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Angling counts: Harnessing the power of technological advances for recreational fishing surveys

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ABSTRACT

As the popularity of recreational fishing gathers global momentum, so does the importance of knowing the number of active anglers and their spatial behaviour. Conventional counting methods, however, can be inaccurate and time-consuming. Here we present two novel methods to monitor recreational fishing applied in Kaunas water reservoir (ca 65 km^2), Lithuania, comparing their performance to a conventional visual count. First, we employed a remotely piloted fixed wing drone which conducted 39 missions distributed over one year and compared its accuracy to conventional visual land or boat-based counts. With these data we developed a linear model to predict the annual number of anglers depending on weekday and ice conditions. Second, we used anonymous data from a popular GPS-enabled sonar device Deeper®, used by anglers to explore underwater landscapes and to find fish. The sonar usage probability was calibrated with angler observations from drones using Bayesian methods, demonstrating that at any given time ~2 % of anglers are using the sonar device during the open water season and ~15 % during the ice fishing season. The calibrated values were then used to estimate the total number of anglers, given the daily records of sonar usage in Kaunas water reservoir. The predicted annual number of anglers from both linear drone-based and Bayesian sonar-based methods gave similar results of 25 and 27 thousand anglers within the area during the period of day surveyed, which corresponded to nearly 110 thousand angling trips in the total reservoir area annually. Our study shows high potential of both drone and fish finder digital devices for assessing recreational fishing activities through space and time.

1. Introduction

In developed nations about one in ten people fish for recreational purposes (Arlinghaus and Cooke, 2009). Worldwide, the estimated number of recreational fishers is close to 220 million (World Bank, 2012; Arlinghaus et al., 2015), which is five times higher than the number of commercial fishers (FAO, 2018). As many developed countries increasingly reduce inland and coastal commercial fisheries, recreational fishing becomes the most important sector and a major ecological force (Arlinghaus et al., 2015, 2019). The strength of this force varies extensively, but there are many cases where recreational catches exceed those of the commercial sector (Coleman et al., 2004; Cooke and Cowx, 2004; Morales-Nin et al., 2005). Growing recognition of the importance of recreational fishing has led to many countries adopting policies requiring assessment of fishing effort (Regulatory Impact Solutions Pty Ltd, 2019), both for ecological reasons to ensure exploitation remains sustainable (Pope et al., 2017), but also as a measure of economic activity. Hyder et al. (2018) estimated that in the European Union (EU) there are 9 million recreational sea anglers and they represent 1.6 % of citizens. Collectively they fish for 78 million days per year, spending on average €5.9 billion annually. EU member states have an obligation to collect annual data from marine recreational fishing (EU, 2001), but fulfilling these requirements remains a substantial challenge. Unlike commercial fishing with compulsory reporting, a lot of recreational fisheries data collection relies on volunteerism (Rotman et al., 2012) or time-consuming surveys. Anglers can be highly mobile in search of

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fishing opportunities (Papenfuss et al., 2015), and fisheries can occur over large geographic areas encompassing all waterbodies in a country.

Conventionally, data on recreational effort and catch is collected using regular onsite surveys such as creel surveys or aerial- and vessel-based counts, recall surveys such as web, phone and postal surveys, angler diaries or high frequency time-lapse cameras and fixed cameras (Steffe et al., 2005; Smallwood et al., 2011; Bellanger and Levrel, 2017; Askey et al., 2018; Conron et al., 2018). All of these have their own challenges and limitations. Phone or postal surveys have increasingly low participation rates, especially as data communication moves onto digital platforms (Tate and Smallwood, 2021), and do not necessarily represent an unbiased sample of the angler population. Boat-based census, roving creel surveys on foot, or aerial surveys, require substantial human and operational resources (vessel, tow vehicle, fuel, airplane hire) and can be time consuming and costly (Ryan et al., 2009). Time-lapse or fixed cameras which can collect information about effort are relatively cheap but are impractical in some places due to equipment loss, immobility, and time-consuming image processing and analyses (Afrifa-Yamoah et al., 2021).

Two recent technological advancements hold promise for improving the accuracy and cost-effectiveness of angler effort assessments. The first one employs camera-equipped remotely piloted aircraft (Chapman et al., 2014), hereinafter - drones. Given the growing success of drones for supporting coastal management, they may also provide a cost-effective solution for collecting data on recreational fishing effort (Provost et al., 2020a). This approach uses aerial surveys to gather a series of instantaneous counts of the number of active anglers and then extrapolates that information to an estimate of angler effort over an entire fishing season (e.g., Fraidenburg and Bargmann, 1982; Vølstad et al., 2006). Despite a rapid uptake of drones in multiple areas, only a few studies have attempted to count anglers using this technology. Desfosses et al. (2019) suggest that multi-rotor drones are not efficient for recreational fishing surveys due to short battery endurance, low flying speed, sensitivity to strong winds, dependence on visual line of sight and regulations requiring certification of operators. They suggested that fixed-wing drones that have extended-visual line of sight (EVLOS) and longer battery life could be viable alternatives but will still be affected by weather conditions. The second approach involves angler smart phone applications (apps) which have grown in popularity over the last decade (Venturelli et al., 2016; Skov et al., 2021). These may be developed by commercial companies or research institutions, and they allow fishers to register and share information with researchers about their trips and catches (e. g. Gundelund et al., 2020). Often, the apps include ancillary features that are attractive to anglers such as social networking, information about rules and regulations, depth profile maps and identifiable sonar features. When designed properly and used by a sufficient proportion of anglers, such apps have the potential to provide sufficiently accurate information on catch rates and angling effort, as in the case of coastal seatrout fishery in Denmark (Gundelund et al., 2021).

In this study, we further advance the drone and smart phone application-based methods for angler assessments, aiming to improve their utility by building on their strengths and redressing their limitations. Throughout one year we conducted a range of surveys in a large (ca 65 km^2) inland water reservoir (W*R*) which is one of the most popular recreational fishing destinations in Lithuania. We compared recreational fishing effort assessment from fixed-wing drone surveys, visual land and boat-based surveys and anonymous data from a smartphone application that integrates with a sonar (fish finder) deployed in the water and developed models to assess recreational fishing effort through space and time. The overall objective was to understand if and when drones and sonar applications for anglers could be used to estimate angling effort.

2. Materials and methods

2.1. Research area

Our study area is Kaunas W*R* (54.87, 24.14), the largest Lithuanian artificial water body, created in 1959 (Fig. 1). It occupies 63.5 km^2, spans 3.3 km at its widest point, and has a maximum depth of 22 m. The reservoir is a highly productive ecosystem and for decades supported an intensive commercial fishery, with annual catches averaging 128 tons during 1999–2012. Due to this intensive fishing, stocks of many species collapsed, and the commercial fishery was completely closed in 2013. Since then, the abundance and biomass of most species has recovered rapidly (Ložys et al., 2020) and the reservoir has become one of the most popular angling spots in Lithuania. The dominant fish species in the reservoir are roach (*Rutilus rutilus*), perch (*Perca fluviatilis*), white bream (*Blicca bjoerkna*), bream (*Abramis brama*) and pikeperch (*Sander lucioperca*) (Ložys et al., 2020).

2.2. Drone missions

The survey period covered one year, starting in March 2020 and finishing on March 2021 encompassing an ice-free ‘open water season’ and a winter ‘ice fishing season’ when the surface waters of the reservoir were frozen. During the survey period we conducted 39 drone missions, distributed throughout the four seasons of the year. Ten flights were flown during each of summer, autumn and winter seasons, and nine missions were performed in spring. During each season four missions were performed on weekends and six during working days, aiming to distribute the missions randomly through seasons and days of the week. Weather conditions did not influence the mission schedule that was set in advance. The main goal of the drone surveys was to estimate the proportion of anglers using the sonar fishfinder device (see below), rather than estimate total recreational fishing effort. To achieve the maximum sample size for calibrating the relative number of anglers, reduce variation due to the time of the day and maximise information related to season and weekday we conducted all drone surveys in the mornings, between 8 am and 11 am, which is the usual peak period of angler activity. Note, the drone surveys were distributed across seasons and days of the week to assess whether the sonar usage probability differs across these times (e.g., people with higher incomes and higher probability of owning a device may be more likely to fish only in summer or on weekends). We did not expect such a difference between times of the day and therefore conducted all drone surveys in the morning. Permission for all flights was granted by the Lithuanian Transport Safety Administration, NOTAMs issued by SE „Oro navigacija“ (State Enterprise Air Navigation). The drone angler surveys were performed using a custom drone SilverBee_V3000 by Thrust® (AeroDiagnostika Ltd.), equipped with two wide-angle RGB video cameras. SilverBee_V3000 is an electric fixed-wing drone with a maximum take-off weight of 7.5 kg and payload of 1 kg. The optimum flight time of the drone with payload is 45–60 min per battery, depending on the weather conditions. Because the northern part of the Kaunas W*R* falls within the local airport no-fly zone, we surveyed about 70 % of the reservoir area, for which flight permits could be obtained. This area covered about 33 km^2 and was surveyed in two flights (northern and southern), operated from one land-based location (Fig. 1). The maximum straight-line distance between the drone and the operator was around 8 km during the flight and all flights were performed beyond visual line of sight. The flights were fully automated and controlled by the drone’s on-board autopilot following the pre-programmed flight trajectory with global navigation satellite system, inertial navigation system and electronic compass to ensure precise geolocation. Real-time drone performance parameters and mission progress status were continuously monitored using 433 MHz wireless radio and/or 4 G mobile connection during the flight.

Several combinations of sensors were tested during the optimisation of angler counting, to maximise efficiency, payload and quality of the

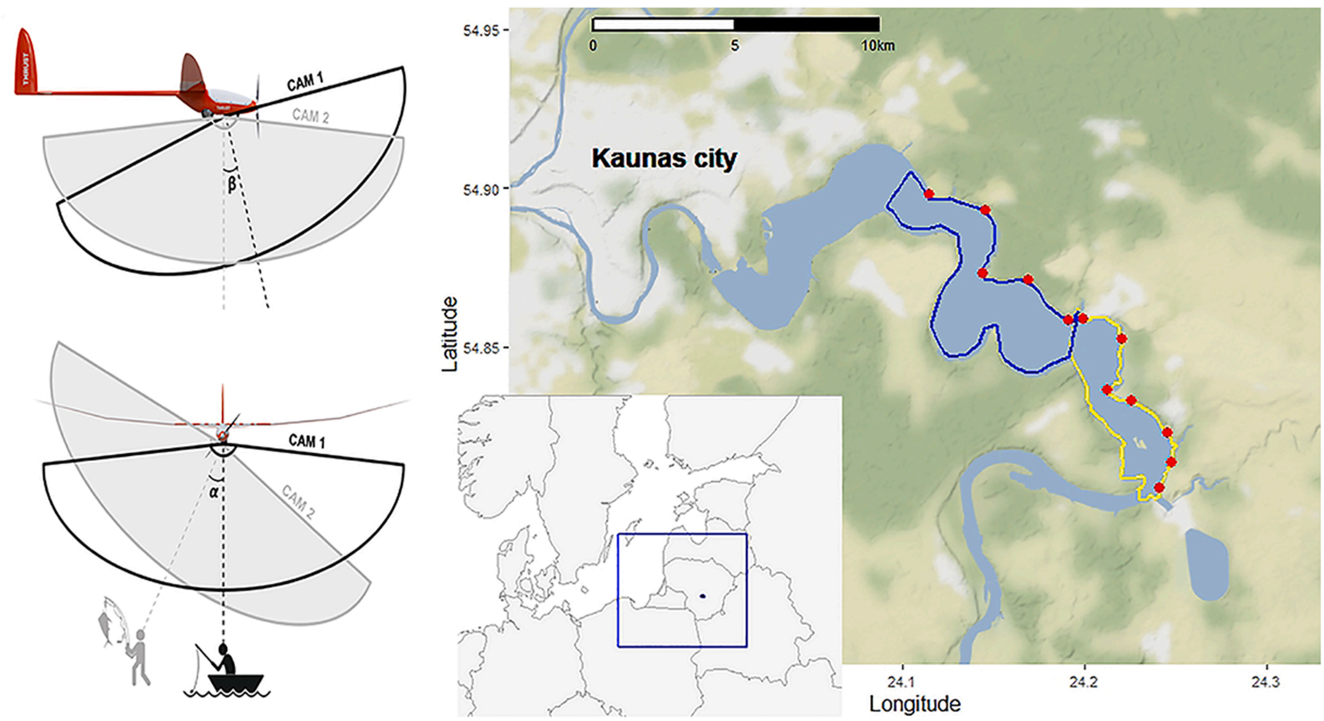

Fig. 1. Side and front views of the wide-angle camera setup used for aerial survey, where CAM1 is facing forward and downward ($\beta \approx 25^{\circ}$) optimized to view boat-based anglers and CAM2 is facing right-side downward ($\alpha \approx 30^{\circ}$) to increase the visibility of anglers at the shoreline. The map of the Kaunas water reservoir shows the two drone flight paths, divided into two mission trajectories (yellow and blue); red points indicate traditional visual observation sites during the ice fishing season. The inset show Kaunas WR location in Lithuania. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

visual data to enable visual identification of anglers in boats and onshore. After testing alternative cameras with resolution ranging 2–50 megapixel, lenses with focal length of 3 –50 mm, and resulting payload of 0.1–1.0 kg, the optimal trade-off in terms of weight, data amounts and angler count accuracy was to use two side-by-side wide-angle (3 mm focal length) 12-megapixel video cameras, with a combined weight of 0.2 kg. One camera was oriented along the flight direction facing forward with a downward angle of $\sim 25^{\circ}$, and the second camera was placed on the right side of the drone, oriented towards the shore at a $\sim 30^{\circ}$ angle (Fig. 1). This allowed us to achieve a $> 180^{\circ}$ angle of view both horizontally and vertically.

The drone trajectory followed the shoreline at a distance of ca 75–100 m and altitude of 50–70 m, flying at a speed of 16–18 m/s (58–65 km/h). This observation angle and flying height gave the width of the survey corridor of 1000–1600 m. This means that in our case a single scan along the perimeter of the reservoir was sufficient to fully cover the study area (Fig. 1), while avoiding surveying overlapping areas and counting the same anglers multiple times, unless anglers relocated to an opposite shore of the W*R* within the 30 min period of one mission (which is highly unlikely due to the distance and short time duration). The width of the survey corridor can be adjusted depending on the site, which can increase the efficiency of the aerial survey compared to grid-like or spiral-like scanning with a smaller field of view. Flights were made during a range of weather conditions, including light rain, fog, snow, strong winds (up to 15 m/s) and low temperatures (-20 C°). In very strong opposing winds, ground speed could be as low as 3 m/s, yet this did not affect the survey because flight trajectories were programmed in advance. Following the completion of each drone mission onsite, the video material from both cameras was analysed manually together with the telemetry logs for geolocation.

2.3. *Visual surveys*

To compare the accuracy and precision of drone-based surveys with traditional land-based methods, we performed five angler count surveys of which three were done from a boat during the open water season (2 weekdays and one weekend day) and two were done by walking during the ice fishing season (one weekday and one weekend day). Boat-based surveys were undertaken from an inflatable boat equipped with a 3 HP engine, travelling at 8–9 km/h speed at a distance of ca. 300 m from the shore (Fig. 1). Anglers were observed using binoculars (DELTA Optical Forest II 8.5 ×50) and each angler was attributed to a category of either “on-shore” or “fishing from a boat” and their approximate coordinates were noted. During the ice fishing season, fishers were counted by the observer from 12 fixed sites, which provided a good field of view across the reservoir (Fig. 1). As per the boat surveys, binoculars were used to count anglers and identify their approximate location.

2.4. *Sonar data*

Deeper® sonars comprise a set of portable wireless sonar-based fish-finders, generally used by anglers for fish finding, depth measuring and making bathymetry maps for personal use. More information about the different DeeperSonar company’s fish-finder models and their technical characteristics is available at https://deepersonar.com/. According to company data and our angler surveys (unpubl. data) about 20 % of Lithuanian anglers own one of several models of this fish finder; these anglers use the device in about 20–50 % of their trips. The anonymous sonar usage information for Lithuania was obtained through a collaborative agreement with the DeeperSonar company, in accordance with the data privacy and protection requirements. The dataset included individual sonar usage events, identified through unique encoded user ID, time and coordinates of the starting point, followed by coordinates of all sonar reading points taken during the trip. For each new reading, the user can select to either start a new trip, or continue the same trip, so in our analyses we filtered unique users per day to exclude repeated missions by the same user. The country-wide dataset was filtered to extract records located within the Kaunas reservoir (with a 50 m buffer, to ensure all anglers on the shore were included), and then divided into smaller datasets that included only anglers within the drone survey area and time period (see below).

2.5. Statistical analysis

To compare visual and drone surveys we used an unpaired t-test (Table 1) (adding Welsh correction for unequal variances gave nearly identical results). In this test we compared total angler count (on shore, in boats and on ice) from the two methods (five sampling days), number of anglers counted on shore (three days), number of boats counted (three days) and number of anglers in boats (three days) (see Results for details and numbers counted). *Post-hoc* power analysis of effect size and minimum detectable difference was undertaken for the t-test results.

To estimate and predict the total number of anglers within the surveyed reservoir area and time period (mornings only), we used the angler counts from the 39 drone surveys in a linear model, where angler numbers were modelled as a function of weekday/weekend, season, open-water/ice, cloudiness (clear, cloudy, rain, fog, snow) and wind conditions, including their interactions. The drone surveys were used to establish a relationship between the number of anglers on the reservoir in the survey area and daily sonar usage data, and not to estimate the total number of anglers in the reservoir. In the linear model, angler numbers were log transformed to ensure that the model did not predict negative values. After exploring model performance and the residuals we identified two outlier day observations, both occurring at the start of the drone survey period (second and third mission), during the peak of the first COVID-19 lockdown (April 2020). On both of these days unusually low angler numbers were observed, and the days were also identified as clear outliers in the dataset, when model residuals were explored. It is likely that such low angler numbers were due to COVID-19 lockdowns during the first wave of the pandemic and did not reflect typical angling activity. To avoid the two outlier days unduly affecting our model predictions we conducted analyses with the two days both excluded and included (Table A.1). When the two outlier days were excluded, model residuals showed an improved and adequate fit to the assumptions of normality. We tested a range of alternative model formulations and identified the most important explanatory variables, in a model selection process based on the Akaike Information Criterion (AIC) and Chi-square test of nested models (see Table A.2 for model formulations and model selection outcomes). Once the best model was selected, we then used this model to estimate the total number of anglers per year.

To compare drone and sonar-based angler counts, we used Bayesian methods to estimate the probability (p_d) of sonar use in each angling trip. This combines the probability that an angler who owns a Deeper® sonar device will use it on a given fishing trip. This probability was estimated using the full data set of drone observations (39 days) described above, where we counted the angler numbers. For this analysis, the sonar usage dataset was filtered in three different ways. First, we selected sonar usage data only from the area and time period surveyed by drones. Drone flights were conducted ca 8–11 am, so we used those sonar data for which the start time of the trips was between 6 am and 12 pm; this aimed to account for the fact that most anglers use the sonar device at the start of the fishing trip, but in theory could also use it later during the same trip. The second dataset of sonar usage included all sonar users within the area surveyed by the drone on each specific day, regardless of when their sonar was used during that day. Finally, to assess the relative proportion of anglers in the surveyed area versus the entire Kaunas W*R*, we also extracted the number of sonar usage trips started anytime during the days of the drone surveys. This last dataset had the largest number of sonar records and was used to estimate the ratio between the total number of anglers in the reservoir fishing at any time of the day, and the number of anglers counted by drones (smaller area confined to the morning). Note, that the northern part of the Kaunas W*R* that was inaccessible for the drone, is also closest to the city of Kaunas, and therefore we expected high numbers of anglers in that area. We assumed that the proportion of sonar users remained similar in different areas of Kaunas W*R* and during different times of the day. The full dataset of anglers counted by drones, as well as the three sets of sonar users is provided in Table A.3.

Each of the three sonar usage datasets was related to the drone angler surveys allowing for the probability of sonar usage to differ on weekdays and weekends. The weekend multiplier a means that the final probability p_d of sonar usage is expressed as $r_0 * e^{(a\mathrm{W})}$, where r_0 indicates the general sonar use probability and W represents weekdays (0) or weekends (1). The value of 0 for the a parameters would indicate the same probability of sonar usage on weekdays and weekends, whereas values of e. g. 1 would mean an almost three-fold higher weekend or ice fishing probability of sonar use. To ensure that the estimated probabilities were always positive in our analyses we used a linearised version of this equation:

$$p_d = 1 - e^{-\left(r_0 e^{a\mathrm{W}}\right)}$$

The r_0 parameter was assumed to be drawn from an exponential distribution with rate parameter r_1 and log likelihood defined as logL $= \log(r_1) - r_1 * r_0$. The weekend probability multiplier was drawn from a normal distribution with zero mean and standard deviation of 10. These probabilities form the basis of our likelihood function and we used Bayesian methods to estimate a and r_0. Our initial analyses showed that sonar usage differed greatly between the open water and ice fishing seasons, because the specific Deeper® sonar device (small, portable) is especially convenient for ice fishing, while during the open water fishing season many anglers use more advanced sonar devices that can be attached to boats. We therefore conducted two separate analyses for open water and ice fishing season.

Finally, we also used Bayesian methods on the sonar dataset to estimate the proportion of anglers in the morning for the surveyed area versus the total number of fishing trips recorded on that day. (i.e. comparing sonar 1 dataset in Table A.3 versus sonar 3 dataset). For these analyses we used all 365 days of sonar observations from March 1, 2020 to March 1, 2021, which were divided into 316 open water days and 49 ice fishing days (based on known weather and ice records). Here the ***r0*** compares the relative number of sonar users in the two sonar datasets,

Table 1

Comparison of angler counts from aerial surveys by drones (A) and land-based visual surveys from a boat or ice (L). T (df): two-tailed paired test t value and degrees of freedom, P: probability of null hypothesis of no difference in the count.

	2020.05.15		2020.08.12		2020.10.24		2021.01.21		2021.02.19			
	L	A	L	A	L	A	L	A	L	A	T (df)	P
Total count	70	72	49	55	205	170	59	51	41	42	0.18 (8)	0.86
No of boats	14	15	24	20	99	98					0.03 (4)	0.97
Boat anglers	18	15	31	33	186	146					0.20 (4)	0.85
Shore anglers	52	57	18	22	19	24					-0.29 (4)	0.78
Ice anglers							59	51	41	42	0.35 (2)	0.76

whereas weekend multiplier *a* estimates whether this ratio differs between weekdays and weekends. Here again, we assumed that the proportion of sonar users among all anglers was similar in different parts of the reservoir and at different times of the day.

Markov Chain Monte Carlo (MCMC) sampling was run for 200 K iterations, of which the first 10 −20 K were discarded as the burn-in, after checking for convergence of the likelihood estimates. The remaining runs were used to generate posterior probability density ranges, after checking that the posterior distributions were unimodal indicating convergence. We conducted analyses with different priors, but solutions always converged to nearly identical posterior parameter estimates. All analyses were conducted in R 4.0.3 or 4.0.5 (R Core Team, 2021), full analysis code and data are available on https://github.com/astaaudzi/anglerCounts and as a supplement to this manuscript.

3. Results

3.1. Drone surveys give accurate estimates of angler numbers when compared with traditional, land-based surveys

During the 39 days of drone surveys a total of 2980 anglers were observed (see Fig. A.1a-h for example photos from drone surveys). The number observed per day varied from 7 to 180, with a median value of 69 anglers. The largest number of anglers was observed during the ice-fishing season (N = 180). Of the 2980 anglers, the majority (2378) were observed during the open-water season; of these 43.0 % were land based and 57.0 % were boat based. During winter (ice fishing season) 602 anglers were observed. Over the five days of visual land and boat-based surveys, 424 anglers were counted in total (324 during open water, and 100 during ice fishing seasons). The number of anglers observed per day varied from 41 to 205, with a median value of 59. During the open-water season 27.5 % of anglers observed visually were land based and 72.5 % were boat based. There were no significant differences between total angler numbers observed by traditional visual methods and drone surveys, including for anglers observed on shore or from boats, or the total number of boats counted (t-test, P values > 0.75, Table 1). A caveat to this result is that due to the low number of replications, the statistical power to detect differences was low at only 5–6 %, so the test would only detect very large difference as significant. Nevertheless, the correlations among the methods were extremely high. Usually, the total count of anglers was almost the same, and small differences were likely due to angler movements and slight differences in survey times. Drone and boat-based surveys sometimes differed by up to 1 h due to different boat and drone movement speeds. The only clear discrepancy was observed when counting anglers in boats, where drone and visual surveys counted 146 and 186 anglers, respectively. These mismatches were mainly due to the different number of anglers in a single boat counted by the two methods, because the number of boats was almost the same (98 vs. 99). Separating passengers and anglers in a boat from drone observations was deemed to be too difficult, and in drone surveys one boat was typically assumed to correspond to one or two anglers. Note that the assumption of one angler per one boat does not affect our calibration of sonar usage from drone data, because usually only one sonar device per boat would be used. This assumption means that we might be underestimating angler numbers, which would make our predictions about the total angling effort conservative.

Linear model selection showed that the best selected model included the interaction of ice cover with weekend / weekday ($R^2 = 0.32$). The second-best model with the same AIC value had only the weekend effect ($R^2 = 0.22$) (Table A.2, Fig. A.2). The model with the two outliers included had an almost identical parameter estimates (Table A.1), suggesting that exclusion of potential outlier points does not affect general model predictions. Naturally, when outlier points were included, the model explained less of the variance ($R^2 = 0.16$) (Table A.1). This means that including the two outlier points would increase the uncertainty in predicting angler numbers. However, since our main angler number prediction was based on the sonar observations (see below) and the drone data were only used to calibrate the sonar usage, inclusion or exclusion of outliers did not influence the final predictions (all data points were used in drone-sonar calibration, see below). In all, the best selected model indicated a significantly higher number of anglers fishing during the weekends, especially on weekends with ice cover (Fig. 2).

The best statistical model could now be used to predict the number of anglers over the entire year. For this we used the one-year period starting from 2020 to 03–01, which includes the ice fishing season between 2021 and 01–10 and 2021–02–28. The estimated mean and confidence intervals of angler numbers in the assessed area were $\sim 25 * 10^3$ ($20 * 10^3$–$31 * 10^3$) (Table 2), which included $22 * 10^3$ for the open water fishing season and ca $3 * 10^3$ for the seven weeks of the ice fishing season. When the two outlier days were included in the analyses, overall predictions were similar, but confidence ranges were wider (mean 22458, 95 % CI of 15868 –32291). Finally, if only a model with weekday and weekend effects was used, then the predicted annual number was almost identical, at 25031 (20739–30212). Note, that this prediction only applies for the surveyed area (ca 70 % of the total reservoir area) and time period (i.e. anglers who fish during the first half of the day). To extrapolate these estimates to the entire area of the Kaunas W*R* using only drone data, we would need independent observations about the relative number of anglers in mornings and afternoons and in the surveyed versus unsurveyed areas. Such independent observations were not available, and any a priori assumptions (e.g., anglers are distributed evenly) would be questionable. Therefore, to estimate the total number of fishing trips conducted at any time of the day in the entire Kaunas W*R* we only used the calibrated sonar data, as described below.

3.2. Angler effort estimated from drones is similar to sonar use data

After establishing that drone surveys can produce accurate measures of angler numbers, we now calibrated sonar usage data against the drone observations. In the first analysis we compared drone-based estimates with the smallest sonar dataset, which only included sonar users who logged the start of their fishing "trip" within the area surveyed by the drone at between 6 am and 12 pm. In the open water fishing season, the estimated baseline proportion of sonar users ($r0$) was ca 1 % (95 % posterior probability density PPD of 0.5–1.7 %) (Table 3, Fig. 3). This probability was ~3.5 times higher on weekends (Table 2, $\exp(a) = \exp(1.24) = 3.46$). As a result, the final average probability of sonar usage was 2.0 % (95 % PPD of 1.5–2.6 %). For the ice fishing season, the probability of sonar usage was considerably higher, because the Deeper® sonar device is particularly popular for this purpose. The proportion of sonar users was similar between weekdays and weekends during the ice fishing season; the final probability was 15 % (12–18 %, Table 3). As expected, when the same analyses were repeated using sonar users who started their trips at any time of the day, the number of sonar users relative to the total number of anglers (counted in the morning) increased. This was most prominent during the open water season, where the estimated proportion was more than twice as large (final probability of 5.4 % rather than 2.0 %). This suggested that drone counts conducted during the morning only detected about half of all the anglers who fished on that day (Figures A.4 and A.5). During the ice season, most angling trips commenced in the morning, and the difference between the two datasets was very small (14.8 % and 17.2 % respectively, Table 3).

To obtain a better extrapolation of angler numbers from the drone counts (mornings only, and the 70 % of the water reservoir area where drones were allowed to fly) to the total number of anglers in the reservoir, we conducted a separate analysis with the daily sonar usage data. These analyses showed that the ratio between the two datasets was ~25 % during the open water and ~20 % in the ice fishing seasons. The majority of anglers concentrated in the northern area of the water reservoir, where drone flights were not allowed, mainly because the

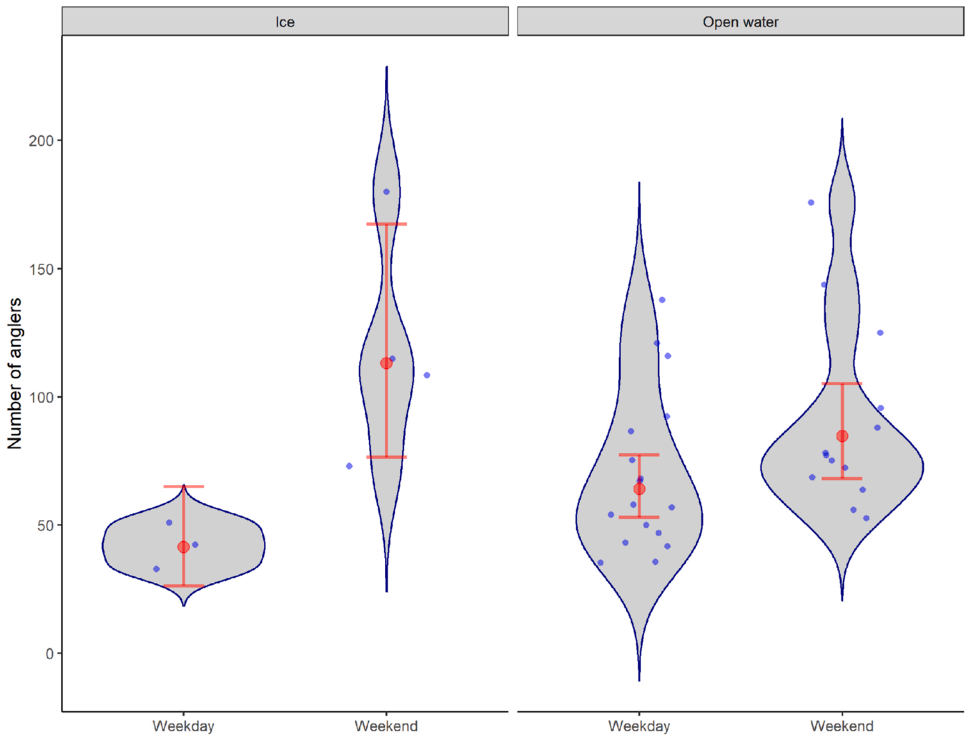

Fig. 2. Observed (blue dots) and model predicted (red confidence ranges) numbers of anglers per day on weekdays and weekends, depending on ice conditions, estimated from 37 drone surveys (two outlier days excluded). The grey area shows the distribution shape of the data. Model with the full dataset from 39 days is shown in Figure A.2. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 2
Predicted annual number of anglers with 95 % confidence ranges based on the linear model from drone estimates, and Bayesian posterior probability median and 95 % credible interval ranges based on daily sonar counts in Kaunas water reservoir. Prediction is for the period of 2020–03–01 to 2021–02–28, which includes the ice fishing season (which lasted between 2021 and 01–15 and 2021–02–28). Estimates of total angler numbers in Kaunas *WR* combine uncertainties for angler proportion in the surveyed area and those for extrapolating to the entire *WR*.

Method	Total number	Open water only	Ice season only
Surveyed area, mornings only			
Linear model (drones)	25 126 (20 086–31 603)	22 097 (18 097–26 984)	3 030 (1 989–4 618)
Bayesian (sonar)	26 696 (14 256–58 201)	24 221 (12 457–54 823)	2 475 (1 799–3 378)
Estimate for the total Kaunas WR (sonar data only)			
method 1	107 175 (52 594–254 563)	97984 (44 489 –236 304)	12 191 (8 104–18 259)
method 2	108 434 (59 359–228 493)	96407 (50 630–212 070)	12 027 (8 729–16 423)

northern area is adjacent to the city of Kaunas.

Bayesian estimates of sonar usage probabilities (Table 3.) could now be used to estimate the annual number of angling trips conducted in the mornings within the drone surveyed area. For this estimation linear model predictions were not required, instead it relied upon the daily numbers of sonar users (Table A.4). As with the linear model analyses, we estimated the annual number of fishing trips starting from 2020-03-01, but unlike the linear model, we used the actual daily number of sonar trips logged in the mornings within the surveyed area and applied the parameter estimates and their 95 % PPD values to convert the number of sonar users to the actual number of anglers (in the mornings within the surveyed area). Here, the estimated annual number of angling trips was ca ~27 * 10^3 (14 *10^3–58 *10^3), which included ~24 * 10^3 anglers during the open water season and ~2.5 * 10^3 during the ice fishing season (Table 2). These numbers were similar to the linear model results with 95 % PPD ranges overlapping with the linear model confidence ranges (note however that these uncertainty estimates are not identical measures, being derived from different assumptions).

To extrapolate this number to the total Kaunas *WR* area for angling trips conducted at any time of the day we used two slightly different methods. For Method 1, we combined two sources of uncertainty – estimates of sonar usage proportion in the mornings for the survey area (Table 3 top) and those for extrapolating from the surveyed area in the mornings to the total numbers of daily sonar users in the reservoir. (Table 3 bottom). This gave a total 50 % posterior probability estimate of 107 * 10^3 annual angling trips in the Kaunas *WR*, which included ca 98 * 10^3 trips during the open water season and 12 * 10^3 for the seven weeks of ice fishing season (Table 2). Alternatively (Method 2), we simply assumed that the probability of sonar usage was identical for the entire Kaunas *WR* during any time of the day. Then we used total the number of sonar users recorded on each day anywhere in the Kaunas *WR* and applied the probability of sonar usage proportion (Table 2 top) for open water and ice fishing seasons separately. The two approaches gave substantially similar results (Table 2), although the uncertainty ranges for the second method were slightly smaller.

4. Discussion

In this comparative study we explored three different methods to assess angling effort in a large water reservoir. We found that traditional vessel-based and fixed-wing drone methods gave similar accuracy, but drone missions were more time effective (with further possibilities for improvement) and also provided objective high-resolution digital records for data quality reassessment and future analyses. A total of 39 surveys conducted over four seasons of a year were sufficient to estimate the annual number of fishing trips with relatively low uncertainty

Table 3
Bayesian parameter estimates (50 % posterior probabilities and 95 % ranges) for the proportion of anglers using a sonar device, compared to the number of anglers counted by drone and the proportion of sonar users in the surveyed area and time period versus total daily number of users in the reservoir.

Parameter	Explanation	Open water season	Ice season
Main drone – sonar analysis (sonar dataset 1, same spatial area, only morning sonar trip)			
r0	initial sonar use probability	0.010 (0.005–0.017)	0.152 (0.114–0.190)
a	weekend multiplier (log)	1.241 (0.606–1.934)	0.079 (0.003–0.346)
p	final sonar use probability	0.020 (0.015–0.026)	0.148 (0.121–0.178)
Drones – sonar dataset 2 (same spatial area, trips started any time of the day)			
r0	initial sonar use probability	0.037 (0.027–0.049)	0.180 (0.137–0.221)
a	weekend multiplier (log)	0.759 (0.405–1.147)	0.074 (0.003–0.306)
p	final sonar use probability	0.054 (0.046–0.063)	0.172 (0.143–0.203)
Ratio of anglers in sonar dataset 1 vs. sonar dataset 3 (all water reservoir, trips started any time of the day)			
r0	ratio of anglers	0.273 (0.235–0.312)	0.222 (0.196–0.248)
a	weekend multiplier (log)	0.248 (0.072–0.450)	0.062 (0.002–0.209)
p	final ratio	0.255 (0.232–0.280)	0.203 (0.185–0.222)

ranges, identifying about ~25 thousand annual fishing trips within the surveyed area for the particular time period of the day. This number was similar to estimates from the daily sonar records (~26 thousand), which although not entirely independent (because of the drone-based calibrations) still provided high resolution daily records of sonar users. Notably, the linear model, with and without ice effect, gave similar overall annual estimates of anglers, suggesting that a simple model with only a weekend effect might be able to capture most of the variation in fishing effort.

4.1. Fixed wing drones can provide fast and accurate methods for angler counts

As recreational fishery becomes one of the most important sources of fishing mortality in many freshwater and coastal marine environments, there is an urgent need to develop rapid angling effort assessment methods, yet such assessments are still remarkably rare (but see Veiga et al., 2010; Pope et al., 2017; Askey et al., 2018; Provost et al., 2020b, for specific examples). The most common methods used to date include roving surveys on foot or from a boat (Veiga et al., 2010; Provost et al., 2020b), high frequency time-lapse cameras (Askey et al., 2018), small drones – quadcopters (Provost et al., 2020b) and small fixed-wing aircraft e. g. Cessna 210 (Veiga et al., 2010). Although fixed-wing drones have been used in fisheries management for a while (Kopaska, 2014), they are mostly applied for habitat mapping or even water quality surveys (Shintani and Fonstad, 2017), but not for enumerating angler activity. Yet, fixed wing drones have many advantages over smaller quadcopter type drones, such as faster flying speed, longer battery life, lower sensitivity to weather conditions and higher payload capacity (González-Jorge et al., 2017; Harris et al., 2019). Fixed wing drones still have shorter flying times than airplane-based surveys, but airplane surveys are likely much more expensive, require highly trained personnel (pilots) and are often not feasible for smaller research projects. Below we compare previous and our current drone and land-based surveys in terms of their accuracy, time and costs, reproducibility and application in different weather and light conditions.

First of all, it must be noted that accuracy and precision of drone-based surveys will strongly depend on the resolution of recorded video and levels of experience of the drone operators. This resolution will be a trade-off between the weight of the cameras, data intensity and analysis accuracy. The optimum resolution used in our study was 4 K cameras and video recording of 30–60 fps. With two cameras working in parallel this produced up to 1 GB of video data for a 1.5-hour mission. Post-processing of all 39 surveys was done by the same person, leading to consistency of final angler counts and rapid post-processing speed after an initial training period. Boat-based surveys were conducted by two experienced people, who, given a relatively slow boat speed could thoroughly survey the entire coastline. As a result, the final angler counts in drone and boat surveys were very similar, except when counting the number of anglers per boat. Here, the drone-based team made a decision to count only one angler per each small motorboat or inflatable rowing boat and eliminate all yachts as non-anglers (the same was done in the visual boat-based surveys). Although in many cases drone footage could identify individual fishing rods, assessing how many people in each boat had rods could create a substantial error and require lengthy post-processing analysis. Such distinction between anglers and non-anglers was easier to make when surveying from a boat, although absence of a permanent digital record means that in each case such decisions remain partly subjective and could be biased. The challenge of identifying people in boats as anglers or non-anglers is not new. For example, angler counts from manned aircraft and drone (quadcopter) systems within a 10.6 km length of Beaver Dam Tailwater (USA) also mostly differed in how anglers in boats were counted (Fernando et al., 2019). More people in boats were considered to be boat anglers using the manned aircraft than the drones as observers in the manned aircraft recorded some non-fishing boat occupants as anglers (confirmed with a detailed analysis of drone records). These results suggest that the permanent record made by a drone has a huge advantage due to its higher precision attained during postprocessing, although this may come at increased analytical costs.

Our results are quite different from Provost et al. (2020b), who compared boat-based counts with those from a small quadcopter drone equipped with one standard integrated camera with a polarising lens. During 16 surveys it was found that on average the drone observed only half of the anglers counted by boat and took three times longer to complete each survey (including time needed for video analysis). These authors concluded that using quadcopter drones was cheaper compared to vessel-based surveys, but the drone surveys took longer and failed to detect all fishers, especially those underneath trees or obscured by objects (Provost et al., 2020b). Obviously, counting anglers obscured by vegetation is a challenge for all visual surveys, but in drone-based analyses this could be partly overcome by using two or three cameras with different viewing angles. In our study the drone was equipped with two cameras, one of them inclined at an angle to provide a better lateral view (Fig. 1). Further, drone-based surveys can have a substantial advantage if they are also equipped with infrared cameras, such as already commonly used in wildlife research (Burke et al., 2019). The application of infrared cameras also opens up a possibility for drone-based angler surveys to be conducted at night or in low visibility conditions.

The second important aspect of comparing traditional and drone-based surveys is the price and accessibility to good quality affordable devices across different countries. In our study, the initial cost of a fully equipped fixed-wing drone was slightly higher (c. 3500 euro) compared to equipment needed for vessel-based missions (c. 2800 euro), yet the price per individual mission was lower for drones due to the

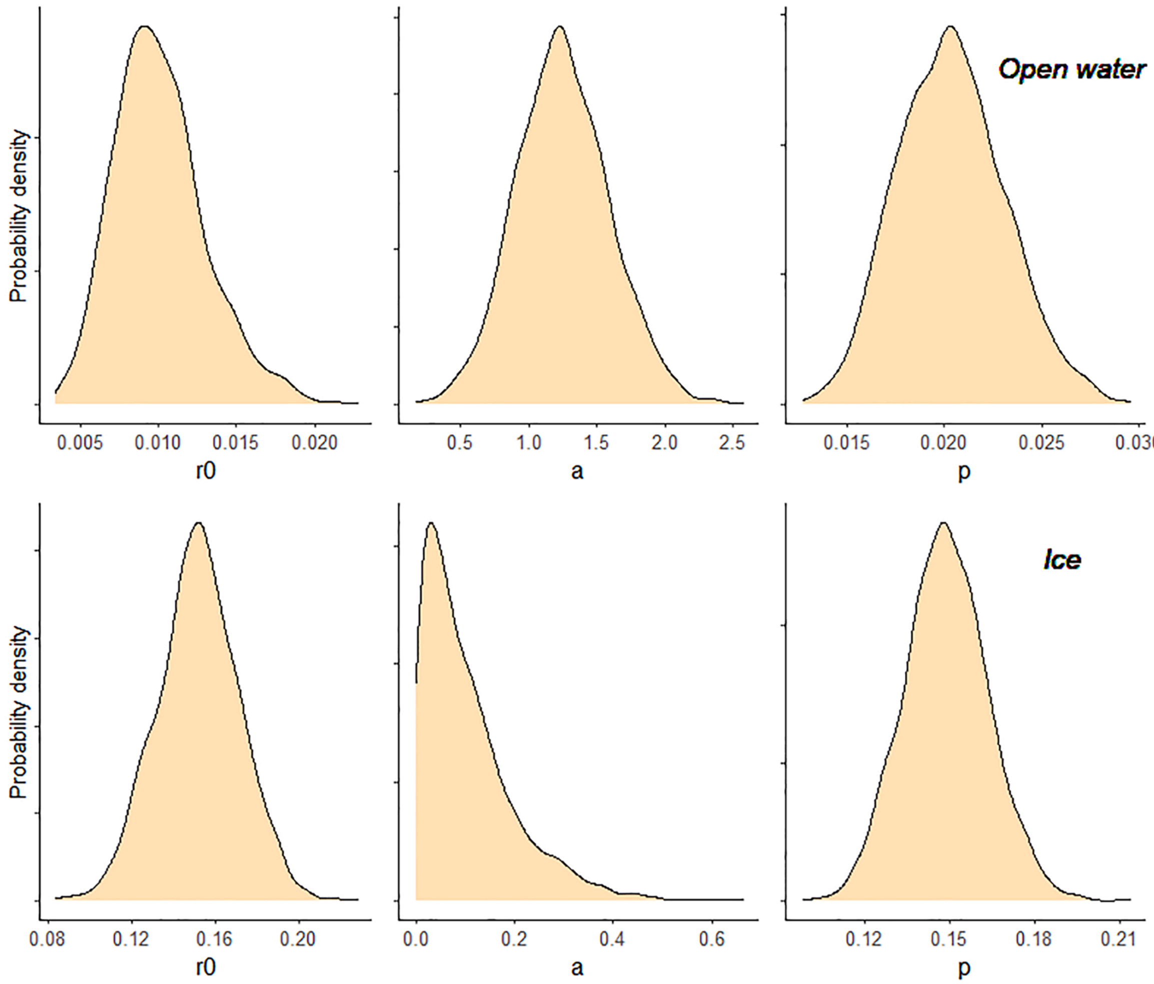

Fig. 3. Posterior probability density plots for parameter estimates for open water (top) and ice (bottom) fishing seasons in the dataset, comparing drone observations and sonar usage in the same spatial area and daytime (mornings only). The initial probability (r0) and the weekend multiplier (a) were used to estimate the final probability of sonar use (p).

considerably shorter time required for analysis. Obviously, initial capital equipment costs can vary dramatically, ranging e. g. c. $900 (c. 850 euro) for an off-the-shelf drone used for fine-scale shark movements (Raoult and Gaston, 2018) to c. $35,000 (c. 33,000 euro) for a custom-made hexacopter used for leopard seal (*Hydrurga leptonyx*) photogrammetry (Krause et al., 2017). Prices of fully equipped fixed-wing drones, similar to the one used in our study, usually range from ca 2000–20000 euros, although in our case the drone was custom made. Nevertheless, given the recurrent nature of angler surveys, and increasing availability of different types of drones, one of the major cost components is the labour required for each mission. Here the prices per mission will mostly depend on the salary costs of relevant personnel – technicians, scientists and pilots operating drones – which all differ among countries, as well as boat fuel costs (not required for drones). In our study the total time required per drone mission was about half of that used in boat-missions, even when including the post-processing time. This difference would be even higher for angler surveys undertaken in larger water bodies, or water bodies with complex shorelines, as these would take considerably longer to survey by boat. To survey 35 km^2 area, the drone we used took about 1–1.5 h depending on the weather conditions, due to its fast-flying speed (50–60 km/h) and ability to pre-program the mission trajectory, which means that minimum piloting was required on site. Data postprocessing is currently the most time consuming and potentially costly aspect of any drone project (Harris et al., 2019). During this study, video analysis was performed manually by one of the research group analysts and took approximately 1–1.5 h per individual mission. Yet, data post-processing can be considerably sped up using machine learning, especially if combined with thermal imagery, multispectral photography, light detection and ranging (LiDAR), and other sensors (Chust et al., 2008; Yang and Artigas, 2010; Klemas, 2015; Yahyanejad and Rinner, 2015).

Finally, an important advantage of fixed-wing drone surveys is the permanent, high resolution and spatially precise digital record, essential for reproducibility of results, reduced bias and future analyses. Moreover, fixed-wing drones can conduct angler counts in a range of weather conditions and, if thermal imagery cameras are used, even at night. To our knowledge night angler-counting surveys are exceptionally rare (but see a study observing angler activity from parking lots, Bova et al., 2018), which leaves a large unknown in angling effort assessments. In our study the drone could be deployed in high winds (15 m/s) and low temperatures (−20 C), all potentially causing challenges for small hexacopter drones, as well as for boat or land-based surveys. Due to their relatively high-flying altitude (50–70 m in current research) and electric engines, fixed wing drones are also inaudible and virtually invisible to anglers, creating less disturbance to their fishing activities.

The major challenge and disadvantage of drone-based surveys could be special aviation restrictions for flying drones, such as the no-fly zone in the western part of the Kaunas W*R* which falls within the restricted airspace of Kaunas Airport (Fig. 1) as well as country specific challenges related to the General Data Protection Regulation (GDPR). For example, if we wanted to estimate angler numbers in the entire Kaunas W*R*, we would need some independent observations to assess relative numbers of anglers in the surveyed area (70 % of the total *WR* area) versus the no-fly zone. Our comparison with the sonar data showed that the 30 % of the *WR* area unsurveyed had very large number of anglers, because it was close to the city. In such cases, other angler assessment methods (traditional visual surveys or smart phone application based) must be conducted in parallel to enable the extrapolation of angler counts.

4.2. Assessments based on fish finder/sonar devices have huge advantages but still require work

Technological development and availability of various fish finding devices and sonars has led to rapid and dramatic changes in all aspects of angling, and in many cases are considered to negatively affect fish species and stocks by increasing the fishing power of anglers (Cooke et al., 2021). These devices enable the measurement of depth, scan for bottom structure and vegetation, but their primary purpose is to locate fish. More advanced devices allow users to store maps from previous fishing trips and create personal databases. If stored online, de-personalised data from such databases may also be used for scientific purposes (Venturelli et al., 2016). We compared de-personalized data from fish finder Deeper® sonar users, with angler numbers obtained from fixed-wing drone missions flown over the same area during the same time interval and were able to calibrate the proportion of sonar users with surprisingly low uncertainty.

For open water fishing about 2 % (1.5–2.6 %) of anglers on any given day used the sonar device, with the proportion being slightly higher on the weekends. During the ice fishing season, the device was considerably more popular and nearly 15 % (12–18 %) of anglers used it on any given day. This is not unexpected, because the Deeper® sonar device is especially useful for ice fishing, since it is relatively cheap, light and portable, making it convenient when fishing from a stable location (ice), but less so if fishing from the confines of a rocking boat. Such high adoption rates of the device allowed better estimates of daily angler numbers and extrapolation to the entire Kaunas *WR*. Importantly, our extrapolation showed that drone surveys conducted within the area where flights were permitted (~70 % of total area) during the mornings, counted about one quarter of all fishing trips. If no other knowledge about angler distribution was available, then the simplest extrapolation would be to assume that anglers are distributed evenly in the Kaunas *WR*, and that half of all anglers fish during mornings. This would imply that drone-based surveys observed about 35 % of all fishing trips. Yet, the no-fly zone was close to the Kaunas City where angler density was expected to be higher, especially during the ice season, hence the observed number of anglers would be less than 35 % of the total. Ideally, drone-based surveys should be conducted during mornings and evenings to assess whether the probability of sonar usage is similar between these periods of the day. However, in this study we relied on visual angler counts from drones which would make angler counting at dusk challenging as infrared cameras were not operationally available (but are currently being tested). Further, given the limited number of drone missions available for this study we focused on minimising error across weekdays and seasons, rather than different times of the day.

Although the uncertainty ranges around the frequency of sonar use are relatively small, when uncertainty is fully propagated, the final annual number of fishing trips in Kaunas *WR* is estimated to be in the range of 52–250 thousand (95 % posterior probability range), with the median of ~107 thousand. In comparison, a 6-month study during 1999–2000 of Lake Dartmouth, a 64 km^2 reservoir located in the mountains of Victoria, southeastern Australia, used automatic car counters to record 2156 vehicle-trailer departures equating to approximately 3600 vessel trips when annualised (Douglas and Giles, 2001). This reservoir is only accessible by boat via a single launching ramp and Hunt et al. (2011) later scaled the vessel counts using concurrent creel survey data from anglers retrieving their vessels at the ramp to estimate total annual effort of 91 thousand angler hours during 1999–2000. Although a popular inland angling destination, Lake Dartmouth is relatively remote and far less populous than the environs of Kaunas *WR*.

For the mornings of the survey area, the linear model and Bayesian analyses gave substantially similar mean values, but Bayesian 95 % uncertainty ranges were considerably wider, especially in the upper portion of the range. Compared with other assessment methods, the combination of the two approaches used here are highly promising not only for estimating the total number of anglers, but also for more detailed assessments of fishing effort. Daily sonar data can help show occasional high peaks in fishing effort that could have substantial impact on fish stocks, yet might be missed in stratified visual sampling and application of linear models. Moreover, the sonar data offers many other unique insights, such as spatial changes in angler movements, response to specific restrictions and other angler behaviour aspects (in preparation). Fish-finder devices can also provide data on bottom structure or vegetation cover, and more importantly they accumulate acoustic data of fish population abundance and, occasionally, size structure. Such acoustic data is used in standard approaches for the evaluation of marine fish stock status (Wassermann and Johnson, 2020), but private fish-finder devices open potentially new opportunities for stock assessments in inland water bodies. Availability of such data, however, is entirely dependent on collaborative efforts between fish-finder manufacturing companies, and we suggest more work should be done to promote and acknowledge successful collaboration initiatives between companies and researchers within and between different countries.

Before the fish-finder device data can be applied widely in assessing stock status, there are some important caveats to be addressed. First, there should be a sufficient uptake of these devices among an angler population to provide acceptably accurate estimates, thus additional studies are needed to determine country and region-specific uptake through time. For example, according to company estimates and our online surveys, nearly 20 % of Lithuanian anglers have the Deeper® sonar device, yet only around 2 % of anglers on a given day used the device during the open water season. It is not entirely clear what minimal total uptake rate (5, 10 or 20 %) among the population of anglers is needed before sufficiently accurate data can be obtained, but the ~20 % of total anglers using the device in Lithuania seems to give relatively narrow uncertainty ranges, at least in Kaunas *WR*, especially keeping in mind that according to Gundelund et al. (2021) 8 –10 % angler app users of total angler population were sufficient to give reliable estimates of e.g. sea trout catches and release rates. Second, calibration studies are and will be required to assess the relative proportion of device users among anglers in locations close and far away from big cities, through seasons, weekdays, different regions of the country and changes through time. Our angler surveys suggest that many anglers only used the device occasionally, some only a few times after their purchase, whereas others used it regularly. The number of sonar users will also depend on further development of the device with additional features and benefits, marketing strategies aimed at convincing anglers of the benefits, economic circumstances affecting future research and development and pricing-affordability, and availability of other devices competing for market share. These kinds of factors will variously influence the proportion of active users which may decrease, increase or remain stable over time with consequential effects on data availability for researchers. A large range of fish-finder devices of different complexity and price both presents an opportunity, but also means that the uptake will vary among anglers and data from a particular type of device might be biased towards more dedicated and specialised anglers (Gundelund et al., 2020) who may have higher avidity. Hence, regular calibration with independent observations will still be required, but could potentially be reduced to a smaller number of missions than the 39 used in this study. Finally, collaboration with fish-finder manufacturing companies also offers an opportunity to engage a population of anglers in citizen science projects, enabling their active participation in stock status assessments. Such opportunities often generate positive outcomes for angler satisfaction and stock status (Lee et al., 2020).

5. Conclusions

This study shows that both fixed-wing drones and anonymous angler data from fishfinder devices or apps can be used as statistically powerful and relatively accurate methods to estimate recreational effort. Compared to traditional creel-based surveys, these methods are faster and generally cheaper, especially if the surveys have to be repeated over longer periods of time, offsetting initial equipment costs of drones. The angler data from a fishfinder device could provide cost-efficient highly resolved spatial and temporal estimates of angling effort. However, this method requires effective collaboration with private companies selling such devices, reasonably high device uptake rate (ca 20 % of anglers in Lithuania own the device, but possibly even 10 % would be enough), and independent calibration through space and time. The fixed-wing drones can be effective for relatively large areas (dozens of kilometres) that don't have flying restrictions. They are environmentally friendly (no air or noise pollution), relatively insensitive to weather conditions, can be automated for rapid data postprocessing and they also provide permanent visual records for future reference. However, such surveys require initial capital equipment costs, as well as suitable skills to obtain flying licences and operate the machines safely and effectively.

CRediT authorship contribution statement

Justas Dainys: Conceptualization, Methodology, Validation, Formal analysis, Investigation, Writing – original draft, Writing – review & editing. **Harry Gorfine:** Formal analysis, Writing – original draft, Writing – review & editing. **Fernando Mateos- González:** Software, Formal analysis, Data curation, Writing – original draft, Visualization. **Christian Skov:** Writing – original draft, Writing – review & editing. **Robertas Urbanavičius:** Methodology, Formal analysis, Investigation, Visualization. **Asta Audzijonyte:** Conceptualization, Methodology, Software, Formal analysis, Writing – original draft, Writing – review & editing, Supervision, Project administration, Funding acquisition.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: JD, HG, FMG, CS and AA declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. RU is a co-owner and manager of a company Aerodiagnostika, which provide fixed-wing drone services. The company Aerodiagnostika has been contracted to conduct angler assessments by the lead authors of.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.fishres.2022.106410.

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