TOWARDS RECIPROCITY IN COMMON RAVENS, *CORVUS CORAX,* NEAR ANTHROPOGENIC FOOD SOURCES IN INTERIOR ALASKA DURING WINTER

by

Amelia Rose Beausoleil

B.S. Ohio State University, 2019

A Thesis Submitted in Partial Fulfillment of the Requirements

for the Degree of

Master of Science

in

Wildlife Biology and Conservation

University of Alaska Fairbanks

August 2024

APPROVED:

Falk Huettmann, Committee Chair
Cory Williams, Committee Member
Knut Kielland, Committee Member
Todd Brinkman, Chair
Wildlife Biology & Conservation Program
Karsten Hueffer, Dean
College of Natural Science & Mathematics
Rich Collins, Director
Graduate School

Abstract

Ravens, *Corvus corax,* and other corvids are intelligent birds that are the focus of many studies, such as in-depth dives into potential facial recognition and tool use to name a few. Despite these numerous behavioral studies, ravens lack an accessible basic universal ethogram and have rarely been observed in their undisturbed, natural state. Due to this, my study focuses on free-roaming common raven behavior in Fairbanks, Alaska, for which I utilize exploratory analysis to identify patterns in collected data. In doing so, I show how data mining and machine learning can further support behavior research with a systems perspective in the Anthropocene using pattern recognition. Using an ethogram and machine learning techniques on open access data for two winter seasons, I examine what factors affect common raven behavior around human-subsidized food sources in Fairbanks, Alaska by answering: 1) What consistent reactions do wild ravens communities show to objects, people, and other organisms (typically small songbirds or dogs) and 2) Do other factors, such as daylight or location, contribute to differing raven behaviors? I found that ravens exhibit predictable responses that vary based on urbanization level. In addition, I found an unusual pattern in raven behavior that indicates that ravens adjust their behavior based on hourly and daily human activity, indicating that raven behavior is scheduled. These results provide evidence that merging modern and classic techniques into behavioral research reveals patterns that may be missed by traditional methods alone.

Acknowledgements

This research would not have been possible without my committee chair, Falk Huettmann, who has contributed observational readings, statistical analysis, and constant support, patience, and guidance throughout this entire process. I would also like to express my gratitude for my defense committee, Knut Kielland and Cory Williams, for their valuable feedback and patience. I am also grateful to my fellow graduate students and teachers Roger Ruess, Greg Breed, and Christa Mulder for helping me shape my thesis from beginning ideas, to statistical analysis, and to a well-written paper. I would like to thank my parents and husband for their unwavering support. They have provided me with housing, food, and motivation from beginning to end and I could not have done this without them. Finally, I would like to give special thanks to my beloved cat, Iggy, who unfortunately passed before my thesis came to an end. Until his end, he was always present to provide love and entertainment and an ever-listening ear for me to vent to, share my ideas with, and celebrate with as thesis struggles and wins occurred.

Table of Contents

LIST OF FIGURES

LIST OF TABLES

Chapter 1: General Introduction

1.1 Introduction

Ravens, *Corvus corax,* are known to be intelligent animals with "one of the largest brain-body ratios of any bird" (Christiansen, 2009). Despite this, little research has been conducted that explores the intelligence of these birds in the wild or on behaviors enacted toward objects and organisms other than humans (Baltensperger et al., 2013). Rather, a majority of raven-based behavior studies have focused on ravens kept captive or in controlled areas (e.g. Bugnyar & Heinrich, 2006; Freidin et al., 2017; Kulahci et al., 2016; Massen et al., 2015), or if the ravens live freely, studies focused on attributes such as temperature regulation, nesting sites, and the relationship between habitat use, resource use, and demographic parameters (Powell & Backensto, 2009; Schwan & Williams, 1978; Webb et al., 2011).

In addition, few studies have been conducted that have created ethograms for common ravens, despite the extensive behavioral studies conducted on the species. Ethograms are essential behavioral research tools which create a catalog of behavior from which future research can be derived from (Howe et al., 2015). Knowing this, the lack of accessible basic behavior ethograms for ravens is surprising. Instead, known raven ethograms consist of study-specific behaviors with captive ravens, such as interactions with a box (Adriaense et al, 2019; Cory, 2016; Hegedič, 2016) or with a window or tray or in response to another raven in an experiment (Lambert et al., 2017). As of 2022, an ethogram was used in Wenig et al.'s study that includes some basic behaviors, but these behaviors focus on grooming, antagonistic, or affiliative behaviors and lack locomotion, foraging, play, or breeding behaviors (Wenig, Pacher, & Bugnyar, 2022).

1.2 Background

The common raven, *Corvus corax*, otherwise known as the northern raven, is the focal species of this research. They are one of few bird species that overwinter in Interior Alaska (Alaska Department of Fish and Game, 2020). This study focused on the subspecies present in Alaska: *C. corax principalis* and *C. corax kamtschaticus*.

Ravens often display play-like behaviors, with reports of ravens performing somersaults, chasing, swooping, and soaring in parallel with other ravens, and even playing with plastic toys containing food (Alderfer & Strycker, 2019; Brinkley, 2008; Floyd, 2008). As opportunistic feeders, arctic and sub-arctic ravens have thrived using adaptations that differ from most birds. These include breeding early in poorer weather, which increases carrion resources due to low overwinter survival of many mammals (Christiansen, 2009; Dare, 1986), and a centuries-long reliance on people for food through following them in the wild and reappearing in cities where they have adapted to urban life and landfill food (Cornell Lab of Ornithology, 2017; White, 2005).

Additionally, ravens are diurnal, meaning they are active during the daytime. Being diurnal in a high-latitude area such as Alaska poses an interesting biological question, as the summers have long days and the winters have long nights. Numerous studies have been conducted focusing on how the hours of daylight affect behavior during the summer, but relatively few have done the same for the winter. Janicke and Chakarov (2007) investigated both summer and winter roosting habits of *Corvus corax* with unlimited food resources in central Germany. They found ravens were most affected by day length in the summer and cloud cover in the winter, with shorter days and cloudless evenings resulting in later arrivals at the roost, indicating animals remained active during twilight conditions in the winter in the winter (Janicke & Chakarov, 2007).

However, in an urbanized area such as Fairbanks, AK, we must also factor in the effects of urbanization on how diurnal animals adjust to changing hours of sunlight. Some studies have investigated the effects of artificial lighting on foraging activity, with Silva et al. (2017) finding only small effects on early foraging time in three out of six songbird species given additional light and no effect on end-of-day foraging. Russ et al.'s 2015 study on the effects artificial light has on European Blackbird, *Turdus merula*, foraging activity used a study site with a highly urbanized area and riparian forest in close vicinity to each other, allowing for the illumination from streetlamps to affect foraging birds differently. Overall, they found that birds in urbanized areas foraged longer than birds in forested areas, but both groups' foraging activity decreased in length as the day length grew shorter, indicating that both hours of daylight and presence of artificial light affect bird behavior (Russ et al., 2015).

With approximately 3.7 hours of sunlight on average on the shortest day of the year in addition to multiple urbanized areas adjacent to rural land, Fairbanks, AK winters provide a unique landscape to find out how diurnal animals such as ravens adjust their behavior to maximize survival (*National Oceanic & Atmospheric Administration Solar Calculator*, 2022).

1.3 Research Objectives

The goal of this research is to investigate, using non-intrusive methods, what factors currently affect common raven behavior around food sources in Fairbanks, Alaska through machine learning analysis. In doing so, we proposed two research questions: 1) What consistent reactions do wild ravens communities show to objects, people, and other organisms (typically small songbirds or dogs) and 2) Do other factors, such as daylight or location and its attributes, contribute to differing raven behaviors on a wider urban landscape?

As our research uses an exploratory analysis to identify patterns in collected data, we chose to use machine learning analysis over null hypothesis testing methods, due to the limitations null hypothesis methods have in biological sciences. While null hypothesis testing can determine whether a pattern is random or not, it lacks the ability to test for variable selection and what causes specific patterns (Anderson et al., 2000; Zhang, 2020).

To address the first question, we use statistical analysis to assess whether particular behaviors tend to be associated with certain objects or behaviors within different raven communities. In this context, raven communities refer to a group of ravens within a certain location at a given time. An example of differing behaviors between communities could be ravens searching truck beds for food at one location, while ravens at another location will avoid cars entirely.

For the second question, we compared behavior with the time of day and location to determine whether ravens adjust their behavior based on visibility, temperature, and location throughout winter. For example, if ravens exhibit playing behavior only at times where it is dark outside, then we would consider playing to be associated with the hours of daylight.

1.4 References

Adriaense, J. E. C., Martin, J. S., Schiestl, M., Lamm, C., & Bugnyar, T. (2019). Negative emotional contagion and cognitive bias in common ravens (Corvus corax). *Proceedings of the National Academy of Sciences of the United States of America*, *166*(23), 11547–11552. https://doi.org/10.1073/PNAS.1817066116

Alaska Department of Fish and Game. (2020). *Winter Bird-Feeding in Alaska*. Alaska Department of Fish and Game. http://www.adfg.alaska.gov/index.cfm?adfg=livingwithbirds.winterfeeding

Alderfer, J., & Strycker, N. (2019). *Backyard Guide to the Birds of North America* (Second). National Geographic.

Anderson, D. R., Burnham, K. P., & Thompson, W. L. (2000). Null Hypothesis Testing: Problems, Prevalence, and an Alternative. *The Journal of Wildlife Management*, *64*(4), 912–923. https://www.jstor.org/stable/3803199

Baltensperger, A. P., Mullet, T. C., Schmid, M. S., Humphries, G. R. W., Kövér, L., & Huettmann, F. (2013). Seasonal observations and machine-learning-based spatial model predictions for the common raven (Corvus corax) in the urban, sub-arctic environment of Fairbanks, Alaska. *Polar Biology*, *36*(11), 1587–1599. https://doi.org/10.1007/s00300-013-1376-7

Brinkley, E. S. (2008). *National Wildlife Federation Field Guide to Birds of North America*. Sterling Publishing Co., Inc.

Bugnyar, T., & Heinrich, B. (2006). Pilfering ravens, Corvus corax, adjust their behaviour to social context and identity of competitors. *Animal Cognition*, *9*(4), 369–376. https://doi.org/10.1007/s10071-006-0035-6

Christiansen, P. (2009). *Encyclopedia of Birds: 400 Species from Around the World* (P. Christiansen (Ed.)). Amber Books.

Cornell Lab of Ornithology. (2017). *All About Backyard Birds: Western North America*. Cornell Lab Publishing Group.

Cory, E. F. (2016). The rooftop raven project: An exploratory, qualitative study of puzzle solving ability in wild and captive ravens. *ProQuest Dissertations and Theses*, 165. https://search.proquest.com/docview/1797593374?accountid=168248%0Ahttp://www.yidu.edu.cn/educhina/educhina.do?artifact=&svalue=The+rooftop+raven+project%3A+An+exploratory%2C+qualitative+study+of+puzzle+solving+ability+in+wild+and+captive+ravens&stype=2&s=

Dare, P. J. (1986). Raven Corvus corax populations in two upland regions of north Wales. *Bird Study*, *33*(3), 179–189. https://doi.org/10.1080/00063658609476918

Floyd, T. (2008). *Field Guide to the Birds of North America*. HarperCollins Publishers.

Freidin, E., Carballo, F., & Bentosela, M. (2017). Direct reciprocity in animals: The roles of bonding and affective processes. *International Journal of Psychology*, *52*(2), 163–170. https://doi.org/10.1002/ijop

Hegedič, M. (2016). *Frustration Or Persistence?: Evolution and Function of Affect in Creative Problem Solving Based on Study of Behavior in Common Ravens* (Doctoral dissertation, M. Hegedič).

Howe, M., Castellote, M., Garner, C., Mckee, P., Small, R. J., & Hobbs, R. (2015). Beluga, Delphinapterus leucas, Ethogram: A Tool for Cook Inlet Beluga Conservation? *Marine Fisheries Review*, *77*(1), 32–40. https://doi.org/10.7755/MFR.77.1.3

Janicke, T., & Chakarov, N. (2007). Effect of weather conditions on the communal roosting behaviour of common ravens Corvus corax with unlimited food resources. *Journal of Ethology*, *25*(1), 71–78. https://doi.org/10.1007/s10164-006-0209-3

Kulahci, I. G., Rubenstein, D. I., Bugnyar, T., Hoppitt, W., Mikus, N., & Schwab, C. (2016). Social networks predict selective observation and information spread in ravens. *Royal Society Open Science*, *3*(7). https://doi.org/10.1098/rsos.160256

Lambert, M. L., Massen, J. J. M., Seed, A. M., Bugnyar, T., & Slocombe, K. E. (2017). An 'unkindness' of ravens? Measuring prosocial preferences in Corvus corax. *Animal Behaviour*, *123*, 383–393. https://doi.org/10.1016/j.anbehav.2016.11.018

Massen, J. J. M., Ritter, C., & Bugnyar, T. (2015). Tolerance and reward equity predict cooperation in ravens (Corvus corax). *Scientific Reports*, *5*, 1–11. https://doi.org/10.1038/srep15021

National Oceanic & Atmospheric Administration Solar Calculator. (2022). Global Monitoring Laboratory. https://gml.noaa.gov/grad/solcalc/

Powell, A. N., & Backensto, S. (2009). *Common Ravens (Corvus Corax) Nesting on Alaska's North Slope Oil Fields*. Coastal Marine Institute, University of Alaska Fairbanks.

Russ, A., Rüger, A., & Klenke, R. (2015). Seize the night: European Blackbirds (Turdus merula) extend their foraging activity under artificial illumination. *Journal of Ornithology*, *156*(1), 123–131. https://doi.org/10.1007/s10336-014-1105-1

Schwan, M. W., & Williams, D. D. (1978). Temperature regulation in the common raven of interior Alaska. *Comparative Biochemistry and Physiology -- Part A: Physiology*, *60*(1), 31–36. https://doi.org/10.1016/0300-9629(78)90033-6

Silva, A. Da, Diez-Méndez, D., & Kempenaers, B. (2017). Effects of experimental night lighting on the daily timing of winter foraging in common European songbirds. *Journal of Avian Biology*, *48*(6), 862–871. https://doi.org/10.1111/jav.01232

Webb, W. C., Marzluff, J. M., & Hepinstall-Cymerman, J. (2011). Linking resource use with demography in a synanthropic population of common ravens. *Biological Conservation*, *144*(9), 2264–2273. https://doi.org/10.1016/j.biocon.2011.06.001

Wenig, K., Pacher, L., & Bugnyar, T. (2022). Testing the contagious nature of allopreening: bystander ravens are affected by conspecifics' affiliative interactions. *Animal Behaviour*, *184*, 71–80. https://doi.org/10.1016/j.anbehav.2021.12.009

White, C. (2005). Hunters Ring Dinner Bell for Ravens: Experimental Evidence of a Unique Foraging Strategy. *Ecology*, *86*(4), 1057–1060. https://doi.org/10.1890/03-3185

Zhang, M. (2020). The use and limitations of null-model-based hypothesis testing. *Biology and Philosophy*, *35*(2), 1–22. https://doi.org/10.1007/s10539-020-09748-0

Chapter 2: Development of a Raven Ethogram in an Urban Winter Landscape

2.1 Abstract

Ethograms are a staple in behavioral research, allowing for consistent data to be collected by multiple individuals. Despite this, widely available ethograms are difficult to find. Here, we create an ethogram of general wild common raven, *Corvus corax*, behaviors in interior Alaska using 30-minute opportunistic focal animal sampling methods within four locations of varying urbanization in Fairbanks, Alaska. This data was obtained November-April of 2019-2021, as this is when large populations of common ravens are active in the chosen locations. Our goal was to create an ethogram that can be utilized in future research as a consistent guide of raven behavior. In addition, this ethogram was used to determine what attributes affect these behaviors using hierarchical clustering to determine the relationship strength and direction of all variables. The analysis showed there were obvious behavior interactions such as interacting by objects and locomotion in air, indicating the ethogram was successful in recording behavior interactions. We also discovered that wild ravens exhibit predictable behavior patterns, indicating that raven behavior can be followed and used to compare behavioral changes based on climate change and/or increasing urbanization of habitats.

2.2 Introduction

Ethograms are pieces of information for conducting behavior research, consisting of a behavior dictionary of an animal to which future researchers can refer in order to collect data in a consistent manner such that it is comparable across space and time (Howe et al., 2015). Despite this, there are multiple species, including the common raven (*Corvus corax*), that either lack universally accessible ethograms or have ethograms that are experiment specific. To date, ethograms for raven behavior were developed using captive animals in experimental settings, resulting in behavior catalogues that are ineffective for general circumstances (Adriaense et al., 2019; Cory, 2016; Hegedič, 2016; Lambert et al., 2017). Here, we create the first ethogram of wild raven behavior in the sub-Arctic winter landscape from which future projects can be derived.

In addition to a general ethogram, we also create an ethogram for generalized reciprocity behaviors. Most behavioral studies focus on direct or indirect reciprocity, where an individual performs a behavior based on the prior behavior experience with a known individual, either through direct experience with that individual or indirectly through knowledge of that individual helping another individual (Nowak & Roch, 2007; Rutte & Taborsky, 2007). However, we focus on generalized reciprocity, where individuals perform behaviors based on previous experiences by anonymous individuals (Pfeiffer et al., 2005; Rutte & Taborsky, 2007). With this in mind, all of our behaviors are categorized with the assumption that a raven is behaving based on a prior "tit for tat" relationship, and some of our categorized reciprocal behaviors involve variables, such as objects, which cannot reciprocate a raven's actions. As such, our behaviors could simply be consistent learned behavioral responses to stimuli in the environment and further research could help to determine whether these behaviors are indeed reciprocal. Specifically, we look into how individuals within specific raven communities respond to the actions of another individual or moving object, including cars, other ravens, people, and species other than ravens or people. Based on findings that ravens tend to perform long-term reciprocation rather than short term reciprocity (Fraser & Bugnyar, 2012), our theory is that these varying raven groups will exhibit different behaviors based on prior experiences that occurred at these locations overtime, meaning that the actions done by an individual (such as a person) at one location will elicit a different response (from a raven) than an identical action done at a different location due to the experiences had with cumulative actions in the past. This would indicate that the raven communities exhibit general reciprocal actions tied to various locations based on prior experience at these locations.

2.3 Methods

2.31 Study System

This research was conducted in Fairbanks North Star Borough, Alaska, USA (Figure 2.1). The area spans 1.9×10^4 km^2 and has an estimated population of 98,971 people (*United States Census Fairbanks, Alaska*, 2019), with most people living in or near the cities of Fairbanks and North Pole. Using the Global Monitoring Laboratory database online, the sunrise and sunset data was found using latitude 64.8401, longitude -147.72 and the Anchorage time zone for the shortest (Dec 21) and longest (Jun 21) days of the year to calculate the average hours of daylight available in Fairbanks, AK on average for Jan 2019 – Dec 2021 and during the times of the study (*National Oceanic & Atmospheric Administration Solar Calculator*, 2022). In addition, I used the online data portal from the Alaska Climate Research Center to determine the average monthly maximum and minimum temperatures at the Fairbanks station from Jan 2019 – Dec 2021 and used the daily maximum and minimum temperatures for the specific study period (Alaska Climate Research Center, 2022). Average temperatures and daylength in the study area range between -34°C to 24°C and 3.7 – 22 hours, respectively (Alaska Climate Research Center, 2022; *National Oceanic & Atmospheric Administration Solar Calculator*, 2022). During the period of this study (Nov-Apr), temperatures ranged from -43°C to 11°C and photoperiod was between 3.7 and 15 hours. The population size of common ravens in Fairbanks is unknown, but a single roost near Fairbanks had at least 800 ravens in 2008 (Schwan, 2008).

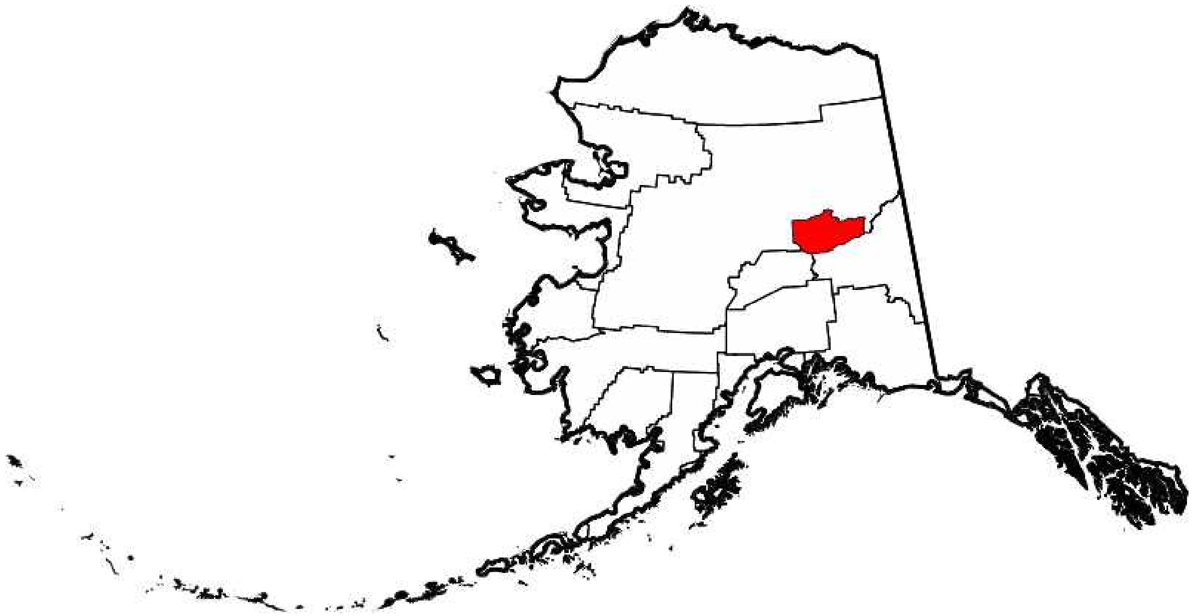

Figure 2.1: Alaska, with Fairbanks North Star Borough indicated in red (Benbennick, 2006)

2.32 Field Work

This research project utilized non-intrusive behavior sightings made from a distance by the master's graduate student and advisor. The advisor and I conducted field studies from November 2019 to April 2020 and November 2020 to April 2021 (Appendix A, B, C). The sites include a large grocery store and three transfer stations (garbage dumps) located on Goldstream Road, Farmers Loop East, and across from the University of Alaska Fairbanks (UAF) campus (Figure 2.2) (Baltensperger et al., 2013). The four sites are within 15 km of each other and have varying levels of urbanization, determined by estimated amount of human traffic, with Goldstream being the least urbanized and the grocery store being the most urbanized. All observations were conducted in the parking lots and georeferenced using a Garmin eTrex 20 GPS (decimal degrees, 6 decimals, World Geodetic System of 1984 (WGS84) of a geographic datum) and aLascar EasyLog EL-USB-2-LCD datalogger placed on the roof of the vehicle to record temperature every ten seconds.

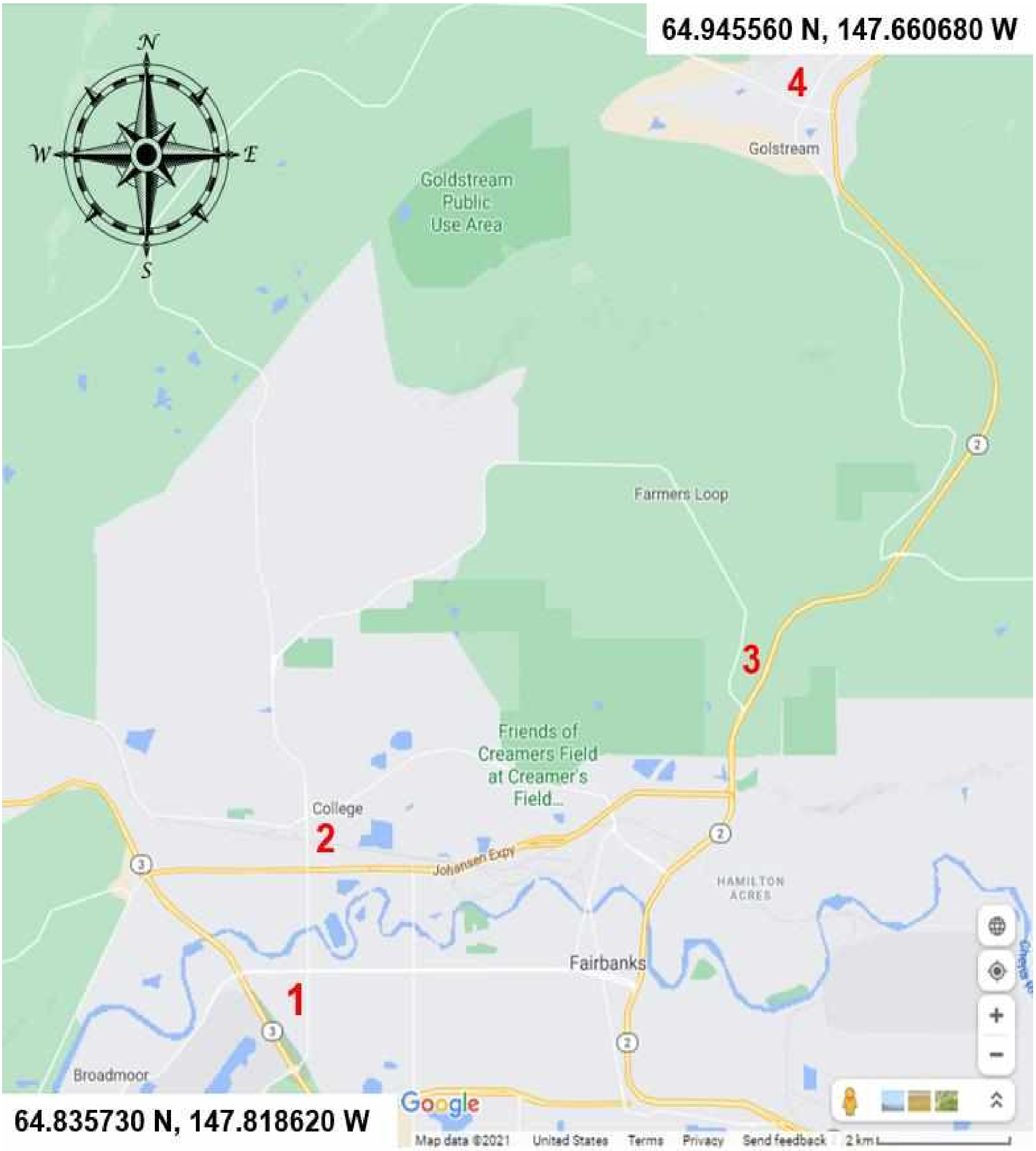

Figure 2.2: Fairbanks, Alaska observation sites. They are numbered from highest level of urbanization (1) to lowest level of urbanization (4). 1 – Grocery Store (64.836330, -147.816150), 2 – University Transfer Station (64.858150, -147.810970), 3 – Farmers Loop Transfer Station (64.871320, -147.674100), 4 – Goldstream Transfer Station (64.946065, -147.660297) (Google, 2021)

2.33 Study Approaches

At these sites, surveys of raven behavior were collected using three approaches during 30-minute field observations once or twice a week sometime between sunrise and sunset, which typically fell between 10:00 and 16:00 during the study period. Sites visited were randomly chosen, but we generally avoided visiting the same site twice in a row. The first protocol, snapshot data, consisted of a quick 360-degree scan count of ravens at the beginning and end of each observation period within 500 m of the site (Baltensperger et al., 2013). The second protocol, *ad-lib* data, was taken opportunistically when a raven was able to be watched clearly using a focal animal sampling method (Howe et al., 2015) (Table 2.1). When a raven moved out of sight, a new raven was chosen as the focal animal. The third approach, specific response, is a subset of the *ad-lib* dataset, where behaviors categorized as “interaction” or “reciprocity” are then further categorized into specific sub-behaviors. All approaches involved collecting data on the year, month, day, hour, minute of the hour (Minutes), minute of the day (Minutes_Day), temperature in degrees Celsius, location of the study site, estimated distance in meters from a raven to the nearest entity, and location of focal raven within the site. The location of the focal raven within the site refers to the main object a raven is on or near and includes being by a post, on the ground, in the air, by a garbage container, on a car, by a car, in a tree, by people, by other ravens, by other non-raven or non-human species, or by an object. In this context, “objects” refer to any unnatural item made of plastic, paper, cloth, etc., such as a restaurant takeout container, menstrual pad, or book. A raven was considered “by” a subject when it was within 50 meters of the subject. All work was conducted under the University of Alaska Fairbanks (UAF) Institutional Animal Care and Use Committee (IACUC) #1515447-1 permit (Appendix D).

2.34 Ethogram

We have created an ethogram (detailed descriptions of behavior) of raven behavior in Fairbanks, Alaska using opportunistic observations of ravens at our four sites over a 6-month period (Table 2.1).

Table 2.1

An ethogram of Common Raven behavior in Fairbanks AK, which defines each behavior variable. Ad-lib refers to the behaviors that were captured opportunistically, while Specific Response is a subset of Reciprocity and Interaction behaviors taken from the ad-lib dataset

Ethogram of Fairbanks Raven Behavior

Behavior	**Description**
Ad-lib	
Calling	any vocalization
Eating	raven lowers beak into something and lifts it up while opening and closing the beak
Groom	any movement where a raven uses its beak or feet on its own body
Interaction	anytime a raven is interacting with an object outside of other behavior contexts listed
Locomotion	movement from one place to another, horizontally or vertically; includes flying
Observe	a raven looking around slowly, typically on high perch; may focus on a specific entity
Reciprocity	any action in response to another organisms' actions or presence
Resting	sitting/standing without moving head or body around
Rubbing	scraping beak against a tree or object
Searching	actively seeking items, typically indicated by looking into garbage containers and/or using beak to dig through objects within containers
Specific Response	
Attack	any act of chasing or pecking or jumping at another raven who is not holding food
Avoid	when a raven moves when approached by a car or living being
Court	actions such as gentle beak or foot grabbing or social grooming, between non-aggressive couple
Interact	any other interaction with an object not described
Peck	any act of a raven quickly moving its beak at and away from an object
Play	actions such as flipping or throwing non-food object >10 sec or flipping or swooping in the air
Steal	any act of interacting with another raven who is holding food, usually in attempt to take the food
TakeOut	when a raven grabs a food item or object and leaves with it, without being chased

In determining the behavior classifications, we started out by noting and describing every behavior observed. We then took these notes and categorized the behaviors into groups based on similarity and number of observations. The *ad-lib* dataset contains the general behavior categories, while specific response contains specific behaviors noted within the "reciprocity" and “interaction” behavior groups. Calling refers to any vocalization produced by a raven, including burbling noises, long series of caws, and short calls. While the types of calls may be made to induce responses, these individual call types were not made enough to extract useful data from them. Eating involves movement of the beak from a low position to a high position accompanied by the opening and closing of the beak. This description is used in contrast to interaction and searching behaviors in which similar movements are made and can be difficult to distinguish from far distances. Searching is similar in that a raven moves its head in a downward or side-to-side fashion, which is potentially followed by the movement of an object. However, searching typically doesn’t involve an upward motion or a repeated closing and opening of the beak. Interaction behaviors are the other actions with a typically singular object which can use some of the other actions listed, but typically do not involve any opening or closing of the beak aside from a few pecks. Grooming involves any self-directed action of moving the beak through the feathers or feet of a raven. Grooming of another raven was recorded under “reciprocity” and further categorized under “courting” as these actions only occurred during breeding season and assumed a previous positive experience with the other raven. Locomotion involves any movement from one location to another, including walking, hopping, and flying. This was initially grouped with flying separate, but with the use of the variables “on_ground” and “in_air” the specific classification was redundant. Observing is a more passive form of looking around an area and typically involves a high perch where a raven’s head either moves laterally or will tilt, letting their eyes scan the horizon or focus on a specific individual. This differs from searching behaviors, where a raven is actively searching in a specific location typically close to the object of interest. Resting involves any action where a raven appeared to be still, not looking around, in either a sitting or standing position. Rubbing involved the scraping of the sides of a raven’s beak against a tree or an object, such as a sign. This was typically performed in a series of two or more scraping actions, similar in how one may use the edge of a rock to scrape mud off one's boots. Last on the *ad-lib* list is reciprocity behaviors, categorized simply by the response a raven has to the presence or action of another individual/object. Reciprocity is used as a categorical whole, consisting of varying types of responses outlined in the specific response dataset, of which the data is used to form an assumed community history from which these reciprocal actions are decided.

The specific response dataset consists of the majority of reciprocity and interaction behaviors observed during field studies. Initially, there were more behavior classifications, but the limited observations of these behaviors resulted in the grouping of these behaviors into broader categories, seen in the ethogram. Attacking is the advancement of a raven onto another raven who is not holding food. This assumes a prior relationship where either the attacker has established a higher ranking than or has had a negative encounter with the victim. Avoiding involves a raven moving when approached by a car or another living being. This assumes the raven has had a negative experience with the other in the past and should avoid being near it. However, this behavior was commonly paired with the distance from the offender, indicating varying levels of comfort between an individual and the offender. Courting includes social grooming, gentle movements, and overall positive interactions with a singular other raven. For this, the reciprocal actions are seen immediately between the two birds, but it can also be assumed they had prior positive experiences with each other in the past to be able to court each other. Interacting, pecking, and playing with an object are similar in description, with pecking involving quick back and forth movements of the beak towards an object, playing involving repeated flipping, throwing, or other combination of actions lasting greater than 10 seconds, and interacting involving all other behaviors with an object. An example of playing with an object would be a raven doing a thorough investigation of an object by manipulating it and seeing what it may do for a long period of time, while a raven just interacting with an object may flip it once or twice and then leave it alone. Pecking could indicate either a negative or positive experience with an object, as pecking can be an act of aggression or the best way to open a container that may contain a reward for the effort. Playing with an object would indicate a lack of a negative experience with an object, as the raven has likely just found a new object to explore or knows that manipulating the object is a positive experience. In addition, playing includes flipping and swopping in the air with other ravens, indicating a past with positive encounters with these ravens. Stealing involves a raven attempting to take a food item from another raven, and could involve actively pecking at the raven, chasing a raven holding food, or stealing a food item within a one-foot radius of the raven. With ravens generally being social creatures, where observations were made of a single raven calling upon finding food so others may join in, this stealing behavior could represent a prior negative experience with an individual or area. This may or may not be immediately followed by a takeout behavior, where a raven keeps a food item/object in its beak/talons and leaves with it. Simply put, the raven is taking that item out of an area, which may indicate a mistrust of other individuals in the area.

2.35 Statistical Analysis

This study is a behavioral investigation using hierarchical cluster analysis to determine whether certain behaviors are associated with one another. Hierarchical cluster analysis takes a complete dataset and creates groups of small clusters of data that are part of a larger cluster, typically shown in the form of a dendrogram (Krastev & Voinohovska, 2021). Similar variables are clustered closer together, allowing for a visual representation of behavior association.

To achieve this goal, the varclus function in R studio was used to create a Spearman's similarity matrix to determine the relationship strength and direction of all variables (Appendix E, F, G). The varclus function performs a hierarchical cluster analysis of the variables which can place variables into clusters that are then analyzed as a single variable, while also pairwise deleting empty datapoints and combining uncommon cells of dummy variables automatically (*Varclus: Variable Clustering*, n.d.). Squared Spearman correlation is used as a default and finds monotonic nonlinear relationships. The Spearman similarity matrix allowed us to evaluate what factors, if any, affect raven behavior; a graphical representation of the spearman rank correlation was used to visually examine the relatedness of variable groups.

In addition, the choice to evaluate every variable at once without combining similar aspects such as day, month, year, hours, or minutes was imparted to allow for the discovery of raven behavior patterns that may be missed when variables are combined. Hourly, daily, monthly, and yearly patterns could be missed when these aspects are all combined into one temporal variable (Schneider, 2001).

2.4 Results

Over the course of the study, we visited the sites a combined total of 42 times. From this, we ended up with a sample size of 1745 data rows for *ad-lib* and 476 rows for specific response. After running this data through R-studio, the data showed multiple correlative patterns between variable clusters (Figs. 2.3 and 2.4). When interpreting the analysis results of the Spearman dendrograms, the y-axis gives the proportion of variance explained by the x-axis variable clusters (Sarle, 1999). The remaining percentage out of 100 indicates the proportion of variance unexplained by the x-axis variables, thereby indicating the remaining variation is due to either other variables or chance.

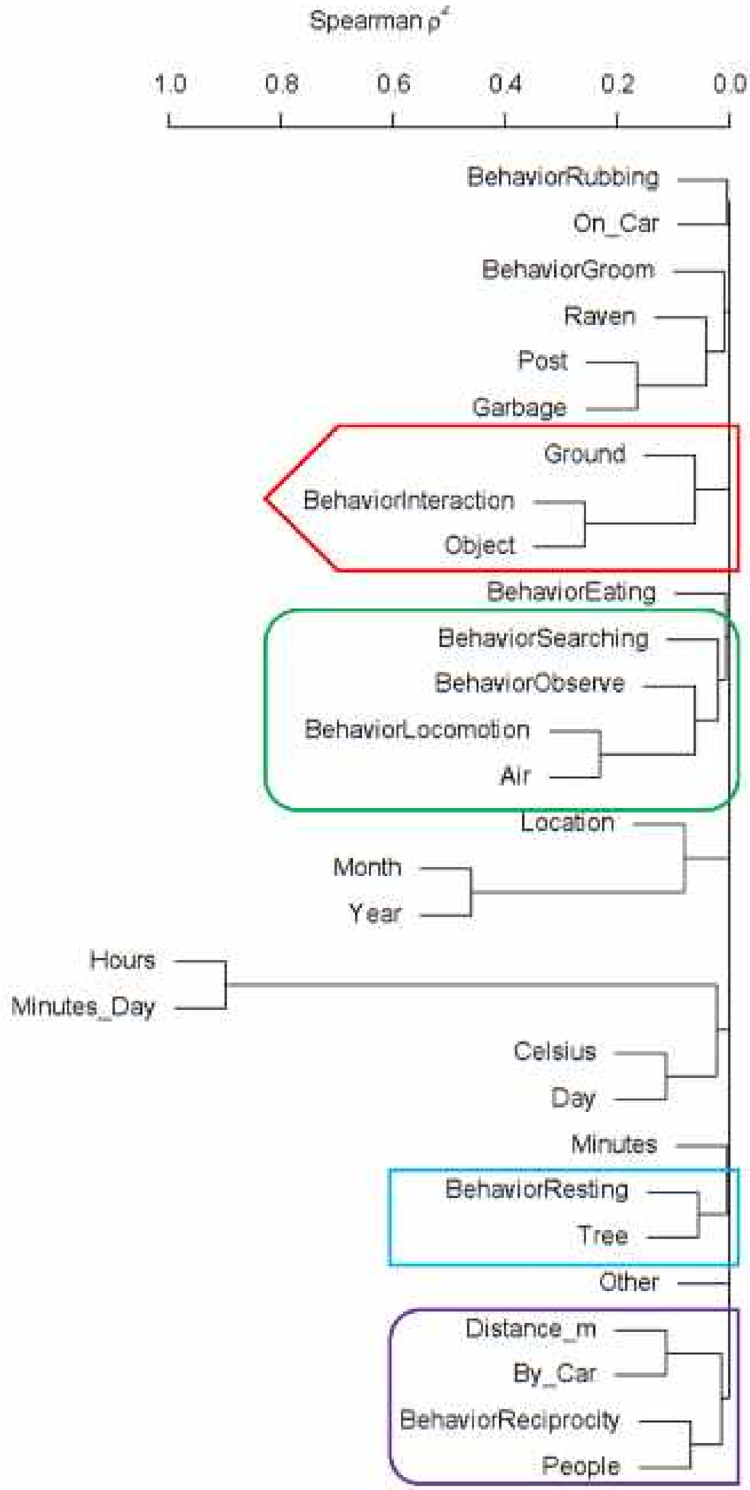

Figure 2.3: Ad-lib Varclus Plot – A Spearman rho similarity measure plot showing levels of relatedness through clustered data. Distances between branches indicate levels of similarity. Each shape is added by the authors and represents the clusters which indicate the strongest correlations of behaviors with other behaviors and variables.

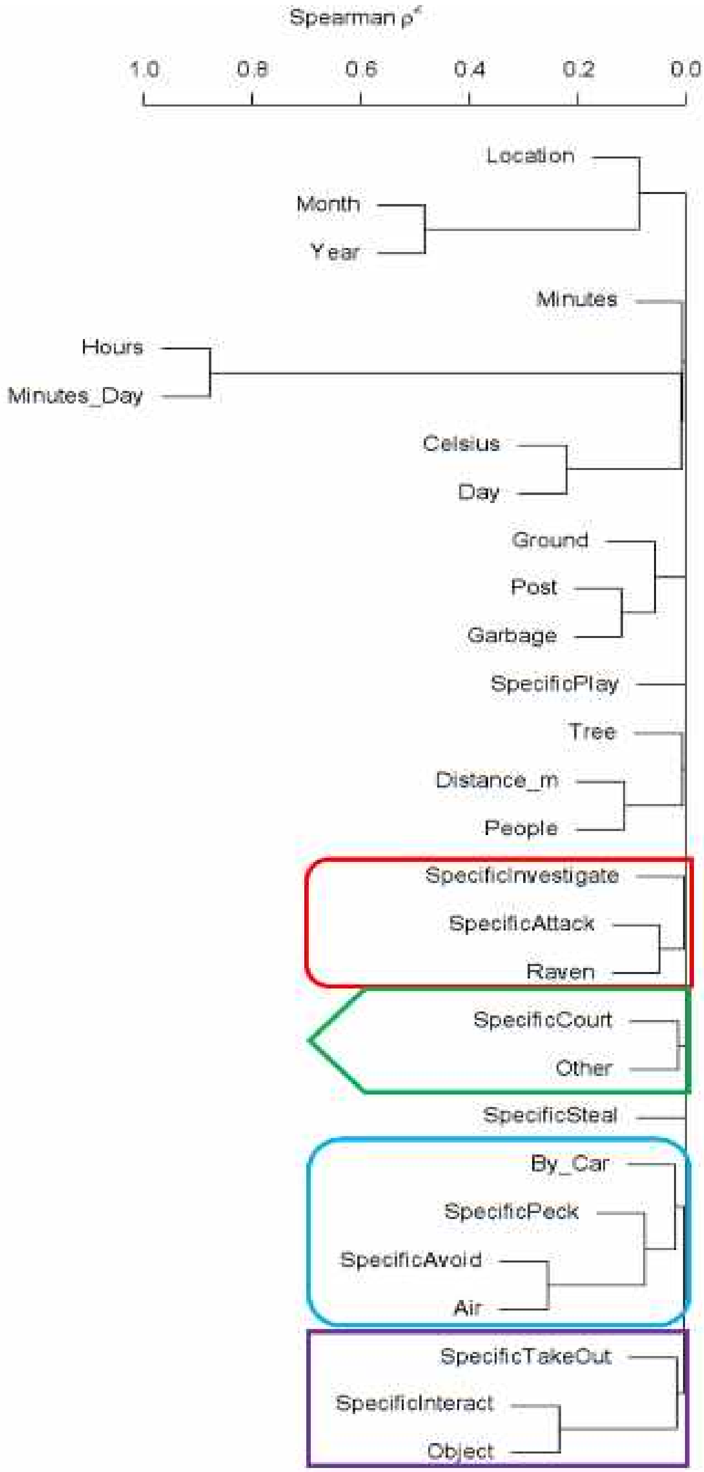

Figure 2.4: Specific Response Varclus Plot – A Spearman rho similarity measure plot showing levels of relatedness through clustered data. Distances between branches indicate levels of similarity. Each shape is added by the authors and represents the clusters which indicate the strongest correlations of behaviors with other behaviors and variables.

For the *ad-lib* dataset, the strongest correlations are between interaction behaviors with objects, locomotion by air, resting in trees, and reciprocal behaviors by people or by cars depending on the distance from the car (Figure 2.3). In addition, interacting with objects frequently correlates to being on the ground, while flying correlates with observing and searching behaviors. For the specific response dataset, the strongest correlations are between avoidance behaviors in the air, interacting by objects, attacking by other ravens, and courting near other organisms (Figure 2.4). In addition, interacting with objects correlates with takeout behaviors, avoiding by flying correlates with pecking behaviors and being near cars, and attacking other ravens also correlates with investigation behaviors. Overall, these obvious behavior groupings may not seem significant, but these results quantify raven behavior as a whole, revealing a behavior map for how ravens spend their time in the wild.

In addition to the varclus plots, we also created similarity matrix tables through varclus to show the highest correlations between behaviors and individual variables for the *ad-lib* (Figure 2.5) and specific response (Figure 2.6) datasets. In examining *ad-lib* predictors that correlate over 10% of the time, we see interaction behaviors by object having the highest correlations at 26%. Second is locomotion in air at 23%, followed by searching behaviors by garbage at 12% (Figure 2.5). These obvious behavior interactions having the highest correlations indicate that the recorded behaviors for the ethogram are accurate.

In examining specific response predictors that correlate over 10% of the time, we see avoidance behaviors in air having the highest correlations at 26% (Figure 2.6). Second is interacting by objects at 23%, followed by takeout behaviors in air at 14%. Tied for fourth is courting on post and pecking in air at 11%, while our fifth highest predictor is avoidance by cars at 10%. Overall, this shows that avoidance behaviors are the easiest to predict.

	Eat	Groom	Interact	Locomotion	Observe	Reciprocity	Rest	Rub	Search
Distance_m	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.00
Celsius	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
Day	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Month	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Year	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.00
Hours	0.01	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00
Minutes	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00
Minutes_Day	0.01	0.00	0.00	0.01	0.01	0.00	0.00	0.00	0.00
Location	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.01
Eat	1	0.00	0.01	0.03	0.01	0.01	0.00	0.00	0.01
Groom	0.00	1	0.00	0.01	0.01	0.00	0.00	0.00	0.00
Interact	0.01	0.00	1	0.06	0.03	0.02	0.00	0.01	0.02
Locomotion	0.03	0.01	0.06	1	0.08	0.06	0.01	0.01	0.04
Observe	0.01	0.01	0.03	0.08	1	0.03	0.01	0.01	0.02
Reciprocity	0.01	0.00	0.02	0.06	0.03	1	0.00	0.00	0.02
Rest	0.00	0.00	0.00	0.01	0.01	0.00	1	0.00	0.00
Rub	0.00	0.00	0.01	0.01	0.01	0.00	0.00	1	0.00
Search	0.01	0.00	0.02	0.04	0.02	0.02	0.00	0.00	1
Post	0.01	0.02	0.00	0.06	0.09	0.01	0.00	0.00	0.03
Ground	0.00	0.00	0.06	0.00	0.00	0.00	0.00	0.00	0.00
Air	0.02	0.01	0.01	0.23	0.06	0.03	0.01	0.01	0.02
Garbage	0.00	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.12
On_Car	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Tree	0.00	0.01	0.00	0.01	0.00	0.00	0.06	0.00	0.00
People	0.00	0.00	0.01	0.01	0.00	0.07	0.00	0.00	0.00
By_Car	0.00	0.00	0.00	0.01	0.00	0.05	0.00	0.00	0.00
Other	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00
Raven	0.00	0.01	0.00	0.00	0.01	0.02	0.00	0.00	0.01
Object	0.01	0.00	0.26	0.02	0.02	0.00	0.00	0.00	0.01

Figure 2.5 – Ad-lib Similarity Matrix. A heat map of relatedness between a behavior (top) and a factor (left). 0 is low and lighter in color, 1 is high and darker in color. These correlations prescreen for signals in our data.

2.5 Discussion

This is the first known ethogram done for ravens in Alaska and in winter. While it can arguably be fine-tuned, we wanted to provide a foundation for future ethograms and behavioral research on winter ravens. Looking into the *ad-lib* dataset, we discovered multiple correlative

	Attack	Avoid	Court	Interact	Investigate	Peck	Play	Steal	TakeOut
Distance_m	0.00	0.03	0.03	0.00	0.00	0.02	0.02	0.00	0.00
Celsius	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.01
Day	0.00	0.00	0.00	0.01	0.00	0.00	0.01	0.01	0.00
Month	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.01	0.00
Year	0.01	0.00	0.00	0.01	0.01	0.00	0.00	0.02	0.00
Hours	0.00	0.00	0.00	0.01	0.01	0.03	0.00	0.00	0.00
Minutes	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
Minutes_Day	0.01	0.00	0.00	0.01	0.01	0.02	0.00	0.00	0.00
Location	0.01	0.03	0.03	0.01	0.00	0.01	0.00	0.00	0.00
Attack	1	0.01	0.00	0.01	0.00	0.02	0.00	0.00	0.00
Avoid	0.01	1	0.01	0.06	0.01	0.08	0.01	0.01	0.02
Court	0.00	0.01	1	0.01	0.00	0.01	0.00	0.00	0.00
Interact	0.01	0.06	0.01	1	0.01	0.08	0.01	0.01	0.02
Investigate	0.00	0.01	0.00	0.01	1	0.02	0.00	0.00	0.00
Peck	0.02	0.08	0.01	0.08	0.02	1	0.01	0.01	0.02
Play	0.00	0.01	0.00	0.01	0.00	0.01	1	0.00	0.00
Steal	0.00	0.01	0.00	0.01	0.00	0.01	0.00	1	0.00
TakeOut	0.00	0.02	0.00	0.02	0.00	0.02	0.00	0.00	1
Post	0.00	0.02	0.11	0.00	0.01	0.02	0.00	0.00	0.01
Ground	0.01	0.05	0.01	0.01	0.00	0.06	0.00	0.00	0.00
Air	0.00	0.26	0.02	0.08	0.02	0.11	0.03	0.00	0.14
Garbage	0.01	0.02	0.02	0.03	0.00	0.01	0.01	0.00	0.01
Tree	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
People	0.00	0.09	0.01	0.03	0.00	0.03	0.00	0.00	0.00
By_Car	0.01	0.10	0.01	0.02	0.00	0.02	0.00	0.00	0.01
Other	0.00	0.00	0.01	0.01	0.01	0.00	0.00	0.00	0.01
Raven	0.05	0.00	0.03	0.03	0.00	0.00	0.01	0.02	0.03
Object	0.02	0.09	0.01	0.23	0.00	0.00	0.00	0.02	0.04

Figure 2.6 – Specific Response Similarity Matrix. A heat map of relatedness between a behavior (top) and a factor (left). 0 is low and lighter in color, 1 is high and darker in color. These correlations prescreen for signals in our data.

patterns between behaviors and their contexts within the dendrogram varclus provided (Figure 2.3). Interaction behaviors occurring near objects is one of our highest behavior predictor groups with ~26% of the variance explained, and that interacting with objects correlates to being on the ground ~6% of the time. The similarity matrix with behavior pairs supports this, with the highest correlation also being interaction near objects 26% of the time (Figure 2.5). This grouping is logical, as objects are commonly found on the ground and ravens are more likely to interact with objects than with other ravens or individuals (Osvath et al., 2014; Osvath & Sima, 2014; Wenig et al., 2021). Our second highest proportion of variance is ~23% of locomotion behaviors explained with in the air, which is likely due to flying being an effective way for a raven to escape danger without being followed and is the quickest way to move between various locations of interest (Figure 2.3). This is also supported by the similarity matrix, with locomotion in air also having a 23% correlation (Figure 2.5). The third highest correlation within the similarity matrix is searching by garbage at 12%, which is also a reasonable behavior pattern, as garbage containers are full of potential food items that ravens must search for (Boarman & Heinrich, 1999). As for the remainder of the dendrogram, flying is commonly grouped with observing with 6% of variance explained and searching with 2% of variance explained, which is logical as flying provides a greater range of sight. As for reciprocity behaviors, which are further evaluated in the specific response dataset, these are explained approximately 6% of the time around people and around 1% of the time with cars at certain distances (Figure 2.3). This behavior most likely occurs most near people as people can be less predictable in behavior than cars and have a wider variety of movements that can potentially harm ravens. In addition, the distance between a raven and a potential threat such as people and cars and how that affects reciprocity behaviors is also logical, as threats at a farther distance are less threatening than those nearby. Similar results have been seen in waterbirds, with them generally showing shorter flight initiation distances around vehicles than people (McLeod et al., 2013), and with American Crows (*Corvus brachyrhynchos*) exhibiting reaction responses to cars that align with predictable car behavior (Mukherjee et al., 2013).

When examining the behavior cluster grouping of the specific response dataset, we see avoidance behaviors having ~25% proportion of variance explained with being in the air, indicating that ravens prefer to fly away from potential threats such as cars, people, and other ravens or organisms (Figure 2.4). This relationship is supported in the similarity matrix, with avoidance correlating 26% of the time with being in the air (Figure 2.6). The specific response dataset also gives a similar result as the *ad-lib* dataset for interaction by objects, with the dendrogram indicating interaction being explained ~25% of the time by objects, and the similarity matrix giving a 23% correlation. The similarity matrix then indicates that the next highest correlation is takeout behaviors 14% of the time in air, indicating that ravens like to fly away with items, which makes sense as flying gets ravens farther away from potential thieves (Beck et al., 2020; Bugnyar & Heinrich, 2006). Next is courting 11% of the time on posts and pecking 11% of the time in air. Courting on posts may be attributed to ravens being able to see threats around them without the fear of being bothered by fellow ravens due to limited perching space. Pecking in the air is difficult to do, and the correlation is supported in the dendrogram with an approximate 6% proportion of variance explained. Finally, avoidance behaviors correlating 10% of the time by cars makes sense as corvids are known to avoid vehicles when necessary (Mukherjee et al., 2013).

2.6 Conclusion

Using field observations, we were able to successfully create a general behavior dictionary of interior Alaskan common ravens in winter that can be used for behavioral research in the future. These include both general and interaction-specific behaviors occurring in the winter urban landscape of interior Alaska. From these behaviors, we found patterns in our data indicating multiple correlations between behavior-variable groups and individuals. Looking into some of the less obvious behavior patterns could lead to future insights into raven behavior, such as research looking into courting behaviors and why some ravens court in the open on telephone poles and light posts as opposed to in the forest. Knowing the behavior patterns of these ravens now can help us to compare behavior changes based on climate change and/or increasing urbanization of wild habitats in the future.

2.7 References

Adriaense, J. E. C., Martin, J. S., Schiestl, M., Lamm, C., & Bugnyar, T. (2019). Negative emotional contagion and cognitive bias in common ravens (Corvus corax). *Proceedings of the National Academy of Sciences of the United States of America*, *166*(23), 11547–11552. https://doi.org/10.1073/PNAS.1817066116

Alaska Climate Research Center. (2022). https://akclimate.org/data/data-portal/

Baltensperger, A. P., Mullet, T. C., Schmid, M. S., Humphries, G. R. W., Kövér, L., & Huettmann, F. (2013). Seasonal observations and machine-learning-based spatial model predictions for the common raven (Corvus corax) in the urban, sub-arctic environment of Fairbanks, Alaska. *Polar Biology*, *36*(11), 1587–1599. https://doi.org/10.1007/s00300-013-1376-7

Beck, K. B., Loretto, M.C., & Bugnyar, T. (2020). Effects of site fidelity, group size and age on food-caching behaviour of common ravens, Corvus corax. *Animal Behaviour*, *164*, 51–64. https://doi.org/10.1016/j.anbehav.2020.03.015

Benbennick, D. (2006). *Map of Alaska highlighting Fairbanks North Star Borough*. Wikimedia Commons. https://commons.wikimedia.org/wiki/File:Map_of_Alaska_highlighting_Fairbanks_North_Star_Borough.svg

Boarman, W., & Heinrich, B. (1999). Common Raven (Corvus corax). *The Birds of North America*, *476*, 1–32. https://doi.org/10.2173/bow.comrav.01

Bugnyar, T., & Heinrich, B. (2006). Pilfering ravens, Corvus corax, adjust their behaviour to social context and identity of competitors. *Animal Cognition*, *9*(4), 369–376. https://doi.org/10.1007/s10071-006-0035-6

Cory, E. F. (2016). The rooftop raven project: An exploratory, qualitative study of puzzle solving ability in wild and captive ravens. *ProQuest Dissertations and Theses*, 165. https://search.proquest.com/docview/1797593374?accountid=168248%0Ahttp://www.yidu.edu.cn/educhina/educhina.do?artifact=&svalue=The+rooftop+raven+project%3A+An+exploratory%2C+qualitative+study+of+puzzle+solving+ability+in+wild+and+captive+ravens&stype=2&s=

Fraser, O. N., & Bugnyar, T. (2012). Reciprocity of agonistic support in ravens. *Animal Behaviour*, *83*(1), 171–177. https://doi.org/10.1016/j.anbehav.2011.10.023

Google. (2021). [Google Maps Fairbanks North Star]. Retrieved from https://www.google.com/maps/@64.8877685,-147.6854719,12z

Hegedič, M. (2016). *Frustration Or Persistence?: Evolution and Function of Affect in Creative Problem Solving Based on Study of Behavior in Common Ravens* (Doctoral dissertation, M. Hegedič).

Howe, M., Castellote, M., Garner, C., Mckee, P., Small, R. J., & Hobbs, R. (2015). Beluga, Delphinapterus leucas, Ethogram: A Tool for Cook Inlet Beluga Conservation? *Marine Fisheries Review*, *77*(1), 32–40. https://doi.org/10.7755/MFR.77.1.3

Krastev, G., & Voinohovska, V. (2021). Application of Hierarchical Cluster Analysis in the Machine Learning. *HORA 2021 - 3rd International Congress on Human-Computer Interaction, Optimization and Robotic Applications, Proceedings*, 2021–2023. https://doi.org/10.1109/HORA52670.2021.9461277

Lambert, M. L., Massen, J. J. M., Seed, A. M., Bugnyar, T., & Slocombe, K. E. (2017). An ‘unkindness’ of ravens? Measuring prosocial preferences in Corvus corax. *Animal Behaviour*, *123*, 383–393. https://doi.org/10.1016/j.anbehav.2016.11.018

McLeod, E. M., Guay, P.-J., Taysom, A. J., Robinson, R. W., & Weston, M. A. (2013). Buses, Cars, Bicycles and Walkers: The Influence of the Type of Human Transport on the Flight Responses of Waterbirds. *PLoS ONE*, *8*(12). https://doi.org/10.1371/journal.pone.0082008

Mukherjee, S., Ray-Mukherjee, J., & Sarabia, R. (2013). Behaviour of American Crows (Corvus brachyrhynchos) when Encountering an Oncoming Vehicle. *The Canadian Field-Naturalist*, *127*(3), 229–233. https://doi.org/https://doi.org/10.22621/cfn.v127i3.1488

National Oceanic & Atmospheric Administration Solar Calculator. (2022). Global Monitoring Laboratory. https://gml.noaa.gov/grad/solcalc/

Nowak, M. A., & Roch, S. (2007). Upstream reciprocity and the evolution of gratitude. *Proceedings of the Royal Society B: Biological Sciences*, *274*(1610), 605–609. https://doi.org/10.1098/rspb.2006.0125

Osvath, M., Osvath, H., & Bååth, R. (2014). An Exploration of Play Behaviors in Raven Nestlings. *Animal Behavior and Cognition*, *1*(2), 157–165. https://doi.org/10.12966/abc.05.06.2014

Osvath, M., & Sima, M. (2014). Sub-adult Ravens Synchronize their Play : A Case of Emotional Contagion? *Animal Behavior and Cognition*, *1*(2), 197–205. https://doi.org/10.12966/abc.05.09.2014

Pfeiffer, T., Rutte, C., Killingback, T., Taborsky, M., & Bonhoeffer, S. (2005). Evolution of cooperation by generalized reciprocity. *Proceedings of the Royal Society B: Biological Sciences*, *272*(1568), 1115–1120. https://doi.org/10.1098/rspb.2004.2988

Rutte, C., & Taborsky, M. (2007). Generalized reciprocity in rats. *PLoS Biology*, *5*(7), 1421–1425. https://doi.org/10.1371/journal.pbio.0050196

Sarle, W. (1999). The VARCLUS Procedure. In *SAS/STAT User's Guide* (Version 8). SAS Institute Inc.

Schneider, D. C. (2001). The rise of the concept of scale in ecology. *BioScience*, *51*(7), 545–553. https://doi.org/10.1641/0006-3568(2001)051[0545:TROTCO]2.0.CO;2

Schwan, M. (2008). *Common Raven*. http://proxy-iup.klnpa.org/login?url=http://search.ebscohost.com/login.aspx?direct=true&db=nts&AN=PB84-135862%2FXAB&site=ehost-live

United States Census Fairbanks, *Alaska*. (2019). https://www.census.gov/quickfacts/fact/table/fairbankscityalaska,fairbanksnorthstarboroughalaska/PST045218

varclus: Variable Clustering. (n.d.). RDocumentation. Retrieved July 5, 2022, from https://www.rdocumentation.org/packages/Hmisc/versions/4.7-0/topics/varclus

Wenig, K., Boucherie, P. H., & Bugnyar, T. (2021). Early evidence for emotional play contagion in juvenile ravens. *Animal Cognition*, *24*(4), 717–729. https://doi.org/10.1007/s10071-020-01466-0

Chapter 3: Using Data Mining for Behavioral Research Analysis of Sub-Arctic Common Ravens in Winter

3.1 Abstract

Machine learning and data mining are underutilized in behavioral research, despite the advantages this programming provides in pattern recognition and data interpretation. Here, we utilize machine learning methods in conjunction with a traditional ethogram to analyze sub-arctic common raven, *Corvus corax*, behavior in winter. Through the TreeNet algorithm (Salford Systems) we extracted patterns and signals from field data to create trees, confusion matrices, and receiver operating curves, giving us new insights into sub-arctic raven behavior in a winter urban landscape. From this, strong, obvious links between behaviors and certain attributes, such as interacting with objects and locomotion in air, were identified that indicate the accuracy of the machine learning program in reading datasets created from observations based on an ethogram. In addition, we discovered that ravens exhibit scheduled behavior that varies based on the level of urbanization they are exposed to, which has not been previously described with ravens. With the discovery of both an hourly and daily behavior schedule, we hypothesize that ravens are attuned to hourly human behavior patterns and the daily sun cycle, but more studies should be done to confirm this hypothesis.

3.2 Introduction

Ravens are intelligent birds, with well-documented behaviors in captive members through a variety of research studies. However, the knowledge of wild raven behavior and how they adapt to life around humans is lacking, with free-living raven studies focusing on attributes such as temperature regulation, nesting sites, and the relationship between habitat use, resource use, and demographic parameters (Powell & Backensto, 2009; Schwan & Williams, 1978; Webb et al., 2011). To rectify this, we utilize machine learning methods in R-studio 3.6.1 and Salford Predictive Modeler 8.3.2 in conjunction with a traditional ethogram to analyze sub-arctic common raven, *Corvus corax*, behavior in winter. Machine learning is becoming more prevalent in biological research, with its ability to fit predictive models to data from large and complex datasets making it a strong analysis tool for pattern recognition (Greener et al., 2022). Therefore, we plan to extract patterns and signals that could indicate whether raven communities show consistent behaviors and responses to stressors such as daylight, location, and objects or organisms in their surroundings, what specific environmental variables affect raven behavior, and if ravens vary their behaviors based on location and amount of daylight available.

To determine whether raven communities show consistent or varied behaviors and responses to stressors such as daylight, location, and objects or organisms in their surroundings, we use one and two factor dependency plots to analyze the power and direction of pattern-causing signals. For example, if a certain behavior is found to be present in ravens consistently at noon but is absent at 17:00, then it can be assumed that behavior correlates consistently with daylight. In addition, if some behaviors only occur after a certain time of day, then we would also assume that ravens vary behavior based on the changing amount of daylight available throughout the year.

To determine what specific environmental variables affect raven behavior, we created confusion matrices, variable importance tables, and receiver operating curves through TreeNet. These models provide the average probability of how well multi-categorical behaviors are predicted based on variables, provide the most important variables for predicting raven behavior, and determine how accurately observations can be classified without random chance. Therefore, if a variable has high accuracy for predicting behaviors correctly and has a high importance score, then it can be assumed that variable correlates with raven behavior. While correlation does not mean causation, correlation is still an important factor to consider in research. With correlational research, independent variables can be left unaltered, which is ideal in observational studies looking into natural behaviors. In addition, correlational research can determine the strength and direction of all variable relationships, which can help distinguish additional explanations for why something is the way it is (Curtis et al., 2015).

3.3 Methods - Quantification, Machine Learning, and Data Mining

The *ad-lib* and specific response datasets from Beausoleil et. al (unpublished) were analyzed through machine learning and pattern recognition, which involved using R 3.6.1 (R Core Team, 2019) Hmisc v4.2-0 (Harrell & Dupont, 2022) package and Salford Predictive Modeler (SPM) 8.3.2 (Humphries et al., 2018; Minitab, 2019c) (Appendix C, D). By using machine learning we find patterns through the analysis of every variable against each other. The use of multiple programs for analyzing the data allows for more accurate data investigation, as seeing consistent results indicates that the collected data has reliable patterns.

Within SPM, we applied the TreeNet algorithm to create trees, confusion matrices, receiver operating curves (ROC), and one and two-factor partial dependency plots. The TreeNet algorithm was chosen due to its ability to resist overfitting, find hard to predict patterns, and factor in potential issues such as quality errors, missing values, and outliers while it creates models (Minitab, 2019a). In essence, TreeNet uses stochastic gradient boosting to minimize predictive errors through repetitive cross-validation until the best model remains (Humphries et al., 2018). While we were unable to use cross-validation due to having numerous categorical predictors and a small dataset, we did use an exploratory training analysis to assess whether our predictors are strongly correlated to presence, absence, and type of behaviors and their environmental attributes over time (Humphries et al., 2018; Jochum & Huettmann, 2010). These trees show patterns in the data, confusion matrices show the percentage of correctly predicted classes by the program compared to the actual results, and the ROC indicates how likely a true positive result will occur over a false positive result in predicting the behavior of ravens based on the variables given (Minitab, 2019b). These ROC curves are used to determine how well a model accurately classifies observations as opposed to random chance. The area under the curve (AUC) is a measure of discrimination, with high AUCs equating to high accuracy in predicting a response. In general, any AUC less than or equal to 0.5 has no discrimination and is entirely random. Anywhere between 0.7 and 0.8 is acceptable, between 0.8 and 0.9 is excellent, and above 0.9 is outstanding and very rare (Hosmer et al., 2013). Another term for true positive rate is Sensitivity and false positive rate is 1 – Specificity (Fan et al., 2006). Finally, partial dependency plots are strong interpretation tools for TreeNet, as they are used as a visual representation of model data that indicates the average trend of a variable, showing how each variable affects the models' predictions, thus helping in the understanding of how variables contribute to predicted response after the effects of all other predictors are considered (Minitab, 2019a). In reading one variable dependency plots, the y-axis is a behavioral occurrence index of how well the tree fits, while the x-axis indicates the strength of a relationship, with a positive relationship indicated with a positive slope and vice versa, data below zero indicating an absence of the behavior, and data above zero indicates a presence of a behavior. In addition, data in between set datapoints is interpolated, meaning that a lack of data after a certain point will result in a smoothed line of best fit that is typically horizontal. These flat, parallel lines are a generalized signal found by the machine learning program whose accuracy is expressed through the receiver operating curves.

In creating these models, the variables chosen to test against behavior were year, month, hour, day, minutes of the hour (Minutes), minutes of the day (Minutes_Day), location, distance in meters (from relevant entity), temperature in degrees Celsius, post, ground, air, tree, garbage (referring to garbage containers), people, object, by car, on car, raven, and other (referring to living beings that are not ravens or people). With these variables, we could determine how accurately a machine learning approach can predict behavior in terms of known interactions, such as locomotion in air, while also allowing the model to find multiple patterns in general. The model applied balanced class weights to each behavior to force the program to treat each variable as equally important, regardless of how many times this behavior was recorded. We used an exploratory model without independent testing, specifying a minimum of two nodes per tree and maximum of 10 nodes per tree and instructed it to build 600 trees, allowing for TreeNet to find as many patterns as possible within a relationship cluster of 2-10 variables.

3.4 Results

3.41 Consistent Reactions in Raven Communities

TreeNet created one and two-predictor dependency plots which analyzed the power and direction of the signals causing the strong patterns within the observe, locomotion, interaction, searching, resting, and reciprocity behaviors of the *ad-lib* dataset found in varclus (Beausoleil et. al. unpublished). The only strong negative correlation was observing in air (Figure 3.1a). Positive correlations include locomotion in air (Figure 3.1b), interaction near objects and on the ground (Figs. 3.1c, 3.1d, and 3.2a), searching by garbage or in air (Figs. 3.1e and 3.1f), resting in trees (Figure 3.1g) and reciprocity behaviors by people and near cars (Figs. 3.1h and 3.1i), within distances less than 2 m and greater than 35m (Figure 3.1j). Using two factor dependency plots, TreeNet also indicates reciprocal behaviors are most likely to occur when both people and

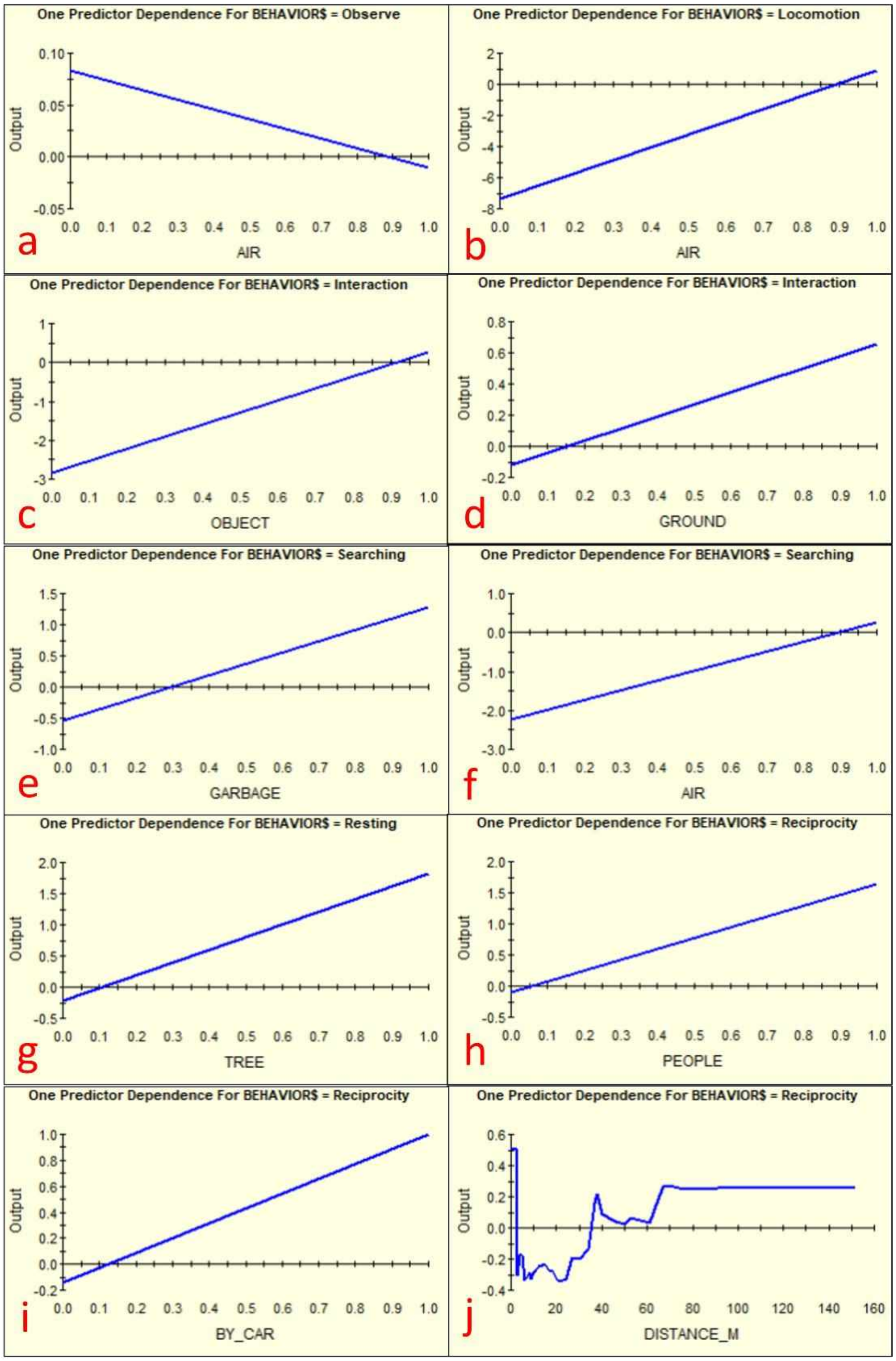

Figure 3.1: Ad-lib One Predictor Dependency Plots for relationships described in varclus. Behaviors for tables a-i were recorded in a binary manner, with 0 indicating an absence and 1 indicating a presence. Everything in between is interpolation. Output refers to the index of absence and presence. Anything above 0 indicates a behavior is likely to be present, and anything below 0 is likely to be absent.

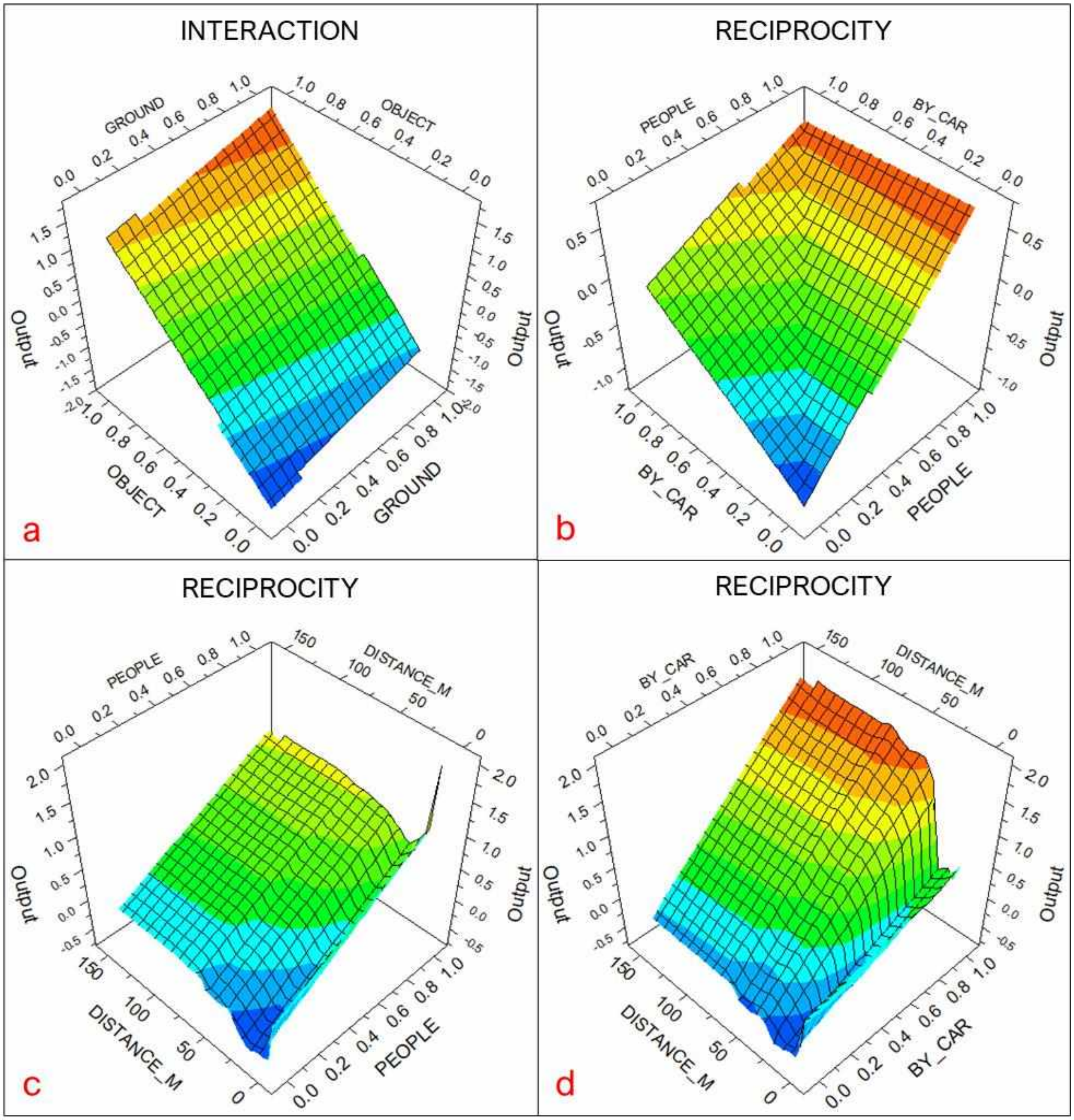

Figure 3.2: Two Predictor Dependency Plots for relationships described in varclus. The predictors for people, car, and raven are recorded in a binary fashion, while distance is a continuous variable. The binary predictors have interpolation between the values of 0 and 1. Warm colors indicate stronger relationships, while cooler colors indicate weaker relationships. Output refers to the index of absence and presence. Anything above 0 indicates a behavior is likely to be present, and anything below 0 is likely to be absent.

cars are present (Figure 3.2b) and occur more often at closer distances to people (Figure 3.2c) and farther distances from cars (Figure 3.2d).

From the specific response dataset, initial analysis using varclus found strong patterns within the investigate, attack, court, avoid, peck, interact and takeout behaviors (Beausoleil et. al unpublished). Further analysis of these patterns using TreeNet shows that the strongest negative correlations are investigating in the presence of other ravens, and pecking in air (Figs. 3.3a and 3.3b). Strong positive correlations include courting on posts and courting in the presence of other species (Figs. 3.3c and 3.3d), avoiding in air and by car (Figs. 3.3e and 3.3f), takeout by objects and in air (Figs. 3.3g and 3.3h), and attacking by ravens, interacting by objects, and pecking by cars (Figs. 3.3i, 3.3j, and 3.3k).

3.42 Factors Contributing to Winter Raven Behaviors

In analyzing what factors contribute to raven behaviors, we use TreeNet's confusion matrix, variable importance, and receiver operating curves (ROC) model outputs. Using the *ad-lib* dataset, the confusion matrix indicates there is an average probability of 78.96% to correctly predict behaviors classified into multiple categories based on variables (Table 3.1), while the specific response dataset has an average probability of 95.01% (Table 3.2) (Minitab, 2021). The average variable importance scores for both datasets indicate that minutes of the hour, minutes of the day, and distance in meters are the three most important variables in determining predicted behavior (Tables 3.3 and 3.4). This emphasizes that timing strongly matters for ravens and their behavior in the studied winter landscape of interior Alaska. This scheduled behavior has never been described with ravens but has been seen in seabirds and gulls (Spelt et al., 2021; Tyson et al., 2015). These results are shown and supported by one-predictor (univariate) partial dependence plots. Together, these results show that ravens have an hourly (Figs. 3.4 and 3.5) and

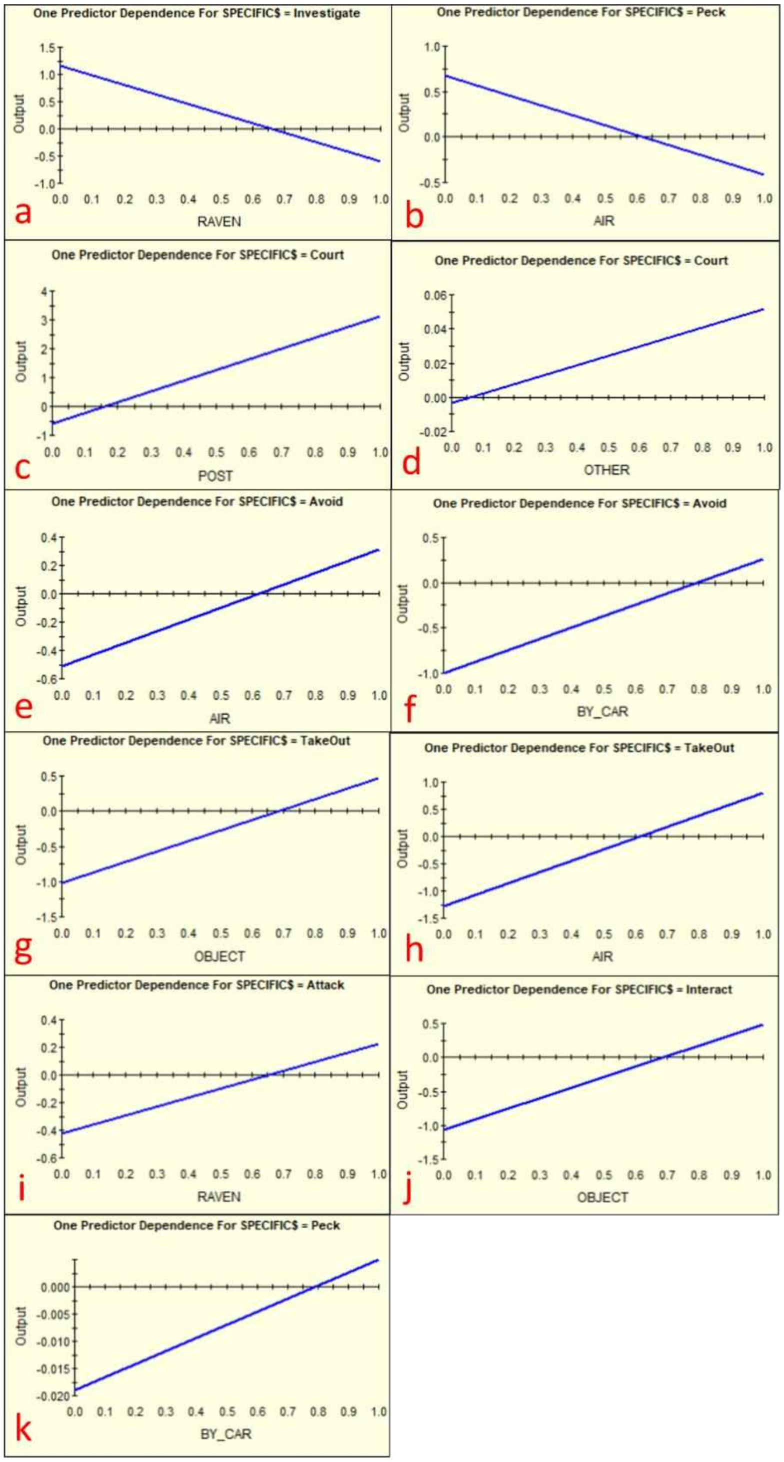

Figure 3.3: Specific Response One Predictor Dependency Plots for relationships described in varclus. Behaviors were recorded in a binary manner, with 0 indicating an absence and 1 indicating a presence. Everything in between is interpolation. The y-axis is the strength of the signal, with larger numbers indicating stronger signals. Anything above 0 is likely to happen, and anything below 0 is unlikely to happen.

daily (Figs. 3.6 and 3.7) behavior schedule and react to threats within certain distances (Figs. 3.8 and 3.9).

For the *ad-lib* dataset, interaction tends to happen at 20 minutes or later in an hour, resting is present towards the beginning of the hour, and grooming, locomotion, and reciprocity have spikes occurring at the beginning or end of the hour (Figure 3.4). The remaining behaviors

Table 3.1

Confusion Matrix of Ad-Lib Dataset. The shaded numbers indicate the number of times a behavior was correctly identified, while the rest indicate where the program would have classified the behavior given a specific set of variables.

		Predicted Classes									
Actual Class	**% Correct**	**Calling**	**Eating**	**Groom**	**Interaction**	**Locomotion**	**Observe**	**Reciprocity**	**Resting**	**Rubbing**	**Searching**
Calling	93.75	**75**	0	1	0	0	1	0	1	0	2
Eating	81.13	5	**86**	2	3	0	2	1	3	3	1
Groom	97.87	0	0	**46**	0	0	0	0	1	0	0
Interaction	76.23	4	17	4	**186**	3	9	2	4	5	10
Locomotion	55.28	13	15	8	39	**272**	32	26	14	17	56
Observe	46.18	19	14	28	15	1	**133**	8	10	25	35
Reciprocity	77.59	4	7	2	8	3	7	**180**	4	5	12
Resting	91.30	1	0	2	0	0	0	0	**42**	1	0
Rubbing	84.91	2	0	1	0	0	0	0	5	**45**	0
Searching	85.35	6	4	0	4	1	0	4	3	1	**134**
Average	78.96										
Overall	68.71										

Table 3.2

Confusion Matrix of Specific Response Dataset. The shaded numbers indicate the number of times a behavior was correctly identified, while the rest indicate where the program would have classified the behavior given a specific set of variables.

		Predicted Classes									
Actual Class	**% Correct**	**Accept**	**Attac k**	**Avoid**	**Court**	**Interact**	**Investigate**	**Peck**	**Play**	**Steal**	**TakeOut**
Accept	96.43	**54**	1	1	0	0	0	0	0	0	0
Attack	92.59	0	**25**	0	0	0	1	0	0	1	0
Avoid	97.78	1	1	**88**	0	0	0	0	0	0	0
Court	94.74	0	0	0	**18**	0	1	0	0	0	0
Interact	91.49	2	0	0	0	**86**	0	4	0	1	1
Investigate	100	0	0	0	0	0	**22**	0	0	0	0
Peck	80.17	1	7	0	1	13	1	**93**	0	0	0
Play	100	0	0	0	0	0	0	0	**10**	0	0
Steal	100	0	0	0	0	0	0	0	0	**10**	0
TakeOut	96.88	0	0	0	0	0	0	0	0	1	**31**
Average	95.01										
Overall	91.81										

Table 3.3

Average Variable Importance Score for the Ad-Lib dataset. A higher score indicates greater importance in determining predicted behavior

Variable	Score
Minutes	100.00
Minutes_Day	97.76
Distance_M	80.30
Celsius	62.29
Day	59.75
Air	45.44
Raven	42.19
Object	41.32
Month	39.53
Location	36.65
Post	35.62
Garbage	34.05
Year	31.85
Tree	31.08
By_Car	30.01
People	26.98
Ground	26.24
Hours	21.77
Other	17.82
On_Car	1.97

Table 3.4

Average Variable Importance Score for the Specific Response dataset. A higher score indicates greater importance in determining predicted behavior.

Variable	Score
Minutes	100.00
Minutes_Day	95.94
Distance_M	80.93
Celsius	65.06
Day	63.88
Raven	62.97
Air	62.77
Object	58.64
Garbage	44.91
Post	44.51
Month	42.53
Year	41.71
By_Car	39.82
Location	38.67
Ground	38.28
People	31.18
Hours	24.54
Tree	21.08
Other	18.75

appear to occur more at random throughout the day and deserve research attention in the future. During the day, interaction and locomotion behaviors occur towards the beginning of the day, grooming, observing, rubbing, and searching happen towards the beginning or end of the day, resting occurs at either the beginning, end, or midday, and calling, eating, and reciprocity behaviors are present from midday onward (Figure 3.6).

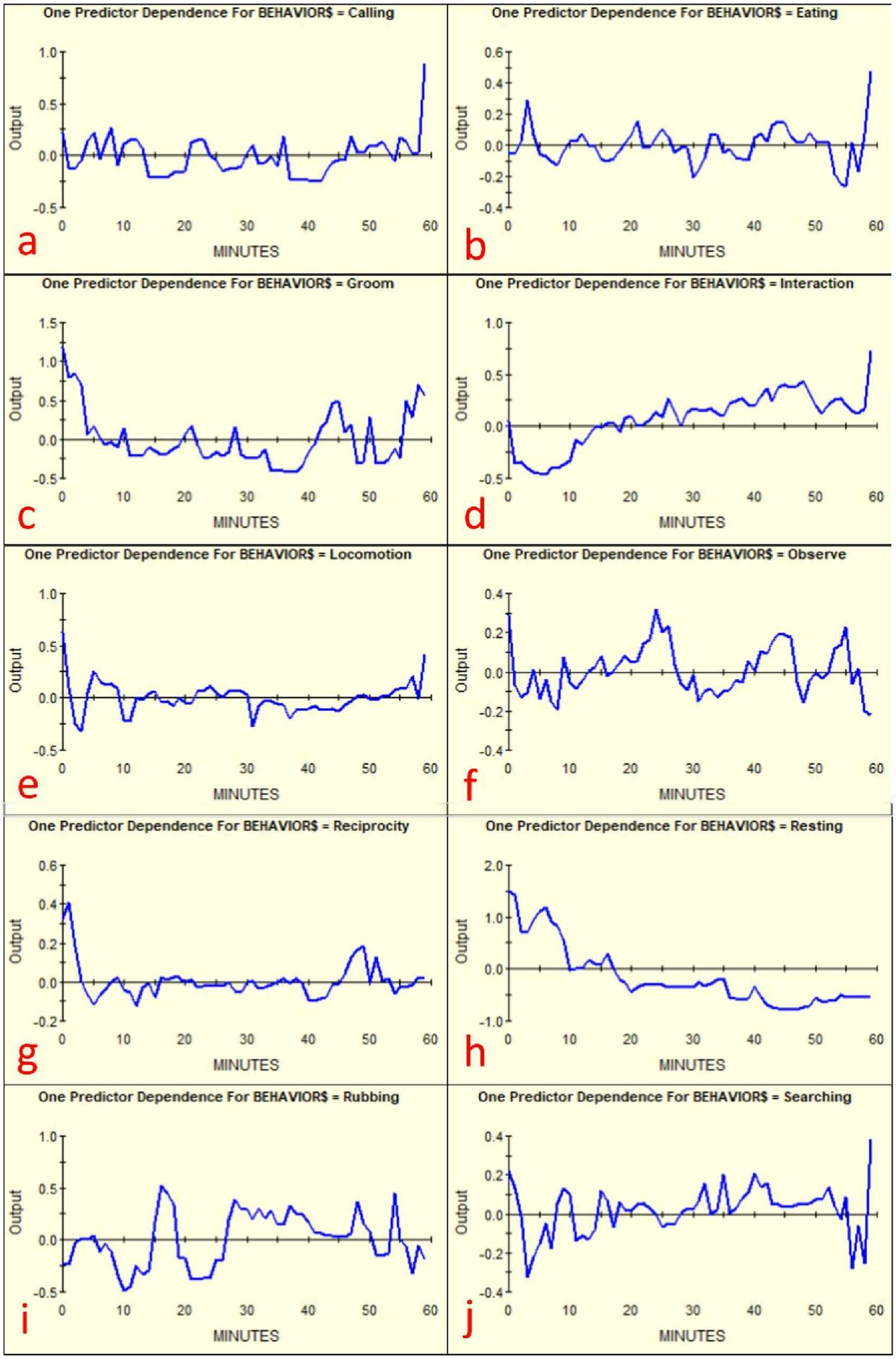

Figure 3.4 – Ad- Lib One Predictor Dependency Plot of Minutes of the Hour for all behaviors

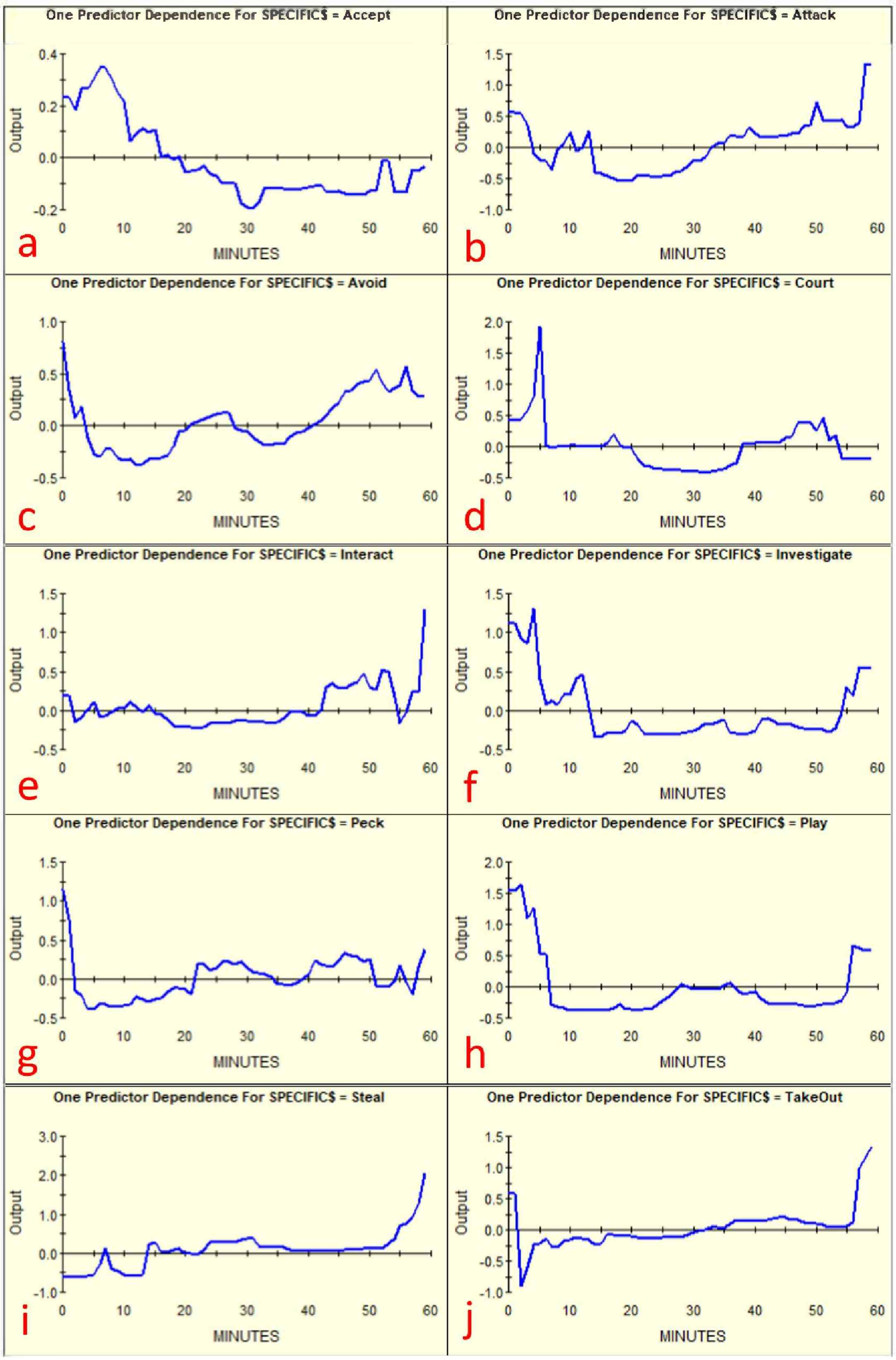

Figure 3.5 – Specific Response One Predictor Dependency Plot of Minutes of the Hour for all behaviors

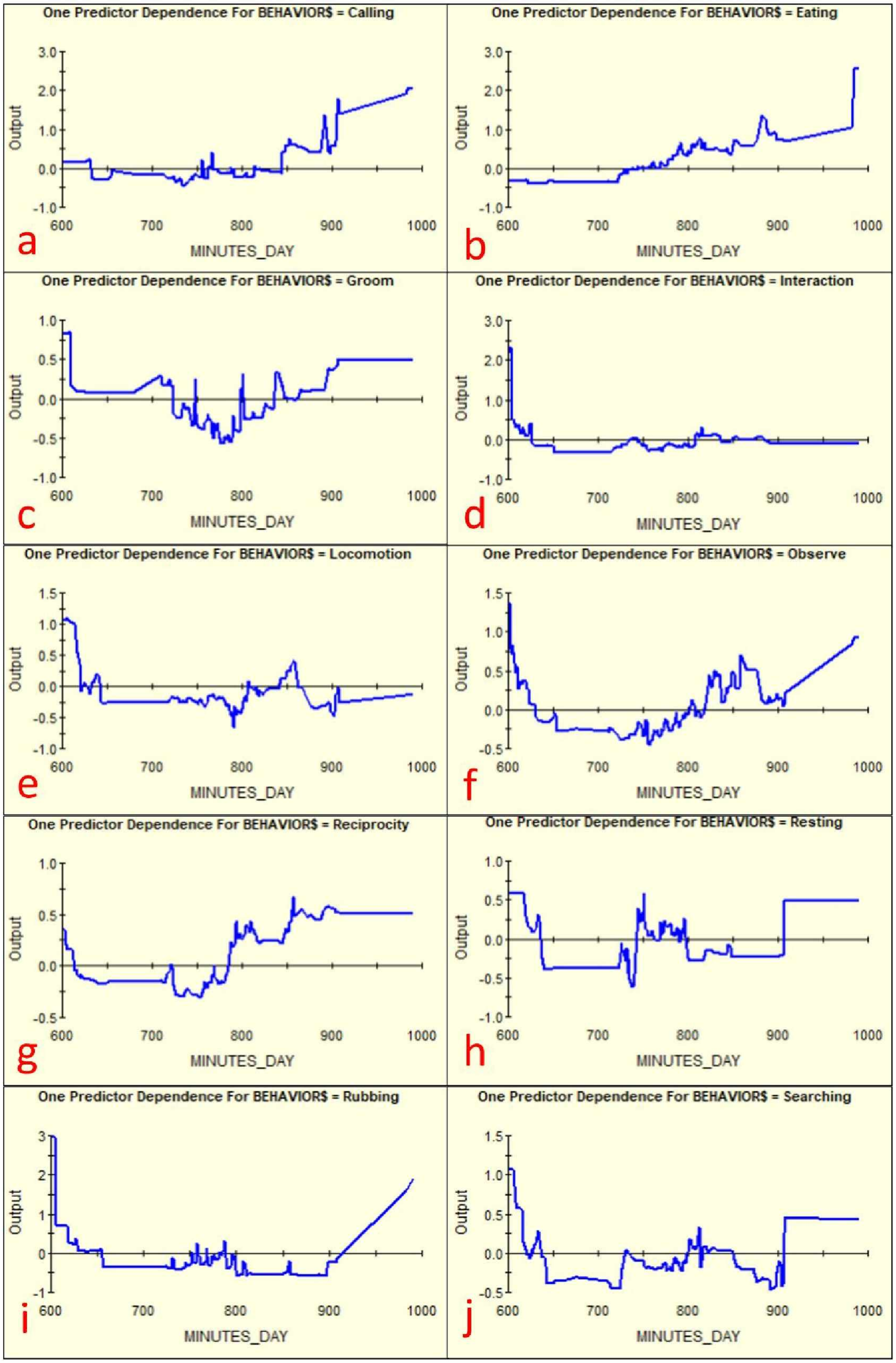

Figure 3.6 – Ad-lib One Predictor Dependency Plot of Minutes of the Day for all behaviors

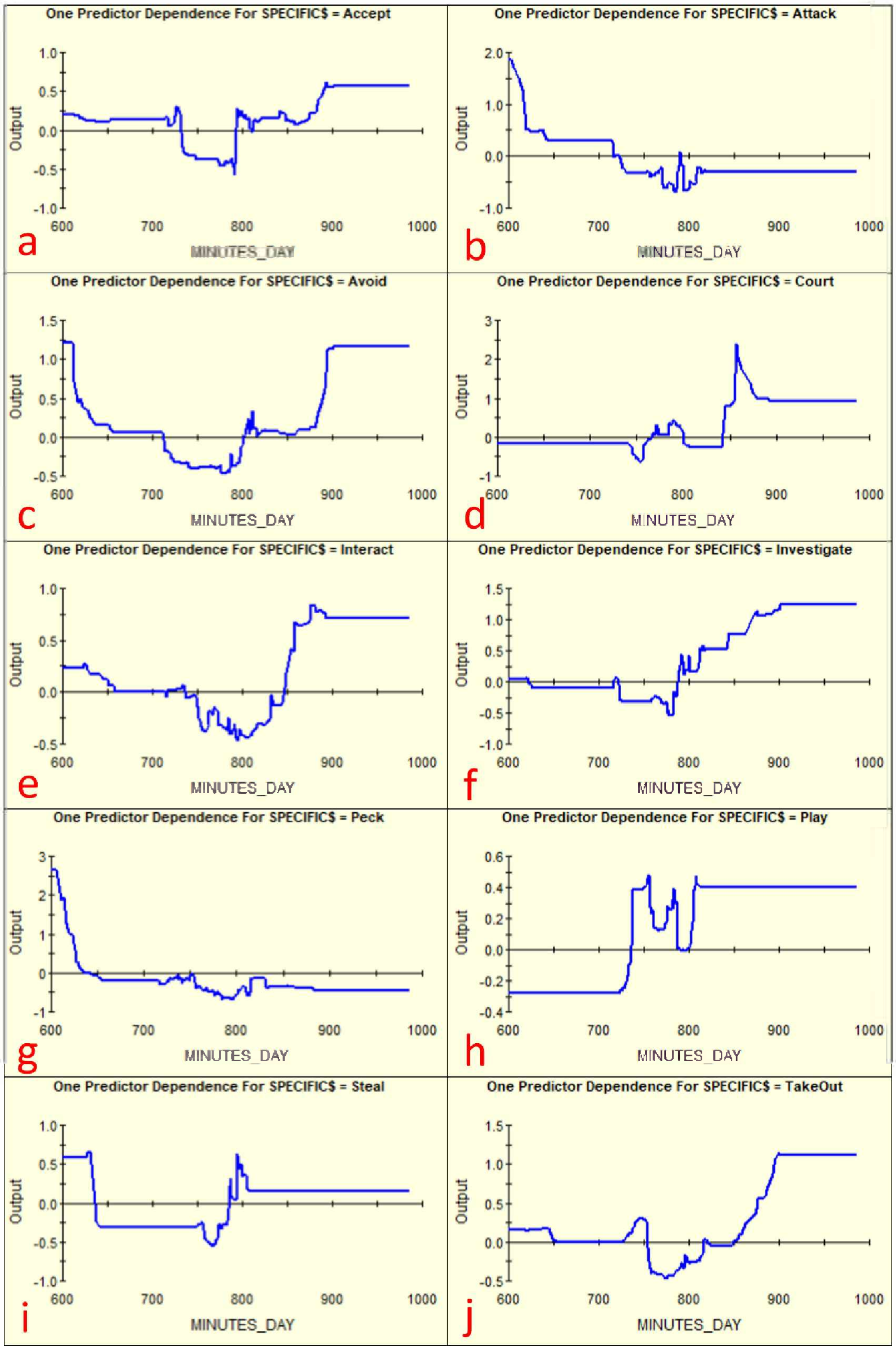

Figure 3.7 – Specific Response One Predictor Dependency Plot of Minutes of the Day for all behaviors

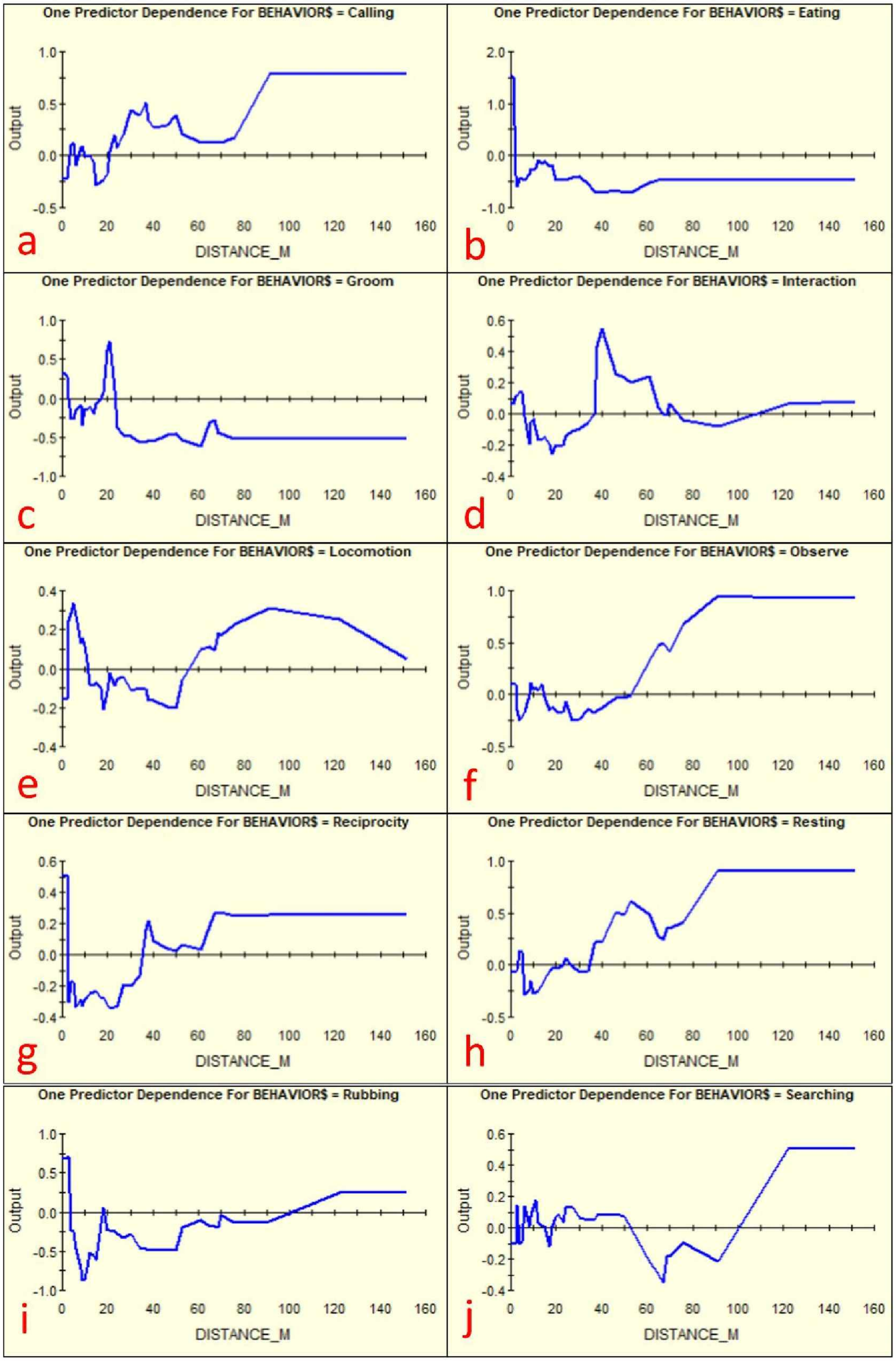

Figure 3.8 – Ad-lib One Predictor Dependency Plot of Distance in Meter from closest entity for all behaviors

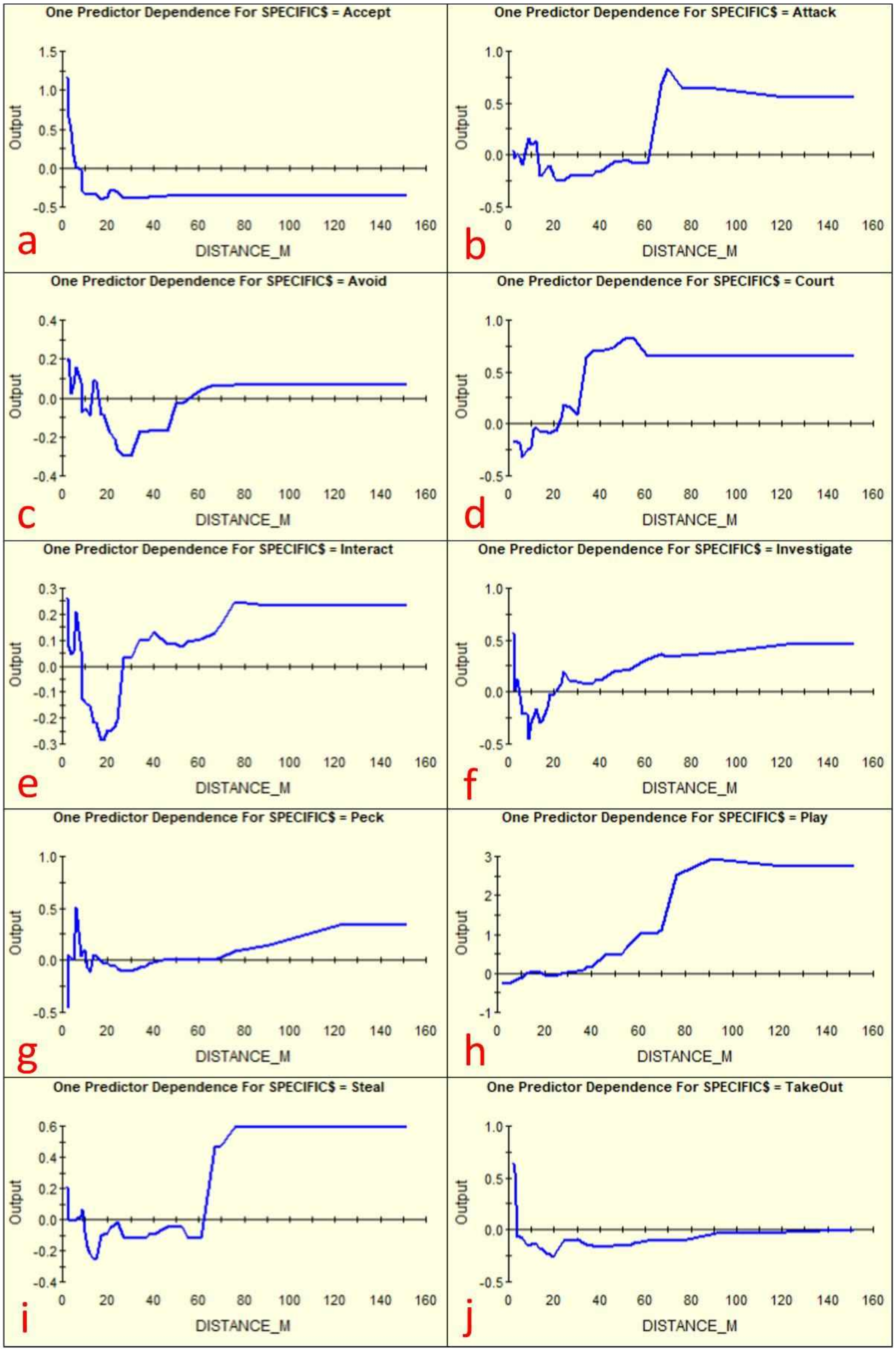

Figure 3.9 – Specific Response One Predictor Dependency Plot of Distance in Meters from closest entity for all behaviors

For the specific response dataset, interaction and stealing tend to happen towards the end of the hour, acceptance occurs towards the beginning of the hour, and attacking, avoiding, courting, investigating, pecking, playing, and takeout tend to occur at the beginning or end of the hour (Figure 3.5). During the day, attacking, and pecking behaviors occur towards the beginning of the day, courting, investigating, and playing occur from midday onward, and accept, avoid, interact, stealing, and takeout happen towards the beginning or end of the day (Figure 3.7).

Distance is more difficult to describe using one-factor dependency plots, as by itself we cannot say what other factor, such as by organisms or vehicles, the predictor itself is affected by. However, using the *ad-lib* data, on average calling occurs over 20 m, eating takes place within 5 m, grooming occurs with 5 m and at 20 m, interaction occurs at less than 5 m, between 35-65 m, and greater than 110 m, locomotion occurs at less than 10 m and greater than 55 m, observing occurs at 50 m or greater, reciprocity occurs at less than 2 m and greater than 35 m, resting occurs at 35 m or greater, rubbing occurs at less than 5 m or greater than 100 m, and searching occurs at less than 50 m and greater than 100m (Figure 3.8). For the specific response data, on average accepting takes place within 10 m, attacking occurs at 10 m and over 60 m, avoiding occurs at less than 20m and greater than 50 m, courting occurs at greater than 20 m, interacting occurs at less than 10 m and greater than 30 m, investigating occurs at less than 5 m and greater than 20 m, pecking occurs at 5 m and greater than 70 m, playing occurs at distances greater than 35 m, stealing occurs at less than 10 m and greater than 60 m, and takeout occurs at less than 5 m (Figure 3.9).

For the ROC curves, we see that the model is highly accurate in classifying observations as opposed to random chance with both datasets, as all AUCs fall above 0.9 except locomotion and observation behaviors, which fall above 0.8 (Tables 3.5 and 3.6). This indicates that most of the behaviors have outstanding accuracy at 96% or higher when being predicted, while locomotion and observation have excellent accuracy at 85 and 89%.

Table 3.5

Area Under the Curve (AUC) for Receiving Operating Curves (ROC) for each behavior in the Ad-lib dataset. In general, any AUC less than or equal to 0.5 has no discrimination and is entirely random. Anywhere between 0.7 and 0.8 is acceptable, between 0.8 and 0.9 is excellent, and above 0.9 is outstanding and very rare (Fan et al., 2006; Hosmer et al., 2013).

Table 3.6

AUC for ROCs for each behavior in the specific response dataset.

3.43 Location and Daylight

In looking into the effects of location, we see that location itself is not the best predictor for a behavior, with it having an average variable importance score of 36.65/100 in the *ad-lib* dataset (Table 3.3) and a 38.67/100 in the specific response dataset (Table 3.4). However, there is evidence that ravens do alter their behaviors based on their location (Figs. 3.10 and 3.11). Using one predictor dependency plots, we can see that there is no behavior that is used consistently across all locations, nor do locations bear the same signal throughout multiple behaviors. Rather, each behavior has its own unique location pattern, indicating that location does affect raven behavior.

As for the effects of hours of daylight on raven behavior, this is more difficult to determine, as there is not a specific predictor for this value. However, it is possible to combine the effects of the minutes of the day and month to get a rough predictor to represent hours of daylight (Figs. 3.12 and 3.13). In Fairbanks, daylight hours range between 520-987 minutes in

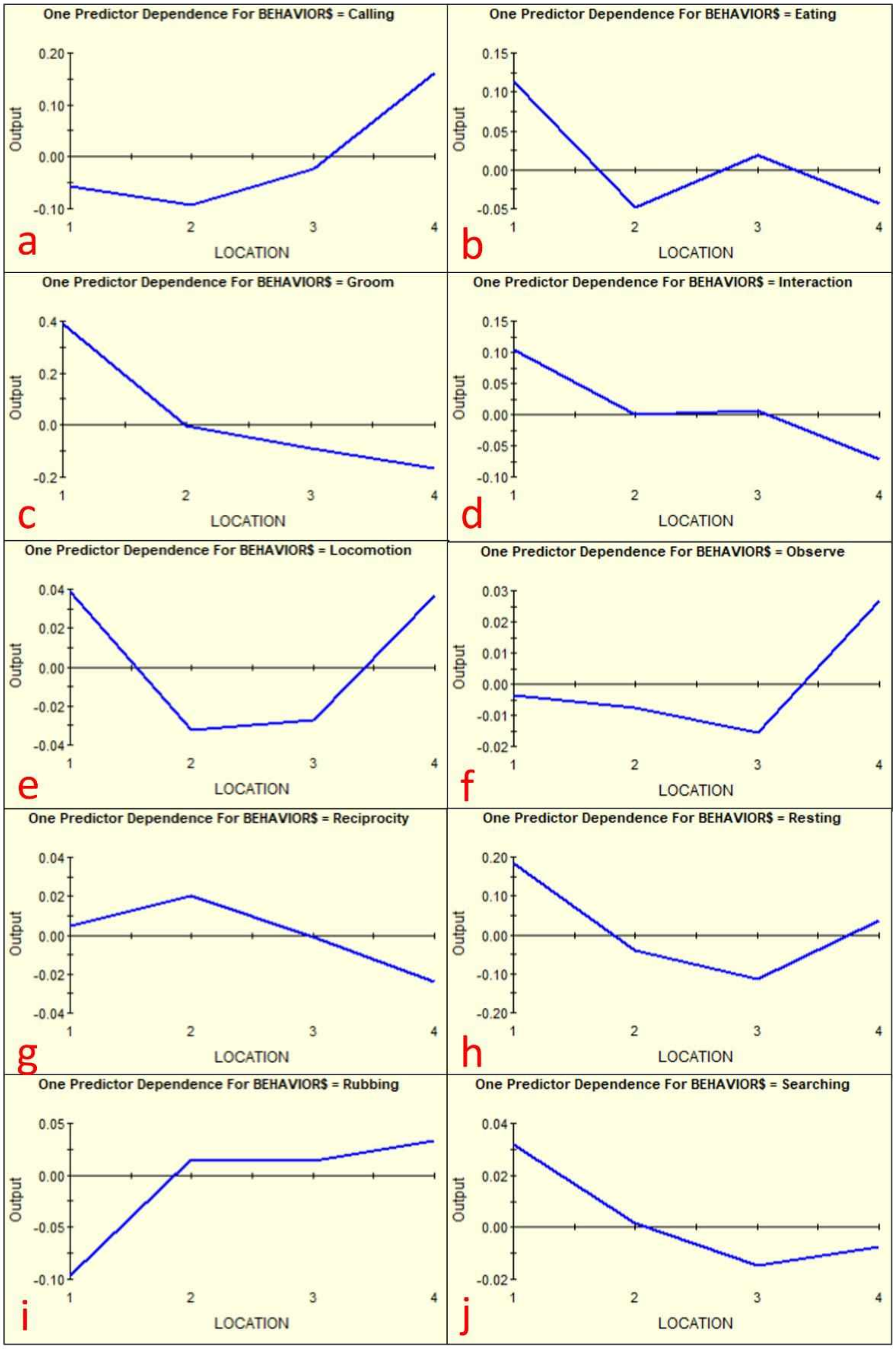

Figure 3.10: Ad-lib One Predictor Dependency Plots of Location for every behavior. Locations 1 – Grocery Store, 2 – University Transfer Station, 3 – Farmers Loop Transfer Station, 4 – Goldstream Transfer Station. Any behavior signal above 0 is likely to happen, and anything below 0 is unlikely to happen.

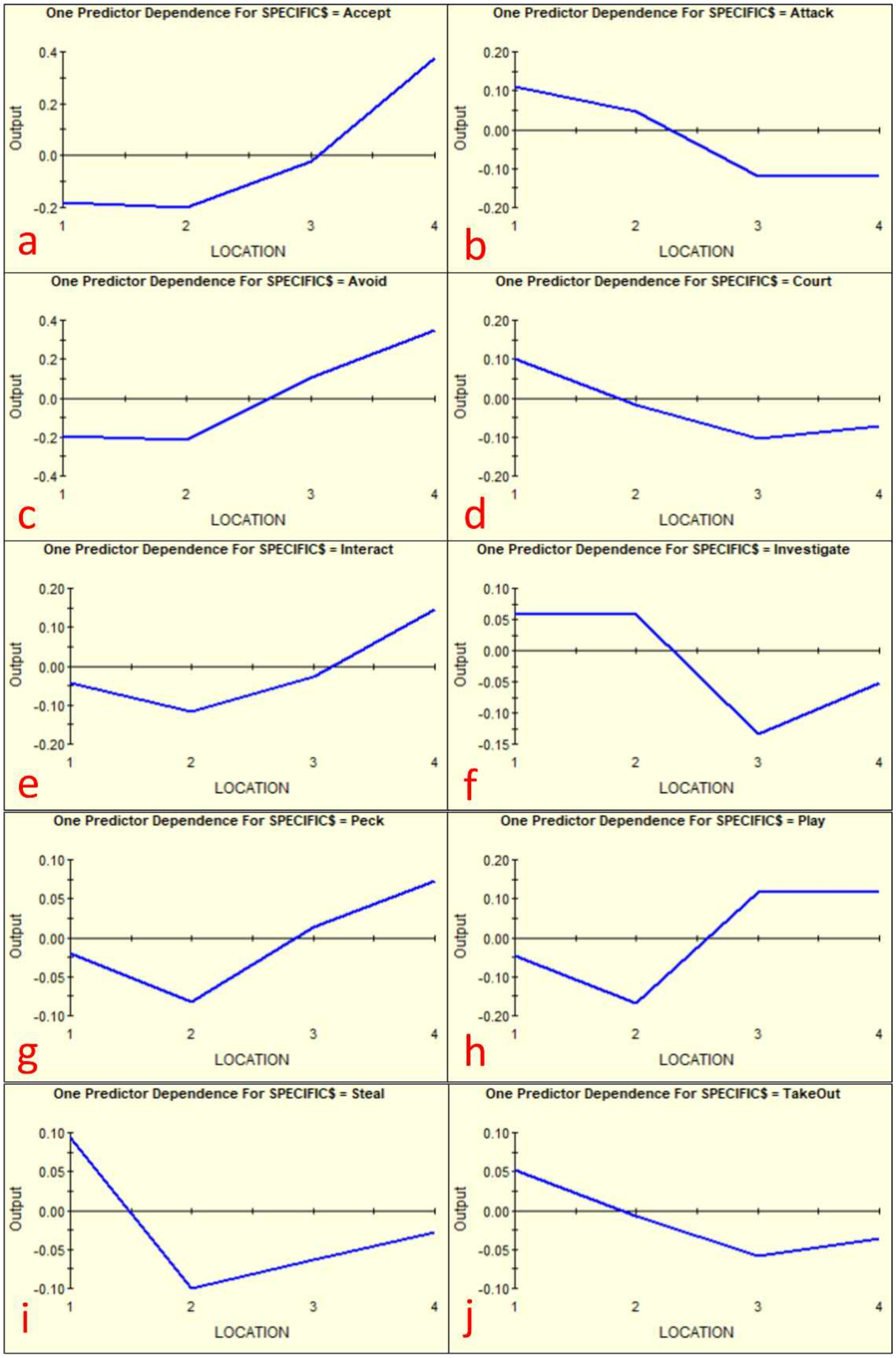

Figure 3.11: Specific Response One Predictor Dependency Plots of Location for every behavior. Locations 1 – Grocery Store, 2 – University Transfer Station, 3 – Farmers Loop Transfer Station, 4 – Goldstream Transfer Station. Any behavior signal above 0 is likely to happen, and anything below 0 is unlikely to happen.

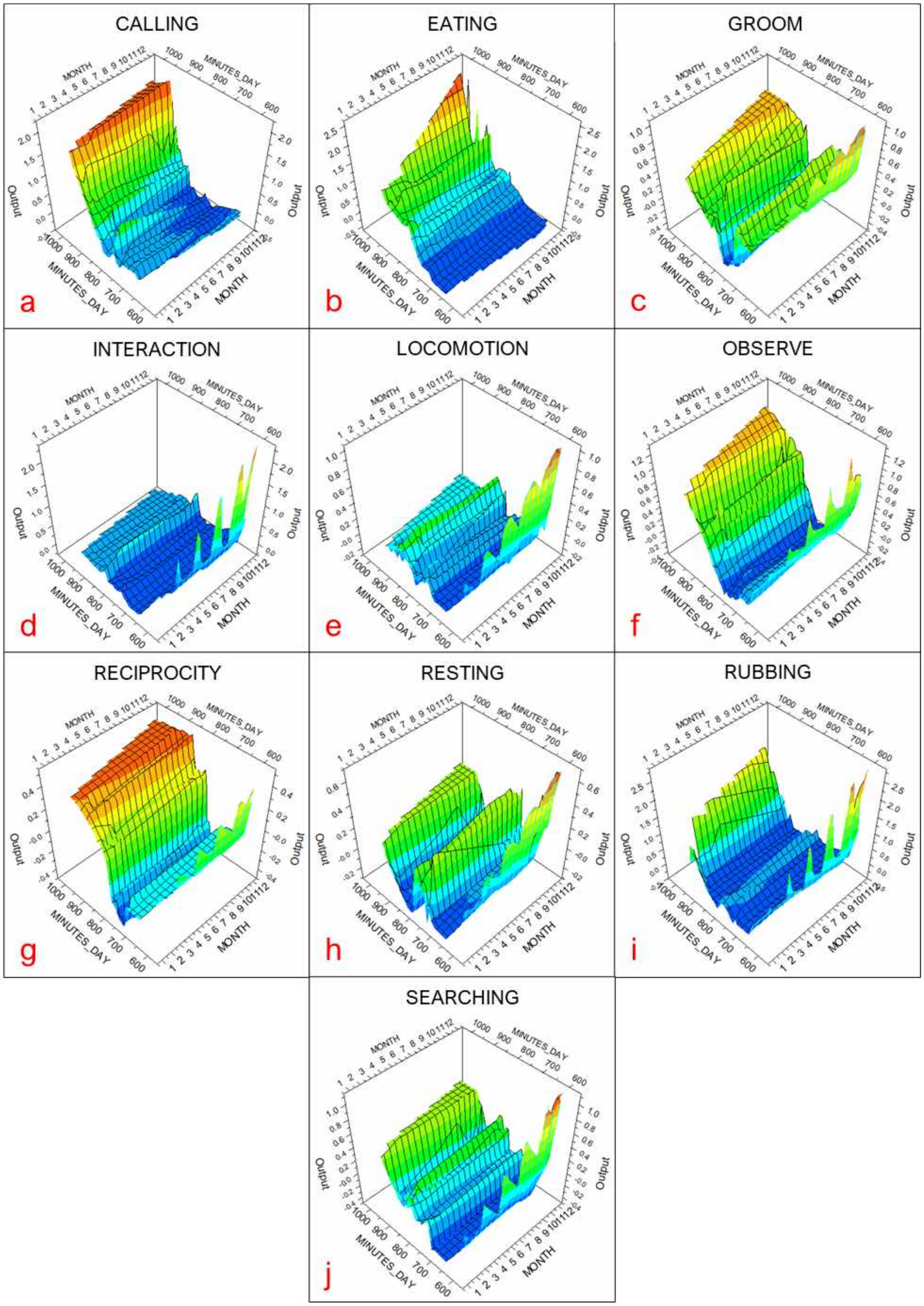

Figure 3.12: Ad-lib Two Predictor Dependency Plots for every behavior using minutes of the day and month to simulate the effect of hours of daylight. 600-1000 minutes is roughly 10am-4pm.

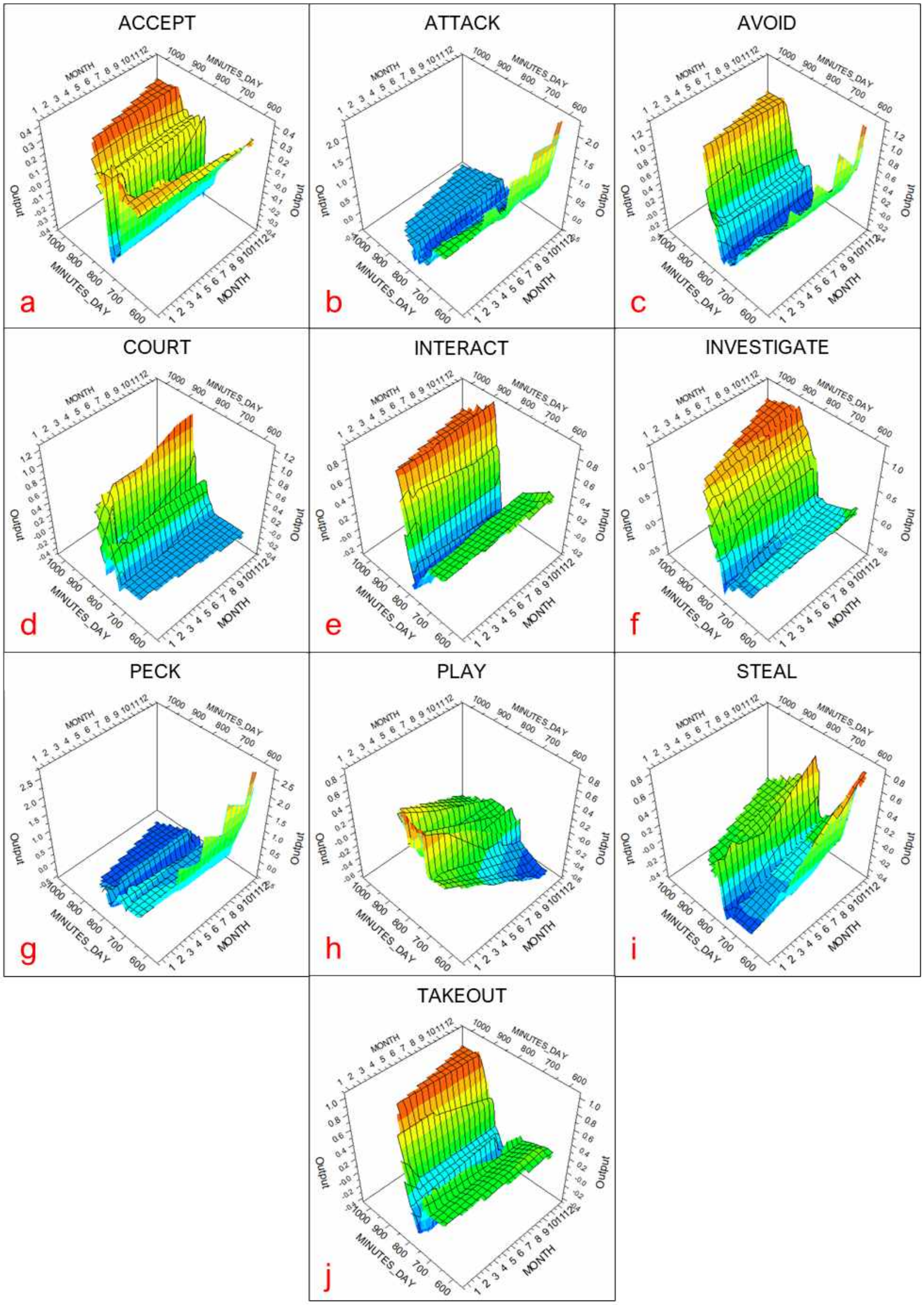

Figure 3.13: Specific Response Two Predictor Dependency Plots for every behavior using the minutes of the day and month to simulate the effect of hours of daylight.

November, 619-901 minutes in December, 578-992 minutes in January, 481-1087 minutes in February, 428-1243 minutes in March, and 319-1340 minutes in April (*National Oceanic & Atmospheric Administration Solar Calculator*, 2022). These daylight hours include the earliest sunrise and latest sunset for the entire month, so hours of daylight fluctuate within the month as well.

Overall, it appears that most behaviors are generally affected by the time of day regardless of the month. In the *ad-lib* dataset, calling, eating, reciprocity, and resting behaviors occurring the most at 900 minutes or later, while interaction and locomotion occurred most often at 600 minutes or earlier (Figure 3.12). In addition, grooming, observation and rubbing had peaks of activity at both the 600 minutes and 900+ minutes, while resting had three peaks at 600, 800, and 900+minutes. While most of these behaviors were not month-specific, grooming, interaction, locomotion, and rubbing behaviors show peaks of morning activity during the months of October-December, with other occurrences rarely happening during other months.

With the specific response dataset, accepting, courting, interacting, investigating, and takeout behaviors occurring the most at 850 minutes or later, stealing occurring most at 600 or 800 minutes, and attacking and pecking behaviors occurring most often at 600 minutes or earlier (Figure 3.13). However, attacking, avoiding, and pecking behaviors all appear to spike more in the mornings during the months of November and December than in mornings of the other months. With play behaviors, the effect of hours of daylight is more notable, with spikes of activity occurring mostly midday during the months of January-April, and rarely during other months.

3.5 Discussion

3.51 Consistent Reactions in Winter Raven Communities

In evaluating whether raven communities show consistent behaviors and responses to environmental stressors and variables such as daylight, location, and objects or organisms in their surroundings, we discovered that ravens do exhibit predictable, quantifiable behaviors (Chapter 2), with most behaviors positively correlated with their corresponding predictors. While these behaviors seem trivial, they are still relevant, as these results quantify overall raven behavior in the wild.

For the *ad-lib* dataset, we see observation behavior negatively correlated with being in air (Figure 3.1a). This is most likely due to ravens preferring to use their flying time to either move between locations, escape, or search for new items as opposed to watching a single item intently. Locomotion positively correlates to being in air, most likely due to flying being the quickest and most effective way to move great distances and avoid threats (Figure 3.1b). Interaction behaviors are seen near objects and on the ground (Figs. 3.1c and 3.1d), most likely as objects are items commonly found on the ground that ravens tend to examine more than food, for example (Figure 3.2a) (Osvath & Sima, 2014). Searching behaviors occur most by garbage containers and in the air, which makes sense as items of interest such as food are commonly found in garbage containers that can be seen from the air (Figs. 3.1e and 3.1f) (Boarman & Heinrich, 1999). Resting occurs in trees, most likely due to these being safe areas where ravens have high visibility and greater levels of protection from the weather and threats (Figure 3.1g). Reciprocity behaviors occur most by people and cars between distances less than 5m and greater than 35m (Figs. 3.1h, 3.1i, and 3.1j). These reciprocal behaviors, such as attacking, pecking, or moving away from an approaching entity, most likely occur more often by people and cars as these are the greatest threats to ravens which therefore require more action, with the presence of people being most important (Figure 3.2b) (McLeod et al., 2013).

As for the distance, this is further broken down with ravens showing greater reciprocal actions by people at approximately 5m (Figure 3.2c), while reciprocal actions by cars are done at distances of 40-150m to the nearest vehicle (Figure 3.2d).

For the specific response dataset, we see investigating behaviors negatively occurring in the presence of other ravens (Figure 3.3a). This could be due to other ravens being potential thieves to interesting objects (Asakawa-Haas et al., 2016; Bugnyar & Heinrich, 2006). Pecking behaviors are negatively correlated with being in the air, probably due to pecking being difficult to do while flying (Figure 3.3b). We see that ravens prefer to display courting behaviors when on posts and another species is nearby (Figs. 3.3c and 3.3d). As we could not find research on why this occurs, we hypothesize that this could indicate that ravens feel safer from potential threats when another animal is nearby, as they are able to alert to threats but are not threats themselves to the courting process. In addition, ravens resting on posts are less likely to be disturbed by other individuals and vehicles on the ground. Avoidance behaviors are shown mostly in air and in close proximity to cars (Figs. 3.3e and 3.3f), most likely due to cars being the biggest threats to ravens and the air being the easiest way to avoid contact with anything but other flying individuals. Takeout behaviors occur most by objects and in air (Figs. 3.3g and 3.3h), most likely due to ravens wanting to take interesting items somewhere else by flying away (Beck et al., 2020; Bugnyar & Heinrich, 2006). Attacking occurs by other ravens, likely due to these being a known threat that can be scared off from food sources instead of running with a single food item (Figure 3.3i) (Fraser & Bugnyar, 2012). Interacting occurs near objects as ravens are curious by nature, while pecking occurs by cars (Figs. 3.3j and 3.3k). However, we are unsure of why this pecking relationship occurs by cars.

3.52 Factors Contributing to Winter Raven Behaviors

In determining if raven behavior is affected by environmental variables, we discovered that raven behavior can be predicted by the context of the environment. Specifically, behaviors are best predicted by the time of day and followed closely by their distance from another living being or object (Tables 3.3 and 3.4). From this, we know that ravens have an hourly (Figs. 3.4 and 3.5) and daily (Figs. 3.6 and 3.7) schedule and show that there are varying distances at which they decide to exhibit differing behaviors (Figs. 3.8 and 3.9). In general, the greatest levels of activity for most behaviors occur at the beginning or end of the hour and day, while some behaviors such as observing, rubbing, playing, and stealing show the most activity mid-hour and midday (Figs. 3.4, 3.5, 3.6, and 3.7). Higher activities at the beginning or end of an hour could be influenced by human activity patterns, which are typically scheduled around the beginning or end of an hour. Birds have been shown to adapt their behavior based on human activity, where the presence of humans can result in greater amounts of food and their absence results in lower levels of disturbance (Clucas & Marzluff, 2013; Schrimpf et al., 2021). While further studies are needed to provide a human activity schedule for Fairbanks transfer stations to confirm this, we hypothesize that higher human activity at these times could result in greater amounts of food waste for ravens to scavenge. The higher activity at the beginning of the day may be due to mornings having less activity from other factors in the environment, while higher activity at the end of the day could be from ravens trying to get as many things done as possible before heading to their forest roosts at night (Schwan, 2008).

As for the distance from features, for most behaviors ravens consistently act at distances less than 10 m (Figs. 3.8 and 3.9). However, they also show jumps in activity for calling, courting, investigating, and playing at distances greater than 20m, interaction, reciprocity, and resting at distances greater than 30m, and locomotion, observing, attacking, avoiding, pecking, and stealing at distances greater than 50m. In addition, grooming has a spike at 20 m and searching occurs below 50 m and above 100m. The high activity levels at distances less than 10m makes sense, as most behaviors are in response to something being within reach. The lack of activity past 10m for avoidance is reasonable, as most items do not need avoiding if there is low risk of contact, but avoidance past 40 m is an odd occurrence which may be caused by particularly jumpy individuals. Courting only occurs at distances greater than 20m from a non-raven subject as these behaviors require a lot of attention that cannot be spent actively looking for threats. As for the high distances required for activity to start back up in attacking, pecking, and stealing, these are probably referring most to distances to non-raven threats. With these threats far away, ravens can focus on proving their dominance among themselves or having fun.

3.53 Location and Daylight

In terms of location, we can comfortably say that ravens do adjust their behavior based on location (Figs. 3.10 and 3.11). They tend to interact more with others at the more urbanized areas with reciprocity, attacking, courting, stealing, and takeout behaviors being present at locations 1 and 2. This could be due to these areas having higher levels of competition and larger choices of mates. Other behaviors in high traffic areas include eating, grooming, resting, searching, and investigating. The eating, searching, and investigating is most likely due to these areas having the most food sources and unusual items around, while grooming and resting could be due to these areas being the busiest and therefore has ravens who possibly stay longer and will take breaks to groom or rest. Calling, observing, rubbing, accepting, avoiding, pecking, and playing occurred the most often in the least urbanized areas. Rubbing and playing could be due to these areas being safer with trees nearby to escape to and less human traffic. Locomotion and interaction happened in the most urbanized and the least urbanized areas. Locomotion at the highest urbanized area could be due to this area having more entities to avoid and more items of interest or items to travel between, while locomotion at the least urbanized area could be due to needing to move around more to be able to find more interesting items, as there is less food available. However, the lack of locomotion for the two middle locations in comparison is odd. These locations may have a level of urbanization that allows potential threats such as people and cars to avoid gathered ravens due to the other options available, thus allowing the ravens to stay put and enjoy their garbage feasts. As for interaction behaviors, the *ad-lib* dataset indicates that interaction happened most often at location 1, which could be due this area having the most objects around to interact with. However, the specific response dataset indicates that interaction occurred most at location 4, which could be due to this area being safer to explore in. As for the difference in interaction behaviors shown between datasets, this most likely occurred from certain behaviors in the initial reciprocal behaviors to be further categorized into additional interaction responses when the specific response dataset was completed.

In terms of daylight, grooming, interaction, locomotion, rubbing, searching, attacking, and pecking behaviors mostly occur in November and December during early hours (Figs. 3.12 and 3.13). Grooming and rubbing in the morning could be due to ravens just getting ready to start their day by fluffing up to warm up, while interaction, locomotion, searching, attacking, and pecking could be caused by ravens being hungrier and more protective of food sources as they spend more time at their roosts as the nights grow longer, making them more active at first light (Schwan, 2008). Calling, eating, reciprocity, accepting, avoiding, interacting, and investigating occur most often at later times of the day no matter the time of year, while resting and stealing occur in peaks at beginning and midday, as well as end of day for resting. Play behaviors rarely occur, but when they do, they occur midday. However, there are minimal effects of hours of daylight on most behaviors, so overall we would not say that hours of daylight are a factor in determining raven behavior.

3.54 Limitations

In consideration of this analysis, we would like to acknowledge the limitations in this study that could affect our results. Our initial behavioral observations assumed that ravens were exhibiting reciprocal "tit-for-tat" relationships, despite the inability to track individual ravens over extended periods of time, and some reciprocal behaviors could simply be behavioral responses, as inanimate objects cannot reciprocate a raven's actions. Further studies could consider banding or chipping birds to track if an individual's behavior is truly reciprocal in nature and varies based on stimuli. Other observational limitations include the lack of field work outside of daylight hours, which could skew our findings on the effects of hours of daylight on raven behavior. To counter this, future research could create daily behavior schedules based solely on the hours of daylight available.

As for our statistical analysis, there are limitations in using exploratory analysis in TreeNet. With a small dataset containing numerous categorical variables, we were unable to split the data into training and testing datasets and thus could not use cross-validation to create a strong model for analysis. As such, our results may have data that is overfitted and is not as accurate or precise as we would like. With the collection of more data, we would be able to create training and testing datasets that we could cross-validate, thus resulting in more robust data analysis that we could confidently say is not overfitted.

3.6 Conclusion

Here, we showed how well data mining with machine learning can be used for raven behavior. Computer learning algorithms assess complex raven data and show new insights. Our studies indicate that raven communities in winter exhibit consistent reactions and timings based on factors in their environment, therefore showing that behaviors can be reasonably predicted in response to landscape stimuli when given a set of variables. In addition, ravens do alter their behaviors based on location and within different contexts, indicating that wild ravens adapt within urbanized communities and can differentiate between risks and when they are necessary, as shown in Corvidae studies on jackdaws and American crows (Davidson et al., 2015; Marzluff et al., 2010). With birds being known to have predictable activity patterns to a certain degree, it is unsurprising to find that Fairbanks Common Ravens exhibit varied behavior based on hours of daylight (Robbins, 1981). They know that early mornings tend to have less traffic and therefore can exhibit behaviors more freely, may be able to tell when humans are most active, and know that highly urbanized areas require more risk, while less urbanized areas can use more conservative behaviors. With these findings, our study provides a baseline for arctic urbanized raven behavior that can be used to benefit further studies in bettering our understanding of wild-urban wildlife.

3.7 References

Asakawa-Haas, K., Schiestl, M., Bugnyar, T., & Massen, J. J. M. (2016). Partner choice in raven (corvus corax) cooperation. *PLoS ONE*, *11*(6), 1–15. https://doi.org/10.1371/journal.pone.0156962

Beck, K. B., Loretto, M.-C., & Bugnyar, T. (2020). Effects of site fidelity, group size and age on food-caching behaviour of common ravens, Corvus corax. *Animal Behaviour*, *164*, 51–64. https://doi.org/10.1016/j.anbehav.2020.03.015

Boarman, W., & Heinrich, B. (1999). Common Raven (Corvus corax). *The Birds of North America*, *476*, 1–32. https://doi.org/10.2173/bow.comrav.01

Bugnyar, T., & Heinrich, B. (2006). Pilfering ravens, Corvus corax, adjust their behaviour to social context and identity of competitors. *Animal Cognition*, *9*(4), 369–376. https://doi.org/10.1007/s10071-006-0035-6

Clucas, B., & Marzluff, J. M. (2013). Coupled Relationships between Humans and other Organisms in Urban Areas. *Urban Ecology*, 135–147. https://doi.org/10.1093/acprof:oso/9780199563562.003.0017

Curtis, E., Comiskey, C., & Dempsey, O. (2015). Correlational Research: Importance and Use in Nursing and Health Research. *Nurse Researcher*, *23*(6), 20–25. http://www.tara.tcd.ie/bitstream/handle/2262/74298/TARA Correlational Research Revised 30.06.15 2.pdf?sequence=1

Davidson, G. L., Clayton, N. S., & Thornton, A. (2015). Wild jackdaws, Corvus monedula, recognize individual humans and may respond to gaze direction with defensive behaviour. *Animal Behaviour, 108*, 17–24. https://doi.org/10.1016/j.anbehav.2015.07.010

Fan, J., Upadhye, S., & Worster, A. (2006). Understanding receiver operating characteristic (ROC) curves. *Canadian Journal of Emergency Medicine, 8*(1), 19–20.

Fraser, O. N., & Bugnyar, T. (2012). Reciprocity of agonistic support in ravens. *Animal Behaviour*, *83*(1), 171–177. https://doi.org/10.1016/j.anbehav.2011.10.023

Greener, J. G., Kandathil, S. M., Moffat, L., & Jones, D. T. (2022). A guide to machine learning for biologists. *Nature Reviews Molecular Cell Biology, 23*(1), 40–55. https://doi.org/10.1038/s41580-021-00407-0

Harrell, F. E., Jr., & Dupont, C. (2022). *Hmisc: Harrell Miscellaneous*. CRAN. https://cran.r-project.org/package=Hmisc

Hosmer, D. W., Lemeshow, S., & Sturdivant, R. X. (2013). Applied Logistic Regression. In *Biometrics* (Third, Vol. 47, Issue 4). John Wiley & Sons, Inc. https://doi.org/10.2307/2532419

Humphries, G. R. W., Magness, D. R., & Huettmann, F. (2018). Machine Learning for Ecology and Sustainable Natural Resource Management. In *Machine Learning for Ecology and Sustainable Natural Resource Management*. Springer. https://doi.org/10.1007/978-3-319-96978-7

Jochum, K., & Huettmann, F. (2010). Spatial Information Management in Wildlife Ecology: Adding Spatially Explicit Behaviour Data to the Equation? In *Spatial Complexity, Informatics, and Wildlife Conservation* (Vol. 9784431877, pp. 1–458). https://doi.org/10.1007/978-4-431-87771-4

Marzluff, J. M., Walls, J., Cornell, H. N., Withey, J. C., & Craig, D. P. (2010). Lasting recognition of threatening people by wild American crows. *Animal Behaviour, 79*(3), 699–707. https://doi.org/10.1016/j.anbehav.2009.12.022

McLeod, E. M., Guay, P.-J., Taysom, A. J., Robinson, R. W., & Weston, M. A. (2013). Buses, Cars, Bicycles and Walkers: The Influence of the Type of Human Transport on the Flight Responses of Waterbirds. *PLoS ONE*, *8*(12). https://doi.org/10.1371/journal.pone.0082008

Minitab. (2019a). *Introducing TreeNet ® Gradient Boosting Machine*. Minitab. www.minitab.com.

Minitab. (2019b). *Salford Predictive Modeler Booklet* (pp. 1–8). Minitab. https://cdn2.hubspot.net/hubfs/3447555/B2BML - NEW FILE MANAGER STRUCTURE/Landing Pages/eBooks /SPM/Digital brochure/SPM 8.3 Digital Brochure.pdf

Minitab. (2019c). *Salford Predictive Modeler Machine Learning and Predictive Analytics Software*. Minitab. https://www.minitab.com/en-us/products/spm/

Minitab. (2021). *Confusion matrix for Fit Model and Discover Key Predictors with TreeNet® Classification - Minitab*. Minitab. https://support.minitab.com/en-us/minitab/20/help-and-how-to/statistical-modeling/predictive-analytics/how-to/treenet-classification/interpret-the-results/confusion-matrix/

National Oceanic & Atmospheric Administration Solar Calculator. (2022). Global Monitoring Laboratory. https://gml.noaa.gov/grad/solcalc/

Osvath, M., & Sima, M. (2014). Sub-adult Ravens Synchronize their Play : A Case of Emotional Contagion? *Animal Behavior and Cognition*, *1*(2), 197–205. https://doi.org/10.12966/abc.05.09.2014

Powell, A. N., & Backensto, S. (2009). *Common Ravens (Corvus Corax) Nesting on Alaska's North Slope Oil Fields*. Coastal Marine Institute, University of Alaska Fairbanks.

R Core Team (2019). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL https://www.R-project.org/.

Robbins, C. S. S. (1981). Effect of time of day on bird activity. *Studies in Avian Biology, 6*(6), 275–286. http://pubs.er.usgs.gov/publication/5210259%5Cnfile://c/Documents and Settings/Cristina/Meus documentos/My Dropbox/Meu Documentos/Papers/1999 and before/Robbins 1981 StudiesAvianBiol.pdf

Schrimpf, M. B., des Brisay, P. G., Johnston, A., Smith, A. C., Sánchez-Jasso, J., Robinson, B. G., Warrington, M. H., Mahony, N. A., Horn, A. G., Strimas-Mackey, M., Fahrig, L., & Koper, N. (2021). Reduced human activity during COVID-19 alters avian land use across North America. *Science Advances*, *7*(39), 1–12. https://doi.org/10.1126/sciadv.abf5073

Schwan, M. (2008). *Common Raven*. http://proxy-iup.klnpa.org/login?url=http://search.ebscohost.com/login.aspx?direct=true&db=nts&AN=PB84-135862%2FXAB&site=ehost-live

Schwan, M. W., & Williams, D. D. (1978). Temperature regulation in the common raven of interior Alaska. *Comparative Biochemistry and Physiology -- Part A: Physiology, 60*(1), 31–36. https://doi.org/10.1016/0300-9629(78)90033-6

Spelt, A., Soutar, O., Williamson, C., Memmott, J., Shamoun-Baranes, J., Rock, P., & Windsor, S. (2021). Urban gulls adapt foraging schedule to human-activity patterns. In *Ibis* (Vol. 163, Issue 1, pp. 274–282). https://doi.org/10.1111/ibi.12892

Tyson, C., Shamoun-Baranes, J., Emiel Van Loon, E., Camphuysen, K., & Hintzen, N. T. (2015). Individual specialization on fishery discards by lesser black-backed gulls (Larus fuscus). *ICES Journal of Marine Science, 72*(6), 1882–1891. https://doi.org/10.1093

Webb, W. C., Marzluff, J. M., & Hepinstall-Cymerman, J. (2011). Linking resource use with demography in a synanthropic population of common ravens. *Biological Conservation, 144*(9), 2264–2273. https://doi.org/10.1016/j.biocon.2011.06.001

Chapter 4: General Conclusion

4.1 Introduction

This chapter will conclude this study through a summary of what we discovered through our research, the limitations of our methodology, and the potential direction that further studies could develop from our study.

4.2 Summary of Results

Using both traditional and modern research techniques, we were able to determine that wild-urban common ravens in the sub-Arctic winter do exhibit predictable patterns when encountering a variety of stimuli. In addition, we found indications that these patterns have evolved over time and vary based on level of urbanization and that ravens are exhibiting timing signals, showing that they recognize and adjust their behaviors based on hourly and daily human activity. This hourly time-telling element is not something we would think to look for in traditional statistical research, while for a modern data mining program it is readily picked up in behavior recognition processes. Thus, the implementation of modern technologies into traditional techniques proves to be useful in both enhancing the analysis and identifying previously missed information that traditional p-value methods may not detect.

4.3 Limitations and Future Research

While the methodology shown did prove to enhance data analysis, we do need to keep in mind that only a select few processes were used in this study and do not encompass all traditional or modern methods of research analysis. Therefore, we may have missed some classic techniques that do provide the analysis shown using modern techniques. Regardless, the goal of this study was to show how well the merging of these two ages of science can be used to complete more thorough analyses with new insights than those seen in research of the past.

From this research, we hope to have provided a baseline ethogram for wild raven behavior in the Arctic that can be used for future behavior research. In addition, we believe that our research provides an introduction into more concrete research into the potential ability for ravens to tell time and how those features change and fit into the wider life history aspects in both a raven's life and raven populations in Alaska.

Appendix A: All Raven Data Excel Sheet

The supplementary file All_Raven_Data_5-7-2021.xlsx found in the google drive linked below contains a Microsoft Excel Sheet with all raw observation data separated into five tabs.

https://drive.google.com/drive/u/1/folders/1rxU7XqU5eaCOnyZU7XxKn6Mwc7KR9n71

Appendix B: Ad-Lib Data CSV

The supplementary file Ad-Lib_5-11-21.csv found in the google drive linked below contains a CSV file of the Ad-Lib data that was converted from the All_Raven_Data_5-7-2021.xlsx Ad-Lib SPM tab.

https://drive.google.com/drive/u/1/folders/1rxU7XqU5eaCOnyZU7XxKn6Mwc7KR9n71

Appendix C: Specific Response Data CSV

The supplementary file SR_5-11-21.csv found in the google drive linked below contains a CSV file of the Specific Response data that was converted from the All_Raven_Data_5-7-2021.xlsx Specific Response SPM tab.

https://drive.google.com/drive/u/1/folders/1rxU7XqU5eaCOnyZU7XxKn6Mwc7KR9n71

Appendix D: IACUC Letters

(907) 474-7800
(907) 474-5993 fax
uaf-iacuc@alaska.edu
www.uaf.edu/iacuc

Institutional Animal Care and Use Committee
909 N Koyukuk Dr. Suite 212, P.O. Box 757270, Fairbanks, Alaska 99775-7270

November 6, 2019

To:	Falk Huettmann Principal Investigator
From:	University of Alaska Fairbanks IACUC
Re:	[1515447-1] Observational Study of Common Ravens, Corvus corax, in Fairbanks, Alaska.

The IACUC reviewed and approved the New Project referenced above by Designated Member Review.

Received:	October 29, 2019
Approval Date:	November 6, 2019
Initial Approval Date:	November 6, 2019
Expiration Date:	November 6, 2020

This action is included on the November 14, 2019 IACUC Agenda.

PI responsibilities:

- *Acquire and maintain all necessary permits and permissions prior to beginning work on this protocol. Failure to obtain or maintain valid permits is considered a violation of an IACUC protocol and could result in revocation of IACUC approval.*
- *Ensure the protocol is up-to-date and submit modifications to the IACUC when necessary (see form 006 "Significant changes requiring IACUC review" in the IRBNet Forms and Templates)*
- *Inform research personnel that only activities described in the approved IACUC protocol can be performed. Ensure personnel have been appropriately trained to perform their duties.*
- *Be aware of status of other packages in IRBNet; this approval only applies to this package and the documents it contains; it does not imply approval for other revisions or renewals you may have submitted to the IACUC previously.*
- *Ensure animal research personnel are aware of the reporting procedures on the following page.*

(The following information is also available in a printable format in the IRBNet Forms and Templates)

HOW DO I REPORT CONCERNS ABOUT ANIMALS IN A UAF RESEARCH FACILITY?

- All "live" animal concerns related to care and use should be reported to the IACUC
- Email: uaf-iacuc@alaska.edu Phone: 474-7800
- Report form: www.uaf.edu/iacuc/report-concerns/
- IACUC Committee Members: www.uaf.edu/iacuc/iacuc-info/
- Additional information: www.uaf.edu/ori/responsible-conduct/research-misconduct/ and www.uaf.edu/ori/responsible-conduct/conflict-of-interest/

WHAT SHOULD I DO IF AN ACCIDENT OR INCIDENT OCCURS IN AN UAF ANIMAL FACILITY?

- **For all immediate *human* emergencies call 911** or UAF Dispatch at 474-7721 for less immediate emergencies.
- If you have **suffered an animal bite or other injury**, complete an "Accident/Incident Investigation form" (personal injury) form available at https://uaf.edu/safety/occupational-safety/accident-reporting.php.
- If an accident such as a **chemical spill** occurs, contact the Environmental Health, Safety, and Risk Management (EHS&RM) Supervisor at 474-5617 or the Hazmat Coordinator at 474-7889.

WHO DO I CONTACT IF I FIND A DEAD, INJURED, OR DISTRESSED ANIMAL IN A UAF RESEARCH FACILITY?

- During regular business hours, immediately contact facility staff and/or Veterinary Services Staff at 474-7020.
- After hours or on weekends, immediately contact facility staff and/or Veterinary Services Staff using the contact numbers posted on the "Emergency Contact Information" in the facility or call UAF Dispatch at 474-7721.
- Contact the IACUC at 474-7800 or uaf-iacuc@alaska.edu if an "Emergency Contact Information" sign is NOT posted in the facility.
- Contact the IACUC if you are not satisfied with the response from Vet Services.

HOW DO I REPORT ANY CONCERNS REGARDING WORK HAZARDS OR ANY GENERAL UNSAFE CONDITIONS?

- Complete an "Unsafe Condition Reporting Program" form, available at the EHS&RM website: www.uaf.edu/safety/unsafe-condition/

WHERE CAN I OBTAIN GENERAL OCCUPATIONAL SAFETY INFORMATION?

- https://www.uaf.edu/iacuc/uaf-policies-procedures/occupational-health-safety/

(907) 474-7800
(907) 474-5993 fax
uaf-iacuc@alaska.edu
www.uaf.edu/iacuc

Institutional Animal Care and Use Committee

909 N Koyukuk Dr. Suite 212, P.O. Box 757270, Fairbanks, Alaska 99775-7270

October 14, 2020

To:	Falk Huettmann Principal Investigator
From:	University of Alaska Fairbanks IACUC
Re:	[1515447-2] Observational Study of Common Ravens, Corvus corax, in Fairbanks, Alaska.

The IACUC has reviewed the Progress Report by Designated Member Review and the Protocol has been approved for an additional year.

Received:	October 7, 2020
Initial Approval Date:	November 6, 2019
Effective Date:	October 14, 2020
Expiration Date:	November 6, 2021

This action is included on the November 12, 2020 IACUC Agenda.

PI responsibilities:

- *Acquire and maintain all necessary permits and permissions prior to beginning work on this protocol. Failure to obtain or maintain valid permits is considered a violation of an IACUC protocol and could result in revocation of IACUC approval.*
- *Ensure the protocol is up-to-date and submit modifications to the IACUC when necessary (see form 006 "Significant changes requiring IACUC review" in the IRBNet Forms and Templates)*
- *Inform research personnel that only activities described in the approved IACUC protocol can be performed. Ensure personnel have been appropriately trained to perform their duties.*
- *Be aware of status of other packages in IRBNet; this approval only applies to this package and the documents it contains; it does not imply approval for other revisions or renewals you may have submitted to the IACUC previously.*
- *Ensure animal research personnel are aware of the reporting procedures detailed in the form 005 "Reporting Concerns".*

Appendix E: Statistical Coding

Ad-Lib Data Code for Varclus in R-Studio

```
library(Hmisc)

RavenData<-read.csv("Ad-Lib_5-11-21.csv")

names(RavenData)

plot(varclus(~ Distance_m + Celcius + Day + Month + Year + Hours + Minutes + Minutes_Day + Location +
Behavior + Post + Ground + Air + Garbage + On_Car + Tree + People + By_Car + Other + Raven +
Object,data=RavenData))

varclus(~ Distance_m + Celcius + Day + Month + Year + Hours + Minutes + Minutes_Day + Location +
Behavior + Post + Ground + Air + Garbage + On_Car + Tree + People + By_Car + Other + Raven +
Object,data=RavenData)
```

Specific Response Data Code for Varclus in R-Studio

```
library(Hmisc)

RavenData<-read.csv("SR_5-11-21.csv")

names(RavenData)

plot(varclus(~ Distance_m + Celcius + Day + Month + Year + Hours + Minutes + Minutes_Day + Location +
Specific + Post + Ground + Air + Garbage + Tree + People + By_Car + Other + Raven +
Object,data=RavenData))

varclus(~ Distance_m + Celcius + Day + Month + Year + Hours + Minutes + Minutes_Day + Location +
Specific + Post + Ground + Air + Garbage + Tree + People + By_Car + Other + Raven +
Object,data=RavenData)
```

Ad-Lib Data Code for Salford Predictive Modeler

```
>USE "C:\Users\Amelia\Desktop\Ad-Lib_5-11-21.csv"
 VARIABLES IN RECT FILE ARE:
     OBSERVER$       DISTANCE_M          CELSIUS               DAY
        MONTH              YEAR            HOURS           MINUTES
  MINUTES_DAY          LATITUDE        LONGITUDE          LOCATION
     BEHAVIOR$             POST           GROUND               AIR
      GARBAGE            ON_CAR             TREE            PEOPLE
       BY_CAR             OTHER            RAVEN            OBJECT

 C:\Users\Amelia\Desktop\Ad-Lib_5-11-21.csv: 1745 records.


 The "USE "C:\Users\Amelia\Desktop\Ad-Lib_5-11-21.csv"" command: 00:06:26

>REM ***Setting General options
>LOPTIONS MEANS = NO, PREDICTION_SUCCESS = NO, TIMING = YES, GAINS = NO, ROC = NO,
PLOTS = NO
>FORMAT = 5
>DISCRETE MAX = 1000,1000
>REM***Setting CART options
>LOPTIONS, NOPRINT = NO, PS = NO
>BOPTIONS SURROGATES = 200 PRINT = 100, COMPETITORS = 200 CPRINT = 200, TREELIST =
100,
>         BRIEF
>REM ***Setting MARS default options
>BOPTIONS PENALTY = 0.000000, SPEED = 4, INTERACTIONS = 1, MINSPAN = 0, BASIS = 15
>MARS SEED = 987654321
>BOPTIONS OLS  = YES
>PRINT = SHORT
>CATEGORY
>AUXILIARY
>MODEL BEHAVIOR$
 Model (target and predictors) reset: BEHAVIOR$
>KEEP
>KEEP AIR, BY_CAR, CELSIUS, DAY, DISTANCE_M, GARBAGE, GROUND, HOURS, LOCATION,
MINUTES, MINUTES_DAY,
>    MONTH, OBJECT, ON_CAR, OTHER, PEOPLE, POST, RAVEN, TREE, YEAR
 KEEP list consists of 20 variables
>LOPTIONS UNS = NO
>CW BALANCED
>SELECT
>PARTITION
>PARTITION NONE
>BLOCK
>TREENET ONETREE = NO, RFLOGIT = NO, LOSS = CLASS, LEARNRATE = AUTO, SUBSAMPLE = 0.5,
>       INFLUENCE = 0.1, TREES = 600, NODES = 10, DEPTH = 100000, MINCHILD = 2, MHESS
= 0,
>       NEWTON = NO, PREDS = 0, TPREDS = 0, RNODES = NO, BSAMPLE = NO
>MONOTONE
>TREENET PLOTS = YES, YES, NO, NO, MV = 30, 30, 0, 0, MP = 0, 500, 0, 0,
>       PP = 500, 5000, 0, 0, CENTER = YES, GB = 10, FULLREPORT = YES, SEED =
987654321,
>       FR = 1
>TREENET SPARSE = NONE, LOWMEMORY = NO, INDEX = YES, LSAMPLING = YES, TRIMPOS = YES,
>       TRIMNEG = YES, TRIMGOOD = YES, TRIMBAD = YES, TRIMAFTER = 0, NODEDETAIL = NO,
>       NEWTON = NO, SIT = NO
>PENALTY
>AUTOMATE
>TREENET GO
```

Specific Response Data Code in Salford Predictive Modeler

```
>USE "C:\Users\Amelia\Desktop\SR_5-11-21.csv"
 VARIABLES IN RECT FILE ARE:
     OBSERVER$       DISTANCE_M          CELSIUS               DAY
        MONTH              YEAR            HOURS           MINUTES
  MINUTES_DAY          LATITUDE        LONGITUDE          LOCATION
     SPECIFIC$             POST           GROUND               AIR
      GARBAGE              TREE           PEOPLE            BY_CAR
        OTHER             RAVEN           OBJECT

 C:\Users\Amelia\Desktop\SR_5-11-21.csv: 476 records.


 The "USE "C:\Users\Amelia\Desktop\SR_5-11-21.csv"" command: 00:01:21

>REM ***Setting General options
>LOPTIONS MEANS = NO, PREDICTION_SUCCESS = NO, TIMING = YES, GAINS = NO, ROC = NO,
PLOTS = NO
>FORMAT = 5
>DISCRETE MAX = 1000,1000
>REM***Setting CART options
>LOPTIONS, NOPRINT = NO, PS = NO
>BOPTIONS SURROGATES = 200 PRINT = 100, COMPETITORS = 200 CPRINT = 200, TREELIST =
100,
>         BRIEF
>REM ***Setting MARS default options
>BOPTIONS PENALTY = 0.000000, SPEED = 4, INTERACTIONS = 1, MINSPAN = 0, BASIS = 15
>MARS SEED = 987654321
>BOPTIONS OLS  = YES
>PRINT = SHORT
>CATEGORY
>AUXILIARY
>MODEL SPECIFIC$
 Model (target and predictors) reset: SPECIFIC$
>KEEP
>KEEP AIR, BY_CAR, CELSIUS, DAY, DISTANCE_M, GARBAGE, GROUND, HOURS, LOCATION,
MINUTES, MINUTES_DAY,
>    MONTH, OBJECT, OTHER, PEOPLE, POST, RAVEN, TREE, YEAR
 KEEP list consists of 19 variables
>LOPTIONS UNS = NO
>CW BALANCED
>SELECT
>PARTITION
>PARTITION NONE
>BLOCK
>TREENET ONETREE = NO, RFLOGIT = NO, LOSS = CLASS, OPTIMAL = AVGLL, LEARNRATE = AUTO,
>       SUBSAMPLE = 0.5, INFLUENCE = 0.1, TREES = 600, NODES = 10, DEPTH = 100000,
>       MINCHILD = 2, MHESS = 0, NEWTON = NO, PREDS = 0, TPREDS = 0, RNODES = NO,
>       BSAMPLE = NO
>TREENET SPARSE = NONE, LOWMEMORY = NO, INDEX = YES, LSAMPLING = YES, SIGMA = NO,
>       TRIMPOS = YES, TRIMNEG = YES, TRIMGOOD = YES, TRIMBAD = YES, TRIMAFTER = 0,
>       NODEDETAIL = NO, NEWTON = NO, SIT = NO
>PENALTY
>AUTOMATE
>TREENET GO
```

Appendix F: All Data Results for *Ad-Lib* Data

The supplementary file Data 5-11-21 AL.pptx found in the google drive linked below contains a Microsoft PowerPoint with screenshots of all raw data gathered from R-studio and Salford Predictive Modeler using the *Ad-Lib* dataset.

https://drive.google.com/drive/u/1/folders/1wVOijOgN6WtdeywuvAzyX9XulRc7PqJU

Appendix G: All Data Results for Specific Response Data

The supplementary file Data 5-11-21 SR.pptx found in the google drive linked below contains a Microsoft PowerPoint with screenshots of all raw data gathered from R-studio and Salford Predictive Modeler using the Specific Response dataset.

https://drive.google.com/drive/u/1/folders/1wVOijOgN6WtdeywuvAzyX9XulRc7PqJU