape representations showed viable geometric outputs but inconsistencies with plant material types. This suggests the integration of generative-AI into collaborative frameworks could balance geometric rending efficiency with human control of aesthetic refinements and selection of plant species. This AI-human control balance is heighted by the conceptualization of our PHI-AI Landscape Design Tool, where evolving input-output relationships are complementary throughout the planning phase of landscape conceptual design.

2.2 Generative AI Model Development

2.2.1 Model Planning

A series of landscape design variations were manually generated to support the planning of the PHI-AI Landscape Design Tool. Five real-world sites were selected as case studies, ranging from 0.2 – 2.5 ha, and included campus landscapes reported in Dawson et al. (2025). We selected these spatial extents to reflect a suitable scale for visual quality assessment of planting design scenarios and support the ease of application, rather than considering complex dynamics at regional scales, for example (Dong et al., 2025). Sites were selected to represent a range of existing canopy cover, infrastructure configurations, and a combination of straight and curved geometric networks.

Designs were rendered as plan drawings with Adobe Photoshop and Illustrator to establish a consistent visual ‘style’ and offer alternative geometric landscape layout options to support model planning. Landscape plantings and elements were then selected for implementation into existing landscapes, resulting in several unique landscape layouts for each site (see Supplementary Material, File 1).

2.2.2 Model Development

The PHI-AI Landscape Design Tool leveraged Google’s multimodal Gemini model. While historical use of machine learning models for real-world applications has typically involved a lengthy architecture development and training process (Bommasani et al., 2018), Gemini is a general-purpose multimodal model that can be used out-of-the-box in a zero-shot or few-shot configuration. We leveraged the Gemini-Flash-Image 2.0 model (also known as “Nano Banana”) for image generation (Fig. 1a) and editing (Fig. 1b), while the more powerful model Gemini-Flash-3.0 (which does not support image generation) was used to calculate PHI scores (Fig. 1c). Model temperature (a parameter affecting the creativity of the model) was adjusted based on the task. For image design, editing, and PHI computation we used multimodal inputs that including a “system prompt” designed to provide general instructions for each task, relevant images, and the user input prompt for generating and editing. For more details see Supplementary Material (File 2).

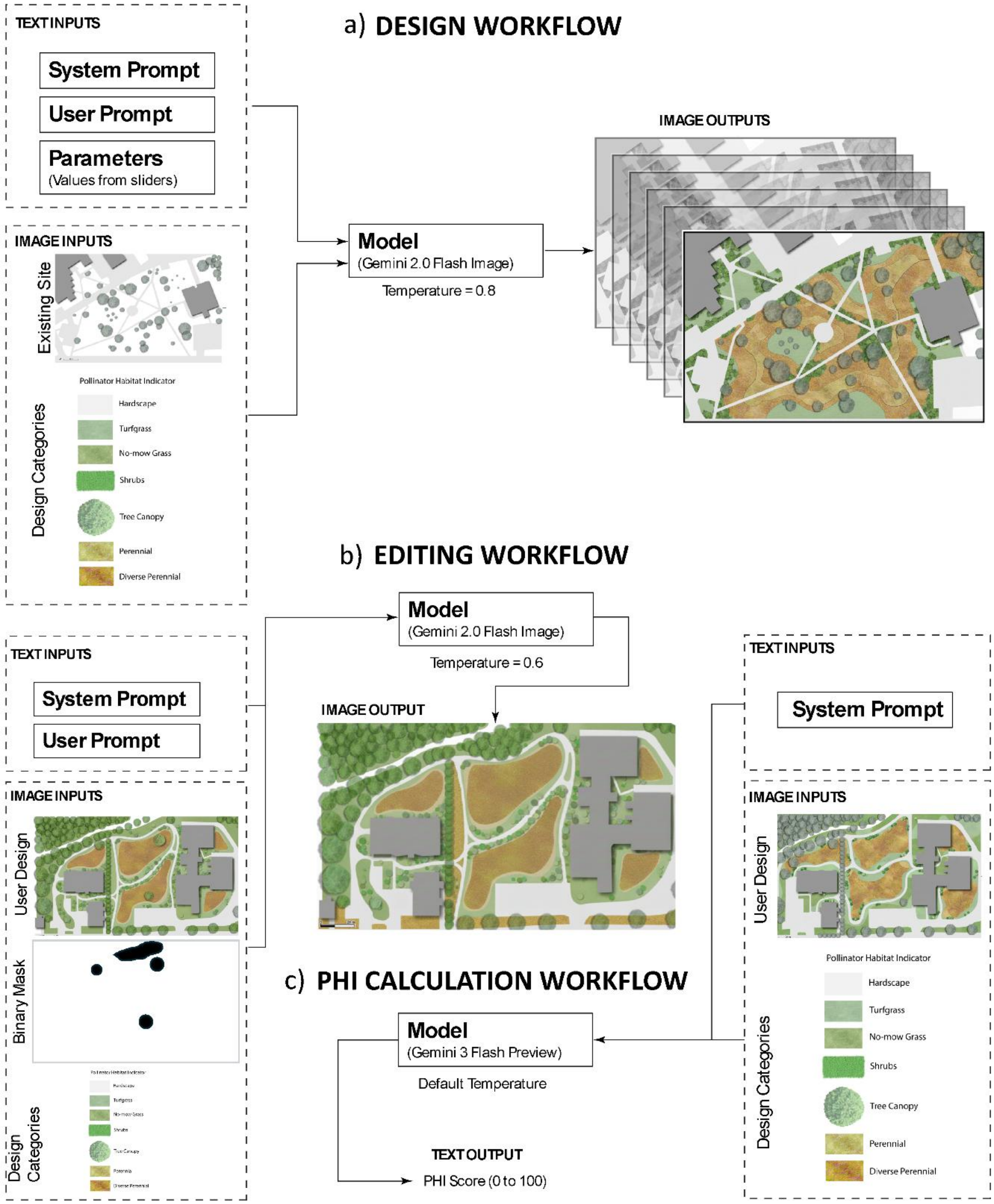

Figure 1: Diagrams showing workflow for a) model design development for generation image variations, b) editing generated images, and c) calculating PHI scores using design categories.

The conceptualization of our AI model aimed at enhancing pollinator conditions by developing a PHI scoring system for referencing generated greenspace variations. PHI scores were categorized by defining a series of landscape 'patch' types with corresponding coefficients weighted by relative ecological quality (e.g., Geppert et al., 2026) and measured by relative spatial extents. Categories and pollinator coefficients provided a pollinator habitat hierarchy (e.g., Fijen et al., 2022), including Hardscape (0.00), Turfgrass (0.17), Now-mow Grass (0.33), Shrub (0.50), Tree Cover (0.67), Perennial (0.83), and Diverse Perennial (1.00) (Fig. 1). Like the well-known Manning's roughness coefficients applied for modelling surface flow responses to vegetated landscapes (Arcement and Schneider, 1989), PHI scores were calculated by patch-type area (m^2), relative coefficients, and total site area (m^2) to provide a scalable value for generated greenspace designs. Calculations for PHI scores are provided in Supplementary Material (File 2).

2.2.3 Model Interface

The PHI-AI model interface includes Design Objectives that offer three sliders to increase the proportional targets for Patch Diversity, Tree Canopy, and Turfgrass. Sliders allow the user to adjust spatial planting coverage for each prompt and can be revised between generated design variations (Fig. 2a). The Design Description is where the user provides a prompt for the design and allows modifiers between generated variations. The interface also provides an option for identifying the number of variations generated per prompt input (Fig. 2b). The Active Design window is where existing landscape drawings or images are uploaded from a local folder (Fig. 2c). Pollinator coefficients are then weighted to derive landscape designs with corresponding PHI scores for each variation. Users can select preferred design variations as 'favourites' or delete unfavourable outputs following each prompt (Fig. 1d).

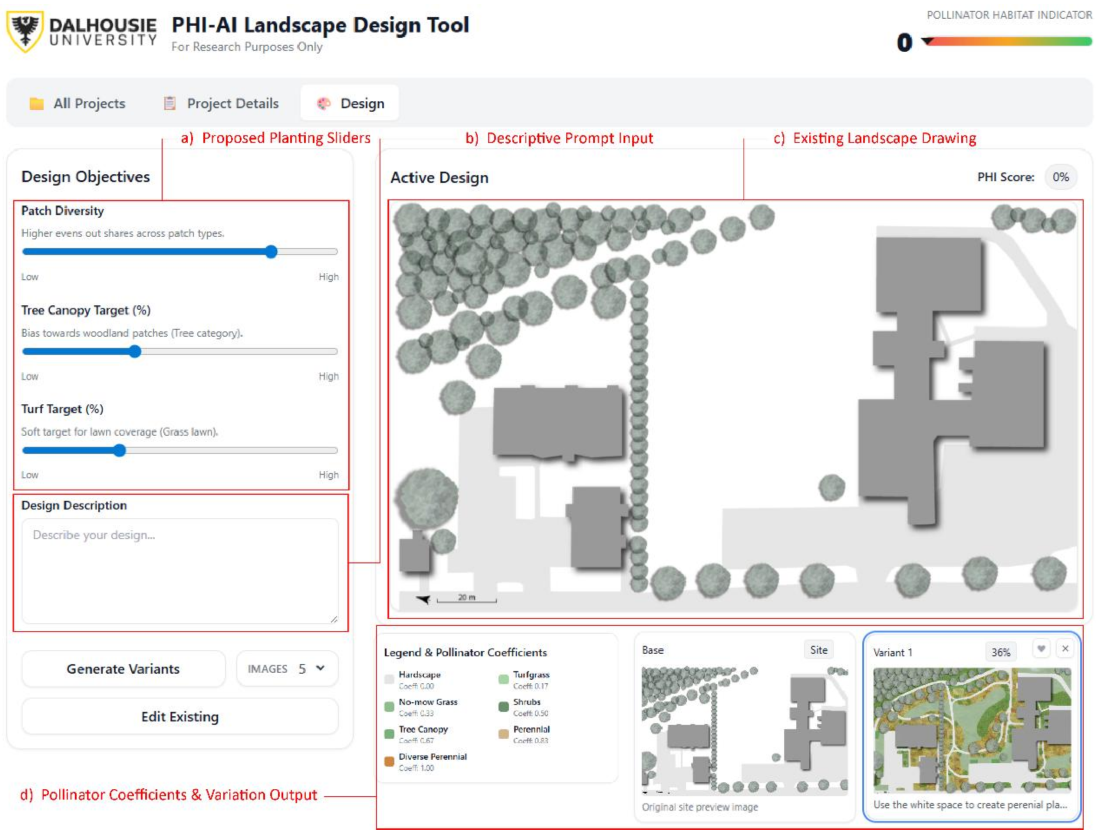

Figure 2: PHI-AI Landscape Design Tool interface showing a) Design Objective sliders, b) Design Description prompt, c) Active Design window, d) and Pollinator Coefficients and Variation output.

2.3 Experimental Design

This study created a conceptual workflow to showcase a four-step process for utilizing the PHI-AI Landscape Design Tool to support project-specific objectives. We developed a descriptive prompt that was applied to a real-world site as a case study in Truro, Nova Scotia, Canada. A collection of greenspace scenarios was derived from a landscape concept aimed at enhancing pollinator habitat with curvilinear geometries (Fig. 3a). A collaborative decision-making process was used to rank AI-generated greenspace designs based largely on perceived aesthetic preferences and a consensus of scenarios variations were selected as favourable by the authors (Fig. 3b). We then compared corresponding PHI scores and complementary metrics values commonly used in landscape ecology. Collaboratively, we determined the best-performing scenario most-likely to meet aesthetic and ecological design objectives (Fig. 3c).

To showcase available editing tools within the model interface, the authors revised the selected design scenario with polygon, line, and circle masks and corresponding descriptive prompts. These edits resulted in a visual greenspace design output to support stakeholder engagement and develop a template for further landscape design development (Fig. 3d). This conceptual workflow demonstrates how aesthetic preferences may be nested within ecological indicators to rank initial greenspace designs and compare post-revision habitat qualities. The workflow illustrates an interactive AI tool that supports multidisciplinary landscape planning through automated and flexible concept design communication.

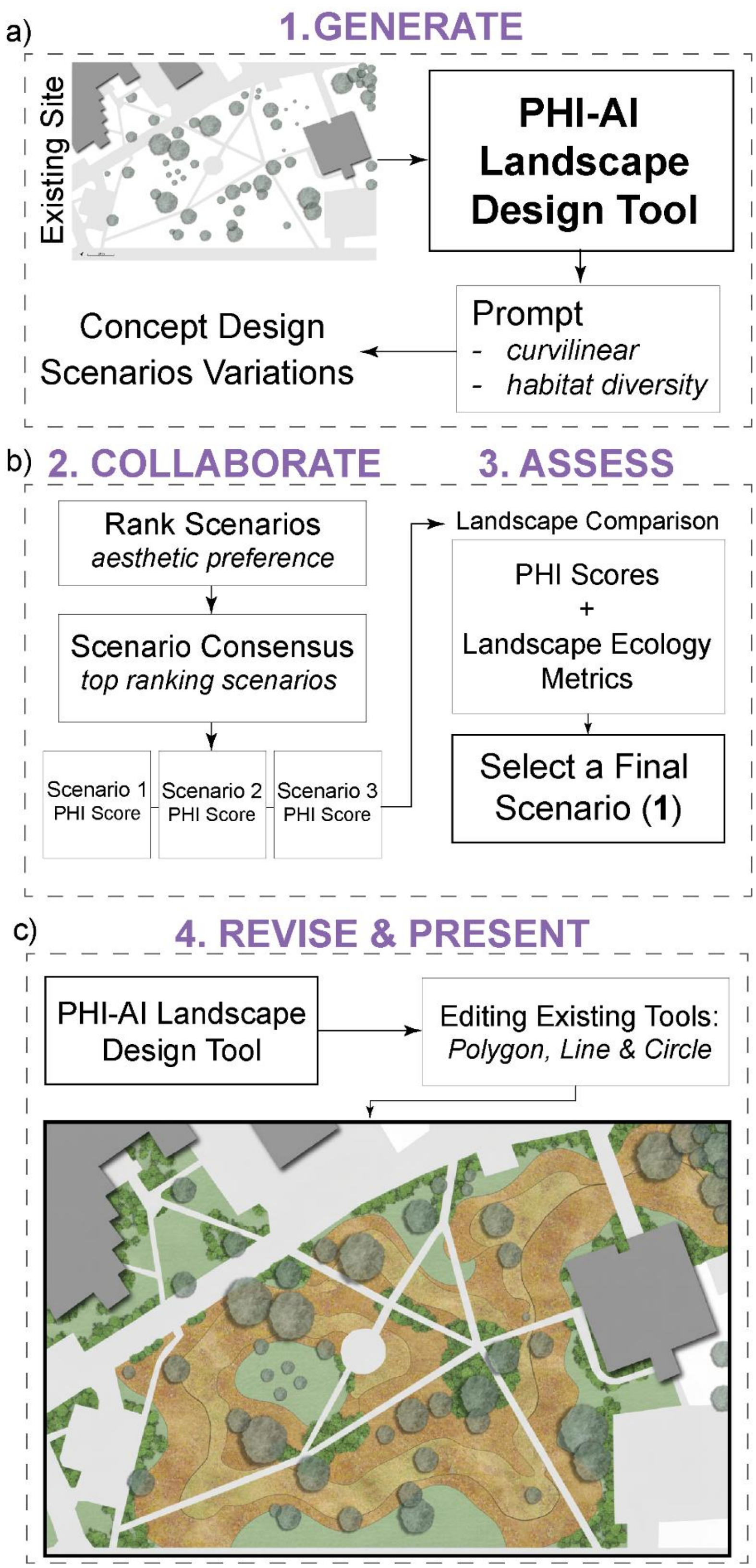

Figure 3: Workflow diagram showing the experimental design process of a) generating a dataset of concept design scenarios, b) ranking aesthetic preferences, c) applying and assessing ecological metrics, and d) revising and presenting a final greenspace design.

2.3.1 Step 1: Generating Greenspace Design Scenarios

Greenspace design scenarios were created by applying one descriptive prompt. The prompt addressed a public landscape preference for broad curves over straight planform geometries (van der Jagt et al., 2014; Gómez-Puerto et al., 2016; Kuper, 2017; Dawson et al. 2025) and aimed to enhance pollinator habitat and ecosystem services through perennial planting diversity enhancement (Sidhu and Joshi, 2016). Like most text-to-image AI tools, more-detailed text descriptions and engineered prompt modifiers improved the quality of generated images (Oppenlaender, 2023). Our prompt defined a design goal to "*create a landscape that enhances pollinator habitats while keeping the landscape functional for human users*", supported by prompt modifiers including curved planting beds and pathways, diverse perennial plantings, and habitat connectivity with an emphasis on existing canopy cover.

The descriptive prompt was run several times to generate a series of greenspace design variations. Sliders were used to adjust the weighted target of patch diversity, tree canopy, and turfgrass for each sequence. We collected 25 greenspace layout variation options to build a scenario dataset and showcase a collaborative design decision-making process. The descriptive prompt, generated scenario dataset, and corresponding PHI scores are provided in Supplementary Material, File 3.

2.3.2 Step 2: Collaborative Decision-Making

Contributing authors evaluated the greenspace design scenarios. Informal visual assessments were completed to trial a theorical decision-making process. Individually, each author ranked their top 10 scenario preferences based on perceived aesthetics and general favourability. Aesthetic favourability pointed to geometric relationships of spatial layouts, feasibility of circulation paths, potential cultural ecosystem services, and perceived pollinator habitat quality. Each author presented their preferred greenspace scenarios, and we compared selected scenarios to identify preference similarities. A consensus of preferred scenarios was reached and selected greenspace designs were further assessed by referencing PHI scores and complementary metrics.

2.3.3 Step 3: Assessing PHI Scores and Complementary Metrics

PHI scores were referenced to identify a preliminary ranking order of the selected greenspace design scenarios. Additional landscape ecology metrics were applied in FRAGSTATS version 4.2 (URL: https://www.fragstats.org/). A Supervised Classification method was used to process scaled multiband design scenario images in ArcGIS Pro 3.5. A customized schema was developed for our classified feature types (Hardscape, Turfgrass, etc.), and an object-based supervised classification was used for training. By simplifying visual landscape patch-types and elements in our PHI-AI Landscape Design Tool, compared to photo-realistic pixel-based training, design scenarios were quickly mapped with polygons referencing the PHI-AI schema.

FRAGSTATS class metrics included Percentage of Landscape (PLAND) and Connectance Index (CONNECT), and the Shannon's Diversity Index (SHDI) was applied as a landscape metric. These metrics are well-known and remain widely used for assessing landscape habitat diversity, connectivity, and suitability (Wang et al., 2014; Borges et al., 2017; Cushman and McGarigal, 2019; Yan et al., 2021; Sütünç, 2024; Zhang et al., 2025). This study was not intended to apply a rigorous ecological landscape quality analysis and habitat quantification of greenspace scenarios. Rather, we are applied these well-known metrics to demonstrate how complementary indices may be applied in the presented workflow and to illustrate how PHI scores and alternative metrics may support design objectives outlined in descriptive prompts.

CONNECT values were of particular interest because ecological connectivity was not directly modelled with the PHI scoring system. However, connectivity may be a suitable design indicator because it complements the intention PHI scores for measuring ecological corridors (Brückmann et al., 2010). The Connectance Index calculates the spatial connectivity of equivalent patch types by identifying functional joinings based on a specified distance, expressed as a percentage (Ene and Mcgarigal, 2023). We defined a threshold distance of 5 m to reflect a buffered general pathway width, providing a fragmentation reference relative to the site extent. Planting type mean values were then weighted in correspondence with our PHI score coefficients, where Diverse Perennial patches (1.00) outweighed Turfgrass (0.17), for example. Weighted means were also applied to resulting PLAND values. These values offered a complementary reference to support the decision-making process and selecting a preferred greenspace scenario.

2.3.4 Step 4: Editing and Presenting the Selected Design Scenario

Here, the flexibility of the PHI-AI Landscape Design Tool was further amplified by offering output editing tools. Users can collaboratively revise best-performing concept designs with custom refinements to visually assess how overall aesthetics adjust to these changes. A combination of prompts and area-specific polygonal masks were used to add tree cover, remove individual trees, and replace turfgrass patches with diverse perennial plantings. While editing tools allow revisions to greenspace images, designers have the option to use the readily available generated image as a template for landscape design development. This may include a charrette-like approach where hand-drawing methods are collaboratively applied and places human control at the center of the decision-making process.

3. Results

3.1 PHI-AI Landscape Design Tool Performance

The PHI-AI Landscape Design Tool efficiently generated a large dataset of greenspace variations, allowing for the collection of 25 greenspace design scenarios for assessment. The tool successfully generated geometric landscape layouts that showed feasible planting and hardscape relationships. This was particularly evident with variations of pathways and planted greenspace patch types. The model generated pathway connections to existing infrastructure that reflected practical circulation systems in landscape architectural practice (see Supplementary Material, File 3). Broad pathway curvatures and planting beds responded positively to design objectives included in the descriptive prompt. The feasibility of generated circulation pathways was also highlighted, and perhaps outperformed, the greenspace design options developed manually in the model planning phase (see Supplementary Material, File 1). This shows that despite Gemini being a general-purpose model, it has an implicit understanding of key concepts important for landscape design that can be leveraged by human users through careful prompting and use of relevant contextual multimodal data.

3.2 Collaborative Decision-Making and Assessment

Based on an informal visual assessment by each contributing author, 10 independent scenario preferences were selected, including the following (see Supplementary Material, File 3):

Author 1: Scenarios 5, 8, 10, **12**, 14, 15, 16, **20**, 23, **24**, 23
Author 2: Scenarios 2, 4, 8, 11, **12**, 18, **20**, 21, **24**, 25
Author 3: Scenarios 1, 3, 10, 11, **12**, 13, 16, **20**, 21, **24**

The authors reached a consensus of three preferred greenspace designs, including Scenarios 12, 20, and 24 with corresponding PHI scores of 40%, 45%, and 49%, respectively (Fig. 4a). A supervised classification was then applied to each scenario with a PHI-AI schema (Fig. 4b) and complementary metrics were run on derived class images in FRAGSTATS.

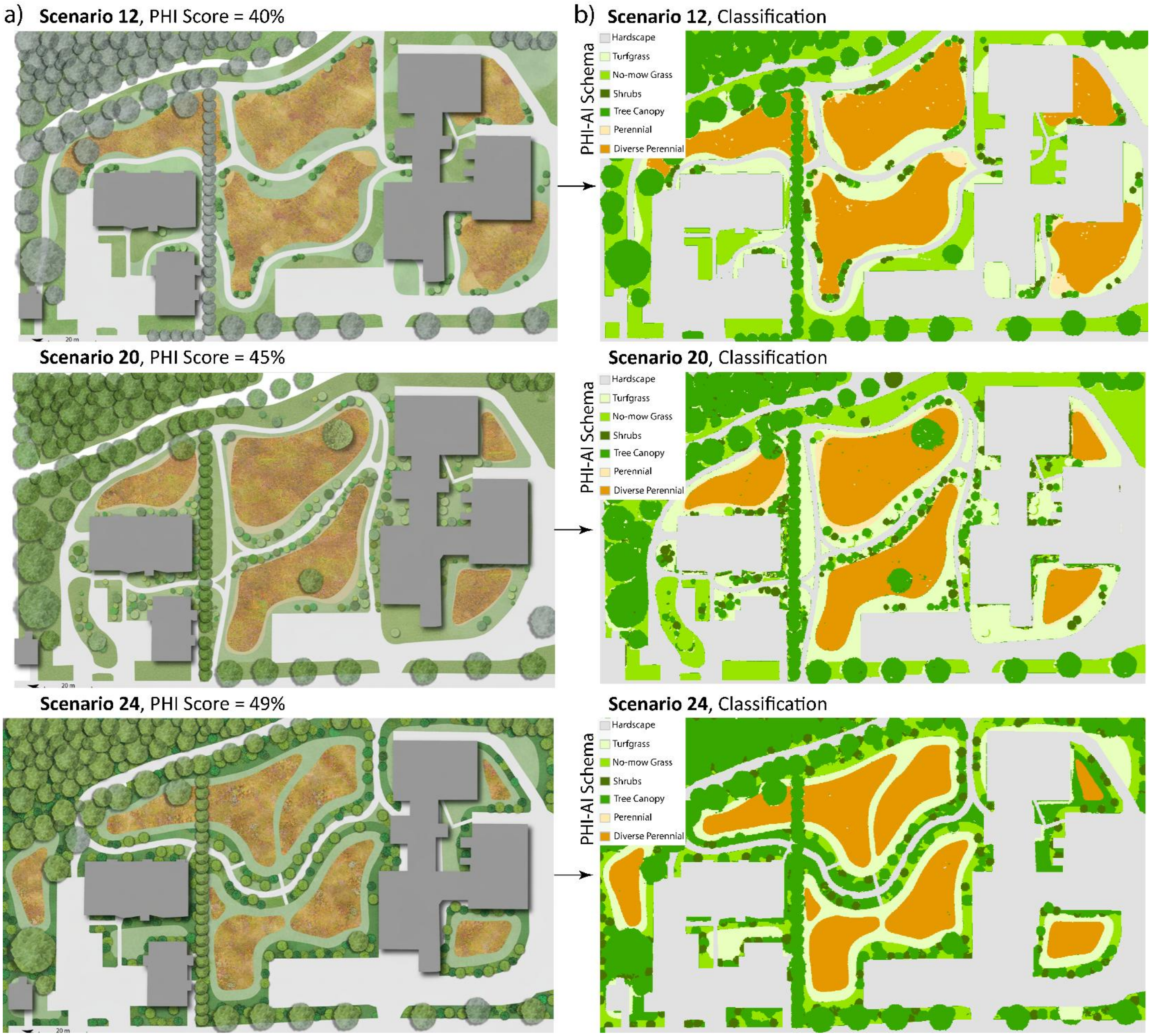

Figure 4: PHI-AI generated greenspace designs a) selected independently by authors as preferred scenarios and b) supervised classification images derived in ArcGIS Pro.

Table 1 showed weighted mean metric values generally supported the PHI score sequence. Scenario 12 showed the lowest relative mean value (8.30) and Scenario 24 showed the greatest mean value (8.84). Scenario 24 showed the greatest weighted mean PLAND value of 7.20%, followed by Scenario 12 (6.18%), and Scenario 20 (5.89%) while Scenario 12 showed the greatest weighted mean CONNECT value of 0.56%, followed by Scenario 20 (0.39%), and Scenario 24 (0.09%). At the landscape extent, Scenario 20 showed the greatest SHDI value of 1.61.

Table 1: Statistics showing resulting values for each planting category, including weighted mean PLAND values, weighted mean CONNECT values, SHDI values, PHI scores, and overall mean values from FRAGSTATS metrics.

Scenario	Planting Category	*Pollinator Coefficient*	PLAND (%)	**PLAND weighted**	CONNECT (%)	**CONNECT weighted**	**SHDI**	PHI Score	**Overall MEAN**
12	Diverse Perennial	*1*	17.14	17.14	2.63	2.63	**1.56**	40%	**8.30**
	Perennial	*0.83*	0.89	0.74	0.42	0.35			
	Tree Canopy	*0.67*	19.7	13.20	0.19	0.13			
	Shrubs	*0.5*	1.15	0.58	0.36	0.18			
	No-mow Grass	*0.33*	10.89	3.59	0.16	0.05			
	Turfgrass	*0.17*	10.66	1.81	0.17	0.029			
Mean				**6.18**		**0.56**			
20	Diverse Perennial	*1*	12.98	12.98	4.76	4.76	**1.61**	45%	**8.39**
	Perennial	*0.83*	1.60	1.33	0.49	0.41			
	Tree Canopy	*0.67*	21.47	14.38	0.09	0.06			
	Shrubs	*0.5*	2.68	1.34	0.10	0.05			
	No-mow Grass	*0.33*	10.08	3.33	0.16	0.05			
	Turfgrass	*0.17*	11.59	1.97	0.09	0.02			
Mean				**5.89**		**0.39**			
24	Diverse Perennial	*1*	13.43	13.43	0.10	0.10	**1.55**	49%	**8.84**
	Perennial	*0.83*	-	-	-	-			
	Tree Canopy	*0.67*	24.37	16.33	0.31	0.21			
	Shrubs	*0.5*	3.60	1.80	0.10	0.05			
	No-mow Grass	*0.33*	6.30	2.08	0.16	0.05			
	Turfgrass	*0.17*	13.83	2.35	0.32	0.05			
Mean				**7.20**		**0.09**			

To select a final greenspace design scenario, the authors collaboratively reviewed class metric results to support the decision-making process. We found that Scenario 20 showed the greatest CONNECT value for the Diverse Perennial category (Table 1). The authors determined that perennial habitat connectivity, coupled with the high PHI score (45%) relative to the overall dataset, was sufficiently balances with mutual aesthetic preferences. Perceived aesthetic preferences included the planting island generated in the south-western parking lot (Fig. 4a). The authors also favoured the balanced turfgrass space and accessible pathway options compared to limited defined pathway options that were largely dominated by tree and shrub buffers in Scenario 24 (Fig. 4a). Therefore, Scenario 20 was selected as the best-performing greenspace design and could be improved by further landscape revisions.

3.3 Collaborative Editing with the PHI-AI Landscape Design Tool

The final stage of our experimental design was to apply PHI-AI editing tools to enhance the quality of the selected greenspace design (Scenario 20). We found that Diverse Perennial connectivity out-performed other scenarios but under-performed in Tree Canopy connectivity (see Table 1). Following a collaborative visual assessment, we selected a Turfgrass area along the eastern pathway for revision. The location showed a fragmented patch of surrounding Tree Canopy, and the polygon mask was used to add dense tree cover to enhance tree connectivity (Fig. 5a). The circle mask was then used to remove individual trees generated within Diverse Perennial beds (Fig. 5b). The authors determined that these individual tree locations were likely not contributing positively to pollinator habitat quality. Finally, the line mask was used to replace existing Turfgrass areas with Diverse Perennial plantings. We selected two patches along the south side of the existing tree line and replaced Turfgrass along the western bordering patch to enhance connectivity and overall pollinator habitat diversity (Fig. 5c).

The resulting image presents the greenspace concept drawing derived from a collaborative workflow of automation and human controlled decision-making processes to support design development (Fig. 5d). Landscape architects may they use this image as a communication product to enhance stakeholder engagement that provides a template for further design development, detailed plant species selection, and refined specifications required for the installation of designed landscapes.

Figure 5: Images of the selected greenspace design scenario showing a) polygon, circle, and line mask tools used for editing the existing design, and b) final greenspace concept drawing layout to support further design development.

4. Discussion

4.1 Advancing Landscape Architectural Design

The PHI-AI Landscape Design Tool was used to present a workflow that significantly increased the efficiency of deriving high quality landscape concept design variations compared to conventional approaches. Generated greenspace scenarios showed a range of spatial layouts, supporting functional geometries that are foundational to human preferences of designed greenspaces (Kaplan et al., 1972). Perhaps the most valuable contribution of our model lies in the collaborative decision-making process, where automation and ecological indicators are linked to human control throughout the conceptualization of landscape design. Prior studies show that AI can support creative design exploration (Schroth & Maier, 2025), assist with planting design with data-driven pattern recognition (Liu et al., 2024), and produce stylistically varied conceptual renderings (Ye et al., 2025; Ashari & Shafaghati, 2025). However, these approaches predominately emphasize visualization and form-finding, and they often lack mechanisms for evaluating landscape performance of ecological indicators. Even advanced GAN and diffusion-based techniques remain constrained in their capacity to produce technically accurate, ecologically grounded site designs, which is a general skepticism of design-focused AI models (Chen et al., 2023; Ashari & Shafaghati, 2025).

Recent advances in AI have demonstrated that large-scale, adaptable models can be successfully translated from experimental settings into real-world decision-support systems across multiple applied domains. These systems demonstrate that AI tools can deliver actionable outputs while remaining embedded within human-centered problem-solving rather than replacing expert judgment. Successful AI adoption depends not only on model performance, but also on governance structures, transparency, and alignment with professional norms and regulatory expectations. The adaptability of foundation models has been particularly valuable in applied planning and spatial decision-making contexts, where problems are inherently open-ended, multimodal, and context dependent (Bommasani et al., 2018). By enabling rapid generation, comparison, and refinement of alternative scenarios, The PHI-AI Landscape Design Tool supports exploratory analysis, stakeholder engagement, and evidence-based ecological indicators without requiring conventionally time-consuming conceptualization for each new application.

These characteristics mirror the needs of landscape architecture and urban planning practice, where design decisions must balance ecological performance, spatial coherence, and social perception across varying scales and sites. Rather than proposing AI-assisted greenspace drawings as finalized products, the PHI-AI Landscape Design Tool advances landscape architecture by embedding pollinator habitat quality indicators directly into a highly flexible and interactive design conceptualization process that remains grounded in visual communication. This moves beyond existing innovations that focus primarily on geometric accuracy, stylistic realism, or model fine-tuning for spatial consistency (Ye et al., 2025).

Our presented workflow complements and extends the collaborative planning benefits reported in geodesign methods and similar actions in nature-based solutions. Tools that incorporate scenario exploration have been shown to support transformative planning, stakeholder communication, and the negotiation of trade-offs between ecological function and implementation needs (Esmail et al., 2025). Few existing tools allow stakeholders to see, compare, and refine ecological outcomes in real time, while offering additional post-generated metric applications through supervised classification. By coupling generative concept design outputs with habitat qualities, our model offers a more transparent and interactive platform for multidisciplinary dialogue. Landscape architects, ecologists, planners, and community members can collectively explore how varying the composition and spatial arrangement of planting patches influence restoration potential. This capability directly addresses the need for AI tools that enhance real-world workflows by automating ecological indicator references while keeping human control as a central component of the design process (Braiden et al., 2025).

4.2 Implications for Pollinator Conservation in Human-Dominated Environments

Our PHI scoring system is consistent with the habitat requirements by bees (Hymenoptera: Apoidea: Anthophila). There are more than 21,000 species of bees described by science (Kilpatrick et al., 2020). Bees and other insects play a crucial role as pollinators – acting as the primary providers of pollination services for approximately two-thirds of all flowering plants. By assigning pollinator indicator values to broad categories of landscape attributes that reflect relative food availability (e.g. no-mow areas, diverse perennial beds, trees and shrubs), and nesting sites (e.g. dead twigs, permeable surfaces), practitioners can adapt the choice of plant material to match environmental conditions and the other human or nature-oriented goals of the site while retaining flexibility to accommodate site-specific restraints. For example, if a bee with a limited dietary niche (e.g. oligolectic or monolectic) is likely to be present – it is imperative to include its host plant within the plants selected for the design.

There is well-established rationale for selecting pollinators as a target taxon for conservation when considering the broader ecological benefits that a landscape design can provide for wildlife. Urbanized environments have the potential to act as conservation hotspots for wild bees, particularly when in landscapes that include features such as botanical gardens, vacant lots, and allotments. Urbanized environments can also provide important habitat for rare species like the Rusty Patch Bumblebee (*Bombus affinis*) which is listed as endangered in the United States and Canada. *Bombus affinis* has declined at least 90% in abundance from since 2005 and now occupies just 0.1% of its former range (U.S. Fish and Wildlife Service, 2017). Many contemporary records of this species are from urban and suburban areas, where bees forage within gardens, and nest in close association with human infrastructure (e.g. adjacent to building foundations) (Boone et al. 2022).

While pollinators tend to be viewed favorably by humans compared to other insects, there is limited awareness or understanding of the: lifecycles, habitat requirements, and diversity of wild pollinators (van Vierssen Trip et al. 2020). In practice, many of the most effective interventions that support biodiversity in urban greenspaces may be perceived as “unsightly”, making it important to communicate the intent of the design decisions to users, particularly as they relate to pollinator conservation. Work by Shwartz *et al* (2014) has found that when pollinator diversity and abundance was experimentally enhanced in urban parks, this change is not perceived by frequent park users – even when those same users hold a favorable opinion of pollinators. To achieve alignment between design and ecological understanding, communicating information about pollinators to landscape users is equally as important as informing the practitioners responsible for designing and maintenance.

4.3 Limitations and Future Research

We developed the PHI-AI Landscape Design Tool to support flexible human-in-the-loop collaborative decision-making rather than relying on the model to generate finalized greenspace design drawing. Therefore, the final AI-generated image should be used a conceptual working drawing where further design refinements and detailing are expected. Some limitations were found during the collaborative workflow where the graphic 'style' of generated greenspace designs showed some inconsistencies. These diversions away from the original patch-type style was more common for later variations and included some outliers after running the descriptive prompt beyond ~5 sequences. However, generated greenspace variations consistently applied the defined patch categories within each design output, supporting the general design objectives defined in the descriptive prompt.

The functionally of mask editing tools could also be improved from further development. We found that generated greenspace elements were frequently generated beyond the spatial extent of masks during the editing process. However, generating additional editing design variations with the consistent mask developed the desired revisions requested through the prompt. We suggest that future versions consider approaches such as image inpainting, which can be used limit changes to a small region in an image, but are not available in the existing Gemini suite of models. Inpainting can be used with other models including Google Imagen and some versions of Stable Diffusion, and a hybrid tool that blends multiple models could likely mitigate some of these issues.

In the current study, we did not explicitly evaluate the domain-specific biases present in the models used or assess the degree of rule-following exhibited by the models. For example, although the PHI scoring task is explicitly outlined in the descriptive system prompt (see Supplementary Material, File 2), we did not evaluate post-hoc to confirm calculation steps were explicitly followed. Recent research has shown that large language models which appear compliant during training or evaluation can later pursue divergent internal objectives, a phenomenon known as alignment faking in which superficial compliance masks deeper misalignment (Greenblatt et al. 2024). While the use of a human-in-the-loop system for the PHI-AI Landscape Design Tool can help to mitigate major deception, there is a risk of the model engaging in subtle deception to nudge designs in a certain direction and should be carefully communicated to users to avoid undermining reliability and trustworthiness for real-world use.

Future research may incorporate more automation in the ecological indexing process and increase the quantity of categorized patch types with more detailed landscape approaches. These patch types may include specific plant species or customize the model for specific design objectives beyond pollinator habitats. The model also offers opportunities to couple the tool with 3D digital surfaces and other interactive methods using geodesign to understand the linkage between spatial, topographic, and ecological contexts.

5. Conclusion

This study showcased how the PHI-AI Landscape Design Tool can advance AI-assisted landscape architecture by embedding ecological indicators, spatial feasibility, and collaborative flexibility within early-stage design workflows. By integrating a Pollinator Habitat Indicator directly into a generative AI framework, the tool moves beyond visualization-oriented applications toward an interactive decision-support system capable of accelerating the production and comparison of greenspace layout variations. The results show that AI-generated concepts can reflect feasible landscape geometry, circulation pathways, and conventional user functionality while supporting pollinator habitat enhancement objectives. The human-in-the-loop design approach allows practitioners and stakeholders to iteratively refine outputs, balancing automation with expert judgment, aesthetic preference, and site-specific constraints. Future research may extend this approach by integrating 3D modelling, species-specific habitat indicators, and long-term performance monitoring to further strengthen generative AI applications in landscape architecture.

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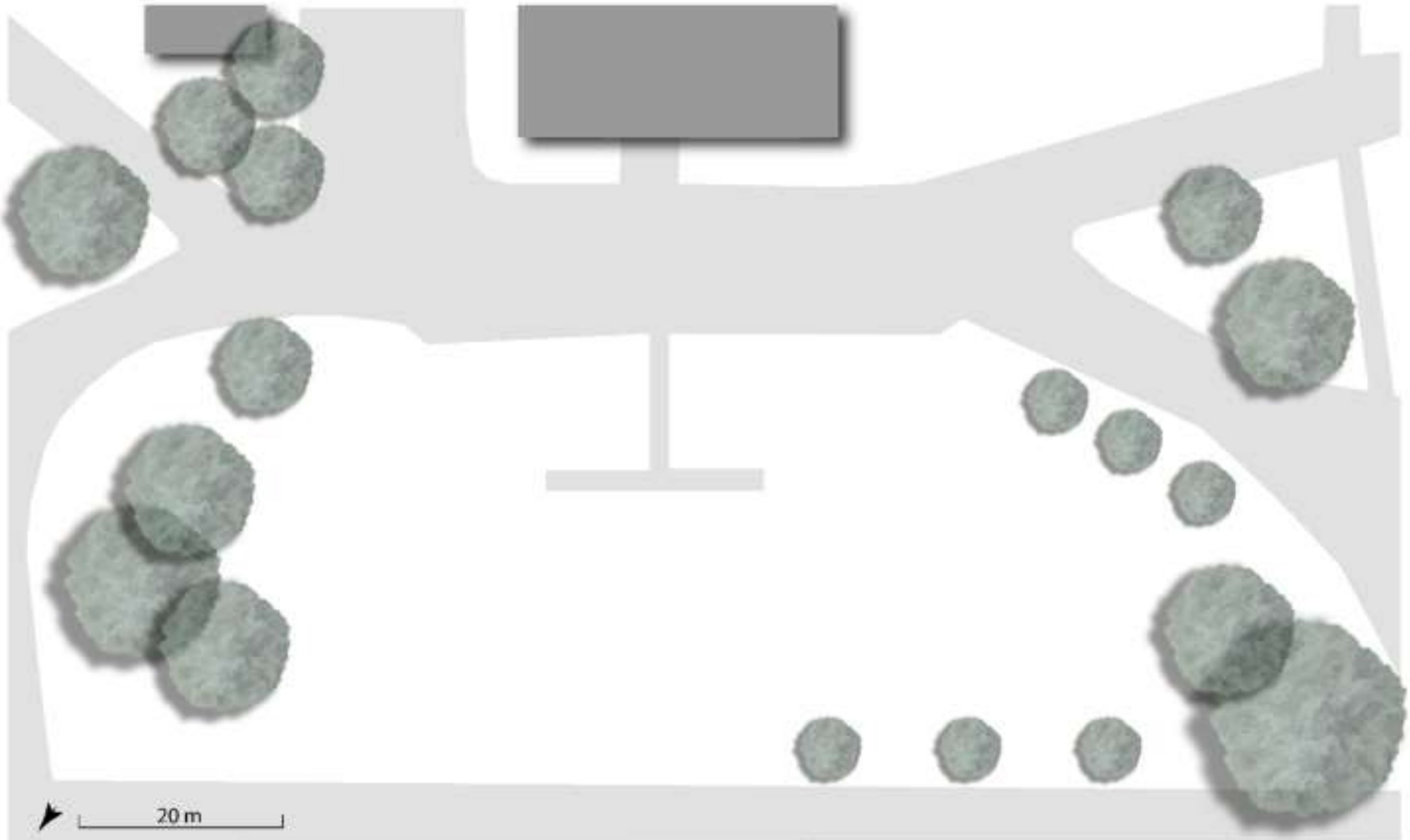
File 1: Landscape cases and rendered design variation used for AI model planning

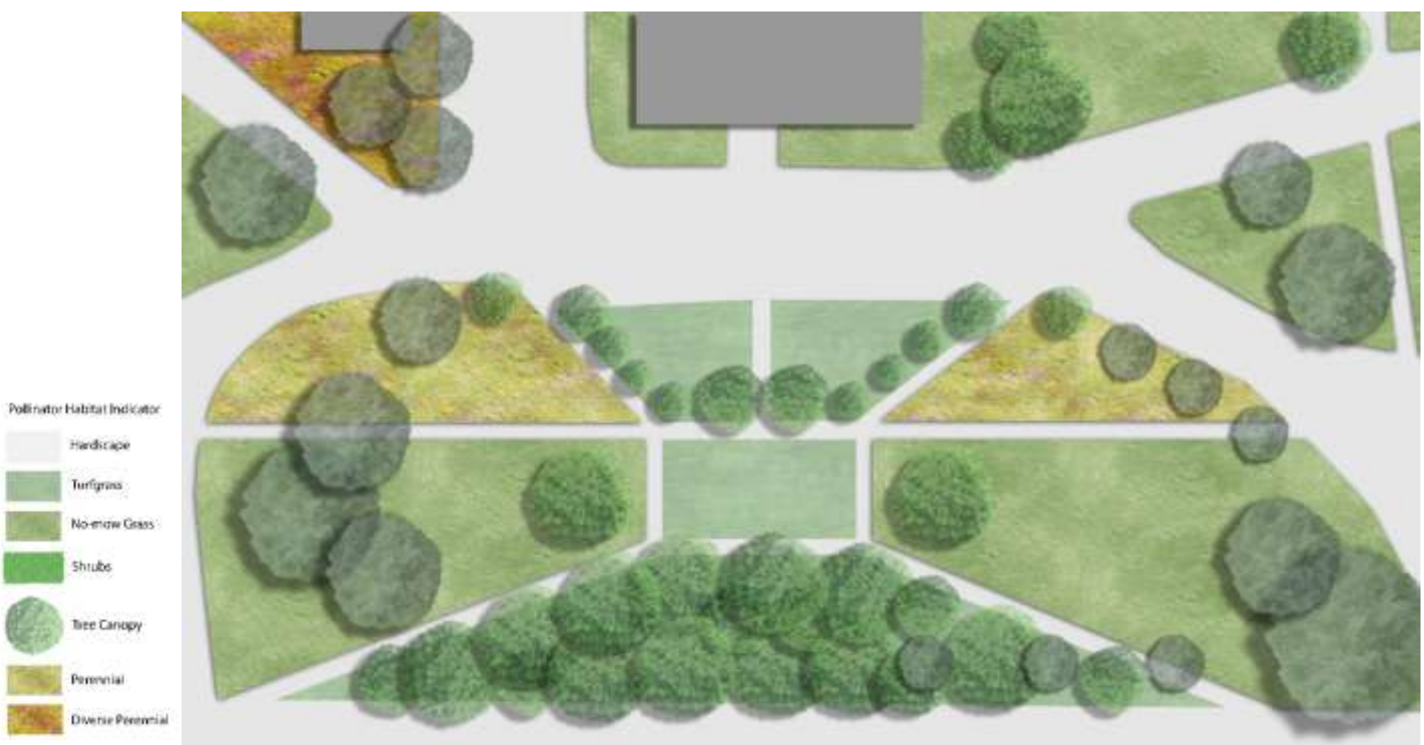
Five real-world sites in Truro, Nova Scotia are provided below. These cases show existing infrastructure and canopy cover conditions. The sites were used as design case studies for planning the PHI-AI Landscape Design Tool features, including graphic style, geometries, scales, and coefficients

Site 1: Existing Infrastructure and Canopy Cover

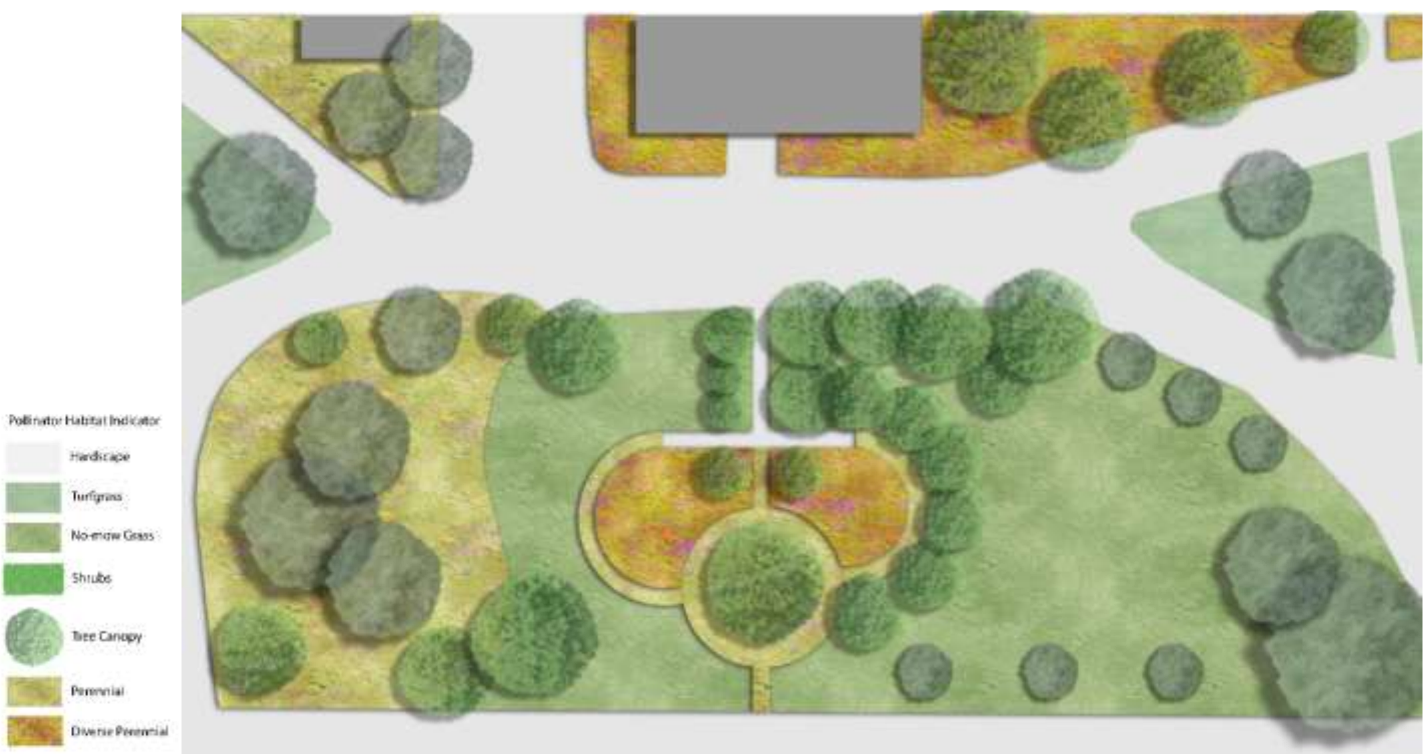


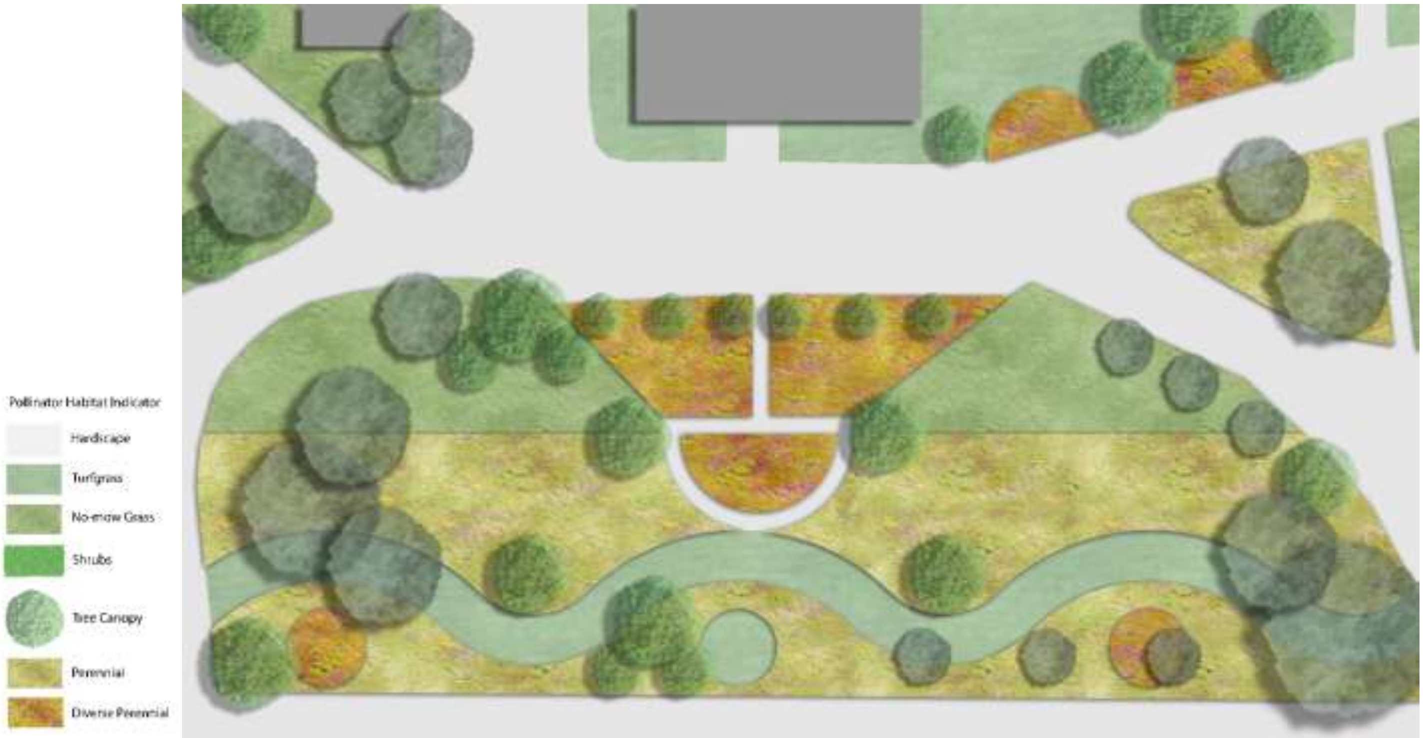
Site 1: Rendered landscape design variations for PHI-AI model planning

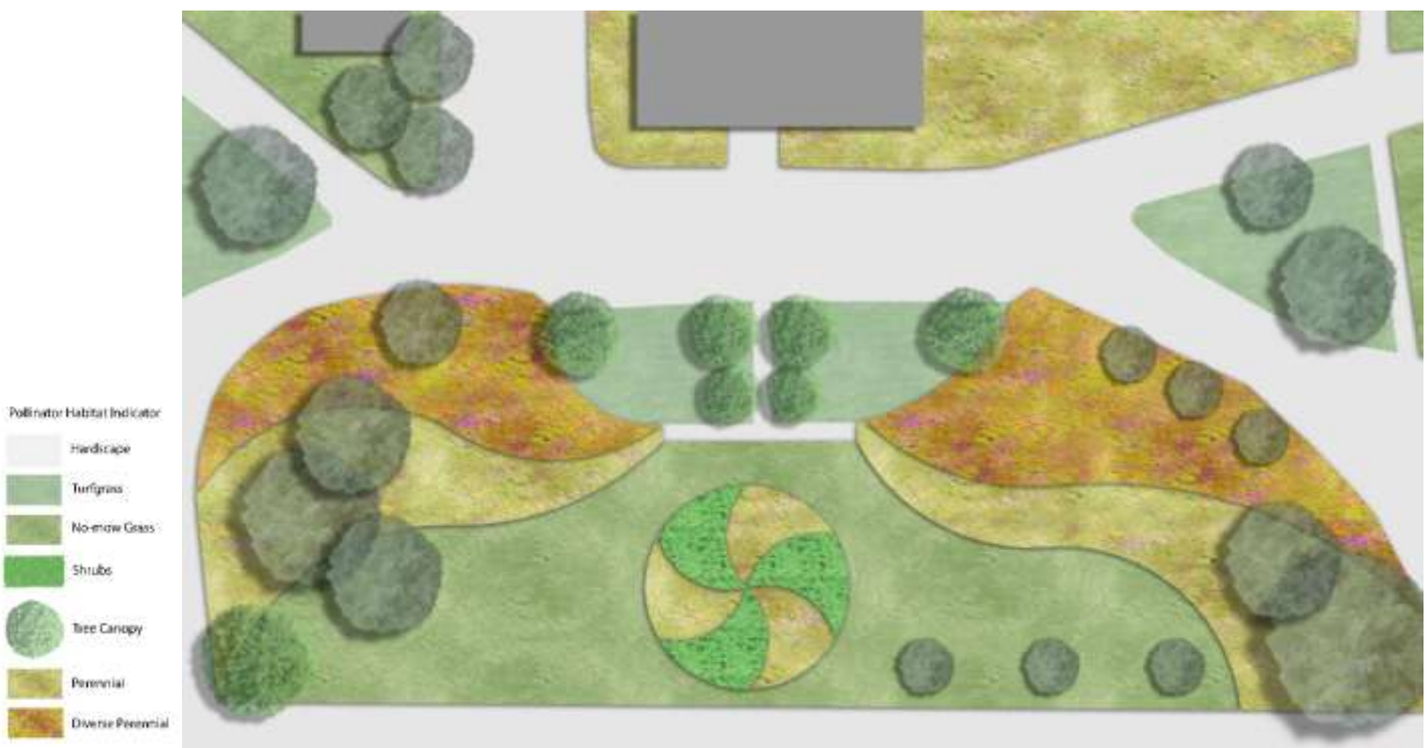

Pollinator Habitat Indicator
Hardscape
Turfgrass
No-mow Grass
Shrubs
Tree Canopy
Perennial
Diverse Perennial

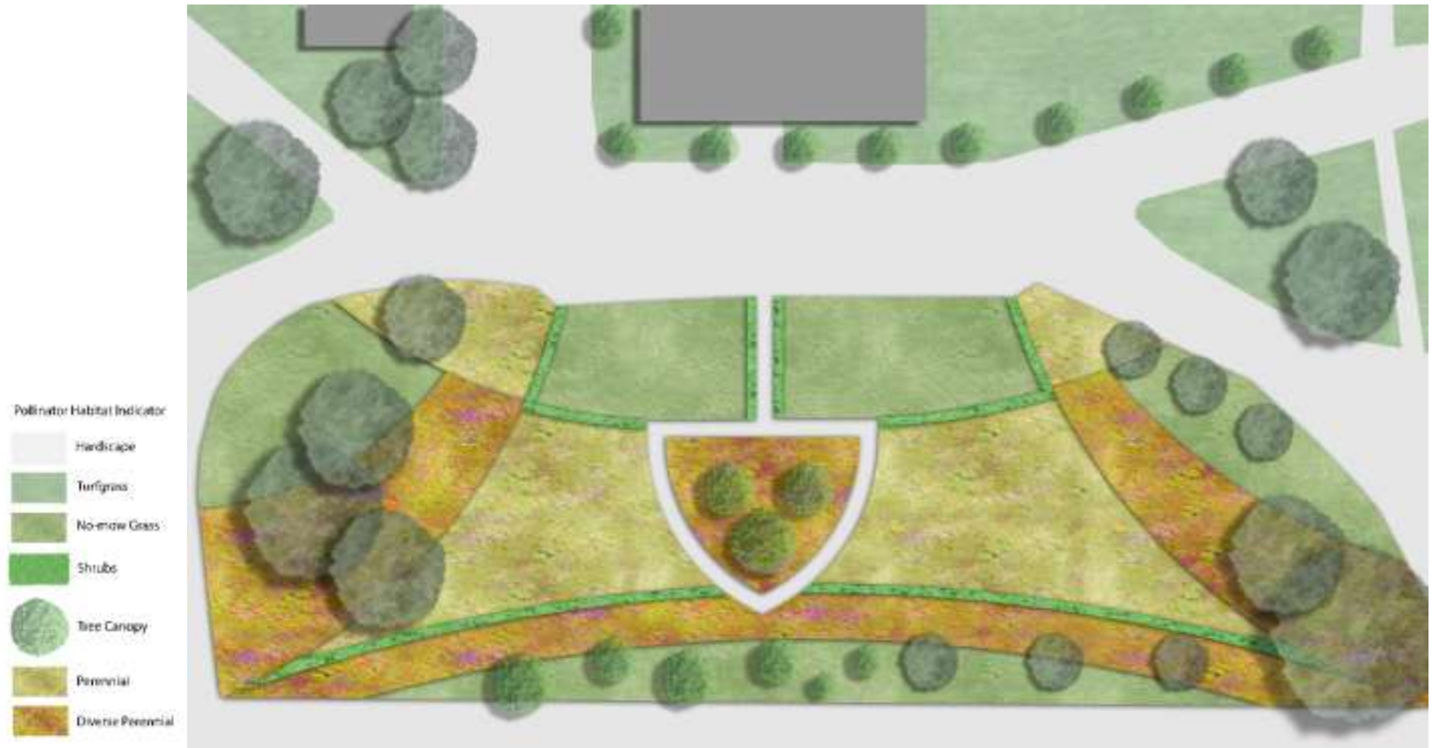

Pollinator Habitat Indicator
Hardscape
Turfgrass
No-mow Grass
Shrubs
Tree Canopy
Perennial
Diverse Perennial


Pollinator Habitat Indicator
Hardscape
Turfgrass
No-mow Grass
Shrubs
Tree Canopy
Perennial
Diverse Perennial

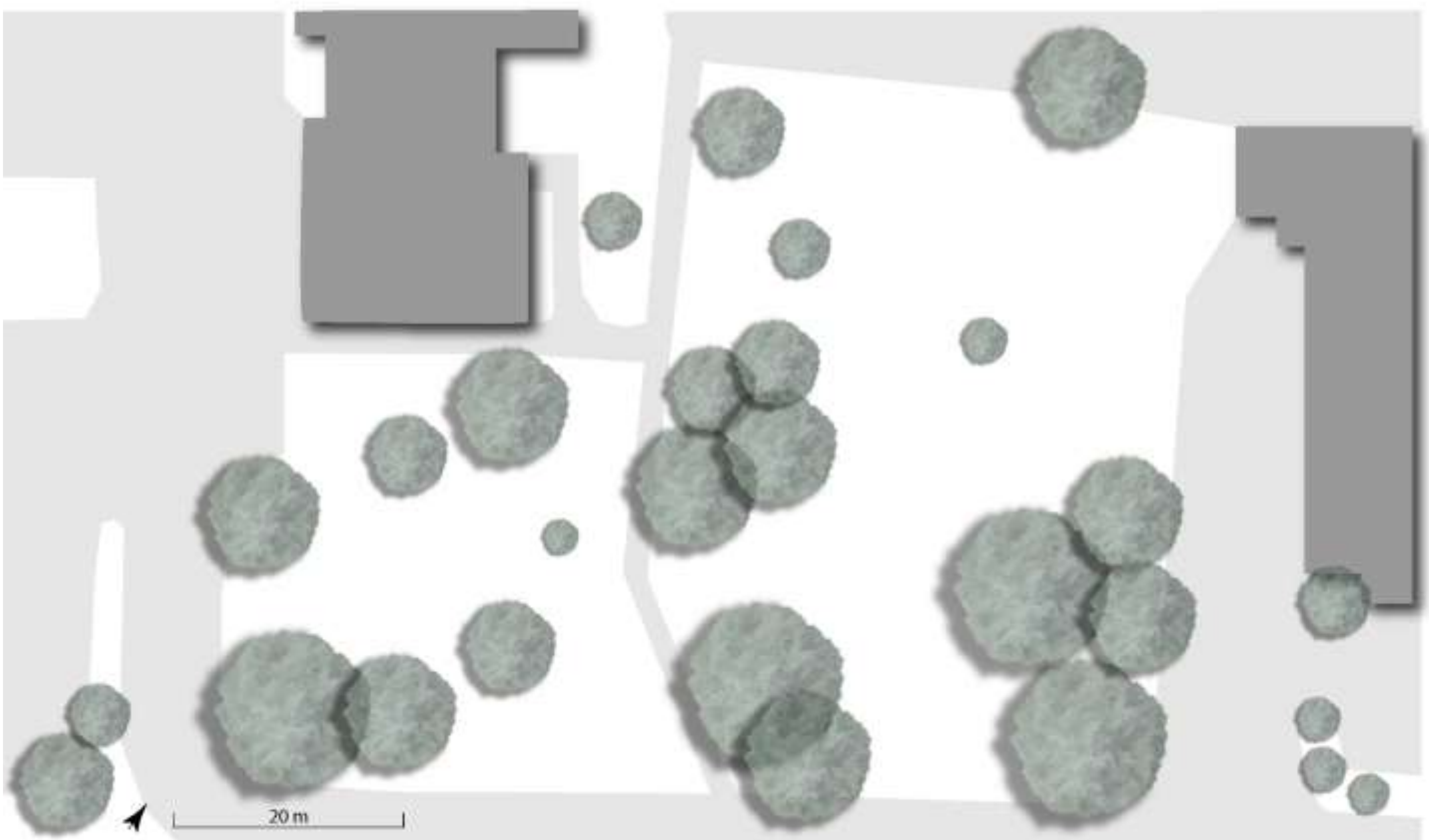

Pollinator Habitat Indicator
Hardscape
Turfgrass
No-mow Grass
Shrubs
Tree Canopy
Perennial
Diverse Perennial


Pollinator Habitat Indicator
Hardscape
Turfgrass
No-mow Grass
Shrubs
Tree Canopy
Perennial
Diverse Perennial

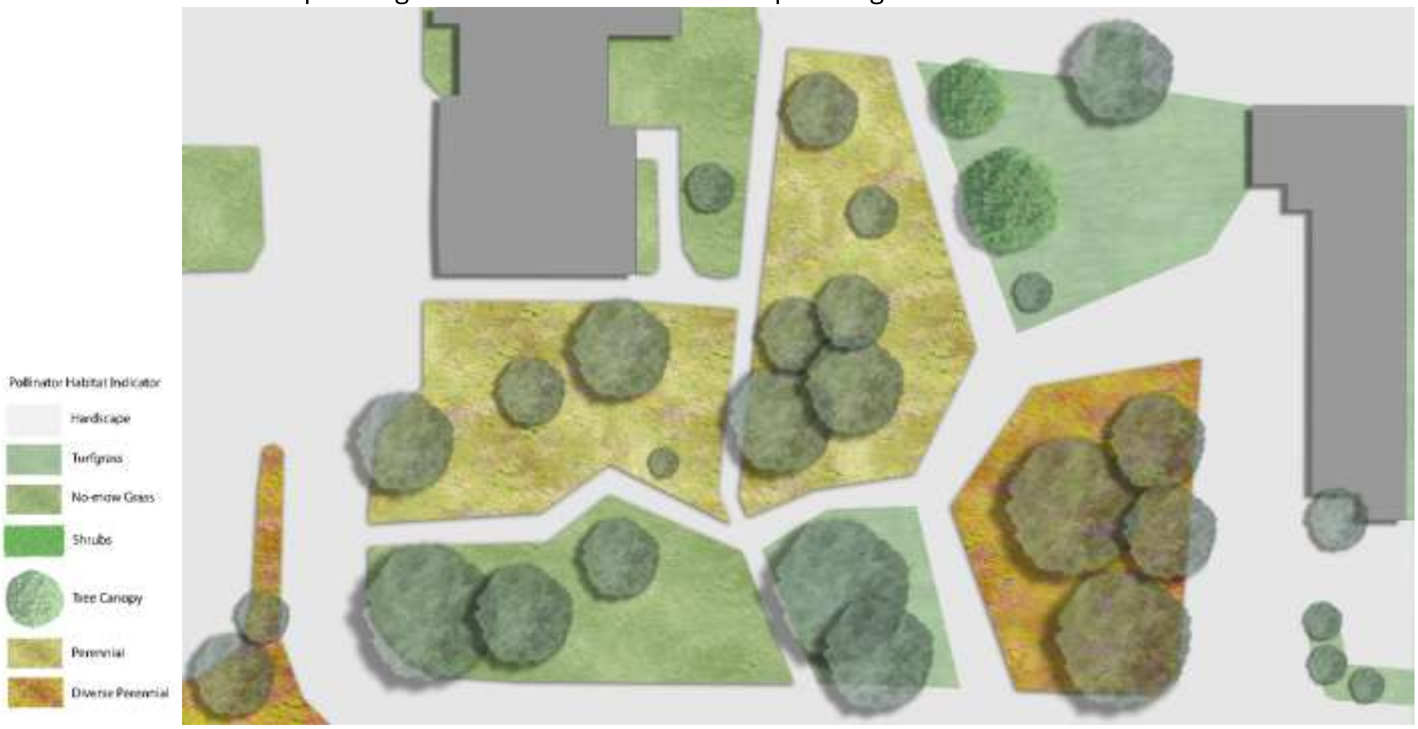

Pollinator Habitat Indicator
Hardscape
Turfgrass
No-mow Grass
Shrubs
Tree Canopy
Perennial
Diverse Perennial

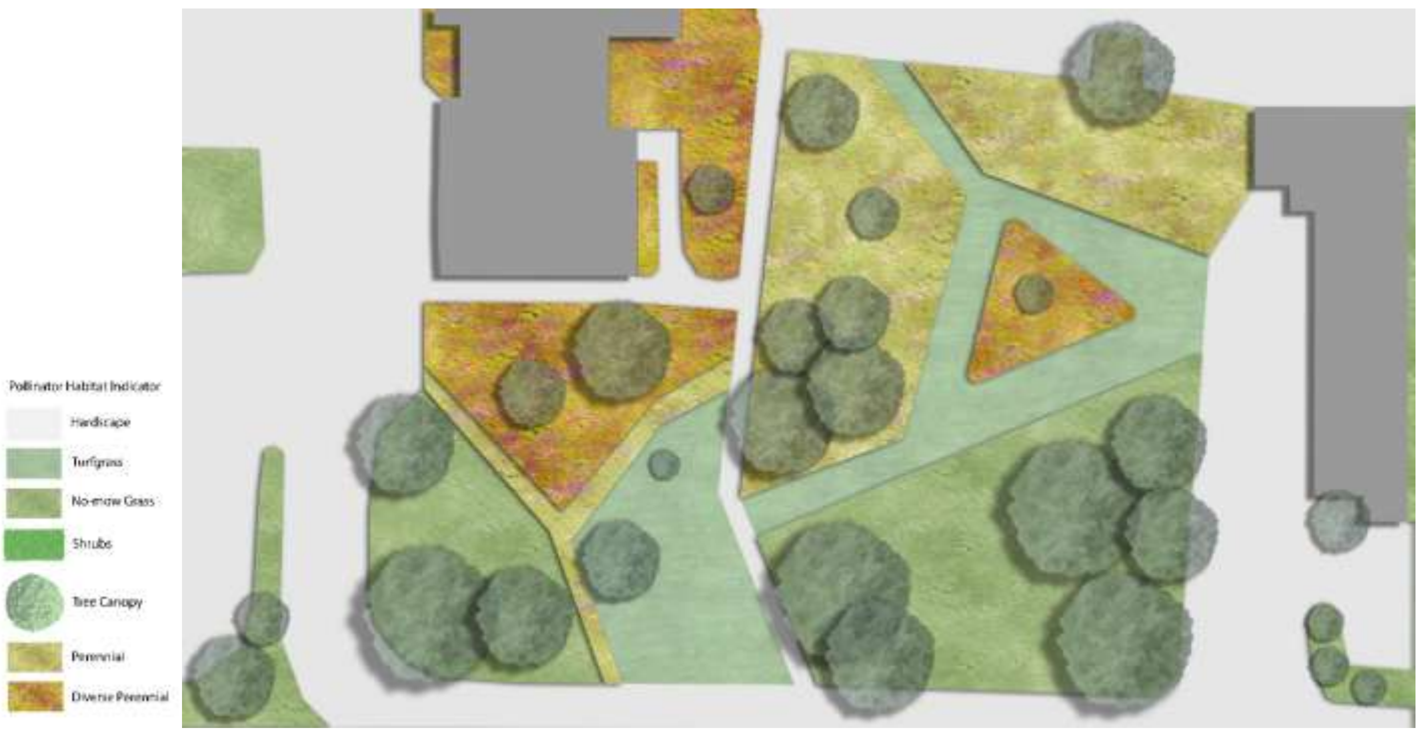


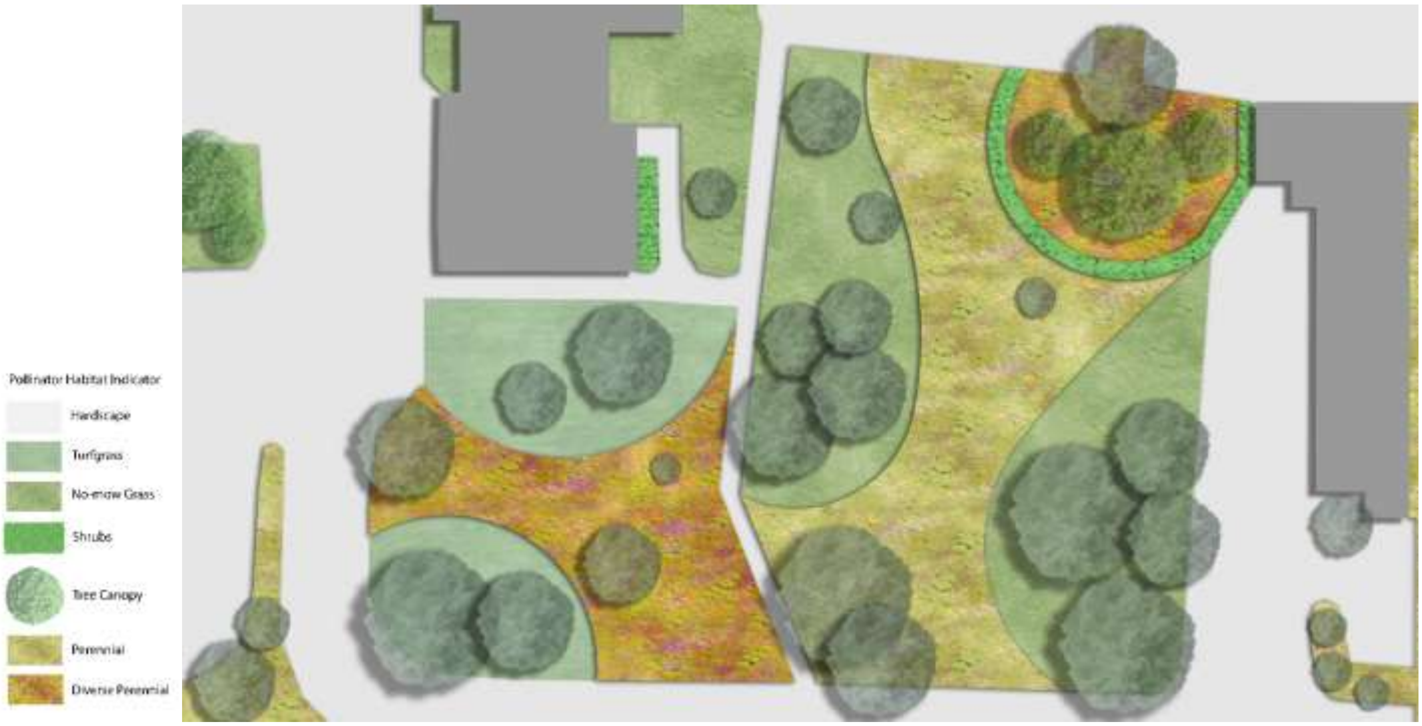
Site 2: Existing Infrastructure and Canopy Cover

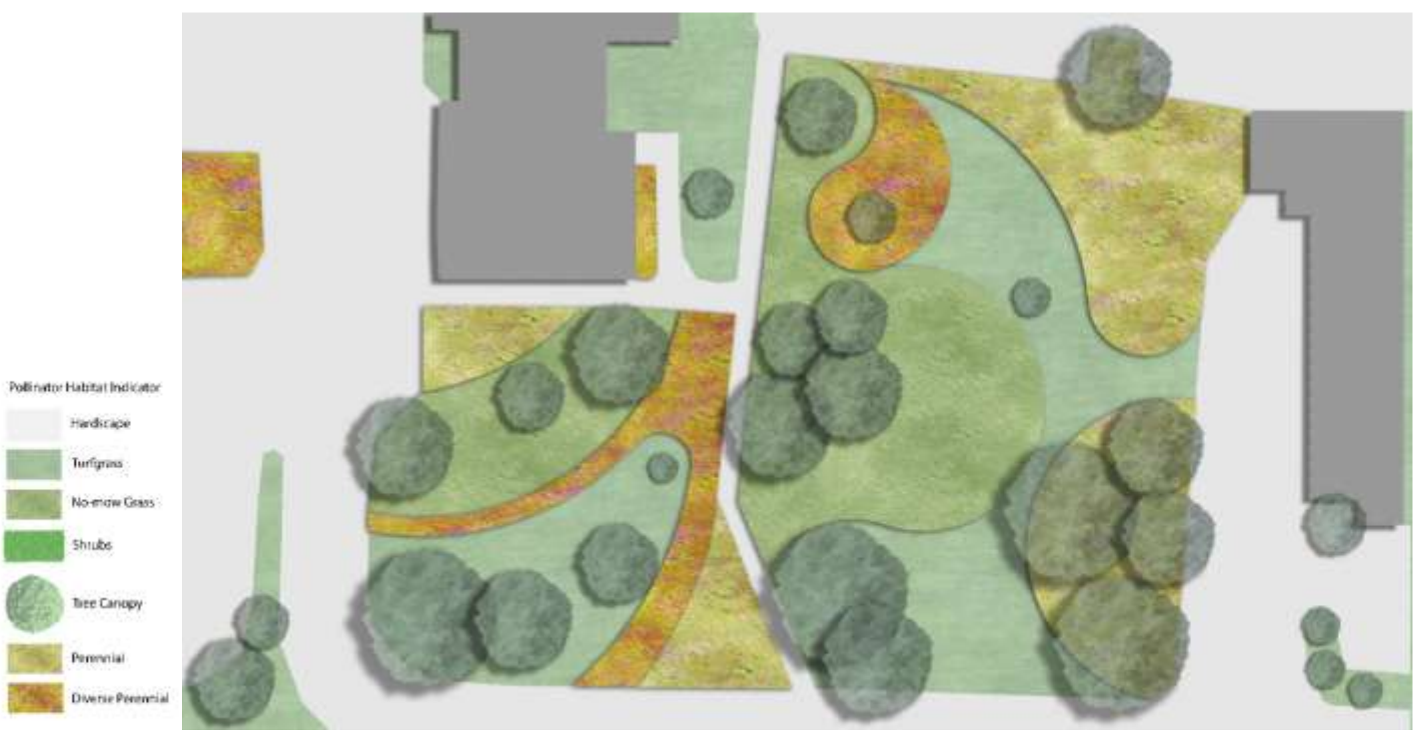


Site 2: Rendered landscape design variations for PHI-AI model planning

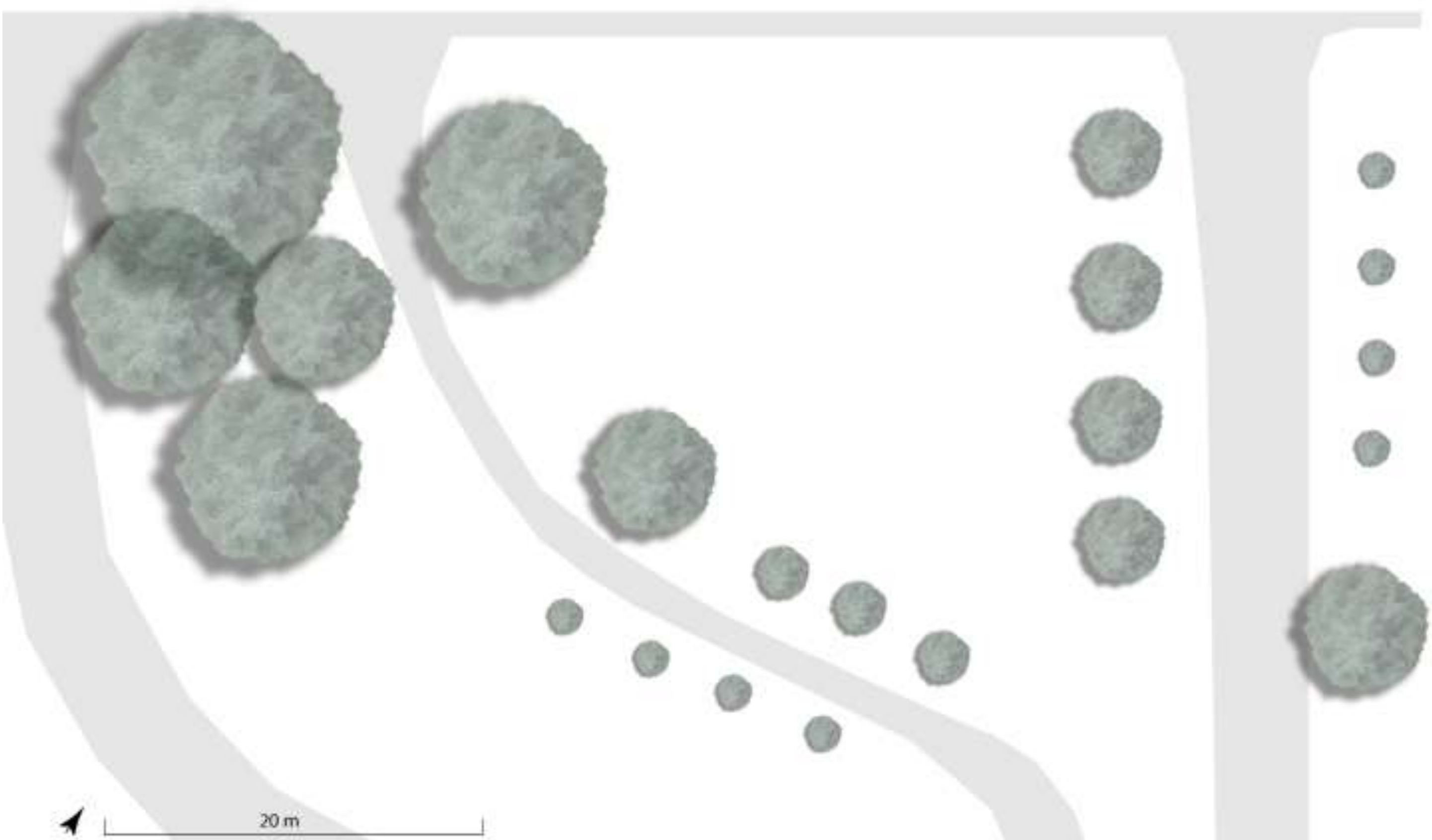




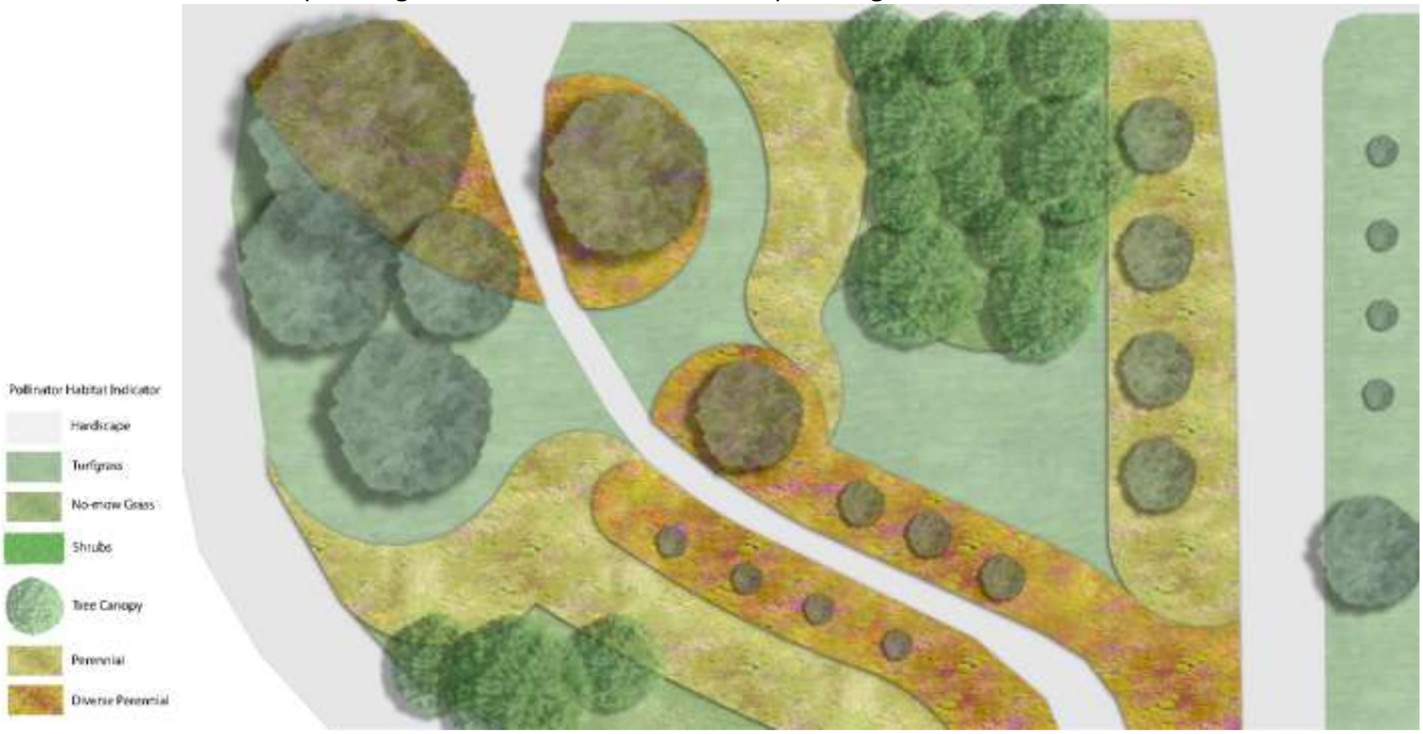

Pollinator Habitat Indicator
Hardscape
Turfgrass
No-mow Grass
Shrubs
Tree Canopy
Perennial
Diverse Perennial

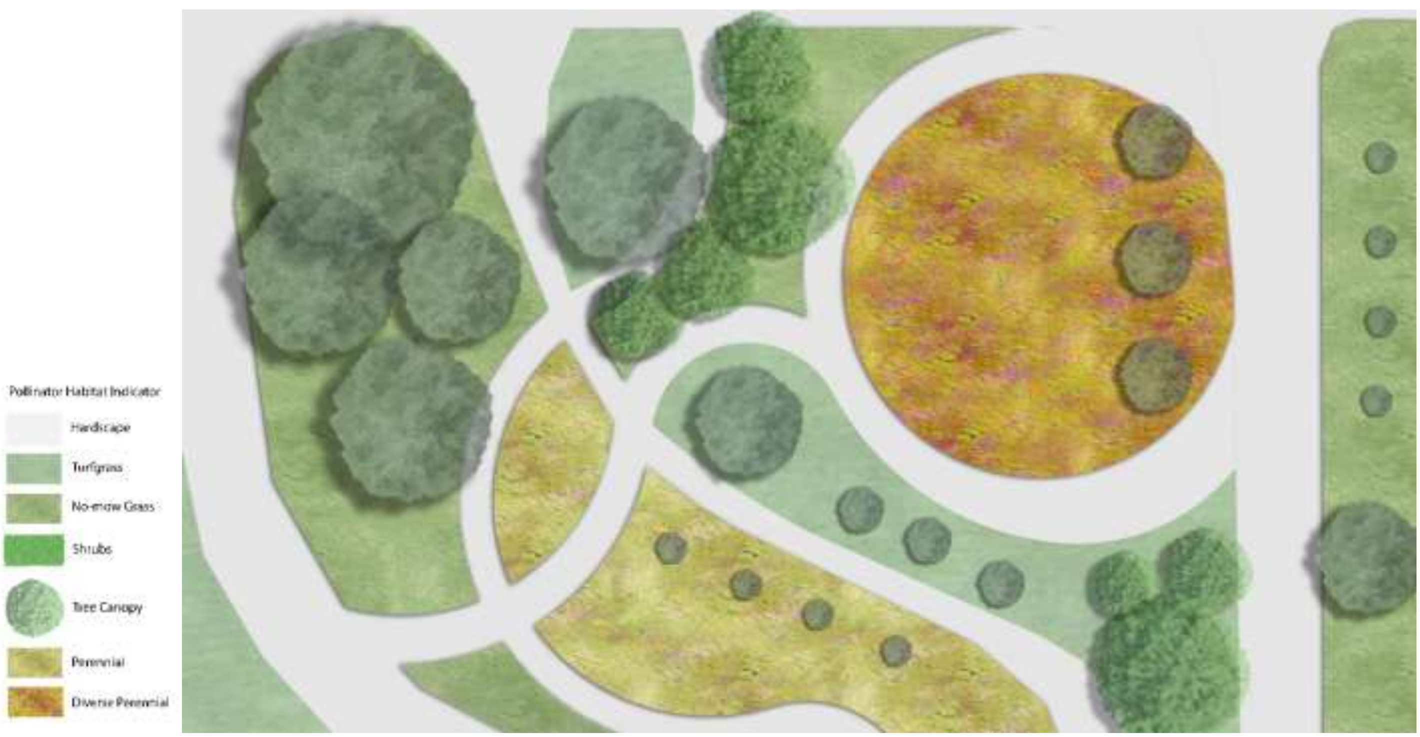

Pollinator Habitat Indicator
Hardscape
Turfgrass
No-mow Grass
Shrubs
Tree Canopy
Perennial
Diverse Perennial

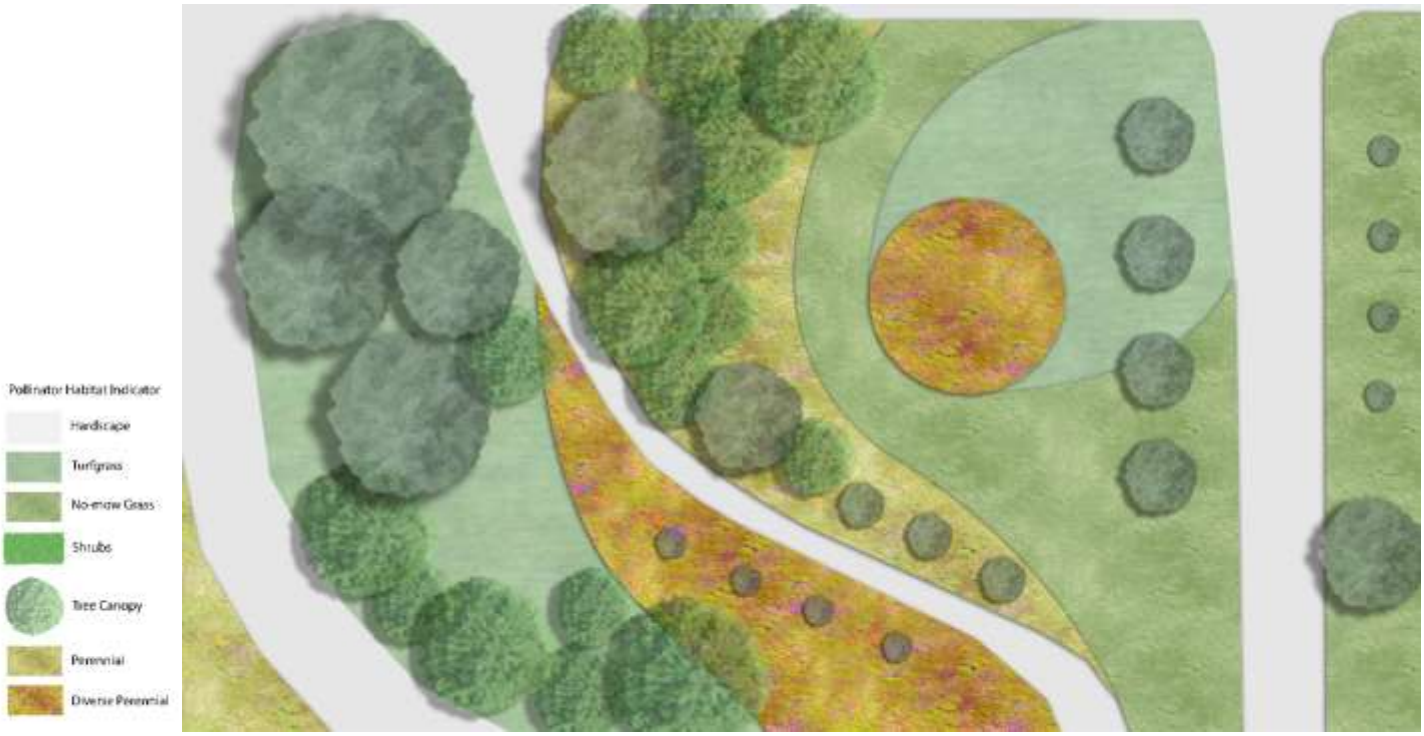
Site 3: Existing Infrastructure and Canopy Cover



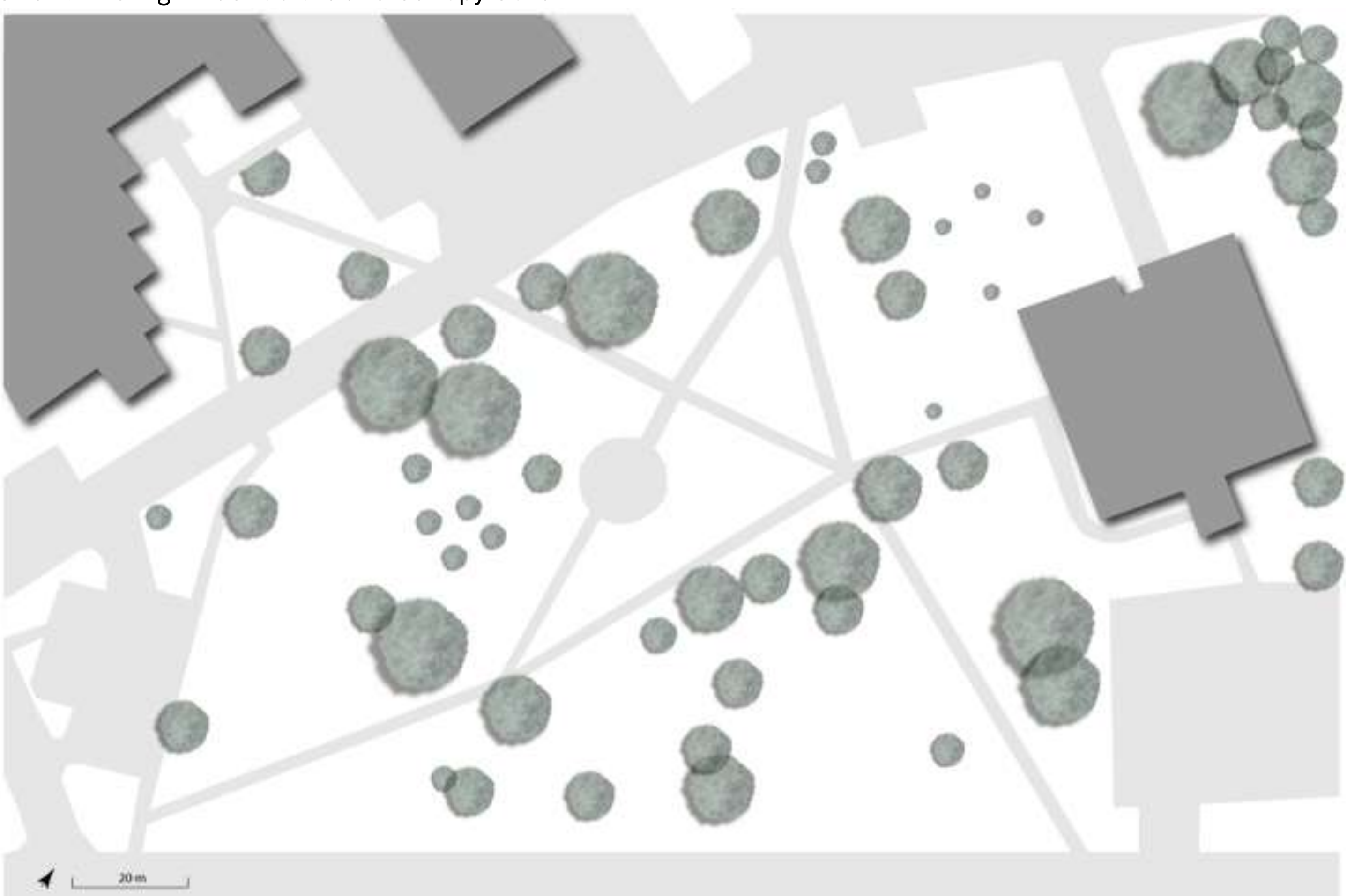
Site 3: Rendered landscape design variations for PHI-AI model planning





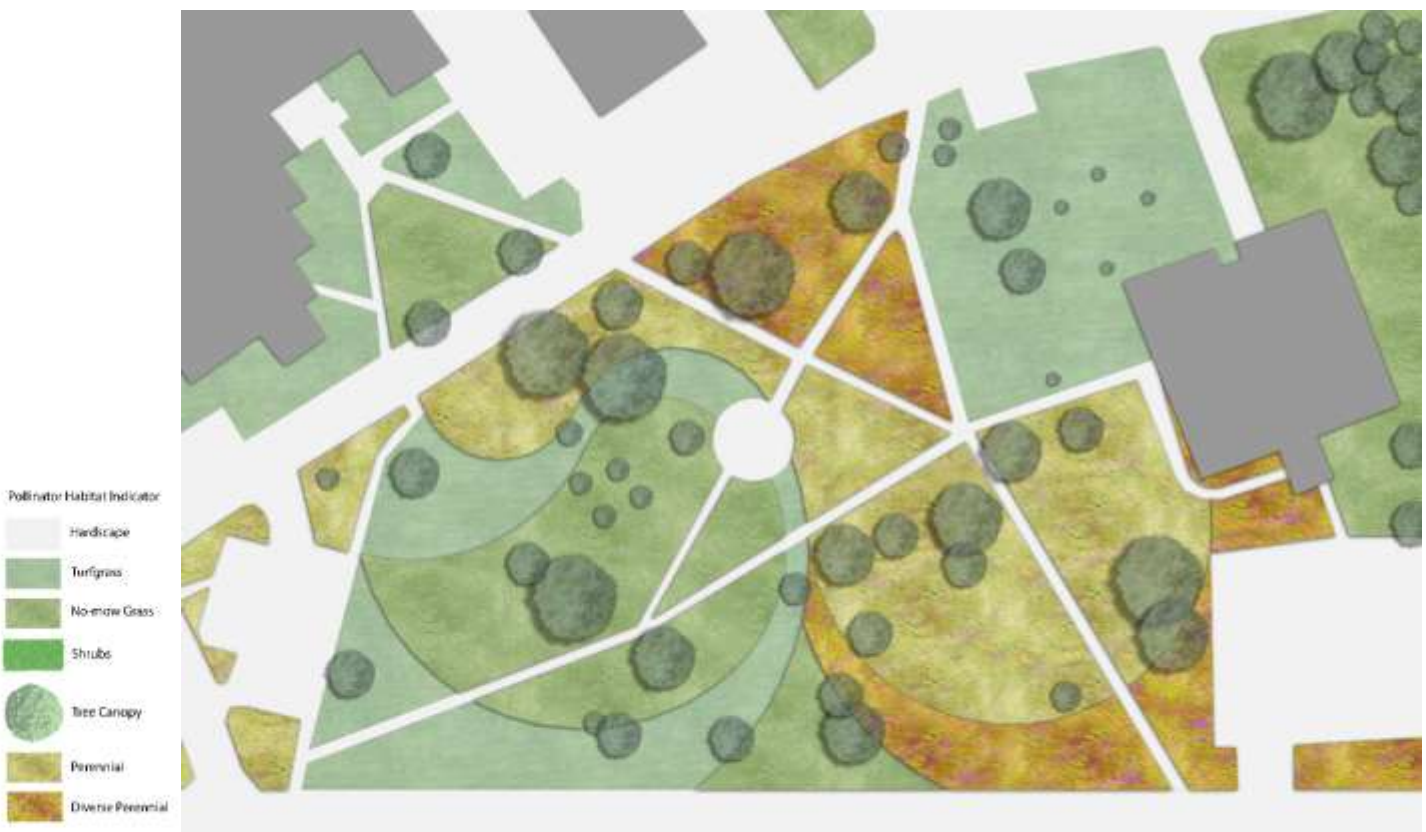


Site 4: Existing Infrastructure and Canopy Cover

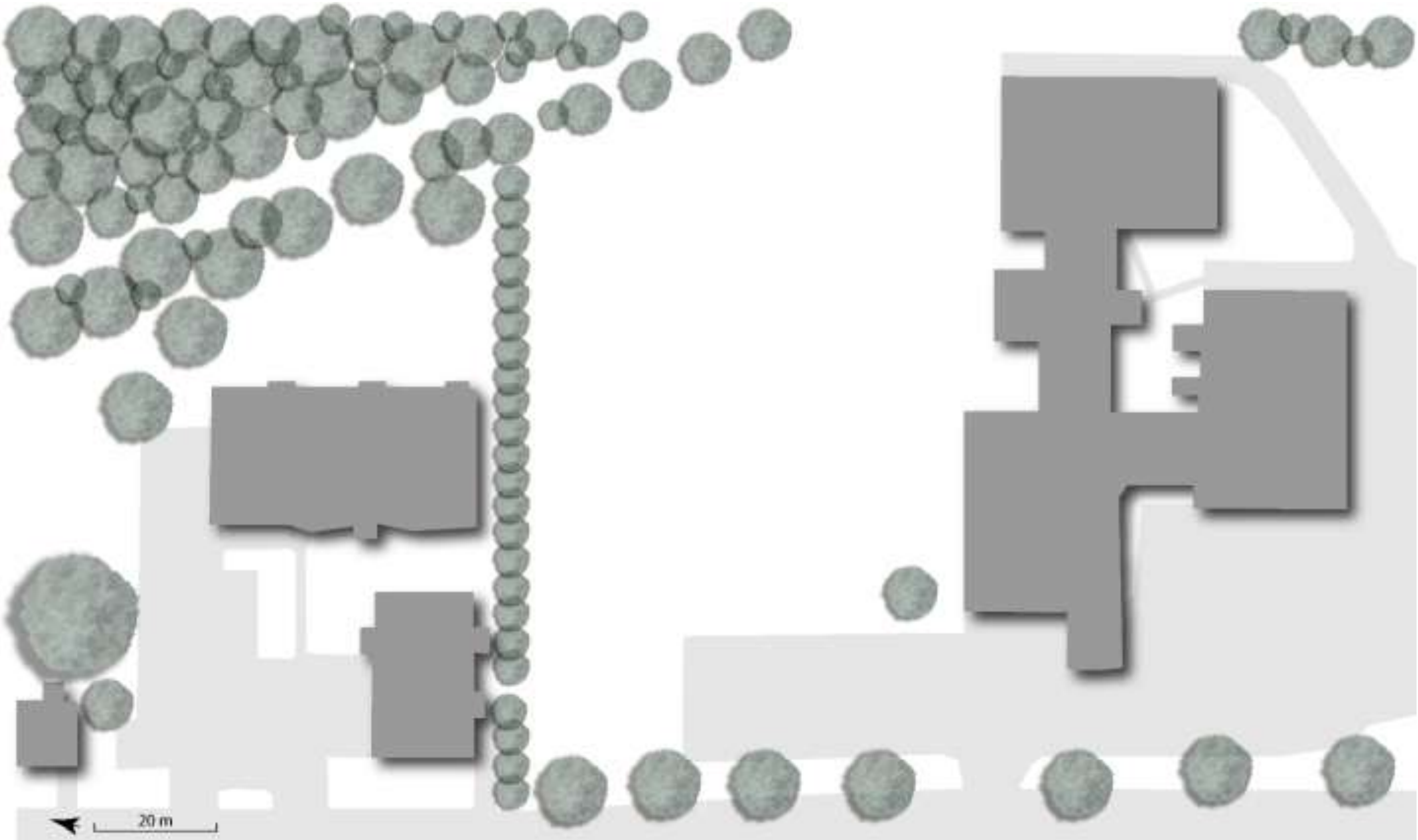


Site 4: Rendered landscape design variations for PHI-AI model planning

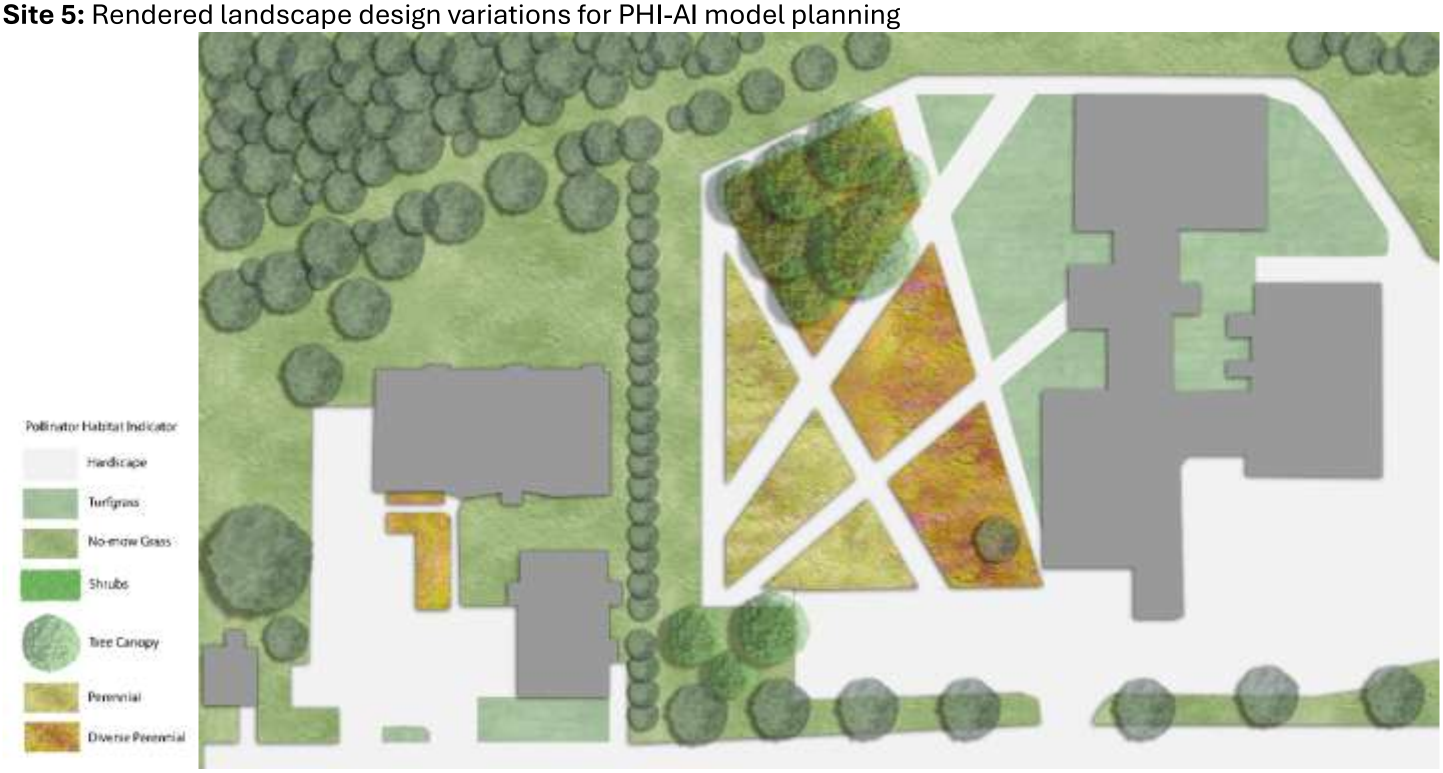

Pollinator Habitat Indicator
Hardscape
Turfgrass
No-mow Grass
Shrubs
Tree Canopy
Perennial
Diverse Perennial


Pollinator Habitat Indicator
Hardscape
Turfgrass
No-mow Grass
Shrubs
Tree Canopy
Perennial
Diverse Perennial

Site 5: Existing Infrastructure and Canopy Cover



Site 5: Rendered landscape design variations for PHI-AI model planning



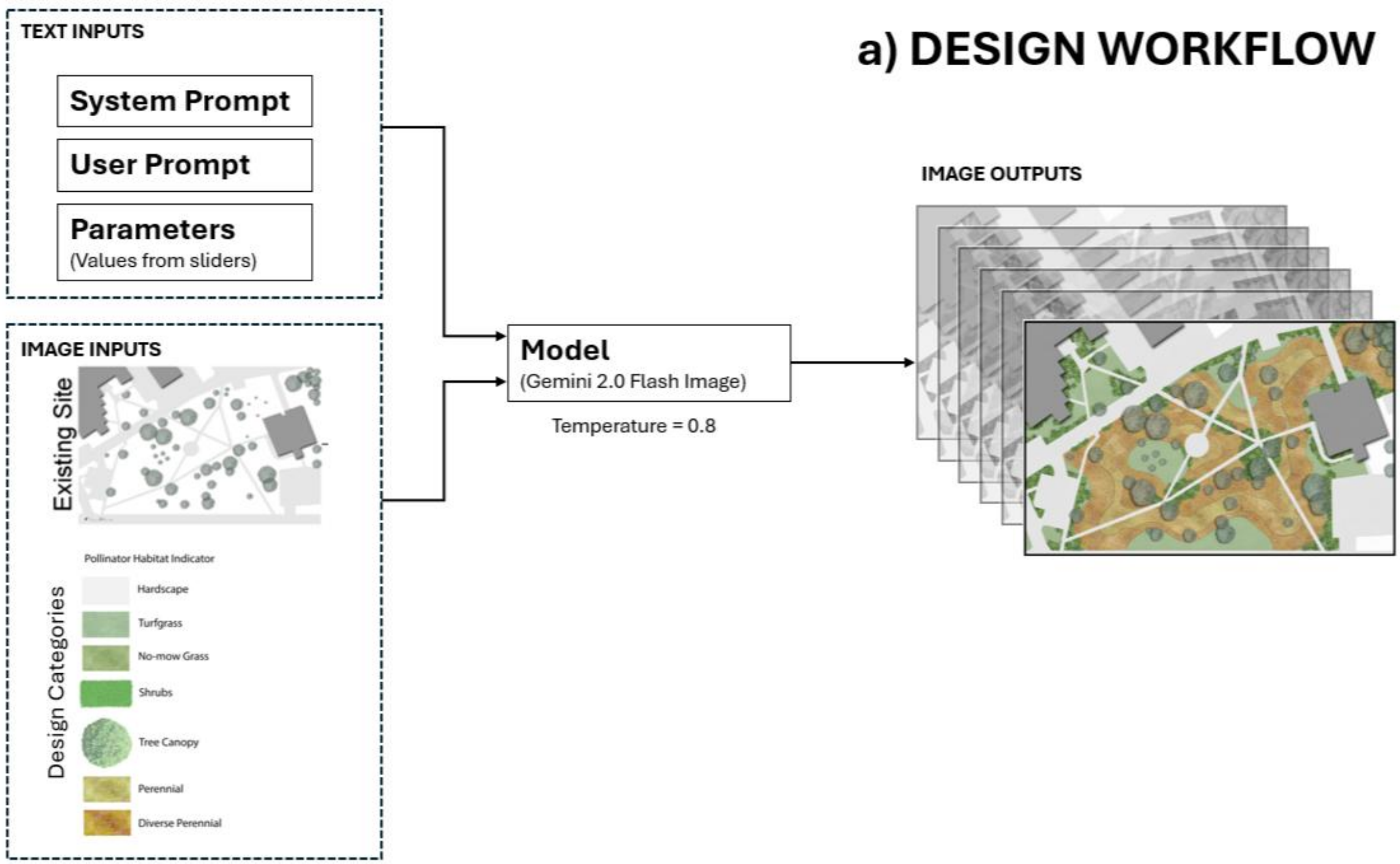

Pollinator Habitat Indicator
Hardscape
Turfgrass
No-mow Grass
Shrubs
Tree Canopy
Perennial
Diverse Perennial


Pollinator Habitat Indicator
Hardscape
Turfgrass
No-mow Grass
Shrubs
Tree Canopy
Perennial
Diverse Perennial

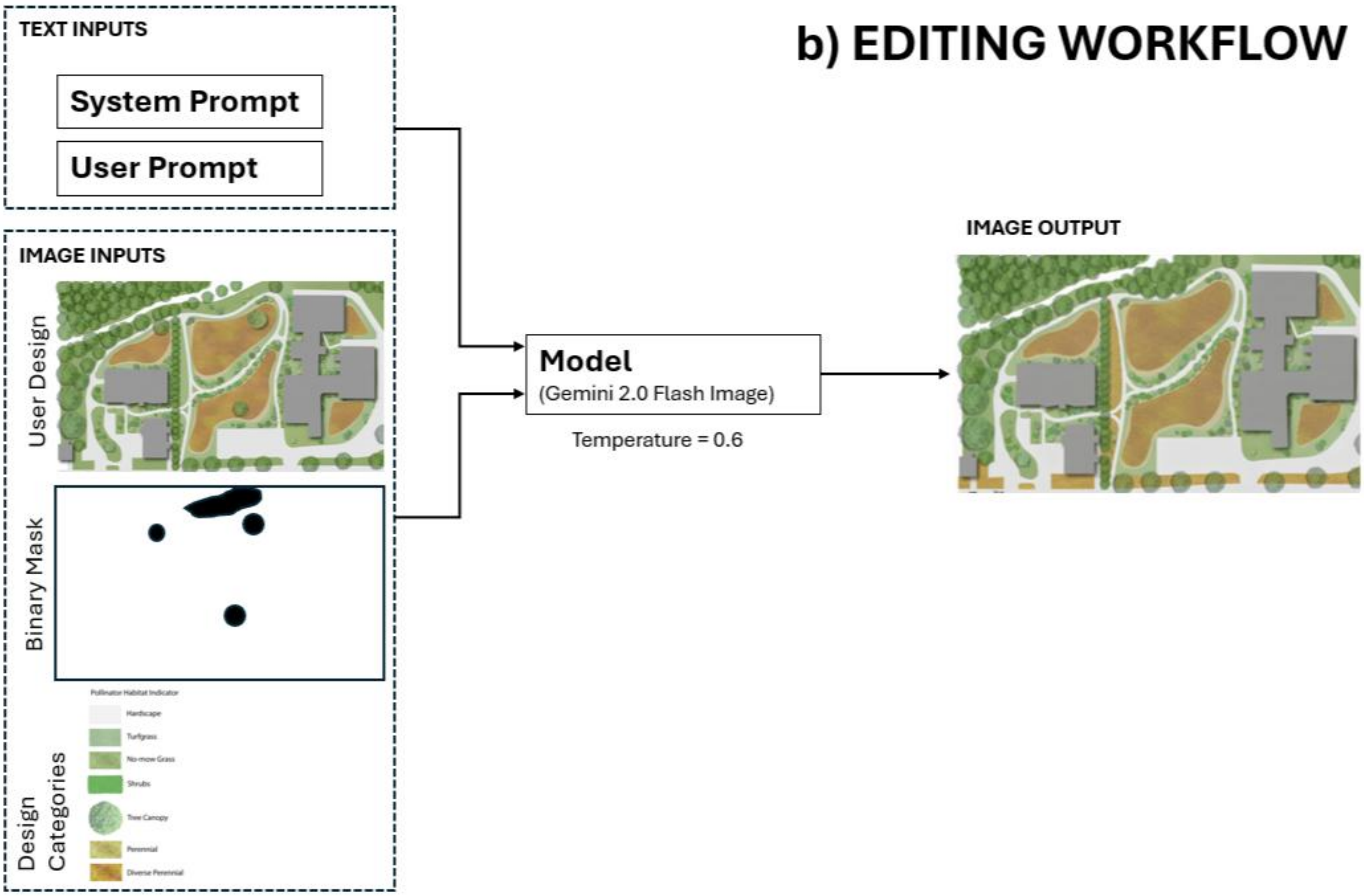

Pollinator Habitat Indicator
Hardscape
Turfgrass
No-mow Grass
Shrubs
Tree Canopy
Perennial
Diverse Perennial

File 2: Model development workflows for design, editing, and PHI calculations

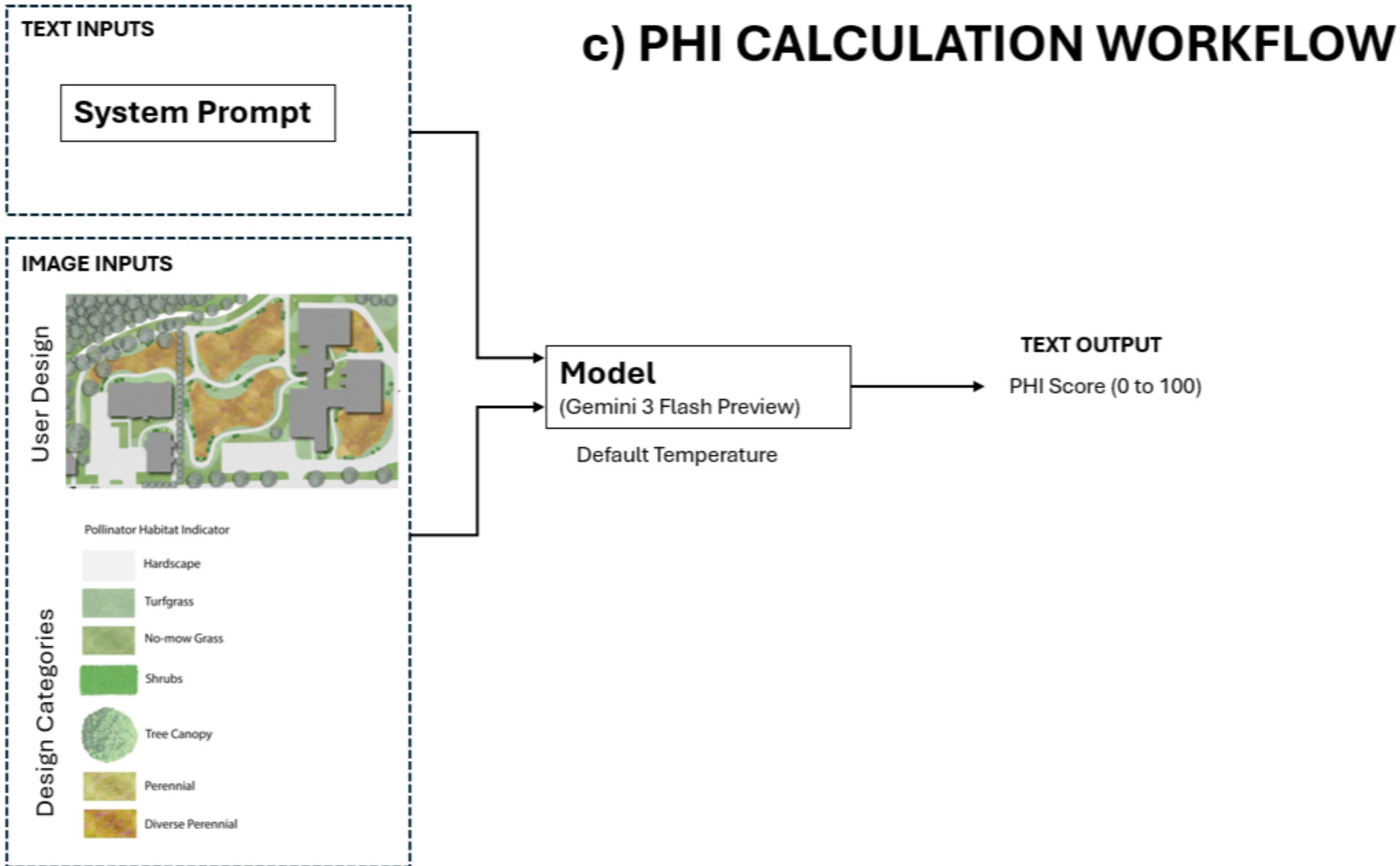
System Prompt: You are a landscape design AI assistant helping to design a site. The first image provided shows the exact patch categories and visual styles you must use. ONLY use these patch styles in your designs: Proposed Hardscape (gray), Grass (lawn) (light green), Grass (no mow) (medium green), Shrub (green texture), Tree (circular green), Perennial (tan/brown), and Perennial (diverse) (colorful). Match the visual appearance of each category exactly as shown. The second image contains the site to be designed. When modifying existing designs, preserve site structure (e.g. existing buildings, existing hardscaping) while applying only these approved patch styles. Create realistic, top-down aerial views that maintain ecological principles and proper patch distributions according to the specified diversity, canopy, and turf parameters. IMPORTANT: Do not include any new text labels in the generated image or leave any white patches.



Editing Prompt: You are assisting a landscape architect in modifying an existing design. The purple areas show the approximate boundaries or regions of the desired changes. When generating an updated image, do not leave any purple lines in the output image. Use your judgement to determine if purple areas and lines should be followed exactly or approximately.



PHI Evaluation Prompt: You are given two images: (1) A legend mapping patch categories to habitat coefficients: Hardscape=0.00, Turfgrass=0.17, No-mow Grass=0.33, Shrubs=0.50, Tree Canopy=0.67, Perennial=0.83, Diverse Perennial=1.00. (2) A landscape design image. Task: Estimate the fraction of total design area covered by each category in (2), using only the categories above. Ignore hardscaping and existing buildings. Use a 10×10 mental grid (100 cells). Assign each cell the dominant category and compute fraction = cells/100. Fractions must be between 0 and 1 and must sum to 1.00 ± 0.02. If uncertain between two categories, split the cell. Compute: weighted = Σ fraction[type] * coefficient[type], score = round(weighted * 100). Output ONLY this JSON (no extra text): { \"fractions\": { ... }, \"weighted_score_0to1\": number, \"score\": integer 0-100 }



File 3: Descriptive Prompt and Generated Greenspace Design Scenarios

1. Descriptive Prompt Used for Deriving Greenspace Scenarios

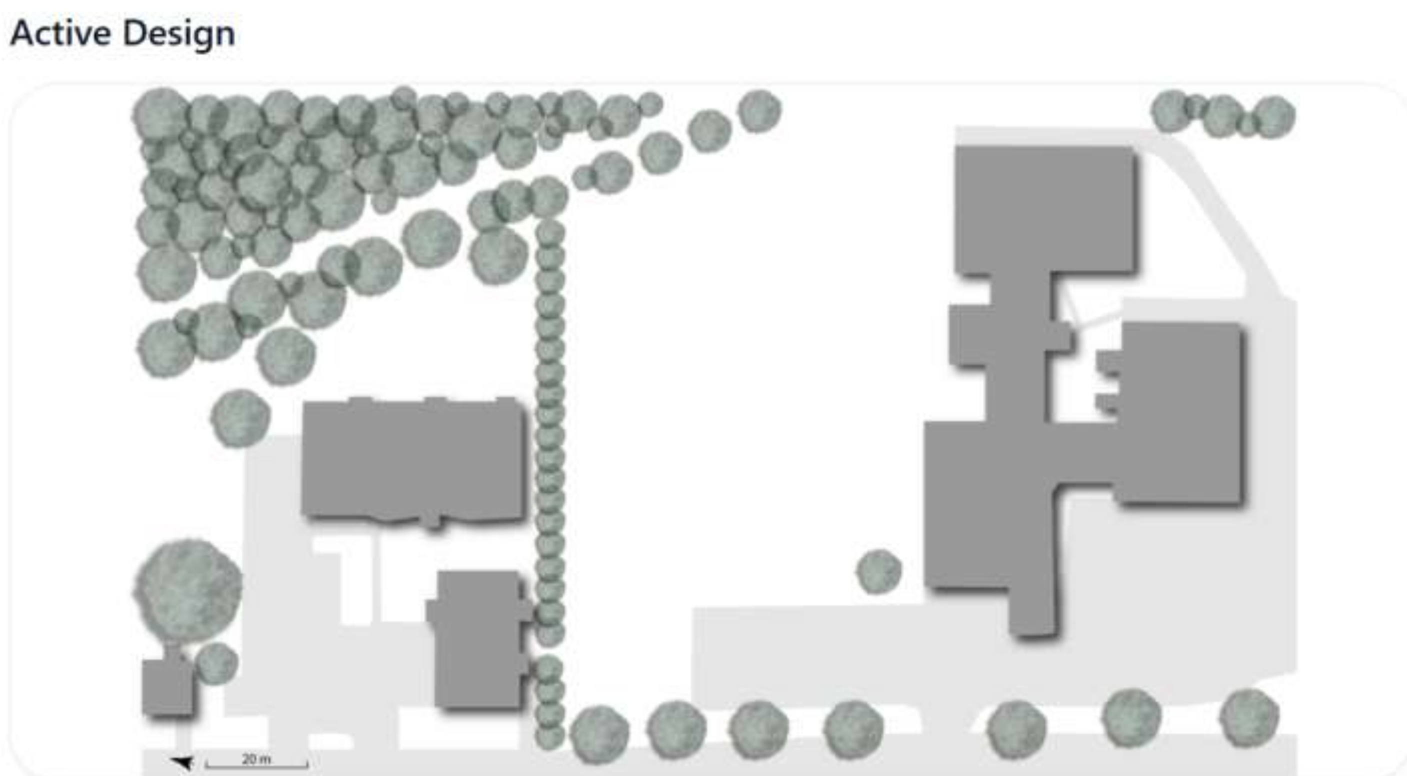
The following prompt was applied in the Design Description window. This prompt was used to generate each scenario in the PHI-AI Landscape Design Tool and sliders were adjusted between each sequence of 5 variations per run.

"*The goal of each greenspace design is to create a landscape that enhances pollinator habitats while keeping the landscape functional for human users. Use the white space to design a series of curved gardens using a mixture of Diverse Perennial plantings. Design curved pathways through the greenspace and include Turfgrass, No-Mow Grass, Shrubs, or Tree Canopy along all the transitional areas between the Perennial plantings. All edges should have broad curves to make a smooth connection of spaces. Emphasize habitat diversity while enhancing connectivity with existing canopy cover in the landscape*."

2. Generated Greenspace Design Scenarios

The following dataset of 25 greenspace design scenarios were derived from a single prompt applied to the existing site drawing. Sliders were adjusted to target variation in patch diversity, tree canopy, and turfgrass coverage. Each scenario was labelled and the authors independently visually evaluated the dataset to select the top 10 designs based on perceived aesthetic preference. Each corresponding PHI score are provided below. However, PHI scores were excluded from the initial visual assessment completed by the authors to focus on general aesthetics.

Existing Site Drawing (Base Image)



Scenario 1 (PHI Score: 21%)

Scenario 2 (PHI Score: 22%)

Scenario 3 (PHI Score: 24%)

Scenario 4 (PHI Score: 25%)

Scenario 5 (PHI Score: 33%)

Scenario 6 (PHI Score: 34%)

Scenario 7 (PHI Score: 36%)

Scenario 8 (PHI Score: 36%)

Scenario 9 (PHI Score: 37%)

Scenario 10 (PHI Score: 39%)

Scenario 11 (PHI Score: 39%)

Scenario 12 (PHI Score: 40%)

Scenario 13 (PHI Score: 40%)

Scenario 14 (PHI Score: 41%)

Scenario 15 (PHI Score: 41%)

Scenario 16 (PHI Score: 42%)

Scenario 17 (PHI Score: 43%)

Scenario 18 (PHI Score: 43%)

Scenario 19 (PHI Score: 43%)

Scenario 20 (PHI Score: 45%)

Scenario 21 (PHI Score: 46%)

Scenario 22 (PHI Score: 47%)

Scenario 23 (PHI Score: 47%)

Scenario 24 (PHI Score: 49%)

Scenario 25 (PHI Score: 49%)