METHODOLOGICAL DEVELOPMENT FOR IDENTIFYING FORAGING BEHAVIORS FROM GPS DATA AMONG ARTISANAL FISHERS IN THE CARIBBEAN

A Dissertation

by

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ABSTRACT

This project addresses questions about human foraging behavior in the ethnographic context of small-scale fishing-foraging in the Commonwealth of Dominica, an island in the Eastern Caribbean. The first goal of this project is to further develop a method of inferring foraging behaviors from GPS data by testing a recent partial sum approach—the CUMSUM method. The principle underpinning this method of research is that remotely gathered movement data can be accurately translated into meaningful data on foraging activities. GPS data produces movement tracks that are used to parse out changes in behavior, but segmentation of GPS tracks into different bouts of foraging activities is not straightforward. Previous research demonstrates that the CUMSUM method has benefits for detecting behavioral shifts and identifying patches of resources behaviorally, but it has seen limited testing across different foraging contexts. Developing this method has broad application across a range of disciplines, and one relevant utility is using CUMSUM segments to test foraging models. A second goal of this project is to demonstrate by testing a prediction of the marginal value theorem. The MVT explores generalized decision-making rules on patch residence time and was primarily developed in experimental settings with non-human animals. There are few tests of the MVT among human populations in naturalistic settings.

Research activities took place across three field sessions in the rural village of Desa Ikan, Dominica, among artisanal fisher-foragers. I tested the CUMSUM method with fishing data and found the method correctly identifies about 90% of patches with relatively small error rates. The strength of this approach is using both directly observed behavioral data to ground-truth simultaneously collected GPS data. I tested an aspect of the MVT using patch data from both observational data and CUMSUM segment data. Observational data supports the theoretical prediction that fishers spend more time in patches with higher travel costs, while support from CUMSUM model-generated data is equivocal.

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The CUMSUM analyses were generated using script provided by Dr. Carlson and after the example of Alvard, Carlson, and McGaffey (2015). All other work conducted for the dissertation was completed by the student independently.

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NOMENCLATURE

ARS	Area-restricted search
MMA	Max-min algorithm
MVT	Marginal value theorem
N10	Sample of ten fishing trips with GPS data and direct observation
N30	Sample of thirty fishing trips with GPS data only

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CHAPTER I

INTRODUCTION

Animals move across the land and seascape in ways that often make direct behavioral observation of activities difficult, expensive, time-costly, and even impossible. To mitigate these constraints, remotely gathered movement data have been used to identify and interpret an array of behaviors (for salient examples and recent reviews, see: Brown, Kays, Wikelski, Wilson, & Klimley, 2013; Clark et al., 2006; Handcock et al., 2009; Harris et al., 1990; Hebblewhite & Haydon, 2010; Löttker et al., 2009; Tomkiewicz, Fuller, Kie, & Bates, 2010; Turner, Udal, Larson, & Shearer, 2000; Ungar et al., 2005). Tracking animal movement for these purposes is now common with the availability of small GPS devices, which record high-resolution movement data. Recording and interpreting animal movement tracks with GPS devices has wide, general applicability and is pertinent for a variety of research questions on animal behavior. For instance, the way in which animals search for aggregations of resources, or patches, frequently makes it difficult to study foraging behavior directly. Researchers have used GPS tracks to identify behavioral shifts and associated patch exploitation during bouts of foraging (Papworth, Bunnefeld, Slocombe, & Milner-Gulland, 2012; Postlethwaite, Brown, & Dennis, 2013).

The general principle underlying this kind of research is that remotely gathered movement data such as GPS tracks can be accurately segmented into meaningful behavioral data that reflects changes in the activities of an animal, such as shifts in foraging strategies (Buchin, Buchin, Gudmundsson, Löffler, & Luo, 2011). The aim of GPS segmentation methods is to pinpoint changes in behavior along a movement trajectory by identifying contiguous points along a movement track that are homogeneous with respect to certain criteria. In other words, GPS segmentation allows a researcher to find series or stretches of adjacent data that are relatively constant or exhibit less variation in variables describing animal movements, including variables such as speed, velocity, and sinuosity or tortuosity. These measures vary in characteristic ways with different behaviors, including common behavioral search modes such as extensive and intensive search, associated with travel between patches or foraging for resources within patches, respectively (Buchin et al., 2011).

Segmenting movement trajectories that contain many potential scales of analysis into biologically meaningful bouts of behaviors is not necessarily a straightforward process. The cross-context applicability of some approaches is uncertain, especially in the case of human foraging. A major utility of further developing methods of remote behavioral observation is that it alleviates constraints associated with studying foraging activities directly. This potentiates further theoretical development. For instance, foraging theory contains general principles explaining decision-making and models that posit generalized solutions to the challenges of making a living—how an organism chooses which resources to exploit or not, habitat choice and movement, and time allocation decisions. Many foraging models were not developed with human foraging data nor with humans in mind. Despite a breadth of research on human foraging, it is still important to further understand how well this body of theory describes, explains, and predicts human foraging activities. I discuss these nuances in chapter two.

This project addresses questions about GPS track segmentation methods and human foraging behaviors in the ethnographic context of small-scale fishing-foraging in the Commonwealth of Dominica, an island-nation in the Eastern Caribbean. To accomplish this, I collected fishing-foraging data from 2014-2016 in Dominica. Research activities took place in the fishing village of Desa Ikan, located on the rural east coast of the island. Dominican fishers employ a suite of small-scale, decentralized foraging strategies to exploit a wide range of marine species. This ethnographic context is ideal for addressing questions about foraging behavior, with different fishing strategies providing multiple, independent conditions for these tests.

My first goal is to test a method of GPS track segmentation, the CUMSUM approach, developed by Knell & Codling (2012). The CUMSUM approach has been noted by other researchers as a potential advancement in identifying discrete behavioral states from empirical movement data albeit without offering any further testing of the method (Bennison et al., 2017;Garriga et al., 2016; Giuggioli & Kenkre, 2014; Hooten & Johnson, 2017; Notling et al., 2015; Patterson et al., 2016; Walker, Rivoirard, Gasper, & Bez, 2015). An exception comes from Alvard, Carlson, & McGaffey (2015), who show the utility of the CUMSUM approach in a far-from-shore, pelagic fishing-foraging context (using FAD technology, which is described in the ethnographic context section). The authors demonstrate that the CUMSUM method has benefits for detecting behavioral shifts and identifying patches of resources behaviorally. I test the CUMSUM method in a near-shore, demersal fishing context (also described below). Overall, the CUMSUM method has seen very limited testing across different foraging contexts. The second goal of my project is to demonstrate how developing segmentation methods potentiates tests of foraging models by offering a test of a general tenet from foraging theory. One salient model, the marginal value theorem (MVT) (Charnov, 1976), explores decision-making rules regarding time allocation. Given a handful of assumptions and general principles (discussed in detail in chapter two), the MVT makes a variety of predictions of how an animal ought to behave under specified conditions. One major prediction from the MVT is the amount of time an organism should spend in any one patch of resources, or patch residence time, in order to maximize the overall return rate from foraging effort (Charnov, 1976; Charnov, Orians, & Hyatt, 1976; Krebs, Ryan, & Charnov, 1974; MacArthur & Pianka, 1966; McNair, 1982). The MVT was primarily developed in experimental settings and with non-human animals (Danchin, Giraldeau, & Cézilly, 2008), but anthropologists invoke the principles defined by this optimality model to explain a variety of human decision-making processes (e.g. Aswani, 1998; Burger et al., 2005; Beckerman, 1983c; De Boer & Prins, 1989; Edwards, Josephson, & Coltrain, 1994; Launchbaugh & Howery, 2005; Metcalfe & Barlow, 1992; Smith et al., 1983; Smith & Wishnie, 2000). However, there are few tests of the MVT among human populations in naturalistic settings.

The strength of this project is using both directly observed behavioral data via focal follows of fishing trips to ground-truth simultaneously collected GPS data. The CUMSUM method has broad theoretical and practical applications across a range of disciplines. Most germane to this project is the application of CUMSUM for behaviorally identifying patches of resources to show how prominent foraging models such as the MVT can be refined to move foraging theory forward with methodological development. Foraging theory (see chapter two) integrates ecological studies of human behavior into the framework of evolutionary theory. Refining foraging theory remains an important endeavor for anthropologists because it improves our understanding of the ultimate causes of human behaviors. Where behavior does not conform to the patterns predicted by foraging theory, we still gain insight by identifying unappreciated constraints or trade-offs and can better appreciate proximate mechanisms that may cause behavior to deviate (Nettle et al., 2017). The primary intellectual merit of this project is linking aspects of biological and cultural anthropology with ecology to address these kinds of core theoretical issues.

This route has the potential to provide new, practical guidance for contemporary issues like resource management and biodiversity conservation (Nettle et al., 2017). In terms of broader impact, developing remote behavioral observation and segmentation methods along with foraging theory works to link evolutionary theory with policy development and intervention initiatives. Refining cost-effective methods of identifying behavioral strategies provides a way to gauge major foraging mechanisms for resource exploitation and resource distribution in an environment (Barraquand & Benhamou, 2008; Knell & Codling, 2012). In this way, characterizing fishing practices is essential for evaluating sustainability and environmental impacts e.g., how coastal reef systems are affected by near-shore, demersal fishing strategies like pot fishing, which can have drastic consequences on ecosystems (Breen, 1990; C. B. Butler & Matthews, 2015; Carr & Harris, 1997; Matsuoka, Nakashima, & Nagasawa, 2005; Renchen et al., 2014; Stelfox, Hudgins, & Sweet, 2016). Elucidating the ultimate motivations and proximate mechanisms of harmful behaviors can help us understand how to change them. I return to this discussion in chapter nine.

The rest of my dissertation is presented with the following organization. Chapter two provides a detailed review of background information. I discuss the major foraging behaviors of interest, pertinent scaling issues and how they relate to the study of ecological processes such as animal movement, and the existing GPS segmentation methods and the CUMSUM approach of Knell & Codling (2012). I also detail the development, merits, major criticisms, and prominent tests of foraging theory and the marginal value theorem. Chapter three is a description of the ethnographic context of this research in terms of the geography and geology of the Commonwealth of Dominica, the peopling and colonial history of the island, and current demographics. I also describe Desa Ikan, the specific village where I conducted fieldwork, in chapter three. Chapter four is an account of the Dominican fishery and the major fishing practices and technologies I observed in Desa Ikan. In chapter five, I provide a summary of my research aims with reference to the specific datasets on fishing-foraging efforts that I use to generate tests of the CUMSUM and MVT. I also give a description of field methods for data collection in chapter five. Chapters six, seven, and eight contain data descriptions, analyses, and results for all the major aims of this project. Finally, chapter nine offers a summary of project outcomes and other concluding remarks.

CHAPTER II

BACKGROUND

Foraging behaviors: major search modes

Behavioral ecologists study the foraging decisions of animals and how they impact survival and reproduction as expressed by changes in aniaml behavior (Dall, Giraldeau, Olsson, McNamara, & Stephens, 2005; Gaillard et al., 2010; McFarland, 1977). Extensive and intensive search are two fundamental, contrasting components of foraging strategies identified among a number of animals, including humans (Bond, 1980; Boyd, 1996; Eifler, Baipidi, Eifler, Dittmer, & Nguluka, 2012; Ford, 1983; Hills, Kalff, & Wiener, 2013; Kareiva & Odell, 1987; Le Boeuf et al., 2000; Macarthur & Pianka, 1966; Senft et al., 1987; Wasko & Sasa, 2012; Wiens, 1976). Extensive search is most often associated with travel between resource patches and includes covering a (usually) larger area in lower detail at relatively higher speeds with low tortuosity of movements (Bond, 1980; Kareiva & Odell, 1987). Intensive search, also called area-restricted search or ARS, (Curio, 1976) includes more efficient, confined, within-patch behaviors. ARS involves covering a smaller area in higher detail at lower speeds with higher tortuosity (Bond 1980; Kareiva & Odell 1987), bounding at the patch boundary (Fauchald & Tveraa, 2003), and even performing memory-based search loops within the patch (Benhamou, 1994). A graphical example of these two behaviors can be found in Figure 11 of chapter six. Benhamou (2014) helpfully frames the differences between behavioral search modes with respect to the density of search effort per unit area:

extensive search includes a lower density of search effort, while intensive search involves a high density effort. The contrasting nature of these behavioral search modes is due to the fact that resource are aggregated into patches and their densities tend to exhibit a contagious distribution. In other words, the behavior of an animal during extensive and intensive search modes will generally be different given differences in the targets for which an animal searches.

Scale & the "stationarity" concept

Extensive and intensive search modes should not be exclusively associated with large and small scales, respectively, because both can occur at the same smaller scales. Scale invokes the associated concepts of range, also known as extent, and resolution, also called grain (Benhamou, 2014; Wiens, 1989). The range, the upper and lower limits over which variation can be measured, is usually inversely related to resolution, the smallest increment measurable with a particular instrument. However, technological innovations have led to devices like the handheld GPS, which can record long series of data over large spatial and temporal ranges with high spatiotemporal resolution. Small-scale can refer to high resolution even over a large range, while large-scale can refer to a large range irrespective of resolution. The following discussion of scaling parallels the more generally known effects of sampling scale on observed patterns. Early, Wiens (1989) showed that sampling scale plays a crucial role in what behaviors are identified or not, which has long been a central issue in ecology (Allen & Hoekstra, 1990; Foster, Schoonmaker, & Pickett, 1990; Foster, 1992; Levin, 1992; Underwood, Chapman, &

Connell, 2000). Incorporating scale-dependent concepts has proven useful for many ecological questions (Börger, Dalziel, & Fryxell, 2008; Habeeb, Trebilco, Wotherspoon, & Johnson, 2005). For example, workers have shown that animal movement processes are scale-specific (Benhamou, 2010; Benhamou, 2011; Simpson, Piercy, King, & Codling, 2013; Wehner, Michel, & Antonsen, 1996). A central consideration for understanding many ecological processes should be determining biologically meaningful or relevant movement scales.

Animal movement processes work at different spatial and temporal scales because the landscapes and ocean-scapes in which they make a living show multi-scale levels of spatiotemporal organization (Chave, 2013; Levin, 1992). The way an animal perceives this multi-scale environment is reflected in its movements, which is driven by scale-dependent balance between factors favoring "stationarity" (Benhamou, 2014) and factors favoring locational shifts (Mueller & Fagan, 2008; Owen-Smith, Fryxell, & Merrill, 2010; Van Moorter et al., 2013; Van Moorter et al., 2009). Benhamou (2014) defines the helpful "stationarity" concept as the statistical stability of variable(s) defining animal movement, e.g. speed, tortuosity, velocity, etc. Said another way, stationarity refers to a probability distribution that does not change across space and/or time for given, relevant movement criteria, at a specific scale of observation. Benhamou (2014) contrasts stationarity with transitional phases marked by variation in the variable or parameters of interest, which occur between stationary phases as animals shift behavioral strategies and activities.

Movement processes at larger or smaller scales will be different due to the effects of other, scale-specific constraints as well (Benhamou, 1992). Patterns are driven by factors such as inter- and intra-specific competition, critical resources, and predation risks, which vary across local and global scales (Boyce, 2006; Fortin, Fryxell, O'brodovich, & Frandsen, 2003; Mayor, Schneider, Schaefer, & Mahoney, 2009). These factors can be linked to, for example, seasonality and diet cycles, which also vary periodically and across different spatial scales (Polansky, Wittemyer, Cross, Tambling, & Getz, 2010; Riotte-Lambert, Benhamou, & Chamaillé-Jammes, 2013; Van Moorter et al., 2013). Depending on the perspective, certain movement could be considered both variable and "stationary" (i.e., relatively constant) at the same scale. Consider this common example: the location of migratory birds varies greatly during migration phases, but they are also constant or "stationary" in terms of overall moving direction (Wiltschko & Wiltschko, 2003). Concepts such as 'stationarity' a la Benhamou (2014) help make explicit the scales of relevance for a given research aim and reveal how processes at one scale relate to and affect processes at immediately smaller or larger scales.

Segmentation

GPS datasets are comprised of information on animal movements and environmental factors, which can be recorded with high spatiotemporal resolution and can contain numerous observation scales for potential analysis. In this sense, the use of GPS devices in behavioral research opens the door to analysis at many different scales.

All methods of GPS track segmentation—where segmentation refers to parsing movement trajectories into distinct bouts of different behaviors—require some degree of a priori information, namely, defining an appropriate sampling scale for the analysis. Thus, parsing GPS tracks into bouts of e.g., extensive search and intensive search behavior, is not often a straightforward process and requires a thorough consideration of scaling. As argued above, researchers must consider which movement scales are most relevant for understanding how an animal makes a living in and interacts with the environment. For example, in a series of movement data like a GPS track, an animal changes its location as it moves through its environment in search of resource patches. As temporal locational shifts correspond to e.g., velocity vectors, movement scales can be defined as the scales at which location time series are stationary (Benhamou, 2014). This may allow the researcher to determine or at least approximate an appropriate scale of analysis for a specific research question.

For segmentation methods, the sampling scale is the scale at which behaviors are determined to be stationary or not for a variable of interest. In application, the sampling scale—also known as the threshold or observation window—refers to a pre-defined, constant numerical value used to segment a movement path into bouts of distinct behaviors like intensive and extensive search (Knell, 2011). In other words, the threshold or window defines the subset of consecutive observations along the movement track on which an analysis locally operates as it moves through the larger sequence of a movement trajectory. In chapter six, I work through an example to show how changing the scale of analysis—the observation window—produces different results in terms of what behavioral shifts are identified or overlooked during segemntation.

When dealing with the high resolution, long series data recorded by GPS devices, the time series of movement parameters like speed and turning angle are expected to be piecewise stationary (Benhamou, 2014), with smaller-scale bouts corresponding to different behavioral modes. Segmenting involves systematic identification of piecewise behavioral shifts at a pre-determined scale of analysis: alternations between stationary to transitional (i.e., non-stationary) phases. These behavioral changes are represented in a segmentation analysis as ‘turning,’ ‘break,’ or ‘cut’ points. Generally, such points are defined as sufficient changes in the statistical parameters of the movement variable(s) of interest (Benhamou, 2014; Knell & Codling, 2012; Lavielle, 2005).

When segmenting a movement trajectory like a GPS track, a sticking point is that determining turning points—transition phases between stationary phases of extensive search and ARS—can be difficult because patterns at smaller scales may interact with the sampling process. It is possible to smooth this ‘noise’ (i.e., shifts at smaller scales) to reveal behavioral patterns at larger scales. In application, Benhamou (2014) suggests that, for a given window or scale of analysis, a series of data is at least roughly stationary if the statistical parameters (e.g. mean and variation) of the variable of interest (e.g. basic movement elements like speed, velocity, or tortuosity) calculated on a half-range width sliding window does not depend on the window location within that range of data. This means that if a range of data is stationary at the given scale of analysis, fluctuations or shifts at smaller scales should be smoothed within that window. However, even if a stationary phase for a given variable at a given scale is relatively obvious or easy to identify across a movement series (e.g., visually discernable along a GPS track), it can be difficult to determine stationary phases at finer scales. This is especially true when transitions between stationary and non-stationary phases are relatively smooth rather than sharp. Similarly, when the duration of transition phases are short, they are easily missed by segmentation methods. In reality, segmenting a movement series into bouts of meaningful behavioral modes can be ambiguous to some degree, even if systematic. I return to this issue in chapter seven with an example.

The importance of identifying behavioral shifts, e.g., between extensive and intensive search modes, has led to the development of several segmentation approaches. The most powerful methods require a deeper knowledge about the system, as the researcher must specify many model parameters (Gutenkunst et al., 2007; Jonsen, Flemming, & Myers, 2005; Morales et al., 2010), but when information on the system is limited, these methods are probably not feasible (Barraquand & Benhamou, 2008). The methods described below—first time passage, residence time, and fractal landscape—provide insight for many questions and work very well in particular contexts but also have limitations affecting wide applicability. Knell & Codling (2012) provide a succinct sum of the limitations common to these methods. The authors assert that these methods are analytically complex, do not effectively handle unexpected behaviors or environmental noise within the window of analysis, and the first and last segments of a track are lost because the observation window must intersect the movement path on both sides of a time-series step to generate movement statistics.

The first-time passage approach (Fauchald & Tveraa, 2003) tells us the duration of time spent within a theoretical, bounded, circular region, determined by summing the number of steps from the center of the circle to its perimeter. This method assumes larger values will correspond to ARS and that patches are circular and of equal magnitude, which is unsupported (Barraquand & Benhamou, 2008). Residence time (Barraquand & Benhamou, 2008) is similar to first-time passage but includes additional forward and backwards steps spent within the circular region. The radius is determined from a range of radii, which should result in an optimal circle size with regards to generality and precision, but the drawback is that this requires additional information about the environment or movement process (Knell & Codling, 2012). The circle radius remains constant throughout both first-time passage and residence time analyses and thus, neither method appears to effectively handle unexpected behaviors or environmental noise. A third approach, the fractal landscape method (Tremblay, Roberts, & Costa, 2007), measures tortuosity of a random search path within a two-dimensional, bounded square region (Dicke & Burrough, 1988). This method assumes parts of the path corresponding to ARS result in increased plane coverage and thus larger fractal dimensions (Knell & Codling, 2012). The method does not provide insight about the distribution of steps within the squares, nor is the optimal square size known. It has also been aptly pointed out that one should avoid fractal analysis unless a constant fractal dimension across a range of spatial scales is demonstrated (Turchin, 1996).

The CUMSUM method

The CUMSUM approach, a partial sum method recently developed by Knell & Codling (2012), also aims to categorize segments of a GPS track into groups of major behavioral strategies e.g., extensive search and ARS. As with the methods described above, the CUMSUM approach still requires a pre-defined threshold for the sampling window but has additional benefits. Overall, the method requires fewer inferred decisions and is analytically simpler to interpret, which may result in wider applicability across a range of research contexts The CUMSUM method uses a cumulative sum equation to generate a time series plot, which is analyzed to determine the underlying behavioral patterns of the moving animal. A partial sum is the sum of a part of a sequence, and a cumulative sum is simply a series of partial sums of a given sequence for a parameter of interest. A CUMSUM time series is based on bouts of deviations from the average values of a variable—in this case, chosen spatiotemporal criteria, such as location, speed, direction, velocity, or sinuosity. I will use speed as the example criterion to describe and explain this approach.

For a GPS track of a foraging trip, the cumulative sum sequence is initiated at the origin of the movement path (Eq. 1) then implemented for increasing increments of time to pool information at each time step (Eq. 2) and plotted as a time series (see Figure 1, this chapter, for an example). A CUMSUM analysis begins by calculating the mean speed ($\bar{S}$) across all steps in the time series, and then for each step (S_t) in the time series, the deviation from the mean speed is calculated (S_t - $\bar{S}$).

Equation 1 & 2 from Knell & Coddling (2012):

$$C_1 = \bar{S} = \frac{\sum_{t=2}^{T} S_2}{T-1} \qquad (1)$$

$$C_\tau = \sum_{t=2}^{\tau} (S_t - \bar{S}) \qquad (2)$$

for $\tau = 2, \dots, T$, where C_τ is the cumulative sum of information e.g. speed at time step τ, and S_t is the value of speed at time step t.

For a sequence of values, where $S_t > \bar{S}$ (S_t as the last summed value in Eq. 2), the cumulative sum of speed (C_τ) increases, and where $S_t < \bar{S}$, C_τ decreases (Knell & Codling, 2012). Put in different terms, if instantaneous speed at a time step (S_t) is greater than the overall mean speed of the trip ($\bar{S}$), the cumulative sum of speed (C_τ) increases, for example. Consistent increases in the cumulative sum (C_τ) result in a positive slope in the CUMSUM time series plot, indicative of travel speeds and possibly extensive search. If instantaneous speed at time step (S_t) is less than the overall mean speed of the trip ($\bar{S}$), the cumulative sum of speed (C_τ) decreases. Consistent decreases in the cumulative sum of speed (C_τ) result in a negative slope in the CUMSUM time series plot, which may designate slow speeds associated with ARS, rest, and other slow movements. Segments of consistent positive or negative deviations in speed correspond to stationarity phases despite that the cumulative sum changes. In other words, these are phases wherein speed exhibits statistical stability in that it remains relatively high or low rather than varying widely. Figure 1 shows an example CUMSUM time series adapted from the study of Alvard, Carlson, & McGaffey (2015) in which the authors used the CUMSUM method to segment a GPS track of a fishing-foraging trip. More discussion on their study is provided below.

In the second major analytical step of the process, the CUMSUM method systematically detects local behavioral shifts along the time series via the max-min algorithm (MMA; Knell, 2011; Knell & Codling, 2012). One expects a change in behavior to occur when a turning point (also called a break or cut point) is exhibited within a time series. A turning point is a step in the CUMSUM series that begins a period of sustained directional change in deviations from the mean, relative to the previous step in the series (Knell & Codling, 2012). In other words, the MMA classifies steps in the time series as a turning point when the cumulative sum of speed changes from consistently higher than the average speed to consistently lower than the average, or vice versa. Behaviorally, for example, a turning point occurs when a forager transitions from high-speed extensive search to low-speed intensive search.

Turning points identified by the MMA represent a possible behavioral shift *if* an appropriate scale of analysis—window size, ϵ—is set. In this way, the crux of the CUMSUM method rests on setting an appropriate window size, as I emphasized at length in earlier sections and later demonstrate in an example in chapter six. The window size—the sampling scale—determines what changes in the variable of interest are identified by CUMSUM as meaningful behavioral shifts or overlooked as noise. In this context, noise can be thought of as statistical changes in the model parameter (e.g. speed) at scales smaller than the specified observation window, which are presumably not relevant for understanding behavioral changes at that particular movement scale (Benhamou, 2014).

Statistically, the MMA methodically categorizes turning points as local maximum and minimum changes to the current cumulative sum value in order to find the initial point in time when these directional changes begin. I will continue using speed as the example spatiotemporal criteria to describe how the MMA assigns turning points. For example, at time step τ, the MMA determines if the cumulative sum of speed is increasing or decreasing, and a maximum or minimum value, $C_{\tau\,max}$ or $C_{\tau\,min}$, is set (Knell & Codling, 2012). If $S_t > \bar{S}$ at $C_{\tau+1}$ compared to C_τ, the maximum value updates and a local maximum speed ($C_{\tau\,max}$) is set. Put differently, if the cumulative sum of speed at a time step is greater than the cumulative value of speed at the previous step, a new speed maximum is assigned. If $S_t < \bar{S}$ at $C_{\tau+1}$, the local maximum value remain unchanged. If $C_{\tau\,max}$ remains unchanged for a pre-determined amount of time, the observation window or threshold (ϵ),the location of $C_{\tau\,max}$ within that window is classified as a turning point in the series.

In practice, decreasing the window size (ϵ) is specifying a finer scale of analysis. Defining a finer scale for the CUMSUM analysis results in a greater number of local maximum and minimum turning points assigned by the MMA. Inversely, increasing the window size is specifying a grosser or coarser scale of analysis. This results in fewer turning points identified by the MMA. I demonstrate how changing the observation window produces different outcomes through an extensive example in chapter six, which further underscores the significance of choosing an appropriate sampling scale.

Alvard, Carlson, & McGaffey (2015) demonstrate the efficacy of the CUMSUM method to correctly identify segments of extensive search and ARS among small-scale fisher-foragers in the Caribbean at the site of Desa Ikan, during deep-water fishing trips utilizing fish aggregating device (FAD) technology. The site and fishing contexts are extensively described in chapters three and four. Using speed as the model parameter and the CUMSUM equations defined above, a time series plot of a typical FAD fishing shows shifts between positive deviations from mean speed and negative deviations from mean speed (Figure 1). Respectively, these MMA-generated segments of positive and negative slopes are associated with bouts travel and ARS, validated by simultaneous direct observation of the fishing trip. However, the authors note that during bouts of ARS, there might be periods of higher speed that are not travel. Rather, these bouts correspond to within-patch behaviors such as reorienting the boat on an ideal mark in the patch (Alvard, Carlson, & McGaffey, 2015). Choosing the correct scale for CUMSUM analysis should result in such behaviors overlooked as noise.

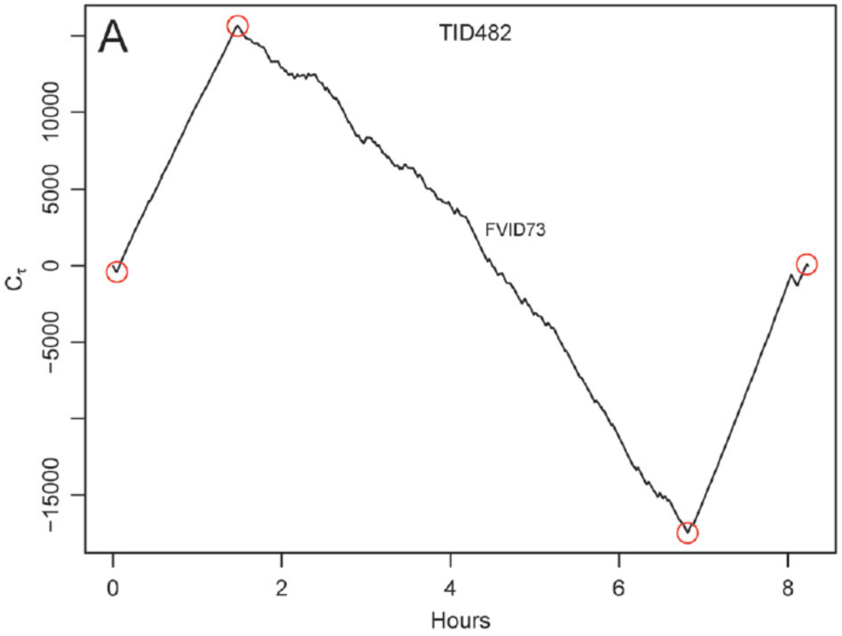


Figure 1. CUMSUM time series plot of a FAD fishing trip, adapted from Alvard, Carlson, & McGaffey (2015). The authors specify a window size of $\epsilon = 1000$ for this analysis. The red circles are cut points determined by the MMA and should correspond to behavioral shifts or transition phases wherein speed is marked by statistical variation. FVID indicates a FAD visit ID number i.e., a patch. The first segment with a positive slope is high-speed travel i.e., extensive search, as fishers move from the central place towards a known FAD location in the open ocean, and the cumulative sum of speed is increasing. This is a phase of stationarity—speed is relatively statistically constant as fishers maintain travel speeds. The second segment has a negative slope due to negative deviations from the overall trip mean speed (the cumulative value of speed decreases) and indicates a bout of ARS at a FAD patch i.e., intensive search. The speed of the boat is statistically stationary in the patch as a fisher conducts ARS and is also a phase of stationarity. The third major segment is positive because the fishers are travelling at speeds higher than the mean to return to shore.

The CUMSUM method overcomes some of the limitations of other segmentation models. The cumulative sum equation allows inclusion of the first and last segments of the track, which can contain information on foraging behavior that is pertinent for some research questions. The MMA also enables the model to better handle unexpected changes in behavior and environmental noise within the sampling window by systematically, statistically identifying local behavioral shifts rather than relying on visual identification by the researcher. Depending on defining an appropriate sampling scale or window (ϵ), the CUMSUM approach appears to smooth small-scale behaviors while accurately classifying major bouts of travel and ARS. The CUMSUM method is promising, but it has seen limited testing and concerns regarding general applicability exist. Alvard et al. (2015) demonstrate that the CUMSUM method correctly identified all the patches exploited across the foraging trips in sample, but the authors also caution generalizing the model across other contexts given that FAD fishing is but one specialized strategy of a suite used by fishers.

Foraging theory

Behavioral ecologists have endeavored to establish some general rules to explain animal behavior, and a source of great insight into these issues lies in the corpus of foraging theory, which ultimately frames this project. In practice, there are difficulties associated with testing foraging models with observational data, but methodological development such as that undertaken here using GPS tracks offers potential for helping to move this body of theory forward. In this section, I review the evolutionary basis of foraging theory and optimality modeling. I also discuss the development of foraging theory in anthropology and cite major benefits and criticisms that have been part of this discourse. Next, I define a specific foraging model, the marginal value theorem (MVT) and describe associated tests among non-human and human populations.

Foraging theory is a family of general principles and models that explains how an animal behaves as it searches for food—what types of resources an animal exploits or not, habitat choice, and time allocation decisions, for example (Stephens & Krebs, 1986). Deriving from the larger field of evolutionary ecology, foraging theory is also anchored by the basic principles of evolutionary adaptation. Most models from foraging theory are based on an assumption of optimality: animals, subject to selection processes that maximizes Darwinian fitness, should make foraging decisions that contribute to overall reproductive success by maximizing energy intake at the lowest cost per unit time (Smith & Winterhalder, 1992). In other words, we expect foraging behavior is designed by selection in a way that maximizes an organism's Darwinian fitness. This approach to behavior is useful for connecting the principles of selection with actual cases and associated diversity (Maynard-Smith, 1978).

Models derived from the corpus of optimal foraging theory define generalized solutions to foraging challenges in an effort to understand decision-making processes across a variety of environmental contexts. There are several components to optimal foraging theory models. Designed after economic cost-benefit analysis, these formal models include goals such as optimizing net energy acquisition rates, a currency like calories for measuring the relevant costs and benefits to an animal, a set of constraints that are typically aspects of the social and environmental context, and finally, a decision and alternative that defines the range of behavioral options to be examined, such as relocating to a new resource patch or remaining in the same one (Davies, Krebs, & West, 2012). These models have often been developed among biologists and with non-human animals (Kacelnik & Brunner, 2002; Oaten, 1977; Owen-Smith et al., 2010; Perry & Pianka, 1997; Pyke, Pulliam, & Charnov, 1977; Sih & Christensen, 2001; Stevens & Krebs, 1986).

Anthropologists have also made some contributions to this body of research (Winterhalder & Smith, 2000), as they have long been interested in how humans manage to make a living in diverse environments. Workers have demonstrated that some aspects of human foraging activities are predictable for a variety of reasons (Beckerman, 1983b, 1983c; Brown, Liebovitch, & Glendon, 2007; Butler, 2001; Commons, Kacelnik, & Shettleworth, 2013; Hames, 1990, 1992; Hames & Vickers, 1982; Hawkes, Hill, & O'Connell, 1982; Hill & Hawkes, 1983; Hill, Kaplan, Hawkes, & Hurtado, 1987; Jones, 2004; Levi, Lu, Douglas, & Mangel, 2011; Smith & Winterhalder, 1992; Winterhalder, 1986; Winterhalder & Smith, 1981, 2000). While researchers have documented a great deal of variation in subsistence patterns, it is evident that humans have spent most of their time as a species in foraging economies. Starting in the 1980's, human behavioral ecologists focused on the analysis of resource selection and production among hunter-gatherers. A great effort has been made to document and explain both the similarities and the extensive differences between distinct hunter-gatherer societies, as well as explaining shifts away from the hunter-gatherer way of life. This route helped us to better understand why we observe these ancestral and modern patterns of human subsistence and behavior from an evolutionary and ecological point of view.

Evolutionists of the nineteenth century such as E.B. Tylor and L.H. Morgan were interested in hunter-gatherer economies, but their ideas were couched in explicitly Eurocentric, racist hierarchies that garnered much negative reaction and were eventually rejected entirely. The work of J. Steward on hunter-gatherers and culture change (Steward, 1936, 1940, 1956, 1972; Steward & Setzler, 1938) honed in on ecological concepts of adaptation. His approach, cultural ecology, prefaced much subsequent research on foragers throughout the late twentieth century. At this time, methodological development and detailed ethnography documented an incredible amount of variation between human societies with which the cultural ecology framework of Steward could not manage (Smith & Winterhalder, 1992). To deal with such extensive diversity, some researchers focused on specific cases while others advanced very general models of forager life. At their respective extremes, neither approach is very satisfactory. The former approach often failed to articulate theory with data, while the later tended to obscure important differences (Smith et al., 1983). It is in this context that the framework of foraging theory became appealing to some anthropologists: it is a deductive scheme that is general enough to apply across taxa and diverse contexts yet can account particular cases with testable hypotheses. In this way, foraging theory positions traditional cultural ecology in a format that is subject to empirical testing.

The anthropological importance of foraging theory rests in its generality. Rather than focusing on very specific tactics used by a forager, foraging theory shifts the focus to strategic rules of decision-making that have wide applicability. Human foragers must be flexible, mobile, and have specialized skills, extensive knowledge about their environment and resources, and a degree of social finesse to solve a number of interpersonal dilemmas when foraging. Resources are often unevenly distributed across a landscape, vary day-to-day and season-to-season, and are further aggregated into mosaic-like patches that a forager must navigate (Kotliar & Wiens, 1990; Stevens & Krebs, 1986; Wiens, 1996). Thus, foragers have to determine where to go to, how long to stay in a particular patch, how much they can gather in a trip, what resource they pursue or pass for potentially better opportunities, and with whom they might coordinate their efforts.

Human behavioral ecologists analyze human foraging choices as products of the environmental context, general decision-making rules, and goals that attempt to maximize returns from subsistence effort. Ideally, such a framework improves our ability to generate explanations of hunter-gatherer diversity by combining principles of adaptation and environmental factors with cultural processes affecting production and organization (Smith et al., 1983). This integrates ecological studies of human behavior into the context of evolutionary theory, which improves our overall understanding of human foraging behavior. This is an important approach because evolutionary forces, including natural selection acting on genetic and cultural variation, shape our species and societies today. Foraging theory helps us identify the varying effects of different selective forces acting on foraging behavior (Winterhalder & Smith, 1981).

Comparing predictions from foraging theory to observed patterns of human foraging is a strong approach. As mentioned, the operational—testable—nature of foraging theory means its claims, scope, and reliability are open to empirical assessment

(Winterhalder & Smith, 1981). This body of theory produces testable hypotheses and explicit predictions about behavioral decisions across a range of environmental contexts. Framing our ideas in a falsifiable way useful even when data fail to support a model because it stimulates further research. A lack of fit between data and a model can still tell us something important about subsistence behaviors by focusing our attention on the appropriateness of model parameters, assumptions, and possible violations. Foraging models generate testable predictions that are sometimes counter to salient notions in ecological anthropology or difficult to observe directly, and call into question some of the assumptions we make about observed patterns.

Any comprehensive explanation of human behavior requires us to consider evolutionary causation (Winterhalder & Smith, 2000), but this idea is not universally shared by all anthropologists. The following critiques of foraging theory that I review echo the more general resistance to an evolutionary approach to human behavior as well as criticism of the adaptationist program (Gould & Lewontin, 1979; Gray, 1987) and the optimization approach (Pierce & Ollason, 1987). Since the inception of optimal foraging theory and through today, many question the utility of foraging theory for explaining human behavior because they doubt its applicability to human culture (Lee, 1979, 1992). Opposition argues that optimality modeling is simplistic and reductionist and thus unrealistic (Keene, 1983). Critics point out that the individual-level focus of decision-making does not account for historical and sociocultural processes that structure human social organization and life. On the other hand, proponents of foraging theory emphasize that it is not intended to be a qualitative and detailed ethnography (Smith &

Winterhalder, 1992). No model can be maximally realistic, precise, and general (Levins, 1966), but foraging theory contains helpful, heuristic models that guide and ground our questions in evolutionary theory. It is true that human cultural systems have no parallel among other animals, but such resistance to using developments from non-human animal research to guide and inform anthropological research often lacks empirical grounds for rejecting (Smith et al., 1983).

Other concerns and critiques exist. Many tests of foraging models demonstrate directional, qualitative agreement between data and theory but stop short in terms of finding definitive, quantitative support. In practice, rigorous tests of foraging models are limited. Most of the basic do not account for stochastic variation introduces at least some degree of uncertainty and risk. There is also difficulty in measuring model parameters like prey encounter rates or defining basic concepts like a patch (Gray, 1987, which has made it difficult to test in naturalistic settings. In general, a major concern is that a model or the parameters of a model may be fundamentally wrong. Perhaps the researcher has not chosen the most appropriate model or parameter for the question asked, a variable has been misidentified, or important parameters have been left out entirely (Davies et al., 2012). A lack of knowledge about the system can lead to errors parameterizing the model, which can reduce how much we learn when data fail to support a model. In a similar vein, the cost-benefit currency of energetic efficiency excludes additional nutrient concerns or considerations of the nonfood qualities of prey. However, adding complexity works to reduce model generality (Smith et al., 1983). In several ways, foraging models are often limited in terms of spatiotemporal scale (Keene, 1983). Models often maximize returns over the short-term, while fitness is usually thought of as a lifetime measure. Most foraging models do not explicitly consider or factor in the effects of cultural transmission on the time-scale of optimization. Spatially, models often assume an individual forager acts in isolation, while ethnographic evidence shows am important effect of regional interactions on foraging decisions (Smith et al., 1983).

Despite criticisms related to the validity of underlying assumptions and questions regarding the applicability of such models to human foragers (Cody, 1974; Gould & Lewontin, 1979; Sahlins, 1976), proponents assert that foraging theory remains valid tools for generating hypotheses and connecting evolutionary outcomes and trends with underlying processes. Foraging theory has advantages as an explanatory framework with cross-disciplinary applicability, and anthropologists should continue to develop foraging theory with data from human populations alongside animal behavioral ecologists.

The marginal value theorem

Time is one of the most precious resources organisms have at their disposal and can be converted to energy through work. The time and energy used for one purpose cannot be used for other purposes, and these time-allocation decisions affect the number of descendants an organism leaves (Hill & Kaplan, 1999). Regarding foraging decisions, foragers must decide which patches to exploit, how long to reside in any given patch, and when to give up on one patch to search for and exploit another. General and mathematically simple, the marginal value theorem (MVT; Charnov, 1976) is a salient model from foraging theory with broad application in evolutionary biology (Hayden, Pearson, & Platt, 2011; Stevens & Krebs, 1986) that addresses the "how long" or "when" questions of foraging. The model proposes a general rule for time allocation decisions for animals in patchy environments and predicts the optimal length of time a forager should spend in a particular patch (Charnov, 1976; Charnov, Orians, & Hyatt, 1976; Krebs, Ryan, & Charnov, 1974; MacArthur & Pianka, 1966; McNair, 1982). The MVT is generally shown as a type of economic cost-benefit, contingency model in that two choices are presented—keep foraging the same patch or give up and leave, with the goal of maximizing e.g., momentary return rates— and there is always a single optimal solution to that end (Bettinger, 2009). In this form of the model, there is the goal, a set of constraints, one cost, one benefit, and behavioral choices.

In the MVT model of Charnov (1976), the time a forager should reside in any patch depends on length of travel time to reach that patch and the density of resources within it. Charnov (1976) constructs the MVT based on a handful of assumption. His model requires that patches in an environment are heterogeneous, distributed at random relative to one another, a forager visits several separate patches during a single trip, and no patch visited twice during the same trip. Foragers are assumed to have complete information about the abundance of resources in the environment such that they know the mean and maximum return rates in order to make the optimal decision (Pleasants, 1989). In cases where foragers do not deplete resources in a patch, energy gained increases linearly with patch residence time. Alternatively, return rates will diminish over time if foraging activity depletes resources in the patch. Thus, the rate of energy acquisition can change as a function of time spent in the patch. The MVT model developed by Charnov and Orians (1973) and Charnov (1976) applies to foraging contexts where resources deplete and returns diminish as a function of time. Figure 2 represents this graphically.

In general, according to the MVT of Charnov (1976), an animal maximizing net return rate should leave a patch when the instantaneous return rate (e.g. calories per minute) for a patch drops to average capture rate for habitat (Figure 2). Said another way, a patch should be exploited until the return rate for that patch equals or falls below the average rate of return across all patches in the habitat. The return rate peaks as a function of resource abundance within the patch and time spent travelling to and foraging within a patch. The optimal patch residence time (T_{opt}) is found by constructing the highest line tangent to the return curve describing patch richness, taking into account extensive search time, i.e., the time it takes to travel to the patch. Upon entering a patch, initial gains are high because the resources are initially plentiful, but they are generally depleted over time due to resource depression caused by the foraging animal (Charnov, 1976). Patch richness determines the shape of the returns curve, which in turn determines the value of slope for tangent AB (Figure 2) and thus the optimal residence time. Though the amount of time it takes to travel between patches should be independent of the amount of time a foragers spends in any patch, the reverse statement is not true. In other words, the time a forager spends in a patch is not independent of travel time. All else equal, a forager maximizes energetic intake by spending more time in a patch when extensive search (travel) time increases. Referring to Figure 2, imagine an increase in travel time for a central place forager because a patch is farther from its home; this decreases the slope of tangent AB and alters where it intersects the diminishing returns curve, thus increasing the amount of time until a forager should give up on that patch and search for a new patch.

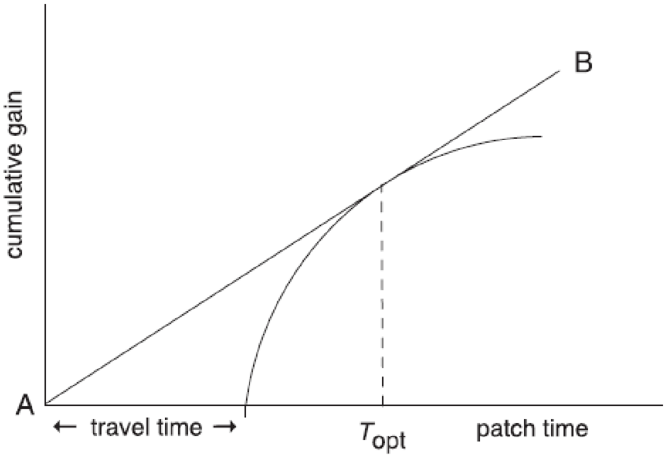


Figure 2. The Marginal Value Theorem adapted from Charnov (1976). The x-axis is in units time, and the y-axis represents energy intake. The diminishing returns curve depicts the intake rate for a patch, given resource depression from foraging activities. The optimal patch residence time (T_{opt}) is found by constructing the highest line tangent to the returns curve, with the tangent AB originating at the start of travel to a patch.

Tests of the MVT

Many studies show how well animals approximate the MVT-predicted optimal solution to patch residence time and how well animals response facultatively to changing environments (Nonacs, 2001), including research with fish, birds, mammals, and insect parasitoids (Agetsuma, 1998; Brown, 1988; Kamil & Clements, 1990; Kramer & Weary, 1991; Marschall, Chesson, & Stein, 1989; Redhead & Tyler, 1988; Van Alphen, Bernstein, & Driessen, 2003; Van Gils, Schenk, Bos, & Piersma, 2003; Wajnberg, Bernhard, Hamelin, & Boivin, 2006; Ydenberg, 1984). In addition, the framework of the MVT has been applied to understand foraging strategies across a wide range of taxa (Danchin, Giraldeau, & Cézilly, 2008). Examples include the optimal duration of copulation for males (Parker & Stuart, 1976), the expected duration of cooperative interactions for cleaner fish (Bshary, Grutter, Willener, & Leimar, 2008), the evolution of the timing of animal migration (Baker, 1978) and clutch-size in insects (Wilson & Lessells, 1994), and the expected rate of animal movement through a habitat (Bélisle, 2005; Bowler & Benton, 2005). For example, Poethke & Hovestadt (2002) apply the principles of the MVT to predict when animals should disperse in fragmented landscapes, in the context of density-dependent population growth. The authors develop an expression for evolutionarily stable dispersal rates in a metapopulation with global dispersal and predict that individual dispersal rates should decrease with patch capacity and increase with population density (Poethke & Hovestadt, 2002). Poethke & Hovestadt (2002) confirm these predictions with individual-based simulation experiments and demosntrate the utility of this analytical, MVT-driven approach.

Generally, human behavioral ecologists have assumed that human foragers are governed by the same rules as non-human animals and thus use models such as the MVT to understand human decision-making mechanisms. Researchers observe that human foraging behavior is at least qualitatively consistent with many foraging models (Beckerman, 1983a; Smith et al., 1983; Winterhalder & Smith, 1981). It should be noted that most tests of foraging models with human data do not actually address time-related questions of subsistence but more commonly focus on prey and patch choice, for example. Despite the relative paucity of tests among human populations, there are some explorations of the MVT. Anthropologists invoke the MVT to explain many time-related decisions made by humans. Examples include when to move a herd to new pastures (De Boer & Prins, 1989; Edwards, Josephson, & Coltrain, 1994; Launchbaugh & Howery, 2005), when to cultivate new forest growth (Smith & Wishnie, 2000), how much time to spend in one foraging habitat versus another (Aswani, 1998; Beckerman, 1983a, 1983c; Smith, 1991), how much a carcass is butchered in archaeological contexts (Burger, Hamilton, & Walker, 2005), and how much time should be spend processing food or butchering a carcass before being carried to a central place (Burger et al., 2005; Metcalfe & Barlow, 1992). Both experimental and observational evidence on how well humans make or approximate optimal time-related decisions is equivocal, but the directional tendency toward MVT-derived principles and optimal solutions is often consistent across studies.

Most work on patch-leaving decisions among humans comes from experiments. In an early experimental test with human subjects, Hart & Jackson (1986) found that patch residence times trend in the direction predicted by the MVT as resource density and travel time between patches varied, but subjects tended to stay in a patch longer than the predicted optimal time. In their experiment, subjects collected sultanas arranged at two different densities on artificial bushes in order to test the effects of sex, patch quality, and travel time on foraging decisions. The authors observed that females spent less time at a patch than males and accumulated resources at a greater rate. Overall, participants increased residence time as patch resource density increased and as travel time increased, but subjects sometimes resided in patches longer than would produce the maximum mean return rate for the habitat (Hart & Jackson, 1986).

Hackenberg & Axtell (1993), based on an earlier study by Wanchisen et al. (1992), simulated patch-leaving decision by requiring human subjects to choose between two time schedules that essentially represented the behavioral decisions to stay or leave. Subjects sat at a computer and pressed a key numerous times to make the decision to stay longer or leave sooner, which earned them a respective rewards based on their decision. Each choice was associated with two rewards, both short and long term payoffs. The short-term and long-term payoffs for each time schedule varied depending on the experimental condition. Overall, the authors found that participants often switched decision patterns facultatively and stabilized at the optimal response for an experimental condition (Hackenberg & Axtell, 1993). Though there was a degree of incomplete experimental control under certain conditions, these results are consistent with contemporary work as well as recent research, among human and non-human study groups (Cuthil, Haccou, & Kacelnik, 1994; Goubault, Outreman, Poinsot, & Cortesero, 2005; Roitberg, Sircom, & Roitberg, 1993; Tentelier, Desouhant, & Fauvergue, 2006; Visser, Van Alphen, & Nell, 1992; Vos, Hemerik, & Vet, 1998; Wajnberg et al., 2006; Wajnberg, Fauvergue, & Pons, 2000; Wanchisen, Tatham, & Hineline, 1992; Wilke, Hutchinson, & Todd, 2004).

More recently, Hutchinson, Wilke, & Todd (2008) conducted an experimental computer mockup of fishing to explore aspects of the MVT. In a virtual simulation, human “fished” at successive “ponds” that varied in quality in order to earn money by catching fish when they appear. Subjects were able to leave the current patch for a new pond at will but incurred significant travel time costs as they moved between ponds. The authors found that, compared to the optimal solution predicted by the MVT, participants took too long to switch to new patches. Regardless of prey distribution, subjects spent much more time at virtual patches where they had found more fish and also shortened the length of time spent in the current location when they experienced greater success in the previous location. This may be an effect of our psychology e.g., a tendency toward confirmation bias, which causes humans to deviate from optimizing behaviors in ways that other animals do not (Hutchinson, Wilke, & Todd, 2008). Overall, the results of this experiment show how patch-leaving decisions can be tempered by recent information in a sub-optimal manner.

Another researcher conducted a lab-based, virtual “berry picking” experiments with roughly homogeneous patches (Wolfe, 2013). Wolfe (2013) showed giving up time is consistent with the predictions of MVT if data are averaged over subjects. In an elaboration of this berry-picking experiment, Zhang, Gong, Fougnie, & Wolfe (2015) demonstrated that average foraging behavior was broadly consistent with MVT predictions, including that subjects foraged for more time when overall habitat richness was reduced. In these tests, the forager was not given complete information on the system before the experiment began. Further, corroborating the results of Hutchinson et al. (2008), the giving up time was effected by the return rate in the immediately preceding patch even when patch quality was randomized (Zhang, Gong, Fougnie, &

Wolfe, 2015), supporting the idea that human foraging behavior is influenced by recent experience and new information in ways that do not necessarily maximize mean return rates.

Rigorous, anthropological tests of the MVT with observational data are not common. Some researchers attempted to explore aspects of time allocation decisions as they evaluated predictions having to do with models such as habitat and patch choice rather than the MVT per se. Beckerman (1983a) found that Bari foragers chose to hunt rather than fish four out of five times despite that fishing resulted in a higher return rate than hunting for all of the time periods sampled. The author observed that time spent fishing increased during months when the ratio of fishing return rates to hunting return rates was higher. The findings of Beckerman (1983a) do not support the prediction that Bari foragers choose patches that yielded the highest average return rates. Smith (1991), working with Inuit foragers, also examined the effects of seasonal variability in return rates on time spent exploiting different habitat types. He compared return rates in terrestrial versus marine habitats to determine if foragers adjusted time in each context according to their respective profitabilities as per season. Consistent with the observations of the Bari by Beckerman (1983a), Smith (1991) found that Inuit foragers spent more time in the more profitable habitat per season but not exclusively despite that return rates are maximized by always selecting the more profitable habitat.

Kaplan & Hill (1992) pointed to several limitations with these early, exemplary studies that made use of observational data. Both studies described above use long-term averages, which does not account for daily changes that affect foraging decision, such as weather and environmental conditions. The cumulative gains functions for various activity and habitat types were unknown in both studies, which means it is possible that features of the fishing patches. Similarly, there are significant differences between hunting and fishing contexts in ways that could result in a higher total gain from hunting despite a lower average return rate. Bar modern, advanced fishing vessels, marine foragers are usually constrained by the amount of time a human can spend on the water (Kaplan & Hill, 1992). On the other hand, hunting is often more open-ended and lasts longer since it is a terrestrial activity.

Most anthropological tests of optimality models are limited to hunter-gatherers in terrestrial habitats with a few exceptions, such as those described above (Aswani, 1998; Beckerman, 1983c; Begossi, 1992; Bird & Bird, 1997; Smith, 1991). This is due to the fact that prey mobility and the spatial characteristics of marine habitats present significant analytical challenges. The work of Aswani (1998) is a good example of how to handle these challenges. He assessed habitat choice and aspects of the MVT among marine foragers in southwestern New Georgia of Solomon Islands. Aswani (1998) used these models to predict the daily and seasonal movement of marine foragers. Aswani (1998) assumed that lagoon coral reef flats and drops exploited by fishers are micro-habitats that experience resource depression as foraging times increase, and hence, the MVT is an appropriate model for this context. On the other hand, he observed that Roviana fisher-foragers often violated the MVT assumption that patches are exploited sequentially and randomly. Aswani (1998) reported that the within-patch movements of Roviana fishers are "haphazard," even if they do not select habitat types at random, suggesting that the MVT remains an appropriate model to use. These considerations provide a good example of the challenges of testing optimal models with humans in naturalistic setting.

Aswani (1998) found that time allocation decisions in the context of habitat types and patches were broadly consistent with predictions from the MVT and theory. Roviana fishers directed more effort to habitats with the highest yields and reduced visits to habitats with lower yields for each of the three tidal seasons studied. Per fishing bout, less time is spent in a patch as habitat productivity increases, unless travel costs to the habitat were also higher. Residence times and the number of patches visited increased because there were alternative, productive patches within range. When habitat productivity decreased, fishers increased residence time because it was too costly to travel to a different patch if the yield was not higher. In sum, the Roviana fishers observed by Aswani (1998) behaved to maximize their foraging efficiency.

Human foragers: additional considerations

In practice, deductive tests of foraging models under naturalistic conditions are limited. Direct observation of foraging activity can be very costly in terms of money, time, and safety. There are also difficulties in measuring phenomena like prey encounter rates and per-patch richness, delimiting patches, and identifying an appropriate temporal scale. Calculating optimal patch residence times requires specifying the exact functional form for the accumulation of gains in the patch, and even then, calculating optimal residence time can be impossible to solve analytically (Calcagno, Mailleret, Wajnberg, & Grognard, 2014). Graphical methods to solve optimal patch residence time (Figure 2 above, for example) are useful for accommodating more arbitrary gains curves (Parker & Stuart, 1976). However, these types of arguments were developed with respect to homogeneous habitats and have restricted scope for predictions in heterogeneous environments without additional considerations of how habitat heterogeneity affects optimal solutions (Calcagno, Grognard, Hamelin, Wajnberg, & Mailleret, 2014; Stevens & Krebs, 1986). In other words, in the context of habitat variability, it may be difficult to assess or attribute robustness and generality to common graphical predictions of the MVT. This includes widely-cited and assumed premises such as the directional relationship between travel time and optimal patch residence time, or the inverse relationship between patch encounter rate and optimal residence time (Calcagno et al., 2014). On the other hand, as already mentioned, falsified MVT predictions provide an opportunity to identify inaccurate assumptions regarding constraints and currencies of particular hypotheses, thereby still proving a valuable tool.

There are aspects of the MVT, and optimal foraging theory in general, that have yet to be confirmed for human foragers. It is important to continue to test and develop foraging models among human populations. How does human foraging deviate from what we might expect, given assumptions and principles outlined by foraging theory? While there is evidence that human prey and food-item encounters within patches are often encountered sequentially (Burger et al., 2005), there is little evidence that human foragers sequentially encounter patches (Kaplan & Hill, 1992). Central-place foragers like humans often leave home with specific patch targets determined in advance, choosing which patches to exploit rather than encountering them completely at random.

This might mean that the classic form of the MVT model is unsuitable and could lead to incorrect predictions about patch use and residence time. Most models do not address the assumption that a forager has perfect or complete knowledge of the environment—how might a researcher address this without also having complete knowledge of the environment? Yet, foragers have been shown to have extensive domain knowledge about the environment, the flora, and the fauna which they utilize, such as the density and abundance of certain food items in the habitat (Stevens & Krebs, 1986). Anthropologists have long since documented how such knowledge is reflected in foraging decisions (e.g., Binford, 1978; Hill & Hurtado, 2017).

Human culture and ultrasociality affect human foraging decision mechanisms in ways that makes us different from other animals (Richerson & Boyd, 1998). Cultural transmission probably affects the time-scale of optimization, which should vary with the ultimate goal of the forager. Given the human capacity for cultural storage of information and forethought (Richerson & Boyd, 2005), deviations from short-term optimization seem much more likely for us than other species. Humans often make foraging decisions that appear to reduce short-term return rates but might provide important information related to future resource distribution and abundance (Kaplan & Hill, 1992). This kind of information can be helpful for determining future productivity of a patch (e.g. if it is worth visiting again tomorrow, or next week, next season, etc.), which can also be communicated to other group members. Relating to future use and our capacity for forethought, and unlike most other animals, perhaps an overriding concern for human foragers is risk minimization and reduced variability of daily resource availability, rather than maximizing net energy acquisition (Caraco et al., 1990; Cashdan et al., 1983; Smith et al., 1983). To be clear, this is not to say that foragers are practicing resource conservation—researchers have shown that human foragers prefer higher short-term return rates over long-term return rates associated with resource conservation (Alvard, 2007; Smith & Wishnie, 2000)—but rather there is additional reason to consider the time-scale of optimization in the case of human foragers.

The effects of evolved, prosocial emotions like trust, empathy, and conformation bias (Richerson & Boyd, 2005) also likely affect foraging decisions in ways that are not observed in other animals. Spatially, foraging models often assume an individual forager acts in isolation or in small groups, but humans are embedded within groups like communities, villages, chiefdoms, etc. with goals beyond self-interest (Cronk & Leech, 2012; Richerson & Boyd, 1999). Ethnographic evidence shows the clear effect of regional interactions on foraging decisions (Smith et al., 1983). Empirical evidence directly supporting group selection of these sorts of pro-social behavior comes from behavioral economics, such as public goods games involving coordination payoffs and punishment of non-normative behaviors (Boyd, Gintis, Bowles, & Richerson, 2003; Henrich & Boyd, 2001; Henrich et al., 2001). A strong reliance on cultural innovations and institutional solutions was a critical aspect of behavioral modernity (Alvard, 2003; Herrmann, Call, Hernández-Lloreda, Hare, & Tomasello, 2007; Kaplan & Lancaster, 2000; Richerson & Boyd, 2005; Tomasello, Carpenter, & Call, 2005) and probably affected our evolved foraging behavior processes as well. It is important to determine the extent to which foraing models are supported by non-experimental data and to understand deviations in human populations. The directional predictions of the MVT have generally been verified among human populations albeit sometimes with varying conclusions (Beckerman, 1983a, 1983c; O'Connell & Hawkes, 1984; Stevens & Krebs, 1986), and observations on time-related foraging decisions are often qualitative and anecdotal.

CHAPTER III

ETHNOGRAPHIC CONTEXT: DOMINICA

Geology & geography

Fieldwork took place in the Commonwealth of Dominica, a Caribbean island-nation of the Lesser Antilles. Research activities were conducted across three field sessions spanning July-August 2014, June-August 2015, and March-July 2016; field methods are described in chapter five. Dominica sits between the Caribbean Sea and the North Atlantic Ocean at 15°25'N, 61°20'W, about halfway between Puerto Rico and Trinidad and Tobago (Figure 3). It is about center in the chain of islands making up the Lesser Antilles archipelago. The island is part of the Windward Islands of the Lesser Antilles along with its immediate French neighbors, Martinique and Guadeloupe, and St. Vincent and the Grenadines, Grenada, and St. Lucia (Macfarlan, 2010).

Dominica is about forty-seven kilometers long and twenty-six kilometers across at its widest point (Evans & James, 1997), featuring a tremendously rugged landscape with sheer precipices that rise out of the sea and throughout the interior. It is far and away the most mountainous island in the Eastern Caribbean, being formed about thirty million years ago by pyroclastic volcanic activity and built on a submarine ridge of Early Tertiary age (about sixty million years or older; Honeychurch, 1995). The backbone of Dominica is made of dormant volcanoes, but at least four of them can become active (Evans & James, 1997). The edge of the Caribbean plate is about eighty kilometers from the east coast of Dominica, and the subduction of the Atlantic plate is responsible for much of the seismic activity experienced in the region (Smith et al., 2013). Due to its location, hurricanes, earthquakes, and landslides are a near constant threat (Evans & James, 1997).

Weather in Dominica is tropical and moderate due to the Northeast trade winds and heavy rainfall. The island is classified as a Marine Tropical Climate that experiences little seasonal variation, with a wet season from June through December and a dry season from January through May (Dominica Meteorological Service, retrieved online 2017). Thanks to this climate, Dominica is known as the "Nature Island" of the Caribbean because of its spectacular biodiversity. There are many fresh-water rivers flowing from the mountainous interior to the sea, which creates a rich ecology that local Dominicans prize (Yarde, 2013). The nature island is about 15.5° from the Equator and lies in the path of the south equatorial current, which flows from the west coast of Africa to South America, intermixes with a branch of the Orinoco River, and then flows into the Caribbean sea (Evans & James, 1997; Honeychurch, 1995). It is generally accepted that most of the early flora and fauna arrived from South America along this route, though some animals were introduced later by humans such as the Agouti, a small rodent, and Manicou, also known as opossum (Honeychurch, 1995).

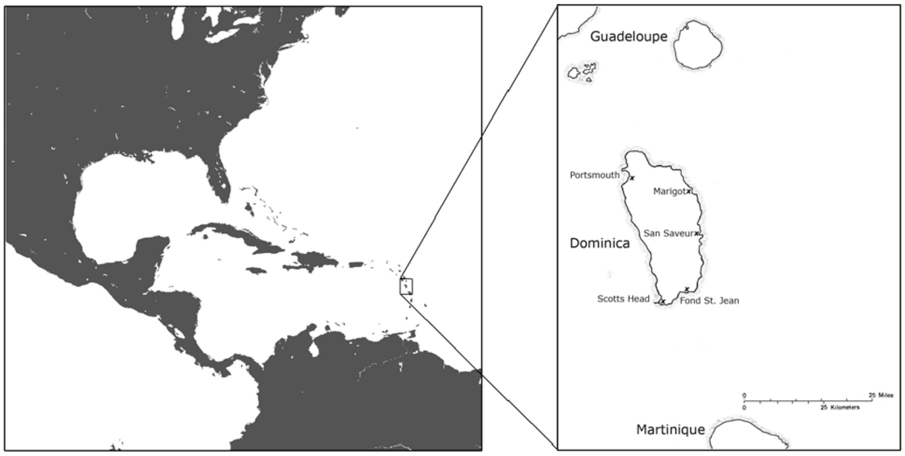


Figure 3. The Commonweath of Dominica and neighboring islands in the Eastern Caribbean (Alvard, unpublished digital image, n.d.).

The peopling of Dominica & a brief colonial history

Honeychurch (1995) provides an excellent synthesis of the history of Dominica, which I highlight throughout this section. The original name of Dominica, given by the earliest Kalinago to inhabit the island, was “Wai’toucoubouli” meaning “tall is her body” (Honeychurch, 1995, p. 21). Christopher Columbus was the one to give the long island the name of Dominica. A folk theory, and the history taught in schools until the late 20th century, tells us that the first people to inhabit Dominica were the “stone people,” who were replaced by the “peaceful Arawaks,” who, in turn, were killed by the “warlike Caribs” (Honeychurch, 1995, p. 27).

Archaeological and anthropological research indicate the first humans to inhabit Dominica probably originated from the Venezuelan coast of South America, travelling on the water from the region of the Orinoco delta as early as five to seven thousand years ago. These people, named the Ortoiroid by Western archaeologists, gradually moved through the Antilles to populate the islands. Archaeologists estimate this group occupied Dominica beginning roughly two and a half to five thousand years ago. Little is known about the Ortoiroid, the earliest inhabitants of Dominica, in terms of who they were and how they lived, but most assume they were hunter-gatherers and fishers based on the relevant albeit scanty archaeological evidence.

Around the fourth century, groups of Arawakan-speaking people started to colonize the Lesser Antillies (Honeychurch, 1995; Quinlan, 2004). One of these groups, the Igneri, settled in Dominica and neighboring Windward islands. The Ortoiroid people who inhabited the region were eventually replaced or assimilated by the new Arawak Igneri group in the tenth to eleventh centuries. The Arawakan-speaking Igneri are the group whom Dominicans refer to as the Arawaks. The Igneri introduced slash-and-burn agriculture and ceramics to the Caribbean and brought their own animistic beliefs to Dominica. Based on ceramic style and design changes, archaeologists identify three successive phases of development for the Ingneri in the region (the Saladoid, the Troumassoid, and the Suazoid, in that order). A Saladoid site found in 1977, located above present-day Soufriere, tells us much about their way of life. They exploited both land and sea resources, depending on gardens for year-round provisions, and they used canoes for migration, trade and interisland affairs, fishing, and hunting along the coasts. Artifacts preserved at this Saladoid site indicates the Igneri traded from South America to as far north as Puerto Rico.

Honeychurch (1995) describes that, from about 1400, the Igneri pattern of life changed as yet another new immigrant group from the Orinoco region in the south gradually imposed themselves and aspects of their culture onto the Igneri people of Dominica and the other Windward Islands of the Lesser Antilles. Living Caribs are the descendants of the people who moved into and occupied the region during this time. Information on these early "Island Caribs," who were contemporaries of Columbus, are from European accounts. "Carib" and "Island Carib" are European appellations. The misnomer appears to have resulted from several derivatives of a term the Taíno (another Arawakan sub-group and one of the largest indigenous groups of the Caribbean) probably used to refer to either a place or any group of hostile people, rather than an ethnic group. The 'Carib' did not call themselves that; they called themselves Kalinago.

The Kalinago imposed the masculine aspects of their ancestral culture on the domestic life of the preceding Igneri culture, but they were immigrants with too few numbers on the island to change the language and culture of the Igneri completely. They were organized around a village chief—more a headman than a formal chief, in anthropological terms—whose status could be ascribed but was more often achieved. They practiced the Igneri form of horticulture, supplementing garden foods with gathered, wild-occurring fruits, vegetables, and hunted game. More important to the Kalinago subsistence and way of life was fishing and the sea. They had a large variety of fishing techniques to exploit a wide-ranging selection of species, with fishing grounds extending well into the Leeward Islands. The Kalinago had their own concept of star constellations to navigate the open ocean and knew the locations of islands intimately.

They crafted well-balanced dugout canoes—a smaller version that carried a few people and a much larger version that apparently could carry thirty to forty people—technologies that persist and are actively preserved by the Kalinago today.

This freedom of movement changed drastically with European colonization of the region, starting with Columbus in the 15th century. By the 1500s, the Spanish destroyed Caribbean Carib populations who were used as labor on sugar cane plantations along with slaves imported from Africa (Randall, 2003). Dominica was one of the last islands in the Caribbean colonized because the topography and unforgiving landscape. The Kalinago staved off total European colonization until the early eighteenth century when the French established a colony, bringing in enslaved populations from West Africa to harvest the natural resources and work sugar cane and pineapple plantations. Even before French occupation, slaves escaped to Dominica or had been captured by the Kalinago from settlements on other islands. The forests protected the Maroons from slavery and provided a place for freed slaves to form communities and later, Maroon rebellion played a major role through European rule. Between 1756 and 1763, Dominica was caught up in the efforts of the Seven Years War. During this time, the French and British fought for control of the island, and eventually, the French ceded possession of Dominica to Great Britain in 1763. Rule went back and forth between the French and British twice more, but by the mid-nineteenth century, conquest was complete and the British ruled the island. The British granted Independence to Dominica in 1978.

French and African language and culture mixed with indigenous traditions as Maroon populations inhabited Dominica and during European colonization of the island, eventually resulting in a Creole language and culture. Given the dates of occupation, Honeychurch (1995) observes that Dominica should be more English compared to other West Indies islands. However, Dominica was positioned between two valuable colonies of the French empire, and this created an imbalance between British occupation and French influence. The result was a heavier French influence in Dominica. The official language of the island is English, but most speak French patois or Antillean Creole. As recently as fifteen years ago, speaking Creole was strictly forbidden. Young people at my field site recount getting their knuckles bruised as children for speaking Creole in public or in school. Individuals learned from one another and from kids raised other villages, particularly more rural villages where such sanctions against Creole were less strictly enforced. Today, there is a sense of great national pride and preservation for Creole language and cultural traditions, but it is sometimes offset by the desire to participate in a global, 'Western' culture.

Current demographics

About seventy-four thousand people live in the 751 km^2 area of Dominica (Central Intelligence Agency, 2016) an increase from the 2011 census of about seventy-one thousand people). The population is distributed mostly along the coast while the mountainous interior is more sparsely populated but includes major sections of the Kalinago reserve. Nearly a third of the total population is concentrated in Roseau, the west-coast capital city, and adjacent neighborhoods. A characteristic of many Caribbean islands, due to the colonial history of the region, is economic marginalization. In

Dominica this has resulted in what can be described as an open, non-corporate peasantry (Macfarlan, 2010; Macfarlan, Remiker, & Quinlan, 2012; Smith, 1977; Wolf, 1957). Dominica is poor (per capita GDP $11,400 est. 2016) and developing: it is among the least developed and most rural country in the Caribbean (Quinlan, 2004). At least 29% of the population lives below the poverty line (CIA, est. 2009). The economy is primarily based on agriculture and ecotourism, and there is currently no export market for the fishing industry in Dominica (more on the Dominican fishery below, this chapter). Households generally meet subsistence needs while horticultural surplus is sold in local communities, but capital is difficult to accumulate (Macfarlan, 2010).

The colonial history of the Caribbean has also greatly influenced the ethnic composition of the region (Macfarlan, 2010). Dominica is diasporic with a long colonial history, and this history shapes the rich, contemporary diversity of the island (Baker, 1997; Honeychurch, 1995). While some Dominicans are indigenous, referring to Kalinago ancestry (2.9%), or of mixed European and indigenous descent (9.1%), most are descendants of African slaves and Maroon populations (86.6%) (CIA, est. 2001). Due to the mountainous terrain, the island was a Carib stronghold, and later, a Maroon stronghold. The island has the only Carib reserve in the region as well. Notably, Dominican plantations were different from others in the Caribbean in that owners were absentee (Honeychurch, 1995). Consequently, and unlike other islands in the region, Dominica is not a black majority ruled by white elites (Quinlan, 2004).

Indigenous traditions mix with African, French, and British language, values, and customs to result in a Creole culture. The official language of the island is English, but most speak French patois and often as a first language (Quinlan, 2004). Catholics, Baptists, Seventh Day Adventists, and Protestants are common in Dominica and are sometimes influenced by African Vodoun and Santeria beliefs (Salter, 1999). The Rastafari movement that emerged in the Caribbean (Barrett, 1977; Owens, 1976) also took hold in Dominica. The Rastafari movement continues to embody resistance to black oppression and marginalization, and perhaps functions as a social levelling mechanism, particularly in rural areas of the island (Barrett, 1988; Campbell, 1985; Hall, 2001; Macfarlan, 2010; Phillips, 2002; Quinlan, 2005).

Desa Ikan: the field site

Data collection on fishing-foraging in Dominica took place at the medium-sized landing site in the village given the pseudonym of Desa Ikan, located on the rural east coast (Figure 4). According to the 2011 census, one hundred individuals live in about forty different households in Desa Ikan. Communities like Desa Ikan can be thought of as geographically bounded, and as Macfarlan (2010) describes, membership is usually restricted to those born and raised in the community. Rural Dominicans such as those in Desa Ikan and surrounding communities as socially homogeneous and poor, who experience little local social stratification relative to other contexts (MacFarlan, 2010). During the data collection periods, there were four rum shops operating, which are important, socially-central local shops that sell household necessities such as soap, toilet paper, and some kinds of dry storage food along with a lot of rum, beer, and other alcohol. Villagers in Desa Ikan gather at these rum shops to socialize, get news, watch sporting events, play dominos, drink, and smoke.

Macfarlan (2010) suggests that rural Dominicans see agricultural work seen as good while self-seeking commerce is not as good, which aligns with many of my own conversations with individuals from Desa Ikan. I also observed that people in Desa Ikan tend to work multiple professions and jobs as opportunities arise. Income is earned through limited wage labor, small-scale gardening, fishing, and remittances (Macfarlan et al., 2012; Quinlan, 2004; Quinlan, 2005). Almost all adults in Desa Ikan practice horticulture, growing food such as yams, taro, plantains, bananas, and pineapples. Fishing is one of the most common and important sources of income for men in Desa Ikan due to the location of the landing site in the village. A handful of people living in rural Desa Ikan commute to larger villages or the capital to work wage-labor jobs.

Figure 4. Images adapted from Google Earth© showing (a) the Commonwealth of Dominica, and (b) an enhanced view of the field site, Desa Ikan. Published by Google (2015). Image (a) shows Dominica, situated between the Caribbean sea off the West coast and the Atlantic Ocean off the East coast, with the field site, Desa Ikan, labeled by white text on the Eastern coast of the island. Image (b) shows the field site, rotated to an Eastern perspective and looking West. Within the black circle nearer the bottom of the image, one can see the boats anchored on the shoreline. In the same black circle, by the ‘n’ in ‘Ikan,’ one can see the human-made stone wave breaker, jetting out into the bay. The black circle indicated just above and left of the center of the image might be thought of as the heart or center of the village, locally referred to as “the flat.” In this circle, there is a primary school that serves Desa Ikan and nearby communities (the “L” shaped building with the reddish roof), a Catholic church (rectangle reddish roof), a few rum shops, and the only bridge and road connecting the Desa Ikan to the capital city and the rest of the Island (with the except of a few villages to the South of Dominica, which are also only connected to the rest of the island through the bridge and road in Desa Ikan). Accessed online on 20 December 2017.

CHAPTER IV

THE DOMINICA FISHERY

Fisheries development since the twentieth century has led to huge growth in the industry around the world (Srinivasan, Watson, & Sumaila, 2012; Watson et al., 2013), and global fish stocks are predicted to collapse around 2050 (Costello et al., 2016; Myers & Worm, 2003; Norse et al., 2012; Pauly, 2010). Work in the Caribbean has shown that the introduction of boat motors in the second half of the twentieth century had the effect of shifting fishing from small-scale subsistence practice to one that generates cash income (Smith, 1977). Fishing has also a long, impactful history in Dominica—from the Igneri to extant Kalinago (Barome, 1966). Boat motors allowed Dominican fishers to target both near-shore and far from shore species (examples below, this chapter), which changed the domestic market for fish, boat design ownership patterns, and crew compositions (Pattullo, 2005).

Currently, there are thirty-two landing sites in Dominica (Sebastian, 2007), including large sites that receive development aid. The Japanese International Cooperation Agency (JICA) has donated millions to Dominica to construct a major landing site on the island. Pattullo (2005) highlights that this is an apparent effort by the Japanese government to encourage Dominican approval of whaling. For example, the JICA funded the construction of a multimillion dollar landing site about twenty-two miles north of the field site of this project, Desa Ikan. The Japanese government has also worked with the Ministry of Agriculture, Fisheries, and Forestry of Dominica in 2008 to conduct a census of fishers in Dominica. The results shows that most fishers were male (96%), single (62%), and that the average age of a Dominican fisherman was fifty-three years old. The census of fishers also showed that 78% completed primary school and 15% completed high school. Fishers went to sea about four days per week, on average, and 90% of fishers indicated that they sold their own fish while only 7% of fish vendors were non-fishers. Venezuela and China has also invested in the Caribbean and Dominican infrastructure projects, albeit not directly related to the fishery of Dominica.

Fishing in Dominica is considered artisanal (Zeller, Booth, & Pauly, 2006). There are currently no commercial fishing trawlers operating from the island. Fishing on the western, Caribbean coast is markedly different from eastern, Atlantic coast. The Caribbean side is usually flat and calm, while the Atlantic side normally experiences two to three meter swells. On both sides of the islands, Dominicans practice nearly the same variety of fish catching methods to target both pelagic and demersal species.

Demersal species live and feed on or near the seafloor and are caught year-round and near the shore. Common demersal species include many species of snapper (*Lutjanidae*) and grouper (Epinephelus), red and rock hind (*Epinephelus guttatas* and *E. adsocensio*), trigger fish (*Balisties vetula*) and a variety of lobster like the Caribbean spiny lobser (*Panulirus argus*) and crab (*Coenobita*). In the next section, I describe two pervasive methods to catch demersal species as practiced at the landing site where research activities took place. These fishing techniques include the so-called ‘bank’ and ‘pot’ catch methods.

Pelagic fish live and feed mostly far from shore and in the open ocean, not near the sea floor (Miller, 2007). Commonly targeted pelagic species include blue marlin (*Makaira nigricans*), yellow and black fin tuna (*Thunnus albacares* and *T. atlanticus*, respectively), dolphin fish (*Coryohaena hippurus*), flying fish (*Hirundichthys speculiger*), barracuda (*Sphyraena barracuda*), skipjack tuna (*Katsuwonus pelamis*), and king mackerel (*Scomberomorus cavalla*). Pelagic fish are frequently exploited two ways in Dominica. First, via 'channel' fishing, which is more common in the winter and spring, and second, via 'FAD' (fish aggregating device) fishing, which is primarily a summer and fall activity. I describe both of these methods below in the context of the field site.

Fishing in Desa Ikan

Fishers live in Desa Ikan and neighboring communities, sometimes travelling about two kilometers to reach the landing site to fish. The landing site at Desa Ikan features a boat ramp, a cement sink for cleaning fish, and a building with about twenty-five lockers (Figure 5). These facilities were funded by the Fisheries Department of Dominica who partnered with the Food and Agriculture of the United Nations (FAO) and French government to further develop the landing site in Desa Ikan (Alvard, personal communication). The project also funded the addition of a large fiberglass boat with 85hp outboard motor, locally referred to as the 'cooperative' boat to reflect that it is not privately owned, as well as an administration building with freezers that serves as the local cooperative.

A road leading to the landing site bay and the road in and out of the village was also constructed, which is best seen in Figure 4b, running along the coast and connecting the two black circles. In 2005, a wave breaker was added to help shelter the bay (best seen in Figure 4b and Figure 6). The wave breaker is a valuable addition to the landing site because it makes entering and exiting the landing site much easier for fishers and protects the boats in the bay from storms and larger waves, to some extent. Finally, in 2010, the local gas station that was built as part of previous deal between the Dominican and Venezuelan governments became functional.

Figure 5. The landing site and facilities at Desa Ikan Dominica. This photo I took in 2015 features the boat ramp and the blue locker facility, which were additions funded by the Fisheries Department of Dominica who partnered with the FAO and French government to enchance the landing site at Desa Ikan. The boats that are dry-docked in this picture were likely pulled on shore for maintenance. The two-toned orange house in the background is privately owned and not part of the fishery complex.

About thirty boats are docked at the Desa Ikan landing site, including boats both dry-docked and in the water. However, this count is liable to change due to, e.g., weather conditions, as fishers arrive by boat to buy fuel at the local gas station, interpersonal conflict, and other personal reasons such as desire to move a boat to a different landing site. Boats operating out of in Desa Ikan are generally fiberglass, wood keeled, or fiberglass with a wooden frame. They range from four to eight meters long and are equipped with two-stroke outboard motors ranging from 15-85hp, with 40hp and 48hp engines as the most common. Figure 6 is a picture of representative boats moored at the landing site during the data collection periods. One well-respected fisher emphasized to me that the major advantage of "upgrading" to a fiberglass boat is that fiberglass boats are built with a rubber bladder in the hull that prevents it from sinking.

Based on my observations, boats usually hold a maximum of three crew members, though two-man crews are the most common composition. Sometimes a man will fish alone, and while nearby islands such as Martinique have enforced sanctions against fishing alone, Dominica has no such laws. Profits earned from fishing are dictated by ownership of the boat and motor as well as who actually does the fishing, which is not always the same. Sometimes one of the fishers owns the boat, motor, and gear he uses, and sometimes a non-fisherman owns the boat and motor. In one case, a fisherman owned a functional boat, but he fished from a second boat that he did not own while his boat was captained by a different man.

Though there is a division of labor during fishing trips, both crewmen share many tasks—it depends on the captain/crew composition. Generally, the captain operates the motor, steers the boat, and is responsible for many aspects of operation. Bowmen are responsible for a variety of other logistical tasks, such as being on the lookout for buoys, birds (which indicate the presence of schools of fish), and any floating debris that attracts fish, as well as raising fish traps, pulling lines, organizing catches on ice, and bailing water from the boat. In a few cases at Desa Ikan, the bowman is responsible for the local sale of fish once back on shore and handling the monetary exchange, but captains often sell fish, too. Other times, the boat owner acts as the middle-man.

Figure 6. Boats moored at Desa Ikan during the data collection periods. This photo from 2015 shows the three types of boats moored at Desa Ikan, behind the stone wave breaker. The blue/orange boat on the far left is a wood keel boat, the orange boat that is second from the left is fiberglass with a wooden frame, and the white/orange boat that is third from the left is a fiberglass boat.

When fishing is productive, villagers gather at the landing site when boats are expected to return to shore, buy fish, and/or simply watch the action unfold. Some individuals, often the same people day-to-day, act as a sort of 'ground crew' for the fishers by helping them unload equipment and catches from boats. The 'ground crew' might be boat owners, kin, friends, or community members who are hoping for fish or money in exchange for labor. Sometimes fish are given away to friends and kin or respected community members, regardless if they provide help to the crew or not.

A portion of catches are sold to local fish buyers. These middle-men will transport and sell the fish in more distant communities, to the national Fishing Cooperative in the capital city, and directly to restaurants and resorts around the island. From my observations during the data-collection periods, one man accounted for the vast majority of such middle-man sales in Desa Ikan. This specific man was often in contact with Desa Ikan fishers before they reached shore (via cell phone) to gauge the type and quality of their catches and secure the purchase when possible. He also bought fish from other landing sites and was a constant source of information on the kinds of catches from all around the island.

Desa Ikan fishers target a variety of both demersal and pelagic species. Fishing trips are diurnal, rarely last more than twelve hours, or travel more than sixty kilometers from landing site. This ethnographic context of this project is ideal for this project. Fishing–foraging in Dominica and Desa Ikan remains small-scale and decentralized, with different fishing strategies providing multiple, independent contexts for testing the

CUMSUM method and foraging models. Next, I describe four common fishing strategies as they are practiced by Desa Ikan and other Dominican fishers.

Demersal fishing: bank

Bank techniques are practiced year-round, near-shore, and in relatively shallow water, from about thirty to forty-five meters to usually no more than one hundred meters, to target demersal species such as snapper (*Lutjanus* spp.) and the others described earlier in this chapter. Patches of resources i.e., aggregates of fish, occur along the insular shelf, whose locations are known to individual fishers by landmarks. These marks include at least three points of reference on the island relative to the position of the boat on the ocean, which is a common technique among many small-scale fishers around the world (Igarashi, 1974). Desa Ikan fishers locate bank patches visually and from memory—without a GPS device. Anywhere from one or two to ten or more patches are visited in a single fishing trip. Most bank fishing trips include two fishers, a captain and a bowman. Bank fishing involves an array of hook and line techniques at varying costs but without rods and reels (Gabriel, Lange, Dahm, & Wendt, 2008).

The most common method of bank fishing in Desa Ikan and around the world is one that uses a stone to sink the line and hooks to the ocean floor (Figure 7). A fisher typically holds one or two of these lines. Once the boat is positioned approximately on the marks of a patch—ideally up-current from the patch to maximize time spend drifting through the patch—lines are dropped overboard. After the stone sinker touches down on the ocean floor, the line is raised slightly to keep it taut. After all fishing lines are raised and fish unhooked, the captain maneuvers the boat back to the mark and repeats the process. The captain approximates an ideal spot up-current from the patch, fishers drop lines and make minor adjustments if necessary, drift through the patch with lines in the water, raise lines to unhook fish or re-bait, and reposition on the mark again if necessary.

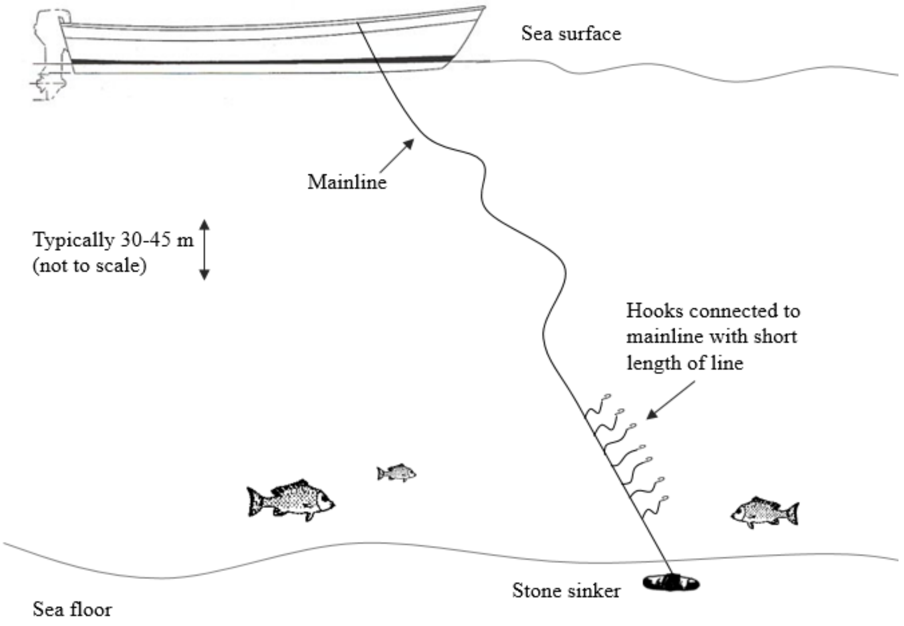


Figure 7. Schematic example of the prevalent "bank" fishing technique in Desa Ikan.

Demersal fishing: pots

A second bank strategy to target demersal species employs a classic Caribbean fish trap (Gabriel et al., 2008), locally known as “pot” fishing. A variety of fish are caught with pots, but the most common are *Balistes* spp. (busse), *Lutjanus* spp. (snapper), and a variety of lobster and crab. In practice, a trap is set on the bottom of the seafloor, about forty to ninety meters deep and within about five kilometers of the shore, designated by a buoy (Figure 8). Similar to bank fishing, the location of a pot is known to the captain by at least three landmarks and is found without the aid of a GPS device. It is not uncommon for multiple pots to be deployed in a spatially proximate area. I observed that Desa Ikan fishers had anywhere from one or two to as many as ten pots deployed at a given time. Property rights are not ambiguous in this context, but sometimes a pot is stolen by other Dominican fishers, referred to locally as pirates. Once a pot is dropped in the open ocean, it is difficult to defend from pirating.

It is difficult for one fisher to raise these pots alone, and thus, trips usually include a captain and a bowman. Only one of four known pot fishers from Desa Ikan routinely raised his pots alone. Boats travel towards the approximate location of a pot and then slow as the captain and crew look for the buoys. The mainline of a fish pot is given a small degree of slack to offset the strain of the current, so the buoy will be found in known radius. Depending on sea conditions, such as the strength of the current, a pot might be found within a minute or two or might not be found at all. Fishers might give up on a particular pot and leave in search of others if it proves very difficult to find. After a pot is found, the fishers work together to pull the pot up and onto the boat.

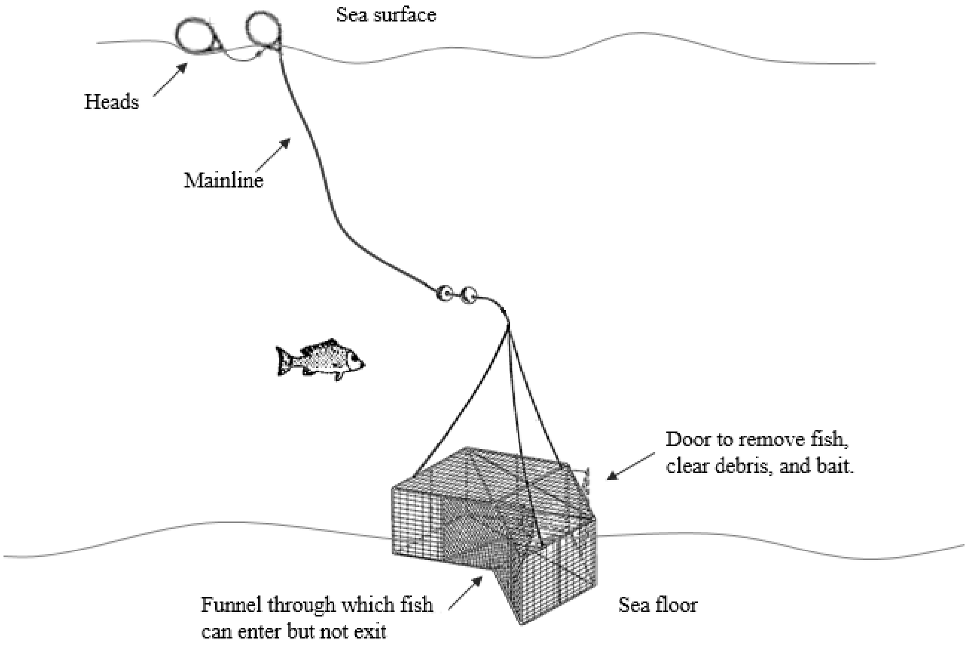


Figure 8. Example illustration of a typical pot constructed and deployed by Desa Ikan fishers.

Figure 9 depicts the common scene of a raised pot resting on the frame of the boat while the captain clears the pot of fish and other debris, completes any maintenance the pot might need, and then re-baits the pot. The bowman provides assistance as necessary. After a pot is cleared and ready to be dropped again, the captain maneuvers the boat back to the original mark before dropping the pot. Often, the pot is dropped in the same location where it was found. Alternatively, the captain may decide to drop the pot in a new location if he is no longer satisfied with the current mark or believes a different patch will result in a better catch.

Figure 9. A pot has been raised by two fishermen and rests on the frame of the boat. The captain clears the pot of the catch, cleans debris, fixes or maintains the pot as necessary, and adds fresh bait before dropping it back overboard to rest to the ocean floor.

A pot is functional for nine months to a year and occasionally longer, with proper maintenance. Pots are one good example of niche construction in the context of fishing at Desa Ikan and significantly reduce search time, effort, and fuel costs for fishers (Laland, Odling-Smee, & Feldman, 2001; Odling-Smee, Laland, & Feldman, 2003). The payoff of pot fishing relative to other strategies seems to be realized in the long term. While pot fishing is not as immediately profitable as e,g, FAD fishing, the day-to-day variation in returns is noticeably reduced. However, pot fishing requires highly specialized knowledge on construction and use. Pot materials are also relatively expensive, and the cost can be prohibitive for any one fisher. Thus, pot fishing it is limited to just a few Desa Ikan fishers. As mentioned, four men regularly raised pots.

Pelagic fishing: channel

A pelagic fishing strategy, channel fishing, takes place in the late winter to early spring seasons, typically eight to fifty kilometers from shore. The target species of channel fishing efforts is dolphinfish (*Coryphaena* spp.), which are found in schools and caught with hook and line. Dolphinfish are attracted to floating patches of debris such as wood, marine litter, trash, and a common type of seaweed (*Sargassum* spp.) and are often associated with schools of small pelagic fish such as flying fish (*Cheilopogon melanurus)*. Rather than look for schools of dolphinfish directly, fishers often search for Frigate birds (*Fregata* spp.), which feed on flying fish, the same pray as dolphinfish, and other kinds of floating debris and marine litter that attract target species.

A channel trip begins with relatively high-speed travel outwards from the shore to the open ocean. Fishers remain vigilant and search for floating debris and/or birds. When a patch of debris or birds are found, and the presence of a school of dolphinfish is confirmed, fishers might troll on the edges of debris where fish are found. Fishers drift fish along with the patch as guided by the current or maneuver the boat to more ideal location on or around the patch. Fishers may visit a single patch or many patches in any given channel trip. It is not uncommon for fishers to troll for bait fish near other known patch locations, such as near deep-water FADs or around near-shore FADs.

Pelagic fishing: FADs

Recently introduced to Dominica, fish aggregating devices ("FADs") consist of a simple technology that floats on or near the surface of the sea, attract migratory and pelagic fish, and facilitates their capture (Dempster & Kingsford, 2004; Dempster & Taquet, 2004). Migratory species move from one part of a body of water to another at variable distances and time scales. Species targeted by FAD fishing are considered highly migratory in that they undertake migrations of significant distances across oceans and have wide geographic distributions (Meltzer, 1994; Miller, 2007). FADs are known ethnographically across the world and have been used by fishers in the Mediterranean and Asia for thousands of years (Davies, Mees, & Milner-Gulland, 2014; Kakuma, 2000; Seaman Jr, Buckley, & Polovina, 1989). The FAO of the UN introduced FADs to Dominican fishers in the late 1980's and earl 1990's, but the technology did not become established on the island until after 1998. At this time, the export market for bananas changed to the disadvantage of Dominica and attention turned to the fishery on the island (Defoe, 2004; Gillett, 2005; Payne, 2008; Theophille & Hutchinson, 2012).

Moored FADs, locally called "buoys," are another example of niche construction at Desa Ikan; they are designed to create resource patches at known locations and significantly reduce search time, effort, and fuel costs for fishers (Alvard et al., 2015). A typical Desa Ikan FAD is moored to the seabed with an anchor made from a halved fifty-five gallon drum filled with cement and placed at a depth of 1,000-3,000 meters, between thirteen and fifty kilometers from shore (Figure 10; Alvard et al., 2015). There are shallow water FADs located close to shore to target barracuda (*Sphyraena* spp), but much research focuses on deep water FADs (Alvard et al., 2015; Brock, 1985; Cayré, 1991; Dempster & Taquet, 2004; Jaquemet, Potier, & Ménard, 2011), which target highly migratory, pelagic species such as tuna (*Thunnus* spp.), marlin (*Makaira* spp.), and dolphinfish. The cost to individually deploy even one FAD is prohibitive, and as a result, men cooperate to build and deploy FADs. Since FADs are often a common pool resource, property rights can be ambiguous, creating social dilemmas. Once deployed, FADs are difficult to monitor and defend from pirates (Alvard et al., 2015).

Travel towards a known deep water FAD anchor point is characterized by ballistic, high speed movement. FAD mainlines are given considerable slack to reduce strain. FAD heads—the buoys visible on the surface of the water–are be found within a very large drift radius (Alvard et al., 2015). Aided by GPS and knowledge of how ocean conditions affect the location of a FAD head, fishers reduce speed as they search for the head of a FAD. Once they locate a FAD, they might troll the area to catch bait first and check how the FAD head is drifting before setting fish traps around it. Traps are made from floats attached to about one hundred meters of fishing line and a baited hook. The free-floating trap is dropped just up-current from the FAD so that it may drift past the FAD head and through the constructed patch. Multiple traps are often dropped at once. Traps that appear to stand upright on the water indicate a fish has been hooked, which a fisher raises by hand. A trap with no fish is collected down-current from the patch. The result in a back and forth pattern within the patch as captains maneuver to above current to drop traps and below current to pick them up (Alvard et al., 2015).

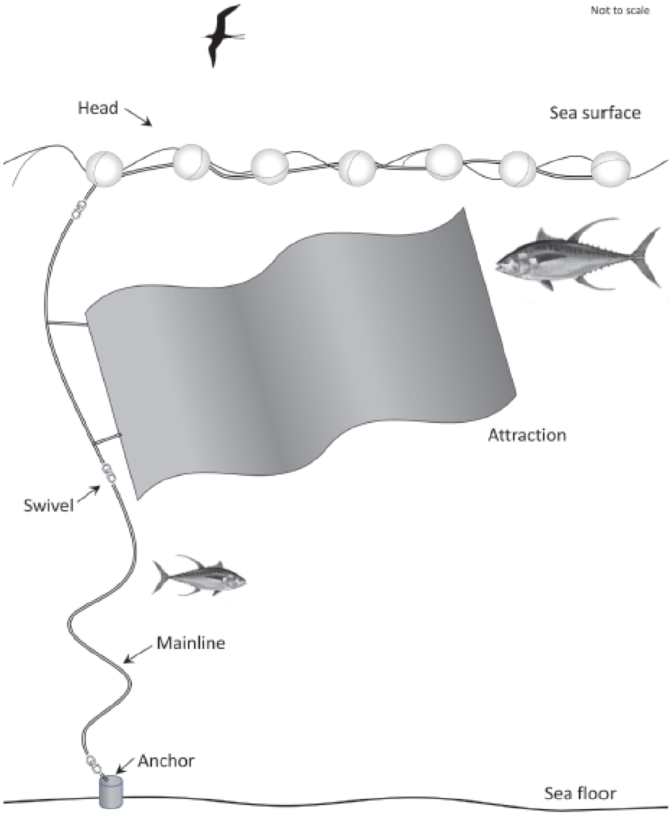


Figure 10. Schematic example of a typical FAD deployed from Desa Ikan, from Alvard et al. (2015).

CHAPTER V

RESEARCH AIMS & FIELD METHODS

Research aims

Scientists infer foraging decision from patterns generated by animal movement and space use, which can be recorded as a movement trajectory like a GPS track. Sometimes relevant patterns are obvious, and segmenting a GPS track into bouts of pertinent behavioral modes can be based on visual assessment (Knell & Codling, 2012). Often, however, behavioral shifts are not obvious or clearly identifiable because patches of resources are not always well-defined, discrete units but non-delimited areas with higher aggregations of resources (Benhamou, 2004). In these cases, bottom-up approaches like those described above in the background section rest on mathematical segmentation to isolate stationary phases corresponding to different behavioral modes that operate at the same scale.

For this project, I use both direct behavioral observation and remotely gathered movement data, GPS tracks, to identify extensive and intensive search in the context of human fishing-foraging activities. The first major goal of my project is to test the effectiveness of the CUMSUM for discerning extensive search from travel in the context of demersal fising, after the example of Alvard et al. (2015). This further develops the usefulness of the CUMSUM method of GPS track segmentation. Is the CUMSUM method for identifying changes in foraging behavior robust across different foraging contexts? I use the CUMSUM method to identify extensive search versus ARS at patches using GPS tracks collected during demersal fishing trips originating from Desa Ikan (see chapter three and four for descriptions). I compare CUMSUM-generated segments of behavior with ground-truth data i.e., direct behavioral observation data from the same fishing trips. This allows me to gauge the efficacy of the CUMSUM approach for distinguishing ARS at patches and extensive search between patches The sample of fishing trips recorded with a GPS device that also have simultaneous direct behavioral observation is referred to as the “N10” sample throughout this paper. A summary of these trips can be found in chapter six.

As a secondary test of the CUMSUM method, I compare the results of visual segmentation with the results of CUMSUM segmentation. First, I visually segment—assign behavioral modes to different portions of tracks—a subsample of thirty additional GPS tracks for demersal trips that do not have simultaneous direct observation (i.e., those not in the N10 sample). I refer to this data as the N30 sample, which is summarized in chapter seven. I also use the CUMSUM method to segment these thirty GPS tracks. I compared the results of visual segmentation with CUMSUM segmentation to identify similarities and differences. I discuss the extent of agreement between the methods and possible sources of error.

Another goal of this project is to show how the above methodological development can help move theory forward by potentiating tests of prominent foraging models in contexts where direct behavioral observation is costly. To this end, I use data from both direct behavioral observation and patches identified by CUMSUM analysis to assess a general prediction of the MVT. I examine if patch residence time increases as a function of increased travel time, measured by patch distance from the landing site where trips originate. Do fishers spend more time in patches that are farther from home (i.e., incur more costs associated with travel time), and less time in patches that are closer to home? The methods I used towards this aim is described in the next section of this chapter. The resulting data along with derived patch residence time and patch distance calculations are described in chapter eight.

Field methods

I collected data across three field sessions, spanning July-August 2014, June-August 2015, and March-July 2016. In total, I observed a total of eight hundred forty-four fishing trips leaving and returning to the field site, Desa Ikan, during these periods. Of these N = 844 trips, N = 536 have associated remote behavioral observation in the form of GPS tracks. N = 130 of the trips with associated GPS tracks are demersal fishing trips, which is the specific foraging context of this project. N = 10 of these demersal fishing trips with GPS tracks also have simultaneous direct observation. The methods I used to collect these data are described below, and the resulting, relevant datasets are described throughout chapters six, seven, and eight in context with subsequent analysis.

Ethics statement

This research was approved by the Commonwealth of Dominica Fisheries Department (RP-05/129-FIS-3) and Texas A&M University's Office of Research Compliance Institutional Review Board (project IRB2009-0209D). The IRB approved the use of oral consent from fishers, as asking for signed consent in this ethnographic context put a significant strain on the research-subject relationship. Subjects were informed concerning the nature of the research, with the option to decline to participate made clear. This project was funded by the NSF via a Research Enrichment for Graduate Students (REG) award (BCS-1260201) and A&M's Anthropology department.

Movement data

Compact, hand-held GPS devices manufactured by LOCOSYS Technology, model GT-31/ BGT-31, were housed in hard plastic, water-proof containers made by Pelican Products, Inc. Fishers often stored these devices within another dry-storage tub where they housed their own supplies and equipment. The plastic barriers did not prevent a device from receiving a signal, and the open sea conditions were favorable for satellite reception. LOCOSYS report a 95% probability that the recorded positions are within a ten meter radius around the actual location of the vessel. The devices use SiRF Star-3 high sensitivity, low power GPS chips and feature a rechargeable, built-in lithium-ion polymer battery.

I collected GPS data for N = 536 of the N = 844 trips observed originating and returning to Desa Ikan, including N = 130 demersal fishing trips. Before fishers departed from Desa Ikan each morning, I handed an activated, encased GPS device to one crewmember from each boat. The men took the GPS aboard the boat while they fished for the day. In the afternoon or evening of the same day, I collected GPS devices from the fishers when they returned to Desa Ikan. Captains who agreed to have a GPS device on board were compensated (3.80 USD per trip).

GPS devices programmed to record at one-second intervals generate high resolution time series, movement tracks with associated spatial coordinates. I downloaded the resulting GPS output files into GPS Track Editor© by MapSphere. Using this software, I modified tracks so that on-shore pre- and post-trip data points were removed and color-coded tracks by speed. I imported the edited GPS track into Google Earth© and overlaid it on top of satellite imagery of the coast and seascape. In Google Earth©, I viewed and animated the track at different spatial and temporal scales to better understand the nature of fishing trips and patch use via visual analysis.

Along with GPS data, I also recorded data on fishing efforts and returns. When fishers returned to the landing site in the afternoon, I documented the number and the species of all fish as catches were unloaded from the boat. I also recorded the weight of each fish they were measured and prepared for local market sale, organized for consumption, and/or prepared for storage in freezers. Boat captains and crews provided me with contextual information about the trip, such as sea conditions, what types of patches were visited, where certain fish were caught, social encounters, and any unexpected issues such as equipment trouble and significant gear loss. I recorded these data in small notebooks and then transferred this information to formal data collection sheets that were used for all field sessions. Finally, I typed and stored a digital copy of these data in Microsoft Access©, keeping data backed up on an external hard drive.

Direct behavioral observation

Ground truth data refers to information collected or observed directly at a location and can be compared to remotely gathered data, such as GPS data collected at the same time (Jensen, 2009). I collected ground-truth data by simultaneous direct observation of fishing trips via focal follows to create a ground-truth dataset with which to compare GPS tracks of the same trips. A focal follow is a method of direct behavioral observation that involves observing the behavior of a focal individual during specific activities and for a given length of time (Altmann, 1974). In this case, the focal individual is the captain of the boat. I identified focal individuals based on their safety practices (e.g. carrying oars and a sail, sobriety, etc.), the consistency and frequency they employed demersal fishing strategies, and their willingness to allow a non-national, female researcher on board, resulting in a convenience sample.

During a focal follow, I synchronized my watch with the GPS device to allow correlation between the GPS tracks and direct observations made on the boat, which is a common ground-truth method (Li & Zhang, 2012; Pohl & Van Genderen, 1998; Xiao et al., 2006). I used event sampling to note changes in behavior and the timing of behavioral shifts, focusing on time entering and exiting patches. In other words, I recorded the exact times and duration of bouts of travel and ARS at patches. Events most germane to this project include travel, search for and navigation to known patches, fishing/ARS, social encounters with other boats, and encounters with floating debris like seaweed patches.

During focal follows, I confirmed my observations of fishing activities and behavioral shifts with the captain and crew, who are experts in the demersal fishing domain. This allowed me to more confidently differentiate between ARS and travel and develop expectations on how that might manifest as a GPS track. I noted the timing of a variety of other events, including: when a fisher was baiting hooks and preparing or maintaining lines, when a fisher had a line (or lines) in the water, when he started raising a line, when a line was back on board the boat, the exact timing of any fish catches, when a fisher was adjusting the position of the boat within a patch, when he had difficulty approximating a patch location or finding a buoy and spend more time searching for the patch, and finally, significant time spent on boat and motor repairs during the fishing trip.

I recorded information on fish catches and efforts during direct observation. I documented the number and the species of all fish as catches were pulled into the boat. I also recorded estimates of the weight of each fish as it was brought on board. I asked the fishers to estimate the weight of each fish as he unhooked it because it was not possible to weigh each fish individually on the boat as they were caught. Once back on shore, I recorded exact weights of catches when possible and compared this to the estimates fishers made. The differences were small and underscored the accuracy of the fishers' approximations. I also recorded how many lines and hooks a fisher used, as well as instances of gear loss and boat or motor trouble during observed foraging trips. I have some data on fuel use, but I do not have complete data on the costs associated with bait, storing catches on ice, or transporting catches for sale elsewhere on the island. Conversation with the fishers before, during, and after focal follows allowed me to learn from their experiences and develop expectations about the overall characteristics, costs, and benefits of demersal fishing.

In addition to the fee for carrying a GPS device on board, I compensated fishers who agreed to participate in a focal follow for the inconveniences associated with having a researcher on board (28 USD per trip). I recorded focal follow notes in waterproof notebooks while in the boat. I typed and stored my notes in Microsoft Word© and Access© immediately after the focal follow ended and backed up these digital files on a hard drive. These field methods resulted in twelve focal follows of demersal trips, but two of these trips are unusable due to lost or corrupt GPS data files. Overall, I collected usable ground-truth data for ten demersal fishing trips—five so-called “bank” fishing trips and give so-called “pot” fishing trips—resulting in the “N10” sample.

CHAPTER VI

N10: ANALYSIS & RESULTS

Data description

Near-shore, demersal strategies—bank and pot fishing—are the subject of this project and account for 29% (N = 241) of all observed trips (N = 844 across all field sessions). Just over half of these trips have associated GPS tracks (N = 130). Ten of these trips have simultaneous direct behavioral observation, for five 'bank' trips and five 'pot' trips. Thus, the primary CUMSUM analysis is limited to the sample of N = 10 trips that include complete GPS track data with complete, simultaneous direct behavioral observation. I refer to this data as the N10 sample.

Table 1 provides summary data for the N10 sample. This sample includes four different captains and four different boats: one boat and captain accounts for 50% of the trips, a second boat and captain accounts for three trips, and the third and fourth captains and boats account for one trip each. Excluding the observer, each trip included two men—a captain and a crew member. The methods described above produced a wide variety of data on fishing efforts and returns. Most relevant to the present example analysis are data on finding and exploiting resource patches—bouts of extensive and ARS—in the context of demersal fishing.

Table 1
Summary of each trip in the N10 sample

TripID	Date	Type	Duration (hr)	Average speed (m/s)	Standard deviation of speed	N
1758	08/14/2014	Pot	3.05	1.49	1.46	11,144
1977	06/19/2015	Pot	3.85	1.66	1.61	13,817
2058	07/17/2015	Pot	3.00	2.02	1.62	10,841
2072	07/21/2015	Bank	8.47	1.24	1.62	30,423
2101	07/29/2015	Bank	10.08	0.91	1.14	35,154
2114	07/31/2015	Pot	4.00	1.77	1.41	14,283
2178	03/17/2016	Bank	9.50	1.42	1.64	34,044
2246	04/09/2016	Pot	3.40	1.88	1.47	12,209
2282	04/19/2016	Bank, Twin	5.37	1.05	1.75	19,083
2369	05/14/2016	Bank	6.40	1.62	1.86	22,759
Mean			5.71	1.51	1.56	

Visual assessment

I first mapped the tracks of each demersal trip in the N10 sample onto the ocean-scape using GPS Track Editor©, an open-source software by MapSphere (http://www.gpstrackeditor.com/). Figure 11, plots A through J, presents the map of each trip. The N10 sample consists of two types of demersal fishing strategies—five pot and five bank fishing trips. At the scale depicted in Figure 11, the movement paths of each trip type are indistinguishable. All movement paths show classic central place foraging (Orians & Pearson, 1979). Fishers travelled from Desa Ikan towards near-shore patches known to them where subsequent bouts of intensive search with travel between patches occurred, then they returned to the starting point.

At the spatial scale depicted in the GPS tracks in Figure 11, travel appears to account for a major portion of each track. Plots of speed versus time, however, reveal temporal heterogeneity in speed across the duration of each trip is more evident than shown in the GPS tracks. Figure 12, plots A through J, shows bouts of both higher speed associated with travel as well as significant bouts of slower speeds associated with drift and low-powered, within-patch movements.

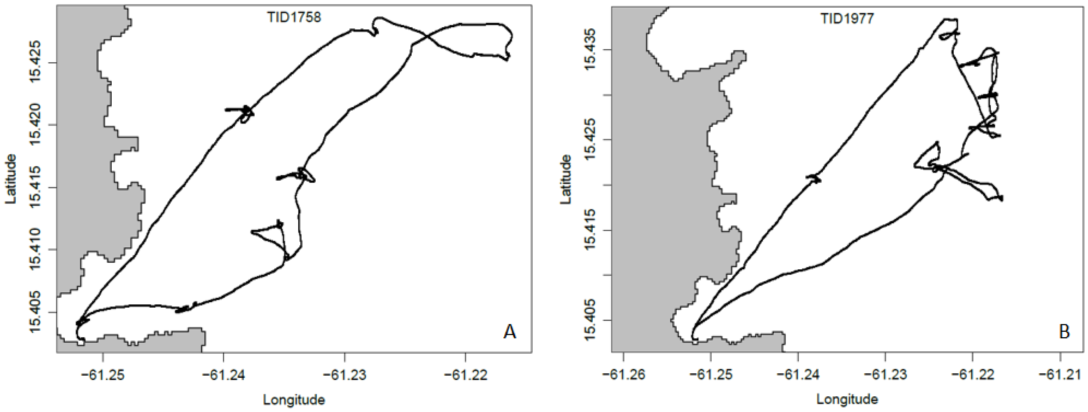


Figure 11. GPS tracks of demersal fishing trips in the N10 sample. Plots A, B, C, F, and H are "pot" fishing trips, while plots D, E, G, I, and J are "bank" fishing trips. The gray-shaded portion is land, and the white portion is the Atlantic Ocean. The black line is the GPS track and shows the movement patch of the boat. Trips originate from Desa Ikan, on the east coast of Dominica and then return to the central place after visiting a number of patches. The long, linear sections of track correspond to travel between patches and to/from Desa Ikan as well as other behaviors involving realtively higher-speed movements. The sinuous and aggregated clusters of tracks are candidates for ARS at patches and other behaviors involving slower, low-powered movements or drift of the boat.

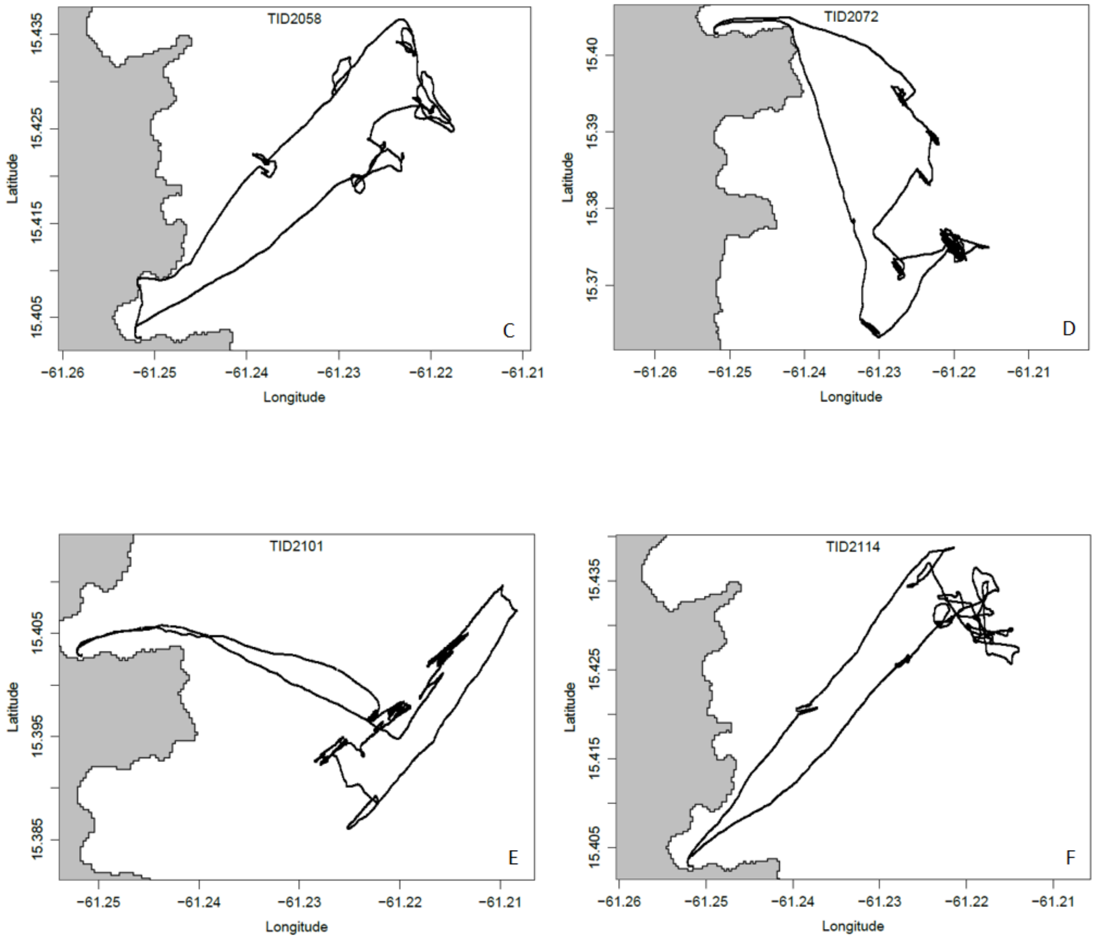
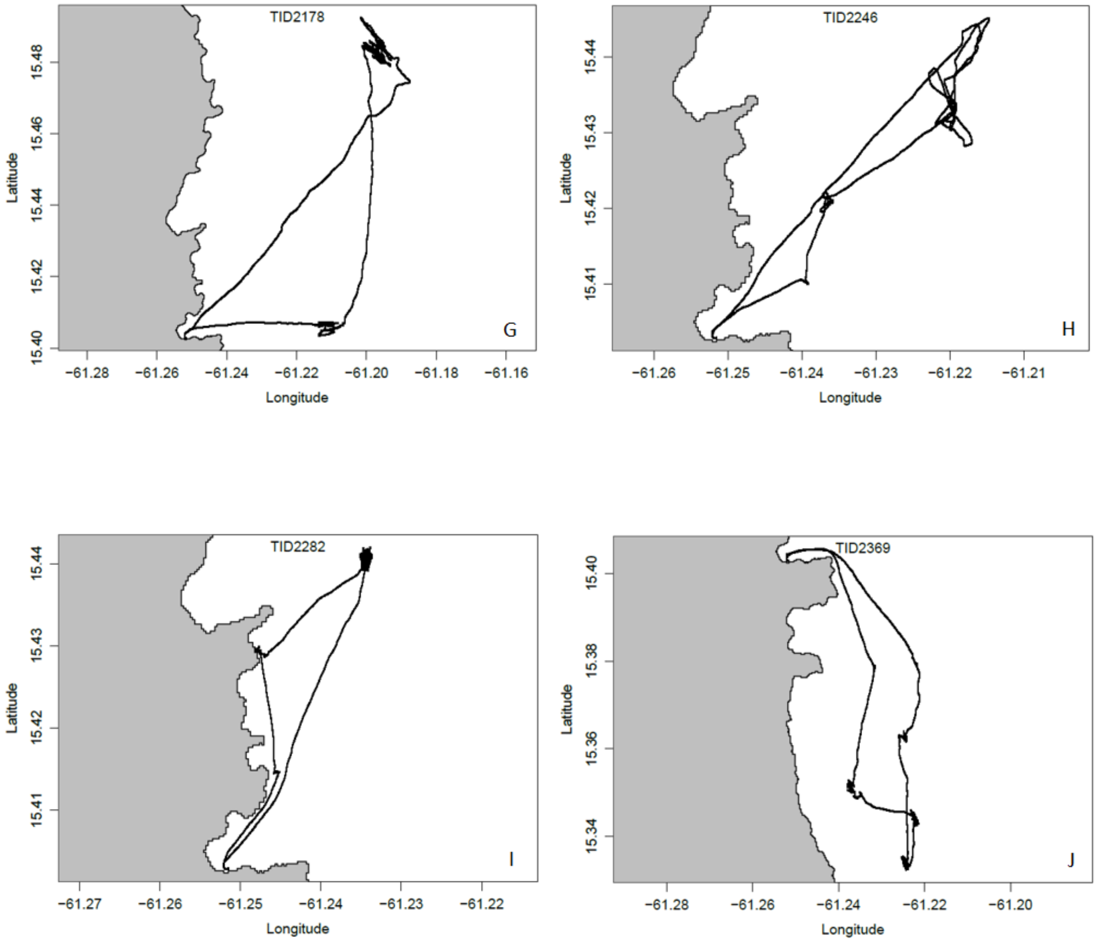


Figure 11. Continued



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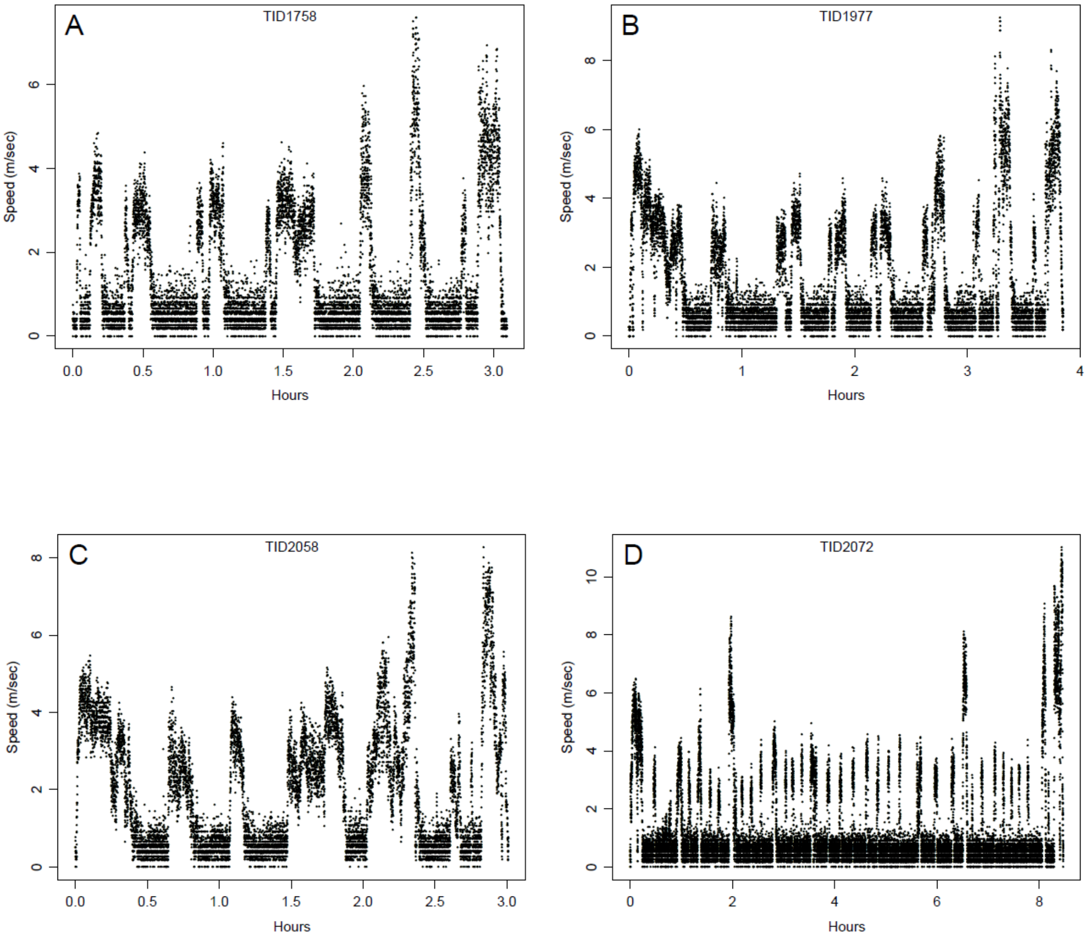


Figure 12. Time series plots of speed for each demersal fishing trip in the N10 sample. Across the duration of a trip, speed exhibits much heterogeneity in speed as fishers sift between behavioral search moves associated with foraging activities.

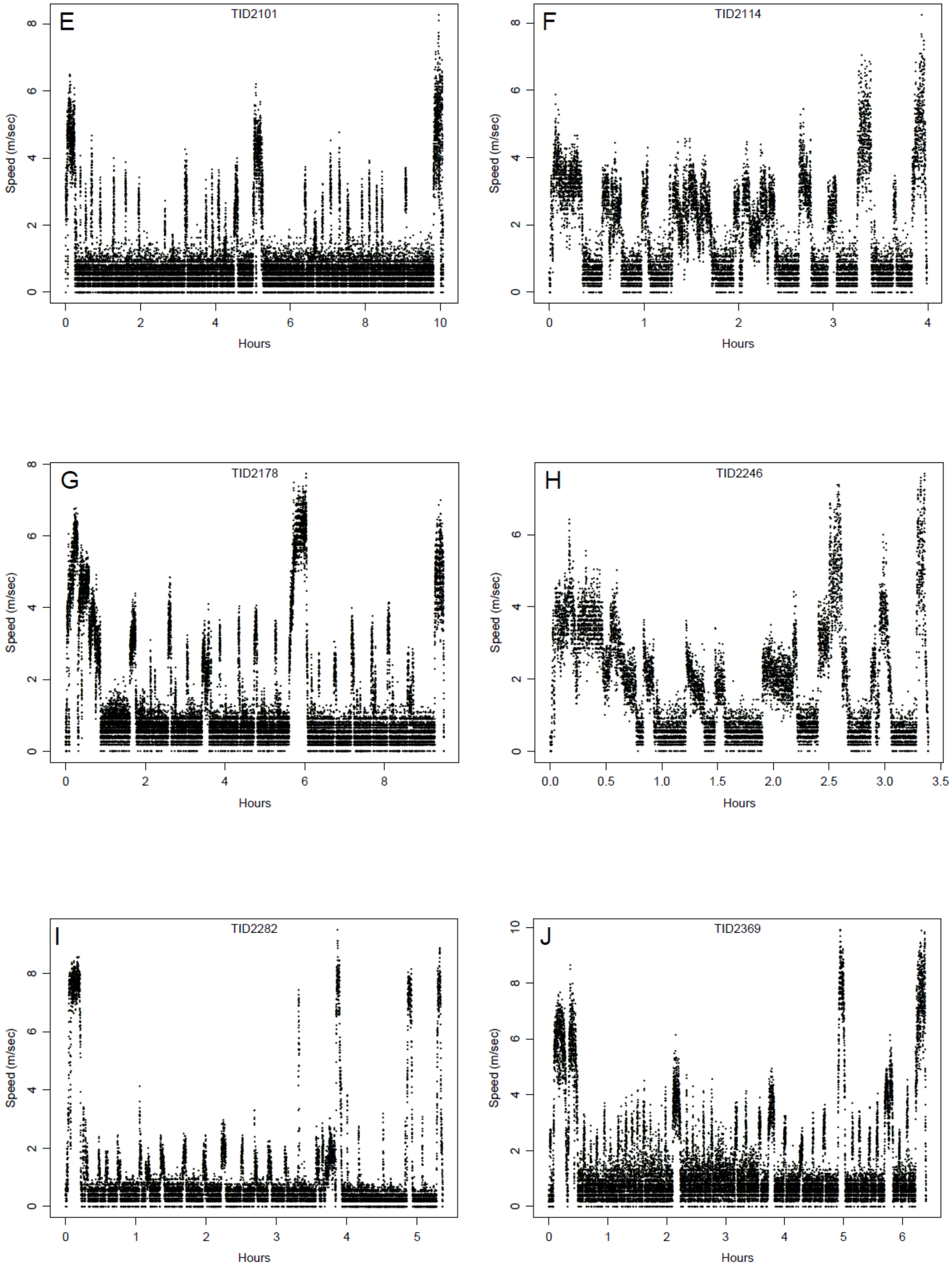


Figure 12. Continued

GPS devices recorded positional data—latitude and longitude—at one second intervals. Using these data, instantaneous travel speed was calculated based on the distance traveled between each pair of consecutive one second points on a track. The mean speed of each trip in the N10 sample ranged from 0.91 meters/second to 2.02 m/s (SD 1.14-1.86; Table 1). Frequency distributions of speed for each trip reveal a bi-modal or somewhat tri-model distribution (Figure 13). The inset scree plots in Figure 13 reveal an inflection point around three groups as well, possibly indicating an increased total within sum of squares for fewer clusters. In other words, for each trip, binning speed into three groups seems to minimize the variance of each of the three clusters compared to the within-cluster variance for two groups.

I further explored the nature of speed for the N10 sample using a k-means cluster analysis. Specifying three groups, I calculated the means, range, and size of each of the three modes of speed for each trip (Table 2). I provide a summary of the modal ranges of means and modal mean of means across all trips in Table 3. During focal follows, I most often observed the speeds associated with modes one and the lower speeds of mode two during ARS at patches, while I observed the higher speeds of mode two and mode three during travel between patches and to/from the central place. The mean range of mode one is 0.39-0.71 meters per second and corresponds to drift. The range of means for mode two is 1.83-3.17 m/s and corresponds to slower, low-powered movements toward the left side of its distribution and some relatively slower travel speeds at the right end of its distribution. Mode three corresponds to travel between patches or the home place and ranges between 3.26-7.26 m/s.

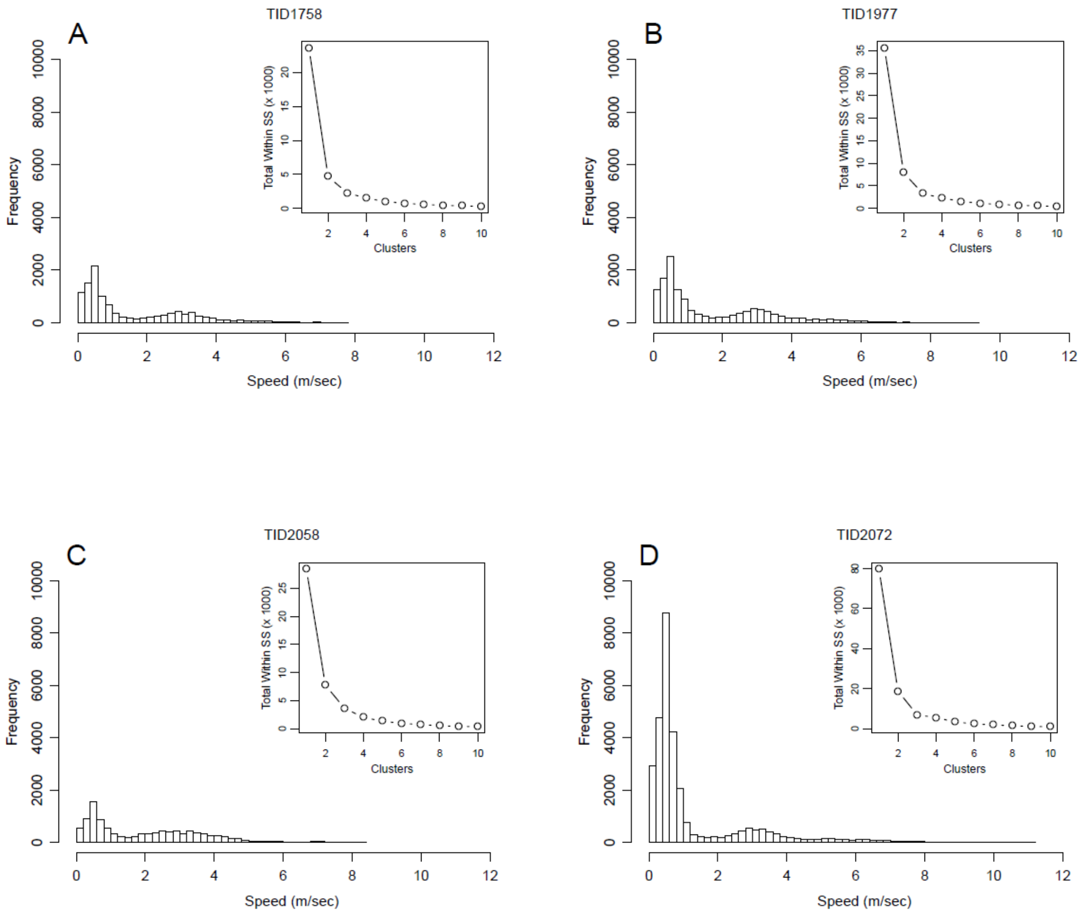


Figure 13. Histograms of speed across the duration of each trip in the N10 sample. Inset scree plot shows the cluster that minimizes the average variance of the clusters per trip, with an inflection point between two to four clusters for all trips.

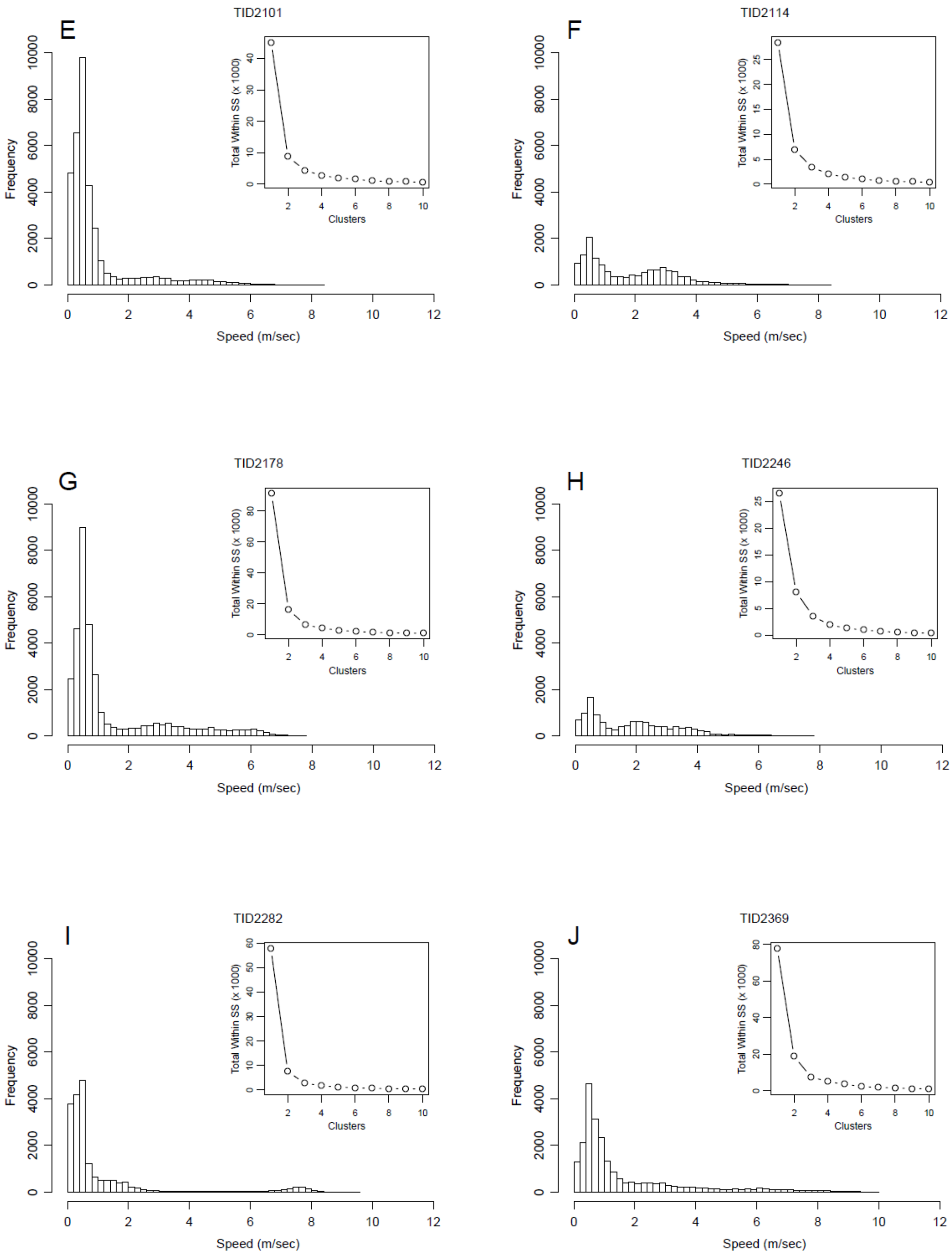


Figure 13. Continued

Table 2

K-means analysis of speed for N10 trips

TID	Mode	Mean (m/s)	Range (m/s)	N
1758	1	0.55	0.00-1.69	7329
	2	2.83	1.70-3.79	2902
	3	4.75	3.80-7.61	913
1977	1	0.59	0.00-1.75	8743
	2	2.93	1.77-4.06	3756
	3	5.19	4.07-9.26	1297
2058	1	0.66	0.00-1.73	5400
	2	2.81	1.73-3.82	3901
	3	4.85	3.83-8.28	1540
2072	1	0.54	0.00-1.85	24315
	2	3.17	1.86-4.80	4439
	3	6.44	4.81-11.01	1636
2101	1	0.50	0.00-1.53	29624
	2	2.57	1.54-3.64	2995
	3	4.72	3.65-8.27	1886
2114	1	0.64	0.00-1.66	7639
	2	2.68	1.67-3.58	5116
	3	4.49	3.59-8.24	1479
2178	1	0.58	0.00-1.79	25661
	2	3.01	1.80-4.20	3885
	3	5.41	4.21-7.73	3429
2246	1	0.57	0.00-1.40	5476
	2	2.24	1.41-3.20	4263
	3	4.17	3.21-7.69	2470
2282	1	0.39	0.00-1.09	14813
	2	1.83	1.11-4.52	2946
	3	7.26	4.55-9.51	1213
2369	1	0.71	0.00-1.90	16860
	2	3.09	1.92-4.85	3811
	3	6.62	4.86-9.92	1927

Table 3

Summary of means from cluster analysis for N10 trips

Mode	Range of means (m/s)	Mean of means (m/s)
1	0.39-0.71	0.57
2	1.83-3.17	2.72
3	3.26-7.26	5.39

The duration of bouts of travel and ARS are known from direct observations of trips. During focal follows, I recorded when fishers shifted behaviors—started and stopped travel and ARS—confirming my observations with the captain and crew (see chapter five for methods details). I sum these observational data in Table 4. Overall, fishers allocated 25% of foraging time to travel (N = 47,700 or 13.25 hours) and 75% of time to ARS (N = 141,840 or 39.40 hours). The length of a bout of travel varies widely, ranging from 0.03-1.38 hours, with a mean of 0.19 hours (SD = 0.22 hours). The length of a bout of ARS also ranges widely, from 0.02-4.73 hours, with a mean of 0.68 hours (SD = 0.92 hours). Noise segments were noted in focal follows as activities that were not related to fishing (e.g., stopping the boat to make a call). Noise segments during travel and ARS accounted for 4.22 hours of total foraging time, which was included in the travel and ARS percentages noted above (mean = 0.15 h, SD = 0.17). In comparison, summing the size of each mode from k-means analysis across all N10 trips (total N = 201,664 or 56 hours) shows that 72% of time is allocated to mode one, 19% to mode two, and 9% to mode three (Table 5). This makes sense given that, as mentioned, speeds falling within mode two correspond to both ARS and travel, at the left or right side of its distribution, respectively.

Table 4

Duration of bouts of travel and ARS for N10 trips from direct observation

Type	Travel	ARS	Noise
Total number of bouts	68	62	29
Range (hrs)	0.03-1.38	0.02-4.73	0.02-0.73
Median (hrs)	0.10	0.23	0.03
Mean (hrs)	0.19	0.68	0.15
SD (hrs)	0.22	0.92	0.17
Total (hrs)	13.25 (25.17%)	39.40 (74.83%)	4.22

Table 5

K-means size of modes across N10 sample

	N (seconds)	Total time (hrs)	Proportion
Mode 1	145860	40.52	0.72
Mode 2	38014	10.56	0.19
Mode 3	17790	4.91	0.09
Total	201664		

Demersal versus pelagic fishing contexts

Recall that I am using speed to describe the movements of human fishers in an effort to broadly characterize major foraging behaviors—travel and ARS at patches. I want to identify shifts between these two behaviors with speed as the model parameter for the CUMSUM segmentation method. I must specify an appropriate scale of analysis—the window size for CUMSUM—to accomplish this with accuracy. At this point, it is useful to provide a comparison between demersal fishing relative to pelagic fishing to contextualize the importance of scale. Comparing the nature of speed during these two independent fishing strategies reveals how they differ in ways that may affect the overall utility of the CUMSUM approach.

The multi-modal distribution of speed for the N10 sample of demersal trips is not as consistent as the tri-modal distribution of speed for the pelagic, FAD trips analyzed by Alvard et al. (2015). The frequency distributions for two representative FAD trips are presented in Figure 14 for comparison, and overall, a clear tri-modal distribution is evident. Compared to the k-means analysis of the N10 sample, the FAD sample shows a mean range of 0.37-1.06 m/s for mode one, 2.84-5.23 m/s for mode two, and 6.17-8.54 m/s for mode three (Alvard et al., 2015). These authors also report that the three modal speeds are consistent with certain behaviors observed during focal follows: mode one is associated with drift, mode two is associated with slower, low-powered movements within movements, and mode three is associated with higher speed travel to and from patches. Their observations concur with my own despite that speeds for the N10 sample do not bin as neatly nor range as widely as the FAD sample. With FAD trips, more time is spent in travel, which increases the mean speed of the trip and makes it easier to distinguish it from ARS (Alvard et al., 2015). Patch residence time is also longer for FAD trips and thus easier to avoid model errors and noise. The differences between the speed of demersal and pelagic strategies likely significantly affect the scale and efficacy of the CUMSUM method (further example below).

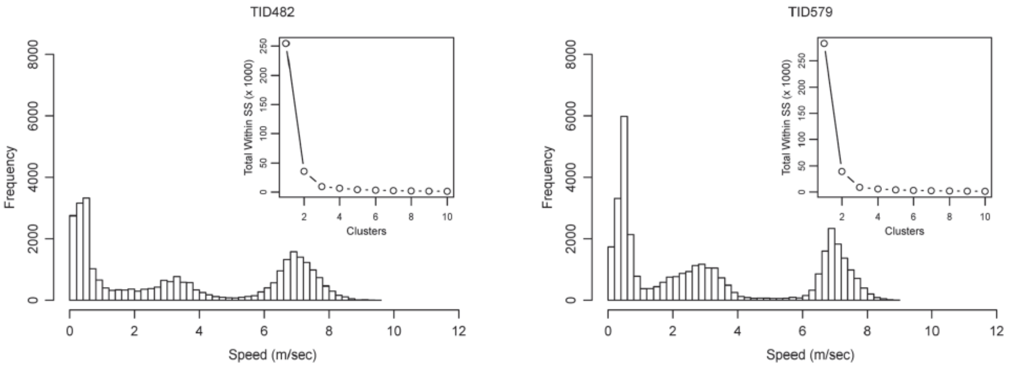


Figure 14. Histograms of speed for two representative FAD trips adapted after Alvard et al. (2015). The inset scree plots also show three groups minimize the average variance of the clusters per trip.

CUMSUM example: TID2072

Time series

In this section, I demonstrate the CUMSUM process by applying the method to an example demersal fishing trip from the N10 sample—bank trip TID2072—using speed as the model parameter to describe movement. The first step of segmenting a GPS track is generating a time series plot using the CUMSUM equations (Eq. 1 and 2 in chapter two) developed by Knell & Colding (2012). Figure 15 provides a CUMSUM-generated time series plot of the cumulative sum of speed (m/s) during each time-step in trip TID2072. Recall that consistent deviations greater than the mean speed of the trip have a positive cumulative sum value and slope (i.e., C_τ increases). Segments with exhibiting an increasing cumulative sum of speed are consistent with relatively higher travel speeds observed during the focal follow. Deviations less than the overall mean trip speed have negative values and slopes when speed at time steps are lower than the mean trip speed (i.e., C_τ decreases). In Figure 15, for example, the first segment is consistent positive deviations from the mean trip speed and results in a positive slope in the time series as C_τ increases. This segment corresponds to observed ballistic travel from Desa Ikan out to sea (*t* = 1 to *t* = 858), known via ground-truth data. The next CUMSUM segment in Figure 15 for TID2072 is a period of lower speed is associated with observed ARS at the first patch visited that trip (*t* = 859 to *t* = 3304), which results in a decreasing C_τ value and negative slope in the time series.

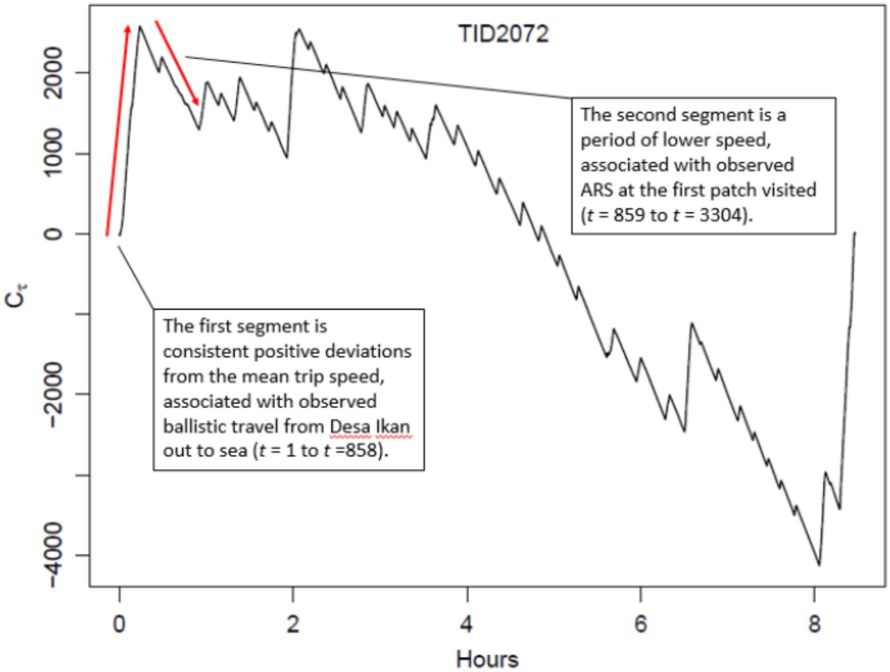


Figure 15. CUMSUM time series for TID2072 with $\epsilon = 600$. Deviations greater than the mean speed of the trip have a positive cumulative sum value and slope (C_τ increases), while deviations less than the mean trip speed have negative values and slopes (C_τ decreases). The first and second segments, labeled above, correspond to travel and ARS at a patch, respectively. These behaviors are known from simultaneous direct observation, which is a common ground-truth method.

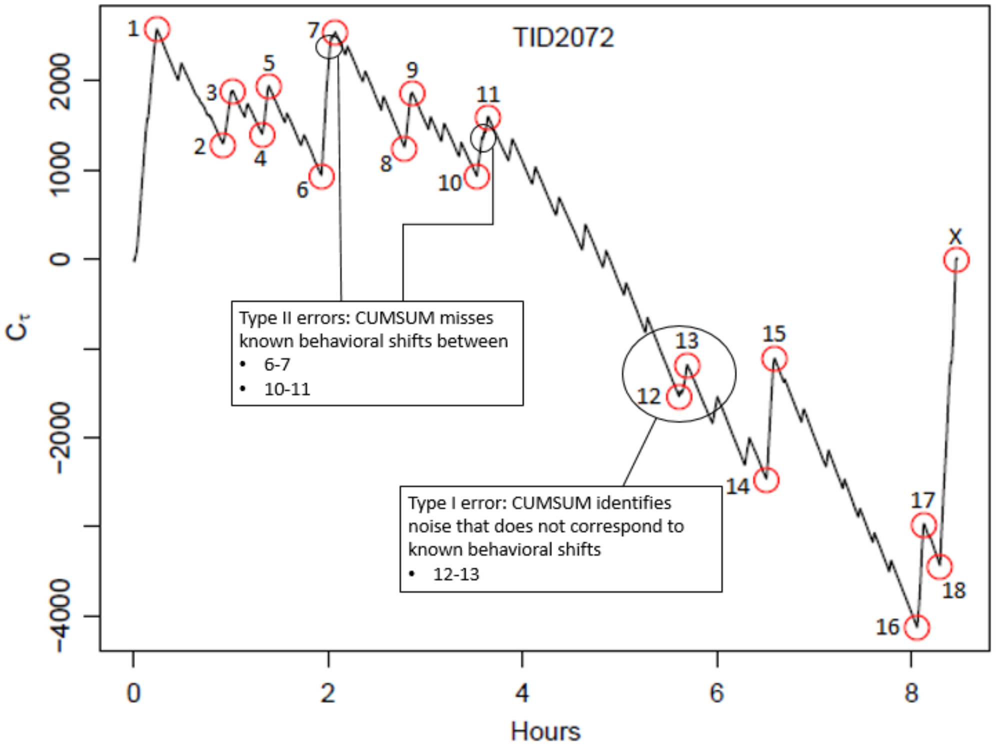
Max-min algorithm & scaling issues

The second step of the CUMSUM method is to parse out behavioral shifts with the max-min algorithm (MMA), but given the scaling issue discussed in chapter two, one must begin by identifying an appropriate resolution. The goal is to identify meaningful shifts from travel to ARS, e.g., identified by the shift from segment one to segment two in Figure 15 above, without identifying noise (type I error)—shifts in speed within patches or at smaller scales not relevant for a given research question. In a time series, noise corresponds to the smaller peaks and valleys such as the additional peak in speed the middle of segment two in Figure 15. Behaviorally, this small peak corresponds to a fisher briefly increasing speed to readjust the position of the boat within the patch. To this end, defining the most appropriate sampling scale—ϵ, the window or threshold in which local speed maxima and minima are identified via the MMA—is key in determining what behaviors are identified or not during segmentation (Knell & Codling, 2012).

If the scale is too fine, there is a risk of a false positive. A false positive, in this context, occurs when peaks or valleys in the cumulative deviations from the mean speed along the time series—noise—is falsely identified as meaningful behavioral shifts. That is, at fine scales, the methods erroneously IDs bouts of travel within ARS segments or bouts of ARS between travel segments. Finer scales correspond to smaller windows (ϵ). Alternatively, if the scale is too coarse, the method can make type II errors. Coarser scales correspond to larger windows. In this case, type II errors occur when the method overlooks significant peaks and valleys along the time series, or said another way, it overlooks actual bouts of ARS at patches and bouts of travel. More discussion on the nature of errors is given below.

Selecting an appropriate window of analysis, ϵ, becomes particularly important when segmenting via the CUMSUM method if there is overall less travel time across the trip (Knell & Codling, 2012). I observed this to be characteristic of demersal fishing in Desa Ikan. My observation is underscored by a k-means cluster analysis for example trip TID2072 in which only 5% of trip time is spent at a higher travel speed. In comparison, Alvard et al. (2015) indicate that travel accounts for 36% of all points across the FAD sample. This example also provides further reason to believe demersal strategies such as bank and pot fishing differ from pelagic strategies like FAD fishing in ways that will affect the scale of analysis.

Alvard et al. (2015) determine an appropriate sampling scale post hoc by finding the smallest window that identifies all FAD patches as ARS without error. Following their example, I compare the MMA, model-generated segments with ground-truth data from the focal follow for example trip TID2072. In this case, a window size of $\epsilon = 600$ identifies most bouts of ARS known from simultaneous direct behavioral observation while minimizing the number of type I and II errors (Figure 16). For TID2072, a finer scale results in additional peaks and valleys of noise being falsely identified as ARS, while a coarser scale overlooks major behavioral shifts. The nature of these errors are discussed below.



Type II errors: CUMSUM misses known behavioral shifts between
- 6-7
- 10-11

Type I error: CUMSUM identifies noise that does not correspond to known behavioral shifts
- 12-13

Figure 16. CUMSUM time series for TID2072 with behavioral cut-points labeled, using a window of $\epsilon = 600$. The red circles (1-18) indicate hypothesized behavioral shifts, local speed maxima and minima identified by the MMA that will be tested against ground-truth data. Patches are identified behaviorally as ARS, which correspond to segments with a negative slope between red circles. Travel corresponds to segments with a positive slope between the red circles. The red circle labeled “X” indicates noise associated with re-entering the landing site at the conclusion of the trip and is thus excluded from analysis. The three black circles—indicated along segments 6-7, 10-11, and 12-13—specify discrepancies between the CUMSUM results and ground-truth data i.e., errors made by CUMSUM.

As an alternatively strategy, Knell & Codling (2012) suggest the optimal window size for CUMSUM segmentation is within the range of values that provide the first relatively long consecutive period without a change in the number of segments identified by the MMA. Figure 17 presents the results of this strategy as a plot of the number of segments produced at varying window sizes for TID2072. Applying the approach of Knell & Codling (2012), I estimate a tentative window size for CUMSUM segmentation as $\epsilon \cong$ 600-800. It appears there is agreement between the post hoc method of Alvard et al. (2015) and the approach of Knell & Codling (2012) for estimating an appropriate scale of analysis for segmentation with the MMA.

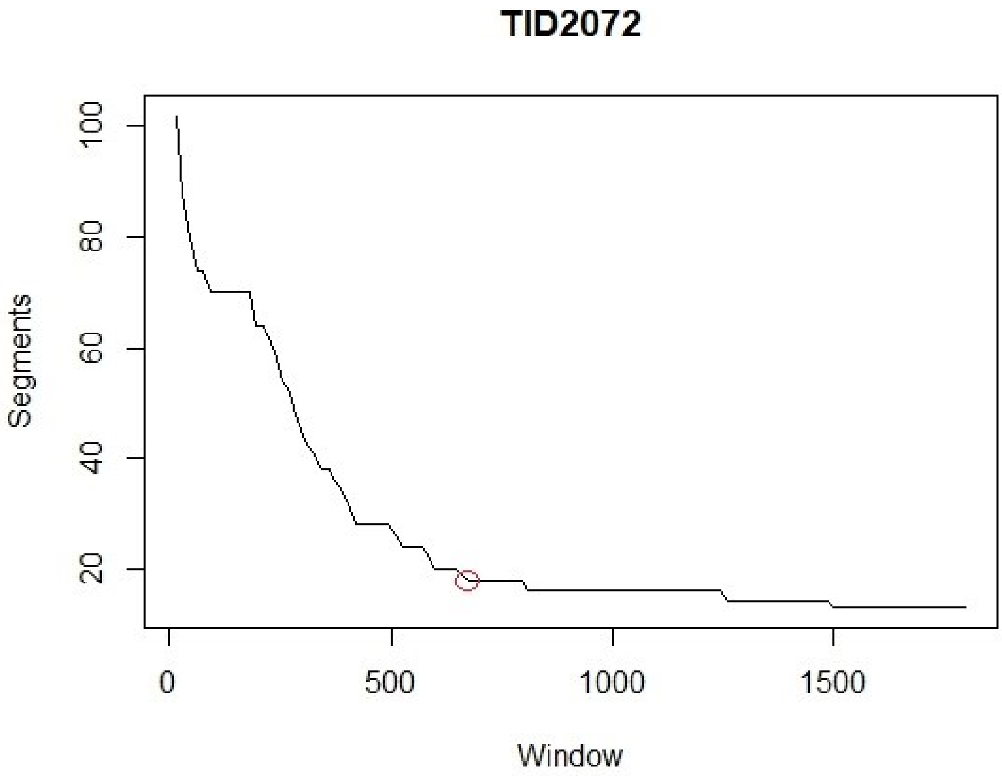


Figure 17. Number of segments produced per window size. Indicated by the circle, $\epsilon \cong$ 600starts the range of the smallest window sizes that provide the first relatively long, consecutive period without a change in the number of segments classified by the MMA. This plot also shows the inverse relationship between the MMA window size and the number of behavioral shifts identified.

Results for TID2072 with $\epsilon = 600$

Ten patches are known from direct behavioral observation via a focal follow I conducted during TID2072. Table 6 sums the nature of these ten patches and the bouts of travel between them. Seven patches correspond to ARS at strictly ‘bank’ patches as characterized by the ‘bank’ fish catching method in chapter four, while two patches correspond to fishing at floating seaweed patches, and one patch corresponds to ARS at a near-shore FAD. The CUMSUM analysis of TID2072 with a window of $\epsilon = 600$ indicates nine patches were visited across the duration of the fishing trip, as shown in Figure 16. The CUMSUM method correctly identifies all seven ‘bank’ patches as well as the one visit to the near-shore FAD. The method fails to detect the two very short bouts of ARS at seaweed patches. These two errors correspond to the type II errors described in Figure 16. Finally, one segment is falsely identified as ARS ($t = 20{,}125$ to $t = 20{,}423$), which corresponds to the type I error also described in Figure 16. In this case, the model incorrectly classifies within patch noise as a behavioral shift to travel and thus gives the impression that there were more patches than exist. In other words, this segment is noise within patch eight (Table 6) and does not represent travel nor subsequent ARS at a new patch. In sum, at a window size $\epsilon = 600$, CUMSUM makes two type II errors and one type I error.

Table 6

Summary of direct observation of TID2072

Behavior/event	Start time	Patch	Patch type
Travel from shore	7:01		
ARS	7:16	1	Bank
Travel	7:57		
ARS	8:02	2	Bank
Travel	8:21		
ARS	8:25	3	Bank
Travel	8:57		
ARS	9:03	4	Seaweed
Travel	9:04		
ARS	9:06	5	Bank
Travel	9:47		
ARS	9:53	6	Bank
Travel	10:33		
ARS	10:33	7	Seaweed
Travel	10:40		
ARS	10:41	8	Bank
Travel	13:30		
ARS	13:37	9	Bank
Travel	15:06		
ARS	15:10	10	Near-shore FAD
Travel to shore	15:18		

Errors at different scales of analysis

Does the CUMSUM method better identify all known patches at finer scales? Overall, no. For TID2072, the two very short bouts of ARS at seaweed patches that were not identified at $\epsilon = 600$ remain overlooked for $\epsilon \leq 575$. At the same time, the number of false positives increases substantially at increasingly smaller window sizes ($\epsilon \leq 575$). To demonstrate, Figure 18 presents the results of CUMSUM segmentation with a window size of $\epsilon = 500$. This scale of analysis results in a total of four type I errors, including the same one type I error made at $\epsilon = 600$ plus three additional type I errors. In comparison with the ground-truth data, these segments are not known behavioral shifts but instead match noise within a single patch. These type I errors all correspond to within patch movements during ARS at patch eight (Table 6), which had much back-and-forth movement as the captain frequently adjusted the position of the boat within the patch. The method makes two type II errors in which the two seaweed patches (patches four and seven in Table 6) remain overlooked. These are the same two errors made by the CUMSUM method with a window of $\epsilon = 600$ as well. In sum, decreasing the window size in which MMA operates, i.e., using a finer scale, does not improve patch identification yet increases the number of type I errors.

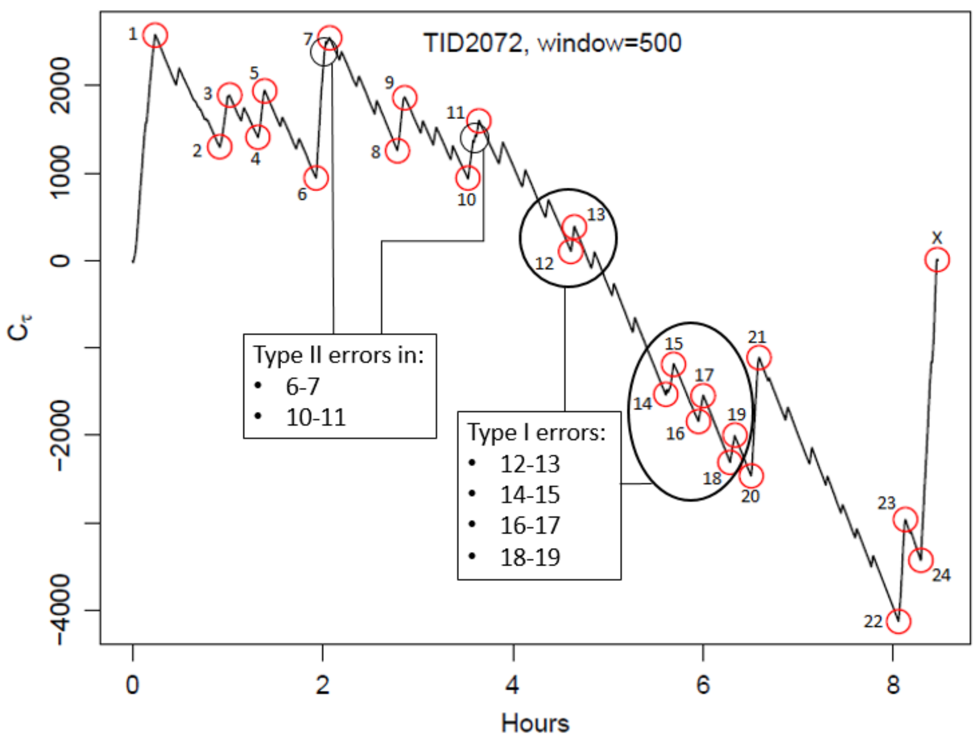


Figure 18. CUMSUM time series for TID2072 with $\epsilon = 500$. Patches are identified behaviorally as ARS, which correspond to segments with a negative slope between red circles. The red circles (1-24) indicate hypothesized behavioral shifts, local speed maxima and minima identified by the MMA that are tested with ground-truth data. The red circle labeled “X” indicates noise associated with re-entering the landing site at the conclusion of the trip and is thus excluded from analysis. The black circles—indicated along segments 6-7, 10-11,12-13, 14-15, 16-17, and 18-19—specify discrepancies between the CUMSUM results and ground-truth data i.e., errors made by CUMSUM.

What is the nature of the errors made by CUMSUM at coarser scales? For TID2072, specifying a larger window ($\epsilon \geq 625$) in which MMA operates results in fewer type I error but more type II errors. Figure 19 shows the results of CUMSUM segmentation with a window size of $\epsilon = 700$. Compared to $\epsilon = 500$, there are fewer type I errors. Compared to $\epsilon = 600$, the same type I error is made where noise in patch eight is falsely classified as a behavioral shift. The method makes three type II errors at $\epsilon = 700$.

The two seaweed patches remain overlooked, and additionally, CUMSUM overlooks the last patch corresponding to ARS at patch ten (Table 6) is also missed. In sum, increasing the window size in which MMA operates does not improve patch identification despite reducing false positives.

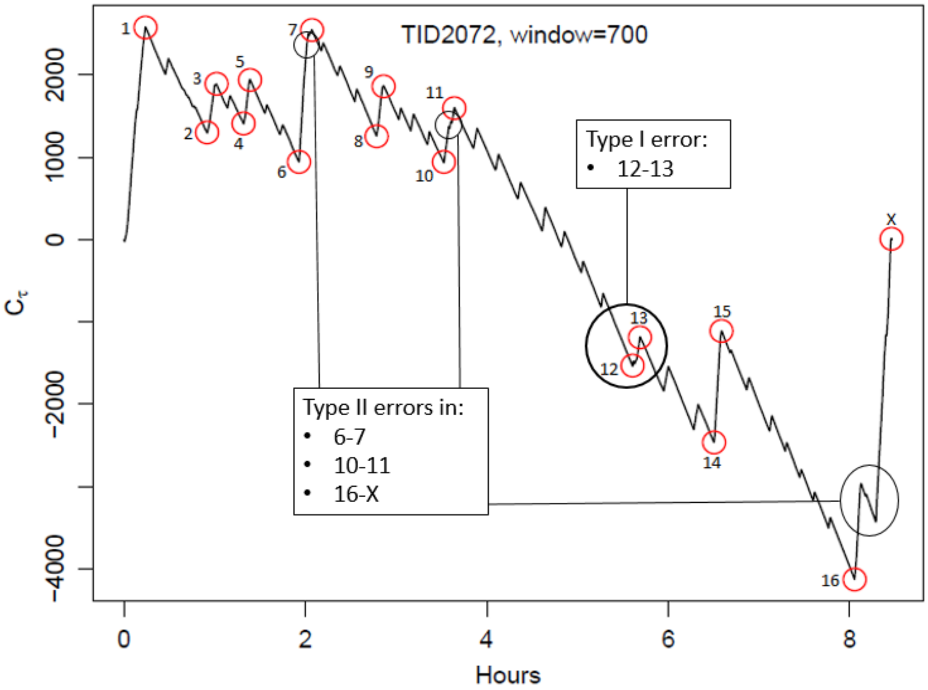


Figure 19. CUMSUM time series for TID2072 with $\epsilon = 700$. Patches are identified behaviorally as ARS, which correspond to segments with a negative slope between red circles. The red circles (1-16) indicate hypothesized behavioral shifts, local speed maxima and minima identified by the MMA that are tested with ground-truth data. The red circle labeled "X" indicates noise associated with re-entering the landing site at the conclusion of the trip and is thus excluded from analysis. The black circles—indicated along segments 6-7, 10-11, 12-13, and 16-X—specify discrepancies between the CUMSUM results and ground-truth data i.e., errors made by CUMSUM.

CUMSUM analysis for the N10 sample

Scaling

I repeated this process for all trips in the N10 sample to identify the optimal window size for each trip and better understand the errors associated with increasing and decreasing scales of analysis. To achieve this, I applied the CUMSUM process with window sizes ranging from $\epsilon = 500$ to $\epsilon = 2000$, at 100-second intervals. I compared segmentation results at each interval with ground-truth data to classify segments as correct (matching focal follow observations) or as errors (type I or II). Table 7 describes the results of CUMSUM analysis in terms of the number of segments produced for each trip per window size. I limit description to $\epsilon =$ 500-1200 because of the great number of type I errors at window sizes less than $\epsilon = 500$ and type II errors at scales greater than $\epsilon = 1200$.

The gray-shaded boxes in Table 7 indicate the optimal range of window sizes for each trip—that which most accurately identifies patches while also minimizing type I and II errors TID2058 and TID 2014 include a window range because the change in window size resulted in a decrease in one error type but increase in the other. This close examination of each trip at various scales of analysis leads me to determine that a window size of $\epsilon = 600$ produces the best results for the N10 sample. In other words, across trips, a window size of $\epsilon \cong 600$ identifies the greatest number of patches while also reducing the number of type I and II errors made by the method. The counts in Table 7 include segments of noise associated with entering and exiting the landing site—behaviors that occurred before or after the fishing trip was fully underway. These segments of noise will not be counted as significant type I errors in the following discussion because they are not factors for the problem at hand, which is determining the best scale of analysis for differentiating travel and ARS at patches during fishing trips. I describe the errors per trip below.

Table 7

Number of CUMSUM-generated segments by window size. The gray-shaded cells indicate the number of segments identified by CUMSUM that best agree with the number of behavior changes known from focal follows, and thus, the best window ranges for segmentation.

TID	$\epsilon =$ 500	$\epsilon =$ 600	$\epsilon =$ 700	$\epsilon =$ 800	$\epsilon =$ 900	$\epsilon =$ 1000	$\epsilon =$ 1100	$\epsilon =$ 1200
1758	15	15	15	14	12	10	10	8
1977	17	16	16	14	12	12	10	10
2058	13	11	10	8	8	8	8	6
2072	26	20	18	18	16	16	16	16
2101	24	24	14	12	12	9	7	7
2114	17	14	14	14	14	14	12	10
2178	19	17	15	15	12	10	10	10
2246	12	10	10	8	8	8	8	6
2282	10	8	8	8	8	8	8	8
2369	13	13	12	12	12	12	12	12

The following discussion revolves around minimum segments—those that the method identifies as potential segments of ARS once the fishing trip was fully underway. Six patches are known from direct observation of TID1758. CUMSUM with ϵ = 500-700 identifies all six patches but makes two type II errors. These two type II errors are not resolved at smaller windows. Above ϵ = 800, the number of type II errors accumulates as CUMSUM overlooks segments of travel between bouts of ARS.

Seven patches are known from direct observation of TID1977. CUMSUM with ϵ = 500 identifies all seven patches but also makes a type I error. Results from ϵ = 600-700 also identify all seven patches. One type II error is make at ϵ = 800, two type II errors at ϵ = 900-1000, and three type II errors at ϵ = 1100-1200.

Four patches are known from direct observation of TID2058. This trip included a good deal of search noise, resulting from a particularly rough ocean current, that made a clean CUMSUM result difficult to obtain. The best scale for this trip is ϵ = 500-600. Specifying a winnow of ϵ = 500 results in identification of all four patches but also results in four type I errors. A window of ϵ = 600 identifies three of four patches, one type II error, but makes only one type I error. As expected, thresholds above ϵ = 800, the number of type II errors accumulates without further reducing type I errors.

Eleven patches plus one social encounter are known for TID2101. The social encounter does not include ARS related to fishing but is nonetheless a sustained period of drift and thus identifies as a segment of below-average speed. A window of ϵ = 500-600 identifies all eleven patches plus the social encounter with no type I or II errors. The threshold range of ϵ = 700-1200 accumulate six to eight type II errors.

Seven patches are known for TID2114. As with TID2058, TID2114 includes significant amount of search noise associated with a rough current. The best range of analysis for this trip is large at ϵ = 500-1000. A window ϵ = 500 identifies all seven patches but also makes two type I errors. A scale range of ϵ = 600-1000 identifies six of the seven known patches, making one type II error but no type I errors. Windows ranging from ϵ = 1100-1200 accumulate additional type II errors.

Four patches are known from direct observation of TID2178. A threshold of ϵ = 500 identifies all four patches but makes four type I errors. At a window of ϵ = 600, the method identifies all four patches but makes three type I errors. The best scale of analysis for this trip is ϵ = 700-800, as all four patches are identified and two type I errors are made. At ϵ = 900, the two type I errors remain but CUMSUM also makes one type II error. For a scale of ϵ = 1000-1200, the method makes one type II error and one type I error.

TID2246 is another trip with a great deal of search noise due to rough sea conditions, and thus, CUMSUM results are also somewhat noisy. Four patches are known from direct observation. A window of ϵ = 500 makes one type II error but also makes two type I errors. A threshold range of ϵ = 600-700 results in the same type II error but only one type I error. The number of type II errors increases for windows of ϵ = 800-1200 without resolving the type II error made at finer scales.

Three patches are known for TID2282. With a windown of ϵ = 500, CUMSUM identifies all three patches but makes one type I error. A scale range of ϵ = 600-1200 identifies all three patches. Analysis in this window range results in no type I or type II errors.

Six patches are known from direct observation of TID2369. A window range of ϵ = 500-600 identifies five of six patches, making one type II error and no significant type I errors. This overlooked bout of ARS is very short and not resolved at finer scales. Specifying a window in the range of ϵ = 700-1200 results in two type II errors.

Results

Across trips in the N10 sample, and as I demonstrated with TID2072, increasing the window size above $\epsilon = 600$ obscures major bouts of ARS, which are counted as type II errors. Decreasing the window size below $\epsilon = 600$ results in more false positives, which are classified as type I errors. Overall, CUMSUM segmentation of the trips in sample N10, with a window of $\epsilon = 600$, produces a total of 148 segments. Table 8 sums the results of this analysis.

Seventy-four segments match sustained, above-average speeds (i.e. maximum segments), which corresponds mostly to travel. These maximum segments have a mean speed of 3.31 meters/second, which falls within the range of mode three from k-means analysis albeit towards the lower end of the distribution of mode three (Table 3). Seventy-four segments match sustained, below-average speeds (i.e. minimum segments), which corresponds to bouts of drift and slower, low-powered movements. These minimum segments have a mean speed of 0.88 m/s, which falls within the range of mode one from k-means analysis (Table 3). As expected, speeds falling within mode two from k-means analysis are classified by CUMSUM as either maxima or minima, depending on the nature of speed at adjacent time steps along the track. Reflecting this, the proportion of time CUMSUM allocates to maximum segments is thirteen hours or 23% of total time. The proportion of time CUMSUM allocates to minimum segments is forty-four hours or 77% of total time. These results generally agree with the k-means distribution of time for the N10 sample, but again, with time from mode two split between maximum or minimum segments.

Table 8

CUMSUM segments (w=600) description for N10 sample

Segment type		Maximum (travel)	Minimum (ARS)
Number		74	74
Speed (m/s)	Range	0.41-6.96	0.30-5.08
	Mean	3.31	0.88
	SD	1.38	0.9
Time (hr)	Range	0.01-0.84	0.01-3.33
	Mean	0.18	0.59
	SD	0.15	0.6
	Total	13.11	44

Table 9 presents a summary of the resulting errors for CUMSUM with a window of $\epsilon = 600$ for each trip in the N10 sample. Across all ten trips, sixty-two patches are known from ground truth data. The CUMSUM methods accurately identifies fifty-six of these sixty-two known patches. The CUMSUM method actually identifies sixty-two segments of potential ARS, but detailed comparison with direct observations reveals that six of the sixty-two CUMSUM segments correspond to noise within patches, *not* separate, independent bouts of ARS. In other words, the method makes six type I errors and six type II errors. Overall, the CUMSUM method accurately identifies N = 56 patches that correspond to the known N = 62 patches, or 90% of patches in the N10 sample.

Table 9

N10 results and error count for CUMSUM with ϵ = 600

TID	Number of known patches	Patches found by CUMSUM	Type I errors	Type II errors
1758	6	6	0	0
1977	7	7	0	0
2058	4	3	1	1
2072	10	8	1	2
2101	11	11	0	0
2114	7	6	0	1
2178	4	4	3	0
2246	4	3	1	1
2282	3	3	0	0
2369	6	5	0	1
Total	62	56	6	6

Figure 20, plots A-J, present the CUMSUM time series and behavioral shifts identified by the MMA with a window size of $\epsilon = 600$ for all trips in the N10 sample in order to demonstrate the efficacy and errors of the method. In these figures, the numbered red circles indicate supposed behavioral shifts, local speed maxima and minima identified by the MMA that should agree with ground-truth data. As specified before, ARS corresponds to segments with a negative slope between red circles, and travel corresponds to segments with a positive slope between red circles. The red circles labeled “X” indicate noise associated with entering and exiting the landing site and are thus excluded from analysis. The black circles indicated along the time series specify a discrepancy between the CUMSUM results and ground-truth data. Type I and type II errors are defined in the black boxes in each of the plots in Figure 20.

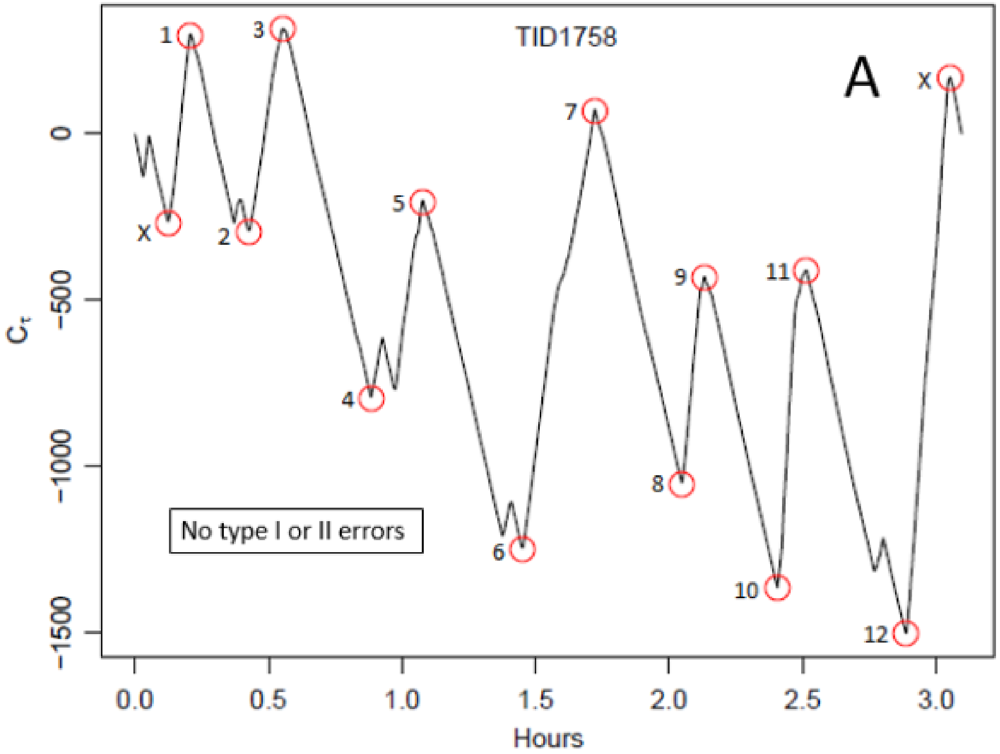


Figure 20. CUMSUM time series plots A-J, all with $\epsilon = 600$, for each N10 demersal trip. The red circles labeled "X" indicate noise associated with entering and exiting the landing site and are thus excluded from analysis. The numbered red circles indicate supposed behavioral shifts, local speed maxima and minima identified by the MMA that should agree with ground-truth data. Patches are identified behaviorally as ARS, which correspond to segments with a negative slope between red circles. The black circles indicated along the time series specify a discrepancy between the CUMSUM results and ground-truth data.

(A) TID1758: Six patches were visited during TID1758, known from ground-truth data; the CUMSUM method identifies all six patches with no error.

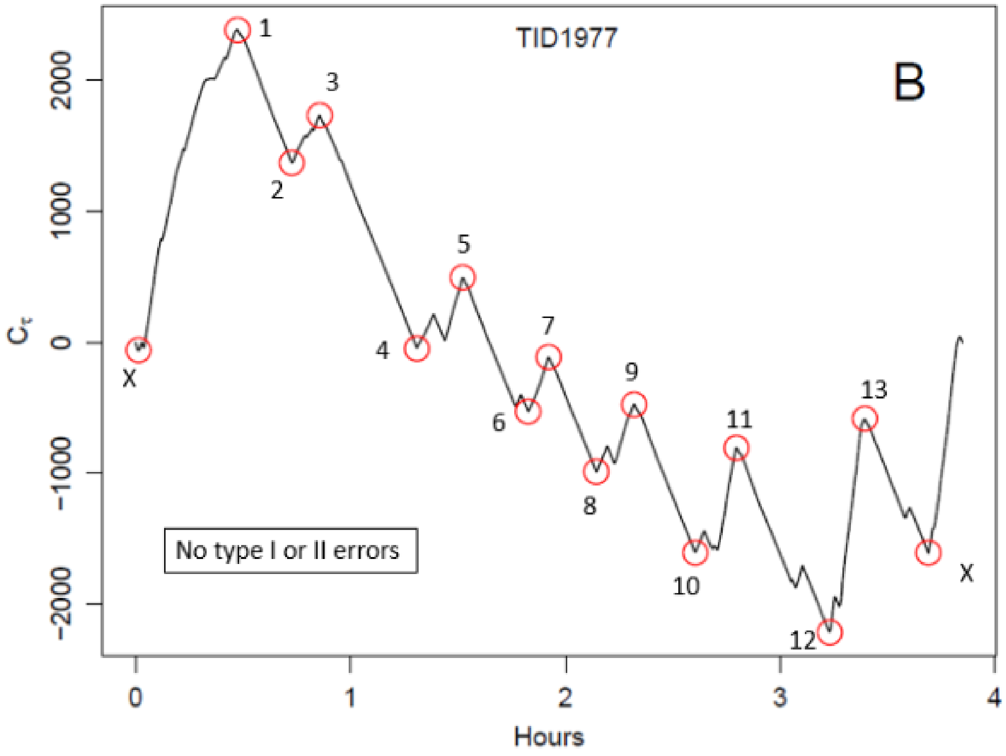


Figure 20. Continued

(B) TID1977: Seven patches are known; the method identifies all seven patches with no error.

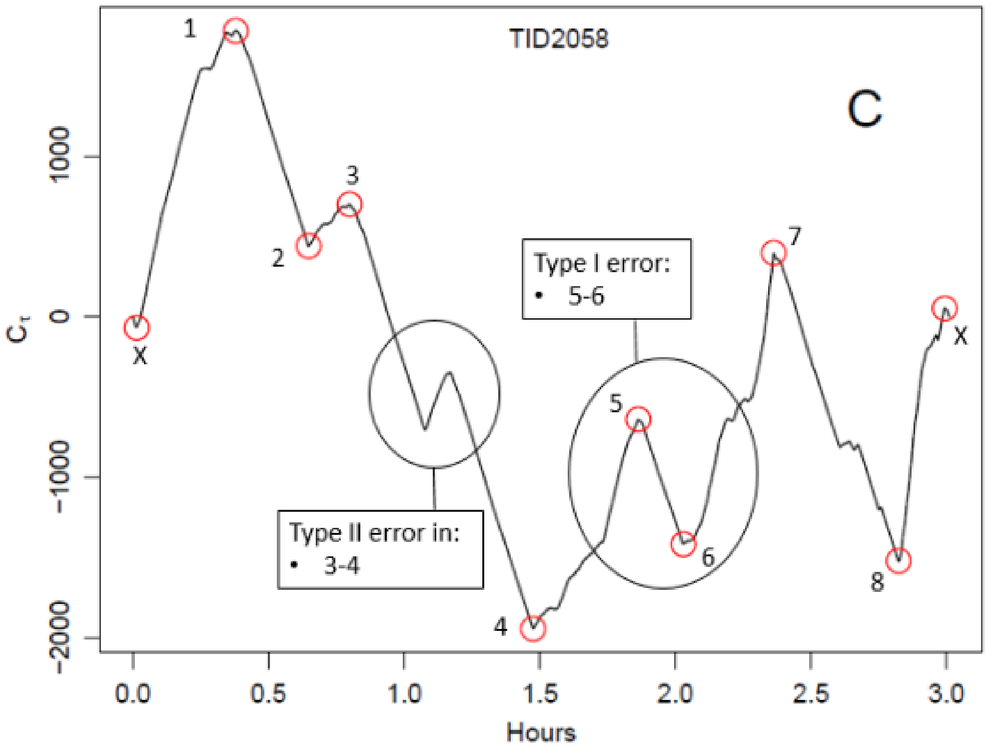
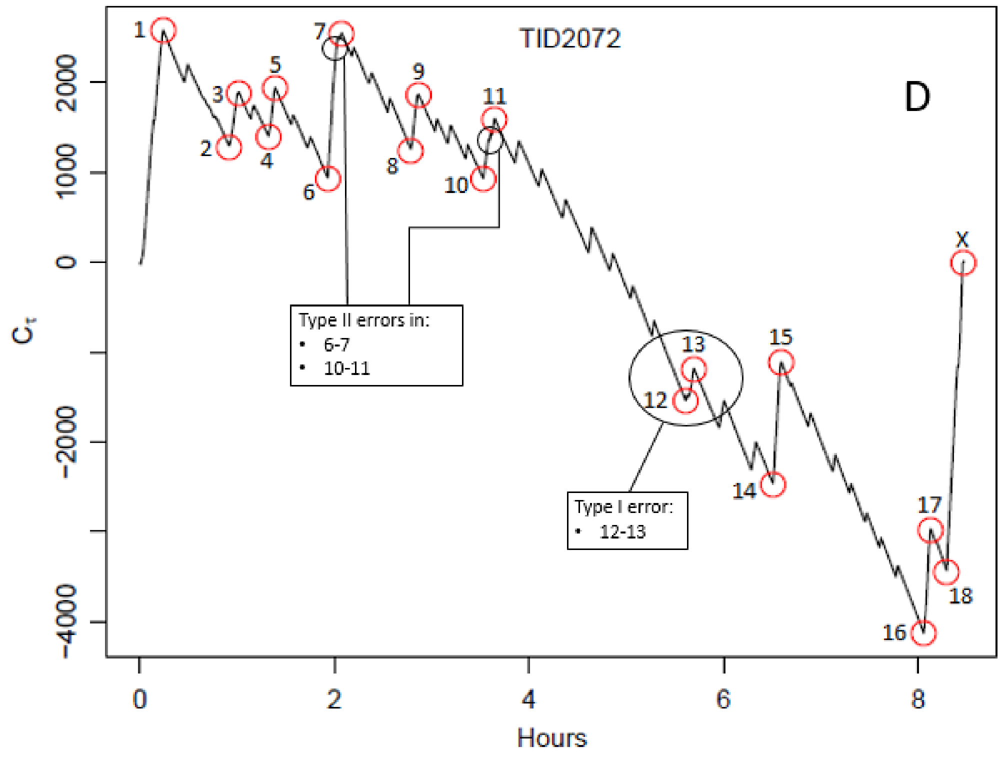


Figure 20. Continued

(C) TID2058: Four patches are known; the method identifies three of four patches, making one type I error and one type II error. The ocean current was rough and resulted in much noise, which made the CUMSUM result somewhat noisy. For example, the segment between circles 5-6 above corresponds to the captain stopping extensive search to eat a snack and wait for the rough current to calm down, not ARS.



Type II errors in:
- 6-7
- 10-11

Type I error:
- 12-13

Figure 20. Continued

(D) TID2072: As discussed above in the scaling section, ten patches are known. The method identifies eight of the ten patches, making one type I error and two type II errors. The two type II errors correspond to very short bouts of ARS at seaweed patches during otherwise higher-speed travel segments. These two type II errors are not resolved at finer scales.

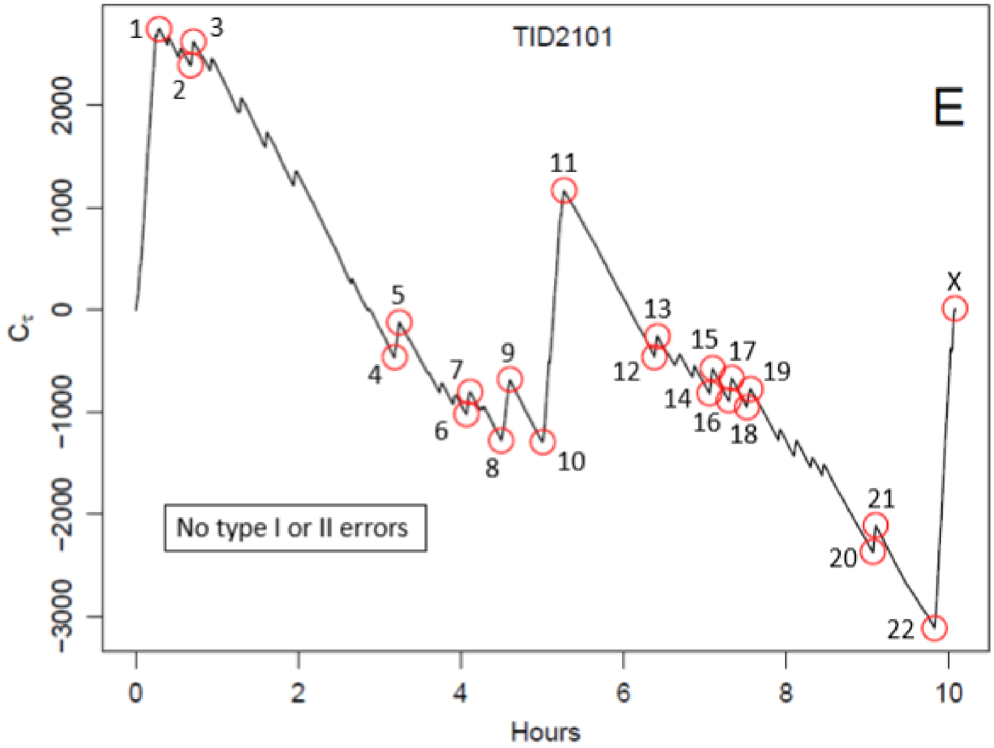


Figure 20. Continued

(E) TID2101: Eleven patches are known; the method identifies all eleven patches despite that ARS bouts were relatively short, as seen in the time series. These short bouts of ARS appear to be spatially contiguous on the GPS track, but during the focal follow, the captain indicated that they were different patches and independent bouts of ARS. This trip includes a social encounter, which also results in a sustained period of drift (i.e. below-average speeds) and is thus identified as a segment of ARS despite that it is not actually ARS (segment 21-22).

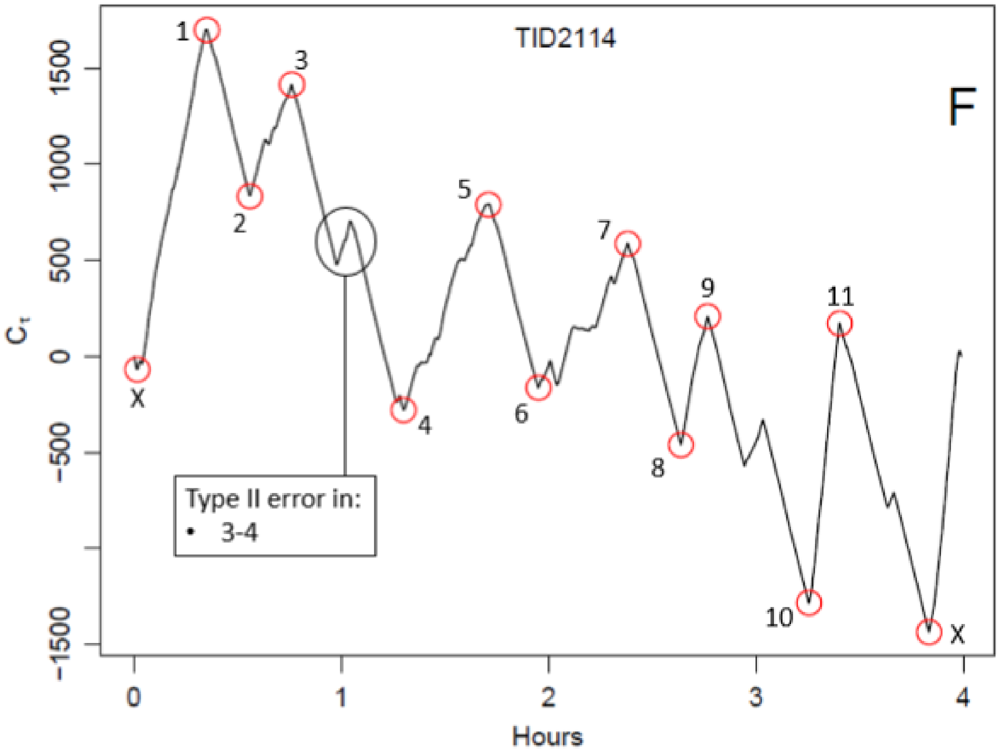


Figure 20. Continued

(F) TID2114: Seven patches are known; the method identifies six of seven patches, making one type II error. This trip had significant search noise associated with a rough current.

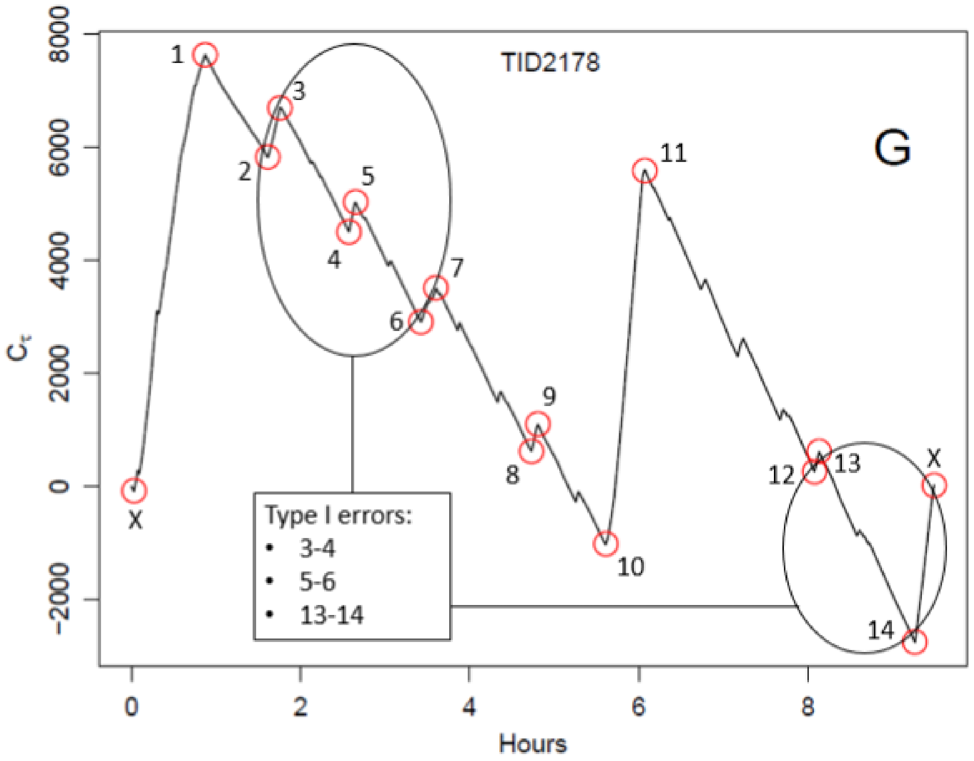


Figure 20. Continued

(G) TID2178: Four patches are known; the method identifies all four patches and makes three type I errors. This trip also had search noise associated with a rough current that make segmentation difficult at all scales.

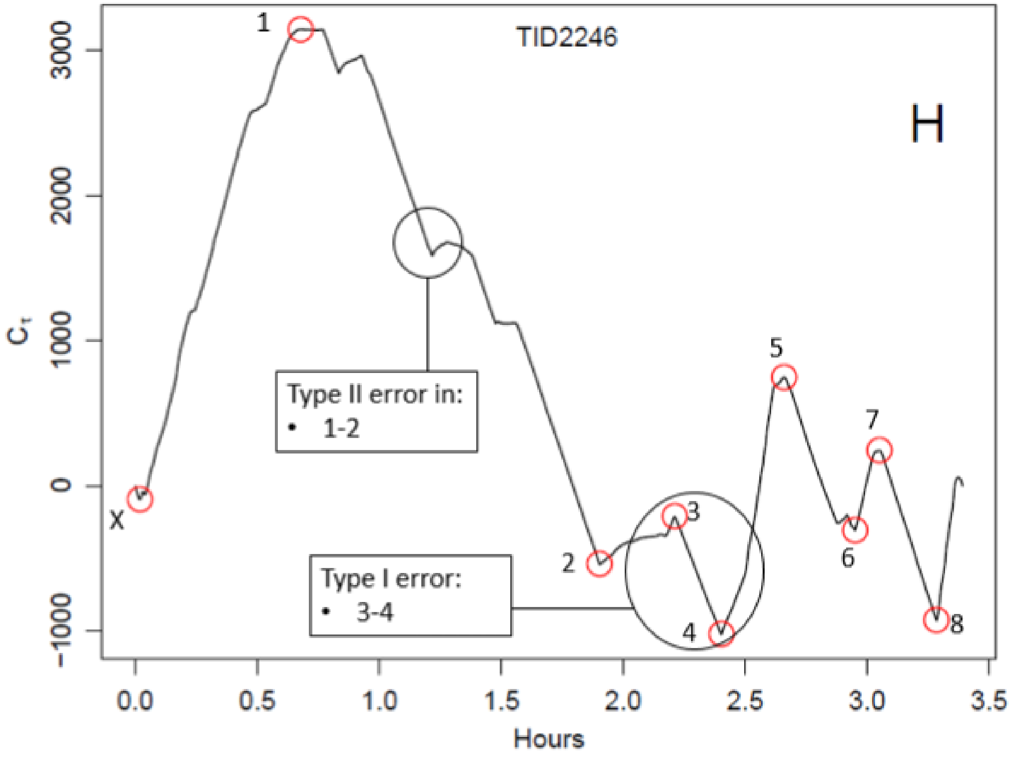


Figure 20. Continued

(H) TID2246: Four patches are known; the method identifies three of four patches, making one type I error and one type II error. This is another trip with a great deal of noise because of rough sea conditions and thus CUMSUM results are noisy.

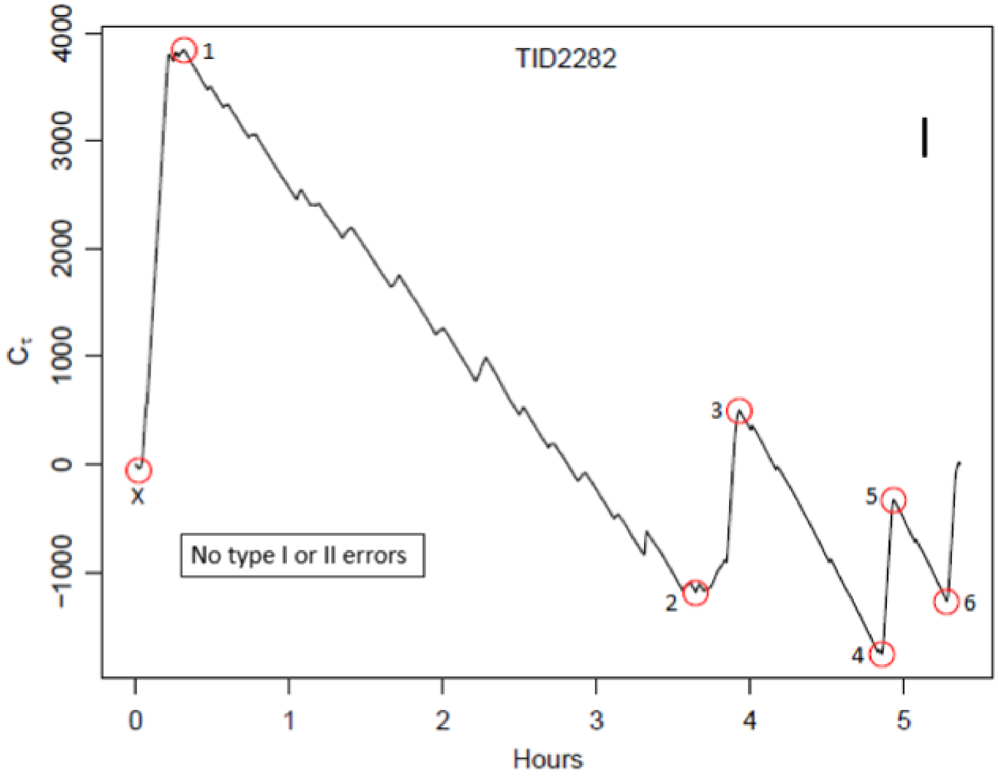


Figure 20. Continued

(I) TID2282: Three patches are known; the method identifies all three patches with no error

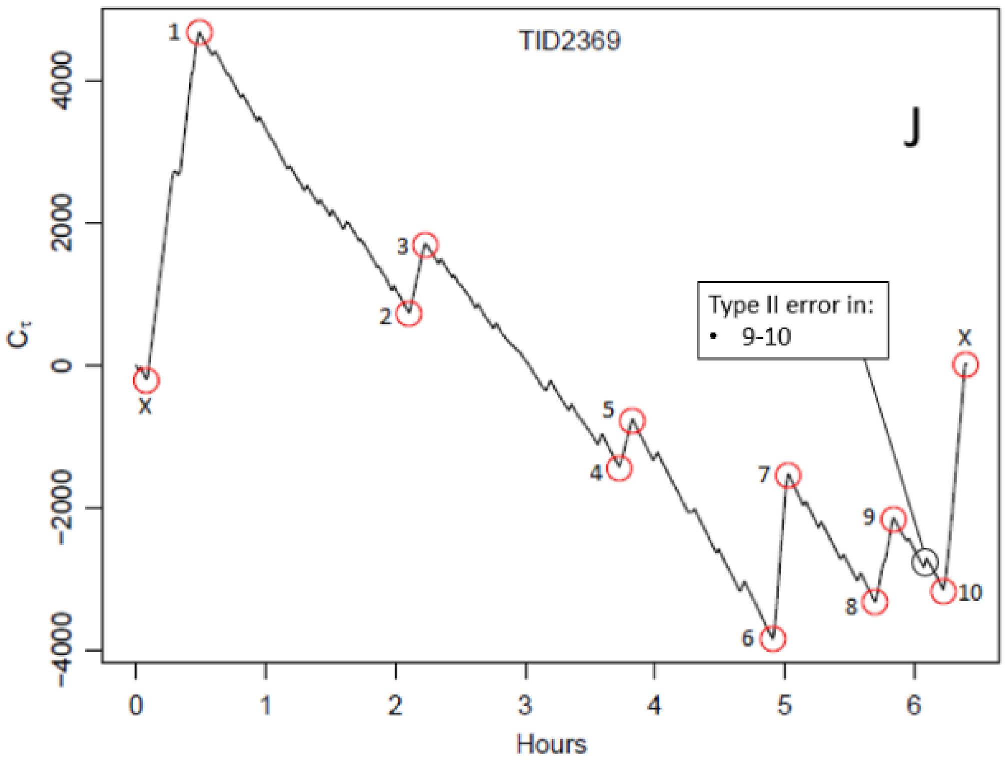


Figure 20. Continued

(J) TID2369: Six patches are known; the method identifies five of six patches, making one type II error. This overlooked bout of ARS is very short and not resolved at finer scales.

It is possible to gauge the accuracy of the MMA method by comparing the predicted cut points—the starts and stops of ARS at patches identified by CUMSUM method—with the observed starts and stops of ARS known via ground truth data. CUMSUM predicts forty-four hours of ARS, equaling an average of about forty-three minutes per patch. The observed total patch residence time is forty hours, with a known average of thirty-nine minutes per patch. The mean of the differences between the CUMSUM-predicted start points and the known start points is about fifty-one seconds.

This degree of error accounts for 2.18% of average patch residence time, which is relatively small even if significant. A paired samples t-test suggests the mean of pairwise differences between the observed and predicted start times of ARS is significantly different from zero [$t(55) = 2.49$, $p = 0.02$). For the majority of cases, the MMA algorithm predicts the start of ARS nearly a minute earlier than direct observation. This is due to the fact that, using speed as the model parameter, CUMSUM is identifying ARS for the patch locations as fishers approximate patch marks or buoys rather than fishing per se. I documented the time when fishers began ARS for fish. The mean of the differences between the CUMSUM predicted end points and the known end points is almost forty-three seconds, which accounts for 1.84% of average patch residence time. This degree of error is also relatively small. A paired samples t-test suggests the difference in means between the observed and predicted end times is not significantly different from zero [$t(55) = 1.49$, $p = 0.14$). While my observations and the MMA algorithm both identify when fishers end ARS, and the forty-three second difference is the difference between when fishers departed a patch and the amount of time it took to reach travel speeds recognized by the MMA algorithm as cut points. My results and observation concur with those of Alvard et al. (2015) in the context of speed during pelagic fishing. The authors find similar discrepancies between the CUMSUM results and ground-truth data in regards to the starts and stops of ARS during FAD fishing.

CHAPTER VII

N30: ANALYSIS & RESULTS

Data description

I generated the N30 sample of fishing trips to provide another test of the CUMSUM method on a set of data that is different from the one that generated the model. For this test, I compared CUMSUM model predations to the results of visual segmentation (methods described below) as opposed to ground-truth data to gauge the efficacy of the method and the applicability of the results from segmenting the N10 sample to other demersal trips. To create the N30 sample, I first compiled a sample of additional data from the same data collection periods (July-August 2014, June-August 2015, and March-July 2016) based on two criteria. A trip must have an associated GPS track, and a trip must be classified specifically as a 'bank' type of trip. In other words, I exclude trips in which fishing techniques other than 'bank' fishing were employed, including channel fishing, raising pots, and fishing FADs or near-shore FADs. The main reason I limit this subsample to 'bank' trips is that including trips with additional demersal methods introduces more variation to a GPS track and thus potentiates additional errors during visual segmentation. This resulted in a subset of eighty bank trips. Next, I systematically randomly sampled the qualifying eighty fishing trips with a sample interval of three) to extract thirty trips for CUMSUM analysis. These N = 30 trips comprise the N30 sample.

Table 10 provides summary data for the N = 30 trip in the N30 sample. Each trip was comprised of two men, a captain and a crew member. The N30 sample includes six captains and six boats. One man captained two different boats, accounting for 47% of trips in the sample (N = 14). This fisher captained one boat for N = 12 trips (40%) and a different, second boat for N = 2 trips (7%). A second fisher also captained the same boat as the first fisher for N = 2 trips, accounting for another 7% of trips. A third boat and captain combination accounts for 23% of trips (N = 7 trips). A fourth boat and captain accounts for 16% of trips (N = 5). Lastly, a fifth and sixth boat and captain combination accounts for N = 1 trip per man, accounting for 3% of trips each.

Table 10

Summary of each trip in the N30 sample

TID	Date	Duration (hrs)	Average speed (m/s)	Standard deviation of speed	N
1646	7/29/2014	11.50	1.03	1.29	41450
1658	7/30/2014	5.67	1.33	1.24	20237
1691	8/9/2014	4.52	0.69	1.08	15951
1762	8/15/2014	7.07	1.32	1.20	25425
1771	8/19/2014	8.18	1.56	2.06	29480
1783	8/20/2014	6.90	1.23	1.42	24840
1808	5/15/2015	8.07	1.44	1.77	28844
1847	5/22/2015	7.38	1.96	1.34	26593
1903	6/4/2015	8.15	1.16	1.44	29413
1943	6/10/2015	7.10	1.14	1.63	24607
1971	6/17/2015	7.13	1.70	1.52	25765
2062	7/17/2015	9.05	0.94	1.33	32595
2079	7/23/2015	9.87	0.95	1.30	35522
2093	7/27/2015	8.33	1.13	2.20	27212
2109	7/31/2015	8.33	0.94	1.07	29740
2139	3/8/2016	7.52	0.92	1.72	26987
2168	3/15/2016	2.67	2.12	2.24	9490
2203	3/29/2016	1.55	2.14	1.70	5584
2225	4/5/2016	6.78	2.36	1.99	24410
2256	4/12/2016	5.10	1.36	1.68	18400
2276	4/15/2016	9.45	1.88	2.12	34035
2269	4/18/2016	8.17	0.79	1.67	29337
2281	4/19/2016	8.07	1.31	2.09	29023
2300	4/25/2016	8.15	2.06	2.34	29291
2339	5/5/2016	8.83	0.91	1.40	31815
2379	5/20/2016	7.90	1.16	1.40	28479
2407	5/26/2016	8.58	1.34	1.91	30755
2420	5/27/2016	6.17	1.27	1.89	22199
2456	6/9/2016	7.27	1.38	1.90	26113
2462	6/10/2016	9.93	1.13	1.65	35801
Mean		7.45	1.35	1.65	

Speed

As with the N10 sample, the movement speeds of the trips in the N30 sample generally exhibit a tri-modal distribution. I used a k-means cluster analysis to explore the nature of speed and calculated the modal ranges, means and sizes, for each trip in the N30 sample (Table 11). Table 12 includes a summary of the means of modes across all N30 trips. The range of mode one means is 0.26-0.82 meters/second and corresponds drift speeds. The mean range of mode two is 0.94-4.73 m/s and corresponds to some slower, low-powered movements as well as low-speed travel. The mean range of mode three is 3.23-8.8 m/s and corresponds to higher-speed travel. Summing the size of each mode across all N30 trips (total N=805,532 or about 224 hours), 71% of foraging time is allocated to mode one, 19% to mode two, and 10% to mode three (Table 13). These values are very similar to the ranges, means, and sizes of modes for the N10 sample. The similarity of the N10 and the N30 samples in terms of speed provides justification that the N10 sample of focal follows is likely representative of the wider dataset of bank fishing trips.

Table 11

K-means analysis of speed for N30 trips

TID	Mode	Mean (m/s)	Range (m/s)	N
1646	1	0.36	0.00-1.40	31262
	2	2.45	1.41-3.14	5369
	3	3.85	3.15-7.55	4819
1658	1	0.46	0.00-1.29	12780
	2	2.14	1.30-2.6	2548
	3	3.23	2.68-5.41	4807
1691	1	0.44	0.00-1.18	14367
	2	1.97	1.21-4.05	845
	3	6.17	4.10-10.49	466
1762	1	0.60	0.00-1.56	17251
	2	2.53	1.57-3.60	6990
	3	4.68	3.61-7.28	1159
1771	1	0.55	0.00-2.07	22453
	2	3.58	2.07-5.45	4744
	3	7.32	5.45-9.76	2283
1783	1	0.50	0.00-1.52	18918
	2	2.55	1.52-3.42	2515
	3	4.31	3.44-7.57	3407
1808	1	0.54	0.00-1.74	21462
	2	2.96	1.75-4.33	4399
	3	5.72	4.36-9.98	2978
1847	1	0.65	0.00-1.61	12239
	2	2.58	1.62-3.20	8762
	3	3.82	3.21-6.88	5590
1903	1	0.54	0.00-1.66	23663
	2	2.78	1.67-4.06	3677
	3	5.34	4.07-9.49	2073
1943	1	0.49	0.00-1.57	19388
	2	2.65	1.57-4.74	3292
	3	6.86	4.76-9.48	1313
1971	1	0.56	0.00-1.71	15276
	2	2.88	1.73-3.68	7334
	3	4.49	3.69-8.35	3143
2062	1	0.45	0.00-1.68	27527
	2	2.92	1.69-4.42	3892
	3	5.93	4.43-10.76	1175
2079	1	0.44	0.00-1.56	29723

Table 11. Continued

	2	2.69	1.57-3.83	3706
	3	5.02	3.85-10.33	2093
2093	1	0.57	0.00-1.57	21177
	2	2.57	1.57-3.57	4382
	3	4.58	3.58-9.13	1562
2109	1	0.43	0.00-0.83	20840
	2	1.34	0.89-2.42	5524
	3	3.52	2.43-9.08	3282
2139	1	0.28	0.00-2.07	23296
	2	3.87	2.08-5.14	2067
	3	6.41	5.15-9.42	1614
2168	1	0.62	0.00-1.59	5668
	2	2.57	1.60-4.33	1897
	3	6.13	4.35-10.13	1915
2203	1	0.82	0.00-1.59	2453
	2	2.38	1.60-4.16	2437
	3	5.94	4.17-9.63	694
2225	1	0.56	0.00-2.18	12719
	2	3.82	2.19-4.58	7918
	3	5.34	4.58-7.25	3773
2256	1	0.44	0.00-1.70	13630
	2	2.96	1.70-3.83	2038
	3	4.74	3.85-9.52	2732
2276	1	0.50	0.00-2.04	18987
	2	3.60	2.05-5.16	7619
	3	6.72	5.16-10.04	2731
2269	1	0.26	0.00-2.49	30531
	2	4.73	2.50-6.75	2952
	3	8.80	6.77-10.39	552
2281	1	0.34	0.00-2.09	23200
	2	3.85	2.10-5.25	3081
	3	6.67	5.26-9.82	2742
2300	1	0.45	0.00-2.02	18623
	2	3.62	2.03-4.87	5301
	3	6.13	4.88-9.88	5367
2339	1	0.38	0.00-1.98	27182
	2	3.60	1.99-5.05	3945
	3	6.52	5.06-10.05	688

Table 11. Continued

2379	1	0.36	0.00-0.60	16061
	2	0.94	0.62-2.37	6970
	3	3.82	2.38-9.67	5448
2407	1	0.41	0.00-2.17	24184
	2	3.94	2.18-5.15	4386
	3	6.36	5.15-9.85	2185
2420	1	0.51	0.00-2.00	18188
	2	3.50	2.01-5.62	1114
	3	7.75	5.62-13.81	2897
2456	1	0.50	0.00-2.04	20787
	2	3.59	2.04-4.85	2693
	3	6.10	4.85-8.89	2633
2462	1	0.47	0.00-1.82	30086
	2	3.18	1.83-4.43	2426
	3	5.67	4.43-8.40	3289

Table 12

Summary of means from cluster analysis of N30 trips

Mode	Range of means (m/s)	Mean of means (m/s)
1	0.26-0.82	0.48
2	0.94-4.73	2.96
3	3.23-8.8	5.6

Table 13

Size of modes across N30 sample

	N (secs)	Total time (hrs)	Portion
Mode 1	575739	159.93	0.71
Mode 2	150059	41.68	0.19
Mode 3	79734	22.15	0.10
Total	805532	223.76	

Visual segmentation of N30 trips

Method & example

Trips in the N30 sample have associated GPS tracks but no simultaneous direct observation. In order to provide a test of the CUMSUM method, I visually and systematically segmented each trip in the N30 sample into bouts of travel and ARS. First, I examined and edited GPS tracks in GPS Track Editor© to exclude portions of track occurring on shore before and after the fishing trip, following the same procedures as with the N10 sample. Figure 21 depicts the GPS track of a trip, TID1762, representative of the N30 sample Next, I color-coded GPS tracks by speed in order to help visually differentiate major bouts of ballistic, high-speed travel and sinuous, low or drift speed clusters of ARS. Figure 22 exemplifies my approach for initially visually segmenting tracks based on gross changes in speed and sinuosity.

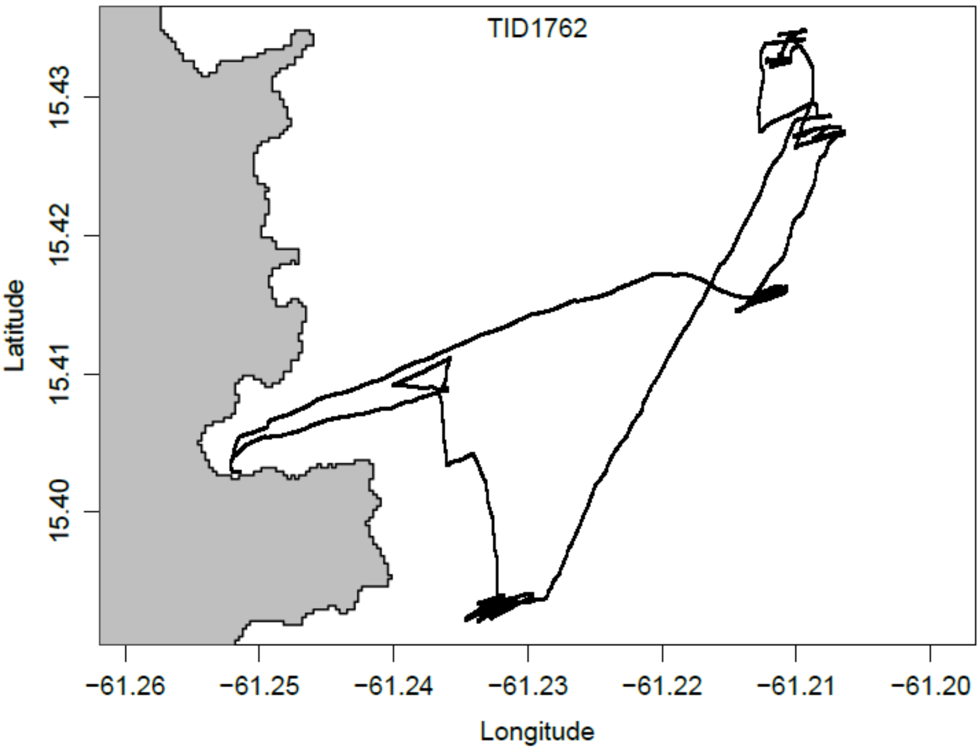


Figure 21. N30 example GPS track of bank fishing trip TID1762. The gray-shaded portion is land, and the white portion is the Atlantic Ocean. The black line is the GPS track and shows the movement patch of the boat. Trips originate from Desa Ikan, on the east coast of Dominica and then return to the central place after visiting a number of patches. The clumps along the track are candidates for ARS at patches and other behaviors involving slower, low-powered movements or drift of the boat.

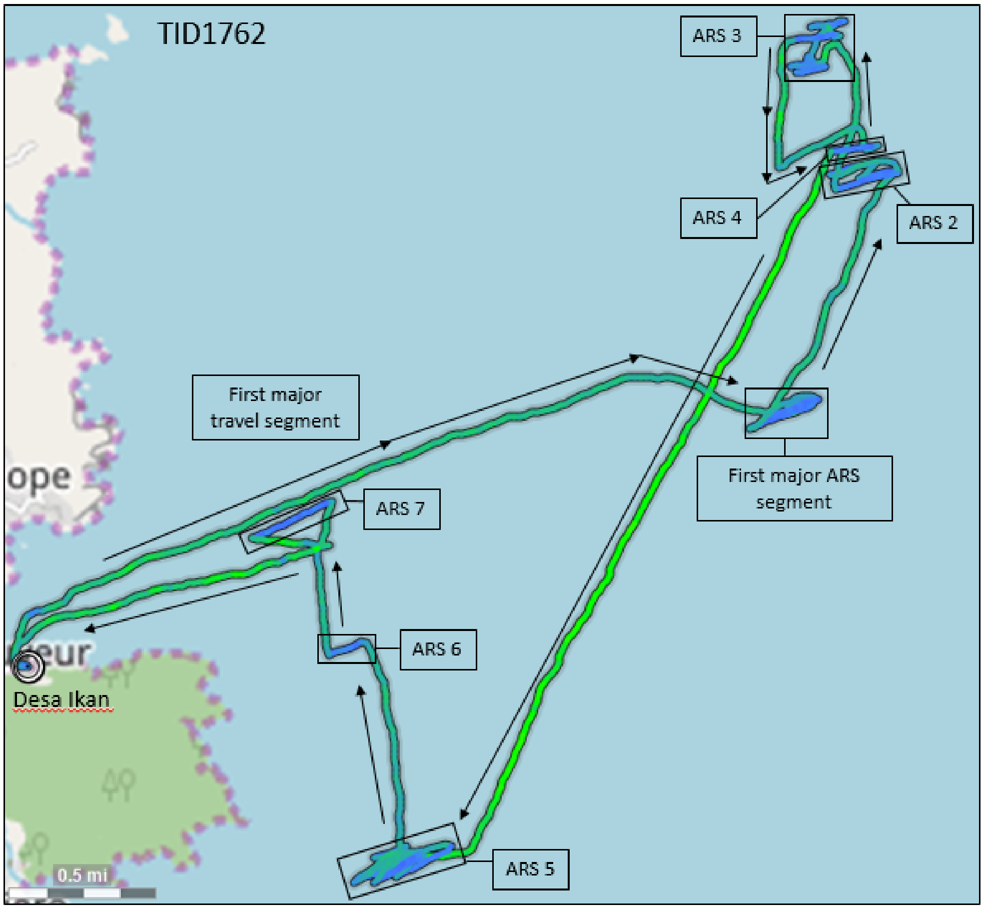


Figure 22. N30 example trip TID1762 with GPS track color-coded by speed. Trips originate from Desa Ikan, on the east coast of Dominica, and then return to the central place after visiting a number of patches in the Atlantic ocean. The green and blue line is the GPS track and shows the movement of the boat. The track is color-coded by speed: green represents relatively higher speeds, while blue represents relatively lower speeds. The black arrows represent the direction of travel. The seven blue clumps along the track, squared and labeled, are major bouts of ARS and other behaviors involving slower, low-powered movements or drift of the boat.

After visually identifying major segments of travel and ARS, I relied on my domain knowledge and experience from focal follows to guide classification of less obvious segments. I also used what I learned from close examination of the GPS tracks in the N10 sample and k-means analysis of the N30 sample to develop quantitative criteria for systematic visual segmentation. These criteria are speed and duration of sustained speed. I based the speed criterion on the mean of mode two for a particular trip from k-means analysis (Table 11). Travel speeds correspond to speeds greater than the mean of mode two for a particular trip. ARS at patches corresponds to speeds that fall below the mean of mode two for a particular trip. The second criterion, regarding the duration of sustained speed, is based on the median size of noise segments known from direction observation (1.8 minutes, or N = 108 seconds; Table 4 in chapter six). I classified a change in speed as a behavioral shift if speed remained relatively higher or lower for longer than the median duration of a noise segment ($N \geq 108$).

In sum, my approach to visual segmentation uses speed (above or below an average) and sustained changes in speed (duration) to systematically define travel and ARS, which is essentially the same process as CUMSUM method. If instantaneous speed increased to greater than the mean of mode two from k-means analysis for that trip (Table 11) *and* remained so for nearly two minutes or more (at least $N \geq 108$; Table 4), I classified it as behavioral shift to travel. If speed fell to below the mean of mode two from k-means analysis *and* remained below this speed for about two minutes or more, I classified it as a behavioral shift to ARS.

Figure 23 shows an example of how I applied this criteria to resolve less obvious shifts between ARS and travel in TID1762. This example demonstrates how, depending on the spatial scale, one might identify a single clump of ARS or several, smaller bouts of ARS at different patches. Viewing the track at a higher resolution, as in Figure 23, reveals several smaller clumps of ARS connected by a shorter segment of travel compared to the inset imagine in Figure 23, adapted form Figure 22. I resolved this issue by applying the criteria of speed and duration of speed. The potential segment of travel in Figure 23, indicated by the black arrow along the track, contains much less sinuous movement and speeds ranging from 0.44-2.69 m/s. Speed rises to above the mean of mode two from k-means analysis for this trip (2.53 m/s; Table 11); however, the vast majority of points along this segment of the trajectory remain well below the mean of mode two. This segment also contains 2.15 minutes of low-powered movement (N = 129 seconds, from N = 9610-9739). In sum, the portion of track in question represents about two minutes of time but speeds remained very low overall despite a few peaks. Thus, I classified this portion of track as within-patch movement/noise and not a shift to travel. This clump of track represents ARS at a single patch.

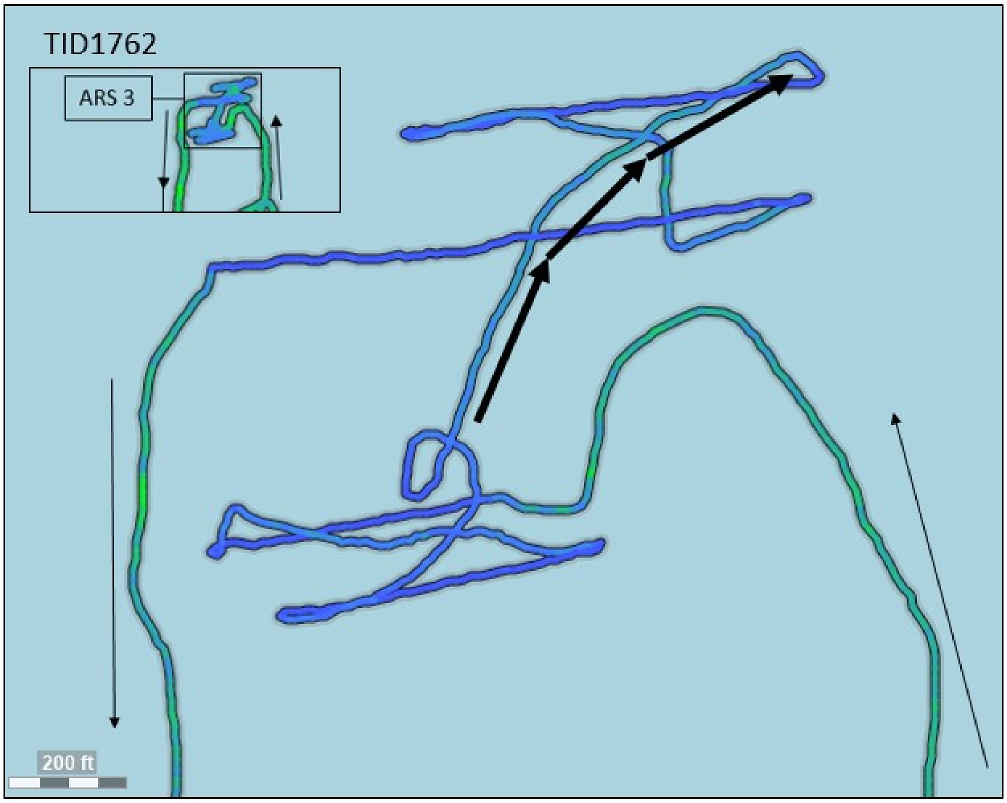


Figure 23. High resolution view of ARS at a patch during N30 example trip TID1762. This bout of ARS corresponds to foraging in patch three (from Figure 22), which is depicted here in the inset in the upper-left corner. The thick, black arrows indicate a portion of track that was difficult to visually classify. Here, the boat appears to travel in a relatively straighter path at somewhat increased speeds, which means that this may or may not be a significant bout of travel and thus two separate bouts of ARS. I resolved this issue by applying the criteria defined above in the text. The portion of track in question represents about two minutes of time but speeds remained very low—I classify the questionable portion of track as within-patch movements, i.e., noise, and *not* travel. Therefore, this portion of track contains ARS at a single patch.

Results

I repeated this visual segmentation process across all trips in the N30 sample in order to provide a comparison and base for assessing the efficacy of the CUMSUM method. Across all thirty trips in the N30 sample, N = 161 patches are known from visual segmentation of GPS tracks. The exact number of patches I identified in each trip can be found in Table 14. The nature of these trips, based on my visual assessment of each GPS track, is as follows. A majority of these trips exhibit clear and distinct bouts ARS versus travel (TIDs 1658, 1762, 1783, 1943, 1971, 2062, 2079, 2093, 2139, 2168, 2203, 2205, 2256, 2300, 2339, 2407, 2420), which the CUMSUM method will likely distinguish accurately. Some trips have patches that appear noisy, probably due to suboptimal weather or ocean conditions where captains must constantly adjusting the position of the boat above the patch (TIDs 1646, 1903, 2109, 2269, 2456). The noisiness of these trips may result in an increase in type I errors during CUMSUM segmentation compared to visual segmentation

Several trips have features which may significantly affect the utility of the CUMSUM method (TIDs 1691, 1771, 1808, 1847, 2276, 2281, 2379, 2462). A few of these trips have very little variation in speed and/or lower overall speed across the duration of the trip. Some trips have segments of probable ARS, indicated by drift speeds, yet these segments are not as sinuous as expected. Some drift segments cover a much larger area than expected for a single bank patch. Finally, some trips have patches that appear highly spatially contiguous and overlapping. Visual segmentation of these sorts of trips was difficult, and I relied on my decision-making criteria for classifying segments.

Table 14
N30 patches identified visually along GPS tracks

TID	Number of patches
1646	6
1658	5
1691	6
1762	7
1771	3
1783	6
1808	8
1847	7
1903	5
1943	5
1971	9
2062	6
2079	7
2093	9
2109	5
2139	5
2168	1
2203	1
2225	5
2256	3
2269	3
2276	8
2281	6
2300	4
2339	8
2379	7
2407	4
2420	5
2456	1
2462	6
Total	161

N30 trip TID2462, shown in Figure 24, is a good example of the problems I encountered while visually segmenting fishing trips. The first three patches visited during TID2462 appear contiguous and linear while covering a larger swath of ocean than seen in most other bank trips. Patches one and two are distinguished by N = 119 seconds of above-average speed. Patches two and three are separated by N = 205 seconds above-average speed. Both ambiguous segments just meet my criteria for significant shifts between ARS and travel and are thus defined as three distinct patches. Yet, as one can see in Figure 24, it appears the captains are navigating back to a point in the previous patch and continuing along the same trajectory. In this way, patches are contiguous or overlapping. Despite treating data systematically, realistically, there is still significant ambiguity on whether behavioral shifts I identified are meaningful or not and if these shifts truly indicate separate patches or not.

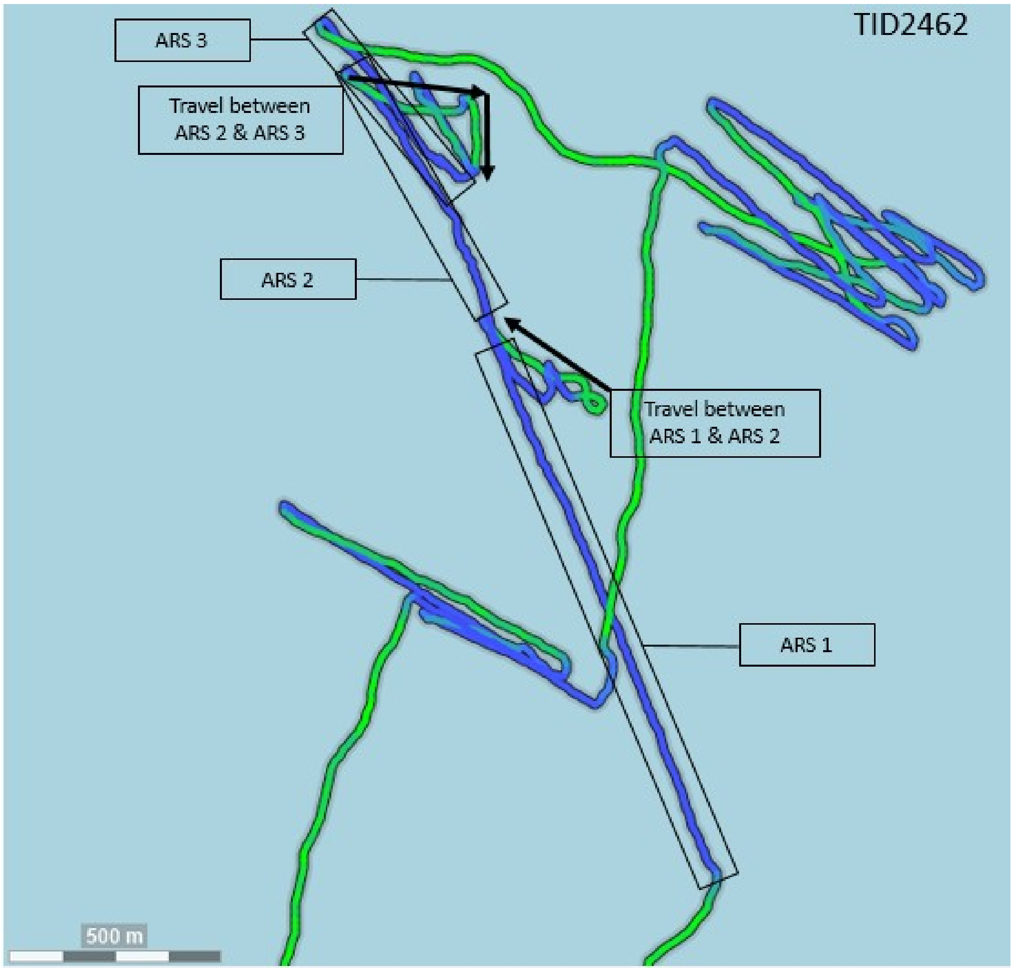


Figure 24. High resolution view of ARS and travel segments during N30 trip TID2462. The green and blue line is the GPS track and shows the movement of the boat in the Atlantic Ocean. The track is color-coded by speed: green represents relatively higher—above average—speeds, while blue represents relatively lower speeds. The three black boxes around portions of blue-colored track indicate major bouts of ARS and other behaviors involving slower, low-powered movements or drift of the boat. One can see the linear and overlapping nature of these three bouts of ARS, which brings into question whether these are actually separate and independent patches or not. I applied my criteria for visual segmentation to resolve this issue. The black arrows along green-colored track between major bouts of ARS represent the direction of travel. First, one can see speeds are above-average for the trip given the green coloring. Second, the arrow labeled "travel between ARS 1 & ARS 2" represents about two minutes of travel, and the arrow labeled "travel between ARS 2 and 3" represents about three and a half minutes of travel. Both segments meet my speed and duration criteria for being classified as a major shift to travel. Thus, ARS 1, 2, and 3 are defined as separate patches.

CUMSUM analysis: results & comparison

CUMSUM segmentation of all trips in the N30 sample, with a window of ϵ = 600, produces a total of N = 437 segments (Table 15). N = 230 segments correspond to sustained, above-average speeds and bouts of travel, or maximum segments. These maxima have a mean speed of 3.36 m/s, which falls within the ranges of both mode two and mode three means from k-means analysis (Table 12). N = 207 segments correspond to sustained, below-average speeds and bouts of drift and slower movements, or minimum segments. These minima have a mean speed of 0.75 m/s, which falls within the range of mode one means from k-means analysis (Table 12). Similar to the result of N10 analysis, speeds falling within mode two from k-means are classified as either maxima or minima depending on the nature of adjacent points along the time series. Overall, CUMSUM allocates 48 hours or 22% of total time to maximum segments or travel, versus 177 hours or 78% of total time to minimum segments or ARS and other slow movements (Table 15). This again reflects the k-means distribution of time for the N30 sample, with time from mode two allocated to either maximum or minimum segments (Table 13). The proportion of time the CUMSUM approach allocates to travel and ARS segments for the N30 sample is also very similar to the known N10 sample ratio of time spent travelling (75%) to conducting ARS at patches (25%) (Table 4, chapter six).

Table 15

CUMSUM segments (ϵ = 600) description for N30 sample

Segment type		Travel	ARS
Number		230	207
Speed (m/s)	Range	0.41-7.80	0.23-7.72
	Mean	3.36	0.75
	SD	1.41	0.92
Time (hr)	Range	0.0003-1.54	0.01-4.87
	Mean	0.21	0.84
	SD	0.24	0.73
	Total	48.24	174.33

As with the N10 sample, the raw counts of maximum and minimum segments in Table 15 include segments of noise associated with entering and exiting the landing site—behaviors that occurred before or after the fishing trip was fully underway. For instance, there are N = 25 minimum segments (out of N = 207 total) that correspond to this sort of behavior. While these beginning and end segments are initially pertinent for characterizing the overall trip, these N = 25 minimum segments do not correspond to ARS at patches. In other words, these segments are not factors determining how well the CUMSUM method differentiates bouts of travel and ARS at patches during fishing trips. In order not to inflate the error count, and to keep the following analysis symmetric to the N10 sample, these noise segments are not counted as significant type I errors in the analysis below. Thus, the remaining number of CUMSUM minimum segments relevant for comparison is N = 182.

The CUMSUM method ($\epsilon = 600$) identifies N = 182 segments of potential ARS across all N30 fishing trips, excluding extra noise segments associated with entering and exiting the landing site. I assessed minimum segments as correct or in error based on agreement or lack of agreement with visual segmentation results. Table 16 summarizes the counts and nature of remaining type I and II errors associated with the N = 182 minimum segments. Overall, N = 148 of these N = 182 segments from Table 16 correspond to visually-identified ARS. Table 17 directly compares the results of my visual segmentation with patches also identified by the CUMSUM analysis ($\epsilon = 600$) for each trip in the N30 sample. As noted, N = 161 patches are known from visual segmentation of GPS tracks. Similar to the N10 sample, the CUMSUM method identifies about 92% of visually-identified patches in the N30 sample.

Thirty-four of the N = 182 CUMSUM minimum segments appear to correspond to noise within patches when compared to the results of visual segmentation (Table 16). In other words, the method may make thirty-four type I errors for the N30 sample. Given that CUMSUM identifies N = 148 of N = 161 patches correctly, compared to the results of visual segmentation, the method makes thirteen type II errors. Additionally, closer comparison of datasets reveals that method misses bouts of ARS from TID1847, resulting in two more type II errors. In both cases, ARS at a patch was initially identified but cut short by several minutes. Here, the MMA accurately identified the beginning of ARS at a patch but then prematurely identified a shift to travel and missed subsequent ARS at that same patch. The CUMSUM analysis probably had difficulty with TID1847 because the transitions from ARS to travel were relatively smooth in that speed differentials were changed very gradually rather than abruptly. Thus, the method makes fifteen type II errors for the N30 sample (Table 16) compared to visual segmentation.

Table 16

Summary of error counts for N = 182 CUMSUM minimum segments for N30 trips

TID	CUMSUM ARS count	Type I error count	Type II error count	Error notes
1646	10	4	0	IDs all but also noise
1658	5	0	0	IDs all
1691	3	0	3	Misses 3 patches
1762	7	0	0	IDs all
1771	4	2	1	Misses 1 patch, IDs noise
1783	6	0	0	IDs all
1808	7	0	1	Misses 1 patch
1847	8	1	2	Misses sig. ARS, IDs noise
1903	8	3	0	IDs all but IDs noise
1943	5	0	0	IDs all 5, but
1971	7	0	2	Misses 2 patches
2062	6	0	0	IDs all
2079	9	2	0	IDs all but also noise
2093	8	0	1	Misses 1 patch
2109	11	7	1	Misses 1 patch, IDs noise
2139	5	0	0	IDs all
2168	1	0	0	IDs all
2203	1	0	0	IDs all
2225	5	0	0	IDs all
2256	3	0	0	IDs all
2269	6	3	0	IDs all but also noise
2276	7	0	1	Misses 1 patch
2281	4	0	2	Misses 2 patches
2300	5	1	0	IDs all but also noise
2339	9	1	0	IDs all but also noise
2379	7	1	1	Misses 1 patch, IDs noise
2407	4	0	0	IDs all
2420	7	2	0	IDs all but also noise
2456	4	3	0	IDs patch but also noise
2462	10	4	0	IDs all but also noise
Total	182	34	15	

Table 17

Comparison of visual segmentation results and CUMSUM results (ϵ = 600) for N30 trips

TID	Visable GPS patches	CUMSUM patches
1646	6	6
1658	5	5
1691	6	3
1762	7	7
1771	3	2
1783	6	6
1808	8	7
1847	7	7
1903	5	5
1943	5	5
1971	9	7
2062	6	6
2079	7	7
2093	9	8
2109	5	4
2139	5	5
2168	1	1
2203	1	1
2225	5	5
2256	3	3
2269	3	3
2276	8	7
2281	6	4
2300	4	4
2339	8	8
2379	7	6
2407	4	4
2420	5	5
2456	1	1
2462	6	6
Total	161	148

CHAPTER VIII

MVT CONSIDERATIONS: ANALYSIS & RESULTS

The second goal of this project is to test a prediction from the MVT to show how developing methods like the CUMSUM approach can help move foraging theory forward. For central place foragers, one key prediction from the MVT is that patch residence time should increase as a function of increasing travel costs (Charnov, 1976). Given the discussion in chapter two, we expect that fishers from Desa Ikan spend more time in patches that take longer to reach and spend less time in patches that take less time to reach. For fisher-foragers in Desa Ikan, travel cost for a patch is measured as how long it takes a fisher to travel between patches—from the end of ARS at one patch to the start of ARS at a subsequent patch.

I explored this question using data on patches from both the N10 sample and the N30 sample. The N10 samples provides direct observation data and CUMSUM-generated data on patches. The N30 sample provides CUMSUM-generated patch information with no simultaneous direct observation to ground-truth results. Here, I assume that near-shore patches constitute microhabitats that experience resource depression due to foraging activities, after the example of Aswani (1998). I cannot measure depletion it to produce the cumulative gains curve characteristic of the MVT, which is a common problem (Aswani, 1998; Bettinger, 2009; Calcagno et al., 2014).

N10 sample

I use data from direct observation for this first test of the MVT with patches in the N10 sample. During focal follows, I used event sampling to document fishing efforts. Refer to chapter five for details on this type of data collection and the specific methods I used. To briefly review, the N10 sample contains ten fishing trips, including five pot trips and five bank trips. There is a total of N = 62 patches across the N10 sample, including N = 34 bank patches and N = 28 pot patches. Table 18 presents a summary of relevant data by trip. It was possible to compute the cumulative distance travelled during a fishing trip as well as the maximum distance travelled from the origin point using the GPS position data.

Table 18

Catch & effort summary for the N10 sample

TID	Number patches visited	Cumulative distance travelled (km)	Maximum distance travelled (km)	Duration (hr)	Total catch (kg)	Average return rate (kg/hr)
1758	6	16.61	4.67	3.05	24.04	7.88
1977	7	23.06	5.12	3.85	60.33	15.7
2058	4	21.95	4.84	3.00	23.59	7.86
2072	10	37.74	4.99	8.47	34.47	4.07
2101	11	33.17	4.68	10.1	24.27	2.41
2114	7	25.51	5.18	4.00	34.02	8.51
2178	4	48.46	11.4	9.50	8.620	0.91
2246	4	22.97	6.14	3.40	8.160	2.40
2282	3	20.24	4.75	5.37	50.80	9.46
2369	6	37.46	8.38	6.40	32.21	5.03
Total	62			57.12	300.5	
Mean				10.39	54.64	6.42

First, I explored the relationship between patch residence time and trip type, given that they are different fishing techniques despite both methods targeting demersal species. Table 19 provides patch type and patch residence time for each trip in the sample. The following computations use the log-transformed values of patch residence times because this variable displays a positive skew before conversion. Log transformation results in a dataset that is amenable to linear modeling. The times reported here have been back-transformed to be more understandable. The patch residence time data are mostly normally distributed after logarithmic transformation, but Levene's test demonstrates hederoskedasticity [$F(1, 60) = 14.76, p = 0.0003$). In other words, patch residence time variances are significantly different for bank (variance = 3.86 minutes) and pot (variance = 1.34 minutes) patches, so I applied corrections for unequal variances. Additionally, a generally accepted standard is that linear models remain fairly robust with some heterogeneity of variance, probably as long as the maximum variance is no more than four times greater than the minimum variance (Brown & Forsythe, 1974; Garson, 2012; Schultz, 1983). Regardless, Welch's two sample t-test shows the difference between the mean residence time of bank patches (M = 33.78 minutes, SD = 3.19) and the mean residence time pot patches (M = 15.33 minutes, SD = 1.72 mins) is significantly different from zero [$t(48.30) = 3.53$, p = 0.0009). Trip type—bank or pot—has a significant effect on patch residence time ($\beta = -1.37$, $t(58) = -2.41$, $p = 0.02$) and explains a portion of variation in patch residence time ($R^2 = 0.13$, $F(3,58) = 4.08$, $p = 0.01$).

Table 19

Patch type and residence times for N = 62 patches from N10 trips

Trip type	TID	PID	Residence time (mins)
Pot	1758	P1	0.22
	1758	P2	0.40
	1758	P3	0.37
	1758	P4	0.30
	1758	P5	0.28
	1758	P6	0.30
	1977	P7	0.25
	1977	P8	0.57
	1977	P9	0.28
	1977	P10	0.28
	1977	P11	0.40
	1977	P12	0.28
	1977	P13	0.23
	2058	P14	0.23
	2058	P15	0.27
	2058	P16	0.32
	2058	P17	0.48
	2114	P39	0.18
	2114	P40	0.05
	2114	P41	0.22
	2114	P42	0.30
	2114	P43	0.25
	2114	P44	0.50
	2114	P45	0.22
	2246	P50	0.05
	2246	P51	0.25
	2246	P52	0.28
	2246	P53	0.22
Bank	2072	P18	0.68
	2072	P19	0.32
	2072	P20	0.53
	2072	P21	0.02
	2072	P22	0.68
	2072	P23	0.67
	2072	P24	0.08
	2072	P25	2.82
	2072	P26	1.48
	2072	P27	0.13
	2101	P28	0.45
	2101	P29	1.90

Table 19. Continued

Bank	2101	P30	0.28
	2101	P31	0.50
	2101	P32	0.30
	2101	P33	0.32
	2101	P34	0.40
	2101	P35	1.12
	2101	P36	0.20
	2101	P37	0.15
	2101	P38	2.60
	2178	P46	1.65
	2178	P47	1.12
	2178	P48	0.82
	2178	P49	3.18
	2282	P54	3.53
	2282	P55	0.93
	2282	P56	0.32
	2369	P57	1.47
	2369	P58	1.50
	2369	P59	1.10
	2369	P60	0.65
	2369	P61	0.22
	2369	P62	0.13

Pot fishing techniques are an example of niche construction and inherently different from other types of bank fishing in ways that affect patch residence time. Pot patch locations are known to the fishers and marked with a buoy; once the pot buoy is visually located, it is a matter of raising the pot, clearing it of a catch, and dropping it back into the sea (see chapter four for more ethnographic detail). Pot fishers need not repeatedly pass the boat through a patch, nor does pot fishing require fishing with a hook and line like bank fishing. As shown in the above section, these differences result in a significantly smaller mean and variance for ‘pot’ patch residence times compared to ‘bank’ patch residence times. Additionally, the type of trip, bank or pot, is highly correlated with whom captained a given trip in the N10 sample. One captain accounted for all of the pot trips, while the other three captains in the sample accounted for bank trips. Due to these factors, the remaining analyses in this section are limited to bank patches.

Residence time as a function of search time

Table 20 presents a summary of catch and effort data for each bank patch (N = 34). During direct observation, I noted the start and end times of travel, or extensive search, between patches as well. Travel costs per patch are measured by the amount of time spent in extensive search between each patch—the start of travel to a patch to the end of travel as a fisher reaches that particular patch. I also recorded the start and end times of ARS in patches during direct observation. Patch residence time equals the amount of time spent conducting ARS in a patch. The following computations use the log transformed value for patch residence times because the data are right-skewed. This transformation corrects the right skew to allow for use of linear regression.

Two major outliers (P21 and P46) were removed from the sample, resulting in a sample of N = 32 bank patches. Inclusion of these two points did not affect the results below but did affect model assumptions. Per patch search time (hr) is a significant predictor of patch residence time (hr) in the predicted direction [$\beta = 3.64$, $t(30) = 3.23$, $p = 0.003$] and explains a portion of the variation in residence time [$R^2 = 0.26$, $F(1, 30) = 10.44$ $p = 0.003$] (Figure 25). The residual plot indicates an adequate fit for the model, and assumptions are satisfied for criteria of the Global Validation of Linear Model

Assumptions (GVLMA; criteria include global statistic, skewness, kurtosis, link function, and heteroskedasticity) at a significance level of 0.05.

Table 20

Summary of N = 34 bank patches from N10 sample

TID	PID	Residence time (hr)	Search time (hr)
2072	P18	0.68	0.25
2072	P19	0.32	0.08
2072	P20	0.53	0.07
2072	P21	0.02	0.10
2072	P22	0.68	0.03
2072	P23	0.67	0.10
2072	P24	0.08	0.03
2072	P25	2.82	0.02
2072	P26	1.48	0.12
2072	P27	0.13	0.07
2101	P28	0.45	0.30
2101	P29	1.90	0.20
2101	P30	0.28	0.05
2101	P31	0.50	0.07
2101	P32	0.30	0.03
2101	P33	0.32	0.10
2101	P34	0.40	0.10
2101	P35	1.12	0.27
2101	P36	0.20	0.05
2101	P37	0.15	0.07
2101	P38	2.60	0.05
2178	P46	1.65	1.77
2178	P47	1.12	0.18
2178	P48	0.82	0.07
2178	P49	3.18	0.47
2282	P54	3.53	0.32
2282	P55	0.93	0.08
2282	P56	0.32	0.07
2369	P57	1.47	0.63
2369	P58	1.50	0.30
2369	P59	1.10	0.12

Table 20. Continued

2369	P60	0.65	0.08
2369	P61	0.22	0.08
2369	P62	0.13	0.03

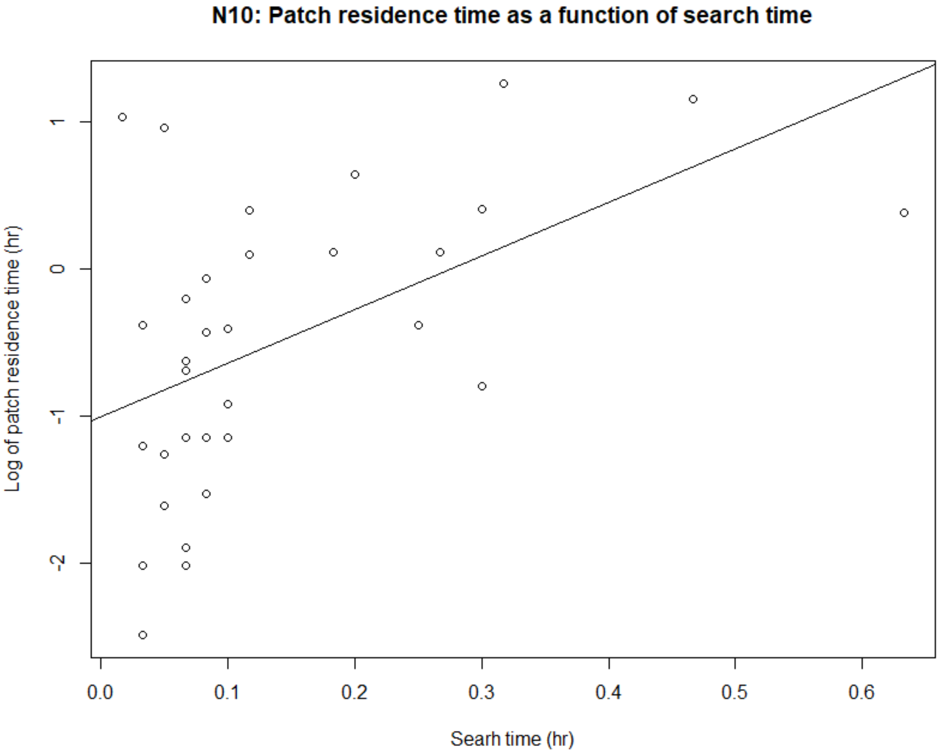


Figure 25. Plot of patch search time (hr) and patch residence time (hr) with regression line for N = 32 bank patches known from direct observation of N10 trips. This plot shows the statistically significant and positive, directional effect of search time on patch residence time, known from the N10 sample.

N30 sample

The CUMSUM method identified N = 148 segments of ARS at patches that also corresponded to visually-identified patches for the N30 sample of bank fishing trips. Table 21 provides relevant trip data for this sample. I used this CUMSUM-generated data to determine travel costs, measured as search time, and residence time for each patch in the sample (Table 22). Four influential outliers were excluded from analysis (P66, P67, P157, and P166) due to the fact that these data affected model assumptions and create a significant relationship compared to the results presented below. Thus, the resulting sample includes N = 144 bank patches for analysis. The following computations use the log transformed value for patch residence times because the data are right-skewed. This transformation corrects the skew to allow for use of linear modeling.

Search time (hr) is not a significant predictor of patch residence time (hr) in the predicted direction [$\beta = 0.07$, $t(142) = 0.81$, $p = 0.81$]. The residual and diagnostic plots for this model indicate an adequate fit, and all assumptions are satisfied for all criteria of the GVLMA at a significance level of 0.05. This equivocal result does not necessarily undermine the results of analyzing the N10 bank patches, but it does not offer much support for the MVT prediction that patch residence time increases as travel cost, measured by search time, increases.

Table 21

Summary of N = 148 bank patches from the N30 sample

TID	Number of CUMSUM-identified patches (N=148)	Cumulative distance travelled (km)	Maximum distance travelled (km)	Duration (hr)
1646	6	42.78	7.65	11.51
1658	5	27.16	5.90	5.68
1691	3	11.36	2.25	4.60
1762	7	33.62	5.75	7.07
1771	2	46.05	10.67	8.19
1783	6	30.58	6.36	6.90
1808	7	41.62	7.40	8.01
1847	7	52.00	12.64	7.39
1903	5	34.04	6.41	8.17
1943	5	29.35	5.22	7.19
1971	7	43.94	10.38	7.17
2062	6	30.66	4.89	9.05
2079	7	33.58	4.93	9.87
2093	8	33.17	4.68	10.08
2109	4	28.24	4.18	8.31
2139	5	24.85	6.56	7.50
2168	1	20.14	7.30	2.64
2203	1	11.95	3.53	1.55
2225	5	57.50	17.63	6.78
2256	3	25.01	6.48	5.11
2269	3	26.78	6.72	9.45
2276	7	55.25	10.92	8.15
2281	4	38.02	6.49	8.06
2300	4	60.42	16.16	8.14
2339	8	29.11	4.77	8.84
2379	6	33.06	6.65	7.91
2407	4	41.07	10.63	8.54
2420	5	28.12	6.16	6.17
2456	1	36.09	9.82	7.25
2462	6	40.47	9.18	9.94

Table 22

Data for N = 148 bank patches from N30 sample

TID	PID	Residence time (hr)	Search time (hr)
1646	P63	0.763	0.112
1646	P64	0.505	0.322
1646	P65	3.902	0.663
1646	P66	0.068	3.421
1646	P67	0.037	0.243
1646	P68	0.472	0.673
1658	P69	0.680	0.096
1658	P70	0.449	0.653
1658	P71	0.393	0.149
1658	P72	0.658	0.161
1658	P73	1.441	0.304
1691	P74	2.654	0.150
1691	P75	0.655	0.033
1691	P76	0.202	0.048
1762	P77	0.928	0.540
1762	P78	0.171	0.155
1762	P79	0.408	0.097
1762	P80	0.611	0.163
1762	P81	0.718	0.107
1762	P82	2.307	0.277
1762	P83	0.143	0.164
1771	P84	1.805	0.162
1771	P85	2.647	0.225
1783	P86	0.668	0.149
1783	P87	0.508	0.047
1783	P88	0.972	0.450
1783	P89	1.001	0.319
1783	P90	1.680	0.094
1783	P91	0.718	0.079
1808	P92	1.155	0.091
1808	P93	0.773	0.112
1808	P94	1.864	0.224
1808	P95	0.406	0.058
1808	P96	0.559	0.182
1808	P97	0.450	0.076
1808	P98	1.029	0.173
1847	P99	0.498	0.928

Table 22. Continued

1847	P100	0.406	0.872
1847	P101	0.110	0.928
1847	P102	0.557	0.249
1847	P103	0.628	0.512
1847	P104	0.339	0.216
1847	P105	0.789	0.174
1903	P106	1.686	0.396
1903	P107	0.808	0.084
1903	P108	1.008	0.112
1903	P109	0.400	0.082
1903	P110	3.157	0.212
1943	P111	0.429	0.151
1943	P112	1.381	0.183
1943	P113	3.087	0.103
1943	P114	0.299	0.087
1943	P115	0.732	0.064
1971	P116	0.471	0.062
1971	P117	0.342	0.293
1971	P118	0.923	0.450
1971	P119	0.170	0.112
1971	P120	0.633	0.447
1971	P121	0.403	0.611
1971	P122	0.987	0.223
2062	P123	1.093	0.124
2062	P124	1.476	0.086
2062	P125	0.490	0.276
2062	P126	1.013	0.072
2062	P127	3.215	0.094
2062	P128	0.840	0.071
2079	P129	1.036	0.151
2079	P130	1.542	0.246
2079	P131	1.460	0.303
2079	P132	2.542	0.062
2079	P133	0.691	0.124
2079	P134	0.470	0.085
2079	P135	0.353	0.121
2093	P136	0.352	0.294
2093	P137	0.453	0.205

Table 22. Continued

2093	P138	0.807	0.226
2093	P139	2.789	0.061
2093	P140	0.270	0.106
2093	P141	0.136	0.079
2093	P142	0.202	0.058
2093	P143	0.345	0.051
2109	P144	1.286	0.040
2109	P145	0.371	0.287
2109	P146	4.542	0.074
2109	P147	1.174	0.158
2139	P148	2.059	0.46
2139	P149	1.032	0.053
2139	P150	1.432	0.041
2139	P151	0.976	0.153
2139	P152	1.043	0.049
2168	P153	1.934	0.379
2203	P154	0.755	0.257
2225	P155	0.128	0.099
2225	P156	0.373	0.615
2225	P157	0.906	1.110
2225	P158	1.353	0.400
2225	P159	0.804	0.604
2256	P160	1.084	0.069
2256	P161	1.527	0.555
2256	P162	1.209	0.306
2269	P163	0.600	0.106
2269	P164	5.899	0.483
2269	P165	2.093	0.049
2276	P166	0.504	1.538
2276	P167	0.235	0.069
2276	P168	0.498	0.067
2276	P169	1.385	0.632
2276	P170	0.878	0.087
2276	P171	0.656	0.156
2276	P172	0.674	0.075
2281	P173	2.191	0.409
2281	P174	1.362	0.265
2281	P175	0.526	0.470

Table 22. Continued

2281	P176	1.078	0.058
2300	P177	0.642	1.012
2300	P178	0.711	0.097
2300	P179	1.209	0.351
2300	P180	2.909	0.292
2339	P181	2.143	0.098
2339	P182	1.271	0.114
2339	P183	0.764	0.102
2339	P184	0.909	0.457
2339	P185	0.619	0.095
2339	P186	1.160	0.035
2339	P187	0.228	0.064
2339	P188	0.529	0.066
2379	P189	0.719	0.127
2379	P190	0.760	0.575
2379	P191	1.061	0.040
2379	P192	1.375	0.086
2379	P193	1.133	0.088
2379	P194	0.890	0.173
2407	P195	0.617	0.988
2407	P196	1.813	0.079
2407	P197	1.519	0.338
2407	P198	2.865	0.204
2420	P199	0.326	0.226
2420	P200	0.363	0.203
2420	P201	0.176	0.075
2420	P202	3.098	0.226
2420	P203	1.200	0.103
2456	P204	5.924	0.568
2462	P205	0.955	0.051
2462	P206	1.218	0.113
2462	P207	1.344	0.773
2462	P208	1.063	0.034
2462	P209	2.541	0.128
2462	P210	1.305	0.109

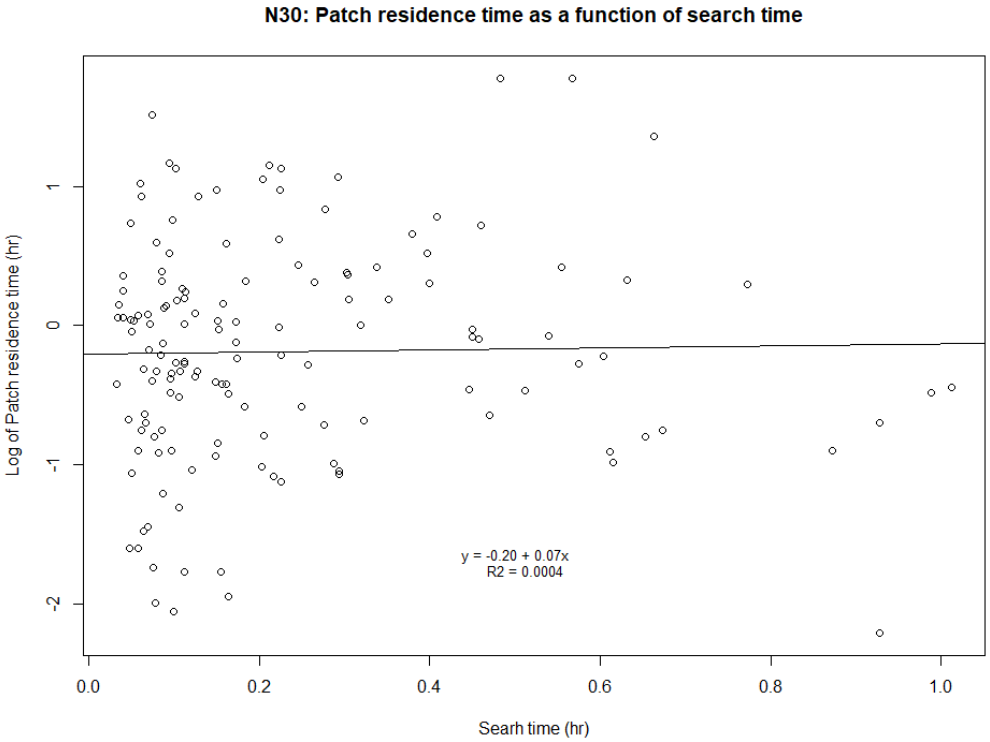


Figure 26. Plot of search time (hr) and residence time (hr) with regression line for N = 144 bank patches from CUMSUM analysis of N30 trips. This model uses patch data from the CUMSUM method rather than direct observation. This regression plot shows a slightly positive but non-significant effect of search time on patch residence time.

CHAPTER IX

CONCLUSIONS

Recording and interpreting animal movement tracks with GPS devices has wide, general applicability for a range of questions on animal behavior. The goal of GPS track segmentation is to identify major changes in animal activities along a movement trajectory that correspond to real, biologically meaningful behavioral shifts. Translating GPS tracks into behavioral data is now common albeit not straightforward, and methods of parsing out behavioral shifts often have limitations. The CUMSUM approach of Knell and Codling (2012) seems to be a methodological advancement, but it has undergone little testing and its cross-context applicability is unclear. The usefulness of the CUMSUM process is that it is analytically simple to make scaling adjustments and interpret. One important assessment of the CUMSUM segmentation method is to determine how well the method identifies shifts between major foraging activities, such as extensive search (travel) and ARS, without identifying within-patch noise during bout of ARS.

The primary goal of this project was to test the CUMSUM method of segmenting GPS data into meaningful behavioral data, specifically to identify shifts between extensive search and ARS. To this end, I demonstrated the utility of this approach in the context of small-scale fishing-foraging in the Commonwealth of Dominica. I conducted the analysis with N = 10 demersal fishing trips, the N10 sample, using speed as the spatiotemporal parameter to describe movement and segment GPS tracks into bouts of extensive search and ARS. This sample of ten fishing trips includes ground-truth data via simultaneous direct behavioral observation. Direct observation provides the known, exact locations and times of travel and ARS at patches, which provide a comparative base to determine the best scale of analysis and overall efficacy of the CUMSUM method.

The first step to all segmentation methods is defining an appropriate sampling scale. In the case of the CUMSUM method, this is the window (ϵ) in which local speed maxima and minima are identified via the max-min algorithm (Knell & Codling, 2012). I examined the results of the CUMSUM process across a range of different window sizes and compared these segmentation results with ground-truth data to classify segments as accurate and matching focal follow observations or as type I or II errors. Across trips in the N10 sample, increasing the window size above $\epsilon \cong 600$ obscures major bouts of ARS, or results in more type II errors. Decreasing the window size below $\epsilon \cong 600$ results in more false positives, or type I errors. A second approach to determining the best scale of analysis, suggested by Knell & Codling (2012), specifies that the appropriate window lies within the range of window sizes that provides the first consecutive period without a large change in the number of resulting segments identified by the max-min algorithm. I applied this method as well and found agreement between each approach—both indicate a window range of $\epsilon \cong 600$ is appropriate for all trips the N10 sample.

After determining the optimal scale of analysis, I segmented each trip in the N10 sample with the CUMSUM method. Compared to ground truth data, CUMSUM correctly identified fifty-six of sixty-two known patches. In other words, the CUMSUM method identified 90% of known patches in the N10 sample while making six type I errors and six type II errors. I also compared CUMSUM-predicted starts and stops of ARS at patches (i.e. behavioral shifts identified by the man-min algorithm) with the observed starts and stops of ARS known from direct observation in order to gauge the accuracy of the method. A paired samples t-test showed that the max-min algorithm predicted the start of ARS nearly a minute earlier than direct observation, which is a statistically significant difference. In using speed as the model criterion for segmenting, the CUMSUM method is identifying ARS for patch locations as they approximated patch marks, while I documented the time when fishers began ARS for fish and dropped a fishing line in the water. A second paired samples t-test suggested the difference in means between the predicted and observed ARS stop times is not significantly different from zero; these differences reflect the time it takes for the captain to accelerate the boat to travel speeds recognized by the algorithm. These tests demonstrate a relatively low error rates as well as the overall efficacy of the CUMSUM method in the demersal fishing context. Overall, the method provides a good way to understand major shifts in foraging behaviors and gross patch use if an appropriate sampling scale is identified. Further, CUMSUM segmentation is accurate even when based on only handful of direct observations, such as the present N = 10 sample of demersal trips with direct observation.

I assessed the applicability of the results from segmentation of the N10 sample to an additional subset of demersal trips, the N30 sample. I used these data to provide another test of the efficacy of the CUMSUM method by comparing model-generated segments of ARS with ARS identified visually. I limited this sample of N = 30 trips to strictly bank demersal trips that have associated GPS tracks. The trips in the N30 sample do not have simultaneous ground-truth data, so I visually segmented these trips to create a dataset with which to compare CUMSUM results. First, I visually segmented each trip in the N30 sample into major, obvious bouts of travel and ARS. For segments of GPS tracks less easily classified, I used additional criteria to maintain systematic visual segmentation. This method of visual segmentation is the same process the CUMSUM method uses to segment a track.

I applied this visual segmentation process across all trips in the N30 sample. While I relied on my decision-making criteria for classifying segments systematically, there is a considerable degree of uncertainty regarding the nature of the behavioral shifts I identified. It is unclear if all patches I identified behaviorally as ARS actually correspond to ARS and fishing activities. It is possible these bouts correspond to some other type of behavior, such as boat maintenance, social encounters with other boats, and other non-foraging activities. In sum, my approach to visual segmentation resulted in identification of N = 161 patches. This provided a comparison for assessing the efficacy of the CUMSUM method for identifying patches behaviorally as ARS.

Next, I segmented trips in the N30 sample with the CUMSUM method using speed as the model parameter and a window of $\epsilon = 600$, as determined from the results of segmenting the N10 sample. The method identified N = 182 segments of potential ARS for the N30 sample. Overall, N = 148 of these N = 182 segments correspond to

ARS also identified visually. The remaining thirty-four segments of the N = 182 are noise within patches when compared to visual segmentation results. In other words, the method made thirty-four type I errors, if visual segmentation is accurate. Overall, the method missed fifteen segments of ARS, or fifteen type II errors.

The CUMSUM approach and visual segmentation showed agreement about 92% of the time for demersal fishing. Visual segmentation takes a long time and subject to human error. The CUMSUM method offers a segmentation approach that takes a fraction of the time and has very similar outcomes in terms of identifying behaviors. The results from the N10 sample were appropriate for scaling and segmenting the N30 sample via the CUMSUM method, which suggests a good degree of generalizability if an appropriate sampling scale can be determined for a particular foraging context. I was able to determine a relatively accurate scale of analysis for the CUMSUM process from just a handful of trips (N = 10 focal follows). This is advantageous if applied to contexts where direct observation of foraging behavior is costly and a large sample is not possible.

Direct behavioral observation of animal behavior is idea but can be dangerous, expensive, or impossible in some cases. Developing methods of remote behavioral observation and segmentation approaches like the CUMSUM method has the advantage of reducing the cost and time of data collection in the long run with broad application across a range of disciplines. For example, methodological development potentiates tests of prominent foraging models that have often been developed with non-human animals and in experimental settings (Owen-Smith et al., 2010; Pyke, Pulliam, & Charnov, 1977), such the well-known and widely-referenced MVT. As a secondary goal of this project, I assessed a major prediction from the MVT to show how the CUMSUM analysis can be used for these kinds of theoretical considerations.

The MVT predicts that, for central place foragers, patch residence time should increase as travel costs increase. To test this, I assumed patches exploited by fishers depleted despite that I was unable measure patch depletion to produce the cumulative gains curve characteristic of the MVT. Specifically, I assumed the patches exploited by fishers constitute microhabitats that deplete due to foraging effort, following the example of Aswani (1998). Given these assumptions, I tested the prediction that patch residence times should exhibit a direct relationship with travel time. First, using data from the N10 sample with direct observation, I used known extensive search (travel) times to measure travel costs of each patch and known patch residence times to show a significant, positive directional relationship between these two factors. Second, I used patch data from the CUMSUM-generated segments to provide a secondary test of this prediction of the MVT, limiting the sample to the N = 148 segments that also correspond to visually identified patches. In this iteration, I used maximum segments, corresponding to extensive search time, to measure per patch travel costs. I used minimum segments, corresponding to ARS at patches, to measure patch residence times. In the case of the N10 sample, regression revealed a significant relationship between search time and patch residence time such that patch residence time increases as a function of increasing search time. Regression using the N30 sample of bank batches shows a positive albeit non-significant relationship between search time and residence time.

Overall, the test with N10 bank patches provide support for the MVT prediction in the context of demersal fishing, and while the test with N30 bank patches is equivocal, it does not necessarily undermine the results from the test with the N10 sample. As discussed, the CUMSUM method seems to identify ARS for patches rather than ARS for fish when tracks are segmented based on deviations in speed. This may not be a problem for understanding gross behavioral changes—intensive versus extensive search—and gauging large-scale patch use patterns. Regarding the relationship between patch residence time and travel costs as predicted by the MVT, identifying ARS for fish rather than ARS for patches is probably more appropriate. Perhaps a different sampling scale or even a different model parameter such as turning angle would be more appropriate for differentiating these types of finer-scale phenomena. The usefulness of an analytically simple method like the CUMSUM approach lies in the ability to investigate many scales of observation, within the same large-range, high resolution datasets, to assess such issues and move theory forward.

When attempting to assess the MVT and similar foraging models, there are difficulties in measuring model parameters like prey encounter rates and delimiting patches. An advantage of the CUMSUM method is that it efficiently and relatively effectively delimits patches. Patches of resources in the ocean are notoriously difficult to define, e.g. due to prey mobility, and it is difficult to discern if ocean patches deplete as the MVT model of Charnov (1976) assumes. An alternative is to assume that patches do not deplete, which results in linear gains function and implies that foragers should never leave such a patch in search of different one (Bettinger, 2009; Kacelnik, Hammerstein,

& Stevens, 2012). It is probably more appropriate to assume many near-shore fishing patches, such as those associated with the demersal context of this project, constitute microhabitats that deplete (Aswani, 1998).

Another assumption of the MVT often violated by purposive human foragers is that patches are exploited randomly and sequentially (Aswani, 1998; Kaplan & Hill, 1992). GPS tracks for the N10 and N30 samples demonstrate that fishers will return to a patch that was already visited that trip and fish it again. Figure 24 in chapter seven provides a good example of how fishers might return to the same fishing patch more than once in a given trip. These kinds of issues are helpful in that they lead researchers to reevaluate their starting assumptions and refine how we frame specific hypotheses and tests. This is particularly relevant in the context of human foraging where proximate, cultural processes may play a significant role in decision-making processes. In an anthropological context, it can be used to refine our understanding of how human foraging approximates and deviates from the widely accepted tenets of theory and the predictions of optimality models. While foraging theory has great benefits as a tool for asking questions and creating hypotheses, some of its main premises remain unconfirmed for human forgers, particularly in a naturalistic setting (Bartumeus & Catalan, 2009).

This avenue allows researchers to identify patches of resources behaviorally and thus assess major mechanisms of resource exploitation, which has major practical significant. Fisheries around the world face over-exploitation as well as conflicts of interest and competition between local, national, and regional entities. Legal structures attempt to regulate fisheries and common-pool marine resources, but management is diminished by weak institutions, ineffective enforcement of regulatory measures, a lack of post-harvest infrastructure for appropriate processing and marketing of catches, and finally, limited involvement of fishers (Salas & Gaertner, 2004). In the past several decades, maritime anthropology has demonstrated the usefulness of integrating evolutionary and foraging theory to understand indigenous coastal management strategies and their effects of the marine environment (Acheson, 1981; Ayers & Kittinger, 2014; Calamia, 1996; Dahl, 1988; Feeny, Berkes, McCay, & Acheson, 1990; Fulton, Smith, Smith, & van Putten, 2011; Martin, 2006; McCay, 1978; McCay & Acheson, 1990; McGoodwin, 2001; Miller, Kaneko, Bartram, Marks, & Brewer, 2004; Moran, 1990, 1993; Munro, 1996; Pinkerton, 2011; Ruddle & Akimichi, 1984; Zhou et al., 2010). The anthropological contexts of much of this research also highlights how important it is to include the participation and agreement of local people, local authorities, and indigenous communities while emphasizing the links between sustainability, poverty, and human well-being (Alexander, Armitage, & Charles, 2015; Alfaro-Shigueto et al., 2010; Béné, Hersoug, & Allison, 2010; Chapin III, Sommerkorn, Robards, & Hillmer-Pegram, 2015; Coulthard, Johnson, & McGregor, 2011; Guo, 2017; Kittinger et al., 2015; Ostrom, 2015; Sandström, Crona, & Bodin, 2014; Shackeroff & Campbell, 2007; Sowman, 2006; Whittingham, Campbell, & Townsley, 2003).

In terms of broader impact, projects that aim to understand local-level fishing practices and outcomes play a major role in informing policy associated with sustainability and conservation efforts, human well-being, ownership, and tenure right to fishery resources and coastal access (Daw, Brown, Rosendo, & Pomeroy, 2011). Local fisheries play a pivotal role in food security for local, national, and international markets, as well as in developing sustainable and equitable resource use and eradicating poverty (FAO, 2015), and small-scale fisheries are a large part of income and food security in most rural, poor, coastal communities. However, these contexts remain poorly documented in national and global fishery statistics (Heyman & Dieseldorff, 2012), which biases management of marine resources towards the short-term, for-profit interests of industrial fleets rather than long-term goals of marine ecosystem health and local community well-being. Documenting small-scale fisheries provides practical information that helps bridge this gap and promotes the involvement of fishers in management strategies, which in turn, increases the success of conversation outcomes. A more inclusive approach that promotes the involvement of fishers and local authority in policy development and regulatory processes has been shown (by Heyman & Dieseldorff, 2012, for example) to improve both the scientific understanding of the marine resources in question, identification of management hotspots, and overall management effectiveness and success. In this way, the importance of small-scale fisheries and local fishing communities like Desa Ikan is not fully realized.

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