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To fly or not to fly? Comparing vantage point and uncrewed aerial vehicle surveys for assessments of seabird abundance and fine-scale distribution

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Abstract

Marine renewable energy developments (e.g. offshore wind, wave, and tidal) are an increasing feature within the marine environment. It is therefore important to understand the potential impacts of such developments on seabirds that use these environments. Land-based vantage point (VP) surveys are widely used to collect data for environmental impact assessments (EIAs) within tidal stream energy sites. However, tidal stream environments are highly dynamic and present challenges when conducting VP surveys, for example there can be varying detectability of seabirds due to near-surface turbulence. In recent years, there has been increasing interest in the use of uncrewed aerial vehicles (UAVs) to quantify animal abundance and distribution. Yet, to be effective for its use in EIAs, this approach needs to be assessed alongside standardised methods. This study provides the first comparison of at-sea abundance and distribution of surface-foraging seabirds in flight within a tidal stream environment using concurrent VP surveys and UAV transects. Applying a combination of GLMMs and GAMs, our results show that the two survey types produced similar counts of surface-foraging seabirds (tern species) in flight and reveal the influence of covariates affecting counts, including tidal state, sea state, and observer ID. Further, we estimated the overlap (Bhattacharyya's affinity) between tern utilization distributions as a function of tidal state to compare the fine-scale distributions derived from each survey type. The distribution of terns detected, particularly by UAV transects indicated that the highest tern density occurred within the near-shore shallows during the ebb tide and extended into the main channel during the flood tide. Specifically, the UAV transects captured the association of terns with a visible shear line extending into the main channel. Therefore, EIAs may benefit from the use of UAV transect surveys alongside VP surveys to identify fine-scale distributions of seabirds more accurately. Despite these potential benefits, the application of UAVs for use in EIAs may be limited by the species resolution achievable using UAV imagery as well as the impacts of adverse weather conditions and low sun angles (glare). Ultimately, the selection of survey techniques will depend on the specific aims of the EIA, the target species, and species behaviour.

Keywords: ornithology, EIA, marine renewable energy, land-based surveys, drone, survey method.

1. Introduction

Marine renewable energy developments (e.g. offshore wind, wave, and tidal) are increasing worldwide to help reach net zero CO_2 targets. Marine renewables represent a largely untapped energy resource, with the potential to fulfil up to 7% of global energy demand (Esteban and Leary, 2012; Fox et al., 2018; Pelc and Fujita, 2002). More specifically, tidal energy alone is estimated to have the potential to deliver approximately 20% of the UK's current electricity needs (Melikoglu, 2018). However, it is well established that nearshore tidal stream environments provide important foraging opportunities for seabirds (Hunt et al., 1999; Warwick-Evans et al., 2016; Zamon, 2003), therefore, interactions between seabirds and renewable energy developments within these areas are likely to occur (Benjamins et al., 2015; Copping et al., 2020). The protected status of many populations of seabirds has resulted in a legal responsibility to assess potential impacts of anthropogenic developments upon them (for example, in the EU, through Environmental Impact Assessments: The European Parliament and the Council of the European Union, 2009).

Environmental Impact Assessments (EIAs) typically involve the collection of baseline data to characterise a site and quantify potential environmental impacts of the proposed development(s) (The European Parliament and the Council of the European Union, 2014; Wright, 2014), and in many cases, seabirds are a key component of the EIA for marine developments (Savidge et al., 2014; Sparling et al., 2015). Typically, primary data of interest for seabird site characterisation are species presence, abundance, and distribution. These surveys allow the extent of spatiotemporal overlap between seabird foraging distributions and potential locations of anthropogenic structures in the marine environment to be quantified; crucial information required to assess the potential for interactions between seabirds and developments (Waggitt and Scott, 2014).

Vantage point (VP) surveys undertaken from the shore are widely used for assessing seabird abundance and distribution within nearshore areas as VP surveys are a cost-effective and logistically feasible method of data collection. However, the ability of VP surveys to gather data suitable for EIAs can be compromised by several biases stemming from detectability issues, particularly with increasing distance from the VP location, and the spatiotemporal resolution of data (Waggitt and Scott, 2014); these biases are exaggerated in tidal stream environments (Benjamins et al., 2015; Waggitt et al., 2014). Tidal stream environments occur primarily in tidal passes found between landmasses and around shallow headlands (Adcock et al., 2013; Lewis et al., 2015). Due to high current speeds, these sites are characterised by a range of hydrodynamic features, such as boils (bottom-generated turbulence erupting at the sea surface), eddies, upwellings, and vertical/horizontal shear which produce pronounced surface-flow turbulence (Benjamins et al., 2015; Holm and Burger, 2002). Such features not only influence seabird habitat use, but also the ability of observers to detect foraging seabirds near the sea surface (Bibby et al., 2000; Buckland et al., 2001). This presents observers monitoring seabirds within high-energy environments with particular challenges. Therefore, it is particularly important that the key issues and challenges outlined above are taken into consideration when devising land-based survey protocols for appropriate site characterisation surveys and monitoring of seabirds within high-energy environments.

In recent years, there has been an increasing interest in the use of uncrewed aerial vehicles (UAVs) to study animal abundance and distribution (Anderson and Gaston, 2013; Christie et al., 2016). UAVs have proven an effective tool for examining the behaviour of both individual and aggregating animals, quantifying animal densities and assessing the potential impacts of anthropogenic activities on vulnerable species or ecosystems (Anderson and Gaston, 2013; Hodgson et al., 2013; Kiszka et al., 2016). UAVs have the potential to survey sites quickly and allow access to remote locations that may be hard to access for traditional survey methods (McClelland et al., 2016). UAVs can also provide a different perspective of fine-scale seabird habitat use, beneficial for investigating interactions between seabirds and anthropogenic installations (Lieber et al., 2019). Yet, to date, the use of UAVs for monitoring seabirds has largely been applied to population size monitoring of ground and cliffnesting birds during the breeding season (Brisson-Curadeau et al., 2017; Chabot et al., 2015; Hodgson et al., 2016; McClelland et al., 2016; Ratcliffe et al., 2015; Rush et al., 2018; Sardà-Palomera et al., 2012). To be effective as an approach for EIAs, this emerging platform needs to be assessed and analysed alongside standardised methods.

This study provides the first comparison of at-sea abundance and distribution of seabirds within a tidal stream environment using conventional VP surveys and concurrent UAV transects. The aim of this study was to improve our understanding of how data collected from UAV transects compares to data collected using traditional VP surveys, in turn assessing the effectiveness of UAVs for use in EIAs. Specifically, this study: (i) compares counts of surface-foraging seabirds (terns *Sternidae*) in flight recorded from traditional VP surveys with those made from UAV transects; (ii) compares counts of surface-foraging seabirds in flight as a function of tidal state (Zamon, 2003); and (iii) assesses the overlap between tern distributions from each survey method to gain insight into the fine-scale distribution (habitat use) of mobile, surface-foraging seabirds in flight and investigates the use of prominent, tidally-derived hydrodynamics present at the site. We discuss the implications of our findings on the marine renewable industry and seabird monitoring.

2. Materials and Methods

2.1 Study site

The study was performed within a dynamic tidal channel ("the Narrows") located in Strangford Lough, Northern Ireland, UK (Figure 1). Concurrent land-based VP surveys and UAV transects were carried out between 20 July and 24 July 2019 (n = 64). The geographic constriction of the Narrows results in a rectilinear flow pattern with strong horizontal current speeds, peaking in excess of 4.5 ms^{-1} during spring tides, offering several tidal stream energy test and demonstration sites (Lieber et al., 2018; Savidge et al., 2014). As a result of strong current speeds and numerous bathymetric features, the tidal channel is characterised by several pronounced wake features. Walter's Rock, an island located on the north-eastern edge of the channel (Figure 1), presents one of these natural wake features, characterised by diverse hydrodynamic features throughout the tidal cycle. Submerged during high water slack, Walter's Rock generates localised boils, a shallow upwelling region during the ebbing tide (on the eastern side) as well as vortices and pronounced shear lines during peak tidal flows extending both into the nearshore shallows and towards the mid-channel. The latter has been shown to present a tidally predictable foraging location for surface-foraging terns, with the highest number of seabirds recorded during the flood tidal cycle (Lieber et al., 2019).

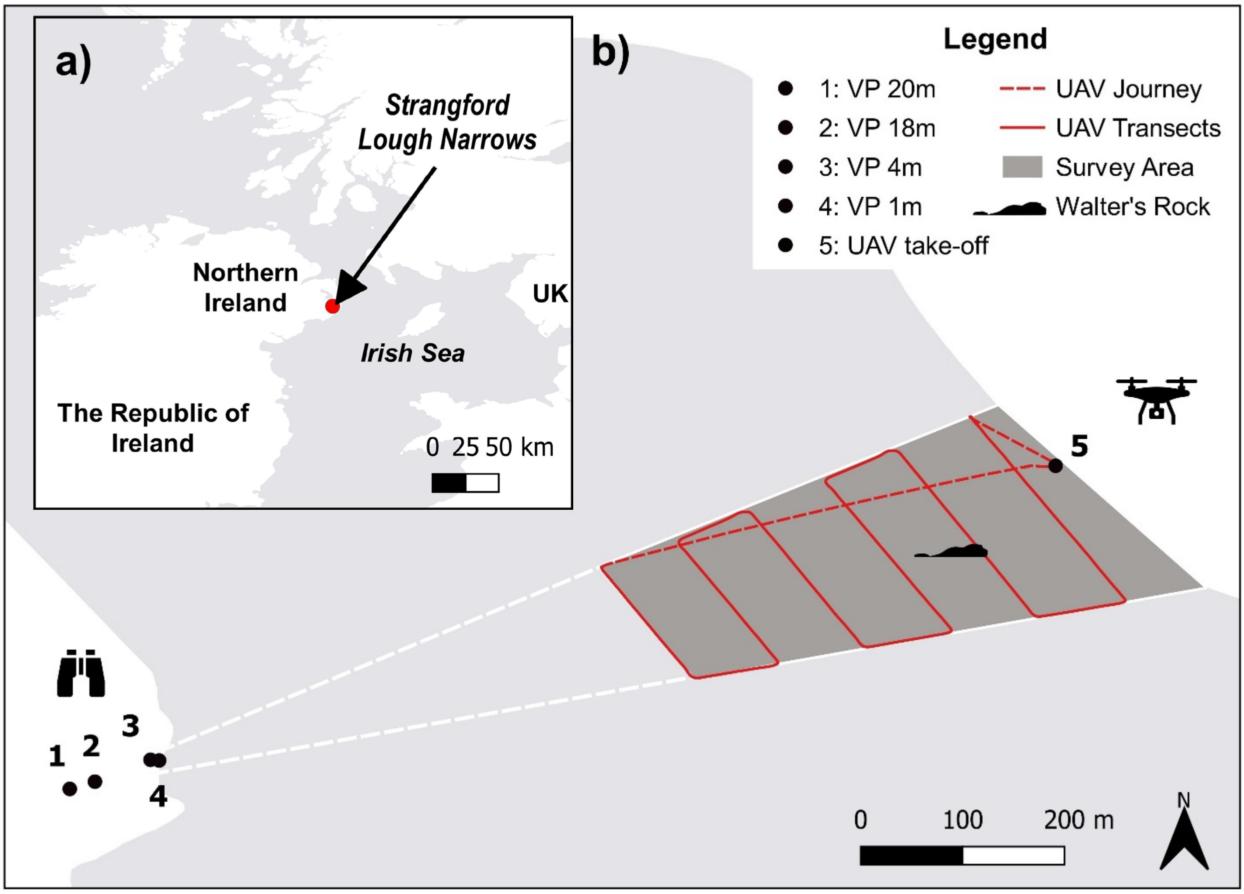

Figure 1. Map showing the study location within the Narrows, a dynamic tidal channel located in Strangford Lough, Northern Ireland, UK. **a)** Overview map showing the study area within the Narrows, highlighted by the red circle. **b)** Location of the survey area, including vantage point (VP) locations (Points 1-4) with associated elevation above sea level shown in metres, and UAV take-off location (Point 5) on the eastern shore of the Narrows. The island symbol within the survey (not to scale) represents the location of Walter's Rock.

2.2 Land-based vantage point surveys

VP surveys (Points 1-4, Figure 1) were carried out from the western shore of the tidal channel (Audley's Castle, 54˚22'47"N, 005˚34'19"W) to record the abundance (use of the term abundance within this study refers to counts of individuals) and distribution of seabirds within the study area (Figure 1), using telescopes (Swarovski ATS/STS HD 80mm) fitted with 20-60x magnification zoom lenses. Surveys were carried out by two independent observers from four VP locations, all within 1.5 km of the survey area. For each survey, VP observers were situated at different locations, these locations varied in elevation above sea level: 20 m, 18 m, 4 m, and 1 m (Points 1-4, Figure 1; see also Supplementary Table 1). Different elevations were used to investigate how VP elevation may influence the comparison of counts made of surface-foraging seabirds in flight from VP surveys to those made from UAV transects. Land-based surveys consisted of scans between 4 and 10 minutes in duration as we aimed to ensure that the VP scan length matched that of the UAV transect survey as closely as possible. The length of scans was also influenced by the number of seabirds present within the study area. Vantage point survey scans such as these are often referred to as 'snapshot' scans as they provide instantaneous counts of birds and their locations (Jackson and Whitfield, 2011; Robbins, 2017).

During each scan, seabird positions were located by triangulation using bearing and distance from the observer. The bearing of each sighting was measured using a handheld compass. The distance of a bird or group of birds from the observer was measured using a graduated rangefinder, as described by Heinemann (1981). However, as the horizon was obscured by land at this site graduated rangefinders were modified from those outlined by Heinemann (1981). Rangefinders were created for each vantage point, taking into account the distance from the VP and a number of given locations on the opposite shoreline to ensure that rangefinders were positioned correctly for any given angle of the survey area. The accuracy of graduated rangefinders was ensured by calibrating each rangefinder using known distances along the shoreline. Additionally, rangefinders for VP 1 (20 m above sea level) were also calibrated using the UAV (see section 2.6 below).

Before each scan, the following variables were recorded: sea state (Beaufort scale), cloud cover (% cover), tidal state (ebb or flood), sea surface glare (scale of 1-4, with 1 being "None" and 4 being "Severe") (Supplementary Table 1), and the bearings of surface glare from the observer. Scans were not performed during precipitation and were limited to when sea state was 3 or lower on the Beaufort scale and visibility was higher than 1.5 km. As the location of each VP was less than 1.5 km from the study area, all seabirds, both on the water surface and in flight could be identified to species level with the exception of common tern *Sterna hirundo* and Arctic terns *Sterna paradisaea* which were combined as 'Commic' terns. Seabird behaviour was also recorded following Camphuysen et al. (2004).

2.3 Uncrewed aerial vehicle transects

To compare the VP-derived abundance and distribution of terns with UAV observations, concurrent parallel-line UAV transects were performed across the survey area using either a DJI Mavic Pro recording 4k video at 24fps or DJI Phantom 3 Advanced recording 2k video at 30fps (Figure 1). The UAV was operated by a CAA (Civil Aviation Authority) approved pilot and programmed to fly six consecutive transect lines using either the AutoPilot v.4.7.191 or the Litchi v2.6.6 autonomous flight application (Supplementary Table 2). The transects were performed at altitudes of approximately 74 m (SD=1.30 m) for the Mavic Pro and 61 m (SD=1.09 m) for the Phantom 3 (giving a pixel ground resolution of 2.5 cm and 3.8 cm respectively for mean altitudes) to obtain the same spatial coverage with the differing camera fields of view (Supplementary Table 2). Each survey (n = 64) resulted in a total flight path of 2082 m. The survey times ranged from 04:25 min to 07:22 min, depending on the wind speed, with an average survey time of 04:55 min. The transect lines were planned such that the field of view (FOV) from adjacent lines (line spacing = 88 m) would overlap by about 10% to ensure complete coverage (Supplementary Figure 1). As this may introduce the possibility of "double-counting" seabird sightings within areas that have previously been covered by the UAV as it progresses along a consecutive transect line, see section 2.5 below on how overlap was accounted for during post-processing. All missions were completed in accordance with local regulations and flown by the same qualified (UK Civil Aviation Authority) pilot. To minimise the potential impact of the UAV upon species behaviour UAV flights were carried out following best practice recommendations (Hodgson and Koh, 2016). This included maintaining reasonable distance from birds during flight (UAV flights were flown at an altitude > 60 m above-surface level), using a relatively small and quiet UAV (Kuhlmann et al., 2022), ensuring that the vertical ascent of the UAV was made before travelling over the survey area and avoiding sporadic flight movements. The take-off and landing site situated on the Eastern shore of Walter's Rock is marked as Point 5 in Figure 1 (54˚23'03.8N, 005˚33'24.1"W). While the VP surveys were performed from the opposite shoreline, this location was chosen as it allowed maximum coverage of the survey area given the 500 m limit from the pilot. Finally, the UAV camera was calibrated in the laboratory using a standard checkerboard method and video sequences post-processed using MATLAB (R2017b; Mathworks).

2.4 UAV video data processing to detect/count seabirds

A custom-built Graphical Unit Interface (GUI) named *TernTagger* was built in MATLAB and was used to count seabirds on a frame-by-frame basis. For this, the video file was opened in the GUI, and individual frames were reviewed by a video observer to manually 'tag' seabirds, thereby creating a mark which generated an associated species ID and a local coordinate (accurate to ~1 m, compared to VP distribution data which had lower precision as distances were assigned to 100 m bands). Where possible, seabirds were tagged when passing the centroid of the UAV's Field of View (FOV) to reduce parallax error (Supplementary Figure 1). As it was possible to easily go between frames or speed up or slow down the video using the GUI, this facilitated accurate marking of even highly mobile individual birds. All three tern species present at the site were marked as 'terns', and other species of birds identified where possible. Sun glare (recorded on a scale of 1-3, with 1 being "None" and 3 being "Severe") was apparent in some of the surveys but did not prevent the video observer from marking moving birds, such as the terns, as they would move in and out of sun glare areas, allowing species identification. Following the tagging, video local coordinates of tagged seabirds were converted to latitude and longitude in decimal degrees with the associated timestamp using the instantaneous recorded GPS position of the UAV, its flight altitude, and the camera calibration information.

2.5 Post-processing of seabird counts accounting for transect overlap

In order to limit possible "double-counting" of seabird sightings, we accounted for line transect overlap (10%) using the following approach. Rather than simply identifying (and excluding) bird locations within the 10% overlap region between two lines, we constructed a spatiotemporal approach using the evolving area of coverage (Supplementary Figure 2). Birds were only excluded if they were located within the overlap between the current field of view (FOV) and the combined area of the previous fields of view up to an along-track distance (d) behind the centre of the current FOV (Supplementary Figure 2). This distance, d, was set to be equal to the diagonal dimension of the current FOV determined by the UAV camera and altitude (Supplementary Figure 2). This method is preferable to a fixed time delay to allow for the variable flight-speed of the UAV that is dependent upon the wind. It can be seen that the combined area of overlaps is irregular in shape at the end of each transect line, ensuring that double-counting is minimised in these regions where the UAV changes velocity.

2.6 Using the UAV to calibrate VP graduated rangefinders

Graduated rangefinders used by land-based VP observers (see section 2.2 above) at 20 m elevation were calibrated by undertaking UAV flights using the DJI Phantom 3. For these calibration flights, the UAV was flown at 10 m altitude to 7 calibration points at various distances from the land-based observers (610 m, 700 m, 800 m, 900 m, 950 m, 1000 m, 1100 m). At each point, the UAV hovered to allow land-based observers enough time to ensure graduated rangefinders were correct.

2.7 Statistical analysis

While all seabird species observed at the site were recorded, terns *Sternidae* (common terns, Arctic terns and Sandwich terns *Sterna sandvicensis*) accounted for a significant proportion of both the VP and UAV observations (0.86 and 0.83 respectively; Supplementary Table 3 and Supplementary Table 4). Therefore, all analyses herein are focused on these three tern species combined (all of which were in flight) (Supplementary Table 5 and Supplementary Table 6).

To investigate 'tidal coupling' i.e. where the abundance and distribution of seabirds varies with tidal state/the ebb-flood tidal cycle (Zamon, 2003), we calculated an average flood/ebb index for each concurrent survey conducted (taking into account the start and end time of each survey method). Flood/ebb index (hereafter referred to as tidal index) is a cyclic variable defined over each flood/ebb cycle based on tide height. Values of:

- > 0 - < 0.5 represent the ebb tidal current.
- > 0.5 - < 1 represent the flood tidal current.
- 0 and 1 represent high water slack.
- 0.5 represents low water slack.

Tidal state refers to the tidal phase, where ebb at the study site is a southeast flow and flood is a northwest flow of water.

To compare the abundance of terns detected by each survey method, the number of individuals counted within VP surveys were modelled as a function of those counted within UAV transects using a generalised linear mixed effect model (GLMM) with a Poisson distribution in the R package *lme4* (Bates et al., 2015). The response variable was the VP survey count of terns. The explanatory variable UAV count was included as a fixed effect, while survey ID and elevation of the VP were treated as random effects. To assess the absolute agreement between the number of terns counted by both survey methods within the same survey the intraclass correlation coefficient (ICC) and its associated uncertainty was calculated using a two-way random effects model based on single unit rating in the R package *irr* (Gamer et al., 2019) and the results were interpreted following the guidelines given by Koo and Li (2016).

To investigate the potential influence of detection parameters upon the abundance of terns detected by each survey method, the number of individuals counted within VP surveys and UAV transects were modelled separately as a function of explanatory variables using GLMMs with a Poisson distribution in the R package *lme4* (Bates et al., 2015). The response variable was the VP/UAV survey count of terns. The explanatory variables tidal state (included as a factor with two levels: ebb or flood), cloud cover, sea state (to account for the potential impacts of sea surface roughness on the detectability of seabirds), glare, VP observer ID, and elevation of the VP were included as fixed effects, while survey ID was treated as a random effect. The explanatory variables VP observer ID and elevation of the VP were not included within the UAV model described above as these variables relate only to the VP data. Collinearity of fixed effects was assessed by calculating variance inflation factors (VIF), ensuring each was below three, which was the case for all fixed effects apart from cloud cover within the UAV model as an interaction was found between cloud cover and glare. As a result, cloud cover was removed from this GLMM. Model selection was performed using a multi-model inference approach, based upon Akaike Information Criterion (AIC) values (Burnham and Anderson, 2002). All combinations of explanatory variables were tested in a series of 65/8 candidate models for the VP/UAV data respectively (Supplementary Table 7 and Supplementary Table 8). The model with the lowest AIC score was selected as the most parsimonious model based on the delta of the corrected Akaike's Information Criterion (ΔAICc), calculated using the dredge function in the *MuMIn* package in R (Barton, 2020). Parameter estimates and 95% confidence intervals were then presented for the most parsimonious models. If 95% confidence intervals did not overlap with zero, this supported the importance of the explanatory variable.

To compare counts of terns detected by each survey method as a function of the tidal cycle, the number of terns were modelled separately as a function of tidal index using generalised additive models (GAMs) using *glmmTMB* (Brooks et al., 2017). Poisson distributions were used as non-linear relationships were expected given the Strangford Lough Narrows has previously been shown to present a tidally predictable foraging location for surface-foraging terns (Lieber et al., 2019). Tidal index was included as a cyclical, non-linear explanatory variable and the number of knots was constricted to seven to avoid over-fitting. Differences in tern abundance across tidal index were tested for significance ($p < 0.05$) using chi-squared tests for each survey method (VP surveys were modelled separately for each observer). VP observers were modelled separately to ensure a one-to-one comparison with terns detected by UAV transects over the tidal cycle. All modelling was performed in R (version 4.0.1, R Development Core Team) using the *lme4* (Bates et al., 2015), *glmmTMB* (Brooks et al., 2017) and *MuMIn* (Barton, 2020) packages for GLMMs and the *mgcv* package for GAMs (Wood, 2017). Data collected from all VP survey elevations were included within these analyses.

To assess the similarity in tern distributions gained from the VP surveys and UAV transects, we estimated 50% and 95% utilization distributions (UDs; Fieberg and Kochanny, 2005) for terns detected by each survey method during different tidal states (ebb or flood currents). Only data collected from concurrent surveys when at least one land-based observer was positioned at higher VP survey elevations (18 and 20 m above sea level, n = 62) were used to remove any bias due to elevation. Additionally, if both VP observers were positioned at higher elevations for the same survey (n = 12), only data from the VP observer located at the highest elevation were retained to ensure a one-to-one comparison, i.e. comparing one VP observer with one UAV transect survey. Kernel density estimation was conducted using the R package *adehabitatHR* (Calenge, 2006). Kernel density estimates were evaluated on 800 m x 500 m grids using a cell size of 1 m^2 and smoothing parameters (h) were estimated using the *ad hoc* '*href*' method. The extent of overlap between the distribution of terns detected by VP surveys (UD_1) and UAV transects (UD_2) during different tidal states were estimated using the *kerneloverlap* function to give Bhattacharyya's affinity (BA), which ranges from 0 (no overlap) to 1 (complete overlap) (Bhattacharyya, 1943; Fieberg and Kochanny, 2005).

3. Results

3.1 Comparing seabird counts

There was a positive relationship between the number of terns counted within VP surveys and the number of terns counted within UAV transects (Figure 2; Table 1) (also see Supplementary Figure 3). The absolute agreement between the number of terns counted by both survey methods within the same survey was also found to be good (i.e. intraclass correlation coefficient was > 0.75; Table 2) (Koo and Li, 2016). The positive relationship between the number of terns counted within VP surveys and the number of terns counted within UAV transects was not linear, with generally higher numbers of terns detected by the UAV than the land-based observers, particularly when the number of terns detected in the survey area was greater than 20 (Figure 2). The number of terns detected within concurrent VP surveys and UAV transects were more closely matched at lower abundances (Figure 2). When considering the potential influence of explanatory variables upon the abundance of terns detected by VP surveys, the most parsimonious model selected sea state, tidal state and observer ID as having the greatest explanatory power (Table 3; Supplementary Table 7; Supplementary Figure 4). 95% confidence intervals supported the importance of each of these explanatory variables (Table 3) (apart from 'Sea State^{1,3}' which represents the comparison between sea state 1 and 3 on the Beaufort scale). There was no support for cloud cover, elevation of the VP and surface glare in explaining any variation in the number of terns counted during VP surveys. When investigating the potential influence of explanatory variables upon the abundance of terns detected by UAV surveys, the most parsimonious model selected sea state and tidal state as having the greatest explanatory power (Table 3; Supplementary Table 8; Supplementary Figure 5). 95% confidence intervals supported the importance of each of these explanatory variables (Table 3) (apart from 'Sea State[1,3]' which represents the comparison between sea state 1 and 3 on the Beaufort scale). There was no support for surface glare explaining any variation in the number of terns counted during UAV transects.

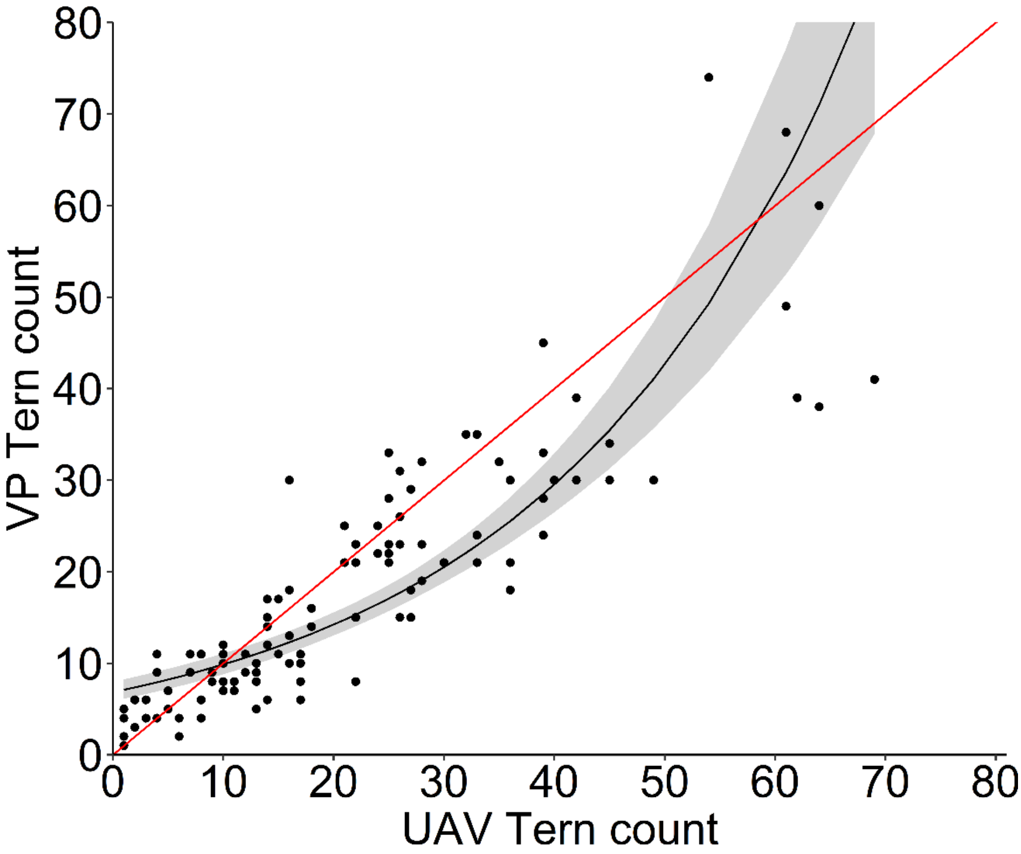

Figure 2. Generalised linear mixed effect model outputs showing a positive relationship between the number of terns counted within vantage point surveys and the number of terns counted within concurrent UAV transects (± SE). The red line represents a 1:1 linear relationship.

Table 1. Parameter estimates showing the relationship between the number of terns counted within vantage point surveys and the number of terns counted within uncrewed aerial vehicle transects with standard error and 95% confidence intervals. Effects are slope estimates from the model and important variables have 95% confidence intervals that do not overlap with zeros, shown in bold.

			95% confidence intervals	
Parameter	Effect	se	Lower	Upper
Intercept	**1.924**			
UAV tern count	**0.037**	**0.003**	**0.032**	**0.041**

Table 2. Intraclass correlation coefficient estimates with 95% confidence intervals and F test values based on a single unit rating, 2-way random effects model measuring absolute agreement in the number of terns counted within vantage point surveys and the number of terns counted within concurrent UAV transects.

		95% confidence intervals		F Test With True Value 0			
	Intraclass Correlation	Lower	Upper	Value	*df*1	*df*2	Sig
Single measures	**0.86**	0.76	0.91	14.9	37.1	110	<0.01

Table 3. Final parameter estimates showing the relationships between the number of (A) terns counted within vantage point surveys and (B) terns counted within uncrewed aerial vehicle transects and supported explanatory variables with standard error and 95% confidence intervals. Effects are slope estimates from the most parsimonious models (Supplementary Table 7 and Supplementary Table 8 respectively). Important variables have 95% confidence intervals that do not overlap with zeros, shown in bold.

			95% confidence intervals	
Parameter	Effect	se	Lower	Upper
(A) Vantage Point				
Intercept	**2.453**			
Observer	**0.176**	**0.049**	**0.080**	**0.273**
Tidal State Flood	**0.554**	**0.158**	**0.245**	**0.864**
Sea State^{1,2}	**-1.557**	**0.339**	**-2.221**	**-0.893**
Sea State^{1,3}	0.061	0.208	-0.347	0.468
(B) UAV				
Intercept	**2.505**			
Tidal State Flood	**0.453**	**0.185**	**0.0895**	**0.816**
Sea State^{1,2}	**-1.833**	**0.404**	**-2.625**	**-1.042**
Sea State^{1,3}	-0.220	0.248	-0.706	0.265

Sea State^{1,2} represents the comparison of two sea state levels: 1 and 2 on the Beaufort scale.
Sea State^{1,3} represents the comparison of two sea state levels: 1 and 3 on the Beaufort scale.

3.2 Comparing ecological relationships

Significant variation was observed in the number of terns across the tidal index (ebb-flood cycle) for each survey method (Table 4; Figure 3). A similar pattern in tern numbers across tidal index was observed from the VP surveys and UAV transects, with the highest number of terns observed during flood tides (Figure 3; Supplementary Figure 6).

Table 4. General-additive model (GAM) outputs of the number of terns recorded across the tidal index from vantage point surveys and UAV transect surveys. Vantage point survey counts are modelled separately for each observer; VP1 = Observer 1 and VP2 = Observer 2. Differences in tern counts across tidal index were tested for significance ($p < 0.05$) using chi-squared tests (χ^2) for each survey method. Estimates, standard errors (Std. error), z-values (z), estimated degrees of freedom (EDF), p-values, adjusted R-squared and the deviance explained are also shown.

Number of terns recorded across tidal index from:	Estimate	Std. error	z	EDF	χ^2	p-values	R^2 (adj.)	Deviance explained (%)
UAV transect surveys	2.975	0.031	94.81	5.891	369.9	< 0.01	0.539	61.5
VP surveys, **VP1**.	2.776	0.034	81.64	5.844	216.3	< 0.01	0.377	51.4
VP surveys, **VP2**.	2.765	0.039	70.09	5.958	307.8	< 0.01	0.66	72.8

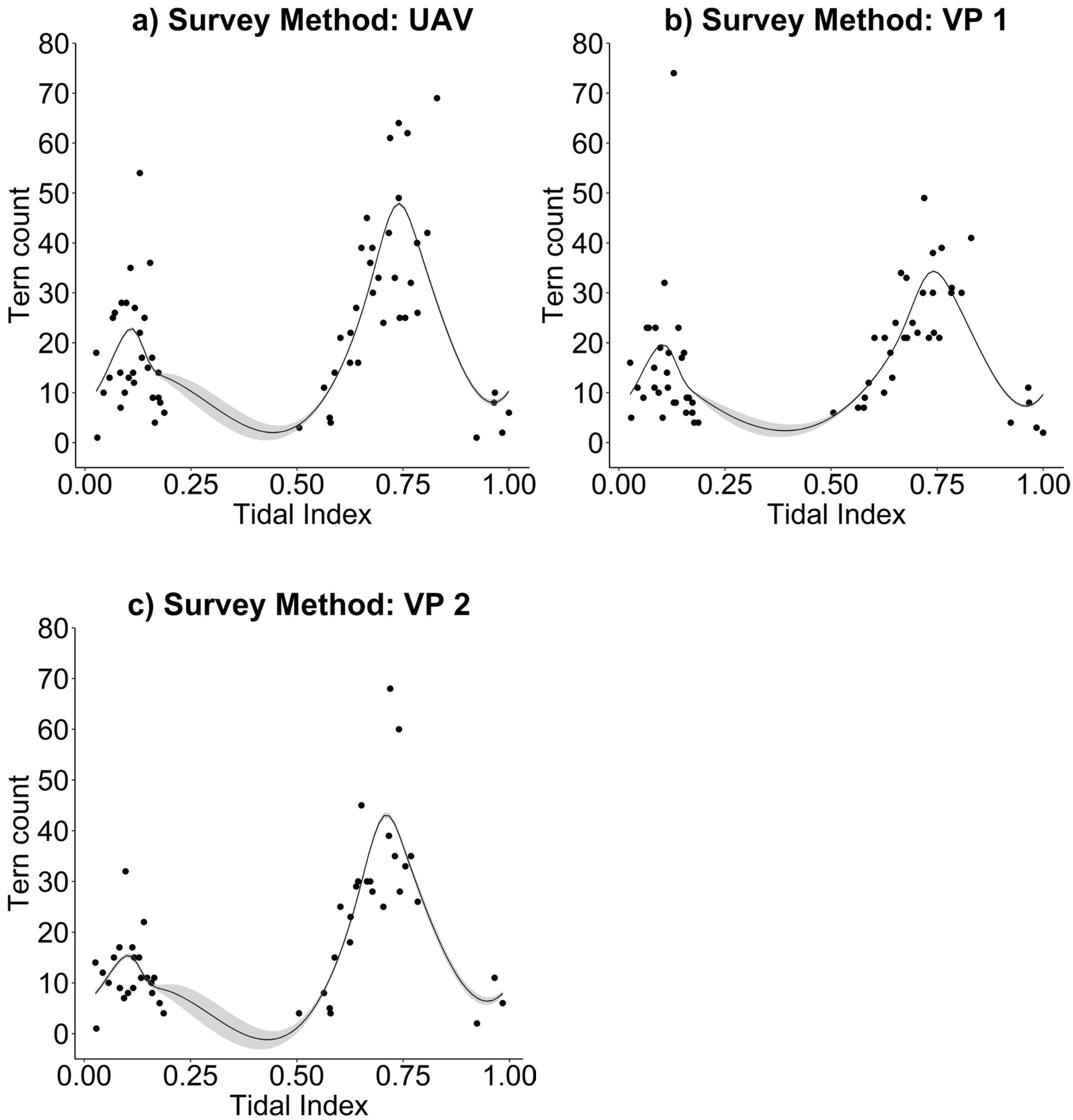

Figure 3. Response curves (± SE) from generalised additive models (GAMs) showing predicted tern counts detected by each survey method with raw data overlaid **a)** UAV transects (n = 64), **b)** VP 1/Observer 1 (n = 63), and **c)** VP 2/Observer 2 (n = 48) as a function of tidal index (0/1 = High water slack, 0.5 = Low water slack).

3.3 Comparing the distribution of terns

The distribution of terns detected within VP surveys and UAV transects indicated that the highest tern density occurred within the near-shore shallows during the ebb tide (Figure 4c) and extended into the main channel during the flood tide (Figure 4b). However, tern distributions recorded by UAV transects showed more of a difference between the ebb and flood tide (Figure 4; Supplementary Figure 7 and 8). The overlap between VP survey and UAV transect 50% UDs was lower than 95% UDs (BA, Table 5). Overlap indices also indicated better concordance between the 95% distribution estimates made for all data and 95% distribution estimates made during the flood tide compared to 95% distribution estimates made during the ebb tide (Table 5). The overall similarity between 95% UDs during the ebb tide (BA = 0.69) were moderate, while 95% UDs made during the flood tide (BA = 0.83) indicated a high overall similarity (BA > 0.8).

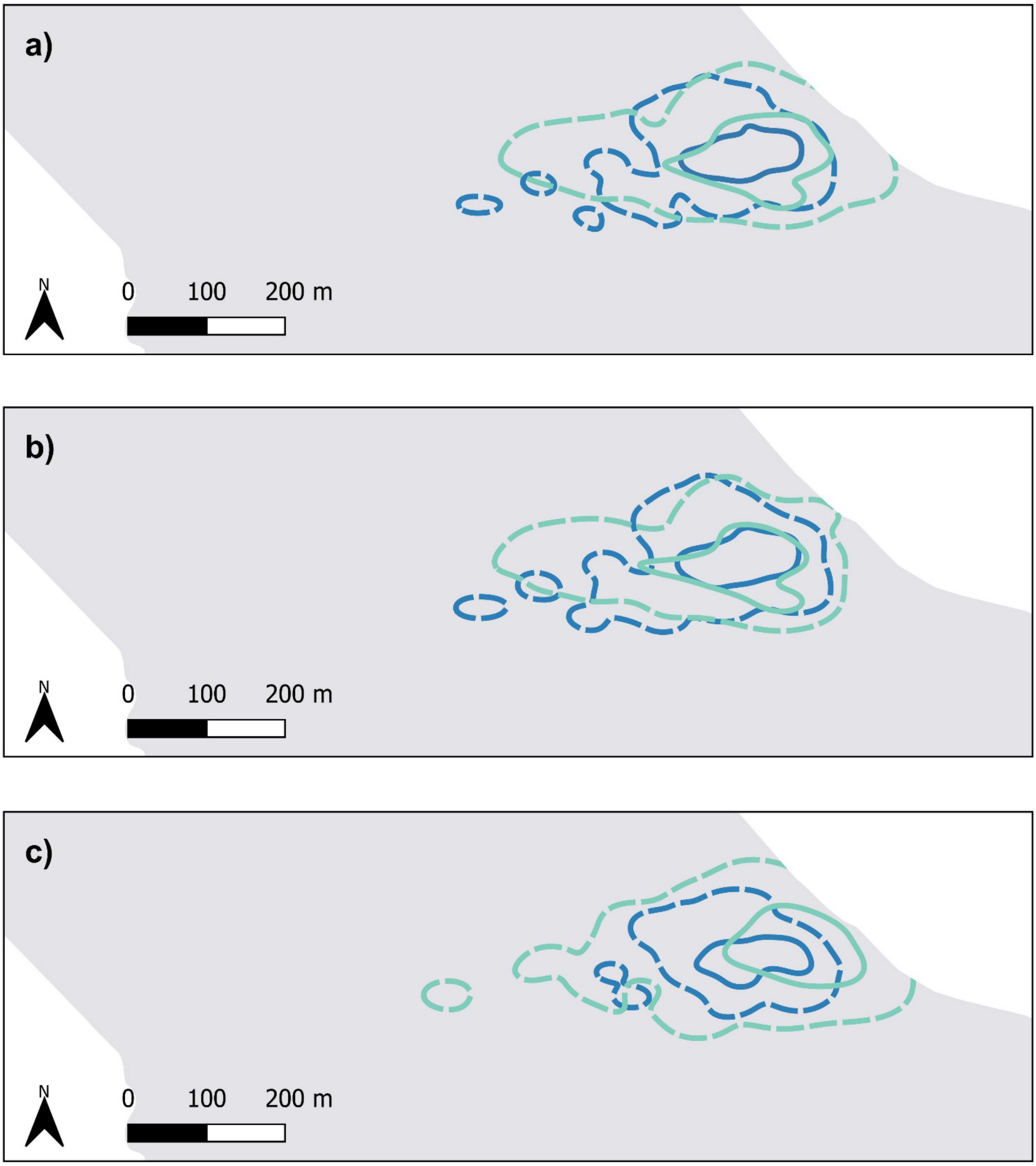

Figure 4. Utilization distributions (UDs) of terns detected within concurrent vantage point surveys (blue) and UAV transects (light blue) at 95% (dotted lines) and 50% (solid lines) carried out when vantage point observers were at high elevations (18 and 20m above sea level, n = 62). **a)** tern distributions detected within all surveys, **b)** tern distributions detected during the flood tide and, **c)** tern distributions detected during the ebb tide.

Table 5. Estimated overlap (Bhattacharyya's affinity, BA) between tern utilization distributions (UDs) estimated using data from concurrent vantage point surveys (UD_1) and UAV transects (UD_2), for data collected from concurrent surveys when at least one land-based observer was positioned at higher VP survey elevations (18 and 20 m above sea level) and for flood and ebb tides. For each UD, we give kernel smoothing parameters (*h*) estimated using the *ad hoc* 'href' method.

UD(%)	UD_1	UD_2	BA	*h*
50	VP, terns	UAV, terns	0.38	19.44 ^{UD1}, 24.93 ^{UD2}
	VP, terns, Flood	UAV, terns, Flood	0.42	21.74 ^{UD1}, 24.81 ^{UD2}
	VP, terns, Ebb	UAV, terns, Ebb	0.22	19.82 ^{UD1}, 29.20 ^{UD2}
95	VP, terns	UAV, terns	0.79	19.44 ^{UD1}, 24.93 ^{UD2}
	VP, terns, Flood	UAV, terns, Flood	0.83	21.74 ^{UD1}, 24.81 ^{UD2}
	VP, terns, Ebb	UAV, terns, Ebb	0.69	19.82 ^{UD1}, 29.20 ^{UD2}

4. Discussion

This study takes a crucial first step towards evaluating the effectiveness of UAVs for use in EIAs. We analysed concurrent VP surveys and UAV transects to quantitatively compare at-sea abundance and distribution of surface-foraging seabirds in flight within a tidal stream environment. By comparing these two survey approaches, we found that both yielded comparable counts of seabirds at the site of interest, while fine-scale distributions differed. The UAV offered a better perspective of seabird habitat use in relation to visible surface-flow features and could therefore be regarded as beneficial to assess seabird-environment interactions during EIAs. Within this study no behavioural disturbance (such as evasive flying/diving behaviours away from the UAV or alarm calling) was recorded by land-based observers. Therefore, it is not thought that the abundances/distributions reported were affected by the presence of the UAV.

4.1 Comparing seabird counts

Our results show that both VP surveys and UAV transects perform similarly when recording counts of surface-foraging terns. A positive relationship was found between the number of terns counted within VP surveys and the number of terns counted within UAV transects. However, generally higher numbers of terns were detected by the UAV, particularly when the number of terns present within the survey area was higher; this means the number of terns detected by both survey methods were more closely matched at lower abundances (< 20 birds). This difference could be driven by potential "double-counting" of seabirds within UAV transects due overlap between UAV parallel transect lines and seabird movement across transect lines (see point 1 below). However, it is also likely that the difference in numbers counted at higher abundances (20-70 birds) was due to the flux of birds entering the survey area at once. This may suggest that particular attention should be paid to ensure appropriate training measures are in place for VP observers to ensure accurate counts of birds where abundance may be high, or birds are in flocks (see points 3 and 4 below) whilst at the same time recording distance and bearing information. Previous studies comparing counts of ground nesting seabirds also indicate that observers in the field typically record lower counts than those from UAV surveys (Hodgson et al., 2016). This difference is usually due to ground nesting birds being obscured due to the oblique angle of observers; the oblique angle of land-based observers could also explain the difference in counts seen within our study (see point 3 below). However, there is also evidence indicating the converse is possible in ground nesting birds (i.e. where counts of ground nesting birds made by observers in the field are higher than those from UAV surveys) (Chabot et al., 2015). As we do not know the true number of birds within the survey area during each survey, given the differences in the number of birds counted by both methods at higher tern abundances, it is not possible based on this single study to determine which survey method may be more reliable. Therefore, we outline below many potential reasons for the differences between VP and UAV counts of surface foraging terns within this study in the hope that these will aid the selection of survey techniques for EIAs and provide a better understanding of the application of UAVs for use in EIAs.

1. “ Over- and -undercounting”. In environments where individuals are targeting a feature and are therefore not moving at random, it is possible that individuals may be counted more than once within UAV transects due to the overlap in the field of view between UAV parallel transect lines. Conversely, mobile individuals which move out from the area covered by the UAV may be missed and not be counted. Although we implemented a spatiotemporal approach to account for the potential “double-counting” of seabirds within UAV transects (overall 337 sightings were removed within the 10% overlap of transects) this approach did not account for seabird movement (for example, terns actively foraging within the survey area) and how this may introduce duplicates into the UAV data. It is important to note that the level of overlap / decision to include overlap between parallel transect lines should be based upon the scale of surveys and required spatial coverage (within this study overlap between UAV transect lines was deemed necessary to ensure complete coverage of the survey area).
2. False positives and perception bias. It is possible that UAV counts were generally higher than VP survey counts due to potential false positives. It is also important to note that only one reviewer manually assessed the UAV video, therefore we did not quantify this possible perception bias. Although not the case in this study, it is important to note when counting birds from digital imagery that the birds may be difficult to distinguish from the whitecaps created by hydrodynamic features present within dynamic nearshore environments, resulting in false positives (Edney and Wood, 2021; Thaxter and Burton, 2009).
3. ‘Viewshed’. The difference in the counts of terns recorded by VP surveys and UAV transects could be due to the difference in perspective of the survey area (i.e. UAVs give a ‘bird’s eye view’ of the survey area while land-based observers view the survey area at an oblique angle). As terns were often aggregated in high numbers within the survey area, birds may have occluded one another, resulting in terns being missed by land-based observers.

4. VP scan protocol. Traditionally VP surveys consist of systematic scans of the survey area carried out by observers with the aim of recording all birds within the scanned area, within a snapshot in time. However, as terns were often aggregated in high numbers in this study, VP observers may have missed terns flying through/transiting through the area when focused on counting or calculating the bearing and distance of seabirds. This would not have been the case for the UAV.

We also investigated the potential influence of detection parameters upon the abundance of terns detected by each survey method. Parameter estimates showing the relationship between the number of terns counted within VP surveys and explanatory variables highlighted the particular importance of VP observer, sea state, and tidal state on the number of terns predicted by the model. The importance of VP observer could be expected as VP observers did not follow the UAV or each other when scanning the survey area, meaning observers may be focused on different areas at different times. Similar differences in the number of birds counted by observers have previously been found (Spear et al., 2004; Van Der Meer and Camphuysen, 1996) and the importance of including the identity of each observer within modelling of observation data to account for variation between individuals has previously been highlighted (Robbins, 2017). Therefore, EIAs may also benefit from trial VP surveys as common practice, such surveys should be undertaken by multiple observers at the same time and elevation to ensure that counts are comparable before fieldwork commences.

Parameter estimates showing the relationship between the number of terns counted within UAV transects and explanatory variables highlighted the particular importance of sea state and tidal state on the number of terns predicted by the model. As this was also the case for the VP surveys it is important to understand how these variables may influence the count of terns by both survey methods. Sea state is usually an important parameter influencing the ability of land-based observers to detect birds on the water (Waggitt et al., 2014). However, due to the 'bird's eye view' of UAV transects it is possible that that some species/individuals may be difficult to distinguish from the whitecaps created by hydrodynamic features present within high-energy environments (as mentioned in point 2 above). A higher number of terns were recorded at lower sea-states for both methods; however, it is important to acknowledge the small sample sizes associated with sea state (Supplementary Figure 4 and Supplementary Figure 5). The influence of tidal state upon the number of terns counted by both survey methods is less intuitive as tidal state itself is not known to influence the ability of either survey method to detect birds. Therefore, it is likely that the importance of tidal state on the counts of terns by both VP surveys and UAV transects is due to its influence on the number of terns using the site over the ebb-flood tidal cycle (changes in tern abundance and distribution with the ebb-flood cycle are discussed in sections 4.2 and 4.3 below). Yet, as certain tidal states have been found to correlate with high numbers of terns (i.e. during the flood tide) it is possible that this increase in individuals resulted in biases in the number of terns counted by both survey methods as previously discussed. Although sea surface glare has the potential to impact counts of seabirds carried out by both VPs and UAVs, glare was not highlighted as an important variable when explaining the number of terns counted by either of these survey methods in this study. Within our study, glare was present within 4.7% of VP surveys (covering a small portion of the survey area), while a larger percentage of the UAV transects were influenced by glare (53%). However, when looking at the UAV video, UAV frames always contained an area free from glare. The glare was limited to one corner of the frame, such that birds could be reliably identified with the human eye as they moved between areas of glare and areas unaffected by glare.

4.2 Comparing ecological relationships

Comparison of counts recorded by VP surveys and UAV transects showed a similar pattern in the number of terns recorded across the ebb-flood tidal cycle (tidal index), with the highest number of terns observed during the flood tide. This is an important comparison in terms of assessing the effectiveness of UAVs for use in EIAs as it indicates that although the number of terns recorded often differed by survey method, the same ecological relationships were detected when investigating site use of terns. Previous studies carried out within the Strangford Lough tidal channel also recorded the highest number of surface-foraging terns during the flood tide (Lieber et al., 2019).

4.3 Comparing the distribution of terns

Finally, we assessed the similarity of tern distributions detected by VP surveys and UAV. The distribution of terns detected, particularly by UAV transects indicated that the highest tern density occurred within the near-shore shallows during the ebb tide and extended into the main channel during the flood tide. This change in foraging location by terns is consistent with the change in discrete hydrodynamic features present within the survey area in relation to the tidal cycle. There are shallow upwelling regions generated by Walter's Rock during the ebbing tide and pronounced shear lines extending towards the mid-channel generated during peak tidal flows, a pattern previously found by Lieber et al. (2019). The differences found here in distributions estimated from the VP surveys and UAV are likely to be due to differences in the accuracy of seabird locations obtained by both survey methods. VP surveys within this study mapped the location of seabirds according to distances estimated from land-based observers using graduated rangefinders; this introduces error as birds are effectively assigned to distance bands (Supplementary Figure 8; Borchers et al., 2010). Another potential reason for this difference in distribution (particularly the difference seen in Figure 4c) is that increasing distance is likely to influence the ability of land-based observers to correctly assign an individual or group of birds into distance bands. As a result, VP surveys may benefit from the use of UAV transect surveys as an additional survey tool to identify fine-scale distributions of seabirds. The use of a laser rangefinder such as a Vector Ornithodolite also has the potential to increase the precision of seabird positions obtained from VP surveys (Largey et al., 2021); however, this method requires validation for use in tidal stream environments (Cole et al., 2019).

4.4 General UAV performance and applicability

While VP surveys and UAV transects were found to produce similar counts of surface-foraging seabirds in flight, future EIAs of tidal stream developments may benefit from the use of UAV transects carried out alongside traditional VP surveys to accurately identify the fine-scale distributions of seabirds or to assess seabird interactions with the environment and/or renewable energy structures. Fine-scale spatial information is crucial for assessing the potential for interactions between seabirds and developments (for example, precise spatial information of seabirds is required to assess collision risk with tidal stream turbine developments; Isaksson et al., 2020). Not only this but the increased accuracy of spatial data recorded within UAV transects also allows seabird distribution to be directly linked to fine-scale hydrodynamic features. This is of particular importance as seabirds may target specific hydrodynamic features associated with tidal stream turbines, which in turn has the potential to increase the risk of underwater collision with moving parts of tidal stream turbines. UAVs also have mission repeatability and produce a permanent record of the imagery collected, allowing data to be referred back to in future.

Despite these potential benefits, the application of UAVs for use in EIAs will not be without challenges. It is important to consider conditions which may prevent the collection of useful UAV-derived data, such as, strong winds, precipitation, and high sun angles. High sun angles may introduce sun glint into the UAV imagery, particularly during the middle part of the day, making targets of interest hard to identify. It is also important to consider the costs associated with using UAVs, such as the initial cost of the UAV (including additional batteries and upgraded camera if required), the cost of a UAV pilot and the costs associated with the subsequent time spent identifying and counting birds from the UAV imagery (within this study the time taken to process UAV imagery was approximately 10 hours and 40 minutes). However, the additional costs associated with the use of UAV surveys alongside traditional VP surveys may be justified where more detailed data on seabird distributions/fine scale habitat use are required. Another important consideration when assessing UAVs as an effective tool for the impact assessment of tidal stream developments is the size of the area of interest as UAVs are limited by battery time and the obligation to maintain direct unaided visual contact with the UAV, known as visual line of sight (VLOS; up to 500 m horizontally from the remote pilot). However, it is possible to seek permission of the CAA to extent or go beyond this range.

The last consideration that should be taken into account when evaluating UAVs as an effective tool for EIAs carried out within nearshore tidal stream environments are the types of data that can be collected. UAVs are not able to record seabird behavioural data within transect surveys; instead, the collection of behavioural data would require separate ‘focal follows’ / UAV hovers (Lieber et al., 2021). This is an important consideration when choosing appropriate survey techniques for impact assessments within tidal stream environments as the collection of behavioural information (diving behaviour specifically) is crucial for the assessment of collision risk with underwater turbines. Lastly, it is crucial to recognise that survey techniques and technology used must be chosen based on the seabird species or family of interest as VP survey are able to carry out species identification to a higher degree of accuracy. Within this study, the UAV flight height and integrated camera used for data collection in this study did not allow for the reliable identification of birds on the water surface (i.e. auks *Alcidae*). Therefore, UAV flight height would have to be lowered in order to give the desired pixel resolution for all birds on the water surface to be identified. However, flying the UAV at lower altitudes may cause disturbance and affect species’ behaviour (e.g. flights and alarm calling) (Brisson-Curadeau et al., 2017; Rush et al., 2018). Alternatively, using a UAV with a higher resolution camera would also increase the opportunity to identify birds on the water surface.

5. Conclusion

As marine renewable energy developments continue to become more widespread, it is increasingly important to understand the potential role emerging technologies/platforms may play in environmental impact assessments or improving understanding of how seabirds may interact with installed renewable installations. Uncrewed aerial vehicles are increasingly being used in ecological studies and although there is a growing body of research assessing the efficiency of UAV-based methods, there is a disconnect between research and the use of UAV-derived data for ecological management and monitoring. This in part is due to a lack of clear guidelines on how to plan and successfully execute UAV flights, but also due to a lack of knowledge as to the capability of this emerging platform to provide data comparable to traditional land-based methods. This is also due to a lack of understanding within some research communities about the EIA process and types of information that may be required.

To our knowledge, this study provides the first comparison of at-sea abundance and distribution of seabirds within a tidal stream environment collected from concurrent VP and UAV surveys. Therefore, this study takes a crucial first step towards understanding the effectiveness of UAVs compared to traditional VP surveys for its use in EIAs within dynamic nearshore tidal stream environments. This study suggests that it is methodologically and logistically feasible to assess seabird abundance and distribution within nearshore areas using off-the-shelf UAVs (e.g. DJI consumer models). However, the selection of specific survey techniques should firstly be based upon the specific needs of a monitoring task and questions to be addressed. For example, when delivering broad site characterisation, VP surveys or boat/aircraft line transects may be appropriate due to the limited area UAVs are able to cover (due to battery time) and the ability of VP surveys to more easily identify individuals to species-level. However, if the questions of interest are to understand fine-scale habitat associations, particularly at operating devices then UAVs may be more appropriate due to greater spatial resolution of data and ability to gather data across multiple conditions, seasons, times of day without costs/resources becoming prohibitive. Lastly, it is important to recognise that survey techniques should be chosen based on the target species and its behaviour, the area of importance, survey length, project budget, and the surrounding conditions of the proposed anthropogenic development. With the above considerations in mind, we suggest, in agreement with Callaghan et al. (2018) and Lyons et al. (2019), that UAVs represent a useful complementary tool, rather than an alternative approach to traditional land-based surveys for use is EIAs.

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