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# A Novel Approach to Estimate the Number of Territorial Birds in a Network of Spatially Distributed Acoustic Recording Units

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## I. Introduction

Modern technologies, such as the development of low-cost passive acoustic monitoring devices (PAM), e.g., AudioMoth (Hill et al., 2019), placed in natural habitats of various species, are increasingly becoming a valuable complement to traditional field studies (Pérez-Granados, 2023). At the same time, significant progress is being made in computer-based, acoustic species recognition of birds. Various innovative approaches and models, e.g., BirdNET (Kahl et al., 2021), contribute to this and are now able to identify bird species based on their call or song (relatively) reliably. Currently, the focus is mainly on identifying whether a species is present at the location where the recording was taken.

We lack methods to acquire the number of individuals of a species in recordings, as automated identification of individuals of the same species is still difficult (Knight et al., 2024). In short, we are only at the beginning of a more sophisticated monitoring approach, the potential of which can already be assessed as immense. In our research, we are taking steps towards a more complex method of bird monitoring that does not require individual identification. We fused biology and computer science knowledge to develop the algorithm TASE—Territorial Acoustic Species Estimation — published in Ecological Informatics (Brüggemann et al., 2025). Using multiple acoustic recording devices and AI-based species identification that form an acoustic sensor network, theoretical computer scientists thought (in the past) about a way to count bird individuals (Stattner et al., 2011). We put their approach into practice and encountered various difficulties or found that assumptions made, are unrealistic. However, their approach inspired us to develop a generalized, easy-to-use method — even with limited computer science knowledge. By applying that algorithm to bird acoustics, we aim to determine the number of breeding birds in spring in a specific area. Our approach was tested in practice on an area of approximately 12 hectares. Initial promising results have been shared in our presentation.

## II. Deployment and problem definition

We deployed 29 AudioMoth PAMs in a nature reserve in North Rhine-Westphalia, Germany on 3 June 2023, recording soundscapes from 4:00 to 10:00 (Fig. 1). Due to their dense outdoor placement, the devices formed an Acoustic Sensor Network (ASN). Their close proximity created overlapping recording ranges, allowing us to capture vocalizations across a large, continuous area. Applying a species classifier to these recordings yields unitless classification scores (ranging from 0 to 1) for each identifiable species, e.g., Wood &

**Figure 1a. Deployment area in a nature reserve in Germany, the icons refer.**

**Figure 1 b, c. Deployment area in a nature reserve in Germany. (b) Exemplary Scene within the forest. (c) PAM in its waterproof to the ARU AudioMoth case.**

Kahl (2024), in the following referred to as *confidence scores*. A score of 0 indicates the species is undetected, while a score of 1 indicates a strong species detection. Across distributed recorders in an ASN, this generates spatially distributed confidence scores for each species.

Figure 2 shows a glimpse of the challenge we are facing: The figure illustrates the confidence score sets over time using bird data from an actual deployment. Each circle represents a recorder that is coloured by the classifier's confidence score. One bird (here Common Redstart *Phoenicurus phoenicurus*) is active in Figs. 2a and 2b in the top right corner, resulting in high confidence scores.

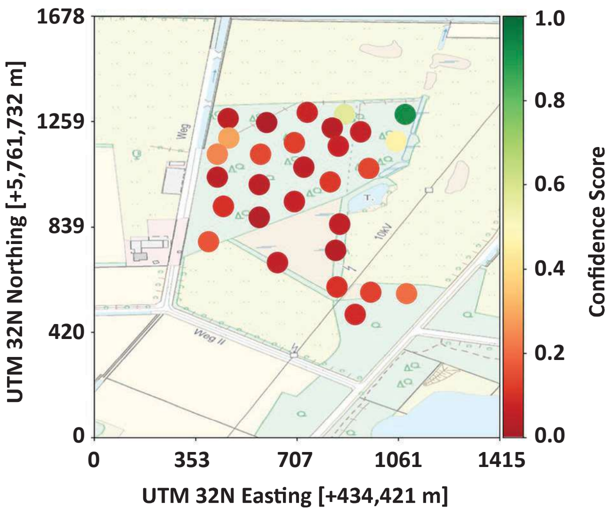
Then, it is silent in Figs. 2c to 2f, and active again in Figs. 2g and 2h. Similarly, another bird in the bottom right is initially inactive, vocalizes, and then becomes silent. The third Common Redstart in the southeast causes high confidence scores at neighboring recorders. Some recorders, such as the green recorder in the west in Fig. 2b, show high confidence scores while their neighbours do not, potentially indicating errors in the classification. The challenge is how to estimate the number of birds from such temporal confidence score sets while coping with potential misclassifications.

## III. Methods

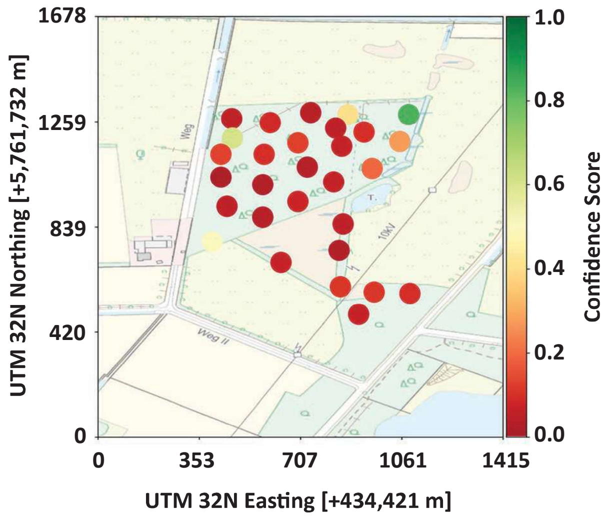
Our algorithm, called TASE, is formalized in Brüggemann et al. (2025), including requirements that must be met. Its concept is based on the observation that the classifier's confidence scores decrease with distance. In other words, PAMs closest to a vocalizing source have higher confidence scores than those farther away. If two birds vocalise simultaneously, the intermediate PAM between the two birds will have a lower confidence score than those closest to the birds. That forms a pattern that we can exploit. We can separate our recorders into distinct groups corresponding to individual vocal sources. Repeating that over long periods, we identify occupied areas, the territories. Eventually, TASE acquires a spatio-temporal point cloud and, by calculating a kernel density estimate, captures territorial spatial patterns.

## IV. Exemplary results

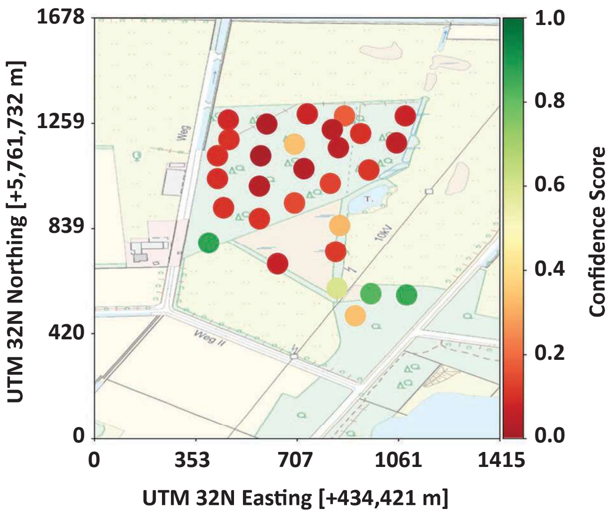
Figure 3 shows an exemplary result, comparing the expert's field monitoring (in red and gray coloured circles) and the density map of our approach (green colors). Notably, we see that the expert assessment and the density map overlap to a large extent with the high-density areas, showing our method's efficiency. However, some green spots lie outside the circles for three reasons: (1) The circles are only a crude estimate of the individual territory, whose actual borders are unknown. Territorial behavior is quite complex, and the species might move more dynamically in the area. (2) Non-territorial birds being present



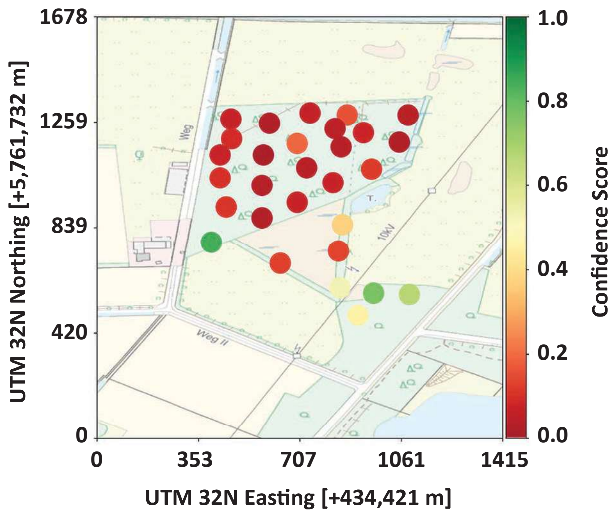

**a) Time: 4:15:00–4:15:03**



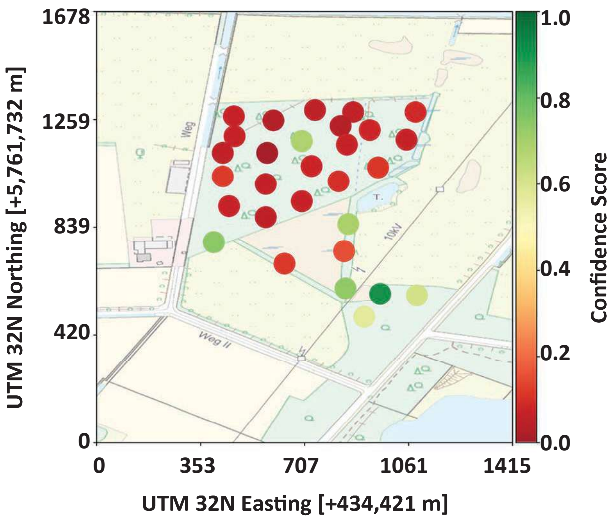

**b) Time: 4:15:01–4:15:04**



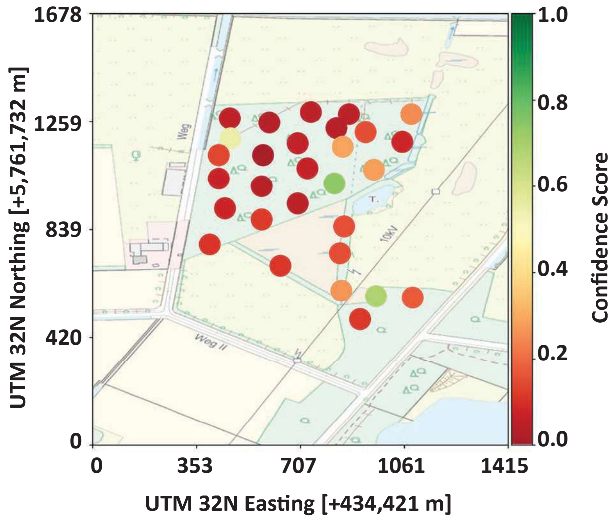

**c) Time: 4:15:02–4:15:05**




**d) Time: 4:15:03–4:15:06**

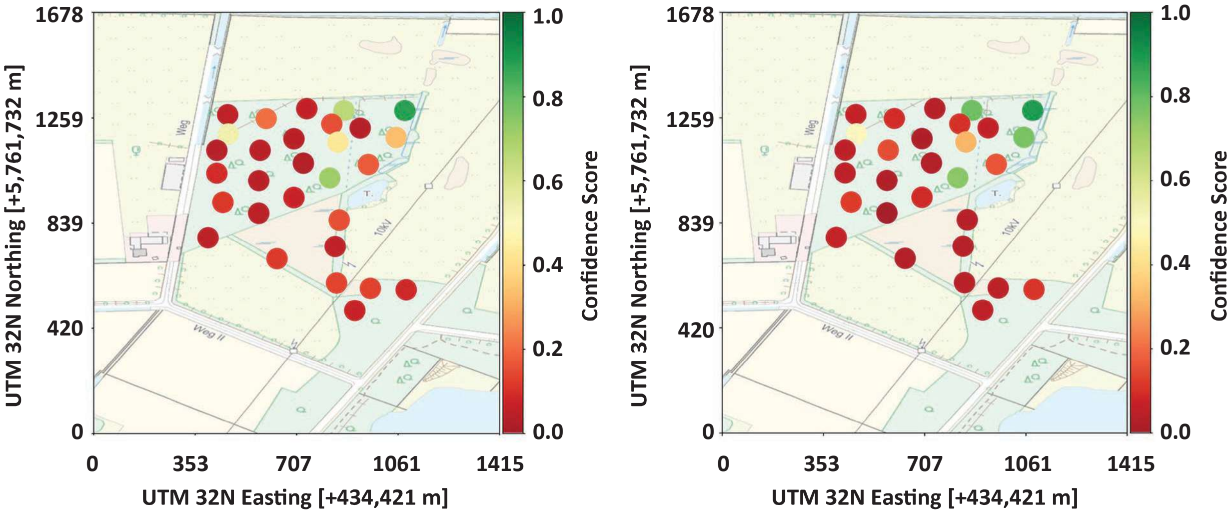



**e) Time: 4:15:04–4:15:07**




**f) Time: 4:15:05–4:15:08**

**Figure 2. Illustration of the Challenge: A real-world ASN of Common Redstarts *Phoenicurus phoenicurus* observations and their identification confidence scores in North Rhine-Westphalia, Germany on 3 June 2023 in three second intervals.**




g) Time: 4:15:06–4:15:09

h) Time: 4:15:07–4:15:10

**Figure 2 continued. Illustration of the Challenge: A real-world ASN of Common Redstarts *Phoenicurus phoenicurus* observations and their identification confidence scores in North Rhine-Westphalia, Germany on 3 June 2023 in three second intervals.**

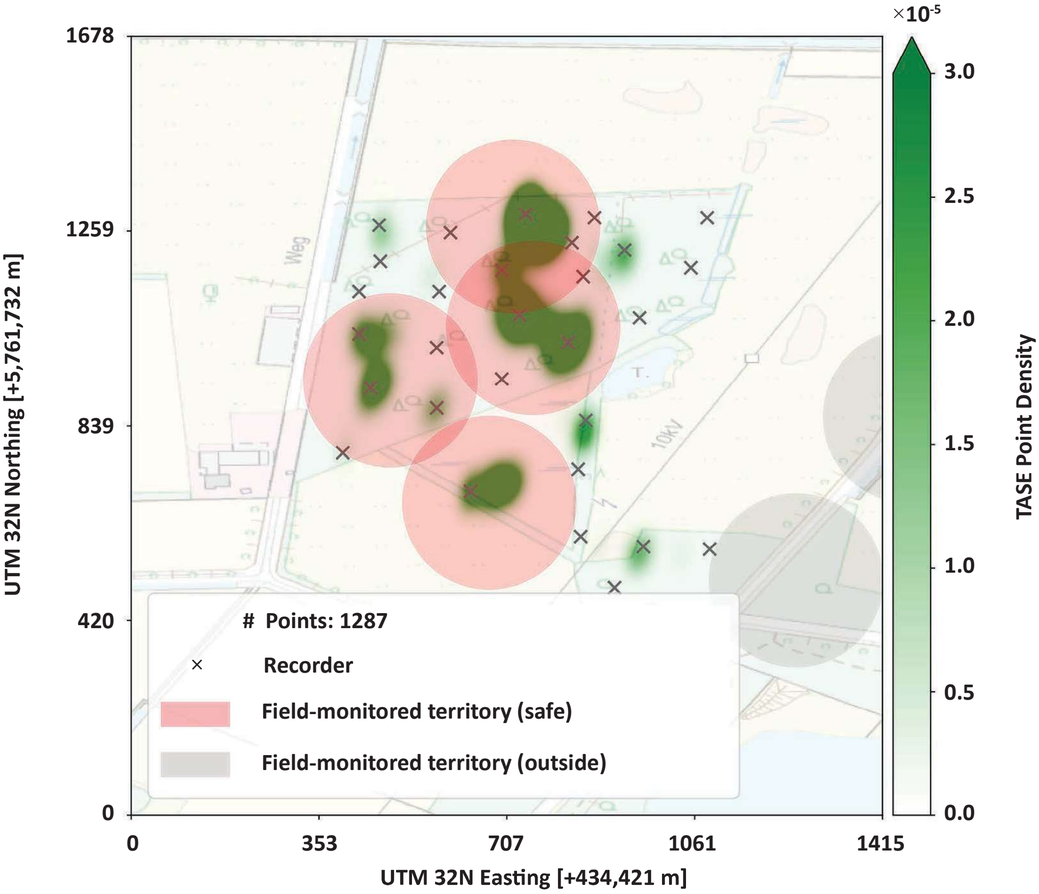



**Figure 3. Kernel density estimate (green) of spatio-temporal detections for the Blackcap *Sylvia atricapilla* generated by TASE, with the expert's territorial assessment shown by red and gray circles.**

in the area vocalize. (3) Our approach requires setting some parameters that might cause methodological errors.

In Brüggemann et al. (2025), we provide a detailed proof-of-concept evaluation of our approach, focusing on eleven species and discussing the opportunities and limitations. The next steps include scaling up to larger, longer deployments and introducing "soft" territorial boundaries with automated spatio-temporal clustering. With these refinements, TASE could deliver reliable data in abundance estimates, whereas conventional monitoring is hard or impossible.

## Map data sources and licensing



## References

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