FOLLOWING USER TRACES IN URBAN CONTEXT :
STIGMERGIC APPROACH AND A MACHINE LEARNING IMPLEMENTATION

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HANDAN AKYÜREK

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ABSTRACT

FOLLOWING USER TRACES IN URBAN CONTEXT : STIGMERGIC APPROACH AND A MACHINE LEARNING IMPLEMENTATION

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Designers are responsible for responding to the user's needs and expectations regarding the design output. Hence, the design feedback mechanism between the user and the designer is crucial to avoid any mismatch between the designer's decisions and the user's needs.

On the other hand, displaying the user's engagement with the design output provides a reliable communication ground for both designer and the user. Integrating state-of-art visualization mediums with the recent participatory design methods creates highly sophisticated communication platforms where the users experience the design ideas more immersively, which gives potential data regarding their engagement with the design ideas. However, these data are not authentic enough because they are retrieved from the user's engagement with the representation of the design outcome, not the real one.

In this context, this thesis focuses on the user's physical traces during the post-occupancy phase as the representation of their engagement with the design output. It formulates a feedback mechanism to understand, learn and provide from the user's preferences to enhance future projects.

Desired paths in urban contexts were selected to examine the user's physical traces to represent the user's preferences regarding the designer's design decisions. A stigmergic approach was created to investigate their self-emerging and spatiotemporal characteristics.

Finally, the desired paths were represented as environmentally mediated signs and formalized as a design feedback mechanism to utilize a machine learning algorithm to create a prediction tool in the urban design context.

Keywords: User experience, design feedback, desired paths, stigmergy, machine learning

ÖZ

KENTSEL BAĞLAMDA KULLANICI İZLERİ : STİMERJİK YAKLAŞIM VE MAKİNE ÖĞRENME UYGULAMASI

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Tasarımcılar, tasarım çıktısı ile ilgili olarak kullanıcının ihtiyaç ve beklentilerine cevap vermekle yükümlüdür. Bu nedenle, kullanıcı ve tasarımcı arasındaki tasarım geri bildirim mekanizması, tasarımcının kararları ile kullanıcının ihtiyaçları arasında herhangi bir uyumsuzluğu önlemek için çok önemlidir.

Öte yandan, kullanıcının tasarım çıktısı ile etkileşimini göstermek, hem tasarımcı hem de kullanıcı için güvenilir bir iletişim zemini sağlar. Son teknoloji ürünü görselleştirme ortamlarını en son katılımcı tasarım yöntemleriyle entegre etmek, kullanıcıların tasarım fikirlerini daha sürükleyici bir şekilde deneyimledikleri, tasarım fikirleriyle etkileşimlerine ilişkin potansiyel veriler sağlayan oldukça gelişmiş iletişim platformları yaratır. Ancak, bu veriler yeterince özgün değildir çünkü bunlar, kullanıcının gerçek çıktının değil, tasarım sonucunun temsiliyle etkileşiminden elde edilir.

Bu bağlamda, bu tez, tasarım çıktısı ile etkileşimlerinin bir temsili olarak, kullanım sonrası aşamada kullanıcının fiziksel izlerine odaklanmaktadır. Gelecekteki projeleri geliştirmek için kullanıcının tercihlerini anlamak, öğrenmek ve sağlamak için bir geri bildirim mekanizması formüle eder.

Kullanıcının tasarımcının tasarım kararlarına ilişkin tercihlerini temsil edecek fiziksel izlerini incelemek için kentsel bağlamlarda istenen yollar seçildi. Kendi kendine ortaya çıkan ve uzay-zamansal özelliklerini araştırmak için stigmerjik bir yaklaşım yaratıldı.

Son olarak, istenen yollar, çevresel olarak aracılık edilen işaretler olarak temsil edildi ve kentsel tasarım bağlamında bir tahmin aracı oluşturmak için bir makine öğrenimi algoritması kullanmak üzere bir tasarım geri bildirim mekanizması olarak resmileştirildi.

Anahtar Kelimeler: Kullanıcı deneyimi, tasarım geribildirimi, desired paths, stigmerji, makina öğrenmesi

To my family and my friends

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I would like to thank my supervisor Prof. Dr. Arzu Gönenç Sorguç, for her support and guidance, which encouraged me at every step of my thesis study.

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LIST OF ABBREVIATIONS

Co-design: Collaborative Design

ABM: Agent-Based Modelling

IVE: Virtual Environments

VR: Virtual Reality

AEC: Architecture, Engineering, and Construction

ABM: Agent-Based Modeling

MAS: Multi-Agent Simulations

GEP: Google Earth Pro

ML: Machine Learning

CNN: Convolutional Neural Networks

FCN: Fully Convolutional Networks

CHAPTER 1

INTRODUCTION

Frazer (1995) highlights *'the perfection and variety of natural forms'* as a result of endless experimentation of evolution and defines this mechanism by the term '*profligate prototyping*,' which identifies the natural forms as a *prototype* rather than an end product (pg. 6). The prototype refers to the up-to-date form, which corresponds to the current balance with its environment. When the circumstances change, the previous prototype evolves into another one, and so on, because the creatures in nature must maintain a balance with their environment to survive. People also need to live in a balance with their artificial settlements. Hence, they design, build, and use the forms. However, these forms as the design outputs are far from the concept of the *prototype* in nature. The traditional design and building methods focus on the end product, which doesn't allow many alterations when any unsatisfaction occurs, such as a mismatch between the designer's decision and the user's needs.

In nature, the designers, the users, and the builders generally refer to the same entity, which makes it easier for them to organize to respond to the requirements of the adaptation. People are also the entities who design, build and use the forms in their world. Historically, the users were the designers and the builders of their dwellers. However, the act of design was professionalized because of the complex need of the modern world. The designer and the user were separated into different actors. As a result, the strong tie between the individuals and the shape of their environment eventually weakened (Sani et al., 2011). Hence, the communication between the designer and the users became crucial to achieving the users' satisfaction with the design output.

Traditionally, the users verbally communicate with the designers about their needs and expectations, and the designers represent their design ideas to the users with drawings and scaled models. These conventional communication mediums don't allow the users to experience the design ideas immersively, raising the question of whether the users comprehend the design suggestions sufficiently. From the designer's perspective, the feedback from the user, whose understanding of the design ideas seems questionable, is unreliable. As a result, these traditional methods are limited to creating a communication ground in which the actors can understand each other sufficiently. Hence, alternative design methods were developed to better focus on the user's needs and even being the user part of the design process, such as collaborative design methods (co-design).

The utilization of recent technologies such as Occupant Behavior Simulations, Agent-Based Modelling (ABM), Immersive Virtual Environments (IVE), Digital Twins, and Serious Games in co-design methods have promising results. Such mediums provide more immersive and dynamic environments for comprehending the design suggestions to the users, who can deliver more sophisticated feedback to the designer. However, these mediums have several disadvantages in representing the most realistic data regarding the users' engagement with the design output, which will be discussed in the literature review section.

On the other hand, the design ideas are created to respond to specific functions which display the user's activities in the design outputs, such as walking, running, sitting, and many more. As a result of these activities, the users left physical traces in the design output that give clues about how the user engages with the space. This thesis formulates these traces as the most realistic design feedback to inform the designer regarding the possible mismatches between the user's preferences and the designer's decisions in the context of design output (Figure 1.1)

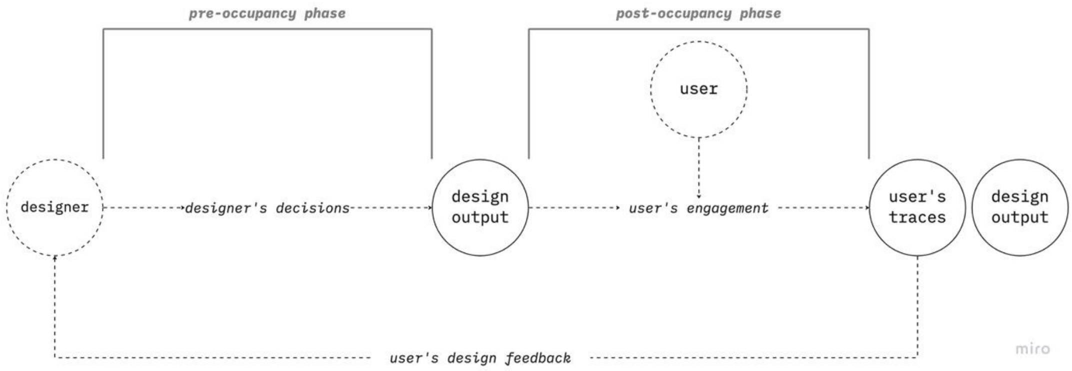


Figure 1.1. Design feedback mechanism between the user and designer that this thesis formulates.

1.1 Problem Statement

Architectural scale makes it challenging to communicate designers with the user through 1 to 1 scale mock-ups. Hence, communication through traditional mediums doesn't give realistic information about the user's engagement with the design output. On the other hand, several co-design methods are used widely to integrate the users into the design process during the pre-occupancy phase. However, such methods are incapable of tracing the real-time user activities in the design output as the realistic design feedback of the user.

The user's engagement with the design output during the post-occupancy phase provides valuable data for the future design project and even the rehabilitation of the determined one. Still, most designers cannot track and document the traces of this engagement because it requires advanced surveillance setups, threatening the occupants' privacy, especially in interior spaces.

Moreover, outdoor spaces give more opportunities to trace and document the user's physical traces, such as desired paths in urban settlements. Figure 1.2 shows a collage representing a desired path as the user's experience toward the designer's suggestion, which was used as inspiration while deciding the type of the design output to investigate the user's physical traces.

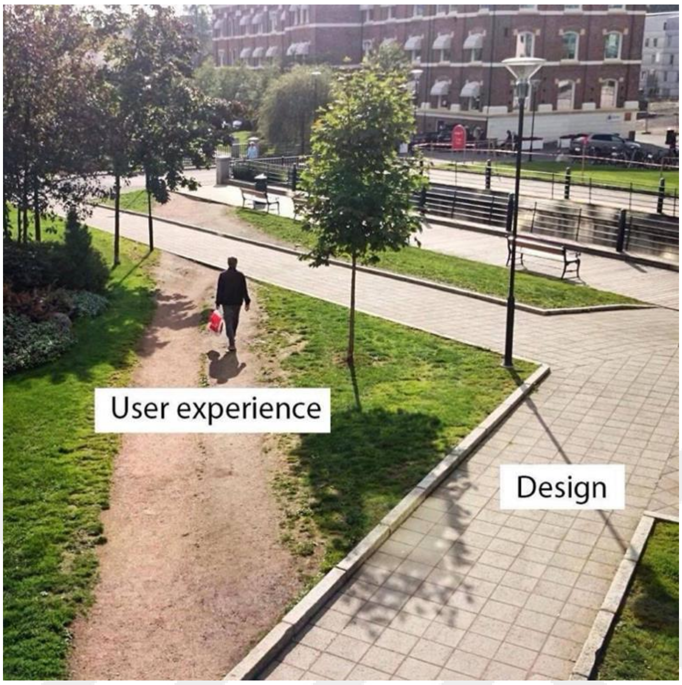


Figure 1.2. The desired path is user experience toward design.

Several studies are focusing on the desired paths in the urban design context. However, their formulation as design feedback is not fully comprehended yet. Also, the literature classifies the desired paths as one of the most primitive forms of stigmergic mechanisms among people (van Dyke Parunak, 2006). Thus, approaching desired paths from the perspective of stigmergy promises a better understanding of the interrelation between the designer, the user, and the design output. Still, there is a research gap regarding desired paths as a stigmergic mechanism in the urban design context. So this thesis focuses on the desired paths as the design feedback mechanism and aims to formulate a stigmergic method to learn and provide from this mechanism.

1.2 Hypothesis

This research hypothesizes that desired path can be considered users' design feedback which the designers can learn from to match better the users' needs and preferences for future projects.

1.3 Research Questions

The research questions were formulated as follows;

-How can the desired paths be traced, documented, and processed as user feedback?

-How can a stigmergic method be formulated to display the actors' roles in the context of desired paths?

-What can the designers learn from desired paths regarding the user's engagement with the design output?

-How can the designers convert the post-occupancy data learned from the desired path into a projection tool as the design input for future projects via machine learning?

CHAPTER 2

LITERATURE REVIEW

This section displays the literature review about co-design, desired paths, stigmergy, and their application in the urban design context. Also, a critical review of the literature will be presented at the end of the chapter.

2.1 Co-Design

Trends in design research move from user-centered design to co-design, which changes the designer's and the user's roles and creates new domains for the collective realm of the design field. The user is formulated as the subject regarding the user-centered design approaches; however, co-design practices consider the user a partner in the design process. Hence, the difference between user-centered and co-design approaches lies in the position they give the user. Today, the products are not designed to respond to the user's needs but to their future experiences, which makes users crucial design partners as the experts of their experiences (Mironcika et al., 2020).

The traditional design disciplines focus on the **designing of** 'products' . . .	. . . while the emerging design disciplines focus on **designing for** a purpose
visual communication design	design for experiencing
interior space design	design for emotion
product design	design for interacting
information design	design for sustainability
architecture	design for serving
planning	design for transforming

Figure 2.1. Emerging Design Practices (Mironcika et al., 2020)

Figure 2.1 highlights the emerging design practices in which their focus transformed from designing a purpose or experience rather than a product.

Co-design emerged around the 1970s in Scandinavia as ‘participatory design. The ‘Collective Resource Approach’ project has been launched to increase industrial production and facilitate a productive workplace while integrating the system experts’ knowledge and the workers’ experience (Bødker, 1996).On the other hand, the concept of participatory design was introduced in the architectural design field during the first international conference of the Design Research Society in 1971.

Luck (2018) divides participatory design history into three stages in the architectural design field. The first stage is the rise of participatory design in the mid-’60s in the US, which takes its roots from the social justice movements at that time. Henry Sanoff pioneered and led in introducing participatory design into architectural education, especially at the Univerisity of California Berkeley and North Carolina State University. This stage is prominent with the importance of the community and society’s involvement in social regeneration projects, which highly influenced social politics. The second stage is the resilient middle years of the participatory design that is responding to the mid-’80s this stage; the changing social-political atmosphere decreased the participatory methods in the design field. However, there were resilient practices. The third phase responds to the beginning of the twenty-first century. The 2008 economic crisis was a crucial stimulus to architects’ thinking about their design practice and its impact on society (Luck, 2018).

Traditionally designers are seen as the only author of the sequential processes called design. However, Lee (2008) defines an in-between place as a realm for collaboration where the users become the participant rather than the object to the design. On the other hand, D’Anjou (2011) refers to three types of the relationship between the designer and the client or user: design paternalism, client autonomy, and collaborative design. Design paternalism refers to the designer’s total control over the process; however, client autonomy refers to the client’s total control over the process. Collaborative design refers to the equal participation of the user and the designer, which creates a collaborative realm for design practice.

The emerging dialogues between design professionals and non-professional people reveal the importance of participatory decision-making (Sanya, 2016), making the design practice a collective creative common for all the participants (Eggertsen Teder, 2019).On the other hand, all people are creative with their way, and they can be valuable participants in the design process if they find participative ways to collaborate (Vaajakallio & Mattelmäki, 2014). Designers should take a role in the co-design process by using their expertise to stimulate the non-experts to be part of the process by creating appropriate tools for them.

2.1.1 Serious Games

Gaming is one of the most natural ways to learn from childhood to adulthood. Paddick (1979) uses Bernard Suits's words to explain the game as 'the voluntary attempt to overcome unnecessary obstacles.' On the other hand, games with more primary purpose than sheer fun are defined as 'serious games.' (Michael & Chen, 2005). Serious games have many applications to co-create with non-expert users.

Gamification of a crowd-driven environment is one of the examples of the integration between serious games and co-design. Synthetic crowd simulations are popular because of their low cost, large scale, and flexible design testing. However, Haworth et al. (2021) state that these simulations strongly depend on fitness criteria. They may ignore or wrongly interpret the valuable solutions. Most importantly, they do not include the designer and the end-user in the design process. Regarding this statement, the authors suggest a gamification approach to design optimization for crowd driven environment to facilitate a collaborative design platform. Their approach changes the traditional roles of the designer and the user. The designer becomes a co-design partner who defines the game environment's rules and constraints. The users compete to find the best design solution according to these rules and constraints instead of an automated crowd optimization simulation.

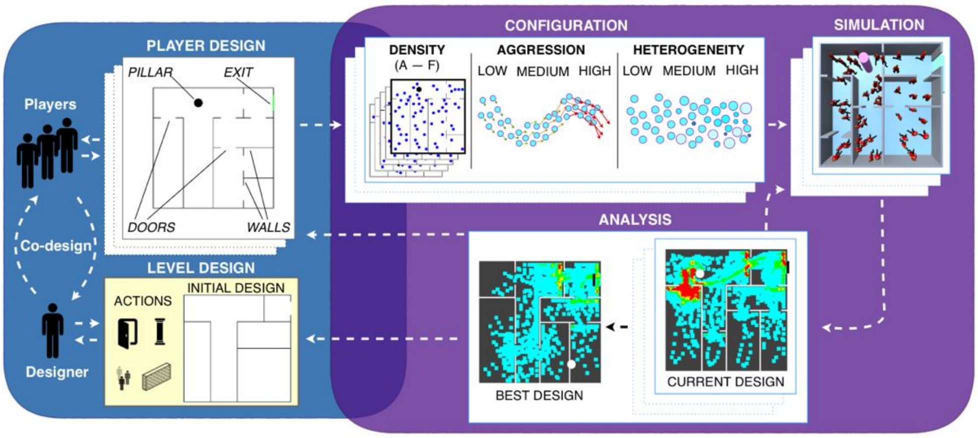


Figure 2.2. Game Design (Haworth et al., 2021)

The game has two options which are single-player mode and multiplayer mode. The multiplayer mode provides a collaborative design environment where users and designers can share their opinions and collaborate to find optimal design solutions. The result of the usability survey test of the game shows that the multi-layer model has been found highly useful even by the non-designer participants.

FakeMuse is a serious game application for archeological museums and archeological artifacts in which the users can take the role of museum curators to ensure the authenticity of artifacts. The game aims to engage the non-experts in archeology and create an entertaining framework to discover and learn about the field. The game's design allows the users to read magazines to learn about the artifact and evaluate them to curate an exhibition in the museum. The survey, applied to gamers, shows the positive effects of the game on non-expert users by increasing their interest in archeology and facilitating an entertaining platform to learn about the field (Zilio et al., 2021).

2.1.2 Digital Twins

Architectural design relies on design tools, which can be digital or physical. The increasing technology provides a wide range of digital tools as design tools, but the physical prototypes' importance and efficiency have been overlooked. Kalantari et al. (2022) suggest a new design tool that merges physical prototyping and digital design technologies 'Ph2D' is a digital twin approach, a hybrid physical and digital toolset for architectural design. The design tool consists of a physical additive scaled model and its digital representation, which simulates the changes and their effects on the digital realm. The scaled physical model helps create design alternatives according to the prototype concept.

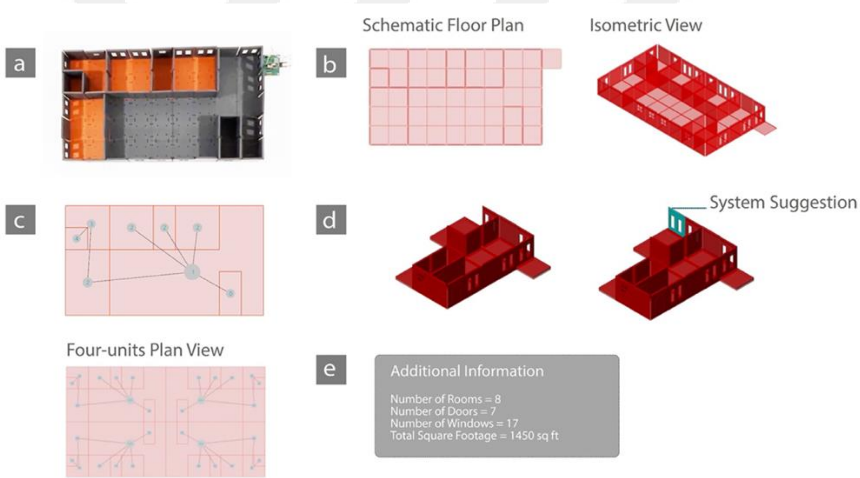


Figure 2.3. Ph2D digital twin model (Kalantari et al., 2022)

On the other hand, the simultaneous digital model calculates the analytical models based on the updates on the physical scaled model, such as energy consumption simulations or connectivity analysis. The digital twins' project provides a participatory platform for non-designer users to understand the effects of the design decision on design space. It provides an efficient communication platform between the designer and the user. Some researchers state that the full-scaled, high-fidelity physical prototypes or hyper-realistic visualizations may not be the proper communication method with the users because these approaches may cause unrealistic expectations in the users. From this perspective, digital twins provide a hands-on, game-like platform for non-designer users to participate more in the design process. The researchers used the Technology Acceptance Model (Davis & Davis, 1989) to evaluate whether the given platform would enhance the user's performance or not to assess the usefulness of the proposed digital twin platform.

	Designer *M (SD)*	Non-Designer *M (SD)*	Total *M (SD)*
Scenario*			
Residential Exploration	3.73 (1.15)	4.07 (0.82)	4.01 (0.89)
Residential Modification	3.65 (1.15)	4.16 (0.76)	4.07 (0.85)
Hospital Exploration	3.75 (1.26)	3.92 (0.86)	3.89 (0.94)
Hospital Modification	3.67 (1.29)	4.05 (0.85)	3.99 (0.93)
Average	3.68 (1.15)	4.05 (0.72)	3.99 (0.81)
TENS-Interface			
Competence	4.03 (0.59)	3.52 (1.01)	3.60 (0.98)
Autonomy	3.28 (0.98)	3.95 (0.67)	3.84 (0.76)
Influences on Physical Prototyping			
Address the Challenges	3.24 (1.23)	3.90 (0.92)	3.80 (1.00)
Increase the Frequency of Use	3.00 (1.26)	3.83 (0.94)	3.71 (1.04)

Figure 2.4. Perceived Usefulness (Kalantari et al., 2022)

The results showed that the platform was rated 3.99 out of 5, which is considered helpful by the participant. On the other hand, the non-designer participant was marked slightly higher than the designer participant. This study shows the potential of the digital twins in co-creation in the design process; however, the researchers state that the platform relies on the modular building system, which makes it unable to create organic forms yet.

2.1.3 Immersive Virtual Environments

There is an increasing interest in the literature about occupant-building interaction, such as how the occupants perceive the building environment. And Immersive

Virtual Environments (IVE) provide a unique opportunity to examine the occupant-building interaction (Alamirah et al., 2022). Figure 2.5 shows IVE's advantages to occupant behavior monitoring and data collecting over more traditional methods such as survey-based and observational studies (Heydarian & Becerik-Gerber, 2017).

	Survey-based Study	Observational Study	Experimental Study	IVE-based experimental Study
Internal validity	Low	Low	Medium to high	High
Ecological validity	Low, medium, high	Medium to high	Medium to high	Medium to high
Time to design	High	High	High	High
Time to conduct studies	Low	High	Medium to high	Medium to high
Cost to design and conduct studies	Low	Low to medium	Medium to high	Low to medium
Possibility of replicating exact experimental environment	Low	Low to medium	Medium to high	High
Experimental control	Low	Low	Medium	High

Figure 2.5. Comparison between the traditional method and IVE (Heydarian & Becerik-Gerber, 2017)

On the other hand, Virtual Reality (VR) technologies are increasingly recognized by the architecture, engineering, and construction industries (AEC) to communicate with the users because these technologies provide immersion to the users in the design process (Kim et al., 2013).

Recent literature reviews with the keywords IVE and AEC have co-occurrence with keywords such as 'user-centered design,' 'design collaboration,' and 'collaborative design,' demonstrating that researchers have increased interest in discovering IVE's potential in collaborative collaboration design (Figure 2.6).

However, IVE provide advantages to occupant behavior monitoring and immerses the user in the design; researchers state several limitations related to IVE-based experiments. One of the limitations is that the participants can immerse in the virtual environment for a short time because using these technologies may cause uncomfortable feelings such as motion sickness, nausea, and eye strain (Heydarian & Becerik-Gerber, 2017).

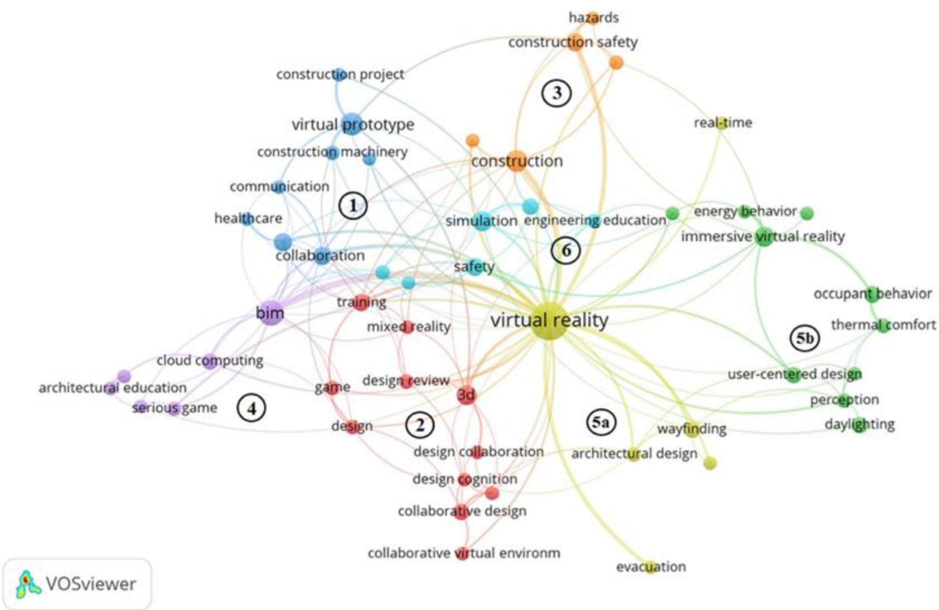


Figure 2.6. IVE keyword co-occurrence (Zhang et al., 2020)

2.1.4 Agent-Based Narratives

Simulation tools are generally used for prediction, visualization, or explanation purposes. And agent-based modelings (ABM) are among the most demanded tools to facilitate a participatory design platform (Edmonds & Meyer, 2017; Vainio, 2016). However, ABM simulations are capable of simulating human behaviors in design space; the researchers highlight several difficulties regarding the validation methods during the simulation (Gilbert, 2005; Macal, 2016). On the other hand, the validation methods supported by surveys or observations are one of the methods, especially in social sciences (Hahn, 2013).

Generating accurate agent rules is another challenge for ABM simulations. Yang et al. (2021) state that the lack of qualitative data describing the environment influences user behavior. Hence, the difficulties in translating user perception regarding the environment are one of the obstacles to generating more realistic ABM simulations.

Yang et al. (2021) present an integrating methodology to overcome this obstacle. The authors suggest using a serious game method to collect qualitative data to feed the ABM and co-design with the neighborhood dwellers to create Transport Infrastructure and Public Space (TIPS) systems in London Hackney Wick. The researchers propose the 'banana' model to explain their methodology. Figure 2.7 represents the conceptual '*banana'* model that integrates co-design, ABM, and serious game as a participatory design methodology for urban design practice.

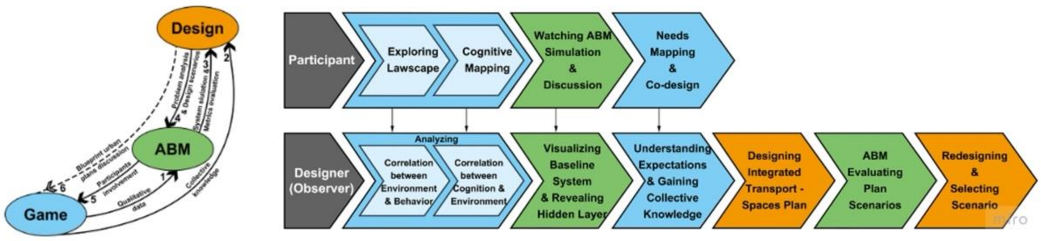


Figure 2.7. The conceptual 'banana' model (Yang et al., 2021)

The researchers use a three-step serious game methodology to gather qualitative data from the participants. For the first step, the participants discover the design area by walking, questioning, and experimenting with the designers. For the second phase, the participants create cognitive maps representing their perceptions about the design area. At the same time, the researchers represent ABM simulations to the participants based on the random properties to visualize the human factor in the design area. The use of ABM as a visualization tool highly impacts the participants. With this awareness, they conclude the game with step three, by needs mappings and collaborative design with the designers.

Figure 2.8. The cognitive and needs mappings (Yang et al., 2021)

After the serious game phases, the obtained insights and qualitative data were transferred to the ABM to update the simulation. The researchers present alternative design scenarios and individual human behavior to the participants. The researchers highlighted that ABM-aided participatory design and game-informed ABM simulations have significant potential to create better understanding and democratic design in the public realm. On the other hand, the researchers state that the lack of a large amount of participation was the main limitation of the research.

On the other hand, Schaumann et al. (2019) propose narrative-based modeling, which integrates top-down and bottom-up Multi-Agent Simulations (MAS) methods with its non-linear and day-to-day use scenario for complex building systems. Narrative-based modelings are centered on a rule-based narrative to create a heterogeneous agent to perform structured activities for complex facilities (Schaumann et al., 2017; Simeone et al., 2013). Figure 2.9 shows the visualizations of the user's activities as one of the simulation results, which display the circulation traces on the ground of the determined building.

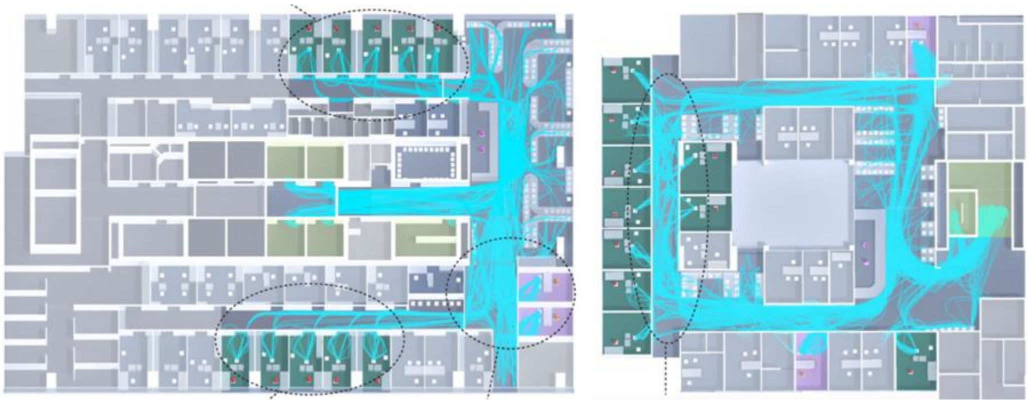


Figure 2.9. The human circulation mappings from the simulation(Schaumann et al., 2019)

Narrative-based modelings distinguish by their ‘distributed intelligence among the different model components’; however, the other MAS are generally equipped with autonomous decision-making tools or centralized schedule arrangements (Schaumann et al., 2019). Figure 2.10 shows the components and the logic of the proposed Narrative-based modeling by the researchers.

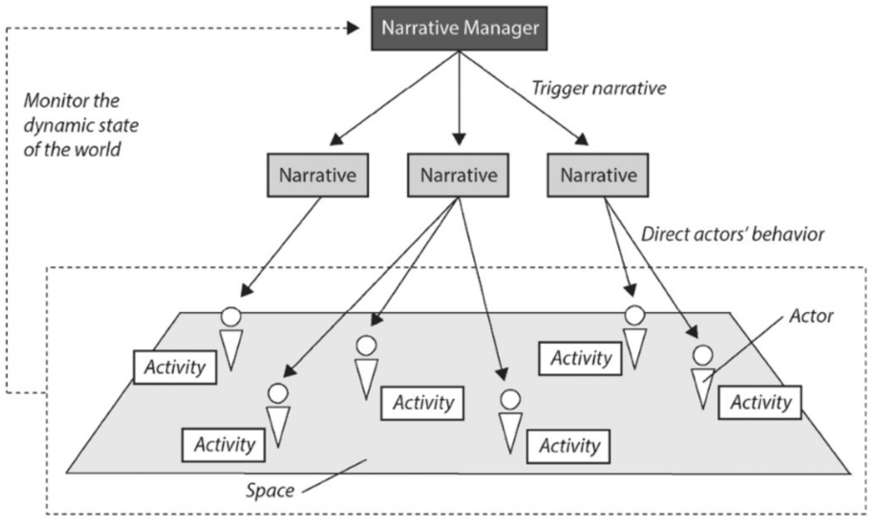


Figure 2.10. Narrative-based modeling components (Schaumann et al., 2019)

The model leads by a ‘narrative manager,’ which displays the current state of the world and triggers the planned or unplanned narratives to attract related agents to simulate the user behavior in that state.

2.2 Desired Paths and Stigmergy

People walk for circulation and leave traces behind on any type of ground, such as; sand, snow, grass, mud, and many more (Macfarlane, 2012). These traces left behind are identified in the literature with several names, desired paths, desired lines, footpaths, cow paths, social trails, and elephant paths. Dorato & Lobosco (2017) identify the desired path as obvious trails on the ground caused by continuous movement. More specifically, a desired path refers to eroded and unpaved paths on a grassy surface due to the repetitive circulation of the people (Neeraj et al., 2020). Figure 2.11 displays examples of desired paths and the different appearances between the designed and desired paths. The designed path refers to the pedestrian circulation trails intentionally designed and applied by designers. However, desired paths are the creations of the self-initiation of the users based on their needs and preferences.

Figure 2.11. Images of the desired path from Copenhagen (Dorato & Lobosco, 2017)

The term desired paths have alternative applications in different fields. For instance, Nichols (2014) articulates the term ‘social desired path,’ which refers to an emergent phenomenon when people face formal social norms are not fit with them. This formulation highlights an essential character of the desired paths when a conflict occurs between the formal structures and the individual's preferences. Broadly, the concept of the desired path represents the individual's initiative against the top-down structures.

Regarding the physical environments, Lidwell et al.(2003) refer to desired paths as the worn-out paths that people primarily circulate, and these paths display realistic indications of how people interact with the determined area. More specifically, the traces left behind by the independently behaving user's in the urban landscapes represent the actual needs and expectations of the individuals in the urban context (Dorato & Lobosco, 2017). According to Kotsiopoulos (1982), the occurrence of the desired paths can be related to the need for paved trails, which do not exist, and the flaws in the applied paved path organization. Many researchers emphasize the desired paths as the user's positioning against the formally designed layout, which can be considered the user's design feedback. For example, (Nichols, 2014a) interprets the presence of the desired path as the dissatisfaction of the users toward the planned use of the designed paths. Also, Norman (2016) defines the desired paths as a sheer signifier of the mismatch between the individual's desire and the designer's vision. Moreover, Smith & Walters (2018) associate desired paths with urban resilience and described them as resistance to rationalizing the urban areas.

On the other hand, desired paths represent a bottom-up emergence rather than a product of central management, highlighting its stigmergic nature. Stigmergy was initially formulated based on studies about social insects. However, several studies question if human-human stigmergy exists and reinterpret specific collective human behaviors in the context of stigmergy. According to Van Dyke Parunak(2006), human-human stigmergy is common and exemplifies this phenomenon in both pre-computational and computational mechanisms in human society. Parunak (2006) states that people need to move in their non-computational environments and often create stigmergic mechanisms to coordinate their activities, such as trail formations in vegetated fields. (Figure 2.12).

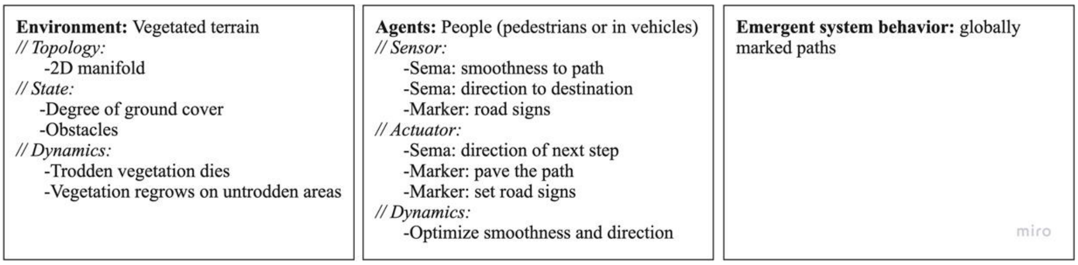


Figure 2.12. Trail formation in vegetated fields (desired paths) is an example of human-human stigmergy.(Van Dyke Parunak, 2006)

The concept of stigmergy was introduced first in 1959 by the French zoologist Pierre-Paul Grasse to define indirect communication phenomenon among social insects (Theraulaz & Bonabeau, 1999). Grasse used the Greek words *stigma,* which means ‘mark or puncture’ and *ergon,* which means ‘work or action’ to define stigmergy as ‘…the stimulation of the workers by the very performances they have achieved is a significant one inducing accurate and adaptable response…’ (Grasse, 1959).

On the other hand, Parunak (2006) reinterpreted the Greek words and defined stigmergy as a communication method between the agents in which an agent’s mark on the environment produces a stimulus for the other agent’s subsequent behavior. Heylighen (2011) highlights the conflicting interpretation of the two keywords, *ergon* (work) and *stigma* (sign), in the context of Grasse and Parunak’s explanations. Grasse indicates *ergon* functions as a stigma; however, Parunak states that stigma is a production of ergon. According to Heylighen (2011), these conflicting explanations highlight the ‘bidirectional nature of stigmergy,’ which refers to a feedback loop in which an action produces a sign for the following action and so on (Figure 2.13).

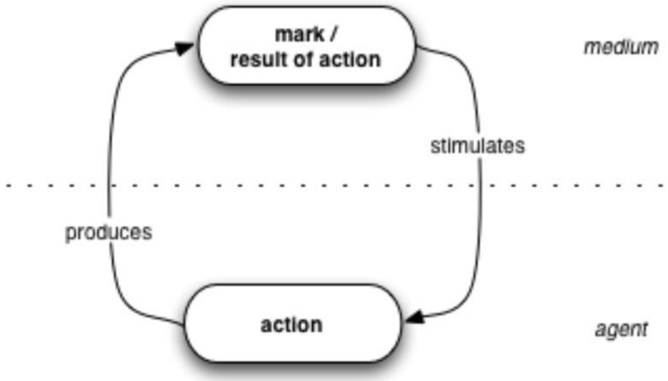


Figure 2.13. Bidirectional nature of stigmergy. (Heylighen, 2011)

Dipple et al. (2014) describe stigmergy as a communication mechanism through environmentally mediated signs that trigger actions among social insects. The *environmentally mediated sign* refers to the *stigma* from Grasse's definition, which refers to indirect communication medium among the insects. Indirect communication is an interaction among social insects in which one individual modifies the environment, and the other responds to the modification later on. (Grosan & Abraham, 2006) Figure 2.14 shows the core components of stigmergy based on the above definitions: agent, sign, and environment.

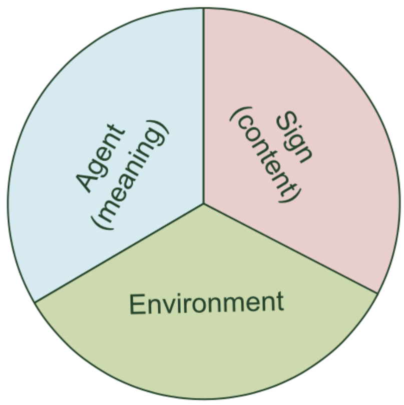


Figure 2.14. The core component of stigmergy (Dipple et al., 2014)

Agent refers to the individuals in a society who share the same environment and indirectly communicate through signs. The insects, as agents, use stigmergy for different motivations, such as construction and foraging. Their organization to achieve their goal is characterized by self-organization rather than a central decision-making mechanism (Theraulaz & Bonabeau, 1999), (Dipple et al., 2014). Every insect behaves according to the local modifications in their environment, and the collective behavior of the insects creates a self-organized complex adaptive system that fulfills their goal most efficiently. Castelfranchi (2009) describes four types of relations between agents in stigmergy; *unilateral, bilateral, reciprocal*, and *mutual*. Unilateral relation refers to an autonomous behavior between the agents. In bilateral relations, the agents behave according to the other agents' traces left in the environment and don't need to have the same goal or motivation. However, reciprocal relations have similar properties to bilateral ones; agents know that they coordinate with each other in reciprocal relations. Finally, agents in a mutual relationship know they are observing each other and share the same motivation (Dipple et al., 2014)

On the other hand, sign, as one of the other core components of stigmergy, has a strong bond with both the environment and the agent. A sign is the result of the action of an agent, which causes a physical modification in the environment and subsequently stimulates an action for another agent in the same environment. Theraulaz & Bonabeau (1999) classifies stigmergy into two distinct types based on the stimulation properties of the sign: *qualitative* and *quantitative*. In qualitative stigmergy, agents perform based on the amount or density of the signs, such as pheromone trails and gradients, in constructing the pillar in termites. Hence, the signs' quantitative properties affect the action's probability, not the type. However, in qualitative stigmergy, agents perform a particular behavior according to the kind of sign. On the other hand, Van Dyke Parunak (2006) divides the stigmergic signs based on the intention of the agents; *marker-based* and *sematectonic*. Maker-based signs refer to the intentional traces left by the agents; however, sematectonic signs are unintentional.

	Marker-Based	Sematectonic
Quantitative	An accumulation of markers denoting a consensus	A trace accumulated through activity denoting a trend
Qualitative	A markers left with the intention of requesting an action	A trace denoting the presence or existence of a particular opportunity

Figure 2.15. The types of signs in stigmergy. (Dipple et al., 2014)

Dipple et al. (2014) reinterpreted the classifications from Parunak and Theraulaz & Bonabeau and described four stigmergy types based on two binary distinctions (Figure 2.15).

The environment has a significant role in stigmergy because the agents create the signs by modifying the environment. Hence, the modified environment can be considered a *spatiotemporal structure* which refers to the sign itself (Dipple et al., 2014). The term *spatiotemporal* relates to space and time simultaneously and displays the importance of the changing physical environmental conditions through time. In another way, an environment is such a structure that materializes the activities of a collectively behaving society and records the action of the agents through time (Theraulaz & Bonabeau, 1999).

Parunak (2006) identifies desired paths as one of the most primitive examples of sematectonic stigmergy that the *active walkers'* circulation activity, walking, erodes the vegetation on the frequently used circulation paths. On the other hand, Dipple et al. (2014) classify the desired paths as *quantitative stigmergy* in which the agents behave *bilaterally*. Helbing et al. (1997) articulate the *active walker models* with *desired paths* based on mathematical modeling. They explain the desired paths as 'a complex interplay between pedestrian motion, human orientation, and environmental changes.

In conclusion, desired paths function as a stigmergic mechanism in the human world and represent stigmergic properties in many ways. Figure 2.16 highlight the stigmergic properties in desired paths.

Agent	Active walkers	(Van Dyke Parunak, 2006), (Helbing et al., 1997)
Sign	Eroded vegetation caused by human circulation	(Van Dyke Parunak, 2006)
Environment	Vegetated Terrains	(Van Dyke Parunak, 2006)
Type of Stigmergy	Quantitative / Sematectonic	(Dipple et al.,2014), (Van Dyke Parunak, 2006)
Type of Agent Relation	Bilateral	(Dipple et al.,2014)
Motivation	//Shortest paths, //Avoiding the bumpy landscapes	(Helbing et al., 1997)

Attractions	//Shops
	//Houses
	// Parking lots
	// Underground stations
		(Helbing et al., 1997)

Figure 2.16. The attributes of the trail formation so-called desired paths as a form of stigmergic mechanism.

2.3 Desired Path and Stigmergy in Urban Design

Desired paths have a long history as the artifact of continuous human circulations. However, the first appearance in the urban design literature originates from the "Chicago Area Transportation Study" reports in 1959 (Throgmorton & Eckstein, 2000). The term was used to understand pedestrian behaviors and provide the outcomes for better-designed urban areas (Smith & Walters, 2018). Afterward, the urban designers provided the desired path when re-designing New York Central Park's pedestrian circulation. On the other hand, the idea became a common-used method for designing inner pedestrian circulation in university campuses in the United States in the 1970s (Dorato & Lobosco, 2017).

The presence of desired paths in public lands concerns many actors with different responsibilities toward the city. Recently, Shuey (2021) highlighted the opinions of the users, designers, and landscape maintenance professionals regarding desired paths based on the survey conducted with 211 volunteers. The results show that most users appreciate the desired paths as a ‘design flaw’; however, most participants see the desired paths as a positive character of the landscape (Figure 2.17). Also, most of the participants preferred paving over the desired paths as a mitigation method, and the least popular method selected by the participants was fencing off the desired path as an attempt to cut user circulation on them.

Figure 2.17. User opinions about desired paths. (Shuey, 2021)

On the other hand, the designers the author interviewed explained that desired paths are chaotic and unsafe compared to the designed paths; hence, they hesitated to provide their potential guidance. Also, the maintenance professionals expressed dissatisfaction with the desired path occurrence because of the economic costs of the mitigation methods. The survey results and interviews show a contradiction between the official decision-makers and the user regarding the desired paths. The results of the study conducted by Foster & Newell (2019) also highlight the positive impact of the desired paths on the user’s point of view. According to the authors, the users interpret the desired path as an answer to poorly designed urban mobility networks. Most users want the desired paths continuously to exist because they see them as better circulation options than the designed ones. On the other hand, Neeraj et al. (2020) highlight the potential dangers the users might face while using the desired paths, such as slippery surfaces, insect bites, and insufficient lighting in the dark.

Designers and decision-makers approach rehabilitating the desired paths based on two comprehensive methods; pre-path mitigation and post-path mitigation (Shuey, 2021). Post-path mitigation refers to the repair of the existing desired paths, such as paving them. However, pre-path mitigation methods function with prediction tools that simulate the possible desired paths in the determined area.

Kulhavy et al. (2018) suggest four solutions for post-path mitigation: using physical or vegetative barriers, paving the desired paths, and reorganizing the formal sidewalk according to the desired paths. For the pre-mitigation methods, there are several tools that the designers can provide to predict future desired paths, such as space syntax, behavioral modeling tools, pedestrian mobility simulations, finite-element-method parametric modeling tools, and machine learning methods (Dorato & Lobosco, 2017; Foster & Newell, 2019; Shuey, 2021).

For example, Dorato & Lobosco (2017) created a parametric predictive modeling system as a planning tool based on desired paths while highlighting the relationship between the topology and spatial behavior in landscape design. The authors were inspired by the path-making method in rural lands in ancient times while creating the desired path prediction script (Figure 2.18). The figure represents the implication of the path-making mechanism of a domestic animal used by farmers in ancient times, a common method to reach the hardly accessible rural lands.

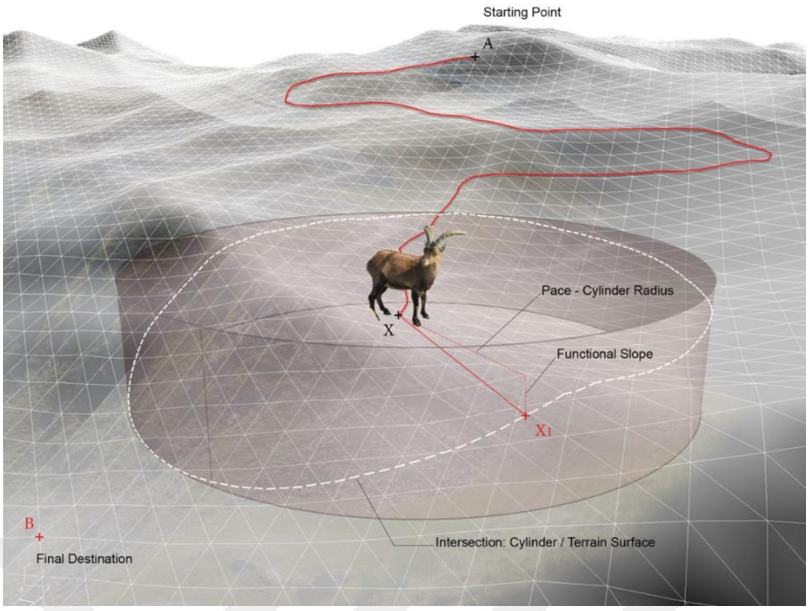


Figure 2.18. Ancient path-making methods inspire the prediction tool. (Dorato & Lobosco, 2017)

On the other hand, stigmergy was derived from biology; researchers from different disciplines, such as computer science, robotics, architecture, and urban design, are highly interested in the applications of stigmergic systems based on their fields.

Chabanyuk & Fonseca (2019) highlights the increasing interest in stigmergic approaches to understanding the self-organizing processes and the emergent interactions of the urban actors in the urban environment. According to the authors, stigmergic applications give the ability to respond to the changing realities of the cities to urban designers. Hence, they formalize a stigmergic approach to identify the actors and their interrelations while studying the residential area in the post-socialist city in Ukraine (Figure 2.19).

Contexts/ Environments	Actors	Time	Place	Actions	Reactions
Economics	State planning	1917–1991	City	State trade, State property	
	Needs and demands	1991<2017	Residential areas	Ground Floor Changes: Commerce and Services	Create nodal places with commerce, market
Institutional	Ideology and politics	1950–1991	Urban territories	State Design Institutes/ Directive planning	Centralisation
	Democracy	1991<2017	-//-	Private Design Institutions/ Market	
Design	State Design Institutes	1950–1991	-//-	Administrative centralized urban planning	
	Architects	1991<2017	-//-	Individual projects	

Figure 2.19. Stigmergic formulation of the actors and their interrelation (Chabanyuk & Fonseca, 2019)

Moreover, Rauws et al. (2020) highlight the limited help of the orthodox top-down approaches to deal with cities' spontaneous and dynamic evolution. Hence, the authors emphasize the importance of stigmergy as a nature-based self-organization method to adjust the planning decisions according to the changing circumstances of the cities.

In conclusion, the concepts of stigmergy and desired paths are getting increasing attention in the urban design context. However, approaching the desired paths with the perspective of stigmergy is not fully comprehended yet.

2.4 Critical Review of the Literature

Regarding the relationship between the designer, the user, and the environment as a design outcome, desired paths have a significant potential to understand the user’s feedback on the design outcome. The literature highlights that desired paths were examined in the context of urban design. However, approaching desired paths with a stigmergic method is not comprehended yet. This research formulates desired paths as the indirect communication medium between the designers and the users.

CHAPTER 3

MATERIALS OF RESEARCH

The primary material of this research was the satellite images extracted from the Google Earth Pro platform. On the other hand, street view images, historical imageries, and the Google Earth Pro layer system have been used as supporting materials during the research process. The desired paths have been marked on Google Earth Pro and then elaborated in Miro. Rhino and Grasshopper have also been used to transform and abstract the designated features on the selected design lands from satellite images to a quantitive data platform.

CHAPTER 4

METHOD OF RESEARCH

This thesis focuses on the physical traces of the user's physical activities on the design outcome. These physical traces were considered the user's design feedback. It has been hypothesized that designers can provide this feedback mechanism to enhance their design outcomes and use them as design guidelines for future projects. Hence, the research method was formulated to prove this hypothesis. It was structured to answer research questions: how can we document the user's physical traces on a design outcome, what can we learn from them, and how can we provide what we learned?

The first research question led the type of the design outcomes to search for the user's physical traces. Following and recording the user's physical traces requires several surveillance mechanisms, which are not commonly used in interior spaces because of privacy issues. However, there are many outdoor surveillance mechanisms to follow users' activities; meantime, physical traces emerge from these activities, even some of these mechanisms are open for public use, such as satellite images in Google Earth. Hence it was decided to focus on users' physical traces in outdoor spaces, especially 'desired paths' generated by the users in the ground of the cities.

The research method consists of four significant phases, which are *data gathering, data pre-processing, learning from data*, and *providing from known* (Figure 4.1)

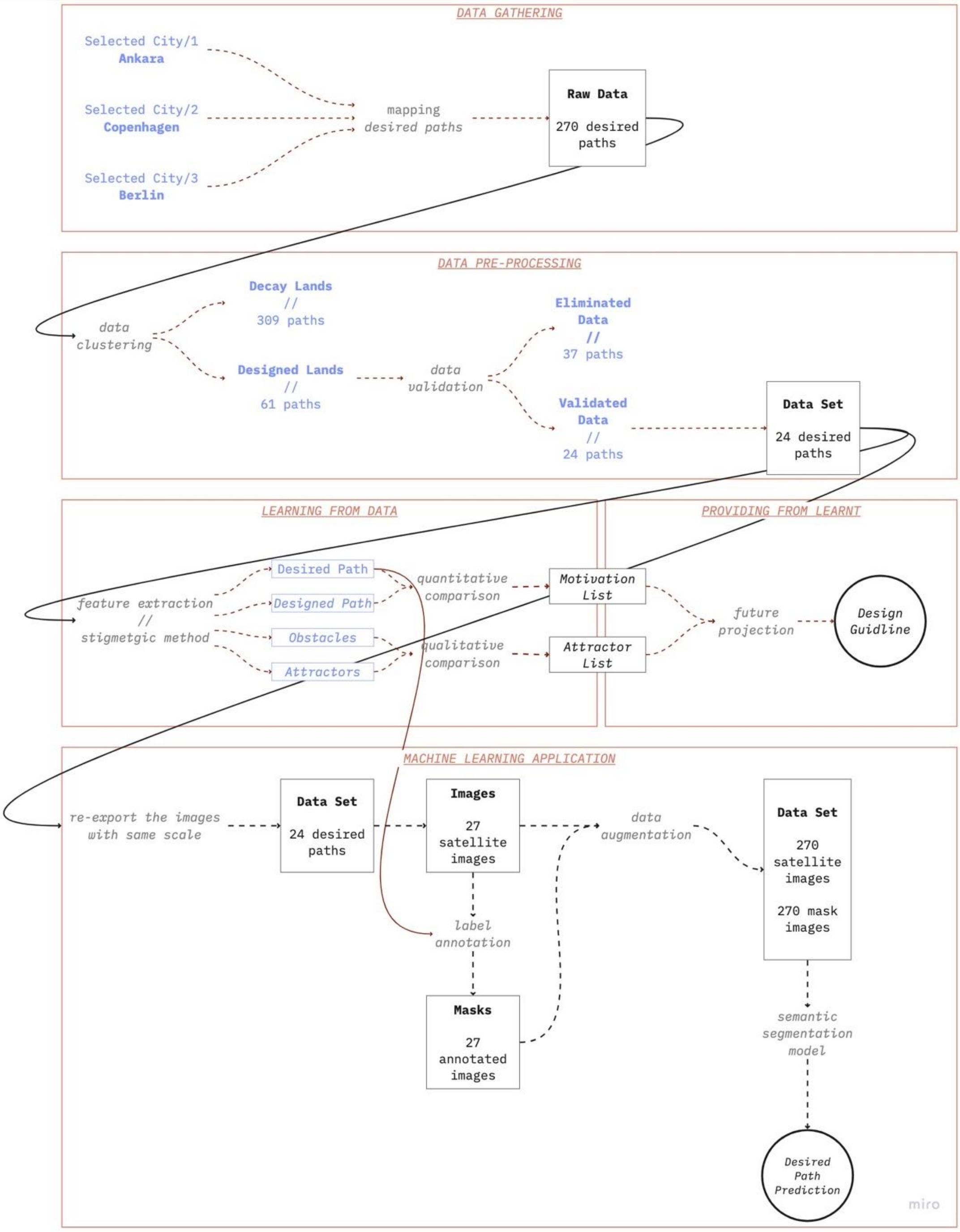


Figure 4.1. Diagram of Research Method

It was aimed to answer the research questions through consecutive phases. *Data gathering* and *pre-processing* phases correspond to the first research question, about tracing and documenting users' physical traces on a design outcome. Regarding the scope of this research, the user's physical traces correspond to the 'desired paths' in the selected cities. Hence the term 'data' mainly refers to the concept of 'desired path.'

During the data-gathering phase, the selected cities were scanned to map *desired paths,* and these mapped paths were formulated as raw data of this research. On the other hand, the raw data was clustered and validated during the data pre-processing phase. Data clustering was operated based on the context of the desired paths. It has been noticed that the paths were located mainly in two types of lands, *designed lands* and *decay lands*. If the land displays any deliberately designed layout by the designers, it has been considered as *designed land,* if not *decayed land*. The paths located on the *designed lands* have been selected to pursue because this thesis is interested in the users' feedback on a design outcome. Subsequently, the selected paths were validated based on the physical evidence for their existence. However, the paths were mapped manually during the data gathering phase; there has been a need to search for additional proof of their presence in real life and whether they are desired or designed paths. Hence the selected paths were validated based on the street views, consecutive historical imagery series, and the road labeling system of Google Earth Pro. Validated data has been formulated as the data set of the research.

Learning from data phase aims to answer the second research question related to the possible learning outcomes from the data set. This phase was characterized by feature extraction operation. The features were formulated based on a stigmergic approach. Each desired path in the data set was abstracted with its context based on this stigmergic approach to understanding the users' behaviors, choices, and eventually their design feedback on the interacted design outcome. The features were identified as *designed path*, *desired path*, *attractors* and *obstacles*. *Attractors* refer to attraction points for the users and their functional properties; however, *obstacles* were considered as blocking physical items for the users' circulation between the attraction points. In that manner, *designed path* refers to the designers' suggestion for the circulation between the *attractors;* however, *desired path* highlights the users' position and intervention regarding this suggestion.

The last phase, providing from learned, corresponds to the final and most important research question of the thesis, how can we provide from what we learned?

The phases of the method will be explained in further chapters.

4.1 Data Gathering

Has been mentioned above, the term *data* refers to *desired paths* according to this thesis scope. Hence this phase is characterized by tracing and marking the *desired paths to* create a raw data set for the research in the selected cities (figure 4.2).

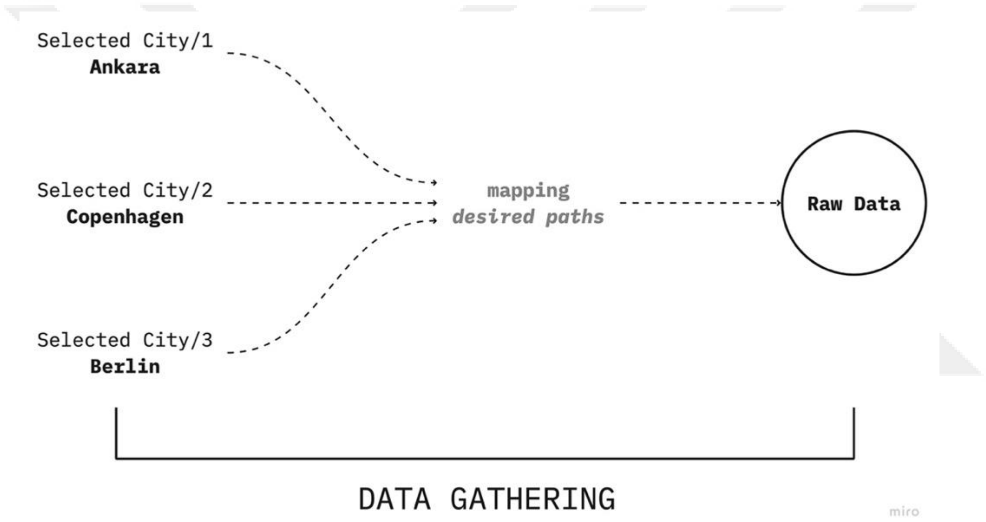


Figure 4.2. Data gathering

Diversity of the data set was one of the primary tasks for the scope of the thesis. Every city has distinctive design cultures as well as characteristic user behaviors related to these design cultures. Hence, the cities have been selected from different countries in Europa. While choosing the cities, the development levels and the quality measures in the cities' urban design have been considered. Ankara, Copenhagen, and Berlin have been selected to trace *desired paths*. Ankara represents a city from a developing country which may refer to a *less-designed* city. However, Berlin and Copenhagen represent well-designed cities in which supposed to see less *desired paths* compared to Ankara.

Regarding the scope of this research, users' interaction with the design outcome, has been mainly focused on the parts of the cities with possible higher human circulation and designed parts of the cities. Hence the search for *desired paths* focused on the central parts of the cities rather than the rural settlements or surroundings of the cities. For example, university campuses, public parks, governmental facilities, public facilities, housing areas, hospitals, schools, city parks, and their surroundings have been prioritized in searching

The satellite images the Google Earth Pro (GEP) platform provided have been utilized as the primary medium to trace and map the *desired paths*. On the other hand, the prioritized zones of the cities mentioned above have been located with the help of the 'Search' tool, 'Border and Labels,' and 'Places' segments on the GEP platform. After highlighting the targeted parts of the cities, the *desired paths* have been marked on the GEP platform with the help of the 'Add Path' tool on GEP.

The paths differentiated from their surrounding grounds based on their distinctive visual properties. These properties were the color and material difference and their continuous organic forms, which mostly interconnect the specific points in their contexts.

Desired paths display distinctive shader properties compared to the color of the ground surface to the paths belongs. The friction caused by continuous human circulation on the paths makes their color slightly lighter than the ground color.

Figure 4.3 shows the desired paths that emerged on the ground with two different materials: grass and earth. It can be easily seen that the paths differ from the ground because of their distinguishable lighter colors.

Figure 4.3. Color difference

One of the other distinctive properties of the desired paths is their continuous organic shapes which don’t display solely linear forms. The *desired paths* are not the outcome of a top-down design process in which the outcomes are designed and constructed as highly rigid and unalterable shapes. In contrast, they are generated by the users’ collective mind time by time to achieve similar goals. When the circumstances change in the context, the users may change the orientation of the paths. Hence, the frequency of a specific path usage may decrease over time. These particular attributes of the desired paths generation create uniquely organic and evolving shapes on their ground (Figure 4.4).

Figure 4.4. Organic form

The desired paths' material attributes are distinctive properties to differentiate them from the designed paths.

Figure 4.5. Material difference

Figure 4.5 shows a ground surface with a designed path and the desired path. The design path has a distinguishable, finely crafted, and hard surface material, indicating the path has been deliberately designed and constructed on the surface. However, the desired path has an ununified grassy texture because the *desired paths* are the eroded version of their grounds' material.

The selected cities' desired paths have been marked according to their distinctive visual properties on the GEP interface to gather the research data set. The selected cities have been approached with the same scale to make a better comparison between them. Each city has been divided into 6x6 subgrids. The prioritized functional facilities and zones of the cities have been localized to define the search area for tracing and marking the desired paths in the cities. The density and distribution of the targeted prioritized zones determined each city's count and place of the subgrids to search for.

Figure 4.6 shows the marked *desired paths* in Ankara. The subgrids selected to search for the desired paths have been highlighted with white color and the desired paths with orange. Twenty-five subgrids have been traced in total.

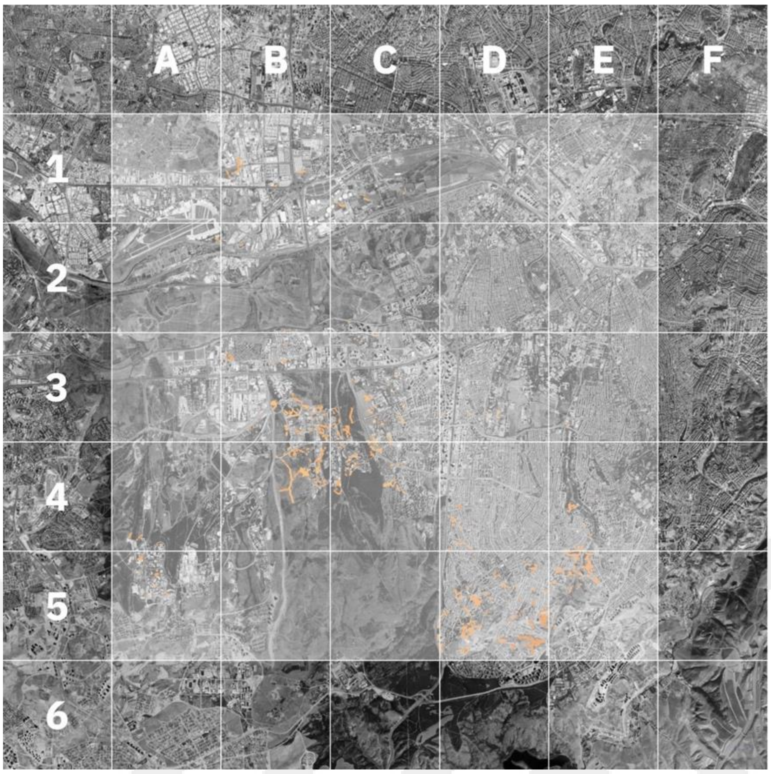


Figure 4.6. Marked *desired paths* in Ankara

In Ankara, the desired paths are primarily located in the university and housing development zones. Especially two of the city's most prominent and historical university campuses, the Hacettepe Beytepe Campus (HU) and the Middle East Technical University (METU), have displayed numerous desired paths. The dense distribution of the desired paths can be seen in the subgrids B3, C3, B4, and C4. On the other hand, D5 and E5 display the dense desired path pattern in a housing development zone of the city.

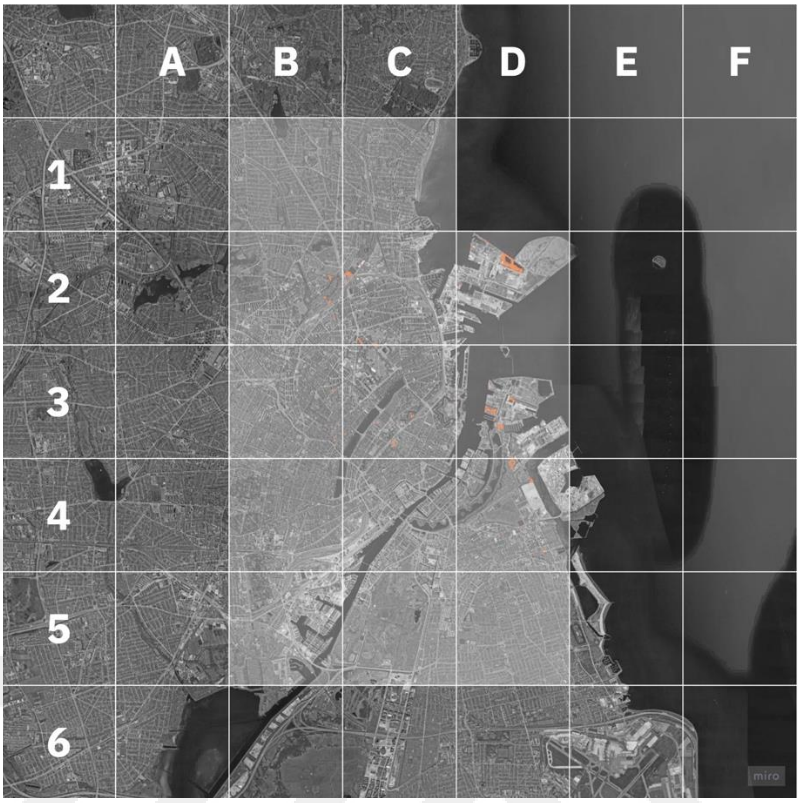


Figure 4.7. Marked desired paths in Copenhagen

Fourteen subgrids have been traced in Copenhagen, and a dense *desired path* pattern has not been seen compared to Ankara. However, the *desired path* occurrence was slightly higher in the see-side areas compared to the inner central zones. The paths were primarily seen in the city's center's public parks, housing gardens, and extensive transportation zones (Figure 4.7).

The desired paths in Berlin also displayed similar density distribution as Copenhagen. The paths have been seen as almost homogenized in the subgrids that have been traced (Figure 4.8).

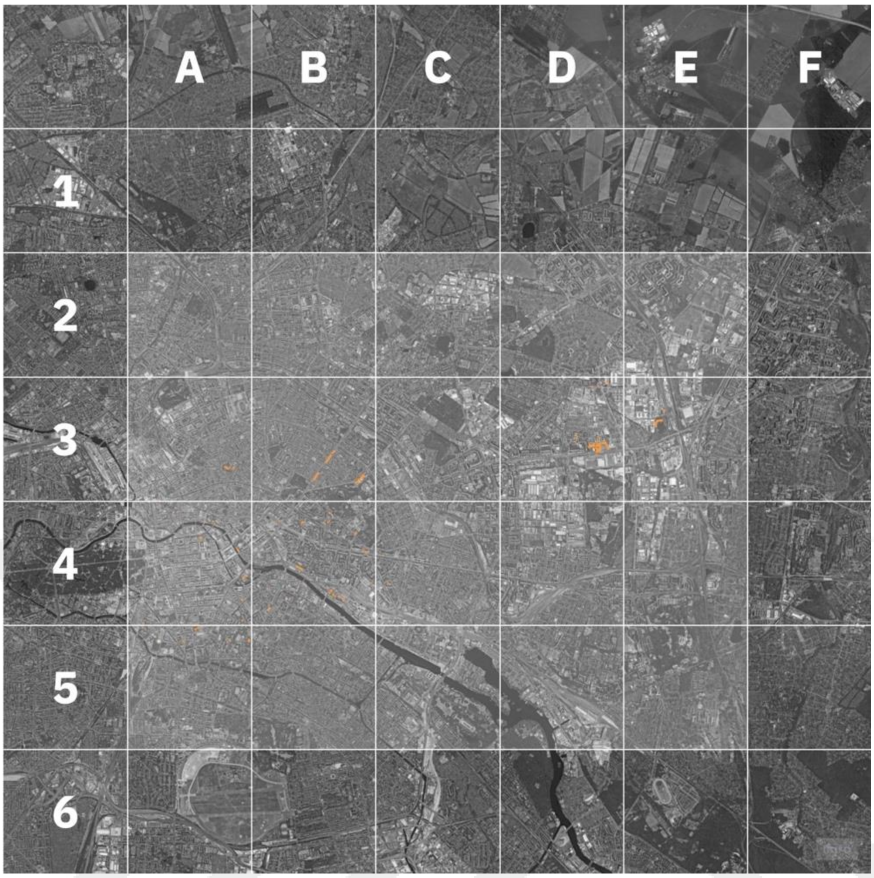


Figure 4.8. Marked desired paths in Berlin

Table 4.1 shows the counts of the desired path and traced subgrids and the count of desired paths per grid in each city. In Ankara, 298 desired paths have been marked in twenty-five subgrids. On the other hand, Copenhagen has displayed 24 desired paths in 14 subgrids, and Berlin has shown 48 design paths in 20 subgrids. The ratio of the desired paths' total number, path count (PC), to the count of searched subgrids, subgrid count (SC), has been formulated as the path density (PD) in each city.

$$PC / SC = PD$$

Table 4.1 The number of desired paths and the traced subgrids, and the path density in each city

City	*DC*	*SC*	*PD*
Ankara	298	25	11,9
Copenhagen	24	14	1,7
Berlin	48	20	2,4
Total	370	59	6,2

In conclusion, the highest density of the desired paths has been seen in Ankara, with 11,9 paths per subgrid, and the least density has been seen in Copenhagen, with 1,7 desired paths per subgrid. The results support the hypothesis formulated at the beginning of this sub-chapter. Ankara was expected to see more desired paths than Copenhagen and Berlin because the city has been categorized as less or not-well-designed than the other two cities. Hence it can be concluded that when the cities are not designed well or enough, the users take the initiative to generate their solutions which can be seen in their physical traces on the design outcomes, such as desired paths.

4.2 Data Pre-Processing

There have been gathered 370 desired paths named raw data during the data phase, and the pre-processing data phase has focused on clustering and validating the raw data to collect the data set of this research (Figure 4.9)

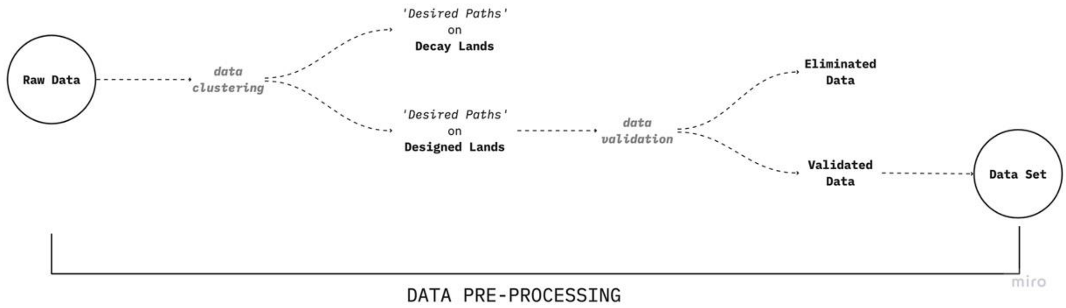


Figure 4.9. Data pre-processing

Data clustering focused on classifying the based on the lands where the paths were marked. On the other hand, the data validation phase concentrated on validating the paths classified as design land.

4.2.1 Data Clustering

This research focuses on the comparison between the designers' suggestions and the users' choices. Hence the desired paths have been clustered based on their contexts' design status; if the paths emerged in a land consisting of design outcomes, these paths were clustered as *paths in design lands.* On the other hand, the paths have been marked on the ground to indicate any sign of design intervention called *paths in decay lands*.

Figure 4.10 represent a decay land where a desired path emerged. The figure on the left is the raw images from GEP. On the other hand, the image on the right shows the markings regarding the footprint of the land and the path formulations. The land highlighted with a blue color doesn't indicate an official design intervention. Hence, the paths marked with the white dashed lines were considered the user's solution regarding their circulation problem, not a manifestation of their preferences regarding the designer's suggestion.

Figure 4.10. Desired paths in a decay land.

On the other hand, figure 4.11 shows a path formulation in a designed land. The figure on the left is the raw image from GEP. The highlighted zone with the blue color represents the footprint of the land. The paths marked with continuous white lines were considered official design indications. However, the paths marked with the white dashed line represent the desired paths which were conceptualized as the manifestation of the user's preferences regarding the designer's suggestions.

Figure 4.11. Desired paths in design land.

As a result, 61 paths were classified as 'desired paths in design land.' In Ankara, 27 lands were identified as designed land, which is 9 percent of the absolute paths marked in the city. On the other hand, 11 lands were named as designed land in Copenhagen, which is 45 percent of the total count of the marked paths in the city.

Finally, 23 lands were identified as designed land in Berlin, representing 61 percent of all the paths marked in the city (Table 4.2)

Table 4.2 Paths on design lands and decay lands.

Cities	*Designed Land*	*Decay Land*	*Total*
Ankara	27	271	298
Copenhagen	11	13	24
Berlin	23	25	48
Total	61	309	370

The paths in design land were named based on the formulation, such as the initial of the city name + the initial of the 'desired land' + the path order. Hence, the desired paths in Copenhagen were named C-DL1 to C-DL11, in Ankara were named A-DL1 to A-DL-27, and in Berlin were named B-DL1 to B-DL-23.

4.2.2 Data Validation

Sixty-one desired paths have been identified that emerged in design paths during the data clustering phase. As the second phase of the data preprocessing stage, these paths were examined with supporting mediums for validation (Figure 4.12). The validation process focused on proving the paths' existence and their classification as desired paths, not a design one.

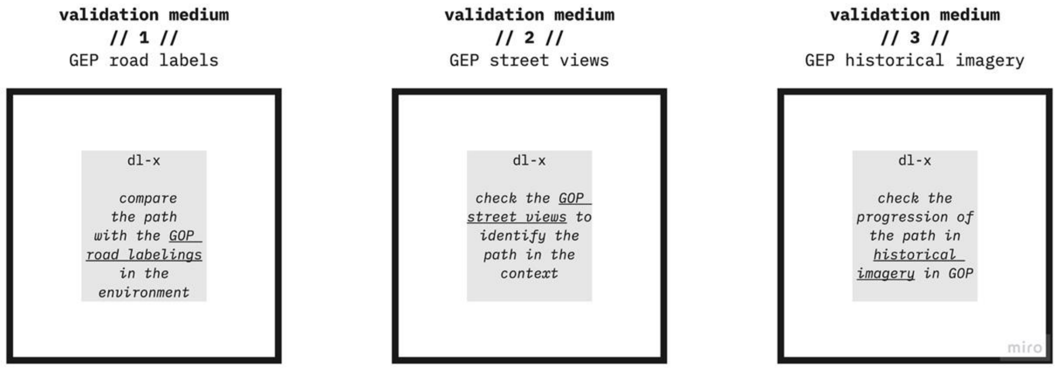


Figure 4.12. Data validation mediums.

GEP provides a 'road' labeling tool that visualizes the circulation road for pedestrians and vehicles. GEP provides official information and real-time surveillance data for labeling the paths people circulate. Hence, the paths labeled from GEP were considered as design paths because the desired paths are not the output of the official design decision. So the paths clustered in designed lands were checked to see if they were marked in the road labeling visualization of GEP.

Figure 4.13 (the image on the left) shows the bird's eye view of C-DL1 from GEP with the road label open. On the other hand, the image on the right highlights the path with the white dash line and the GEP road labeling with continuous black lines, which don't overlap. This is supporting evidence regarding validating C-DL1 as a desired path.

Figure 4.13. C-DL1 and GEP road labeling

On the other hand, figure 4.14 shows the situation of B-DL14 regarding GEP road labeling. The image on the top left is the raw image from B-DL14, and the paths were marked on it with a white dash line (the image top-right). On the other hand, the image bottom left represents the GEP road labels which overlap with the white dash line representing the desired path (the image bottom-right). This situation questions the desired path classification of B-DL14.

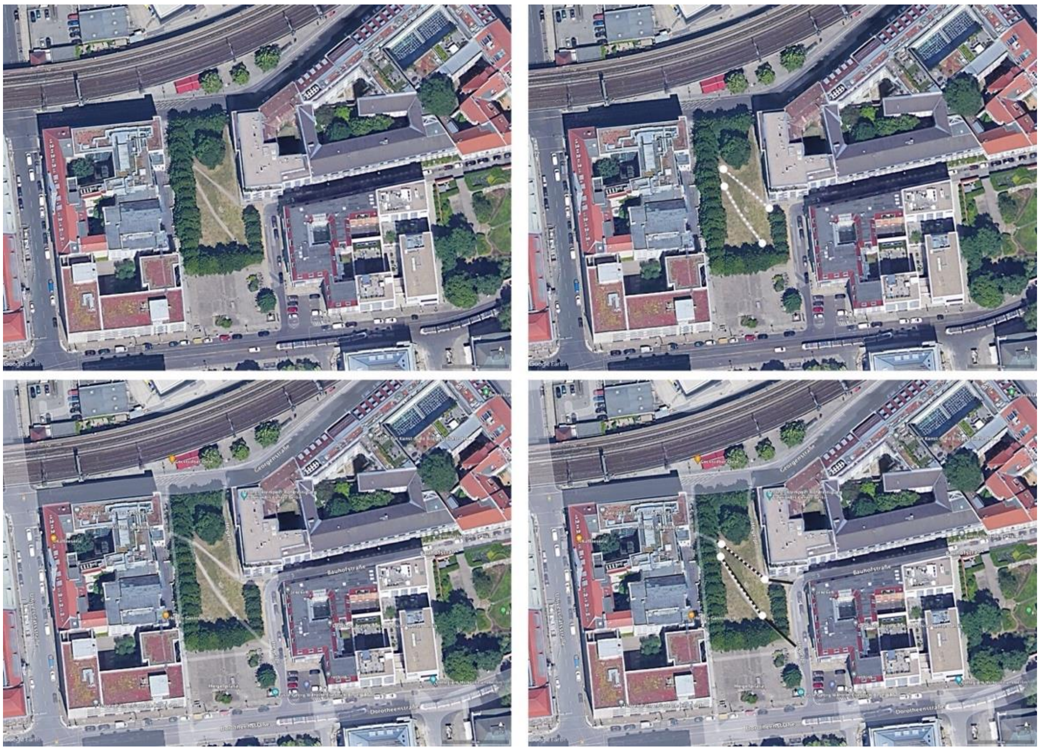


Figure 4.14. B-DL14 and the GEP road labeling

The paths were mapped on GEP's birds' eye view based on the identification criteria discussed in the data gathering section. However, there was a need for more supporting data if these mapped trails existed as paths for pedestrian circulation. Hence, the street-view images from GEP were used to visualize the human-eye view, especially from the beginning and the end of the paths. Figure 4.15 (the image on the left) shows the street view from C-DL1. The path can be seen marked with a white dash line (the image on the right), which is another supporting evidence for identifying C-DL1 as a desired path.

Figure 4.15. C-DL1 street views

GEP also provides a historical imagery tool that displays historical images from the selected areas. The tool functions with a cursor which allows the user to travel through the previous years. Hence, this tool was utilized to create a timeline matrix of the design lands to visualize the emergence and the evaluation of the paths marked as desired paths. As the literature highlight, desired paths emerge from the collective behavior of the active walkers. So when the environment's circumstances and user preference change, it reflects on the physical appearance of the path. In this context, these changes were expected to be seen in the timeline matrixes as an indication of desired path classification.

Figure 4.16 shows an example of a timeline matrix that visualizes the images in the C-DL1 from 2002 to 2022. The matrix on the left consists of the raw images ordered according to the time. The paths marked on each image belong to a different year, highlighting the path's evolution through time. (The matrix on the right). In some years, the paths almost disappeared and appeared again, which was considered an indication to classify C-DL1 as a desired path.

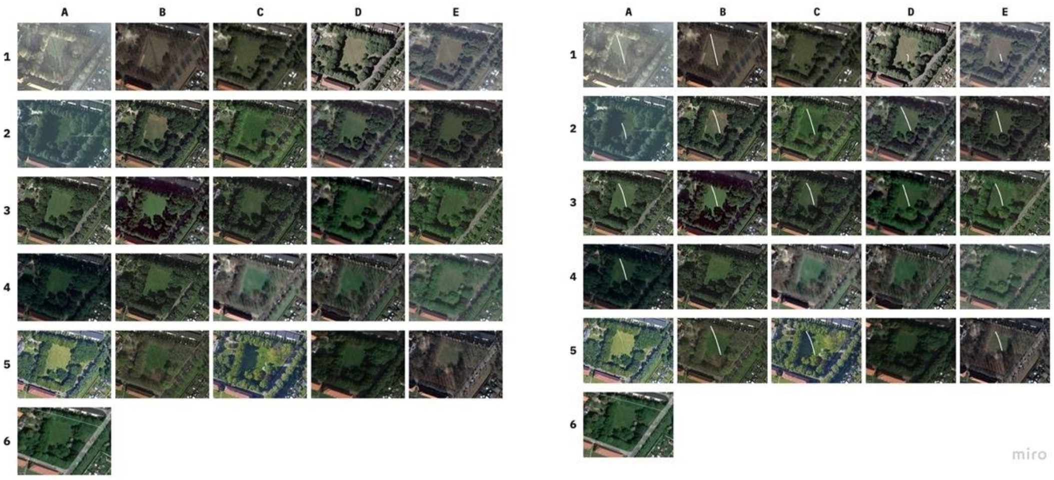


Figure 4.16. Timeline matrix of C-DL1

4.2.3 Results

At the end of the validation process, seven paths were in Ankara, eleven in Berlin, six in Copenhagen, and twenty-four paths were validated. The name of the validated paths in Ankara was adl1, adl2, adl17, adl22, adl25, adl26, adl27, in Berlin; bdl2, bdl5, bdl6, bdl10, bdl12, bdl13, bdl16, bdl17, bdl18, bdl21, bdl22 and, in Copenhagen cdl1, cdl3, cdl4, cdl5, cdl7, cdl11.

Figure 4.17 shows the validation process and the result for the cdl1 and bdl14. Cdl1, fit every validation criteria and was validated. However, bdl1 didn't fit two validation criteria and was eliminated. The validated twenty-four paths were further examined for the scope of this research.

	validation medium // 1 // GEP road labels	validation medium // 2 // GEP street views	validation medium // 3 // GEP historical imagery	validation status
	// no overlap	// views are accessible // path identified in the views	//seen the dramatical in path's physical appearance through time	//validated
C-DL1	✓	✓✓	✓	✓
B-DL14	✗	✓✓	✗	✗

Figure 4.17. Validation results of C-DL1 and B-DL14

4.3 Learning from the Data

The validated data was named the data set of this thesis. This chapter focuses on learning from the data set with the help of the stigmergic method formulated by the author (Figure 4.18)

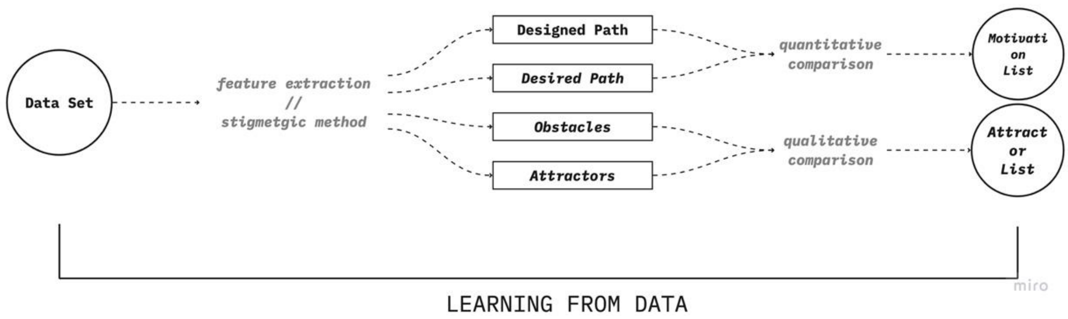


Figure 4.18. Learning from the data

4.3.1 Stigmergic Approach

As the literature highlighted, desired paths are one of the most primitive stigmergic mechanisms among people. The active walkers indirectly communicate through environmentally mediated signs which refer to desired paths. However, this thesis interprets the desired paths with an alternative perspective and formulates them as an environmentally mediated sign, representing the user's design feedback to the designer's decisions in the post-occupancy phase (Figure 4.19).

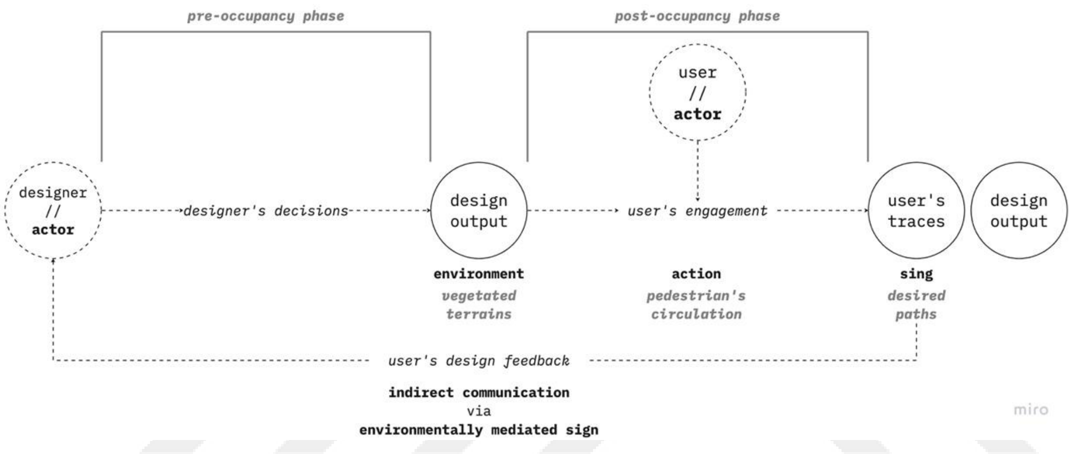


Figure 4.19. The integration of the desired paths, stigmergy, and design feedback mechanism.

Regarding the design feedback mechanism shown in Figure 4.19, a stigmergic approach was formulated. The approach focuses on conceptualizing the desired paths in the context of stigmergy to investigate their self-emergence as the user's design feedback. Hence, the desired paths were deconstructed based on the stigmergic features explained in the literature review. The stigmergic features and their references in design paths are:

Environment: It responds to the design land the desired path emerged. The context and the function of the land were also taken into consideration.

Agents: They respond to the users and designers in the context of design output.

Action: It responds to the user's activity, which causes the desired paths to emerge.

Designed Path: It refers to the sign of the designer's design decisions.

Desired Path: It is the environmentally mediated sign as the user's feedback.

Attractors: They are the entities that trigger the users to gravitate toward them.

Obstacles: They refer to the blocking entities of the user's circulation in the environment.

4.3.2 Feature Extraction from Desired Paths

The desired paths, which refer to the data set of this research, were deconstructed based on the stigmergic approach introduced in the previous chapter. The stigmergic features were extracted based on the method shown in Figure 4.20.

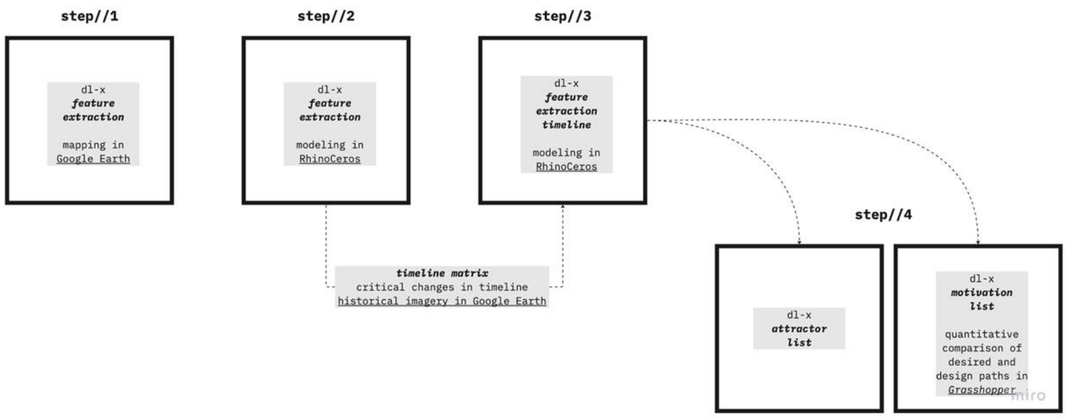


Figure 4.20. Feature extraction method

Figure 4.21 represents the stigmergic features in a theoretical context. The stigmergic features- the environment, attractors, obstacles, designed paths, and desired paths- were shown abstractly. The figure also represents the visualization style and attributes while converting the extracted features in GEP to the RhinoCeros environment, which refers to the progression from step 1 to step 2 in Figure 3.20.

On the other hand, figure 4.21 shows that the environment represents the footprint and the context where the desired path emerged. Hence the design and desired paths are located inside the environment. The desired paths represent the user's engagement with the environment apart from the designed paths. On the other hand, the attractors are the nodes connected by the desired paths.

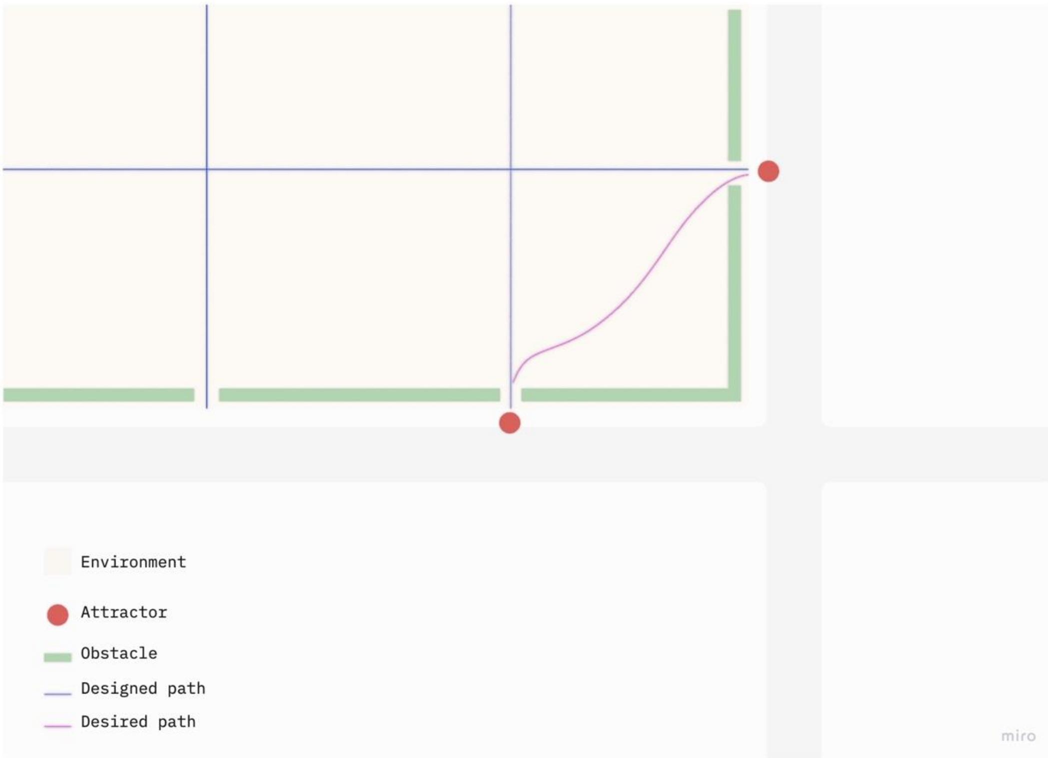


Figure 4.21. Stigmergic features in a hypothetical context

Regarding the method shown in Figure 4.20, step 1 refers to mapping the stigmergic features in the bird's eye views from GEP. Then the elements were transformed into the RhinoCeros environment with the abstraction method shown in Figure 4.21. Figure 4.22 shows the conversion of the features mapped in GEP into abstracted visualization in RhinoCeros of A-DL1. The features, such as design and desired paths were mapped in the GEP based on the method explained in the Data Gathering chapter. On the other hand, the attractors and obstacles were identified with the help of the GEP street view and labeling system.

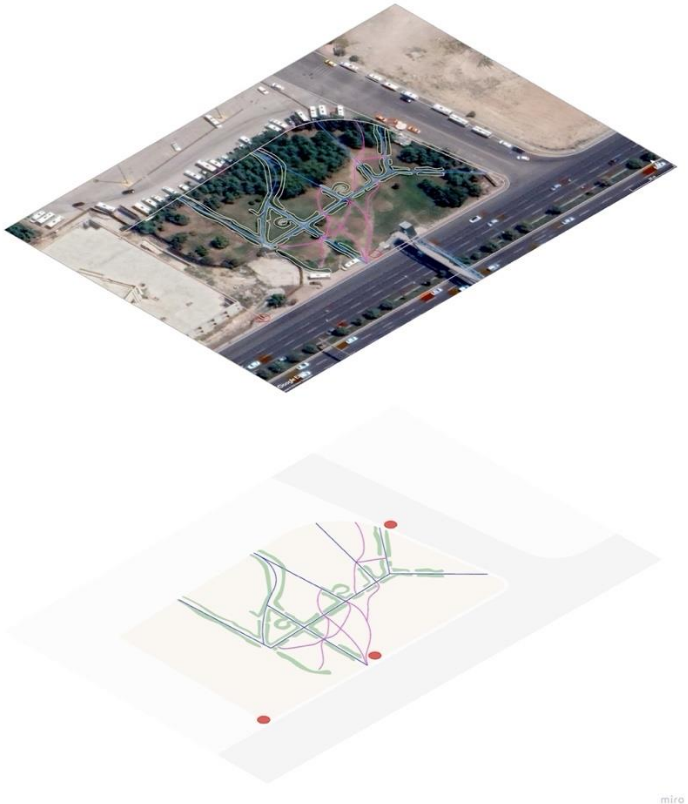


Figure 4.22. The abstraction phase, Conversion from GEP to RhinoCeros of A-DL1

As the literature highlighted, stigmergic mechanisms are prominent with their spatiotemporal attributes, which refer to physical indications of the adaptational behavior in the environmentally mediated signs through time. Hence, the desired paths were examined with their timeline matrixes to highlight the dramatical physical changes and investigate the reasons which caused these kinds of modifications (Figure 4.23).

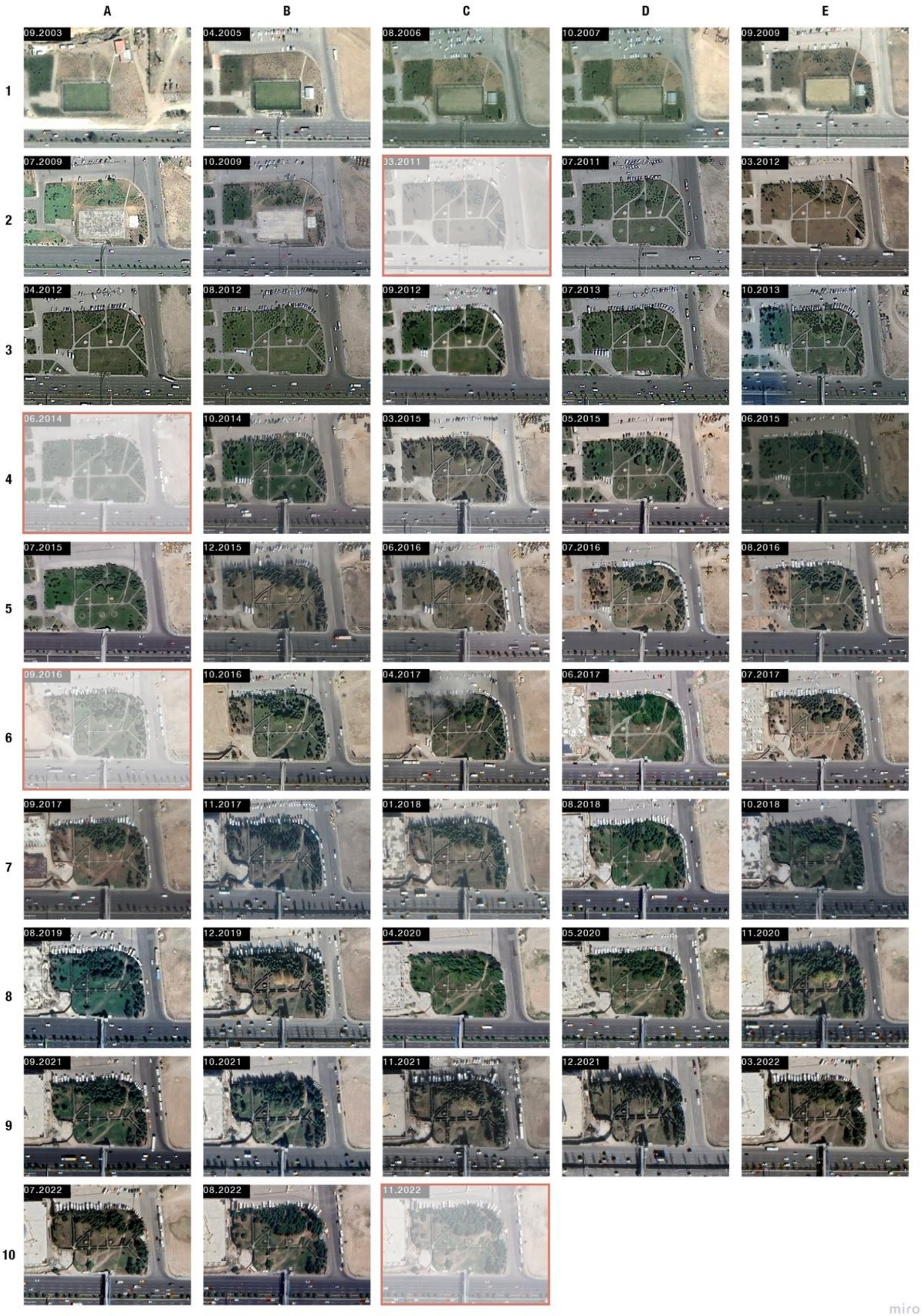


Figure 4.23. Timeline matrix of A-DL1 with selected sequences

The highlighted images in the timelşne matrixes were named sequences representing glimpses of the emergence of the desired paths. Hence the selected sequences were also transformed into RhinoCeros environment while extracting their features.

Figure 4.24 shows the selected sequences and their feature-extracted representation of A-DL1. Sequence 1 shows when the design intervention was first introduced to the environment. Then the first desired path appears in sequence 2. The attractor which caused the emergence of the first was a pedestrian overpass. However, there can be seen construction site indications in sequence 3. The protection barriers were located in the environment, making some parts of the designed paths unusable. Hence these barriers represent the obstacles that cause differences in the user's circulation habits in the environment. And finally, sequence 4 shows today's environment with dense desired pathd network and their integration with their context.

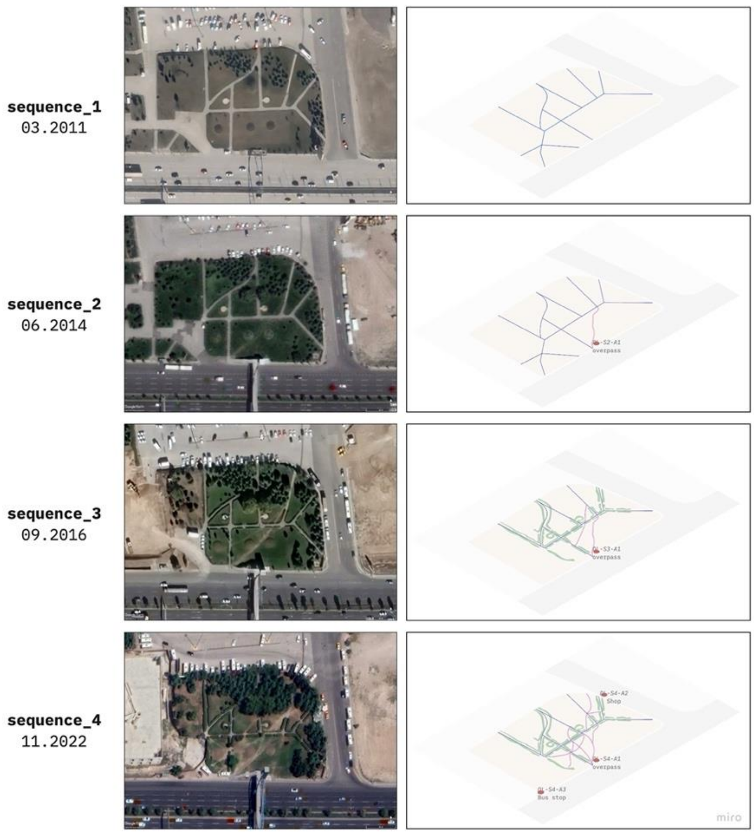


Figure 4.24. Timeline matrix of A-DL1 with selected sequences with features

This thesis concentrates on discovering the attractor's types and the user's motivations regarding the environments where the desired paths emerged to utilize them as a projection tool for predicting the user's preferences in a similar context. Hence, step 4 focuses on the attractors, triggering users to gravitate toward them.

Figure 4.25 shows the feature-extracted visualization of A-DL1 in which the desired paths and attractors were slightly more highlighted in their context. The dense formulation of the desired paths between the attractors shows the user's engagement with the environment and their preferences to circulate between these attractors, which alternate with the designed paths. In the context of A-DL1, the attractors were listed as a shop, an overpass, and a bus stop which will be utilized in the 'Providing from the learned chapter.

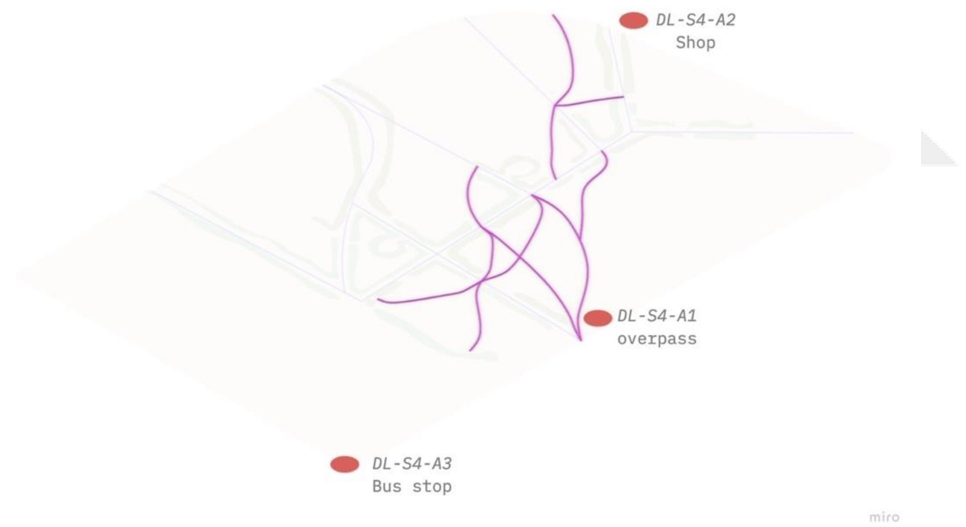


Figure 4.25. A-DL1, desired paths, and attractors highlighted

As it was shown in Figure 4.25, the paths emerge between the attractors. In most cases, the designed paths allow the users to circulate between the attractor. However, the users formulate alternative paths with a particular purpose which refers to the user's motivation in the context of this thesis. Hence, figure 4.26 shows the highlighted version of the desired and design paths in A-DL1 with their quantitative features. The quantitative aspects of the paths refer to the length of the paths regarding this thesis context. The total length of the desired and designed paths that alternate each other was compared. As a result, the desired paths were shorter than the designed ones, which indicates the user's motivation as circulating faster between the attractors.

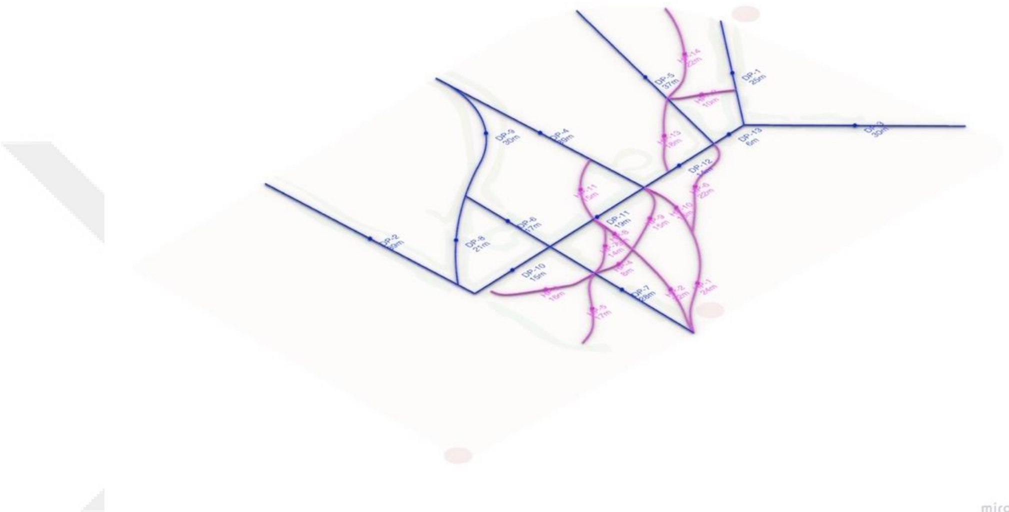


Figure 4.26. A-DL1 desired paths and design paths with their lengths

Finally, figure 4.27 shows the stigmergic features extraction visualization of A-DL1, which resulted with the help of the method shown in Figure 4.20. This visual also represents the general visualization template for examining each desired path in the data set of this thesis.

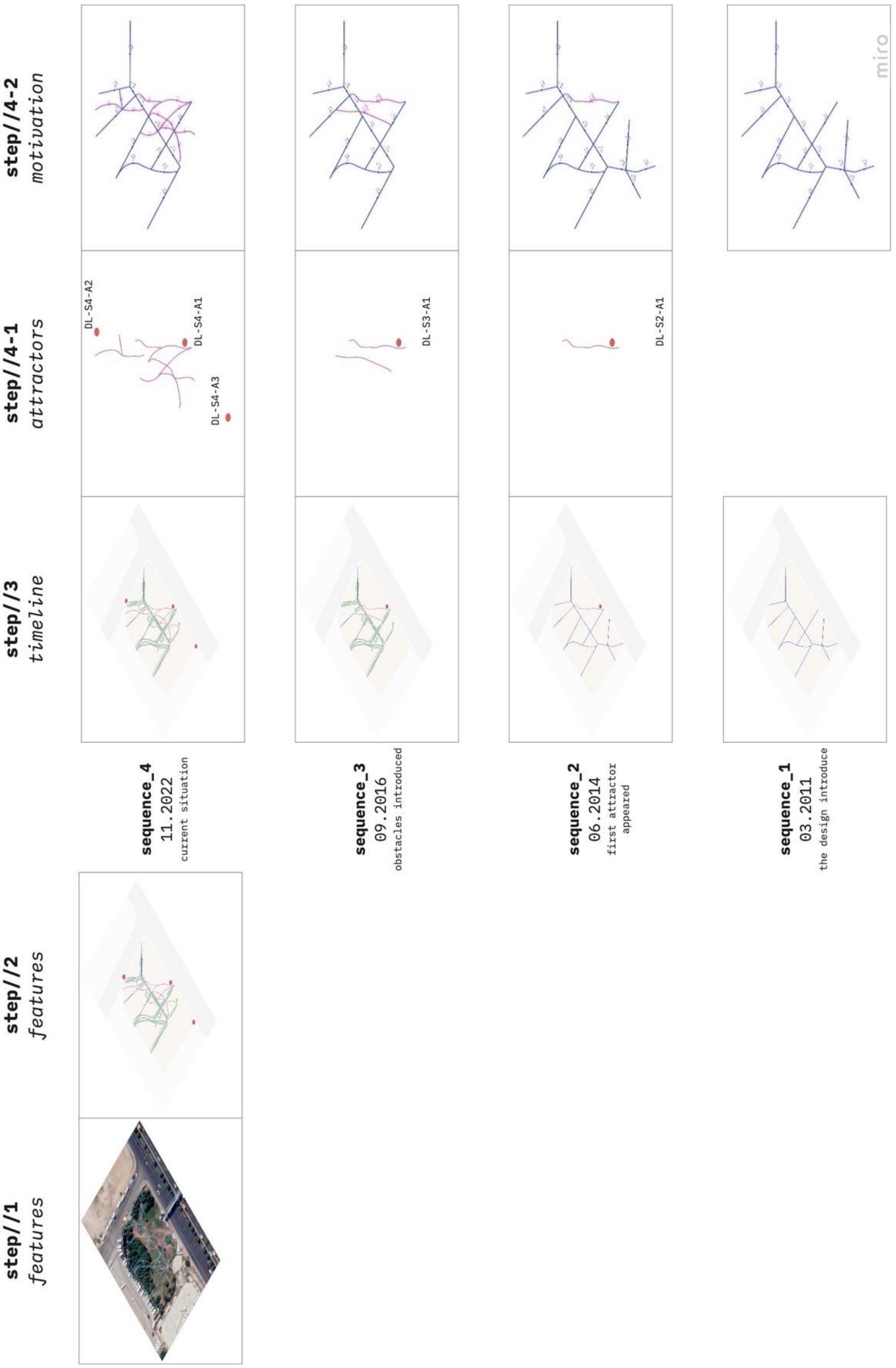


Figure 4.27. Feature extraction visualization template from A-DL1

4.3.3 Results

Figure 4.29 shows the results of the stigmergic feature extraction from nine desired paths from the data set of this research while highlighting the attractors and the motivations of the users'.

The results show that the attractors identified during the 'Learning from the data' phase are mostly related to transportation entities for the users. In general, the attractor functions were identified, such as;

- Car parking lots

-Bike parking points

-Pedestrian overpasses

-Pedestrian crossings

-Hitchhiking spot

-Bus stops

-Building entries

On the other hand, the function of environments where the paths emerged were public parks, university campuses, working blocks, and housing blocks. Finally, the general motivation of the users can be classified as shorter paths, avoiding stairs, and seeking aligned direction between the attractors.

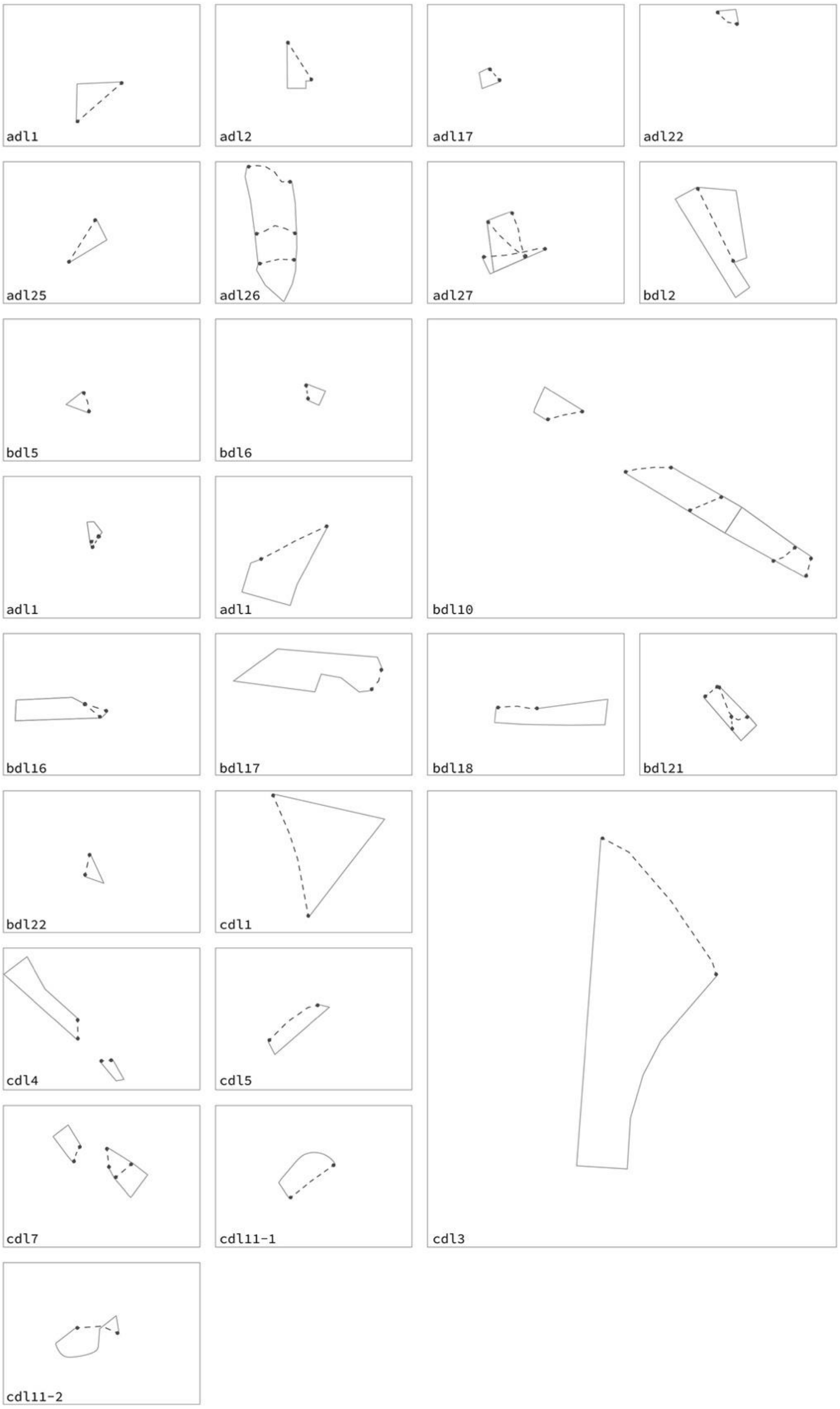


Figure 4.28. The formal comparison between the desired paths and designed paths.

	environment	agents	action	obstacles	attractors	*motivation*
A-DL1	public park	pedestrians	circulation	-vegetation barriers -construction barriers	**-bus stop** **-overpass** **-shop**	***-shorter path***
A-DL2	university campus	pedestrians	circulation	-vegetation barriers	**-car parking lot** **-Building entry**	***-shorter path***
A-DL3	university campus	pedestrians	circulation	-vegetation barriers	**-bus stop** **-Hitchhiking**	***-shorter path*** ***-aligned direction***
C-DL1	public park	pedestrians	circulation	-	**-pedestrian crossing**	***-shorter path***
C-DL2	public park	pedestrians	circulation	-vegetation barriers	**-bike parking lot**	***-shorter path*** ***-aligned direction***
C-DL3	transportation hub	pedestrians	circulation	-	**-bus stop**	***-shorter path*** ***-avoiding from the stairs***
B-DL1	Garden of a historical building	pedestrians	circulation	-vegetation barriers	**-bus stop**	***-shorter path***
B-DL2	working blocks	pedestrians	circulation	-	**-car parking lot**	***-shorter path***
B-DL3	housing block	pedestrians	circulation	-	**-Building entries**	***-connection of the attractors***

Figure 4.29. Results from feature extractions

4.4 Reflections on Findings

This chapter concentrates on the attractor's types and the user’s motivations listed in the ‘Learning from the Data’ chapter regarding the environments where the desired paths emerged to utilize them as a projection tool for predicting the user’s preferences for future projects in the similar contexts (Figure 3.30)

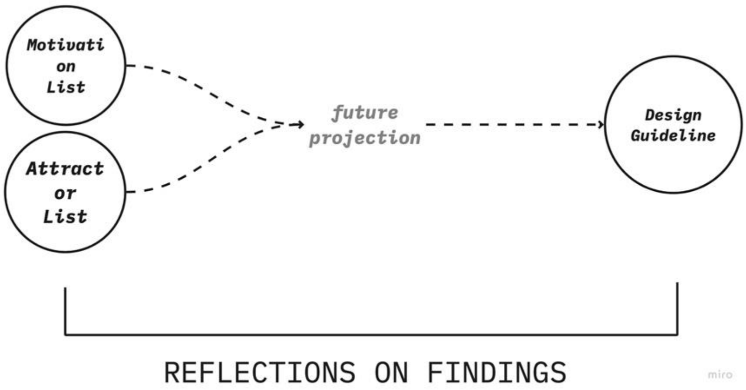


Figure 4.30. Providing from the data

Figure 4.31 shows the prediction formulations based on the context of the environment, the type of attractors, and the users' motivation. These predictions can be utilized in the selected cities to predict the user’s engagement and preferences in the environments highlighted in the predictions to guide the designers during the preliminary design phase.

environment	attractors	motivation	prediction
public park	-bus stop -overpass -shop	-shorter path	Users tend to create **shorter** and **aligned paths** to reach the **transportation entities** such as, bus stops, pedestrian overpasses and crossings, shops, bike parking lots in the context of **public parks**
	-pedestrian crossing	-shorter path	
	-bike parking lot	-shorter path -aligned direction	
university campus	-car parking lot -Building entry	-shorter path	Users tend to create **shorter** and **aligned paths** to reach the entities such as, car parking lots, building entries, bus stops, hitchhiking spots in the context of **university campuses**
	-bus stop -Hitchhiking	-shorter path -aligned direction	
transportation hub	-bus stop	-shorter path -avoiding from the stairs	Users tend to create **shorter** and **aligned paths** to reach the entities such as, bus stops, car parking lots and building entries in the context of **housing and working blocks, transportation hubs and, historical facilities.**
Garden of a historical building	-bus stop	-shorter path	
working blocks	-car parking lot	-shorter path	
housing block	-Building entries	-connection of the attractors	

miro

Figure 4.31. Generated predictions from the result of feature extractions

4.5 Machine Learning Application

This chapter represents several experiments and their results regarding machine learning applications on the validated desired paths dataset. As explained in earlier chapters, the examined desired paths in the context of this research were discovered manually in the selected cities. These paths were reviewed with a stigmergic approach, and the stigmergic features were extracted from them. These features were processed to understand the triggering effect of the desired path emergence in the given context. These understandings evolved a design guideline consisting of generalized rules to predict desired path emergence in similar contexts. However, predicting the desired paths still relies on human effort in limited contexts. Hence, the machine learning experiments with examined desired paths aimed to automate the desired path detection and prediction in any given context.

Figure 4.32 shows the machine-learning application methodology diagrammatically. A semantic segmentation model was chosen to recognize the desired paths in the satellite images. The satellite images were annotated regarding the stigmergic features that were extracted earlier. However, four different stigmergic features were identified in each desired path context; only 'desired paths' was annotated during the semantic segmentation process to deal with the complexity of the dataset.

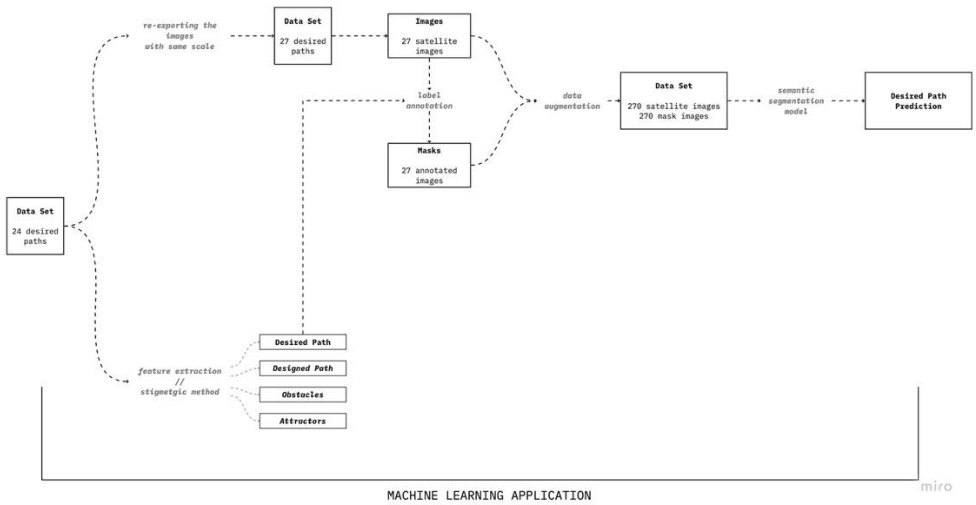


Figure 4.32. Diagram of Machine Learning Application

4.5.1 Re-scale, Re-size, and Label Annotation of Images

The concept of scale in GEP is related to the bird-eye view height, which can be adjusted while changing the ‘scale bar’ option. When zooming in a selected context, the bird-eye view height would decrease and display a close-up view in the regarding context. The twenty-four validated paths that were examined with the stigmergic approach earlier had been exported from GEP with unique scales because of their various contextual properties. The validated paths were re-exported with the same bird-eye view height to maintain a shared context, dimensional properties, and scale for the ML training. The selected bird-eye view height was 30 meters, suitable for displaying each path in its context.

adl1_00 // 58 meters above

adl1_30 // 30 meters above

Figure 4.33. Image scale conversation

Figure 4.33 shows the scale conversation in a selected path. The bird-eye view height of the original satellite image was fifty-eight meters. The height was converted to thirty meters and re-exported the path with the name adl1-30.

While re-exporting the re-scaled paths, some were divided into several parts to fit the new bird-eye view height. Figure 4.34 shows bdl10_00 and its re-scaled version, divided into bdl10_1_30, bdl10_2_30, and bdl10_3_30.

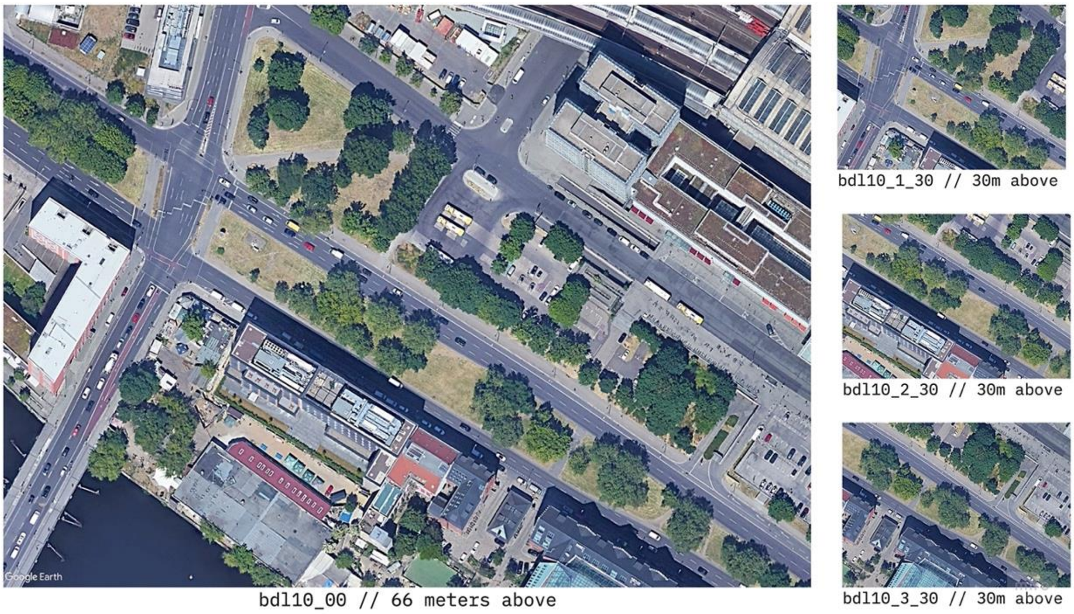


Figure 4.34. Image division while scale conversation of bdl10

Figure 4.35 also shows a similar operation for cdl11_00. Similarly, cdl11_00 was split into cdl11_1_30 and cdl11_2_30.

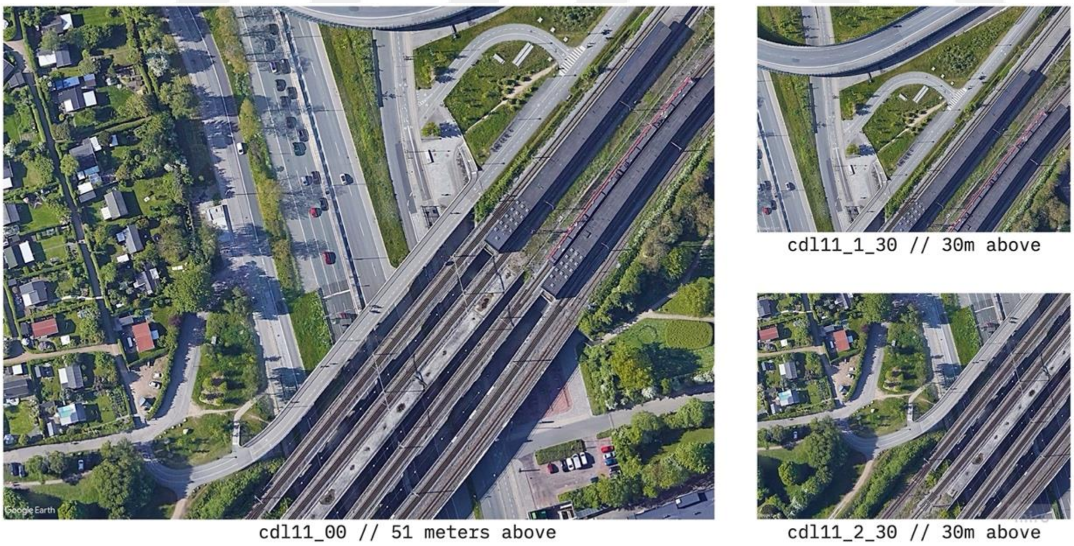


Figure 4.35. Image division while scale conversation of cdl11

As a result of the division in bdl10 and cdl11, the initial desired path count for the ML training increased from twenty-four to twenty-seven, which were named adl1, adl2, adl17, adl22, adl25, adl26, adl27, bdl5, bdl6, bdl10-1, bdl10-2,bdl10-3, bdl12, bdl13, bdl16, bdl17, bdl18, bdl21, bdl22, cdl1, cdl3, cdl4, cdl5, cdl7, cdl11-1, cdl11-2.

After re-scaling the exported satellite images of the paths, their corresponding annotated mask images were created to use in the semantic segmentation model. Semantic segmentation models require an original image in which several objects would like to be segmented while the training process and a corresponding mask image highlighting the objects to be segmented (Ronneberger et al., 2015). The objects that would like to classify during the segmentation process correspond to the unique labels in the annotated mask images, which can be binary or multi-class.

Figure 4.36 shows a HeLa cell's original microscopic image and annotated mask images, a binary classification annotation. The cell is annotated with white color, and the background is annotated with black, which is a typical method for binary segmentation tasks.

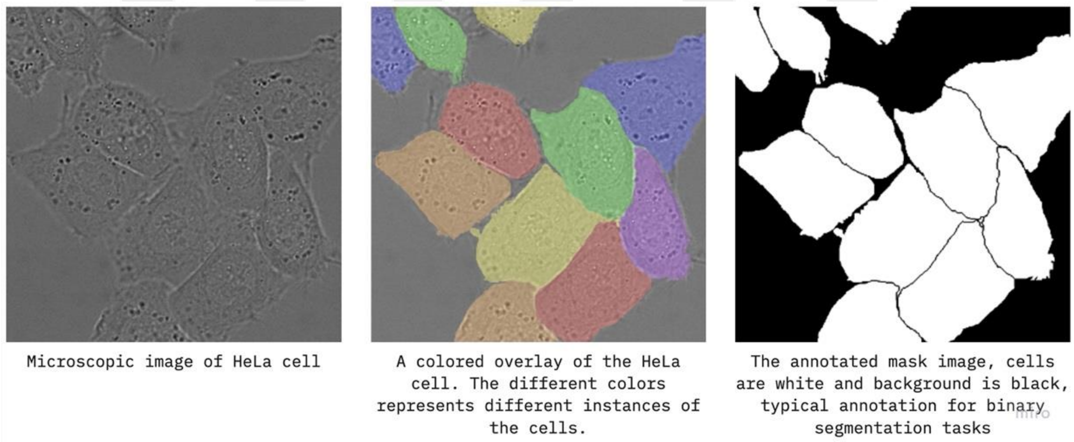


Figure 4.36. The microscopic image and its annotated mask image of HeLa cells. (Ronneberger et al., 2015)

On the other hand, figure 4.37 shows a multi-class annotation on a satellite image. As the figure highlights, the annotated mask consists of four colors corresponding to a unique label; background, woodland, building, and water.

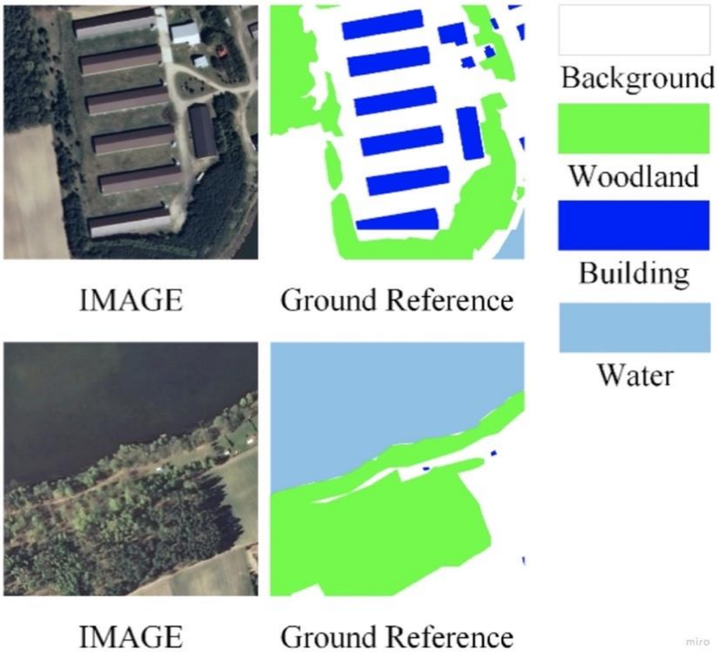


Figure 4.37. Satellite image annotation with multi-class labeling (Wang et al., 2021)

Regarding the context of this research, the stigmergic features, which were; desired path, designed path, attractors, and obstacles, were intended to assign as the unique labels for the semantic segmentation task while annotating the satellite images. However, only the desired paths were annotated in the scope of ML application in this research as the beginning step, which made the segmentation task a binary classification.

Figure 4.38 shows adl1 with two different scales and their corresponding feature masks with different styles. The stigmergic features image of adl1-00 represents the abstracted label annotation which has been used to investigate the reasons behind the path emergence in the given context. However, the black and white annotated mask image was created to use during the ML application.

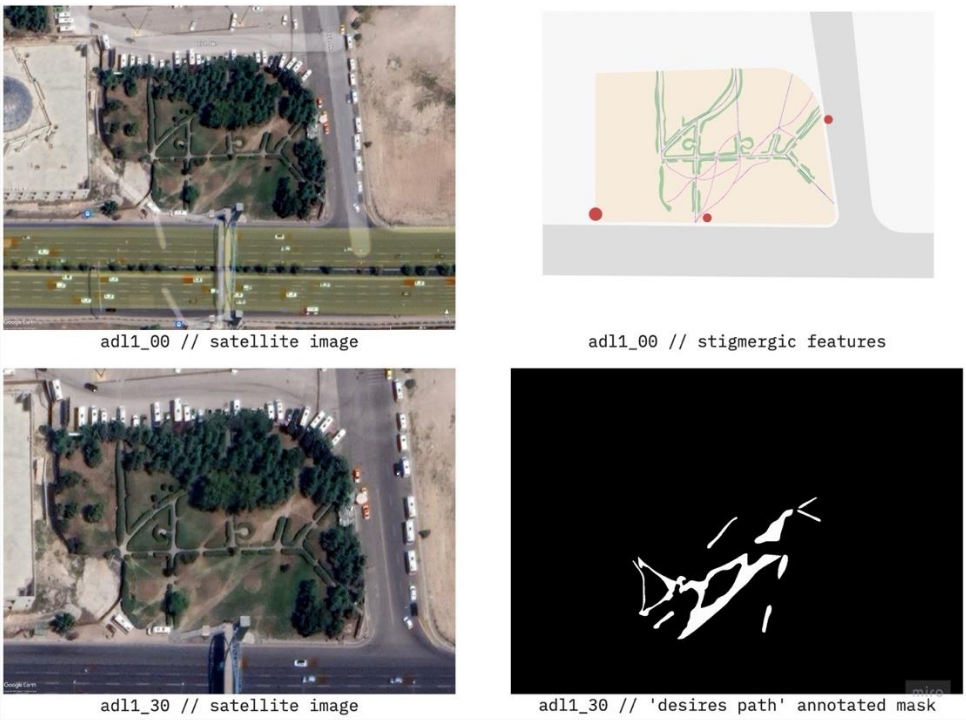


Figure 4.38. Insert figure caption here

While creating the mask images for each path's satellite image, it was realized that there were several occasions when the footprint of the desired path in the annotated mask was significantly small, which would affect the performance of the ML training while recognizing the paths. Hence another re-scale operation was applied to the already re-scaled images to balance the desired path and background footprints in the mask images. Each path was re-scaled with a unique factor during this re-scale operation because their size was diverse.

Figure 4.39 shows an example of the problem in the mask image of the first re-scale operation, which was aimed to re-export the satellite image with the same scale as the bird-eye view at thirty meters. The mask image of bdl12-30 looks problematic regarding its desired path and background properties. Hence, the satellite images were re-scaled with a unique factor to balance the mask image's paths and background proportion. The paths were renamed pathname-xx after this operation.

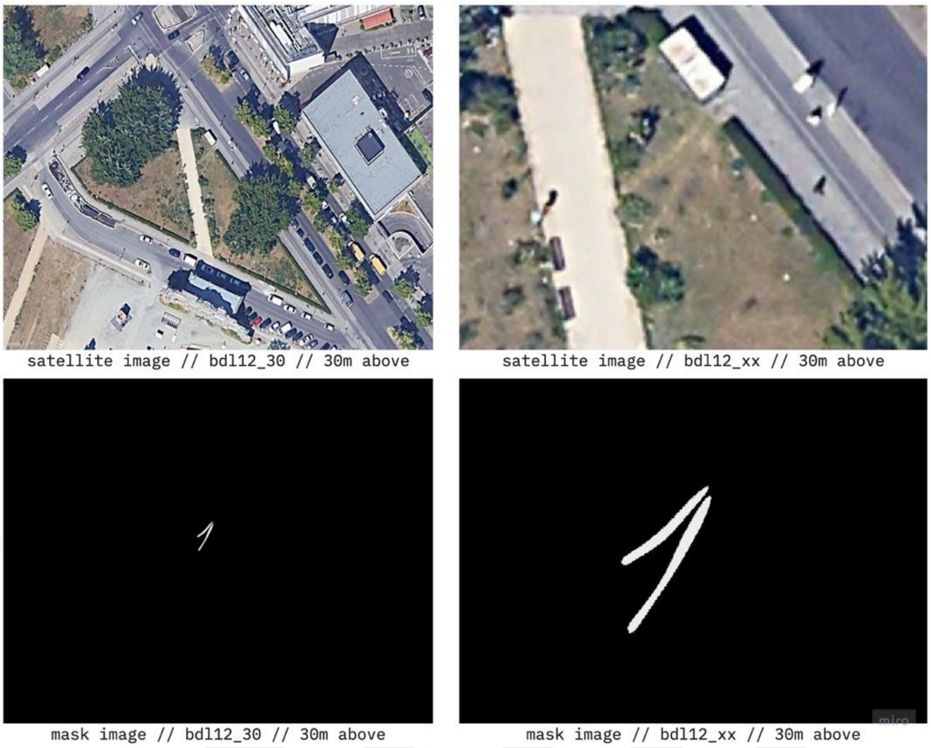


Figure 4.39. Differently scaled versions of bdl12

After re-scaling operations, the satellite images were re-sized to a smaller dimension to fit the ML training requirements. The size of the images which were exported from GEP was 2350x1694 pixels. This size might cause issues during the ML training process. So the image size decreased to 608x448 for each satellite image and its corresponding mask image. Figure 4.40 shows every re-scale and re-sized operation for adl1.

	adl1_00	adl1_30	adl1_30rs	adl1_xxrs
GEP Scale	58m above	30m above	30m above	xx m above
Image Size	2350x1694	2350x1694	608x448	608x448
satellite image				
annotated image				

Figure 4.40. Image re-scales and re-sizes

4.5.2 Data Augmentation and Training Datasets

Data augmentation is a common method to increase the samples in a dataset regarding ML applications. In the case of this research, the initial dataset consists of twenty-seven satellite images and their corresponding mask images. Several transformation operations were applied to the satellite and mask images in the initial data set to increase the total samples in the training dataset. These operations were horizontal flip, vertical flip, 90-degree clockwise rotation, 90-degree counter-clockwise rotation, 180-degree clockwise rotation, and four different random-scale-rotation, increasing the training data set from 27 to 270 for the segmentation model.

Figure 4.41 shows the transformation operations, which were applied satellite image and its corresponding mask of adl1-30 and adl-xxrs.

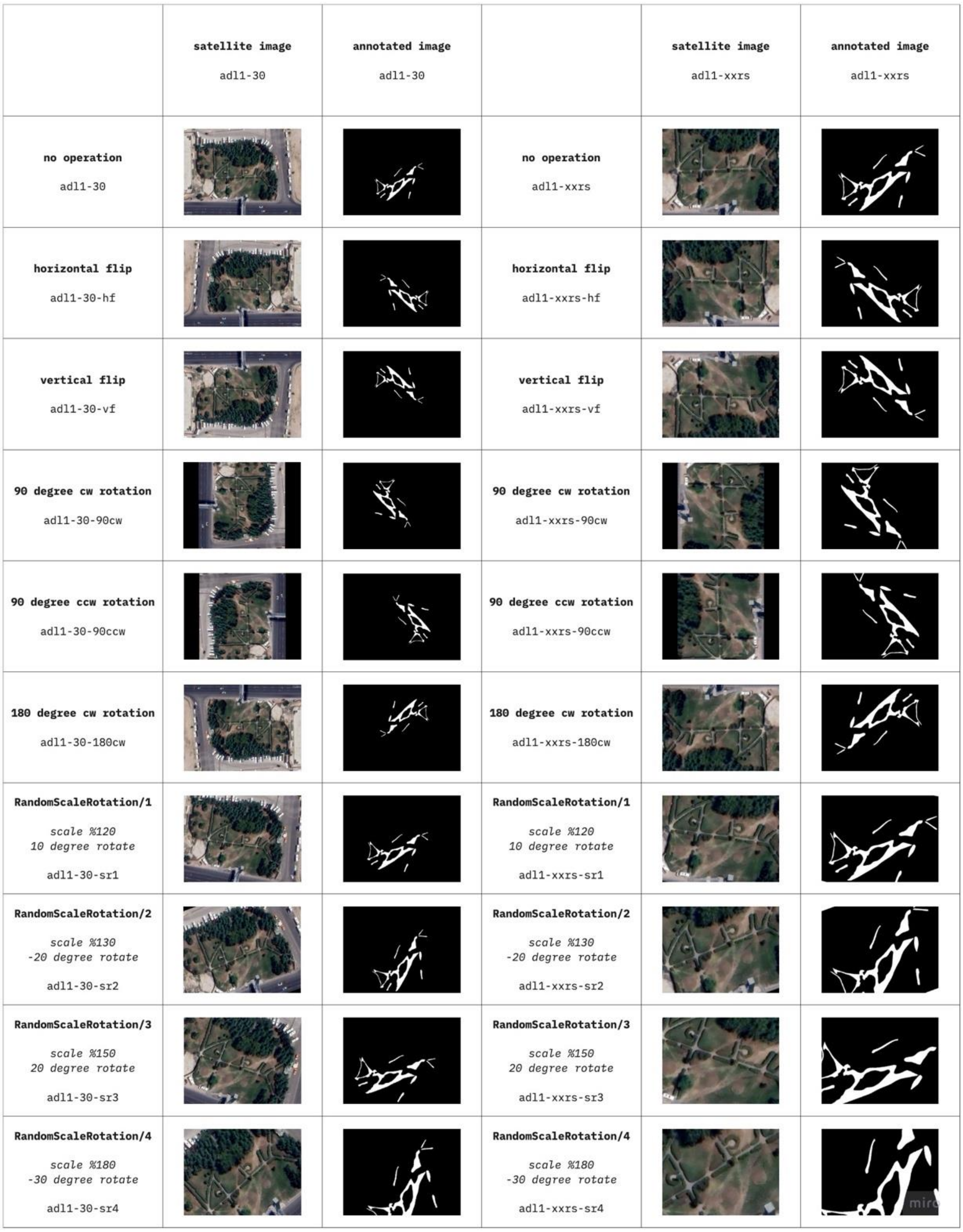


Figure 4.41. Data augmentaiton of adl1-30 and adl1-xxrs

On the other hand, figure 4.42 represents the re-scale, re-size, and data augmentation configurations to create different datasets to use with the segmentation model.

	pathname-30 image size 2350x1694	pathname-30rs image size 608x448	pathname_xxrs image size 608x448
no augmentation *27 satellite images* *27 annotated images*	dataset_30_noaug	dataset_30rs_noaug	dataset_xxrs_noaug
augmented *270 satellite images* *270 annotated images*	dataset_30_aug	dataset_30rs_aug	dataset_xxrs_aug

Figure 4.42. Datasets for the segmentation model

4.5.3 Semantic Segmentation Model

Semantic segmentation models utilized by Convolutional Neural Networks (CCN) are widely used for pixel-level image segmentation. Pixel-level image segmentation refers to assigning each pixel in an image to pre-decided binary or multi-class labels. The general aim of the segmentation models is to identify the objects or regions based on their visual characteristics, such as color, texture, and shape. A segmentation model takes an image as input and processes it with the corresponding mask image. A mask image indicates pixel-level class association in which a specific color is defined for each shape or region to match the targeted class. Segmentation models identify the objects willing to be classified with the help of mask images.

Figure 4.43 shows how the segmentation model utilizes the mask image to segment the desired path shape in adl1-xxrs. The image above represents the input data for the segmentation model: the satellite image and black and white mask. Then the image below shows how the pixels colored with white are defined as the ‘desired path’ and how the pixels colored with black are processed as ‘background’ by the segmentation model.

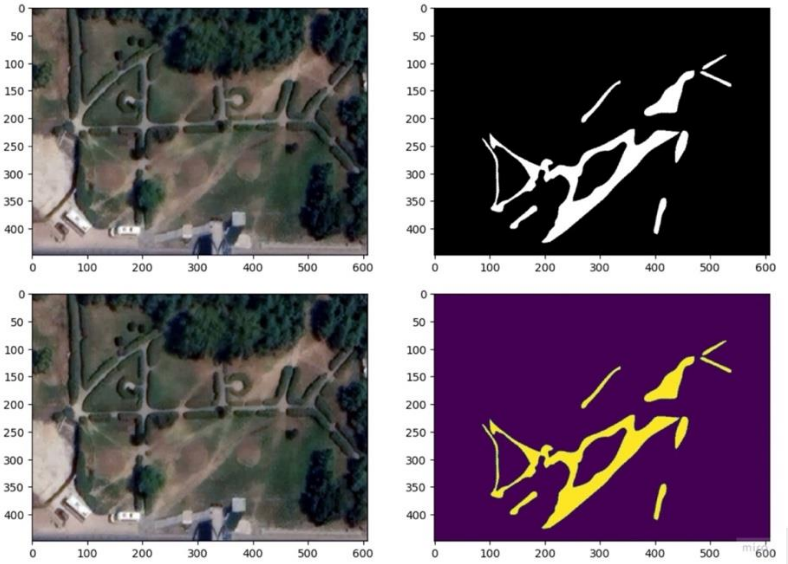


Figure 4.43. adl1 satellite images, mask image, and assigned class visual of the mask image.

CNNs are neural network architectures generally used for image segmentation or classification. A CNN architecture consists of interconnected layers such as; pooling and convolutional layers. The architecture of a typical semantic segmentation model is based on an encoder-decoder framework. The encoder typically comprises several convolutional layers that extract high-level features from the input image. The decoder then takes these features and produces a segmentation mask of the same size as the input image, with each pixel labeled according to its corresponding class (Figure 4.44)

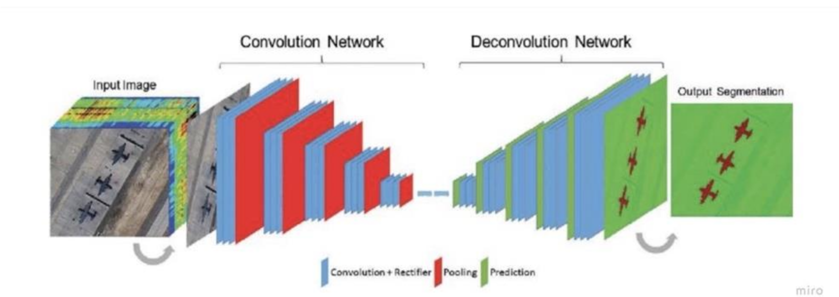


Figure 4.44. A CNN architecture for the semantic segmentation task (Chen et al., 2018)

On the other hand, in 2015, a Fully Convolutional Neural Network (FCN) named Unet was introduced to biomedical image segmentation, especially for the segmentation tasks with limited images in the training dataset (Ronneberger et al., 2015). The architecture relies on a symmetrical U shape, consisting of a contracting path to capture context and a symmetric expanding path that enables precise localization (Figure 4.45)

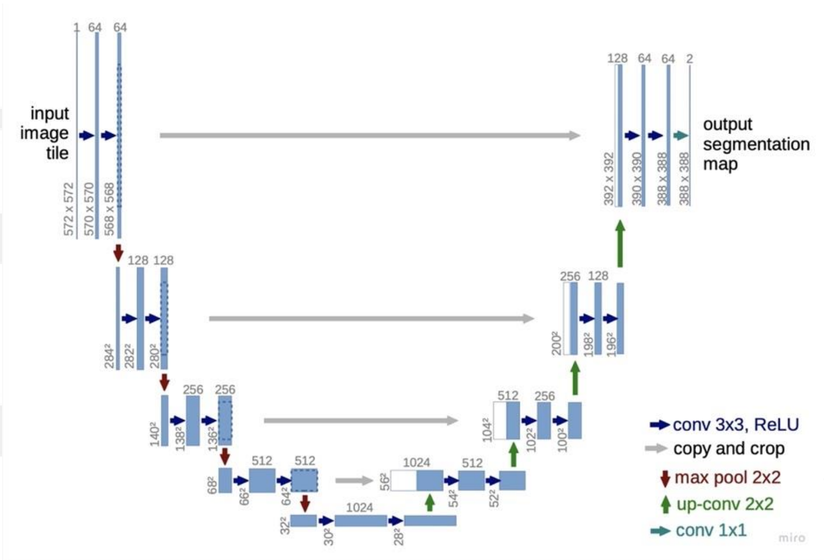


Figure 4.45. Unet architecture (Ronneberger et al., 2015)

When considering the limited size of the training dataset for the scope of this research, the Unet architecture was chosen for the training for the semantic segmentation model. For the training, the Google Collab environment was preferred to provide GPU as the hardware accelerator and the High Ram option in the pro version of the environment. The training and validation algorithms were developed with Python 3.7 and Keras with Tensorflow backend. The Unet architecture was implied with built-in Keras segmentation models. The 'resnet50' encoder was utilized with a transfer learning method to provide the pre-defined weights of the 'imagenet' dataset.

A cost function was utilized to perform the segmentation model satisfactorily. Cost functions are mathematical equations that compare the predicted and ground truth output. Cross entropy is one of the common cost functions for semantic segmentation tasks, which encourages the network to assign the correct labeling to the corresponding pixel values. The two types of cross-entropy functions were used separately for the scope of this research;

Binary Cross Entropy is used for binary segmentation tasks and calculated as following;

$$J = -[y*log(y\_hat) + (1-y)*log(1-y\_hat)]$$

where "y" is the true binary label (0 or 1), "y_hat" is the predicted probability of the positive class, and "log" is the natural logarithm.

Categorical Cross Entropy is generally used for multi-class segmentation tasks and calculated as following;

$$J = -sum(y*log(y\_hat))$$

where "y" is a one-hot encoded vector of the true class label, "y_hat" is a vector of predicted probabilities for each class, and "log" is the natural logarithm. The sum is taken over all classes.

4.5.4 Training and Results

As explained in the earlier chapters, six different datasets were created based on different configurations of re-scale, re-size, and augmentation of the initial twenty-seven satellite images and their corresponding mask of the selected desired paths. Each dataset was trained with the segmentation model explained above, and the results were documented and compared to each other.

To train and validate the segmentation algorithm, the datasets were split into training and testing datasets with %80 and %20, respectively. Several commonly used evaluation metrics were defined to evaluate the performance of the segmentation training. The metrics are calculated based on the ground truth and predicted pixels.

pd=Predicted Pixels

gt=Ground Truth Pixels

The accuracy metric calculates the proportion of the correctly predicted pixels and all predicted pixels and is calculated as follows;

accuracy = (number of pixels where ***pd*** *is equal to* ***gt****) / (total number of pixels)*

Mean Intersection over Union (Mean IoU) calculates the overlap between each class's predicted segmentation mask and ground truth mask and is calculated as follows;

$$IoU = (gt \cap pd) / (gt \cup pd)$$

$$Mean\ IoU = (1 / N) * sum(IoU\_class1 + IoU\_class2 + ... + IoU\_classN)$$

Pixel Accuracy calculates the percentage of correctly predicted pixels and is calculated as follows;

TP = True Positive pixels are correctly predicted to the given class

TN = Trues Negative pixels are correctly identified as not belonging to the given class

FP = False Positive pixels are wrongly identified to the given class

FN = False Negative pixels are wrongly identified as not belonging to the given class

$$Pixel\ Accuracy = (TP+TN) / (TP+TN+FP+FN)$$

Frequency Weighted IoU (FWIoU) considers both IoU and the frequency for each class to calculate a balanced model evaluation.

$$FWIoU = \Sigma\_c(n\_c * IoU\_c) / \Sigma\_c n\_c$$

Where;

- *Σ_c denotes the summation over all classes*
- *n_c is the number of pixels belonging to class c in the ground truth*
- *IoU_c is the intersection over union (IoU) score for class c*

Higher values for all the evaluation metrics mentioned above indicate better-performed training. The cost function can also be an evaluation metric for the training process. However, in contrast with the other metrics, the higher cost function value indicates insufficient training.

On the other hand, higher evaluation metrics don't always correlate with a good prediction on the test dataset. The training overfitting can occur several times, meaning the model doesn't learn the pattern and just memorize the given input.

Figure 4.46 represents the six different datasets utilized to train the segmentation algorithm. The datasets with the image size of 2350x1694 pixels were too big to complete the training process. Hence, the datasets with image size 608x448 were focused on training the algorithm. As mentioned earlier, one of the most significant limitations of this research was the relatively low amount of sampling in the dataset. The not augmented datasets consist of 27 satellite images and 27 mask images; using them to train the algorithm might give unreliable results.

For this reason, the augmented datasets with the 608x448 were much more promising for getting reliable results in terms of path prediction. Another distinctive property between the datasets was the path proportions in their context. The satellite and mask images in the datasets named with the ‘xxrs’ suffix display a more balanced ratio between the annotated desired path and its background than those with the ‘30rs’ suffix. So the dataset, ' xxrs_aug,’ was expected to perform during the training process.

	pathname-30 image size 2350x1694	**pathname-30rs** image size 608x448	**pathname_xxrs** image size 608x448
no augmentation *27 satellite images* *27 annotated images*	dataset_30_noaug	dataset_30rs_noaug	**dataset_xxrs_noaug**
augmented *270 satellite images* *270 annotated images*	dataset_30_aug	**dataset_30rs_aug**	**dataset_xxrs_aug**

Figure 4.46. All the datasets used for training and the selected ones to visualize the evaluation results

Figure 4.50 shows the training results of the datasets, highlighted in pink in Figure 4.46. As predicted initially, only the training with the ‘xxrs_aug’ dataset provided the prediction images with both ‘desired path’ and ‘background’ existed. The success of the predictions was varied. Figure 4.47 show several examples from the prediction of the test data. Predictions one and two represent a respectively successful prediction compared to the ground truth mask. However, prediction three displays a path prediction; the predicted area doesn't match where the desired path would be located, which indicates a false prediction regarding the ground truth mask. Finally, prediction four displays any pixels associated with the desired path, which can be related to the dataset's insufficient amount, homogeneity, and variety.

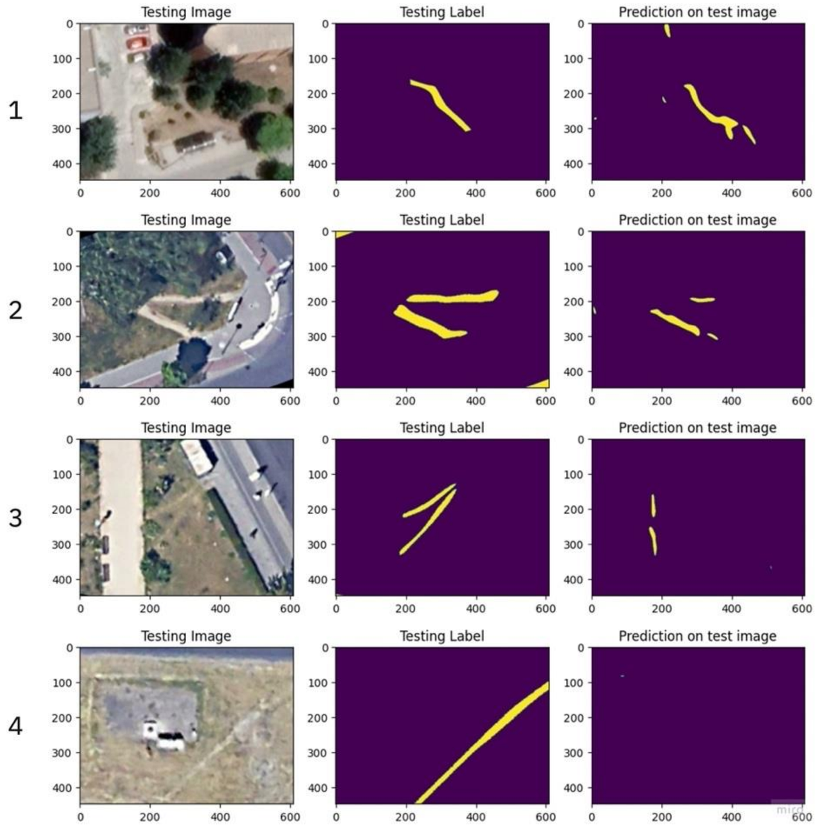


Figure 4.47. Selected prediction results from the training with dataset ‘xxrs_aug’

The training with ‘30rs_aug’ performed well based on the evaluation metrics; however, the predicted images only display the ‘background,’ not any desired path prediction. Figure 4.48 shows a selected prediction from the training with dataset ‘30rs_aug’. This dataset consists of the same amount of training and test sampling as the dataset ‘xxrs_aug. However, the proportions of the paths were smaller when compared to their background. For this reason, the training algorithm might fail to identify, learn and predict the paths regarding their given context. The high results on the evaluation metrics might be correlated with the class imbalance in the dataset. The pixels assigned as ‘background’ took a huge part compared to those assigned as ‘desired path.’ Hence the true positive and true negative pixels significantly overweight the false positive and false negative ones.

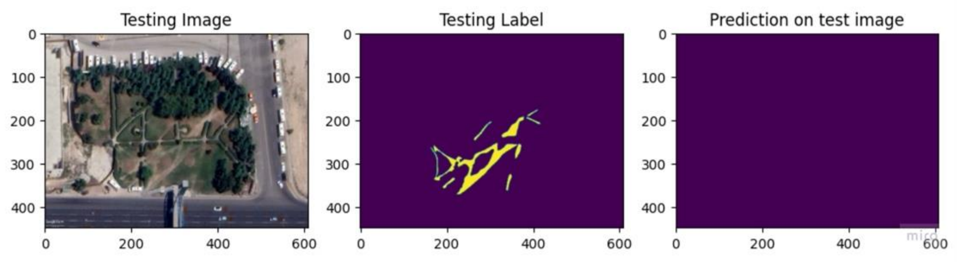


Figure 4.48. Selected prediction results from the training with dataset ‘30rs_aug’

The training with the dataset ‘xxrs_noaug’ also displayed high performance based on the evaluation metrics. However, the predictions resulted in no ‘desired path’ pixels assigned similarly to the training with the dataset ‘30rs_aug.’ This data set consists of the training and test samples with the same scale as the dataset ‘xxrs_aug’ but not the augmented. So this dataset was limited to only twenty-seven satellite and mask images which might cause overfitting during the training process.

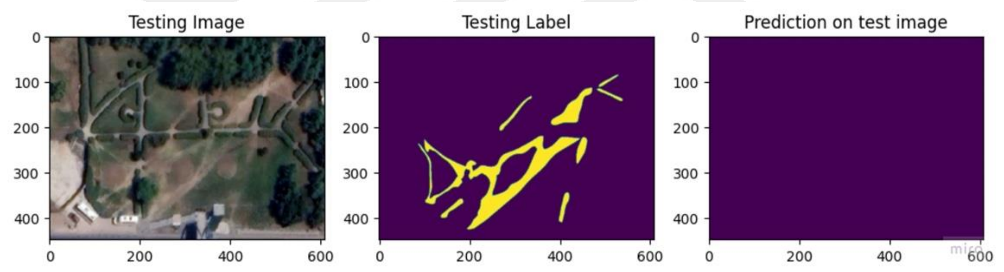


Figure 4.49. Selected prediction results from the training with dataset ‘xxrs_noaug’

After concluding the best-performing dataset as ‘xxrs_aug,’ the training process with this dataset repeated with a different cost function, categorical cross-entropy, to experiment with the algorithm and the dataset more. Figure 4.50 shows the training results of the algorithm with binary and cross-entropy functions as the cost function for the training process. However, the results of the evaluation metrics look pretty similar for both training; the predicted path formations were slightly better for the algorithm with categorical cross-entropy.

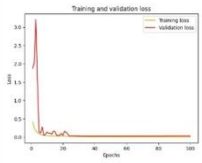
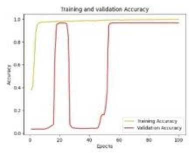
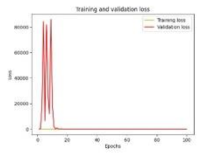
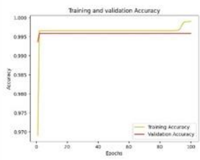
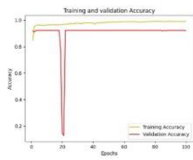
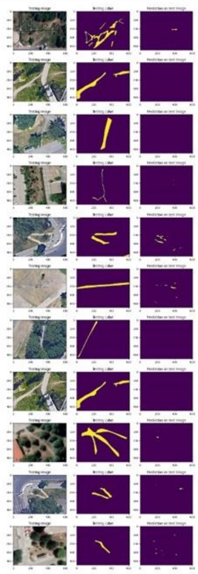
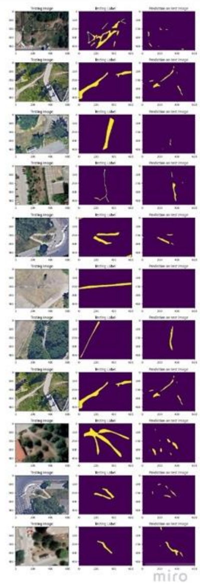
	model_Unet dataset_30rs_aug loss=binary cross entropy	model_Unet dataset_xxrs_noaug loss=binary cross entropy	model_Unet dataset_xxrs_aug loss=binary cross entropy	model_Unet dataset_xxrs_aug loss=categorical cross entropy
Loss	0,034	0,193	0,404	0,512
Accuracy	0,995	0,967	0,919	0.920
Pixel Accuracy	0,995	0,967	0,919	0,920
Mean-IoU	0,497	0,483	0,463	0,549
FW-IoU	0,991	0,935	0,850	0,860
training and validation loss				
training and validation accuracy				
Selected Predictions				

Figure 4.50. Training results of the selected datasets.

Regarding the overall comparison between the selected datasets to train the algorithm, only the 'xxrs_aug' dataset provides desired path predictions in the test dataset, which indicates the importance of the amount of sampling, homogeneity, and class proportion balance in the sampling images and masks.

In conclusion, the prediction results of the training with dataset ‘xxrs_aug’ were promising. However, the trained model is most likely incapable of predicting a random desired path formation in a given context because of the limited sampling on the training dataset. Even though the initial dataset samples increased with augmentation operations, a well-performed segmentation model still requires more variety and amount in the dataset. Therefore, it is concluded that training the same algorithm with more samples would be used to depict and predict the desired path formations in a given context.

CHAPTER 5

CONCLUSION

The physical traces of the user's design outputs can be utilized as a design feedback mechanism between the users and the designer. The stigmergic approach in the context of the desired path has been investigated during this thesis, proving that these feedback mechanisms can be utilized as a design guideline for the designers as an alternative participatory design method.

Furthermore, an ML application was intended to automate path prediction in any context. It was hypothesized that every path could be evaluated in its environment based on its stigmergic features: ' desired path,' 'designed path,' 'attractors,' and 'obstacles.' Each path emerges between the 'attractors' as an alternative to the 'designed paths.' In this context, the ML application was supposed to predict the possible desired emergence in a given context with the help of the identified stigmergic features in the environment.

Transferring the stigmergic features from abstracted visualization to the mask annotation for the segmentation model was the most challenging phase for this research. For example, most 'attractors' were represented as simple nodes in the abstracted visuals. However, the segmentation model requires a well-defined boundary for each representing class. For the scope of this research, the attractors defined, such as; car parking lots, bus stops, or building entries, have significantly different physical properties in the given satellite images. Hence, it was impossible to articulate a common physical property for the 'attractors' to annotate them for the maks images during the dataset preparation phase for ML application.

On the other hand, the physical similarity between the 'desired path' and ' designed path' in the given satellite image was the other major challenge while converting the abstracted stigmergic features visuals into the designed path class annotation to the mask image. The limited amount of sampling in the dataset might cause a miss interpretation between the designed and desired path while the algorithm assigns the class prediction.

In conclusion, because of the complexity of annotating every stigmergic feature in the mask images for the segmentation model and the limited amount in the training dataset, the ML application initially focused on only segmenting the desired paths in a given context. After several experiments with datasets, the segmentation model could generate some promising prediction results, which slightly fulfill the aim of this research and provide encouragement to investigate further the annotation conversation between the abstracted stigmergic features and annotated mask images in the segmentation dataset.

5.1 Limitations

There were several limitations while conducting the research, which were listed;

-There was no sophisticated method to map the paths in the GEP environment, highlighted in the literature, such as a machine learning algorithm that automatically detects the paths in the given context. Hence, a method formulated by the author to map the paths manually, extending the process's length.

- The paths mapped in GEP were located in different countries; hence it was difficult for the author to visit and validate the existence of each path. However, the street views in GEP were used instead of the site visit during the data validation process, which might have caused the wrongly eliminating of some of the paths that the street views were not assessable in GEP.

-One of the other negative consequences of the diverse location of the desired paths in the validated data set was observing their functioning by the users while visiting the site and interviewing the users, the designers, and the maintenance professionals to better define the stigmergic features of them.

- The terrain of the environments where the paths emerged was not taken into consideration during the environment modeling in RhinoCeros because of the data complexity. This might cause misconceptions regarding the motivation of the users.

-Only the lengths of the paths were highlighted as the quantitative features to compare them with the designed paths. However, their thickness and color differences might give more information about their use frequency by the users.

- Regarding the ML application, even with the augmentation applied to the initial dataset, the amount of sampling for the training process was insufficient to get successful predictions.

-Regarding the ML application, each stigmergic feature could not be annotated in the mask images for the segmentation model because of their various physical presence in the satellite images. The stigmergic feature visuals were created by abstracting the forms in the given satellite image. However, annotation masks require clear pixelations for each class annotation.

5.2 Future Work

Approaching desired paths with the stigmergic approach is promising for understanding the reason for the emergence and their physical formations. Also, conceptualizing the desired paths as an alternative indirect communication between the designers and the users is encouraging. Hence, a similar approach can be applied to the other design outputs if the designers can monitor, track, and document the user's physical traces.

Also, the number of paths can be increased for better predictions regarding the ML application phase. Furthermore, the timeline images for each desired path which display their emergence and changes in their physical form can be processed as a dataset to train a desired path evolution model to predict the desired path emergence in a given context.

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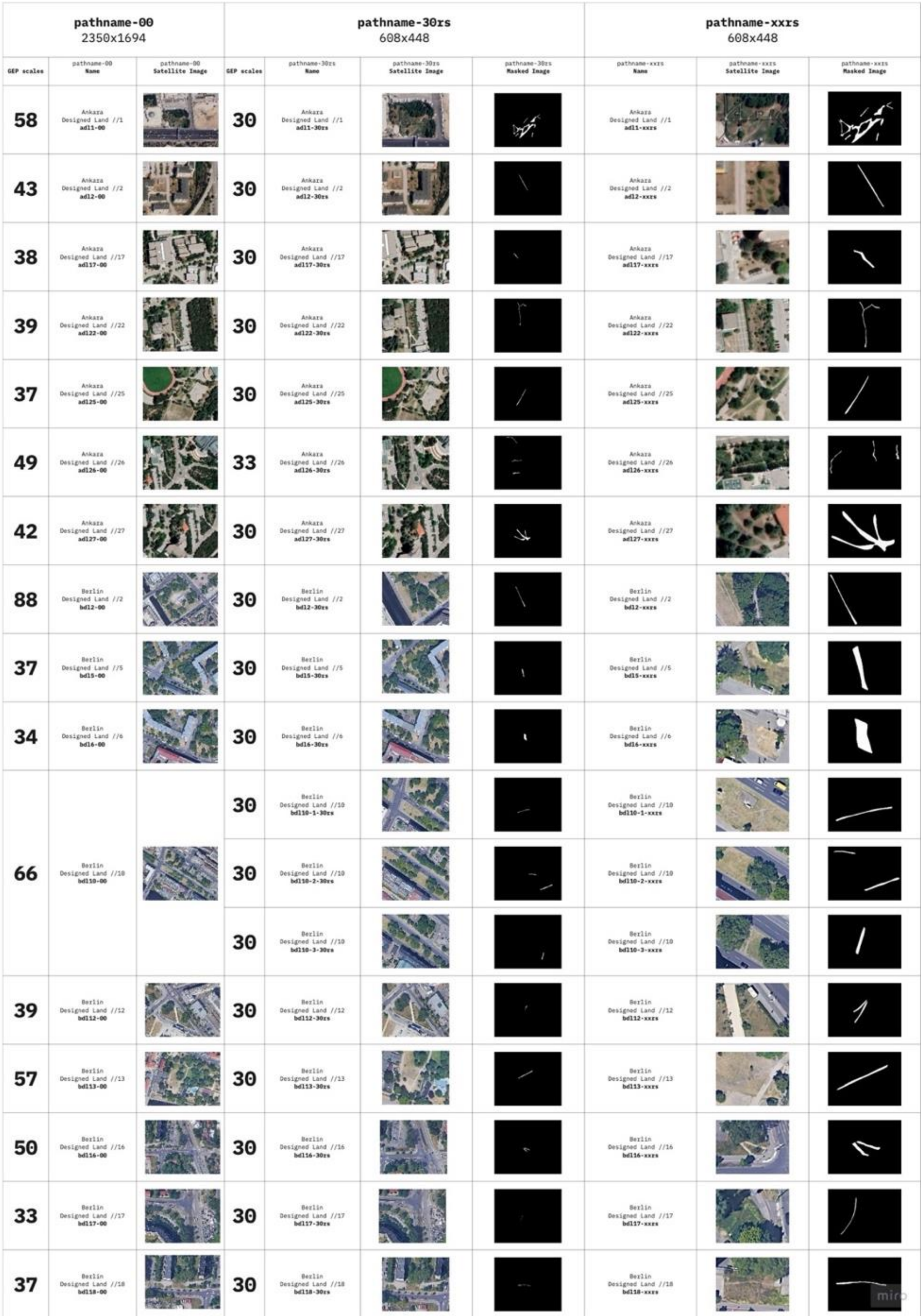
APPENDICES

A. Size and scale variation of the satellite images-1

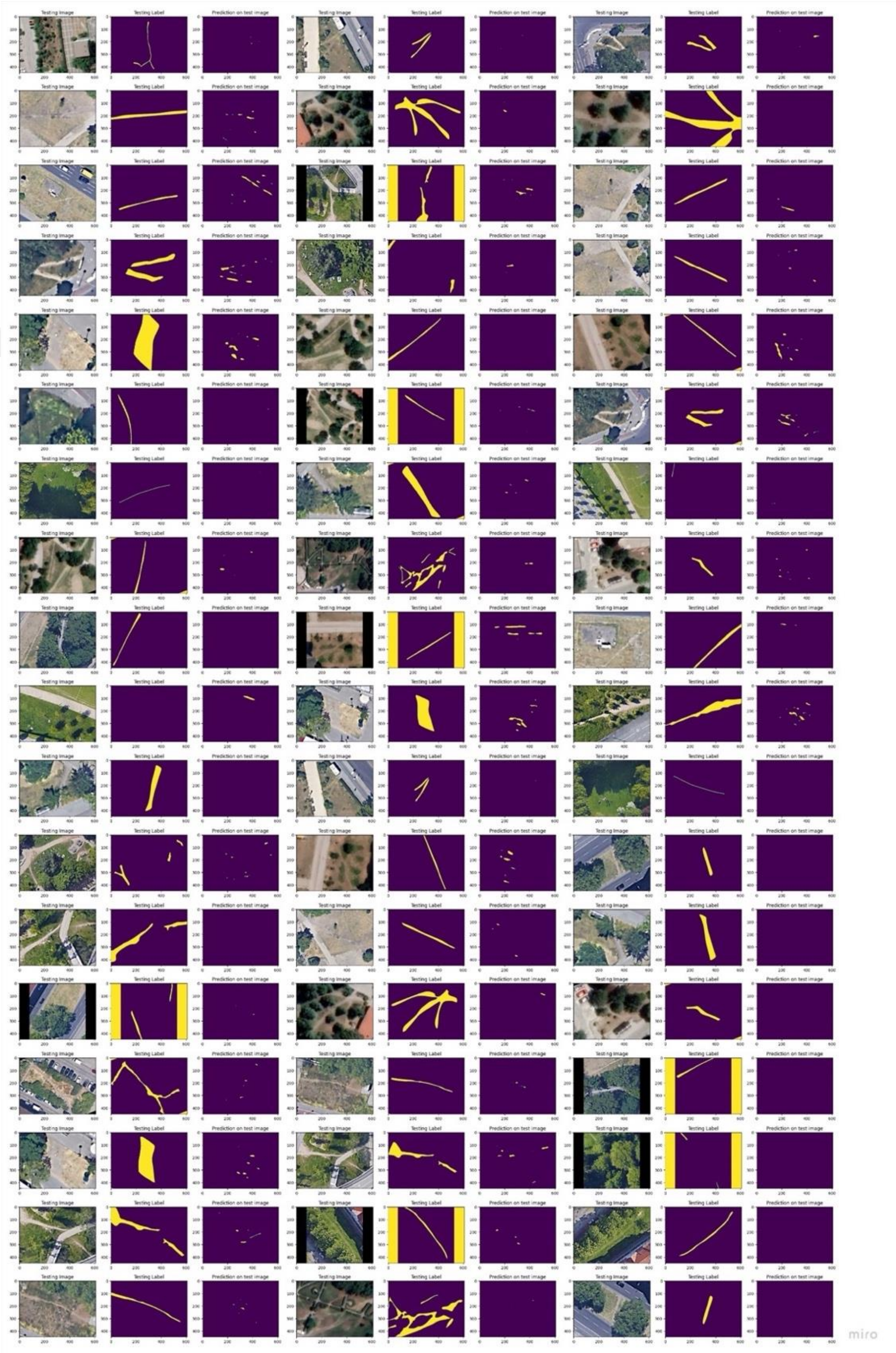


B. Size and scale variation of the satellite images-2

pathname-00 2350x1694			pathname-30rs 608x448				pathname-xxrs 608x448		
GEP scales	pathname-00 Name	pathname-00 Satellite Image	GEP scales	pathname-30rs Name	pathname-30rs Satellite Image	pathname-30rs Masked Image	pathname-xxrs Name	pathname-xxrs Satellite Image	pathname-xxrs Masked Image
37	Berlin Designed Land //21 bdl21-00		30	Berlin Designed Land //21 bdl21-30rs			Berlin Designed Land //21 bdl21-xxrs		
47	Berlin Designed Land //22 bdl22-00		30	Berlin Designed Land //22 bdl22-30rs			Berlin Designed Land //22 bdl22-xxrs		
37	Copenhagen Designed Land //1 cdl1-00		35	Copenhagen Designed Land //1 cdl1-30rs			Copenhagen Designed Land //1 cdl1-xxrs		
105	Copenhagen Designed Land //3 cdl3-00		30	Copenhagen Designed Land //3 cdl3-30rs			Copenhagen Designed Land //3 cdl3-xxrs		
74	Copenhagen Designed Land //4 cdl4-00		30	Copenhagen Designed Land //4 cdl4-30rs			Copenhagen Designed Land //4 cdl4-xxrs		
38	Copenhagen Designed Land //5 cdl5-00		30	Copenhagen Designed Land //5 cdl5-30rs			Copenhagen Designed Land //5 cdl5-xxrs		
35	Copenhagen Designed Land //7 cdl7-00		30	Copenhagen Designed Land //7 cdl7-30rs			Copenhagen Designed Land //7 cdl7-xxrs		
51	Copenhagen Designed Land //11 cdl11-00		30	Copenhagen Designed Land //11 cdl11-1-30rs			Copenhagen Designed Land //11 cdl11-1-xxrs		
			30	Copenhagen Designed Land //11 cdl11-2-30rs			Copenhagen Designed Land //11 cdl11-2-xxrs		

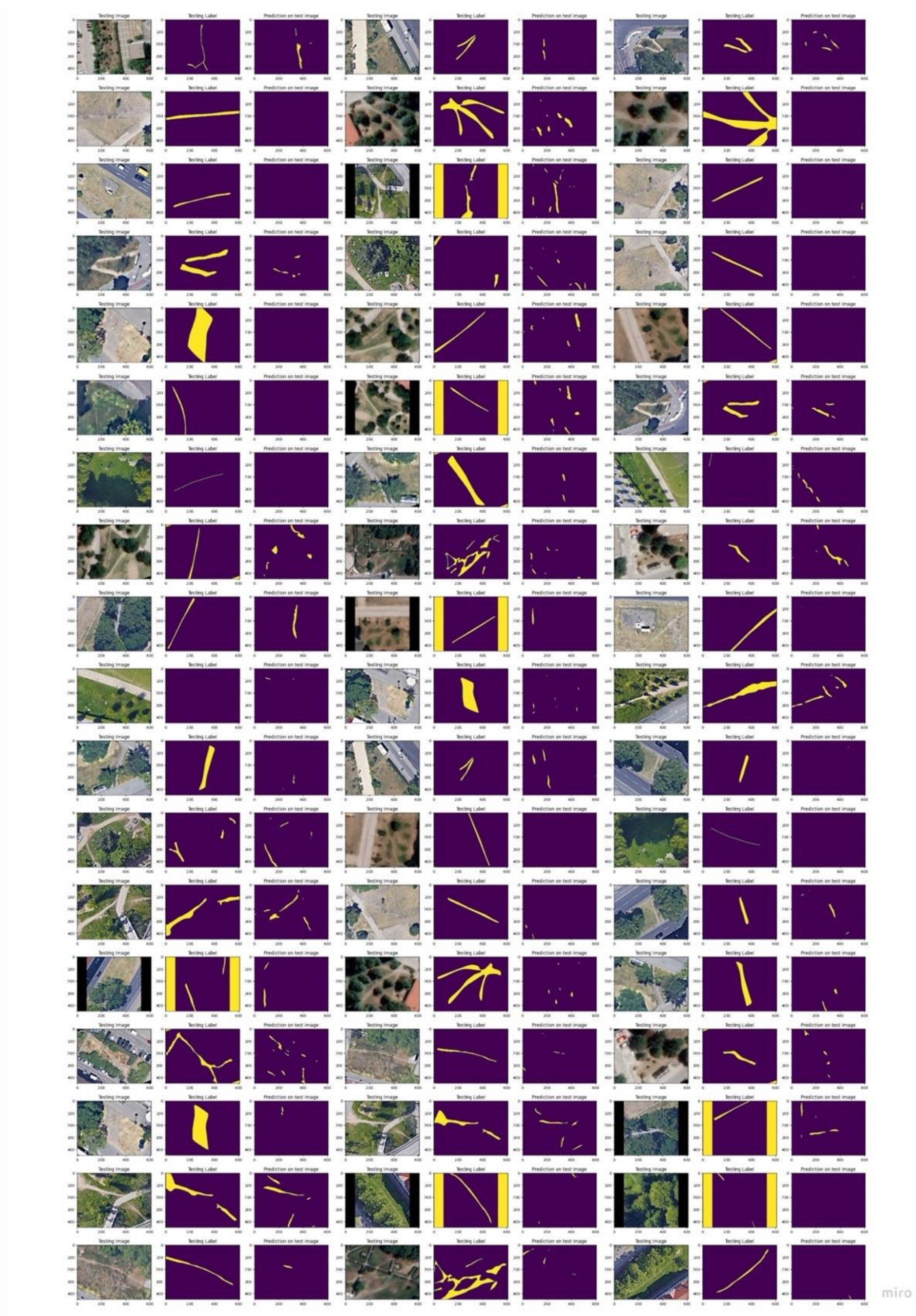
C. Segmentation model predictions-1

Xxrs-aug data set with binary-cross entropy

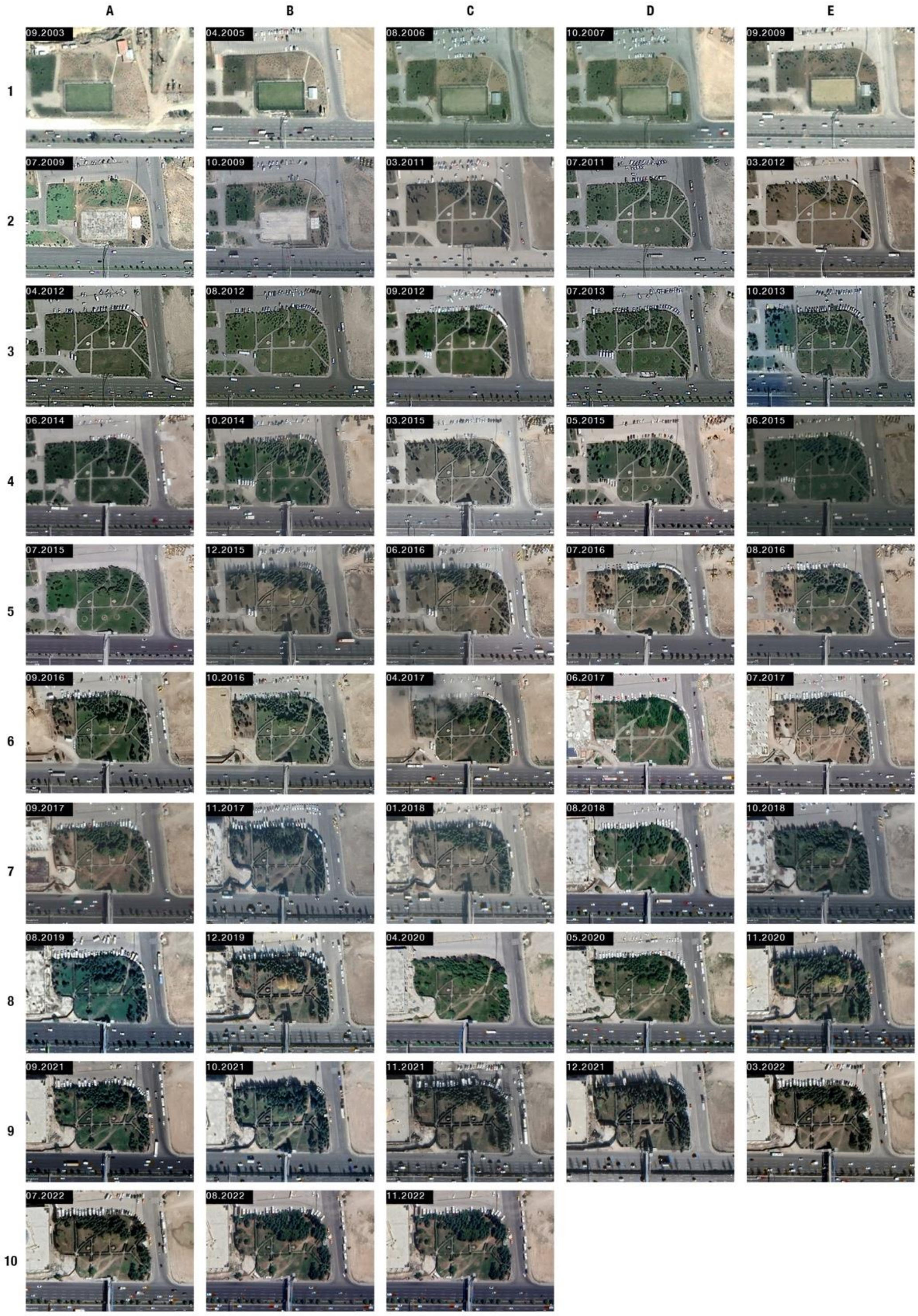


D. Segmentation model predictions-2

Xxrs-aug data set with categorical-cross entropy



E. Timeline matrix of adl-1



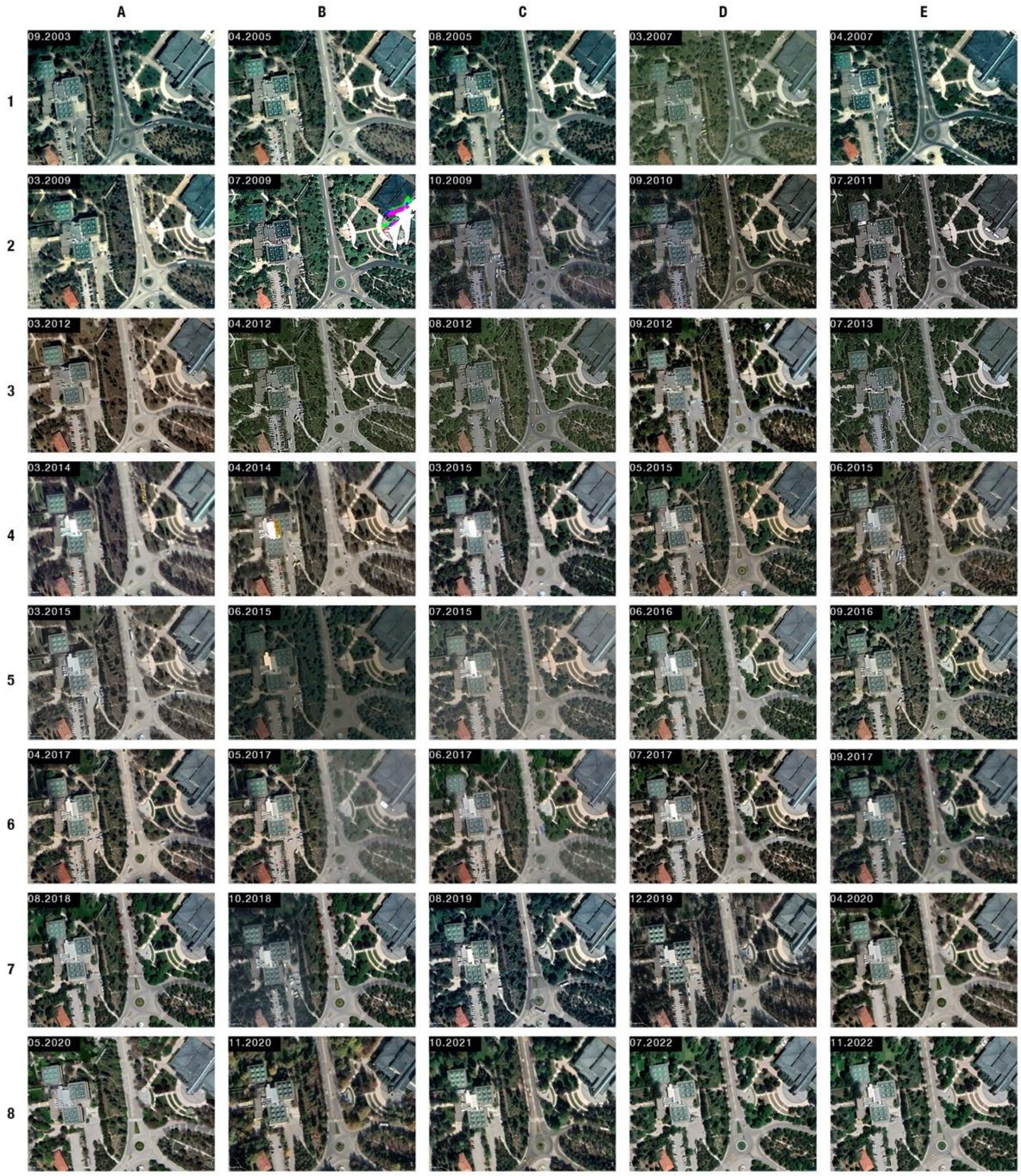
F. Timeline matrix of adl-2

G. Timeline matrix of adl-17

H. Timeline matrix of adl-22

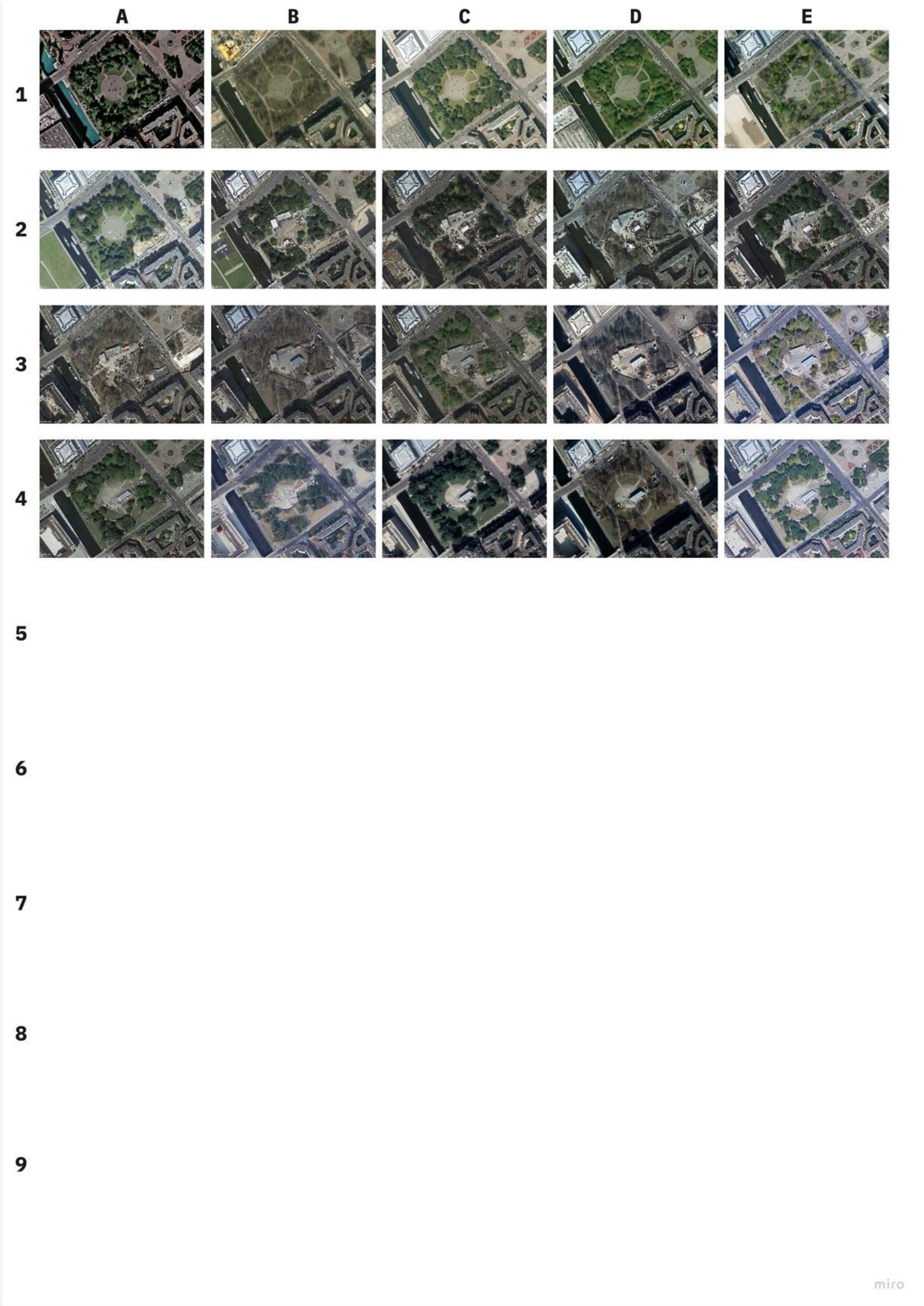
İ. Timeline matrix of adl-25

J. Timeline matrix of adl-26

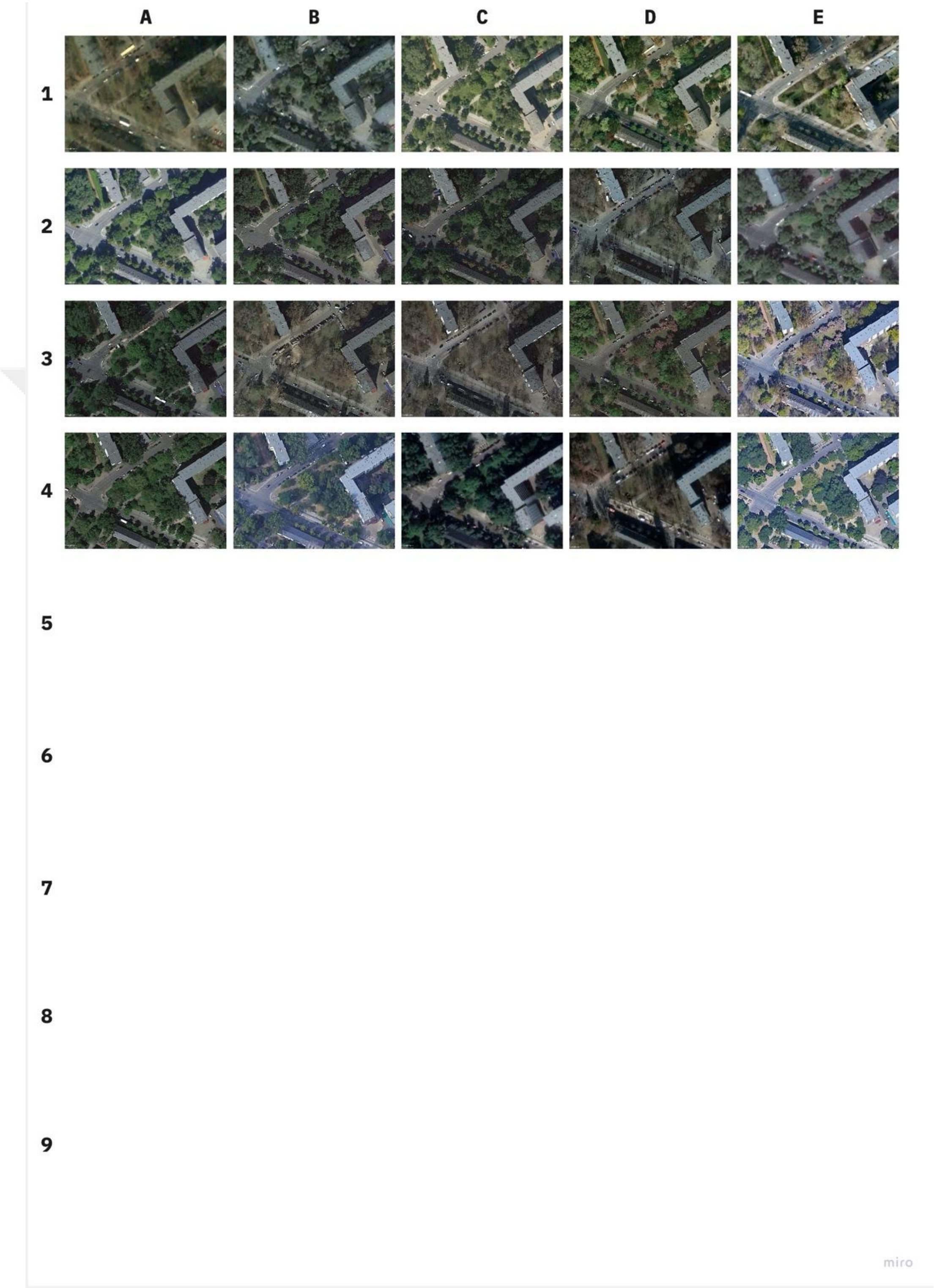


K. Timeline matrix of adl-27

L. Timeline matrix of bdl-2

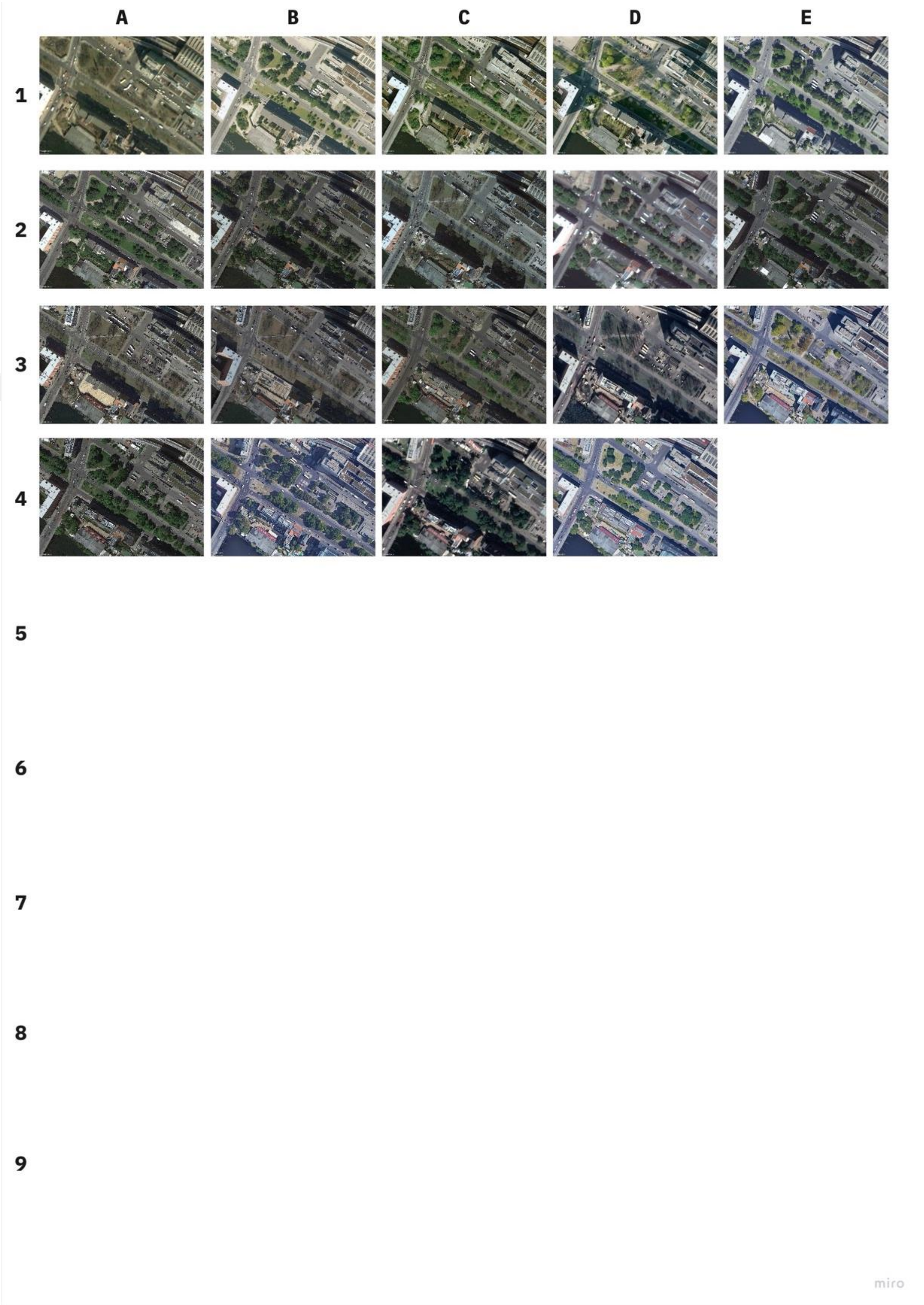


M. Timeline matrix of bdl-5

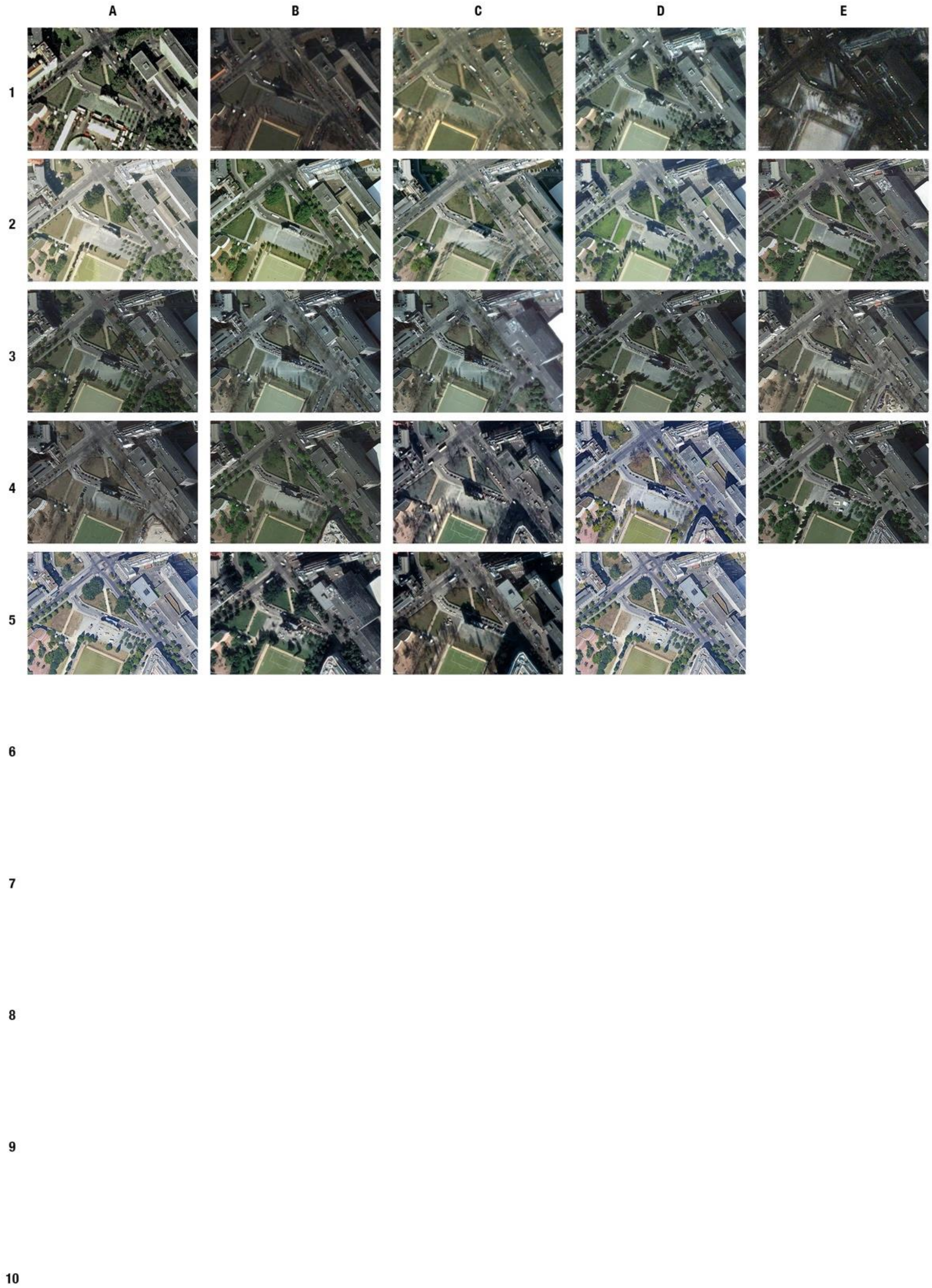


N. Timeline matrix of bdl-6

O. Timeline matrix of bdl-10

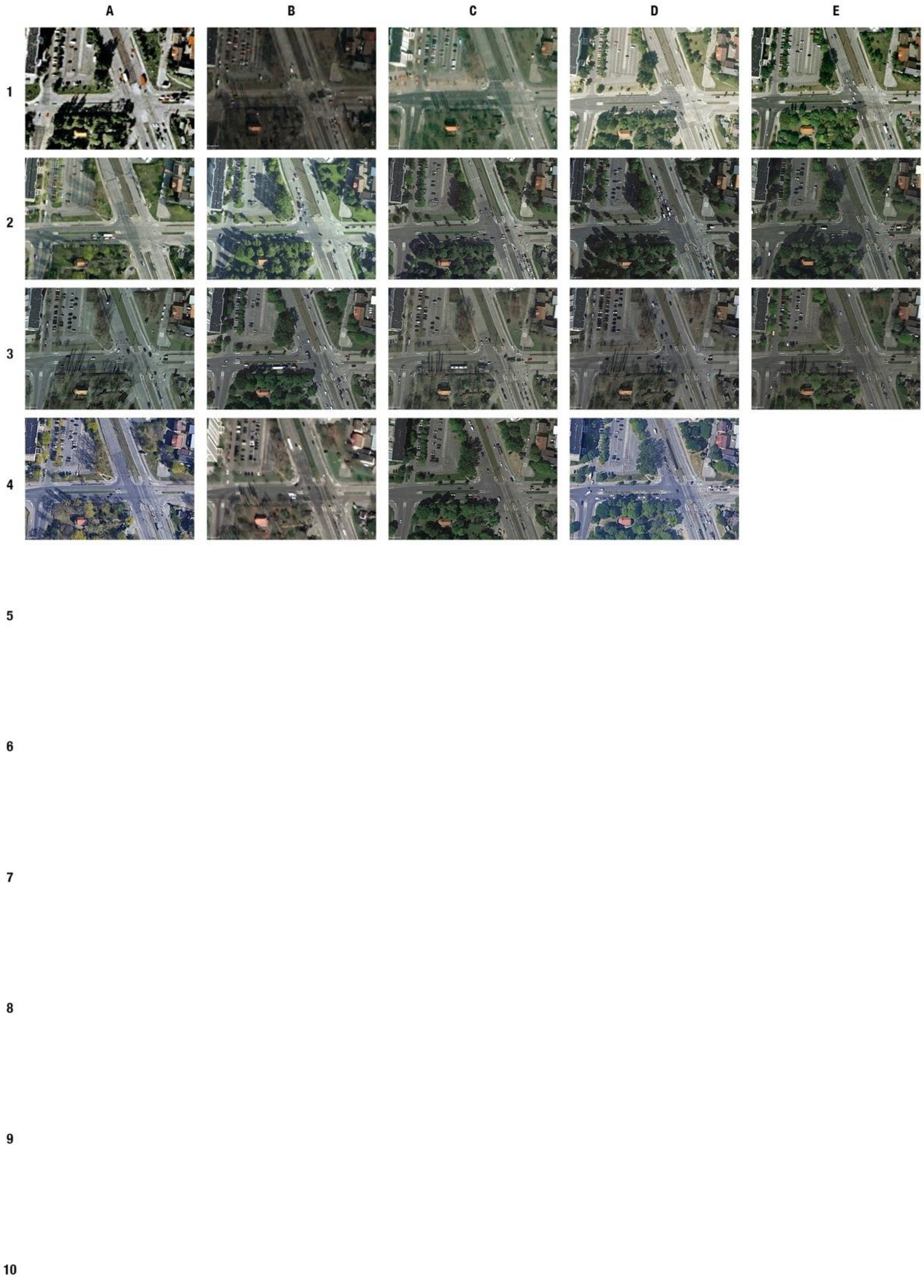


P. Timeline matrix of bdl-12

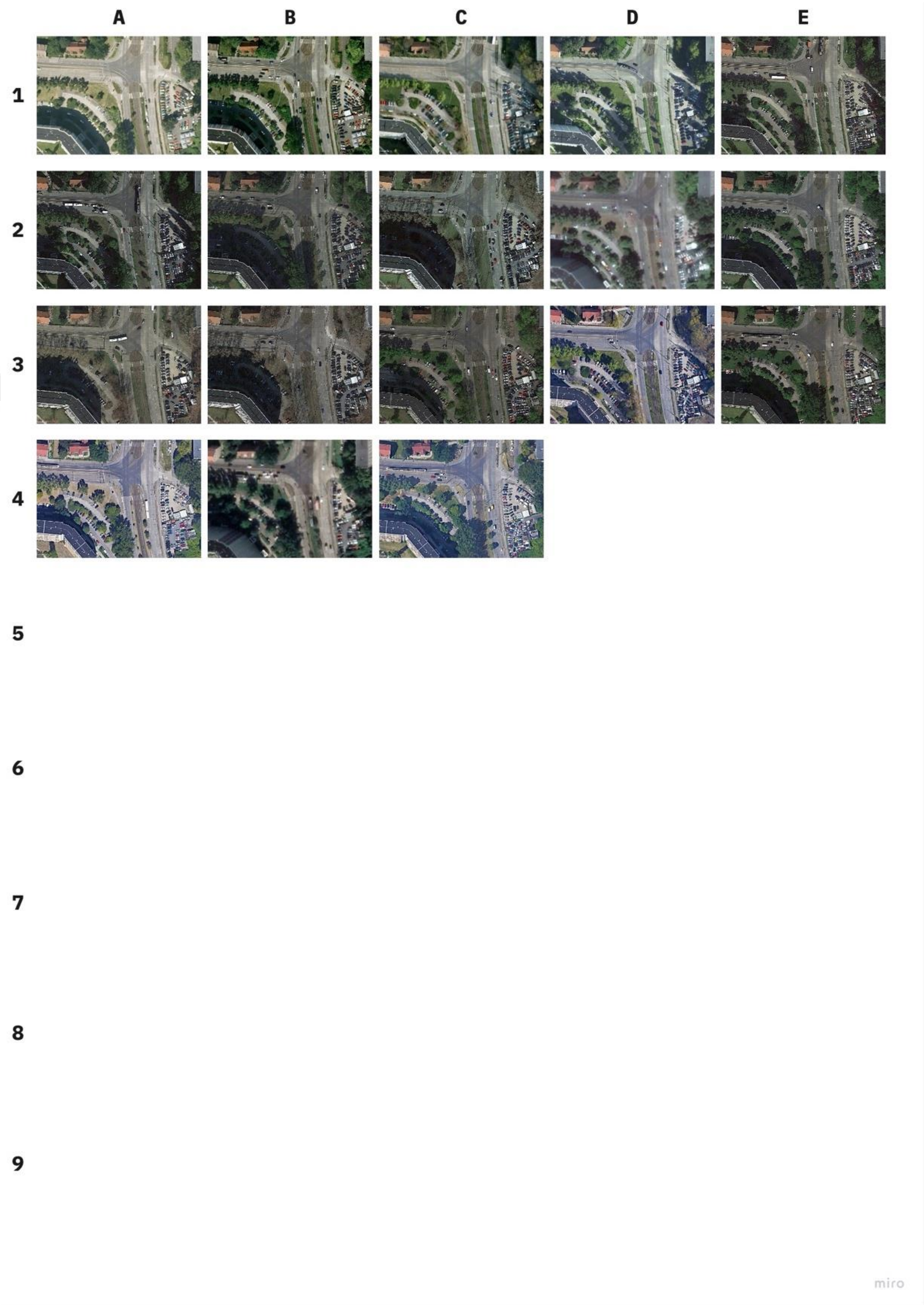


Q. Timeline matrix of bdl-13

R. Timeline matrix of bdl-16



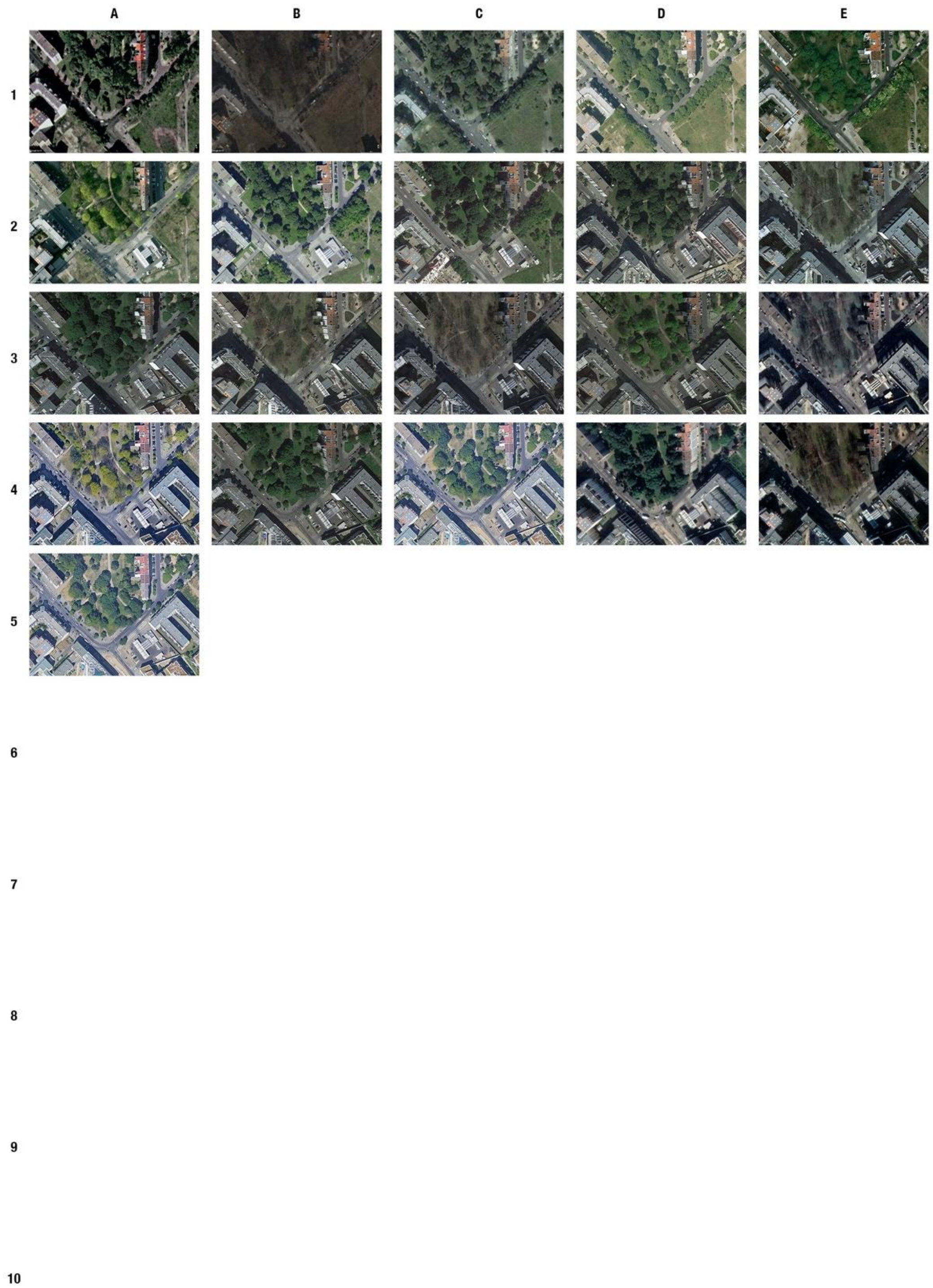
S. Timeline matrix of bdl-17



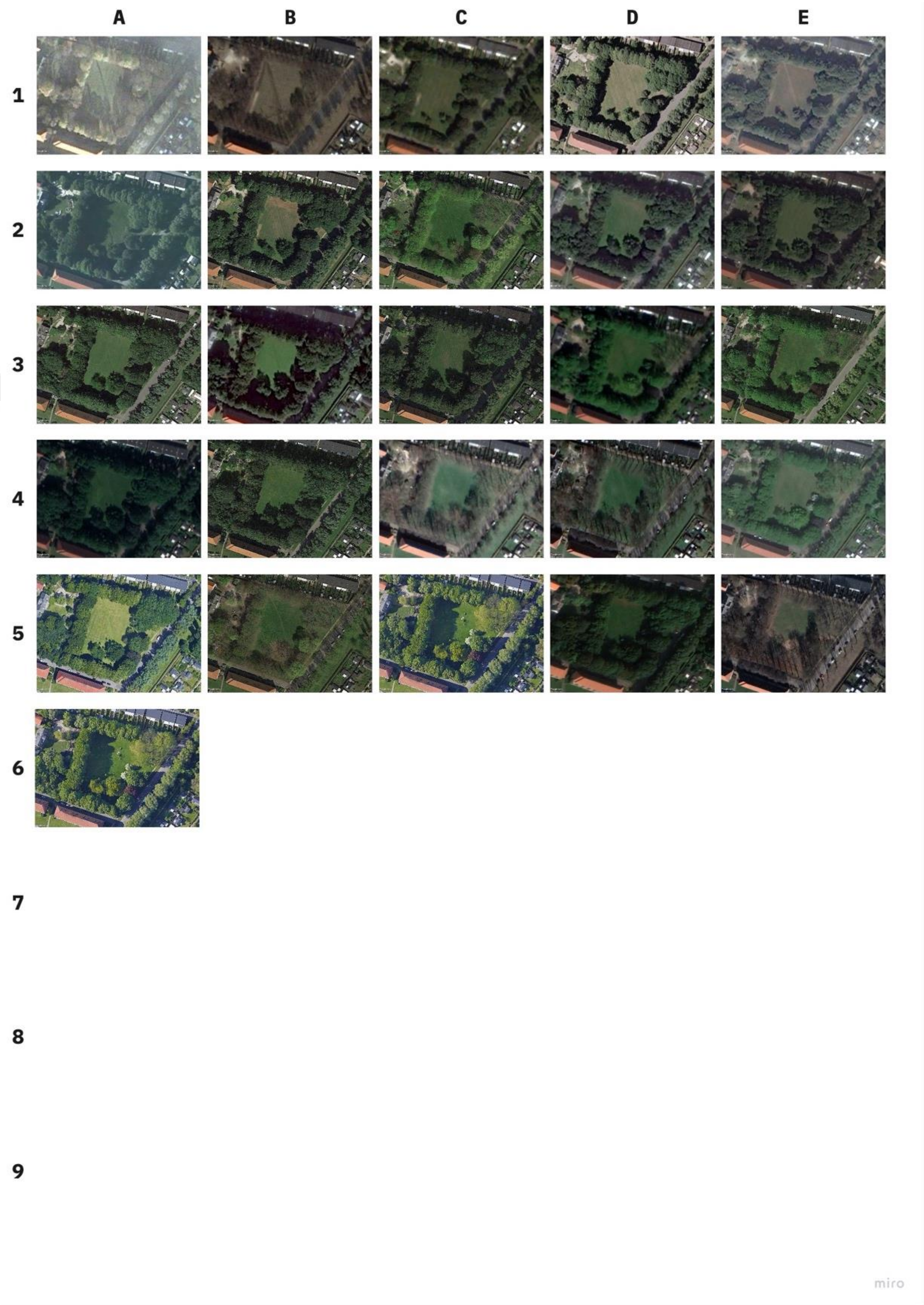
T. Timeline matrix of bdl-18

U. Timeline matrix of bdl-21

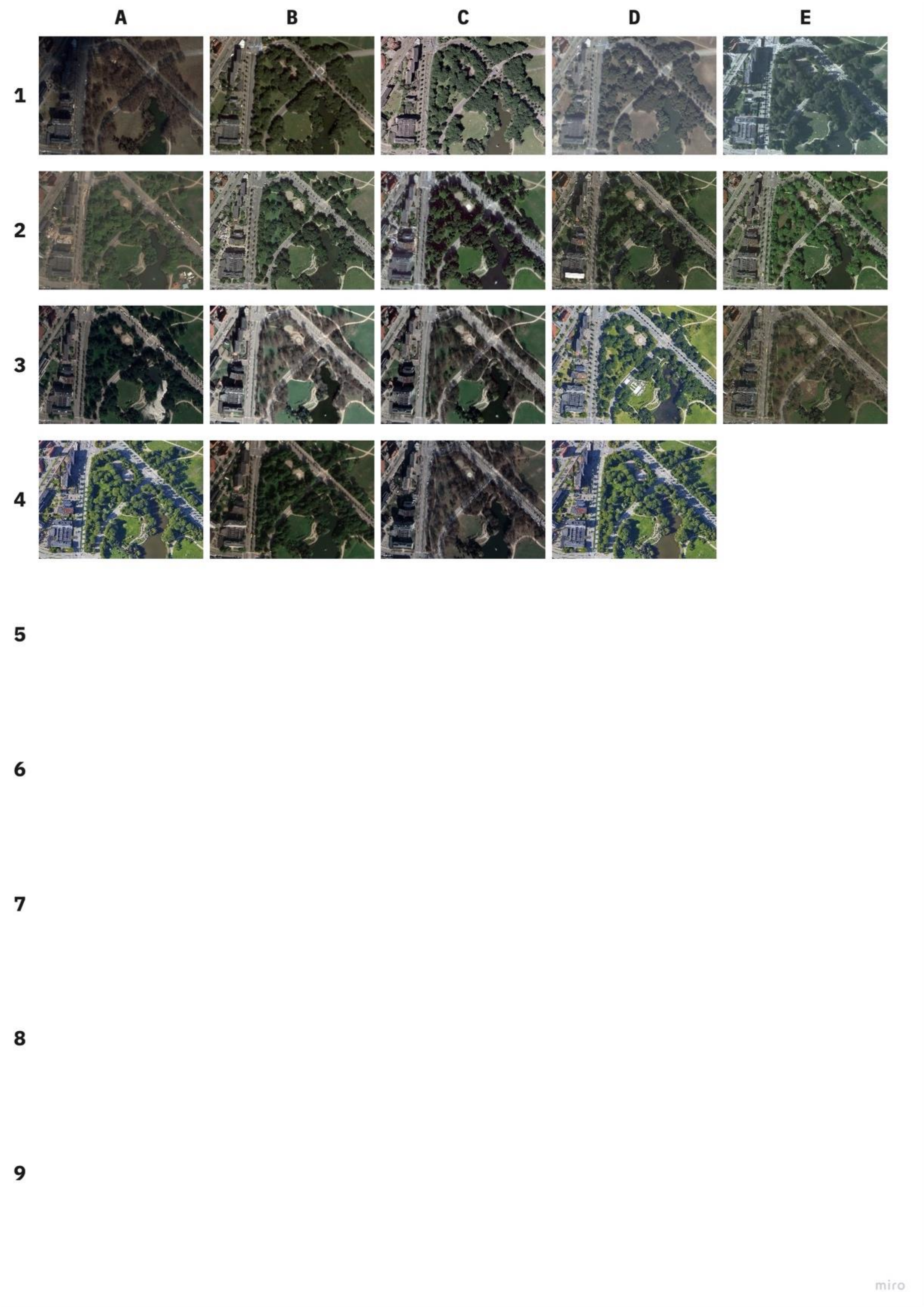
V. Timeline matrix of bdl-22



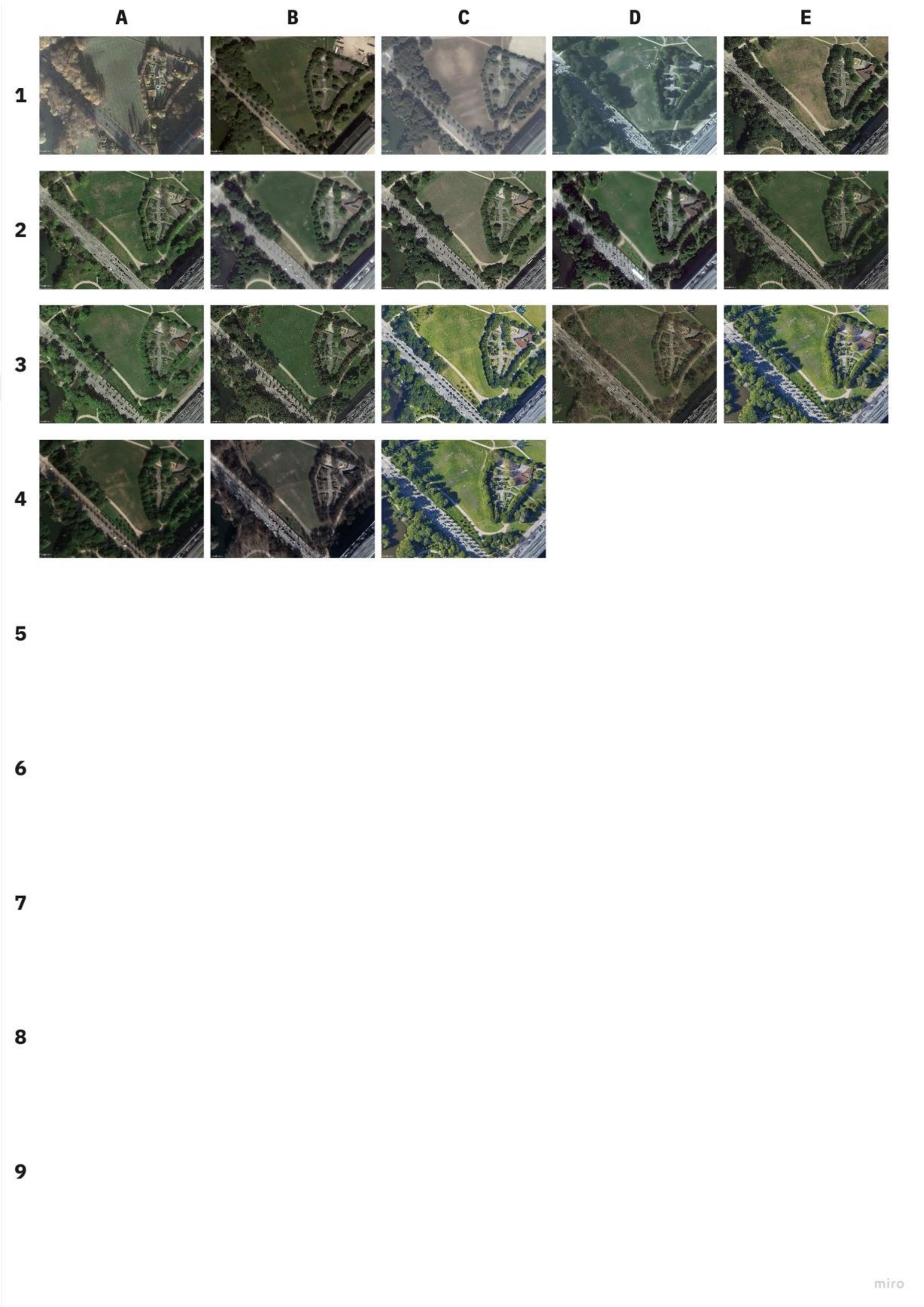
W. Timeline matrix of cdl-1



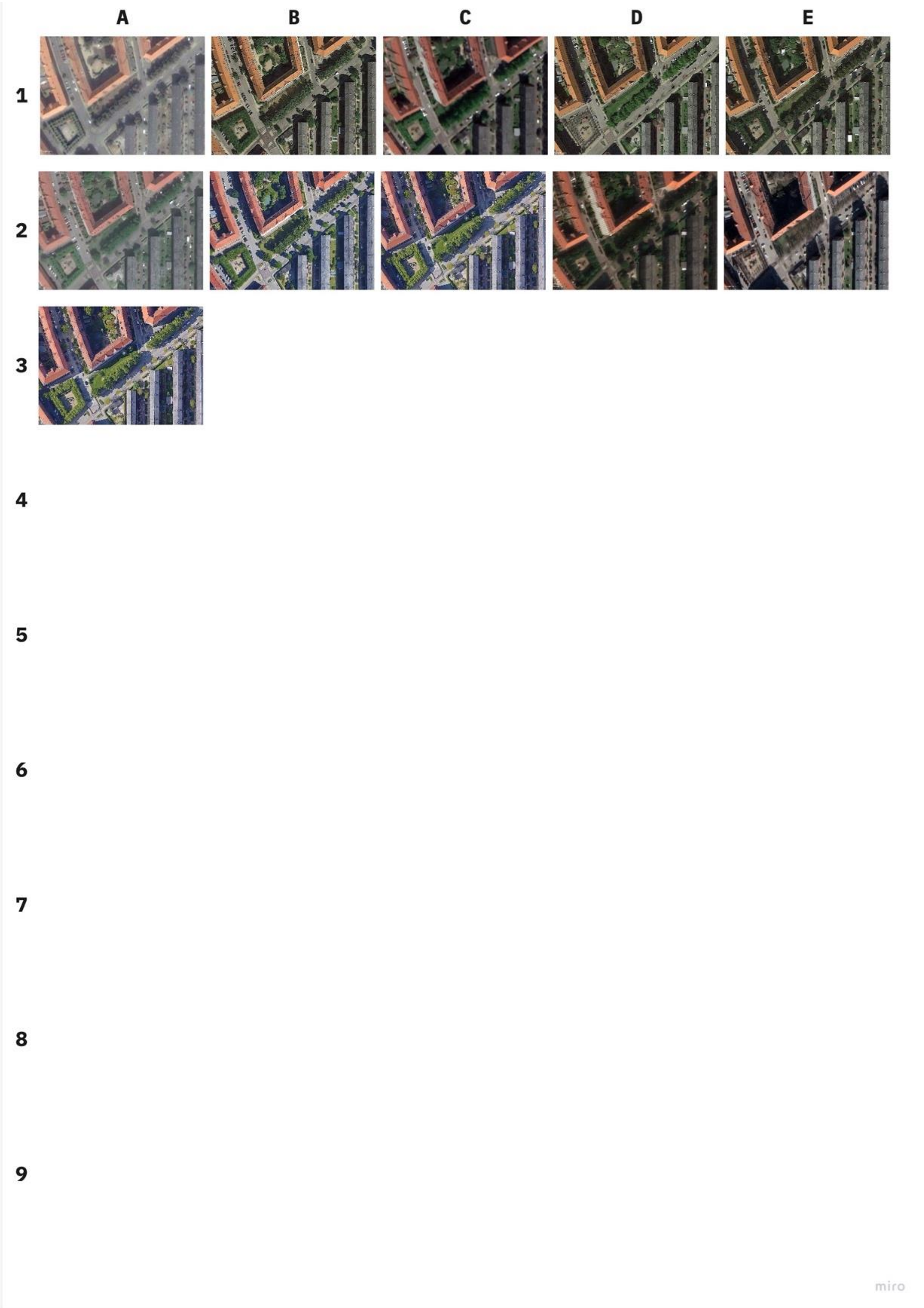
X. Timeline matrix of cdl-3



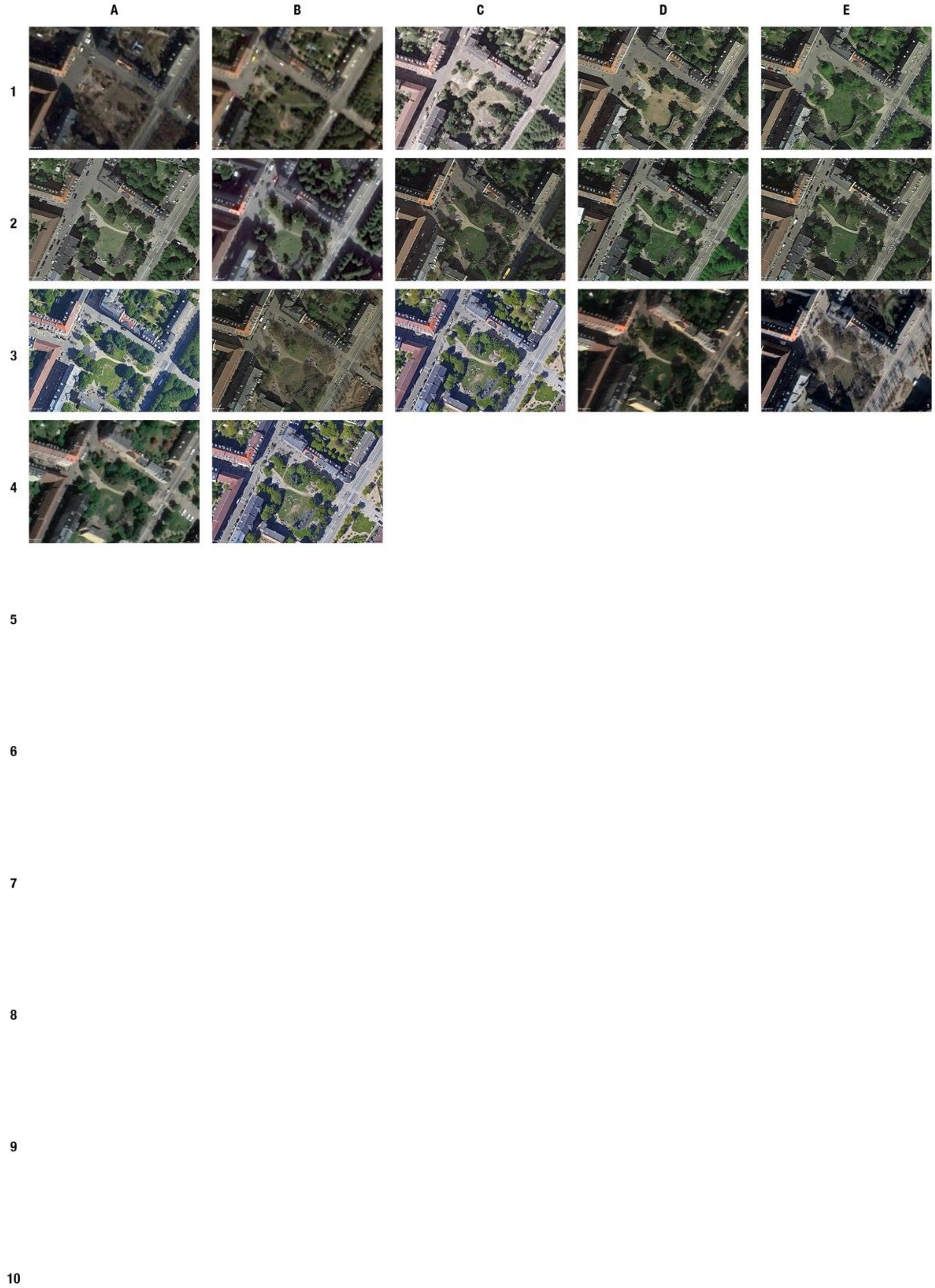
Y. Timeline matrix of cdl-4



Z. Timeline matrix of cdl-5



AA. Timeline matrix of cdl-7



BB. Timeline matrix of cdl-11