FINE-SCALE CHANGE DETECTION USING UNMANNED AIRCRAFT SYSTEMS (UAS) TO INFORM REPRODUCTIVE BIOLOGY IN NESTING WATERBIRDS

By

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ABSTRACT

FINE-SCALE CHANGE DETECTION USING UNMANNED AIRCRAFT SYSTEMS (UAS)
TO INFORM REPRODUCTIVE BIOLOGY IN NESTING WATERBIRDS

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Aerial photographic surveys from manned aircraft are commonly used to estimate the size of bird breeding colonies but are rarely used to evaluate reproductive success. Recent technological advances have spurred interest in the use of unmanned aircraft systems (UAS) for monitoring wildlife. The ability to repeatedly sample and collect imagery at fine-scale spatial and temporal resolutions while minimizing disturbance and safety risks make UAS particularly appealing for monitoring colonial nesting waterbirds. In addition, advances in photogrammetric and GIS software have allowed for more streamlined data processing and analysis. Using UAS imagery collected at Anaho Island National Wildlife Refuge during the peak of the nesting bird season, I evaluated the utility of UAS for monitoring and informing the reproductive biology of breeding American white pelicans (*Pelecanus erythrorhynchos*). By using a multitemporal nearest neighbor analysis for fine-scale change detection, I developed a novel, automated method to differentiate nesting from non-nesting individuals. All UAS images collected were of sufficient pixel resolution to differentiate adult pelicans from chicks, surrounding landscape features, and other species nesting on the island. No visual signs of disturbance due to the UAS were recorded. Pelican counts derived from UAS imagery were significantly higher than counts made from the ground at observation stations on the island. Analysis of multitemporal images provided more accurate classifications of nesting birds than did monotemporal images, on the condition that multitemporal images aligned with less than 0.5 m error. Nest classifications using multitemporal imagery were not significantly different when conducted across a 24 hour period compared to a 2 hour period. This technology shows promise for greatly enhancing the quality of colony monitoring data for large colonies and a species that is highly sensitive to disturbance.

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INTRODUCTION

Wildlife managers often rely on data collected visually by observers on the ground or in low-flying aircraft to estimate distribution and abundance of target species. In many cases, aerial surveys are the only viable option for collecting data over large areas or challenging terrain where methods such as ground counting take too much time and effort. Aerial remote sensing technology has been traditionally used for mapping static landscape features, but wildlife biologists have been experimenting with aerial photography for wildlife surveys since at least the first half of the 20th century (Salmon and Lockley 1933, Leedy 1948). Remotely sensed imagery as a source of population estimates provides a permanent record, allowing for repeated analysis by multiple investigators or application of different methods (Terletzky et al. 2012).

Aerial photography captured using fixed-wing aircraft or helicopters is commonly used for monitoring colonial nesting birds and marine mammal haul-outs (Anderson et al. 2004, Capitolo et al. 2011, Weigand et al. 2012). Photographic counts of bird colonies have been found to be significantly more accurate than real-time observer estimates (Frederick et al. 2003) and are recommended for some species (Pacific Flyway Council 2013*a*). Continuous, unsupervised photography that produces images for both detection and enumeration of individuals has only recently begun to be used in mammal and bird surveys (Heide-Jorgensen 2004, Martin et al. 2012, Sardà-Palomera et al. 2012, Vermeulen et al. 2013, Chabot et al. 2015, Hodgson et al. 2016). While the use of aerial photography reduces observer bias and improves accuracy, safety concerns, logistical challenges, cost and disturbance remain significant challenges. In particular, the costs associated with manned flights often prohibit short-term repeated sampling. Similarly, conducting counts of wildlife from satellite imagery is typically limited by high costs and relatively low spatial and temporal resolutions (Loarie et al. 2007, Linchant et al. 2015)

Unmanned aircraft systems (UAS), commonly referred to as “drones,” are gaining attention for their potential utility in multiple areas, including natural resource management. “Unmanned” systems have been used for decades for remote sensing. Kites, balloons, and even pigeons have been used for military missions and photography for over a century, with many missions predating manned flights (Watts et al. 2012). The design and development of modern unmanned aircraft has been driven primarily for military applications, with a focus on missions deemed too dull, dirty, or dangerous for a human to be present in the aircraft (Marshall et al. 2016). Wildlife surveys commonly utilize manned flights flown under visual flight rules (VFR) and at low-altitude (e.g., 200 ft. Above Ground Level [AGL]), making them inherently hazardous to pilots and observers. For example, 91 job-related deaths of wildlife biologists were documented from 1937 to 2000 in the United States, with 39 aviation accidents accounting for 66% of deaths (Sasse 2003). Where applicable, UAS have the potential to greatly reduce safety risks associated with aerial wildlife surveys as well as reduce the risk of disturbance to study species (Chabot and Bird 2015).

UAS consist of a flight platform, sensor payload, and ground control station. UAS platforms range greatly in size and overall design. UAS platforms may be large like the

NASA Ikhana platform (a modified Predator B with a 66 ft. wing span) or tiny enough to fit into the palm of your hand like the Prox Dynamics Black Hornet nano UAS. The Federal Aviation Administration (FAA) currently classifies any unmanned aircraft weighing less than 55 lbs. as small UAS, or sUAS. Due to their relative affordability, transportability, and size, sUAS are commonly being used for natural resource missions. sUAS platforms are generally classified as either VTOLs or fixed-wing aircraft. VTOL UAS may have a single or multiple rotors, or in some cases ducted fans, that allow them to hover and be launched without the need for a runway. Fixed-wing UAS are generally capable of flying relatively faster and for longer periods of time than VTOLs. Depending on the size of the platform, they may be hand-launched or require a runway for takeoff and landing.

Until recently, sensors and instruments necessary for many natural resource applications have been too large or expensive for UAS missions. Technological advancements over the past decade have not only improved the design of smaller, safer platforms but also the size and cost of sensors. This miniaturization has greatly increased the potential for various natural resource purposes by reducing costs, risks, and increasing image resolution. A review of literature related to aerial photographic wildlife surveys shows that although there have been relatively few, albeit an increasing number, of UAS studies targeting wildlife to date, there are numerous applications where UAS may someday replace surveys conducted with manned aircraft (Table 1).

Table 1. Review of studies using aerial photography to census wildlife

Survey Platform	Species Targets	Authors
UAS	Waterfowl/Waterbirds	Abd-Elrahman et al. 2005, Chabot and Bird 2012, Sardà-Palomera et al. 2012, Chabot et al. 2015, Dulava et al. 2015, Hodgson et al. 2016
	Terrestrial Vertebrates (Birds, Marine Mammals, Reptiles)	Pierce et al. 2006, Martin 2012, Bureau of Ocean and Energy Management 2013
	Marine Mammals	Hodgson et al. 2013, Maire et al. 2013
	Large Mammals	Vermeulen et al. 2013, Goebel et al. 2015
Kite	Seabirds	Fraser et al. 1999
Manned Aircraft	Waterfowl/Waterbirds, Marine Mammals	Heyland 1972
	Waterfowl/Waterbirds	Salmon and Lockley 1933, Provan 1942, Chattin 1952, Grzimek and Grzimek 1960, Bartholomew and Pennycuick 1973, Ferguson and Kuck 1979, Sidle and Ferguson 1982, Haramis and Goldsberry 1985, Benning and Johnson 1985, Gilmer et al. 1988, Bajzak and Piatt 1990, Anthony and Anderson 1995, Dolbeer et al. 1997, Wilson 2011, Neill et al. 2012, Buckland et al. 2012, Bako et al. 2014
	Small Mammals	Doiron and Wilson 1974, Driscoll and Watson 1974, Tietjen et al. 1978
	Seabirds	Kadlec and Drury 1968, Harris and Lloyd 1977, Trathan 2004, Capitolo et al. 2011, Groom et al. 2013
	Marine Mammals	Mathisen and Lopp 1963, Dohl 1975, Braham et al. 1977, Scott and Winn 1978, Hiby et al. 1988, Lowry et al. 1996, Westlake et al. 1997, Udevitz et al. 2008, Schweder et al. 2010, Koski and Thomas 2013
	Large Mammals	Watson and Turner 1965, Huddleston and Roberts 1968, Sinclair 1969, 1972, D.F. Perkins 1971, Croze 1972, Pegau and Hemming 1972, Eltringham and Woodford 1973, Griffiths 1973, Lavigne and Øritsland 1974, Bente and Roeneau 1978, Valkenburg et al. 1985
	Fish	Eicher 1953, Visser et al. 2002

Regardless of how they are obtained, processing and obtaining data from imagery can be time consuming (Linchant et al. 2015). If processing time is high and a high level of geospatial experience is required to regularly process data, the tradeoff of collecting cheaper and less reliable data may appear to be a more feasible option. To counteract this, the design of a cost-effective, efficient approach for data collection, analysis, and management is necessary. Several attempts have been made to develop automated counting methods for wildlife (Bajzak and Piatt 1990, Laliberte and Ripple 2003, Trathan 2004, Descamps et al. 2011, Normandeau Associates Inc. 2012, Groom et al. 2013, Maire et al. 2013, Conn et al. 2014, Lhoest et al. 2015), but few examples exist for developing automated methods for assessing additional population measures such as reproductive success.

For colonial waterbirds, counts of adults at nesting colonies may not provide managers with a meaningful index of population trends. Measures of productivity are more commonly used to assess trends in overall population health and as indicators for the health of the surrounding aquatic ecosystem. Measuring reproductive success is often difficult in colonial nesting species because of the frequent inability to mark adults, conduct daily monitoring, and track juveniles from hatching until fledging (Erwin and Custer 2013). In addition, frequent in-colony searches cause disturbance and can increase mortality (Boellstorff et al. 1988, Nisbet et al. 1990). When intensive nest searches and frequent monitoring are not feasible, annual fledging success, defined as the number of fledglings divided by the number of active nests in a given year, is a commonly used metric of reproductive success (Wiens and Reynolds 2005).

Snapshots in time may offer estimates of total adults present, but in order to estimate the number of active nests, adults sitting on nests must be differentiated from non-nesting birds (e.g., courting birds, loafing birds, attending mates, and fledglings). In addition to numerical estimates, spatial data for active nest locations may be useful for monitoring nests throughout the nesting season. The advent of UAS technology, with its ability to collect imagery more frequently than manned aircraft and satellite imagery, provides a novel approach to estimating active nests by detecting birds that are stationary through time. Sardà-Palomera et al. (2012) utilized multiple sequential UAS flights and this technique to manually track nests of black-headed gulls. While using fine-scale change detection may provide highly accurate nest estimates, data processing times may be prohibitive if such efforts are conducted manually, particularly for large colonies of nesting birds. This highlights the need to develop automated methods not only for feature extraction but for change detection to detect movement and thus differentiate active nests from non-nesting birds.

Anaho Island National Wildlife Refuge’s recently released Natural Resource Management Plan identified monitoring reproductive success of the island’s breeding American white pelicans as a need for management (Hoffman et al. 2015). I partnered with the U.S. Fish and Wildlife Service (USFWS) and U.S. Geological Survey (USGS) to conduct proof-of-concept UAS flights for monitoring nesting American white pelicans at

Anaho Island National Wildlife Refuge. I tested available UAS and GIS technology for collecting spatial data of pelicans present on Anaho Island and developed a novel automated approach for classifying actively nesting birds in monotemporal and multitemporal imagery.

The goals for this study were to 1) assess the utility of UAS for monitoring nesting American white pelicans and 2) develop an analytic framework for distinguishing sedentary, nesting birds from loafing adults using fine-scale change detection (Figure 1). I addressed three primary questions to inform these goals: 1) How do UAS-derived pelican counts compare to refuge protocol ground counts? 2) Is change detection using multitemporal images more accurate for distinguishing nesting from non-nesting birds than a single (monotemporal) image? 3) What is the appropriate length of time between flights to maximize accuracy of the multitemporal approach?

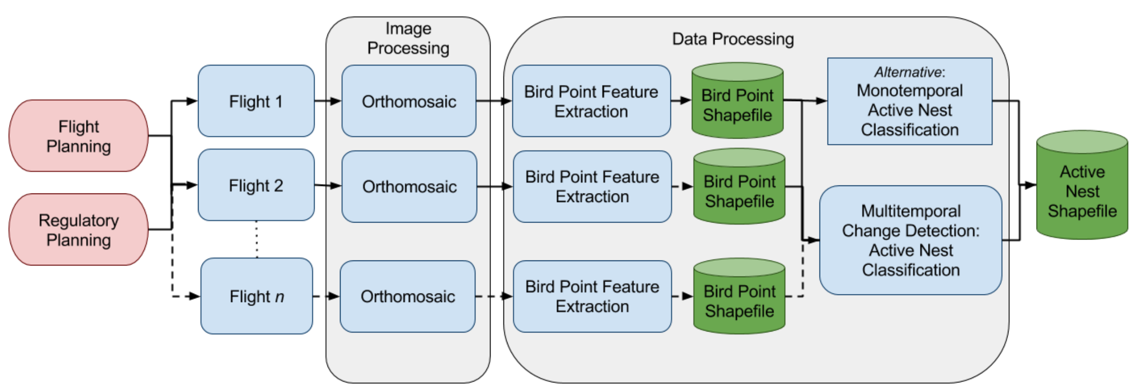

Figure 1. Workflow summarizing steps to obtain active nest spatial data from UAS survey

MATERIALS AND METHODS

Study Site and Species

Anaho Island National Wildlife Refuge (NWR) (39°57'08.1"N 119°30'49.1"W), a rocky, tufa-covered island located on Pyramid Lake in Washoe County, Nevada, is managed by the USFWS under an agreement with the Pyramid Lake Paiute Tribe (**Error! Reference source not found.**). It hosts the second largest breeding colony of American white pelicans *(Pelecanus erythrorhynchos*) in the western United States (Pacific Flyway Council 2013*a*). It is also a regular breeding ground for double-crested cormorants (*Phalacrocorax auritus*), California gulls (*Larus californicus*), Caspian terns (*Hydroprogne caspia*), and great blue herons (*Ardea herodias*) (U.S. Fish and Wildlife Service 2002). The Refuge's Comprehensive Conservation Plan and Natural Resource Management Plan designate monitoring of colonial nesting waterbirds as a priority activity (U.S. Fish and Wildlife Service 2002, Hoffman et al. 2015). USFWS biologists currently monitor colonial nesting waterbirds at Anaho Island by conducting ground surveys on and off the island. Sensitivity to human disturbance, particularly for breeding pelicans, restricts survey locations (D. Withers, personal communication). Aerial photography taken from aircraft is the recommended method for counting American white pelican and double-crested cormorant breeding colonies and is the current method used to assess breeding population numbers for the majority of active colonies within the Western Population (Pacific Flyway Council 2013*a*, *b*). This strategy is defined in the Anaho Island Inventory and Monitoring plan with a goal of pilot implementation by the end of 2015 (Hoffman et al. 2015). In addition to contributing adult numbers to national monitoring efforts, the Refuge is interested in collecting data on reproductive success that could be used to trigger management or research should levels fall below a set threshold (Hoffman et al. 2015). UAS would allow Anaho Island staff to transition to a more standardized waterbird monitoring approach while potentially saving money (compared to manned flights), decreasing safety risks, and minimizing disturbance.

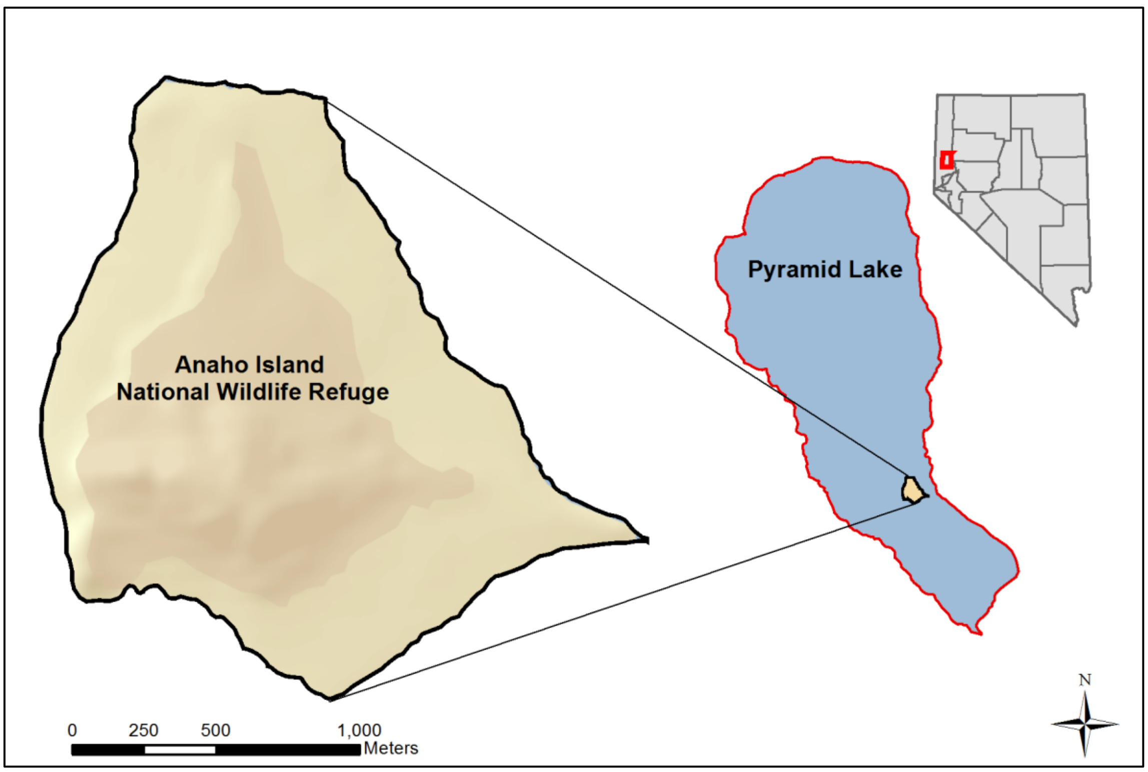

Figure 2. Anaho Island National Wildlife Refuge in Pyramid Lake, Washoe County, Nevada

American white pelicans are a large (127 to 165 cm in length) waterbird with white plumage (Knopf and Evans 2004), making them easily distinguishable in aerial imagery. They are colonial and nest on the ground in a mostly uniform dispersion approximately one meter from their neighbors when measuring from the center of the nest (Schaller 1964). Nests consist of shallow, low-rimmed depressions in the ground that are sometimes lined with vegetation (Knopf and Evans 2004), making them difficult to locate post-season. On Anaho Island, nests sometimes persist over nesting seasons due to the dry desert climate (D. Withers, personal communication). Nesting phenology is variable but typically occurs between April and August (Knopf and Evans 2004), with peak numbers on Anaho traditionally occurring in mid-May (D. Withers, personal communication). American white pelicans lay one to two eggs per clutch. Both parents take turns incubating and eggs are continuously guarded (Schaller 1964). Eggs hatch approximately thirty days after laying (Knopf 1979). Nidicolous young are attended by adults for another two to three weeks until leaving to form creches with other juveniles (Evans 1984).

American white pelicans breed in several nesting colonies on the eastern and southeastern portions of Anaho Island (Figure 5). The location of individual nests and extent of sub-colony areas varies annually. Although pelicans make up the majority of nesting birds on the island, some areas are shared with other species. Refuge records indicate that historically, mixed-species colonies were not as common and additional sub-colony areas were utilized that are not currently active, but the majority of the nesting activity was and remains on the east side of the island (U.S. Fish and Wildlife Service 2015).

American white pelicans are highly sensitive to human disturbance during the nesting season. Human activity, including close, loud passes by motorboats and aircraft, can cause parents to leave nests, exposing eggs and chicks to temperature extremes and predation by avian predators such as gulls. It is recommended that any research and monitoring activities take precautions to minimize undue disturbance (Johnson Jr and Sloan 1976, Boellstorff et al. 1988, Pacific Flyway Council 2013*a*). Human intrusions into breeding colonies, particularly during the courtship and early incubation phases, can cause colony desertion and are discouraged (Knopf and Evans 2004). This presents a problem to managers who require quality population monitoring data to inform management actions, such as those pertaining to pelican depredation on fish resources.

Surveys

This project was a collaborative effort between Humboldt State University, the U.S. Fish and Wildlife Service, and the U.S. Geological Survey (USGS). The USGS National Unmanned Aircraft Systems Project Office piloted UAS and maintained operational control over missions at Anaho Island. The Anaho Island mission was flown under an existing Memorandum of Agreement between the FAA UAS Integration Office (AFS-80) and the Department of the Interior (DOI) Office of Aviation Services (OAS) and thus did not require the acquisition of a Certificate of Authorization or Agreement (COA).

Flights over Anaho Island were conducted using the RQ-11A Raven sUAS. The Raven is a hand-launched, fixed-wing platform classified as a small unmanned aerial vehicle (Figure 3, Table 2). It is equipped with a high-resolution point-and-shoot camera along with additional optics for transmitting live airborne video images, compass headings and location information to a ground control unit (GCU) and remote video terminal (RVT). The system employs a self-stabilizing aircraft configuration with stability augmentation avionics. The Raven system is typically operated by a two-person team consisting of a Pilot and Mission Controller.

Figure 3. RQ-11A Raven UAS and ground control station (photos courtesy of USGS)

Table 2. Specifications for USGS RQ-11A Raven UAS

Specifications	
Platform Type	Fixed-Wing
Wingspan	55 in.
Length	36 in.
Weight	4.2 lbs.
Payload Nose Weight	6.5 oz.
Operating Altitude	150 to 1,000 ft. AGL
Cruise Speed	30 mph (13.5 m/s)
Range	10 km (Line of Sight)
Motor	Direct drive electric
Aircraft Batteries	LiS02 (single-use) Li-Ion (rechargeable)
Flight Duration	60-90 min
Launch and Recovery	Hand-Launched, Deep Stall Landing, Autoland
Ground Control Station	Falconview
Features	Hand launched, Autonomous Navigation

A Canon S100 12.1 megapixel (4,000 x 3,000 pixel image) GPS-enabled point and shoot camera was attached to the Raven platform. The camera was set to shoot at a continuous rate (1 image/3 seconds) during each flight in order to capture overlapping images with a minimum of 60% forelap and sidelap. GPS data (x,y,z coordinates) were automatically recorded into the image metadata during flights.

USGS National UAS Project Office pilots conducted flights across the eastern edge of Anaho Island where nesting colonies were known to occur on May 12 and May 13, 2015, the peak of American white pelican nesting on Anaho Island. A ground control station was set up on the mainland along the eastern shore of Pyramid Lake, approximately 1 km from the nearest edge of the island. Two observers (in addition to the pilot) maintained line-of-sight with the UAS at all times; one observer was stationed with the pilot on the mainland and the other was stationed on a boat within Pyramid Lake. A total of three flights (hereafter flights 1, 2, and 3) were completed on pre-programmed North-South transects using overlapping still photography. Camera settings, flight altitude, and the resulting mean ground sample distance for imagery collected over Anaho Island are documented in Table 3. All images were 8-bit and stored in JPEG (Joint Photographic Experts Group) image files with an approximate 4:1 compression ratio.

Flight 1 took place on May 12, 2015 taking off at 10:26 AM and landing at 10:54AM for a total flight duration of twenty-eight minutes. Imagery of the island was collected for twenty minutes between 10:29AM and 10:49AM. A total of 812 images of the island were collected at approximately 122 meters (400 feet) above ground level.

Flight 2 took place on May 13, 2015 taking off at 10:07AM and landing at 10:47AM for a total flight duration of forty minutes. Imagery of the island was collected for thirty-three minutes between 10:10AM and 10:43AM. A total of 1,322 images of the island were collected at approximately 122 meters (400 feet) above ground level.

Flight 3 took place on May 13, 2015 taking off at 12:10PM and landing at 12:42PM for a total flight duration of thirty-two minutes. Imagery of the island was collected for twenty-seven minutes between 12:11PM and 12:38PM. A total of 538 images of the island were collected at approximately 91.5 meters (300 feet) above ground level.

Table 3. Camera settings, altitude, and resulting mean ground sample distance for still photography flights at Anaho Island

Flight	ISO	Aperture	Focal Length (mm)	Shutter Speed (seconds)	Target Altitude (m)	Mean Ground Sample Distance (cm)
1	125	f/2	24	1/2000	122	5.89
2	80	f/2.5	24	1/2000	122	4.43
3	80	f/2.5	24	1/2000	91.5	3.50

Refuge staff placed twelve ground control points around known nesting locations on the island prior to the 2015 breeding season. A ground control point (GCP) is a feature on the ground with known geographic coordinates that can be accurately located in an image. GCPs were used to enhance the geometric accuracy of imagery by acting as tools for geometric ground truthing. GCPs were composed of 30 cm diameter orange paint bucket lids with a black and white checkerboard pattern chosen for easy visibility against the rocky island background (Figure 4). Staff from the USGS Nevada Water Science Center surveyed GCPs using real time kinematics to maximize accuracy.

Figure 4. Ground Control Point at Anaho Island NWR

Flights were scheduled to capture windows of suitable weather and lighting conditions and to avoid times when pelicans were most active. Peak activity at Anaho Island occurs during mate nest swaps in late morning, when pelicans return from foraging and swap incubation duties with their mates (D. Withers, personal communication). One biologist with knowledge of waterbird behavior was designated to monitor birds for signs of disturbance (i.e., birds shifting or moving off of nests, multiple birds lifting and stretching wings or taking flight) while the UAS was overhead. If birds showed any signs of disturbance or if there was a threat of a potential bird strike, the observer was to inform UAS operators and UAS would increase in altitude. Initial flights started at the regulation

UAS flight ceiling (122 m) and gradually lowered to the target flight altitude (between 122 and 92 m), to reduce the risk of disturbance while still acquiring the minimal resolution needed to identify pelicans.

During UAS flights on May 13, three biologists (including myself) conducted ground counts of all colonial nesting birds. The number of nesting pelicans on Anaho Island are counted annually (with varying effort from year to year) from several locations situated above the nesting colonies. In order to compare the counts obtained by UAS to the legacy protocol, we conducted ground counts of all nesting bird species from four established locations (Figure 5) along the eastern ridge of the island. The observation stations were selected to provide the optimal vantage point for observing the birds without causing undue disturbance. We followed the current Refuge survey protocol (U.S. Fish and Wildlife Service 2015) and constrained each count to the historically delineated colony boundaries. These were determined by visually comparing permanent landscape features to colony maps and photographs taken from observation points. Multiple observers counted each colony independently to account for observer bias, resulting in two to four independent counts for each colony. We used spotting scopes to scan through colonies and clickers to tally the number of adult birds (nesting and non-nesting), nesting birds (active nests), and unattended chicks (chicks that were no longer constrained to the nest). We defined active nests as those that contained one or more eggs or chicks or with at least one adult in direct attendance, either incubating or standing directly on a nest (U.S. Fish and Wildlife Service 2015). All data were collected in accordance with HSU Animal Care Protocol #13/14.W.106.-E.

In addition to “ocular” counts, I took photographs of each colony during ground counts in order to assess the accuracy of observer counts within the same visual range. I took multiple overlapping photographs using a Canon EOS Rebel T3i 18.0 MP Digital SLR Camera with a Canon 55-250mm lens. Refuge staff mosaicked the resulting images in Adobe Photoshop Elements software (Figure 6). I added polygon colony boundaries based off of colony maps and permanent landscape features using ArcMap v.10.2 (ESRI, Redlands, CA, USA). I then manually digitized point features on all birds visible within the boundaries in the mosaicked images.

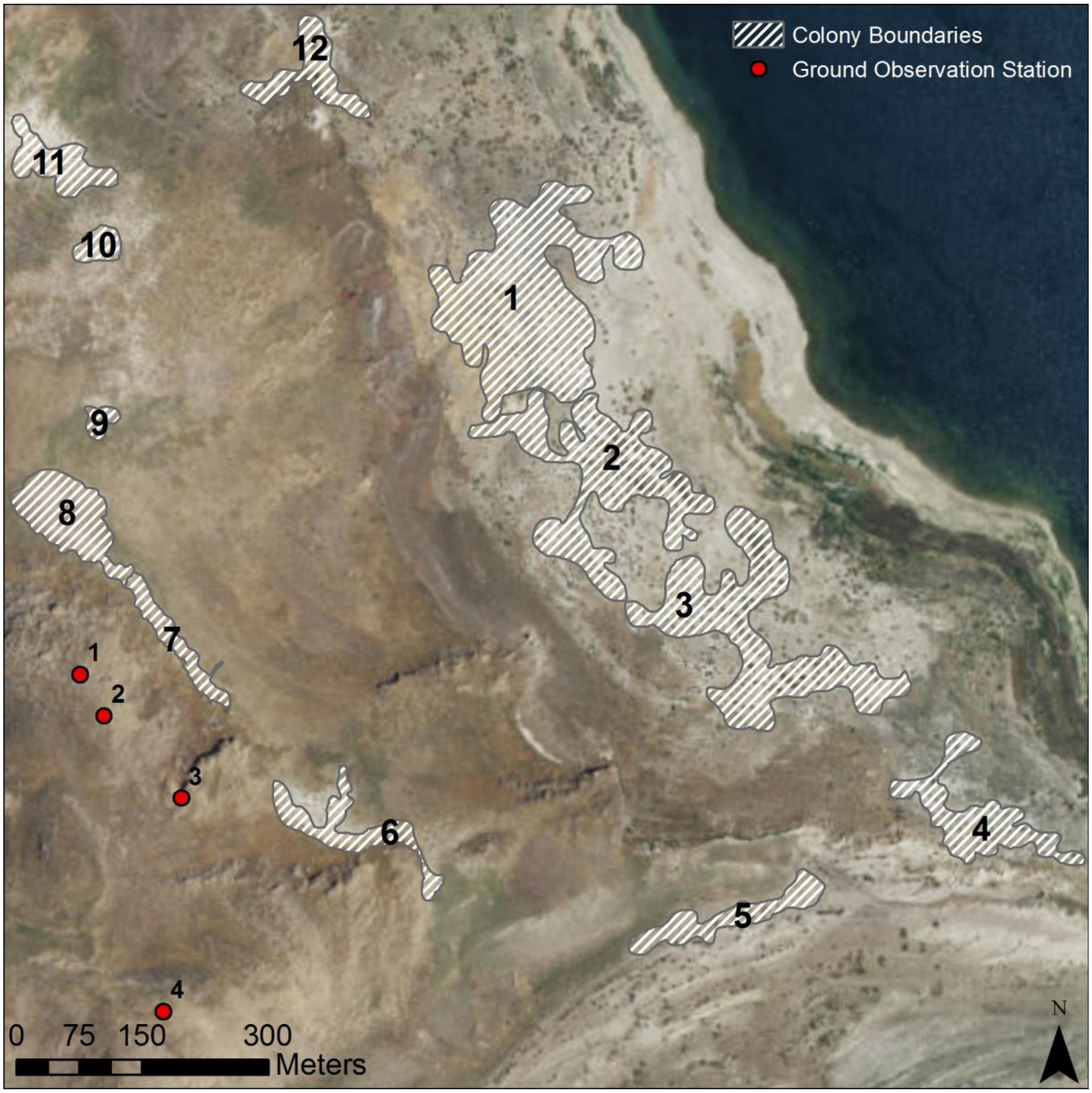

Figure 5. Location of ground observation stations and American white pelican nesting colonies on Anaho Island using 2015 nesting season boundaries. 1 = A North to Rocks, 2 = A Rocks to Mushroom, 3 = A Mushroom to Fissure, 4 = A Fissure to East, 5 = South Slope, 6 = Saddle, 7 = Bluff South, 8 = Bluff North, 9 = B South, 10 = B North, 11 = C, and 12 = D. World Imagery Sources: Esri, DigitalGlobe, GeoEye, Earthstar Geographics, CNES/Airbus DS, USDA, USGS, AEX, Getmapping, Aerogrid, IGN, IGP, swisstopo, and the GIS User Community

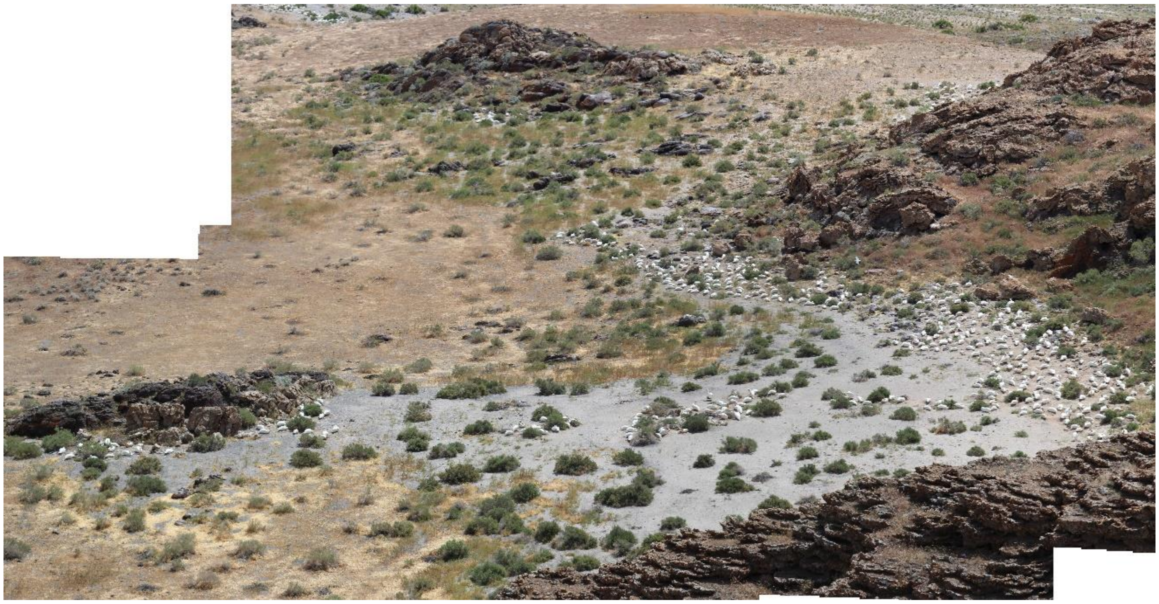

Figure 6. Example of mosaicked ground-based photography (Saddle Colony from Observation Station #2)

Data Processing

Complete coverage of all American white pelican colonies was obtained for flights 1 and 2, and near-complete coverage for flight 3. Georeferenced orthomosaic raster files were created by both myself and the USGS National UAS Project Office (Figure 7, Figure 8, Figure 9). For each flight, images, along with location data for GCPs, were aligned and processed using Agisoft Photoscan Professional Edition v.1.1.5 (Agisoft LLC, St. Petersburg, Russia), a standalone photogrammetry software program. Using automated tie point generation along with information from GCPs, Photoscan created three-dimensional point clouds that were used to orthorectify mosaicked imagery.

A camera calibration was modeled using the frame model within Photoscan and lens distortions were corrected via Photoscan's bundle adjustment. The images' terrains were corrected to the corresponding digital elevation models that were created in Photoscan. To maximize the positional fit between images, I used the Georeference tool in ArcMap to manually adjust misaligned areas within colonies. This is done by linking control points between images to build polynomial transformations that shift the raster to the intended new location.

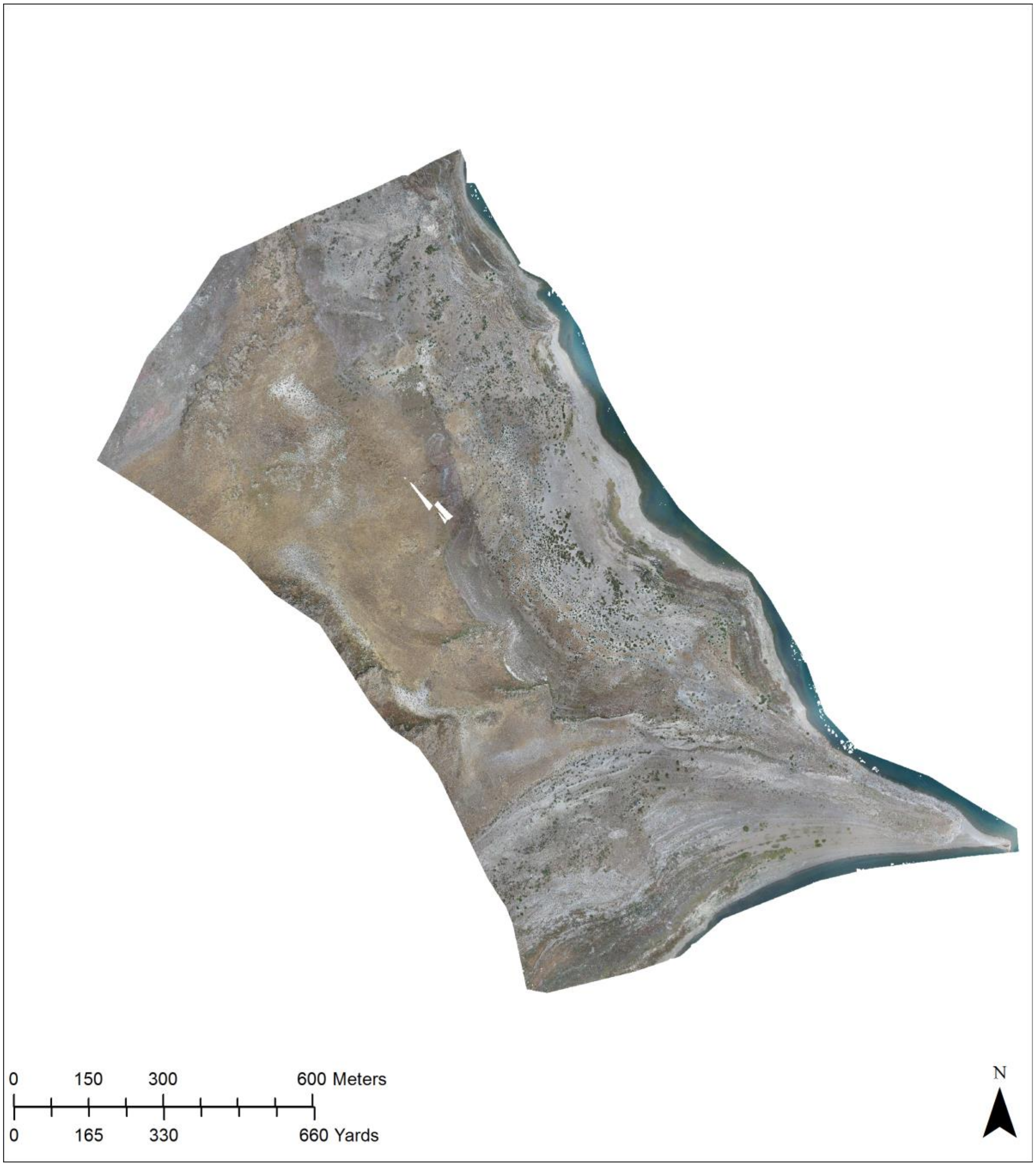

Figure 7. Orthomosaic of Anaho Island colonial nesting bird area generated using Agisoft Photoscan and images from flight 1

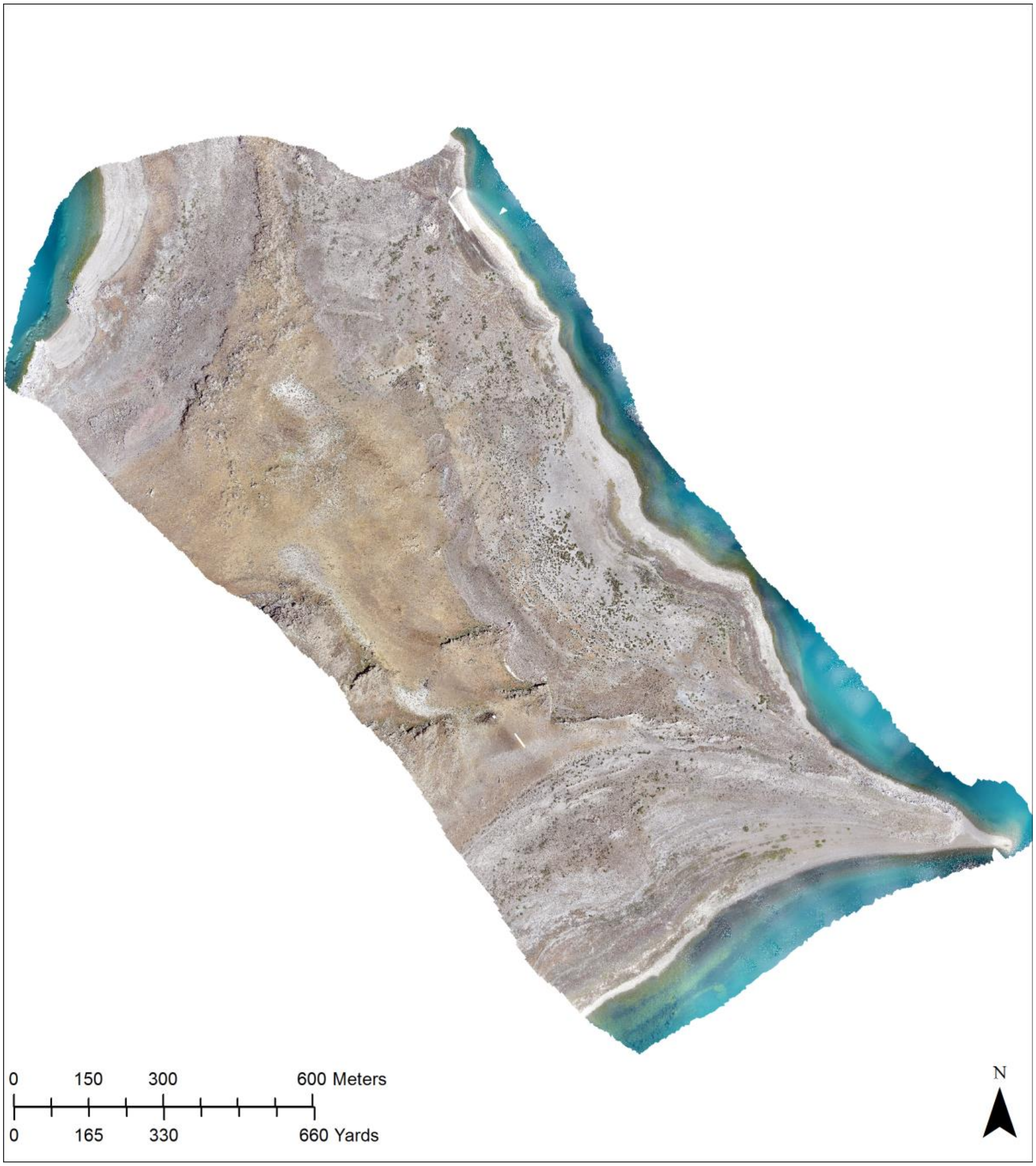

Figure 8. Orthomosaic of Anaho Island colonial nesting bird area generated using Agisoft Photoscan and images from flight 2

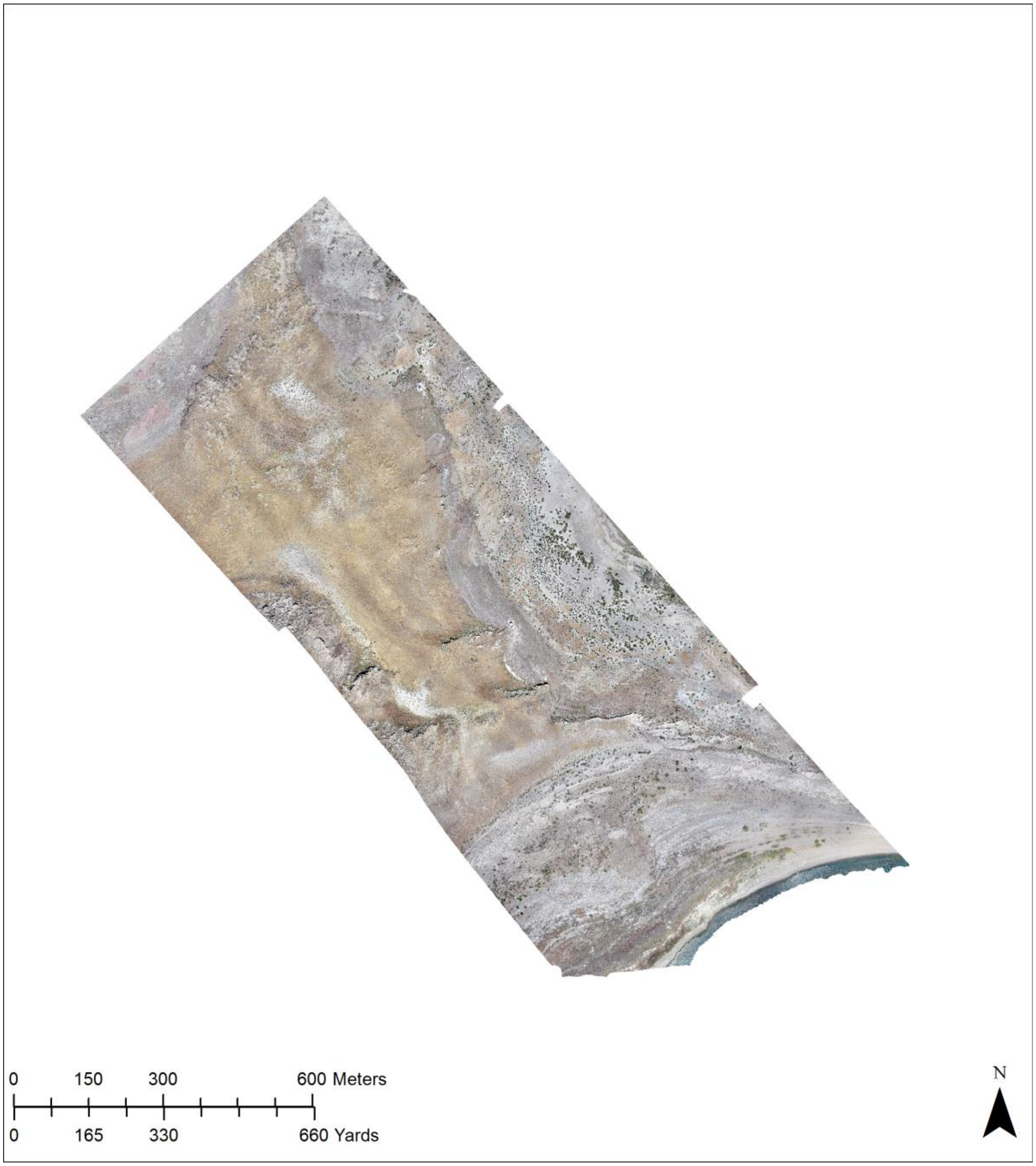

Figure 9. Orthomosaic of Anaho Island colonial nesting bird area generated using Agisoft Photoscan and images from flight 3

When detecting changes across multitemporal images, the relative positional accuracy between images (how well the coincident images are aligned) is more important than absolute positional accuracy (how well the image matches a map base) (Horning et al. 2010). To quantify the horizontal (x and y) image-to-image alignment error, or misregistration, between orthomosaics, I created a series of corresponding checkpoints on permanent features for all three images. I used a minimum of twenty points per colony, as per Federal Geographic Data Committee guidelines (Federal Geographic Data Committee 1998). I calculated the root mean square error (RMSE) and 95% confidence levels for each colony between flights 1, 2, and 3 using the formula

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\Delta Xi^2 + \Delta Yi^2)}$$

where *n* is the number of checkpoints, *i* is the checkpoint number, ΔXi is the X misregistration checkpoint distance, and ΔYi is the Y misregistration checkpoint distance. To calculate 95% confidence levels, I multiplied the RMSE values by 1.7308, as x and y errors were normally distributed (Federal Geographic Data Committee 1998). I used the resulting values to assess how alignment errors between images affected my multitemporal change detection results.

The large number of pelicans present on Anaho Island warranted the use of automated feature extraction methods over manual digitization methods. The features surrounding nesting pelicans on Anaho Island include light-colored, often white-washed rocks, making it necessary to use object based analysis (both spectral and spatial characteristics) rather than relying on spectral characteristics alone. I used Feature Analyst (Overwatch Systems, Ltd.), a user-assisted feature extraction application for ArcMap, to create iterative pelican feature extraction models. The USGS National Unmanned Aircraft Systems Project Office has successfully used Feature Analyst for counting American white pelicans and other waterbird species in UAS imagery (Mark Bauer personal communication). Feature Analyst utilizes a suite of inductive learning algorithms to classify object-specific features specified by the user. After a sample of target features are digitized by the user, Feature Analyst uses spectral and spatial context characteristics to classify similar features in the imagery. A hierarchical learning approach allows the user to further refine the classification by providing feedback (e.g., removing clutter by selecting correctly and incorrectly classified features) (Opitz and Blundell 2008).

I used this process, along with the “Convert to Point” Vector Tool, to create point features on the backs of pelicans in all three orthomosaics (Figure 10). Training data consisted of polygons digitized over a sample of pelican backs. For supervised learning I used input representation “Bull’s Eye 2”, size 7, aggregated small classified regions with a minimum of 15 pixels, and removed large regions that were over 3 square meters (Table 4). I masked areas outside of colony boundaries to reduce processing time. I ran individual extraction models for each colony in each set of imagery to see how factors such as resolution and background affect commission and omission error rates. I converted the resulting polygons to points that were centered on all pelican features and were reviewed and manually edited as necessary. In order to differentiate birds between and across images, I assigned all pelican point features a unique identifier attribute; a combination of flight and numeric object ID (e.g., “F1_300”).

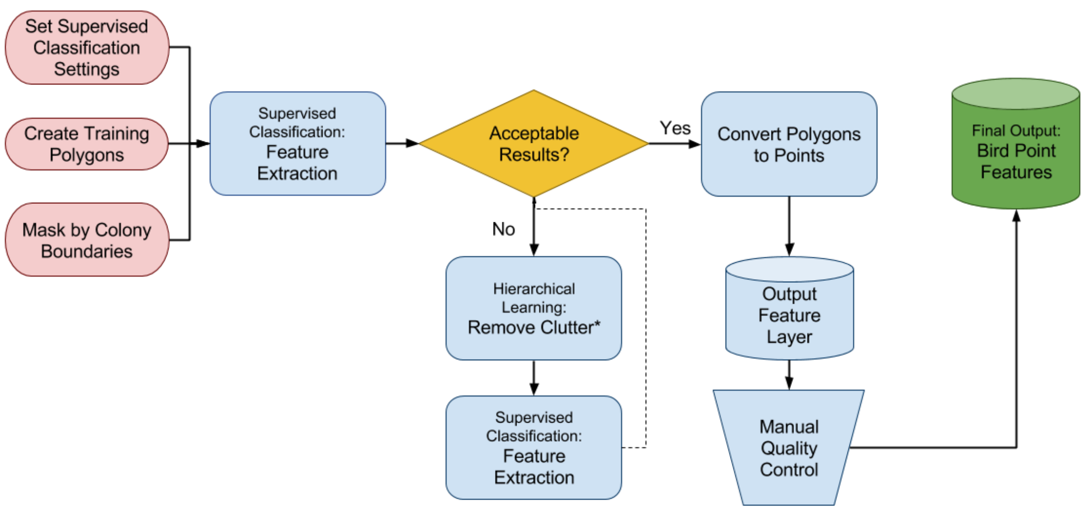

Figure 10. Flowchart for creating bird point features using Feature Analyst. *Select a sample of correctly and incorrectly classified features to provide feedback for features to keep and remove

Table 4. Learning parameters used for supervised classification of pelican features

Parameter	Setting
Feature Selector	N/A
Resample	Image Resolution
Find Rotated Features	Enabled
Input Representation	Bull's eye 2, size 7
Mask By Pixel Value	Disabled
Output Format	Vector
Aggregate Small Regions	Enabled; 15 pixel minimum[1]
Remove Large Regions	Enabled; 3 meter maximum
Smooth Shapes	Disabled
Fill Background Regions with Shapes	Disabled
Masking	Mask by colony boundaries

[1] The minimum pixel value is dependent on pixel resolution of imagery

Data Analysis

Validation data set

Due to the risk of disturbance, I was not able to conduct any in-colony walk-throughs to validate the number and locations of active pelican nests. As a substitute validation data set, I used imagery from sequential UAS flights to manually identify all nesting birds present on Anaho Island. I categorized birds as "nesting" if they occurred in the same location across all three flights (a period of 26 hours) (Figure 11). I created a binary response for each bird in the imagery as either 1 (active nest) or 0 (non-nesting).

Non-nesting birds included attending mates, unpaired birds, birds that were searching for nest sites, and any other loafing birds.

Figure 11. Example of birds marked as non-nesting indicated by red circles. From left to right: Flight 1, Flight 2, Flight 3. Red (circle) points indicate bird point features from Flight 1, green (triangle) from Flight 2, blue (square) from Flight 3.

Prior to conducting any nest classifications, I reviewed colonies for courting flocks. During the nesting season, American white pelicans tend to form flocks of un-paired, courting birds that are denser than nesting colonies (Knopf 1979). This dense cluster of birds was visible both by ground counters and in UAS imagery. I used Program R (R Development Core Team, 2016) package 'spatstat' (Baddeley and Turner 2005) and the 'nndist' function to visually inspect the imagery for clusters of birds that had nearest neighbor distances of less than 0.7 m (Figure 12**Error! Reference source not found.**). I removed one such flock, which was confirmed as a courting flock by ground observers, prior to conducting any analyses on nesting colonies.

Figure 12. Pelican point features in A Rocks to Mushroom colony showing densely spaced courting flock in upper left corner: Gray points indicate birds with a nearest neighbor distance under 0.7m

Ground to aerial comparison

I conducted multiple comparisons between UAS, ground, and ground-based photography counts of nesting birds using Program R and a significance level of 0.05. I ran linear regression analyses with observed UAS nest counts as the independent variable and the corresponding ground and ground image counts as the dependent variables, and with ground-based image counts as the independent variable and “ocular” ground observer counts as the dependent variable. I conducted additional linear regression analyses to test for a significant correlation between the percent error of ground-based counts from manual counts of UAS nests and the following dependent variables: percent greasewood and viewing angle from observation station to colony. I noted the regression coefficients (β), the significance of the regression (F, P), the coefficient of determination (R^2), and compared the regression lines with the ideal regression line (equal densities in UAS and ground counts y = x) to test the efficiency of ground counts to UAS counts (Laursen et al. 2008). I used non-parametric Wilcoxon signed-rank tests to assess if median nest counts varied significantly between ground and ground-based image counts, and if UAS counts were significantly greater than ground counts. I calculated correction factors for converting ground counts to observed UAS values using the mean ground count values for each nesting colony. I used counts of total adults rather than nest counts to account for fluctuating ratio of nesting to non-nesting birds throughout the nesting season.

Automated nest classification

I examined two approaches to differentiate active nests from non-nesting birds: a monotemporal (single image) method and a multitemporal (sequential image) change detection method. My goal was to develop a method to estimate both the number as well as the location of active nests. I hypothesized that while a monotemporal method for active nest classification requires less data acquisition and processing time, multitemporal methods would perform better at classifying active American white pelican nests. I conducted nearest neighbor analyses using the Program R package ‘spatstat’ to estimate the number and location of active nests in each colony. For every colony that had complete overlap of all three flights, I tested whether a monotemporal or multitemporal set of orthomosaics was suitable for estimating the number of active nests. Both Program R scripts were written so that users can automatically generate nest locations and estimates without any manual data manipulation after the feature extraction process.

Monotemporal nest classification.

In general, nests of American white pelicans on Anaho Island are uniformly distributed within colonies with some clustering around greasewood (*Sarcobatus vermiculatus*). The reported average distance from the center of one American white pelican nest to another is 1.19 m (0.74-1.85, SD = 0.2 m) (Schaller 1964). Individuals that are either much closer than this distance or much farther apart may be considered attending mates or loafing birds. Chabot et. al. (2015) estimated the number of nesting terns by considering any birds in close proximity as a pair and thus only counting them as one bird. Rather than using a thresholding technique to identify birds on only one end of a distance-to-nearest-neighbor distribution, I excluded birds on both ends of the distribution. Within nesting colonies, I hypothesized that birds with large distances from their nearest neighbors (>1.85 m) and birds with very small distances from their nearest neighbors (<0.74 m) were non-nesting birds or attending mates.

I developed a semi-automated approach using Program R to remove all bird point features with large nearest neighbor distances as well as remove only one bird out of a pair of close neighbors (Figure 13). I loaded point features from a selected flight into

Program R and used the Spatstat package to convert them into Spatial Point Patterns. I used the Spatstat 'nnwhich' function to identify the nearest neighbor to each point, and the 'nndist' function to find the distance to that nearest neighbor. To remove only a single bird out of a close pair, I first identified any points that were reciprocal nearest neighbors, or nearest neighbors of each other, and coded one out of the pair as a 0, and the other a 1. Any points coded as 0 and less than 0.74 m from their neighbor remained a 0, or non-nesting bird. I also coded any points with nearest neighbor distances greater than 1.85 m as non-nesting birds. I coded all the remaining points as 1, or nesting bird.

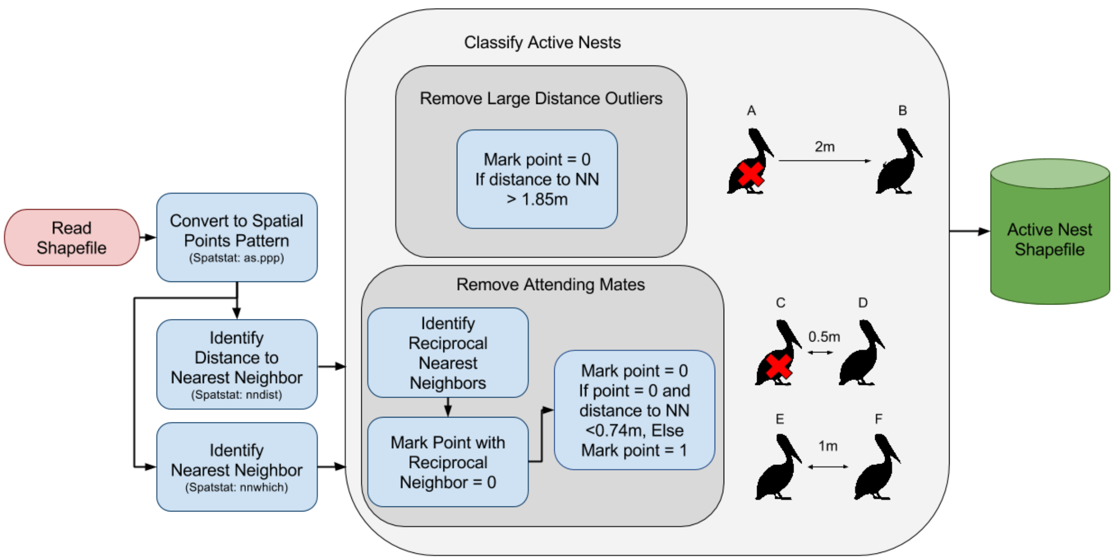

Figure 13. Workflow depicting nest classification using monotemporal nearest neighbor analysis in Program R

<u>Multitemporal nest classification.</u>

Sardà-Palomera et al. (2012) found that using sequential images to estimate the number of nests in a Black-headed gull colony was a more accurate method than estimating nests from a single image. I conducted a nearest neighbor analysis using point features derived from orthomosaics of consecutive flights to estimate the number and location of active pelican nests. Because the flights occurred over two days within the span of twenty-six hours, I assumed that no new nests would be initiated or abandoned between the first and second day. I identified any pelican features that moved, appeared, or disappeared between any given image sets and classified them as non-nesting birds. If a pelican stayed in the same location across any given image set, I coded it as an active nest.

I used a reciprocal nearest neighbor change-detection approach to identify and estimate the number of active nests rather than using a distance threshold approach in order to create a method that would be amenable to minor misregistration errors of sequential images. Assuming a high level of spatial accuracy, a bird point feature from one flight should have a very small distance to a bird point feature from another flight if the bird in the imagery has not moved off the nest. In this case, nearest neighbors should be reciprocal. For example, if the nearest neighbor of Point *x* from Flight A is Point *y* from Flight B, then the nearest neighbor of the same Point *y* from Flight B will be Point *x* from Flight A. If, however, a bird is not in a particular location in *n* number of images (it has moved or disappeared), then this point feature will have a much larger distance to its nearest neighbor in the consecutive image and nearest neighbors will not be reciprocal.

To test this method, I developed a function in Program R to identify active nests from the existing point features using a reciprocal nearest neighbor analysis across multiple images (Figure 14). I loaded all sequential point features into Program R and converted them into Spatial Point Patterns. I used the Spatstat function ‘nncross’ to identify the nearest neighbor bird point feature from each sequential flight to the currently selected flight. If an individual bird point feature had a reciprocal nearest neighbor in consecutive flights, it was automatically coded as a 1, or nesting bird. If the bird point feature did not have a reciprocal nearest neighbor, it was coded as 0, or non-nesting bird. To account for varying alignment errors as well as the variance in the number of birds within each flight, I compared the mean results of every combination of flights (six combinations were possible, e.g., Flights 1,2,3 and Flights 2,1,3 and Flights 3,2,1 etc.) to observed values that I had checked by hand for each colony.

Using this same approach, I also compared every combination for only two sequential images. This allowed me to assess how estimates of nests and their locations changed based on how far apart images were taken (e.g., twenty-four hours vs. two hours).

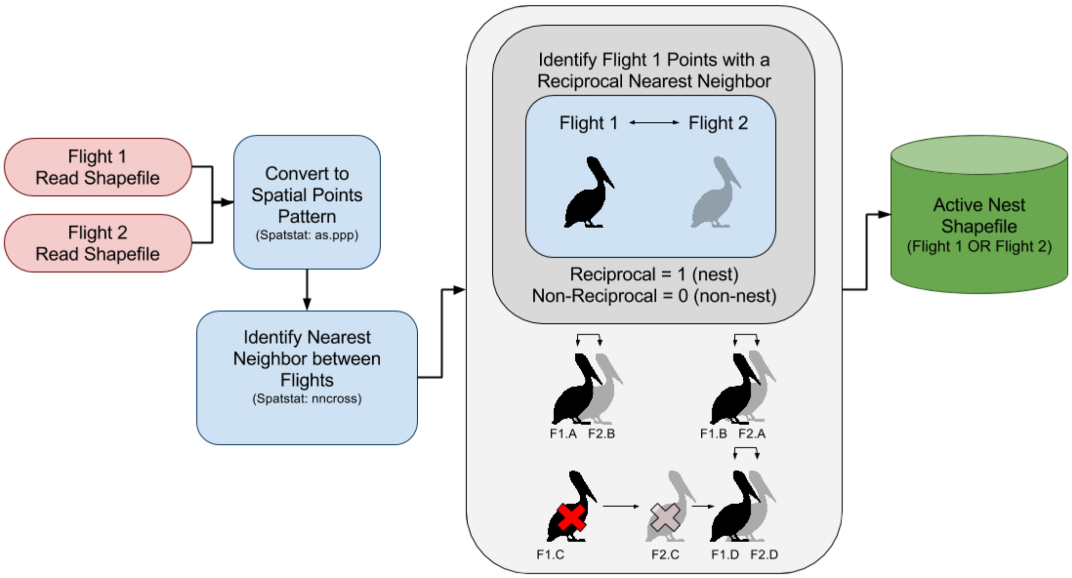

Figure 14. Workflow depicting nest classification with multitemporal reciprocal change detection between two flights in Program R. The same workflow can be applied to *n* number of flights.

Statistical Analyses

I used the following confusion matrix-derived statistics to assess the accuracy of my nest classifications: True Skill Statistic, Cohen's Kappa, percent correctly classified (PCC), area under the curve (AUC), specificity, and sensitivity (Table 5). I reviewed the results of multiple statistics to account for different nest prevalence rates. Sensitivity can be defined as the conditional probability that case X is correctly classified, p(X_{Alg}| X_{True}), whereas specificity can be defined as the inverse, p(not X_{Alg} | X_{False}) (Fielding and Bell 1997). AUC, or Area Under the (Receiver Operating Characteristic) Curve, is equal to the probability that a classifier will rank a randomly chosen positive instance higher than a randomly chosen negative one (Fawcett 2006). Cohen's Kappa is a measure of agreement that can be used to assess agreement between alternative methods of categorical assessment. The following ranges of agreement for the Kappa statistic were suggested by Landis and Koch (1977): poor $K < 0.4$; good $0.4 < K < 0.7$; excellent $K > 0.75$. Despite the widespread use of Kappa in ecology and remote sensing, several studies have criticized it for its dependence on prevalence (Allouche et al. 2006, Pontius et al. 2011). Because the ratio of nesting to non-nesting birds in colonies was very high, I also calculated the true skill statistic (TSS) as an alternative measure of agreement to Kappa. TSS, also known as the Hanssen-Kuipers discriminant, is equal to sensitivity + specificity -1, and ranges from -1 to 1, with 1 signifying perfect agreement and values of zero or less signifying performance no better than random. Like Kappa, TSS takes into account both omission and commission errors and success as a result of random guessing; however, unlike Kappa, it is not affected by prevalence or the size of the validation set (Allouche et al. 2006).

Table 5. Accuracy assessment measures for nest classification, where a is the number of true positives (active nest), b is the number false positives, c is the number of false negatives, d true negatives (non-nesting bird), and n (a+b+c+d) is the total number of sites

Accuracy Assessment Measures	Formula
Sensitivity	a/(a + c)
Specificity	d/(b + d)
Percent Correctly Classified	(a + d)/n
True Skill Statistic	$\frac{ad - bc}{(a + c)(b + d)}$
Kappa	$\frac{(a + d) - [(a + c)(a + b) + (b + d)(c + d)]/n}{n - [(a + c)(a + b) + (b + d)(c + d)]/n}$
Area Under the Curve	$A = \int_{\infty}^{-\infty} TRP(T)FPR'(T)dT$

Using package ‘PresenceAbsence’ (Freeman and Moisen 2008) in Program R, I created confusion matrices of my predicted versus observed data for every nesting colony. I compared the results of the nearest neighbor reciprocal analysis for monotemporal and multitemporal imagery. I also compared the resulting statistics in order to assess whether sequential flights conducted within a two hour period were comparable to flights conducted with twenty-four and twenty-six hour periods. Due to the skewed distribution of the resulting statistics, I used non-parametric Wilcoxon signed-rank tests to test if mean TSS values differed by timing between sequential flights (i.e., 2 hours, 24 hours, and 26 hours apart).

Minor distortions were present in the orthomosaicked images, thus affecting image-to-image alignment and the location of the corresponding bird point features. I conducted a linear regression analysis using TSS as the independent variable and the maximum RMSE between three images as the dependent variable to quantify the effect of alignment errors on the results of the three-image reciprocal nearest neighbor analysis. I used linear regression on all data points and on only data points where the RMSE was less than 0.5 m (half the average nesting distance for American white pelicans) and compared the resulting slopes to see if RMS errors only affect TSS after a 0.5m threshold.

RESULTS

Surveys

American white pelicans, double-crested cormorants, California gulls, and great blue herons showed no notable response to UAS. Temporary wing flapping by pelicans in the Bluff colonies, the only recorded disturbance, occurred due to the presence of ground observers. Both adult American white pelicans and chicks were visible in imagery from all three flights and were distinguishable from other species nesting on the island (Figure 15). Double-crested cormorants, California gulls, and great blue herons were also identifiable in imagery. Caspian terns were not recorded in either ground or UAS counts, but would likely be indistinguishable from California gulls at the collected pixel resolutions (3.5 - 5.89 cm). A total of 12,882 adult American white pelicans were counted in imagery from flight 1 and 12,485 from flight 2. Totals for flight 3 are not reported due to incomplete coverage. The total adult counts for individual colonies are summarized in Table 7.

Figure 15. UAS images of nesting species on Anaho Island: A) Adult American white pelicans and double-crested cormorants, B) adult and juvenile American white pelicans, great blue herons, and double-crested cormorants, C) great blue herons, double-crested cormorants, and adult American white pelicans, and D) California gulls.

Data Processing

The amount of image-to-image alignment error varied between flights and within colonies (Table 6). The mean RMSE at a 95% confidence level for colony imagery was 0.47 m (range = 0.09 – 0.55 m) between flights 1 and 2, 0.36 m (range = 0.15 – 0.97 m) between flights 2 and 3, and 0.38 m (range = 0.13 – 0.93 m) between flights 1 and 3. Bluff North colony imagery had the highest error between all flights due to patches of distortion that were created during image processing.

Table 6. Calculated RMSE and corresponding 95% Confidence Levels for horizontal alignment error of imagery within pelican colony boundaries between flights

Colony	RMSE (m)			95% Confidence Level		
	Flights					
	1 & 2	2 & 3	1 & 3	1 & 2	2 & 3	1 & 3
A Rocks to Mushroom	0.14	0.13	0.07	0.25	0.22	0.13
A Mushroom to Fissure	0.13	0.11	0.13	0.23	0.18	0.22
A Fissure to East	0.2	0.14	0.18	0.35	0.25	0.31
B South	0.2	0.08	0.2	0.35	0.15	0.34
B North	0.05	0.11	0.09	0.09	0.19	0.16
D	0.21	0.14	0.19	0.36	0.25	0.33
C	0.24	0.21	0.19	0.41	0.37	0.32
Saddle	0.28	0.47	0.34	0.49	0.82	0.59
South Slope	0.29	0.1	0.3	0.5	0.18	0.52
Bluff North	0.3	0.56	0.54	0.52	0.97	0.93
Bluff South	0.31	0.23	0.19	0.54	0.4	0.33

Feature extraction produced point shapefiles for pelicans in all colonies across the three orthomosaics. In all cases, no more than one hierarchical learning iteration was needed to reach acceptable results. Some errors of omission (i.e., missed birds) or commission (i.e., non-bird features incorrectly classified as birds) were present in all colonies prior to manual editing. Across all colonies and images, the mean omission rate was 8.42% (range = 0.60 – 30.83%) and the mean commission rate was 2.11% (range = 0 – 10.10%).

Data Analysis

Ground to aerial comparison

Ground observers counted a mean 7,867 adult American white pelicans, while 7,903 were counted in ground-based photographs and a mean 12,684 were counted in UAS imagery (Table 7). Excluding the A North to Rocks colony (due to incomplete coverage), ground observers counted a mean 6,156 pelican nests, while 8,628 nests were observed in a manual count of UAS imagery across all three flights. The percent error of ground-based "ocular" nest counts from UAS nests ranged from 3 to 73% (all observers) and 3 to 68% for ground-based image counts (Figure 16). Ground observers underestimated the number of nests compared to manual UAS values ($W = 293$, $Z = 3.5$, $p < 0.001$). Counts from ground-based imagery significantly underestimated the number of nests as well ($W = 55$, $Z = 2.8$, $p < 0.001$). There was no significant difference between ground counts and counts made from ground-based imagery ($W = 118.5$, $Z = 0.9$, $p = 0.392$).

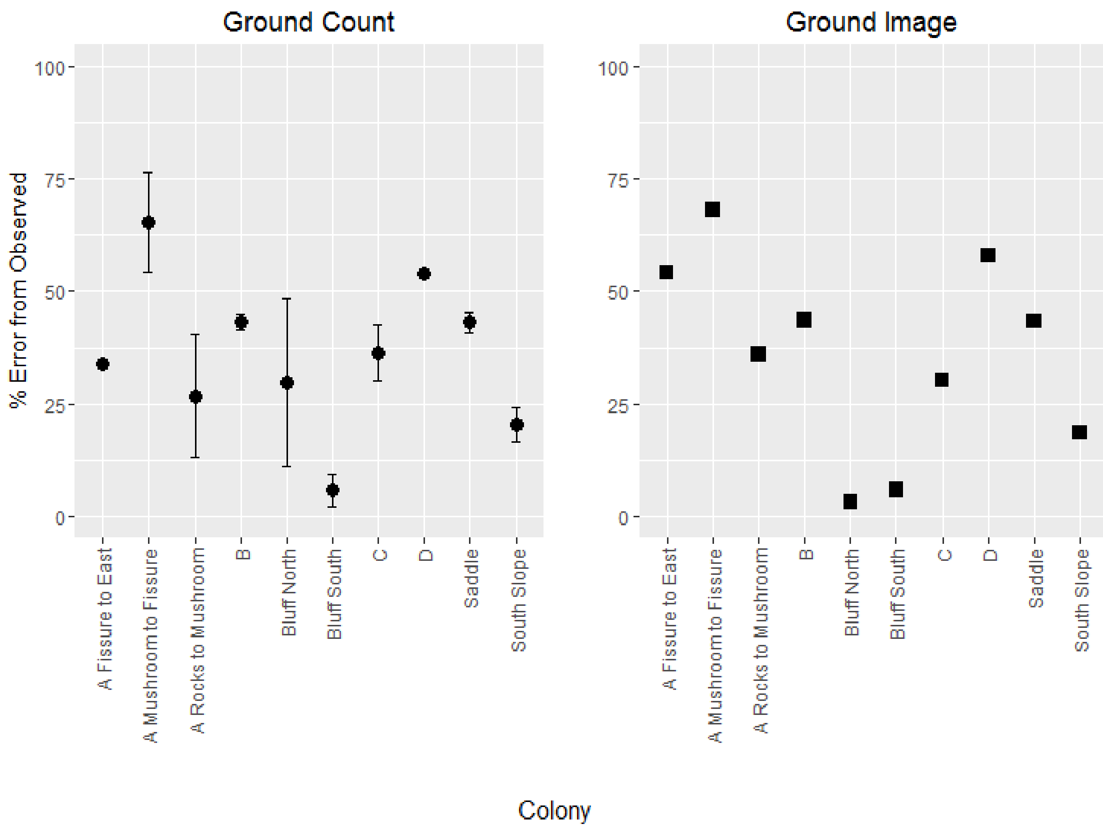

Figure 16. Percent error of ground-based image and mean ground nest counts to observed UAS nests. Mean and standard deviation values for ground counts are based off multiple observer counts.

There was a significant positive relationship between the manual count of nests from UAS imagery and counts of nests by ground observers and in ground-based images ($\beta_{UASground}$ =0.62, 95% CI = 0.45-0.79, $F_{1,23} = 52.20,\ P < 0.001, R^2 = 0.69$) (Figure 17). However, ground counters underestimated the number of nests in all but the largest colony (Bluff North), where two out of three observers over-counted. For ground-based imagery counts, nests were undercounted in all colonies ($\beta_{UASgimage}$ =0.79 (95% CI = 0.46-1.12, $F_{1,8} = 22.52,\ P < 0.01, R^2 = 0.74$)). There was a strong positive relationship between ground-based image counts to ground "ocular" counts ($\beta_{ggimage}$ =0.76 (95% CI = 0.63-0.89, $F_{1,23} = 128.2,\ P < 0.001,\ R^2 = 0.85$).

Angle of view to the colony from the observations stations had a strong, negative impact on percent error for both ground counts (β_{Angleg} =-1.88 (95% CI = -2.76- -1.00,$F_{1,23} = 17.6,\ P < 0.001, R^2 = 0.43$)) and ground-based image counts ($\beta_{Anglegi}$ =-2.71 (95% CI = -4.15- -1.28, $F_{1,8} = 13.8, P < 0.01, R^2 = 0.63$)). There was no significant correlation between percent error to the percent of greasewood cover for either ground counts or ground-based imagery counts (P= 0.22, 0.08).

Table 7. Summary of ground, ground-based photography, and UAS counts of American white pelicans. Total adult counts encompass nest counts. Standard errors for ground counts were based on multiple observer counts. Standard errors for UAS adult totals were based on image counts for multiple flights. Percent error for ground nest counts was based on observed UAS nest counts. Correction factors (C.F.) for ground adult counts were based on mean ground and mean UAS total adult counts and should be updated with future UAS flights. Correction factors are meant to correct total adult counts rather than nest estimates due to fluctuations in nesting to non-nesting ratios across colonies and time.

	Ground				Ground Image	UAS Observed				
	Adult Total		Nest Total		Total	Adult Total		Nest Total	Nest	Adult Total
Colony	$\bar{X}$	s.e.	$\bar{X}$	s.e.	X	$\bar{X}$	s.e.	X	% Error	C.F.
A Fissure-East	463	17.0	473	3.0	347	758	10.7	714	33.75	1.64
A North-Rocks*	1482	0.0	1416	0.0	2062	3226	0.0	-	-	2.13
A Rocks -Mushroom	585	0.0	488	64.0	475	1228	31.9	666	26.73	2.10
A Mushroom-Fissure	532	0.0	431	98.0	401	1312	22.2	1243	65.33	2.47
B	230	7.0	227	4.1	230	413	1.0	400	43.25	1.79
Bluff North	1977	375.0	1970	412.7	1765	1857	8.3	1811	8.78	0.94
Bluff South	473	0.0	470	12.5	469	509	1.2	498	5.62	1.08
C	526	8.5	518	29.5	566	829	2.1	812	36.21	1.58
D	289	5.0	285	3.0	261	624	2.8	617	53.81	2.16
Saddle	486	1.5	483	11.2	484	860	0.9	849	43.11	1.77
South Slope	824	24.7	811	22.4	843	1046	5.8	1018	20.33	1.27
Totals*	7867	-	7572	-	7903	12684	-	8628	28.65	1.60

*Total for percent error based off of values that do not include colony A North to Rocks

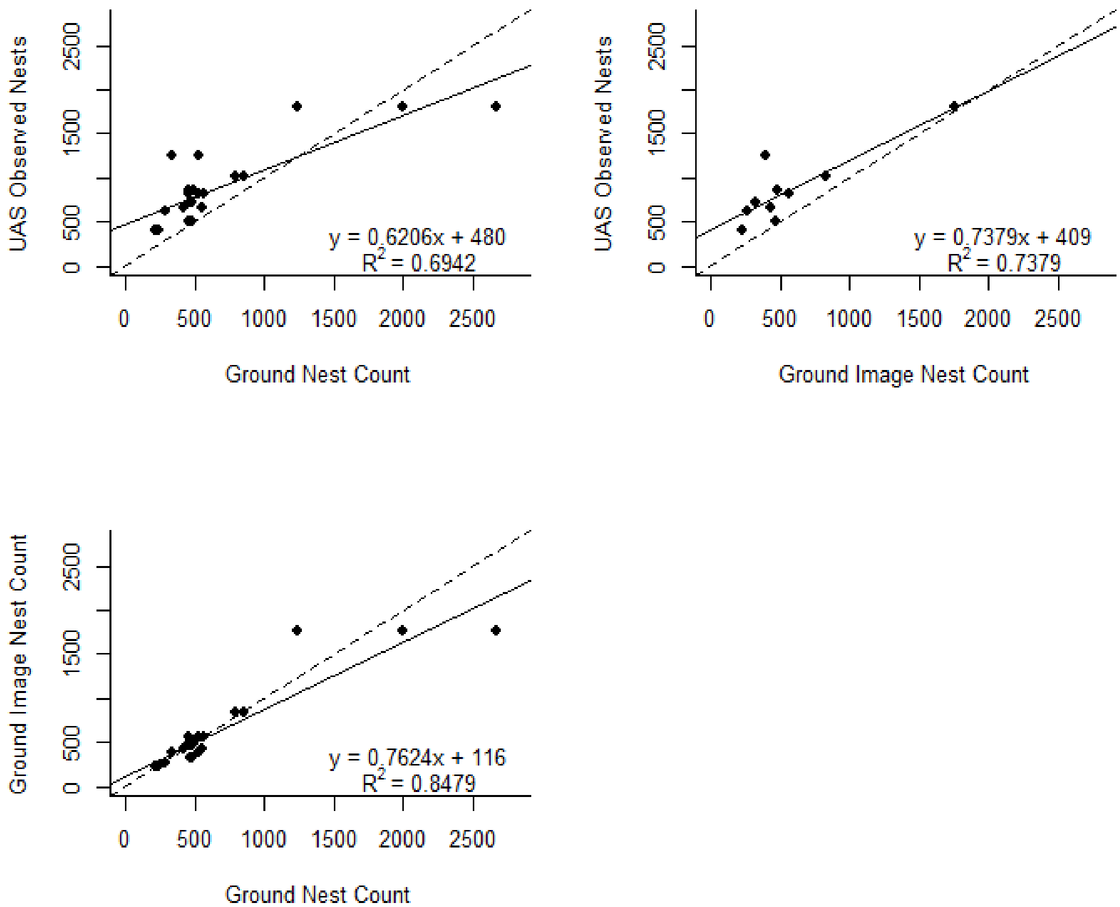

Figure 17. Linear regression of manual UAS nest counts to ground nest counts, UAS nests to ground-based image nest count, and ground-based image nest count to ground counts. Dashed lines depict slope=1 and intercept=0, i.e. a perfect relationship between count methods

Automated nest classification

Monotemporal nest classification. The single image nearest neighbor method correctly classified 74% to 98% (mean PCC = 93%, n = 33) of nesting and non-nesting birds (Figure 18). However, TSS values ranged from -0.03 to 0.52 (mean = 0.17) and Kappa values ranged from -0.03 to 0.36 (mean = 0.14), indicating a poor level of agreement to observed data across all colonies. Sensitivity scores ranged from 0.94 to 0.99 (mean = 0.96) while specificity scores ranged from 0 to 0.44 (mean = 0.20). Area Under the Curve scores ranged from 0.51 to 0.70 (mean AUC = 0.58).

Multitemporal nest classification. The multitemporal reciprocal method using all three flight images correctly classified 95% to 100% (mean = 99%, n = 66) of the nesting and non-nesting birds when conducted across all three flights (Figure 18). TSS values ranged from 0.91 to 1 (mean = 0.99) and Kappa values ranged from 0.47 to 1 (mean = 0.92), indicating an overall excellent level of agreement to observed data across all colonies. Sensitivity scores ranged from 0.95 to 1 (mean = 0.99), specificity scores from 0.95 to 1 (mean = 1.00), and Area Under the Curve scores from 0.95 to 1 (mean = 1.00).

The multitemporal reciprocal method using two flight images correctly classified 93% to 100% (mean = 99%, n = 66) of the nesting and non-nesting birds when conducted between all combinations of two flights (Figure 18). TSS values ranged from 0.55 to 1.00 (mean = 0.88) and Kappa values ranged from 0.49 to 1 (mean = 0.89), indicating an overall very good level of agreement to observed data across all colonies. Sensitivity scores ranged from 0.97 to 1 (mean = 1.00), specificity scores from 0.67 to 1 (mean = 0.88), and Area Under the Curve scores from 0.83 to 1 (mean = 0.94).

For flights conducted on the same day (2 hours apart, n = 22), 96% to 100% (mean = 99%) of birds were correctly classified, TSS values ranged from 0.64 to 1 (mean = 0.85), Kappa from 0.49 to 1 (mean = 0.87), sensitivity scores from 0.97 to 1.00 (mean = 1.00), specificity scores from 0.64 to 1.00 (mean = 0.85), and Area Under the Curve scores from 0.82 to 1.00 (mean AUC = 0.94) (Figure 19). For flights conducted on two consecutive days (24 and 26 hours apart, n = 44), a 93% to 100% (mean = 99%) of birds were correctly classified, TSS values ranged from 0.55 to 1 (mean = 0.90), Kappa values from 0.58 to 1.00 (mean = 0.91), sensitivity scores from 0.97 to 1.00 (mean = 1.00), specificity scores from 0.55 to 1.00 (mean = 0.90), and Area Under the Curve scores from 0.77 to 1.00 (mean AUC = 0.95). TSS values from flights conducted two hours apart were not significantly different from flights conducted 24 hours apart (P = 0.12), but were significantly different from flights conducted 26 hours apart (P = 0.02). TSS values from flights conducted 24 hours apart were not significantly different from flights taken 26 hours apart (P = 0.06, Figure 20).

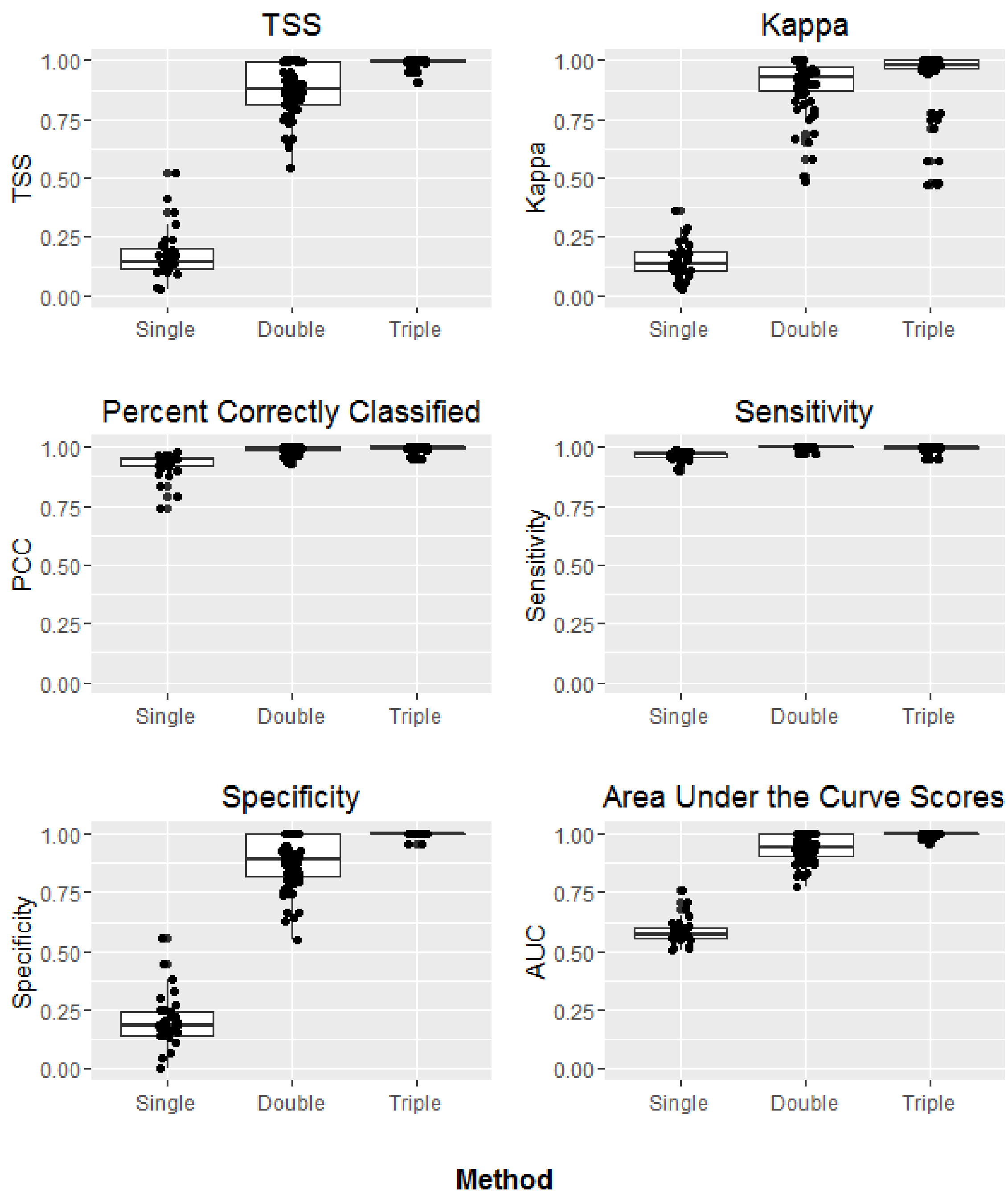

Figure 18. Boxplots showing True Skill Statistic, Kappa, Percent Correctly Classified, Sensitivity, Specificity, and Area Under the Curve values for nest classification conducted using a monotemporal method (Single) and reciprocal change detection method for two flights (Double) and three flights (Triple)

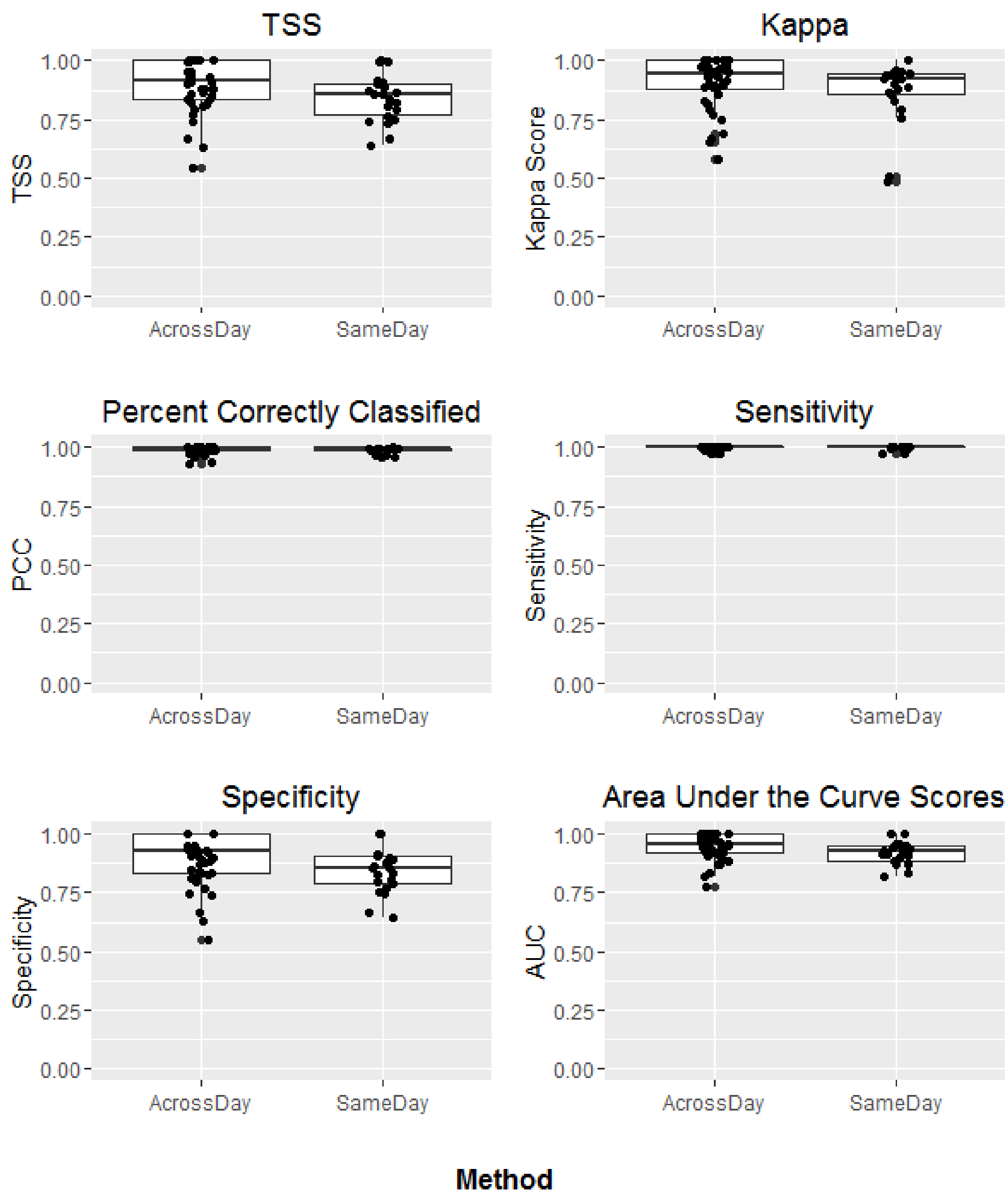

Figure 19. Boxplots showing True Skill Statistic, Kappa, Percent Correctly Classified, Sensitivity, Specificity, and Area Under the Curve values for nest classification using the reciprocal neighbor change detection method for two flights with 2 hour intervals (SameDay) and 24-26 hour intervals (AcrossDay) flight intervals

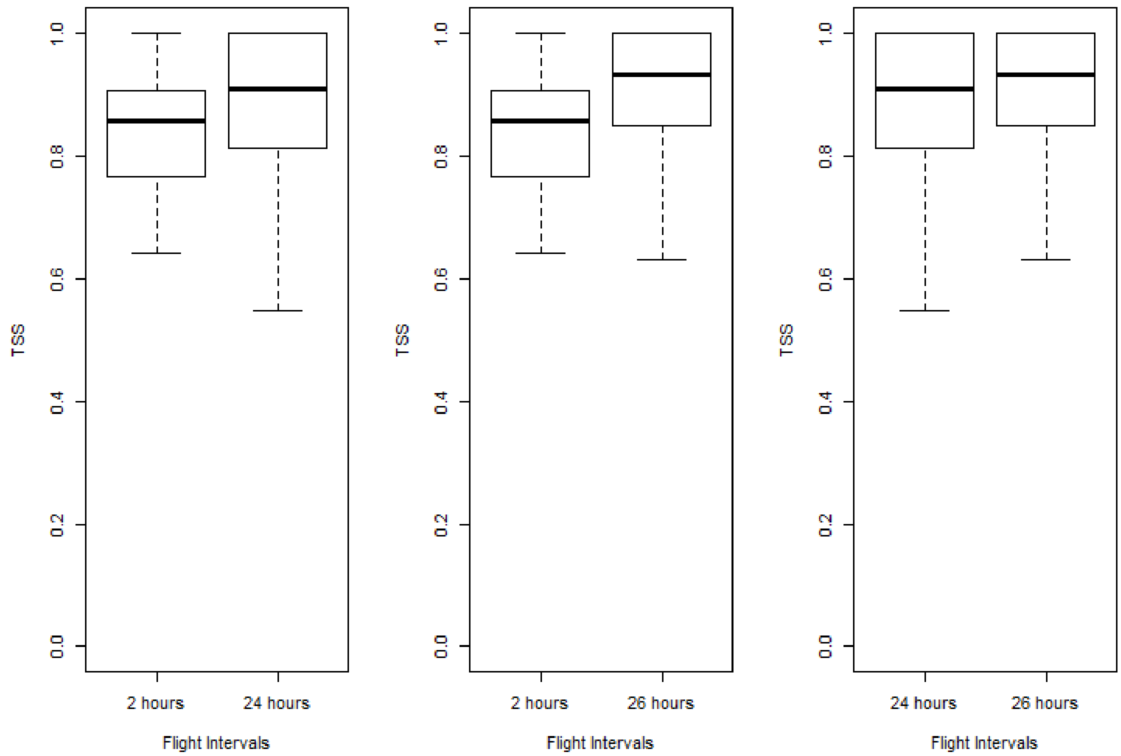

Figure 20. Boxplots of True Skill Statistic values for two flight change detection comparing 2-hour to 24-hour flight interval, 2-hour to 26-hour flight interval, and 24-hour to 26-hour flight interval. TSS values are also affected by varying alignment accuracy across colonies

Results of the reciprocal method for all three flight images strayed from observed values due to image-to-image alignment errors that varied based on colony. Nest classification accuracy (TSS) was negatively related to alignment error (β =-0.07, 95% CI = -0.097 – 0.051, $F_{1,9} = 40.52,\ P < 0.001, R^2 = 0.82$) between images (Figure 21). However, classification accuracy was not related to alignment error when errors were under 0.5 m (β =0.003, 95% CI = -0.003 – 0.001, $F_{1,9} = 0.65,\ P = 0.45, R^2 = 0.09$).

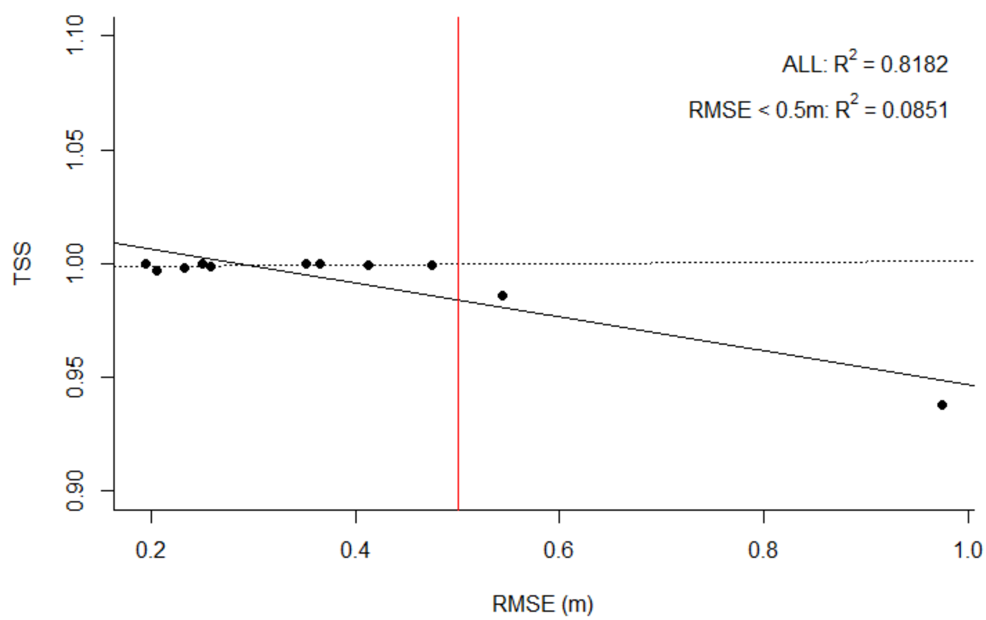

Figure 21. Linear regression of True Skill Statistic score from 3-image change detection to horizontal alignment error for each colony, represented here by the maximum root mean square error between all 3 images. The solid line represents a regression of all data, the dotted line represents regression of data with RMS errors under 0.5 m, and the red line is the 0.5 m breakpoint.

DISCUSSION

This study demonstrates the utility of using UAS for monitoring nesting American white pelicans and provides a novel analytic framework for distinguishing sedentary, nesting birds from non-nesting birds. I addressed three critical questions and found the following: 1) Ground counts of pelicans were significantly lower than UAS-derived counts with errors increasing with more oblique viewing angles; 2) Using a multitemporal change detection approach for distinguishing nesting from non-nesting pelicans was more accurate than using a monotemporal nearest neighbor analysis, but required image registration with alignment errors not exceeding 0.5 m; 3) Conducting sequential flights across two days was marginally better for distinguishing pelican nests than conducting flights only two hours apart.

Surveys

Based on the results of this study, UAS are capable of collecting imagery of sufficient resolution to identify and differentiate adult American white pelicans from chicks and other nesting species on Anaho Island with a minimal risk of disturbance. In addition, UAS were able to collect data with high temporal resolution and very high spatial accuracy in order to test minimally invasive methods for assessing reproductive success for highly sensitive species like American white pelicans. It is unknown if any pelican fledglings were present during our survey, or if they would be discernable from adult pelicans in imagery. Late-season surveys with higher resolution cameras would help address this question.

Due to the UAS regulatory environment at the time of the flights, USGS UAS pilots were only able to collect three sets of imagery. Future work should involve conducting many sets of flights throughout the nesting season to further assess nest classification methods and their ability to track nests throughout the season, particularly where birds nest in waves. This will also help to inform recommendations for spacing of flight sets (e.g., two sequential flights conducted every three weeks throughout the nesting season). If multiple flights throughout the nesting season are not possible, regular (e.g., biennial) flights capturing total adult pelican counts can be used to update correction factors for ground counts.

Data Processing

The tradeoff to conducting a UAS or any other aerial flight versus conducting a ground count is the amount of time that is needed to process the data. Image processing and bird feature extraction techniques using commercially available software are rapidly becoming more available and user-friendly, thus reducing the amount of time needed to conduct counts as well as the need for expert assistance. Feature Analyst performed well at extracting pelicans in UAS imagery. Digitizing training polygons, training, and running models took minutes to perform. However, landscape features such as rocks, whitewash, and shadows contributed to omission and commission errors as high as 31%, resulting in additional time needed to manually edit point features. Free and open source software programs are available for feature extraction and although not tested here, may perform at or above the level of Feature Analyst. Currently, however, few create spatial data while also being so user-friendly.

For difficult to access sites like Anaho Island, UAS surveys conducted from the mainland may save time and effort, particularly if precise counts or measures of reproductive success are required in monitoring plans. Streamlined workflows including a semi-automated approach to identifying active nests will complement new and emerging suites of tools designed for user-friendly remote sensing applications.

Data Analysis

While UAS may be useful for surveying disturbance-sensitive species, this trait made it difficult to conduct ground validation within colonies. I assumed that if a bird was present in the same location across all three images in the 26 hour timespan that would provide sufficient evidence to classify the bird feature as an active nest. Sardà-Palomera et al. (2012) recorded a 0.8% difference in UAS counts of black-headed gull nests using a sequential image method to a direct, in-colony ground count (n=229). During incubation, American white pelicans incubate for 1 to 3 days, only stepping off the nest to swap with a mate (Schaller 1969). This near-continuous nest attendance makes it unlikely that a significant number of nests were missed due to birds being off the nest. In addition, in-colony observations are not immune to observer error. Additional flights within a 24 to 48 hour period, in addition to ground observations made on smaller, most easily visible colonies, will strengthen active nest assumptions for American white pelicans.

Counts of nesting and all adult pelicans made from the ground were significantly lower than UAS counts in all but one colony. Hodgson et al. (2016) reported similar results for penguin and frigatebird colonies and also reported less variance in counts derived from UAS imagery than from ground counts, indicating UAS imagery is a more precise method for counting colonies. Counts derived from ground-based imagery were not significantly different from "ocular" counts made by ground observers, indicating that observer bias may play less of a role in undercounting as viewing angles from observation stations.

Classification of nests using imagery from a single flight performed well at classifying nesting birds as nesting, but performed poorly at classifying non-nesting birds as non-nesting, largely due to the lack of a clear distance threshold. Within a single image, nearest neighbor distances between nesting and non-nesting birds largely overlapped, while there was little to no overlap in sequential images (Figure 22). Although monotemporal nest classification was overall much less accurate than using multitemporal images, it may work better for some species than others. Chabot et al. (2015) found that by removing common terns thought to be attending mates in monotemporal imagery, they could yield estimates in the 93-96% range of ground validation counts. For species that have a high degree of mate attendance, removing a single bird out of a close pair might be more informative than it is for pelicans. American white pelicans perform brief nest relief ceremonies (0 to 65 minutes, mean 8.4 minutes) every one to three days, and a relieved mate may stay near the nest for a short time at an average of 4.4 minutes (Schaller 1964). In addition, large birds such as pelicans are unlikely to land near their partners' nests, thereby increasing the chances that a pelican walking through a nesting colony to attend its mate may not be easily detected in a single image.

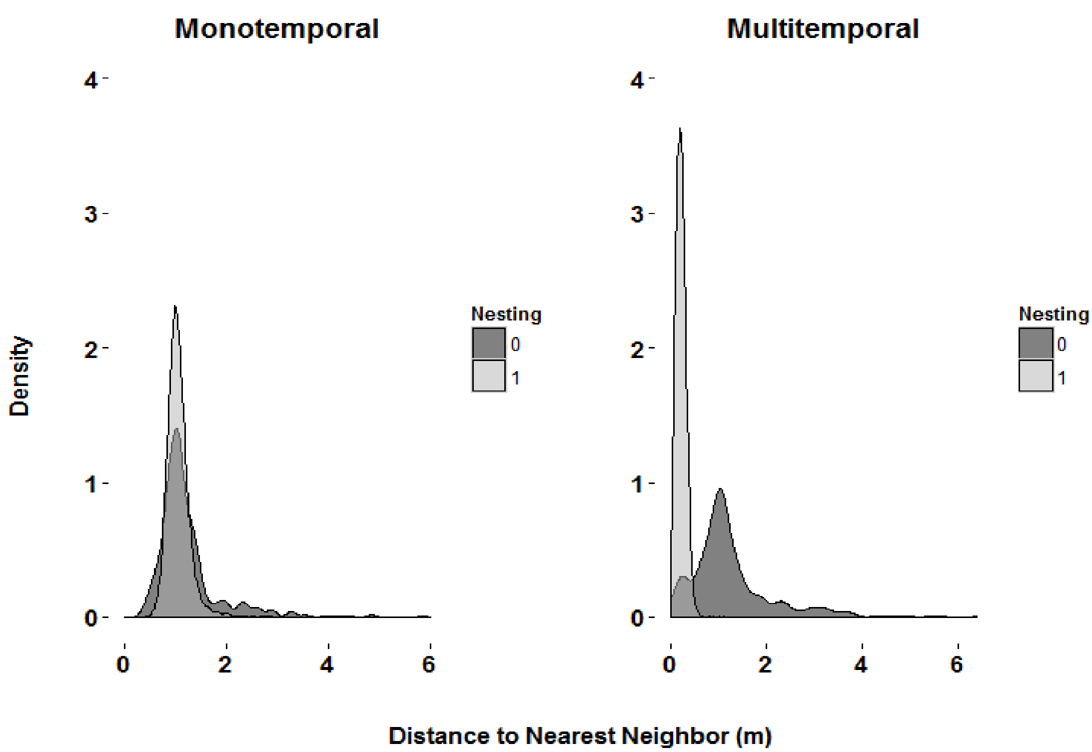

Figure 22. Density of nearest neighbor distances in meters within a single (monotemporal) flight and between sequential (multitemporal) flights for nesting (1) and non-nesting (0) birds.

I assumed that when two birds were very close to each other, only one was an attending mate and the other was nesting. When the R function for monotemporal imagery is run, it cannot distinguish between the nesting bird and the attending mate, therefore this may decrease the accuracy of this approach. One alternative solution would be to remove a point if the nearest neighbor is also close neighbors with another bird. However, due to variation in nesting patterns, it is unlikely that this would significantly alter accuracy statistics.

If a count of active nests is only required once in a season, or if weather, time, or financial constraints prohibit multiple flights, conducting a nearest neighbor analysis may be sufficient to obtain more conservative nest estimates. In addition, a nearest neighbor analysis in a single image that identifies all outliers on both ends of the nearest neighbor distribution may aid to identify courting flocks, which typically have smaller nearest neighbor distances than nesting birds do (Knopf 1979). If only one flight can be conducted, it should be flown during the peak nesting season in order to capture nesting birds, potential future nesters (in courting flocks), and likely past nesters (birds with chicks that have left the nest).

The multitemporal reciprocal nearest neighbor approach for classifying nests achieved good to excellent rates of agreement to the observed nest data for classification across three flights and two flights. I must stress that the observed data are non-independent, and the reciprocal analysis conducted across all three flights should have, in theory, matched the observed data. Colonies with very low RMS errors (< 0.5 m) across flights had the highest classification accuracy statistics. Specificity, or the proportion of correctly classified non-nesting birds, was the primary source of error in analysis across three flights, leading to lower estimates of nests. Specificity scores of less than one were due to minor distortions in imagery and the corresponding bird point features, which resulted in larger nearest neighbor distances that altered which neighbors were reciprocals. Target image-to-image alignment accuracy should take survey species into account. For example, if the target species has nests that are spaced one meter apart, then RMS errors should be less than half that nesting distance (<0.5 m) across the colony in order to avoid misclassifying birds. Insufficient overlap, platform movement, bird movement interference with tie point generation in software, and insufficient ground control can all contribute to distortion in imagery. GCPs surveyed using RTKs will produce better absolute and relative positional accuracy and reduce the amount of time needed to manually adjust distortions in orthomosaics. For nesting colonies, semi-permanent GCPs (e.g., rebar that can hold a replaceable patterned object in place) are helpful because they do not need to be re-surveyed annually.

Nesting bird estimates from two sequential flights were nearly as accurate as three sequential flights. The A Rocks to Mushroom colony had the highest error from observed data, but had a relatively low RMS error at 0.14 m (95% C.L. = 0.25m). This colony also had the highest prevalence of non-nesting birds present (45%), indicating that additional flights may be necessary to increase accuracy and reduce the risk of overestimating nests in colonies with large numbers of non-nesting birds. Mean and median TSS scores were slightly higher for flights conducted across days (0.90, 0.92) than flights conducted on the same day within two hours (0.85, 0.86), but there was no statistical significance in TSS scores for flights conducted 24 hours apart. Due to the small sample size of this data set, I recommend additional data collection in future aerial surveys to further investigate optimal timing of flights. Although loafing flocks tend to rest near shore outside of nesting colonies, flights conducted in a time span of less than a few hours risk identifying resting attending mates, fledged birds, or other loafing birds as active nests. However, flights conducted far apart (e.g., several days) risk violating closure assumptions and may incorrectly classify newly established or failed nests.

A multitemporal approach for nest classification relies on a majority ratio of nesting to non-nesting birds. Because unique individuals cannot be identified (marked) across all images (reciprocal neighbor points created independently for each flight are assumed to be a nest), when the prevalence of non-nesting birds is higher than that of nesting birds dispersion patterns are no longer uniform and movement may not be detected. To avoid inflated nest estimates, courting flocks or other densely flocking non-nesting birds should be identified and removed prior to conducting nest classification. Flights targeting active nests should be scheduled during peak nesting times, avoiding the early and late part of the nesting season. In addition, bird species must nest in generally uniform patterns and on even terrain for any nearest neighbor classification utilizing two dimensional Euclidian distance approach to work. However, because digital elevation models are easily created using photogrammetry software like Photoscan, it may be possible to calculate nearest neighbor distances based on three dimensional (x, y, z) space, such as rocky sea cliffs.

Although it was not tested here, the multitemporal reciprocal neighbor approach can theoretically be used to track nests and record new nests with additional flights later in the season. Assuming multiple waves of nesting, the maximum number of active nests can, in theory be recorded by conducting several sets of sequential flights across the nesting season (Figure 23).

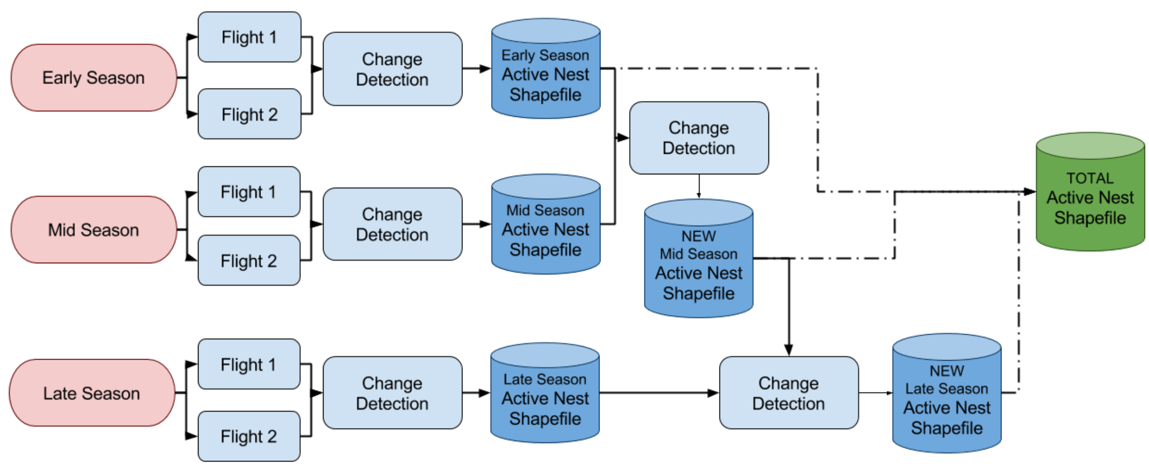

Figure 23. Example workflow for tracking nests using reciprocal neighbor change detection. Change detection is performed at two levels; active nests are estimated using total adult shapefiles at several points in the season, and nests are tracked and total nest attempts calculated using active nest shapefiles across the season.

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