



A simple method for mapping winter recreational fishing ecosystem services supply in lakes. A contribution to mapping freshwater ecosystem services



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ABSTRACT

Although urban areas negatively impact the environment, they supply a wide range of ecosystem services (ES), mainly cultural ones. Recreation near urban green areas is widespread, including fishing. In northern latitudes, during the winter, lakes are frozen, and several urban dwellers practice ice fishing. Although this activity is well known, no attempts were made to assess and map winter recreational fishery ES supply in lakes. In this work, we developed a methodology to map this ES, taking an urban lake in Vilnius (Lithuania) as an example. A standardized protocol was developed using an unmanned aerial vehicle (proximal sensing), further georeferencing and correcting the gathered images, vectorizing the fishing ice holes, and mapping them using two different methods: Kernel and Point Density. The method developed in this work can be applied in northern areas to identify recreational fishing ES during the winter.

- A novel method was developed to map winter recreational fishery ES supply in lakes;
- High-resolution images were taken from an unmanned aerial vehicle to identify fishing ice holes in an urban lake.
- The method maps a cultural ES, which is trendy in northern latitudes.

Specifications table

Subject area:	Environmental Science
More specific subject area:	Cultural Ecosystem Services
Name of your method:	Recreational winter fish mapping
Name and reference of original method:	NA
Resource availability:	DJI Mavic 3 M Computer Intel(R) Core (TM) i9–10900X CPU @ 3.70 GHz 3.70 GHz and 64.0 GB Memory ArcGIS Pro (ver. 3.1.2)

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Background

Ecosystem Services (ES) are the benefits humans receive from nature and are classified as provisioning, regulating and cultural ES [1]. In urban areas, ecosystems are strongly altered by human impact. Anthropogenic pressure is also responsible for the degradation of ecosystem conditions (e.g., pollution) and their capacity to supply ES [2,3]. Urban ecosystems comprise several land use types, such as built-up areas, forests, croplands, grasslands, wetlands, rivers and lakes [4]. They provide multiple regulating and provisioning ES. However, in an urban context, they are crucial for cultural ES, such as recreation [5,6]. Among the different recreational activities that urban ecosystems can supply, fishing in rivers or lakes is among the most important in some environments [7,8]. Due to the negative temperatures, water bodies are frozen in northern latitudes, and people frequently fish in the middle of lakes and rivers [9,10].

Mapping is key to understanding natural, social and economic phenomena [11] and has been recognized as a tool to identify ES spatial patterns. For this reason, it became one of the main tools that brought forward ES research [12]. Technological development contributed to the array of ES mapping and assessment options. Recently, remote sensing has been increasingly utilized to improve ES mapping and assessment. At large scales (e.g., country, region), they are useful to assess ES proxies (e.g., indicators) or serving as input data for ES models [13]. At small scales (e.g., urban parks, lakes), proximal sensing (e.g., unmanned aerial vehicle (UAV)) is adequate to collect information at a higher resolution and identify small-scale patterns [14]. For instance, in some regions, winter recreational activities are popular in urban areas, and people's preferences can be identified by using UAVs [15]. In the case of winter recreational fishing in lakes, fishers make holes in the ice through which they can reach liquid water. According to the Common International Classification of Ecosystem Services (CICES)¹ 5.1.v this services ES is classified as "Direct, in-situ and outdoor interactions with living systems that depend on presence in the environmental setting, i.e. broadly recreational activities" (Code 3.1.1.1) at group level. The holes can be identified through high-resolution UAV images. So far, a methodology has yet to be developed to map this recreational activity in lakes, which is important in northern latitudes. This work aims to develop a simple methodology based on high-resolution imagery taken using UAV to map lakes' winter recreational fishing supply.

Method details

The method was applied in an urban artificial lake (17,527.11 m²) located in Vilnius, Lithuania (Fig. 1), during the winter, when it is frozen. An urban park surrounds the lake. We used the DJI Mavic 3 M drone with RGB and multispectral capabilities to map winter recreational fishing in lakes. The drone specifications can be consulted on the DJI website.² The most relevant are shown in

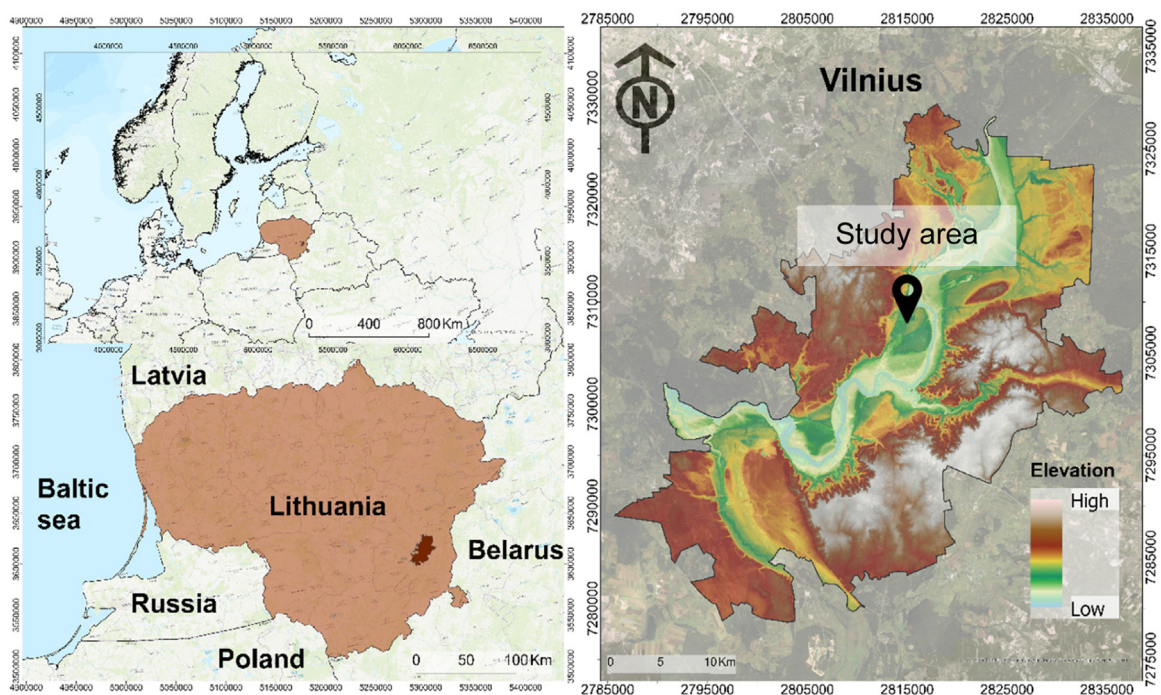


Fig. 1. Study area.

¹ <https://cices.eu/>.

² <https://enterprise.dji.com/mavic-3-m/specs>.

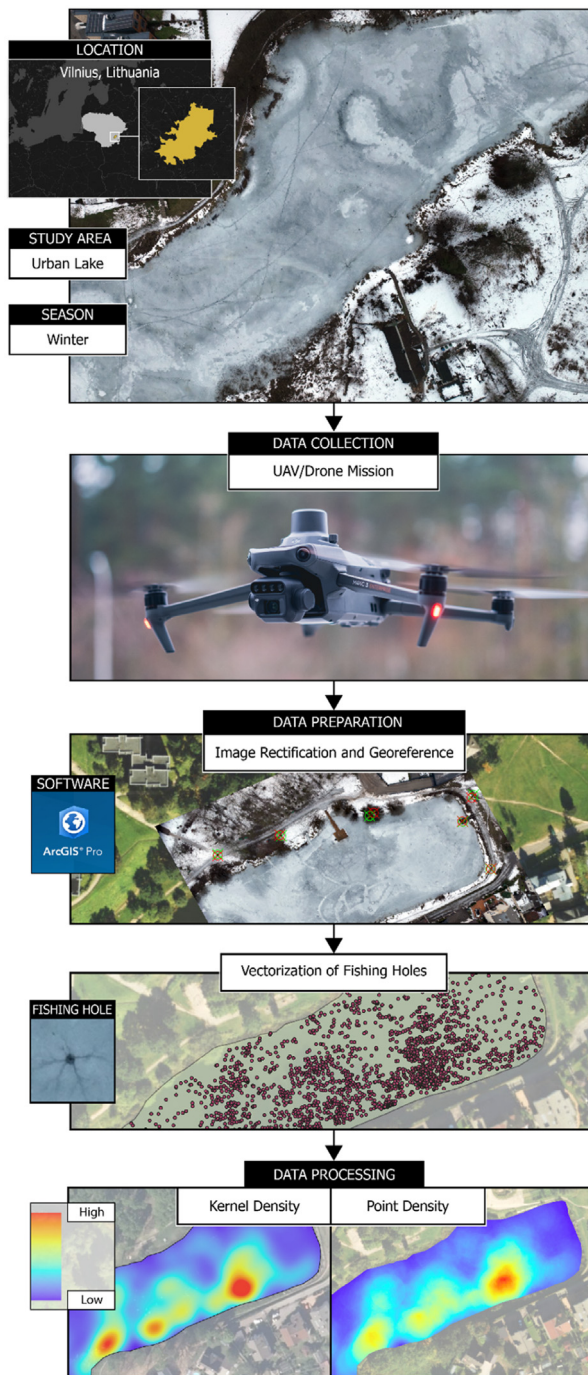


Fig. 2. Framework applied in this study.

Table S1. The methodological framework established in this work is shown in Fig. 2. The drone flight was conducted on February 04, 2024. Before going to the field, a flight mission was planned and uploaded into the drone software. During this process, extending the mission beyond the lake limits is important to ensure that the images taken cover the whole lake’s surface area. In this work, we extended the mission 140 m further away from the lake shoreline. In total, 38,867.7 m² were mapped. The ground sample distance³ (GSD) was 2.15 cm, and the flight lasted 18 min and 31 s. In total, 646 photos were taken at an altitude of 60 m (Fig. 3). DJI Mavic

³ <https://enterprise-insights.dji.com/blog/ground-sample-distance>.

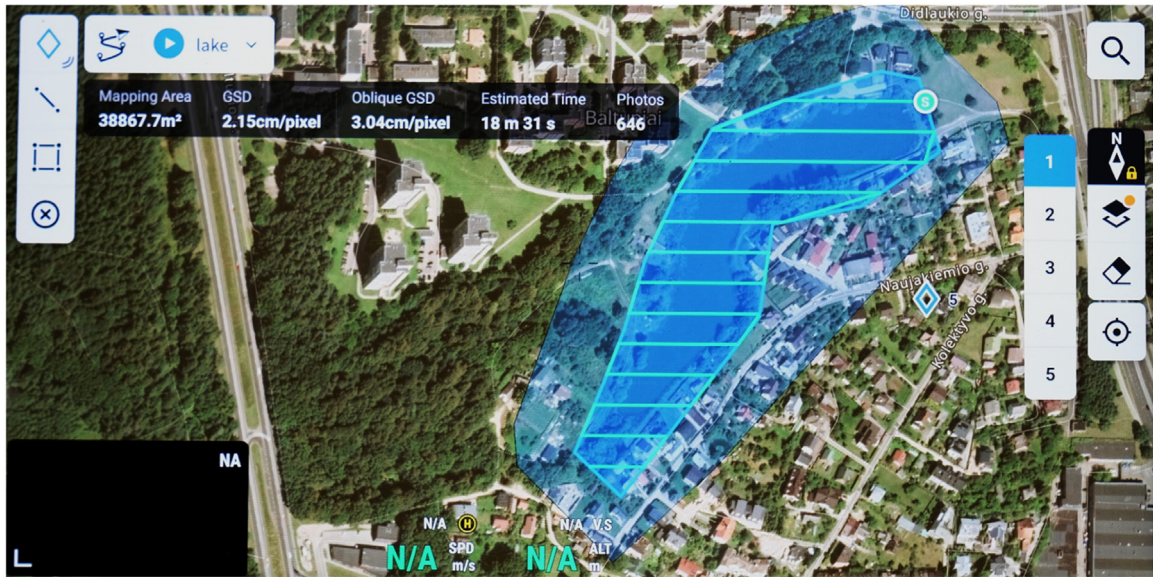


Fig. 3. Mission Snapshot.

3 M saved the images in a micro-SD card that were later downloaded to the computer for further treatment. In ArcGIS Pro (ver. 3.1.2) environment (Georeference Raster Tool⁴), the RGB images were georeferenced and corrected to match the true limit of the lake using the Second-order polynomial transformation (Fig. 2). As a base map, we used the orthophoto map from the Spring of 2023.⁵ To georeference the images correctly, many points are needed to ensure maximum accuracy and minimize error. During the georeferencing process, more than 3000 control points were used to rectify the images.

Once the images were prepared, we carefully vectorised the fishing ice holes (Fig. 2). During this stage, it is crucial not to misinterpret the holes with other features (e.g., steps in the ice, branches/vegetation, cracks in the ice, or different ice colouration). Nevertheless, fish holes have a specific geometry (circular) (Fig. 2) and are not difficult to identify. In any case, paying attention to the potentially disturbing elements and noise that can affect their identification is crucial. Subsequently, we created a point shapefile⁶ in ArcGIS Pro (ver. 3.1.2) to vectorise the fishing ice holes. An extremely laborious work was conducted to identify the fish holes in the georeferenced RGB images accurately. We identified 3268 fishing ice holes, representing the areas where recreational fishers go (Figs. 2 and 4). This is also an indicator of the high supply. Once all the fish holes were vectorised, we mapped the data using 1) Kernel Density and 2) Point Density. Kernel Density is a widely applied method to identify the density of occurrences in different domains, such as ecological corridors [16], traffic violations [17], cigarette littering [18] and COVID-19 outbreak [19]. We calculated it using ArcGIS Pro (ver. 3.1.2) Kernel Density tool,⁷ which uses the following formula developed by Silverman [20]

$$Density = \frac{1}{(radius)^2} \sum_{i=1}^n \left[\frac{3}{\pi} \cdot pop_i \left(1 - \left(\frac{dist_i}{radius} \right) \right) \right] \tag{1}$$

Where: $i = 1, \dots, n$ are the input points. Only include points in the sum if they are within the radius distance of the (x,y) location. pop_i is the population field value of point i , which is an optional parameter, and $dist_i$ is the distance between point i and the (x,y) location.⁸ As bandwidth, we applied the standard distance method.⁹ The Bandwidth was calculated using the formula:

$$SearchRadius = 0.9 * \min \left(SD, \sqrt{\frac{1}{\ln(2)}} * D_m \right) * n^{-0.2} \tag{2}$$

Where: “ D_m is the (weighted) median distance from the (weighted) mean centre. n is the number of points if no population field is used, or if a population field is supplied, n is the sum of the population field values, and SD is the standard distance”⁷.

In this work, the Standard distance was calculated using the unweighted distance using the following formula:

$$SD = \sqrt{\frac{\sum_{i=1}^n (x_i - \bar{X})^2}{n} + \frac{\sum_{i=1}^n (y_i - \bar{Y})^2}{n} + \frac{\sum_{i=1}^n (z_i - \bar{Z})^2}{n}} \tag{3}$$

⁴ <https://pro.arcgis.com/en/pro-app/3.1/help/data/imagery/georeferencing-a-raster-to-a-referenced-layer.htm>.

⁵ <https://www.maps.lt/>.

⁶ <https://pro.arcgis.com/en/pro-app/latest/help/data/shapefiles/working-with-shapefiles-in-arcgis-pro.htm>.

⁷ <https://pro.arcgis.com/en/pro-app/latest/tool-reference/spatial-analyst/kernel-density.htm>.

⁸ <https://pro.arcgis.com/en/pro-app/latest/tool-reference/spatial-analyst/how-kernel-density-works.htm>.

⁹ <https://pro.arcgis.com/en/pro-app/latest/tool-reference/spatial-statistics/standard-distance.htm>.

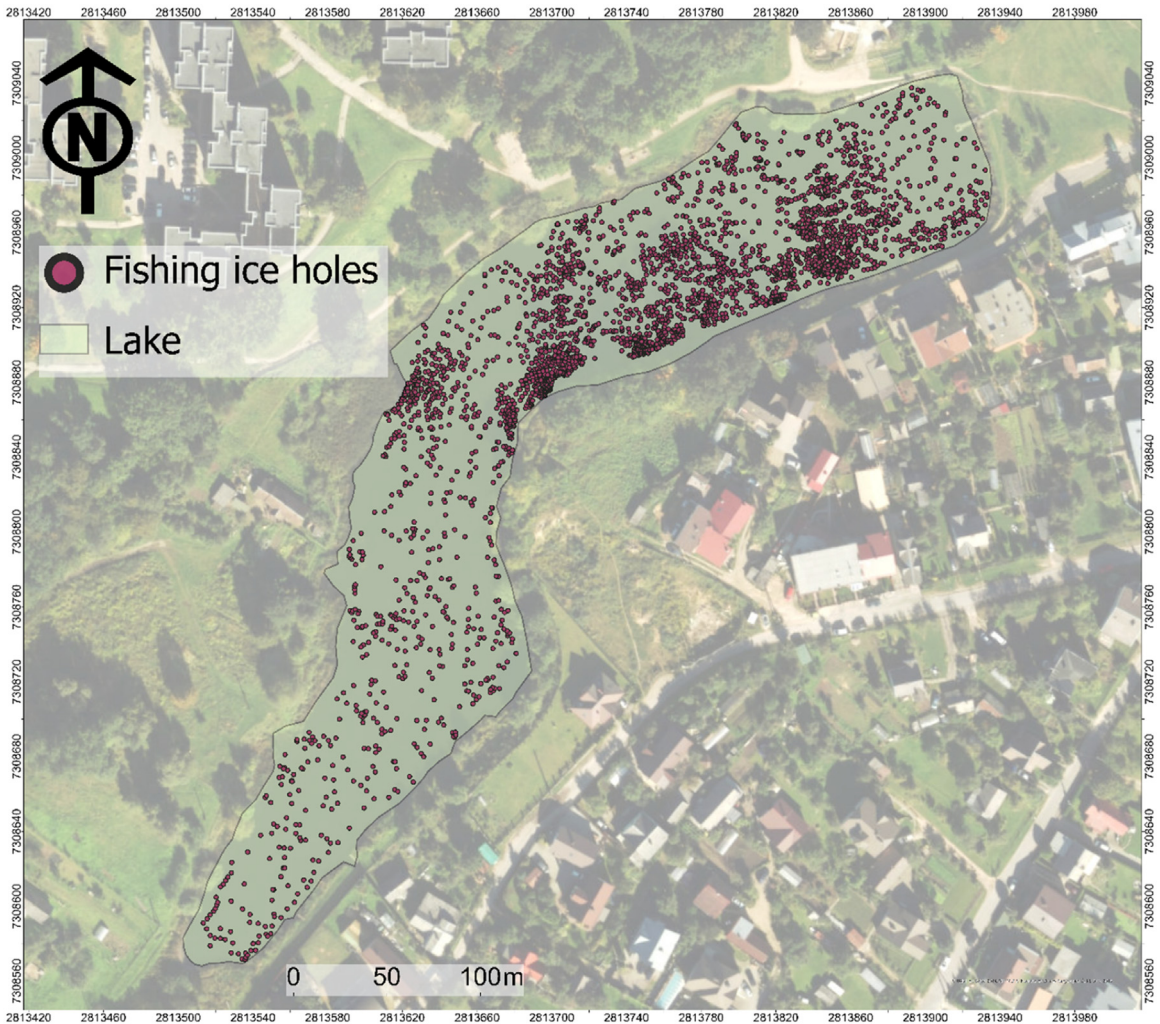


Fig. 4. Vectorized fishing holes ($N = 3268$).

Where: “ x_i , y_i and z_i are the coordinates for feature i , \bar{X} , \bar{Y} and \bar{Z} represent the mean center for the features and n is equal to the total number of features”.¹⁰

Before applying the tool, we defined the different parameters. Area units, we defined as “square map units,” output cell values as “densities,” and the method as “planar”. We selected the planar option because it “is appropriate if the analysis is to be performed at a local scale with a projection that accurately maintains the correct distance and area”. As input barrier features, we used the “lake shapefile”. Since the lake shape is not quadrangular, the distance between the points is likely affected by the lake morphology.¹¹

Point Density “Calculates a magnitude-per-unit area from point features that fall within a neighbourhood around each cell.”¹² In this work as “Neighbourhood”, we selected a circle with a “Ratio” of 20 m and a “unit type” map. Point density has been applied in several domains, such as the COVID-19 outbreak [21] and water pollution [22].

The Kernel and Point Density maps’ resolution was 1 cm, and the output density was m^2 . To visually represent the results, we used the stretch¹³ symbology, and as a stretch type, the minimum-maximum value. The difference between Point and Kernel density is that meanwhile, in point density, “a neighbourhood is specified that calculates the density of the population around each output cell”, while in Kernel Density “spreads the known quantity of the population for each point out from the point location. The resulting surfaces surrounding

¹⁰ <https://pro.arcgis.com/en/pro-app/latest/tool-reference/spatial-analyst/how-kernel-density-works.htm>.

¹¹ <https://pro.arcgis.com/en/pro-app/latest/tool-reference/spatial-analyst/how-kernel-density-works.htm>.

¹² <https://pro.arcgis.com/en/pro-app/latest/tool-reference/spatial-analyst/an-overview-of-the-density-tools.htm>.

¹³ <https://pro.arcgis.com/en/pro-app/latest/help/analysis/raster-functions/stretch-function.htm>.

Table 1
Descriptive Statistics.

	Kernel density (m ²)	Point density (m ²)
Mean	0.0588281873	0.0568670299
Median	0.0309792105	0.0310352147
Standard Deviation	0.0605282967	0.0537388281
Minimum	0.0000072915	0
Maximum	0.3770553172	0.309556365
Skewness	1.856100958	1.4990275906
Kurtosis	6.6325054858	4.8552579798

each point in kernel density are based on a quadratic formula with the highest value at the centre of the surface (the point location) and tapering to zero at the search radius distance¹⁴”.

The final result of the Kernel and Point Density maps is shown in Fig. 5. In both maps, it is visible that the area where recreational fishers go is in the eastern part of the lake (high density). The statistical results are similar as well. On average, the Kernel Density of fish holes in the lake was 0.058 m², and the Point Density was 0.056 m² (Table 1; Fig. 5). In both cases, the distribution was majorly located in the low values (positive Kurtosis). This shows that only a few areas had a high accumulation of fish holes, with a high winter recreational fishery supply. Comparing both density methods, the Kernel Density results had a higher positive Skewness and Kurtosis distribution than the Point Density method. This shows that the Kernel Density method distribution had a higher heterogeneity than Point Density. This is also observed in the Standard Deviation results (Table 1; Fig. 5). Although the statistical analysis results are similar, the application of Kernel Density is more appropriate than Point Density because it produces maps with smoother surfaces and is less biased. Nevertheless, it is important to assess case by case depending on the phenomena in the study. Further studies need to be conducted, considering Kernel Density and Point Density. In other circumstances, Point Density can perform better than Kernel Density.

Method limitations and implications

The method developed is novel, simple to apply and is non-destructive. In addition, doing this assessment on the ice is dangerous since the ice can crack. This may pose some challenges when validating the model results. Although we may assume that the ice is thick enough because recreational fishers are going there, this depends significantly on the air temperature in the previous weeks. For safety reasons, we did not walk on ice because the ice was unstable on the day of the UAV flight. Validation may be possible in other conditions (prolonged periods of below-zero temperatures), and it is encouraged to conduct. UAV proximal sensing is a safe and accurate method to identify fish holes. Since they have small dimensions, using a UAV to take high-resolution photos is important. Applying this method in urban areas may pose significant challenges, such as restrictions in flying zones, which must be considered before establishing the mission. Also, treating this data is crucial for powerful computers with high RAM. In this case, the data was treated using a Dell with Intel(R) Core (TM) i9–10900X CPU @ 3.70 GHz processor with 64.0 GB RAM (Table S2), which allowed us to process the data quickly. The studied lake is small, and the method is easy to apply. It will be more challenging to apply it in larger lakes since the number of photos needed to make a reasonable assessment will be very high, and the data processing (e.g., georeferencing, identifying fish holes, Kernel and Point Density mapping) is lengthy. Another important aspect is that larger lakes require a longer flight time. Using a UAV like ours, we have one battery and approximately 37 to 43 min of flight time (Table S1). In conditions with strong wind, the flight time and capacity to complete the mission in a large lake can be reduced. Therefore, having more than one battery to field the mission in large lakes is important, especially in strong wind conditions. This may impose some challenges and limitations if applied to large lakes. Another limitation of the method is that it is only applied in areas where the temperature drops below 0 °C during a sustained period. This allows recreational fishers to walk on the ice in the middle of the lakes. Therefore, the method cannot be applied in areas with warm climates.

Although the method has some limitations, it is crucial to map recreational fisheries in lakes during winter, an activity very popular in northern latitudes. Kernel and Point Density are well-known tools; however, the method of fish hole identification is new. The method developed in this work could be helpful in mapping and assessing freshwater cultural ES in urban environments. It can be applied in freshwater/marine environments that freeze seasonally and ensure a safe assessment of the fishing recreation ES. In our case, we could identify the areas preferred (high number of holes) by the recreational fishers connected with the areas with reed. Reed areas are known as essential for fish nurseries [23]. Therefore, the abundance of fish in these places is likely to be high. The results obtained can contribute to a better management of this lake. For instance, it is crucial to maintain the lake in good ecological conditions and protect the vegetation to maintain good ecological conditions for the fish nursery. This will be key to maintaining the lake's value for recreation fishers and developing sustainable recreation/tourism practices in this area. From a governance point of view, integrating ES mapping and assessment in planning and management is essential to improve decision-making and understanding of the ES supplied in different environments. This has been substantially highlighted in previous works [24–26].

¹⁴ <https://pro.arcgis.com/en/pro-app/latest/tool-reference/spatial-analyst/differences-between-point-line-and-kernel-density.htm>.

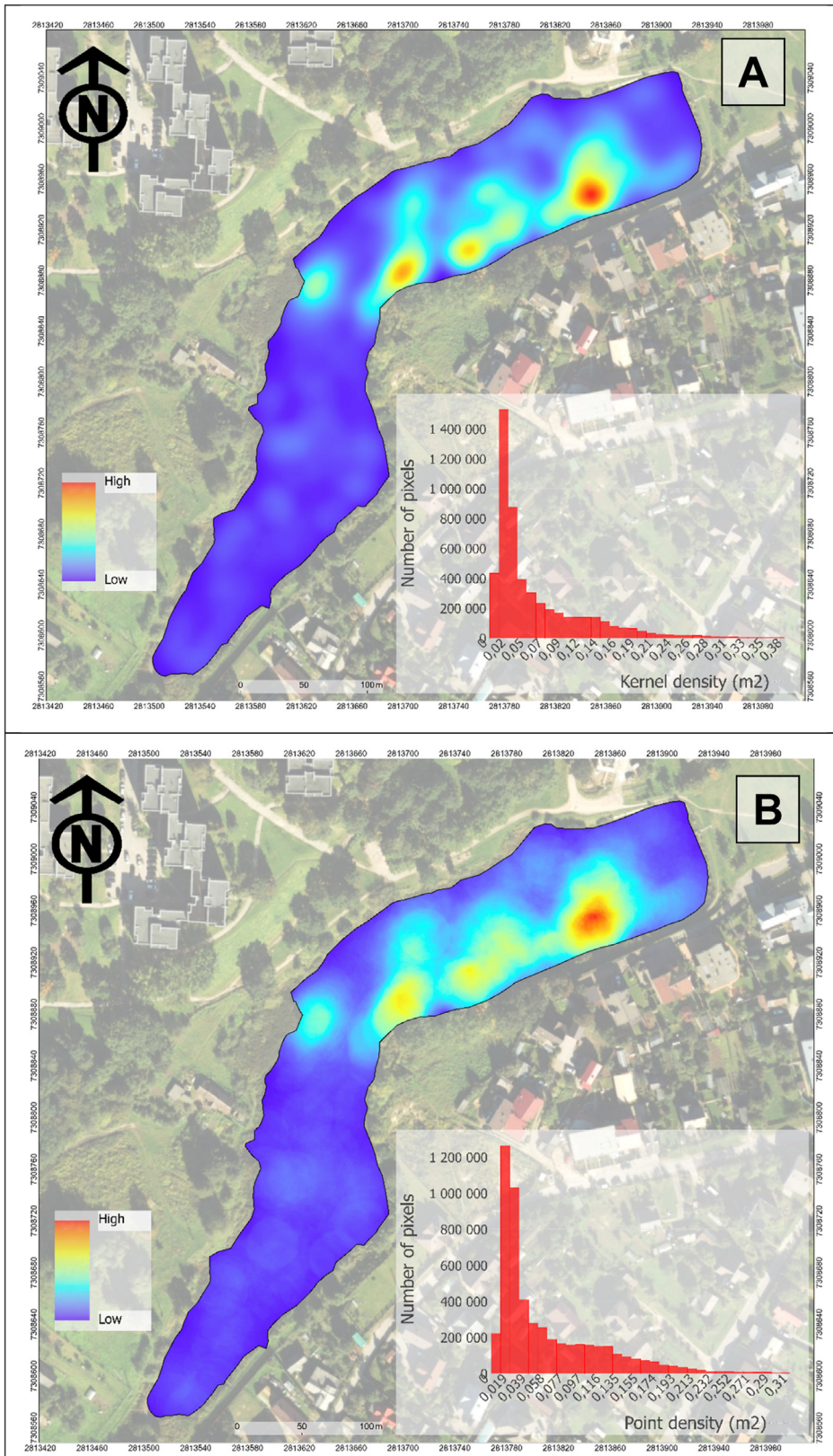


Fig. 5. Kernel (A) and Point (B) density results.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRedit authorship contribution statement

Paulo Pereira: Conceptualization, Methodology, Investigation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Project administration. **Marius Kalinauskas:** Methodology, Visualization, Writing – review & editing. **Luis Valenca Pinto:** Methodology, Visualization, Writing – review & editing. **Damia Barcelo:** Writing – review & editing. **Wenwu Zhao:** Writing – review & editing. **Miguel Inacio:** Methodology, Investigation, Resources, Writing – original draft, Project administration.

Data availability

Data will be made available on request.

Ethics statements

The work did not involve human beings.

The work did not involve animals.

The work did not involve data collected from social media platforms.

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Supplementary materials

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References

- [1] A. La Notte, D. D'Amato, A. Mäkinen, M.L. Paracchini, C. Liqueste, B. Egoh, D. Geneletti, N. Crossman, Ecosystem services classification: a systems ecology perspective of the cascade framework, *Ecosystem Indicators* (2017) 392–402, doi:[10.1016/j.ecolind.2016.11.030](https://doi.org/10.1016/j.ecolind.2016.11.030).
- [2] P.Y. Tan, J. Zhang, M. Masoudy, J. Berhane Alemu, P.J. Edwards, A. Grêt-Regamey, D.R. Richards, J. Saunders, X.P. Song, L.W. Wong, A conceptual framework to untangle the concept of urban ecosystem services, *Landsc. Urban Plan.* 200 (2020) 103837, doi:[10.1016/j.landurbplan.2020.103837](https://doi.org/10.1016/j.landurbplan.2020.103837).
- [3] L. Liang, P. Gong, Urban and air pollution: a multi-city study of long-term effects of urban landscape patterns on air quality trends, *Sci. Rep.* 10 (2020) 18618, doi:[10.1038/s41598-020-74524-9](https://doi.org/10.1038/s41598-020-74524-9).
- [4] L.V. Pinto, M. Inacio, K. Bogdzevic, M. Kalinauskas, E. Gomes, P. Pereira, Factors affecting cultural ecosystem services use in Vilnius (Lithuania): a participatory mapping survey approach, *Heliyon* 9 (2023) e15384, doi:[10.1016/j.heliyon.2023.e15384](https://doi.org/10.1016/j.heliyon.2023.e15384).
- [5] C. Cortinovis, D. Geneletti, A performance-based planning approach integrating supply and demand of urban ecosystem services, *Landsc. Urban Plan.* 201 (2020) 103842, doi:[10.1016/j.landurbplan.2020.103842](https://doi.org/10.1016/j.landurbplan.2020.103842).
- [6] M.C. Dade, M.G.E. Mitchell, G. Brown, J.R. Rhodes, The effects of urban greenspace characteristics and socio-demographics vary among cultural ecosystem services, *Urban Forestry & Urban Gardening* 49 (2020) 126641, doi:[10.1016/j.ufug.2020.126641](https://doi.org/10.1016/j.ufug.2020.126641).
- [7] R.T. Melstrom, How diverse are preferences for urban fisheries? Evidence from a choice experiment, *Human Dimensions of Wildlife* 25 (2020) 503–516, doi:[10.1080/10871209.2020.1758251](https://doi.org/10.1080/10871209.2020.1758251).
- [8] R. Nikolaus, M. Schafft, A. Maday, T. Klefoth, C. Wolter, R. Arlinghaus, Status of aquatic and riparian biodiversity in artificial lake ecosystems with and without management for recreational fisheries: implications for conservation, *Aquatic Conservation: Marine and Freshwater Ecosystems* 31 (2021) 153–172, doi:[10.1002/aqc.3481](https://doi.org/10.1002/aqc.3481).
- [9] Z.S. Feiner, M.H. Wolter, A.W. Latzka, I will look for you, I will find you, and I will [harvest] you”: persistent hyperstability in Wisconsin's recreational fishery, *Fish. Res.* 230 (2020) 105679, doi:[10.1016/j.fishres.2020.105679](https://doi.org/10.1016/j.fishres.2020.105679).
- [10] E. Tammiksaar, K. Kangur, Fish and fishing in Lake Peipsi (Estonia/Russia) since 1851: similarities and differences between historical and modern times, *J. Great Lakes Res.* 46 (2020) 862–869, doi:[10.1016/j.jglr.2020.04.005](https://doi.org/10.1016/j.jglr.2020.04.005).
- [11] P. Pereira, E. Brevik, E. Trevisani, Editorial: mapping the environment, *Sci. Total Environ.* 610–611 (2018) 17–23, doi:[10.1016/j.scitotenv.2017.08.001](https://doi.org/10.1016/j.scitotenv.2017.08.001).
- [12] J.P. Schägner, L. Brander, J. Maes, V. Hartje, Mapping ecosystem services' values: current practice and future prospects, *Ecosystem Services* (2013) 33–46, doi:[10.1016/j.ecoser.2013.02.003](https://doi.org/10.1016/j.ecoser.2013.02.003).
- [13] C.C. Araujo Barbosa, P.M. Atkinson, J.A. Dearing, Remote sensing of ecosystem services: a systematic review, *Ecol. Indic.* 52 (2015) 430–443, doi:[10.1016/j.ecolind.2015.01.007](https://doi.org/10.1016/j.ecolind.2015.01.007).
- [14] M. Villoslada Peciña, T.F. Bergamo, R.D. Ward, C.B. Joyce, K. Sepp, A novel UAV-based approach for biomass prediction and grassland structure assessment in coastal meadows, *Ecol. Indic.* 122 (2021) 107227, doi:[10.1016/j.ecolind.2020.107227](https://doi.org/10.1016/j.ecolind.2020.107227).
- [15] K. Park, K. Christensen, D. Lee, Unmanned aerial vehicles (UAVs) in behavior mapping: a case study of neighborhood parks, *Urban Forestry & Urban Greening* 52 (2020) 126693, doi:[10.1016/j.ufug.2020.126693](https://doi.org/10.1016/j.ufug.2020.126693).
- [16] J. Dong, J. Peng, Y. Liu, S. Qiu, Y. Han, Integrating spatial continuous wavelet transform and kernel density estimation to identify ecological corridors in megacities, *Landsc. Urban Plan.* 199 (2020) 103815, doi:[10.1016/j.landurbplan.2020.103815](https://doi.org/10.1016/j.landurbplan.2020.103815).
- [17] Y. Li, M. Abdel-Aty, J. Yuan, Z. Cheng, J. Lu, Analyzing traffic violation behavior at urban intersections: a spatio-temporal kernel density estimation approach using automated enforcement system data, *Accident Analysis & Prevention* 141 (2020) 105509, doi:[10.1016/j.aap.2020.105509](https://doi.org/10.1016/j.aap.2020.105509).
- [18] R. Valiente, F. Escobar, J. Pearce, U. Bilal, M. Franco, X. Sureda, Estimating and mapping cigarette butt littering in urban environments: a GIS approach, *Environ. Res.* 183 (2020) 109142, doi:[10.1016/j.envres.2020.109142](https://doi.org/10.1016/j.envres.2020.109142).

- [19] B. Li, Y. Peng, H. He, M. Wang, T. Feng, Built environment and early infection of COVID-19 in urban districts: a case study of Huangzhou, *Sustainable Cities and Society* 66 (2021) 102685, doi:[10.1016/j.scs.2020.102685](https://doi.org/10.1016/j.scs.2020.102685).
- [20] B.W. Silverman, *Density Estimation for Statistics and Data Analysis*, Chapman and Hall, New York, 1986 1986.
- [21] W. Shi, C. Tong, A. Zhang, B. Wang, Z. Shi, Y. Yao, P. Jis, An extended weight kernel density estimation model forecasts COVID-19 onset risk and identifies spatiotemporal variations of lockdown effects in China, *Commun. Biol.* 4 (2021) 126, doi:[10.1038/s42003-021-01677-2](https://doi.org/10.1038/s42003-021-01677-2).
- [22] J. Xu, M. Xu, Y. Zhao, S. Wang, M. Tao, Y. Wang, Spatial-temporal distribution and evolutionary characteristics of water environment sudden pollution incidents in China from 2006 to 2018, *Sci. Total Environ.* 801 (2021) 149677, doi:[10.1016/j.scitotenv.2021.149677](https://doi.org/10.1016/j.scitotenv.2021.149677).
- [23] C.H.A. van Leeuwen, J.J. de Leeuw, J.J.J. Volwater, O.A. van Keeken, H. Jin, A.M. Drost, D. Waasdorp, E. Reichman, L. Ursem, E.S. Bakker, Creating new littoral zones in a shallow lake to forward-restore an aquatic food web, *Sci. Total Environ.* 904 (2023) 166768, doi:[10.1016/j.scitotenv.2023.166768](https://doi.org/10.1016/j.scitotenv.2023.166768).
- [24] J. Maes, B. Egoh, L. Willemsen, C. Liqueste, P. Vihervaara, J.P. Schägner, B. Grizzetti, E.G. Drakou, A. La Notte, G. Zulian, F. Bouraoui, M.L. Paracchini, L. Braat, G. Bidoglio, Mapping ecosystem services for policy support and decision making in the European Union, *Ecosystem Services* 1 (2012) 31–39, doi:[10.1016/j.ecoser.2012.06.004](https://doi.org/10.1016/j.ecoser.2012.06.004).
- [25] C. Cortinovis, D. Geneletti, A performance-based planning approach integrating supply and demand of urban ecosystem services, *Landsc. Urban Plan.* 201 (2020) 103842, doi:[10.1016/j.landurbplan.2020.103842](https://doi.org/10.1016/j.landurbplan.2020.103842).
- [26] L. Mandle, A. Shields-Estrada, R. Chaplin-Kramer, M.G.E. Mitchell, L.L. Bremer, J.D. Gourevitch, P. Hawthorne, J.A. Johnson, B.E. Robinson, J.R. Smith, L.J. Sontter, G.M. Verutes, A.L. Vogl, G.C. Daily, T.H. Ricketts, Increasing decision relevance of ecosystem service science, *Nature Sustainability* 4 (2021) 161–169, doi:[10.1038/s41893-020-00625-y](https://doi.org/10.1038/s41893-020-00625-y).