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Extending the Conversation: A Vision for Urban Accessibility for Diverse Mobilities through GeoAI

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Extending the Conversation: A Vision for Urban Accessibility for Diverse Mobilities through GeoAI

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Abstract. This paper envisions creating more inclusive communities through accessible urban places for not only those who identify as disabled but all equity-deserving groups. Concentrating on the street scale of the urban places, we propose identifying street scale accessibility features, and then, with the help of spatial data science and geospatial artificial intelligence, collecting and analyzing reliable data on these features to assess the accessibility of the urban places for movement diversity.

Keywords: Accessible Urban Place · Equity-Deserving Groups · Street-scale Accessible Features · Remote Sensing · Deep Learning

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1 Introduction: Accessibility Beyond Disability

Urban places are vital for vibrant city life since they act as mobility features and destinations. However, urban places can restrict the full participation of people with disabilities. The urban environment plays an important role, especially as we consider the social model of disability, which suggests that "disability is an experience of discrimination resulting from inaccessible built environments" [1]. The way the urban environment is planned, designed, and managed determines who is, and is not, welcome in urban spaces.

Research on accessible built environments for people with disabilities within the spatial data science literature has largely focused on sidewalk assessment and improvement [2–5]. The number of studies employing (semi)automated data-driven methods for sidewalk assessment is also growing [6–10]. This research area is in its infancy. Further research from spatial data scientists is required to make our cities more accessible. In this regard, urban accessibility for disabilities and the need for new data collection and analysis techniques were addressed in SDSS 2021 in the session "The Future of Global-Scale Spatial Data Collection and Analyses on Urban (in)Accessibility for People with Disabilities" [11]. Here, panelists mainly addressed the latest methods for measuring sidewalks' quality, condition, and accessibility, focusing on people with disabilities.

Building on this critical work, we aim to create more inclusive urban environments by extending the conversation to include the diverse mobility needs of equity-deserving groups (EDGs): those with differing and intersectional physical abilities and identities, including women, LGBTQ+, seniors, children, and neurodiverse. Our goal is to envision urban places that enable the full participation of all members of society. In this paper, we discuss accessible urban places at the street scale and then explore opportunities for geospatial artificial intelligence (GeoAI) to fill the data gaps. We conclude that expanding interdisciplinary discourses is a vital step to more accessible communities that accept and support diversity.

2 Accessible Urban Places at Street Scale

Social inclusion and diversity are becoming a growing interest among urban policymakers and researchers [12–15]. Accessible space for EDGs can be understood as "a public space for all," where everyone "feels welcomed, included, and not discriminated against by their gender, age, sexuality, race, ethnicity, religion, cultural background, socioeconomic status, and personal values when being in the space" [16].

In addition to physical features in space, places encompass human experience and interpretation [17] and what distinguishes a place from other spaces is its meaning. According to Healey [18] place is about the meaning people give to their surroundings and their capacity to influence people's feelings, a process that results in creating the sense of place. For a sense of place to be created, "there is a need for a long and deep experience of a place, and preferably involvement in the place" [19]. The users need not only reach a place, the common understanding of accessibility, but be welcome to spend time in that place. This extends the meaning of urban accessibility; a place could be accessible when it is not only reachable but also usable in all its features: accessible sidewalks to be used to reach the place, accessible benches to be used to sit on, accessible light posts to be used to feel safe at dark hours, accessible landmarks to be used to refer to, among many other accessibility features.

In this study, an important factor in identifying place accessibility features is the scale of inquiry. In multi-scalar mobility research, Sheller [20] identifies five scales of mobility justice concerns: body, street, urban, national, and planetary scales. Focusing on urban places in this study, we are most concerned with the street scale. At the street scale, such as urban streets, squares, and parks, we interact closely with the urban environment during our everyday life, and our feelings are affected by urban places' welcoming or unwelcoming features.

We believe that the physical accessibility of urban places at the street scale could be improved by representing, modeling, and simulating street-scale accessible features, as the physical elements at the street scale that make the urban places reachable and usable for all. Specifically, data collection on these features for analyzing, mapping, and measuring is necessary for the assessment of urban place accessibility conditions. However, we lack complete data on street-scale accessible features and too often use roads as a proxy for these types of analysis [10]. The biggest challenge we see moving forward to assessing and improving the accessibility of urban places is filling in these data gaps.

3 Opportunities for GeoAI to Fill Data Gaps

The difficulty in collecting reliable data on street-scale accessible features with sufficient resolution remains the main challenge. In traditional accessibility mapping, data collection and analysis on the built environment are conducted via in-person street audits and manual data processing [2]. These methods have been proven to be labor-intensive, costly, and error-prone, especially for larger urban areas of investigation. A growing state-of-the-art approach toward accessibility mapping is the (semi)automated data-driven approach. Studies in (semi)automated approach, what we are most interested in, have relied on crowdsourcing data contributed through platforms like designed mobile apps [3, 5, 21], Google Street View data (e.g., Project Sidewalk [22]), and corresponding digital map visualizations (e.g., Wheelmap.org [23]).

Since the focus of this study is on the accessibility of urban places at the street scale, the data types employed in the studies above do not provide the necessary details. The platforms used in these studies largely rely on online digital maps like Google Maps and OpenStreetMaps [24], which despite their significant progress, still lack complete details of street-scale features. High-resolution remotely sensed data seem to be an appropriate choice. Some studies have employed aerial imagery to extract sidewalks, their condition or material using AI capabilities [6, 25, 26]. However, street-scale features are likely to be blocked by overhead obstacles like building shadows and trees. These features are best identified from an on-ground pedestrian point of view. However, Google Street View images, which are from an on-ground perspective, miss spaces between road networks such as urban parks and squares.

For our study purpose, a promising data source is ground-based mobile LiDAR (Light Detection and Ranging) data. LiDAR scanners can quickly collect 3D information by producing dense, unorganized points that require further processing to identify ground features [27]. Compared with imagery, LiDAR data offers positional information, 3D information, and scaled models of the objects [28] which is more appropriate for mapping and measuring the identified features. However, with LiDAR scanners, it is not always possible to fully capture the object in question due to the occlusion of target objects [28]. This restriction is magnified in aerial LiDAR systems for collecting data on street-scale accessible features that might be occluded by overhead obstacles. Instead, mobile LiDAR systems "provide the possibility of acquiring data in a complex environment in high detail" [29]. In this study, hence, we will use mobile LiDAR scanners integrated into smartphones, like iPhones 12 and 13 Pro [30], for their capabilities to collect ground-based points of view as well as scalable data.

LiDAR data contains less semantic information, compared with imagery [28]. However, deep learning, as a type of machine learning and a subfield of artificial intelligence (AI), allows the extraction of semantic information from LiDAR point clouds. Four main deep learning techniques to work with point clouds are object classification, parts segmentation, object detection, and semantic segmentation [31]. Semantic segmentation technique seems more relevant to our research goal and has been applied in different studies at scales comparable to this study [32–34]. Semantic segmentation is "the process of classifying point clouds into multiple homogeneous regions and the points in the same region will have the same properties" [35]. Using semantic segmentation models, each point of the LiDAR data can be assigned to a street-scale accessible feature class.

Given that we approach this work as urban design and traditional GIS experts, rather than programmers or computer scientists, we will utilize the ESRI platform that makes available a range of deep learning [36] and automation tools [37] that were previously unavailable to us. ArcGIS API for Python, including the arcgis.learn module [36], allows training semantic segmentation models to detect and classify street-scale accessible features from LiDAR data. Though the ESRI platforms have limited deep learning models for working with point clouds, they provide a rich environment to integrate the LiDAR data with other data types (like OpenStreetMaps), detect, classify and map street-scale accessible features, and store, manage, and present the data in various forms.

4 Conclusion: Continuing the Conversation

This paper puts forward a vision for urban environments that are inclusive of all EDG members by creating places that are accessible in all their physical features. We emphasize the significance of the street scale of these places for diverse mobilities and explore the combination of on-ground mobile LiDAR data and ESRI's AI capabilities to detect the features from the LiDAR data for further processing.

As we begin to experiment with our approach, we acknowledge that there might be limitations in employing GeoAI for creating accessible urban places. For instance, LiDAR's irregular and unstructured nature, as well as slow data collection, inconsistent positional accuracy, and shorter range of smartphones LiDAR scanners are some restrictions. On the other side, LiDAR's positional and 3D information and ability to penetrate areas blocked by shade or vegetation make it promising data here. Also, the smartphone LiDAR scanners, as novel, cost-effective alternatives, provide the opportunity for generating scalable data for future crowdsourcing purposes.

Here we tried to extend the accessible mapping conversation from SDSS 2021 to include our urban design perspective. This is not the end of the conversation. The future of accessible cities demands more constructive dialogues between experts from both academia and industry with diverse points of view. As society is diverse and as barriers to accessibility are multifaceted, we strongly believe that expanding multidisciplinary conversations is the key to more inclusive accessible communities.

References

1. Hamraie, A.: Universal Design and the Problem of 'Post-Disability' Ideology. Design and Culture **8**(3), 285–309 (2016)
2. Hayat, S., Fast, V.: Classifying and Mapping Accessible Mobility on Post-Secondary Campuses. Spatial Knowledge and Information Canada **7**(5),3 (2019)
3. Cardonha, C., Gallo, D.,Avegliano, P., Herrmann, R., Koch, F., Borger, S.: A crowdsourcing platform for the construction of accessibility maps. Proceedings of the 10th International Cross-Disciplinary Conference on Web Accessibility - W4A '13 ,1–4 (2013) https://doi.org/10.1145/2461121.2461129
4. Matthews, H., Beale, L.,Picton, P., Briggs, D.: Modelling Access with GIS in Urban Systems (MAGUS): capturing the experiences of wheelchair users.Area **35**(1), 34–45 (2003)
5. Hamraie, A.: Mapping access: Digital humanities, disability justice, and sociospatial practice. American Quarterly **70**(3), 455–482 (2018)
6. Hosseini, M., Saugstad, M., Miranda, F., Sevtsuk, A., Silva, C., Froehlich, J.: Towards Global-Scale Crowd+ AI Techniques to Map and Assess Sidewalks for People with Disabilities. arXiv preprint arXiv:2206.13677 (2022)
7. Hara, K., Le, V., Sun, J., Jacobs, D., Froehlich, J.:Exploring early solutions for automatically identifying inaccessible sidewalks in the physical world using google street view. Human Computer Interaction Consortium (2013)
8. Luaces, MR., Fisteus, JA., Sánchez-Fernández, L., Munoz-Organero, M., Balado, J., Díaz-Vilariño, L., Lorenzo, H.: Accessible routes integrating data from multiple sources.ISPRS International Journal of Geo-Information **10**(1), 7 (2020)
9. Hou, Q., Ai, C.: A network-level sidewalk inventory method using mobile LiDAR and deep learning.Transportation research part C: emerging technologies **119**, 102772 (2020)
10. Fast, V,. Guo, J.: Putting Pedestrians First: Sidewalk Infrastructures, Width Patterns and COVID–19. GI Forum 2021 **9**, 242–250 (2021)
11. Froehlich, J., Saugstad, M., Mooney, SJ., Caspi, A., Feldner, H., Sharif, A., Saha, M., Shen, Q., Eisenberg, Y., Labbé, D., Hammel, J.: The Future of Urban Accessibility for People with Disabilities: Data Collection, Analytics, Policy, and Tools.Spatial Data Science Symposium 2021 (2021)
12. Burton, E., Mitchell, L.: Inclusive urban design: Streets for life. 1st edn. routledge, London (2006)
13. Irazábal, C., Huerta, C.: Intersectionality and planning at the margins: LGBTQ youth of color in New York. Gender, Place and Culture **23**(5), 714–732 (2016)
14. Lui, CW., Everingham, J., Warburton, J., Cuthill, M., Bartlett, H.: What makes a community age-friendly: A review of international literature. Australasian journal on ageing **28**(3), 116–121 (2009)
15. Kern, L.: Feminist city: claiming space in a man-made world. 1st edn. Verso Books, Location (2021)
16. Zhou, S.: Understanding 'Inclusiveness' in Public Space: Learning from Existing Approaches. Greenest City Scholar Project, Vancouver (2019)
17. Falahatkar, H., Aminzadeh, B.: The sense of place and its influence on place branding: a case study of Sanandaj natural landscape in Iran. Landscape Research **45**(1), 123–136 (2018)
18. Healey, P.: Making better places: The planning project in the twenty-first century. Bloomsbury Publishing (2017)

19. Shamai, S,. Ilatov, Z.: Measuring sense of place: Methodological aspects.Tijdschrift voor economische en sociale geografie **96**(5), 467–476 (2005)
20. Sheller, M.: Mobility justice: The politics of movement in an age of extremes. 1st edn. Verso Books (2018)
21. Zimmermann-Janschitz, S.: The application of geographic information systems to support wayfinding for people with visual impairments or blindness. In Visual Impairment and Blindness-What We Know and What We Have to Knowe. IntechOpen 301–322 (2019)
22. Saha, M., Saugstad, M., Maddali, HT., Zeng, A., Holland, R., Bower, S., Dash, A., Chen, S., Li, A., Hara, K., Froehlich, J.: Project sidewalk: A web-based crowdsourcing tool for collecting sidewalk accessibility data at scale.Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems 1–14 (2019) https://doi.org/10.1145/3290605.3300292
23. Mobasheri, A., Deister, J., Dieterich, H.:Wheelmap: the wheelchair accessibility crowdsourcing platform. Open Geospatial Data, Software and Standards **2**(1), 1–7 (2017)
24. Froehlich, JE., Brock, AM., Caspi, A., Guerreiro, J., Hara, K., Kirkham, R., Schöning, J., Tannert, B.:Grand challenges in accessible maps.interactions **26**(2), 78–81 (2019)
25. Ning, H., Ye, X., Chen, Z., Liu, T., Cao, T.: Sidewalk Extraction Using Aerial and Street View Images. Environment and Planning B: Urban Analytics and City Science **49**(1), 7–22 (2022)
26. Luo, J., Wu, G., Wei, Z., Boriboonsomsin, K., Barth, M.: Developing an aerial-image-based approach for creating digital sidewalk inventories. Transportation research record **2673**(8), 499–507 (2019)
27. Wandinger, U.: Introduction to lidar. In Lidar 1–18. Springer (2005)
28. Habib, AF., Ghanma, MS., Tait, M.: Integration of LIDAR and photogrammetry for close range applications. International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences **35**(B5), 1045–1050 (2004)
29. Zhu, L., Hyyppa, J.: The use of airborne and mobile laser scanning for modeling railway environments in 3D. Remote Sensing **6**(4), 3075–3100 (2014)
30. Luetzenburg, G., Kroon, A., Bjørk, AA.: Evaluation of the Apple iPhone 12 Pro LiDAR for an Application in Geosciences. Scientific Reports **11**(1), 1–9 (2021)
31. Bello, SA., Yu, S., Wang, C., Adam, JM., Li, J.: The Hessigheim 3D (H3D) benchmark on semantic segmentation of high-resolution 3D point clouds and textured meshes from UAV LiDAR and Multi-View-Stereo. ISPRS Open Journal of Photogrammetry and Remote Sensing **1**, 100001 (2021)
32. Kölle, M., Laupheimer, D., Schmohl, S., Haala, N., Rottensteiner, F., Wegner, JD., Ledoux, H.: The Hessigheim 3D (H3D) benchmark on semantic segmentation of high-resolution 3D point clouds and textured meshes from UAV LiDAR and Multi-View-Stereo. ISPRS Open Journal of Photogrammetry and Remote Sensing **1**, 100001 (2021)
33. Hackel, T., Wegner, JD., Schindler, K.: Fast semantic segmentation of 3D point clouds with strongly varying density. ISPRS annals of the photogrammetry, remote sensing and spatial information sciences **3**, 177–184 (2016)
34. Sun, Y., Zhang, X., Xin, Q., Huang, J.: Developing a multi-filter convolutional neural network for semantic segmentation using high-resolution aerial imagery and LiDAR data. ISPRS Journal of Photogrammetry and Remote Sensing **143**, 3–14 (2018)

35. Nguyen, A., Le, B.: 3D point cloud segmentation: A survey.2013 6th IEEE Conference on Robotics, Automation and Mechatronics (RAM) 225-230 (2013) https://doi.org/10.1109/RAM.2013.6758588
36. ESRI, https://www.esri.com/arcgis-blog/products/api-python/analytics/deep-learning-models-in-arcgis-learn. accessed Jul 2022
37. Toms, S.: rcPy and ArcGIS–Geospatial Analysis with Python. Packt Publishing Ltd (2015)