Redlining's Legacy and Gentrification in Urban Wilderness: Human Risk Perception of Coyotes in San Francisco, 2017-2022

Finnian Whelan

ABSTRACT

Research regarding urban human-wildlife conflict and human risk perception of urban wildlife has extended to encompass the dynamism of the social-ecological human-wildlife interface in our cities. Both human-wildlife conflict and risk perception of wildlife are correlated with certain socioeconomic identifiers. San Francisco has a complex socioeconomic history and landscape, molded by redlining and gentrification. In San Francisco, human-coyote conflict has been shown to have a significant association with neighborhoods of high household median income. To understand how city policy, development, and redesign impacts the human-coyote interface through spatial distributions of socioeconomic-related risk perception, it is critical to look at patterns of conflict over historic and current heterogeneous socioeconomic grades like redlining and gentrification. In this study, I used coyote observation reports detailing sightings and conflict that were sent to San Francisco Animal Care and Control from 2017 to 2022. Using Chi-Squared tests and Geographically Weighted Regression, I analyzed the relationship between conflict and redlining grades, and conflict and gentrification. While there was no significant correlation between redlining and instances of human-coyote conflict in both analyses (Chi-squared $p = 0.0591$), there was a positive correlation between instances of conflict and areas that are experiencing advanced gentrification or financial exclusivity (Chi-squared $p < 0.0001$). Knowing these socioeconomic identifiers are related to higher instances of perceived conflict and, therefore, likely higher risk perception can inform the spatial distribution of future education campaigns to minimize risk perceptions of coyotes.

KEYWORDS

urban human-wildlife interface, human-coyote conflict, financial exclusion, landscapes of socioeconomic heterogeneity, geospatial regression

INTRODUCTION

The coyote (*Canis latrans*) is a prominent character within North America's cities yet is constantly villainized. Because urban development has fragmented habitat and, therefore, pushed larger apex predators - like black bears (*Ursus americanus*) and mountain lions (*Puma concolor*)- from urban centers and peripheries (Bateman et al. 2012), mesopredators, such as coyotes, have risen atop the food-chain and taken advantage of new predatory niches within the city landscape (Prugh et al. 2009; Ritchie and Johnson 2009). Coyotes are adept at filling this role, as they are flexible predators that take advantage of their hunting and scavenging skills developed through experience (Beam et al. 2023; Bateman and Flemming 2012; Lehner 1976). For example, studies comparing urban coyote behavior and diets with those of their rural counterparts have found urban coyotes consume significantly more anthropogenic resources like pets, pet food, human food scraps, and trash (Murray et al. 2015; Bartlett 2024[1]). Urban coyotes also exhibit more boldness and risk-taking behavior compared to their rural counterparts (Breck et al. 2019; Parren et al. 2022). Higher reliance on anthropogenic food sources, and the behavioral boldness underpinning this reliance, encourages more frequent interaction between coyotes and humans, which, without correct management, can lead to greater instances of conflict (Baker and Timm 1998; 2016), and, as a result, sensationalized negative publicization of coyotes (Neisner et al. 2024; Alexander and Quinn 2011; Baker and Timm 2016). While the chance of human-coyote conflict can be greater in urban environments, there is a possibility for coexistence between people and coyotes with the help of management strategies that thoughtfully consider all urban citizens: coyotes and humans alike.

One way to manage human instigation and perception of human-coyote conflict is by targeting urban residents with higher than average risk perception of coyotes. human-wildlife conflict is influenced by people's concern with affective risk, or a potential hazard (Sponarski et al. 2018). In regards to urban coyotes, these potential hazards include damage to one's property, pets, children, or self (Sponarski et al. 2018; Wilkerson 2005). Fear of these damages situates itself in a person's and their surrounding community's understandings of what they have to lose as well as cultural histories of the specific wildlife they fear (Dickman 2010; Benavides 2013). Perceptions

[1] See *SFGate* article "New study reveals what urban coyotes are really eating in San Francisco" by Amanda Bartlette covering Tali Caspi's unpublished study of coyote diets in San Francisco.

of these risks are influenced by many factors, such as personal beliefs, past experiences, and socioeconomic status (Dickman 2010). For instance, in San Francisco, human-coyote conflict was more commonly reported within neighborhoods with higher median incomes (Wilkinson et al. 2023). This is possibly because these neighborhoods tend to have a higher prevalence of coyote-friendly habitat, or because these residents may be more likely to spend time outdoors and encounter coyotes (Wine et al. 2014; Wilkinson et al. 2023). San Francisco specifically offers a unique landscape where relations between risk perception, human-coyote conflict, and socioeconomic patterns can be further explored due to its heavily impactful social-financial history and changes within historically low-income neighborhoods due to the processes of redlining and gentrification.

Redlining and, now, gentrification, are processes that have underpinned the distribution of financial, racial, and social inequalities in our cities (Richardson et al. 2019; Aaronson et al. 2021; Xu 2023) and have shown to inform the distribution of environmental access and risk. Redlining was a system used by the U.S. government in the 1930s to rate neighborhoods' financial risk based on racial composition, in which areas marked most "hazardous" targeted racial minorities and severely impacted People of Color's abilities to accumulate generational wealth (Appel and Nickerson 2016; Hillier 2003). Historically redlined areas are significantly correlated with environmental disparities such as limited tree cover (Schell et al. 2020; Nowak et al. 2022) and lacking biodiversity (Schmidt and Garroway 2022; Wood et al. 2024) when compared to areas ranked with less financial risk. However, San Francisco, like many other major U.S. cities that were once redlined, is seeing socioeconomic, compositional changes in the face of gentrification, which is marked by wealth and capital flowing into lower-income, inner city neighborhoods and began in the city in the 1990s (Mirabel 2009). Gentrified areas are correlated with higher than average biodiversity metrics (Fidino et al. 2024) and have shown to be encouraged by recent implementation of green space and greenways (Cole et al. 2017; Rigolon et al. 2019). However, little research has been done to evaluate how redlining's legacy and gentrification have interacted with urban wildlife presence and interactions with people, as well as how redlining and gentrification have impacted people's perceptions of urban wildlife. I plan to address this gap by questioning how redlining's legacy and gentrification in San Francisco have interacted with one another to shape the human-coyote interface and, more specifically, people's perceptions of coyotes in San Francisco.

In this thesis, I will answer the following central question: How has redlining's legacy informed human-coyote interactions in San Francisco, and how have these interactions changed with gentrification? To best structure my study, I will partition it into three sub-questions. I specifically ask, 1) How does historic redlining typology align with San Francisco neighborhoods' current gentrification status?; 2) How, if at all, are instances of coyote sightings and human-coyote conflict related to spatially heterogeneous historic HOLC grades?; and 3) How do trends in coyote sightings and conflict reports differ among locations of varying gentrification status? Due to the dynamism of San Francisco's housing and job markets, many historically red or yellow lined areas may be heavily gentrified now, thus generating differences between historic redlining typology and current gentrification status. I predict that reports of coyote sightings and conflict will originate from historically greenlined and/or exclusive, gentrified neighborhoods, specifically neighborhoods that were greenlined and have remained financially exclusive. To test these hypotheses, I will use a Kruskal-Wallis test, Chi-squared tests, and Geographically Weighted Regression to analyze the distribution of gentrification stages across HOLC grades and the distribution of coyote observation reports sent to San Francisco Animal Care and Control from 2017-2022 along historic HOLC and gentrification maps.

FRAMEWORK

San Francisco: A meeting ground for social and natural change

This study focuses on the city of San Francisco, California, as it has a large estimated urban coyote population and a dynamic history that has generated forms of socioeconomic exclusion through processes like redlining and gentrification. After a period of vigilant coyote population control and eradication of the species during the latter half of the 20th century, a coyote was officially spotted in the Presidio in 2002, most likely having crossed the Golden Gate Bridge from Marin (Taylor 2020). As the coyote population has grown since 2002, mixed feelings have stirred in the public about the reestablishing mesopredators (Wilkinson et al. 2023). In response, officials of the San Francisco Recreation and Parks Department and San Francisco Animal Care and Control (SFACC) are educating the public on certain routines to ensure safety for pets and people as well as proper hazing tactics to keep coyotes fearful of humans (SFACC 2014; Chitins 2023).

However, public complaints and education tactics are not evenly distributed throughout the city. They have been heavily associated with proximity to green spaces and neighborhoods with higher median incomes (Wilkinson et al. 2023). These two factors are greatly intertwined, as proximity and access to green space are correlated with higher socioeconomic status (Hoffiman et al 2017; Carroll 2017). Because of San Francisco's complex contemporary history of racial and economic exclusion that is historically indicated by redlining and is now punctuated by gentrification, the distribution of higher than average instances of conflict and related higher coyote risk perceptions throughout San Francisco may be influenced by many different socioeconomic patterns and dynamics. How redlining and gentrification - two major socioeconomic processes - have interacted with one another to inform a spatial human-coyote interface of differentiated risk perception is critical to understand in order to prepare for future development and redesign in San Francisco.

Coyotes' connotations in cities

People tend to negatively perceive urban coyotes more than other urban wildlife, primarily due to sensationalized media coverage. For example, urban red foxes (Vulpes vulpes) were significantly favored over urban coyotes by the public, perhaps because urban coyotes are bigger in size and affiliated more with conflict than the red fox (Nardi et al. 2020). While coyotes can occasionally pose a theoretical threat to people and their pets, cases of attack are rare (Nardi et al. 2020; Gehrt et al. 2022). In fact, from 1977 to 2015, only 367 attacks have occurred in all of the U.S. and Canada (Baker and Timm 2016). Yet the media's tendency to highly publicize these instances of conflict heavily impact the public's perception of coyotes and the risk associated with them (Alexander and Quinn 2011; Baker and Timm 2016).

Such intense sensationalism of coyotes has led to what Niesner et al. (2024) term a "cloud coyote," which forms when a resident posts about a coyote sighting on an online platform, like Nextdoor, and readers of the post then feel as though they have seen the coyote and, in reaction, feel threatened. To best reach a place of tolerance of the actual and perceived risks that coyotes impose, human perceptions are incredibly important to consider. With my study, I hope to help identify specific patterns of heightened conflict and negative perceptions of coyotes over the spatially heterogeneous historic HOLC grades and varyingly gentrified landscape of San Francisco.

A balance of conflict and coexistence in human-coyote interactions

Urbanity and nature are far less binary than people tend to believe. Human-wildlife relations are constant and dynamic: peoples' and wildlife's actions, habits, and behavior consistently influence one another. Urban wildlife ecologists consider this human-wildlife interface a continuum of exchanges that range from "coexistence" to "conflict" (Bhatia et al. 2019; Frank et al. 2019). "Coexistence" is defined by human tolerance of risk imposed by human-wildlife relations and active management of those risks so they do not escalate to become unbearable (Pooley et al. 2020) and result in "conflict." "Conflict" is typically characterized by harm to one or both parties (Redpath et al. 2014; Conover 2002).

However, another theory argues that this conflict-coexistence framework is too simplistic and should be altered to account for multiple outcomes by looking at human wildlife interactions as a life cycle that occurs over wide spans of time rather than in concrete incidents to better account for the dynamic, fragile processes that occur within in the human-wildlife interface (Harris et al. 2023). Finding an ideal balance of charged and neutral instances within the life cycle of human-coyote interactions is a consistent challenge in many North American cities including San Francisco, Edmonton, Denver, Los Angeles, and San Diego (Wilkinson et al. 2023; Farr et al. 2023; Poessel et al. 2013; Baker and Timm 2016). Michelfelder (2018) explains that to reach a balance, managers must stimulate educated, mutual engagement between wildlife and people rather than indifferent tolerance. This education to foster neutral, engaged interactions is needed as cities continue to change at accelerated paces (Magel et al. 2012 & Patterson et al. 2003). San Francisco is marked by notable public debates about management of the growing coyote population and increasing human-coyote conflict (Greer 2021). To foster active coexistence in San Francisco, future education strategies must be informed not just by coyote behavior, but by human behavior and related factors that impact how coyote-related risk is perceived by urban residents.

Risk perception & socioeconomic factors

How a person perceives risk, just like any other subjective perception, is influenced not just by a concrete instance of threat or conflict but that person's life experiences, biases, resources, and social position within their communities. Rather than an "assessed" risk based upon expert evaluation (Decker et al. 2018), risk perception is a person's subjective idea of a potential threat under a given set of conditions (Sponsarski et al. 2018). While subjective, the perception of risk is not freely chosen; as Sjöberg (1997) explains, people want to be free of their irrational fears or objects of their rational fears, but these fears or perceptions of risk are biologically manufactured as an integral part of human survival and structured by socially shared histories and cultural understandings (Pooley et al. 2016. For instance, Manzolillo et al. (2019) discuss the "Big Bad wolf memory," which is based on Western historical values and socially-shared stories villainizing wild canids. This heightened risk perception of wild canids stems from how they preyed on livestock and threatened humans as trophic competition thousands of years ago (Flores 2016). However, while these nightmares of wild canids remain fresh in our collective memory, this risk perception may be encouraged by people's limited knowledge of the current conditions they face today.

Perceived risk involves an element of uncertainty, where there is a perceived possible threat in a situation where its outcome is still unknown (Sjöberg et al. 2004). This fear of uncertainty, therefore, can lead to perceptions of a situation that reflect conflict but may not actually be conflict. For example, when raising pups, coyotes may shepherd a person away from their den with no intent of attack, but that person, unaware that coyotes have this behavior, may believe the coyote is chasing them, which generates, what is called "perceived detriments" (Zuluaga 2022) or "perceived conflict" (Wilkinson et al. 2023; Draheim et al. 2019; Marker 2003). To reduce instances of "perceived conflict," city and wildlife management can use public education campaigns and target areas with social indicators associated with higher instances of conflict.

To manage human-wildlife interactions and respond to fear of wildlife or wildlife-caused damage, officials typically have three baseline assumptions: 1) the level of damage caused by wildlife is directly proportional to the conflict that ensues; 2) "the level of conflict elicits a proportional response;" and 3) that resulting conservation effects will be proportional to the response elicited by conflict (Dickman 2010). However, these assumptions are often undermined by humans' varied perceptions of risks and disproportionate responses to wildlife, which are both results of compounding environmental and social factors, and heavily contribute to human-wildlife conflict (Dickman 2010; McInturff et al. 2020; Eden et al. 2020). Uneven wildlife-related risk perception in an area has also been linked to variation of social factors, like gender (Gore and Kahler 2012) and education levels (Clearly et al. 2021). Specifically, people in areas with a higher median household income are positively associated with the propensity to encounter a coyote and then report such interaction to an official entity (Wine et al. 2014; Wilkinson et al. 2023). So not only are the parks and green spaces that act as urban coyote habitat (Grinder and Krausman 2001) typically closer to higher income residents, but higher-income residents also have a greater propensity to fear and perceive conflict with coyotes than others. This study will explore what forms, informants, and histories of economic wealth are correlated to higher than proportional responses to risk perceived from human-coyote interactions.

Redlining: Officiating landscapes of social and economic exclusion

Redlining was a tool used by the U.S. government to officiate methods of socioeconomic and racial discrimination along inner-city residential boundaries. Redlining was a historical practice established by the Home Owners' Loan Corporation (HOLC) in the 1930s, in which HOLC divided cities, including San Francisco, into blocks by ranking economic validity and risky loan areas based on the racial make-up of residents (Appel and Nickerson 2016). The four rankings, their associated financial risk, and codified racial policies follow (Appel and Nickerson 2016):

- Green = "best;" minimal financial risk; all white and born in the U.S.
- Blue = "still desirable" and mostly white but existent financial risk due to "infiltration of a less desirable class of people" (Federal Home Loan Bank Administration and United States 1936)
- Yellow = "definitely declining;" high financial risk posed by an increase in racial minorities (Latinx, African American, Asian, non-white) present
- Red = financially "hazardous" due presence of racial minorities[2]

Redlining led to the impoverishment of many American cities in the mid-20th century through urban divestment, and, in turn, generated urban landscapes marked by differentiated financial

[2] According to Appel and Nickerson (2016), areas even with minimal black populations were given a "hazardous" ranking.

opportunities and risks (Hillier 2003). Through loan and property-ownership exclusion, redlining has prohibited culmination of generational wealth among many Communities of Color, even past its abolishment via the Fair Housing Act of 1968 (Sullivan et al. 2015; Appel and Nickerson 2016; Pearcy 2020). Redlining established deeply rooted, racialized inequalities in American cities, which are being further exacerbated yet also altered by new processes, like gentrification.

Gentrification: Shifting landscapes of social and economic exclusion

Gentrification is a dynamic delicate process that is restructuring the socioeconomic landscape of our cities. Gentrification has been defined as "the rehabilitation of working class inner-city neighborhoods for upper-middle class consumption" (Smith and LeFaivre 1984), but this "rehabilitation" has led to both "direct and indirect" displacement of poorer urban residents to peripheral neighborhoods surrounding the city and, therefore, to the suburbanization of poverty (Hochstenbach and Musterd 2017). Gentrification has been shown to be related to the legacy left behind by redlining, as areas with larger residential Communities of Color and lower property values have shown to be more vulnerable to gentrification (Richardson et al. 2019; Rigolon and Németh 2019). Gentrification occurs through movement of wealthier residents into poorer neighborhoods, changes in public policy and investment, and an influx of private, commercial capital (Zuk et al. 2015). Changes in policy and investment increase housing and rental costs and, as a result, displace low-income, predominantly racial-minority residents (Chappel and Zuk 2015).

San Francisco's gentrification often involves indirect displacement, which gradually forces lower income residents out of their neighborhoods due to higher rent burdens and changing social composition of the neighborhood (Versey et al. 2019). Lower income residents have become financially and socially insecure in their neighborhoods due to the technological boom and public investment to attract higher paying technology jobs emanating from Silicon Valley (Maharawal 2014). In fact, four of the ten most expensive housing markets in the United States are located in the San Francisco Bay area (Zuk and Chapple 2015). Considering neighborhoods in these remarkably expensive counties were once redlined, marked as financially risky, and, suffered the many health and environmental consequences of unequal wealth distribution -ie lacking greenspace within a one mile radius (Jacques-Menegaz 2006) and poorer health in once redlined areas (Nardone et al. 2020) - understanding how gentrification's changes to the socioeconomic landscape of San Francisco are now interacting redlining's legacy is critical to understand the current dynamics between San Francisco's citizens, their surrounding environment, and, specifically, the surrounding wildlife.

A solution to understand redlining and gentrification along the human-coyote interface: Geospatial modeling

The methods of my thesis rely on the fact that reporting of coyote sightings and conflict do not just occur at a certain time and produce a certain result (fear, injury, etc), but also occur in a certain location. Each report can be spatially situated in a neighborhood of San Francisco, that may be impacted by a historic HOLC ranking as well as current gentrification processes. Furthermore, these reports can measure an instance of coyote-related risk perception. The mere act of reporting a coyote observation, especially conflict, can arguably be considered a perception of risk. One response to risk includes mitigation of perceived risk to "the greatest extent possible" (Boussabaine and Kirkham 2008). The public, as seen in previous studies, have used reporting methods to official agencies in other cities to report coyote sightings, conflict, and feelings of coyote-imposed threat in order to mitigate this perceived risk (Baker and Timm 1998; Poessel et al. 2013). Therefore, these reports can act as georeferenced instances of public coyote-related risk perception.

To establish if redlining's legacy or gentrification have an impact on peoples' coyote-related risk perception, I mapped public reports of coyote sightings and conflict over both historic maps generated by HOLC's redlining practice and current gentrification maps of San Francisco and then used spatial analysis to establish any significant spatial relationships. Spatial analysis reduces the bias of regular statistical testing, as it accounts for relationships determined on a geographic plane and by proximity to and/or distance from a certain determinant variable (Ward and Gleditsh 2007). Many studies have utilized spatial regression to determine statistical relationships between discrete events and heterogeneous landscapes. For example, one study used spatial analysis to determine how redlining's legacy has impacted frequency of Covid Cases over various neighborhoods in Cook County, Illinois (Bertocchi and Dimico 2020), and another used spatial analysis to determine how connectivity of urban parks impact bird population numbers (Yang et al. 2022). By modeling reports of coyote sightings and conflict over a heterogeneous socio-economic landscape, I am able to evaluate critical relationships between redlining's legacy, gentrification, and public risk perceptions of coyotes needed for effective and targeted coyote-conflict management, specifically public education and outreach programs, in San Francisco.

METHODS

Study site

San Francisco City is a metropolis in Northern California. It measures about 46.87 mi^2 and is a peninsula bordered by the Pacific Ocean on the West and North sides of the city and the San Francisco Bay on the East side of the city. San Francisco typically has moderate winters and summers, thanks to its Mediterranean climate due to its mid-latitudinal position and closeness to the ocean (Null 1978). The city is composed of many neighborhoods characterized by localized histories, architecture, landmarks, and dynamics both on the social scape and the human-wildlife interface.

Data collection

To collect data for this thesis, I used three major sources: digitized, historical Home Owners and Loan Corporation (HOLC) data (Nelson et al. 2023); The Urban Displacement Project (UDP; Chapple et al. 2021); and community coyote sightings data gathered by San Francisco Animal Care and Control (SFACC).

Socioeconomic inequality data

HOLC, when designating grades of financial risk across American cities, created maps to color demarcated areas with their previously mentioned grading scheme. These maps were, for the most part, created in the 1930s. To be included in geographic, statistical analysis now, they have been georeferenced and digitized. For this particular project, I utilized Nelson et al. (2023) digitized versions of the San Francisco HOLC financial risk grade map.

The Urban Displacement Project (UDP) provides geographically referenced data on many current and historic socioeconomic processes, specifically redlining and gentrification, which I downloaded and altered to use later in data analysis. The Urban Displacement Project was generated by social scientists, geographers, and spatial analysts to measure socioeconomic change, particularly through gentrification, that has caused displacement of urban residents.[3]

Data transformations: categorial to ordinal

In this study, I conducted geographic analysis with numeric variables. Both HOLC and UDP layers, the determinant variables of this study, were originally in categorical form, so Ichanged the formatting of these data in order to better interpret geographic analysis. Altering redlining data was relatively simple, as I changed the data's display from categorical HOLC letter grades to corresponding ordinal grades in ArcGIS Pro (Version 3.2).

Altering the UDP data required assigning numeric rank to each georeferenced census tract by studying and dissecting Urban Displacement Project's publicly available code that enables users to create displacement typology maps for other cities of interest and their documented method used to assign gentrification typologies. UDP created eleven typologies to map gentrification risk and advancement in San Francisco (Table 1).

Table 1. UDP gentrification and displacement typologies. Table listing all eleven UDP typologies that compose the map depicting vulnerabilities to, and stages of gentrification and financial exclusion.

Eleven Typologies
Low-income/ susceptible to displacement
Ongoing displacement of low-income households
At risk of gentrification
Early/ongoing gentrification
Advanced gentrification
Stable/ moderate mixed income
At risk of becoming exclusive
Becoming exclusive
Stable/ advanced exclusive
High Student Population
Unavailable or Unreliable data

[3] Displacement typologies can be seen in Table 1.

To generate these typologies, the Urban Displacement Project utilized data from Zillow and the SF Bay Area's 1990, 2000, and 2018 census to account for any long-term and short-term changes in the racial, economic, and residential conditions of San Francisco's census tracts (Thomas et al. 2020). Five of these typologies, "Low-income/ susceptible to displacement," "Ongoing displacement of low-income households," "At risk of gentrification," "Early/ongoing gentrification," and "Advanced gentrification" constitute the 5 gentrification typologies as they encompass current or previously predominantly low-income census tracts that are at risk to or have experienced gentrification since at the earliest 1990 (Thomas et al. 2018). Three other typologies, "At risk of becoming exclusive," "Becoming exclusive," and "Stable/ advanced exclusive" constitute the three financially exclusive typologies, as they encompass predominantly moderate to high income census tracts that have seen increases in housing costs (Ibid). The "Stable/ moderate mixed income" typology in the UDP legend falls in the middle of the five gentrification typologies and the three financially exclusive typologies as it is predominantly mixed-income and has not seen great change (Ibid). For the purpose of this study, only census tracts that fell into the nine aforementioned typologies were analyzed. Census tracts marked as having a "High Student Population" or "Unavailable or Unreliable data" did not have enough financial, socioeconomic, or historic indicators to assess their gentrification advancement, which is the basis of my binning process to create an ordinal UDP ranking system.

In order to bin these typologies, I followed a similar process to Fidino et al. (2024), who created a gentrification binary through a modification of the Urban Displacement Projects' (Thomas et al. 2018) process. They marked gentrifying areas by identifying tracts with greater than 500 residents, tracts that were vulnerable to gentrification in 2010, and tracts that had at least two of the three qualities: "1) a median income less than the city's median income, 2) a proportion of college-educated residents less than the city median, and 3) a proportion of non-White residents greater than the city median" (Fidino et al. 2024). However, to be able to look at gentrification and financial exclusivity at a finer scale as well as run geospatial analysis, I decided to use this process to create an ordinal ranking system rather than a binary system using UDP typologies.

When reading through Thomas et al. 's (2018) open source UDP code, I found three major variables generated from census, rent, and housing price data from 1990 to 2018 that demonstrated advancement of gentrification. These determined if a census tract 1) was at one point vulnerable to gentrification, 2) had a "hot"/ in demand housing market, and 3) had experienced gentrification prior to 2018. Census tracts vulnerable to gentrification were those with higher property values and rent values compared to city average and census tracts that had ¾ of the following identifiers: higher than city-average percentage of renters, higher than city-average percentage of low income residents, higher than city-average percentage of non-white residents, and higher than city-average residents older than 25 years with a college degree (Thomas et al. 2018). Census tracts with a "hot" housing market were marked when an area had a change in rent or housing value that was above the regional median when looking at the time periods of 1990-2000, 2000-2018, and 2012-2018 (Ibid). Areas that had experienced gentrification prior to 2018 had been vulnerable to gentrification prior, had experienced a hot housing market, and had seen above average increases in college educated residents, household income as well as above average decreases in low income residents and low income housing (Ibid). I used these general indicators along with the predominant income types in a typology to then bin together typologies to create an ordinal ranking system, which demonstrates a census tracts' advancement towards gentrification on a scale from 1-5.

San Francisco Animal Care and Control data

In order to utilize these numeric socioeconomic data as a base layer in ArcGIS to establish which, if any, redlining and gentrification typologies are significantly associated with higher risk perception of coyotes, I gathered point data to display georeferenced coyote reports sourced from SFACC. Since 2006, SFACC has been collecting coyote observation reports, which were first synthesized and utilized for data analysis by Wilkinson et al. (2023). In these reports, the public are encouraged to report coyote sightings and/or conflict with coyotes. For the purpose of this study, we chose to use report data from 2017 to 2022 due to an upgrade in reporting technology in 2017 and to ensure a temporal alignment between these report data and UDP data, which is based on 2018 demographic and housing data.

Before I could display these data within ArcGIS, I sorted observations that were sent to SFACC from 2022 to 2023 using the methodologies from Wilkinson et al. (2023). These reports were typically sent directly through SFACC's website's coyote observation form, but also consisted of memos, emails, or phone calls from the public who wished to report a sighting of or incidence of conflict with one or more coyotes.

When reporting through the website's form, users were asked to provide their name, their contact information, date of observation, time of observation, location of coyote observation, a description of what they observed, further comments if needed, and a few other descriptors that include if hazing was used or a dog was involved. (See Appendix A for example of SFACC online observation report sheet). However, only date, time, location, description and extra comments were used when sorting and cleaning data. Date and time were included in order to separate data throughout the years of 2017 to 2023 and enable further temporal analysis for future users of the data set. Location was used in order to later georeference the observation report. Observation descriptions and extra comments were included to establish whether the report was a perceived conflict or not. Since community observation reports are inherently informed by the perceptions of the reporter, we classified both perceived (i.e., a reporter says they were chased) and actualized (i.e. a person's cat was seen being taken by a coyote) conflict as "conflict" (Wilkinson et al. 2023). Wilkinson et al.'s (2023) requirements for conflict follow:

- Coyote(s) touching, following,[4] stalking, chasing, or attacking a person, pet, or domestic animal.[5]
- Coyote(s) threatening (i.e., baring teeth, snarling, growling, etc.) a person, pet, or domestic animal.
- Coyote(s) killing a pet or domestic animal.[6]
- Coyote(s) struck by vehicle or described as disrupting traffic patterns.
- Off-leash dog(s) chasing coyote(s).

After sorting each observation in a binary to describe whether conflict (perceived or actual) occurred, these data were then transferred into georeferenced point data utilizing the locations provided and/or described in the report. I included the binary conflict information in the metadata of each georeferenced point for further analysis. If it was unclear whether the observation involved conflict or not, it was sorted as "unknown." If the provided location was not descriptive enough, for example, if a street without a number was the only location indicator, the observation was omitted from the cleaned and sorted data set.

[4]*Did not distinguish between following at near vs. far distance as this was not discernable in most reports. Regardless of distance, following may be perceived as conflict.*

[5]*Did not distinguish between domestic and feral cats since human perception and apparent emotional impact tend to be similar for both.*

[6] *See above note in regards to feral cats constituting a "domestic animal."*

I added previously cleaned, sorted, and georeferenced the reports created between 2017 and 2021 created by Wilkinson et al. (2023) to my own set of georeferenced points for the year of 2022.

Data analysis

Redlining's legacy and gentrification's alterations

In order to establish how gentrification statuses and risk of displacement were distributed across historical HOLC grades, I used a Kruskal-Wallis test and a Chi-Squared test. The Kruskal-Wallis is a non-parametric version of ANOVA -a one-way analysis of variance test - and used in this case, to establish if there is a significant difference between the calculated median UDP ordinal gentrification rank among the four HOLC grades. Chi-Squared is another way to find a significant difference among the four categorical HOLC grades, except this test analyzes the frequency of census tracts ranked with the 1-5 UDP ranking system within each HOLC grade.[7] The Kruskal-Wallis test has been used to assess differences in spatial distributions of age, population size, land surface temperature, and canopy area across HOLC grades (Hicks et al. 2023; Jung et al. 2024). Similarly, the Chi-squared test has been used to assess differences in frequencies of sex, race, and health conditions geospatially falling within given HOLC grades (Lynch et al. 2021; Hicks et al. 2023). While ordinal UDP bins were designed for GWR analysis, they were used as categorical variables in Chi-Squared.

To find the assigned UDP score and HOLC grade per census tract, in ArcGIS Pro 3.2, I used the Intersect tool to join the HOLC shapefile's attribute data to the altered UDP data. I then calculated the mean UDP continuous score measuring level of gentrification and risk of displacement for each of the four HOLC grades. Using RStudio and the readxl and tidyverse packages (R Core Team 2023; Wickham and Bryan 2023; Wickham et al. 2023), I ran the Kruskal-Wallis and Chi-Squared tests for the four grades as neither of these tests require normal distributions across all four HOLC grades (Ostertagová et al. 2014; Connelly 2019). I calculated a multiple comparisons test (for Kruskal-Wallis) with the dunn.test package (Dinno 2024) to isolate which HOLC grades are significantly different from one another. As a post-hoc test is difficult to

[7] These census tracts were established in 2018; the area or official identification of these tracts may be different now.

calculate when a contingency table has more than two groups and categories, I had to find another way to compare what HOLC grades were significantly different from the null hypothesis in the Chi-squared test. To do so, I calculated adjusted standardized residuals. RStudio's default residual calculation uses the Pearson method (Rdocumentation.org 2024), which divides the raw residual between observed and expected values by the square root of the expected value (Sharpe 2015). However, the adjusted standardized residual requires the following operation:

Adjusted Standardized Residual = (Observed-Expected)/√(Expected*(1-RowMarginal/n)*(ColumnMarginal/n)

where column and row marginals represent the sums of each column and row, respectively, for the corresponding cell (Ibid). If adjusted standardized residual absolute values are greater than 2.00, those contingency table cells contributed to a significant Chi-squared statistic (Ibid), so to establish which observed rank counts were significantly less or more than expected for each HOLC grade, I calculated adjusted standardized residuals with Excel 2403 (Build 17425.20176) and isolated those with absolute values greater than 2.00.

Conflict and non-conflict reports along HOLC grades

To establish if there was a significant correlation between coyote reporting frequency and specific HOLC grades, I used the Chi-Squared test and Geographically Weighted Regression (GWR). To run Chi-squared, I again in ArcGIS Pro, used the Spatial Join tool to join HOLC shapefile's attribute data to the coyote report data from 2017-2022, which included the aforementioned conflict binary. I then ensured that the data's distribution matched the Chi-Squared test assumptions that the categories -HOLC grades- are mutually exclusive, the study groups -observation and conflict frequencies- are independent, and that 80% of cells have an expected count greater than 5 (McHugh 2013). After creating a frequency table of observed instances counted along HOLC grades and an expected frequency table in RStudio, I then used these tables to run the Chi-Squared test (R Core Team 2023; Wickham and Bryan 2023; Wickham et al. 2023). This Chi-squared Test produced a frequency table with Chi-Squared residuals and listed a Chi-Squared Statistic, the degrees of freedom, and a p-value to establish any significant correlation between conflict incidences and HOLC grades. If the p-value was significant, I then ran a post-hoc test to compare how significant HOLC grades were compared to one another's observed frequencies.

However, because these points of perceived conflict and non-conflict are geospatial data, these data may actually not be independent, which GWR accounts for. GWR is a form of Spatial Analysis, which accounts for spatial autocorrelation in spatial analysis. Spatial autocorrelation relies upon Tobler's First Law of Geography (1970) that states "everything is related to everything else, but near things are more related than distant things." (Sited in Miller 2004). GWR, therefore, determines if there is significance between two geospatial phenomena with an altered form of regression analysis that accounts for increasing dependence between two events as the distance between them decreases (Thapa and Estoque 2012). The formula for GWR is as follows: $y_i = B_0 (u_i, v_i) + \sum_k B_k(u_i,v_i)x_{ik} + \varepsilon_{i.}$ In which y_i is the estimated value of the dependent variable for the event i, which, in this case, would be 1 or 0 to signify the respective presence or absence of reported coyote conflict incident. k represents the number of explanatory variables (x) that relate to y (Páez and Wheeler 2009). $B_0 (u_i, v_i)$ represents the event's location in space, and $B_k(u_i,v_i)$ signifies the continuity of the function at event i, which is why geographically weighted regression requires analysis upon continuous surfaces (Thapa and Estoque 2012). ε_i accounts for error (et al).

In order to account for the potentially spatially impacted relationship between report incidences and HOLC grades, ArcGIS Pro required that I establish a Nearest Neighbor Parameter, which itself defines the kernel function that sets a window over clusters of events and relates each event to a focal point (Páez and Wheeler 2009). In order to determine my nearest neighbor, I used the Golden Search Distance Band method, which calculates the distance for localized logistic regressions in order to optimize the corrected Akaike information criterion (AICc) (Oshan et al. 2019). The optimal AICc has been used as criterion to select specific GWR models that predict other discrete environmental-related phenomena like relationships between mosquitoes and human densities (Lin and Wen 2011), instances of human leptospirosis (Mohammadinia et al. 2017); and occurrence of cholera (Nkeki and Osirike 2013). For this study, I used a logistic model where the explanatory variable, HOLC grades, were represented by an ordinal schema (A=4; B=3; C=2; and D=1) and the dependent variable, conflict/nonconflict binary points, were analyzed as discrete points distributed over HOLC grades. The final product was a map of San Francisco that included points of varying standard deviance residuals, where higher, positive residuals represented discrete points in space where conflict is most likely.

Conflict and non-conflict reports along ordinal UDP gentrification score

To answer my third sub-question and understand if there is a significant correlation between coyote reporting frequency and specific gentrification statuses determined by the Urban Displacement Project, I again used the Chi-Squared and GWR methods described in the previous subsection detailing my steps to determine if there was a significant correlation between instances of conflict and HOLC grades. However, there were a few differences when it came to temporal break-up of data.

To collect data for my Chi-squared tests and run logistic GWR, I again used ArcGIS Pro 3.2. I calculated Chi-squared results and ran GWR a total of eight times with different temporal selections of report data. Because the UDP gentrification score is based on 2018 data and gentrification is a very rapid and dynamic process, my scoring system for gentrification may not have been capable of encompassing all socioeconomic change in the city and, therefore, resulted in unknown associations between gentrification scores and human-coyote conflict. I chose to calculate Chi-squared statistics and run GWR per year to evaluate if different associations occurred at different time periods. I then grouped 2018, 2019, 2020, 2021, and 2022 data together as all of these years proceed after UDP's data timeframe. I then ran another round of Chi-squared and GWR analysis to encompass all conflict and non conflict data over my study's total time period. To run GWR specifically, I used the conflict binary data set as the dependent variable in and used ordinal UDP ranking system as explanatory variable. The output of these statistical runs included standardized deviance residuals, in which, again, the more positive residuals indicated discrete points in space significantly associated with instances of perceived conflict.

Determining whether HOLC Grades or Gentrification Scores are more statistically significant

However, this method only answered part of my question. In order to establish if there was a significant difference between reporting considered in terms of redlining's legacy or in terms of current gentrification, I compared the p-values and GWR results ran to evaluate associations between the distributions of 2017-2022 conflict and observation (non-conflict) report points over both HOLC grades and my UDP ranking system.

RESULTS

Data collection results

San Francisco Care and Control data collection results:

From 2017 to 2022, I gathered a total number of 2,771 reports. The average number of reports is 461.8 per year. Using Kernel Density Estimation, the distribution of observation reports over a search radius of 900m^2 shows notable density values marked by dark to mild greens in the south-west region of the city, just west of the Mission district, and in the north-east corner of the city (Figure 2).

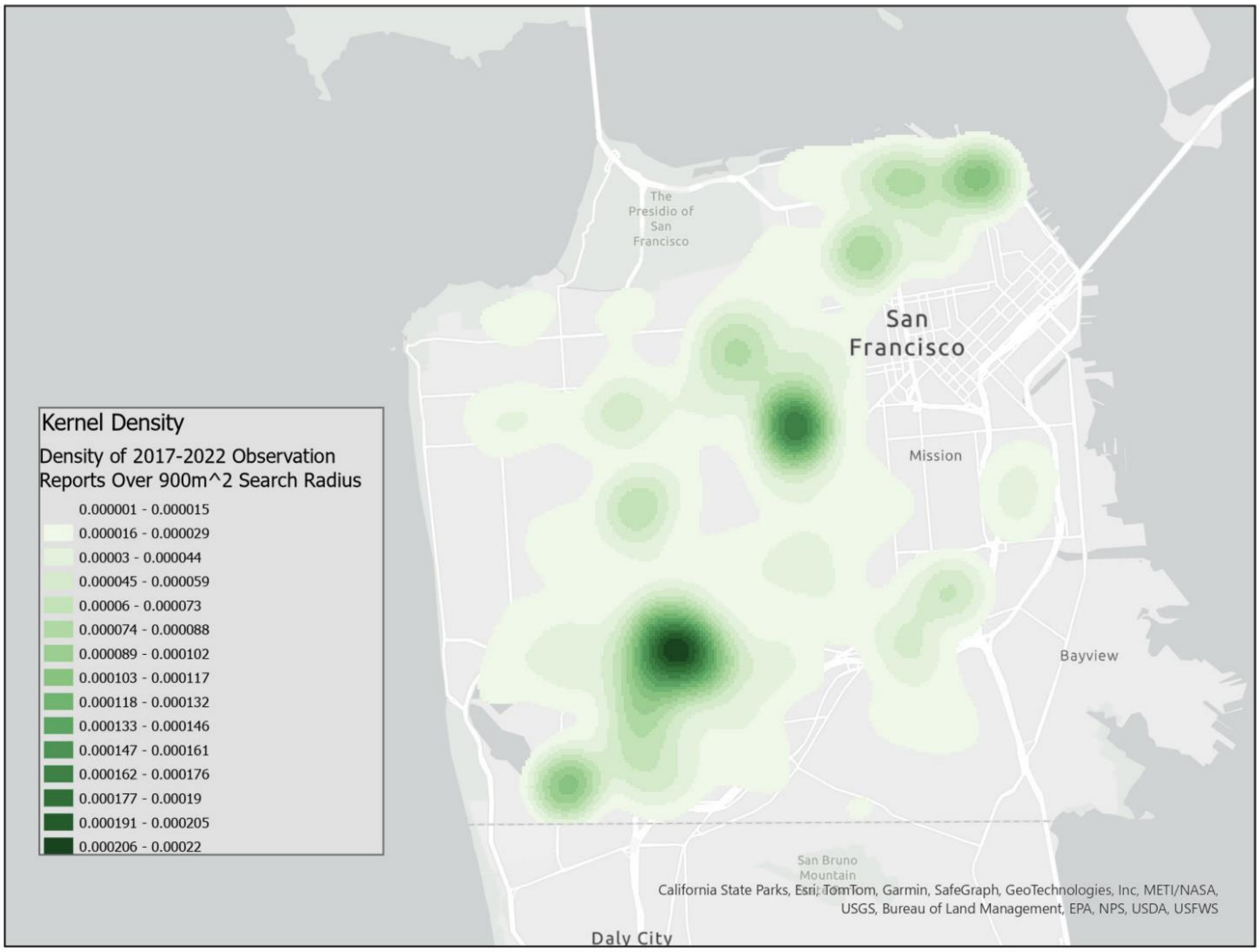

Figure 2. Kernel density estimation of SFACC 2017-2022 observation reports. This density estimation was based on the map of all georeferenced reports (conflict and non conflict) in SF from 2017-2022, and created to maintain the privacy of reporters' locations.

However, all of the data points I collected were not included in my analysis. 223 reports were difficult to distinguish between conflict and non-conflict, were marked as "unknown," and not considered in this study. Also, historic HOLC grades and UDP typologies did not cover the entire city. HOLC could not evaluate large parks as they did not have official residents and could not evaluate some areas because they were "Sparsely settled" or "Industrial and Commercial" (Nelson et al. 2023), so observation points that fell in these two types of areas were not included to answer sub-question two, which left me with 1,548 points to analyze.

Furthermore, as previously mentioned, the census tracts marked by UDP as "High Student Population" and "Unavailable or Unreliable Data" were not considered in my ranking system, so reports that fell in these areas were also not considered in my study when answering my third question. In order to understand the potential relationship between my UDP ranking system and instances of conflict and non-conflict while accounting for these gaps in UDP data, I used 2,247 points. Specifically, when conducting yearly analysis, I utilized 332 georeferenced reports from 2017; 373 georeferenced reports from 2018; 560 georeferenced reports from 2019; 230 georeferenced reports from 2020, 367 georeferenced reports from 2021, and 373 reports from 2022.

Data transformation results:

HOLC grades. To transfer HOLC grades (A,B,C,D) into an ordinal ranking system, I used HOLC's "Best" to "Hazardous" ranking ideology (Appel and Nickerson 2016). Areas with the "Best" financial grade were assigned a 4, areas marked as "Still desirable" were assigned a 3, areas marked "In decline" were assigned a 2, and areas marked as "Hazardous" were assigned a 1. As the HOLC methodology was not actually based on financial riskiness but race, I decided to construct this ranking system rather arbitrarily in order to run GWR. This ranking system would also work if "Best" was assigned a 1, "Still desirable" was assigned a 2, ect.

UDP typologies. After considering UDP's three general markers [1) was at one point vulnerable to gentrification, 2) had a "hot"/ in demand housing market, and 3) had experienced gentrification prior to 2018] and the dominant income types [high, mixed-high, mixed-moderate,

moderate, and low] that composed the varying UDP typologies, I created the following ranking system[8] (Table 3):

Table 3. UDP Ranking System and Respective Typologies. Created by breaking down publicly available code on GitHub that created UDP gentrification typologies based on Census and Zillow data (Thomas et al. 2018).

Ordinal Rank	Binned Typologies
1	Stable/ moderate mixed income
2	Low-income/ susceptible to displacement
3	Ongoing displacement At risk of gentrification Early/ongoing gentrification
4	Advanced gentrification At risk of becoming exclusive Becoming exclusive
5	Stable/ advanced exclusive

This ranking system organizes UDP typologies in a similar succession of gentrification and financial-exclusivity advancement as the Urban Displacement Project (Thomas et al. 2018; Chapple et al. 2021). However, while the "Stable/ moderate mixed income" rests in between gentrification typologies and financially exclusive typologies on UDP's scale, I decided tracts sorted under this typology would be marked lowest as "1" on the scale of advance gentrification/ financial exclusivity. "Stable/ moderate mixed income" are tracts that have have seen the least amount of gentrification and displacement through financial exclusion as they are predominantly moderate, mixed-moderate, mixed-high, or high income but have remained stagnant in reference to resident's racial, educational, and financial composition as well as in reference to the tract's housing market (Thomas et al. 2018).

[8]I originally created and ran initial analysis with five other UDP ranking systems, which can be found in the appendix. Dhruthi Sri Mandavilli, Cesar Omar Estien, and Christine Wilkinson helped create this and the five other ranking systems.

When separating UDP's 5 gentrification typologies, I considered the predominant income markers of each typology as well as the extremity of socioeconomic change they have experienced since 1990. The "Low-income/ susceptible to displacement" typology was binned as "2" -the second least advanced gentrification rank- because, while these tracts are low-income, and, therefore susceptible to gentrification, they have not seen increases in housing values or severe compositional change in residential racial or education characteristics. This separation from the other gentrification typologies was further encouraged as even Thomas et al. (2018) specified in their code to write all low income tracts that did not constitute "Ongoing displacement," "At risk of gentrification," and "Early/ongoing gentrification" as ""Low-income/ susceptible to displacement."

"Ongoing displacement," "At risk of gentrification," and "Early/ongoing gentrification" were binned to together as "3" -the third most advanced gentrification rank in regards to financial exclusivity- because they all include low-income census tracts that have at least seen a loss of low-income residents, and at most, severe increases in living costs and gentrification beginning in 1990 at the earliest. The "Advanced gentrification" typology was separated from the other four gentrification typologies as this typology marked census tracts of predominantly high-income. However, this typology was not placed alone in its ordinal ranking bin.

The "Advanced gentrification" typology was binned in the second most financially exclusive/ gentrified ordinal rank - rank 4 -with the other two typologies: "At risk of becoming exclusive" and "Becoming exclusive." All three of these typologies are predominantly moderate, mixed-moderate, mixed-high, or high income and all three have seen a percent change greater than zero in real housing cost from both 2000-2018 and 2012-2018 (Thomas et al. 2018).

Finally, the "Stable/advanced exclusive" typology was binned by itself in rank 5 as the most advanced financially exclusive typology as it is the only typology that marks solely high-income census tracts and has seen varying levels of increases in housing costs (Thomas et al. 2018).

Data analysis results

Gentrification patterns along historic HOLC grades

In analyzing the distribution of continuous gentrification scores across HOLC grades, I found that there is a significant relationship between HOLC grades and UDP gentrification ranking systems. The Kriskal-Wallis test showed a significant difference between the median UDP gentrification ranks of each HOLC grade H(4) = 81.434, p = 2.2*10^-16. HOLC grade A had a median of 5, B had a median of 2, and C as well as D had a median of 4 (Figure 4). HOLC grade A had an outlier at the rank value of 1 and had a smaller range of UDP scores compared to the other HOLC grades (Figure 4).

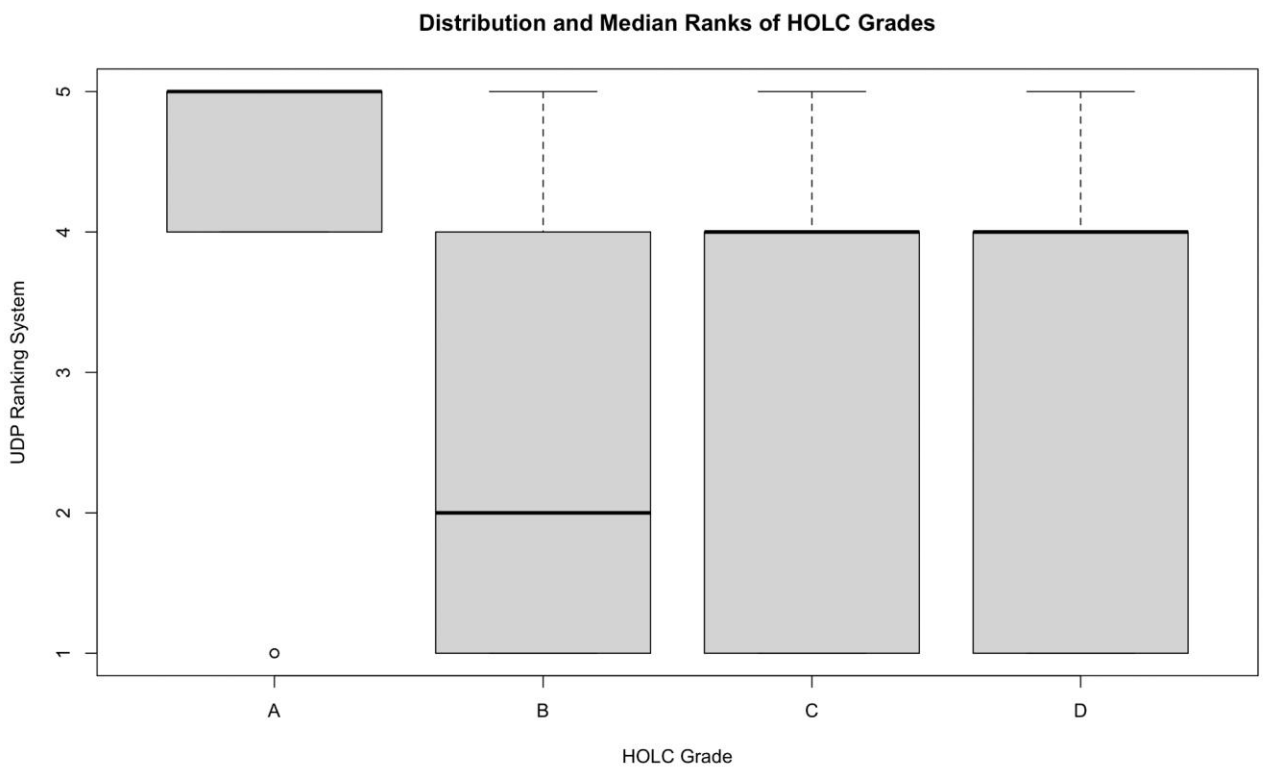

Figure 4. Quantile plot depicting median ranks of each HOLC grade. Historically, A was marked as financially and racially "best," B as "still desirable," C as "in decline" and D as "hazardous" by the HOLC. The UDP ranking system marks census tracts based on UDP collected census and Zillow data on a scale of 1-5 where lower ranks signify compositionally stagnant mixed or low income tracts and higher ranks represent tracts that have undergone advanced gentrification or experience great financial exclusivity. This table was made in RStudio using readxl and tidyverse packages (R Core Team 2023; Wickham and Bryan 2023; Wickham et al. 2023).

Specifically, the multiple comparison results from using the Kriskal-Wallis test using the Bonferroni method (Table 5) shows that, when considering the median values from Rank 6 -the y-variable,- HOLC grade A is significantly larger than the medians of B, C, and D grades. This significance is illustrated by the stars in the p.adj.signif column when group 1 equals A. However, no other HOLC grades are significantly different than the other in terms of median gentrification rank value.

Table 5. Multiple comparisons results of Kriskal-Wallis test using Bonferroni method. This table was made in RStudio using ggpubr and rstatix packages (R Core Team 2023; Kassambara 2023).

.y.	Group 1	Group 2	n1	n2	statistic	p	p.adj	p.adj.signif
Rank	A	B	47	134	-5.63	0.0000000176	0.000000105	****
Rank	A	C	47	147	-4.95	0.000000725	0.00000435	****
Rank	A	D	47	133	-4.86	0.00000116	0.00000694	****
Rank	B	C	134	147	1.05	0.925	1	ns
Rank	B	D	134	133	1.06	0.288	1	ns
Rank	C	D	147	133	0.0420	0.966	1	ns

The Chi-squared test comparing frequencies of census tracts evaluated in 2018 for characteristics of gentrification and financial exclusion by UDP (Thomas et al. 2018) and then ranked by me on a scale from 1-5 over HOLC grades, illustrates a similar pattern as the results of the Kriskal-Wallis test. There is a very significant association between the frequency of census tracts binned with the UDP gentrification ranking system and HOLC grades, X2 (12, N = 461) = 123.21, $p < 0.0001$.

The observed and expected frequencies that contributed to this Chi-squared were significantly different from one another (Table 6.1) and resulted in some residuals that contributed to the significance of the Chi-squared statistic (Table 6.2). The largest Pearson residual by far is 7.256, which illustrates the excess observed tracts marked with the UDP rank of 5 that fell into HOLC grade A compared to those ranked 5 expected to fall into HOLC grade A; according to this cells' corresponding adjusted standardized residual, 3.873, the observed count of census tracts ranked as 5 that fell into historic HOLC A graded areas did indeed contribute to a significant Chi-squared statistic (Table 6.2). This large residual supports the Kriskal-Wallis test results, which also found census tracts marked by a higher UDP rank are heavily correlated with HOLC grade A.

However, this Chi-squared test and adjusted standardized residual comparison provide a bit more insight into how historic HOLC grades and stages of gentrification are correlated. Notably, the lacking observed rank 2 tracts in HOLC grade A and the excess observed rank 2 tracts in HOLC grade D compared to expected counts both contribute to the Chi-squared statistic's significance, as both their absolute values are greater than 2 (Table 6.2). Therefore, census tracts ranked with the value of 2 were significantly less than expected in areas historically graded as A by the HOLC and were significantly more than expected in areas historically graded as D by the HOLC.

Table 6.1. Observed and expected frequencies of 1-5 gentrification ranks in census tracts overlapping HOLC grades for Chi-squared test. Observed tracts are composed of the counts of all census tracts that fell into historic HOLC grades, and expected tracts were calculated for the Chi-squared test based on the sums of each observed row and column. This table was made in RStudio using readxl and tidyverse packages. (R Core Team 2023; Wickham and Bryan 2023; Wickham et al. 2023).

HOLC Grade	Observed 1 Tracts	Observed 2 Tracts	Observed 3 Tracts	Observed 4 Tracts	Observed 5 Tracts	Expected 1 Tracts	Expected 2 Tracts	Expected 3 Tracts	Expected 4 Tracts	Expected 5 Tracts
A	9	0	0	11	27	16.618	2.345	0.510	20.186	7.341
B	66	2	0	43	23	47.380	6.685	1.453	57.553	20.928
C	54	6	0	70	17	51.976	7.334	1.594	63.137	22.959
D	34	15	5	74	5	47.026	6.636	1.442	57.124	20.772

Table 6.2. Pearson residuals and adjusted standardized residuals from Chi-squared test comparing frequencies of census tracts with gentrification ranks of 1-5 within HOLC grades. Italicized adjusted standardized residuals mark cells that contributed to the significance of the Chi-squared statistic, which are adjusted standardized residuals with an absolute value greater than 2. This table was made in RStudio using readxl and tidyverse packages. (R Core Team 2023; Wickham and Bryan 2023; Wickham et al. 2023).

HOLC Grade	Pearson Res 1 Tracts	Pearson Res: 2 Tracts	Pearson Res 3 Tracts	Pearson Res 4 Tracts	Pearson Res 5 Tracts	Adj Res 1 Tracts	Adj Res 2 Tracts	Adj Res 3 Tracts	Adj Res 4 Tracts	Adj Res 5 Tracts
A	-1.869	-1.531	-0.713	-2.044	7.256	-0.601	*-3.403*	~0	-0.590	*3.873*

B	2.705	-1.812	-1.205	-1.918	0.452	0.428	-1.960	~0	-0.269	0.117
C	0.281	-0.492	-1.263	0.864	-1.244	0.042	-0.505	~0	0.115	-0.306
D	-1.899	3.247	2.962	2.233	-3.461	-0.298	*3.527*	~0	0.315	-0.903

The counts of differently ranked census tracts over historic HOLC grades notably varies (Figure 7). A large count of census tracts ranked as “5” - rank demarking tracts most advanced in financially exclusivity,- represented by the red-orange color, in HOLC grade A compared to the other rank bins that fell into grade A and when considering the overall proportions of rank bins in other HOLC grades. A great number of census tracts binned as rank 4 fell into C and D grades, meaning that many of the tracts marked by second-most advanced stages of gentrification/ financial exclusivity overlapped with historically red and yellow-lined areas (Figure 7). Many historic HOLC grades lacked counts of census tracts marked by the ordinal ranks of 2 or 3 -marked by light and dark blue respectively,- but grade D had the most counts of these 2 and 3 ranked tracts compared to the other grades (Figure 7).

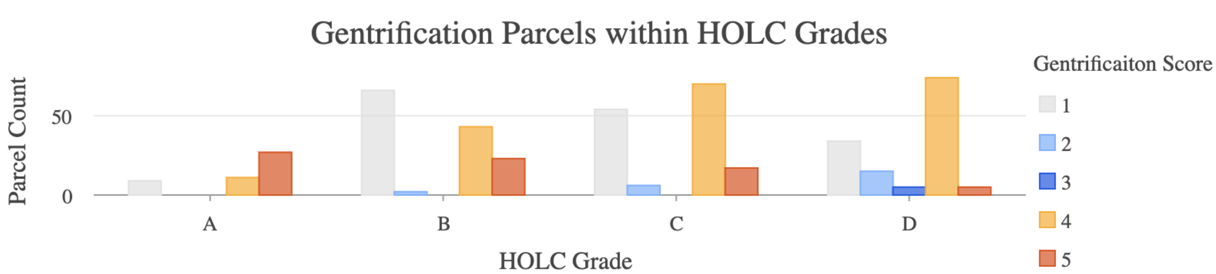

Figure 7. Bar chart of UDP ranking system parcel distribution across HOLC grades in San Francisco city. The UDP ranking system marks census tracts based on UDP collected census and Zillow data on a scale of 1-5 where rank 1, marked by a light gray color, represents stagnant, mixed income tracts; ranks 2 and 3, marked by light and dark blue respectively, represent low income tracts that are vulnerable to or experiencing early gentrification; and ranks 4 and 5, marked by a light and dark orange respectively, represent high-income census tracts that are experiencing advanced gentrification and processes of financial exclusion. This chart was made using the Intersect tool and chart design options in ArcGIS Pro (Version 3.2).

From these statistical tests, overall, I found that San Francisco census tracts that fall within historically green-lines areas are, on average, more likely to experience incredibly advanced financial exclusion. Furthermore, historically red-lined areas are more likely to hold low-income census tracts that are vulnerable to gentrification. While a lot of gentrification and medium financial exclusivity developed in historically C and D graded areas (Figure 7), this socioeconomic compositional change was not significant in either the Kruskal-Wallis no Chi-squared test.

Distribution of conflict and non-conflict along HOLC grades

Chi-squared test. When utilizing a Chi-squared test, I found that there are no significant associations between instances of conflict and certain HOLC grades. While there is proportionally more conflict in historically green and redlined areas compared to yellow and blue lined areas (Figure 8), these observed differences (Table 9) were not significantly different enough than those expected (Table 9) in initial Chi-squared Analysis [X2 (3, N = 1547) = 7.4406, p = 0.0591]. (See Table 9 also for residuals).

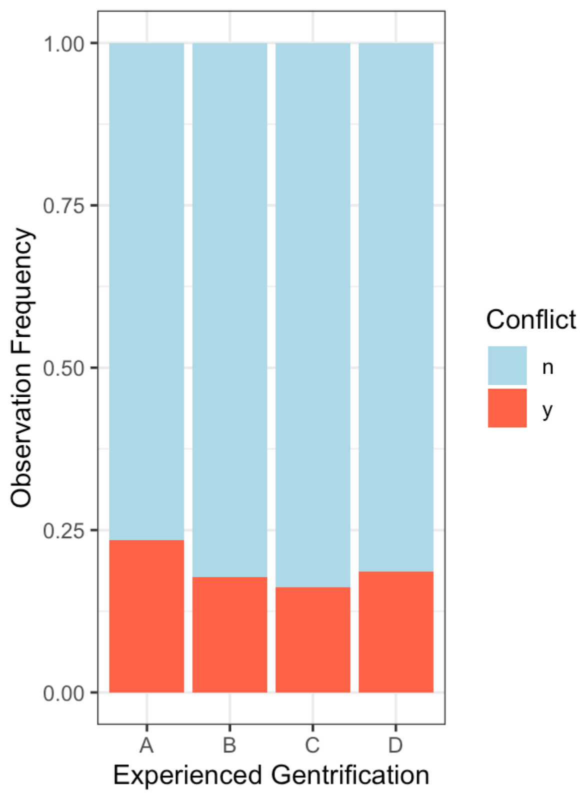

Figure 8. Stacked Bar Plot Depicting Conflict and Non-Conflict Frequencies Across HOLC Grades. Where n = the frequency of non conflict reported and y = the frequency of conflict reported per HOLC grade. A total of 1,547 reports were analyzed to make this chart with RStudio packages readxl and tidyverse (R Core Team 2023; Wickham and Bryan 2023; Wickham et al. 2023).

Table 9. Chi-squared observed and expected frequency table with residuals for Chi-squared Test comparing conflict and non-conflict frequencies over HOLC grades. Calculated with all observation report data points from 2017-2022 that fell within HOLC grades A,B,C, and D in Rstudio with packages readxl and tidyverse (R Core Team 2023; Wickham and Bryan 2023; Wickham et al. 2023). The residuals were calculated using the Pearson method.

HOLC Grade	Observed: Instances Non-conflict	Observed: Instances Conflict	Expected: Instances Non-conflict	Expected: Instances Conflict	Residuals: Non-conflict	Residuals: Conflict
A	254	78	270.193	61.807	-0.985	2.060
B	333	72	329.603	75.397	0.187	-0.391
C	440	85	427.262	97.737	0.616	-1.288
D	232	53	231.943	53.057	0.004	-0.008

Logistic Geospatial Weighted Regression. When accounting for Spatial Autocorrelation, a GWR showed no specific HOLC grade that was associated with clusters of points with higher deviance residuals (1.5-2.5), which are symbolized by a darker aqua color and mark points in space that are more likely to see conflict than not (Figure 10). While the largest cluster of these positive residual points is in the south region of the city west of the Bayview neighborhood, these points fall on areas marked by a mix of A, B, and C grades. Furthermore, another sizable cluster of aqua-colored points slightly north and east of the largest cluster falls along D graded blocks near the Mission district, and, just north of this cluster, there is another scattered along areas with C and D grades. In concurrence with Chi-squared results, positive GWR residuals showed no visually significant clustering in blocks historically marked by one given HOLC grade (Figure 10).

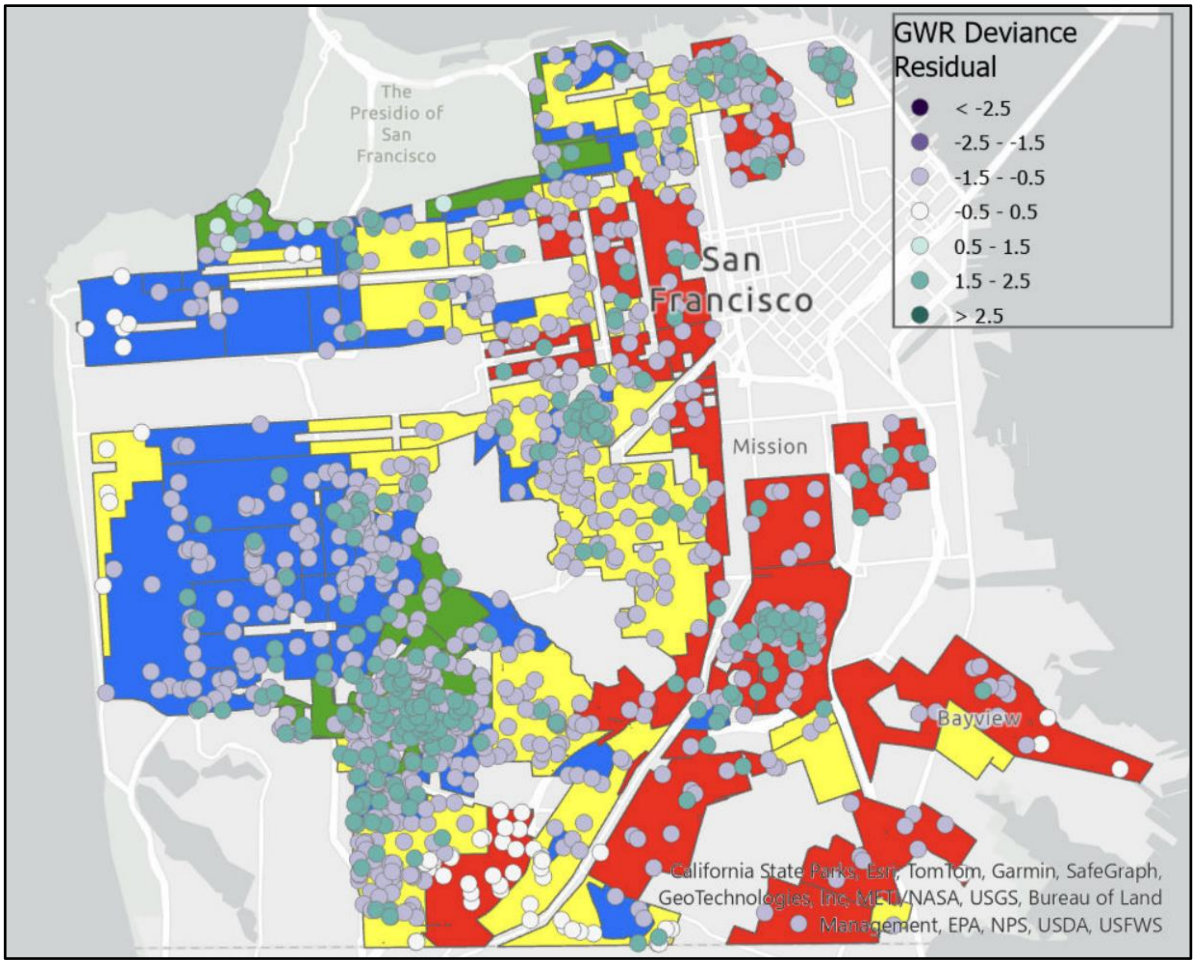

Figure 10. Logistic GWR results analyzing distribution of conflict and non-conflict across HOLC grades. Map of San Francisco depicting historical HOLC grades as well deviance residuals generated from running GWR with binary conflict data (0= not conflict; 1= conflict) from 2017-2022. Areas with higher, positive deviance residuals demarcated by darker teal/ aquamarine dots have more instances of conflict. Red = D grade, Yellow = C grade, Blue = B grade, and Green = A grade, where, for GWR purposes, A was set to equal 4, B was set to equal 3, C was set to equal 2, and D was set to equal 1. Made with ArcGIS Pro (Version 3.2) in WGS 1984 UTM Zone 10 projection.

Distribution of conflict and non-conflict along ordinal UDP rank system

Chi-squared test. I found a significant association between coyote human conflict and gentrification. I specifically encountered a significant difference between conflict and non-conflict frequencies over differently ranked census tracts when using the Chi-squared test for all data from 2017-2022, X2 (4, N=2,242) = 29.039, $p < 0.0001$. The observed and expected counts that were used to calculate the X2 statistic were significantly different from one another, which resulted in larger residuals (Table 11). Groups 1, 2, and 4 are all significantly different from group 5 when it comes to conflict, as the p.adj values are lower than 0.05 according to the post-hoc test that compared the observation table's cells' significance (Table 12). A visual representation of conflict/non-conflict frequency over the gentrification ranks illustrates the notable amount of conflict in Rank 5 compared to all other groups (Figure 13).

Table 11. Observed and expected non-conflict and conflict counts for 2017-2022 with residuals for UDP rank Chi-squared Test. For coyote observation report data from 2017-2022. Calculated with RStudio packages readxl and tidyverse (R Core Team 2023; Wickham and Bryan 2023; Wickham et al. 2023). The residuals were calculated using the Pearson method.

UDP Rank	Observed: Non-conflict	Observed: Conflict	Expected: Non-conflict	Expected: Conflict	Residuals: Non-conflict	Residuals: Conflict
1	576	103	560.281	118.719	0.664	-1.442
2	144	14	130.375	27.625	1.193	-2.592
3	19	0	15.678	3.322	0.839	-1.823
4	671	140	669.202	141.798	0.070	-0.151
5	440	135	474.466	100.535	-1.582	3.437

Table 12. Post Hoc Analysis for UDP rank and 2017-2022 conflict/non-conflict Chi-squared Test. Based on a contingency table with coyote observation report data from 2017-2022. Group 1 and Group 2 are the groups compared in each row. When the p.adj value is less than 0.05, the comparison is significant in that it goes against the null hypothesis, which states the difference between the two groups is small enough to have occurred by chance. Calculated with RStudio packages rstatix, readxl, and tidyverse (R Core Team 2023; Wickham and Bryan 2023; Wickham et al. 2023; Kassambara 2023).

Group 1	**Group 2**	**p**	**p.adj**	**p.adj.signif**
1	2	0.0533	0.267	ns
1	3	0.131	0.392	ns
2	3	0.367	0.617	ns
1	4	0.308	0.617	ns

2	4	0.0116	0.0813	ns
3	4	0.937	0.375	ns
1	5	0.000246	0.00221	**
2	5	0.0000842	0.000842	***
3	5	0.0336	0.202	ns
4	5	0.00526	0.0421	*

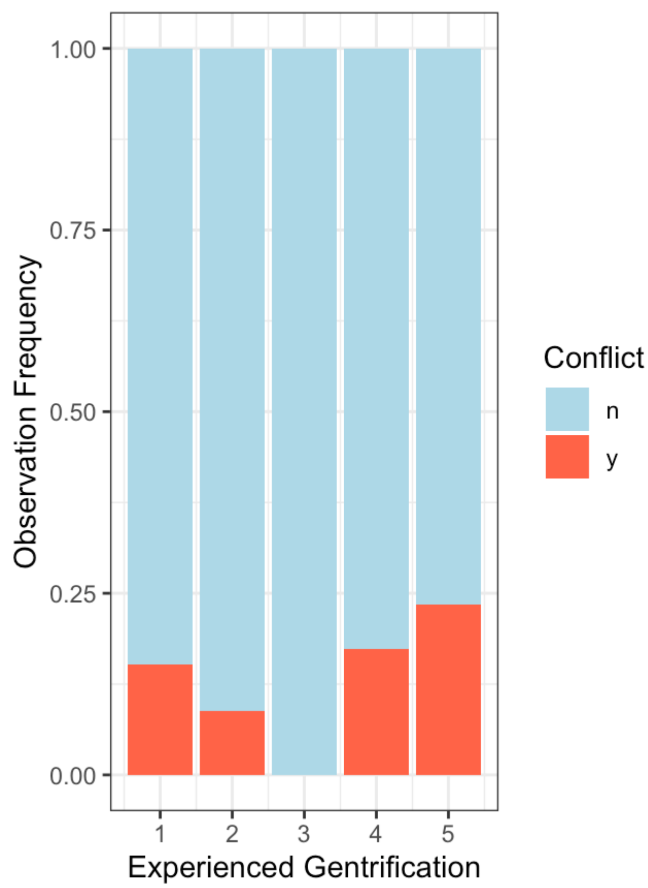

Figure 13. Stacked plot of binary 2017-2022 conflict/ nonconflict frequencies across UDP ranks. “n,” marked by light blue, symbolizes the frequency of non-conflict instances per rank, and “y,” marked by red, symbolizes the frequency of conflict instances per rank. A total of 2243 observation reports mapped over my UDP ranking system were analyzed to make this chart. This graphic was created using observation points from 2017-2022 in RStudio with packages readxl, tidyverse, and ggplot2 (R Core Team 2023; Wickham and Bryan 2023; Wickham et al. 2023; Wickham 2016).

However, when I broke up the data based on specific time periods (yearly and from 2018-2022) to assess if there were any temporal changes in conflict relations and gentrification due to the time constraint of UDP data, I found there were only significant differences among UDP ranking bins in the year of 2020 and in the time period between 2018-2022 when utilizing a Chi-Squared test. The table with the observed and expected frequencies of conflict/non-conflict contributing to the Chi-squared test for the 2020 ($p = 0.0246$) and 2018-2020 ($p < 0.0001$) analysis as well as resulting residuals can be found in the appendix. The results of the respective post hoc tests, which showed no significant differences in observed conflict between any specific UDP ranks for 2020 but significant differences in observed conflict between UDP rank 5 and rank 1, 2, and 4 for 2018-2022, can also be found in the appendix.

Logistic Geospatial Weighted Regression. When accounting for spatial autocorrelation in GWR, specifically for the entire 2017-2022 period, a UDP score that demarcated an advanced stage of gentrification or financial exclusivity was associated with an increase in conflict. Points across San Francisco with higher deviance residuals (1.5-2.5 & >2.5) that demarcate an area more likely to experience conflict than others in the city are predominantly clustered in census tracts ranked as five (maroon) and four (orange) (Figure 14). These clusters predominantly fall parallel to Golden Gate Park longitudinally or south of Golden Gate Park. However, specifically in the north-east corner of the city and south-west of that corner about five miles, there are two smaller clusters of positive deviance residuals in a census tract ranked as 2 (light blue) and another marked as 1 (light gray), respectively (Figure 14).

GWR analysis using logistic regression for each separate year of 2017, 2018, 2019, 2020, 2021, and 2022 shows different temporal contributions to clusters of points of predicted conflict. Specifically, 2017 data (Figure 15.1a) predominantly fed into the all-years cluster located just east of Golden Gate park (Figure 14) and was assisted in this by 2020 (Figure 15.1d), 2021 (Figure 15.2e), and 2022 (Figure 15.2f) data. Every year seemed to contribute the largest cluster in south-west San Francisco mainly intersecting with census tracts that fall into the 5 rank bin. However, 2019 data (Figure 15.1c) and 2021 data (Figure 15.2e) contribute to the largest cluster far more than any other years. The data of years with more observation reports - 2019 (Figure 15.1c), 2020 (Figure 15.1d), 2021 (Figure 15.2e), and 2022 (Figure 15.2f) - seem to contribute most to the cluster east of the largest cluster as well as the cluster in the north-east corner in the city (Figure 14).

The GWR results I calculated when breaking up conflict-binary observation reports per year share broader clustering patterns, but differ in dispersal of data points on a smaller scale as well as the degree of positive/negative polarization of deviance residuals. All yearly maps portray some GWR residual point clustering in the south-west region of the city, just east of Golden Gate park, and in the north-east corner of San Francisco. However, while there are broad patterns of clustering, there is a lot more spatial dispersal of conflict/non-conflict residual prediction points in 2018 GWR results (Figure 15.1b) and in 2019 GWR results (Figure 15.12b), specifically south of Golden Gate Park. General values of these residuals also differ between maps; when comparing the 2018 GWR results (Figure 15.1b) with all other maps, many of 2018 GWR residual values are far more neutral (demarcated by white dots) than in other maps. Furthermore, the GWR results for 2020 (Figure 15.1d) have more residual points that are positive but less extreme (0.5-1.5; demarcated by light aqua) compared to other maps. However, when data from all years are combined (Figure 14), these points influence one another more according to Tobler's law and generate different residual values than if all individual yearly results were calculated separately and then all placed together on one map.

When comparing the logistic GWR results produced when using binary reports from 2017-2022 (all years; Figure 14) as the dependent variable and the logistic results produced when using binary reports from 2018-2022 (after UDP typologies were created; Figure 15.2g), there are relatively similar patterns of predicted conflict, especially when considering the four major clusters previously mentioned. However, after subtracting 332 extra binary conflict/non-conflict report points when accounting for possible socioeconomic differences between 2017 and the years after UDP typologies were created, it seems, some of the localized logistic regression formulas changed to result in more negative or positive standardized deviance residuals (Figure 15.2g). This shift towards more polarizing residuals in 2018-2022 GWR results can be seen by the lower amount white dots (where the residual is between -0.5 and 0.5) (Figure 15.2g) compared to the GWR results for all years (Figure 14). More data points used in the 2017-2022 GWR enable greater specification in localized regression models, which allows for more specific residual estimation. While important to create GWR models for different temporal spans, calculating a GWR model for the entire compilation of 2017-2022 data creates for a broader picture of conflict/non-conflict patterns across the city, especially because most singular year GWR results are not drastically different from one another in data clustering, which resemble the clustering patterns seen in GWR results for 2017-2022 (Figure 14).

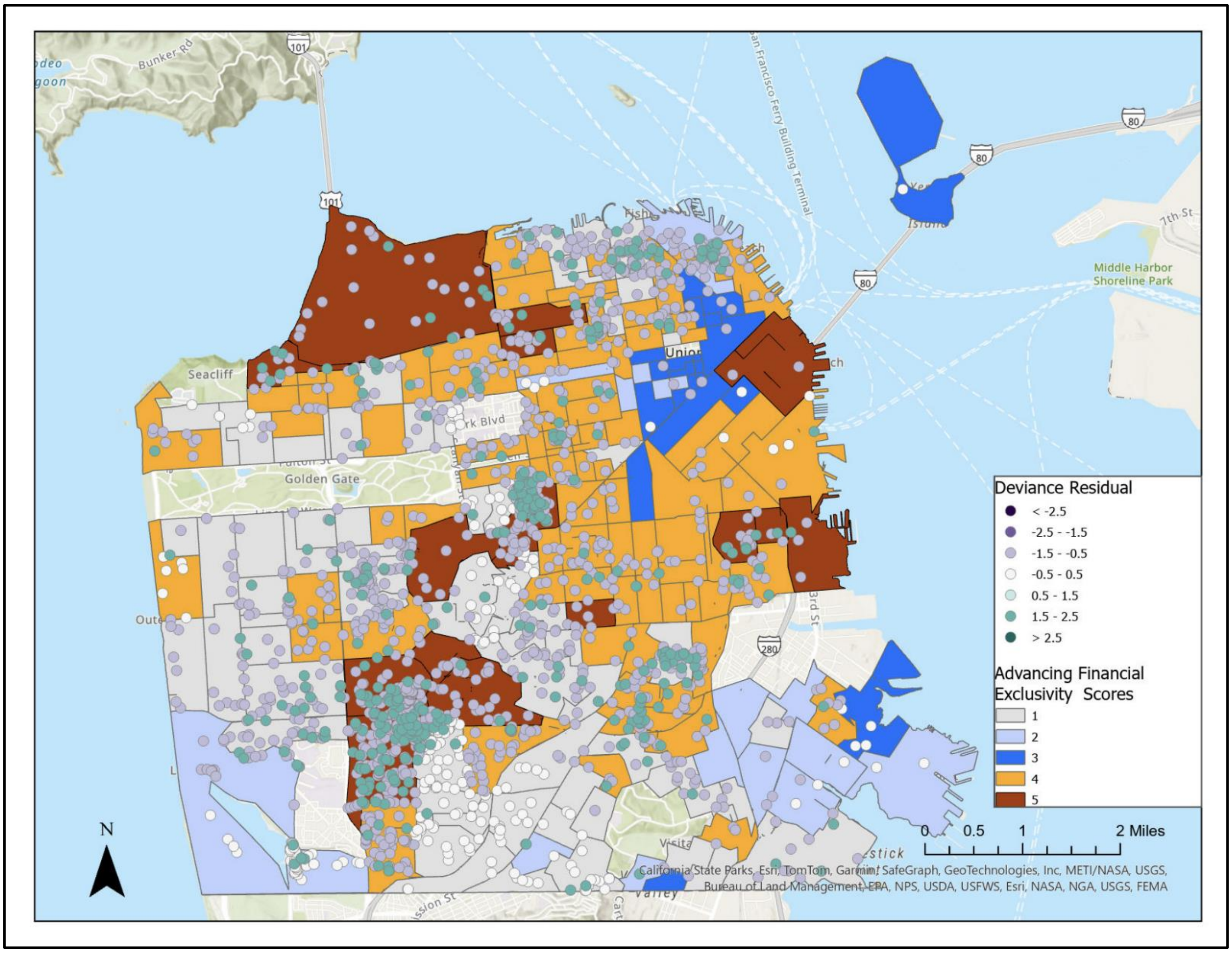

Figure 14. GWR results predicting points of conflict/nonconflict over the UDP ranking system using all data. Using a logistic model, GWR results were based on observation point data from 2017-2022 that was translated into a conflict binary, which acted as the dependent variable, and the UDP Ranking System, which acted as the explanatory variable. Made with ArcGIS Pro (Version 3.2) in WGS 1984 UTM Zone 10 projection.

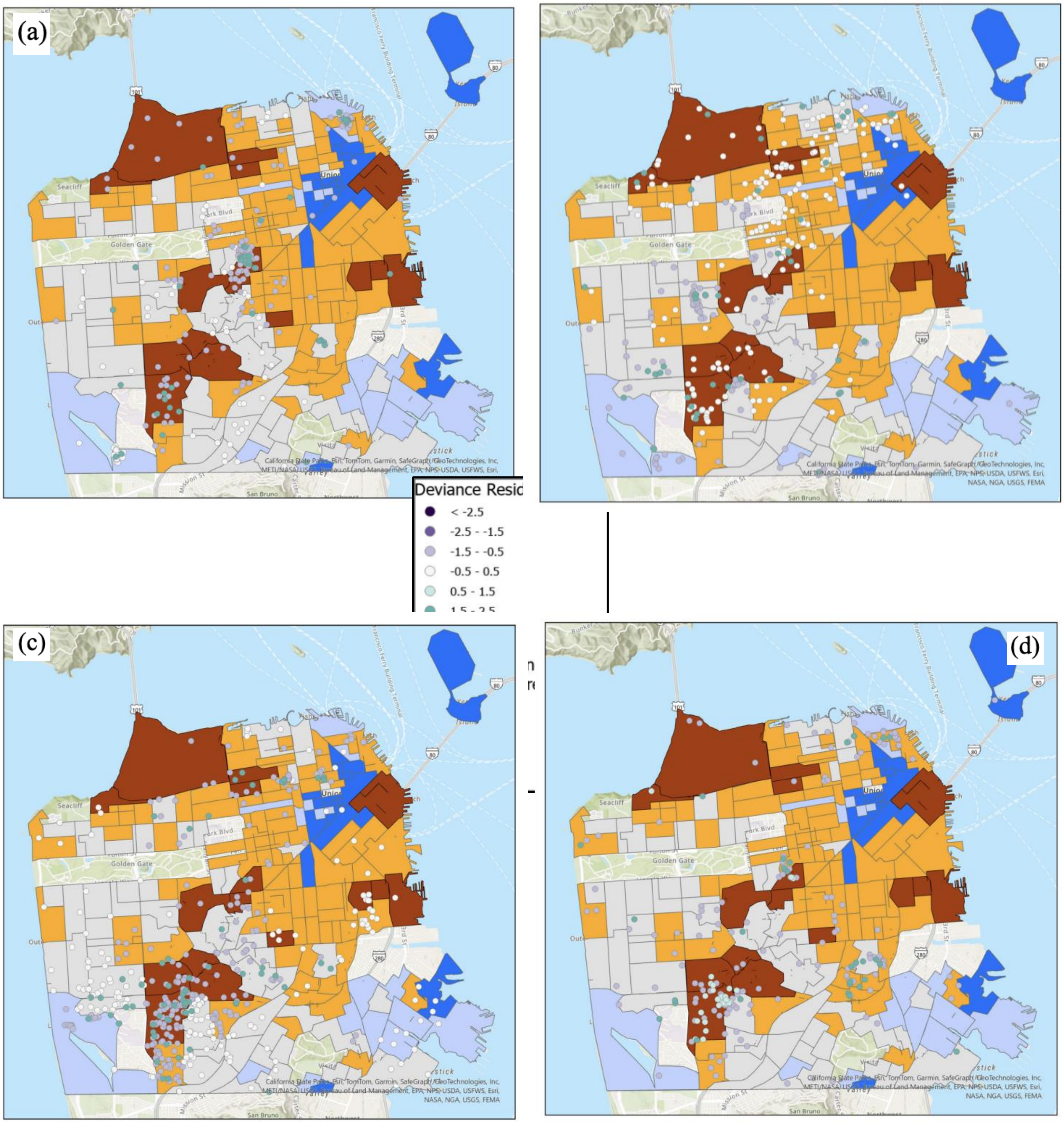

Figure 15.1. GWR results predicting points of conflict/nonconflict over the UDP ranking system. Logistic models. Legend for all maps depicted in the middle. These maps depict GWR results where the dependent variables were a) 2017 conflict-binary observation reports, b) 2018 conflict-binary observation reports, c) 2019 conflict-binary

observation reports, and d) 2020 conflict-binary observation reports. Made with ArcGIS Pro (Version 3.2) in WGS 1984 UTM Zone 10 projection.

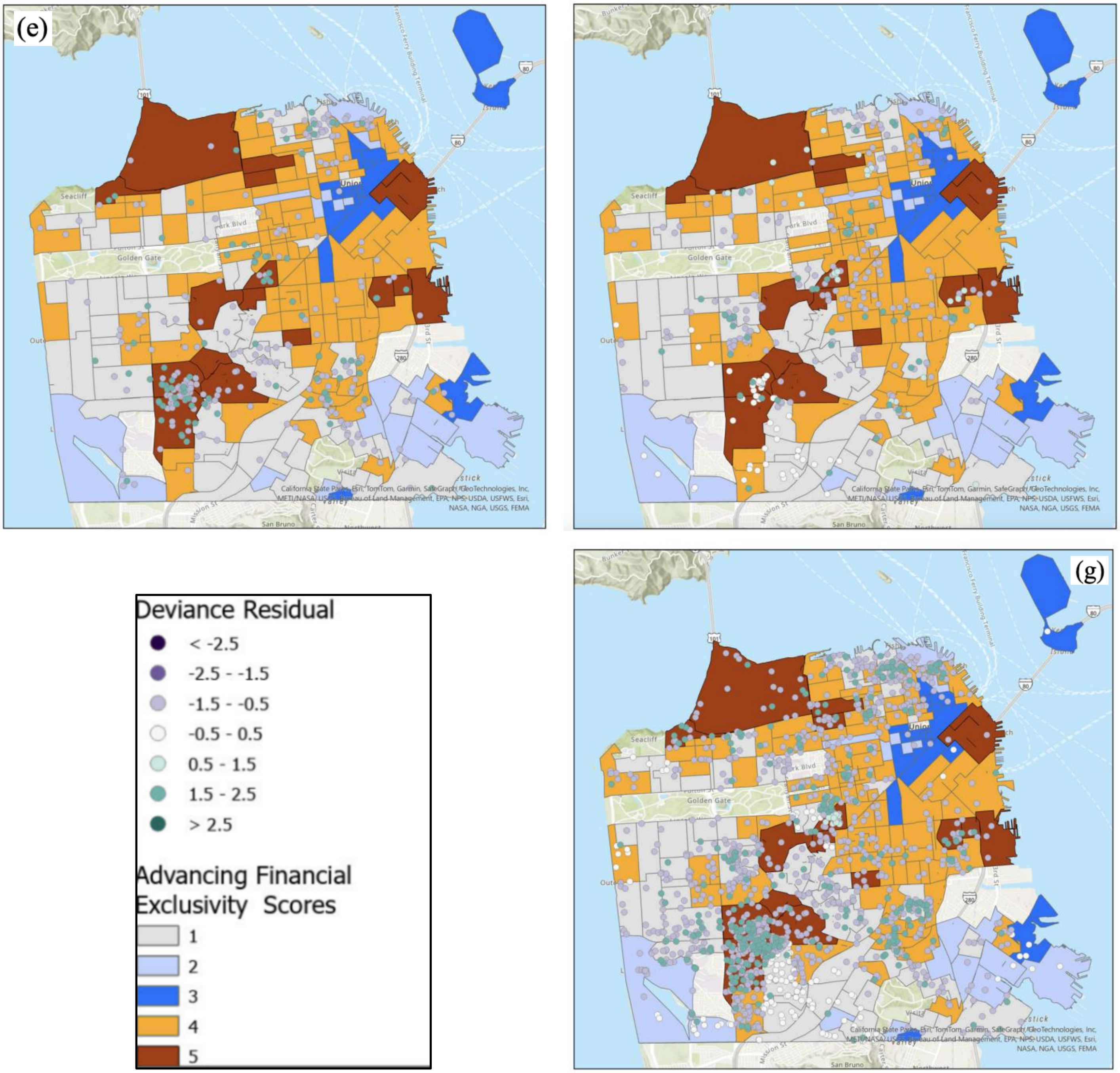

Figure 15.2. GWR results predicting points of conflict/nonconflict over the UDP ranking system. Logistic models. Legend for all maps depicted in the bottom left corner. These maps depict GWR results where the dependent

variables were e) 2021 conflict-binary observation reports, f) 2022 conflict-binary observation reports, and g) 2018-2022 conflict-binary observation reports. Made with ArcGIS Pro (Version 3.2) in WGS 1984 UTM Zone 10 projection.

A strong legacy or stronger change: How significant is redlining vs gentrification in identifying socioeconomic relations?

In evaluating the relationships between human-coyote conflict, historic HOLC grades, and gentrification UDP data, I found that gentrification is more significantly related to human-coyote conflict compared to historic redlining legacies. Both Chi-Squared and Geographic Weighted Regression showed no significant relation between instances of conflict and HOLC Grades, but these statistical tests and models did yield significant results when evaluating the relationship between instances of conflict and my UDP ranking system.

DISCUSSION

Introduction

Proficient human-coyote conflict management requires understanding of human behavioral patterns in the urban wilderness, especially in regards to risk-perception. Through this study, I found significant patterns between higher instances of reported human-coyote conflict and between extremely gentrified and financially exclusive neighborhoods, which suggests that socioeconomic grades with higher income and predominately white residents are affiliated with greater risk perception. Spatial segregation of residents based on income and race officiated by redlining has been altered by gentrification, suggesting that, while redlining's legacy is a potent influencers of San Francisco's gentrification patterns, much of the observed spatial heterogeneity of citizen's wildlife risk perception is more related to current gentrification processes. As both gentrification and redlining have seemed to inform San Francisco's socioeconomic heterogeneity, both should be used as predictors for wildlife management to identify neighborhoods with higher than average wildlife risk perception. However, gentrification's notably significant influence on risk perception of coyotes demonstrates that to effectively manage our urban wildlife interface, we must consider how we invest in our cities and spur economic change.

Gentrification's distribution over historic HOLC grades

While my visualization of differently ranked census tracts across historic grades show a variety of ranks across historically HOLC graded areas, my statistical tests did not indicate that redlined areas are significantly correlated with incredible socioeconomic changes like advanced gentrification or great shifts towards financial exclusivity. Rather, HOLC grades tend to reinforce socioeconomic disparities in San Francisco. Likewise, my results insinuate historically greenlined areas in San Francisco seemed to reinforce patterns of financial exclusivity. According to my research, historically redlined areas are correlated with current low-income census tracts. This is surprising, as previous literature argues that San Francisco's inner-city neighborhoods, which were predominantly ranked as "declining" and "hazardous" and marked by yellow and red respectively, have, since the late 20th century, strongly attracted forms of gentrification (Jackson 1987). A more recent study regarding the relationship between redlining and gentrification in San Francisco also illustrated that by 2018, 87% of gentrifying areas were rated as "hazardous" and 45% of the city's financially exclusive neighborhoods were once rated as "best" or "still desirable" by HOLC in the 1930s (Chapple et al. 2021), suggesting significant socioeconomic changes that I did not find in my statistical analysis.

However, similar to my findings, other research has found redlining's legacy has reinforced the socioeconomic and racial disparities that HOLC officiated. Redlined areas tend to now hold greater than average populations of racial minorities, specifically Black populations, as well as lower than average property and rent values in many US cities (Mickney and Winling 2020; Preis et al, 2021; Norris 2023), including San Francisco (Ivashov 2022). Therefore, there seems to be factors I did not consider when analyzing redlining, its legacy, and how that impacts current socioeconomic and human-coyote conflict patterns in San Francisco. These unaccounted for factors are a limitation to my study.

Gentrification is a dynamic process informed by many other factors apart from an area's socioeconomic history, and these factors can even alter how gentrification is correlated to historic redlining practices. For instance, other determining factors of gentrification include shifts in local job markets (Meltzer and Ghorbani 2017); a neighborhood's proximity to a city's downtown center (Rigolon and Németh 2019; Gibbons 2023); presence of historical housing (Rigolon and Németh

2019); and the presence of greenspace (Kim and Wu 2021; Schinasi et al. 2021). One factor that specifically influences how gentrification relates to redlining is time. In Gibbons' study (2023), they surveyed the socioeconomic changes of many US cities over decades and concluded that previously redlined areas were much more likely to undergo gentrification in the 1980s, but, by the 2000s, redlined areas had a negative correlation with ongoing gentrification. While HOLC grades have been shown to be related to current gentrification and displacement vulnerability, my study was limited in that I did not consider other factors that inform current socioeconomic spatial heterogeneity in US cities when analyzing causes for varied wildlife risk perception across socioeconomic gradients.

How risk perception is informed by historic redlining and gentrification

Redlining's legacy

Redlining's legacy had an insignificant influence on human-coyote conflict. However, when it comes to broader patterns of environmental risk exposure and perception, this has not always been the vase. Previously redlined areas have overall experienced greater exposure to environmental risks and health like disparities in healthy food (Li and Yuan 2022) and greenspace (Nardone et al. 2021) as well as over exposure to air pollution (Cushing et al. 2022; Lane et al. 2022), higher air temperatures, and flooding (Conzelmann 2023). Furthermore, most likely as a result of the racialized environmental injustices perpetrated by redlining's legacy, low income residents and People of Color have shown to have greater risk perceptions of air pollution, water pollution, exposure to agricultural chemicals, GMOs, climate change and nuclear power generation (Macias 2016; Chakraborty et al. 2017; Lo 2014; Marigano et al. 2018). Yet, in my study, redlined areas, nor any specific HOLC grade for that matter, seem to be correlated with higher instances of human-coyote conflict, which in some cases are actual and some cases perceived.

Limitations. I found no correlation between redlining and instances of human-coyote conflict. Yet these instances of conflict are highly correlated with privileges like access to greenspace (Wilkinson et al. 2023; Wine et al. 2014). Furthermore, higher incidents of human-coyote conflict are heavily correlated with neighborhoods of greater than average median household income (Wilkinson et al. 2023). Theoretically, if redlining's legacy enforces methods of socioeconomic exclusion, as I found in previous results and discussed above, conflict should be significantly greater in greenlined areas, but this was not the case. Processes of gentrification may answer for redlining's insignificant legacy when it comes to informing instances of human-coyote conflict.

This analysis was also limited by the spatial scope of HOLC grades themselves. Because of this issue, I was unable to use all coyote observation report data points. HOLC did not rank the large San Francisco parks when redlining the city, and large parks are frequent locations included in coyote observation and conflict reports to SFACC. Because there was no clean way to divide parks using adjacent HOLC grades, these reports and any others within the city bounds but not plotted within the four HOLC grades were not considered in statistical analysis.

Gentrification's alterations

Analysis of all reports (2017-2022). According to my results, gentrification and advancement of financial exclusivity are associated with higher than average instances of conflict. Very little research has been done on this topic, but urban identities have been shown to inform risk perception of meso-predators. For instance, residents of commercial cities tend to perceive more risk related to coyotes than those of tourism-driven cities (Drake et al 2020). Similarly, risk perception relating to feral cats has also been shown to increase with income (Gramza, 2016). In the same vein, my Chi-squared analysis showed that conflict was significantly higher than expected in areas marked by UDP rank 5 (the most financially exclusive bin) than rank 1, 2, and 4. Rank 3 had no instances of conflict, which may have disrupted the post-hoc test. Furthermore, when accounting for spatial autocorrelation with GWR, both the rank 4 I had created by binning together UDP typologies for predominantly mixed-moderate, mixed-high, or high-income census tracts that had seen increases in housing costs over the past 18 years since 2018 and the rank 5 I had created by isolating the UDP typology that marked predominantly high-income census tracts with increases in housing costs were significantly associated with higher than average instances of human-coyote conflict compared to other ranks.

As San Francisco neighborhoods that have become heavily gentrified and financially exclusive tend to produce more instances of conflict than other areas in the city, it is most likely that the residents in these neighborhoods have greater risk perception of coyotes and are more prone to report instances of conflict. Higher coyote-related risk perception in historically wealthier neighborhoods may be attributed to the wealthier residents feeling as if they have more to lose than those in lower-income or stable, mixed-income neighborhoods (Dickman 2010). Wealthier people can also afford greater time budgets for more flexible leisure experiences (Jäckel and Wollscheid 2007), which may allow them more time to explore their neighborhood and, as a result, encounter and report coyotes more often. More time may also allow them to search for and encounter news articles that sensationalize human-coyote conflict and contribute to the "coyote cloud" (Niesner et al. 2024). Even more so, those in neighborhoods with greater financial exclusivity may have very different stressors that influence them to report conflict more than those in low-income neighborhoods vulnerable to or experiencing early gentrification. For instance, US citizens of lower income tend to experience greater stress on a daily basis (Santiago 2011), and US citizens of higher income tend to experience less daily sadness (Kushley et al. 2015). When lacking free time and more concerned with greater emotional burdens, residents of lower income are far less likely to notice and be more risk averse to urban wildlife.

Temporal changes in UDP and conflict analysis results and Covid-19. As discussed in my results, the relationship between human-coyote conflict and advancement of gentrification varied from year to year. While slight variation is to be expected, 2019 contributed far more data points compared to any other year and the localized clustering and dispersal patterns of data were quite different each year. The Covid-19 pandemic most likely explains -at least partially- the yearly variation in results. In response to Covid-19 quarantine and lockdown ordinances, people were forced to shutdown and halt usual anthropogenic activities like driving to work as well as production and sale of commercial goods to such a degree that air pollution decreased in major cities (Kumari and Toshniwal 2020; Adam et al. 2021). Unable to conduct business as usual and interact with others inside, many went outside and began to value greenspaces more (Broitman 2023). As a result, many began to notice and interact with urban wildlife more than pre-pandemic (Zelmer et al. 2020). However, this luxury of greater interaction with urban nature and increases in urban wildlife sightings tended to be reserved for more affluent residents (Murray et al. 2022), most likely because low-income residents' excess-exposure to daily stressors increased during the pandemic.

During quarantine, many in-person services were shut down, which meant many lost their in-person jobs, and the feasibility of transferring work to a remote setting tended to increase with income (Gallacher and Hossain 2020). Furthermore, compared to high-income households, low income families during Covid-19 were significantly more likely to be concerned with meeting needs of basic survival, like providing food for their families or catching Covid when going to their in-person work (Hall et al. 2022). While high income residents in San Francisco were able to transfer to remote work in the pandemic, gain greater appreciation for greenspace, and interact with wildlife more; low income residents were fighting to survive like never before. Covid-19 exacerbated greenspace and wildlife-interaction inequity, which most likely impacted my yearly results.

Limitations. Similar to my study of human-coyote conflict and its relation to HOLC grades, there was not enough census and Zillow data for UDP to evaluate parks in terms of gentrification. As a result, in my analysis of how my UDP gentrification ranking system is related to instances of reported human-coyote conflict and coyote-related risk perception, I did not consider points that fell in parks, even though greenspaces tend to hold notable amounts of sightings and conflict (Wilkinson et al. 2023). I also did not include georeferenced coyote observation report points that fell into other tracts marked as having “Unavailable or unreliable data” or a “High student population” by UDP. Excluding these points may have negated data important to the study, and future directions may pursue possible solutions to rank or mark these areas other ways to consider the coyote observation report points that fall within them.

Furthermore, gentrification is an incredibly dynamic process, and utilizing census and Zillow data solely from 2018 to understand gentrification’s impact on reports of human-coyote interaction that span from 2017-2022 may not be enough to encapsulate gentrification’s dynamism and the human-coyote interface’s sensitivity to these changes. Gentrification has been described as a complex, adaptive system, in which the minutiae of the process interact often in non-linear ways (Torrens and Narra 2007) and, now, in ways that are more chaotic than ever before (Hwang 2016). These fast-acting, disorderly minutia often lead to just as quick and violent outcomes; for example, in San Francisco, between 2009 and 2013, 476 evictions happened under the Ellis Act, which allows landlords to evict tenants in rent-controlled units under the condition that the landlord removes the property from the market for five years before listing the rental at market value (Chapple and Zuk 2015). Furthermore, drivers of gentrification in certain areas are sometimes fickle and sporadic. Opillard (2015) describes how the “Tech Boom 2.0” introduced a large influx of capital into the city in 2013 and 2014, and this quick shift in investment resulted in large amounts of gentrification and displacement (Ibid). This gentrification resulting from the Tech Boom 2.0 has pivoted yet again since the ever-growing on reliance remote work during Covid-19 resulted in a disinvestment from in-person city tech offices and has shown to halt some gentrification processes occurring just a few years before (Ding and Hwang 2022). Gentrification is an incredibly sensitive and dynamic process, and I would highly encourage future directions to take this into consideration when assessing human-wildlife interactions in socioeconomic heterogenous spaces over moderate to long periods of time.

A neo-colonial informant of coyote-related risk perception in urbanity

While my discovery that gentrification informs coyote-related risk perception is a novel one for urban social-ecology, the understanding of how gentrification conquers greenspace and Others of wildlife is not. In the wake of gentrification, greenspaces have become sites for "social reproduction of settler colonialism," in which affluent residents conquer spaces of nature to avoid the chaos of over-developed urbanity (Parish 2019). Similarly, gentrification has been described as a neo-colonial process that works to Other pre-existing wildlife in gentrifying neighborhoods and campaign for and execute their eradication (Hubbard and Brooks 2021). The Othering of wildlife roots itself in the racialized, colonial logics that informed redlining and reinforced gentrification (Deckha and Pritchard 2016), Furthermore, this "Othering" of animals originates in a hegemonic urban need to domesticate animals and make them palatable for city gentry; if urban wildlife cannot conform to the will of those socioeconomically "dominant," these animals - Othered as "wild"- are banned to marginalized, impoverished spaces, like rats to sewers (Philo and Wilbert 2004). Coyotes, in this case, have proven too wild for neighborhoods experiencing advanced gentrification and financial exclusion. Coyotes' resistance to de-wilding and domestication has pushed residents to question the coyote conservation efforts of San Francisco officials, as seen in Cestone's (2016) study and in related local San Francisco media coverage highlighting citizen's unease with coyotes around themselves, their pets, and children. (Firmite 2017; Graff 2021; Mohamad 2023). Residents in more advanced and financially exclusive areas feel threatened by conservation of the wild and Othered coyote, as they perceive coyotes not only to endanger themselves, children, and pets, but also their ability to enjoy the groomed, domesticated parks and neighborhoods they pay highly for and are therefore entitled to.

Conclusion and Future Directions

In San Francisco, human-coyote conflict is more likely to be conflated by higher perceptions of coyote-related risk in neighborhoods that have undergone advanced gentrification and experience financial exclusion. Considering socioeconomic processes -like shifts in investment, inflation of hyper-local housing markets, and displacement of low income residents- will be critical in predicting residential areas that may be more prone to higher rates of perceived human-coyote conflict and Othering coyotes. When designing new public education programs to reduce inflated coyote-related risk perception within the San Francisco public, I highly urge managers in SFACC, San Francisco Recreation and Parks, and other related local establishments to take neighborhoods' socioeconomic composition and gentrification status into account.

To better inform public education program design, it may be worthwhile to assess the effectiveness of current signage in and near parks in regards to conflict and if posting signage in neighborhoods holding residents with likely higher-risk perception would be effective use of San Francisco Animal Care and Control Funding. Furthermore, working to understand to what degree residents in neighborhoods experiencing varying stages of gentrification and financial exclusion are willing to deflate their own risk-perception of coyotes through educational opportunities will be incredibly important, as public education will unlikely penetrate closed-minds. On the other hand, research should also pursue the effects of public outreach to predominantly lower income neighborhoods to the city, especially children, as this study suggests a deficit in low income interaction with urban wilderness. Overall, true conflict management rests on public understanding of assessed risk rather than perceived risk, which can only be addressed by an understanding of both coyote behavior and one's own behavior that may encourage conflict, making public education a critical facet of urban wildlife management.

ACKNOWLEDGEMENTS

This thesis would not have been possible without the wise and dedicated guidance of my advisor, Christine Wilkinson, who graciously allowed me to use cleaned observation data from 2017 to early 2022. I have learned so much from her and am inspired by her diligence and immense knowledge of the urban-wildlife management field. I would also like to thank Christopher Schell of Schell labs, who connected me with Christine and helped form the concept of this thesis along with Christine. Thank you to Dhruthi Sri Mandavilli and Cesar Omar Estien, who helped Christine and I sort through the UDP code and create the UDP gentrification ranking systems. I also greatly appreciate the officers and employees at San Francisco Animal Care and Control for making this project possible and looking out for people and wildlife everyday. Furthermore, I am so grateful for the ESPM 100ES and ESPM 175 teaching teams, especially Patina Mendez, Jessica Craigg, Melissa von Mayrhauser, and Annie Miller who helped guide me through the project planning, researching, data analysis, and writing processes. I could not have done it without them. Finally, I would like to thank my friends and family. I have been so lucky to share the experience of studying Environmental Sciences with my two close friends, Meg Kalaw and Isabel Gatdula, who have supported me and inspired me in and outside of school since sophomore year. Kalea Papandrew has also been such a wonderful presence, willing to listen about my thesis this year and all of the other college projects and experiences that have allowed me to complete such a major project. Thank you to my dad, boyfriend, sister, and dog for loving me and supporting me, and thank you to the trees, grass, creeks, coyotes, and all other critters for sparking my curiosity and reminding me why I love environmental science.

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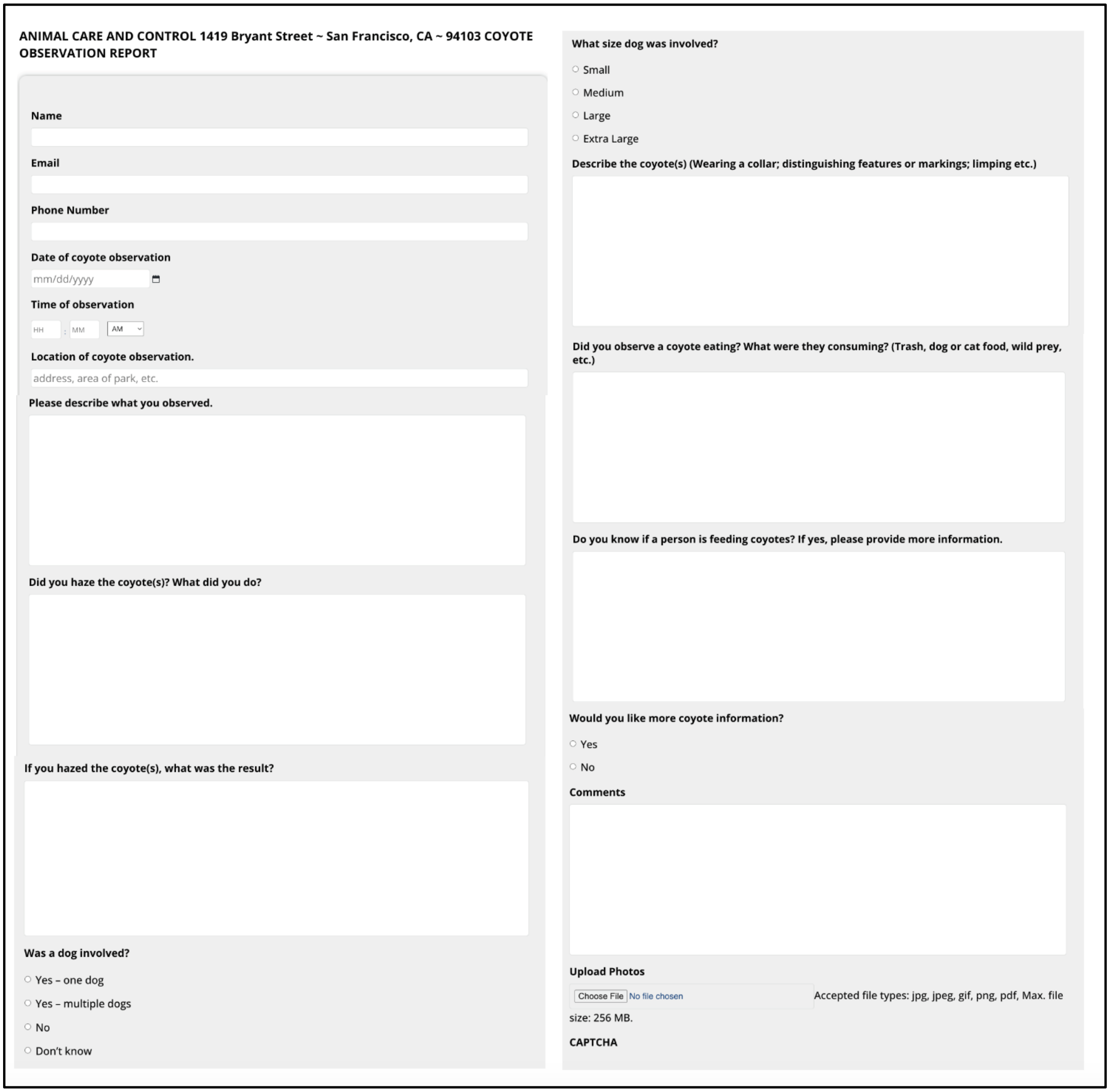
APPENDIX A: SFACC Coyote Observation Report Index



ANIMAL CARE AND CONTROL 1419 Bryant Street ~ San Francisco, CA ~ 94103 COYOTE OBSERVATION REPORT

Name

Email

Phone Number

Date of coyote observation

mm/dd/yyyy

Time of observation

HH : MM AM

Location of coyote observation.

address, area of park, etc.

Please describe what you observed.

Did you haze the coyote(s)? What did you do?

If you hazed the coyote(s), what was the result?

Was a dog involved?

- Yes – one dog
- Yes – multiple dogs
- No
- Don't know

What size dog was involved?

- Small
- Medium
- Large
- Extra Large

Describe the coyote(s) (Wearing a collar; distinguishing features or markings; limping etc.)

Did you observe a coyote eating? What were they consuming? (Trash, dog or cat food, wild prey, etc.)

Do you know if a person is feeding coyotes? If yes, please provide more information.

Would you like more coyote information?

- Yes
- No

Comments

Upload Photos

Choose File No file chosen Accepted file types: jpg, jpeg, gif, png, pdf, Max. file size: 256 MB.

CAPTCHA

Figure A1. Current observation report sheet offered by SFACC. Created for the public to notify management about coyote sightings and conflict and provide extra details helpful to researchers looking at possible contributors to conflict. Can be found at https://www.sfanimalcare.org/living-with-urban-wildlife/coyote-sightings/ .

APPENDIX B: UDP data and ranking system index

Table B.2. Original six ordinal UDP ranking systems used for preliminary geographic regression and Chi-squared tests. For the purposes of this study, I chose to only include my results from using Rank A, as it seemed to bin typologies in an efficient yet diligent way. Rank A also binned together the typologies that did not contribute at all to conflict with the value of 3. However, for future directions, using all ranking systems may be beneficial to look at gentrification stages on different scales. The UDP typologies "Unavailable or unreliable data" and "High Student Population" were excluded from all ranking systems.

UDP Typology	Rank A Value	Rank B Value	Rank C Value	Rank D Value	Rank E Value	Rank F Value
Stable Moderate/Mixed Income	1	1	1	1	1	1
Low-Income/ Susceptible to Displacement	2	2	2	2	2	2
Ongoing Displacement of Low-Income Households	3	3	2	3	3	2
At Risk of Gentrification	3	4	2	3	4	3
Early/Ongoing Gentrification	3	5	2	3	5	3
Advanced Gentrification	4	6	2	3	6	3
At Risk of Becoming Exclusive	4	6	3	4	7	4
Becoming Exclusive	4	6	3	4	8	4
Stable/ Advanced Exclusive	5	7	3	4	9	4

APPENDIX C: UDP Rank 2020 and 2018-2020 Chi-squared Results

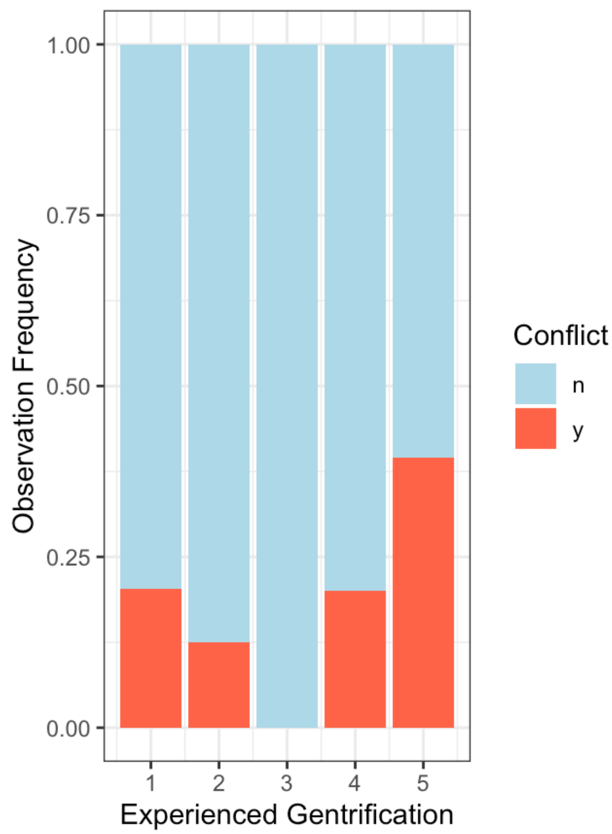


Figure C.1. Stacked plot of binary conflict/ nonconflict frequencies from 2020 across UDP ranks. This graphic was created using observation points from 2020 in RStudio with packages readxl, tidyverse, and ggplot2 (R Core Team 2023; Wickham and Bryan 2023; Wickham et al. 2023; Wickham 2016).

Figure C.2. Observed and expected non-conflict and conflict counts for 2020 with residuals for UDP rank Chi-squared Test. Results of Chi-squared test for 2020 follow: X2 (4, N=230) = 11.18, p = 0.0246. For coyote observation report data from 2020. Calculated with RStudio packages readxl and tidyverse (R Core Team 2023; Wickham and Bryan 2023; Wickham et al. 2023). The residuals were calculated using the Pearson method.

UDP Rank	**Observed: Non-conflict**	**Observed: Conflict**	**Expected: Non-conflict**	**Expected: Conflict**	**Residuals: Non-conflict**	**Residuals: Conflict**
1	47	12	43.609	15.391	0.514	-0.864
2	7	1	5.913	2.087	0.447	-0.752
3	2	0	1.478	0.522	0.429	-0.722
4	68	17	62.826	22.174	0.658	-1.099
5	46	30	56.174	19.826	-1.357	2.285

Table C.3. Post-hoc analysis for UDP rank and conflict/non-conflict Chi-squared Test for 2020. Based on a contingency table with coyote observation report data from 2020 Calculated with RStudio packages rstatix, readxl, and tidyverse (R Core Team 2023; Wickham and Bryan 2023; Wickham et al. 2023; Kassambara 2023).

Group 1	**Group 2**	**p**	**p.adj**	**p.adj.signif**
1	2	0.96	1	ns
1	3	1	1	ns
2	3	1	1	ns
1	4	1	1	ns
2	4	0.964	1	ns
3	4	1	1	ns
1	5	0.0282	0.254	ns
2	5	0.263	1	ns
3	5	0.692	1	ns
4	5	0.0111	0.111	ns

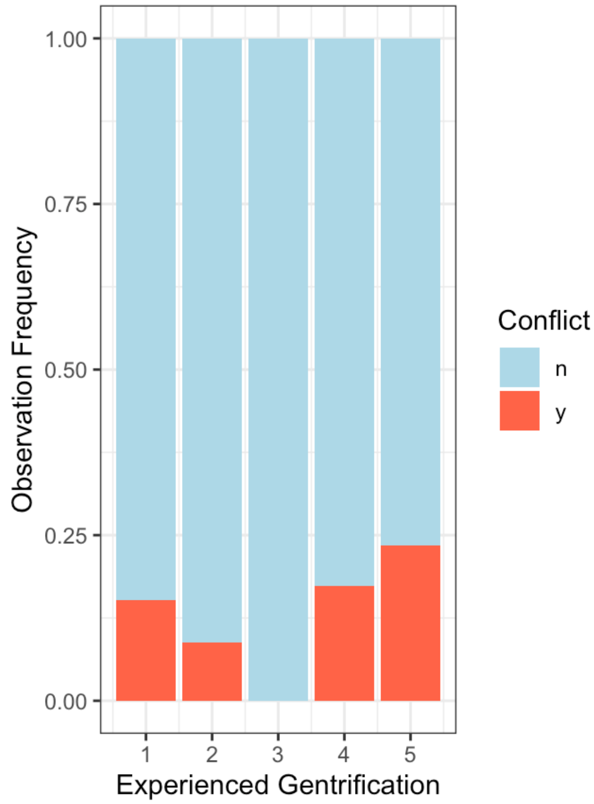


Figure C.4. Stacked plot of binary conflict/ nonconflict frequencies from 2018-2022 across UDP ranks. This graphic was created using observation points from 2018-2022 in RStudio with packages readxl, tidyverse, and ggplot2 (R Core Team 2023; Wickham and Bryan 2023; Wickham et al. 2023; Wickham 2016).

Figure C.5. Observed and expected non-conflict and conflict counts for 2018-2022 with residuals for UDP rank Chi-squared Test. Results of Chi-squared test for 2018-2022 follow: X2 (4, N=2,242) = 29.039, $p < 0.0001$. For coyote observation report data from 2018-2022. Calculated with RStudio packages readxl and tidyverse (R Core Team 2023; Wickham and Bryan 2023; Wickham et al. 2023). The residuals were calculated using the Pearson method.

UDP Rank	Observed: Non-conflict	Observed: Conflict	Expected: Non-conflict	Expected: Conflict	Residuals: Non-conflict	Residuals: Conflict
1	524	97	509.070	111.930	0.662	-1.411
2	92	8	81.876	18.024	1.107	-2.361

3	16	0	13.116	2.884	0.796	-1.698
4	558	118	554.157	121.843	0.163	-0.348
5	370	120	401.682	88.318	-1.581	3.371

Table C.6. Post-hoc analysis for UDP rank and conflict/non-conflict Chi-squared Test for 2018-2022. Based on a contingency table with coyote observation report data from 2018-2022 Calculated with RStudio packages rstatix, readxl, and tidyverse (R Core Team 2023; Wickham and Bryan 2023; Wickham et al. 2023; Kassambara 2023).

Group 1	**Group 2**	**p**	**p.adj**	**p.adj.signif**
1	2	0.064	0.32	ns
1	3	0.172	0.536	ns
2	3	0.521	0.832	ns
1	4	0.416	0.832	ns
2	4	0.0246	0.172	ns
3	4	0.134	0.536	ns
1	5	0.000287	0.00287	**
2	5	0.000443	0.00399	**
3	5	0.0491	0.295	ns
4	5	0.00413	0.0331	*