

Restoration as recovery: participatory urbogeosystemic pedagogy of Karazin University for the Erasmus+ project *FutureLand*

*Sergiy Kostrikov*¹

DSc (Geography), Professor, K. Niemets Department of Human Geography and Regional Studies,
¹V.N. Karazin Kharkiv National University, Kharkiv, Ukraine,

e-mail: sergiy.kostrikov@karazin.ua,  <https://orcid.org/0000-0002-4236-8474>;

*Liudmyla Niemets*¹

DSc (Geography), Professor, K. Niemets Department of Human Geography and Regional Studies,

e-mail: ludmila.niemets@karazin.ua,  <https://orcid.org/0000-0001-9943-384X>

ABSTRACT

Introduction and previous works done. The 2024 European Nature Restoration Law (NRL) introduces binding restoration targets that – for the first time – explicitly include urban habitats. It challenges higher education to prepare practitioners who can bridge technical diagnostics and community priorities. The *FutureLand* Erasmus+ project answers that call through MOOCs, micro-credentials and participatory Learning Labs. Within *FutureLand* the authors propose a participatory restoration pedagogy tailored to post-war urban recovery, building on prior urbogeosystemic research with urban remote sensing and open geospatial toolkits. Thus, the main **research objective** of this paper is to introduce a transferable, trauma-informed participatory pedagogy.

Exposition of the main research materials. KGNU's pedagogy rests on a dual representation of the city within the frameworks of the urbogeosystemic approach. The conceptual framework demonstrates how the urbanistic environment (UE), urbogeosystem (UGS), and urban ecological system (UES) are structurally connected: raster diagnostics, vector governance, and socio-ecological processes converge into a coherent model. All three constituents enable restoration pedagogy to translate spatial evidence into socially legitimate and ecologically grounded urban futures. Together, UE and UGS translate pixel- and point-cloud signals into place-based narratives usable by municipalities. Methodologically, we follow an “Open-Data-First” principle: OpenStreetMap, global DEMs and available municipal LiDAR are combined with pragmatic 2.5D typological heuristics to produce LOD1/1.5 proxies and conditional volume estimates. Multi-method change detection (vector footprint differencing, hybrid volumetric proxies, and airborne LiDAR comparison) generates candidate urban changes that are then verified in participatory annotation workshops. Lightweight, explainable artificial neural networks, trained on community-annotated datasets and interpreted with Grad-CAM and SHAP, support urban pattern recognition, while keeping model decisions transparent and trustworthy. Pedagogically, the Learning Lab – with trauma-informed facilitation, participatory mapping, memory walks and mixed technical–social assignments – yields evidence packages that balance scientific rigor, civic legitimacy and NRL reporting needs. In these labs students, municipal officers, NGOs and residents co-collect, annotate and validate spatial and narrative data. Pilots in Kharkiv show that student–community teams can produce usable restoration scenarios, data-stewardship templates, syllabi, teacher-training modules and containerized software stacks that lower technical barriers for partners.

Conclusion. Our model shows how universities can catalyze ecological recovery and social renewal in urban areas by pairing open, reproducible technical workflows with trauma-aware, community-centered pedagogy. By aligning urbogeosystemic reasoning universities can serve as convenors and translators – producing governance-ready, community-endorsed evidence even in resource-constrained, post-war settings. Our approach is intentionally pragmatic and scalable: open data, modular lab units and clear documentation enable transfer to other cities lacking LiDAR or extensive municipal data. The pedagogical model helps bridge a gap between spatial science and equitable restoration practice, that gap the NRL now requires us to close.

Keywords: *European Nature Restoration law, participatory pedagogy, urbogeosystemic approach, urban ecological system, learning labs, urban remote sensing, LiDAR, ANN.*

In cites: Kostrikov Sergiy, Niemets Liudmyla (2025). Restoration as recovery: participatory urbogeosystemic pedagogy of Karazin University for the Erasmus+ project *FutureLand*. *Visnyk of V. N. Karazin Kharkiv National University. Series Geology. Geography. Ecology*, (63), 234-255. <https://doi.org/10.26565/2410-7360-2025-63-18>

Introduction and previous works done

The adoption of the *European Nature Restoration Law (NRL)* in 2024 marked a watershed moment in European environmental governance [17]. For the first time, binding obligations require member states to restore degraded ecosystems across terrestrial, marine, and urban domains, with explicit targets of restoring at least 20% of European Union (EU) land and sea by 2030 and all ecosystems in need by 2050 [17, 18]. This legislation reflects a growing recognition that ecological degradation is not confined to rural landscapes or wilderness areas but is equally acute in cities, where biodiversity

loss, climate vulnerability, and social inequities intersect [28, 36, 38, 57]. Urban habitats and green infrastructures are now explicitly recognized as restoration priorities, demanding new forms of evidence, governance, and education.

The European Nature Restoration Law (NRL), enacted in 2024, converts high-level conservation ambitions into binding obligations. It requires member states to restore large swathes of degraded land and sea, and for the first time explicitly includes urban habitats and green infrastructure as restoration targets [49, 50]. Cities are thus squarely in the NRL's sights: biodiversity, climate resilience, and

social equity in urban areas now demand the same careful, spatially explicit attention historically reserved for rural or wild landscapes [3, 9, 18].

This legal shift raises two interconnected challenges. First, municipalities need governance-ready evidence: spatial indicators and maps that are robust, transparent, and tailored to reporting. Second, restoration must be socially legitimate. It means developed in ways that reflect local histories, rights, and interests. Meeting both demands requires graduates who are technically fluent (remote sensing, GIS, modelling) and socially literate (participatory facilitation, ethical reflexivity, policy communication).

The *FutureLand* Erasmus+ project responds to these needs by embedding NRL principles into higher education through MOOCs (massive open online courses), micro-credentials, and participatory *Learning Labs* [21]. Within the consortium, the scientific team of the K. Niemets Department of Human Geography and Regional Studies at V. N. Karazin Kharkiv National University (hereafter either “KKNU”, or “the KKNU team”) offers a distinctive contribution: a pedagogy calibrated to post-war urban recovery, where socio-ecological repair is inseparable from humanitarian recovery, contested memory, and social justice.

Thus, the ultimate **research objective** of this paper is to develop and introduce the concept of a transferable, trauma-informed participatory restoration pedagogy that equips students, graduates, and scientists to co-design, document, and implement community-legitimate, governance-ready restoration proposals for post-war urban contexts aligned with the EU Nature Restoration Law.

KKNU’s approach rests on two complementary ideas. Conceptually, the city is treated as a *coupled urbogeosystem* [28, 29]. One lens – *the Urbanistic Environment (UE)* – captures continuous surface dynamics (vegetation indices, impervious surfaces, thermal gradients). The other – *the Urbogeosystem (UGS)* – models discrete objects (buildings, parks, parcels) and attaches governance, ownership, and social attributes. This duality bridges spectral signals and municipal decision-making: pixel changes become place-based narratives that planners and citizens can act on. At last, *the Urban Ecological system (UES)* unites these two issues in cities together.

Methodologically, KKNU favors an *open-data-first stance*. Many municipalities lack the budget for routine LiDAR surveys; therefore, the pedagogy builds on *OpenStreetMap*, *Sentinel/Landsat imagery*, *global DEMs*, and local open data. Where vertical information is missing, typological heuristics produce transparent 2.5D proxies with documented uncertainty. This pragmatic stance preserves reproducibility and lowers technical barriers for students and partner cities.

Pedagogically, the heart of the model is the *Learning Lab* – a space where students, municipal officers, NGOs, and residents co-produce evidence. Activities may include participatory mapping (PGIS, P3DM), memory walks, oral histories, image annotation workshops, and lightweight machine learning experiments. All these methods and techniques were already developed up to fifteen years earlier [15, 16]. Crucially, the labs are trauma-informed: facilitation practices prioritize safety, informed consent, psychosocial referral pathways, and benefit-sharing so that participation is empowering rather than extractive [26].

Pilots in Kharkiv (pilot components of a larger piloting project) will show this model in action: student–community teams generated verified change maps and restoration scenarios that local authorities found usable for early planning. These pilots will suggest that universities can be more than research centers: they can act as conveners, translators, and capacity builders – producing evidence packages that are scientifically robust and socially endorsed.

The remainder of our paper unpacks this contribution: first by situating the model in the literature on restoration pedagogy and human geography, then by detailing policy alignment with the NRL, the open-data, urban remote sensing, and ANN (artificial neural networks) workflows, the Kharkiv pilots, and finally the lessons for scaling and policy translation. All these mentioned constituents have been based on the official documents issued previously, research completed, and academic works done besides those we already referred to above [1-4, 6, 9, 10, 12, 17, 18, 20, 26, 34, 37, 41, 51, 61, 63, 66, 67].

The idea that ecological restoration can serve as both an object and a medium of learning has gained traction in recent decades. Ballard and Belsky [2] argue that *participatory action research (PAR)* in ecological contexts not only generates data, but also builds civic capacity and resilience. Restoration as pedagogy thus positions students and community members as coresearchers who coproduce knowledge, prototype interventions, and reflect critically on values and power relations. This aligns with traditions of service-learning and critical pedagogy, which emphasize reciprocity, civic engagement, and the cultivation of ethical reflexivity [12, 63].

In the context of the Nature Restoration Law (NRL), this pedagogical stance is particularly relevant. The NRL requires outputs that are not only technically robust but also socially legitimate and governance-ready [17, 18]. Restoration pedagogy must therefore train graduates to produce evidence that municipalities can adopt while ensuring that interventions resonate with community values [14, 45].

Exposition of the main research material.

Key theoretical and practical basics. Human

geography, contested place, and post-war landscapes. Restoration can be both a subject of study and an educational method: PAR and service-learning traditions show that hands-on restoration builds civic skills and social capital while producing usable knowledge. Under the NRL, restoration education must therefore produce both technically sound outputs and socially legitimate processes.

Human geography teaches that places are socially produced and layered with memory, power, and identity. In post-war cities, parks and brownfields are often both ecological assets and memorial sites. Restoration projects that ignore cultural meaning risk rejection; pedagogy must teach how to surface narratives, map stakeholders, and design interventions that respect contested histories.

Working in post-war settings requires trauma-aware facilitation: prioritize safety, trust, choice, collaboration, and empowerment. In practice, this means flexible participation, trigger warnings, referral pathways, anonymization, and benefit-sharing. Embedding these practices protects participants and strengthens the legitimacy of the research. Restoration education benefits from methodological pluralism: qualitative tools (interviews, oral histories, transect walks, photovoice) reveal values and memories, while geospatial tools (PGIS, OBIA – traditional pixel-based methods, Urban Remote Sensing - URS) provide visual evidence and scenario affordances. The pedagogical aim is to use GIS/URS tools not as an authoritative replacement for local knowledge, but as a transparent, accessible complement. The following visual, a diagram, exposes geospatial data pipeline, which can be employed by human geography for the post-war landscapes' evaluation (Fig. 1).

The flowchart depicts a staged pipeline that ingests and synthesizes multiple geospatial data sources into validated spatial indices. Six primary sources – OpenStreetMap (OSM), Sentinel, Landsat, a global DEM, airborne LiDAR, and municipal portals – feed a central preprocessing stage where formats are normalized and raw inputs cleaned. From there the data pass through harmonization, index computation and a final validation step, producing robust, interoperable spatial products ready for analysis and decision-making. This pipeline is intentionally designed to meet the needs of human geography in contested, post-war places: it generates multiscale evidence to map shifting land uses, document infrastructure damage, and reveal patterns of informal occupation that matter for claims to space and contested place-making.

Harmonization and index computation yield comparable metrics – for example, built-up change, elevation-based accessibility, and vegetation recovery – that translate lived, local experiences into de-

monstrable spatial change. Validation anchors those products in trustworthy evidence, which is crucial when maps are used for reparative planning, resettlement decisions, or to substantiate contested claims after war. Practically, each source contributes distinct insight: OSM surfaces community-edited features and emergent informal settlements as well as civic infrastructure updates; Sentinel and Landsat time series enable temporal change detection for vegetation regrowth, burn scars and broad land-cover transitions; a global DEM reveals terrain constraints on movement, flood risk and strategic or defensible locations; airborne LiDAR supplies fine-scale assessments of building damage, footprints and restoration needs; and municipal portals provide cadastral records, planning layers and administrative boundaries needed to adjudicate claims. Together, these elements form a coherent, defensible workflow for spatially grounded post-war analysis.

Machine learning can significantly help detect urban change, but in civic contexts models must be interpretable [7, 13, 24, 32]. Lightweight ANNs trained on community-annotated data, together with explainability tools (GradCAM, SHAP), allow both students and community members to see how models make decisions – building trust and aligning outputs with policy needs [48].

Nonetheless, key gaps remain within the mentioned domain: longitudinal tracking of student and community outcomes, comparative evaluation of mixed-method bundles, and domain adaptation of models to different urban contexts. *FutureLand's* cross-lab exchanges create an opportunity for comparative learning and refinement.

In synthesis, a *participatory, urbogeosystemic pedagogy* may link pixel-level and cloud-based diagnostics with object-level governance narratives, grounds models in community annotation, and embeds trauma-aware facilitation to produce NRL-compatible, socially endorsed evidence [1, 11, 13-16, 20, 25, 26, 44, 45, 47, 63].

Educational implications, the FutureLand Erasmus+ project, and KGNU's strategic role. The NRL's scope creates a profound demand for new professional competencies. Restoration specialists must be able to: translate remote sensing and GIS outputs into governance-ready indicators [4, 22]; facilitate participatory processes that ensure social legitimacy [2, 12]; integrate trauma-informed approaches in post-war or vulnerable contexts [10, 26]; communicate uncertainty transparently, enabling municipalities to make informed decisions under conditions of risk on the base of geospatial pipeline by implementing early algorithmic approaches to building extraction, which are now integrated into OBIA workflows for post-war urban reconstruction, damage assessment, and restoration planning [43, 55].

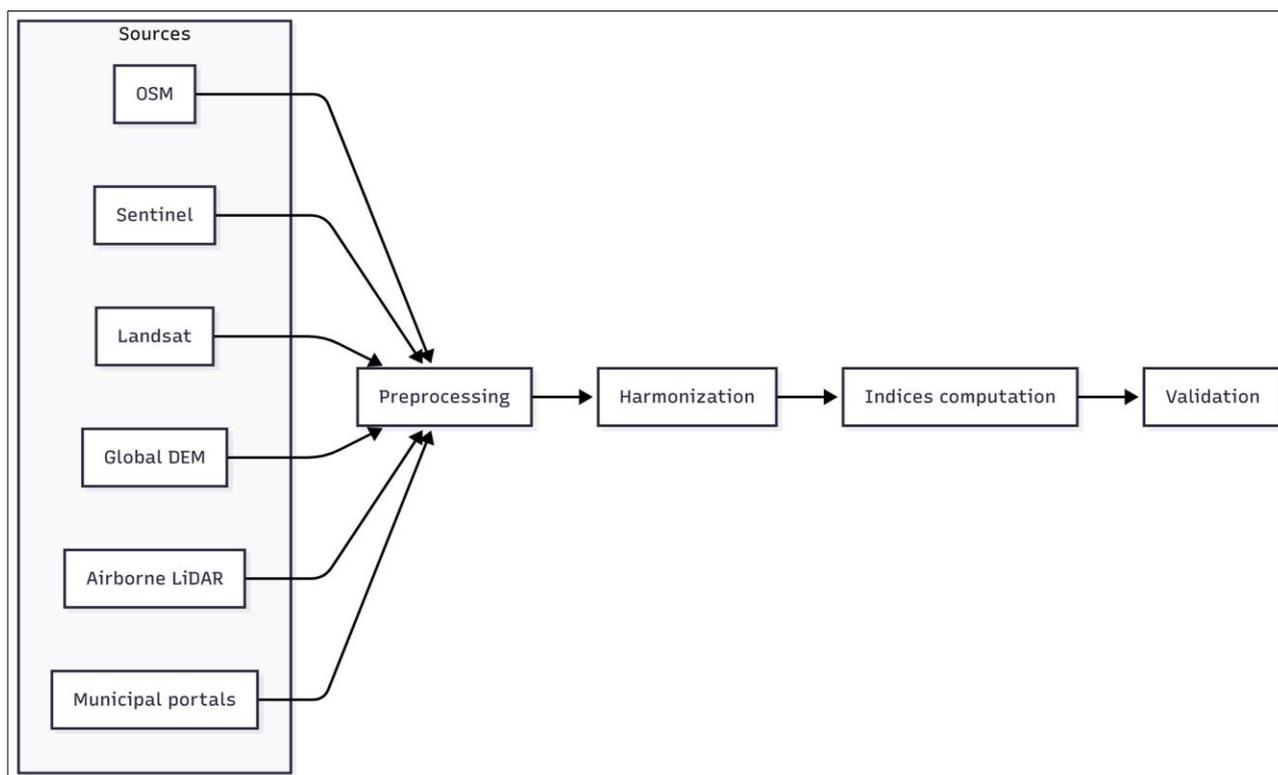


Fig. 1. Geospatial data pipeline for contested, post-war landscapes

Higher education institutions are thus central to the NRL agenda. They must produce graduates who are technically skilled, ethically reflexive, and capable of bridging science, governance, and society [6, 61]. The *FutureLand* consortium has been established to operationalize these educational imperatives. Funded under Erasmus+ KA220HED, it brings together universities, municipalities, and NGOs across Europe to codesign curricula, MOOCs, micro-credentials, and participatory Learning Labs [21]. Its objectives include:

- Embedding NRL principles into higher education curricula (the primary goal);
- Producing open educational resources (OERs) and MOOCs accessible across Europe;
- Piloting participatory Learning Labs that generate NRL-aligned evidence packages;
- Building municipal capacity through training toolkits and policy briefs;
- Facilitating cross-lab exchanges to compare methodologies and outcomes.

FutureLand thus serves as both an educational innovation and a policy instrument, ensuring that the NRL's ambitious targets are supported by a skilled, socially literate workforce.

Within the project consortium, our KKNU's team plays a pivotal role. Its mandate includes:

- Designing participatory *Learning Labs* in post-war urban contexts;
- Developing trauma-informed pedagogical protocols;

- Producing open educational resources (OERs) and MOOCs that integrate human geography, participatory ethics, and open-data GIS workflows.

Piloting this approach in Kharkiv – a city that has suffered extensive urban damage since 2022 – offers both urgency and a real-world testing ground. Kharkiv functions as a living laboratory: its damaged parks, industrial sites, brownfields, residential blocks and public spaces are at once ecological habitats, memorial landscapes, and contested arenas of identity and rights to place. Many of the mapped objects were damaged or destroyed between 2022 and 2025. The first author has previously reported the urbogeosystemic LiDAR-based change detection of hostilities in Kharkiv's most heavily impacted district, *Northern Saltivka* [28, 31]. Below we reproduce an original visual of the consequences of the hostilities – a 2D map highlighting morphological urban changes due to damaged and ruined residential buildings in red (Fig. 2).

Restoration here cannot be reduced to technical repair; it must integrate humanitarian recovery, contested memory, and social justice [20, 44]. KKNU's pedagogy therefore combines urbogeosystemic modeling (*UE/UGS duality* and *UES/UE/UGS triplicity*) with PAR and challenge-based learning (CBL), ensuring that outputs are both technically robust and socially legitimate [2, 12].

Policy translation and dissemination. A distinctive feature of KKNU's role is its emphasis on poli-

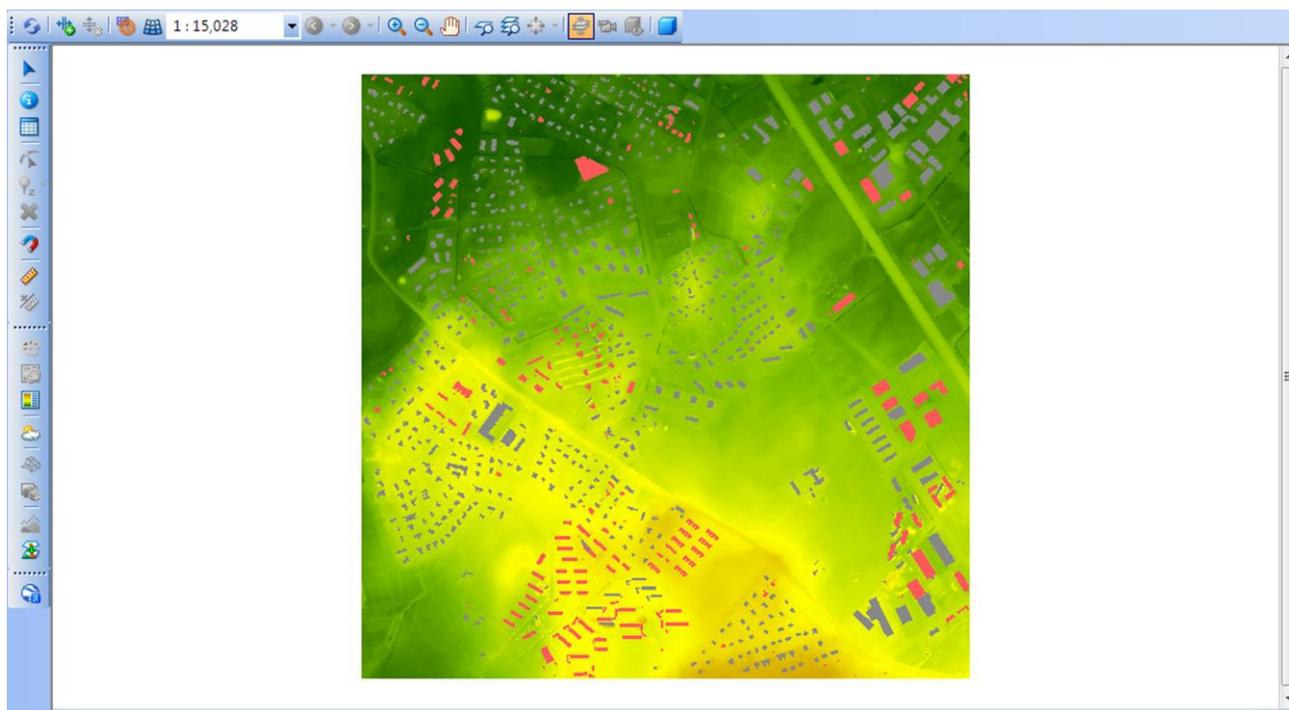


Fig. 2. Change detection results as a *2D map* produced in the *City Change Management* interface (developed by the first author) from the multitemporal LiDAR dataset (2019–2022) for the *Northern Saltivka* district, Kharkiv. Footprints of architectural and structural change are shown in red

cy translation. Outputs from Learning Labs are packaged as NRL-aligned evidence briefs, comprising executive summaries, mapped indicators, uncertainty statements, and implementation roadmaps. Dissemination strategies may include story maps, films, translated briefs, and low-band-width OERs, foregrounding community voices [65, 66]. This ensures that evidence is not only academically rigorous but also accessible to municipal officers, NGOs, and communities.

Risks and opportunities. The policy context also highlights risks. Security constraints may disrupt fieldwork; consultation fatigue may burden communities; expectation mismatches may arise between student proposals and municipal capacities [1]. Moreover, these risks are counterbalanced by opportunities: the chance to embed participatory pedagogy in curricula, to scale OERs across Europe, and to demonstrate that even under post-war conditions, universities can operationalize the NRL.

Conceptual framework: urbogeosystemic thinking and restoration pedagogy. Restoration as a socio-ecological process. Restoration in the NRL era is not merely a technical exercise of repairing degraded ecosystems; it is a socioecological process that integrates ecological diagnostics with social legitimacy. Scholars emphasize that ecological interventions succeed only when they are embedded in governance frameworks and community values [2, 20]. In post-war cities, such as Kharkiv, restoration must also address trauma, contested memory, and

humanitarian recovery due to existing evaluations of all these issues [37, 44, 62]. The conceptual framework developed by our KKNU's team therefore positions restoration as both ecological repair and social rehabilitation, as well as civic pedagogy, where students, communities, and municipalities coproduce knowledge and interventions.

Urbogeosystemic thinking: UE / UGS duality and UE / UGS /UES triplicity. At the heart of KKNU's model is the urbogeosystemic framework, which conceptualizes the city as a coupled system with three complementary representations already mentioned in this text above:

- **Urbanistic Environment (UE):** A quasi-raster model capturing continuous surfaces and dynamic flows such as vegetation cover, imperviousness, and thermal gradients. Raster indices like NDVI, NDBI, and SAVI are used to monitor ecological dynamics [46, 69], while LiDAR cloud-based models have been efficiently used to reconstruct massive UE for a whole city scale [35].
- **Urbogeosystem (UGS):** A quasi-vector model representing discrete urban objects—buildings, parcels, parks, and infrastructures, firstly presented by the authors of this paper [29]. Further developments of the UGS models can be considered along with their semantic attributes such as use, ownership, and institutional links [4, 58], and can be efficiently implemented in the digital city projects [34].

- The urban ecological system (UES) brings these two views together by placing both continuous environmental flows and discrete urban objects within the wider socio-ecological processes that shape resilience, biodiversity, and human well-being. In this structure of triplicity the UE functions as the diagnostic layer, revealing patterns and signals in the urban environment; the UGS provides the governance anchor, linking those signals to institutions, regulations and decision-making; and the UES offers the normative frame, connecting analysis to questions of sustainability, equity and restoration. When the three are aligned, technical indicators gain ecological meaning and social legitimacy, allowing restoration-focused pedagogy to move seamlessly from diagnosis to governance to the civic values that guide collective recovery.

The EE/UGS duality allows translation of pixel/cloud-level signals into object-level narratives (Fig. 3). For example, canopy loss in UE-rasters

corresponds to tree removal in a UGS-park polygon; spectral evidence of collapsed roofs translates into building footprint changes with ownership implications. Such translation is essential for producing NRL-aligned indicators that municipalities can act upon [25, 51]. Figure 3 visualizes the urbogeosystemic duality through two interconnected panels. The upper panel (UGS) represents the city as a collection of discrete vector objects—buildings, a church, trees, roads, and land parcels—while the lower panel (UE) depicts the same area as a continuous, quasi-raster surface composed of grid cells that express vegetation, impervious cover, and transitional gradients. A double-headed arrow links the two panels, indicating the bidirectional translation between them: pixel- and point-cloud patterns in the UE correspond to object-level features and meanings in the UGS. For example, a canopy loss detected in the raster domain may translate into the removal of trees within a park polygon, while spectral evidence of roof damage can alter building footprints and update associated ownership records.

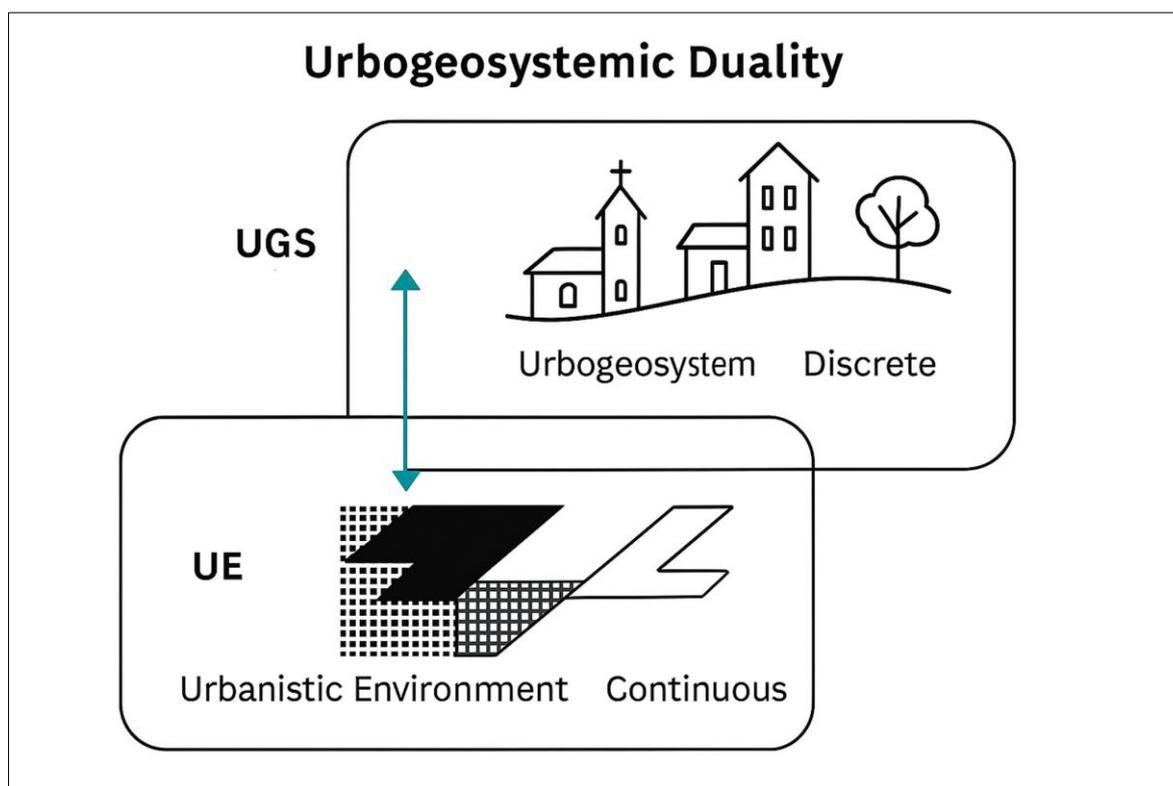


Fig. 3. Urbogeosystemic Duality: linked *Urbanistic Environment (UE)* quasi-raster surfaces and *Urbanistic Environment (UGS)* quasi-vector objects, showing how continuous pixel/point-cloud signals translate into discrete object-level narratives (e.g., canopy loss → park polygon tree removal; spectral roof collapse → building footprint change with ownership implications), enabling NRL-aligned indicators for municipal action

Participatory pedagogy and action research. The urbogeosystemic framework is embedded within a participatory pedagogy grounded in PAR and CBL. PAR emphasizes cyclical action-reflection and positions community members as coresearchers

[12]. CBL situates learning in real-world challenges, compelling students to negotiate ecological aims with social realities [61]. Together, these traditions argue that restoration education must cultivate technical, governance, and ethical literacies in tandem.

In Kharkiv, this means that students do not merely analyze satellite imageries. Taking into account security regulations due to the war going on, they also conduct memory walks, collect oral histories, and facilitate participatory mapping workshops. These activities surface contested narratives of place and ensure that restoration proposals are socially legitimate [26, 52].

Trauma-informed pedagogy. A distinctive feature of KGNU's framework is its trauma-informed orientation. Postwar contexts require facilitation that prioritizes safety, trust, choice, collaboration, and empowerment [1, 10, 56]. Trauma-informed pedagogy in restoration involves:

- Consent protocols and plain-language data use statements.
- Optional participation modalities for sensitive sessions.
- Referral pathways to psychosocial services.
- Anonymization of sensitive testimonies.
- Ethical audits with community representatives.

By embedding these safeguards, the KGNU's team ensures that Learning Labs avoid extractive tendencies and instead foster resilience and reciprocity. This aligns with broader calls for humanitarian ethics in community-engaged research [20].

Open data first and pragmatic modeling. The framework also incorporates a methodological stance: *open data first*. Many municipalities lack resources for regular airborne LiDAR surveys. The KGNU's team therefore prioritizes freely available datasets such as OSM, Sentinel, Landsat, DEMs, and municipal open LiDAR portals [4, 22, 33-35]. Where height data are missing, typological heuristics estimate building heights based on footprint area and building type, producing pragmatic 2.5D models. These approximations are explicitly presented with uncertainty intervals, ensuring transparency and trust. Such approach reflects a broader pedagogical principle: technology should be supportive, not determinative. Students learn to use GIS and remote sensing as tools that complement, rather than replace, participatory processes [15, 16, 66].

Artificial neural networks as pedagogical tools. Machine learning is integrated into the framework not as an opaque automation but as a pedagogical tool. Lightweight Artificial Neural Networks (ANNs)—such as similarity networks and contrastive Siamese architectures—are introduced to demonstrate pattern recognition and anomaly detection [23, 27, 39, 64]. Training datasets are produced through participatory annotation workshops, grounding models in local realities [2]. Explainability techniques such as *GradCAM* [54] and *SHAP* [42] are used to show how models arrive at decisions, fostering transparency and civic trust.

Integration with the NRL. The conceptual frame-

work is explicitly aligned with the NRL's requirements. The UE / UGS duality, and UE / UGS / UES triplicity both support the production of spatially explicit indicators; participatory pedagogy ensures stakeholder inclusion; trauma-informed facilitation guarantees ethical safeguards; open data workflows enhance reproducibility; and ANN explainability fosters transparency. Together, these elements produce NRL-compatible evidence packages that municipalities can adopt for reporting and planning [5, 17].

Synthesis due to the conceptual framework. In sum, KGNU's conceptual framework integrates urbogeosystemic thinking, participatory pedagogy, trauma-informed facilitation, and open data pragmatism into a coherent model of restoration education. It reframes restoration as a socioecological and educational process, where technical diagnostics are inseparable from community narratives and ethical safeguards. This framework not only addresses the immediate needs of post-war Kharkiv, but also offers a transferable blueprint for other European contexts facing ecological degradation, governance complexity, or social contestation.

Methodology: open data, pragmatic modeling, neural networks, and participatory workflows.

Open data first strategy. A cornerstone of the KGNU team approach within *FutureLand* is the open data first principle. Many municipalities, particularly in post-war or resource-constrained contexts, lack the financial or logistical capacity to commission regular airborne LiDAR surveys or high-resolution proprietary datasets. Instead, the pedagogy prioritizes freely available and reproducible sources:

- OpenStreetMap (OSM) building footprints and attribute tags, which provide a dynamic, crowdsourced baseline of urban morphology [8, 22];
- Sentinel2 and Landsat imagery, offering multitemporal optical data for vegetation indices (NDVI, SAVI) and built-surface monitoring (NDBI) (40, 69);
- Global DEMs such as SRTM and ALOS, which provide elevation baselines for terrain and conditional volume proxies [59];
- Municipal open data portals with LiDAR point clouds and cadastral archives, local monitoring results, where available, to supplement global datasets with local specificity [29, 30, 33];
- Historical maps and crowdsourced imagery, which allow diachronic comparison and community validation [52].

This strategy not only reduces costs, but also enhances reproducibility and transparency, aligning with open science and open pedagogy principles

[Wiley, Abernathy, 2023]. All preprocessing scripts are stored in version-controlled repositories, ensuring that workflows can be replicated and adapted across *FutureLand* partners.

Preprocessing and harmonization. To ensure comparability, all datasets undergo a reproducible ingestion pipeline:

- Reprojection to a common coordinate reference system.
- Cloud masking and atmospheric correction for optical imagery.
- Band normalization and computation of spectral indices (NDVI, NDBI, SAVI).
- Topology checks and attribute harmonization for vector layers.

This harmonization is critical for producing NRL-aligned indicators that are consistent across time and space [17, 45].

Pragmatic 2.5D modeling. LiDAR point cloud processing is the most efficient technology for urban space reconstruction [53]. Where LiDAR is unavailable, our team employs typological heuristics to estimate building heights. These heuristics draw on footprint area, building type tags, and local typologies (e.g., single-family residential, midrise multi-family). Spot checks using street photos or municipal metadata validate these estimates, and uncertainty bands are explicitly recorded [4, 2015, 35]. We can illustrate pragmatic 2.5D modeling with the following original explanatory visual (Fig. 4):

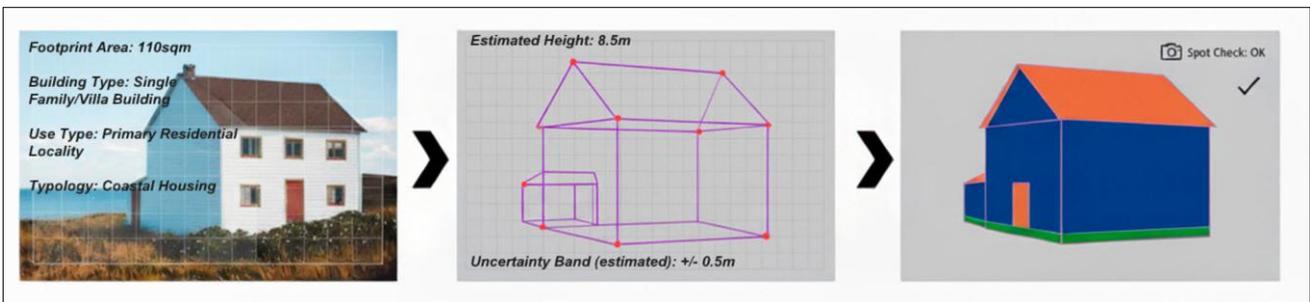


Fig. 4. Pragmatic 2.5D building-modelling workflow: *left* – street photograph with extracted *footprint area* (116 m^2) and typological tags; *center* – *wireframe height estimate* (8.5 m) with explicit *uncertainty band* ($\pm 0.5 \text{ m}$); *right* – shaded 3D rendering with *verification flag* (*Spot Check OK*)

The figure above illustrates a three-stage 2.5D modeling workflow that complements the typological heuristics outlined earlier. On *the left*, a street-level photograph shows a single-family house alongside its extracted metadata – footprint area (116 m^2), building type, use, and local typology. In *the center*, a wireframe 3D model presents the estimated building height (8.5 m) together with an explicitly defined uncertainty range ($\pm 0.5 \text{ m}$). On *the right*, a shaded 3D rendering of the same footprint carries a verification flag (“*Spot Check OK*”), confirming that the model has been successfully validated against aerial imagery or municipal records. Together, these panels demonstrate how footprint-based heuristics, quantified uncertainty, and selective spot checks can be integrated to produce practical, reliable 2.5D building representations for urban analysis and planning as well as for educational purposes.

By combining footprint polygons with DEMs and inferred heights as described above, the URS segment of the urbosystemic pedagogy produces operational 2.5D approximations (LOD1/LOD1.5). These are adequate for neighborhood-level conditional volume proxies, which support prioritization of restoration interventions. Importantly, conditional volumes are always presented with uncertainty intervals, ensuring that municipal users understand

limitations and can make informed decisions [31, 33, 35, 58].

Multi-method change detection. A robust detection pipeline integrates multiple methods, each with complementary strengths:

- Pixel-based spectral differencing: Temporal deltas of NDVI, NDBI, and other indices flag vegetation loss and impervious surface changes [69];
- Object-Based Image Analysis (OBIA): Segmentation of scenes produces coherent objects that map to OSM footprints, supporting semantic comparisons across epochs [25];
- Vector footprint differencing: Comparing timestamped OSM or cadastral polygons identifies added, removed, or altered footprints [22];
- Hybrid volumetric proxies: Footprint deltas combined with typological height priors yield conditional volume-change estimates, prioritizing structural assessments [53];
- Urban change detection with LiDAR: This *Change Detection* technique provides monitoring of a city’s architectural (geometric) changes over a selected period of time. An automated comparison of two LiDAR point clouds, takes into account all three generally

accepted tasks that must be addressed for representative 2.5D/3D change detection: 1) coordinate system alignment; 2) spatial comparison; and 3) detected changes representation and analysis [28, 30, 57, 60].

Each stream from the list above produces candidate changes for human verification and ANN training. This multimethod triangulation enhances robustness and aligns with NRL's demand for credible, transparent evidence [17]. For example, urban change detection based on the LiDAR monitoring results has efficiently reconstructed the hostilities'

impact on UE in Kharkiv, which can be depicted either as a *2D map* (Fig. 2), or – even in more representative way – as a *3D scene* in a spatial modeling interface (Fig. 5).

Participatory annotation and labeling. High-quality labeled datasets of the various sensors are essential for ANN training. Our team organizes participatory annotation workshops, where students and community volunteers crosscheck satellite imagery, LiDAR surveys, Google street photos, and local knowledge to label instances as *Added*, *Removed*, *Modified*, or *Unchanged*.

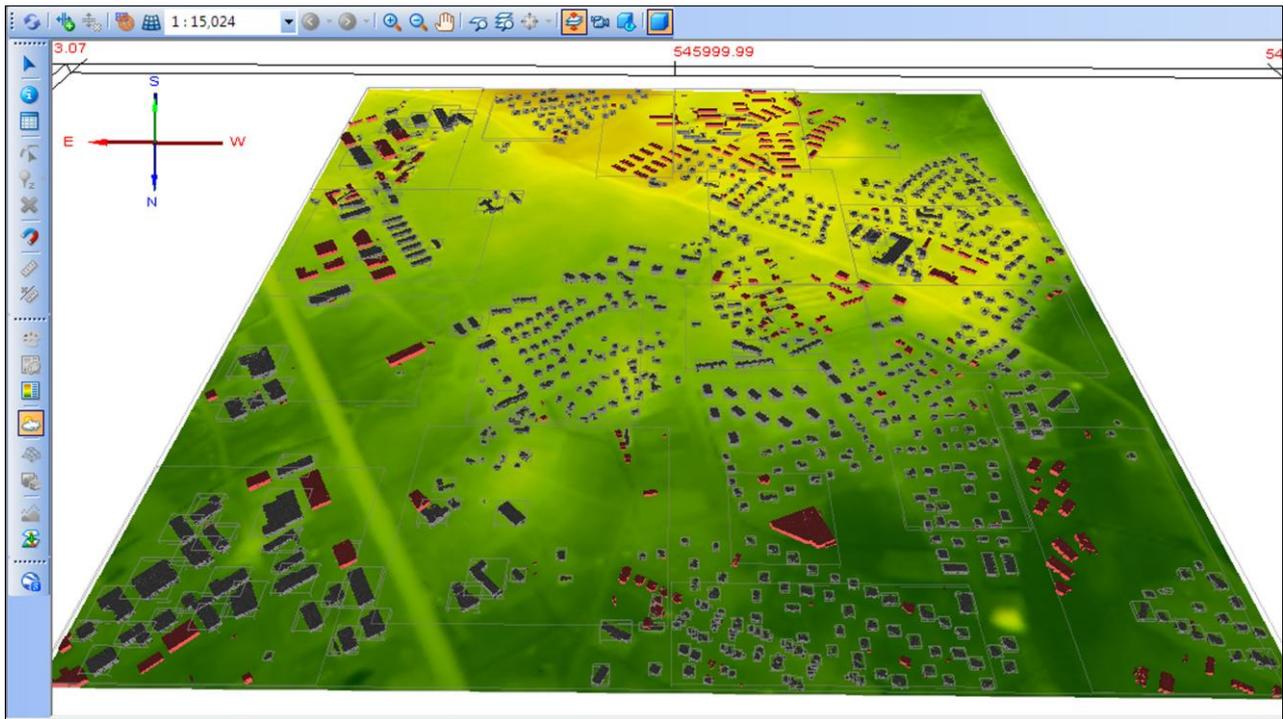


Fig. 5. Change detection results as a *3D scene* produced in the *City Change Management* interface (developed by the first author) from the multitemporal LiDAR dataset (2019–2022) for the *Northern Saltivka* district, Kharkiv. Features of architectural and structural change are shown in red.

We start with freely available, reproducible sources: *OpenStreetMap* footprints, Sentinel-2 and Landsat imagery for multispectral indices (NDVI, NDBI, SAVI), free airborne LiDAR datasets (if available), global DEMs (SRTM/ALOS), municipal open-data, and historical imageries. These inputs enable reproducible preprocessing and lower barriers for partners.

All datasets should be harmonized through a reproducible pipeline: consistent coordinate systems, cloud masking and atmospheric correction for optical data, band normalization, spectral indices, and topology/attribute checks for vectors. Scripts and notebooks are version-controlled so partners can reproduce and adapt workflows.

Where or if LiDAR is absent, typological rules estimate building heights from footprint area and land use tags. Combined with DEMs, these priors yield 2.5D approximations (LOD1 / LOD1.5) and

conditional volume proxies. Every estimate includes explicit uncertainty bands and validation spot checks using street photos or municipal metadata.

Urban change is detected with complementary methods:

- Pixel differencing (temporal deltas of NDVI, NDBI) to flag vegetation or surface change;
- OBIA to create coherent segments linked to OSM footprints;
- Vector footprint differencing to detect added/removed/changed buildings;
- Hybrid volumetric proxies combining footprint deltas and typological heights or conditional volume change;
- Where and if LiDAR datasets are available, a relevant pipeline should be implemented, since it already provided a robust output (Fig. 2, 5).

Candidate changes are human-verified and then used to build training samples for machine learning.

Students and community volunteers label imagery in workshops (*Added, Removed, Modified, Unchanged* classes), producing labeled data that is both technically useful and democratically grounded.

Artificial neural networks in urbogeosystemic pedagogy. We use two pedagogical ANN approaches intended to be applied within the Learning Labs activities of the *FutureLand* project (Fig. 6): *Similarity-oriented networks* that fuse image patch CNN embeddings with tabular descriptors to score similarity between paired observations; *Contrastive (Siamese) networks* that separate changed from unchanged pairs in embedding space.

This figure provides a clear schematic of two stacked ANN pipelines that are applied in Learning Labs for *urban change detection* and *restoration analysis*. These two pipelines represent further development of our ANN-methodology reported earlier [32]. The upper visual pipeline (the Enhanced ANN Similarity model) combines visual embeddings derived from a convolutional neural network (CNN) with tabular descriptors processed by a multi-layer perceptron (MLP), resulting in a joint embedding and a similarity score. The lower pipeline (the Contrastive Siamese model) uses shared-weight CNN branches to generate paired embeddings and a distance-based loss function, which ultimately drives a binary decision of *Changed* or *Unchanged*. The model processes both image and tabular inputs. Image data are provided as small pairs of patches – in the upper pipeline, these are labeled as *A/B* and in the lower pipeline as *anchor/compare*. Tabular inputs include attributes like area, volume height (all obtained from LiDAR) NDVI difference, and typology, which are processed through MLPs. Preprocessing involves standard image normalization and tabular scaling, with visual and tabular streams kept separate until they are fused.

In the Enhanced ANN Similarity pipeline, the CNN backbone generates 512-dimensional visual embeddings for each patch, while the tabular MLP produces 64-dimensional embeddings. These are concatenated to form a 256-dimensional joint embedding, which is then processed by a similarity head to produce a 0-1 similarity score. The pipeline ranks patch pairs by similarity, supporting prioritization and near-duplicate detection. It also includes explainability features through Grad-CAM (for vision) and SHAP (for tabular inputs).

The Contrastive Siamese pipeline uses twin CNN branches with shared weights to produce 512-dimensional embeddings for each patch pair. The embeddings are compared using Euclidean or cosine distances, and a contrastive or triplet loss function is used to maximize separation between *changed* and *unchanged* pairs.

The final output is a thresholded binary classifi-

cation, indicating whether the changes are significant or not. Training for both pipelines involves participatory annotations and curated patch pairs, supervised for both similarity and contrastive objectives. Evaluation metrics include ROC/AUROC, correlation, precision, recall, F1 score, and embedding-margin separation. To ensure interpretability, Grad-CAM visualizations highlight key spatial features, while SHAP values are used to quantify the influence of tabular descriptors.

In the research workflow, the Enhanced Similarity Pipeline is used in Learning Labs to prioritize and rank potential change pairs, while the Contrastive Siamese Pipeline performs final, high-confidence urban change detection. Both pipelines feed results into downstream stages, such as triage, stakeholder review, and urban restoration planning, where rapid, explainable assessments of visual and contextual changes are crucial.

This architecture combines deep learning with interpretable tabular modeling, offering a transparent and data-efficient framework for urban change detection and restoration analysis for cities. It strikes a balance between quantitative accuracy and qualitative insights, aligning computational methods with participatory, human-centered research objectives.

Community members will also participate in annotation workshops, labeling satellite imagery, LiDAR point clouds, and street photos to identify *Added, Removed, Modified, or Unchanged* urban structures. This not only produce robust training data for ANN models but also ground technical outputs in local realities.

Municipal roundtables and policy uptake. Outputs from the Learning Labs were presented in municipal roundtables, where local officials, NGOs, and community representatives reviewed evidence packages. These packages will include:

- Verified change maps of building footprints, change detected features and green cover;
- Neighborhood summaries of lost area, conditional volume proxies, and restoration priorities;
- Draft restoration scenarios aligned with NRL indicators;
- Executive summaries with cost bands and implementation roadmaps.

Municipal officers will emphasize the value of transparent uncertainty statements and community validation, which increased the credibility and uptake of the outputs.

Outcomes and lessons learned. The Kharkiv pilots will produce several key outcomes:

- Technical outputs: Verified change maps, ANN similarity/dissimilarity scores, and NRL-aligned restoration scenarios;
- Pedagogical outcomes: Students gain compe-

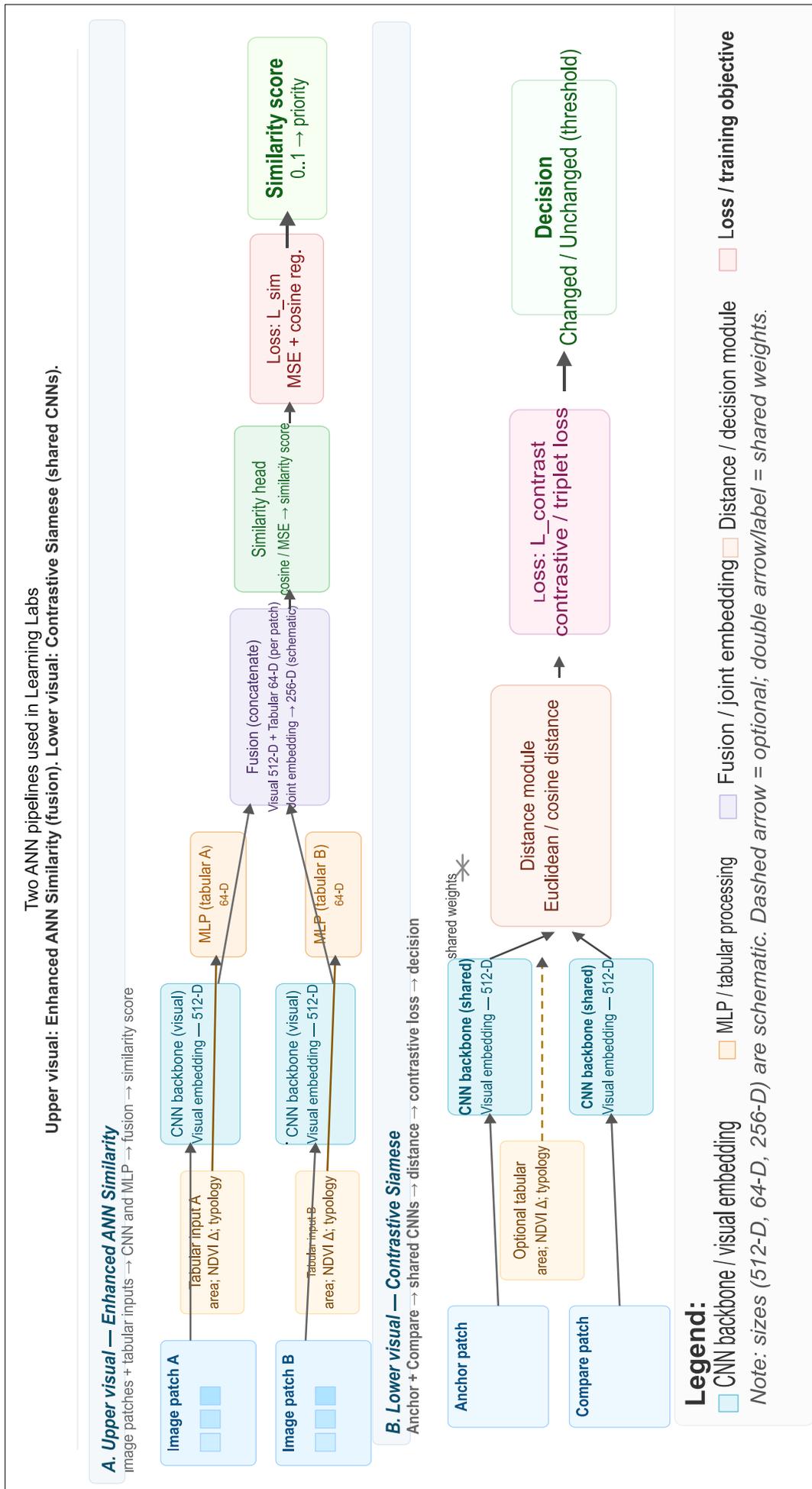


Fig. 6. Two Artificial Neural Networks' pipelines planned to be used in Learning Labs: *Upper visual* – Enhanced ANN Similarity (fusion); *Lower visual* - Contrastive Siamese (shared convolutional neural networks)

tencies in open data workflows, participatory facilitation, and ethical reflexivity.

- Community outcomes: Residents would reengage in shaping their urban futures, and their narratives will be embedded in restoration planning.
- Policy outcomes: Municipal officers will receive actionable, NRL-compatible evidence packages that informed early restoration planning.

Lessons learned include the importance of multimethod triangulation (pixel, object, vector, volumetric), the value of participatory annotation for both technical and civic legitimacy, and the necessity of trauma-informed facilitation in post-war contexts [1, 25, 47].

Scaling and transferability. The Kharkiv pilots also will provide insights for scaling. Crosslab exchanges with Venice, Girona, and Joensuu are planned to compare methodologies and outcomes, addressing evidence gaps in comparative evaluation [14]. Shared repositories of OERs, benchmark datasets, and municipal toolkits will enable replication across Europe [21, 66]. While the model is tuned to postwar urban contexts, its principles—open data pragmatism, urbogeosystemic modeling, participatory pedagogy, and trauma-informed facilitation—are transferable to other European regions facing ecological degradation, governance complexity, or social contestation [20, 61].

Synthesis due to the methodology. The Kharkiv pilots demonstrate that even under conditions of war and resource scarcity, universities can operationalize the NRL through participatory pedagogy. By integrating open data workflows, urbogeosystemic modeling, ANN explainability, and trauma-informed facilitation, the KGNU team will produce outputs that are scientifically credible, socially legitimate, and governance-ready. More importantly, the pilots reengaged communities in shaping their urban futures and trained a new generation of restoration specialists. This dual achievement - technical innovation and civic empowerment - illustrates the transformative potential of the participatory urbogeosystemic pedagogy in the NRL era.

Results and policy translation. *Learning Labs circle and technical outputs.* The schematic in Fig. 7 summarizes *the Learning Lab* as an iterative, evidence-driven cycle that links technical workflows with community-centered decision-making. The pipeline starts with reproducible data curation – assembling and cleaning imagery, LiDAR, OSM, municipal layers and field notes while documenting provenance and uncertainty – and proceeds to lightweight, interpretable ANN models that surface candidate changes for human review. At the heart of the cycle, students, residents and municipal staff jointly

inspect, label and correct model candidates; those community-validated labels then refine the models and feed back into new rounds of analysis. Outputs are translated into governance-ready briefs (maps, uncertainty statements and short implementation roadmaps) that municipalities can use directly, and field validation closes the loop by informing sensitivity tests and subsequent annotations.

In Kharkiv, these labs will produce a coherent set of technical products, that demonstrate the feasibility of an open-data, participatory, urbogeosystemic approach. Student teams – working with community members and municipal officers – produce verified change maps that distinguish *Added*, *Removed*, *Modified* and *Unchanged* building footprints (combining LiDAR monitoring, OSM updates, Sentinel-2 differencing and participatory annotation); neighborhood summaries quantifying lost area, conditional volume proxies and green-cover change aligned to Nature Restoration Law indicators; restoration scenarios that integrate ecological, social and memorial dimensions; and ANN similarity scores that efficiently prioritize sites for triage (Fig. 7).

Crucially, whether using airborne LiDAR or pragmatic 2.5D approximations from open imagery, the Learning Lab cycle yields policy-ready evidence: reproducible workflows, explicit uncertainty statements, and participatory validation that municipalities can trust in reparative planning.

These outputs demonstrate that either with LiDAR, or even without it, pragmatic 2.5D modeling and participatory validation can produce policy-ready evidence for urban restoration.

Pedagogical and community outcomes. Equally significant are the pedagogical outcomes. Students develop competencies in open data workflows, participatory facilitation, and ethical reflexivity. They learn to communicate uncertainty transparently, a skill critical for NRL reporting. For communities, the pilots provide opportunities to reclaim agency in shaping their urban futures. Memory walks and participatory mapping enabled residents to articulate losses and aspirations, embedding their narratives in restoration planning. This process fosters trust and reinforces the legitimacy of outputs.

Policy translation: evidence packages. To ensure municipal uptake, outputs were packaged as NRL-aligned evidence briefs. Each package included:

- Executive summary with prioritized plots and estimated intervention cost bands;
- Methodology and data provenance appendix, ensuring transparency and reproducibility;
- Mapped indicators with uncertainty statements, covering area lost, conditional volume, and green cover change;
- Validation annex, including photos, community testimony summaries, and annotation records;

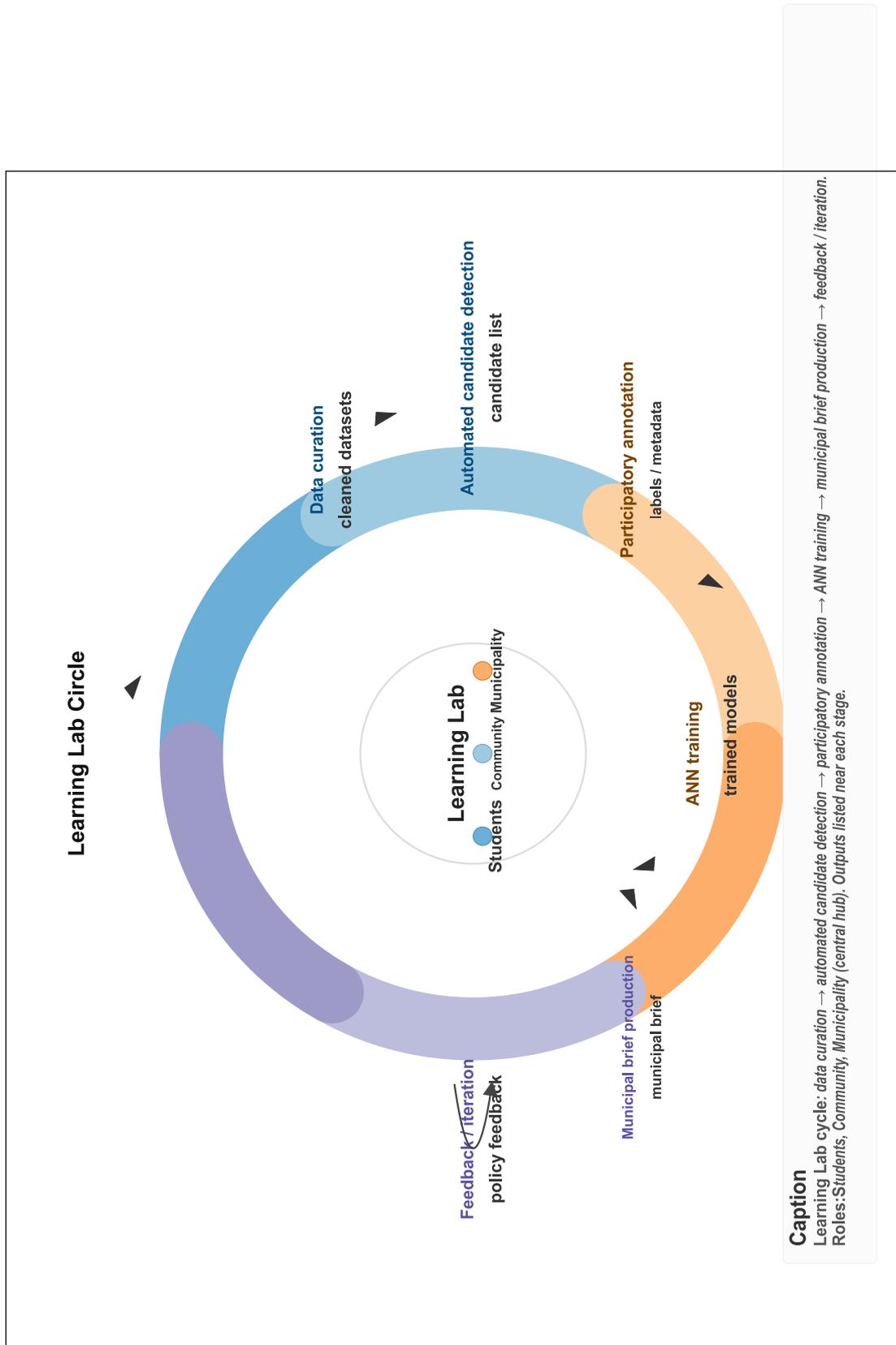


Fig. 7. The *Learning Lab* Cycle: participatory, iterative workflow linking data, models, and community validation

- Implementation roadmap, outlining short, medium, and long-term steps.

These packages were presented in municipal roundtables, where officials and community representatives jointly reviewed and refined them. The inclusion of uncertainty intervals and community validation increased credibility and facilitated integration into municipal information systems [5, 45].

Dissemination and uptake. Dissemination strategies emphasize accessibility and narrative richness. Outputs will be shared through story maps, short films, translated briefs, and low-band-width OERs, foregrounding community voices [21, 65]. MOOCs and micro-credentials integrate pilot results into curricula, ensuring scalability across the consortium.

It is expected the municipal officers report that the evidence packages are directly useful for early restoration planning, particularly in prioritizing inspections and aligning with NRL reporting obligations. The participatory validation process also enhance political legitimacy, reducing the risk of contested decisions [20].

Lessons for policy translation. The Kharkiv pilots highlight several lessons for translating participatory pedagogy into policy impact:

- Triangulation is essential: combining pixel, object, vector, and volumetric methods enhances robustness and credibility [25, 51];
- Transparency builds trust: explicit uncertainty statements increase municipal confidence in outputs [43];
- Community validation ensures legitimacy: participatory annotation and memory walks ground technical evidence in lived realities [2, 52];
- Narrative dissemination matters: story maps and films make evidence accessible to non-technical audiences, enhancing uptake [15, 16, 66].

Synthesis due to results and policy translation. The results of the Kharkiv pilots will demonstrate, that universities can act as catalysts of both socio-ecological recovery and urban renewal. By producing NRL-aligned evidence packages that are scientifically credible, socially legitimate, and governance-ready, the KGNU's team shows how participatory urbogeosystemic pedagogy can operationalize the NRL in post-war urban contexts. The translation of outputs into policy briefs, validated by communities and adopted by municipalities, underscores the transformative potential of this approach for Europe's restoration agenda.

Discussion: strengths, constraints, and scaling implications. *Strengths of the Kharkiv model.* The Kharkiv pilots are expected to demonstrate several notable strengths that position the model as a valuable contribution to the *FutureLand* consortium and

the broader NRL agenda. Accessibility and reproducibility are central. By adopting an open data first strategy, the model reduces dependence on costly proprietary datasets and airborne LiDAR campaigns. Instead, it employs OSM, Sentinel, Landsat, DEMs, and free LiDAR sources, ensuring that workflows are replicable across municipalities with limited resources. This aligns with the NRL's emphasis on transparency and inclusivity.

Pedagogical innovation is another strength. The Learning Labs integrate technical training with participatory facilitation and trauma-informed pedagogy (Fig. 7). Students acquire not only geospatial competencies but also governance literacy and ethical reflexivity, preparing them to act as mediators between science, policy, and society. This dual focus on technical and civic capacities reflects the NRL's demand for socially legitimate restoration planning.

Community legitimacy is perhaps the most distinctive strength. By embedding memory walks, participatory annotation, and municipal roundtables, the model ensures that outputs reflect lived realities and contested narratives of place. This participatory validation increases the likelihood of municipal uptake and reduces the risk of contested decisions.

Finally, the model's policy relevance is clear. Outputs are packaged as NRL-aligned evidence briefs, complete with executive summaries, uncertainty statements, and implementation roadmaps. This format ensures that municipalities can integrate outputs directly into reporting and planning processes.

Constraints and limitations. Despite these strengths, the Kharkiv model faces several constraints too. Volumetric precision remains a challenge, despite significant involvement of LiDAR processing. Typological heuristics for 2.5D modeling provide useful proxies, but cannot replace engineering-level surveys. For structural assessments requiring high accuracy, LiDAR or unmanned aerial vehicle (UAV) photogrammetry remains necessary [68].

Dependence on labeling quality is another limitation. ANN performance is highly sensitive to the quality and representativeness of training data (Fig. 6). While participatory annotation enhances legitimacy, it also introduces variability and requires significant facilitation.

Transferability poses further challenges. Models, which are expected to be trained in Kharkiv, may not generalize to other urban contexts without domain adaptation. Typological heuristics, for example, are context-specific and require calibration to local building forms and governance structures [19].

Security and continuity risks are also significant. Fieldwork in post-war contexts is vulnerable to disruption, and institutional continuity may be threatened by staff turnover or shifting priorities [1]. These risks necessitate flexible participation for-

mats, remote workflows, and embedding pedagogy in curricula for sustainability.

Scaling implications. Despite mentioned constraints, the Kharkiv model may offer valuable lessons for scaling across Europe. Crosslab exchanges within *FutureLand* (e.g., with Venice, Girona, Joensuu) provide opportunities for comparative evaluation of methodological tool-bundles, addressing evidence gaps identified in the literature [14]. Such exchanges will help refine the balance between qualitative, participatory, and technical methods. Shared repositories of benchmark datasets, OER modules, and municipal toolkits can facilitate replication. By curating open repositories with annotated datasets, model cards, and participatory facilitation guides, the consortium can lower barriers for adoption in other contexts.

Selective UAV campaigns and municipal surveys can be integrated cost-effectively to calibrate typological heuristics and improve volumetric accuracy. This hybrid approach balances open data pragmatism with targeted precision. Narrative dissemination is also critical for scaling. Story maps, films, and translated briefs make outputs accessible to nontechnical audiences, enhancing uptake across diverse governance contexts.

Finally, the Kharkiv model underscores the importance of trauma-informed pedagogy as a transferable principle. While developed in a postwar context, its emphasis on safety, trust, and empowerment is relevant to other vulnerable or marginalized communities across Europe.

Synthesis due to discussion. The Kharkiv pilots will illustrate both the promise and the challenges of participatory urbogeosystemic pedagogy in the NRL era. Strengths include accessibility, pedagogical innovation, community legitimacy, and policy relevance. Constraints include volumetric precision, labeling dependence, transferability, and security risks. Scaling requires crosslab exchanges, shared repositories, hybrid data strategies, narrative dissemination, and trauma-informed facilitation.

In sum, the Kharkiv model demonstrates that universities can act as catalysts of ecological recovery and social renewal, even under conditions of war and scarcity. By aligning open data pragmatism, participatory pedagogy, and urbogeosystemic thinking with the NRL governance requirements, the KKNU team offers a transferable blueprint for Europe's restoration agenda.

Synthesis and broader implications. The preceding sections of our paper have outlined a pedagogy and methodological pipeline designed to make nature restoration both technically robust and socially legitimate in post-war urban contexts. Synthesizing these threads points to several interlocking implications for how higher education institutions,

municipal partners, and civil society can co-produce restoration knowledge and action.

First, the integration of open technical workflows with participatory, trauma-aware facilitation creates opportunities to deliver evidence that is both scientifically defensible and credible to local communities. The technical pipelines – from multispectral preprocessing to object-based change detection and lightweight neural networks – generate actionable spatial outputs; the participatory processes ensure those outputs are interpreted, validated and contextualized against lived experience and local priorities. This combination reduces the risk that technical maps are perceived as external impositions, and increases their likelihood of uptake in municipal planning.

Second, the Learning Lab model fosters reciprocal capacity building. Students gain methodological fluency and ethical competency, while municipal staff and community participants acquire practical tools and documentation they can use beyond the immediate project. Where universities operate as convenors, they can help translate cross-sectoral knowledge into municipal roadmaps for phased restoration. The co-creation of evidence packages – including executive summaries, uncertainty statements, and implementation roadmaps – makes academic work legible and useful to decision-makers who must balance ecological objectives with social and economic constraints.

Third, the emphasis on explainable machine learning and human-verified training sets addresses a common tension in civic AI applications: transparency versus performance. By basing models on community-annotated samples and pairing outputs with explainability artifacts (heatmaps, feature-attribution summaries), the pedagogical pipeline avoids black-box solutions and empowers local stakeholders to understand and challenge model findings. This practice supports not only better technical outcomes, but also stronger democratic oversight of algorithmic tools used in public decision-making.

Fourth, the 2.5D pragmatic modeling approach is a practical compromise where full airborne LiDAR is unavailable. While vertical precision is reduced compared with full LiDAR, typological height heuristics and conditional validation provide useful proxies that keep workflows reproducible and accessible. Importantly, every proxy is accompanied by explicit uncertainty bands and validation notes so municipal planners can weigh evidence proportionally. This transparent treatment of uncertainty – documented in methodological appendices and model cards – increases trust and supports incremental decision-making under resource constraints.

Fifth, the pedagogical emphasis on site-specific

memory, cultural values and social infrastructure reframes restoration away from purely ecological metrics toward integrated social-ecological goals. Restoration scenarios that do not attend to displacement, access to services, or cultural meaning risk generating interventions that are technically sound but socially counterproductive. Embedding narrative methods – oral histories, memory walks, and community workshops – ensures that restoration choices reflect not only biophysical potential but also community conceptions of wellbeing, dignity and place.

Sixth, the pilots will highlight the importance of flexible, contingency-aware project design in contexts affected by war. Remote-friendly formats, low-bandwidth resources, and modular lab units help sustain participation despite disruptions. Moreover, the practice of building multiple entry points for engagement (online annotation, small-group workshops, municipal briefings) may increase inclusivity and reduce single points of failure. These practical designs may be especially important in fragile contexts where travel, access to datasets, or institutional continuity may be limited.

Seventh, the dissemination strategy proposed in *WP5* package [21] – combining storytelling, multilingual materials, and targeted roundtables – amplifies impact. Storytelling and visual narratives make technical findings accessible to non-specialist audiences and help shift public conversation about restoration from abstract policy to concrete local initiatives. Meanwhile, targeted exchanges with municipalities and NGOs support the translation of learning lab outputs into pilot projects, funding proposals, and regulatory advice. Ensuring Ukrainian voices are central in these dissemination channels reinforces equity and helps to reframe European debates about restoration to include experience from war-affected territories.

Eighth, scaling and transferability will require careful governance and methodological documentation. Cross-lab comparability demands standardized metadata practices, shared model cards, and reproducible scripts so that evidence generated in different cities can be meaningfully compared. The *FutureLand* consortium's cross-lab exchanges provide a platform for iterative refinement: comparative experiments will reveal which bundles of methods perform consistently, and which require local adaptation. Institutional memory – in the form of well-documented workflows, OERs and policy briefs – will be essential for long-term adoption.

Ninth, monitoring and evaluation frameworks must capture both learning outcomes and community-level change. Traditional academic metrics (publications, citations, course completions) are inadequate for judging success in participatory restora-

tion. Instead, success metrics should combine student competency measures with indicators of community benefit: documented improvements in access to green space, evidence of local uptake of co-designed measures, and sustained partnerships between universities and municipal actors. Mixed-method evaluation designs, including pre-post competency testing, community surveys, and process tracing of policy uptake, will provide more holistic evidence of impact.

Tenth, ethical governance and data stewardship remain central challenges. Even with strong participatory protocols, questions about data ownership, benefit-sharing and long-term stewardship persist. Clear agreements are needed about who holds annotated datasets, how sensitive locations are masked, and how benefits from restored sites are distributed. Institutional arrangements that formalize these norms – through memorandum of understanding, community data trusts, or municipal- university agreements – will help protect participants while enabling reuse of evidence for planning.

Eleventh, the educational implications for curricula are significant. Restoration education should not be an elective add-on but integrated across urban planning, geography, environmental science and humanitarian studies. Course sequences that combine technical skills (remote sensing, GIS, basic machine learning) with participatory competencies (facilitation, ethics, community engagement) produce graduates capable of navigating the interdisciplinary nature of contemporary restoration work. Micro-credentials and stackable modules, made available through the MOOC and partner institutions, can accelerate capacity building among practitioners already in the field.

Twelfth, future research priorities include longitudinal studies of lab impacts, cross-cultural model adaptation, and the economics of phased restoration. Longitudinal tracking of learning labs will show how student competencies evolve, and whether municipal partners continue to use evidence packages after project close. Research that compares methodological bundles across contrasting governance contexts will sharpen transferability. Finally, cost-effectiveness studies of incremental restoration strategies – combining low-cost green infrastructure with targeted social investments – will help municipalities prioritize interventions under fiscal constraints.

Practical recommendations and concluding reflection. From the synthesis above, a set of pragmatic recommendations emerges for partners and practitioners who aim to adopt the KGNU model:

1. Prioritize participatory annotation early in workflows to ground models in lived experience.

2. Publish model cards and uncertainty statements with every evidence package to support municipal decision-making.
3. Use modular lab units that can be recombined depending on access and bandwidth constraints.
4. Invest in trauma-aware facilitation training for students and staff working in post-war contexts.
5. Formalize data governance and benefit-sharing agreements with community partners.
6. Design monitoring frameworks that capture both learning and community-level outcomes.

In combining open technical workflows with human geographical and humanitarian practices, the KGNU model offers a practical route toward restoration pedagogy that is both rigorous and humane. The pilot work in Kharkiv will illustrate how universities act as convenors and translators – producing evidence that municipal decision-makers can use and communities can trust. As *FutureLand* progresses, iterative refinement through cross-lab exchanges, careful documentation, and a sustained commitment to participation will be essential. The enduring goal is to enable restoration that heals ecological systems while restoring social fabrics – a dual purpose that is both technically demanding and morally imperative.

Addendum: practical tools, templates, and teaching aids. To support rapid adoption, partners should be provided with a compact toolkit of practical resources that can be applied directly in Learning Labs and municipal collaborations. These resources include: a short workshop template for a one-day participatory mapping event, a compact syllabus for a four-week module on *Urban Post-War Nature Restoration*, an assessment rubric for mixed-method projects, and a lightweight data stewardship checklist. The workshop template outlines objectives, a one-day timetable, materials checklist, ethical safeguards, and a simple facilitation script for trauma-aware engagement. The syllabus provides week-by-week learning outcomes, readings, practical assignments, and guidance for integrating remote sensing exercises with community workshops. The assessment rubric balances technical correctness, ethical facilitation, community engagement, and policy relevance, giving equal weight to reproducibility and social legitimacy.

A compact data stewardship checklist clarifies roles and responsibilities: where annotated datasets are stored, who controls access, how sensitive locations are masked, and how community partners can request data deletion or review. These governance templates should be adaptable: some partners will need municipal-level memorandum, others will benefit from informal agreements that match communi-

ty norms. The goal is to lower transaction costs for faculty and partners so that labs can focus on evidence generation and dialogue instead of negotiating basic procedural elements.

Practical software stacks and deployment tips are equally important. For classroom use, provide containerized notebooks (or cloud-hosted GEE scripts) that perform core preprocessing tasks: coordinate harmonization, cloud masking, index computation, and simple OBIA segmentation. Offer a small set of curated LiDAR subsets or DEM-based 2.5D proxies so students can run end-to-end exercises on standard laptops. Include example annotation projects with step-by-step guides for workshop facilitation and quality control checks. A brief troubleshooting appendix should cover common issues: mismatched projections, cloud contamination, and imbalance in training samples.

The *City Change Management* desktop software [28, 31] will play a key performance in all these activities.

Finally, build a compact teacher training module: a short, modular course that prepares instructors for trauma-aware facilitation, participatory annotation management, and the integration of explainable AI outputs into community dialogues. The training emphasizes reflective practice: instructors should be encouraged to keep short process journals that record choices, ethical dilemmas and community feedback. These reflective notes are valuable both for iterative improvement and for documenting civic impact in project reports and policy briefs.

Together, these pragmatic templates and resources reduce entry barriers, encourage methodological consistency, and help sustain high-quality, people-centered restoration pedagogy across diverse partner contexts.

Closing note on collaboration. Sustained collaboration requires time, trust and modest resourcing. Small investments – a shared dataset repository, modest travel support for community partners, and a recurring review meeting – yield disproportionate returns when partnerships are built on mutual respect and shared purpose. By committing to iterative learning, transparent documentation, and active listening, partners can turn pilot successes into long-term municipal practices that restore both urban ecosystems and civic life within the cities. We remain committed to co-design, to rigorous evidence, and to listening as the first act of restoration.

Conclusion

The Kharkiv pilots within the Erasmus+ *FutureLand* project demonstrate that urban restoration in the NRL era must be understood as both an ecological, socio-environmental, and educational process. By combining urbogeosystemic thinking, open data pragmatism, participatory pedagogy, and trau-

ma-informed facilitation, the KGNU team will develop a model that would be simultaneously scientifically credible, socially legitimate, and governance-ready.

Technically, the model shows that open datasets - OSM, satellite imageries, DEMs, LiDAR point clouds. If combined with pragmatic 2.5D modeling and participatory annotation it can generate NRL-aligned indicators even in resource-constrained, post-war contexts. Multimethod change detection and lightweight, explainable ANN workflows provide robust evidence while remaining accessible to students and municipalities.

Pedagogically, the Learning Labs cultivate a new generation of restoration specialists who are not only proficient in geospatial analysis but also skilled in facilitation, ethical reflexivity, and policy translation. Trauma-informed protocols ensure that community engagement is safe, respectful, and empowering, avoiding extractive tendencies and fostering resilience.

For communities, the pilots will reengage residents in shaping their urban futures, embedding memory, identity, and aspirations into restoration planning. For municipalities, the outputs will be delivered as concise, NRL-aligned evidence packages, complete with uncertainty statements and implementation roadmaps, enhancing both credibility and uptake.

The Kharkiv experience underscores the potential of universities to act as catalysts of urban ecological renovation and social recovery. By aligning technical innovation with participatory ethics and policy imperatives, our team offers a transferable blueprint for Europe's restoration agenda. Future scaling will require crosslab exchanges, shared repositories, and hybrid data strategies, but the foundation is clear: restoration as recovery is not only possible, it is essential for building resilient, democratic, and sustainable urban futures, particularly, in Ukraine after this awful war.

List of Abbreviations

ANN – artificial neural network
 CBL – challenge-based learning
 CNN - convolutional neural network
 KGNU – V.N. Karazin Kharkiv national university
 LiDAR – light detection and ranging
 MLP - multi-layer perceptron
 MOOC – massive open online course
 NRL – nature restoration law
 OBIA – object-based image analysis
 OER – open educational resources
 OSM – open street map
 PAR – participatory action research
 UAV - unmanned aerial vehicle
 UES – urban ecological system
 UE – urbanistic environment
 UGS – urbogeosystem
 URS – urban remote sensing

References

1. Anderson R. K., Landy M., Sanchez V. [and other] (2023). *Trauma-informed pedagogy in higher education: Considerations for the future of research and practice*. *Journal of Trauma Studies in Education*, 2(2). Available at: <https://journals.library.appstate.edu/index.php/JTSE/article/view/212>
2. Ballard H. L., Belsky J. M. (2010). *Participatory action research and environmental learning: Implications for resilient forests and communities*. *Environmental Education Research*, 16(5-6), 611–627. DOI: <https://doi.org/10.1080/13504622.2010.505440>
3. Battisti C., Baiani D. S. (Eds.). (2022). *Urban agglomeration: Models and strategies for regeneration of residential buildings and outdoor public spaces*. *IntechOpen*. DOI: <https://doi.org/10.5772/intechopen.102366>
4. Biljecki, F., Stoter, J., Ledoux, H., Zlatanova, S., & Çöltekin, A. (2015). *Applications of 3D city models: State of the art review*. *ISPRS International Journal of Geo-Information*, 4(4), 2842–2889. DOI: <https://doi.org/10.3390/ijgi4042842>
5. BirdLife International. (2024). *State of the World's Birds: 2024 Annual Update*. Available at: <https://datazone.birdlife.org/articles/state-of-the-worlds-birds-2024-annual-update>
6. Birney L. B., McNamara D. M. (2023). *The Curriculum and Community Enterprise for Restoration Science: Making STEM accessible, equitable, and environmentally relevant*. *NSF Public Access Repository*. Available at: <https://par.nsf.gov/biblio/10346894>
7. Boulila W., Ghandorh H., Khan M. [and other] (2021). *A novel CNN-LSTM-based approach to predict urban expansion*. *Ecological Informatics*. 64, 101325. DOI: <https://doi.org/10.1016/j.ecoinf.2021.101325>
8. Brovelli M. A., Zamboni G. (2018). *A New Method for the Assessment of Spatial Accuracy and Completeness of OpenStreetMap Building Footprints*. *ISPRS International Journal of Geo-Information*, 7(8), 289. DOI: <https://doi.org/10.3390/ijgi7080289>
9. Brenner C. (2000). *Extracting urban objects from airborne laser scanner data*. *International Archives of Photogrammetry and Remote Sensing*, 33(B3/2), 29–36.
10. Carello J., Butler L. D. (2015). *Practicing what we teach: Trauma-informed educational practice*. *Journal of Teaching in Social Work*, 35(3), 262–278. DOI: <https://doi.org/10.1080/08841233.2015.1030059>
11. Cheng L., Wu Y., Tong L., Chen Y., Li M. (2015). *Hierarchical registration method for airborne and vehicle LiDAR point cloud*. *Remote Sensing* 7, 13921–13944. <https://doi.org/10.3390/rs71013921>.

12. Chevalier J. M., Buckles D. J. (2013). *Participatory action research: theory and methods for engaged research*. London: Routledge: 496. DOI: <https://doi.org/10.4324/9780203107386>
13. Chollet F. (2017). Xception: Deep learning with depth-wise separable convolutions. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 1800–1807. DOI: <https://doi.org/10.1109/CVPR.2017.195>
14. Durrant E., Howson P., Puttick B. [and other] (2023). Existing evidence on the use of participatory scenarios in ecological restoration: a systematic map. *Environmental Evidence*, 12, 27. DOI: <https://doi.org/10.1186/s13750-023-00314-1>
15. Elwood S. (2009). Integrating participatory action research and GIS education: Negotiating methodologies, politics and technologies. *Journal of Geography in Higher Education*, 33(1), 51–65. DOI: <https://doi.org/10.1080/03098260802276565>
16. Elwood S. (2009). Critical issues in participatory GIS: Deconstructing the specter of objectivity. *Annals of the Association of American Geographers*, 99(1), 128–143. DOI: <https://doi.org/10.1080/00045600802633309>
17. European Commission (EC). (2024). *Nature Restoration Regulation*. European Commission – Environment. Available at: https://environment.ec.europa.eu/topics/nature-and-biodiversity/nature-restoration-regulation_en
18. European Parliament (EP) (2024). *Legislative resolution of 27 February 2024 on the proposal for a regulation of the European Parliament and of the Council on nature restoration (COM(2022)0304 – C9-0208/2022 – 2022/0195(COD))*. Official Journal of the European Union, C/2024/6757. Available at: <EUR-Le>
19. Feng H., Chen Y., Luo Z. [and other] (2022). Automated extraction of building instances from dual-channel airborne LiDAR point clouds. *International Journal of Applied Earth Observation and Geoinformation*, 114, 103042. DOI: <https://doi.org/10.1016/j.jag.2022.103042>.
20. Fox H., Cundill G. (2018). Towards increased community-engaged ecological restoration: A review of current practice and future directions. *Ecological Restoration*, 36(3), 208–218. DOI: <https://doi.org/10.3368/er.36.3.208>
21. FutureLand Consortium (FLC). (2025). *FutureLand – Nature Restoration: challenges and opportunities for future landscape specialists (KA220-HED application)*. Unpublished application.
22. Goodchild M. F. (2009). Geographic information systems and science: Today and tomorrow. *International Journal of Geographical Information Science*, 23(10), 1371–1374. DOI: <https://doi.org/10.1080/19475680903250715>
23. Goodfellow I., Bengio Y., Courville A. (2016). *Deep Learning*. MIT Press. Available at: <https://www.deeplearningbook.org/>
24. He K., Zhang X., Ren S., Sun J. (2016). Deep residual learning for image recognition. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 770–778. DOI: <https://doi.org/10.1109/CVPR.2016.90>
25. Hussain M., Chen D., Cheng A., Wei H., Stanley D. (2013). Change detection from remotely sensed images: From pixel-based to object-based approaches. *ISPRS Journal of Photogrammetry and Remote Sensing*, 80, 91–106. DOI: <https://doi.org/10.1016/j.isprsjprs.2013.03.006>
26. Johnson-Lawrence V., Sneed R., Dotson K. [and other] (2024). *Trauma-informed approaches and community engagement in post-war mapping*. National Library of Medicine. RTI Press. Available at: <https://www.ncbi.nlm.nih.gov/books/NBK607457/>
27. Kingma D. P., Ba J. (2014). Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980*. <https://doi.org/10.48550/arXiv.1412.6980>
28. Kostrikov, S., Serohin, D. (2025). Urban change detection with airborne LiDAR for hostilities' impact estimation: a case study of Kharkiv. *European Journal of Remote Sensing*, 58 (1). DOI: <https://doi.org/10.1080/22797254.2025.2491750>
29. Kostrikov S., Niemets L., Sehida K. [and other] (2018). Geoinformation approach to the urban geographic system research (case studies of Kharkiv region). *Visnyk of V.N. Karazin Kharkiv National University. Series "Geology. Geography. Ecology"*, (49), 107-121. DOI: <https://doi.org/10.26565/2410-7360-2018-49-09>
30. Kostrikov S., Seryogin D. (2022). Urbogeosystemic Approach to Agglomeration Study within the Urban Remote Sensing Frameworks. *Urban Agglomeration*. Edited by A. Battisti and S. Baiani: Intech Open, London, Milan, Zagreb. 251-273. DOI: <http://dx.doi.org/10.5772/intechopen.102482>
31. Kostrikov S., Niemets L., Robinson D., Mezentsev K., Kravchenko K., Serohin D. (2024). Delineation of the Hostilities' Impact on Urban Environment by LiDAR Data Processing (a Case Study of Kharkiv). In: Morar, C., Berman, L., Erdal, S., Niemets, L. (eds) *Achieving Sustainability in Ukraine through Military Brownfields Redevelopment*. NATOARW 2023. NATO Science for Peace and Security Series C: Environmental Security. Springer, Dordrecht. DOI: https://doi.org/10.1007/978-94-024-2278-8_22
32. Kostrikov S. (2025). Analyzing urban morphology changes using neural networks. *Visnyk of V.N. Karazin Kharkiv National University. Series Geology. Geography. Ecology*, (62), 219-236 <https://doi.org/10.26565/2410-7360-2025-62-17>
33. Kostrikov S., Pudlo R., Bubnov D., Vasiliev V. (2020). ELiT, multifunctional web-software for feature extraction from 3D LiDAR point clouds. *ISPRS International Journal of Geo-Information*. 9(11), 650-885. DOI: <http://dx.doi.org/10.3390/ijgi9110650>

34. Kostrikov S., Kravchenko K., Serohin D., Bilianska S., Savchenko A. (2023). *The performance of the digital city projects in urban studies of the megalopolises (the case studies of Kharkiv and Dnipro cities)*. *Visnyk of V. N. Karazin Kharkiv National University, series "Geology. Geography. Ecology"*, (59), 140-165. DOI: <https://doi.org/10.26565/2410-7360-2023-59-11>
35. Kostrikov S., Pudlo R., Bubnov D., Vasiliev V., Fedayay Y., 2020. *Automated Extraction of Heavyweight and Lightweight Models of Urban Features from LiDAR Point Clouds by Specialized Web-Software*. *Adv. Sci. Technol. Eng. Syst. J.* 5, 72-95. DOI: <https://dx.doi.org/10.25046/aj050609>
36. Kowarik I., Fischer L.K., Haase D. [and other] (2025). *Promoting urban biodiversity for the benefit of people and nature*. *Nat. Rev. Biodivers.* 1, 214–232. DOI: <https://doi.org/10.1038/s44358-025-00035-y>
37. Kravchenko K., Niemets L., Sehida K. (2024). *War consequences and prospects for post-war reconstruction (case of Ukrainian urban agglomerations)*. *Visnyk of V. N. Karazin Kharkiv National University. Series Geology. Geography. Ecology*, (61), 193-211. DOI: <https://doi.org/10.26565/2410-7360-2024-61-16>
38. Langemeyer, J., Busse, S., Arabas, A. et al. (2025). *Social-ecological justice in cities: a spatial vulnerability approach*. *npj Urban Sustain* 5, 46. DOI: <https://doi.org/10.1038/s42949-025-00234-8>
39. LeCun Y., Bottou L., Bengio Y., Haffne, P. (1998). *Gradient-based learning applied to document recognition*. *Proceedings of the IEEE*, 86(11), 2278–2324. DOI: <https://doi.org/10.1109/5.726791>
40. Lin T.-Y., Goyal P., Girshick R., He K., Dollár P. (2017). *Focal loss for dense object detection*. *Proceedings of the IEEE International Conference on Computer Vision (ICCV)*, 2980–2988. DOI: <https://doi.org/10.1109/ICCV.2017.324>
41. Lohmus A. (2025). *recognizing and mitigating key uncertainties about the future in ecological restoration planning*. *Restoration Ecology*, 32(8), e13321. DOI: <https://doi.org/10.1111/rec.70158>
42. Lundberg S. M., Lee S.-I. (2017). *A Unified Approach to Interpreting Model Predictions*. *Proceedings of the 31st International Conference on Neural Information Processing Systems (NeurIPS)*, 4768–4777. DOI: <https://doi.org/10.48550/arXiv.1705.07874>
43. Maas H.-G., Vosselman G. (1999). *Two algorithms for extracting building models from raw laser altimetry data*. *ISPRS Journal of Photogrammetry and Remote Sensing*, 54(2–3), 153–163. DOI: [https://doi.org/10.1016/S0924-2716\(99\)00004-0](https://doi.org/10.1016/S0924-2716(99)00004-0)
44. McMahon B. J. (2023). *Trauma-informed pedagogy: A framework for teacher preparation and practice*. In E. Stromberg (Ed.), *Trauma-Informed Pedagogy in Higher Education: A Faculty Guide for Teaching and Learning*, 45-60. Routledge. DOI: <https://doi.org/10.4324/9781003260776>
45. Moore E., Howson, P., Grainger M. [and other]. (2022). *The role of participatory scenarios in ecological restoration: a systematic map protocol*. *Environmental Evidence*, 11, 23 (2022). DOI: <https://doi.org/10.1186/s13750-022-00276-w>
46. Morar, C., Lukić, T., Valjarević, A. [and other]. (2022). *Spatiotemporal analysis of urban green areas using change detection: A case study of Kharkiv, Ukraine*. *Frontiers in Environmental Science*, 10, 823129. <https://doi.org/10.3389/fenvs.2022.823129>
47. Mueller H., Groeger A., Hersh A. [and other]. (2021) *Monitoring war destruction from space using machine learning*, *Proc. Natl. Acad. Sci. U.S.A.* 118 (23) e2025400118. DOI: <https://doi.org/10.1073/pnas.2025400118>
48. Narkhede J. *Comparative Evaluation of Post-Hoc Explainability Methods in AI: LIME, SHAP, and Grad-CAM*, "2024 4th International Conference on Sustainable Expert Systems (ICSES), Kaski, Nepal, 2024, 826-830, DOI: <https://doi.org/10.1109/ICSES63445.2024.10762963>
49. Penca J., Tănăsescu, M. (2024). *The transformative potential of the EU's Nature Restoration Law*. *Sustainability Science*. Advance online publication. DOI: <https://doi.org/10.1007/s11625-024-01610-6>
50. Perissi I. (2025). *Assessing the EU27 potential to meet the Nature Restoration Law targets*. *Environmental Management*, 75(4), 711–729. <https://doi.org/10.1007/s00267-024-02107-9>
51. Radke, R. J., Andra, S., Al-Kofahi, O., & Roysam, B. (2005). *Image change detection algorithms: A systematic survey*. *IEEE Transactions on Image Processing*, 14(3), 294–307. DOI: <https://doi.org/10.1109/TIP.2004.838698>
52. Rambaldi G. (2010). *Participatory Three-Dimensional Modelling: Guiding Principles and Applications*. Technical Centre for Agricultural and Rural Cooperation (CTA). Available at: <https://participatorygis.blogspot.com/2010/10/our-forest-our-dignity-forest-dependent.html>
53. Sampath A., Shan J. (2010). *Building reconstruction from airborne LiDAR point clouds*. *ISPRS Annals of Photogrammetry, Remote Sensing and Spatial Information Sciences*, I-3, 163–168. DOI: <http://dx.doi.org/10.1109/TGRS.2009.2030180>
54. Selvaraju R. R., Cogswell M., Das A., Vedantam R., Parikh D., Batra, D. (2017). *Grad-CAM: Visual explanations from deep networks via gradient-based localization*. *Proceedings of the IEEE International Conference on Computer Vision (ICCV)*, 618–626. DOI: <https://doi.org/10.1109/ICCV.2017.74>
55. Shafian S., He C., Hu D. (2025). *DamageScope: An Integrated Pipeline for Building Damage Segmentation, Geospatial Mapping, and Interactive Web-Based Visualization*. *Remote Sensing*, 17(13), 2267. DOI: <https://doi.org/10.3390/rs17132267>

56. Stephens D. W. (2020). *Trauma-Informed Pedagogy for the Religious and Theological Higher Education Classroom*. *Religions*, 11(9), 449. DOI: <https://doi.org/10.3390/rel11090449>
57. Stilla U., Xu Y. (2023). *Change detection of urban objects using 3D point clouds: A review*. *ISPRS J. Photogram. Remote Sens.* 197, 228-255. <https://doi.org/10.1016/j.isprsjprs.2023.01.010>.
58. Stoter J., van den Brink L., Ledoux H. (2016). *3D cadaster implementations and challenges*. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, III-4, 1–8. DOI: <https://doi.org/10.5194/isprs-annals-III-4-1-2016>
59. Tadono T., Ishida H., Oda F., Naito S., Minakawa K., Iwamoto H. (2014). *Precise Global DEM Generation by ALOS PRISM*. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, II-4, 71–76. DOI: <https://doi.org/10.5194/isprsannals-II-4-71-2014>
60. Tian S., Zhong Y., Zheng Z. [and other] (2022). *Large-scale deep learning based binary and semantic change detection in ultra high resolution remote sensing imagery*. *ISPRS Journal of Photogrammetry and Remote Sensing*, 193, 164–186. <https://doi.org/10.1016/j.isprsjprs.2022.08.012>
61. Toomey, A., Smith, J., Becker, C., Palta, M., & Moore, T. (2023). *Towards a pedagogy of social–ecological collaborations: Engaging students and urban nonprofits for an ecology with cities*. *Urban Ecosystems*, 26, 425–432. DOI: <https://doi.org/10.1007/s11252-023-01343-x>
62. UNECE. *UN4UkrainianCities. Supporting Kharkiv's Path to Recovery with the Comprehensive Restoration Program*. UN Report (2024). Available at: <https://www.un4ukrainiancities.org/news/supporting-kharkivs-path-to-recovery-with-the-comprehensive-restoration-program-1>
63. Vance-Chalcraft H. D., Hurlbert A. H., Styrsky J. N. [and other] (2022). *Ecological service-learning positively impacts classroom climate and empowers undergraduates for environmental action*. *Ecosphere*, 13(5), e4039. DOI: <https://doi.org/10.1002/ecs2.4039>
64. Wang X., Zhang L., Li H. (2020). *A deep Siamese network with hybrid convolutional feature extraction module for change detection in multi-sensor remote sensing images*. *Remote Sensing*, 12(2), 205. DOI: <https://doi.org/10.3390/rs12020205>
65. Webster S., Thompson P., Carello J. (2022). *Trauma-informed pedagogies: A guide for responding to crisis and inequality in higher education*. Textbook. Springer. DOI: <https://doi.org/10.1007/978-3-030-92705-9>
66. Wiley D. R., Abernathy D. R. (2023). *The next layer: Towards open pedagogy in geospatial education*. *Transactions in GIS*, 27(2), e13081. DOI: <https://doi.org/10.1111/tgis.13081>
67. Yu D., Fang, C. (2023). *Urban Remote Sensing with Spatial Big Data: A Review and Renewed Perspective of Urban Studies in Recent Decades*. *Remote Sensing*, 15(5), 1307. DOI: <https://doi.org/10.3390/rs15051307>
68. Zhou Y., Rupnik E., Meynard C., Thom, C., Pierrot-Deseilligny M. (2020). *Simulation and Analysis of Photogrammetric UAV Image Blocks–Influence of Camera Calibration Error*. *Remote Sensing*, 12(1), 22. DOI: <https://doi.org/10.3390/rs12010022>
69. Zhu Z., Woodcock C. E. (2014). *Continuous change detection and classification of land cover using all available Landsat data*. *Remote Sensing of Environment*, 144, 152–171. DOI: <https://doi.org/10.1016/j.rse.2014.01.011>

Authors Contribution: All authors have contributed equally to this work

Conflict of Interest: The authors declare no conflict of interest

Відновлення через відбудову: партисипативна урбогеосистемна педагогіка Каразінського університету для проєкту Erasmus+ *FutureLand*

Сергій Костріков¹

д. геогр. н., професор, кафедра соціально-економічної географії
і регіонознавства імені Костянтина Немця,

¹ Харківський національний університет імені В.Н. Каразіна, Харків, Україна;

Людмила Немець¹

д. геогр. н., професор, кафедра соціально-економічної географії
і регіонознавства імені Костянтина Немця

Стаття описує концепцію педагогічної та методологічної моделі, яка буде розроблена у рамках проєкту *FutureLand*. Модель спрямована на впровадження вимог Європейського закону про відновлення природи (NRL), який зобов'язує відновлювати міські екосистеми, зокрема в постраждалих від війни містах. Ключовою інновацією стане урбогеосистемна педагогіка, що поєднує відкриті геопросторові дані з партисипативними Навчальни-

ми лабораторіями та травма-орієнтованою фасилітацією. Автори пропонують партисипативну методику викладання, адаптовану до пост-воєнної відбудови та подальшого відновлення. Методика спирається на підходи урбогеосистемного аналізу та геопросторові інструменти. Отже, головною дослідницькою метою цієї статті є представлення трансферної (модель, що має потенціал масштабування) травма-орієнтованої партисипативної педагогіки. Методологічно майбутня модель будуватиметься на урбогеосистемній концепції міста. Остання демонструє, як Урбаністичне середовище, Урбогеосистема та Міська екологічна система структурно пов'язані: растрова діагностика, векторне подання та соціо-екологічні процеси сходяться в єдиній моделі. Разом вони дозволяють педагогіці відновлення трансформувати просторові дані у соціально легітимні та екологічно обґрунтовані міські середовища. Методологічно модель також спирається на принцип «open data first»: використання відкритих геопросторових даних та муніципальних LiDAR-порталів. Для виявлення урбаністичних змін поєднуються хмари лідарних точок, а також легкі нейронні мережі з пояснюваними результатами. Ключовим інструментом педагогічної моделі стануть Навчальні лабораторії, де студенти, громади та представники міської влади спільно збиратимуть й аналізуватимуть дані, проводитимуть «прогулянки пам'яті», партисипативне картографування та оцінку результатів. Можна сподіватися, що пілотні застосування у Харкові доведуть практичну ефективність моделі: буде створено карти змін забудови та зелених зон, підготовлено сценарії відновлення, буде розроблено пакети доказів для муніципалітету з чіткими показниками та планами реалізації. Таким чином, представлена концепція демонструє, що навіть у післявоєнних умовах наш університет, завдяки участі у проєкті *FutureLand*, може стати каталізатором інфраструктурної відбудови, екологічного відновлення та соціального оновлення. Модель, що відповідає запропонованій концепції, буде масштабованою та може бути адаптована для інших європейських міст, які стикаються з викликами деградації довкілля та складного врядування.

Ключові слова: *Європейський закон щодо відновлення природи, партисипативна педагогіка, урбогеосистемний підхід, урбаністична екосистема, навчальні лабораторії, міське дистанційне зондування, лідар, ШНМ.*

Внесок авторів: всі автори зробили рівний внесок у цю роботу

Надійшла 1 вересня 2025 р.

Конфлікт інтересів: автори повідомляють про відсутність конфлікту інтересів

Прийнята 23 жовтня 2025 р.