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PERSPECTIVE

Counting animals in orthomosaics from aerial imagery: Challenges and future directions

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Abstract

1. The use of drones to survey and monitor wildlife populations has increased exponentially. A common protocol used for data collection is planning flights with substantial overlap between successive photographs and lateral lines and then creating orthomosaics by merging the collected images. Because available methods for orthomosaic building assume that landscapes are static, unintended errors arise when counting moving animals. Here, we describe these sources of error and discuss potential solutions and future developments needed.
2. Individuals can appear multiple times, be omitted or appear as faint ghosts or cut in half in the final mosaic. These errors can significantly impact abundance estimates but are rarely acknowledged. Researchers should carefully consider if using orthomosaics is really needed for surveying wildlife. Currently, there is a lack of methods to prevent these errors from arising and to explicitly accommodate them in modelling approaches.
3. Future developments should focus on (a) creating methods to build orthomosaics that minimize these errors in the context of counting moving animals; (b) developing modelling approaches to estimate abundance while accounting for these errors; and (c) exploring alternative flight settings (e.g. amount of lateral overlap, sensor type, flight height and speed).
4. Using an example on Giant Amazon Turtles, we illustrate potential solutions with a method for orthomosaic building that prioritizes moving animals and a modelling approach to estimate the detection errors and correct abundance estimates. The developed prototype approach for creating orthomosaics revealed many more turtle individuals than the conventional approach, although it presented more double counts as well. In the modelling approach, we found that a turtle available for detection during the survey can have a probability of 31% of being omitted or ghosted during the conventional orthomosaic building process. We also found that 12% of the turtles appearing in a conventional orthomosaic correspond to double counts.

KEYWORDS
abundance estimation, detection errors, drones, photogrammetry, population monitoring, wildlife

1 | INTRODUCTION

Given the rapid anthropogenic environmental changes that wildlife species are experiencing worldwide, it has become crucial to develop and implement efficient methods to assess wildlife population size and monitor it over time (Besson et al., 2022; Butchart et al., 2010). Drones (also known as unoccupied aerial vehicles) have emerged as a cutting-edge tool for wildlife surveys, holding the promise of delivering accurate and timely abundance estimates (Christie et al., 2016; Linchant et al., 2015). The use of drones to count animals has increased exponentially in the last decade (Dujon & Schofield, 2019; Elmore et al., 2023) for a wide myriad of species and environments, such as elephants in savannas (Vermeulen et al., 2013), whales in the ocean (Gray et al., 2019), primates in tropical forests (de Melo, 2021) and crocodilians in marshes (Scarpa & Piña, 2019). However, the establishment of the use of drones as a reliable and effective tool for sampling wildlife still faces important challenges due to multiple potential sources of bias in the procedures for converting collected imagery into abundance estimates.

A very common approach used in wildlife drone surveys is to fly drones with great overlap (e.g. 80%) between successive pictures and lateral lines (Elmore et al., 2023). This great overlap allows for the collected photographs to be merged into a single image mosaic (i.e. orthomosaic or orthophoto mosaic), which is then used to count individuals (Box 1). This procedure is particularly common when counting individuals that are spatially aggregated, such as nesting colonies of birds (e.g. Lyons et al., 2019; Weinstein et al., 2022), breeding colonies of seals (e.g. Sorrell et al., 2019) and basking areas of turtles (Bogolin et al., 2021). Orthomosaics are a conventional high-resolution mapping product from aerial images, derived from the combination of overlapping images that have been corrected for camera tilt, surface undulation and camera lens distortion (Westoby et al., 2012; Wolf et al., 2014). Critically, available methods to build these mosaics typically assume a static landscape but, because animals often move during flights, several unintended errors typically arise when using these orthomosaics to survey wildlife populations. Because the workflow of these methods is highly automated, users are typically not aware of these errors. Ultimately, these sources of error in orthomosaic building, together with other detection errors already widely acknowledged in the literature, may result in substantial bias in abundance estimation.

BOX 1 Creating orthomosaics from drone imagery

The creation of orthomosaics from aerial surveys requires the flight to be planned with a high degree of overlap between successive photographs and lateral flight strips (e.g. ≥70% for drone imagery) such that each point on the ground appears in multiple images. These multiple points of view (i.e. stereoscopic view) allow the identification of unique features in different images, resulting in an estimate of depth (three-dimensional information) (Eltner et al., 2016; Wolf et al., 2014). Current methods to build these mosaics are based on photogrammetric techniques (e.g. Structure-from-Motion) that automatically identify the matching points in different overlapped images (Eltner et al., 2016; James & Robson, 2012; Westoby et al., 2012). The procedure to create orthomosaics involves three general steps:

- Step 1: The recognized image features (key-points) are matched in the multiple images and used to estimate and correct the camera positions and angular orientations at the moments of the exposure.
- Step 2: A denser set of the matched features is created, and the estimated three-dimensional information is connected to generate a digital surface model (DSM) of the scene.
- Step 3: A horizontal 2D grid is populated with colour/brightness values based on the 3D DSM coordinates and the back-projected image coordinates from the associated photographs.

This procedure results in a high-resolution georeferenced mosaic corrected for camera tilt and surface undulations with known scale (i.e. orthorectified), which can be considered an accurate planimetric map. The approaches adopted to fill these orthomosaic cells typically involve selecting photographs whose centre region is closest to the cell and/or averaging brightness/colour from multiple images (Luhmann et al., 2023). It is important to note that the degree of overlap between images (i.e. number of stereoscopic views) plays an important role in the quality of the orthomosaic (Eltner et al., 2016). Nevertheless, increasing the overlap results in more flight lines needed to cover the same area, potentially increasing some of the errors when counting moving animals. Other aspects that can also affect the quality of the final mosaic include the use of ground control points (Sanz-Ablanedo et al., 2018) and image texture and resolution (Westoby et al., 2012) but for brevity, we do not address these here.

We describe here the potential sources of errors in animal counts that arise from the creation of orthomosaics and discuss future developments needed to deal with them. Since these sources of bias are widely ignored in the literature, our intention is to raise awareness about these problems and provide some direction for future explorations. We exemplify these errors and pathways for future solutions using a dataset of Giant Amazon River Turtles (*Podocnemis expansa*) surveyed using drone imagery captured over a sandbank in the Guaporé/Iténez River (in the Brazil-Bolivia border) during a mass nesting event.

2 | SOURCES OF ERROR WHEN COUNTING ANIMALS IN ORTHOMOSAICS

Wildlife counts in orthomosaics are subject to multiple sources of error. Generally, aerial count data, including counts based on orthomosaics, are subject to availability error, perception error and misidentification (Brack et al., 2018). Availability error occurs when an individual is unavailable for detection by being hidden from view (e.g. below vegetation or submerged underwater) or because it is temporarily outside the area during the flight. Perception or observation errors arise because, even when an individual is visible (i.e. available) in the imagery, a human reviewer or an algorithm can fail to detect it. Alternatively, other similar species (or even background feature) can be misidentified as the target species during the review process, especially when using automated detection algorithms (e.g. deep learning). These errors are already discussed in the wildlife literature and occur regardless of how images are processed (Brack et al., 2018, 2023; Caughley, 1974; Delisle et al., 2023; Pollock & Kendall, 1987). In this article, we focus on other sources of error that arise during the process of creating orthomosaics (Figure 1). Because the main origin of these errors is due to the movement of individuals during the flight, it is important to note that the magnitude of these errors will depend on the characteristics of the species (e.g. movement behaviours) and of the survey design (e.g. flight plan).

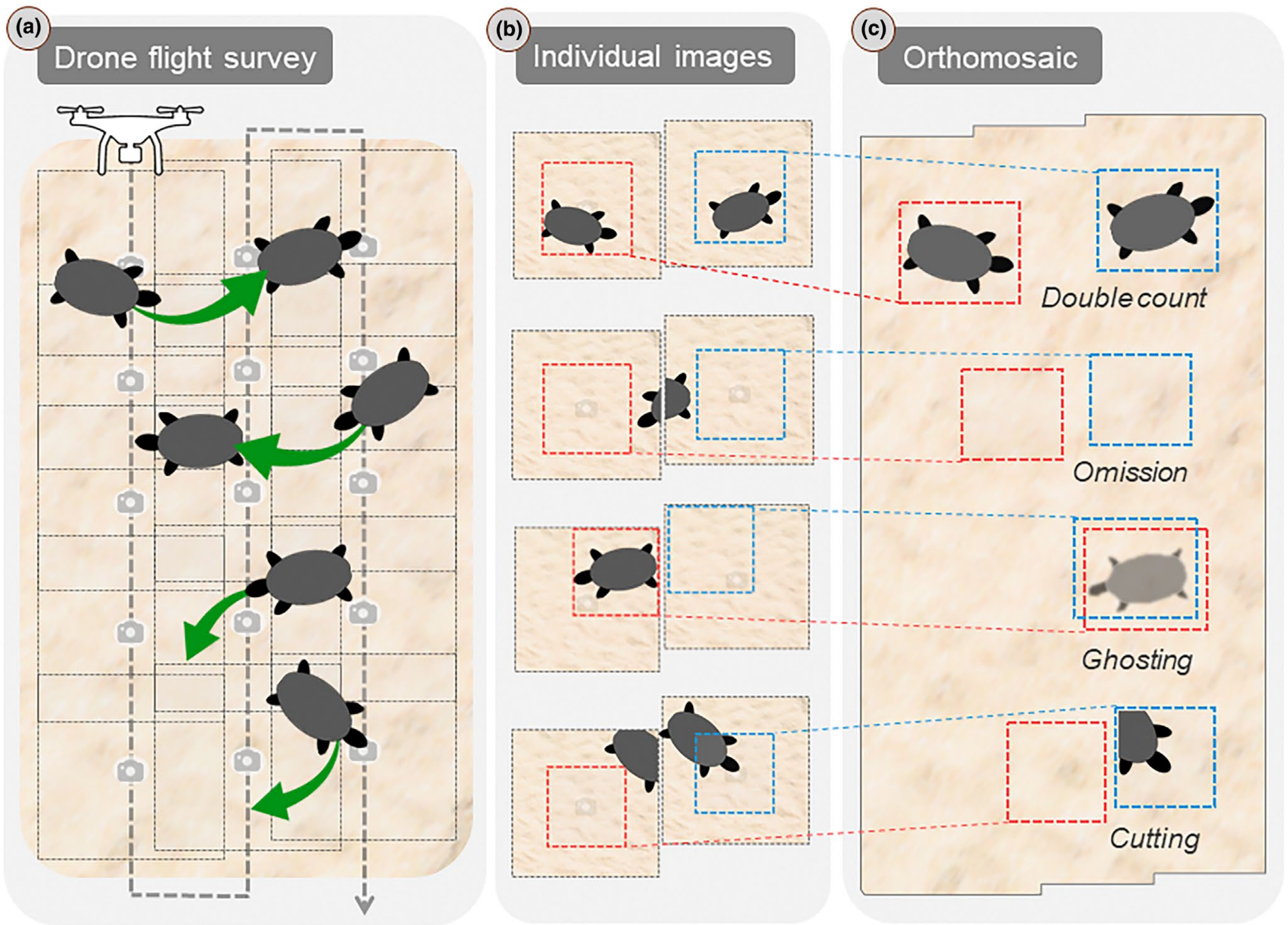

FIGURE 1 Detection errors resulting from merging multiple aerial images for the creation of orthomosaics when individuals are moving. (a) Flight with overlap between successive photographs and lateral strips while animals are moving. (b) Selected photographs from the collected imagery that will be projected into the final orthomosaic. (c) Resulting orthorectified mosaic with examples of the types of error that can arise when counting wildlife in orthomosaics.

2.1 | Double count

The same individual may appear more than once in the orthomosaic because the individual was moving during flight (Brack et al., 2018). Since the time between successive images is commonly very short (e.g. ≤1 s), double counts are more prone to occur when the individual is moving between flight lines (Figure 1).

2.2 | Omission

An individual that is present in the area of interest during the flight (and available for detection) might not appear in the orthomosaic due to two processes. First, if an animal moves in the opposite direction to the flight path of the planned lines (Figure 1), it may cross from an unsampled area into one that has already been surveyed and hence it might not appear in the imagery. This error would be similar to the availability error. Indeed, some have suggested that, when the movements of individuals in an area are at random, appearances (double counts) and disappearances (omission) may cancel each other out (Brack et al., 2018; Delisle et al., 2023). Second, even if a moving individual is present in the collected photographs, it may disappear in the final mosaic because of the way the orthomosaic cells are filled. For instance, a set of mosaic cells can be populated with colour and brightness information from the images that were collected when the individual was not there.

2.3 | Ghosting and cutting

Similar to the omission during the process of filling the orthomosaic pixels, some individuals may appear ghosted or cut (Figure 1). The averaging of the colour and brightness in the orthomosaic cells, derived from different images with and without the individual, can produce a ghosting or faded effect. On the contrary, if a single image is used to determine the colour and brightness values for each orthomosaic cell, the use of images from different flight lines may result in only part of a moving individual appearing in the final mosaic. The consequence of ghosting and cutting is that some individuals might be missed or, even if they are seen, it might be difficult to properly observe their characteristics (e.g. species, size, sex or unique marks).

3 | POTENTIAL SOLUTIONS FOR ADDRESSING ORTHOMOSAIC COUNTING ERRORS

In this section, we explore potential solutions to overcome or mitigate the sources of errors when counting wildlife in orthomosaic and suggest future directions for methodological developments. Firstly, when planning drone-based surveys to estimate wildlife abundance, one should consider if using an orthomosaic is really necessary. It is possible that, in some situations, flights might have been planned with high overlap between images and orthomosaics have been used to count individuals only because this is the traditional workflow for drone surveys. This workflow is facilitated by available software used to plan drone flights as this software typically requires the drawing of a polygon around the area of interest and the programme automatically plans the flight path with overlapping photographs. However, this workflow to create orthomosaics can introduce unintentional errors that do not occur when counting individuals in single images. Importantly, foregoing the use of orthomosaics to count wildlife would potentially involve rethinking flight plans (e.g. planning flights with very low or even no overlap) and image reviewing procedures (e.g. manually removing double counts).

Nevertheless, the use of orthomosaics might be desirable in various contexts for counting wildlife, especially when surveying aggregated populations, such as nesting or breeding colonies (e.g. Kellenberger et al., 2021; McKellar et al., 2021; Sorrell et al., 2019; Weinstein et al., 2022). Additionally, when there is an interest in measuring individuals or distances accurately, orthomosaic building might be a valuable approach (e.g. Aubert et al., 2024). Thus, proper approaches are needed to eliminate, mitigate or estimate the sources of error that may affect counts conducted in orthomosaics in order to obtain reliable abundance estimation. We discuss potential approaches and the needed developments under three different strategies: (1) adapting orthomosaic building methods; (2) estimating errors and accounting for them when modelling abundance; and (3) considering alternative survey equipment and designs. We show examples of potential solutions for Strategies 1 and 2 using surveys of Giant Amazon Turtles in Section 4.

3.1 | Adapting orthomosaic building method

Current approaches to create orthomosaics typically assume that the landscape is static and there is no available method for the situation when the object of interest is moving during the flight. Some software suites can detect moving objects, but this is done to enable their automatic elimination from the final mosaic (e.g. removing vehicles from streets in the 'Deghosting' processing option of Pix4Dmatic https://support.pix4d.com/hc/en-us/articles/360048200292#blend). Hence, there is a great need for algorithmic approaches to build orthomosaics that detect and prioritize wildlife individuals. Recall that traditional methods to populate orthomosaic cells rely on average brightness and colour values of several photographs or on photographs that have their central regions closest to the target cell (see Box 1). An alternative approach would be to prioritize the species of interest when selecting photographs to populate the orthomosaic cell (see example in Section 4.1). This could be done by recognizing pixels (e.g. through spectral signatures) or specific regions (e.g. using machine learning algorithms) in the single images that correspond to the species of interest and making sure that this information is used to fill the generated orthomosaic. Such an approach would avoid the ghosting or omission of individuals, but double counts would still be a problem.

3.2 | Estimating errors for abundance modelling

Modelling approaches to estimate and accommodate orthomosaicking errors in abundance estimation are imperative since we believe that it is not possible to completely avoid these errors from occurring. The probability of omitting or double counting individuals in orthomosaics may be estimated using additional information. For example, by marking some individuals in a way that is recognizable in the drone imagery, it is possible to estimate the proportion of omissions and double counts (see example in Section 4.2). Alternatively, these proportions can also be estimated if some individuals have been tagged with telemetry devices. One could even model (or simulate) movement patterns to estimate or predict the number of appearances and disappearances during a flight (Hodgson et al., 2017). As a result, using these estimates of detection error rates, it is possible to estimate abundance by correcting counts (e.g. using a Horvitz-Thompson estimator, Corcoran et al., 2020) or by explicitly incorporating these estimates into a modelling approach (e.g. as informative prior distributions under a Bayesian approach, Martin et al., 2015). One option to formally accommodate these errors is to create an integrated model to analyse two or more datasets (Isaac et al., 2020; Zipkin & Saunders, 2018). In such approaches, an auxiliary dataset containing high-quality information about one or more observation processes (e.g. mark-recapture data) is combined with overall population counts into a single modelling structure to obtain more accurate estimates.

3.3 | Adjusting equipment and survey design

Some sampling design strategies involving the type of equipment used and/or flight path may be explored in order to mitigate errors associated with moving animals in the orthomosaic building processes. Specifically, the fewer the number of flight lines needed to cover an area and the faster an area is covered, the smaller the errors will be. These two aspects can be achieved by reducing the overlap between images (but recall that this may limit the ability to create orthomosaics), flying higher using a very-high-resolution sensor (e.g. the 128 Mpx P5 camera from Phase One; https://www.phaseone.com/), and/or by conducting flights at high speeds (e.g. >70 km/h). Importantly, most of the available flight planning software allows users to set the main direction of flight lines as well as the desired amount of frontal and lateral overlap. For instance, if the area of interest is flat (and high horizontal accuracy is not needed), an uncontrolled mosaic could be created using standard image stitching methods (e.g. Microsoft Image Composite Editor, see Gross & Heumann, 2016) with lower overlap between images (e.g. 30%–40%), reducing considerably the number of lines required. Another option is to use multiple drones at the same time, reducing the overall time needed to cover the entire area of interest. Furthermore, different flight lines configurations may result in different magnitudes of error associated with moving individuals, especially when there is a preferable moving direction. For example, if flight lines are planned perpendicular to the major direction that animals move, the number of double counts will tend to be much higher than when flight lines are parallel to the movements. This particular topic has received limited attention in wildlife surveys (e.g. Baxter & Hamilton, 2018; Hodgson et al., 2017); therefore, further explorations on flight lines configurations that take into account movement patterns of individuals are needed. Finally, conducting the flights at moments when the individuals are less likely to move, such as flying over bird colonies close to sunset, can also help in mitigating these errors.

4 | EXAMPLES OF POTENTIAL SOLUTIONS USING GIANT AMAZON TURTLE SURVEYS

We exemplify an approach for orthomosaic building (Strategy 1) and for estimation of the detection errors for abundance modelling (Strategy 2) using a dataset of drone-based surveys of Giant Amazon River Turtles (*Podocnemis expansa*) (licence SISBIO/ICMBio no. 80087). Surveys were carried out during a mass turtle nesting event in October 2021 in the Guaporé/Iténez River (12.46° S, 63.83° W; Bolivia-Brazil border) (Figure 2). Four flights were conducted each day (at 6–7 AM) over a sandbank where the female turtles were nesting, using a multirotor drone Mavic Enterprise Advanced (DJI). Flights were preprogrammed to collect data at 50 m above-ground level and with 70% and 80% of lateral and frontal overlap, respectively. We marked with white paint approximately 100 turtle individuals every day 3 h prior to these flights (i.e. 3 AM). Because of the unique markers in their carapaces, these data allowed us to assess the different sources of error.

4.1 | Prioritizing animal individuals when creating orthomosaics

We used the images of one surveying day to explore a prototype approach to prioritize the projection of turtles in the orthomosaic. The approach relies on preprocessed products from a standard Structure-from-Motion/photogrammetric software, to which we then apply specific customizable criteria to populate the orthorectified mosaic. We provide a description of the proposed prototype

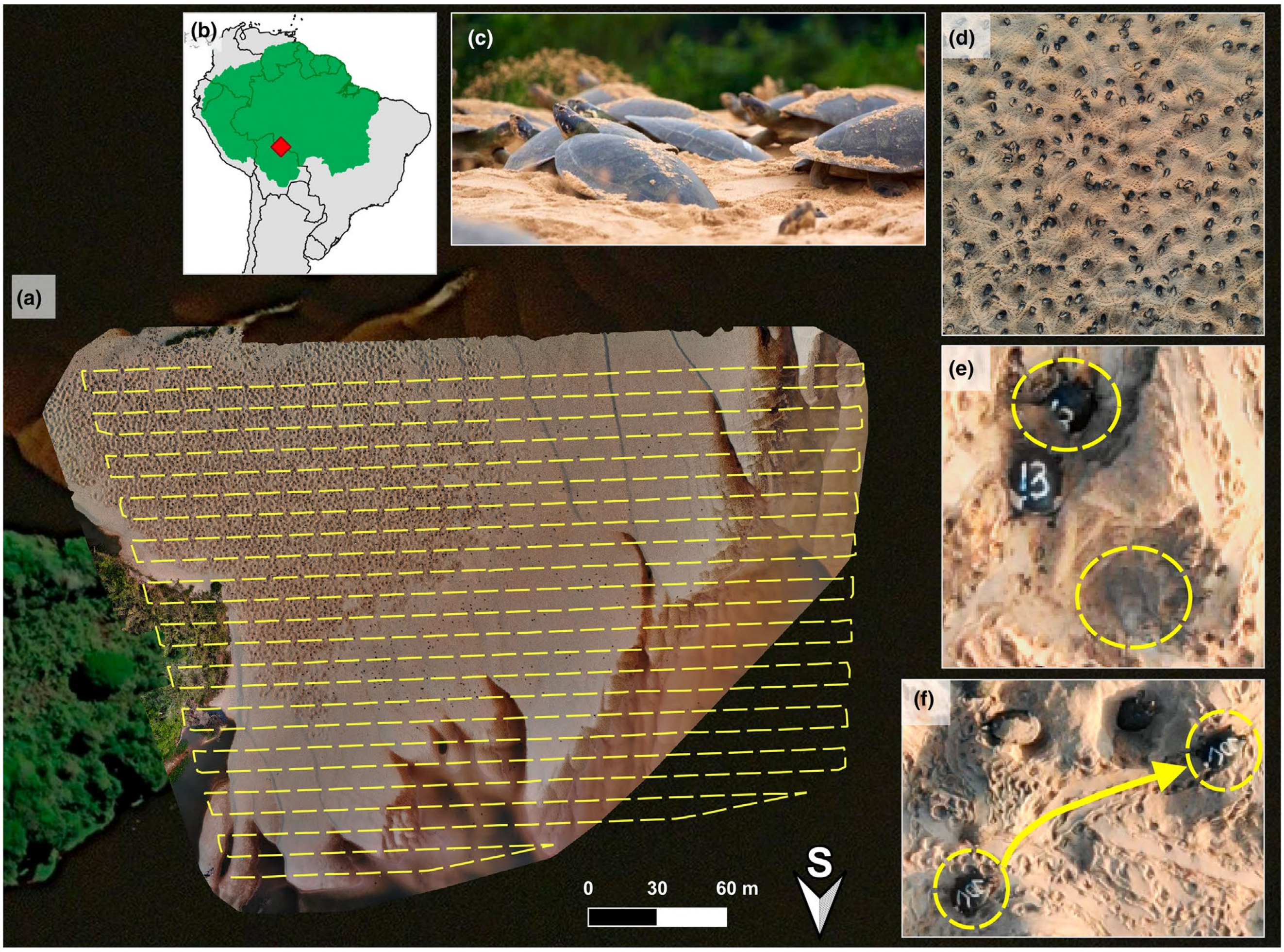

FIGURE 2 Flight path, resulting orthomosaic and detection errors in drone-based surveys conducted during the mass nesting event of Giant Amazon Turtles. (a) Flight path (yellow lines) over the area of interest (river sandbank). (b) Location of the study area in the Amazon biome (green polygon); (c) Female turtles nesting. (d) Zoom-in of the orthomosaic showing turtles seen from above. Detection errors associated with orthomosaic building process: (e) A marked individual that appears a second time cut in half and a ghosted turtle individual. (f) Double count of a moving individual.

approach in Appendix S1. The products extracted from the SfM software (Pix4Dmapper v. 4.8.4) were as follows: (i) the drone images corrected for lens distortion; (ii) corrected three-dimensional orientation and position of the camera during the shot; and (iii) a digital surface model of the entire area of interest. Then, for each cell of the 2D orthomosaic, we obtained the corresponding images that overlap that cell and applied a rule to fill this cell that prioritizes pixels containing the species of interest. If the selected images contained pixels corresponding to the spectral characteristics of the species, we projected the animal pixels closest to the centre of the image. If the selected images did not have animal pixels, we only projected the pixels closest to the image centre. For this example, we used a saturation metric calculated from the red-green-blue (RGB) values to define the spectral signature of the turtles, but different rules can be applied depending on the scene and target species.

We show in Figure 3 a comparison of the resulting orthomosaic based on a conventional method and on our proposed prototype approach. It is possible to see that, in addition to the three individuals projected using the conventional method, there are three more individuals projected by our approach, demonstrating its potential to mitigate omission and ghosting errors. It is important to note that the double count errors still remain and may have their magnitude increased under this approach. Future developments could explore different criteria for pixel selection of different species, or more sophisticated machine learning algorithms (e.g. object-based image analysis or deep learning techniques; Chabot & Francis, 2016; Weinstein, 2017).

4.2 | Estimating detection errors for abundance estimation

To illustrate how the different errors can be estimated for modelling abundance, we use the turtle dataset containing overall counts in the orthomosaics (created using a conventional approach) for

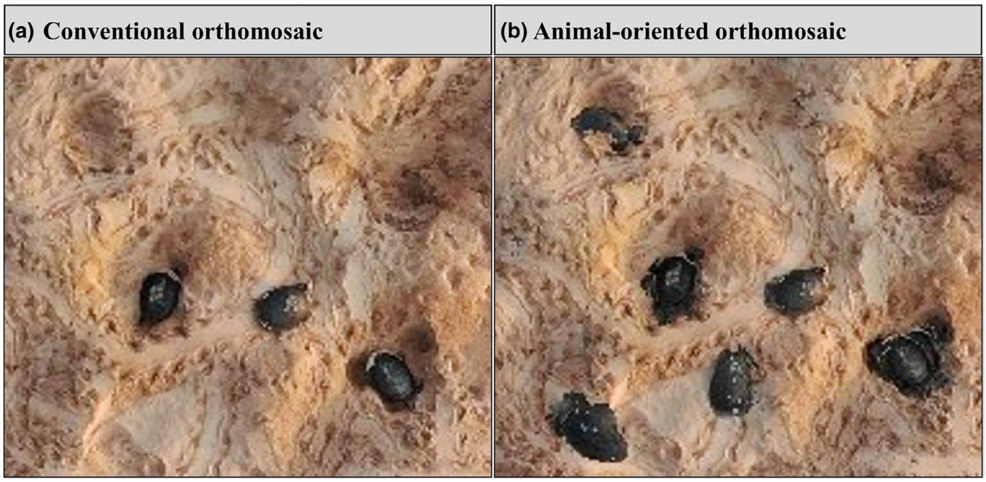

FIGURE 3 Comparison of the resulting orthomosaic from Giant Amazon Turtle surveys, using (a) a conventional mosaic building approach; and (b) the proposed approach for prioritizing pixels of the animal of interest.

TABLE 1 Counts and estimated abundance of Giant Amazon River Turtles for three orthomosaics derived from drone-based surveys over a sandbank in the Guaporé/Itenez river (Brazil/Bolivia).

	Marked individuals							
Date	*N* ortho	*N* single	*N* 3 AM	*N* 6 AM	*N* total	*N* doubles	Overall count	Estimated abundance (95% CI)
2 October	62	88	108	41	80	18	2989	6649 (5772–7671)
3 October	75	108	115	49	82	7	4073	9060 (7865–10,453)
4 October	78	116	100	38	82	4	3581	7966 (6915–9190)

Note: *N* ortho: number of unique marked individuals detected in the orthomosaic; *N* single: number of unique marked individuals detected in the single images; *N* 3 AM: number of individuals marked in that day at 3 AM; *N* 6 AM: number of unique individuals marked in that day that were detected in the mosaic; *N* total: total number of detections of marked individuals in the mosaic; *N* double: number of double counts of marked individuals.

three consecutive days and compiled information from the marked individuals (Table 1). We used three different pairs of counts from the marked individuals to estimate three detection errors: (i) availability (ϕ), based on the number of individuals marked in the same day of the flight that appear in the orthomosaic ('N 3 AM' and 'N 6 AM' columns in Table 1); (ii) omission/ghosting (ψ), using the number of unique marked individuals detected in the single images that do not appear in the orthomosaic ('N ortho' and 'N single' in Table 1); and (iii) double counts (ω), using the proportion of double counts of marked individuals in relation to the total detections of marked individuals ('N doubles' and 'N total' in Table 1). Then, we used these estimated probabilities to correct the counts, resulting in an adjusted abundance estimate for each day of survey. We provide a detailed description of the model in Appendix S2.

We estimated the probability of an individual to be available in the sandbank during flight as 0.58 (95% CI = 0.49–0.67), the probability of an individual present in the single images to be omitted or ghosted in the orthomosaic (i.e. disappearing) as 0.31 (95% CI = 0.26–0.37), and the proportion of double counts as 12% (95% CI = 8%–16%). Thus, the estimated abundance varied from 6649 to 9060 female turtles per day (Table 1). We used here the estimated detection errors from the marked individuals as correction factors for the daily overall counts in the orthomosaic; however, more complex model structures can be explored building on the modelling ideas presented here (e.g. the combination of different datasets discussed in the Section 3.2). Also, other sources of auxiliary data than counts of marked individuals, such as tracking data from telemetry devices, could be used to estimate the errors.

Finally, although we do not explore different sampling alternatives as discussed in Strategy 3 (Section 3.3), some straightforward options could be considered for future surveys of river turtles to reduce the errors related to moving animals. For example, using two drones simultaneously to fly over the sandbank would reduce the time needed to cover the sandbank from about 1 h to half an hour. Another option is to decrease the lateral overlap from 70% to 50%, which would shorten the total flight path from 7.2 km to approximately 4 km. Given that the area is considerably flat, this reduction in the lateral overlap is not expected to significantly compromise the quality of the final orthomosaic (though it could be tested in the field). By combining these two strategies, the time needed to cover the sandbank would be significantly reduced (from 1 h to 15–20 min), ultimately minimizing substantially the double counts, omissions, ghosting and cutting errors.

5 | CONCLUSIONS

The creation of orthomosaics from drone imagery is an increasingly common approach to count wildlife and obtain estimates of population size. However, to the best of our knowledge, the unintended errors described here that arise during the process of creating these mosaics have been widely overlooked in the literature. Critically, we demonstrate that, if not properly accounted for, these errors may substantially bias abundance estimates. For example, the surveys of Giant Amazon turtles revealed that the magnitude of these errors can be high (12% of double counts and 31% of omission and ghosting) when counting individuals in the orthomosaics. Currently, there is a lack of methods to prevent these errors from arising and to explicitly accommodate them in modelling approaches. When planning drone surveys for wildlife counting, one should first consider alternatives to conducting flights to build orthomosaics. In particular, we argue that using flight plans without much (or no) overlap and counting individuals on the resulting images can often be a simpler solution for wildlife drone surveys.

Nevertheless, there might be some contexts in which the use of orthomosaics is desirable, for example, when surveying aggregated populations or when fine-scale measurements of animals or distances between individuals are important. Future developments should focus on exploring sampling design strategies to mitigate errors in orthomosaic counts, developing methods to build mosaics that prioritize moving wildlife species, and approaches to accommodate these errors in abundance modelling. With methodological advancements addressing these challenges, we foresee significant improvements in the accuracy and reliability of wildlife drone-based surveys.

AUTHOR CONTRIBUTIONS

Ismael Brack: Writing—review and editing; writing—original draft; conceptualization; investigation. Camila Ferrara, German Forero-Medina, Omar Torrico, Enrique Domic-Rivadeneira and Kevin Wanovich: Writing—review and editing; investigation; data curation. Benjamin Wilkinson: Writing—review and editing; conceptualization. Denis Valle: Writing—review and editing; conceptualization; supervision.

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CONFLICT OF INTEREST STATEMENT

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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DATA AVAILABILITY STATEMENT

Data and code are available on the FigShare repository https://doi.org/10.6084/m9.figshare.28771217.v1 (Brack et al., 2025).

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

Appendix S1: Prototype approach to generating wildlife oriented orthomosaics.

Appendix S2: Model description for estimating detection errors and estimating.

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