Integrating QoS Indicators and Consumer Complaints for Mobile Monitoring

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***Abstract*— This work proposes a framework integrating technical network indicators from Brazil's Telecommunications Service Quality Regulation with consumer complaints filed at the national regulatory agency for Mobile Service (2022–2025). Complaint rates per thousand subscribers are spatially smoothed using Empirical Bayes estimation and associated with eight quality indicators through Spearman correlation, Random Forest, and LightGBM analyses. Results reveal weak associations ($|\rho| \leq 0.17$), with jitter, latency, and availability exhibiting the highest importance. The weak coupling suggests that technical indicators and complaints capture distinct yet complementary dimensions of service quality, supporting integrated regulatory monitoring.**

***Keywords*— Quality Regulation, QoS, Mobile Service, RQUAL, consumer complaints.**

I. Introduction

The mobile service currently represents the main communication infrastructure in Brazil, with more than 230 million subscribers [1]. The Brazilian National Telecommunications Agency (Anatel) established its quality monitoring model through the Telecommunications Services Quality Regulation (RQUAL) [2]. The model is based on three complementary dimensions: Quality of Service (QoS) with Service Quality Index (IQS), Quality of Experience (QoE) with Perceived Quality Index (IQP), and the consumer complaints index (IR), based on reports submitted through Anatel's official channels.

Aligning with international best practices and following International Telecommunication Union (ITU-T) Recommendations E.803 and E.804 [3], [4], Anatel categorizes QoS indicators into: (1) *relationship-related aspects*, associated with commercial and customer-service processes, including service offering, contracting, installation, customer support, billing, repair requests, and service cancellation; and (2) *network-related aspects*, associated with the technical performance of telecommunications services, encompassing dimensions such as service availability, accessibility, connection stability, latency, packet loss, and continuity of service delivery. For mobile services, RQUAL establishes eight QoS indicators related to network aspects. While the complaints index reflects consumer reactions, the QoS indicators are reported by operators and measurement platforms. In principle, both dimensions should converge: municipalities with poorer technical infrastructure would be expected to concentrate higher complaint rates. However, socioeconomic and behavioral factors such as education level, income, service usage intensity, and awareness of complaint channels may also affect complaint propensity. Because such variables are not included in the present dataset, their role is treated here as a hypothesis rather than an empirically established explanation. The relationship between technical performance and formal complaints remains insufficiently explored, particularly at the municipal level and with operator-level disaggregation.

Bridging these two dimensions presents three operational challenges. First, the small-number problem makes crude complaint rates highly unstable in small municipalities [5], where isolated occurrences generate statistically meaningless extreme values. Second, valid comparisons with technical indicators require consistent filtering by operator, time window, and complaint category. Third, missing values in technical indicators, especially in municipalities with limited sampling density, require careful preprocessing.

This work addresses these challenges through an integrated analytical framework for mobile service quality assessment that combines complaint-based and QoS indicators at the municipal level. The contribution is not a new machine-learning algorithm; rather, it is the integration of public regulatory datasets with spatial stabilization and complementary statistical analyses in a single monitoring pipeline. Rather than treating each data source in isolation, the framework combines spatial smoothing, rank-based correlation, and machine learning-based feature analysis in a procedure that can be reproduced for other regulatory periods or operator subsets, provided the implementation settings reported below are preserved.The analysis progresses from a national-level aggregated assessment to operator-level views, enabling the identification of differences in the relationship between technical performance and user complaints across operators. The main contributions are:

- Spatially comparable complaint rates: a municipality-level metric normalized by the number of subscribers and stabilized through spatial Empirical Bayes estimation, enabling methodologically consistent comparisons across municipalities and operators of different sizes.
- Complementarity between data sources: evidence at both the municipal and operator levels that RQUAL technical indicators and user complaints capture partially independent dimensions of mobile quality.
- Exploratory indicator relevance assessment: complementary use of Random Forest (RF) and LightGBM feature

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importance to rank which QoS indicators exhibit greater association with complaint distribution, highlighting the predominance of latency (IND5), jitter (IND6) and availability (IND8) and providing a basis for future predictive modeling.

II. Methods

A. Datasets

The analysis focused on mobile services and was based on the RQUAL dataset [2], comprising the QoS indicators IND1–IND8 presented in Table I, as well as Anatel's consumer complaints data, which includes records by municipality, provider, year, month, service type, and subject [1]. To capture network-related reports, a filtering procedure based on complaint categorization was applied, selecting only records classified under the "Quality, operation, and repair" category, thereby isolating technical issues while excluding commercial complaints.

TABLE I
QoS indicators with regulatory bounds.

Indicator	Description	Lower Ref.	Upper Ref.
IND1	Call connection	95%	99%
IND2	Call dropping rate	3%	1%
IND3	Mobile data connection	95%	99%
IND4	Speed compliance	65%	95%
IND5	Bidirectional latency	65%	95%
IND6	Data connection response time variation (jitter)	65%	95%
IND7	Data connection packet loss	65%	95%
IND8	Availability	98%	99.99%

The analysis covers the period from 2022-S2 to 2025-S1, corresponding to the interval with simultaneous availability of RQUAL and complaint data for the three major operators. More recent semesters (2025-S2 and 2026-S1) were excluded to avoid undercounting caused by records still under processing. Operator Oi and smaller providers were also excluded due to discontinued operations and limited geographic coverage, respectively.

Data were aggregated semiannually according to Anatel's IQS methodology [2], in which IND1–IND3, and IND8 are computed as the average across the months of each semester, whereas IND4–IND7 correspond to the value observed in the last available month of the semester [2]. Data were disaggregated by municipality (IBGE code) and service provider. Each indicator was additionally normalized to a 0–10 scale anchored on its regulatory reference bounds (Table I), with higher values denoting better quality (inverted for IND2, where lower is better); this normalized scale feeds the correlation and machine-learning analyzes.

In addition to the RQUAL and complaints datasets, two other public sources were used in this study:

1) Mobile subscribers dataset [6]: monthly subscriber counts by municipality, used to normalize complaint volumes.
2) Brazilian digital municipal grid [7]: IBGE municipal boundaries for the 5,570 Brazilian municipalities, used to construct the Queen contiguity matrix.

B. Raw and smoothed complaint rates

The raw complaint rate for municipality i, semester t, and operator k is defined as

$$\tau_{i,k,t} = \frac{r_{i,k,t}}{a_{i,k,t}} \times 1000, \tag{1}$$

where $r_{i,k,t}$ denotes the number of complaints and $a_{i,k,t}$ represents the average monthly subscriber counts during the semester. Municipalities with $a_{i,k,t} < 1000$ subscribers were excluded due to high statistical variability.

The spatial *Empirical Bayes* smoothed rate is defined as a weighted combination of the local complaint rate and the mean rate of neighboring municipalities defined by the Queen contiguity matrix W:

$$\widehat{\tau}^{EB}_{i,k,t} = \omega_{i,k,t}\,\tau_{i,k,t} + (1 - \omega_{i,k,t})\,\overline{\tau}_{N(i),k,t}, \tag{2}$$

where $\overline{\tau}_{N(i),k,t}$ denotes the average rate among the neighbors of municipality i, and $\omega_{i,k,t} \in [0, 1]$ is a weight determined by the local variance relative to the global variance. Municipalities with few subscribers or complaints receive less weight on the raw rate and greater weight on the neighborhood mean, reducing random fluctuations [5], [8], [9].

C. Correlation and spatial autocorrelation analysis

The congruence between each QoS indicator and $\widehat{\tau}^{\,EB}$ was evaluated using Spearman correlation, computed separately for each operator across all (municipality, semester) pairs with complete data. Spearman correlation was selected because of its robustness to non-linear relationships and the presence of outliers, both of which are common characteristics of municipal-level network quality series. The expected sign of each correlation follows the regulatory semantics described in Table I. The analysis was conducted both contemporaneously and with temporal lags of three and six months to evaluate whether complaints respond to the technical performance observed in previous periods.

Additionally, RF and LightGBM models were used as exploratory multivariate tools to assess the relative importance of each QoS indicator in explaining the variation in the smoothed complaint rate. Their purpose in this study is complementary to the Spearman analysis: tree-based models can represent non-linearities and interactions among indicators, while feature-importance scores provide a multivariate ranking that can be compared with the bivariate correlation results. The models are not used here to establish causal effects.

Models were fit on the N=21,047 records (across 3,347 municipalities) with at least one complaint, using the eight normalized indicators and a one-hot encoded operator as features and the normalized complaint rate as the response. The RF regressor (scikit-learn 1.7 [10]) used 200 trees, maximum depth 15, and minimum leaf size 20; LightGBM (via its scikit-learn API [10]) used 200 estimators, learning rate 0.1, 31 leaves, and minimum child samples 20; both used a fixed random seed (42). To prevent information leakage between neighboring municipalities, validation followed 3-fold *GroupKFold* cross-validation [10] grouped by municipality, so that all records of a given municipality remained in the

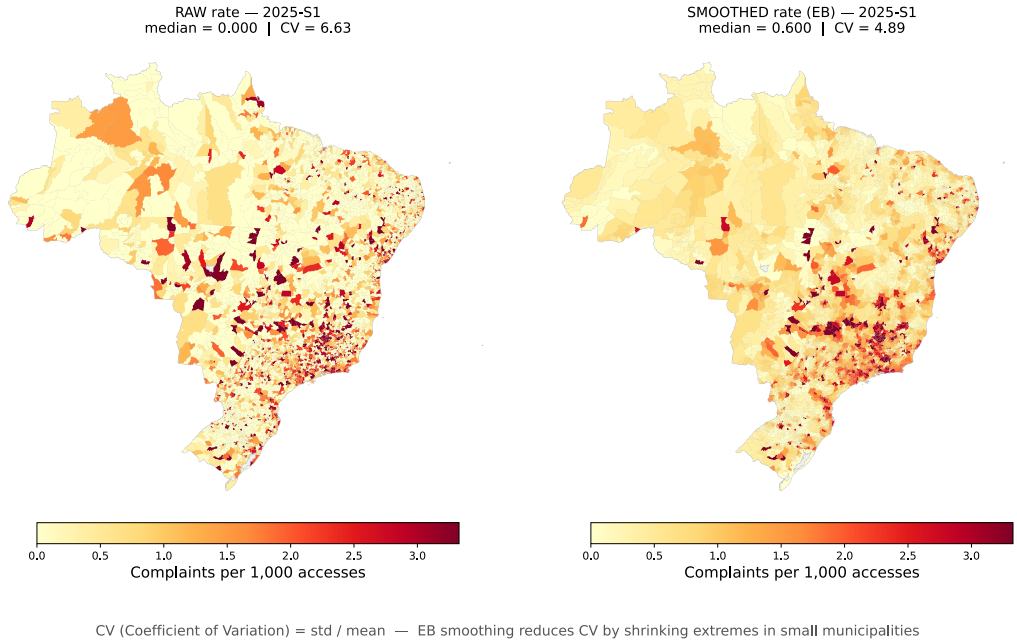


Fig. 1. Raw complaint rate (left) versus spatial Empirical Bayes smoothed rate (right), aggregated across all operators, 2025-S1. Areas shown in gray have no available data, after the data cleaning step.

same fold. Predictive performance was evaluated using R^2 and MAE; these metrics are reported only to confirm whether the fitted models contain explanatory signal beyond the feature-importance ranking, and the substantive interpretation remains exploratory rather than predictive.

D. Considerations regarding complaint rates

The raw number of complaints alone provides limited information for comparative purposes. Large municipalities naturally accumulate more complaints without necessarily exhibiting worse relative service quality, and operators with larger subscriber bases tend to concentrate more complaints simply because of greater exposure. Only normalization by subscriber counts, followed by spatial smoothing, enables analytically valid territorial and inter-operator comparisons that are not biased by operator size.

Moreover, complaint rates cannot be interpreted as a direct measure of network performance because they are reactive behavioral outcomes. Municipalities with similar technical indicators may exhibit distinct complaint volumes for reasons not observed in the present data. Socioeconomic characteristics, network usage intensity, digital literacy, and awareness of formal complaint channels are plausible mediators discussed in prior work, but this study does not test their effects directly.

III. Results

A. Aggregated Brazil-wide view and smoothing effects

Figure 1 compares the raw and smoothed complaint rates for Brazil aggregated in 2025-S1. In the raw rate map, small municipalities exhibit extreme values due to sampling fluctuations: one or two complaints among only a few thousand subscribers produce a visually noisy map dominated by local *outliers*, in which isolated cases with limited epidemiological significance drive the color gradient.

The smoothed rate, by borrowing information from neighboring municipalities through the Queen contiguity matrix and by enforcing a minimum subscriber-count threshold, compresses the tails of the distribution, reducing the coefficient of variation (CV) from 6.63 to 4.89, and reveals the underlying spatial structure. While many isolated spikes in the North and Northeast regions are smoothed out into lower rates, high-intensity clusters prominently emerge and stabilize across the Center-West, South, and Southeast regions. This stabilization filters out local noise and makes comparisons between municipalities of different sizes methodologically more robust and statistically defensible.

B. Operator-level view

When the normalized rate is disaggregated by operator, differences emerge in both intensity and spatial distribution. Figure 2 presents $\widehat{\tau}^{EB}$ by municipality for each operator during the first semester of 2025. Vivo exhibits the highest complaint intensity, particularly across the Southeast. TIM shows a more geographically restricted pattern, with hotspots concentrated along the southeastern and southern coast, while Claro presents a more dispersed distribution, including isolated hotspots in the North and Center-West. The number of municipalities with sufficient data also varies across operators, reflecting differences in geographic coverage and subscriber density. These results show that national-level findings may

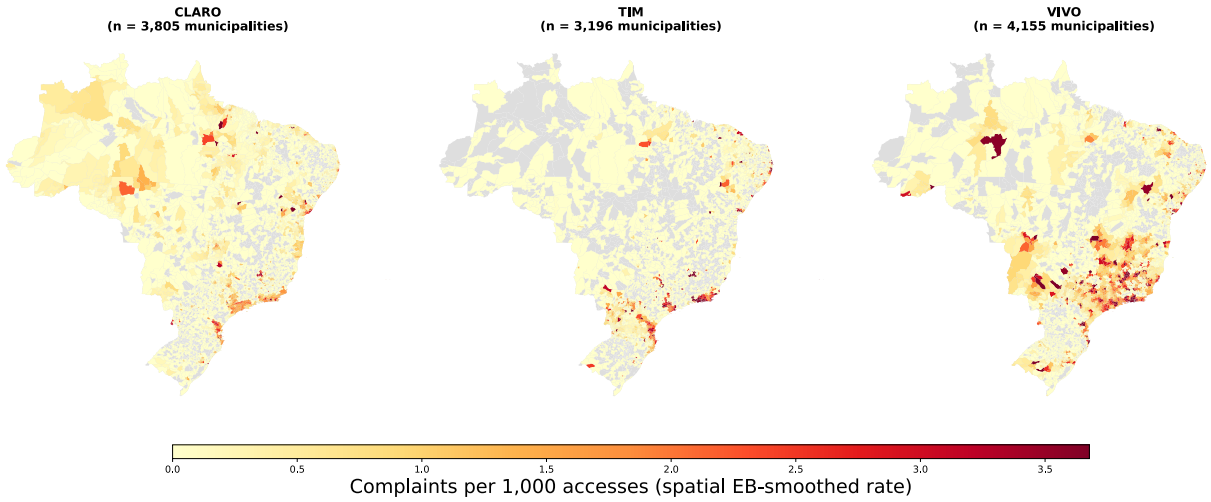


Fig. 2. Spatially smoothed complaint rate by municipality during the first semester of 2025, separated by operator (data obtained from [1]). Areas shown in gray have no available data, after the data cleaning step.

conceal regional and operator-specific patterns relevant to regulatory monitoring.

C. Congruence between indicators and complaints

As presented in Table II, indicators IND4–IND8 show weak but directionally consistent correlations with the smoothed complaint rate ($|\rho| \leq 0.17$), with data-experience indicators tending toward the expected sign. In contrast, IND1–IND3 exhibit correlations close to zero with no consistent directional pattern across operators, a behavior explained by their limited variability since these indicators operate near the upper regulatory ceiling (see Table I), the narrow margin between reference limits causes operators to cluster near the performance ceiling, compressing the normalized scale and eliminating the dispersion necessary for meaningful correlation. Thus, the near-zero correlations for IND1–IND3 should not be interpreted as evidence that these indicators are unrelated to service quality; within this dataset, their limited observed variability restricts the ability of correlation analysis to distinguish an association. Consequently, the operator with the highest complaint rate in a region is not necessarily the one with the worst QoS indicators, reinforcing that these two dimensions carry uncorrelated information.

As a robustness check, the analysis was repeated using temporal lags of three and six months to examine whether the observed associations materially change when technical performance precedes complaints. The lagged correlations remained close to contemporaneous values for most indicator–operator combinations. Given the semiannual aggregation and the weak magnitude of the correlations, this result should be interpreted conservatively: the available data do not show a pronounced lag pattern, but they are not sufficient to establish the timing or direction of any causal response.

Weak correlations are compatible with the fact that formal complaints are not purely technical measurements. Prior studies discuss factors such as digital literacy, income, satisfaction, and awareness of complaint channels as possible determinants of complaint behavior [11], [12], [13]. However, because these variables are not included in the present analysis, they cannot be used here as empirical explanations for the observed coefficients; they are hypotheses to be tested in future work.

TABLE II
SPEARMAN CORRELATION BETWEEN QOS INDICATORS (NORMALIZED) AND COMPLAINT RATE BY OPERATOR.

Indicator	CLARO		TIM		VIVO	
	Raw	Within	Raw	Within	Raw	Within
IND1	0.016	-0.008	0.009	-0.010	-0.004	-0.017
IND2	0.024	0.012	0.001	0.005	-0.006	0.005
IND3	-0.002	-0.025	-0.004	-0.029	-0.013	-0.016
IND4	0.021	-0.032	**0.128**	-0.080	0.000	-0.096
IND5	**0.134**	-0.045	**0.173**	-0.036	0.001	-0.028
IND6	**0.100**	0.073	0.075	0.012	-0.005	-0.024
IND7	-0.081	**-0.157**	0.061	**-0.111**	0.025	0.066
IND8	0.070	0.043	0.014	-0.097	-0.014	-0.039

Within: demeaning by municipality, capturing temporal variation within each city for each company. A positive correlation (*raw* column) may reflect composition across cities; the *within* correlation reduces time-invariant between-municipality heterogeneity but should not be interpreted causally. Bold values: $|\rho| \geq 0.10$.

Within the scope of the analyzed data, these weak correlations provide a regulatory indication that QoS indicators and complaint rates contain substantially non-redundant information about service quality. Relying solely on QoS indicators risks missing quality problems felt by users that do not trigger technical thresholds, while relying exclusively on complaints risks misattributing socioeconomic variation to network degradation.

Complementary RF and LightGBM models were employed to evaluate which technical indicators receive greater multivariate importance when the smoothed complaint rate is used as the response. This analysis is intended as an exploratory

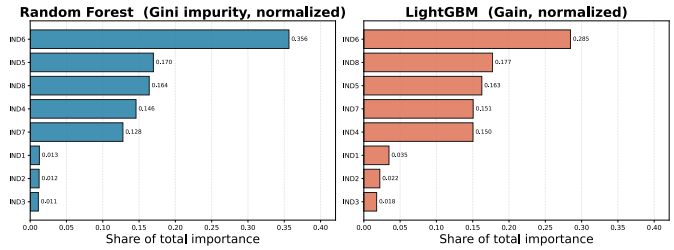


Fig. 3. Relative importance of QoS indicators estimated by RF and LightGBM models for predicting the smoothed complaint rate $\widehat{\tau}^{EB}$.

ranking, not as evidence of causal impact. Under the grouped cross-validation protocol, both models exhibited limited predictive power (RF: $R^2 \approx 0.06$, MAE ≈ 2.22; LightGBM: $R^2 \approx 0.05$, MAE ≈ 2.23), consistent with the weak bivariate correlations and confirming that the fitted models capture only a modest share of the variation in complaint rates; their value here lies in the comparative ranking of indicators rather than in prediction.

As shown in Figure 3, both models converge on the same ranking: IND6, IND5, and IND8 dominate model importance, collectively accounting for more than 60% of total importance in both algorithms (RF: 0.36, 0.17, and 0.16; LightGBM: 0.29, 0.18, and 0.16), while IND1–IND3 exhibit minimal contribution. The agreement between two architecturally distinct algorithms shows that the same ranking pattern appears under both fitted models. This cross-model agreement is a robustness check on the ranking itself, but it does not substitute for predictive validation and should not be interpreted as proof that the indicators have causal effects on complaints.

IV. Conclusions

This work presents a reproducible framework for mobile service quality monitoring, integrating, at the municipal and operator levels, technical network indicators from Brazilian regulatory quality indicators and consumer complaints registered at Anatel, using spatial Empirical Bayes smoothing to stabilize rates in small municipalities.

Three contributions were demonstrated. First, the spatially smoothed complaint rate, normalized by subscriber counts and stabilized via Empirical Bayes over a Queen contiguity matrix, enables methodologically consistent comparisons across municipalities and operators of different market shares, as illustrated by the reduction in distributional noise shown in Figure 1. Second, the empirical analysis showed that QoS indicators and complaints capture partially distinct dimensions of service quality, with Spearman correlations remaining weak ($|\rho| \leq 0.17$) and heterogeneous across operators. Third, exploratory machine-learning feature-importance analysis ranked jitter (IND6), latency (IND5), and service availability (IND8) highest in both fitted models, while call connection (IND1), call dropping (IND2), and data connection (IND3) received lower importance.

Taken together, these findings support the use of both data sources for a more complete regulatory monitoring view, rather than establishing that either source is individually insufficient in every setting. QoS indicators may fail to capture dimensions of user-perceived quality reflected in complaints, while complaint data may also incorporate behavioral and socioeconomic effects beyond network performance. Importantly, these results are specific to the eight RQUAL indicators evaluated and should not be generalized to other QoS frameworks with different indicator definitions or regulatory priorities.

Future work should incorporate socioeconomic datasets from IBGE, including population size, distance from major urban centers, and per-capita income, to test explicitly whether such variables mediate complaint propensity. Formal stationarity testing and causal analyzes of regulatory interventions on smoothed complaint rates also remain directions for future research.

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