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Improving Our Ability to Estimate Vital Rates of Endangered Fishes on the San Juan River Using Novel Applications of PIT-Tag Technology

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IMPROVING OUR ABILITY TO ESTIMATE VITAL RATES OF ENDANGERED FISHES ON THE SAN JUAN RIVER USING NOVEL APPLICATIONS OF PIT-TAG TECHNOLOGY

by

J. Benjamin Stout

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ABSTRACT

Improving Our Ability to Estimate Vital Rates of Endangered Fishes on the San Juan River Using Novel Applications of Pit-Tag Technology

by

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Utah State University, 2020

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The ability of PIT-tag data to improve demographic parameter estimates has led to the rapid advancement of PIT-tag systems. However, ghost tags, i.e., tags that have been shed from either live or dead fish, create uncertainty about detected tag status (i.e., live fish or ghost tags; ghost tags are PIT tags left in the environment after a fish dies or sheds its tag) when using mobile interrogation systems. I first describe my raft-based mobile PIT-tag antenna system and use it to describe the movements of 5,000 "seeded tags" (i.e., PIT-tags we placed in the river as ghost tag analogs) and their interactions with habitat features in the San Juan River. Total distances moved ranged from 0.8 to 4,124 m, but 75% of movements were less than 100 m. Flow conditions causing the smallest to largest movements were (1) base flows, (2) spring runoff flows, (3) flash flood flows, and (4) the combination of runoff and flood flows. Based on Ivlev's electivity index, tags were more likely to be detected in riffles than runs. Secondly, we developed a method to differentiate between live fish and ghost tags using a random

forest classification model with a novel data input structure based on our known fate PIT-tag detections (i.e., our seeded tags). I used the model to classify detected tags with an overall error rate of 6.8% (1.6% ghost tags error rate and 21.8% live fish error rate). The important variables for classification were related to distance moved and response to flood flows; however, habitat variables did not appear to influence model accuracy. We conducted 4-5 floats per year with our system, but more floats or additional years of data would only improve the accuracy of the system, since data is constantly being updated with new passive and active captures. Our results and approach allow the use of mobile detection data with confidence and allow for greater accuracy in movement, distribution, and habitat use studies, potentially helping identify influential management actions improving our ability to conserve and recover endangered fish.

(82 pages)

PUBLIC ABSTRACT

Improving Our Ability to Estimate Vital Rates of Endangered Fishes on the San Juan River Using Novel Applications of Pit-Tag Technology

J. Benjamin Stout

Estimating demographic parameters, such as survival and abundance, with accuracy and precision is vital for detecting trends in populations and assessing the effectiveness of management actions. In most cases, a lack of capture data make estimating parameters very challenging. The use of new technologies to increase the amount of remotely collected data is increasing, but brings new limitations and analytical issues to be resolved. One of those new technologies is the use of a mobile floating PIT-tag antenna to detect PIT-tagged fish. The issue that arises with this technology is determination of the status of detected tags (i.e., live fish or ghost tag; a tag left in the environment when a fish dies or sheds its tag). The objective of this study was develop a method to determine the status of tags detected with a mobile floating antenna. I determined the movement dynamics of known ghost PIT-tags and contrasted them with known live fish. I used a random forest analysis to develop a classification model for the two different states. I found ghost tags exhibited movement that is to be expected based on sediment transport analysis and that the distance and direction moved, and response to changes in flow were the most important variables for correctly determining tag status. This study provides a useful framework for developing models for other systems, even though the relative importance of specific predictor variables will most likely vary with location and species of interest.

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Ben Stout

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CHAPTER I

INTRODUCTION

Successful management of sport fisheries, conservation of native fish, and endangered species recovery rely on the ability to accurately assess the effectiveness of focused management actions (Parma 1998, Pine et al. 2009, and Clark et al. 2018). In order to assess the impact of management actions, managers often estimate demographic parameters such as survival and abundance (Gibbs et al. 1998, Maxwell and Jennings 2005, and Osmundson and White 2017). Detecting population trends depends on accuracy and precision of estimates. However, for many species there is still uncertainty regarding the processes limiting their recovery and the effectiveness of management actions due to a lack of accuracy and precision in some estimates of vital rates (Al-Chokhachy et al. 2009, Osmundson and White 2017, and Clark et al. 2018).

Mark-recapture analysis from active sampling techniques (e.g., electrofishing) is one of the most common ways to generate estimates of survival and abundance of fishes (Mesa and Schreck 1989 and Osmundson and White 2017). Active sampling is expensive and gear intensive (Schramm Jr. et al. 2002 and Evans et al. 2017), which can limit the amount of effort expended per survey and can have negative impacts on fishes (Dwyer and White 1997, Ruppert and Muth 1997, and Snyder 2003). Limited sampling effort can result in low rates of detection or recapture causing problems for estimating demographic parameters (Osmundson and White 2017). Low capture probabilities are exacerbated when studying rare or endangered species in complex environments. Collectively, these

issues demonstrate a need for new sampling techniques with higher capture/detection probability and lower impact on the fish.

The use of passive integrated transponder (PIT) tags and passive integrated antennas (PIAs) can reduce sampling stress and still produce large amounts of individual-based detection data. Data from PIAs has been used to significantly improve estimates of fish vital rates when combined with data from other sources (Pine et al. 2003, Webber et al. 2012, and Webber and Beers 2014). One of the limitations of PIAs is that PIAs are stationary, which limits the detections to fish that are inclined to move (Snook et al. 2016). Mobile PIT tag antennas have been created to address some of the limitations of PIAs (Fischer et al. 2012, Hodge et al. 2015, and Richer et al. 2017).

While mobile antennas can increase the probability of detection, there are limitations and analytical issues to be resolved. One of the main concerns are ghost tags. Ghost tags are PIT-tags that are left in the environment when a fish either dies or sheds its tag (O'Donnell et al. 2010). Ghost tags can create bias in estimated vital rates due to an inflated number of fish perceived as alive and detected with a mobile antenna (O'Donnell et al. 2010). Importantly, the detection of live fish cannot a priori be differentiated from the detection of ghost tags, but that knowledge is critical for using mobile systems effectively.

In Chapter 2, my goal was to determine the effect of high flows and habitat features on the movement and detection of ghost PIT-tags in lotic waters. First we described and quantified how 'seeded tags" (bare PIT-tags we placed in the river; ghost tag analogs) move during base flows, flash flood flows, spring runoff flows, and the

combination of flash flood and spring runoff flows. Secondly we described the interactions of seeded tags with habitat features (e.g., rifles, runs, etc.).

In Chapter 3, my goal was to develop a methodology to classify each detected PIT-tag as a live or ghost tag based on tag location data, and demonstrate an approach that could be used in other systems if the proper data were available. The overall approach was to perform multiple passes of sampling with a mobile floating antenna system in the San Juan River and then use the collected movement and habitat use data of known fate tags to create a classification model using random forest analysis.

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CHAPTER II

WE AIN'T AFRAID OF NO GHOSTS: TRACKING HABITAT INTERACTIONS AND MOVEMENT DYNAMICS OF GHOST PIT-TAGS UNDER DIFFERING FLOW CONDITIONS IN A SAND BED RIVER[1]

Abstract

The use of passive integrated transponder (PIT) tags has rapidly proliferated since their introduction, and new mobile detection methods have been developed. However, the presence of ghost tags (i.e., PIT-tags left in the system after a fish dies) creates uncertainty about the status (live or dead) of tags detected. Herein, we describe our raft-based mobile PIT-tag antenna system and use it to describe the movements of "seeded tags" (i.e., PIT-tags we placed in the river as ghost tag analogs) and their interactions with habitat features. We deployed 5,000 seeded tags into the San Juan River, a large sand bed river in the southwest U.S. Total distances moved by PIT-tags ranged from 0.8 to 4,124 m, but 75% of movements were less than 100 m. Flow conditions causing the smallest to largest movements were (1) base flows, (2) spring runoff flows, (3) flash flood flows, and (4) the combination of runoff and flood flows. Based on Ivlev's electivity index, tags were more likely to be detected in riffles than runs. These findings will help classify mobile PIT-tag detections as ghost tags or live fish, a critical data gap limiting accurate estimation of demographic rates, population status metrics, and descriptions of habitat use of fishes.

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[1] Stout, J.B., Conner, M.M., Budy, P., Mackinnon, P.D., and McKinstry, M.M.

Introduction

The ability to track individual animals through time and space has allowed researchers and biologists to answer some of the more interesting and challenging questions in fisheries ecology and management. The introduction of technology to the marking of individuals in fisheries began with the use of sonic tags to observe salmon movement in relation to dams in the Pacific Northwest in 1956 (Trefethen 1956). In 1984, passive integrated transponder (PIT) tags were first used in fisheries as a part of a study involving salmon in the Pacific Northwest (Prentice and Park 1984). PIT-tag use has increased dramatically since their introduction, in part because of the relatively low cost of tags. PIT-tags have been used widely to explore fish behavior (Fetherman et al. 2015), describe habitat use (Bottcher et al. 2013; Conner et al. 2016; Richer et al. 2017), quantify movement patterns (Zydlewski et al. 2001; Homel and Budy 2008; Cathcart et al. 2018), assess fish passage (Lokteff et al. 2013; Pennock et al. 2018; Baker et al. 2019), estimate survival (Osmundson and Burnham 1998; Budy and Schaller 2007; Conner et al. 2015), and estimate abundance (Fetherman et al. 2015; Richer et al. 2017). Collaborations across spatial scales and the creation of databases to share data allow the tracking of fish beyond individual study goals. The PIT-tag database for the Columbia River Basin, PTAGIS, contains records of over 42 million tags (PTAGIS 2018). The STReaMS database, which is used for endangered fish in the Colorado River Basin, has over 1 million tag records (STReaMS 2018). Despite the large numbers of PIT-tags deployed, marking fish provides little information in itself; subsequent detections or recaptures are needed to estimate demographic vital rates, population status metrics,

and/or to describe habitat use and movement. This need has led to a corresponding increase in the number and diversity of interrogation techniques.

Even though stationary antennas have the potential to provide a large amount of data, there are still limitations. Despite the increases in tag numbers and use of stationary antennas, the probability of recapture or detection is often low, especially for desert fishes (Hewitt et al. 2010; Dudgeon et al. 2015; Osmundson and White 2017). Fish behavior can make it difficult to improve the probability of detection or recapture, as fish may move in ways that might not take them past antennas (Brodersen et al. 2014; Holmes et al. 2014), or use reaches or tributaries without antennas (Bottcher et al. 2013; Cathcart et al. 2018). Furthermore, many individuals appear sedentary and do not move more than a few kilometers for years at a time. Mobile PIT-tag detection tools and techniques have been developed to complement data collected with traditional capture methods and stationary antennas. Mobile methods allow sampling of large spatial extents and areas otherwise unsampled, including reaches of streams between stationary antenna arrays (Holmes et al. 2014; Hodge et al. 2015). Many different mobile detection methods have been developed. In marine environments, researchers have developed towed sledges with attached antennas used like a trawl to survey for Turbot *Psetta maxima*, a large benthic flatfish (Sparrevohn et al. 2014). Boat mounted antennas have been used to survey mussels in non-wadeable habitats (Fischer et al. 2012), and in wadeable streams, backpack antennas have been used to sample fish (Hill et al. 2006; O'Donnell et al. 2010; Hodge et al. 2015). Some systems combining a PIT-tag interrogation system with a raft and global positioning system (GPS) have been developed (Fetherman et al. 2014; Richer et al. 2017) with the ability to cover long reaches (> 5 km), but our system, the Passive

Integrated Transponder Portable Antenna SystemS (PITPASS), is capable of floating much greater distances (> 32 km in a day depending on flows). Because these mobile methods can sample larger areas, they potentially allow us to increase detection probability and fill in knowledge gaps in life histories and demographics, habitat use, and movement. However, mobile sampling detection data cannot be used as easily as data from either stationary antennas or traditional capture methods because the status (e.g., live or dead) of detected PIT-tags is uncertain.

The status of PIT-tags detected with mobile detection tools is uncertain because of the presence of ghost tags in aquatic systems. Ghost tags are PIT-tags left in the environment after being expelled from live fish or after the fish dies (O'Donnell 2010). PIT-tags theoretically have an infinite life because the tags do not require a battery, and thus, tags can continue to be detected long after being shed. The combination of mobile sampling and the presence of ghost tags prevents the classification of live fish and ghost tags without additional information. In smaller streams, pinpointing a PIT-tag's location with backpack scanners potentially allows the tag's status to be confirmed (Fetherman et al. 2014; Bond et al. 2018), but this technique is impractical on bigger rivers with large floating antenna arrays. In some cases, movement of PIT-tags has been used to assume a detection belongs to a live fish (Zydlewski et al. 2001), but PIT-tags can still move after a fish dies. Fish carcasses can move large distances after the fish dies (Havn et al. 2017), but carcasses can shed PIT-tags relatively quickly after death. For example, the average amount of time for white sucker carcasses to shed an abdominally located tag into the environment was only 73.3 hours (Muhametsafina et al. 2014); however, this shed rate has rarely been quantified and remains largely unknown in natural systems. Even after

tags are shed, they can still move (Bond et al. 2018). There is currently little data available about ghost dynamics because of the relative novelty of these mobile antennas systems.

Our goal was to determine the effect of high flows and habitat features on the movement and detection of ghost PIT-tags in lotic waters, towards a broader goal of informing PIT tag based analyses of demographic rates and population indices. First, we described and quantified how “seeded tags” (seeded tags are bare PIT-tags we placed in the river; ghost tag analogs) move during base flows, flash flood flows, spring runoff flows, and the combination of flash flood and spring runoff flows. Secondly, we described the interactions of seeded tags with habitat features (e.g., riffles, runs, etc.). In order to accomplish these goals, we used a new configuration for a mobile PIT-tag antenna system, PITPASS.

Methods

Study Site — The San Juan River basin is part of the upper Colorado River Basin and covers about 99,200 km^2 in Colorado, New Mexico, Utah, and Arizona. The river is about 616 km long with the headwaters located in the San Juan Mountains of Colorado. Navajo Dam was completed in 1962 and is the only major impoundment on the river. The Animas River, the largest and largely unregulated tributary, joins the San Juan River 70 km downstream of Navajo Dam resulting in a more natural hydrograph below the confluence. Since 1993, the dam has been operated to match flows with the Animas River to mimic natural flow regimes for the benefit of native fish (Gido and Propst 2012). The San Juan River contains ~280 km of designated critical habitat for multiple federal

endangered species (U.S. Fish and Wildlife Service 1990; U.S. Fish and Wildlife Service 1998).

Native fish, including Razorback Sucker *Xyrauchen texanus*, Colorado Pikeminnow *Ptychocheilus lucius*, and Flannelmouth Sucker *Catostomus latipinnis*, are routinely PIT-tagged as part of a large recovery program (San Juan River Basin Recovery Implementation Program; https://www.fws.gov/southwest/sjrip/) in the San Juan River. Fish are tagged before stocking and when encountered in the river through sampling efforts. Overall, we completed thirteen sampling passes of various sections of the San Juan River and sampled ~2,233 km during differing flow conditions (Table 2.S.1) using the PITPASS. Our study area began at the Public Service Company of New Mexico diversion at river kilometer (rkm) 268.2 (measuring from the inflow of Lake Powell) and ended at the Clay Hills takeout at rkm 4.6, just upstream of the Lake Powell inflow area (Figure 2.1). We sampled from July to October in 2016 and 2017. The optimum flow rate for sampling (deep enough to prevent boats from becoming grounded, but shallow enough to still detect PIT-tags) in the San Juan River is ~28.3 cubic meters per second (m^3/s), but some sampling occurred when precipitation events unexpectedly raised flows above this level while we already were on the river (after a pass began, there was no opportunity to take out until the end).

Antenna System — We used a mobile floating PIT-tag antenna system, PITPASS, developed by the U.S. Bureau of Reclamation and Utah State University researchers beginning in 2008. Since 2008, there have been many improvements to the system. The current PITPASS (Figure 2.2) was comprised of five components: (1) two 3.1 m x 0.9 m Biomark (Boise, ID, USA) high-density polyethylene rigid antennas (for a total antenna

length of 6.1 m), (2) a multiplexing transceiver system consisting of one Biomark IS1001 Master Controller and two Biomark IS1001 auto-tuning tag readers, (3) a 24-volt 50 amp hour battery bank, (4) a 30 watt solar panel, and (5) a solar controller. The Master Controller, tag readers, battery bank, and solar controller were housed in a plastic, waterproof enclosure with the solar panel mounted on top. The solar panel eliminated the need for a generator to recharge the batteries of the system on multi-day trips. We used two 3.1 m antennas to maximize detection distance and total scanning area and allow greater portability. We used a 4.2 m frameless cataraft (AIRE, Boise, ID, USA), in order to avoid possible noise issues associated with metal frames (Fetherman et al. 2014), with the two antennas attached parallel with the main tubes underneath the boat.

We used an Xplore Bobcat (Xplore Technologies, Austin, TX, USA) rugged tablet to collect data. The Xplore tablet was chosen for its extended battery life, ability to handle heat (field conditions could exceed 38ºC in direct sunlight), and its waterproof rating. A Bluetooth dongle allowed the Master Controller to send detection data to the tablet, while at the same time the software (Biomark Data Logger Suite) on the tablet collected the GPS data. GPS data was collected from a Qstarz BT-Q818XT Bluetooth GPS (Qstartz International, Taipei, Taiwan) receiver with a 10 Hz refresh rate (updates GPS satellite data every 0.1 seconds). We collected and organized the data with Biomark software, which also allowed for the immediate input of habitat data with each detection while floating.

We measured and recorded detection distance, antenna noise, and antenna power every two hours to ensure the system was functioning correctly while on the river. We checked detection distance for each antenna while floating down the river to determine

detection distance under normal operating conditions. We measured detection distance vertically from the edge of the antenna. The PIT-tag used to test detection distance was held oriented horizontally and perpendicular to the antenna. Detection distance fluctuated, but generally ranged from 51 to 99 cm.

We used three PITPASS boats to maximize our coverage of the river. We sampled a different section of the river with each boat: river left, river right, and the center. Boat operators oriented the boats perpendicular to the flow of the river and shoreline unless river conditions dictated a different orientation for maneuvering around obstacles. Tag orientation is known to be a factor affecting the detection distance of PIT-tag antennas (Zydlewski et al. 2001). When choosing how to orient the boats on the river, tag orientation was considered, but it is impossible to know at what angle a tag in a fish or a dead/shed tag will meet the antenna. Therefore, boat orientation was chosen to maximize area covered, and we moved slowly with the current.

Seeded Tags — We seeded 5,000 bare PIT-tags into the San Juan River to mimic tags shed from either live or dead fish. Half of the tags were seeded at the beginning of each field season (i.e., 2,500 in 2016 and 2,500 in 2017). We used Biomark Inc. HPT12 tags (frequency 134.2 kHz, dimensions 12.5 [length] x 2.12 [diameter] mm and a weight of 115 mg [±20 mg], density 2.61 g/cm^3), the same tags used for all PIT-tagged fish in the San Juan River. We seeded the tags randomly across all available habitat features from moving rafts at a rate of one tag per minute. The spacing of seeded tags minimized the possibility of tag collisions. We distributed one third of the tags from each boat. After tags were scanned, they were dropped into the river from the upstream side of the raft.

We distributed the seeded tags in ~16 km each of two distinct morphological units: canyon and braided. The canyon reach was bound on both sides by canyon walls and was characterized by a deeper, narrower, single thread channel. The braided reach was not constrained on both sides at the same location and was characterized by a wide, shallow, multi-thread channel (Bliesner and Lamarra 2000). Generally speaking, the braided reach was wider, shallower, and slower moving than the canyon reach. The braided reach began at the Hogback Diversion near Farmington, NM at rkm 255 and ended at the bridge in Shiprock, NM at rkm 238. The canyon reach began when both walls of the canyon converged about 14.4 km below Bluff, UT at rkm 109 and ended about 8 km above Mexican Hat, UT at rkm 93 (Figure 2.1). We seeded each reach with ~1,250 tags per year. We distributed tags during the first sampling trip of 2016, July 11-22 and during the first sampling trip of 2017, July 8-17.

Tag Movement — We recorded the PIT-tag number, time and date of detection, latitude and longitude (WGS84), GPS error as determined by the GPS receiver, habitat feature, and habitat unit for each detection. We calculated total distance a tag moved, average distance moved per day, distance of individual movements, and distance moved during different flow events. We calculated the total distance as the sum of all movements of a tag and the average distance moved per day by dividing the total distance moved per tag by the number of days in between the first and last detection (initial release was considered first detection). We performed a linear regression with distance moved as a function of time to test whether time spent in the river was related to the distance a tag moved.

We calculated linear distance (ignoring the sinuosity of the river) between observed locations in program R (package geosphere, function distGeo; Hijmans 2017). Another possible method for making the calculation, which we did not use, calculates the difference between points on a river network. A river network is represented by a series of lines in GIS, and as a result, many PIT-tag detections do not fall directly on the lines. In order to calculate distance, the GPS points are "snapped" to the nearest point on the network. This method accounts for the sinuosity of the river in its calculations, but is most useful in smaller streams and rivers, because error is introduced to the measurement when moving GPS points to the river network (line). We did not use this method because the San Juan River is up to 150 m wide in some places, meaning the resulting error could be up to 75 m for each detection. Most of the distances we calculated were small and would be described by a straight line in the channel; therefore, our calculations would be appropriate even when considering the sinuosity of the river. River sinuosity may have caused some of the larger distances to be underreported. We would urge others calculating distances to use the linear or actual distance (accounting for sinuosity) moved as appropriate for your system of interest depending on sinuosity and scale of study area. We classified (while moving; according to depth, velocity, and flow direction) habitat features as riffle, run, pool, shoal, or low velocity as the PITPASS floated over the detected tag. We classified habitat units as belonging to two different classifications, canyon bound or braided reaches and single thread or multi-thread reaches.

We used the Shields entrainment criteria (Wilcock et al. 2009) to calculate the flow depths necessary for PIT-tag movement and the Rouse number (Rouse 1937) to predict how PIT-tags would be transported (bedload, suspended load, or wash load).

Based on tag specifications reported above, we performed the calculations using 2 mm grain size (PIT-tags were held by a 2 mm sieve, and therefore, classified as a gravel), and used a τ_{cr} value of both 0.02 and 0.06. Based on a calculated slope of 0.002 for the San Juan River (Bliesner and Lamarra 2000), when the river's depth exceeds 0.19 m, we expect to see movement of ghost PIT-tags in the system. Flows experienced 100% of the time in the San Juan River (U.S. Geological Survey 2018) are capable of moving PIT-tags. Nevertheless, stream velocities are typically low near banks and backwaters and we might expect PIT-tag deposition in these areas. Physical analysis predicts the potential for ghost tags to be widely distributed in the system. Our Rouse number calculations predict the tags will move in the bedload, and we should expect deposition in the same locations as gravels.

High Flow Events — We expected environmental variables, such as flow regime, to have the greatest influence on tag movement. High flow events (spring runoff or flash floods) can move the majority of sediment loads in rivers, including sediment particles the same size/density of PIT-tags (Malmon et al. 2004); therefore, high flow events would likely cause different tag movement than base flows. During the study, two natural high flow events occurred allowing us to examine their influence on the movement of seeded tags. A large flash flood occurring between August 5 and August 9 in 2016 was the first high flow event. This flash flood occurred because of monsoonal rains in the basin, and its duration was much shorter than a spring runoff event driven by snow melt. The river rose from 56.3 m^3/s to over 566 m^3/s in less than 12 hours, but then returned to 56.3 m^3/s three days later. The second high flow event was the spring runoff of 2017.

During this snowmelt flood, the high flows were above 141 m^3/s for about two months and peaked at around 254 m^3/s (U.S. Geological Survey 2018).

We considered tag movements to be a result of base flows when both detections occurred between high flow events. In other words, either both detections occurred in 2016 before the flash flood, both detections occurred in 2016 after the flash flood, or both detections occurred in 2017 after spring runoff. Tag movements during the flash flood were defined as tags initially detected in 2016 before the flash flood and then again in 2016 after the flash flood. Tag movements during spring runoff were detected first in 2016 after the flash flood and then again in 2017 after spring runoff. We considered movements affected by both runoff and flood flows when tags were first detected in 2016 before the flash flood and then again in 2017 after spring runoff. We conducted an ANOVA to evaluate the effect of flow conditions on movement, and if significant effects were detected ($P < 0.05$), we used the Tukey HSD test to quantify differences.

Electivity Index — One of our goals was to determine how the seeded tags were distributed among different habitat types and how the distribution changed over the course of two field seasons. We used an electivity index to describe the distribution among habitat types. Electivity indices are often used to determine how diet items are consumed relative to their abundance in the environment (Figueroa et al. 2010; Friedenberg et al. 2012) or the distribution of organisms relative to the availability of habitat features (Acolas et al. 2017). We used an electivity index to describe how the river sorted PIT-tags into different habitat features relative to the abundance of the habitat features in the river.

Available habitat began at the Hogback diversion where we began distribution of PIT-tags and continued downstream to the location of the most downstream detected PIT-tag. We only considered habitat features contained within wetted width at base flows as available. We used ArcGIS to calculate the availability of habitat features by drawing polygons around habitat features on aerial imagery to calculate their surface area. We only included the tags seeded in 2016 for use in the electivity indices to better describe how the tags interacted with habitat features over time and with the influence of various flows. The first location was the random location from the initial distribution at the beginning of the 2016 field season. The second set of locations were subsequent detections in 2016, and the third set of locations were detections in 2017.

All electivity indices exhibit some bias regarding rare items; any item composing less than 10% of the available options should be omitted from the analysis because of this bias (Lechowicz 1982). With this caveat, we omitted three habitat types (pool, shoal, and low velocity) from our initial analysis because combined these habitat types constitute less than 3% of available habitat. We used Ivlev's original electivity index (Ivlev 1961) as:

$$E_i = (r_i - p_i)/(r_i + p_i)$$

where i is the habitat type, E_i is the index value, r_i is the proportion of tags in the habitat type, and p_i is the proportion of the habitat type available in the environment. The index scales from negative one to positive one, a value of zero indicates a random association, positive values indicate positive correlation (e.g., more PIT-tags were found in a habitat type than would be expected by random association given the proportion of that habitat

available in the study reach), and negative values indicate negative correlation. We report how those index values change over time.

Results

We were able to describe 1,401 movements of seeded tags based on the resight data we collected. In the 2016 field season, we detected 305 of the 2,500 tags seeded for a raw resight rate of 12.2%. The 305 unique tags moved a total of 430 times. When all of the resights from both years were combined after the 2017 field season, the overall raw resight rate improved to 18% with 899 unique tags detected. The 899 resighted tags moved a total of 1,401 times. We were able to describe more movements than tags because some tags were detected more than two times (up to eight times, translating into seven movements). Despite our efforts to determine differences of movement in the canyon and braided reaches of the river, we resighted only 12 of the tags distributed in the canyon reach. The raw resight rate for the braided reach was 35.5%, and the raw resight rate for the canyon reach was 0.5%. All data is combined in our results.

Tag movement was extremely variable, but distances moved were generally small. Total distances moved ranged from 0.8 to 4,124 m ($\bar{x}$ = 1098.7 m; Table 2.1), with 90% of all movements being less than 250 m. Movement rates (meters moved per day) were also generally low, but we did observe some extremely high values. The tags generally moved in a downstream direction, but 15.9% of movements were directed upstream. The movements upstream ranged from 0.3 to 99.7 m ($\bar{x}$ = 8.3 m), with 97% of all upstream movements being less than thirty meters. These distances help demonstrate the potential error band of tag detection using our GPS equipment because PIT-tags most likely are not moving upstream.

We were only able to explain a small amount of the variability in distances moved based on our linear model, which we used to describe the relationship of time between detections and distance moved. The time between the first and last detections was extremely variable (0-469 days; 0 days between detections occurred when more than one boat detected the same tag on the same day) as were the movements associated with them. Although the model was statistically significant ($F_{1,1399} = 261.4$, $P < 0.0001$), we only described a small amount of the variability (Figure 2.3; R^2 = 0.16) with our linear regression.

PIT-tags move greater distances during times of higher discharge (Figure 2.4). The median distance moved during different flow conditions, from smallest to largest, were 1) base flows (7.9 ± 177.6 m [median ± SD]), 2) runoff flows (18.3 ± 501.4 m), 3) flash flood flows (37.2 ± 387.1 m), and 4) the combination of both flash flood and spring runoff flows (192.6 ± 699.4 m). Base flows and the combination of flash flood and spring runoff flows were both significantly different than all other flow conditions (P < 0.001), but flash flood and spring runoff flows were not significantly different from each other (P = 0.87). The mean distances moved were 3-14 times larger than the median distances for all categories. Minimal tag movement occurred during base flows (93% moved < 100 m).

Based on the electivity index, we predict PIT-tags will be more likely to settle in riffles than runs (Figure 2.5). Riffle habitat's E value trended in a positive direction through time, and run habitat's E value trended in a negative direction over the course of the study. These trends demonstrate tags moved out of run habitats and into riffle habitats over time.

Discussion

Herein, we quantified the movement of ghost tags and their interactions with habitat features and flows in a riverine system and described a new portable floating PIT-tag antenna system, PITPASS. Tag movements were generally small (e.g., 90% < 250 m), but large movements were much greater than expected (e.g., 4 km). The magnitude of movements increased with higher flows whether from spring runoff or monsoonal flash floods. As expected based on physical analysis, ghost tags were more likely to be found in riffles than runs. Our results suggest ghost tag dynamics are driven by their interactions with flow and habitat features.

Unsurprisingly, distances moved by ghost tags were influenced by discharge. Base flows produced the smallest movements, and the combined effects of runoff and flood flows produced the largest movements. As one might expect, the combination of the two high flow events produced the largest movements. In addition to the cumulative effect of the greater discharge, the additional time at base flows between the two events allowed for even more movement. In contrast and unexpectedly, there was no statistical difference between movements of monsoonal flash flood flows and spring runoff flows despite important hydrologic differences in the two flow events. The magnitude of runoff flows were one-fourth that of flash flood flows, even though flash flood flows only lasted one-twentieth the duration of the runoff flows. Also, flash floods can move more sediment than spring runoff flows under certain conditions (Malmon et al. 2004; Vanmaercke et al. 2010). Burial and exhumation of sediments (Hassan 1990; Hassan and Church 1994) and PIT-tags (Bond et al. 2018) through vertical mixing can occur during high flows. Burial and exhumation could explain, in part, smaller movements during base

flows (i.e., they were buried) compared to those during high flow events (i.e., they were exhumed and move). Additionally, even though burial generally does not affect the detection of PIT-tags, vertical mixing can move PIT-tags to depths exceeding the detection distance of mobile systems.

The electivity index indicated seeded tags tended to settle differentially in riffles in this river system relative to runs. This result is unsurprising because our Rouse number calculations indicate the tags should move in the bedload at all flows (Rouse 1937) and, as a result, settle in similar locations as gravels. The San Juan River is a sand dominated river, and the substrate characteristics of habitat features could have contributed to the deposition of tags into riffles. Larger interstitial spaces occur in riffles because the coarsest bed materials are likely to be deposited in riffles (Hirsch and Abrahams 1981), and there is a lack of fine sediment deposition (Keller 1971). Also, if tags collected in the troughs of larger bedforms (i.e., dunes) at a depth exceeding our detection distance, our ability to detect tags in runs may have been limited. In either case, based on seeded tags dynamics, we predict ghost tags will differentially be detected in riffles in sand bed rivers.

Some ghost tags moved much greater distances than we expected, despite movements being generally small (90% of movements were less than 250 m and 97% were less than 1 km). This is an important observation to inform future movement studies, as the lack of movement has been used to signify death of the fish (e.g., Carr and Whoriskey 2008). In some cases this may be appropriate, but both dead fish (Havn et al. 2017) and ghost tags can move large distances, as demonstrated here and elsewhere (Bond et al. 2018). As such, we recommend investigators should determine some

measure of ghost tag movement in their system of interest. This can be done by seeding some tags, as was done here, or if there are known dead tags in the system of interest, the movement of those tags could be used (the age span of the fishes can also provide information regarding ghost tags).

Although we describe patterns of movement and habitat association of seeded tags, there are some issues to consider, including GPS error and habitat-based detection bias. There is a higher level of uncertainty about tag movements when all of the potential sources of GPS error are considered cumulatively. Our GPS antenna was located in the center of our PITPASS system and a tag detected at either end of the system could be up to 6 meters away. Depending on which end of the system the tag was subsequently detected this could easily account for 12 m of error not counting error from the GPS itself. Therefore, GPS error could explain most of the upstream movements of tags, which makes sense intuitively. Despite potential errors, the difficulty of acquiring satellites in the canyon reach was not to blame for upstream movements as none of the upstream movements occurred in the canyon reach. Also, small upstream movements could result from circular currents in eddies, but only 8% of upstream movements occurred in habitat that could have been classified as an eddy; therefore, eddies could not account for all upstream movements. When we consider habitat based detection bias, a couple of factors could have influenced our resight rate. First, the width of the river limited the area sampled. The San Juan River measures up to 150 m in width, and at most, all of our boats combined could only sample 18 m at a time. Second, detection distance of the antennas or depth of the river could also account for undetected tags (Connolly et al. 2008; O’Donnell et al. 2010; Fischer et al. 2012). This effect was evident

in the canyon reach where we only resighted 12 PIT-tags, most likely due to the depth of the river. In the braided reach, the San Juan River is generally shallow, but in places the depth did exceed the detection distance of PITPASS, although this was rare.

River depth or detection distance can limit the number of tags detected by mobile systems. The inability to effectively detect tags in deeper habitats might have created a bias in our electivity index. However, in the braided reach of the San Juan River, deeper habitats (pools) are extremely rare (~0.1% of available habitat). Therefore, the area that we might have ineffectively sampled in the braided reach was small. Also, we suggest that this is unimportant. Ghost tags only become an issue for users of mobile detection systems when they are detected. If ghost tags are not detected because of depth (i.e., in the canyon reach), then there is no issue, regardless of the research or management question.

In many studies using PIT-tags, the antenna efficiency or tag detection probability can be an important variable to quantify (Aymes and Rives 2009; O'Donnell et al. 2010; Richer et al. 2017). For example, when evaluating the effectiveness of a fish passage structure (Castros-Santos et al. 1996), quantifying antenna efficiency can allow correction of bias caused by undetected fish. We were investigating the movement of PIT-tags and habitat characteristics of tag locations and antenna efficiency was not important to accomplish the goals of our study. Therefore, there was no effort made to measure or quantify the efficiency or tag detection probability.

Our work contributes to the growing body of literature on mobile PIT-tag detection systems and tag fate beyond the life of the fish. Mobile PIT-tag detection systems range from backpack systems (Hill et al. 2006; O'Donnell et al. 2010; Hodge et

al. 2015), to raft-based (Fetherman et al. 2014; Richer et al. 2017) and boat-based (Fischer et al. 2012; Sparrevohn et al. 2014) systems. Although limited to larger rivers and streams, our system improved on previous raft-based systems (Fetherman et al. 2014; Richer et al. 2017) by providing the ability to float long distances (> 32 km in a day), increasing maneuverability to navigate technical water (e.g., we successfully navigated class 3 rapids), allowing flexibility in the size of the antenna array by adding or subtracting antennas, was operable by an individual, and by eliminating the need to post process the habitat type for detections. All of these features combined will allow us to study broad-scale fish distribution and habitat type by association, as well as many other aspects of fish ecology in river systems and with the added benefit of minimal capture and handling and associated stress to often imperiled fishes. We demonstrated the potential for large movements of ghost tags, which could bias data collected with floating antenna systems, and the effects of habitat features on their fate. We recommend an evaluation of the movement of ghost tags before using “lack-of-movement” as an indicator of mortality and subsequently using raw detections to estimate survival, for example, or infer fish movement patterns. To fully develop the emerging picture of ghost tag dynamics, we recommend researchers evaluate tag dynamics in other aquatic systems with different geomorphic characteristics. The next step is to develop a statistical classification approach for determining if a detected PIT-tagged fish is alive or dead; we suggest a random forest classification approach will work well to correctly sort detected tags based on distance and direction moved and response to high flow events (Stout et al., *in review*).

Ignoring the possibility of ghost tag detection is not an option, as the presence of ghost tags can lead to incorrect conclusions regarding habitat use, fish movement, and even strong bias in estimates of survival and abundance. As more mobile systems are developed and PIT-tag use continues, the number of ghost tags in rivers will only increase. Improved understanding of ghost tag dynamics will become increasingly important. As such, there are several important insights gained from our study. First, because ghost tags are capable of large movements, lack of tag movement should no longer be used to characterize fish death. Second, high flow events cause the largest movements of ghost tags in river systems. This knowledge could help managers and researchers when designing studies using mobile sampling methods. The timing of sampling could be chosen to minimize the movement of ghost tags (i.e., sampling during low flows). Third, there are conditions in rivers, where the presence of ghost tags may not matter when using mobile systems. In deeper habitats detection distance will limit the ability to detect ghost tags, perhaps making their presence irrelevant. These insights into the dynamics of ghost tags in lotic systems will assist us in achieving a broader goal of classifying mobile antenna PIT-tag detections as live fish or ghost tags, which is essential for using mobile antenna data without bias.

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Tables and Figures

TABLE 2.1. Cumulative distances (meters) moved by individual seeded PIT tags detected with the PITPASS in the San Juan River study area during 2016 and 2017. Total number of unique PIT tags detected more than once was 899.

	Median	Mean	SD	Max
Total distance	22.8	168.4	413.1	4,124.0
Meters per day	1.6	15.9	174.3	4,086.0

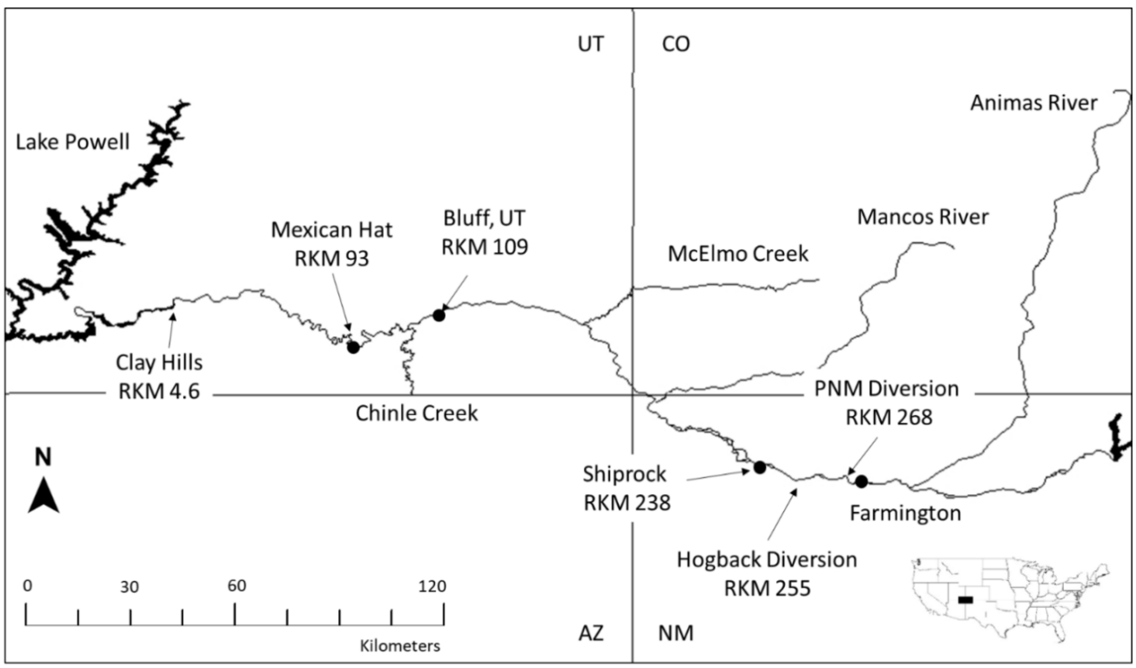

FIGURE 2.1. San Juan River study area. The vertical and horizontal lines are the state lines dividing the states of Colorado, Arizona, New Mexico, and Utah, USA. River kilometers (RKM) are provided for select landmarks.

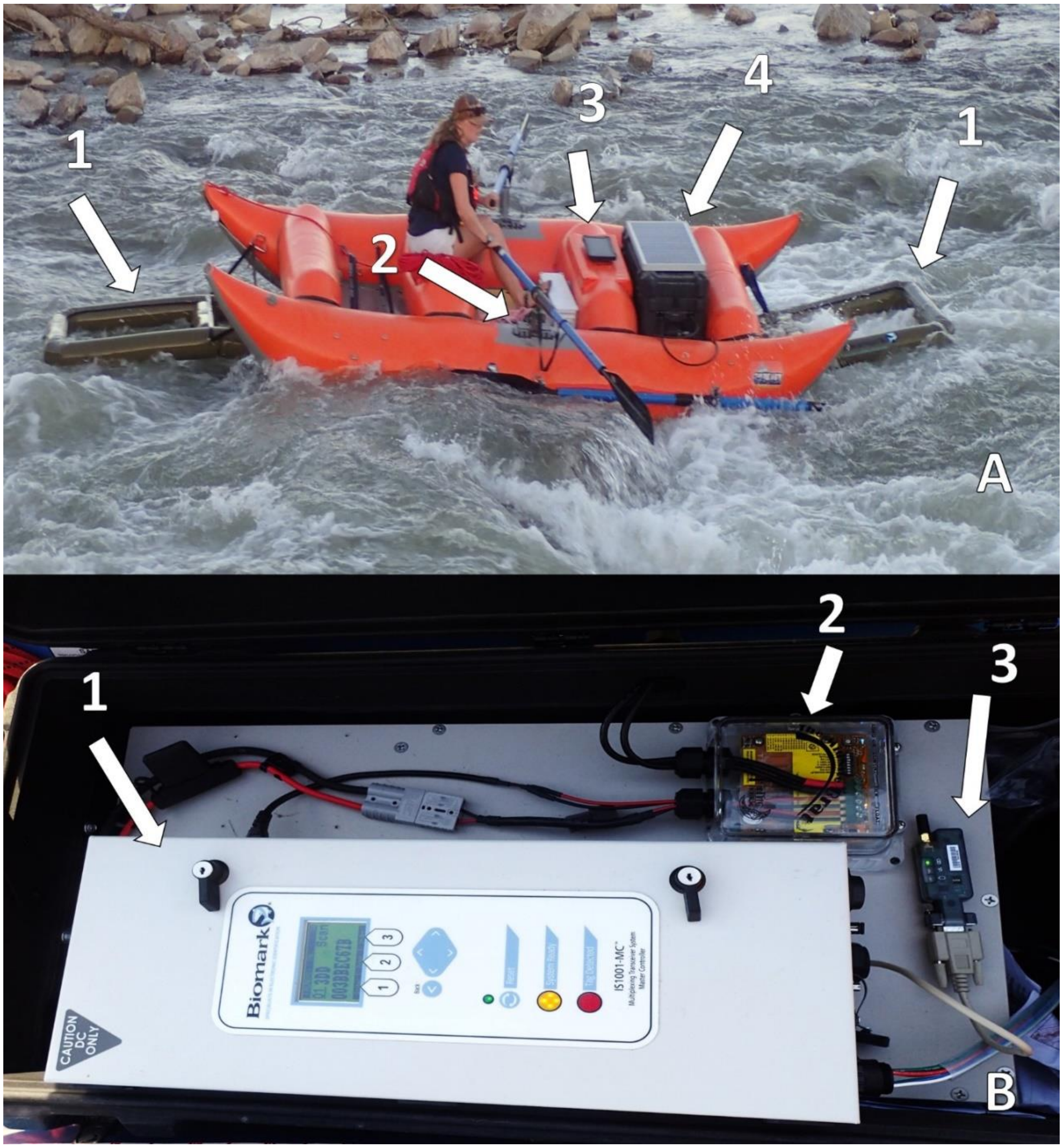

FIGURE 2.2. (A) The PITPASS on the San Juan River sampling during 2016 and 2017. Parts labeled: 1) two antennas – 3.05m x 0.9m each, 2) location of GPS receiver, 3) tablet collecting data through Bluetooth, and 4) plastic waterproof box with solar panel mounted on top, housing electronics – consisting of Master Controller, tag readers, and battery bank. (B) Interior of electronics box. Parts labeled: 1) Biomark Master Controller, 2) solar converter, and 3) Bluetooth dongle.

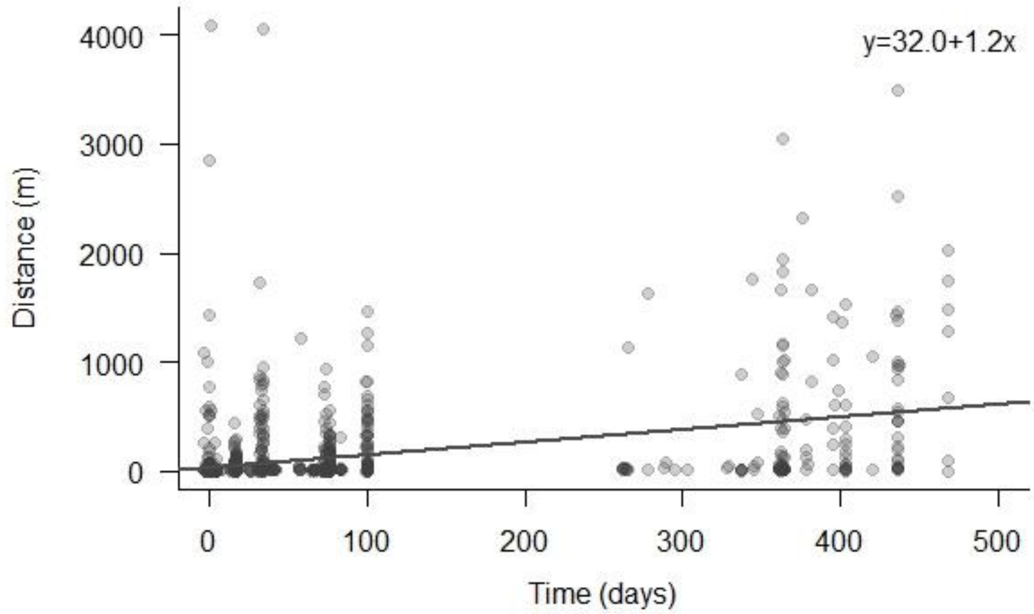

FIGURE 2.3. The relationship between the number of days between detections and the distance moved (m) between detections of seeded tags in San Juan River study area in 2016 and 2017. Each circle represents one seeded tag movement (darker areas are a result of many circles on top of each other). The line represents the linear regression fit to the data (R^2 = 0.16, $F_{1,1399} = 261.4$, P < 0.001).

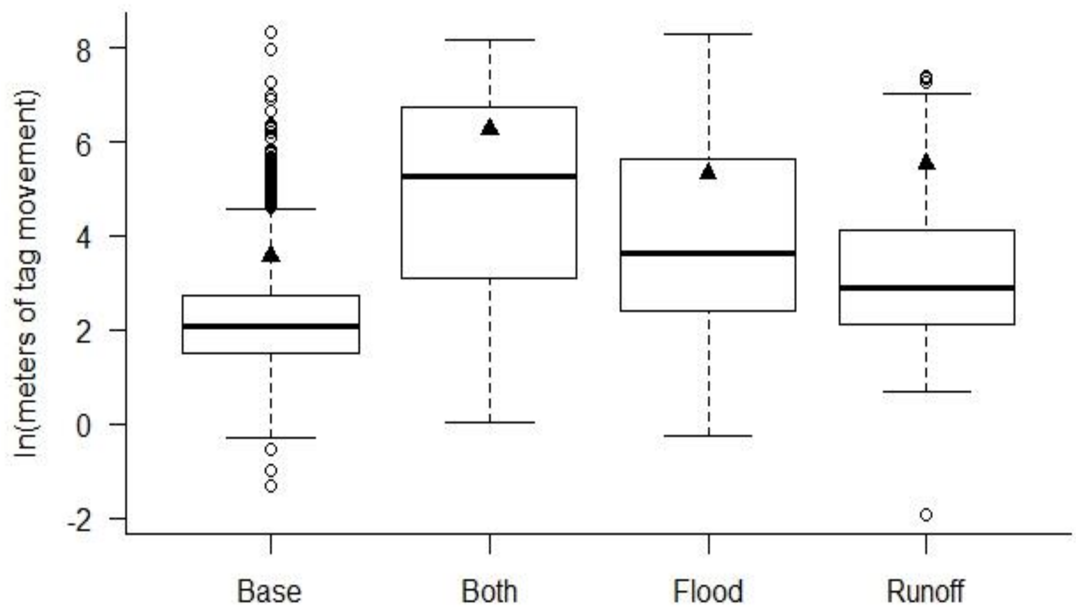

FIGURE 2.4. Distribution of distances moved (ln transformed) by seeded tags grouped by flow conditions during time of the movement, in the San Juan River study area in 2016 and 2017. Flow condition labels are: base = base flows, both = movements experiencing both flood and runoff flows, flood = flash flood flows, and runoff = spring runoff flows. Triangles represent the mean distance moved (ln transformed) for each flow condition.

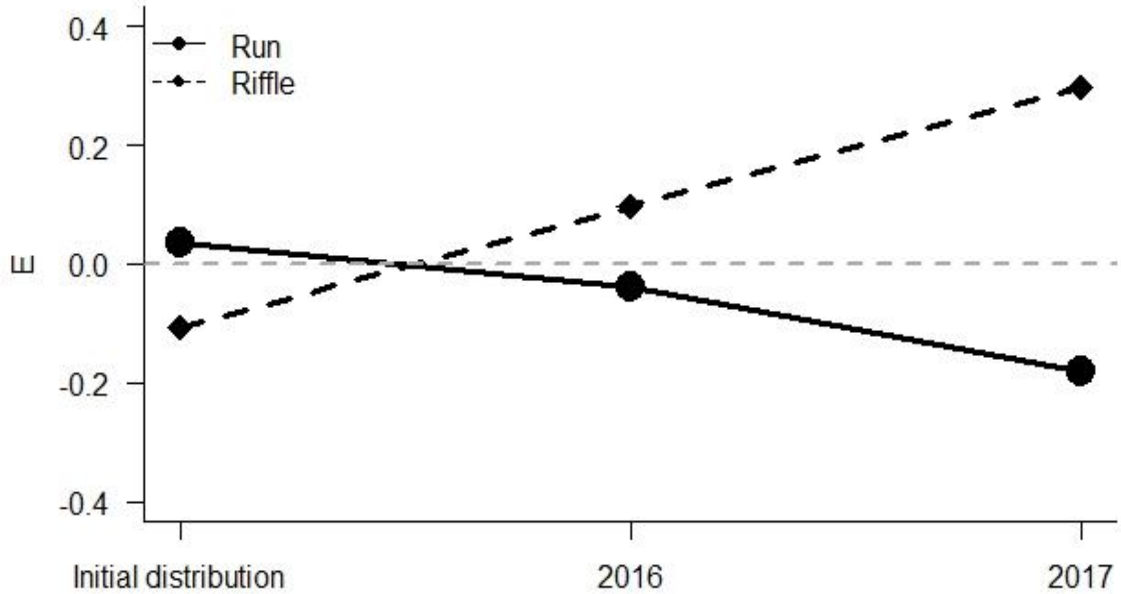

FIGURE 2.5. Ivlev's E values for association of seeded tags with riffle and run habitat types in the San Juan River study area from 2016 to 2017. Lines are drawn only to help illustrate the trend of habitat association of each habitat type and do not have any statistical meaning. The dashed line at zero indicates where a random distribution across the available habitat features would lie.

Supplemental Materials

TABLE 2.S.1. Trip statistics for all sampling trips on the San Juan River study area in 2016 and 2017. Kilometers is the number of river kilometers sampled per trip.

Pass #	Start date	End date	Total days	Kilometers	Low flow (m^3/s)	High flow (m^3/s)
1	7/11/16	7/22/16	12	263.6	14.1	42.5
2	7/28/16	8/6/16	10	263.6	14.1	623
3	8/14/16	8/24/16	11	263.6	11.3	36.8
4	9/24/16	10/1/16	8	183.5	19.8	39.6
5	10/19/16	10/27/16	9	183.5	14.1	17.0
6	7/8/17	7/17/17	10	253.0	22.7	32.6
7	7/26/17	7/29/17	4	115.1	26.9	49.6
8	7/30/17	8/2/17	4	115.1	42.5	130.3
9	8/12/17	8/15/17	4	115.1	18.4	13.6
10	8/16/17	8/19/17	4	115.1	12.7	14.1
11	8/20/17	8/23/17	4	115.1	12.7	19.3
12	9/22/17	9/27/17	6	132.4	12.7	18.4
13	10/24/17	10/28/17	5	115.1	15.6	22.7

CHAPTER III

KEEPING IT CLASSY: CLASSIFICATION OF LIVE FISH AND GHOST PIT-TAGS DETECTED WITH A MOBILE PIT-TAG INTERROGATION SYSTEM USING AN INNOVATIVE ANALYTICAL APPROACH[2]

Abstract

The ability of PIT tag data to improve demographic parameter estimates has led to the rapid advancement of PIT tag systems. However, ghost tags create uncertainty about detected tag status (i.e., live fish or ghost tag) when using mobile interrogation systems. We developed a method to differentiate between live fish and ghost tags using a random forest classification model with a novel data input structure based on known fate PIT tag detections in the San Juan River, NM, CO, and UT, USA. We used our model to classify detected tags with an overall error rate of 6.8% (1.6% ghost tags error rate and 21.8% live fish error rate). The important variables for classification were related to distance moved and response to flood flows; however, habitat variables did not appear to influence model accuracy. Our results and approach allow the use of mobile detection data with confidence and allow for greater accuracy in movement, distribution, and habitat use studies, potentially helping identify influential management actions improving our ability to conserve and recover endangered fish.

Introduction

Successful management of sport fisheries, conservation of native fish, and endangered species recovery rely on the ability to accurately assess the effectiveness of focused management actions (Parma 1998, Pine et al. 2009, and Clark et al. 2018). In

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Stout, J.B., Conner, M.M., Budy, P., Mackinnon, P.D., and McKinstry, M.M.

order to assess the impact of management actions, managers often estimate demographic parameters such as survival and abundance (Gibbs et al. 1998, Maxwell and Jennings 2005, and Osmundson and White 2017). However, the ability to detect population trends depends on both the accuracy and precision of estimates. Vital rates can be affected by sampling efforts, methods, gear, and data analysis (e.g., Walther and Moore 2005). Due to a lack of accuracy and precision in some estimates, for many species there is still uncertainty, regarding the processes limiting their viability, probability of persistence or recovery, and the effectiveness of management actions (Al-Chokhachy et al. 2009, Osmundson and White 2017, and Clark et al. 2018).

Currently, one of the most common methods to generate estimates of survival and abundance of fishes is to sample with active gear (e.g., electrofishing) and perform a mark-recapture analysis of the collected data (Mesa and Schreck 1989) despite negative impacts on the sampled fishes (Dwyer and White 1997, Ruppert and Muth 1997, and Snyder 2003). Active sampling is expensive and gear intensive (Schramm Jr. et al. 2002 and Evans et al. 2017) which can limit the amount of survey effort expended per survey. Even without electricity, netting and handling can have negative effects on fishes, and all of these effects can be exacerbated by water temperatures at time of capture (e.g., higher water temperatures can cause greater impacts, Paukert et al. 2005 and Hunt et al. 2012). In addition to the potential negative effects of physically capturing fish, low rates of detection or recapture can be problematic for estimating demographic parameters (Osmundson and White 2017). Endangered fishes, by definition, have low abundances, and can be difficult to detect in large rivers in general. Desert rivers in particular also experience high turbidity, which can further reduce the capture probability of fishes

(Lyon et al. 2014). In some systems with rare or endangered fish species, low recapture rates have resulted in poor estimates of demographic parameters (Hewitt et al. 2010 and Dudgeon et al. 2015) potentially exacerbating factors limiting our conservation efforts.

Collectively, these issues clearly indicate a need for more effective ways to sample and monitor fish with fewer potential negative consequences and higher recapture/resight rates. The use of passive integrated transponder (PIT) tags and passive integrated antennas (PIAs) can reduce sampling stress (capture and handling of fish is not required after the initial capture and tagging event) and still generate large amounts of individual-based movement data. PIAs can be used singly to answer questions about total numbers of fish moving past a point (Burke and Jepson 2006), or paired to determine direction of movement (Fetherman et al. 2015) in order to answer questions about fish passage and use of tributaries for spawning or habitat use (Cathcart et al. 2015 and Howell et al. 2016). In addition, remote sighting data, such as data from PIAs, has significantly improved estimates of fish vital rates and abundance when added to data collected with other methods (Pine et al. 2003, Webber et al. 2012, and Webber and Beers 2014). However, PIAs rely on the fish swimming past a fixed point, which can limit the numbers of fish detected to fish that are inclined to move (Snook et al. 2016). Different forms of mobile PIT tag antennas (Fischer et al. 2012, Hodge et al. 2015, and Richer et al. 2017) have been created to address some of the limitations of PIAs.

The Passive Integrated Transponder Portable Antenna SystemS (PITPASS) was created by Bureau of Reclamation and Utah State University researchers (McKinstry and MacKinnon) in order to increase the resight rate of endangered fishes in the Colorado River Basin, with the hope of expanding use to other systems, complementing the data

collected with standard active capture methods and stationary PIT tag antennas. The PITPASS is a mobile floating raft-based PIT tag antenna system with integrated GPS (3 m accuracy; Stout et al. 2019) and is now also being used in the Rio Grande River. Mobile PIT tag detectors have been used previously (Fischer et al. 2012, Hodge et al. 2015, and Richer et al. 2017), but this is the first time they have been used on a river as large as the San Juan River (study reach length of ~264 river kilometers (rkm) and up to 150 meters in width). While the PITPASS system can increase the probability of detection, there are limitations and analytical issues to be resolved. One of the main concerns are ghost tags. Ghost tags are created when tag loss, predation, and natural mortality leave a PIT tag in the environment (O'Donnell et al. 2010). These ghost tags create bias in estimated vital rates due to an inflated number of fish perceived as alive and detected with the PITPASS or other mobile passive gear (O'Donnell et al. 2010).

Importantly, the detection of live fish cannot a priori be differentiated from the detection of ghost tags, yet that knowledge is critical in order for the PITPASS or other mobile techniques to be used effectively. The objective of this study was to develop a methodology to classify each detected PIT tag as a live fish or a ghost tag based on tag location data, and build a set of guidelines or rules that could be easily modified or adjusted for use in other systems if the correct data were available. Our overall approach was to perform multiple sampling passes of the San Juan River using the PITPASS and then use the collected movement and habitat use data of known fate tags to create a classification model using random forest analysis.

Methods

Study Site

Our study site encompassed ~264 river kilometers (rkm) of the San Juan River from the PNM diversion near Farmington, NM at rkm 268.2 to the Clay Hills takeout near Lake Powell at rkm 4.6 (Figure 3.1). The San Juan River contains federally designated critical habitat for multiple endangered fish species (U.S. Fish and Wildlife Service 1998 and U.S. Fish and Wildlife Service 1990), is a part of the upper Colorado River system, and covers approximately 99,200 km^2 in Colorado, New Mexico, Utah, and Arizona. The river is approximately 616 kilometers long with the headwaters located in the San Juan Mountains of Colorado. The Navajo Dam was completed in 1962 and is the only major impoundment on the river. The Animas River, which is the largest tributary of the San Juan River, is largely unregulated and joins the San Juan River downstream of Navajo Dam resulting in a more natural hydrograph below its confluence. Historically, discharge was snowmelt driven (during our study spring runoff discharge peaked at ~254 m^3/s) with potential for large flash floods (during our study the large flood discharge peaked at ~566 m^3/s) during monsoonal rain events. Since 1993, dam operations have also attempted to match flows with the Animas River in order to mimic natural flow regimes for native fish conservation (Gido and Propst 2012).

The San Juan River supports seven native species including: Colorado Pikeminnow *Ptychocheilus lucius*, Razorback Sucker *Xyrauchen texanus*, Flannelmouth Sucker *Catostomus latpinnis*, Bluehead Sucker *Catostomus discobolus*, Roundtail Chub *Gila robusta*, Speckled Dace *Rhinichthys osculus*, and Mottled Sculpin *Cottus bairdi*. In addition, there are over 20 nonnative fishes in the river with the most abundant being

Channel Catfish *Ictalurus punctatus*, Smallmouth Bass *Micropterus dolomieu*, and Common Carp *Cyprinus carpio*. The Colorado Pikeminnow and Razorback Sucker, two large bodied and long lived (up to 50 years) fishes, endemic to the Colorado River basin, are listed as endangered under the U.S. Endangered Species Act. The decline of these two species is attributed to the creation of diversions, the major impoundment of Navajo Dam, habitat alteration from nonnative vegetation, and predation by and competition with nonnative species (U.S. Fish and Wildlife Service 1998 and U.S. Fish and Wildlife Service 1990). These two species were considered essentially extirpated in the San Juan River in 1992, and stocking of both species began soon after. Since 1994, approximately 50,000 Colorado Pikeminnow and 150,000 Razorback Sucker have been PIT tagged in the San Juan River (STReaMS 2018). However, the long lifespans of the fishes eliminates the possibility of classifying tags as ghosts based solely on age of fish in the San Juan River. The Flannelmouth Sucker, the Bluehead Sucker, and the Roundtail Chub, some of which are also PIT tagged in the San Juan River, are considered to be Species of Special Concern in at least two of the following states: Wyoming, Utah, Colorado, New Mexico, and Arizona (Bezzerides and Bestgen 2002) and in some states are managed under a range-wide conservation agreement (Budy et al. 2015). Given the amount of tagging in the system (and elsewhere), ghost tags are a problem of increasing concern.

Sampling Methods

In Stout et al. (2019), we describe the PITPASS, our sampling method, the distribution and detection of known ghost tags, and the data recorded for each detection in greater detail. We used three PITPASS boats and each sampling pass varied in length (from 115 -264 rkm) and flow rate of the river (11.3 – 130.3 cubic meters per second). In

total, we sampled ~2,233 rkm during 13 passes over the course of two field seasons. The data recorded or calculated from our detection data included distance moved between detections, direction moved relative to flow, meters moved per day, which habitat feature a tag was detected in (riffle, run, pool, low velocity, and shoal), whether a detection occurred in a single or multi-thread channel, whether a detection occurred in a canyon or broad alluvial valley, whether a movement occurred during the flash flood, and whether a movement occurred during overwinter/spring runoff.

For this study, we divided the data collected during field sampling into three categories; live fish, ghost tag, or unknown tag. Ghost tag refers to the PIT tags we distributed randomly in the river to simulate ghost tags. We distributed 5,000 total known ghost tags into two distinct morphological reaches ~16 km in length (a shallow braided reach and a deeper canyon bound reach). Each reach received ~1,250 tags per year distributed on the first sampling trip of the season. We randomly distributed one third of the tags from each boat at a rate of one tag per minute across all habitat types (Stout et al. 2019). Unknown tag refers to any PIT tag implanted in a fish at any time in the San Juan River. We used data from the STReaMS database, which is the repository for all PIT tag data collected in the Upper Colorado River Basin and the San Juan River Basin (STReaMS 2018), to confirm detections as live fish. A fish was considered live if the fish associated with the tag was physically captured or detected at a PIA system in the same field season as our detection or any time after. PIAs in the San Juan River are overwhelmingly in either fish passage structures or tributaries because of the size of the river and its substrate (sand bed river up to 100 m wide). In order for a tag to be detected by a PIA in the San Juan River after being detected in the main channel by the PITPASS,

a tag would have to move upstream into a tributary or a fish passage structure. Therefore, we considered it appropriate to consider tags demonstrating these movements as live fish, as it is unlikely a ghost tag would move this way.

Analysis: Random Forest

We used random forest analysis to develop and evaluate models for classifying tags (into two classes: live fish and ghost tags) using the known fate tag data. We used the randomForest function in package randomForest in R (Liaw and Wiener 2002) to create our models using the default parameters (500 trees and 4 variables tried per split). Random forest is a method for classification and regression, and was used, in part, because it makes no assumptions about the distribution of data and its strength as a statistical classifier (Cutler et al. 2007). We used the randomForest function which develops classification trees using a bootstrapping method leaving out roughly one third of the data to be used for testing. The unevaluated third of data is referred to as out-of-bag and is used to evaluate the accuracy of the constructed model. Since out-of-bag data is not used for developing the trees, out-of-bag error estimates serve as cross-validated accuracy estimates (Cutler et al. 2007). We used the out-of-bag error estimates to assess model performance.

We structured the input data for the random forest analysis in two different ways to achieve the most accurate model. Typically in random forest classification models, each site or individual is only observed one time (Cutler et al. 2007), and sites or individuals are considered independent. In our case, we considered each observed movement independent and unrelated to any other movements even if made by the same tag (despite the obvious fact that a second movement of a tag will begin where the first

tag ended, possibly introducing bias regarding habitat use). We refer to the models using this data structure as independent, and include an example of the input data structure in the supplemental materials (Table 3.S.1). The variables used for classification in the independent model included two variables for distance moved (total distance and meters moved per day), one variable for direction moved (direction), six variables for habitat (hab_start, hab_stop, channel_start, channel_stop, habunit_start, and habunit_stop), and two variables for flow conditions (flood and overwinter; all variables defined in Table 3.1).

We developed a novel data input structure that condensed all movements of a single tag into one observation in order to connect all movements of a single PIT tag. In our study, some tags were resighted up to seven times giving us repeated measures of the same individual. An example of this data structure, which we will refer to as dependent, is included in the supplemental materials (Table 3.S.2). The new variables we used for classification in the dependent model included the total distance moved in a specific direction relative to flow: up, down, left, and right. We also included two variables encompassing cumulative distance moved (total and meters moved per day), and two variables for flow conditions observed during movement (flood and overwinter). For habitat data, we used a count of how many times a tag was detected in each habitat type (run, riffle, shoal, pool, low velocity, single thread channel, multi-thread channel, canyon, and braided; variables defined in Table 3.2). Of the two data structures, the model with the lowest out-of-bag error rate was chosen as the most accurate.

Our initial model used all live fish detected for classification, regardless of species. Then, we limited our input data to a single species at a time and reanalyzed each

data structure to determine differences between the species, because while the species detected exhibit similar movement behaviors, the habitat associations may be different. In each case, the entire ghost tag dataset was used. The only three species detected and subsequently used for analysis were Razorback Sucker, Flannelmouth Sucker, and Colorado Pikeminnow (listed from most to least abundant in our sample); however, limiting our live fish data to a single species decreased the number of observations used to construct each model.

We used a backwards stepwise variable selection method to evaluate the influence of the predictor variables on the best model (based on the out-of-bag classification error rates; Cutler et al. 2007). We performed this step to determine which variables were necessary to maintain the accuracy of the model while reducing its complexity. Random forest models rank variables in order of importance for correct classification based on the 'mean decrease in accuracy', which describes the loss in accuracy of the model when a variable is not used in the analysis (Cutler et al. 2007). Based on the ranking of variables, we removed the worst performing variable (i.e., the variable with the lowest mean decrease in accuracy) in the model, and reran the analysis. These steps were repeated until only one variable remained, and the accuracy of each version of the model was examined. Then, we examined the variables identified as important by our variable selection process (removal from the model led to a decline in accuracy) using partial dependence plots to determine the differences in live and ghost tag dynamics. Partial dependence plots display the logit of probability of belonging to a specific class and all values of the variable of interest. For partial dependence plots, all other variables are held

to an average value; therefore, partial dependence plots are a vast simplification of complex data and should be interpreted with caution.

Results

Tag Detections

Our detection data allowed us to describe the movement of 899 known ghost tags over two seasons. Of the 5,000 known ghost tags distributed in the San Juan River, 899 were detected more than once, for a raw resight rate of 18%. Of those 899 tags, there were 1,401 pairs of detections where movement could be measured, because some tags were detected more than two times (Table 3.3).

The detection of unknown tags allowed us to describe the movement of 302 confirmed live fish over two seasons. We detected a total of 3,958 unique unknown tags, but only 847 of those tags were detected a second time, for a raw resight rate of 21%. Of those 847 tags, there were 1,190 pairs of detections for which we could measure movement. However, we were only able to confirm 302 of those tags as live fish, with 370 pairs of detections where we could measure movement (Table 3.3). All of the data from both confirmed live fish, and the known ghost tags were used in the construction of the random forest classification models.

Random Forest Models

The random forest models using the dependent data structure were more accurate than the independent models. Further, limiting input data by species did not improve either model. With the independent model, we were able to differentiate the live fish from the ghost tags with an overall error rate of 7.6% (out-of-bag estimate of error rate). When

examined separately, the two classes exhibited error rates of 28.9% (live fish incorrectly classified as ghost tags) and 1.9% (ghost tags incorrectly classified as live fish, Figure 3.2). Our ability to classify was better with the dependent model than the independent model, lowering the overall error rate to 6.8% (an 11% reduction in error). The accuracy of both classes improved, and when examined separately, demonstrated error rates of 21.8% (live fish, a 25% reduction in error) and 1.6% (ghost tags, a 15% reduction in error, Figure 3.2). Separating known live detections by species led to decreases in model accuracy (specifically of the error rate of the live class) when using either independent or dependent data structures. The ranking of models from best to worst (based on error rate of the live class) for both data structures were: 1) all species combined, 2) Razorback Sucker only, 3) Flannelmouth Sucker only, and 4) Colorado Pikeminnow (Figure 3.2).

We used the ranking of predictor variables to determine that the five most important variables for correct classification of detected tags were: 1) distance moved up, 2) total distance moved, 3) meters moved per day, 4) distance moved down, and 5) flood (Figure 3.3). All of the variables related to habitat use or association were ranked lower, with regard to importance, as were the variables describing movement perpendicular to the river's flow. When any of the top five variables were removed, the accuracy of the model declined (Figure 3.4). Habitat features and measures of river complexity did not appear to influence the accuracy of the models, as the performance of the model did not change with their removal from the analysis.

When the five most important variables were examined individually using partial dependence plots, some patterns emerged (Figure 3.5). We reiterate here that partial dependence plots are simplifications of complex data, where all other variables are held

constant while examining the variable of interest. Larger total distances and upstream distances moved are more likely to belong to a live fish. The probability of being a live fish increased with larger upstream movements up to ~2,000 m, at which point a larger distances moved upstream no increased the probability of classification as a live fish. Distance moved upstream is an example of the limited interpretability of these plots. It would be expected that any movement upstream should belong to a live fish, and it would also be expected that the probability of being classified as a live fish would be higher than the maximum probability of ~75% this variable achieves when a tag moves more than 2 km in an upstream direction. The probability of being a live fish increased as the total distance moved increased up to ~8,000 m, at which point a further increase in distance no longer increased the probability of classification as a live fish. The probability of being a live fish increased as distance moved downstream increased until ~8,000 m, when a larger distance no longer increased the probability of classification as a live fish. The highest probability of indicating a live fish, based on the number of meters moved per day, occurs around 650 m. Known ghost tags had a higher probability of having a flood affected movement as demonstrated by the negative relationship shown on the graph (Figure 3.5).

Discussion

Our study is the first to evaluate a classification method for determining PIT tag status (live versus ghost) when using mobile interrogation systems. We were successful with a very high degree of overall accuracy. While we could identify ghost tags with a high degree of accuracy (only 2% were misclassified as live fish), the model was less effective with live fish. Using our current error rates as a guide, approximately 20% were

misclassified as a ghost tag. This degree of error makes our classification of live tags conservative. However, only ~20% of all detected tags were ever resighted, meaning 80% of tags detected were never classified during our two year sampling period. A longer sampling period and more detection passes would obviously increase detections and subsequent resights potentially allowing greater accuracy in classification of live fish.

Our top model used the dependent data structure and combined the data from all detected species. The dependent structure took into account the possibility of a tag being detected more than two times and resulted in a better description of an individual tag's movements and a greater ability to classify it correctly. When the input data was limited to a single species, there was a lower number of observations to build the model, and the subsequent decline in accuracy of the model appeared to correspond to the decline in the number of observations. Even when all species were combined, there was still an imbalance in our classes, which can cause problems with overfitting. However, random forest models have been shown to perform well despite class imbalance at much higher ratios than our situation of ~3 (ghost tags):1 (live fish; Khoshgoftaar et al. 2007, Elrahman and Abraham 2013, and Muchlinski et al. 2015). Since all three species analyzed exhibit similarities in movement behavior (McKinney et al. 1999, Irving and Modde 2000, and Zelasko et al. 2010), we believe combining all species for the analysis was appropriate. Combining all species might not work in other cases where the species are less related or exhibit very different movement behaviors.

We expected differences in movement between ghost tags and live fish would be important in classification. Razorback sucker, flannelmouth sucker and Colorado pikeminnow are all known to move very large distances (McKinney et al. 1999, Irving

and Modde 2000, and Zelasko et al. 2010), and while ghost tags can move large distances (Bond et al. 2018 and Stout et al. 2019), we observed a large difference between the two classes. It is perhaps unsurprising then that, of the five variables identified as influencing the accuracy of the model, four were related to the distance moved by a tag. As expected, live fish generally moved greater distances than the ghost tags. Also, fish and other organisms exhibit behavioral changes to minimize the effect of high flows (Lytle and Poff 2004), and ghost tags respond to higher flows similar to sediment (Bond et al. 2018 and Stout et al. 2019). Therefore, we expected ghost tags and live fish to exhibit different responses to changes in discharge, and this expectation was demonstrated by the fifth variable influencing classification, flood.

Despite our expectation that live fish behavior and ghost tag deposition would result in differences in habitat association, habitat type did not appear to be important in the correct classification of tags. We believe this disconnect between tag location and habitat might not be true for all river systems. The PIT tags we used to simulate ghost tags were an artificial addition to the system randomly placed in the river in all habitat features. However, as time passes and these tags move, their distribution tends to favor riffles over runs (Stout et al. 2019). We believe the signal from this phenomenon could be masked by the overwhelming numbers of tags randomly associated with habitat as per our initial distribution. Additionally, the San Juan River has very few large pools or deep-water habitat where tags, and possibly even fish, could accumulate, further reducing the ability to detect differences in habitat association.

Mobile PIT tag interrogators have been developed to supplement low recapture rates and reduce negative effects of capture and handling of organisms (Paukert et al.

2005, Hunt et al. 2012, and Reynolds et al. 2012), but the inability to separate ghost tags from live fish based on detection data is one of the recurring points of discussion in studies using mobile systems (e.g., O'Donnell et al. 2010, Fetherman et al. 2014, and Richer et al. 2017). Extensive use of PIT tags has led to large numbers of potential ghost tags in aquatic systems, and in other work, extensive movement of ghost tags has been observed (from 2.0 km in Bond et al. 2018 to 4.1 km in Stout et al. 2019), which highlights the need for a classification system. Our study demonstrates the possibility of classifying detected tags, yet there is uncertainty associated with the method. In particular, our system relies on detecting the tag at least twice, which is not always possible. With limited sampling (i.e, passes), a short study-period, or remote areas or complex habitats that are difficult to access, this system may be limited in its applicability.

Despite the capabilities of our system, one limitation is the time required to collect comprehensive data. The small sample size of confirmed live fish (only 30 individuals) from our first year of sampling made it difficult to successfully classify detected tags. However, we were able to achieve a much higher level of model accuracy with the addition of the second year's data (272 additional live fish). However, the low number of redetections for live fish made it impractical to use mobile detection data to estimate survival rates without another source of data (i.e., electrofishing or detections at stationary antenna). We note these limitations to emphasize this process is iterative, and potential users need to remember classification techniques will require multiple passes, ideally within and across years. Once classification models are devised for a system, they can be continuously improved upon with the addition of subsequent data.

While we were unable to use individual characteristics of tagged fish as predictor variables in our classification model (known ghost tags were never in a fish), this approach could be useful elsewhere. Potential individual variables which could influence movement or habitat used by individuals include: 1) the age of the fish or how long the tag has been deployed, 2) species of fish tagged, 3) length and/or weight at last capture, and 4) sex. In the San Juan River, fishes can be extremely long lived (up to 40-50 years; McCarthy and Minckley 1987, Scoppettone 1988, and Osmundson et al. 1997); therefore, no tags could be classified as ghosts based on age. However, in systems with shorter lived fishes (e.g., Rio Grande Silvery Minnow *Hybognathus amarus*, which live <4 years), some ghost tags can be classified definitively based on age and used to model ghost tag movement to calibrate a classification model. This approach to identifying ghost tags has been used successfully in streams with coho salmon, which have a definitive age/time of mortality (Bond et al. 2018).

Mobile PIT tag detection systems could be extremely useful in the future in habitat use and association studies. Habitat restoration is an increasingly popular option for conservation and recovery of fishes, and due to the high cost of restoration (Bernhardt et al. 2005), plans should be based on accurate response data. Electrofishing and snorkeling are two methods typically used for habitat use and selection studies, but they each have issues that can bias the results. Electrofishing can sacrifice some accuracy as fish are disturbed before capture (Heggenes et al. 1990 and Persinger et al. 2004), and snorkeling is limited by turbidity and cover limiting visibility (Fausch and White 1981, Pert et al. 1997, and Persinger et al. 2004). With PITPASS, we demonstrated the ability to cover large areas and detect largely undisturbed fish using mobile PIT tag detection

methods. However, this method still requires the boatman to determine habitat type, but classification of habitat type can be both quick and accurate with proper training and calibration (Roper and Scarnecchia 1995).

Our study was the first to use movement and location data to classify PIT tags detected by a mobile sampling method. We were able to build a random forest model with a novel input data structure accounting for the ‘relatedness’ of a detected tag’s movements and identified the variables important for correct classification in our system and most likely other large sand bed rivers. The analytical framework we describe herein will be useful in developing similar models for other systems, even though we expect the relative importance of specific predictor variables to vary with location and species of interest. Future applications of this method should examine how the addition of individual characteristics (length, weight, sex, etc.) of the tagged fish affects the model’s classification accuracy. While we believe this methodology can be an excellent contributor for habitat use studies, in order to quantify vital rates (e.g., survival), other data sources or more intensive sampling will be required.

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Tables and Figures

Table 3.1. Descriptions of variables used to create the model with the independent data structure for random forest analysis of data from the San Juan River study area in 2016 and 2017.

Variable Group	Variable Name	Type	Description
Distance moved	distance	continuous	distance moved between detections (meters)
	m_per_day	continuous	distance divided by number of days between detections (meters)
Direction moved	direction	categorical	direction moved relative to flow (up, down, left, and right)
Habitat	hab_start	categorical	habitat type of first detection (run, riffle, pool, shoal, low velocity)
	hab_stop	categorical	habitat type of second detection (run, riffle, pool, shoal, low velocity)
	channel_start	categorical	type of channel of first detection (single or multi thread)
	channel_stop	categorical	type of channel of second detection (single or multi thread)
	habunit_start	categorical	habitat unit of first detection (canyon or braided reach)
	habunit_stop	categorical	habitat unit of second detection (canyon or braided reach)
Discharge	Flood	Binary	whether or not the movement occurred during the flash flood flows
	Overwinter	Binary	whether or not the movement occurred during the spring runoff flows

Table 3.2. Descriptions of variables used to create a live vs ghost tag classification model with the dependent data structure for random forest analysis of data from the San Juan River study area in 2016 and 2017.

Variable Group	Variable Name	Type	Description
Direction	Up	continuous	sum of movements upstream relative to flow direction (meters)
	Down	continuous	sum of movements downstream relative to flow direction (meters)
	Left	continuous	sum of movements towards river left (meters)
	Right	continuous	sum of movements towards river right (meters)
Cumulative distance	Total	continuous	sum of all movement regardless of direction (meters)
	m_per_day	continuous	total divided by number of days between first and last detection (meters)
Habitat	Run	discrete	number of times detected in run habitats
	Riffle	discrete	number of times detected in riffle habitats
	Shoal	discrete	number of times detected in shoal habitats
	Pool	discrete	number of times detected in pool habitats
	low_velocity	discrete	number of times detected in low velocity habitats
	Single	discrete	number of times detected in single thread areas of channel
	Multi	discrete	number of times detected in multi-thread areas of channel
	Canyon	discrete	number of times detected in the canyon reach
	Braided	discrete	number of times detected in the braided reach
Discharge	Flood	binary	whether or not the movements observed occurred during the flash flood flows
	Overwinter	binary	whether or not the movements observed occurred during the spring runoff flows

Table 3.3. Total number of tags detected, numbers of total movements observed, and numbers of unique tags detected more than one time (unique resights) in the San Juan River study area during 2016 and 2017 for both known ghost tags, unknown status tags, and live fish.

	Total detected	Unique resights	Movements
Ghost tags	5000	900	1405
Unknown tags	3958	847	1190
Live fish	302	302	370

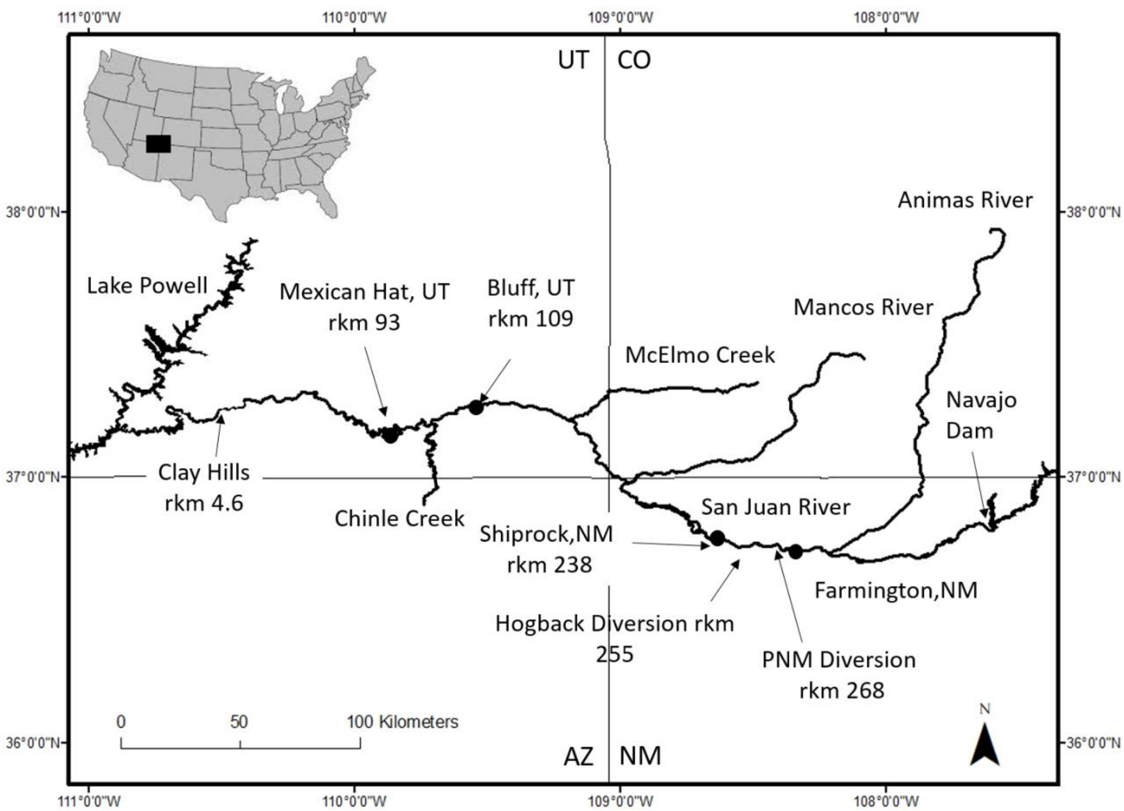

Fig. 3.1. The San Juan River study area began at the PNM diversion at river kilometer (rkm) 268 and ended at Clay Hills at rkm 4.6. Horizontal and vertical lines are state boundaries, and state abbreviations are UT (Utah), CO (Colorado), AZ (Arizona), and NM (New Mexico). Cities are represented by filled circles and select landmarks are shown with rkm. Map data is from Esri, National Atlas of the United States, and the United States Geological Survey.

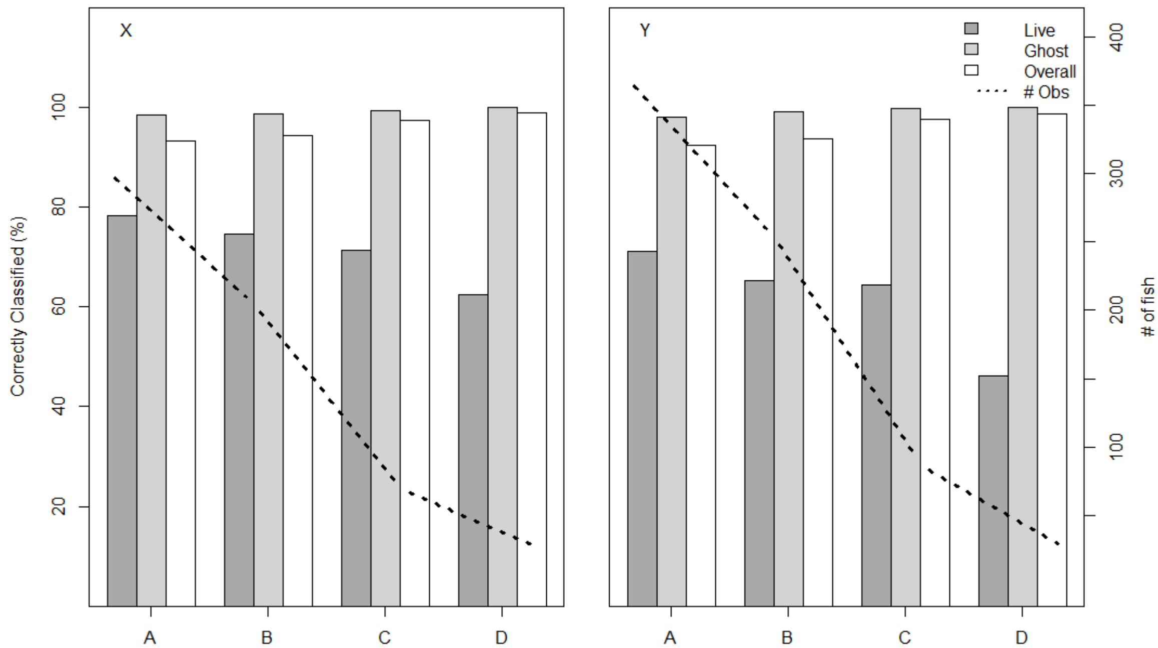

Fig. 3.2. Change in accuracy of the random forest model, using the dependent (X) and independent data structure (Y), when all species of live fish are combined and then limited to a single species. The models are A) all species combined, B) only Razorback Sucker, C) only Flannelmouth Sucker, and D) only Colorado Pikeminnow. The # Obs is the number of observations of confirmed live fish used to create the model for each species. Data are from the San Juan River study area in 2016 and 2017.

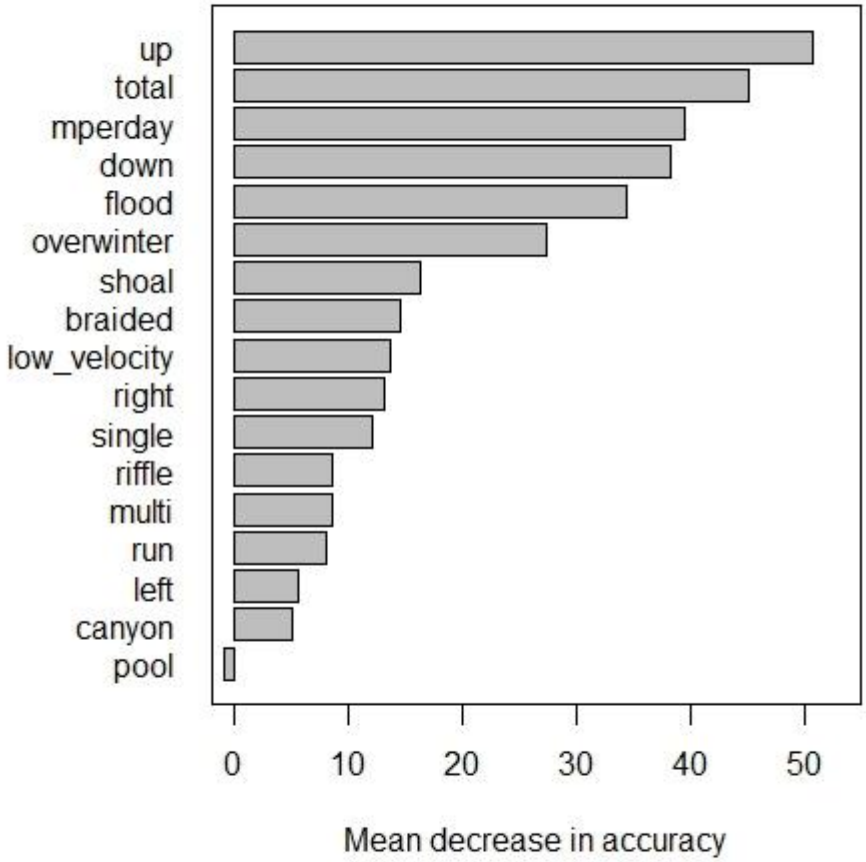

Fig. 3.3. Variable importance plot of the predictor variables used to create the classification model ranked from top (most important) to bottom (least important). The x-axis demonstrates the decrease in accuracy of the model when each variable is removed; higher values indicate more important variables for classification. Data are from the San Juan River study area in 2016 and 2017.

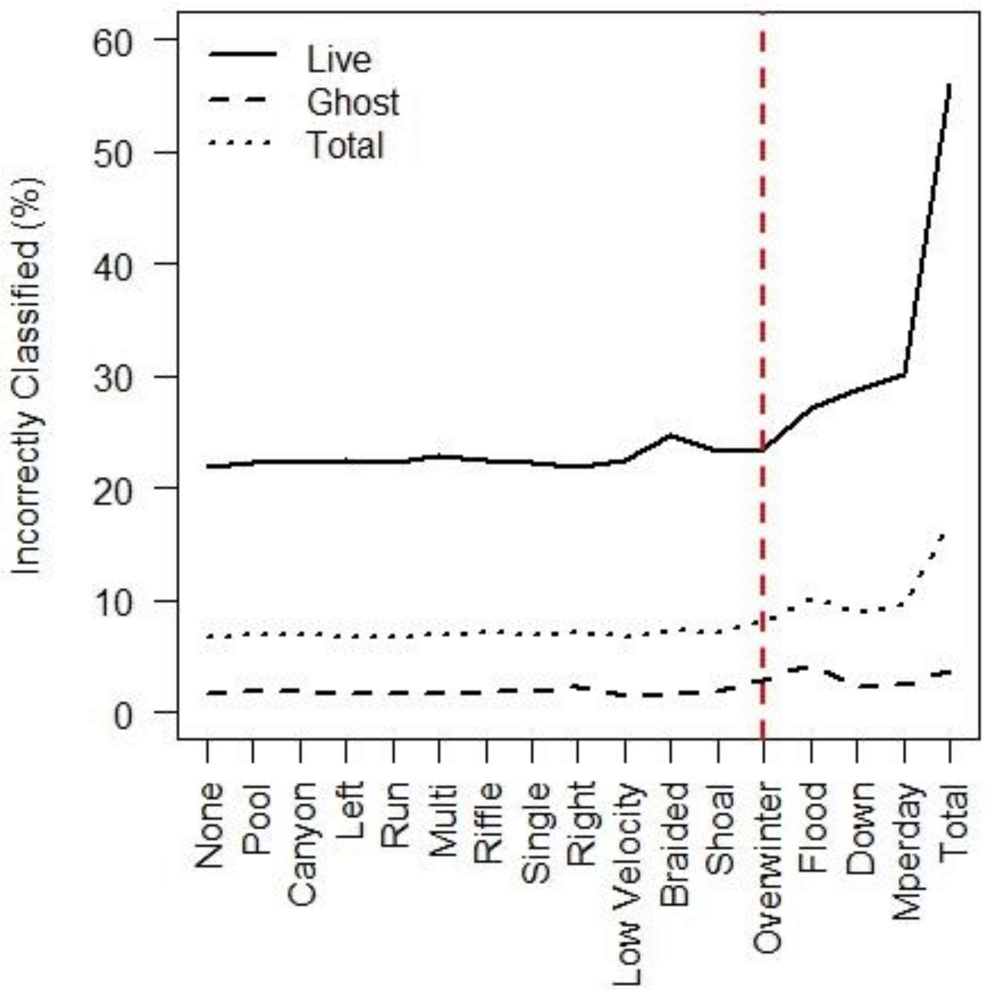

Fig. 3.4. The change in classification error when predictor variables are removed from the model. The x-axis lists which variable has been removed sequentially from left to right (and in order from least important to most based on the variable importance plot, Figure 3.3), beginning with “none” (no variables have been removed yet; all variables used in the model) and ending with “total”. The variable “up” is never removed, since one predictor variable is required to build the model. The vertical line delineates the beginning of a large increase in classification error. Data are from the San Juan River study area in 2016 and 2017.

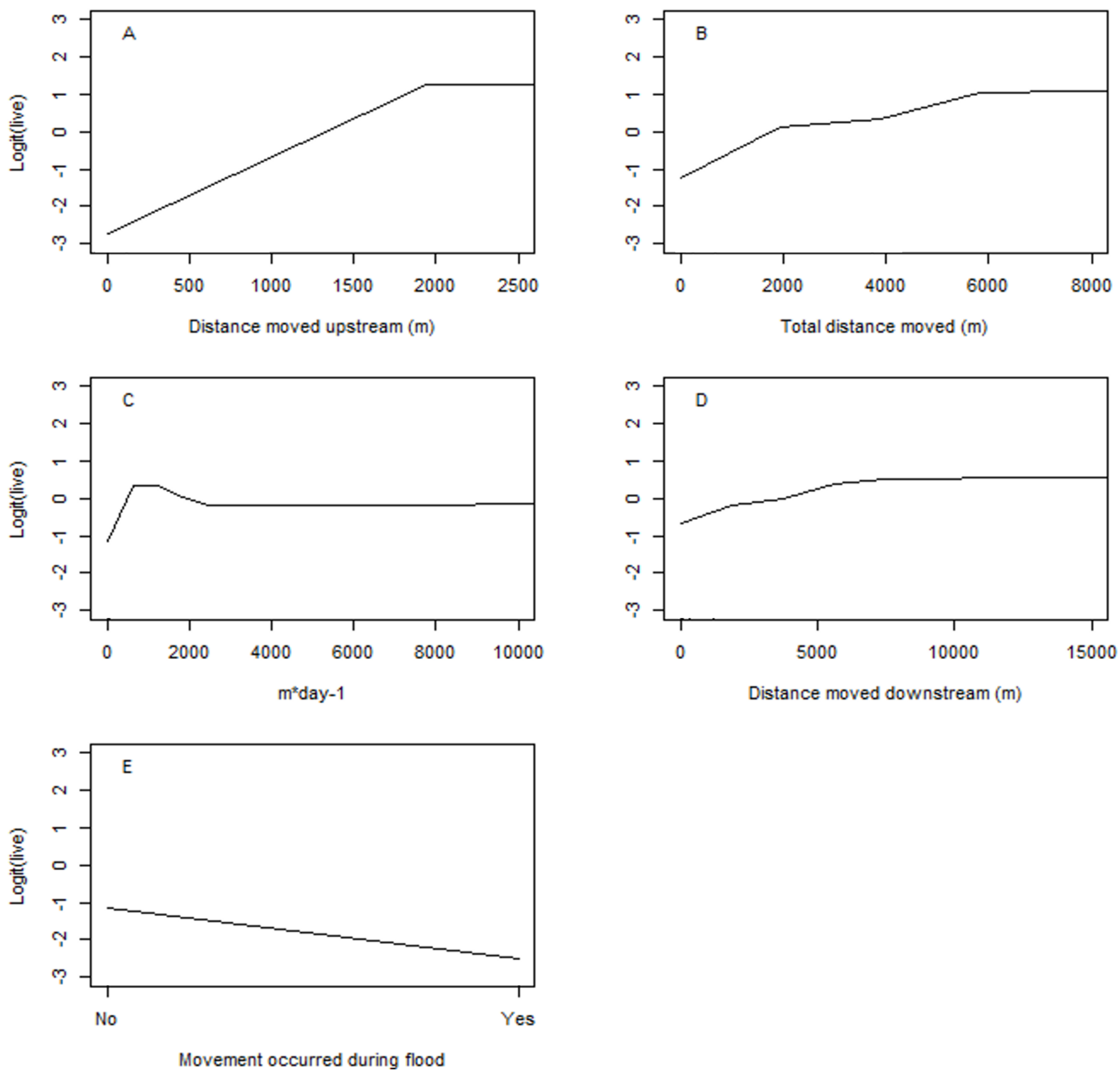

Fig. 3.5. Partial dependence plots for the five variables (A) up, B) total, C) mperday, D) down, and E) flood) identified by variable selection as important to predicting classification of tags as live or ghost. The y-axis for each panel is the logit transformed probability of being a live fish. A higher value indicates a higher probability of being alive (0 is equivalent to a 50% probability of being alive and 2 is equivalent to 88% probability). Data are from the San Juan River study area in 2016 and 2017.

Supplemental Materials

Table 3.S.1. Structure used to build the independent structure data model. Two tags are shown along with all of their movements across 2016 and 2017 in the San Juan River study area.

id	species	Distance	M_per_day	Direction	status	hab_start	hab_stop	channel_start	channel_stop	habunit_start	habunit_stop	flood	overwinter
3D9.1C2D5A9CC9	razorback sucker	1946.5	47.5	up	live	N/A	N/A	single	single	unconfined	unconfined	0	0
3D9.1C2D5A9CC9	razorback sucker	13578.7	41.4	up	live	N/A	Run	single	single	unconfined	unconfined	0	1
3D9.1C2D5A9CC9	razorback sucker	13567.5	387.6	down	live	Run	Run	single	single	unconfined	unconfined	0	0
3D9.1C2D5A9CC9	razorback sucker	619.7	20.0	down	live	Run	Run	single	single	unconfined	unconfined	0	0
3DD.003BBEC008	N/A	16.0	0.2	down	ghost	N/A	N/A	single	single	unconfined	unconfined	1	0
3DD.003BBEC008	N/A	1130.8	4.3	down	ghost	N/A	Shoal	single	single	unconfined	unconfined	0	1
3DD.003BBEC008	N/A	3.3	0.1	down	ghost	Shoal	Run	single	single	unconfined	unconfined	0	0
3DD.003BBEC008	N/A	4.5	1.1	down	ghost	Run	Run	single	single	unconfined	unconfined	0	0
3DD.003BBEC008	N/A	2.6	0.7	right	ghost	Run	Run	single	single	unconfined	unconfined	0	0
3DD.003BBEC008	N/A	5.2	0.2	up	ghost	Run	Riffle	single	single	unconfined	unconfined	0	0
3DD.003BBEC008	N/A	4.3	0.1	left	ghost	Riffle	Run	single	single	unconfined	unconfined	0	0

Table 3.S.2. Structure used to build the dependent structure data model. The same two tags shown in Table S.1 have been used to illustrate the difference between structures using data from the San Juan study area from 2016 and 2017.

id	status	down	left	right	up	total	mperday	low_velocity	na	pool	riffle	run	shoal	braided	canyon	multi	single	flood	overwinter
3D9.1C2D5A9CC9	live	14187.2	0	0	15525.2	29712.4	68.3	0	2	0	0	3	0	5	0	0	5	0	1
3DD.003BBEC008	ghost	1154.6	4.308608597	2.6	5.2	1166.8	2.5	0	2	0	1	4	1	8	0	0	8	1	1

CHAPTER IV

CONCLUSIONS

Fisheries scientists use estimates of demographic parameters to answer a broad range of questions about the status of populations. PIT-tags are increasingly used to gather individual-based capture data and the use of PIT-tags is increasing worldwide, leading to an increase in the numbers of ghost tags left in aquatic systems. Ignoring the possibility of ghost tag detection is not an option, as the presence of ghost tags can lead to incorrect conclusions regarding habitat use, fish movement, and even strong bias in estimates of survival and abundance. As more mobile systems are developed and PIT-tag use continues, the number of ghost tags in rivers will only increase. Improved understanding of ghost tag dynamics and a system for classification of live and dead tags will become increasingly important.

The results from Chapter 2 suggest ghost tag dynamics are driven by their interactions with flow and habitat features. Tag movements were generally small (e.g., 90% < 250 m), but large movements were much greater than expected (e.g., 4 km). The magnitude of movements increased with higher flows whether from spring runoff or monsoonal flash floods. As expected based on physical analysis, ghost tags were more likely to be found in riffles than runs. There are several important insights gained from our study. First, because ghost tags are capable of large movements, lack of tag movement should no longer be used to characterize fish death. Second, high flow events cause the largest movements of ghost tags in river systems. This knowledge could help managers and researchers when designing studies using mobile sampling methods. The

timing of sampling could be chosen to minimize the movement of ghost tags (i.e., sampling during low flows). Third, there are conditions in rivers, where the presence of ghost tags may not matter when using mobile systems. In deeper habitats detection distance will limit the ability to detect ghost tags, perhaps making their presence irrelevant. We recommend an evaluation of the movement of ghost tags before using "lack-of-movement" as an indicator of mortality and subsequently using raw detections to estimate survival or infer fish movement patterns. To fully develop the emerging picture of ghost tag dynamics, we recommend researchers evaluate tag dynamics in other aquatic systems with different geomorphic characteristics.

Mobile PIT tag interrogators have been developed to supplement low recapture rates and reduce negative effects of capture and handling of organisms (Paukert et al. 2005, Hunt et al. 2012, and Reynolds et al. 2012), but the inability to differentiate ghost tags from live fish based on detection data is one of the recurring points of discussion in studies using mobile systems (e.g., O'Donnell et al. 2010, Fetherman et al. 2014, and Richer et al. 2017). The results presented in Chapter 3 are the first to evaluate a classification method for determining PIT tag status (live versus ghost) when using mobile interrogation systems. We were successful with a very high degree of overall accuracy. The analytical framework we describe herein will be useful in developing similar models for other systems, although we expect the relative importance of specific predictor variables to vary with location and species of interest. Future applications of this method should examine how the addition of individual characteristics (length, weight, age, sex, etc.) as well as environmental variables (antecedent and precedent flows, season, habitat types, etc.) of the tagged fish affects the model's classification

accuracy. While we believe this methodology can be an excellent contributor for habitat use studies, in order to quantify vital rates (e.g., survival) or population number, other data sources or more intensive sampling will be required.

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