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When defines where: how rural digital divide, customers' mobility and usage patterns have shaped mobile infrastructures

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When defines where: how rural digital divide, customers' mobility and usage patterns have shaped mobile infrastructures.

Abstract

Extending and upgrading communication networks in rural areas is particularly challenging, due to the difficulties to recover the substantial investments it requires. Scholar and policymakers have identified mobile infrastructures as the most viable solution for these regions, owing to their flexibility and lower deployment costs. Techno-economic assessments supporting these recommendations typically rely on bottom-up demand models, with population as the primary input variable.

In contrast to this traditional approach, our study shifts the focus to other variables that are highly relevant for mobile service providers: the number of fixed wireless access (FWA) subscriptions, customers' mobility patterns, and the spatiotemporal dynamics of communication services usage. We analyzed voice and broadband traffic data from all sites operated by a Spanish mobile service provider across different time frames, alongside data on FWA subscriptions per site and the number of mobile visitors per municipality. We began with a descriptive analysis of available data, segmented by municipality size, which revealed the unique characteristics of communication services usage in rural areas. These insights informed the development of both linear and non-linear demand models aimed at identifying the most influential variables driving communications demand at the municipal level. The results underscore the crucial role of non-resident users and FWA services in shaping demand—and, by extension, in guiding infrastructure investment decisions.

1. Introduction.

Over the last 30 years communication services have become a critical component of nearly every human activity. Initially focused on voice and later expanding to broadband, the infrastructures supporting these services have been widely deployed and continuously upgraded to meet ever-increasing demand (Lee et al., 2011). However, this expansion and densification require substantial investments, which can be unfeasible in sparsely populated areas (Oughton et al., 2023). As a result, incentivizing the deployment of communication services in rural regions has become a key objective of policymakers, given the outstanding impact of communication infrastructures in economic development and civic participation (Koutroumpis, 2019; Denzer, 2021; Nevado-Peña et al., 2019; Van der Wee et al., 2015).

In a world increasingly dominated by Information and communication technologies (ICT), “Digital Divide” has emerged as a new cause of inequality. Various factors contribute to the exclusion of segments of the population from the digital world -geography, income level, digital literacy and age are among the most frequently cited causes. Rural areas are very vulnerable to all these factors, giving rise to the concepts of the *rural digital divide*, or *urban-rural gap*. To address this issue, the European Union has launched since 2010 several major initiatives and strategic plans to expand broadband services, particularly in rural and underserved regions. The *Digital Agenda* (European Commission, 2010), The *Gigabit Society* (European Commission, 2016) and the *Decade Policy Programme* (European Commission, 2021) have successively set ambitious targets to ensure connectivity reaches every corner of the Union. However, even in a wealthy continent

with substantial resources, implementing these plans has proven highly challenging, as illustrated by [Ferrandis et al. \(2021\)](#) and [Feijoo et al. \(2018\)](#).

Mobile services have been critical in solving digital divide between urban and rural areas ([Ovando et al., 2015](#); [De Souza et al., 2021](#)). As a clear case of path dependency, mobile networks first provided voice services in zones out of reach for fixed networks, and a decade later were the vehicles to cater these same areas with Broadband (BB) data services. The advantage of mobile over fixed services in the less populated regions is clear: costs are significantly smaller, as we don't need to build an expensive infrastructure to connect the network and the customer. It's in the air ([Laitsou et al., 2022](#); [Schneir and Xiong, 2016](#)). If demand stays low, mobile services offer a good performance at reasonable costs, as demonstrated by [Ioannou et al. \(2020\)](#) and [Izydorek et al. \(2019\)](#). Policymakers and regulators have naturally bet on it as costs to deploy new generation broadband services in low-density areas began to pile up. Fixed Wireless Access (FWA) have emerged as the ideal solution for these regions ([Lappalainen et al., 2022](#)).

But much more important than mobile services' lower costs¹ is their flexibility. Compared to other brick-and-mortar infrastructures like roads, water distribution systems, or electric grids, whose topology is almost impossible to redesign and which, once deployed, are difficult to grow in capacity, mobile infrastructures can easily adapt to any change in demand volume and location. Mobile network engineers have a rich toolbox for it: adding frequencies², redefining sectors, evolving to a new technology, or building new sites are always at hand. While fixed services are deployed "once and forever" in its final form, mobile operators have always designed their networks to adapt to the dynamic nature of customer demand ([Rendon et al., 2007](#)). This approach has transformed mobile networks into a vibrant infrastructure where traffic distribution reflects actual usage patterns and (at times, sporadic) population presence ([Naboulsi et al., 2014](#)).

We aim to investigate the geographical distribution of communication demand and other key characteristics of communication services using real-world data. Subsequently, we will develop demand models to identify the relative importance of the different factors that shape this footprint. Our main contribution is to highlight the heterogeneity of communication demand across municipalities—an insight that challenges the validity of one-size-fits-all models. Furthermore, we underscore the critical reliance on mobile networks to bridge the digital divide in rural areas, as well as the pivotal role of fixed wireless access and non-resident mobile customers in determining traffic volumes at the municipal level.

Our study leverages a comprehensive dataset from a major Spanish operator, encompassing voice and data traffic volumes as well as fixed wireless access (FWA) subscriptions per site over the course of a full year. Additionally, we incorporate data from official sources, aggregated at the municipal level, including monthly counts of mobile visitors and population figures. Traffic, FWA subscriptions and mobile visitors represent dynamic variables that capture the spatiotemporal patterns of demand. In contrast, population is a static external variable with significant implications: regulatory conditions related to spectrum licenses are often tied to municipal population size, and techno-economic assessments—such as those by [Martins and Wernick \(2021\)](#)—typically rely on bottom-up models grounded in population data. The heterogeneity among municipalities with fewer than 5,000 inhabitants poses a significant challenge for accurately modeling communication demand. Building on the methodologies

¹ that aren't so low as demand surges, and we need to add capacity.

² More properly, we would speak about adding new bearers or increasing bandwidth in what we have.

employed by other researchers addressing similar challenges (Ji & Liu, 2023; Grömping, 2009), we integrate both simple and multiple linear regression models alongside random forest algorithms to analyze our dataset. Additionally, municipalities have been categorized into geotypes for the linear models to account for significant differences in scale across the primary demand variables.

Taking all this into account, our research questions are as follows:

- 1) How relevant is population size in predicting the demand for communication services, and how does this dependence vary with the size of municipalities?
While traditional assessments and demand models use the *residing population* as the main variable determining demand, we aim to analyze the influence of the *floating population* coupled to short- and long-term human mobility, incorporating these variables to our modeling processes.
- 2) How much has fixed wireless access influenced the demand for communication services in rural areas and helped to bridge the urban-rural digital divide?

By exploring these two questions, we expect to obtain significant conclusions about future investment and deployment needs, especially in rural areas.

Our paper is organized as follows: in section 2, we will review the related literature, in section 3 we will describe the starting data, their sources and criteria to classify the municipalities in geotypes, as well as the modeling methodologies. Section 4 will be devoted to descriptive analysis of data and the modeling results. In section 5, we will summarize the conclusions and possible avenues of research based on what was observed, while section 6 will be devoted to bibliography.

2. Literature review

The costs associated with deploying telecommunication networks have significantly influenced policy and regulatory decisions in the sector. A fundamental step in techno-economic assessments is the understanding and modeling of communication demand. Notable studies in this area include Sarfaraz and Hämmäinen (2016) and Sum et al. (2021). Other researchers have addressed these challenges in more specific contexts: Mocnej et al. (2018) focused on IoT traffic; Leo et al. (2016) analyzed mobility events; and Lim et al. (2016) developed models to predict application usage in mobile devices.

There is extensive literature on the economic aspects of communication infrastructures deployment (Bohlin, 2007; Smail and Weijia, 2017; Oughton and Frías, 2018). Specifically focused on rural areas, relevant contributions include Krizacovic et al., 2018; Schneir and Xiong, 2016; Ovando et al., 2015 and Frías et al., 2015. The use of fixed wireless access has also been explicitly analyzed: Adityo et al. (2021) examined its application in urban residential areas, while Lappalainen et al. (2022, 2023) and Hasan et al. (2021) explored its role in rural contexts. Topyan and Ulema (2020), on the other hand, provided a broader perspective on the technical and financial challenges associated with FWA.

In contrast to these assessments, which are primarily based on static data, network operators typically rely on dynamic models for network design and deployment. Todd and Doucette (2017) proposed a framework for long-term planning, whereas Bendicho (2021) summarized service providers' strategies based on time-series analysis of real-world data.

Studies about human mobility have benefited from the incredibly rich data they can obtain from mobile networks. Urban and emergency services planning (Ahola et al., 2007; Bergroth et al., 2022), public transport strategies (Batty, 2011), tourism analysis (Kubo et al., 2020), epidemic control (Grantz et al., 2020), land usage analysis (Calegari et al., 2016) and even demographical studies over people's participation in the public sphere through social media (Luo et al., 2016) are different areas where data from mobile services and networks have contributed significantly. Surprisingly, studies focusing on human mobility and its impact on communication infrastructure remain scarce. Alessandretti et al. (2020) and González et al., (2008) provide valuable insights into the spatiotemporal patterns of human mobility, illustrating how individuals move between physical “containers,” with distances varying depending on the time frame analyzed. In contrast, Barbosa et al. (2021) explored the relationship between mobility patterns and income levels across several towns in the United States and Brazil.

3. Data sample and methodology

3.1 Data sample – municipalities and population

We have adjusted the geographical granularity of data and our studies to match the maximum granularity from official data sources, which are given at municipality level.

Our sources also impose certain limitations on our study. Many small villages are served by mobile network sites located in a nearby municipality. So, we have data for 6,081 out of a total number of 8,116 municipalities. This problem arises both for traffic data, which we attribute to the municipality where the site is located, and for visitors’ data obtained from Instituto Nacional de Estadística (INE)³. Table 1 summarizes the universe under study and the data sample with which we will work.

| Pop. Range | Universe | | Data Sample | | Observations | |
|------------|----------------|------------|----------------|------------|--------------|-------------|
| | Municipalities | Population | Municipalities | Population | % Mun. | %Population |
| <1k | 4,971 | 1,438,466 | 3,093 | 1,055,115 | 62.2% | 73.4% |
| 1k-5k | 1,832 | 4,262,462 | 1,694 | 3,985,929 | 92.5% | 93.5% |
| 5k-20k | 896 | 8,781,961 | 877 | 8,614,051 | 97.9% | 98.1% |
| 20k-50k | 266 | 7,837,670 | 266 | 7,837,670 | 100.0% | 100.0% |
| 50k-300k | 139 | 15,249,875 | 139 | 15,249,875 | 100.0% | 100.0% |
| >300k | 12 | 9,903,486 | 12 | 9,903,486 | 100.0% | 100.0% |
| Total | 8,116 | 47,473,920 | 6,081 | 46,646,126 | 74.9% | 98.3% |

Table 1. Universe of Spain’s municipalities and data sample analyzed

3.2 Geotypes

We have grouped municipalities in geotypes following the conditions of spectrum licenses for mobile services in Spain. These concessions are always associated to obligations to deploy the new technology/spectrum by a specific due date in a set of municipalities, defined by their population, and have strongly influenced the strategy and scope of operators’ investments.

While 3G and 4G licenses set conditions to serve municipalities with fewer than 5,000 inhabitants (Order ITC/889/2011 (2011), Order ITC/1074/2011 (2011)), we find a different suite

³ National Statistics Institute (INE) is the Spain’s official statistical data agency.

of requirements for 5G. In this case, we can find conditions for larger towns (as well as relevant roads and infrastructures), with 20,000 and 50,000 inhabitants as references, according to [Order ETD/534/2021 \(2021\)](#).

We decided to use additional references for 1,000 and 300,000 inhabitants to better characterize two very special sets. As can be seen in the Gini graph for municipality sizes in Figure 1, villages with fewer than 1,000 inhabitants account for 3% of the population and 41% of the territory, making them a special and influential set. The descriptive analysis of data in section 4 will demonstrate the exceptional behavior of this group across all analyzed variables. Towns with over 300,000 inhabitants are also distinct and thus considered as a group of their own.

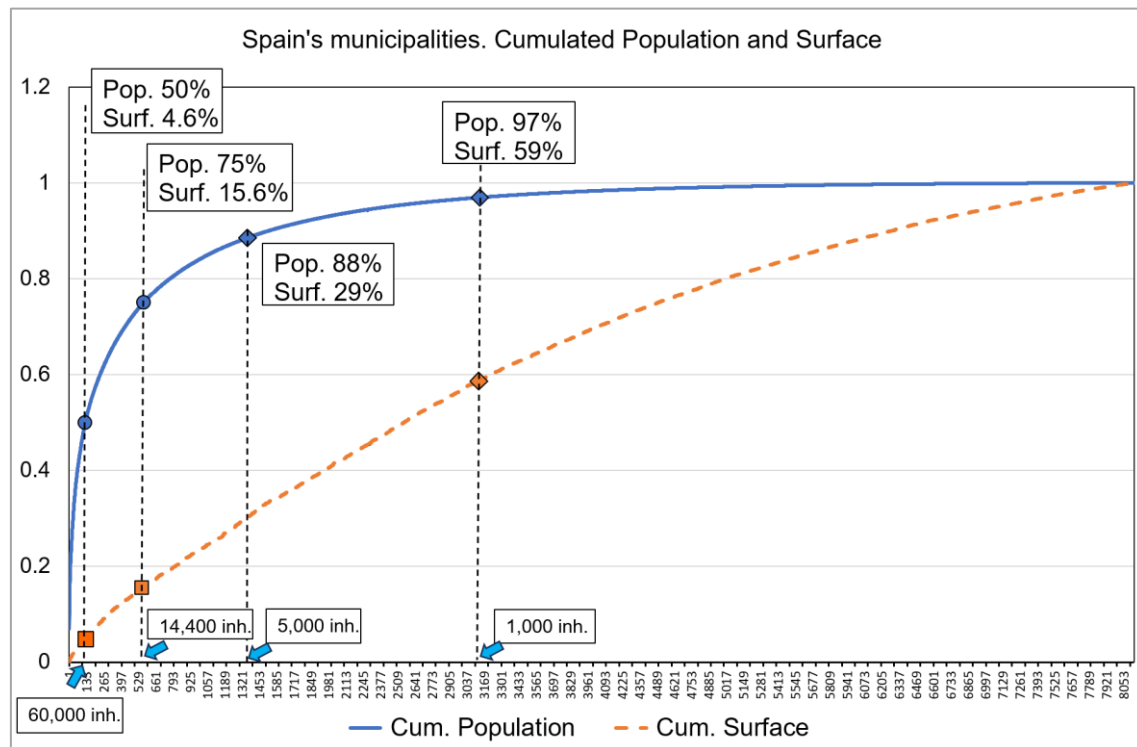


Fig. 1 Gini graph for municipalities population size and associated territory. Source: INE

3.3 Population and visitors per municipality

From INE we have obtained:

- Municipalities' population size
- Nº of visitors per municipality (from mobile networks point of view)

We also studied datasets of households, dwellings and businesses per municipality from INE. These sets weren't finally included in our models, given their high correlation with population.

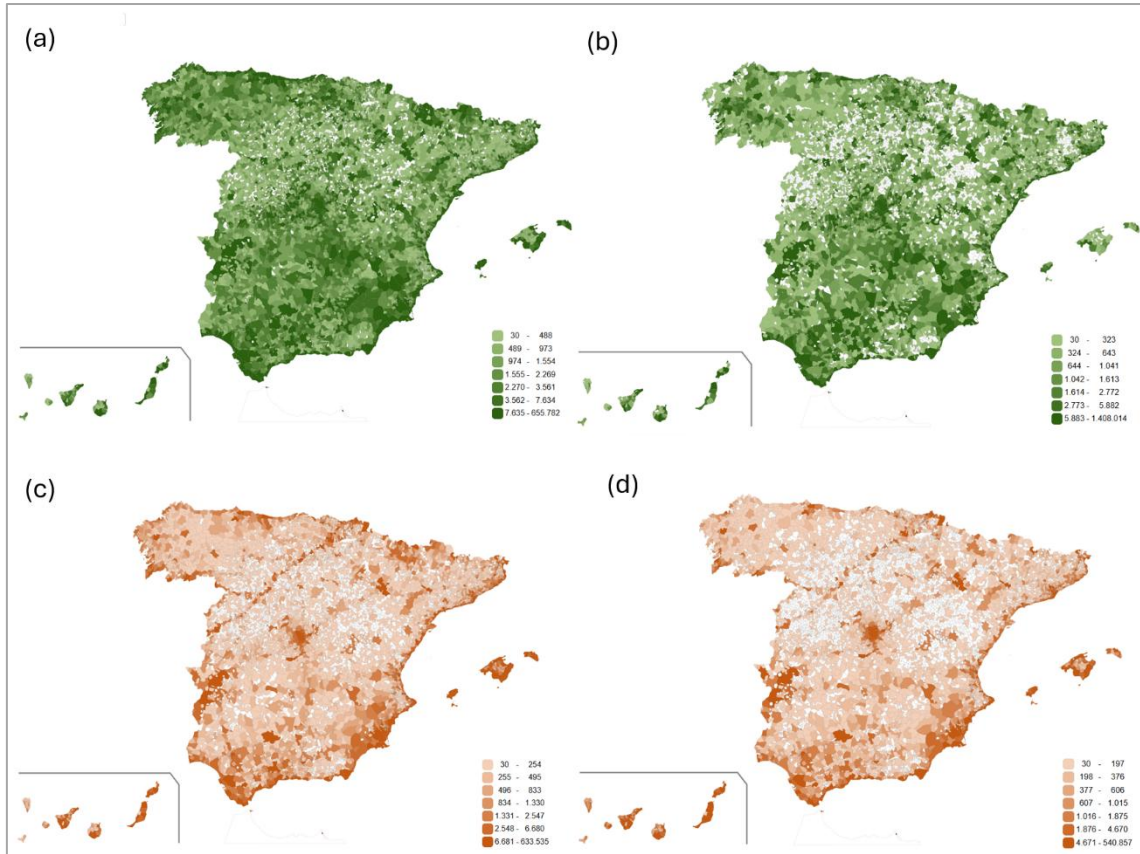


Fig. 2 Number of monthly visitors per municipality. (a) Internal tourists, aug'2023 (b) Internal tourists nov'23 (c) Foreign tourists, aug'2023 (d) Foreign tourists, nov'23. Source: INE

3.4 Traffic and fixed wireless access subscription data

We have access to traffic data from a major Spanish mobile communications provider that holds over one-third of the market share in terms of both customers and traffic. This operator also hosts several prominent Mobile Virtual Network Operators (MVNOs), enabling the dataset to reflect a comprehensive range of customer consumption profiles—from cost-sensitive, mobile-only users to premium subscribers with high-end service bundles. Furthermore, the operator's network covers 99% of the population and offers a broad portfolio of services tailored to residential, business, and government clients. These characteristics make this provider a highly representative proxy for the overall market.

Traffic data granularity in terms of location has been adjusted according to the detail level for the time dimension. We have characterized intra-week seasonality (weekdays vs. weekends) for voice and data, as well as year-long seasonality (winter vs. summer) by comparing traffic in November and in August. Fixed wireless access (FWA) subscriptions associated to each site have been grouped by municipality.

3.5 Methodology

Almost all demand assessments for communication services are based in bottom-up models, which start with an estimate of future communications demand per person. By multiplying this estimated individual consumption by the number of inhabitants in a given area, we obtain a prediction of future demand. Our primary objective is to evaluate the correctness of this method. If there were a direct relationship between traffic and population, a linear regression using these two variables should provide a reliable prediction of traffic.

3.5.1 Single Linear regression

Linear regression is a foundational statistical technique used to model the relationship between a dependent variable and one or more independent variables. Our initial approach employs **simple linear regression**, modeled as:

$$Y \approx \beta_0 + \beta_1 X + \epsilon \quad (1)$$

Where:

Y is the dependent variable (municipal traffic)

X is the predictor or independent variable (municipal population).

β_0 is the y-intercept

β_1 is the slope of the regression line.

ϵ is the error term

Following the methodology outlined by [James et al. \(2017, Ch. 3\)](#), we estimated the coefficients using least squares fitting, and assessed their reliability through standard error, t-statistics, and p-values. Model performance was evaluated using the coefficient of determination R^2 .

We applied this model to four traffic types (voice-summer, voice-winter, data-summer, data-winter), disaggregated by geotype, due to the significant differences observed in the descriptive analysis. Surprisingly, the model performed poorly in less populated geotypes, revealing a weak correlation between population and traffic in most municipalities.

3.5.2 Multiple Linear regression

To improve model accuracy, we extended our analysis using multiple linear regression, incorporating additional predictors such as seasonality, number of mobile visitors, and FWA (Fixed Wireless Access) subscriptions:

$$Y \approx \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_p X_p + \epsilon \quad (2)$$

Although more complex, this approach allows for a multidimensional understanding of traffic determinants. We used Microsoft Excel™ to compute coefficients and evaluate model statistics. While this method improved accuracy, it still underperformed in certain scenarios—particularly for winter voice and data traffic in municipalities with fewer than 5,000 inhabitants.

3.5.3 Random forests

Although multiple linear regression provided better results than simple linear regression in terms of models' accuracy, these were still poor for certain scenarios. Furthermore, it was complicated to interpret the relative importance of the different variables as predictors of traffic with these linear models. To address the limitations of linear models, we adopted a **nonlinear modeling approach** using **Random Forests**, a robust ensemble learning method well-suited for high-variance, low-signal environments ([Breiman, 2001](#)). Random forests construct multiple decision trees and aggregate their predictions:

There isn't a single formula for random forest, but we can express the prediction for regression as:

$$\hat{y} = \frac{1}{N} \sum_{i=1}^N T_i(x) \quad (3)$$

Where:

\hat{y} is the predicted value

N is the number of trees in the forest

$T_i(x)$ is the prediction of the i-th tree for input x

As can be seen in [James et al. \(2017\), chapter 8](#), the random forest algorithm involves the following steps:

1. Bootstrap Sampling: Randomly select subsets of the training data with replacement.
2. Decision Tree Construction: For each subset, construct a decision tree using a random subset of features at each split.
3. Aggregation: Combine the predictions of all the trees to produce the final output. For classification, this is done by majority voting; for regression, by averaging the predictions.

To build our trees at step 2, our algorithm uses Gini impurity as decision criterion. Gini impurity determines the likelihood of incorrect classification of a randomly chosen element if it were randomly labeled according to the distribution of labels in the node. It ranges from 0 (pure node) to 0.5 (maximum impurity for a binary classification).

Assuming that, at each split in our tree, we need to assign elements to a class, Gini impurity is calculated as:

$$G = 1 - \sum_{i=1}^k p_i^2 \quad (4)$$

Where k is the number of classes, or new branches that sprout from our node and p_i is the proportion of elements belonging to class i in the node.

Each time we need to split a node in a decision tree, the algorithm compares the impurity of the parent node with the weighted impurity of the child nodes. Then it evaluates all possible splits and selects the one that minimizes the Gini impurity, repeating this process recursively to build the tree.

It is this step 2 which makes random forest able to detect the importance of less-influential variables. Since many trees are constructed without the dominant features, when we aggregate all the predictions at step 3, it becomes possible to evaluate the influence of less relevant variables that would never have appeared in a conventional regression tree.

4. Results

4.1 Descriptive analysis – time-related patterns

4.1.1 Hourly traffic patterns

If we analyze mobile voice usage along a day (see Figure 3), it presents two instances of maximum usage, with very similar intensity, at 13:00 and 20:00 on weekdays, and 13:00 and 21:00 on weekends. For weekdays, we can assume that the afternoon maximum corresponds mainly to

professional usage, while the evening is reserved for family and friends. Both peaks have almost the same magnitude during weekends, while we can appreciate a bigger difference on weekdays.

We have highlighted the hour of minimum traffic, whose level is between 1% and 4% of the traffic during the hour of maximum usage. Humans rest at night from voice communications.

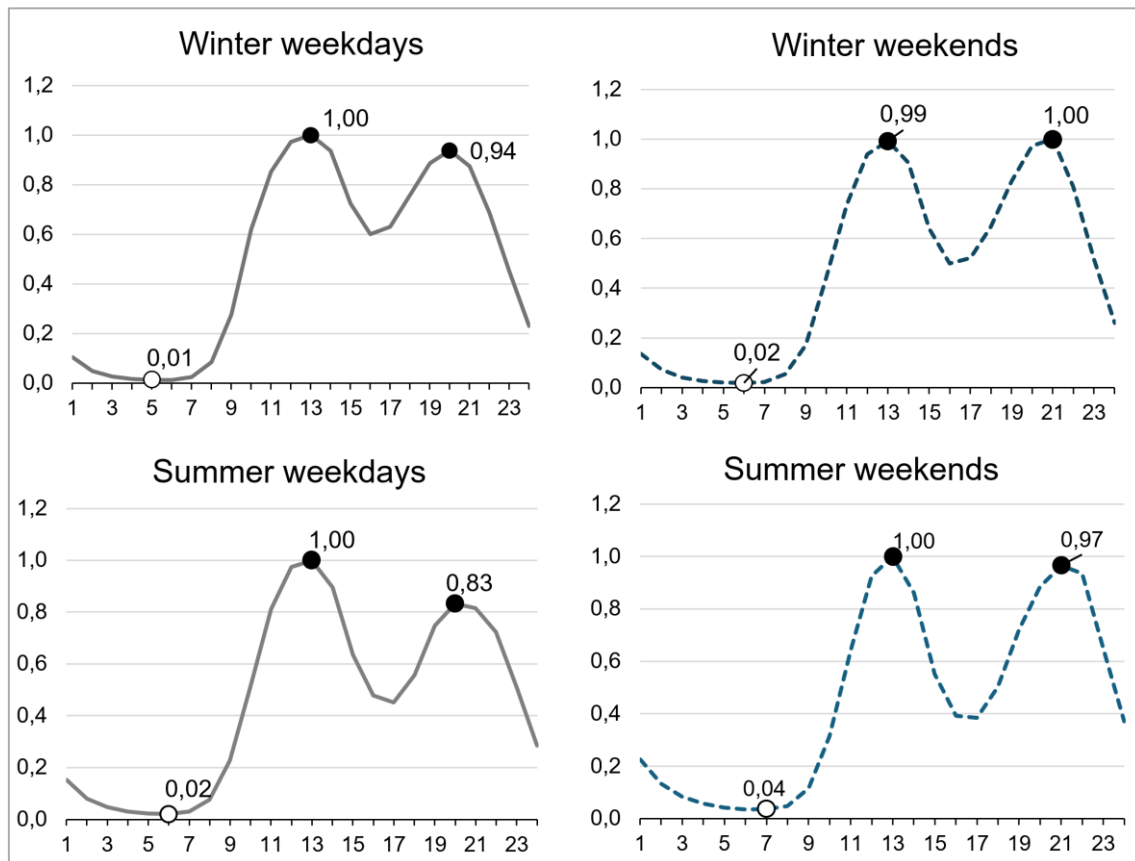


Fig. 3 Voice traffic hourly profile for weekdays and weekends. Source: Spanish operator proprietary data

Mobile data traffic behaves differently, as we can see in figure 4. It has only one peak, at 23:00 in winter and 24:00 in summer. The hours of higher usage are clearly associated with leisure activities. Data services' customers never rest; usage at the hour of minimum traffic is around 16%-19% of peak-hour traffic.

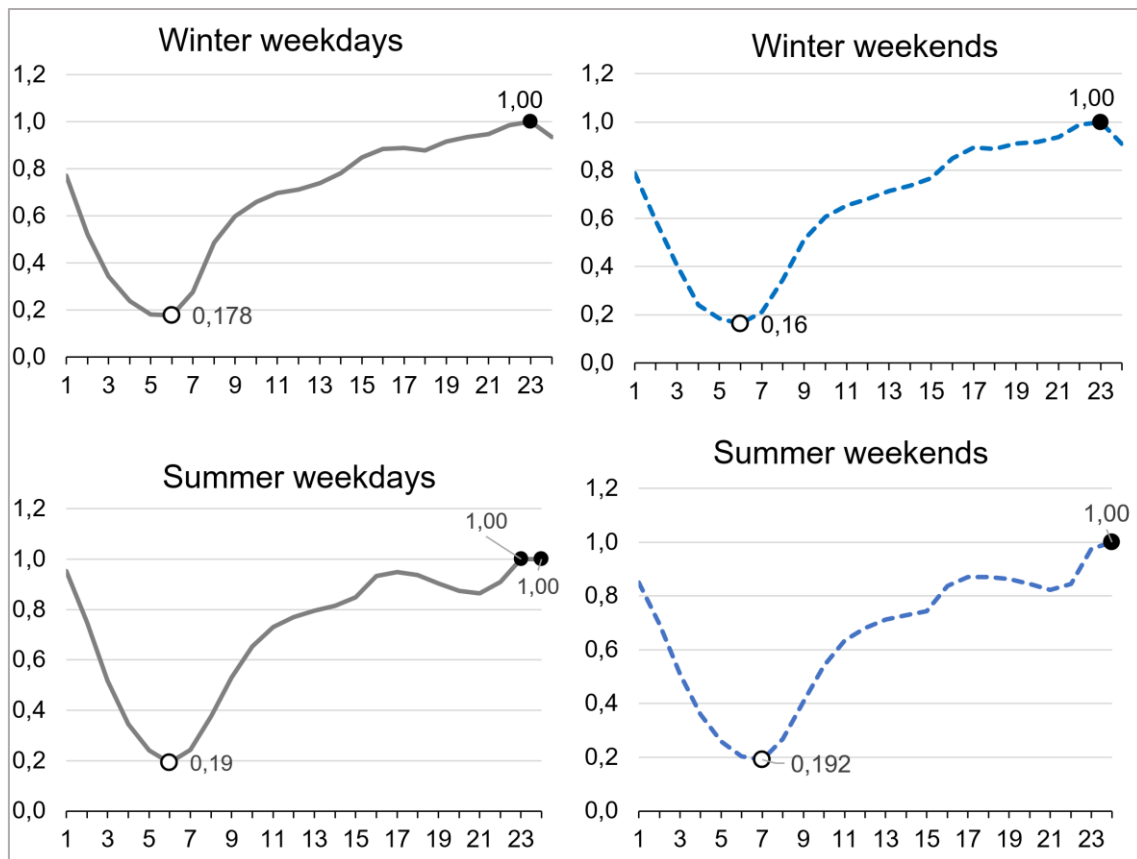


Fig. 4 Data traffic hourly profile. Source: Spanish operator proprietary data

4.1.2 Weekly traffic patterns

We can clearly see the extent to which voice traffic is associated with professional activities through its weekly profile. Weekdays register roughly twice as much demand as weekends. Figure 5 exhibits a normalized traffic profile for two different months in 2023 (november and august), where the reference is the day of minimum traffic (summer Sundays). This way we can compare daily traffic in both seasons, as well as the difference of magnitude between winter and summer voice demand.

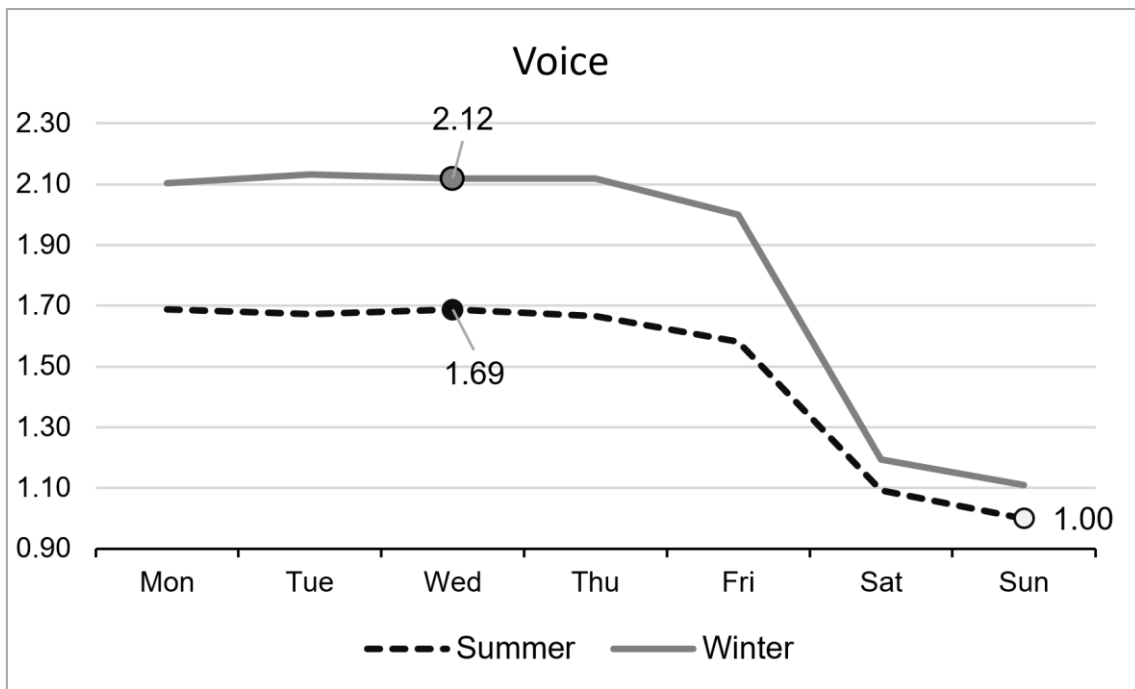


Fig. 5 Voice traffic weekly profile (summer and winter). Source: Spanish operator proprietary data

The weekly profile for data traffics also shows the relation between data communications and leisure, as can be seen in Figure 6. We have highlighted the maximums, which occur during the weekend. In winter, weekends data traffic is clearly higher than during weekdays, but in summer, we hardly distinguish weekdays from weekends, as a large percentage of customers are on holiday. We will later analyze traffic indicators in relation to municipalities' size to make sense of this data in terms of geography. Here the reference is the traffic in winter Mondays.

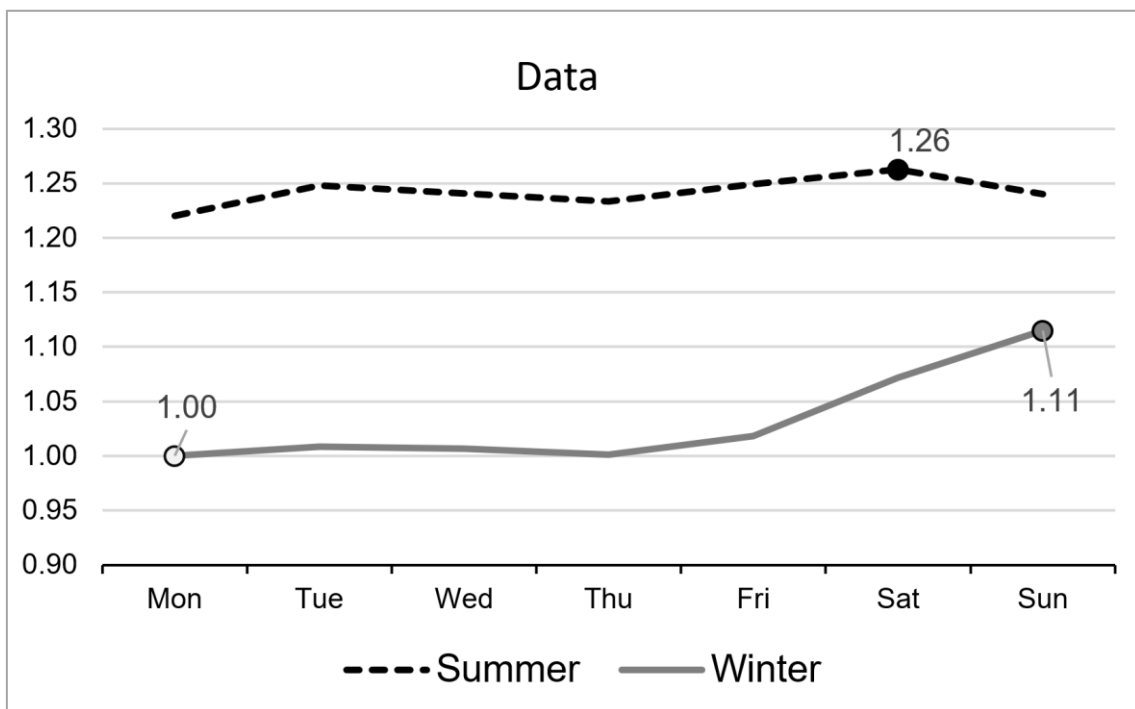


Fig. 6 Data traffic weekly profile (summer and winter). Source: Spanish operator proprietary data

4.1.3 Monthly traffic patterns

To analyze year-long seasonality in traffic patterns, we preferred to group traffic per week. Since weekdays have double the voice traffic of weekends, monthly figures are very sensitive to the number of working days, weekends and bank holidays, creating a rugged graph which can be a little misleading. By analyzing the weekly traffic figures throughout the year, we can clearly appreciate how opposed voice and data behaviors are. While voice demand reaches its minimum in August, data traffic registers its maximum in the same month. The different bank holidays all over the year also illustrate this difference, highlighting the fact that we can summarize as “data is for leisure, voice is for work”.

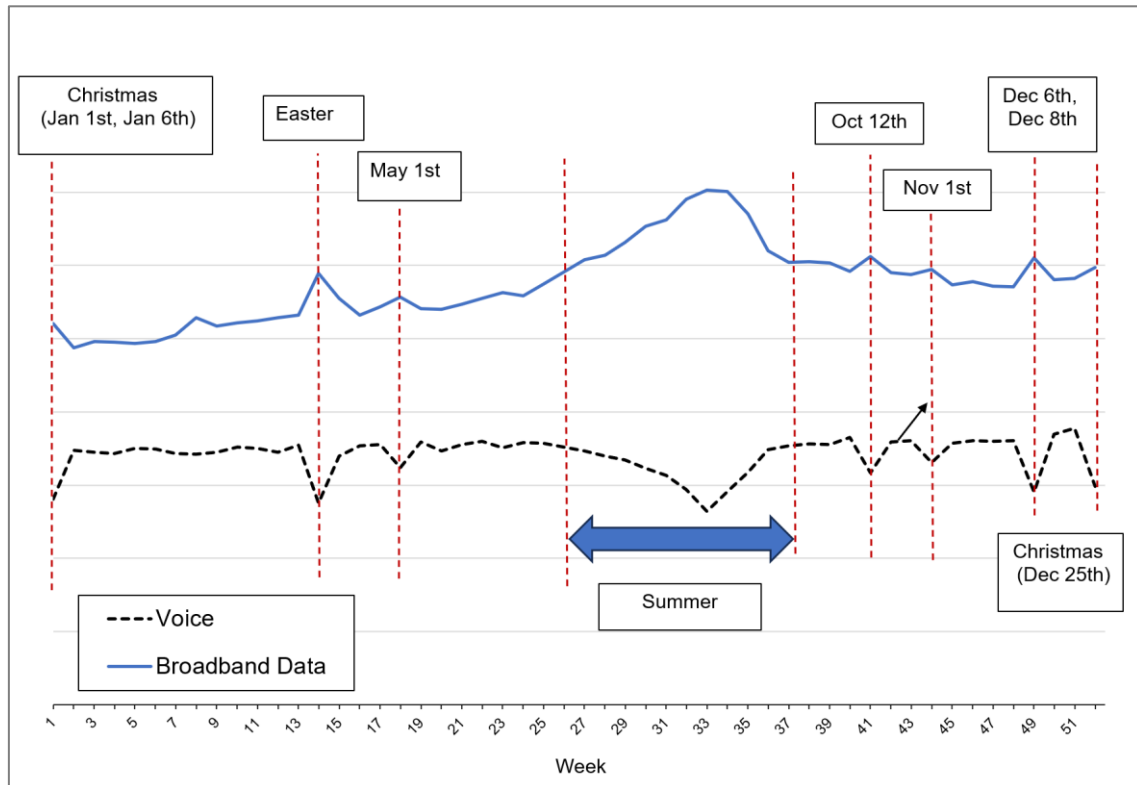


Fig. 7 Voice and data traffic per week in 2023. We have highlighted the days corresponding to bank holidays in Spain. Source: Spanish operator proprietary data

4.2 Descriptive analysis - Geographical patterns

Once we have studied when customers use communication services, it's time to analyze where they use them. Figure 8 shows weekly traffic patterns for our set of geotypes, while monthly behavior for voice and data per geotype is illustrated in figures 9 and 10.

4.2.1 Weekly traffic patterns

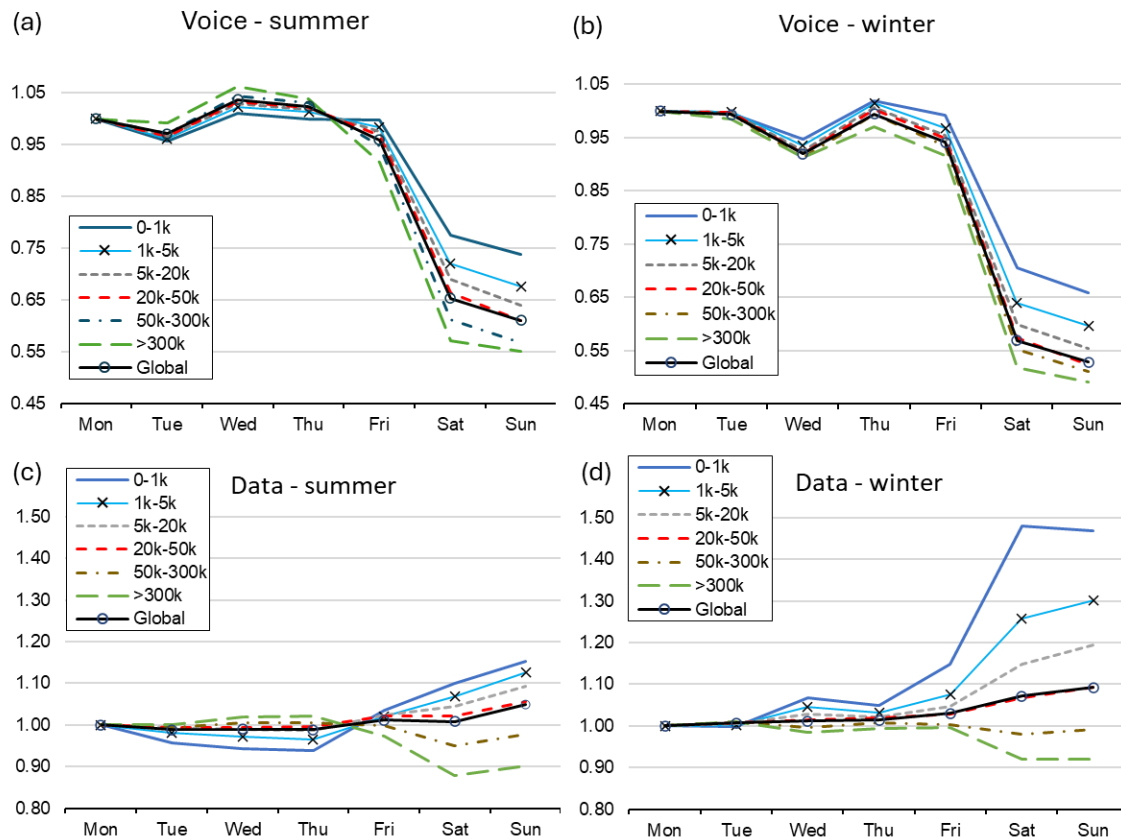


Fig. 8 Traffic weekly profile for each geotype. (a) Voice-summer (b) Voice-winter (c) Data-summer (d) Data-winter. Source: Spanish operator proprietary data

Weekly traffic patterns clearly illustrate that there is an inverse relationship between traffic on weekends and municipalities' population, both for voice and for data. Data traffic on Saturdays in winter in municipalities with fewer than 1,000 inhabitants is 50% above its value on Mondays. The difference in summer isn't as exaggerated but is also significant. The graphs clearly indicate that traffic comes from municipalities with over 50,000 inhabitants.

4.2.2 Monthly traffic patterns

We observe a similar phenomenon with monthly traffic, which reaches its annual minimum in August for voice in municipalities over 50,000 inhabitants, while maintaining its level in smaller cities. For villages with less than 1,000 August is the month with maximum voice traffic.

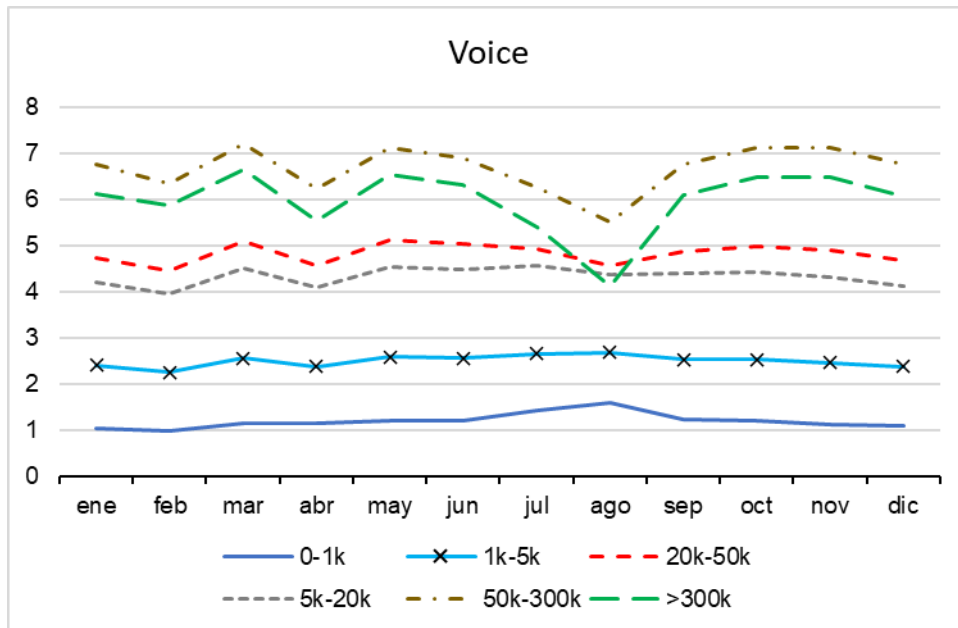


Fig. 9 Monthly voice profile for each geotype. Source: Spanish operator proprietary data

On the other hand, data traffic is essentially leisure traffic and reaches its annual maximum in august for all geotypes where tourists are significant when compared to residents. Once again, municipalities with above 50,000 inhabitants are the exception.

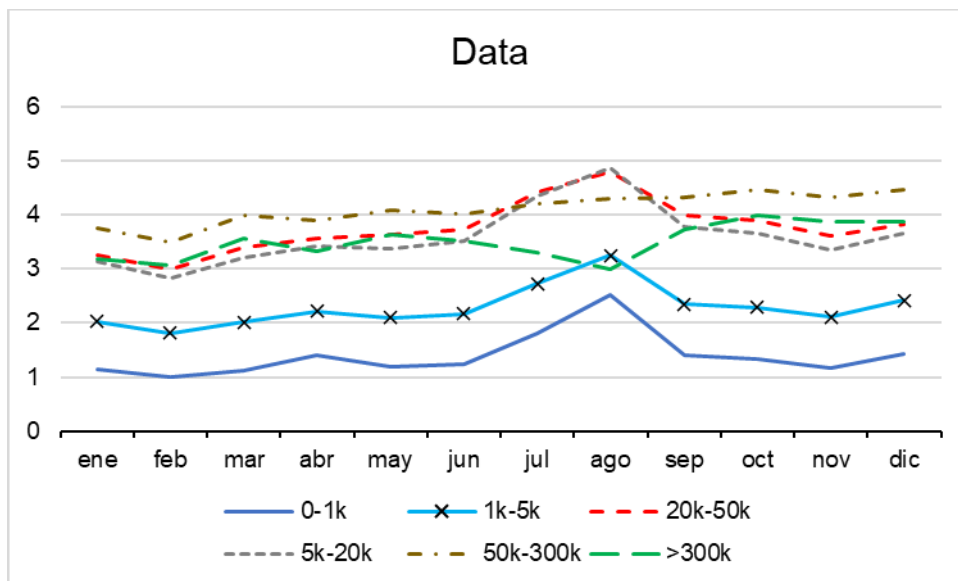


Fig. 10 Monthly data profile for each geotype. Source: Spanish operator proprietary data

4.2.3 Other relevant indicators

Our hypothesis is that mobile networks' demand is much more intense in less populated municipalities, since fixed networks cannot be deployed everywhere at a reasonable cost. This is the realm of fixed wireless access, which promises to solve the digital divide in rural areas. Tourism also adds a new factor to mobile services' demand, creating a "floating population", which can only use mobile services, given the sporadic nature of their presence. To illustrate the dependence on mobile services for different geotypes we have analyzed various indicators in relation to population. Fig 11 summarizes the information of voice and data traffic per inhabitant

per geotype for summer and winter, as well as the number of FWA subscriptions and the number of visitors per inhabitant. We are working with average values for each set of municipalities, i.e., we have summed all traffic (or FWA subscriptions, or visitors) encountered in the municipalities belonging to each geotype and then divided by the population living in those municipalities.

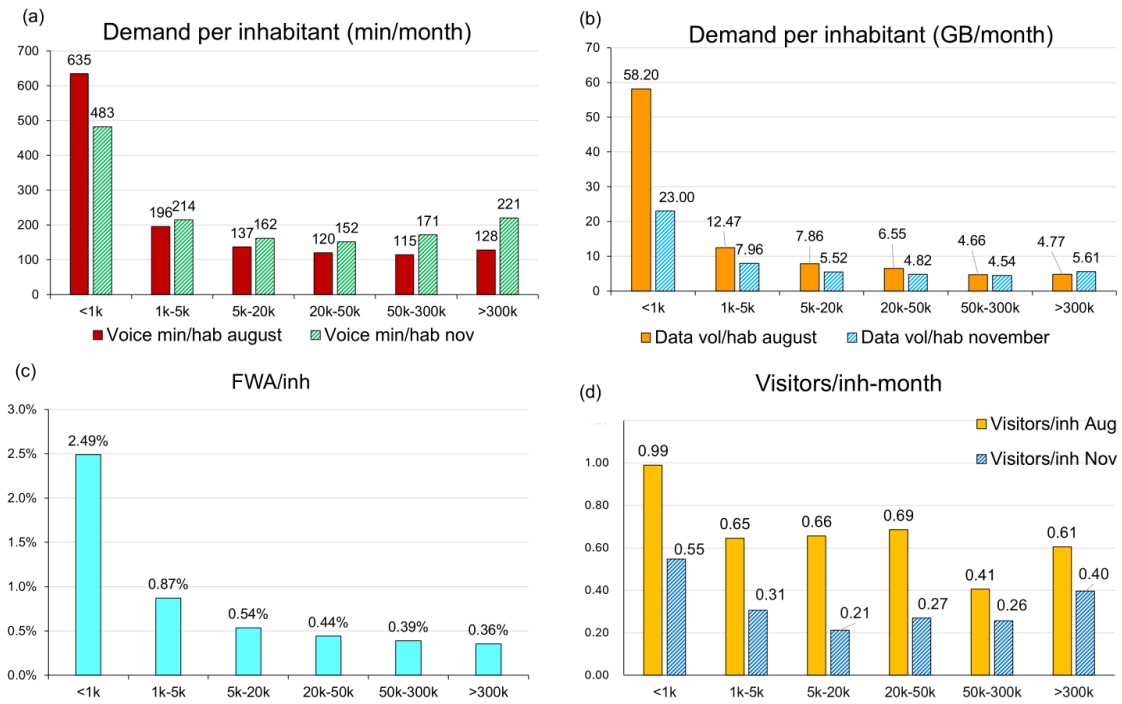


Fig. 11 Main mobile services demand indicators per inhabitant for each geotype. (a) Voice demand in November and august (b) Data demand in November and august (c) FWA subscriptions (d) visitors in November and august. Source (a,b,c): Spanish operator proprietary data. Source (d): INE. When we handle data obtained from one operator, we must consider that it represents roughly one-third of the market. Nevertheless, as our objective is to compare geotypes and analyze sensitivity to different variables, it's perfectly suitable to maintain the original ciphers.

For municipalities with fewer than 1,000 inhabitants voice demand per inhabitant in august is between three and four times the typical value for other geotypes, while in winter the multiplicative factor is between two and three. For summer data traffic, demand per inhabitant in municipalities under 1,000 is ten times the average demand in cities with over 50,000 inhabitants for the same period. Municipalities between 1,000 and 5,000 inhabitants also exhibit significantly higher values of traffic per inhabitant than the average, but the effect is not as pronounced.

Other factors influencing dependence on mobile services, such as FWA subscriptions per inhabitant or number of monthly visitors per inhabitant also stand out in municipalities with fewer than 1,000 inhabitants. The dependence on FWA for rural areas, on the other hand, can be better understood with the help of Figure 12, where we have represented the proportion of households with effective FTTH coverage for small municipalities.

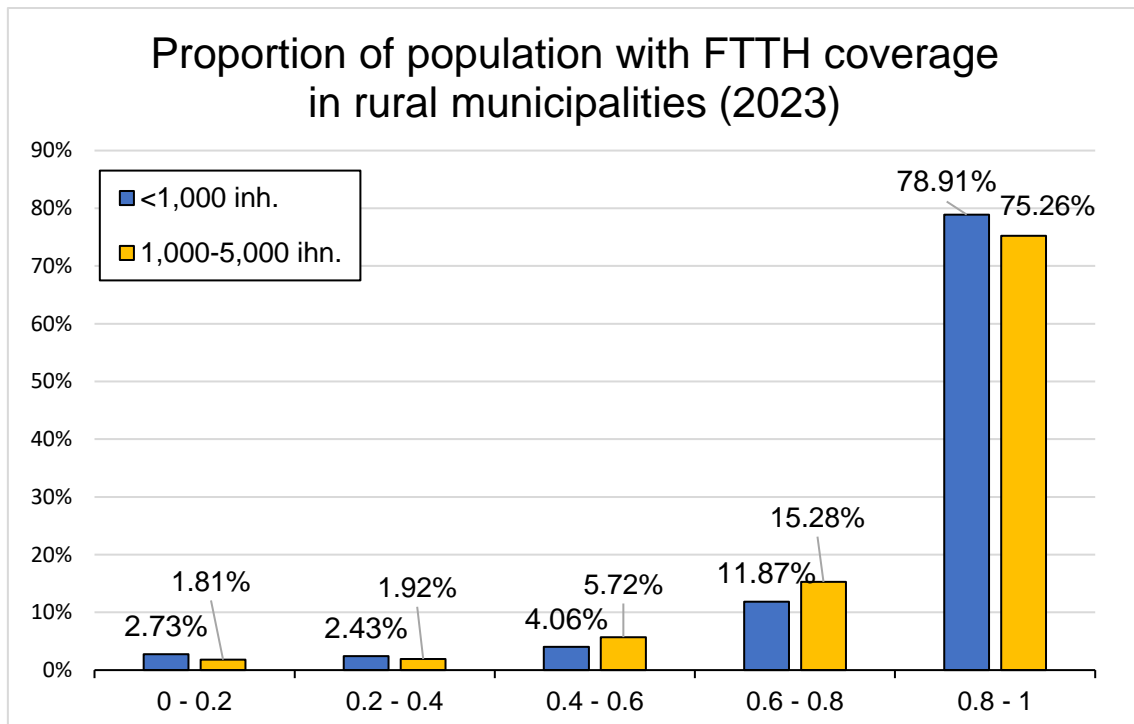


Fig. 12. Effective FTTH coverage for municipalities with fewer than 5,000 inhabitants. Source:

We have also analyzed the seasonality of traffic per geotype, as shown in Figure 12. We compare daily traffic on weekdays and weekends, as well as monthly traffic for November and August. In general, the difference in traffic for weekdays and weekends, on one hand, and between winter and august, on the other, increases with population size.

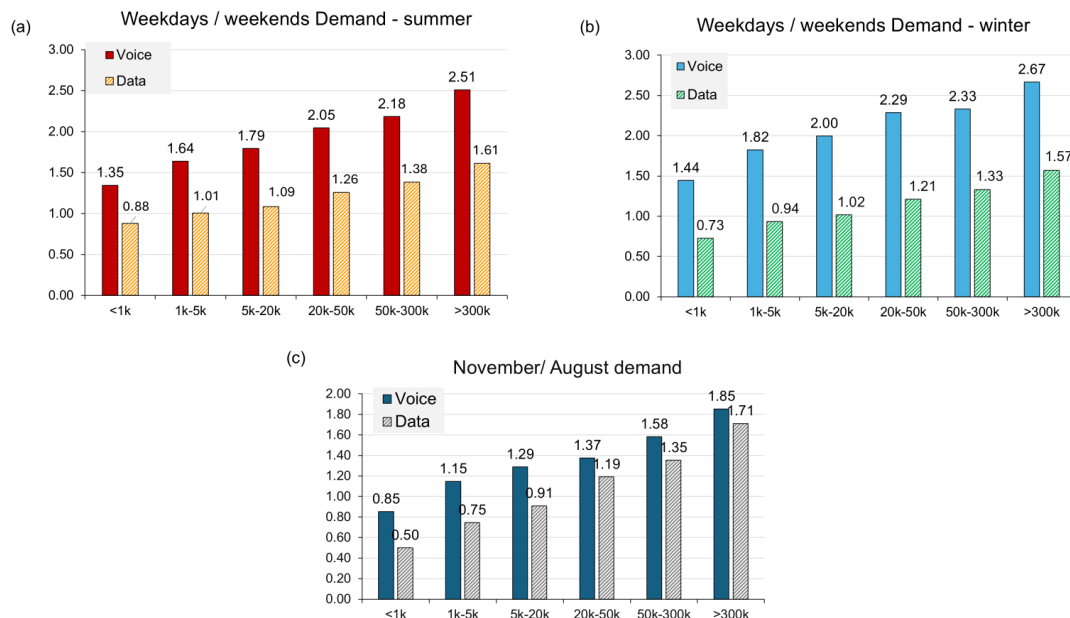


Fig. 13 Main seasonality indicators per geotype. (a) Weekdays/weekends ratio – summer; (b) Weekdays/weekends ratio – winter; (c) Winter vs. summer.

4.3 Results. Models for communication services demand

Sections 4.1 and 4.2 provide a general overview of communication services demand patterns, highlighting important features that depend on municipalities' population size. Grouping the

information by municipalities' size has allowed us to shed light over the stress that mobile networks experience in less populated areas. But all the indicators we have obtained by geotype are only averages over hundreds or thousands of municipalities, indeed quite heterogeneous among them. We needed to explore our rich set of data per municipality with more powerful statistical tools. Our aim is to understand which variables more heavily determine communication services demand in a municipality.

4.3.1 Linear models

In line with our initial research question, our first point was to explain the relationship between traffic and population. More specifically, we wanted to make clear if there is a direct linear relationship between population and traffic. With average data traffic per inhabitant being ten times higher in municipalities with less than 1,000 inhabitants than in big cities it's clear that we cannot expect to use the same model for all geotypes. Therefore, we attempted to obtain a linear model for each geotype.

Our simple naïve model employed a linear regression to predict traffic as a function of population for each geotype. We developed models for each type of traffic (voice and data, for November and for August). Table 2 shows the R^2 of the models obtained, which generally poor, except for cities with more than 50,000 inhabitants. This answers our first investigation question and implies that, for municipalities under 50,000 inhabitants, demand estimations based solely on population are far from accurate. Indeed, for data traffic in summer, demand estimations for municipalities between 50,000 and 300,000 inhabitants based only on population are also clearly misleading ($R^2=0.34$).

| Linear regression - only population | | | | |
|-------------------------------------|----------------|--------------|---------------|-------------|
| Geotype | Voice-November | Voice-August | Data-November | Data-August |
| <1k | 0.26 | 0.16 | 0.16 | 0.09 |
| 1k-5k | 0.26 | 0.20 | 0.18 | 0.07 |
| 5k-20k | 0.38 | 0.29 | 0.23 | 0.11 |
| 20k-50k | 0.24 | 0.13 | 0.13 | 0.02 |
| 50k-300k | 0.67 | 0.64 | 0.66 | 0.34 |
| >300k | 0.90 | 0.88 | 0.93 | 0.90 |

Table 2. R^2 for linear regression models of traffic with population as the only one variable used as predictor.

Given that population alone proved to be a poor predictor of demand, we decided to explore how much we could improve these results by considering other important variables, such as weekly and yearly seasonality, number of visitors or FWA subscriptions. The results of our simple and multiple linear models for each geotype are summarized in Tables 3 to 8, to which these general observations apply:

* For each regression, we use the number of national and foreign visitors corresponding to the period under analysis (november/august)

** For each regression we use the ratio Weekday/Weekend traffic corresponding to the kind of traffic (voice, data) and the period (winter, summer)

*** For each regression we use the ratio November/August traffic corresponding to the kind of traffic under analysis (Voice, data)

We have shaded the cells corresponding to non-significant coefficients, whose p-value were greater than 0.005⁴.

| <1k | | | | |
|-------------------------|--------------|--------------|---------------|---------------|
| N.Observations: 3,090 | | | | |
| Single Linear model | | | | |
| | Voice-winter | Voice-summer | Data - winter | Data - summer |
| Adjusted R ² | 0.2686 | 0.1568 | 0.1495 | 0.0947 |
| F | 1,134 | 576 | 544 | 324 |
| Intercept | 39,910 | 67,911 | 39,910 | 67,911 |
| Population | 226 | 203 | 226 | 203 |
| Multiple Linear model | | | | |
| Adjusted R ² | 0.5079 | 0.6208 | 0.5749 | 0.6275 |
| F | 532 | 844 | 697 | 868 |
| Intercept | -47,416 | | -5,187,527 | 22,631,969 |
| Population | 96 | 73 | 22,650 | |
| FWA | 11,497 | 12,564 | 4,215,798 | 7,873,705 |
| Nat. visitors* | -27 | | | 19,401 |
| For. visitors* | | -13 | | |
| Lab/Wkn ** | 13,757 | | | |
| Nov/Aug*** | 23,853 | | 5,788,093 | -10,782,181 |

Table 3. Multiple and single linear regression models result for municipalities under 1,000 inhabitants

| 1k-5k | | | | |
|-------------------------|--------------|--------------|---------------|---------------|
| N.Observations: 1697 | | | | |
| Single Linear model | | | | |
| | Voice-winter | Voice-summer | Data - winter | Data - summer |
| Adjusted R ² | 0.2576 | 0.1985 | 0.1822 | 0.0696 |
| F | 589 | 421 | 379 | 128 |
| Intercept | 100,094 | 142,529 | 48,457,084 | 105,970,462 |
| Population | 161 | 121 | 38,423 | 44,793 |
| Multiple Linear model | | | | |
| Adjusted R ² | 0.4564 | 0.5650 | 0.5197 | 0.7157 |

⁴ We have checked that a multiple linear regression without these variables offered the same values of Adjusted R², so we can ignore them.

| | | | | |
|----------------|-------------|--------|----------------|-------------|
| <i>F</i> | 238.33 | 368.18 | 306.80 | 868.11 |
| Intercept | -399,578.83 | | -21,315,577.21 | |
| Population | 99 | 73 | 20,727 | 11,194 |
| FWA | 10,889 | 10,955 | 4,057,807 | 7,293,291 |
| Nat. visitors* | | 24 | | 30,119 |
| For. visitors* | | | 3,211 | |
| Lab/Wkn** | | | | |
| Nov/Aug*** | 344,786 | | 30,089,918 | -31,816,079 |

Table 4. Multiple and single linear regression models result for municipalities between 1k and 5k inhabitants

| 5k-20k | | | | |
|-------------------------|--------------|--------------|---------------|---------------|
| N.Observations: 877 | | | | |
| Single Linear model | | | | |
| | Voice-winter | Voice-summer | Data - winter | Data - summer |
| Adjusted R ² | 0.3777 | 0.2862 | 0.2324 | 0.1082 |
| <i>F</i> | 533 | 352 | 266 | 107 |
| Intercept | | | 93,792,910 | |
| Population | 144 | 122 | 32,947 | 50,519 |
| Multiple Linear model | | | | |
| Adjusted R ² | 0.4570 | 0.6938 | 0.6114 | 0.8477 |
| <i>F</i> | 124 | 332 | 231 | 814 |
| Intercept | -513,579 | | | |
| Population | 107 | 65 | 12,922 | |
| FWA | 8,294 | 11,697 | 4,509,958 | 8,356,145 |
| Nat. visitors* | | 27 | | 25,421 |
| For. visitors* | | | 14,298 | 12,575 |
| Lab/Wkn** | | | | |
| Nov/Aug*** | 449,128 | | 43,382,788 | |

Table 5. Multiple and single linear regression models result for municipalities between 5k and 20k inhabitants

| 20k-50k | | | | |
|-------------------------|--------------|--------------|---------------|---------------|
| N.Observations: 265 | | | | |
| Single Linear model | | | | |
| | Voice-winter | Voice-summer | Data - winter | Data - summer |
| Adjusted R ² | 0.2354 | 0.1278 | 0.1304 | 0.0199 |
| <i>F</i> | 82 | 40 | 41 | 6 |
| Intercept | | 1,124,602 | | |
| Population | 132 | 82 | 29,488 | |

| Multiple Linear model | | | | |
|-------------------------|-----------|--------|-----------|-----------|
| Adjusted R ² | 0.2724 | 0.6367 | 0.6301 | 0.8399 |
| F | 23 | 78 | 76 | 232 |
| Intercept | | | | |
| Population | 106 | 38 | 17,205 | |
| FWA | 9,679 | 15,485 | 4,259,067 | 9,173,264 |
| Nat. visitors* | | | | 18,499 |
| For. visitors* | | | 17,944 | 13,166 |
| Lab/Wkn ** | | | | |
| Nov/Aug*** | 1,052,359 | | | |

Table 6. Multiple and single linear regression models result for municipalities between 20k and 50k inhabitants

Municipalities with fewer than 50,000 inhabitants are clearly different from larger towns. For these geotypes, single linear regression based only on population provides poor results. However, population has a significant influence in multiple linear regression models for all scenarios considered, except for data summer demand. When considering all the variables available to create our linear models, FWA subscriptions are always relevant for predicting demand. Yearly seasonality (the ratio of November vs August traffic) is important in all cases, excepting summer voice traffic for municipalities under 20k inhabitants, and for villages between 20,000 and 50,000 inh., it is only significant for winter voice traffic. National visitors are relevant in villages with fewer than 5,000 inhabitants, as well as for the range between 5,000 and 50,000 for data summer traffic. Foreign visitors are important for summer traffic (voice and data) in municipalities over 20,000 inhabitants.

| 50k-300k | | | | |
|-------------------------|------------------|------------------|---------------|---------------|
| N.Observations: 139 | | | | |
| Single Linear model | | | | |
| | Voice- winter | Voice- summer | Data - winter | Data - summer |
| Adjusted R ² | 0.6687 | 0.6408 | 0.6609 | 0.3416 |
| F | 280 | 247 | 270 | 73 |
| Intercept | | | | 1,365,158,884 |
| Population | 173 | 103 | 32,300 | 24,832 |
| Multiple Linear model | | | | |
| Adjusted R ² | 0.7681 | 0.7644 | 0.8104 | 0.8200 |
| F | 77.17 | 75.62 | 99.31 | 105.79 |
| Intercept | | | | |
| Population | 102.33 | 49.25 | 16192.36 | 5846457 |
| FWA | | 14699.01 | 3073010.07 | 20344 |
| Nat. visitors* | 235.37 | | 29360.06 | 14508 |
| For. visitors* | | | 20043.57 | |
| Lab/Wkn** | | | | |
| Nov/Aug*** | | | | |

Table 7. Multiple and single linear regression models result for municipalities between 50k and 300k inhabitants

In municipalities between 50,000 and 300,000 inhabitants, demand is strongly influenced by population except for data summer traffic, as can be seen for the adjusted R^2 in single linear models. Nevertheless, multiple linear models explain variance much better, with adjusted R^2 between 0.76 and 0.82. The most influential variables are population, FWA, national visitors, and for data in winter, foreign visitors.

| >300k | | | | |
|-----------------------|--------------|--------------|---------------|---------------|
| N.Observations: 12 | | | | |
| Single Linear model | | | | |
| | Voice-winter | Voice-summer | Data - winter | Data - summer |
| Adjusted R^2 | 0.9033 | 0.8799 | 0.9340 | 0.9027 |
| F | 104 | 82 | 157 | 103 |
| Intercept | | | | |
| Population | 232 | 110 | 46,802 | 29,423 |

Table 8. Multiple and single linear regression models result for municipalities above 300k inhabitants. With only 12 observations, it makes no sense to try a multiple linear regression.

Big cities represent a very small set to consider. We obtain a remarkable R^2 with single models, so we decided not to create a more complex linear model.

4.3.2 Nonlinear models

Even the most complex linear models we developed fail considerably to explain traffic demand variance for the smaller municipalities, with adjusted R^2 between 0.50 and 0.63 for municipalities below 1,000 inhabitants. Additionally, it is difficult to analyze the relative importance of the different variables from these linear models, so we have worked with nonlinear models. Therefore, we decided to explore random forest models over the whole set of municipalities, as the best means to evaluate the impact of other less important variables on demand. Tables 9 summarizes the parameters and performances of our four random forest models, while Table 10 comprises the relative importance of variables for each scenario, calculated from the Gini impurity index.

These models allow us to identify FWA subscriptions and national visitors as the most determinant variable to explain traffic per municipality, followed by population.

| Random forest models - parameters | | | | |
|--------------------------------------|--------------|--------------|---------------|---------------|
| | Voice-winter | Voice-summer | Data - winter | Data - summer |
| Number of trees | 500 | 500 | 500 | 500 |
| No. of variables tried at each split | 12 | 12 | 7 | 8 |
| % Var explained | 59.17 | 61.09 | 61.72 | 69.67 |

Table 9. Parameters and performance metrics of random forest models

| Random Forest models - variables importance | | | | |
|---|------------------|------------------|------------------|------------------|
| | Voice- winter | Voice- summer | Data - winter | Data - summer |
| Population | 52.18% | 14.55% | 27.01% | 28.91% |
| National Visitors - August | 6.85% | 29.00% | 12.73% | 11.89% |
| National Visitors- November | 11.81% | 38.73% | 23.10% | 28.19% |
| Foreign Visitors - August | 3.71% | 1.92% | 2.18% | 3.00% |
| Foreign Visitors- November | 6.89% | 3.55% | 1.97% | 2.76% |
| FWA | 18.52% | 12.22% | 32.92% | 24.89% |
| Lab/Wkn Data -Aug | 0.01% | 0.01% | 0.01% | 0.05% |
| Lab-Wkn Data-Nov | 0.01% | 0.02% | 0.03% | 0.03% |
| Lab/Wkn Voice-Nov | 0.01% | 0.00% | 0.01% | 0.05% |
| Lab/Wkn Voice-Aug | 0.00% | 0.01% | 0.01% | 0.03% |
| Voice Traffic Nov/Aug | 0.01% | 0.01% | 0.02% | 0.05% |
| Data Traffic Nov/Aug | 0.02% | 0.01% | 0.01% | 0.14% |

Table 10. Relative importance of variables as demand predictors in random forest models

| Random Forest models – grouped variables importance | | | | |
|---|------------------|------------------|------------------|------------------|
| | Voice- winter | Voice- summer | Data - winter | Data - summer |
| Population | 52.18% | 14.55% | 27.01% | 28.91% |
| Visitors | 29.25% | 73.19% | 39.98% | 45.85% |
| FWA | 18.52% | 12.22% | 32.92% | 24.89% |
| Traffic | | | | |
| Seasonality | 0.05% | 0.05% | 0.09% | 0.35% |

Table 11. Relative importance of groups of variables as demand predictors in random forest models

5. Conclusions

Our study reveals two often-overlooked characteristics of mobile networks:

- Mobile services are critically demanded when users are away from home. Visitors are (much) more important than population as predictors of communication demand for voice and data in summer, as well as for data in winter.
- Mobile networks have played a pivotal role in delivering communication services to sparsely populated areas without requiring unaffordable infrastructure investments.

The most influential variables affecting traffic demand are the number of (mobile) visitors, population, and the presence of Fixed Wireless Access (FWA). Their impact varies depending on the type of service (voice or data) and the season (winter or summer). Population alone proves to be a poor proxy for communication demand—particularly in municipalities with fewer than 5,000 inhabitants—raising concerns about the validity of traditional bottom-up models in techno-economic assessments.

Long-term mobility, such as weekend and holiday travel, significantly affects traffic demand, especially in small municipalities. Leisure-related travel places considerable stress on mobile infrastructure for both voice and data services. This effect is particularly pronounced when comparing cities with over 50,000 inhabitants to villages with fewer than 5,000.

Our analysis quantifies the extent to which mobile networks contribute to bridging the digital divide in rural areas. In summer, per capita traffic in municipalities with fewer than 1,000 inhabitants is four times higher for voice and ten times higher for data than in cities with over 300,000 inhabitants. In general, per capita demand for both voice and data services is inversely proportional to population size, with the disparity most evident in municipalities under 5,000 inhabitants. This indicates a clear over-reliance on mobile services in less populated areas.

Small municipalities also exhibit distinct communication patterns. As recipients of mobile service usage from visiting populations, they show marked seasonality across all time frames. The weekday/weekend traffic ratio and annual usage profiles suggest that mobility and temporal variability combine to create a "perfect storm" of mobile service demand in these areas.

Moreover, the differing behaviors of voice and data traffic across time frames underscore the need to analyze each service type separately when forecasting future demand. Consequently, the spatiotemporal patterns of voice and data services result in distinct geographical footprints.

While mobile infrastructure is less costly than fixed networks, it also offers more limited capacity. Mobile networks cannot match the performance of fixed networks unless demand remains low. Therefore, any assessment of whether mobile services can meet demand in a given area must begin with a reliable forecast of future demand—typically based on assumed per capita consumption. Our findings demonstrate that models relying solely on population data poorly reflect actual demand, particularly in smaller municipalities where accurate assessments are most critical.

Above all, our study highlights the heterogeneity of small municipalities. Neither single nor multiple linear regression models explain more than 62% of the variance in communication demand (in the best case, summer data traffic), and they perform even worse for winter voice traffic (below 50%). The most significant contribution of our work is showing that additional variables—such as FWA presence, number of visitors, and demand seasonality—must be included alongside population to produce reliable demand forecasts.

Non-linear models offer only modest improvements, explaining between 59% and 70% of the variance. However, they underscore the critical role of visitors and Fixed Wireless Access—often overlooked—in predicting communication demand.

Our study has several limitations stemming from the source data. We analyzed 6,081 out of 8,122 Spanish municipalities. Most of the missing municipalities fall into the smallest category (fewer than 1,000 inhabitants), where our sample still covers 63% of municipalities and 72% of the population—figures we consider representative. Given Spain's mobile coverage exceeds 95%, the population not explicitly included in our dataset is likely served by neighboring municipalities. This "hidden population" may slightly affect our per capita KPI calculations. We estimate a margin of error of approximately 1.7%, as our dataset omits around 828,000 people out of a total population of 47.48 million.

Another limitation of our study is that the traffic data originates from a single operator, which holds approximately 30% of the market share. However, due to the operator's diverse customer base—including both high- and low-end users—its comprehensive service portfolio (covering residential, business, and government clients), and its extensive nationwide coverage, we consider the dataset to be a reliable proxy for the overall market.

Despite these limitations, our study sheds light on previously unexplored aspects of communication demand and geography. These include the crucial role of mobile infrastructure in reducing the rural-urban digital divide, the importance of FWA in demand forecasting, and the influence of mobility on usage patterns. Our findings also open new avenues for research, such as the relationship between mobile demand and tourism, or the historical evolution of communication indicators. While our data pertains to 2023, it would be valuable to investigate how communication services and their geographical distribution looked prior to the deployment of 4G.

Bibliography

Adityo, M. K., Nashiruddin, M. I., & Nugraha, M. A. (2021, November). 5G fixed wireless access network for urban residential market: A case of Indonesia. In 2021 IEEE International Conference on Internet of Things and Intelligence Systems (IoTIS) (pp. 123-128). IEEE.

Alessandretti, L., Aslak, U., & Lehmann, S. (2020). The scales of human mobility. *Nature*, 587(7834), 402-407.

Barbosa, H., Hazarie, S., Dickinson, B., Bassolas, A., Frank, A., Kautz, H., ... & Ghoshal, G. (2021). Uncovering the socioeconomic facets of human mobility. *Scientific reports*, 11(1), 8616.

Bohlin, E. (2007). Business models and financial impacts of future mobile broadband networks. *Telematics and Informatics*, 24(3), 217-237.

Breiman, L. (2001). Random forests. *Machine Learning*, 45(1), 5–32. <https://doi.org/10.1023/A:1010933404324>

De Souza, M. A., Kuribayashi, H. P., Saraiva, P. A., Farias, F. D. S., Vijaykumar, N. L., Francês, C. R. L., & Costa, J. C. W. A. (2021). A techno-economic framework for installing broadband networks in rural and remote areas. *IEEE Access*, 9, 58421-58447.

Denzer, M., Schank, T., & Upward, R. (2021). Does the internet increase the job finding rate? Evidence from a period of expansion in internet use. *Information Economics and Policy*, 55, 100900.

"European Commission. (2010). A Digital Agenda for Europe. Brussels: European Commission. <https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:52010DC0245>"

"European Commission. (2016). Connectivity for a European Gigabit Society. <https://digital-strategy.ec.europa.eu/en/library/connectivity-european-gigabit-society-brochure>"

"European Commission. (2021). Europe's Digital Decade: digital targets for 2030. https://commission.europa.eu/strategy-and-policy/priorities-2019-2024/europe-fit-digital-age/europes-digital-decade-digital-targets-2030_en"

Feijóo, C., Ramos, S., Armuña, C., Arenal, A., & Gómez-Barroso, J. L. (2018). A study on the deployment of high-speed broadband networks in NUTS3 regions within the framework of digital agenda for Europe. *Telecommunications Policy*, 42(9), 682-699.

Ferrandis, J., Ramos, S., & Feijóo, C. (2021). An assessment of estimation models and investment gaps for the deployment of high-speed broadband networks in NUTS3 regions to meet the objectives of the European Gigabit Society. *Telecommunications Policy*, 45(7), 102170.

Frías, Z., González-Valderrama, C., & Martínez, J. P. (2015). Keys And Challenges To Close The Rural Broadband Gap. The Role Of LTE Networks In Spain.

Gonzalez, M. C., Hidalgo, C. A., & Barabasi, A. L. (2008). Understanding individual human mobility patterns. *nature*, 453(7196), 779-782.

Grömping, U. (2009). Variable importance assessment in regression: linear regression versus random forest. *The American Statistician*, 63(4), 308-319.

Hassan, S. M., Marzuki, A. M., Amiruddin, M. F., Bujang, S., Samingan, A. K., Salleh, M. K., ... & Abidin, K. Z. (2021, October). Bridging the digital divide in Malaysia using fixed wireless access. In 2021 26th IEEE Asia-Pacific Conference on Communications (APCC) (pp. 74-78). IEEE.

Ioannou, N., Katsianis, D., & Varoutas, D. (2020). Comparative techno-economic evaluation of LTE fixed wireless access, FTTdp G. fast and FTTC VDSL network deployment for providing 30 Mbps broadband services in rural areas. *Telecommunications Policy*, 44(3), 101875.

Izydorek, S., Gravey, A., & Tadayoni, R. (2019, June). How, when and where can Fixed Wireless Access compete with FTTH?. In 2019 European Conference on Networks and Communications (EuCNC) (pp. 63-68). IEEE.

James, G., Witten, D., Hastie, T., & Tibshirani, R. (2017). *An Introduction to Statistical Learning: With Applications in R* (2nd ed.). Springer.

Ji, Y., & Liu, X. (2023). Importance Measurement of the Influencing Factors of Long-Term Nursing Status in Long-Term Nursing Insurance Based on Multiple Linear Regression, Random Forest and Xgboost Models. *Fractals*, 31(06), 2240177.

Koutroumpis, P. (2019). The economic impact of broadband: Evidence from OECD countries. *Technological Forecasting and Social Change*, 148, 119719.

Krizanovic Cik, V., Zagar, D., & Grgic, K. (2018). A framework for optimal techno-economic assessment of broadband access solutions and digital inclusion of rural population in global information society. *Universal Access in the Information Society*, 17(3), 517-540.

Laitsou, E., Ioannou, N., & Katsianis, D. (2022). 5G Fixed Wireless Access for rural broadband.

Lappalainen, A., & Rosenberg, C. (2022). Can 5G fixed broadband bridge the rural digital divide?. *IEEE Communications Standards Magazine*, 6(2), 79-84.

Lappalainen, A., Zhang, Y., & Rosenberg, C. (2022). Planning 5G networks for rural fixed wireless access. *IEEE Transactions on Network and Service Management*, 20(1), 441-455.

Lee, S., Marcu, M., & Lee, S. (2011). An empirical analysis of fixed and mobile broadband diffusion. *Information economics and policy*, 23(3-4), 227-233.

Leo, Y., Busson, A., Sarraute, C., & Fleury, E. (2016). Call detail records to characterize usages and mobility events of phone users. *Computer communications*, 95, 43-53.

Lim, K. W., Secci, S., Tabourier, L., & Tebbani, B. (2016). Characterizing and predicting mobile application usage. *Computer Communications*, 95, 82-94.

Mocnej, J., Pekar, A., Seah, W. K., & Zolotova, I. (2018). Network traffic characteristics of the IoT application use cases (pp. 1-20). Wellington, New Zealand: School of Engineering and Computer Science, Victoria University of Wellington.

Naboulsi, D., Stanica, R., & Fiore, M. (2014, April). Classifying call profiles in large-scale mobile traffic datasets. In *IEEE INFOCOM 2014-IEEE conference on computer communications* (pp. 1806-1814). IEEE.

Nevado-Peña, D., López-Ruiz, V. R., & Alfaro-Navarro, J. L. (2019). Improving quality of life perception with ICT use and technological capacity in Europe. *Technological Forecasting and Social Change*, 148. <https://doi.org/10.1016/j.techfore.2019.119734>

Oughton, E. J., & Frias, Z. (2018). The cost, coverage and rollout implications of 5G infrastructure in Britain. *Telecommunications Policy*, 42(8), 636-652.

Oughton, E. J., Amaglobeli, D., & Moszoro, M. (2023). What would it cost to connect the unconnected? Estimating global universal broadband infrastructure investment. *Telecommunications Policy*, 47(10), 102670.

Ovando, C., Pérez, J., & Moral, A. (2015). LTE techno-economic assessment: The case of rural areas in Spain. *Telecommunications Policy*, 39(3-4), 269-283.

Rendon, J., Kuhlmann, F., & Alanis, J. P. (2007). A business case for the deployment of a 4G wireless heterogeneous network in Spain. *Proceedings of the 18th European Regional International Telecommunications Society*.

Sarfaraz, A., & Hämmäinen, H. (2019). Radio Access Network Traffic Forecast Analysis for Mobile Network Operators in Anticipation of 5G.

Schneir, J. R., & Xiong, Y. (2016). A cost study of fixed broadband access networks for rural areas. *Telecommunications Policy*, 40(8), 755-773.

Smail, G., & Weijia, J. (2017, March). Techno-economic analysis and prediction for the deployment of 5G mobile network. In *2017 20th Conference on innovations in clouds, internet and networks (ICIN)* (pp. 9-16). IEEE.

Sun, F., Wang, P., Zhao, J., Xu, N., Zeng, J., Tao, J., ... & Guan, X. (2021). Mobile data traffic prediction by exploiting time-evolving user mobility patterns. *IEEE Transactions on mobile computing*, 21(12), 4456-4470.

Topyan, K., & Ulema, M. (2020, May). Architectural and financial considerations for deploying 5G based fixed wireless access. In *2020 IEEE International Black Sea Conference on Communications and Networking (BlackSeaCom)* (pp. 1-6). IEEE.

Van der Wee, M., Verbrugge, S., Sadowski, B., Driesse, M., & Pickavet, M. (2015). Identifying and quantifying the indirect benefits of broadband networks for e-government and e-business: A bottom-up approach. *Telecommunications Policy*, 39(3-4), 176-191.