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METHODS PAPER

Using the BirdNET algorithm to identify wolves, coyotes, and potentially their interactions in a large audio dataset

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Abstract
Passive acoustic monitoring has emerged as a scalable, noninvasive tool for monitoring many acoustically active animals. Bioacoustics has long been employed to study wolves and coyotes, but the process of extracting relevant signals (e.g., territorial vocalizations) from large audio datasets remains a substantial limitation. The BirdNET algorithm is a machine learning tool originally designed to identify birds by sound, but it was recently expanded to include gray wolves (*Canis lupus*) and coyotes (*C. latrans*). We used BirdNET to analyze 10,500 h of passively recorded audio from the northern Sierra Nevada, USA, in which both species are known to occur. For wolves, real-world precision was low, but recall was high; careful post-processing of results may be necessary for an efficient workflow. For coyotes, recall and precision were high. BirdNET enabled us to identify wolves, coyotes, and apparent intra- and interspecific acoustic interactions. Because BirdNET is freely available and requires no computer science expertise to use, it may facilitate the application of passive acoustic surveys to the research and management of wolves and coyotes, two species with continental distributions that are frequently involved in high-profile and sometimes contention management decisions.

Keywords Gray wolf · *Canis lupus* · Coyote · *Canis latrans* · Passive acoustic monitoring · Machine learning · BirdNET · Bioacoustics

Introduction

As a globally distributed apex predator that can radically influence entire ecosystems (Estes et al. 2011) and inspire human emotions ranging from fear to reverence, wolves have been the subject of human inquiry for millennia. In contrast, although Coyote features prominently in Indigenous North American mythology, coyotes are widely regarded as a pest in contemporary American society. Yet the widespread extermination of North American apex predators has facilitated a continental-scale expansion of coyotes—an event with potentially significant implications for biodiversity across the Americas (Prugh et al. 2009; Levi and Wilmers 2012; Hody and Kays 2018). The return of wolves to some parts of their range has revealed complex competitive dynamics (Merkle et al. 2009), while potential modes of coexistence, such as partitioning of space (Benson and Patterson 2013) or time, are threatened by habitat loss and human activity (Gaynor et al. 2018), respectively. A range of invasive and noninvasive techniques have been used in the study and management of these and other canids, but their typically nocturnal and wide-ranging behavior has posed a persistent challenge (Blanco and Cortés 2012). However, their extensive use of vocal communication makes them excellent candidates for passive acoustic monitoring (PAM).

Indeed, PAM has been applied to canid research (e.g., Suter et al. 2017; Shoemaker and Miles 2020; Sadhukhan et al. 2021). The vocalizations employed by wolves and coyotes for long-range communication tend to be the target signals: gray wolves tend to produce long (6–10 s), low-frequency (300–600 Hz) howls with relatively little frequency modulation (e.g., Fig. 1, bottom spectrogram; Fig. 2, middle spectrogram); in contrast, coyotes tend to produce shorter (3–5 s) howls at higher frequencies with much greater modulation

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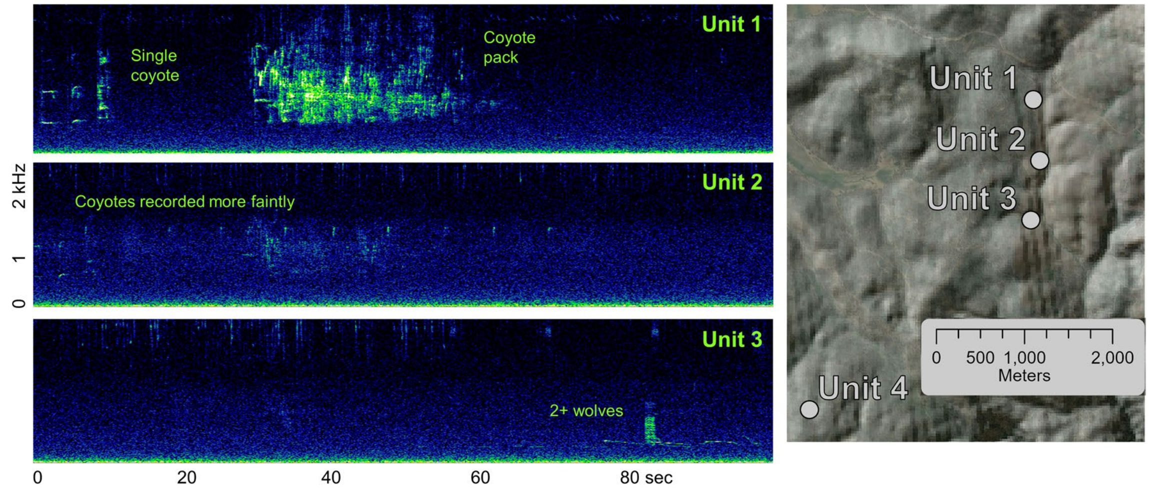

Fig. 1 Gray wolves and coyotes were recorded during passive acoustic surveys in the northern Sierra Nevada, USA, in May 2018, and were detected with the BirdNET algorithm. At 5:30 (local time), an individual coyote and then a pack vocalized close to Unit 1 and was recorded 700m away at Unit 2; approximately 20 seconds later, at least two wolves were recorded closest to Unit 3. All three spectrograms had the same settings

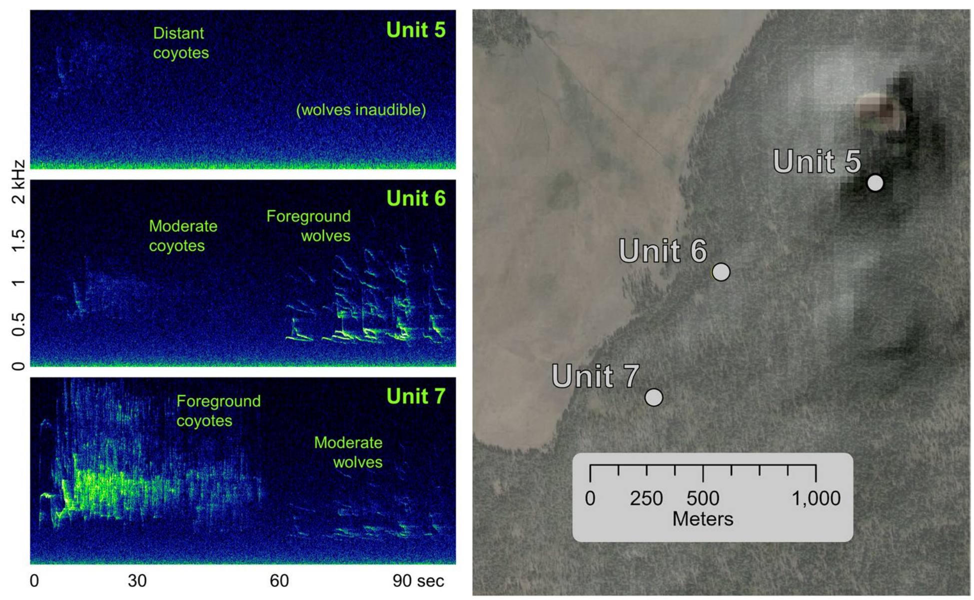

Fig. 2 A pack of coyotes chorused at 3:40 (local time), July 7, 2018, in the northern Sierra Nevada, USA (first 60 s of each spectrogram), followed by a group of at least three wolves (last 40 s of each spectrogram). Both species were detected with the BirdNET algorithm at Units 6 and 7. All three spectrograms had the same settings

(500–1500 Hz) (e.g., Fig. 1, top spectrogram; Fig. 2, bottom spectrogram). PAM can be less expensive and more efficient than other methods (Garland et al. 2020). However, identifying the target vocalizations in large audio datasets amassed via the deployment of autonomous recording units (ARUs) remains a time-intensive task (Suter et al. 2017; Gibb et al. 2019).

Machine learning algorithms have proven highly effective at animal sound identification in large audio datasets, though most efforts to date have focused on birds. Automated identification of wolf howls in PAM data using such algorithms has been demonstrated with captive animals (Stähli et al. 2022) but has not yet been applied to wild populations and remains inaccessible to those without computer science expertise. The BirdNET algorithm is a deep convolutional neural network originally designed to identify birds by sound (Kahl et al. 2021); it was recently expanded to include > 6000 species, including the gray wolf, coyote, and domestic dog. Critically, BirdNET is freely available and requires no computer science expertise to use. Using a case study from the northern Sierra Nevada, USA, we demonstrate that BirdNET can identify both gray wolves and coyotes in PAM data, and we identify persistent challenges to this tool and ways in which it may facilitate research on a globally prominent apex predator, the gray wolf, and a rapidly expanding mesocarnivore, the coyote.

Methods

We tested BirdNET's ability to identify wolves and coyotes in two audio datasets in which the species were known to occur. Both were recorded with the same model of ARU (SwiftOne recorder, K. Lisa Yang Center for Conservation Bioacoustics) with identical settings (mounted on trees ~ 1.5 m from the ground; one omnidirectional microphone; gain = +38 dB, sample rate = 32 kHz) such that BirdNET scores could be directly compared across datasets (the prediction scores made by BirdNET and other tools can be sensitive to even minor changes in audio characteristics, such as sample rate).

A small proof-of-principle dataset for wolves only was recorded via a brief deployment of two ARUs located 100–600 m from captive wolves at the Wolf Conservation Center in New York in 2022, which houses captive gray wolves. We manually reviewed 10 h of audio and found 167 wolf howls (26.9 min total, ranging 2.9 s to 1.9 m) from one to five or more individuals.

A second, much larger test dataset was recorded in 2018, when 200 ARUs were rotated across > 900 locations throughout the Lassen National Forest in the northern Sierra Nevada, California, USA, from mid-May through mid-August. Individual deployments lasted approximately 6 days, and each site was surveyed on two or three occasions during which time the ARU recorded continuously 18:00–10:00 local time. Deployments were clustered such that groups of two or three ARUs were no closer than 500 m, while clusters were at least 1.5 km apart (see Wood et al. (2019) for further detail). Historical records suggest that wolves may have populated most of California prior to Euro-American colonization (Park 2013), but by the early 1920s wolves were extirpated from California (Schmidt 1991). In late 2011, wolves naturally returned to northern California from Oregon, and by 2022, there were three known packs (California Department of Fish and Wildlife 2022). We selected 11 ARUs that intersected areas known to be utilized by wolves and in which we had already positively identified the vocalizations of both wolves and coyotes, and applied BirdNET to the 10,511 h of audio recorded by those units.

Next, we scanned both audio datasets with the BirdNET algorithm. BirdNET is freely available (https://github.com/kahst/BirdNET-Analyzer) and can be executed via the command line interface, a graphical user interface, or Raven Pro v1.6.5 + (K. Lisa Yang Center for Conservation Bioacoustics). We used the command line interface to analyze our target audio with BirdNET via the "analyze.py" script. We used the default sensitivity and overlap settings (1.0 and 0, respectively) and a custom species list: Canis lupus_Gray Wolf; Canis latrans_Coyote; Dog_Dog. We did not expect to encounter domestic dogs in the audio because ARUs were not deployed near residential areas, so the inclusion of dogs acted as a negative control to test whether BirdNET was correctly discerning the three canids. BirdNET analyzes audio in 3-s chunks; for each such chunk of our 1-h-long input files, it generated a unitless "confidence score" prediction ranging from 0 to 1 for each of the three species on our list. For each input audio file, BirdNET generated a corresponding Raven Pro selection table containing any predictions that exceeded its default minimum threshold of 0.01. After scanning all target audio, we had one output file for each input audio file.

We reviewed all outputs associated with the 10-h proof-of-principle audio dataset in order to calculate precision and recall. For the 10,511-h Sierra Nevada dataset, we conducted a two-step process of reviewing BirdNET results. The more robust testing of BirdNET performance related to wolves reflects their much more prominent role in North American wildlife management.

First, we used the "segments.py" script to randomly select BirdNET predictions for each of the three species. We generated 75 predictions from confidence scores of 0.1 to 1.0 and 25 predictions from scores of 0.85 to 1.0. We reviewed all the randomly selected predictions and classified each as correct or incorrect. We then used logistic regression to relate prediction outcome (correct or incorrect) to BirdNET score and tested for a relationship between BirdNET score (confidence score and its original logit scale; see (Wood et al. 2023a) for further detail).

Second, we began reviewing the BirdNET outputs from the Sierra Nevada dataset. We sorted all BirdNET outputs (i.e., Raven Pro selection tables formatted as.txt files) by file size and began our review with the largest files because file size increases with the number of BirdNET predictions (i.e., selection boxes) that were within the hours of 3:00–6:00 local time, which we anecdotally observed to be the local peak of wolf vocal activity. If a "large" output file (e.g., > 20 BirdNET-based wolf predictions) contained predictions with a confidence score > 0.90, we used Raven Pro to manually output files that high-scoring putative wolf and coyote observations in the dataset. When we confirmed that a BirdNET prediction was indeed a wolf observation (i.e., a true positive), we manually reviewed 30 min of audio before and after any that observation to determine whether any other vocalizations had been recorded but had not been correctly identified (i.e., a false negative). Additionally, we manually reviewed the audio recorded at the same time at adjacent ARUs to determine if that vocalization had been recorded at multiple units. When a howl was recorded at multiple ARUs (and detected there via either BirdNET or manual review), we considered the ARU at which the vocalization had been recorded with the greatest amplitude to be closest to the vocalizing individual. Such an approach can allow for approximate triangulation but would not be suitable for true acoustic localization without source volume estimation and synchronizing clocks across ARUs.

Results and discussion

In our 10-h dataset of audio recorded at the wolf sanctuary, BirdNET made 258 Gy wolf predictions above a confidence score of 0.1; 256 were correct and they correctly identified 113 of the 167 wolf vocalizations (precision = 0.99, recall = 0.68). However, manually validating the randomly generated BirdNET predictions from the 10,511-h Sierra Nevada dataset (i.e., phase one of our review process) revealed quite different performance: there were only four true positives out of 150 predictions. Thus, we were unable to fit a logistic regression model to the wolf data. BirdNET can identify wolves when they are present, but our initial test dataset was not an accurate reflection of the acoustic conditions in our larger dataset. However, BirdNET performed exceptionally well for coyotes in the Sierra Nevada dataset. There was a strong positive relationship between prediction score and the probability that a prediction is correct, and we found that BirdNET's original logit scores are a better predictor than the confidence scores ($AIC_{\text{null model}} = 134.8$; $AIC_{\text{confidence score model}} = 103.5$; $AIC_{\text{logit score model}} = 101.9$). BirdNET could identify coyotes in our dataset with a < 1% chance of a false positive at high score thresholds (Fig. 3). Finally, as expected, domestic dogs were absent from our audio dataset. An absence of true positives meant that we could not fit a logistic regression model; scores were overwhelmingly low (there were only two predictions above a confidence score of 0.85, and both were false positives). Differential classification performance across species is expected, so direct interspecific comparisons must be made judiciously (Wood et al. 2023b). For example, acoustic co-occurrence may be feasible but comparing vocal activity rates may not be.

Long-duration, low-frequency signals such as wolf howls may be intrinsically difficult to detect with high precision using BirdNET. First, BirdNET analyzes audio in 3-s chunks to optimize the identification of short-duration bird vocalizations (Kahl et al. 2021); consequently, long-duration signals will be broken into clusters of consecutive predictions, many of which may have similar scores. Thus, when conducting a manual review of the Sierra Nevada outputs (described below), we prioritized clustered predictions for review. However, second, low-frequency signals are subject to more interference than higher-frequency signals, and a variety of high-amplitude, low-frequency sounds may degrade such that they begin to resemble the relatively simple signature of a wolf howl (e.g., Fig. 2, bottom spectrogram). Thus, a cluster of high-scoring predictions is insufficient to determine wolf presence without verification. Indeed, our review

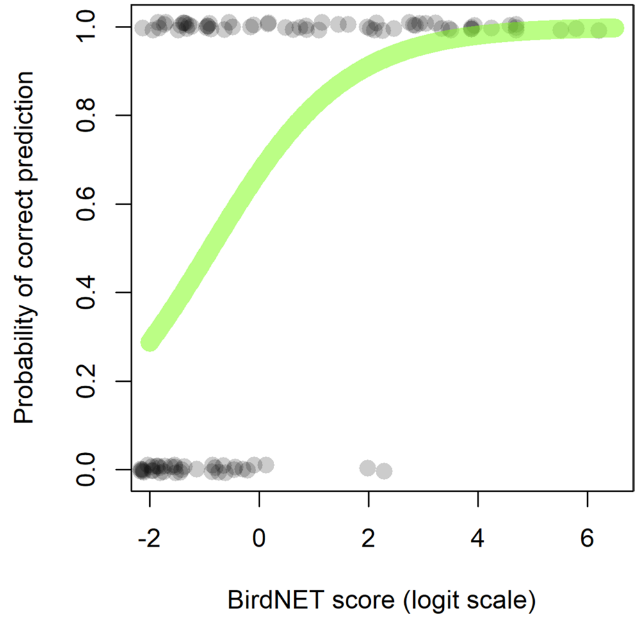

Fig. 3 BirdNET could identify coyotes with > 95% accuracy based on logistic regression (green curve) that related the manually confirmed outcome of 150 randomly selected predictions (gray dots) as correct (top row) or incorrect (bottom row). BirdNET scores were back transformed from unitless "confidence scores" to their original logit scores

of the Sierra Nevada dataset revealed that misclassifications (false positives) were dominated by geophony (wind) and anthrophony (train horns), both of which are, like wolf howls, long-duration sounds relative to BirdNET's 3-s analysis window. Despite these challenges, we believe BirdNET can be a viable tool for wolf research and especially for coyote research. Careful post-processing (e.g., prioritizing for review the outputs with many wolf predictions recorded during likely periods of vocal activity, as we did) is likely to be necessary for an effective application of BirdNET to wolf bioacoustics. Another possibility is using a newly developed feature of BirdNET, the ability to train a custom detector, to develop bespoke wolf detectors that can take advantage of project-specific training data (see (Ghani et al. 2023) and https://github.com/kahst/BirdNET-Analyzer#5-training).

Extensive manual review of the Sierra Nevada dataset (105 of the 10,511 h we scanned) revealed that BirdNET correctly identified numerous wolf and coyote vocalizations, enabling us to generate coarse-resolution location data for both species and to identify likely wolf-wolf and wolf-coyote acoustic interactions. (The near-total absence of correct wolf predictions in the randomly selected predictions generated by "segments.py" suggests that false positives vastly outnumber true positives in that particular dataset.) Below, we highlight two events that involve multiple putative acoustic interactions of wolves and coyotes. Unless otherwise noted, all vocalizations were detected by BirdNET. Within the audio we manually reviewed, observed recall for both species was high, with false negatives predominantly extremely distant (i.e., low-amplitude) vocalizations.

Wolf-coyote pack interaction

Shortly before dawn on May 18th, wolves and coyotes were recorded across four ARUs (Units 1–4) deployed 700–4500 m apart over a 32-min period (Fig. 1). At 5:05 local time, a wolf howled three times and was recorded (and detected) at Units 1 and 3. It was closest to Unit 3 and was not recorded at Unit 2 (complex local topography and dense forest may have caused this ARU not to record these and other vocalizations). Twenty-five seconds later, two coyotes were detected at Unit 1; manual review revealed that they were recorded faintly 700 m and 4500 m southwest at Units 2 and 4, respectively, but not at Unit 3. Ten seconds after the coyotes began vocalizing, multiple wolves began howling. Both species were correctly identified at Unit 1, but the wolves were still closer to Unit 3, and howled intermittently for several more minutes.

At 5:30, after 19 min during which no vocalizations were recorded at any of the six ARUs in the area, one coyote and then a pack howled near Unit 1 (Fig. 1, top spectrogram). The chorus was also detected at Unit 2 (Fig. 1, middle spectrogram); it was recorded but not detected at Units 3 and 4. Ten seconds later, at least two wolves howled close to Unit 3 (Fig. 1, bottom spectrogram), though it was recorded faintly at Unit 1 as well (Fig. 1, far right of the top spectrogram).

Wolf-coyote and wolf-wolf interactions

During the night of 7 July approximately 18 km from the previous vocal interactions, vocalizations of wolves and coyotes were recorded at three ARUs (Units 5–7) deployed 650–1400 m apart (Fig. 2). From 3:12 to 3:14 local time, a wolf was recorded howling intermittently close to Unit 7 and more faintly 650 m northeast at Unit 6. Six minutes later, two wolves were recorded howling for 40 s at Unit 6 and, more faintly, at Unit 5. In the audio recorded at both ARUs, the amplitude of both individual's vocalizations was similar, suggesting that both wolves may have been in roughly the same location. Howling is often employed by canids to regroup, and it is possible that the two vocally active wolves close to Unit 6 were responding to one vocally active wolf closer to Unit 7. It is also possible that the wolf initially recorded closer to Unit 7 than 6 was one of two that was recorded 6 min later closer to Unit 6 than 7, but the subsequent recordings revealed that the minimum wolf group size was three.

After 20 min during which no vocalizations were recorded, a 50-s coyote chorus was detected close to Unit 7, much more faintly at Unit 6, and manually identified at Unit 5 (Fig. 2). Ten seconds later, at least three wolves were recorded chorusing for 45 s close to Unit 6 and faintly at Unit 7 (Fig. 2). The amplitude of all three wolf howls was nearly identical at both ARUs, suggesting that each individual was the same distance from both ARUs (i.e., all three were in the same location).

Implications for wolf and coyote research

Bioacoustics has a long history in wolf and coyote research, and PAM can be a cost-effective and noninvasive wolf survey technique method that yields detection probabilities that are equivalent to or greater than those achieved by camera trapping (Garland et al. 2020). The many challenges to surveying these wide-ranging predators incentivize further improvement to canid-oriented PAM techniques (Blanco and Cortés 2012; Suter et al. 2017). It is comparatively easy to collect many thousands of hours of audio data; identifying sounds of interest is a major bottleneck. We have shown that a freely available machine learning tool with graphical user interface (GUI) and command line implementation options, BirdNET ((Kahl et al. 2021); https://github.com/kahst/BirdNET-Analyzer), can correctly identify wolf and coyote vocalizations. Thus, PAM and BirdNET can facilitate the fundamental task of assessing the distribution of either or both species across the landscape.

Yet far more information that species' distributions may be attainable. Efficient identification of wolf or coyote vocalizations can facilitate estimates of group size (Passilongo et al. 2015) and may be helpful in identifying individuals (Larsen et al. 2022). Because wolf and coyote pups make distinctive sounds, researchers could also use PAM to identify demographically critical events like successful reproduction. BirdNET's feature embeddings, a pre-species classification layer of information accessible via the "embeddings.py" script, has been successfully used to identify reproductive events in owls and to search for distinctive sounds in large datasets (McGinn et al. 2023). Finally, it may be fruitful to explore interspecific interactions.

In both of our case studies, it is plausible to infer call-response dynamics both within and between species. In case one, a wolf appears to elicit a coyote chorus which elicits further wolf vocalizations, and, later, one coyote appears to initiate a group chorus, which again elicits a wolf chorus. In case two, vocalizations appear to have facilitated one wolf apparently joining two others; that group then appears to respond together to a nearby group of coyotes (Fig. 2, middle and bottom spectrograms). Wolf populations suppress coyote populations (Levi and Wilmers 2012), with the former species competitively dominant in most contexts (Merkle et al. 2009) leading to spatial segregation between species in areas of sympatry (Benson and Patterson 2013). Where wolves have returned to their former range, violent interactions with coyotes tended to decrease over time (Merkle et al. 2009), suggesting complex behavioral dynamics that could be elucidated at least in part via passive observation of their vocal communication. The behavioral ecology of these putative interspecific interactions may be particularly important in the context of wolf recolonization and reintroduction across western North America and hemisphere-scale coyote expansions (Hody and Kays 2018).

BirdNET's ability to accurately and efficiently identify coyote vocalizations suggests that it can be immediately applied at scale for this species; as noted above, further work is necessary to apply BirdNET efficiently to wolf ecology. Both gray wolves and coyotes have continental distributions and are involved in a diverse range of conservation and management challenges; BirdNET may help facilitate more effective research and conservation of these species by making scalable passive acoustic surveys a viable approach.

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Author contribution Conceptualization: CMW; software: SK; data curation: DS, KB, and CMW; writing—original draft: DS and CMW; writing—review and editing: DS, KB, SK, and CMW.

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Data availability Example audio clips are available as supplementary material. The authors welcome inquiries about specific data requests from the larger dataset.

Declarations

Competing interests The authors declare no competing interests.

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