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Design-based inference and data integration allow the efficient estimation and mapping of onshore wind turbines presence across large spatial scales

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ABSTRACT

Wind energy development is a major driver of change for terrestrial ecosystems. As wind turbines are seldom mapped on a regular basis, conservationists increasingly use aerial/satellite images to address this gap. Nevertheless, the manual identification of turbines is labour intensive, preventing conservationists from mapping wind energy development across large spatial scales.

In this study we adopted a design-based sampling approach to render sustainable this effort for estimating the total number of onshore wind turbines in Sardinia (Italy) and to map their spatial distribution from high-resolution aerial images (1:500). We also adopted data integration to incorporate previous knowledge on wind turbines presence, achieved from an opportunistic survey, to improve the quality of our estimate and map. We finally estimate the precision of the total estimate and map from a pseudopopulation bootstrap procedure that exploits the estimated map as a pseudopopulation.

We estimated a total of 1168 turbines with a relative standard error of 0.7%, and a bootstrap 0.95 confidence interval of 1155–1181 turbines. We also provided a map that estimated a very scarce presence of turbines outside the area covered by the opportunistic survey. The resulting map will be crucial to identify overlaps between wind turbines and biodiversity hotspots, as well as to study spatiotemporal patterns of wind energy development.

1. Introduction

Wind energy development is a major driver of terrestrial ecosystem change (Jones et al., 2015; Katzner et al., 2019), currently accounting for about 8% of total energy production (https://www.iea.org/energy-system/renewables) and expected to increase in the near future. At the landscape level, onshore wind turbines modify ecosystem structure and functioning, altering ecosystem services and disrupting environmental connectivity (Diffendorfer et al., 2019; Jones et al., 2015; Hastik et al., 2015). They also impact wildlife populations through different mechanisms, including collision mortality (Estellés-Domingo and López-López, 2024; Marques et al., 2014; Thaxter et al., 2017; Voigt, 2021), altered interspecific relationships (e.g., prey-predator dynamics, Gómez-Catasús et al., 2021; Thaker et al., 2018) and reduced fitness caused by disturbance, stress, or energy costs of avoidance behaviour (May, 2015).

Mapping wind energy development is thus crucial for conservation planning and for prioritizing prevention or mitigation measures. However, reliable and updated maps of onshore wind turbines are still lacking. Existing datasets at global (Dunnett et al., 2020) or continental scale (Assandri et al., 2024; Gauld et al., 2022) can severely underestimate the number of turbines (Cerri et al., 2024a), limiting the assessment of their ecological impacts (Cerri et al., 2024b).

Over the last 20 years, the growing availability of satellite and aerial images (Pettorelli et al., 2014) greatly improved mapping of human activities and infrastructures worldwide (Ibisch et al., 2016; Paolo et al., 2024; Venter et al., 2016) and has also proven promising for mapping infrastructures associated with the production of renewable energy (e.g. solar parks, Plakman et al., 2022). In contrast, large scale applications for detecting wind turbines have been almost entirely limited to offshore facilities (Hoeser et al., 2022; Xu et al., 2020).

This gap reflects the difficulty of training machine learning algorithms to detect onshore wind turbines, as they occupy only a few pixels

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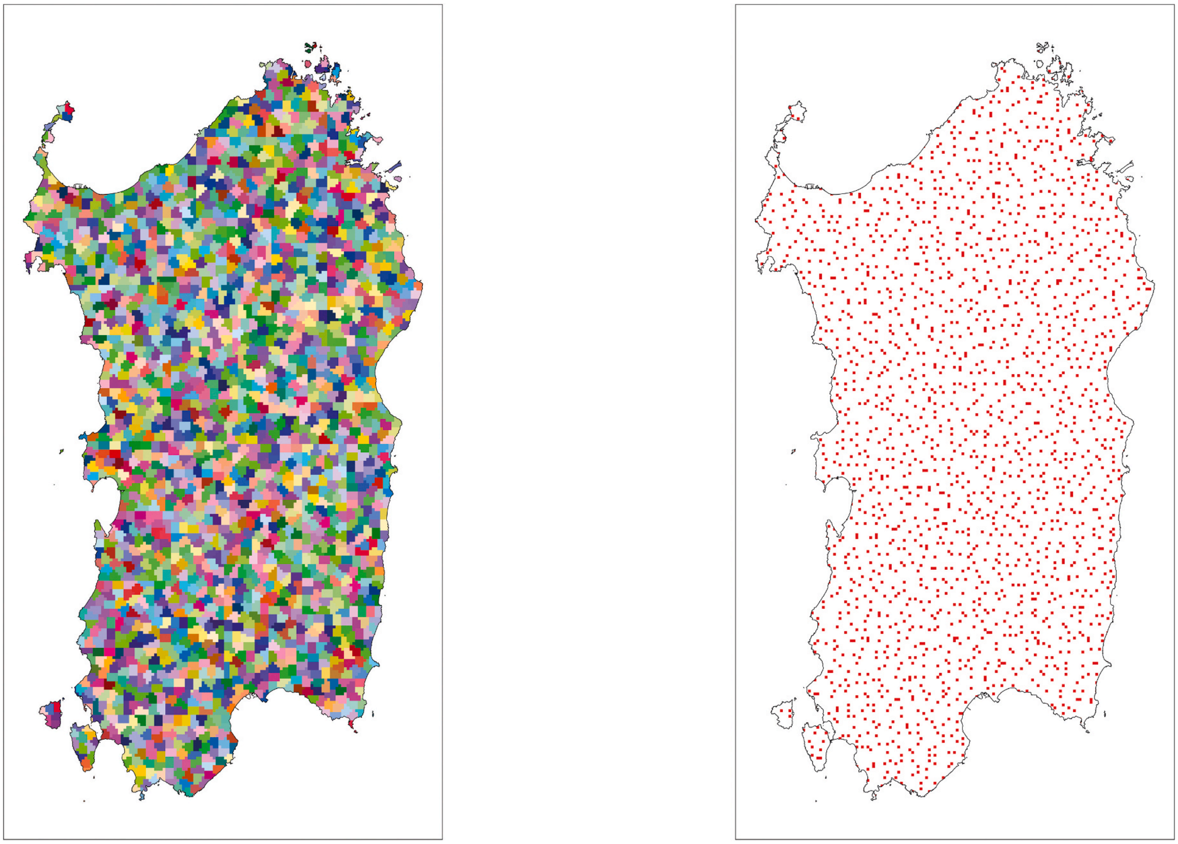

Fig. 1. Left: Graphical representation of the stratification performed on the Sardinia region. The region was firstly covered by a grid of 25,046 quadrats of size 1 km2, subsequently partitioned into 2,000 coloured strata of 12 or 13 neighbouring quadrats. Right: Graphical representation of the spatial balance achieved by the 2,000 sampled quadrats (red) randomly selected one per stratum.

in satellite images. In terrestrial ecosystems, satellite images are much more complex in terms of colours and contrasts than in marine environments (Mandroux et al., 2022). Thus, onshore wind turbines are still identified manually (Cerri et al., 2024a), a labour-intensive process that limits mapping across large areas.

To overcome this issue, statistical inference can be used by selecting a relatively small number of landscape patches, manually identifying turbines within them and estimating their total number and spatial distribution. This approach is useful to assess changes in the number of turbines through time, or to identify overlaps between wind energy development and areas of conservation value (e.g., biodiversity hotspots, Dunnett et al., 2022; e.g., the distribution range of vulnerable species, Morant et al., 2024; Palacín et al., 2023; e.g., migratory routes, Gauld et al., 2022; Merlet et al., 2025; Oppel et al., 2021; Voigt; et al., 2012).

In this framework, design-based inference (Hankin et al., 2019) is particularly suitable, as the design-based statistical properties of estimators and maps are entirely determined by the sampling scheme adopted to select the sample, without any model or assumption (Gregoire, 1998). As noted by Särndal et al. (1992, p. 21), "Design-based inference is objective, nobody can challenge that the sample was really selected according to the given sampling design. The probability distribution associated with the design is real, not modelled or assumed".

In this study, we aim to estimate the total number of onshore wind turbines and to map their spatial distribution in Sardinia (Italy), a hotspot of wind energy development that also hosts highly valuable natural habitats and vulnerable bird and bat species. As the number of turbines is expected to increase strongly in the near future (approx. +80%, see Cerri et al., 2024a), the total estimation and mapping of the current onshore turbines in the island is essential to avoid excessive cumulative effects on ecosystems and sensitive species of wildlife.

2. Study area

Sardinia is the second largest island in the Mediterranean Sea, covering 24,094 km^2. Due to its remoteness and limited urbanization, it has one of the lowest human footprints in Southern Europe and it hosts a wide range of Mediterranean habitats of conservation concern, protected by a network of Natura2000 sites spanning across 8646 km^2 and by regional and national parks covering 1273 km^2.

Sardinia also hosts several flying vertebrate species of conservation concern, which may be affected by the large-scale development of onshore wind farms. These include large soaring birds, such as the Griffon Vulture (*Gyps fulvus*, Berlinguer et al., 2024), the Golden Eagle (*Aquila chrysaetos*, Di Vittorio et al., 2020), the Red Kite (*Milvus Milvus*, De Rosa et al., 2021), a reintroduced population of Bonelli's Eagles (*Aquila fasciata*, ISPRA, 2023), the last Italian population of Little Bustard (*Tetrax tetrax*, Santangeli et al., 2023) and, since 2019, a breeding couple of Egyptian Vultures (*Neophron percnopterus*, De Rosa et al., 2024). Moreover, Sardinia hosts the only known populations of the endemic Sardinian long-eared bat (*Plecotus sardus*, Ancillotto et al., 2021) and a significant amount of the global population of the Sardo-Corso goshawk (*Accipiter gentilis arrigonii*, Londi et al., 2013).

Thanks to favourable wind conditions throughout the year, Sardinia is highly suitable for wind energy production (https://www.anev.org/wp-content/uploads/2022/07/Anev_brochure_2022.pdf) and it has become a hotspot of onshore wind energy development, particularly since 2020 (Cerri et al., 2024b). However, there are no requirements about the design (Christie et al., 2019) or the implementation (Nilsson et al., 2023; Ravache et al., 2024) of pre- and post-construction impact assessment. After reported collisions, there is no legal obligation to implement mitigation measures, such as selective turbine stopping (Ferrer et al., 2022). The only limitation concerns construction in protected areas (e.g., national and regional parks) and urban areas, where turbines cannot be constructed due to several regional and national laws, as well as by Natura2000 sites, where any authorization requires a preliminary impact assessment. However, the extent to which restrictions are implemented and the quality of preliminary assessments are unclear, as Cerri et al. (2024a) reported the presence of 54 turbines within Natura 2000 sites and 40 turbines within urban areas.

3. Methods

Following Cerri et al. (2024a), we covered Sardinia by a grid of $N = 25,046$ squares of size 1 km^2, defining the target population U, where y_j was the number of wind turbines within the quadrat j. The total number of turbines

$$T = \sum_{j \in U} y_j \tag{1}$$

and the single values $\left\{ y_j, j \in U \right\}$ were the unknown parameters to be estimated. To readily achieve spatial balance, i.e., an even distribution of the sampled quadrats across the region (Fattorini et al., 2015), we selected a sample S of $n = 2,000$ quadrats using one-per-stratum stratified sampling (OPSS) by partitioning the population U into $n = 2,000$ strata $U_1, \cdots, U_n$ constituted by $N_1, \cdots, N_n$ neighbouring quadrats. To obtain strata of approximately the same size, we created 1046 strata of 13 quadrats and the remaining 954 strata of 12 quadrats (Fig. 1, left). In accordance with OPSS, we randomly selected one quadrat per stratum achieving the final sample S (Fig. 1, right). The first-order inclusion probabilities of quadrats, necessary for the computation of the Horvitz-Thompson (HT) estimate of T (Särndal et al., 1992, section 2.8), were $\pi_j = 1/13$ for each quadrat j within a stratum U_l of size $N_l = 13$ or $\pi_j = 1/12$ for each quadrat j within a stratum U_l of size $N_l = 12$.

For each quadrat $j \in S$, we recorded y_j by identifying and counting wind turbines from Google Satellite aerial pictures. Images on Google Satellite originate from multiple private companies and space agencies and they include a mixture of pictures collected by airplanes, drones, balloons or kites (https://blog.google/products/maps/google-maps-101-how-imagery-powers-our-map/). Aerial images are displayed in natural colours using Red, Green and Blue spectral bands, combined to provide a natural representation of the earth's surface. For Sardinia, pictures were taken between the 1st of January 2022 and the 31st of December 2023. We visualized 1 km^2 Google Satellite tiles (https://mt1.google.com/vt/lyrs=s&x={x}&y={y}&z={z}) in Quantum GIS (version 3.30; QGIS Development Team, 2023; available at https://qgis.org/) and identified wind turbines at a scale from 1:500 to 1:1000. The recording procedure was conducted over the course of one month by two researchers working simultaneously.

We adopted the HT criterion:

$$\widehat{T}_{HT} = \sum_{j \in S} \frac{y_j}{\pi_j} = \sum_{j \in S} N_{l(j)} y_j \tag{2}$$

to estimate the total, where $l(j)$ denoted the label of the stratum containing the quadrat j (Fattorini et al., 2022a). We adopted the NN interpolator

$$\widehat{y}_j = I(j \in S) y_j + \frac{I(j \notin S)}{card(V_j)} \sum_{i \in V_j} y_i \tag{3}$$

to estimate the single population values $\left\{ \widehat{y}_j, j \in U \right\}$, where V_j denoted the set of labels of the sample quadrats that were nearest to quadrat j, i.e.,

$$V_j = \left\{ i : d_{i,j} = \underset{h \in S}{argmin} d_{h,j} \right\} \tag{4}$$

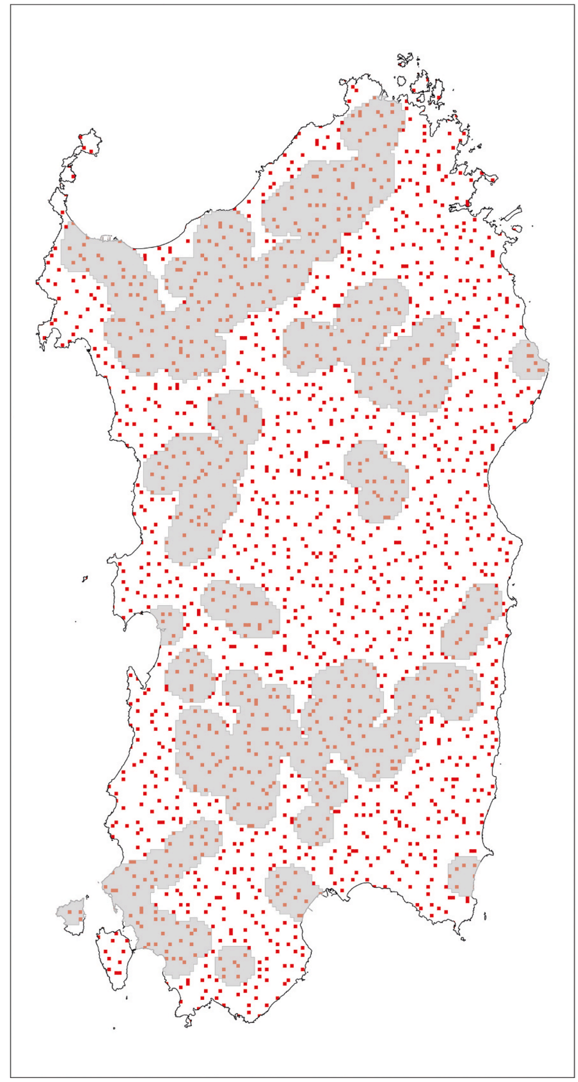

Fig. 2. Graphical representation of the portion of the region covered by the purposive surveys of 9,056 quadrats (shaded area) and of the 2,000 sampled quadrats (in red).

and $d_{h,j}$ was the distance between the centres of quadrats h and j (Fattorini et al., 2022b).

The interpolated map achieved from (3) was treated as the pseudo-population from which 10,000 bootstrap samples $S_1^*, \cdots, S_{10,000}^*$ were generated by replicating the OPSS scheme adopted for selecting the original sample S (Fattorini et al., 2022b). From each bootstrap sample, we performed the HT estimation by (2) and the NN interpolation by (3). Finally, from the 10,000 bootstrapped outputs, we achieved the pseudo-population bootstrap (PPB) estimates of the variance of (2) and of the mean squared errors of (3). We computed the square roots of the PPB estimates to achieve the estimate of the standard error of (2) and of the root mean squared errors of (3). The 0.95 PPB confidence interval for the total was derived from the 250-th and 9750-th ordered bootstrap distribution of the 10,000 HT estimates.

A previous opportunistic survey (Cerri et al., 2024a) examined publicly available open-source datasets and assessed the actual presence of wind turbines using high-definition satellite imagery. It emerged that wind energy development in Sardinia exhibits a clustered distribution, with turbines grouping in specific areas. Consequently, a 5 km buffer was applied around each validated turbine to identify additional wind energy installations, counting the number of turbines in a sub-set U_0 of $N_0 = 9,056$ quadrats throughout the region (Fig. 2). The whole

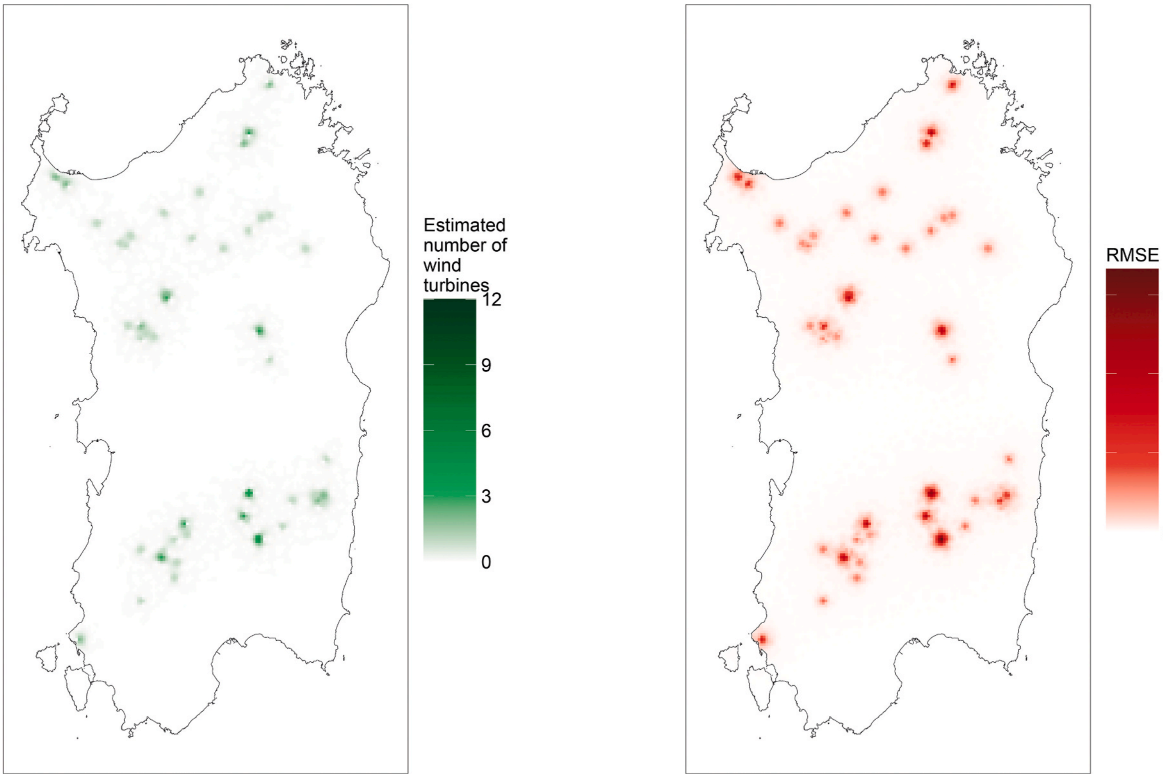

Fig. 3. Left: Graphical representation of the NN map reporting the estimated number of turbines in each quadrat. Right: Graphical representation of the bootstrap estimates of root mean squared errors.

procedure was carried out by one researcher over approximately three months, followed by 10 days of independent validation by two additional researchers.

We incorporated this additional information $\left\{y_j, j \in U_0\right\}$ in the HT estimation of total. Based on this additional knowledge, we rewrote the total (1) as

$$T = \sum_{j \in U_0} y_j + \sum_{j \in U - U_0} y_j = T_0 + \sum_{j \in U - U_0} y_j \tag{5}$$

where the first term was a known constant and the second was the unknown quantity to be estimated. Based on (5), we adopted the DI estimator

$$\widehat{T}_{DI} = T_0 + \sum_{j \in S \cap (U - U_0)} N_{l(j)} y_j \tag{6}$$

(Kim and Tam, 2021). We also adopted the whole integrated information $\left\{y_j, j \in S \cup U_0\right\}$ to perform the DI version of the NN interpolation

$$\widetilde{y}_j = I(j \in S \cup U_0) y_j + \frac{I(j \notin S \cup U_0)}{card(V_{0j})} \sum_{i \in V_{0j}} y_i \tag{7}$$

where now V_{0j} denoted the set of labels of the sample quadrats and of those detected by the opportunistic survey that were nearest to quadrat j, i.e.,

$$V_{0j} = \left\{ i : d_{ij} = \underset{h \in S \cup U_0}{argmind_{h,j}} \right\} \tag{8}$$

The DI map achieved from (7) was again treated as the pseudo-population from which $10,000$ bootstrap samples $S_1^*, \cdots, S_{10,000}^*$ were selected repeating the OPSS scheme adopted for selecting the original sample S. From each bootstrap sample we performed the DI estimation by (6) and the DI interpolation by (7). We then repeated the same steps performed in the PPB procedure based on the sole sample data to achieve the estimate of the standard error of (6), of the root mean squared errors of (7) and of the 0.95 PPB confidence interval for the total.

Estimation and mapping were performed using R (R Core Team, 2023) on a standard workstation (AMD Ryzen 5 PRO 5650G with 6 cores, 12 logical processes, and 32 GB of RAM). The source code used for performing both estimation and mapping with and without the exploitation of opportunistic information is available here: https://gist.github.com/rm-dib/276990ebd95f71a079f7567fe738e393.

4. Results

The OPSS scheme successfully produced a spatially balanced sample of the 2,000 quadrats well spread across Sardinia (Fig. 1, right). Most sampled quadrats (1953) contained no turbines, while, among the remaining 47 sampled quadrats, 30 contained one turbine, 9 contained two, 6 contained three, one contained four and one contained five, for a total of 75 turbines detected in the sample.

Using the HT estimator (2), we estimated a total of 938 wind turbines in Sardinia and, using the NN interpolator (3), we achieved the map (Fig. 3, left) that was adopted as a pseudo population for performing PPB. We achieved a PPB standard error estimate of the HT estimator of 58.44 turbines (6%), a 0.95 PPB confidence interval of 826–1,057 turbines and the map of the PPB root mean squared error estimates of interpolated values (Fig. 3, right).

The HT estimate of 938 turbines was lower than the 1155 turbines detected in the opportunistic survey by Cerri et al. (2024a). After integrating this information into the DI estimator (6), the estimated total increased 1168 turbines. Through the DI interpolator (6) we achieved the map (Fig. 4, left) that was adopted as a pseudo population for performing PPB. We achieved a PPB estimate of the root mean squared error of the DI estimator of 8.28 turbines (0.7%), a 0.95 PPB confidence interval of 1155–1181 turbines and the map of the PPB root mean squared error estimates of interpolated values (Fig. 4, right).

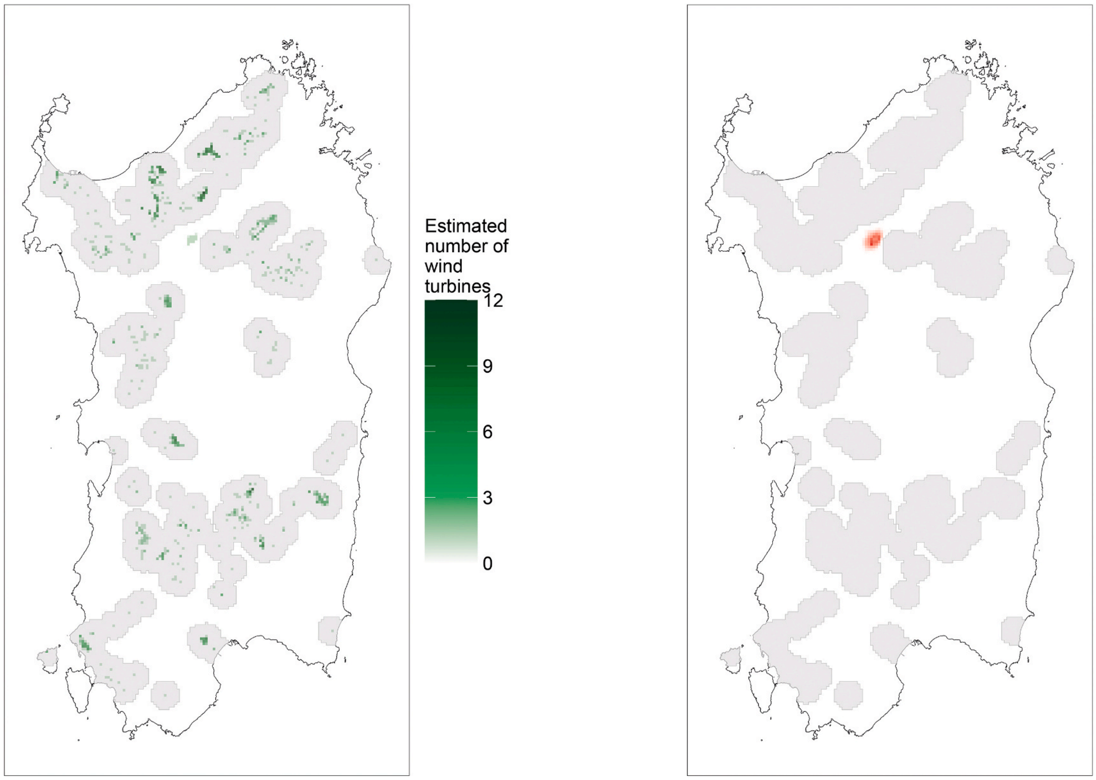

Fig. 4. Left: Graphical representation of the DI map reporting the estimated number of turbines in each quadrat. Values in the shaded area covered by the purposive survey are without errors and show the presence of large clusters of turbines partially missed by the probabilistic sampling. Values outside the shaded area are estimates and show the unchanging absence of turbines with the exception of a cluster generated by the presence of one turbine in a sampled quadrat outside the shaded area. Right: Graphical representation of the bootstrap estimates of root mean squared errors that are 0 within the shaded area where the values are without errors and are invariably equal to 0 also outside the shaded area with the exception of some positive errors in the quadrats of the cluster generated by the presence of one turbine in a sampled quadrat outside the shaded area.

5. Discussion

The results evidence the practical potential of DI strategy. First of all, it is important to note that the real number of turbines in Sardinia is currently unknown, as no complete official inventory exists. In addition, the datasets achieved from incomplete opportunistic surveys performed on portions of the region gave rise to unreliable and contradictory results, with a heavy presence of geolocation errors. In particular, as reported by Cerri et al. (2024a), the datasets by Atlaimpianti, OpenStreetMap and Smeraldo et al. (2020) respectively assessed the presence of 507, 766 and 914 turbines, against the 1155 turbines assessed by the same authors from a wide opportunistic survey covering approximately 36% of the total area. The dataset by Cerri et al. (2024a), updated to 2023 and validated by high-quality satellite imagery, is by far the most accurate. However, even if the number of 1,155 turbines was exact, it is referred only to a portion of the study area and cannot be extended to the whole region because the surveyed portion was opportunistically selected. On the other hand, the probabilistic sample of 2,000 quadrats selected by OPSS was expanded using the HT estimator (2) by weighting with inclusion probabilities. Then, in contrast to opportunistic surveys, the resulting estimate of 938 turbines is complete, in the sense that it referred to the whole region, but affected by a sampling error. In particular, the PPB indicated an average sampling error of about 6%, mainly due to the highly clustered distribution of turbines. Despite the even coverage of the study region provided by the 2,000 sampled quadrats, some large clusters of turbines were missed in the sample, giving rise to an inadmissible estimate smaller than the number of turbines identified in the opportunistic survey. In this scenario, DI provides an effective solution. By integrating the freely available opportunistic data into the DI estimator (6), we obtained a total estimate of 1168 turbines. The slight increase of the estimated total number of turbines compared to those identified in the opportunistic survey was due to the scarce presence of turbines outside the area covered by this survey, as is apparent from the DI map (Fig. 4 left). The PPB results achieved from this map demonstrated the great improvement of the precision entailed by DI. Without any increase of the sampling effort, we achieved a PPB standard error estimate of the DI estimator of 8.28 turbines, corresponding to a very satisfying sampling error of 0.7% from which it was possible to conclude that the PPB interval 1155–1181 contained the true number of turbines with a probability of about 0.95. The improvement was also demonstrated by the map of PPB estimates of the root mean squared errors of the interpolated values, that showed no error everywhere with the exception of the quadrats in the cluster generated by the presence of one turbine in a sampled quadrat outside the area covered by the opportunistic survey (Fig. 4, right).

In addition to the cognitive importance of these findings in monitoring the ongoing wind energy development and its potential cumulative impacts, from a methodological point of view our DI proposal constitutes one of the first attempts, in ecological studies, to merge the information acquired in opportunistic surveys with the information acquired in rigorous surveys designed by probabilistic sampling. Regarding the long-debated issues if using purposive or probabilistic surveys, Chiarucci (2007) stigmatizes naturalists that continue to collect their data on the basis of preferential choices, suggesting that in these cases they should avoid the term sampling and should avoid any statistical inference, simply describing their works as descriptive field recognitions of natural communities. On the same issue, Albert et al. (2010) point out that probabilistic sampling is often difficult to perform when surveying natural communities owing to logistic problems and that this often leads to the implementation of simplified convenience sampling designs which, like all non-probabilistic designs, suffer from unknown biases. In addition, Boyd et al. (2023) evidence as, in the era of big data, naturalists have now available very large non-probability samples that should not be wasted but exploited in statistically sound estimation procedures. All these concerns can be bypassed by DI. Even if logically predictable, the improvement entailed by the DI estimator and interpolator (Eqs. (6) and (7)) with respect to the crude HT estimator and NN interpolator (Eqs. (2) and (3)) has been theoretically proven in the Appendix A and B of the Supplementary Material file. Based on these findings, the DI estimator and interpolator proposed in this paper constitute efficient tools of wide applicability in ecological studies in which the study region is tessellated by polygons of equal size.

CRediT authorship contribution statement

Jacopo Cerri: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Investigation, Data curation, Conceptualization. **Chiara Costantino:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Agnese Marcelli:** Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Formal analysis. **Rosa Maria Di Biase:** Writing – original draft, Validation, Software, Methodology, Formal analysis. **Fiammetta Berlinguer:** Writing – review & editing, Validation, Supervision, Resources, Investigation, Funding acquisition, Conceptualization. **Lorenzo Fattorini:** Writing – review & editing, Writing – original draft, Validation, Supervision, Software, Resources, Methodology, Investigation, Funding acquisition, Formal analysis.

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.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jnc.2026.127339.

Data availability

Data will be made available on request.

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