Spatial-temporal analysis of road traffic accident injuries in Italy during 2017-2022

HDA: Group 7

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Abstract

This retrospective ecological study conducted a provincial-level spatial-temporal analysis of road traffic accident (RTA) injuries across Italy during 2017–2022. Bayesian hierarchical Poisson log-linear models analysed monthly RTA injury counts, provincial population data, mean monthly temperature, and social vulnerability indices to estimate relative risks and evaluate the effect of temperature and social vulnerability. Five models were systematically developed, from a spatial-only model to spatial-temporal models with Type I and II interactions. Results revealed substantial spatial heterogeneity in injury risk, with consistently higher-than-average risks in Northern provinces, possibly due to higher traffic volumes. Notably, Southern provinces like Cosenza were identified as high-risk, with posterior probabilities exceeding 0.8 across models, despite lower raw injury rates. This suggests different mechanisms driving RTA risk across Italy: more RTAs in the North versus potentially greater injury risk from RTAs in the South. Neither mean monthly temperature nor social vulnerability demonstrated substantial associations with injury risk. The study highlights the value of granular provincial-level analysis over regional aggregation, challenging the narrative that RTA injury risk is predominantly a Northern phenomenon. These findings provide actionable insights for targeted interventions, supporting efficient resource allocation and contributing to achieving World Health Organization targets to halve RTA injuries by 2030.

Introduction

Road traffic accident (RTA) injuries represent a major global public health challenge, ranking as the twelfth leading cause of all-age mortality and the leading cause among young people aged 5–29 years (WHO 2023). For individuals aged 10–49 years, RTAs are the leading contributor to disability-adjusted life-years, imposing substantial economic costs of 1–3% of countries' GDP annually (Vos et al. 2020; WHO 2023). In Italy specifically, despite a 6.9% decrease from pre-pandemic levels, RTA injuries rose by 0.5% from 2022 to reach 224,634 injuries in 2023, with an estimated economic burden of approximately 22.3 billion euros (ISTAT 2024). This concerning trend indicates Italy is not on track to meet World Health Organisation (WHO) and European Union (EU) targets of halving RTA injuries by 2030, relative to respective baselines of 2013 (WHO) and 2019 (EU), highlighting the urgent need for targeted interventions.

Previous research on RTAs in Italy has provided valuable but limited insights. Studies have consistently identified Northern Italy as a higher-risk region and highlighted driver distraction, speeding, and alcohol use as key contributing factors (ISTAT 2024) (La Torre et al. 2007) (Gariazzo et al. 2021). However, these studies analysed what is now outdated data, used less granular regional analyses, and all employed methodologies that are not able to account for spatial dependencies essential for understanding neighbourhood effects. For example, Torre et al. analysed regional mortality using multivariate regression of 1999-2002 data, while Gariazzo et al. examined temperature impacts using lag non-linear models on 2013-2015 data without accounting for spatial structure. Camilloni et al.'s study linking lower socioeconomic status to higher rates of RTA-related hospitalisation and death using Poisson regression was limited to Rome in 2005, restricting its generalisability (Camilloni et al. 2013).

Despite progress in understanding RTA risk factors in Italy, important research gaps remain which hinder effective interventions. Previous studies predominantly analysed RTAs at regional scales, potentially obscuring local patterns, and while extreme temperatures and socioeconomic status have been independently identified as risk factors, no study has examined their combined impact at a provincial level. This gap is particularly urgent given increasing extreme weather events due to climate change, which may exacerbate existing socioeconomic inequalities (Frigerio et al. 2018). By conducting a comprehensive spatial-temporal analysis using recent data (2017–2022), this study addresses these gaps and is the first to use methods that account for spatial dependencies.

This study addresses two key research questions:

1. What are the spatial and temporal patterns of RTA injuries across Italy from 2017 – 2022? Can provincial-level analysis identify provinces with consistently higher-than-average injury rates?
2. How do variations in monthly mean temperature and social vulnerability influence the risk of RTA injury, controlling for spatial and temporal variation?

By identifying provinces most at risk and as the first study to analyse the combined effect of temperature and socioeconomic status, this study aims to provide actionable insights that inform targeted public health interventions in Italy — essential steps towards meeting the WHO and EU targets of halving RTA injuries by 2030.

Methods

In this retrospective ecological study, we employed Bayesian hierarchical models to analyse the spatial-temporal patterns of road traffic accident (RTA) injuries across Italy's 107 provinces from 2017-2022 and assess how environmental and socioeconomic factors influence injury risk. Monthly RTA injury counts and provincial population data were obtained from the Italian National Institute of Statistics (ISTAT

2024), mean monthly temperature data from the ERA5 reanalysis dataset (Hersbach et al. 2020), and socioeconomic vulnerability from Frigerio et al.'s vulnerability index incorporating 16 socioeconomic indicators (Frigerio et al. 2018). These covariates were selected for their potential relevance to RTA injury risk patterns and their availability for the complete study period.

Hierarchical Poisson log-linear modelling was used to estimate relative risks of RTA injury while accounting for population differences. As expected injury counts were not available, we used population scaled by 100,000 as an offset, effectively modelling the rate of RTA injuries per 100,000 population. To determine whether to model a space-time interaction, we plotted temporal trend plots of log-relative risks by province. These demonstrated non-uniform patterns across provinces supporting the inclusion of spatial-temporal interaction in our models.

Our modelling approach followed a systematic progression from simple to complex specifications to enable rigorous model comparison and isolate the effects of different components. We began with a spatial-only model (Model 1) to establish baseline spatial patterns and quantify geographic heterogeneity in injury risk, providing a reference point for subsequent models. This was followed by a spatial-temporal model without interaction (Model 2), which incorporated temporal trends while assuming these trends were uniform across all provinces—a necessary comparison to determine whether province-specific temporal patterns existed. After establishing these foundational models, we introduced spatial-temporal interactions with increasing complexity: Model 3 with Type I (completely unstructured) interaction allowing for province-specific temporal deviations without assuming correlation between neighbours; Model 4 with Type II interaction (unstructured in space, structured in time) allowing for spatial correlation in temporal effects; and finally Model 5, which added temperature and vulnerability covariates to the best-performing model from 1-4. This stepwise approach enabled us to evaluate whether the added complexity of each component was justified by improved model fit according to WAIC scores. All models are described in the formulas below and employed the Besag-York-Mollié (BYM2) prior for spatial random effects, with models 2-5 using a Random Walk order 1 model for temporal effects.

$$
\begin{aligned}
&\textbf{Model}-\mathbf{1}\\
O_i &\sim \text{Poisson}(\rho_i E_i)\\
\log \rho_i &= b_0 + b_i\\
\mathbf{b} &= \frac{1}{\sqrt{\tau_b}}(\sqrt{1-\phi}\mathbf{v}_* + \sqrt{\phi}\mathbf{u}_*)
\end{aligned}
$$

$$
\begin{aligned}
&\textbf{Model}-\mathbf{2}\\
O_{it} &\sim \text{Poisson}(\rho_{it} E_{it})\\
\log \rho_{it} &= b_0 + b_i + \gamma_t\\
\boldsymbol{b} &= \frac{1}{\sqrt{\tau_b}}(\sqrt{1-\phi}\boldsymbol{v}_* + \sqrt{\phi}\boldsymbol{u}_*)\\
\gamma_t &\sim \text{RW}(1)
\end{aligned}
$$

$$
\begin{aligned}
&\textbf{Model}-\mathbf{3,4}\\
O_{it} &\sim \text{Poisson}(\rho_{it} E_{it})\\
\log \rho_{it} &= b_0 + b_i + \gamma_t + \psi_t + \delta_{it}\\
\boldsymbol{b} &= \frac{1}{\sqrt{\tau_b}}(\sqrt{1-\phi}\boldsymbol{v}_* + \sqrt{\phi}\boldsymbol{u}_*)\\
\gamma_t &\sim \text{RW}(1)\\
\psi_t &\sim \text{Normal}(0, \sigma_\psi^2)\\
\delta_{it} &\sim \text{Normal}(0, \sigma_\delta^2)
\end{aligned}
$$

$$
\begin{aligned}
&\textbf{Model}-\mathbf{5}\\
O_{it} &\sim \text{Poisson}(\rho_{it} E_{it})\\
\log \rho_{it} &= b_0 + b_i + \gamma_t + \psi_t + \delta_{it} + \beta_T \times Temp_{it} + \beta_V \times Vuln_{it}\\
\boldsymbol{b} &= \frac{1}{\sqrt{\tau_b}}(\sqrt{1-\phi}\boldsymbol{v}_* + \sqrt{\phi}\boldsymbol{u}_*)\\
\gamma_t &\sim \text{RW}(1)\\
\psi_t &\sim \text{Normal}(0, \sigma_\psi^2)\\
\delta_{it} &\sim \text{Normal}(0, \sigma_\delta^2)
\end{aligned}
$$

For province i at time t:

- O_{it} is the observed number of RTA injuries, and E_{it} is the population scaled by 100,000
- ρ_{it} is the relative risk of RTA injuries per 100,000 people
- $\boldsymbol{b}$, the spatial random effect, is specified by a Besag-York-Molli'e (BYM) prior (Besag, York, and Mollié 1991) composed by u_i and v_i, where u_i is the spatially structured component defined by an intrinsic CAR prior (IARC 2016): $\boldsymbol{u} \sim ICAR(\boldsymbol{W}, \sigma_u^2)$, and v_i is the unstructured component defined with prior: $v_s \overset{iid}{\sim} \text{Normal}(0, \sigma_v^2)$
- τ_b is the precision parameter controlling the marginal variance of the random effect with its prior defined as $P(\sigma_{\tau_b} > 0.5/0.31) = 0.01$, and ϕ is the mixing parameter measuring the proportion of the marginal variance with its prior defined as $P(\phi < 0/5) = 2/3$ (Riebler A 2016)
- γ_t is the temporal random effect that captures the overall time trend across all provinces
- ψ_t is the unstructured temporal random effect that captures year-specific variations not following the smooth trend represented by γ_t, allowing the model to account for temporal anomalies
- δ_{it} is the space-time interaction term that allows for province-specific temporal deviations from the national trend
- Temp_{it} is the mean monthly temperature and Vuln_i is the social vulnerability index
- β_T is the log-relative risk change associated with a 1 degree Celsius increase in Temp_{it} while controlling for other factors, and β_V is the log-relative risk change associated with a one-unit increase in Vuln_i while controlling for other factors

To identify high-risk provinces, we calculated exceedance probabilities $P(b_i > 0)$ from the spatial random effects, with provinces having probabilities >0.8 considered high-risk areas. Model performance was assessed using the Watanabe-Akaike Information Criterion (WAIC).

Results

Descriptive Analysis Our analysis of RTA injuries across Italy from 2017-2022 revealed distinct spatial and temporal patterns with several novel findings at the provincial level. Table 1 shows the annual totals of RTA injuries with a substantial 34.03% decrease in 2020 coinciding with the COVID-19 pandemic. Figure 1 summarises the provincial injury rates per 100,000 population, and the spatial distribution of social vulnerability and mean monthly temperature across Italian provinces.

Temporal Trend, Model Comparison and Hyperparameters Figure 2 presents temporal trends of log-relative risks for each province from 2017–2022. The diverging patterns across provinces support the inclusion of spatial-temporal interaction terms in our models to capture area-specific trends that evolve differently over time. Among models 1-4, the spatial-temporal model with Type I interaction had the lowest WAIC (63,419.91), indicating it had the optimal balance of accuracy and parsimony. Model 5 was thus fit with Type I interaction and the mean monthly temperature and social vulnerability covariates and had a similar but higher WAIC (63,423.80). Table 3 shows the posterior estimates of key hyperparameters from the best-fitting model with the overall lowest WAIC (Model 3). The precision for the spatial random effects (median: 12.71, 95% CI: 9.31-17.34) indicates moderate spatial variability in RTA injury risk across provinces. The Phi value of 0.5 (95% CI: 0.29-0.7) suggests a balanced contribution between structured and unstructured spatial components, with approximately 50% of the spatial variation being explained by spatially structured effects where neighbouring provinces have similar risk patterns. The high precision for the spatial-temporal interaction (44.48 95% CI: 42.44 – 46.67) suggests that the spatial-temporal interaction is well-estimated and plays an important role in explaining the variation in the data, alongside the main spatial and temporal effects.

Spatial Pattern and Covariates Our provincial-level analysis identified previously unrecognised high-risk areas in Southern Italy, particularly in provinces such as Cosenza and Potenza, which were masked in previous regional-level studies that primarily reported Northern Italy's elevated risk. Figure 3 displays these provincial-level risk patterns through maps of residual relative risks and posterior probabilities, while Figure 4 shows exceedance probabilities that highlight both the expected Northern high-risk zones and these newly identified Southern hotspots. Contrary to previous studies, neither mean monthly temperature nor social vulnerability demonstrated statistically substantial associations with RTA injury risk (Table 4). The 95% credibility intervals for both covariates included zero (temperature: -0.006 to 0.003; social vulnerability: -0.103 to 0.015), suggesting that other unmeasured factors may play a more role in influencing RTA risk.

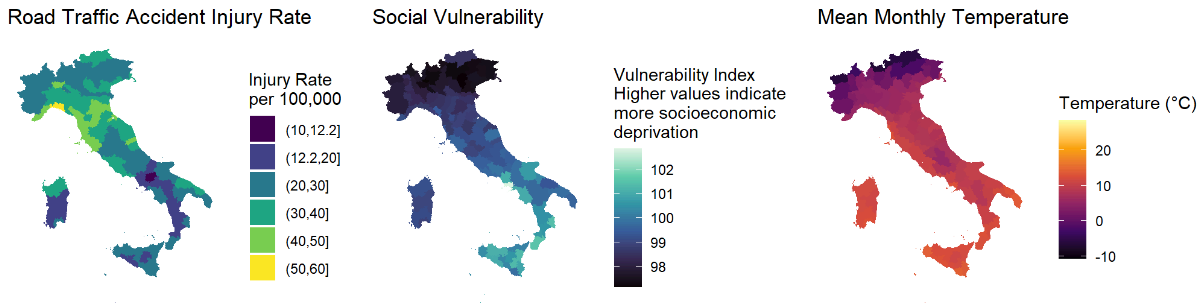
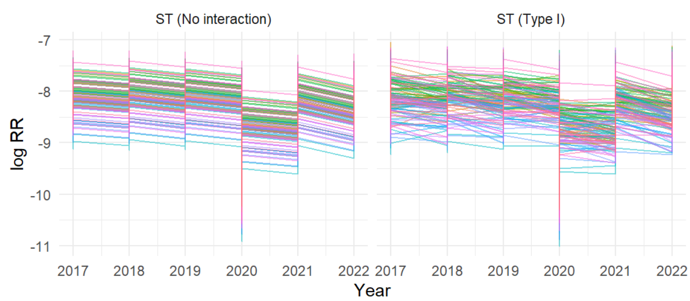


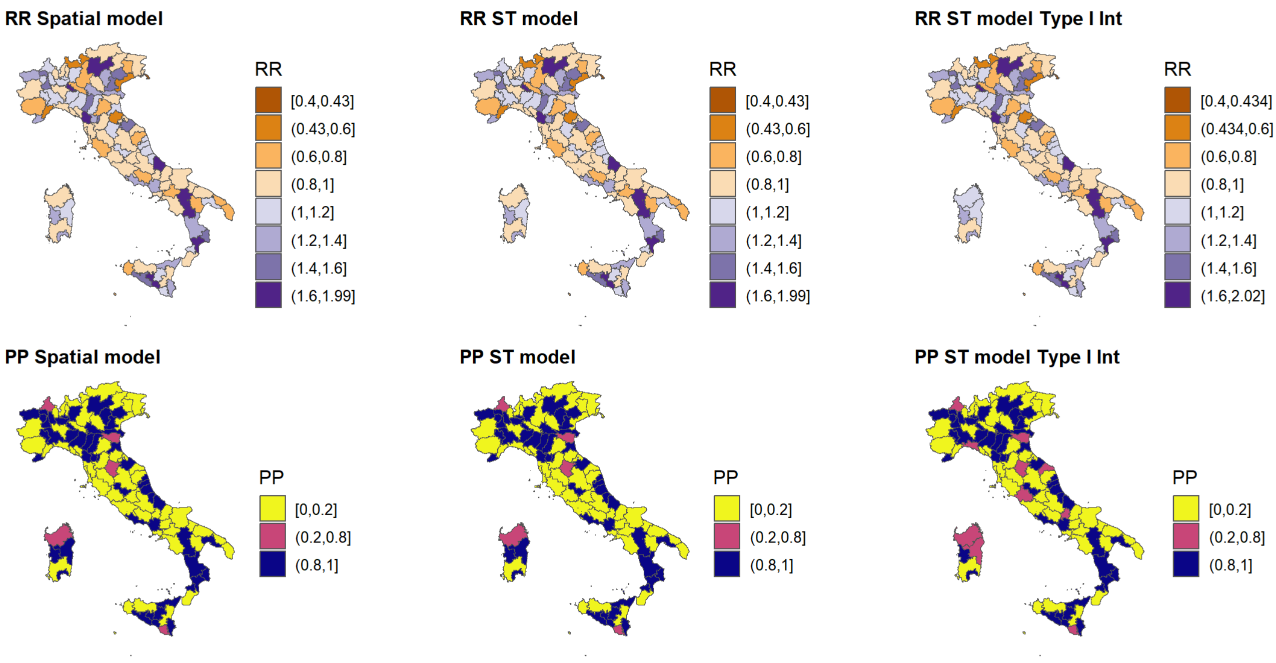
Figure 1. Road injury rates (left), social vulnerability (middle) and mean monthly temperature (right) across provinces of Italy [2017-2022]

Table 1. Total injuries in Italy in 2017-2022

Year	Total Road Injuries	Change from Previous Year
2017	246750	NA
2018	242919	-1.55%
2019	241384	-0.63%
2020	159248	-34.03%
2021	204728	28.56%
2022	223475	9.16%

Figure 2. Temporal trend of log-relative risk by province without (left) and with space-time interaction (right)





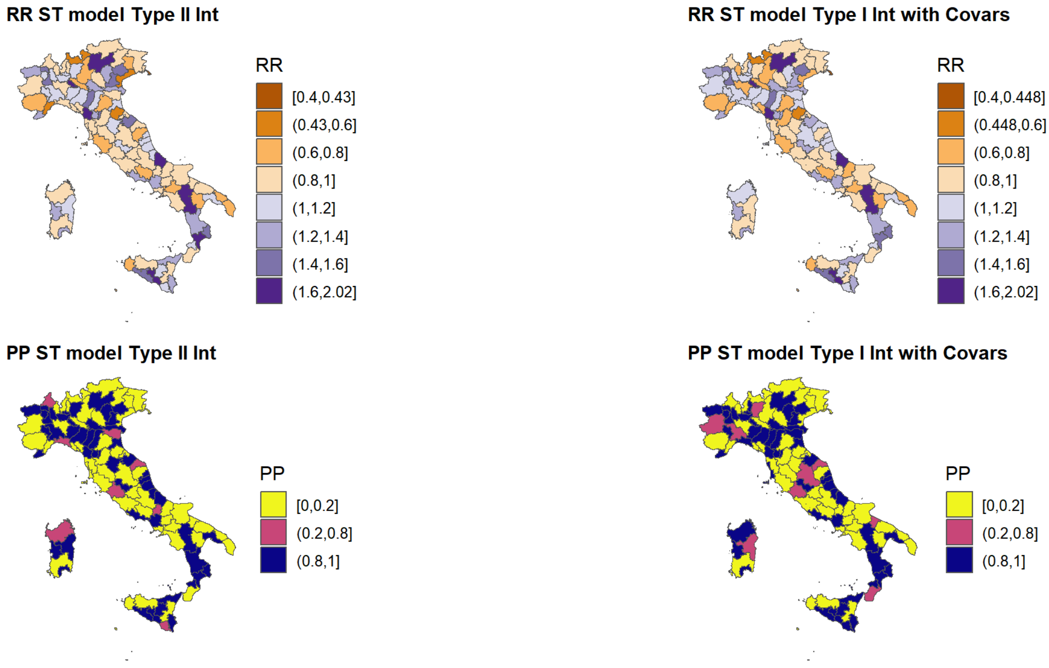


Figure 3. Map of residual relative risks (rRR) of RTA injury (top) and posterior probabilities that rRR > 1 (bottom) across provinces of Italy [2017-2022] for each model

Table 2. WAIC of the different models

Model	WAIC
1) Spatial	602554.29
2) SpatTemp (No int)	107361.37
3) SpatTemp (Type I)	63419.63
4) SpatTemp (Type II)	65250.92
5) SpatTemp (Type I) [Covars]	63426.58

Table 3. Posterior medians with 95% credibility Intervals of Model 3 hyperparameters (the best-performing model)

	Median	Lower limit	Upper limit
Precision of spatial random effects	12.66	9.22	17.25
Phi of spatial random effects	0.5	0.29	0.71
Precision of time random effects (structured)	15.08	10.38	21.67
Precision of time random effects (unstructured)	737.77	174.52	3158.64
Precision of space-time interaction	44.46	42.41	46.63

Figure 4. Map of exceedance probabilities that relative risk > 1 across provinces of Italy [2017-2022]

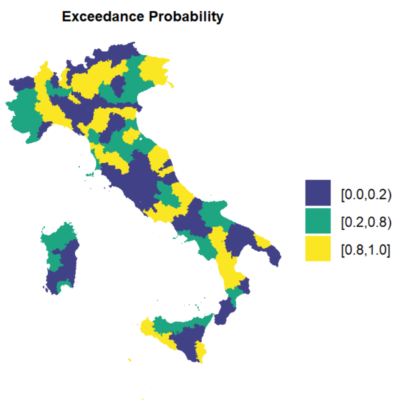


Table 4. Posterior median with 95% credibility interval of the covariates

Covariate	Posterior median	Lower limit	Upper limit
Social Vulnerability	-0.044	-0.103	0.015
Mean monthly temperature	-0.002	-0.006	0.002

Discussion and conclusion

Key results This study provides the first comprehensive provincial-level spatial-temporal analysis of road traffic accident (RTA) injuries across Italy from 2017–2022, filling a notable gap in Italian road safety research. Our results demonstrate marked spatial heterogeneity, with provinces in Northern Italy consistently exhibiting higher-than-average injury rates. Posterior probability maps (Figure 3) confirm this spatial pattern across all models, with the Type I interaction model providing the clearest differentiation between high- and low-risk provinces.

A noteworthy finding is the identification of high-risk provinces in Southern Italy, such as Cosenza and Potenza, despite lower raw injury rates in Southern regions (Figure 1). These provinces exhibit posterior probabilities exceeding 0.8 across multiple models, particularly those incorporating spatial-temporal interactions. This discrepancy between raw rates and model-adjusted risk estimates may reflect a phenomenon similar to that observed by Torre et al., that while traffic mortality rates (deaths per population) were higher in Northern regions, case-fatality rates (deaths per RTA) were highest in Southern Italy (La Torre et al. 2007). Our models may be detecting areas where RTAs, though less frequent, result in higher severity or poorer outcomes when they occur — potentially due to healthcare access disparities, or different crash characteristics. Infrastructure vulnerabilities are another potential contributor; the Southern region Calabria, where Cosenza is located, has older road networks susceptible to damage during extreme weather events (Petrucci and Pasqua 2012). Additionally, while social vulnerability was not statistically substantial in our study, it is noteworthy these provinces rank among Italy's most socially vulnerable regions (Figure 1), potentially compounding RTA risks through limited access to safer transportation options or reduced road maintenance.

Regarding our second research question, neither monthly mean temperature nor social vulnerability demonstrated statistically substantial associations with RTA injury risk, as evidenced in Table 4. This contrasts with previous studies and may reflect methodological limitations including insufficient data resolution or non-linear relationships not captured by our linear modelling approach.

Our model comparison reveals that incorporating spatial-temporal interactions, particularly Type I interactions in this study, substantially improves the delineation of spatial risk patterns (Figure 3). Model 3 incorporating a Type I space-time interaction, which assumes unstructured interaction between space and time, had the lowest WAIC score. The high precision for the spatial-temporal interaction in this model (Table 3) suggests that while province-specific temporal deviations from national trends are minimal, capturing these structured interactions still meaningfully improves model performance.

Contribution and comparison to existing literature This research advances the existing understanding of RTA injuries in Italy through use of Bayesian hierarchical models at the provincial level. The visualisation of residual relative risks (Figure 3) demonstrates how our approach captures spatial variability undetected by previous studies which employed regional aggregation or simpler analytical frameworks.

While our finding of elevated RTA risks in Northern Italy aligns with Torre et al.'s conclusions regarding traffic mortality, our provincial-level analysis provides novel insights into risk distribution. Specifically, our exceedance probability map (Figure 4) builds on existing literature by simultaneously identifying both the expected Northern high-risk clusters and previously unrecognised Southern hotspots. This pattern suggests different mechanisms may drive RTA risk in different regions of Italy: considering the higher population, high exposure (traffic volume) may predominate in the North, while the South may experience greater risk of injury from RTA despite lower frequency. This is an important distinction to delineate as it would require geographically tailored interventions rather than a national strategy.

Our non-substantial findings for temperature and social vulnerability diverge from previous research. This contrasts with Gariazzo et al. who reported extreme temperatures as a risk factor for RTA. This discrepancy may stem from methodological differences in geographic resolution (provinces versus macro-regions) and temporal aggregation (monthly averages versus hourly measurements), and our linear modelling approach being unable to capture the non-linear relationships between temperature extremes and RTA risk. Similarly, our results differ from Camilloni et al.'s reporting of increased RTA hospitalisation and death in the most deprived socioeconomic groups, possibly because our analysis employed a static vulnerability index from 2011 rather than contemporaneous indicators, thus failing to capture dynamic socioeconomic changes during the study period.

Strengths and limitations The primary strength of this study lies in its methodological approach, which decomposes RTA risk into spatial, temporal, and interaction components while adjusting for potential confounders. Our Bayesian hierarchical framework provides robust uncertainty quantification which is essential for evidence-based policy decisions. The systematic comparison of different interaction structures in Figure 3 demonstrates how Type I interactions, which assume unstructured space-time relationships, provide a better fit than simpler models. This suggests neighbouring provinces tend to have different temporal patterns in RTA risk, a finding that has important implications for regional policies.

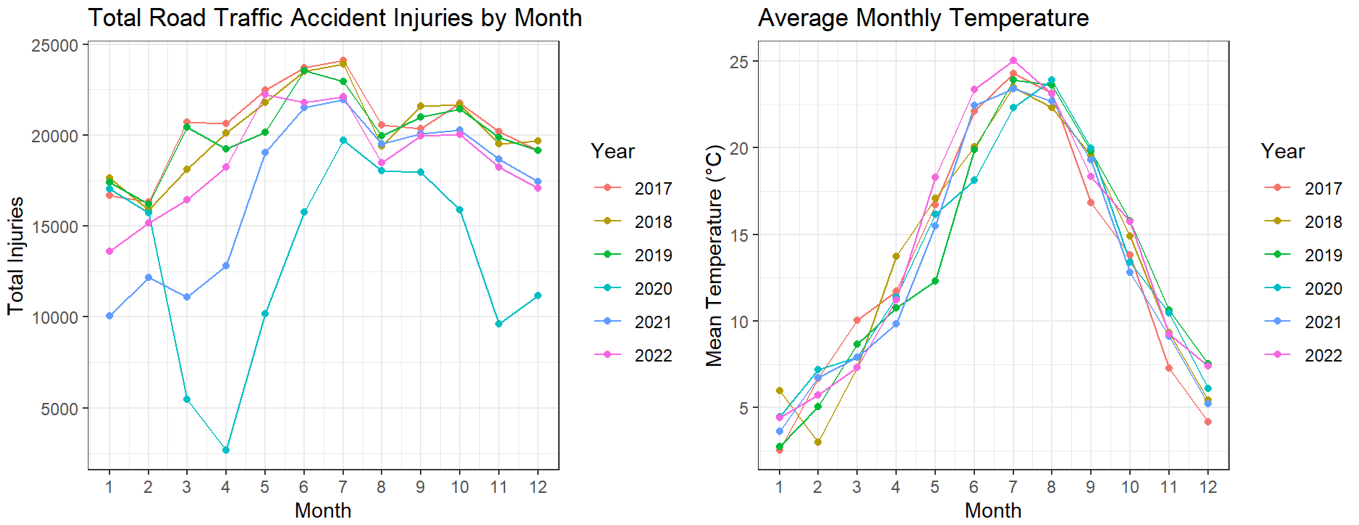
However, our findings should be interpreted in the context of several limitations. Firstly, our reliance on a social vulnerability index based on 2011 data—though more comprehensive than single-variable proxies used in previous studies—assumes constant socioeconomic conditions throughout 2017-2022 - potentially missing important dynamic changes, particularly during the COVID-19 pandemic when socioeconomic disparities likely widened. Secondly, the use of monthly mean temperatures potentially obscures effects of short-term extreme weather events on RTA risk, which may be better captured with daily or hourly data. Thirdly, the absence of behavioural factors known to affect RTA injury risk (e.g., mobile phone use, alcohol consumption, seat belt compliance) means there is likely potential unmeasured confounding. Fourth, our models assume linear relationships between covariates and log-relative risks, potentially missing threshold effects or complex non-linear associations. Lastly, the 34.03% drop in RTA injuries during 2020 results in a significant temporal discontinuity in our dataset, effectively dividing the analysis period into pre-pandemic and pandemic phases. This complicates the interpretation of temporal patterns and makes it challenging to distinguish long-term provincial risk trends from temporary effects, particularly as provinces likely experienced differential pandemic impacts based on their economic structure, tourism dependence and enforcement practices. Cautious interpretation is therefore essential when using these findings to inform long-term policy planning.

Future recommendations Our findings have direct implications for targeted road safety interventions in Italy. Considering the potential distinct risk patterns between the North and South, future research should focus on insights guiding regionally tailored interventions. For example, by researching if Northern provinces may benefit from traffic volume management and collision prevention, while investigations in high-risk Southern provinces should examine emergency response times, healthcare access disparities and road infrastructure quality (particularly drainage systems vulnerable to flooding) (Petrucci and Pasqua 2012).

Future research should also address the limitations of this study by incorporating: 1) time-varying socioeconomic indicators to capture dynamic vulnerability patterns, 2) high-resolution environmental data to model non-linear effects and extreme weather events, 3) behavioural risk factors to minimise unmeasured confounding, 4) including methods able to capture non-linear effects which may better characterise factors affecting RTA injury, and 5) analysing both RTA frequency and the severity of outcomes simultaneously. These methodological improvements could potentially reveal associations undetected in our study and provide a more comprehensive understanding of regional risk patterns.

Implementation of these recommendations, coupled with targeted interventions in high-risk provinces identified through our exceedance probability analysis, has the potential to substantially advance public health strategies aimed at reducing RTA injuries in Italy. Such approaches could contribute significantly to meeting the WHO and EU targets for halving RTA injuries by 2030 while addressing previously overlooked geographic inequalities in road safety across the country.

Supplementary material



Supplementary Figure 1. Monthly trend of total road injuries (top) and mean monthly temperature (bottom) in Italy [2017-2022]

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