■ Title

Distance sampling with vehicle-mounted cameras for the estimation of farmland bird abundance over a wide area

■ Author details

Nao Kumada[1], Keita Fukasawa[1], Akira Yoshioka[2], Naoe Tsuda[3], Hirofumi Ouchi[2]

[1] Biodiversity Division, National Institute for Environmental Studies, Tsukuba, Ibaraki, Japan

[2] Fukushima Regional Collaborative Research Center, National Institute for Environmental Studies, Miharu, Fukushima, Japan

[3] Center for Climate Change Adaptation, National Institute for Environmental Studies, Tsukuba, Ibaraki, Japan

■ Abstract

1. Agricultural birds are declining due to farmland abandonment and agricultural intensification, and monitoring approaches, including efficient survey methods, are crucial for the development of effective conservation strategies. Roadside surveys (RS), especially those using vehicle-mounted video cameras, can be used to efficiently search for targets; however, they are limited by the unknown detection range. Distance sampling (DS), in which animal density or abundance is estimated from the distance between the observer and the detected individual, can provide a complimentary approach to address this limitation of RS.

2. We developed a DS model robust to location uncertainty based on video-based RS. We integrated location errors determined by an independent field test using RS and unmanned aerial vehicles (UAVs) into a stochastic DS model. We estimated the abundance of herons and egrets in farmlands in and around the evacuation zone of the Fukushima Daiichi nuclear power plant accident by combining RS and DS.
3. The video-based RS covered 7,031 km of roads and 24.41 km^2 of farmlands. All herons and egrets were observed around the evacuation zone and none were detected in the zone. The predicted abundance of herons and egrets differed substantially between areas inside ($0.0158 \pm 0.0174/km^2$) and outside of the zone ($4.62 \pm 5.41/km^2$).
4. Integrating location uncertainty into the DS model did not affect predicted heron and egret population densities (4.62 ± 5.41 vs. $4.66 \pm 5.45/km^2$, with or without integrating location uncertainty, respectively). Accordingly, our survey method combining RS and DS is robust to location uncertainty. The study system (i.e., herons and egrets in farmlands) and the inability of location error to exceed the size of one farmland separated by levees may contribute to the accuracy of RS in this study.
5. *Synthesis and Applications:* Combining RS with vehicle-mounted cameras and DS considering location uncertainty is widely applicable to open land species and can improve the efficiency of monitoring. When large location errors are expected by conventional

approaches, DS models incorporating location uncertainty determined by RS and UAVs could be effective for abundance estimation over wide areas.

Keywords

Roadside survey, Distance sampling, Action camera, Agricultural birds, Abandoned farmlands, UAV, Fukushima Daiichi nuclear power plant accident

Introduction

Population sizes of many farmland birds are declining due to agricultural intensification and the abandonment of cultivation (Fujioka, Don Lee, Kurechi, & Yoshida, 2010; Fuller et al., 1995; Siriwardena et al., 1998; Stanton, Morrissey, & Clark, 2018). To implement appropriate conservation strategies for farmland birds, information on their abundances and related environmental factors is essential. Various methods have been developed for monitoring farmland birds, including point count, transect count, territory mapping, and capture-recapture methods (Birrer et al., 2007; Chiron, Filippi-Codaccioni, Jiguet, & Devictor, 2010; Gillings & Fuller, 1998). Survey methods for birds are often labor-intensive and costly to conduct over a large area. Cost-effective methods for monitoring are needed to better understand population patterns and environmental drivers of farmland birds at a large spatial scale and hence to

develop effective conservation measures.

The roadside survey (RS) approach, involving species searches from vehicles on the road, has the capacity to obtain data for species abundance indices over a wide area at a low cost (Catry, Moreira, Deus, Silva, & Águas, 2015; Milton & Dean, 1998). Recently, RS using vehicle-mounted cameras, including Google Street View, has been used to monitor birds in various habitats (Olea & Mateo-Tomás, 2013; Rousselet et al., 2013). However, RS with digital images has been limited to areas where there are clearly no gaps in the search area (e.g., birds nesting on a cliff, Olea & Mateo-Tomás, 2013). A major difficulty in applying vehicle-mounted cameras to farmland bird monitoring as well as other open-land habitats is that the detection range is unknown. Ignoring the effect of detection range on the number of detected individuals can lead to biases in estimates of abundance and the impact of environmental drivers (Buckland, Marsden, & Green, 2008).

Distance sampling (DS) can resolve the issue of bias in abundance estimation by video-based RS. DS estimates animal density or abundance from the distance between the observer and the detected individual, accounting for the decrease in detection probability due to distance (Buckland et al., 2001; Fox et al., 2017; Hara, Yamaji, Yokota, Thaitakoo, & Sampei, 2018; Howe, Buckland, Després-Einspenner, & Kühl, 2017; Kvasnes, Pedersen, & Nilsen, 2018). DS can be used to estimate trends in farmland bird populations in RS. However, there might be

uncertainty in the distance between the observer and the detected individual measured from video images. For robust abundance estimation, an independent field test of location uncertainty in DS is required (Hefley, Boyle, & Mohankumar, 2020).

Comparison of the observer–target distances measured by RS and unmanned aerial vehicles (UAVs) is expected to be a feasible independent field test. UAVs have become an effective tool for monitoring animal populations and individual locations (Iwamoto, Nogami, Ichinose, & Takeda, 2022; Witczuk, Pagacz, Zmarz, & Cypel, 2018). Although their application to large spatial areas remains costly, this method is highly accurate because UAVs can measure animal positions from almost directly above. If the same individuals are observed by both RS and UAV, location uncertainty in RS can be quantified. Integrating location uncertainty obtained by these small-scale measurements into a stochastic DS model will allow us to moderate cost–accuracy trade-offs and estimate abundance at a large spatial scale.

In Japan, the Fukushima Daiichi nuclear power plant accident in 2011 led to uninhabited areas and the cessation of agricultural activities due to an evacuation order for the contaminated area (Yoshioka, Mishima, & Fukasawa, 2015). Although observable effects of ionizing radiation at the population level on terrestrial organisms were unlikely (UNSCARE, 2017), land abandonment in the evacuation zone can have indirect effects. These environmental changes are thought to have a significant impact on the organisms that use farmlands. Therefore, extensive

monitoring in the farmlands throughout the region is needed to evaluate the effect of farmland abandonment in the evacuation zone. However, with respect to radiation protection, it is advisable for researchers not to stay in the evacuation zone for a long time, necessitating an efficient monitoring scheme. Farmland birds such as herons and egrets are suitable indicator species of the farmland environment. They are the main predators in farmlands and are susceptible to the abandonment of rice fields (Amano & Katayama, 2009; Lane & Fujioka, 1998). Their large size and conspicuous whitish body color make herons and egrets foraging in farmlands easily detectable from roads.

The purpose of this study was to estimate the population density of herons and egrets in farmlands in and around the evacuation zone of the Fukushima Daiichi nuclear power plant accident by RS. In particular, we surveyed the locations of herons and egrets by using a vehicle-mounted camera and then estimated population densities by using a DS model incorporating location errors. The magnitude of location errors for herons and egrets by RS was determined by a field test comparing RS with UAV-mounted cameras. To evaluate the importance of accounting for location uncertainty, population densities were compared between analyses with and without location errors. We demonstrated the impact of farmland abandonment due to the evacuation order by comparing the population density with a counter-factual scenario without an evacuation order.

■ Materials and methods

Field test of location errors of herons and egrets using UAVs

Location errors of the vehicle-mounted camera were validated by comparison with the accurate values determined by UAV images (UAV-truth). The survey was conducted on farmlands in two regions, the district of Inashiki in Ibaraki Prefecture and the city of Minamisoma in Fukushima Prefecture. These farmlands are about 5 square kilometers and are used for foraging by herons and egrets. The survey was conducted in Inashiki in July 2019 and May 2020 and in Minamisoma in June 2020. During the survey period, herons and egrets in the farmlands were recorded simultaneously by a vehicle-mounted video camera (VIRB X; Garmin Ltd.) and a video camera in a UAV (Phantom 4; DJI). The GPS trajectories of vehicle-mounted video cameras were recorded by VIRB X simultaneously.

Locations of herons and egrets were determined from the movies captured by the vehicle-mounted cameras. If the researcher observed herons and egrets in the video, the movement trajectory information recorded at the time the video was taken was used to determine the location of the camera. Then, using information on the camera location with orthographical aerial imagery layers as background maps (GSI Tiles) and views surrounding herons and egrets (paddy levees, houses, telegraph poles, etc.) in the video image, the locations of herons and

egrets were manually determined and recorded using QGIS ver.3.4.3.

To obtain correct locations of herons and egrets, georeferenced images obtained by the UAV were used. Georeferencing was performed using Georeferencer (Transformation type: Projective, Resampling method: Linear) in QGIS. The measurement errors of locations obtained by vehicle-mounted cameras were calculated as the Euclidean distances between the locations of the herons and egrets determined by the vehicle-mounted cameras and the UAV-truth values.

Roadside survey of herons and egrets around the evacuation zone

The RS with vehicle-mounted cameras of abandoned and cultivated farmlands was conducted in eastern Fukushima, which includes the evacuation zone of the Fukushima Daiichi nuclear power plant accident (Fig. 1). The evacuation zone was designated after the Fukushima Daiichi nuclear power plant accident in March 2011 and is divided into three categories according to radiation levels: Difficult-to-Return Area, Restricted-Residential Area, and Preparing for the Lifting of the Evacuation Order Area (Cabinet Office, Government of Japan, 2013). In all three categories, cropland cultivation did not resume until 2016, except in some test fields. The study area covered farmlands within 18 municipalities located inside and outside the evacuation zone. Farmland polygons in this area were created from aerial photographs taken in 2006–2015 (see Appendix 1 for detailed methods). The farmland polygons included upland

fields, pastures, and abandoned farmlands, and more than 70% of the farmland area was rice fields in Fukushima prefecture before the nuclear power plant accident (in 2010) (Ministry of Agriculture, Forestry and Fisheries, 2020).

From early May to early July between 2014 and 2016, roadside video recording surveys were conducted on farmlands by vehicle-mounted cameras. Video cameras with GPS (VIRB Elite or VIRB X; Garmin Ltd.) were mounted on the side windows of a vehicle, which was driven on roads adjacent to farmlands for video recording (Fig. 2). Videos recorded by the two camera models (VIRB Elite or VIRB X) simultaneously at the same location showed no obvious differences. Although the video cameras were mounted on both sides of a car in many cases, some surveys were carried out using a video camera mounted on one side only. The GPS trajectories of the car were also recorded simultaneously. Videos were shot at 1920 × 1080 p/30 fps for all models and saved in mp4 file format. The speed of the car during the survey varied depending on the speed limit (60 km/h or less) and road congestion; however, the frame rate was sufficiently high to detect herons and egrets under all speeds in the study.

To identify farmlands within the viewshed from the vehicle-mounted cameras, farmland polygons in the direction of the camera and not hidden by obstacles such as forest and houses were selected as follows (Fig. 3). First, we extracted the farmland polygons in the direction of the camera and intersecting within a straight-line distance of 10 m from the trajectories of the

car; these were defined as the viewshed. Ten meters was set as an approximate threshold for adjacency (i.e., no obstacles) between the road and farmland. Second, we sequentially included farmlands that were within 10 meters from the viewshed obtained in the previous step. Farmlands were not included in the viewshed when the distance from the movement trajectory was more than 500 m because this was too far to detect herons and egrets. We visually verified that the selection criteria could effectively extract farmlands within the viewshed of the camera.

We played the videos back and searched for herons and egrets in farmlands. Then, we determined the locations on the map following the same method used to test location errors described above. Because it was difficult to identify species from the video images correctly, except for grey heron, we merged all species of herons and egrets for further analyses. The following herons and egrets may be found in the study area: grey heron *Ardea cinerea*, great egret *A. cinerea*, intermediate egret *A. intermedia*, little egret *Egretta garzetta*, and cattle egret *Bubulcus ibis*. All of these herons and egrets are colonial and breed in the summer. In addition, flooding status (i.e., flooded or not) was recorded for the rice fields where herons and egrets were found.

Statistical analysis

We employed a fully model-based approach to estimate the abundance of herons and egrets

and the effect of land abandonment based on a DS considering individual location uncertainty. As our observations consisted of the camera-based DS results with location uncertainty and the independent field test of location errors based on correct locations determined by UAV, we integrated the likelihoods and estimated all parameters simultaneously.

A common approach for model-based DS without location uncertainty is to treat the occurrence of individuals in relation to the distance from an observer as a realization of an inhomogeneous Poisson process (IPP) (Johnson, Laake, & Ver Hoef, 2010). The likelihood of DS without location uncertainty is expressed by the following equation (Johnson, Laake, & Ver Hoef, 2010).

$$L_{IPP}(\alpha, \beta, \gamma|\mathbf{Y}) = \prod_{i=1}^{n} \lambda(\mathbf{y}_i|\alpha, \beta)\delta(\mathbf{y}_i|\gamma) \exp\left(-\int_{\mathcal{S}} \lambda(\mathbf{z}|\alpha, \beta)\delta(\mathbf{z}|\gamma)d\mathbf{z}\right)$$

(eqn. 1)

where $\mathbf{Y} = (\mathbf{y}_1, \mathbf{y}_2, ..., \mathbf{y}_n)$ are true locations of observed individuals, $(\alpha, \boldsymbol{\beta}, \gamma)$ are model parameters, and $\mathcal{S}$ is the spatial domain(s) that is potentially observable. $\lambda(\mathbf{z}|\alpha, \beta)$ is an intensity function of the population density at location $\mathbf{z}$ and is commonly specified as follows.

$$\lambda(\mathbf{z}|\alpha, \boldsymbol{\beta}) = \exp(\alpha + \boldsymbol{\beta}x(\mathbf{z}))$$

where α is the intercept, $\boldsymbol{\beta} = (\beta_1,...,\beta_p)'$ is a vector of regression coefficients, and $x(\mathbf{z})$ is a vector of covariates on population density at location $\mathbf{z}$. $\delta(\mathbf{z}|\gamma)$ is the detection probability, which is expressed as a thinning function as follows.

$\delta(z) = \exp(-\gamma D(\mathbf{z}))$

where $D(\mathbf{z})$ is the Euclidian distance from an observer to location $\mathbf{z}$.

Let us consider the case when observed location $\mathbf{Y}' = (\mathbf{y}'_1, \mathbf{y}'_2, ..., \mathbf{y}'_n)$ is assumed to vary around the true location $\mathbf{Y}$ due to location error. The likelihood of IPP incorporating location uncertainty can be obtained by integrating out $\mathbf{y}_i$ over the surveyed region (Hefley et al., 2020).

$$\mathrm{L}(\alpha, \beta, \gamma, \boldsymbol{\sigma} | \mathbf{Y}') = \prod_{i=1}^{n} \int_{\mathcal{S}_i} \mathrm{p_{err}}(\mathbf{y}'_i | \mathbf{y}_i, \boldsymbol{\sigma}) \lambda(\mathbf{y}_i) \delta(\mathbf{y}_i) \mathrm{d}\mathbf{y}_i \exp\left(-\int_{\mathcal{S}} \lambda(\mathbf{z}) \delta(\mathbf{z}) dz\right)$$

(eqn. 2, parameters α, $\boldsymbol{\beta}$, γ were not included on the right side for simplicity)

where $p_{err}(\mathbf{y}'|\mathbf{y}, \boldsymbol{\sigma})$ is a probability distribution of location error, $\boldsymbol{\sigma}$ is a vector of location error parameters, and $\mathcal{S}_i$ is subset of $\mathcal{S}$ in which $\mathbf{y}_i$ exist. For simplicity, we assume that the location error is isotropic and normally distributed.

$p_{err}(\mathbf{y}'|\mathbf{y}, \boldsymbol{\sigma}) = N_2(\mathbf{y}'|\mathbf{y}, f(\mathbf{y}', \mathbf{y}, \boldsymbol{\sigma})\mathbf{I})$ (eqn. 3)

where $f(\mathbf{y}', \mathbf{y}, \boldsymbol{\sigma})$ is a function of the standard deviation depending on the true location. In general, the greater the distance from the observer, the lower the accuracy of the observation position. The relationship was assumed to be described by a power function of Euclidean distances between $\mathbf{y}'$ and $\mathbf{y}$, $D(\mathbf{y}', \mathbf{y})$, with two parameters $\boldsymbol{\sigma} = (\sigma_0, \sigma_1)$ as follows.

$f(\mathbf{y}, \mathbf{y}, \boldsymbol{\sigma}) = \sigma_0 D(\mathbf{y}, \mathbf{y})^{\sigma_1}$ (eqn. 4)

The likelihood function required integration over spatial domains, which is difficult to solve analytically. A practical approach is discretizing spatial domains into grid cells and replacing

integration with piecewise summation as follows.

$$\int_{\mathcal{S}_i} \mathrm{p_{err}}\left(\mathbf{y}_i^{'} \ |\mathbf{y}_i\right)\lambda(\mathbf{y}_i)\delta(\mathbf{y}_i)\mathrm{d}\mathbf{y}_i \approx \sum_{q\subset\mathcal{S}_i} A_q \mathrm{p_{err}}\left(\mathbf{y}_i^{'} \ |\mathbf{y}_q\right)\lambda(\mathbf{y}_q)\delta(\mathbf{y}_q)$$

$$\int_{\mathcal{S}} \lambda(\mathbf{z})\delta(\mathbf{z})d\mathbf{z} \approx \sum_{q\subset\mathcal{S}} A_q\lambda(\mathbf{z}_q)\delta(\mathbf{z}_q)$$

where $\mathbf{z}_q$ and A_q are the centroid and area of grid cell q, respectively.

The location error parameter $\boldsymbol{\sigma}$ in the likelihood function described above is not identifiable without an independent survey of location error. In this study, the location error and UAV-truth were included simultaneously in the DS model for the estimation of all parameters. When the true location is available, the error distribution (eqn. 3 and 4) can be written equivalently by the Rayleigh distribution (i.e., Weibull distribution with shape parameter 2) for the Euclidean distance between the observed and true location.

$$\mathrm{p_{err}}(D|\boldsymbol{\sigma}) = D/\left(\sigma_0{}^2 D^{2\sigma_1}\right)\exp\left(-D/\left(2\sigma_0{}^2 D^{2\sigma_1}\right)\right)$$

Given the vector of distances obtained by the field test D($\mathbf{y}$□, $\mathbf{y}$) = (D(y'_1, y_1), ..., $D(y'_m, y_m)$), the joint likelihood is given as follows.

$$\mathrm{L}\left(\alpha, \beta, \gamma, \boldsymbol{\sigma}|\mathbf{Y}^{'}, \mathbf{D}(\mathbf{y},\mathbf{y})\right)$$
$$= \prod_{i=1}^{n}\sum_{q\subset\mathcal{S}_i} A_q \mathrm{p_{err}}\left(\mathbf{y}_i^{'} \ |\mathbf{y}_q\right)\lambda(\mathbf{y}_q)\delta(\mathbf{y}_q)\exp\left(-\sum_{q\subset\mathcal{S}} A_q\lambda(\mathbf{z}_q)\delta(\mathbf{z}_q)\right)\prod_{j=1}^{m}\mathrm{p_{err}}(D_j)$$

Both the maximum likelihood method and Bayesian method can be used for parameter estimation. When the Bayesian method is applied, prior information and constraints on

parameters can be incorporated as a prior distribution.

We estimated the effects of the evacuation order (evacuation zone or not) (Cabinet Office, Government of Japan, 2013), the area of water bodies (rivers and lakes) (Ogawa et al., 2013) around the farmlands, and the year of the study on the abundance of herons and egrets. We defined farmland polygons within the viewshed of the camera as a multi-part domain $\mathcal{S}$ and discretized it into grid cells with a resolution of 10 m. Then, these variables and the Euclidean distances from the camera were assigned to each cell. Even when location error is taken into account, the error is reasonably assumed to be within a farmland polygon because paddy levees act as sharp borders dividing farmland polygons. Therefore, we assumed that the subdomain $\mathcal{S}_i$ containing the true location of the observed individual i was restricted to a farmland polygon where the individual was observed.

In this study, we applied the Bayesian default prior (Gelman, Jakulin, Pittau, & Su, 2007) to stabilize the coefficients and to prevent overfitting. The IPP model is often limited by overfitting, and it is common to apply regression shrinkage techniques. We applied a weakly informative prior, Student's *t*-test (df = 5, mean = 0, scale = 2.5), to regression coefficients $\boldsymbol{\beta}$ to avoid overfitting. For other parameters, improper flat priors $p(\theta) = 1$ were used. The maximum *a posteriori* (MAP) estimate of each parameter was calculated using a quasi-Newton algorithm.

To estimate credible intervals of parameters, we obtained posterior samples by importance

sampling (Gelman et al., 2013) with a proposal distribution that approximates the posterior. For the proposal distribution, we used a multivariate *t*-distribution with four degrees of freedom whose mean vector and scale matrix are the MAP estimate and the inverse of the Hessian matrix at the MAP, respectively. We drew 10,000 samples from the proposal distribution and obtained 3,000 posterior samples.

We calculated the abundance of herons and egrets by applying MAP estimates of each parameter to grid cells in farmland polygons throughout the study area, with and without accounting for measurement error, and compared the two abundance results. The predicted values were aggregated for each 1-km square grid. To evaluate the effect of farmland abandonment in the evacuation zone on the population size of herons and egrets, we predicted the population size in the study area under a counter-factual scenario in which no evacuation order had been given. All analyses in this study were implemented using R (R Core Team, 2021) (Appendix 2).

■ Results

Field test of location error of herons and egrets

In total, 78 herons and egrets (24 in July 2019, 31 in May 2020 in Inashiki and 23 in June 2020 in Minamisoma) were located with GIS by the vehicle-mounted camera and the camera on

the UAV. The Euclidean distance between the locations of the herons and egrets determined by the vehicle-mounted camera and the true locations determined by the UAV was defined as the measurement error (Fig. 4).

RS with vehicle-mounted cameras and abundance estimates of herons and egrets

The total distances traveled while recording with cameras were 3,675 km in the evacuation zone and 3,356 km outside the evacuation zone. The areas of farmland polygons (including abandoned fields in response to the evacuation order), selected as the viewshed, were 10.07 km^2 in and 14.34 km^2 around the evacuation zone.

A total of 56 individual herons and egrets were observed around the evacuation zone. No herons or egrets were observed in the evacuation zone (Fig. 5). All herons and egrets were found in flooded rice fields. The frequency distribution of observed distances to herons and egrets was more concentrated near zero than the distribution of distances to roads for all grid cells of farmland polygons. Although all polygons had a median distance of 133.3 m from roads, the polygons containing heron and egret discovery sites had a median distance of 47.1 m and a maximum of 104.4 m (Fig. 6).

The MAP estimates and summary statistics obtained by importance sampling are shown in

Table 1. The water body area had a positive association with the abundance of herons and egrets. Abundance was lower in the evacuation zone than outside the zone. Although the signs (i.e., positive or negative) of parameter estimates were similar between the models with and without the location error, the parameter values differed slightly. The distance from the camera had a negative association with the probability of detection (Fig. 4). The probability decreased to half at 35.4 m (95% credible interval: 29.6–42.8 m) from the camera. The scaling factor and power value when measurement errors are expressed as a power function of the distance from the camera were 0.644 and 0.614. The measurement errors tended to increase with increasing distance from the camera on the car but exhibited a concave downward trend.

The predicted abundance of herons and egrets were substantially larger outside the evacuation zone than inside the zone (Table 2, Fig. 7). This trend did not differ between the models with and without location error. The predicted total population of herons and egrets in the study area was 7,820 individuals. Assuming that the evacuation zone was never designated, the predicted population would have increased by 2,647 individuals to 10,467 individuals (Fig. 8).

■ Discussion

We developed an efficient method for monitoring farmland birds using RS with vehicle-

mounted cameras and DS. By performing DS considering location error, we resolved the issue of the lack of a clear observation range of RS. The spatially explicit approach enabled us to estimate the impact of large-scale land abandonment on heron and egret populations. The estimated number of foraging individuals around the evacuation zone did not deviate significantly from the value obtained by a researcher's count in a previous study of approximately 30 individuals/km^2 (Lane & Fujioka, 1998) and is considered a reasonable estimate.

While the RS approach benefits from the ability to efficiently survey a wide area, the use of vehicle-mounted cameras will further improve efficiency. For example, in this study, 237 hours of video was recorded to search for herons and egrets. In a field survey, experts would be required for the full time period; however, the RS method with vehicle-mounted cameras does not require expertise in bird identification in the field. In addition, the work of sorting farmlands without herons and egrets, accounting for the majority of each video, does not require expertise; instead, experts only need to check images with suspected herons and egrets. Crowdsourcing this sorting process can promote the participation of birders in remote areas who are interested in the survey. In the future, automated counting may be possible (Norouzzadeh et al., 2018).

An accurate distance between the observer and target is required for DS to estimate density; accordingly, when the distance accuracy could not be guaranteed, it is necessary to

account for measurement error in DS (Hefley et al., 2020). The incorporation of measurement error in the location of egrets and herons did not significantly change density estimates. This result showed that the distance accuracy of RS with vehicle-mounted cameras in our study was sufficient for density estimation by DS. The study system can explain the good performance of RS. The herons and egrets were found in farmlands, and the location error could not be larger than the size of one farmland separated by paths or levees. However, use of a UAV to estimate location errors for incorporation into a DS model may be an effective approach in situations where measurement errors are likely. RS by vehicle-mounted cameras may be a feasible strategy for various situations by using this method.

The direct effects of radiation exposure from the Fukushima Daiichi nuclear power plant accident on wildlife populations and ecosystems are not large enough to be observable at the population level (UNSCEARE 2017). However, the evacuation orders in response to the nuclear accident have resulted in short-term changes in land use and human activities (Tamaoki, 2016; Yoshioka et al., 2015), and these changes may have important impacts on wildlife populations and ecosystems (Fujimoto, Mitsunaga, & Takeuchi, 2015; Lyons, Okuda, Hamilton, Hinton, & Beasley, 2020; Matsushima, Ihara, Inaba, & Horiguchi, 2021; Yoshioka et al., 2015). The strong negative impact of the evacuation order on heron and egret populations can be attributed to the decrease in food availability due to the widespread abandonment of farmlands. Farmland

abandonment leads to the growth of dense vegetation, which is not a common foraging environment for herons and egrets (Katayama, Osawa, Amano, & Kusumoto, 2015; Maeda, 2005). In addition, herons and egrets feed on fish and frogs in flooded rice fields (Tojo, 1996), which can be maintained by cultivation (Maeda, 2001). Our results clearly demonstrated that cropland abandonment in evacuation zones affects the distribution of birds over a wide area. These findings are consistent with the observation that the long-term abandonment of farmland reduces the biodiversity of farmlands (Koshida & Katayama, 2018). Since 2016, the evacuation zone has been reduced and agricultural cultivation has begun to resume. In the future, the effect of resumption should be tested by continued monitoring following the protocols developed in this study.

The detection probability depends on the distance from the observer as well as various covariates, in which case multiple-covariate DS is appropriate (Marques & Buckland, 2003; Thomas et al., 2010). In this study, we did not consider the evacuation zone as a covariate, despite the potential effect of this parameter on the detection probability, because no herons or egrets were observed in the evacuation zone. However, we believe the absence of herons and egrets in the evacuation zone reflects differences in true population densities resulting from the abandonment of farmland because dense vegetation is generally not suitable for foraging by these species (Katayama, Osawa, Amano, & Kusumoto, 2015; Maeda, 2005). These species

were not found in the evacuation zone, even near roads in which detectability is less affected by the vegetation.

The escape behavior of birds during surveys might result in biases in population estimates (Hutto & Young, 2003; Roberts & Schnell, 2006). At farmlands bordering roads, herons and egrets may fly away to avoid the approach of vehicles carrying cameras. Herons and egrets at a distance from the camera can therefore be overlooked, which can lead to biases in the detection function and population estimates. However, the videos obtained in this study did not reveal any herons and egrets in flight, which could be a response to an approaching vehicle. In fact, waterbirds are not substantially impacted by approaching vehicles (McLeod, Guay, Taysom, Robinson, & Weston, 2013). Similarly, in this study, the effect of approaching vehicles was considered negligible for herons and egrets. If this method is applied to broader taxa, the use of fisheye lenses or 360-degree cameras may be a viable option to capture individuals before they are affected by an observer.

In our survey, we estimated the number of herons and egrets using farmlands; however, these estimates cannot be interpreted as total counts for the study area. The survey was conducted during the breeding season, and one member of each nesting pair always stays in the nest. In addition, because herons fly over a wide area in search of good foraging sites, it is thought that they frequently move in and out of the evacuation zone and travel to and from the

study area. It is necessary to consider whether the number of herons obtained in this study is an indicator of the quality of the farmland as a foraging site. However, we believe that the density of herons and egrets foraging in farmlands is a viable indicator of biodiversity in agricultural land because it is a common parameter for assessing the quality of farmlands as foraging sites (Amano & Katayama, 2009; Katayama et al., 2019; Lane & Fujioka, 1998).

Another limitation of our study is that we were unable to identify the herons and egrets at the species level. We considered the total abundance of herons and egrets. The five species in the study area have overlapping ecological niches; they forage in farmlands and often share colonies (Mashiko & Toquenaga, 2014). In addition, the number of herons and egrets is related to the abandonment of farmland and taxon diversity and can therefore be used as an indicator of species richness on farmlands (Katayama, Mashiko, Koshida, & Yamaura, 2021; Katayama et al., 2019; Koshida & Katayama, 2018). In the future, technological improvements such as increased camera resolution may make it possible to identify species and evaluate responses.

The combination of RS using vehicle-mounted cameras and DS made it possible to determine the abundance of large farmland birds and their limiting factors in and around the evacuation zone. This method could be applied to the monitoring of large birds and mammals in open areas, including tidal flats, grasslands, and agricultural fields; some of these species are endangered and others cause agricultural conflicts. Furthermore, when combined with an infrared camera,

this method might be used to estimate the population of nocturnal mammals. In recent years, open street-level imagery, such as Mapillary (https://www.mapillary.com), has become widely available, with the potential to minimize field survey costs. With advances in image recognition technology for species detection, identification (Norouzzadeh et al., 2021), and distance estimation (Johanns, Haucke, & Steinhage, 2022), our approach may enable global monitoring.

■ Authors' contributions

N.K., K.F. and A.Y. conceived the ideas and designed the methodology; All the authors collected the data; N.K. and K.F. analysed the data; N.K., K.F. and A.Y. led the writing of the manuscript. All the authors reviewed and contributed critically to the draft and gave final approval for publication.

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Figures and tables

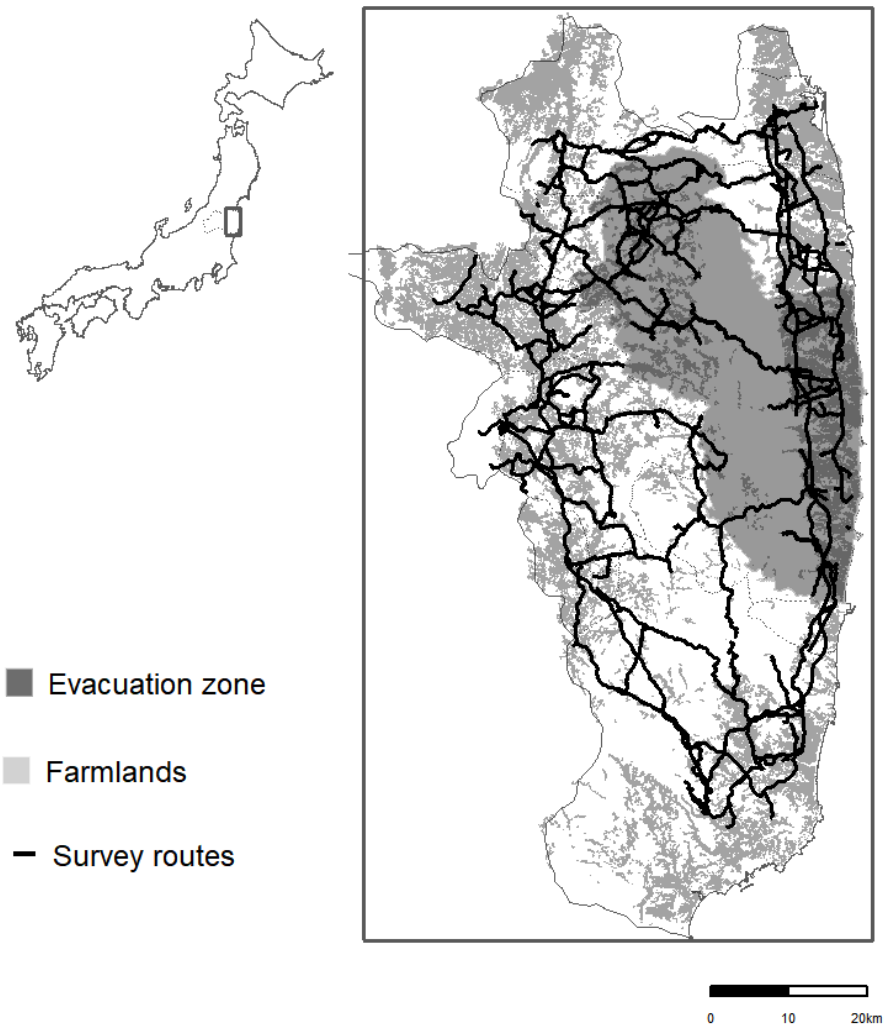

Figure 1 Map of survey routes (black lines) in Eastern Fukushima prefecture. Dark grey area shows the evacuation zone of the Fukushima Daiichi nuclear power plant accident. Light grey areas show farmland polygons.

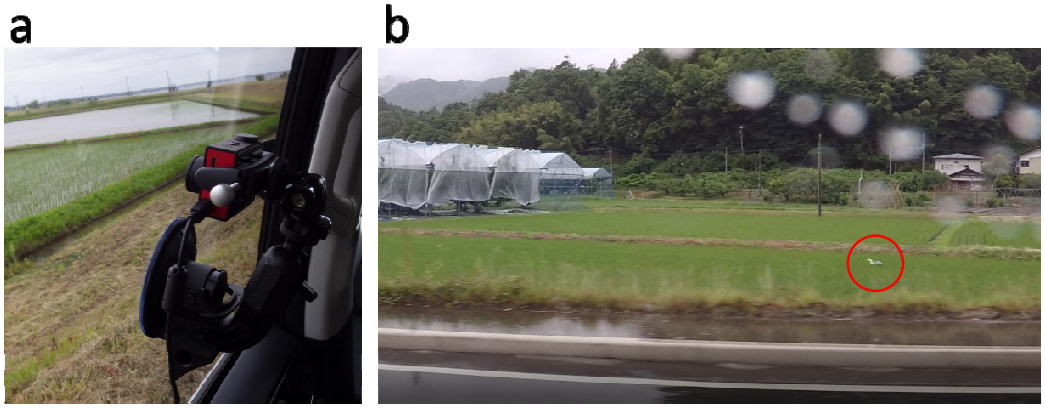

Figure 2 Photo showing a video camera with GPS mounted on a side window of a vehicle (a) and photo, captured from a video recorded by a vehicle-mounted camera, showing a heron in a rice field (b).

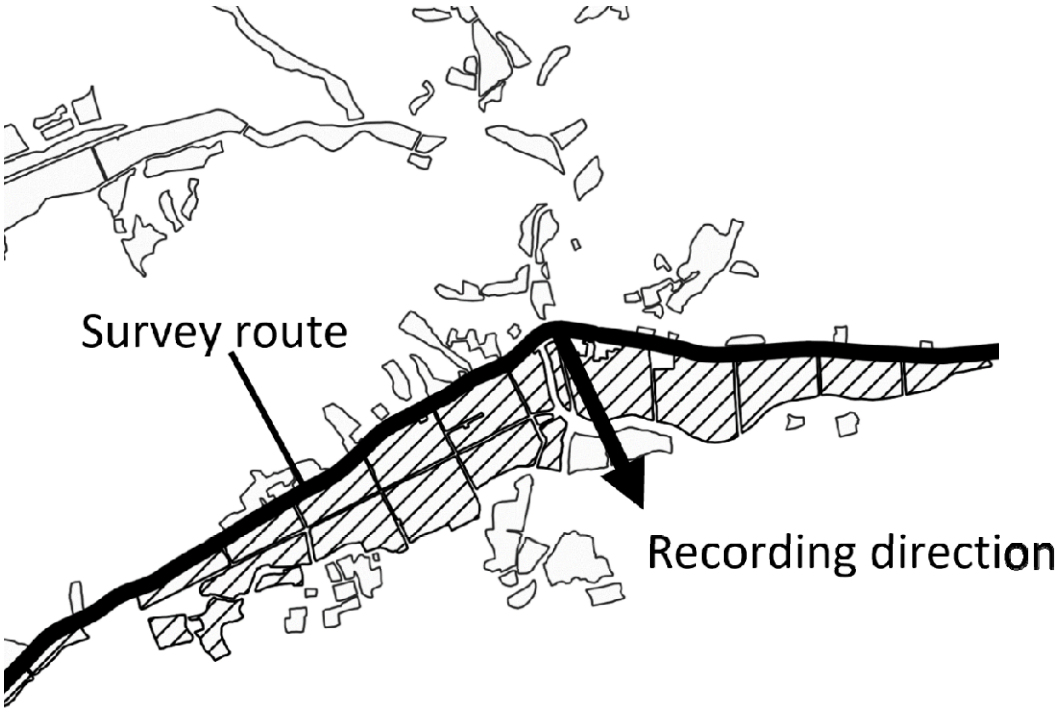

Figure 3 Illustration of the selection of farmlands within the viewshed. A survey route (bold line) and farmland polygons (surrounding lines) are shown. The polygons that meet the criteria (see text) are selected as viewsheds (shaded areas).

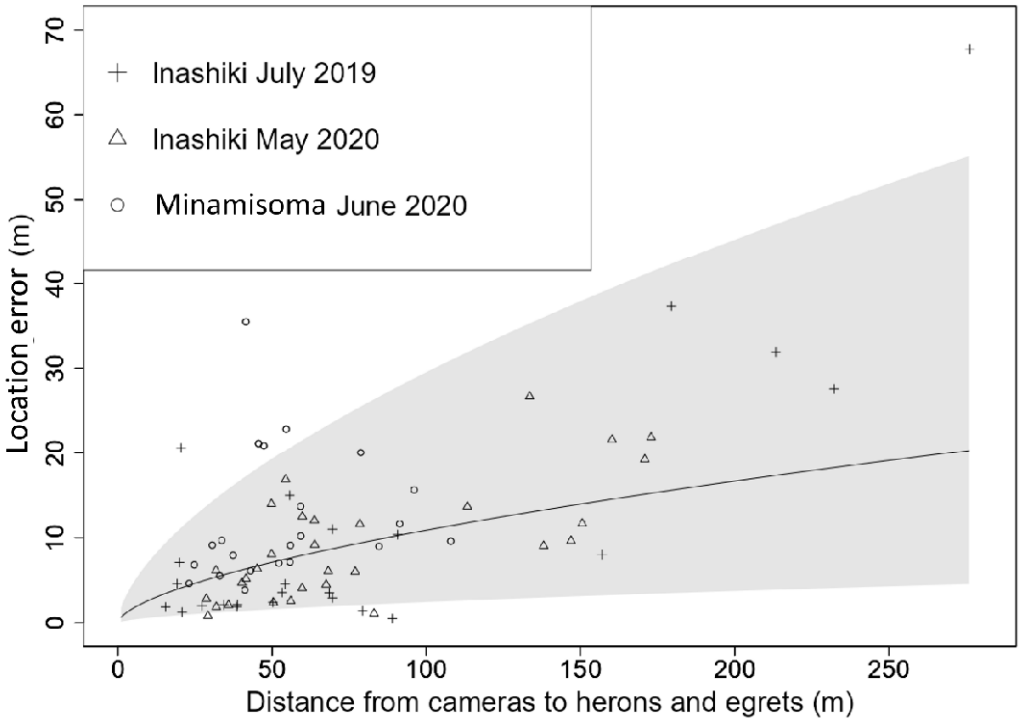

Figure 4 Relationship between the distance from cameras to herons and egrets and location errors. Black line and grey area show the maximum likelihood estimates and 95% credible interval for the regression function.

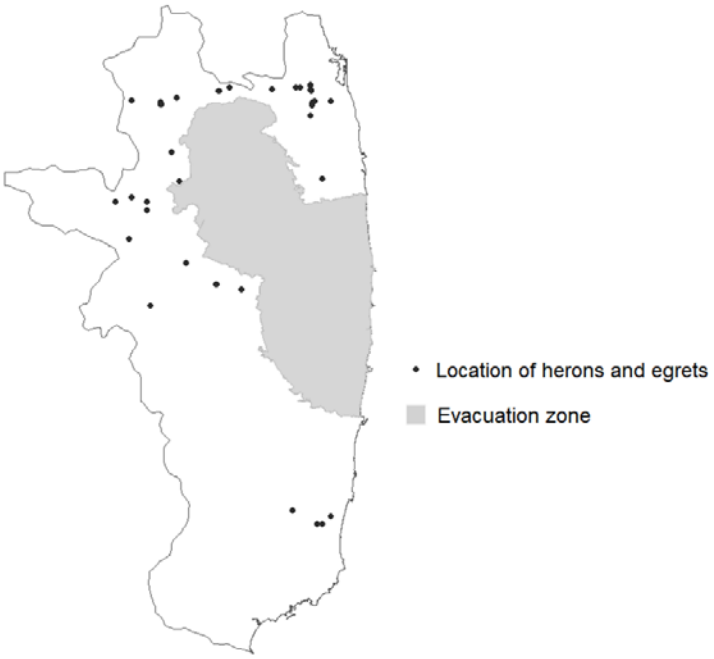

Figure 5 Location of herons and egrets observed by roadside survey.

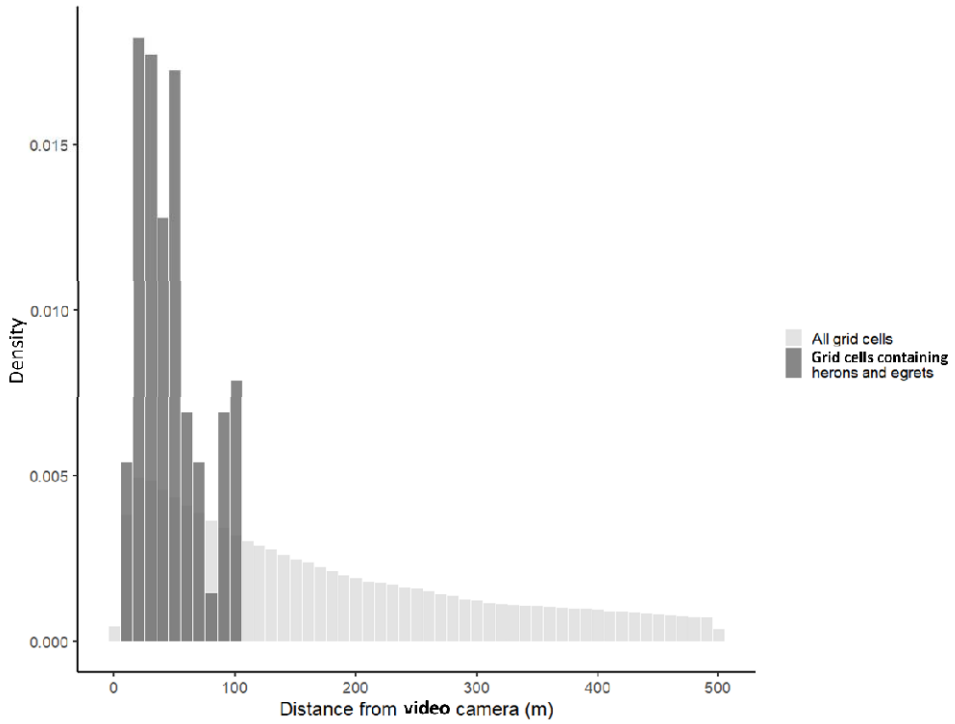

Figure 6 Histograms of the distance from the video camera to all grid cells of farmland polygons (light grey bars) and grid cells containing herons and egrets (dark grey bars).

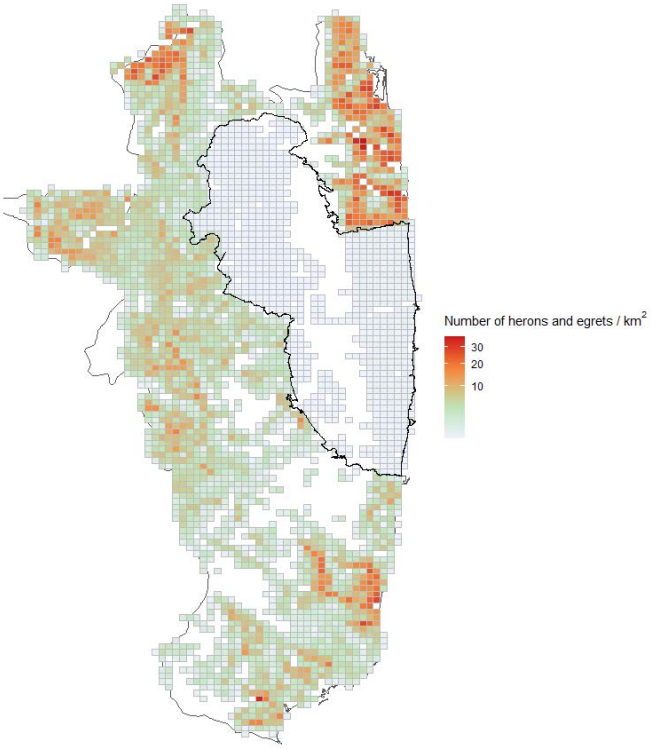

Figure 7 Prediction map of number of herons and egrets per square kilometer. Only grids that contain farmland area are included. The evacuation zone is circled by solid black lines.

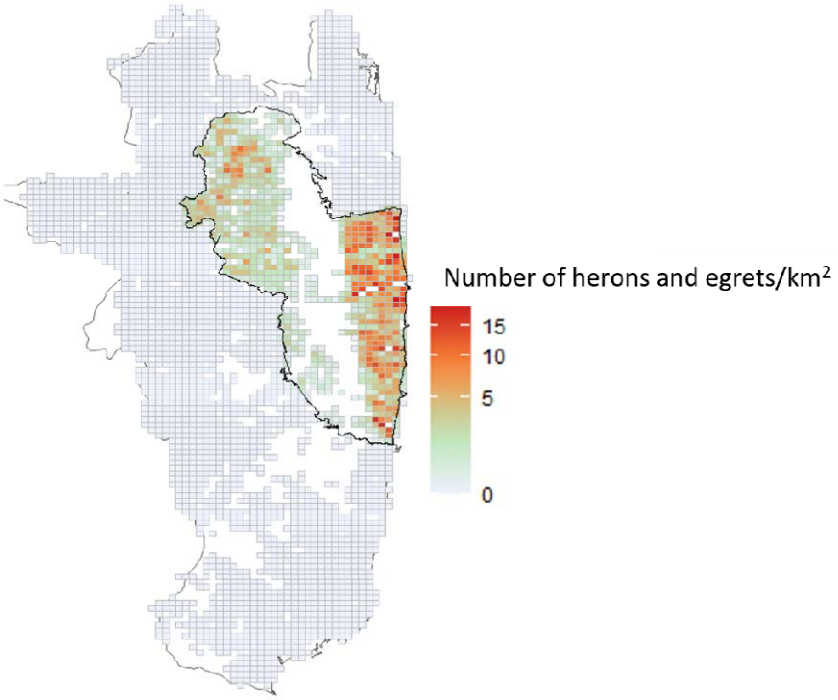

Figure 8 Map of the difference between the two predicted values for the numbers of herons and egrets per square kilometer. The actual value and the value obtained when assuming a counterfactual condition that the evacuation zone was not established were compared.

Table 1 MAP estimates and summary statistics via importance sampling with and without the location error.

	With the location error					Without the location error				
Parameter	Map	Mean	S.D.	CI2.5	CI97.5	Map	Mean	S.D.	CI2.5	CI97.5
Intercept	7.15	7.71	1.43	5.41	10.8	7.16	7.78	1.53	5.39	11.3
Distance	−0.0196	−0.0197	0.00180	−0.0234	−0.0162	−0.0197	−0.0199	0.00175	−0.0233	−0.0166
Water	0.545	0.541	0.0696	0.399	0.674	0.546	0.540	0.0701	0.395	0.671
Evac zone	−5.86	−6.43	1.40	−9.50	−4.16	−5.86	−6.50	1.52	−9.96	−4.18
Year(2015)	−0.139	−0.132	0.234	−0.568	0.335	−0.140	−0.135	0.230	−0.580	0.338
Year(2016)	−1.08	−1.07	0.230	−1.52	−0.624	−1.08	−1.07	0.234	−1.50	−0.578

Table 2 Predicted values for the number of herons and egrets per square kilometer using the model with and without location error.

	With the location error		Without the location error	
Area category	Mean	S.D.	Mean	S.D.
Outside the evacuation zone	4.62	5.41	4.66	5.45
Inside the evacuation zone	0.0158	0.0173	0.0159	0.0174