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Rural Feet Voting of Leisure Explorers

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ABSTRACT

In the COVID-19 period, spatial leisure behavior, often driven by the desire to escape urban life, reflected health and environmental concerns. This study examines how pandemic-induced spatial motives and changes impacted disparities in leisure mobility, specifically urban-to-rural tourism, in Sweden. Analyzing pre-pandemic, during pandemic, and post-pandemic periods, using anonymized mobile phone and socioeconomic data, the paper explores urban–rural leisure mobility variations. Despite a decline in professional geographical mobility, mainly of people in affluent urban areas, due to remote work, the spatial leisure activities remained rather stable? Our findings, based on a negative binomial regression analysis, reveal also exacerbated socioeconomic segregation in recreational trips. The disruption in mobility accessibility due to COVID-19 appears to amplify existing socioeconomic disparities, notably in urban-to-rural leisure travel. Our research sheds new light on the widening gap in geographical leisure activities, emphasizing the need for equitable access to nonurban destinations.

1 | Introduction

During their leisure time, people have an innate desire to seek out unique and profound experiences deeply connected to specific geographic locations. This notion was already recognized by Walter Christaller, a prominent German geographer who emphasized the significance of rural and natural environments as compelling attractions that offer a sense of well-being to those who yearn for the allure of "roads less traveled" (Christaller 1964). However, in an era dominated by mass tourism, the availability of unconventional and personalized leisure opportunities has dwindled, leading to overcrowding and diminished satisfaction. Notably, the pull of rural areas and the repulsion from urban settings have become so pronounced that an increasing number of leisure travelers now prefer to explore nonurban or rural destinations, seeking respite from busy urban life or urban chaos (Müller and Trubina 2020).

These tourists can be likened to "leisure feet-voters," actively choosing to explore locations beyond their everyday routines to indulge in nonurban leisure amenities. The concept of the "geography of rhythms," championed by French geographers (see, e.g., Claval 2009; Lefebvre 2004), pays deep attention to this phenomenon of leisure mobility. It recognizes that individuals intentionally disrupt their stable daily rhythms in their home environments to escape to places that offer relaxation and fresh experiences. Thus, leisure mobility represents a deliberate choice influenced by various factors that determine where and when one decides to go. Extensive research in the field of tourism geography has examined the mechanisms behind tourists' choices, including mode of transportation and destination selection. In a recent article by Toger et al. (2023), these spatial choice behaviors have been encapsulated by the term "feet-voting," denoting the dynamic interplay between geographical repulsion and attraction forces between origins and destinations that drive spatial mobility.

Traditionally, determinants such as income, education, location, environmental quality, needs satisfaction and weather conditions have been the primary focus when analyzing spatial leisure mobility. Until recently, the impact of health-related motivations on spatial choice situations, apart from wellness tourism (see, e.g., Romão, Machino, and Nijkamp 2017, 2018), remained relatively understudied. However, the advent of the COVID-19 pandemic shed new light on the importance of healthy spatial conditions, ranging from urban density and local air quality to hygienic standards in cities and accommodations. These factors have emerged as significant considerations influencing individuals' spatial leisure mobility choices (Mitra et al. 2014).

During the unprecedented times of the pandemic, the spatial and destination choices of travelers were heavily influenced by health and hygiene concerns. Consequently, leisure choices shifted away from densely populated areas. However, they did not automatically extend beyond urban peripheries to encompass rural peripheries as well. The delicate equilibrium between the forces repelling people from urban areas and the attractions of rural regions sometimes favored low-density, non-urbanized areas, but in other cases, it changed only slightly or not at all. To analyze this complex interplay, we model flows separately between urban to rural destinations, rural to urban, and rural to rural, in addition to examining wealth at the origin. This force field is mapped out in Figure 1.

The significance of ensuring sustainable leisure and tourism mobility to nonurban and rural areas has witnessed a notable surge, driven by the growing popularity of outdoor recreational activities and the increasing desire to avoid crowded environments during and after the COVID-19 outbreak. However, the limited availability of public transit connections and travel barriers exacerbate disparities in transportation accessibility to nonurban or rural regions. Given that leisure mobility is a discretionary activity, it is highly responsive to travel constraints and has the potential to exacerbate socioeconomic inequalities when mobility is restricted. An understanding of the motivations and mechanisms behind mobility flows for leisure and tourism to nonurban areas is crucial for addressing the complexities of sustainable development in these destinations.

This paper utilizes gravity-type of spatial interaction models (SIMs) to investigate leisure-time spatial mobility toward nonurban or rural areas around the large Stockholm–Uppsala metropolitan area. We analyze mobile phone data records, complemented by OpenStreetMap data, which provide detailed information on land cover, as well as amenities such as commercial, health, and cultural facilities. Additionally, we make use

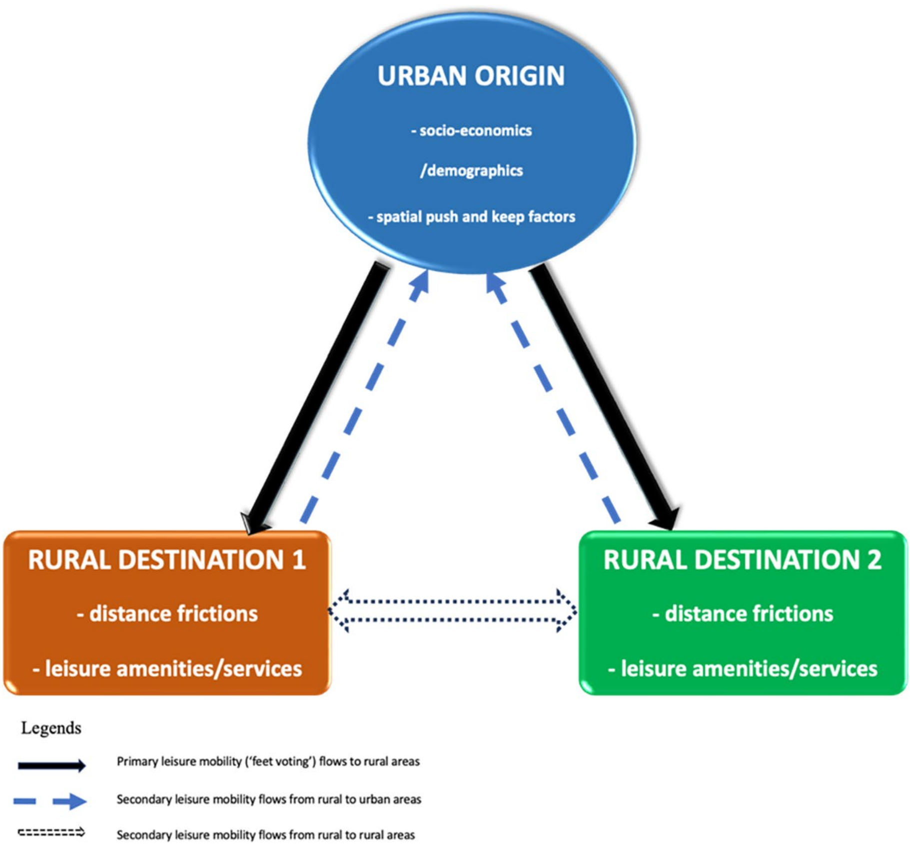

FIGURE 1 | Separating the effect of spatial "feet-voting" for different origins and destinations.

of ecologically linked register data for socioeconomic variables related to the origins.

To explore leisure mobility, we employ an adjusted SIM geared toward tourism flows. In our empirical estimation, we employ a Generalized Linear Model (GLM) with a negative binomial distribution. Our analysis spans distinct time periods, including both working days and weekends in the months of March, as well as holiday workdays and weekends in the months of July, covering years from pre-COVID to post-COVID phases. The mobility data under scrutiny comprise the number of trips as the dependent variable, with origin–destination Cartesian distance serving as the co-variate. Negative binomial regression proves well suited for modeling count data due to its ability to handle the overdispersion commonly observed, where the variance surpasses the mean. This approach facilitates more accurate estimation and inference in contrast to simpler models like ordinary least squares (OLS) regression.

Our model is designed to be flexible in capturing the intricate relationships between predictors and the outcome variable. This methodology provides a robust framework for analyzing mobility patterns by incorporating a wide range of individual-level covariates and accounting for time-varying effects. By acknowledging unobserved variations across observations, it effectively encapsulates the various factors that may influence mobility. In our regression analysis, we meticulously consider covariates related to both origin and destination attributes, enhancing the comprehensiveness of our study. These covariates encompass natural and man-made amenities, as well as the socioeconomic structure of both origin and destination areas. Our analyses are conducted separately for pairs of urban and rural destinations (see also Figure 1), enabling us to unveil disparities in leisure mobility between urban and rural regions and among different socioeconomic groups.

In this paper, we explore the dynamics of leisure mobility and spatial decision-making in the context of the COVID-19 pandemic. By modeling the "feet-voting" patterns of urban leisure explorers, our aim is to identify critical factors that influence their decisions during these challenging times. By comprehending the shifts in travel preferences toward rural and nonurban destinations, we can better grasp the implications for tourism development and management in a post-pandemic world. Drawing inspiration from the works of Christaller (1964), Claval (2009), Mitra et al. (2014), Müller and Trubina (2020), Toger et al. (2023), and Östh et al. (2023), we integrate theoretical perspectives on tourism geography and health-related spatial decision-making to offer a comprehensive analysis of the "rural rendezvous" phenomenon (which we will define in a subsequent section) and its implications for urban leisure explorers in the era of the COVID-19 pandemic.

This study is structured as follows: In the subsequent Section 2, we present the theoretical background, research questions, and hypotheses. Then, in Section 3, we detail the data and methods utilized. Section 4 presents the empirical modeling results and their interpretations, while Section 5 offers concluding comments.

2 | Literature Review

The primary objective of this paper is to investigate the "rural rendezvous" phenomenon and model the patterns of "feet-voting" among leisure explorers in the context of the COVID-19 pandemic. The notion of a "rural rendezvous" suggests that people from different places (in this case, tourists/recreationists) escape from their origins in order to move temporarily to a different and attractive place to enjoy specific common experiences (in this case, the presence of natural amenities and low densities). The spatial substitution effect in leisure mobility during corona times has been extensively analyzed in a study by Kourtit, Lim, and Nijkamp (2024) on the changes in destination choices between urban entertainment and nature visits (see for tourism mobility Kourtit et al. 2022). In this section, we provide a background for our model by examining concisely topics such as urban-to-rural tourism, push–pull effects, tourist attraction-repulsion dynamics, health motives, the impact of COVID-19, the utilization of mobile phone data, and existing models of rural tourism.

Urban-to-rural tourism has experienced a significant surge in popularity in recent years, with more individuals seeking unique and authentic experiences beyond urban settings. These experiences often involve a desire to escape the fast-paced urban lifestyle and connect with the serenity of nature and rural landscapes (Hjalager 2010; Hjalager and Richards 2018). Various push and pull factors have been identified, which have been extensively studied in the realm of tourism literature. Recent studies have associated tourist behavior, particularly in remote or natural settings, with sustainable or environmentally friendly lifestyles, notably in areas like food and culture. Modal choices, distances, and destination choices are integral aspects of this broader decision-making spectrum. Furthermore, a healthy lifestyle has increasingly become a motivating factor for nonurban recreation and tourism. Tourist attraction–repulsion effects shed light on the factors influencing travel decisions. Tourists may be attracted to specific destinations due to their unique offerings while feeling repelled by aspects of their current location (Butler 1980). For instance, urban leisure explorers may be drawn to rural areas for their natural beauty and slower pace of life, while simultaneously being repelled by urban congestion and stress.

The push-pull framework serves as a valuable lens for comprehending the motivations behind travel decisions. Push factors relate to the negative aspects of urban areas that repel individuals, such as overcrowding, congestion, and pollution (Cohen 1972). In contrast, pull factors encompass the positive attributes of rural areas that attract tourists, including natural beauty, tranquility, and cultural heritage (Getz 1986).

The COVID-19 pandemic significantly impacted tourism, including the travel patterns of urban leisure explorers heading to rural areas. Health motives have gained prominence as individuals prioritize safety and well-being in their travel choices. The pandemic has shifted preferences toward less populated and socially distanced destinations, driving urban leisure explorers to seek rural areas with lower population densities (Gössling, Scott, and Hall 2020). Additionally, the pandemic has underscored the importance of health-related factors, such as air quality, sanitation measures, and access to outdoor spaces in destination selection.

To map out and explain complex tourist choices, mobile phone data have emerged as a valuable tool for studying travel patterns and behaviors in rural tourism. It allows for the analysis of visitor flows, trip durations, and activity patterns, providing insights into the spatial and temporal dynamics of tourism (Ahas, Silm, and Tiru 2015). By harnessing mobile phone data, researchers can gain a more comprehensive understanding of the movements, preferences, and behaviors of urban leisure explorers during the COVID-19 pandemic.

Several models have been developed to analyze and predict rural tourism patterns. Destination choice models, such as the gravity model and the random utility model, offer insights into the factors influencing tourists' decisions (Mak, Lumbers, and Eves 2012). These models consider variables like distance, accessibility, socioeconomic characteristics, and destination attributes. Moreover, agent-based models and network models have been employed to simulate travel behavior and explore the intricate interactions between individuals and their environments (Li, Chen, and Ye 2017). In understanding mobility, SIMs have proven vital for comprehending flows in commuting, freight, innovation spill-overs, and recreational mobility, among others. In this study, we adopt the approach of modeling leisure mobility using SIMs and assume that travelers "feet-vote" for destination locations based on their amenities to enhance their utility (Toger et al. 2023). The previous literature overview has clearly indicated that natural amenities, escape from daily urban environments, health motives, distance frictions, and socioeconomic inequities are driving forces of new and green mobility behavior of residents during the COVID-19 period. Based on the reviewed literature, this paper puts forth five hypotheses:

- H1: Natural amenities are expected to act as pull factors, attracting people during leisure time to nonurban areas.
- H2: The influence of nonurban pull factors is anticipated to be more pronounced during holidays and leisure periods compared to regular working days, as individuals seek relaxation and an escape from their daily routines.
- H3: The effect of nonurban pull factors will be attenuated during the COVID-19 pandemic, with variations based on individuals' socioeconomic characteristics and their ability to travel.
- H4: Distance decay, indicating reduced mobility with increasing distance, will exhibit the opposite pattern. Specifically, there will be less distance decay from urban to nonurban areas during the pandemic due to the desire to avoid crowded interactions.
- H5: Residents from high- versus low-income areas will exhibit different leisure patterns.

By examining and testing these hypotheses using relevant data, this study aims to contribute to the understanding of urban-to-rural tourism dynamics in the context of unprecedented global challenges.

3 | Methodology and Data

3.1 | Model Specification

In our study, we employ the following SIM model to scrutinize human mobility:

$$F_{ij} = K * O_i^{\beta} * D_j^{\alpha} * f(d_{ij}) \tag{1}$$

where F_{ij} represents the flows between locations i and j, signifying the intensity of interaction. O_i stands for origin attributes, which encompass the socioeconomic characteristics of departure neighborhoods and relevant natural and urban planning factors. Dj denotes destination attributes, defined in a similar manner to departure neighborhoods, and $f(d_{ij})$ is a function of Cartesian distance between i and j. A power distance-decay specification is used in our application because it is shown to be suitable for modeling long-distance trips (De Vries, Nijkamp, and Rietveld 2009; Östh, Lyhagen, and Reggiani 2016; Zhang, Cheng, and Jin 2019).

Equation (1) assumes that the mobilities observed in the mobile phone dataset have a proportional relationship with origin and destination attributes, while distance is treated as a cost. Various methods are used in the literature to estimate this model, including OLS and, most commonly for flow data, Poisson regression (Flowerdew and Aitkin 1982). For our estimation, we utilize a GLM with a negative binomial distribution. This choice is specifically made due to the overdispersion observed in the data. A Poisson distribution assumes that the mean and the variance of the outcome variable are equal. As shown in Table 1, while the mean of the flows is 15.02, the standard deviation is significantly higher (with a variance of 4151). In such overdispersion cases, a negative binomial distribution offers a more flexible solution (Zhang, Cheng, and Jin 2019). The corresponding regression model can be formulated as follows:

$$F_{ij} = \mathrm{NB}\left(K * \exp\left(\beta * \log(O_i) + \alpha * \log(D_j) * \rho \log(d_{ij}), \mathrm{alpha}\right)\right) \tag{2}$$

where ρ represents the distance decay factor, and alpha is the dispersion parameter.

Our primary aim is to analyze the flows of individuals from distinct origins to nonurban areas. To achieve this, we estimate Equation (2) by separate models based on the characteristics of origins and destinations. While it is possible to run a single model and allow slopes to vary by the type of origin and destination, this approach would test different hypotheses than the ones we propose. Specifically, a single model with interactions would examine whether residents compare urban and rural areas when choosing a destination for their leisure activities. However, our study focuses on identifying the types of amenities that attract residents to nonurban areas. This approach requires a comparative study, where we specify separate models with interaction terms for the level of amenities. Such a model allows us to compare the availability of specific amenities at different spatial levels. In our final analysis, we also estimate Equation (1) for spatial mobilities toward rural destinations from any origin, dissecting the data based on the

TABLE 1 | Summary statistics.

Variable	Mean	Min	Max	SD
Flow	15.02879	20	3054	64.429
OriginsN_phones	1215.409	10	4597	840.4951
Destination_N_phones	516.263	5	1469	416.0838
O_age_mean	44.69765	0	93	10.81979
O_wealthyR	0.34027	0	1	0.160343
O_HighEduR	0.428905	0	1	0.184583
O_VMR	0.132254	0	1	0.142347
lndist	7.846456	6.907755	12.78791	0.739729
O_Wat500r	0.036625	0	1	0.098641
D_Wat500r	0.070728	0	1	0.158762
O_Comm500r	0.015643	0	0.728395	0.060383
D_Comm500r	0.013445	0	0.728395	0.054509
O_Farm500r	0.037773	0	1	0.105623
D_Farm500r	0.058289	0	1	0.152583
O_For500r	0.289099	0	1	0.248285
D_For500r	0.301885	0	1	0.262711
O_Ind500r	0.02447	0	1	0.082766
D_Ind500r	0.023439	0	1	0.079603
O_Res500r	0.27127	0	1	0.23008
D_Res500r	0.214143	0	1	0.228873
O_park500r	0.030376	0	0.851852	0.058384
D_park500r	0.030618	0	0.851852	0.070714

share of wealthy residents in a certain neighborhood of origin. Our models account for various distinct factors, including land use–related variables in both origin and destination locations, socioeconomic characteristics of origin places, and time fixed effects.

The time periods considered in our analysis range from the pre-COVID era to the late COVID period and encompass working days, weekends in March, and holidays in July. These time periods were selected to capture variations in human mobility patterns across different temporal contexts, particularly for comparing leisure mobilities with mobilities during workdays and months.

Overall, our methodology integrates the use of a GLM with a negative binomial distribution, mobile phone data analysis, consideration of different time periods, and the inclusion of covariates related to origin and destination attributes. By employing these methods, we aim to offer a comprehensive analysis of the leisure mobility patterns of urban leisure explorers during the COVID-19 pandemic, shedding light on the factors influencing their travel decisions and revealing potential disparities in mobility among different destination types and socioeconomic groups.

3.2 | Data

The mobility data for this study originate from the Swedish MIND database, a substantial dataset containing pseudonymized mobility records of mobile phone users from one of the major Mobile Phone Network (MPN) providers in Sweden. The MPN data were aggregated into an origin–destination (OD) matrix, representing locations in units of $1 \times 1\,\mathrm{km}^2$ for each origin and destination, along with the flow data, which represent the count of phones traveling from O to D. Origins were defined as home locations estimated from the duration-weighted average phone position at night, while destinations were represented as day locations, indicating the duration-weighted average position during the day. Additionally, the OD Cartesian distance variable is used as a covariate.

The socioeconomic data used in this study are derived from the PLACE register database in Sweden and ecologically linked to each origin and destination location. It includes information on education, income, age, and the share of visible minorities from the k-nearest neighbors (KNN) for each location, where $k = 3200$. We also used population-based location data to classify areas into urban and nonurban categories based on the Cartesian distance to KNN, where d_knn_3200 is greater than 3 km.

Amenity data were sourced from OpenStreetMap (OSM 2015) and were aggregated by the "domination" of the chosen land-cover within a 500 m radius around the origin and destination locations. This resulted in several quantitative variables, notably: O_Wat500r and D_Wat500r (water amenities at the origin and destination), O_Comm500r and D_Comm500r (commercial amenities), O_Farm500r and D_Farm500r (farms), O_For500r and D_For500r (forests), O_Ind500r and D_Ind500r (industrial areas), O_Res500r and D_Res500r (residential areas), and O_park500r and D_park500r (park amenities). The summary statistics of the variables used in the analysis are presented in Table 1.

4 | Empirical Results

In this section, we present the results obtained from our extensive empirical analysis using negative binomial regressions. Our empirical analysis has yielded noteworthy findings that provide valuable insights into the dynamics of leisure mobility patterns among urban leisure explorers. Through the use of negative binomial regressions and the careful control of various factors, we have uncovered significant insights into the factors influencing mobility flows.

4.1 | Regression Outputs

The results, as presented in Table 2, offer an intricate overview of the findings derived from various models and mobility flows. The table is structured into four columns, each capturing distinctive mobility patterns. The first column encompasses the full model, incorporating all variables and factors. The second column delves into mobilities from urban to rural areas, exploring the determinants of this specific flow. The third column focuses on mobilities from rural to urban areas, shedding light on the factors influencing this direction of movement. The fourth column narrows its focus to mobilities within rural areas, providing insights into interactions within rural regions.

Our analysis has unveiled consistent patterns that map out insights into the dynamics of mobility. First, we have found that the number of phones both at the origin and destination positively influences mobility flows. This suggests a push effect from origin areas and a pull effect from destinations, indicating that areas with higher phone usage experienced increased mobility. These phone variables have proven to be valuable proxies in our spatial interaction model.

Shifting our attention now to socioeconomic factors, we have uncovered intriguing dynamics. When examining urban-to-rural mobilities, an increase in the average age of the origin neighborhood appeared to be correlated with higher flows, suggesting a connection between older populations and urban-to-rural mobility. In contrast, rural-to-urban and rural-to-rural mobilities decreased as the average age increased. Additionally, high-income neighborhoods exhibited lower mobility flows, whereas areas with a higher proportion of highly educated residents demonstrated greater mobility from rural origins. Notably, neighborhoods with a concentration of visible minorities generally saw high mobility flows, except when considering flows from urban to rural areas, indicating potential differences in mobility preferences and opportunities. This discrepancy may reflect varying preferences and perceptions of leisure destinations among different socioeconomic groups. Regarding the mean mobilities of high-income groups, the results indicate that their mobilities were lower in all directions. This finding regarding mean mobilities for high-income groups contrasts with our fifth hypothesis. However, to gain a comparative understanding of the changes in mobilities between leisure and workdays, as well as during the pre and COVID periods, we will introduce interaction effects later in this section. Additionally, our results regarding the socioeconomic attributes of neighborhoods are further analyzed in Table 3.

Returning to the outputs in Table 2, the impact of distance decay, which reflects the decline in mobility as distance increases, was particularly pronounced in flows between rural areas. Our findings suggest that longer distances between rural areas act as significant barriers to mobility, resulting in a strong deterrence effect.

When examining the influence of land use variables and natural amenities, we made intriguing observations. The dominance of water bodies at the origin served as a push factor for urban-to-rural areas, attracting individuals away from urban environments and towards rural destinations. However, the presence of water bodies acted as a pull factor only for mobilities towards urban areas, indicating that water bodies possess an attractive quality for urban destinations in Sweden. The domination of water bodies is a predictor of natural amenities; however, in the Swedish context, proximity to water is often associated with an urban quality. This implies that our first hypothesis, which posited that water bodies, as a natural amenity, attract individuals to nonurban locations rather than urban ones, is not supported by the findings.

Additionally, the domination of commercial activities in an area emerged as a destination effect, attracting mobilities from rural to urban areas. This finding aligns with our first hypothesis, suggesting that as an urban quality, commercial activities attract rural-to-urban mobilities. On the contrary, farm domination acted as a pull factor specifically from rural to urban areas. This result also appears to be related to the specific geography of Sweden and contrasts with the first hypothesis. As seen in Figure A1, farm-dominated areas are surrounded by detached houses and other rural-like qualities found in urban areas. The dominance of farmland in urban areas can potentially act as a proxy for the natural amenities available within an urban context, complemented by the presence of attractive urban facilities. Similarly, forest domination acted as a pull factor solely for flows from rural to urban areas, while industrial domination also played a role in shaping mobility patterns, serving as a pull factor from rural to urban areas.

Furthermore, residential domination, indicating the predominance of residential areas, served as a pull factor for all mobilities except for urban-to-rural flows, suggesting that mobilities often occur between residential areas in both urban and rural contexts. Lastly, green amenity domination, represented by the abundance of parks and natural spaces, consistently acted as a pull or attraction factor across all mobility flows for individuals

TABLE 2 | Regression outputs from modeling flows between urban and rural mobilities.

Variables	(1) Full model	(2) Urban to rural	(3) Rural to urban	(4) Rural to rural
OriginsN_phones	0.0005***	0.0001***	0.0004***	0.0007***
	(0.0000)	(0.0000)	(0.0001)	(0.0000)
Destination_N_phones	−0.0000	0.0008***	0.0001	0.0020***
	(0.0000)	(0.0001)	(0.0001)	(0.0001)
O_age_mean	0.0037***	0.0036***	−0.0036***	−0.0013***
	(0.0004)	(0.0013)	(0.0008)	(0.0002)
O_wealthyR	−0.1744***	−0.2505**	−0.1757**	0.0050
	(0.0460)	(0.1099)	(0.0700)	(0.0215)
O_HighEduR	−0.0252	0.0854	0.4209***	0.1466***
	(0.0336)	(0.0968)	(0.0973)	(0.0152)
O_VMR	0.1856***	−0.1500*	0.1119***	0.1159*
	(0.0576)	(0.0787)	(0.0371)	(0.0693)
lndist	−0.8907***	−0.1574***	−0.1806***	−0.4809***
	(0.0257)	(0.0166)	(0.0385)	(0.0191)
O_Wat500r	−0.3472***	0.1851**	0.0517	−0.2692***
	(0.0254)	(0.0887)	(0.0914)	(0.0452)
D_Wat500r	−0.2387***	−0.1661***	0.2195**	−0.0491
	(0.0182)	(0.0232)	(0.0963)	(0.0343)
O_Comm500r	−1.3303***	−0.1107	−1.9776	−0.7779
	(0.0500)	(0.0973)	(1.7601)	(1.5712)
D_Comm500r	0.5376***	−1.6213**	0.9046***	0.6113
	(0.0731)	(0.6320)	(0.2410)	(0.4039)
O_Farm500r	−0.0459	0.2832***	−0.1066	−0.5830***
	(0.0309)	(0.0500)	(0.0965)	(0.0503)
D_Farm500r	−0.3388***	−0.1140***	0.6935***	0.0703
	(0.0192)	(0.0357)	(0.1472)	(0.0569)
O_For500r	0.1224***	0.2726***	0.0211	−0.2693***
	(0.0125)	(0.0399)	(0.0475)	(0.0127)
D_For500r	−0.2833***	−0.0013	0.2120***	−0.0029
	(0.0143)	(0.0206)	(0.0652)	(0.0308)
O_Ind500r	−0.0555*	−0.0478	−0.6753***	−1.2668***
	(0.0317)	(0.0402)	(0.2091)	(0.1390)
D_Ind500r	−0.1523***	−0.0730	0.4882***	−0.7497***
	(0.0285)	(0.0792)	(0.1098)	(0.1510)
O_Res500r	−0.0243	0.0307	0.1167	−0.2640***
	(0.0287)	(0.0224)	(0.0764)	(0.0296)
D_Res500r	0.2866***	−0.1409*	0.2903***	0.6375***
	(0.0343)	(0.0815)	(0.0581)	(0.0363)
O_park500r	−0.6737***	−0.2928**	−4.3842	−5.9868***
	(0.0344)	(0.1208)	(4.0723)	(1.4251)
D_park500r	0.2448***	1.1583*	−0.0632	4.1086***
	(0.0333)	(0.6348)	(0.1445)	(0.8452)
16.Mar.19 (ref. 14.Mar.19)	−0.1706***	−0.0781***	−0.0608***	−0.0097**
	(0.0072)	(0.0013)	(0.0066)	(0.0047)

(Continues)

	(1)	(2)	(3)	(4)
Variables	Full model	Urban to rural	Rural to urban	Rural to rural
18.Jul.19	−0.3148***	−0.1672***	−0.1598***	0.0844***
	(0.0088)	(0.0021)	(0.0078)	(0.0159)
20.Jul.19	−0.3817***	−0.1599***	−0.1331***	0.1024***
	(0.0109)	(0.0032)	(0.0150)	(0.0168)
12.Mar.20	0.0335***	−0.0003	0.1325***	0.0144***
	(0.0028)	(0.0019)	(0.0061)	(0.0019)
14.Mar.20	−0.1728***	−0.1604***	−0.1690***	0.0658***
	(0.0139)	(0.0022)	(0.0078)	(0.0097)
16.Jul.20	−0.2733***	−0.1674***	−0.1487***	0.1635***
	(0.0117)	(0.0035)	(0.0055)	(0.0160)
18.Jul.20	−0.2863***	−0.1807***	−0.1036***	0.2226***
	(0.0131)	(0.0040)	(0.0151)	(0.0166)
11.Mar.21	−0.0478***	−0.0740***	0.0362***	0.0881***
	(0.0094)	(0.0032)	(0.0098)	(0.0055)
13.Mar.21	−0.1191***	−0.0881***	−0.1400***	0.1082***
	(0.0136)	(0.0012)	(0.0072)	(0.0091)
15.Jul.21	−0.2730***	−0.1553***	−0.1365***	0.1684***
	(0.0107)	(0.0035)	(0.0135)	(0.0157)
17.Jul.21	−0.2639***	−0.1185***	−0.1242***	0.2232***
	(0.0119)	(0.0059)	(0.0162)	(0.0168)
12.Mar.22	−0.0901***	−0.0395***	−0.0134	0.0912***
	(0.0115)	(0.0017)	(0.0094)	(0.0068)
14.Jul.22	−0.2644***	−0.1365***	−0.0898***	0.1676***
	(0.0151)	(0.0020)	(0.0214)	(0.0145)
16.Jul.22	−0.2493***	−0.0874***	−0.0932***	0.2112***
	(0.0160)	(0.0031)	(0.0220)	(0.0153)
Constant	8.1915***	2.0653***	2.1586***	4.5619***
	(0.1891)	(0.0891)	(0.2691)	(0.1631)
Observations	270,269	10,184	1072	45,816

Note: Robust standard errors in parentheses.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

seeking recreational activities, relaxation, and a connection with nature. This highlights the appealing qualities of green spaces and natural environments in shaping individuals' mobility choices. In alignment with the results related to residential domination and commercial activities, this finding reveals an intriguing dynamic. Planned greenery and urban planning act as attractive factors in a country abundant in natural amenities, present in both rural and urban locations.

Furthermore, to capture the impact of time and the COVID-19 pandemic, we introduced time fixed effects into our model. Our findings revealed that overall mobility was lower during the pandemic compared to the pre-pandemic period, reflecting the influence of travel restrictions and social distancing measures. However, an interesting exception was observed in the increased mobility between rural areas, and urban-to-rural mobilities did not decrease as much as other O–D pairs compared to the pre-pandemic period. This finding suggests a potential shift in travel preferences, with individuals being more inclined to travel between and toward rural destinations.

4.2 | Interactions

To capture the complex dynamics of nonlinear flows and to understand variations across different years and seasons, we employed an advanced SIM modeling approach. We introduced interactions between each factor in the spatial interaction model and the date variable, focusing specifically on urban-to-rural mobilities. This method allowed us to unveil nuanced relationships and patterns that emerge over time. As a visual aid to enhance our presentation, Figures 2–6 have been included to highlight the interaction effects, providing a captivating glimpse into the rich tapestry of mobility

TABLE 3 | Regression outputs from modeling flows between from any origin to rural destinations by the share of wealthy residents in origin neighborhoods.

	(1)	(5)	(3)
Variables	**< 0.25**	**0.25 < l ≥ 0.50**	**l > 0.50**
OriginsN_phones	0.000***	0.000***	0.001***
	(0.000)	(0.000)	(0.000)
Destination_N_phones	0.001***	0.001***	0.000***
	(0.000)	(0.000)	(0.000)
O_age_mean	−0.000*	−0.003**	0.000
	(0.000)	(0.001)	(0.001)
O_HighEduR	0.169***	0.118***	0.073**
	(0.039)	(0.026)	(0.029)
O_VMR	−0.272***	−0.700***	−0.226***
	(0.076)	(0.112)	(0.061)
lndist	−0.392***	−0.457***	−0.436***
	(0.015)	(0.011)	(0.017)
O_Wat500r	−0.222***	−0.269***	−0.035
	(0.067)	(0.049)	(0.087)
D_Wat500r	−0.048*	−0.023	−0.310***
	(0.027)	(0.023)	(0.047)
O_Comm500r	−1.901***	−1.033***	−1.988***
	(0.479)	(0.189)	(0.177)
D_Comm500r	−1.508	1.650**	−3.765
	(1.064)	(0.784)	(3.229)
O_Farm500r	−0.373***	−0.293***	−0.379***
	(0.036)	(0.037)	(0.088)
D_Farm500r	0.045	0.017	−0.155***
	(0.056)	(0.053)	(0.050)
O_For500r	−0.232***	0.007	−0.132***
	(0.017)	(0.025)	(0.025)
D_For500r	−0.020	−0.109***	−0.127***
	(0.022)	(0.032)	(0.025)
O_Ind500r	−0.612***	−0.412***	−0.566**
	(0.071)	(0.123)	(0.255)
D_Ind500r	−0.023	−0.271***	−1.040***
	(0.130)	(0.083)	(0.171)
O_Res500r	−0.477***	−0.193***	−0.616***
	(0.058)	(0.025)	(0.054)
D_Res500r	1.086***	0.721***	0.327***
	(0.064)	(0.049)	(0.059)

(Continues)

TABLE 3 | (Continued)

Variables	(1) < 0.25	(5) 0.25 < l ≥ 0.50	(3) l > 0.50
O_park500r	−2.842***	−0.980***	−0.489**
	(0.420)	(0.144)	(0.204)
D_park500r	1.291	1.476***	6.639***
	(0.921)	(0.529)	(2.022)
16.Mar.19 (ref. 14.Mar.19)	−0.002	−0.050***	−0.043***
	(0.004)	(0.003)	(0.008)
18.Jul.19	0.015	−0.019	0.031
	(0.016)	(0.013)	(0.022)
20.Jul.19	0.059***	−0.019	0.059**
	(0.017)	(0.014)	(0.024)
12.Mar.20	0.003	0.007***	−0.014***
	(0.003)	(0.002)	(0.003)
14.Mar.20	0.020*	−0.013	0.019
	(0.010)	(0.009)	(0.013)
16.Jul.20	0.094***	0.015	0.148***
	(0.016)	(0.013)	(0.022)
18.Jul.20	0.128***	0.068***	0.214***
	(0.017)	(0.014)	(0.023)
11.Mar.21	0.037***	0.021***	0.032***
	(0.006)	(0.006)	(0.010)
13.Mar.21	0.054***	0.038***	0.049***
	(0.010)	(0.008)	(0.014)
15.Jul.21	0.099***	0.043***	0.100***
	(0.016)	(0.013)	(0.022)
17.Jul.21	0.150***	0.080***	0.219***
	(0.017)	(0.013)	(0.023)
12.Mar.22	0.078***	0.070***	−0.037***
	(0.006)	(0.004)	(0.011)
14.Jul.22	0.095***	0.050***	0.141***
	(0.015)	(0.013)	(0.022)
16.Jul.22	0.162***	0.099***	0.177***
	(0.016)	(0.013)	(0.021)
Constant	4.097***	4.810***	4.439***
	(0.135)	(0.108)	(0.165)
Observations	18,681	25,827	12,479

Note: Robust standard errors in parentheses.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

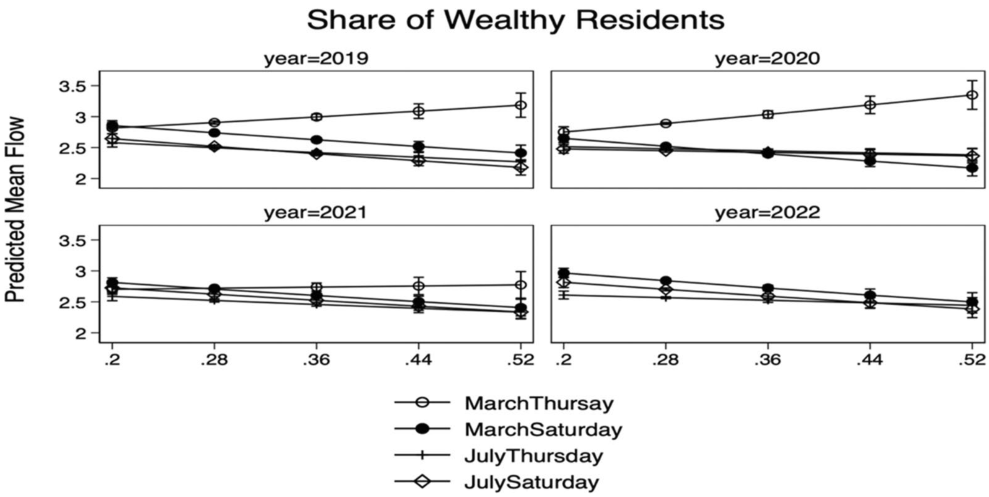

FIGURE 2 | Predicted mean flows by the share of wealthy residents in origin neighborhoods.

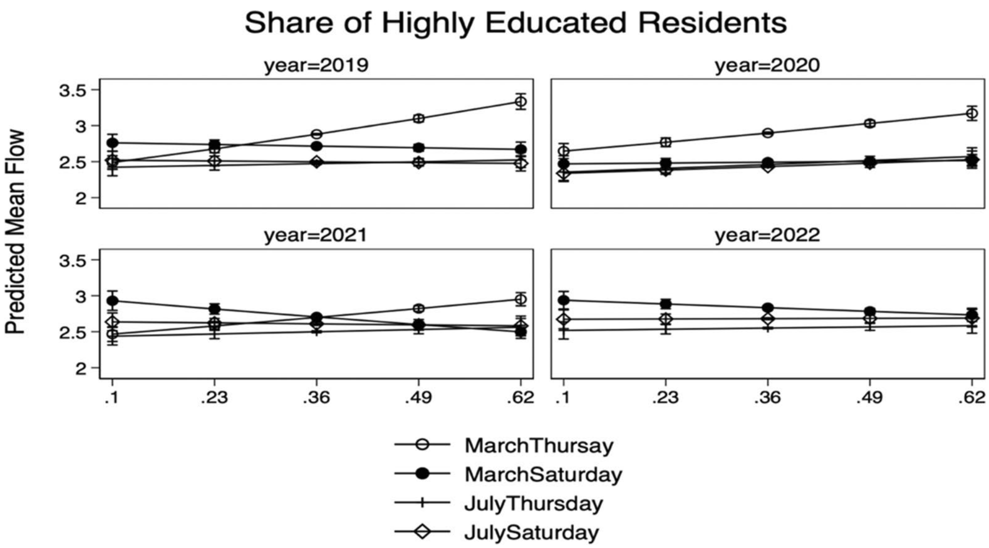

FIGURE 3 | Predicted mean flows by the share of highly educated residents in origin neighborhoods.

dynamics and offering valuable insights into their underlying mechanisms.

Figure 2 illustrates the mobility dynamics based on the share of wealthy residents in departure neighborhoods. In low-income neighborhoods, mobilities appear to be similar between working and leisure days. However, a noticeable trend emerges among wealthy residents, showing higher mobility during working days. Departures from wealthy neighborhoods exhibit lower mobility during weekends and in July.

This trend appears to persist from the pre-COVID period to March 2020 (Thursday when COVID restrictions were not in place in Sweden). However, starting from July 2020 and continuing until 2022, regardless of the working or leisure date, all departures experience reduced mobility as the share of wealthy residents increases in departure neighborhoods. Figure 3 depicts similar trends for departures by education attainment. The mobility patterns show comparable dynamics for different levels of education among departing individuals.

Figure 4 presents the effect of distance on mobilities, comparing working days and leisure time mobility across different years. We observed distinct patterns in mobility flows based on distance, considering both working days and leisure months. During working days, we found that shorter distance flows from urban to areas with rural characteristics were common, but the slope for these days in all years was steep. This indicates that as the distance increases, fewer flows are observed. On leisure months, the degree of decrease in flows (distance decay) was low and even lower for the month of July. Remarkably, this trend persisted from the pre-COVID to the late COVID periods. The findings indicate that although total mobility decreased during the pandemic, the effect of distance on mobility remained relatively stable. This contradicts our fourth hypothesis, which anticipated that the pandemic would lead to less distance decay as rural destinations had become more attractive. Although Table 2 indicates that rural destinations have attracted higher flows during COVID, especially from other rural destinations, distance was regarded as costly, as in the pre-COVID period. The consistent distance decay patterns suggest that factors other than the pandemic's restrictions may have influenced mobility flows during this period.

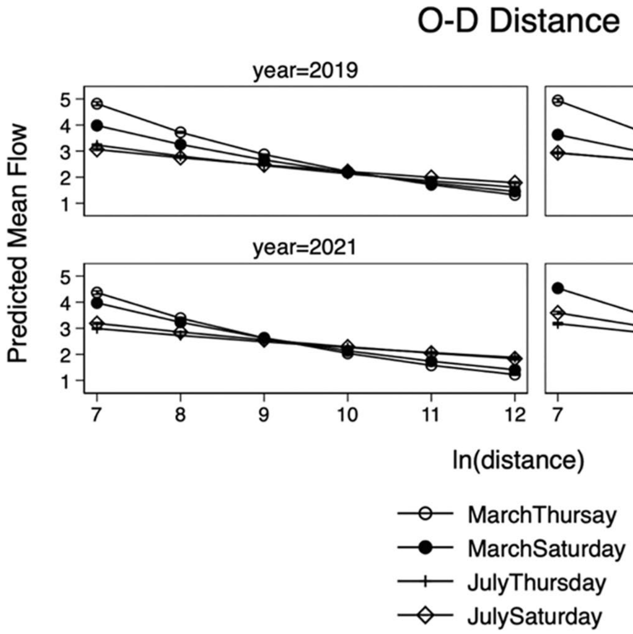

FIGURE 4 | Predicted mean flows by origin–destination distances.

In Table 2, the most influential factor for flows in all directions appeared to be the dominance of parks as planned greenery, both at origin and destination points. Consequently, we incorporated interactions involving the date of mobility and park domination at both origins and destinations into our analysis. Figures 5 and 6 depict the predicted flows resulting from these interactions for origins and destinations, respectively.

Figure 5, focusing on origin effects, reveals that residents tended to be less mobile in locations with higher park domination, especially on weekdays in March 2019. In contrast, during the initial pandemic days in 2020, there was no discernible effect of parks on mobility. However, in the late COVID periods (2021 and 2022), high park domination was associated with reduced flows toward rural locations, particularly noticeable on March Saturdays (Figure 6). This suggests that weekend leisure mobility was less common among individuals with greater access to planned greenery in their immediate surroundings.

4.3 | Regression Outputs From Modeling Rural Destinations by Socioeconomic Origins

To explore the socioeconomic dimension of leisure mobility towards rural destinations, we conducted an analysis using Equation (2) for flows from any origin to rural destinations, stratified by the share of wealthy residents in origin neighborhoods. Table 3 presents the results of the negative binomial regression, displaying the output in three distinct columns.

In the first column, we present the regression output for origin neighborhoods with less than 25% of wealthy residents. The second column provides results for neighborhoods where the share of wealthy residents falls between 25% and 50%, while the third column displays the findings for neighborhoods with more than 50% wealthy residents. This stratified approach allows us to assess how the influence of wealthy residents on leisure mobility toward rural destinations varies across different socioeconomic contexts. The results highlight the abundance of water bodies and forests in Sweden. Interestingly, these natural qualities do not primarily contribute to destination attraction factors but instead manifest as origin effects. Specifically, the findings demonstrate that the presence of natural qualities in the origin neighborhoods generates pull effects, leading to a decrease in flows for all income groups.

In contrast, when considering planned features such as parks, residential domination, commercial sites and industrial areas, disparities emerge between socioeconomic groups. It becomes evident that neighborhoods with lower income levels (where less than 25% of residents are wealthy) exhibit reduced mobility as the domination of parks in their origin neighborhoods increases. However, they are still somewhat drawn to areas dominated by parks, although not to the same extent as wealthier neighborhoods (where more than 50% of residents are wealthy).

In fact, wealthier neighborhoods show a preference for destinations featuring planned greenery but display less interest in industrial areas, particularly for leisure purposes. Notably, commercial areas in rural settings often house outlets offering products at relatively lower prices than central shops. Both wealthier and lower-income neighborhoods, constrained by budget considerations related to both mobility and shopping, tend to be less attracted to these malls (outlets). However, for neighborhoods with medium incomes, commercial areas act as significant pull factors.

This nuanced interplay between natural amenities, planned features, and socioeconomic factors underscores the complexity of mobility patterns in Sweden. It highlights how different qualities and socioeconomic considerations interact to shape residents' preferences and choices regarding urban and rural destinations.

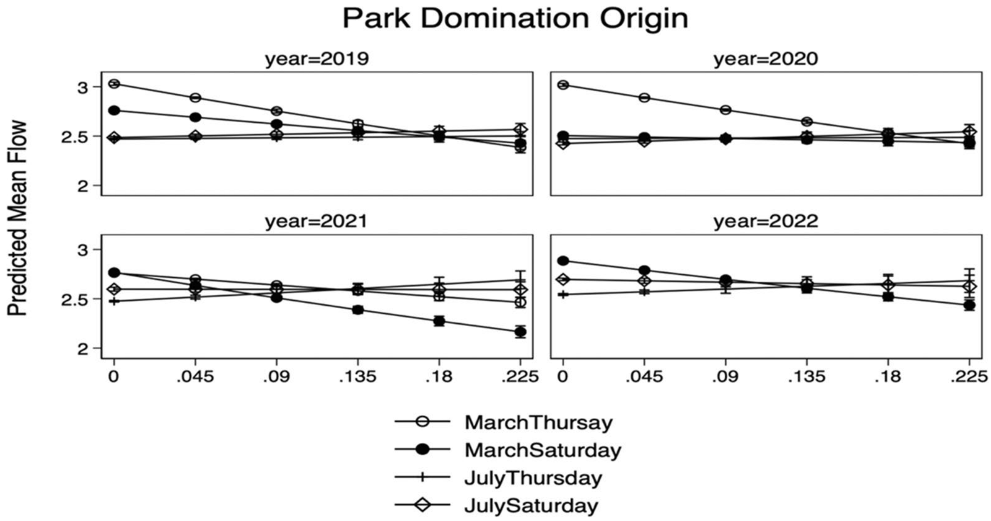

FIGURE 5 | Predicted mean flows by the share of parks in origin neighborhoods.

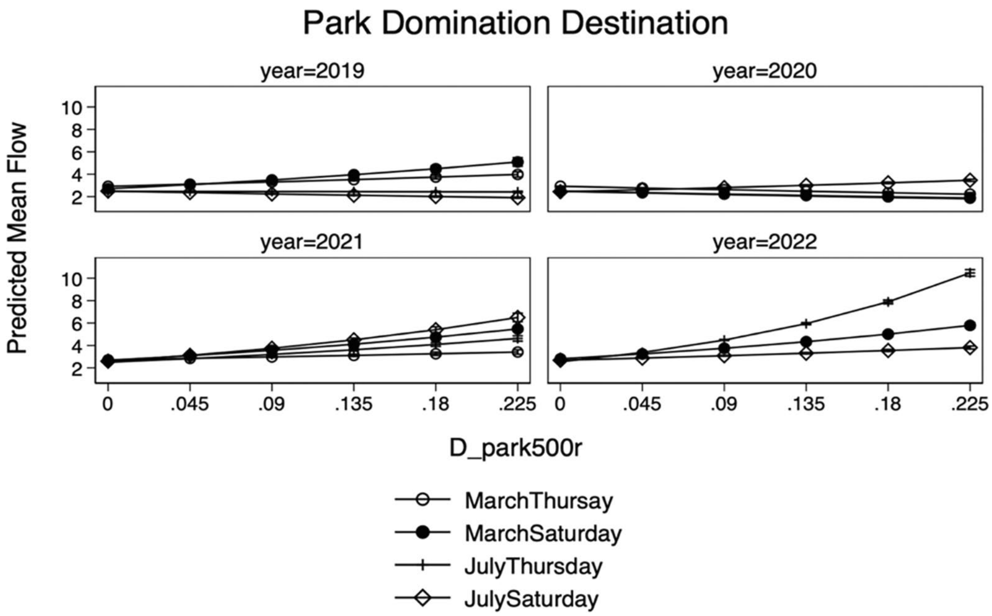

FIGURE 6 | Predicted mean flows by the share of parks in destination neighborhoods.

4.4 | Summary

In summary, our empirical analysis offers valuable insights for policymakers, destination managers, and urban planners in understanding the complex dynamics of mobilities between urban and rural areas, as well as within rural areas among urban leisure explorers. The findings provide a nuanced understanding of the factors influencing mobility patterns, including socioeconomic characteristics, land use variables, natural amenities, and the impact of the COVID-19 pandemic. By recognizing these factors that shape travel patterns, stakeholders can make informed decisions to optimize tourism development, enhance destination attractiveness, and address potential disparities in mobility between urban and rural areas. Additionally, the insights gained from analyzing the impact of the COVID-19 pandemic can inform strategies for crisis management and recovery in the tourism industry. These findings contribute to the broader discourse on spatial mobility and can inform policymakers and urban planners in making informed decisions to shape sustainable and inclusive urban and rural development.

5 | Conclusion

In our study, we have delved into the leisure mobility patterns of urban leisure explorers within the context of the COVID-19 pandemic. By integrating theoretical perspectives on tourism geography, health-related spatial choice behavior and empirical analysis using mobile phone data, we were able to identify the factors that influence travel decisions and the potential disparities in mobility among different destination types and socioeconomic groups. Our analysis has unveiled compelling findings that illuminate the dynamics of leisure mobility patterns and their implications for tourism development and management in a post-pandemic world.

Throughout our analysis, we have identified consistent behavioral patterns in rural or nonurban tourism. The number of mobile devices at both the origin and destination locations exerted a positive influence on mobility flows, indicating both push effects from origins and pull effects from destinations. Socioeconomic factors, such as average age, income, and education, have also played significant roles in shaping mobility patterns, underscoring the intricate interplay between demographic characteristics and travel choices. Moreover, the impact of distance decay was most pronounced in flows between rural areas, underscoring the significance of geographic proximity as a barrier or facilitator of mobility.

Our analysis of land use variables and natural amenities has uncovered interesting dynamics. Water bodies, for instance, acted as both push and pull factors, attracting individuals from urban to rural areas and vice versa. Commercial activities, agricultural opportunities, forests, and industrial sites emerged as substantial factors influencing mobility patterns, enticing individuals from rural areas to urban centers. Residential areas and green amenities consistently acted as pull factors across various mobility flows, emphasizing their importance in shaping travel behavior. Our analysis regarding socioeconomic divisions has further underlined that the abundance of natural qualities in Sweden renders them more of an origin effect than a destination effect, highlighting that inequality in leisure mobility is particularly pronounced in planned locations such as parks, commercial, and residential areas. This implies that when examining leisure mobility toward rural areas, location-specific influences must be carefully considered.

The COVID-19 pandemic has profoundly impacted leisure mobility patterns. Overall mobility was lower during the pandemic, reflecting the influence of travel restrictions and social distancing measures. Nevertheless, an intriguing pattern has emerged, revealing a noticeable surge in travel between rural areas, signifying a noteworthy change in people's preferred destinations compared to the time before the pandemic. The pandemic has played a crucial role in accentuating the utmost significance of health-related considerations when deciding where to go. Nowadays, individuals assign greater importance to ensuring safety and well-being as they make their travel decisions.

By incorporating time fixed effects and analyzing the interaction effects between different factors, we have gained an additional understanding of the temporal dynamics and nonlinear flows in leisure mobility patterns.

Our findings offer valuable insights for policymakers, destination managers, and urban planners in optimizing tourism development, enhancing destination attractiveness, and addressing potential disparities in mobility between urban and rural areas.

In conclusion, our study contributes to the recognition of differences in leisure mobility patterns among urban-to-rural leisure explorers, particularly in the context of the COVID-19 pandemic. By uncovering the factors influencing travel decisions and examining disparities in mobility, we were able to provide a foundation for informed decision-making in tourism development and corona crisis management. The insights gained from our analysis can guide policymakers and urban planners in shaping sustainable and inclusive urban and rural development strategies, ensuring that leisure travelers can enjoy unique and immersive experiences in nonurban locations that offer respite from repulsion factors or negative externalities in the city.

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Ethics Statement

This project strictly adheres to ethical principles throughout the research and implementation phases. All data collected, analyzed, and presented in this research are anonymized to protect the privacy and confidentiality of participants. No personal or identifying information has been collected.

Data Availability Statement

The data used in this analysis were provided by a private company under a contractual agreement. As part of this agreement, the data are proprietary and cannot be shared with third parties. Access to the data is restricted in accordance with the terms of the contract, and any requests for data must be directed to the providing company.

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Appendix

Characteristics of Swedish Landscape

Figure A1 provides an illustration of specific landscape characteristics in Sweden, differentiating between urban and rural areas, particularly in relation to proximity to parks, water, forests, farmlands, and industrial sites. The images selected aim to represent instances of mixed-use areas, each with distinctive landscape features, in particular:

A. Depicts urban areas juxtaposed with farmland or fields.
B. Indicates urban areas neighboring forests.
C. Shows rural areas with adjacent farmland or fields.
D. Illustrates urban areas in proximity to water.
E. Highlights rural areas adjacent to parks.
F. Portrays rural areas in the vicinity of industrial sites.
G. Maps urban areas alongside parks.
H. Displays rural areas in close proximity to both water and forests.
I. Depicts urban areas alongside industrial sites.

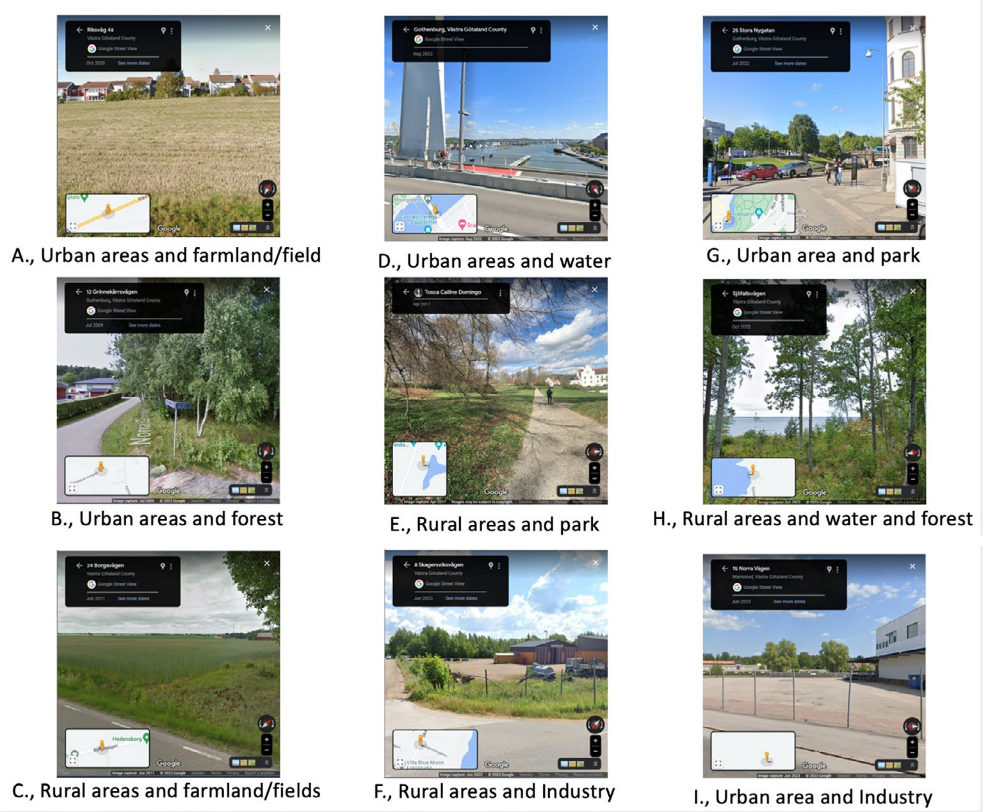

FIGURE A1 | Specifics of the Swedish landscape characteristics.