Spatial and Spatio-Temporal Modelling of Auto Insurance Claim Frequencies During Pre-and Post-COVID-19 Pandemic

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Abstract: This study explores the dynamics of automobile insurance claim frequencies, shedding light on spatial patterns indicative of regional diversity. By examining data from urban, rural, and suburban areas, we discern disparate claim frequencies across both geographical and temporal dimensions, offering pivotal insights for insurers and regulators seeking to enhance risk assessment and pricing methodologies. Our analysis of auto insurance loss data from Ontario, Canada, unveils a marked divergence in relative claim frequencies between the expansive northern regions and the densely populated south. Furthermore, by scrutinizing various accident years, including those influenced by the COVID-19 pandemic, distinct temporal trends emerge. Applying sophisticated spatio-temporal models facilitates precise predictions, equipping insurers with the tools necessary for adept navigation of the ever-evolving landscape of uncertainties. This research enhances our comprehension of the dynamic nature of territory risk within spatio-temporal contexts. These insights provide valuable assistance to insurance companies and auto insurance regulators in effectively managing territorial risk.

1 INTRODUCTION

The landscape of auto insurance claim frequencies reveals discernible spatial patterns, indicating the diverse characteristics of different territory risk. Across urban, rural, and suburban areas, claim frequencies vary both spatially and temporally (Ong and Sung, 2003). Understanding these spatial and temporal patterns is important for insurers and regulators to develop effective risk assessment, pricing strategies, and regulatory frameworks (Li et al., 2010). The spatial distribution of auto insurance claims is heavily influenced by the demographics of geographical locations. Urban areas typically exhibit higher driver density compared to rural regions, leading to different driving behaviors (Ong and Sung, 2003)). Therefore, it is essential to model spatial dynamics, especially during the pre and post-COVID-19 pandemics to uncover its impact. Also, it is possible to consider both spatial and temporal dynamics in a given model so that insurance loss patterns can be captured using more characteristics from the model used.

In this study, we analyzed auto insurance claim data from Ontario, Canada. Data visualization indicates that northern regions, characterized by expansive landscapes and sparse populations, may experience relatively lower relative claim frequencies compared to the densely populated southern areas. Conversely, the Greater Toronto Area, ranked seventh globally for its traffic congestion, is anticipated to demonstrate heightened relative claim frequencies. However, this spatial pattern may change over time and a global health crisis may lead to a significant change of such pattern. Because of this, our research incorporates a temporal dimension by examining data from various accident years, including periods affected by the COVID-19 pandemic. This temporal modeling approach reveals distinct trends in relative claim frequency, highlighting the impact of the pandemic (Abraham and Mumma, 2021; Babuna et al., 2020; Nebolsina, 2021). Our approach to modelling focuses on both spatial and spatio-temporal domains to better reveal the nature of the claim frequency patterns.

Recent studies in auto insurance, such as those conducted by (Farmaki et al., 2022; Honan et al., 2023; Jha et al., 2022), uncover the impact of the COVID-19 pandemic from both societal and economic perspectives. Understanding the spatial and temporal dynamics before and after the pandemic is crucial for insurers to comprehend the evolving nature of auto insurance claims. Consequently, the uti-

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lization of advanced spatio-temporal models, such as the spatial Besag York Mollié Model (BYM) (Wahl et al., 2022) and spatio-temporal BYM model (Bauer et al., 2023), facilitates more precise prediction of future claim trends. The insights derived from these research findings are invaluable for insurance companies, aiding them in risk management, strategy formulation, pricing decisions, and case reserve management. The integration of loss data analytics within the framework of auto insurance, particularly through the spatial-temporal model, allows insurers to identify spatial clusters characterized by varying relative claim frequencies. By pro-actively anticipating the effects of events such as pandemics, insurers can allocate resources strategically and prepare for dynamic and challenging scenarios. Ultimately, the adoption of such robust modeling approaches enhances insurers' operational optimization, enabling them to navigate uncertainties with greater efficiency and effectiveness. Although modelling is done on relative claim frequency data, a similar study can be carried out by applying the techniques to claim severity, or loss cost, which captures the theoretical insurance premiums.

This research is structured around two objectives. Firstly, it aims to discover spatial patterns in claim frequency by Ontario's Forward Sortation Areas (FSAs). This entails investigating whether claim frequency exhibits clustering, autocorrelation, or localized trends, shedding light on underlying risk factors, infrastructure considerations, and socio-economic disparities. Secondly, the study aims to explore the temporal dimension, analyzing relative claim frequency patterns before, during, and after the COVID-19 pandemic. By uncovering spatio-temporal patterns, this research endeavors to refine risk assessment methodologies, and offer valuable insights for the formulation of auto insurance regulations. The significance of this research lies in its innovative application of spatial data science techniques to auto insurance loss analysis. Moreover, it advocates for the adoption of advanced models of insurance rate regulation to enhance statistical robustness. The study contributes to the advancement of sound regulatory frameworks and promotes a more comprehensive understanding of insurance risk dynamics.

The remainder of this paper is structured as follows. In Section 2, we outline the data employed in this study and describe the proposed methods, including Moran I statistics and, Besag-York-Mollie spatial and spatio-temporal model. In Section 3, we critically analyze the results that we obtained. Finally, in Section 4, we conclude our study and offer insights obtained from this research.

2 MATERIALS AND METHODS

2.1 Data

The data sets used in this work consist of claim counts and risk exposures collected from all auto insurance companies in Ontario, Canada. The accident half-year data from 2018 to 2022 is considered to address the potentially different patterns between pre- and after the pandemic. The claim counts and written number of vehicles (i.e. risk exposures) are aggregated by FSA over a six-month period. The following aggregated observations are computed for each FSA: total claim counts, total vehicle counts. The relative claim frequency per car was computed as the total number of claim counts divided by the total vehicle counts. To construct the map, the shape files in the FSA boundaries data set from Statistics Canada are used to delineate the boundaries of the FSA regions in Ontario. These shape files enable the visualization and mapping of relative claim frequency patterns, facilitating the identification of clusters, trends, and potential spatial correlations.

2.2 Global Moran's I

To evaluate spatial auto-correlation within insurance claim frequency data across Ontario's FSA regions, we conducted a Global Moran's I analysis. This statistical method gauges the extent of spatial clustering or dispersion within the dataset, shedding light on whether similar values tend to aggregate (positive spatial auto-correlation) or scatter (negative spatial auto-correlation). Using geographical coordinates, we visually represented FSA regions on a map. Moran's I was computed utilizing a formula that considers standardized observation values, spatial weights, and the overall mean relative claim frequency. The resulting Moran's I value ranges from -1 (indicating perfect dispersion) to +1 (indicating perfect clustering), with 0 denoting no spatial auto-correlation.

2.3 Besag-York-Mollié Model

Selecting an appropriate model to tackle spatial auto-correlation for the real-world application remains an enduring difficulty in spatial statistical analysis. In our study, we choose the Besag-York-Mollié (BYM) model to confront potential spatial correlation among FSA based claim frequency. Therefore, this paper explore the intricacies of the BYM model, demonstrating how it enhances our research objectives. From statistical perspectives, the BYM model is a spatial

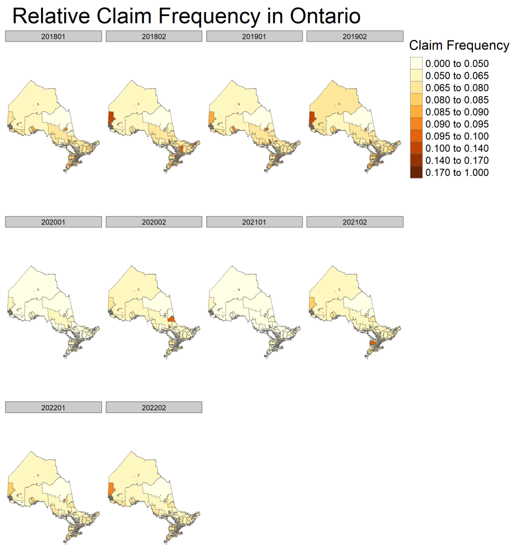

Figure 1: Time evolutionary spatial patterns of relative claim frequency, spanning from accident years 2018 to 2022, for the entire Ontario.

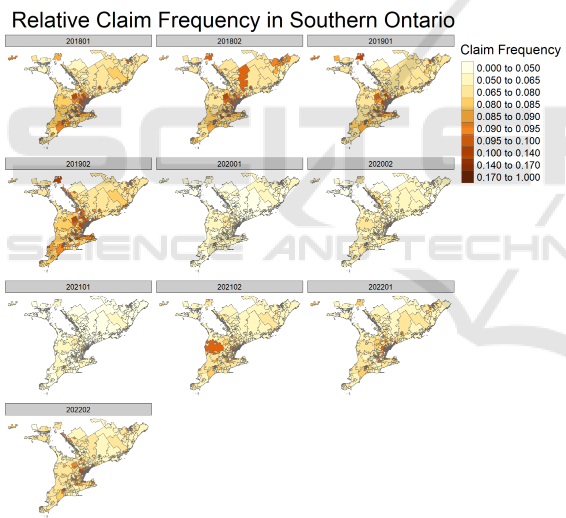

Figure 2: Time evolutionary spatial patterns of relative claim frequency, spanning from accident years 2018 to 2022, for the southern Ontario.

model that treats spatial correlation as a stochastic variable. The model applies the Bayesian framework to account for the impact of region as a risk factor on relative claim frequency, acknowledging potential correlations among claim frequencies in neighboring locations. By applying the BYM model, we aim to gain deeper insights into the spatial distribution of relative claim frequency within our study focus, offering valuable insights for insurance rate regulation. The BYM model is specified as follows:

$$log(\lambda_i) \approx \beta_0 + \gamma_i + \theta_i, \quad (1)$$

$$\theta_i \sim N(0, \sigma_\theta), \quad (2)$$

$$\gamma_i \mid \gamma_{-i} \sim N(\frac{1}{N_i}\sum_{j=1}^{n} a_{ij}\gamma_j, s_i^2), \quad (3)$$

$$\gamma \sim N(\mathbf{0}, \mathbb{Q}^{-1}). \quad (4)$$

Here λ_i represents relative claim frequency that associated with ith regions. The collection of all regions is denoted by $A = \{1, 2, 3, ..., n\}$ using their indexes, so $i \in A$, and $-i \in A \setminus \{i\}$ represents all regions except the ith region. γ_i is to explain the spatially structured random effect and θ_i is further capture the unstructured random effect. N_i is the number neighbours of region i, and $s_i^2 = \sigma_u^2 / N_i$, while the variance parameter σ_u^2 controls the amount of variation between the spatially structured random effects. a_{ij} is 1 if areas i and j are neighbours and 0 otherwise. $\mathbb{Q}$ is the precision matrix, representing conditional independence. Whenever the two FSA regions are not neighbours, they are conditionally independent, and hence the corresponding element is 0 in the precision matrix. $\mathbb{Q}^{-1} = (\mathbb{I} - \phi\mathbb{W})^{-1}\mathbb{S}^2$, considering $\mathbb{W}$ as a matrix of generic elements $W_{ij} = a_{ij}/N_i$ and $\mathbb{S} = diag(s_1, s_2, ..., s_n)$, and ϕ remains constant, which is set to 1 in this work.

Given that the response variable represents claim counts, a Poisson model is the appropriate choice to account for the number of occurrences data. In the context of Poisson models, the Bayesian framework allows us to incorporate structured random effects, which are particularly relevant when considering spatial dependencies among the observations. Moreover, the spatial random effect and independent identically distributed (iid) unstructured random effects included in the BYM model allow for reflecting the overdispersion. The BYM model is well-suited for addressing the intricacies of claim frequency patterns by effectively accounting for both spatially structured and unstructured random effects. This stage involved fitting the spatial BYM model independently using the accident half year data.

2.4 Spatio-Temporal Besag-York-Mollié Model

After visualizing the observed relative claim frequency and their fitted values after modelling, it became evident that there were temporal variations in the claim frequency over time. Hence, recognizing the temporal fluctuations, we incorporated temporal dynamics into our analysis. The selection of the spatio-temporal auto-regressive model is driven by its

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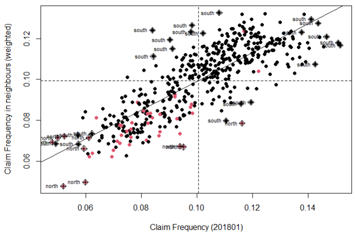

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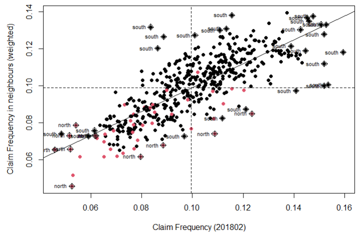

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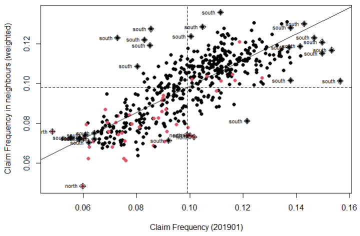

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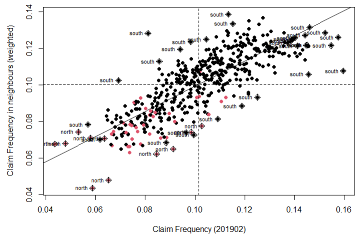
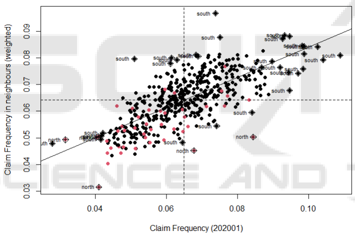


(d)

Figure 3: The scatter plots depict the relationship between the relative claim frequency of each FSA region (x-axis) and the average relative claim frequency of its neighboring regions (y-axis) during various accident half-years before the COVID-19 pandemic. The subplots illustrate the cases for different periods: (a) 1st half of 2018, (b) 2nd half of 2018, (c) 1st half of 2019, and (d) 2nd half of 2019.



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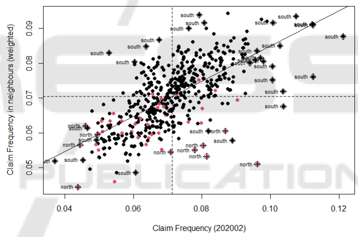

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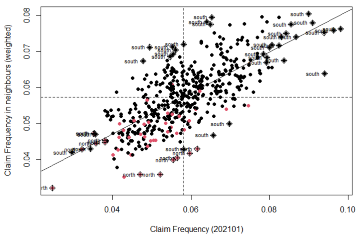

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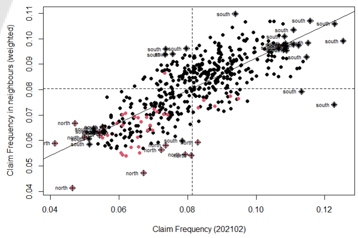

(d)

Figure 4: The scatter plots of the relative claim frequency of each FSA region (x-axis) and the average value of relative claim frequency of its neighbours (y-axis), for different accident half years during COVID-19 pandemic. The subplots illustrate the cases for different periods: (a) 1st half of 2020, (b) 2nd half of 2020, (c) 1st half of 2021, and (d) 2nd half of 2021.

inclusion of both spatially and temporally structured random effect terms. By integrating both spatial and temporal dimensions, this model can capture the underlying spatial patterns, temporal trends, and potential interactions between them. The model is again using Poisson as the error distribution function. The spatial component allows for the incorporation of spatial auto-correlation, revealing how neighbouring regions influence each other's claim frequency. On the other hand, the temporal component acknowledges the temporal persistence observed in insurance claim data. It accounts for the temporal auto-correlation, al-

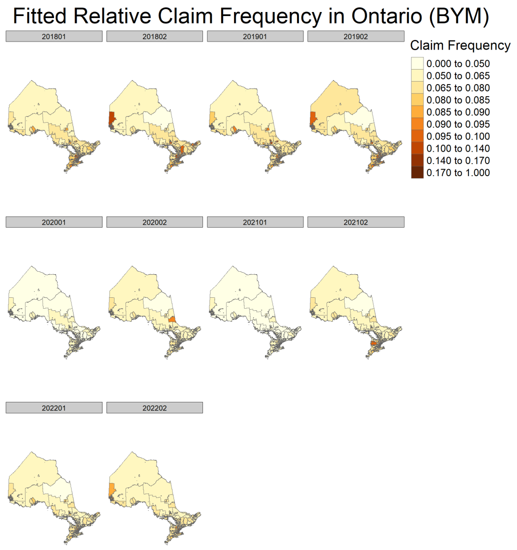

Figure 5: Fitted relative claim frequency for spatial BYM model using data from the entire province of Ontario.

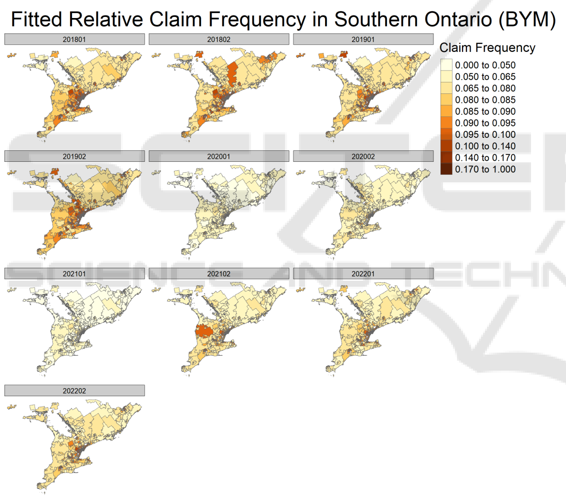

Figure 6: Fitted relative claim frequency for spatial BYM model using data from the southern Ontario.

lowing the current claim frequency to be influenced by its historical values. This recognition of temporal trends is pivotal for capturing any consistent patterns, fluctuations, or cyclical variations that contribute to the overall claim frequency landscape. Through this model, we can uncover how the interplay between spatial and temporal factors contributes to the variations in claim frequency across different regions. The outcomes from the models enable a comprehensive understanding of how both spatial and temporal factors collectively shape insurance risk patterns, thereby enhancing the precision of risk assessment strategies and informing policy decisions. In this study, we have fitted a spatio-temporal auto-regressive model of order 1 to the data. The model specification is outlined as follows:

$$log(\lambda_{it}) \approx \beta_0 + \gamma_i + \theta_i + \eta_t \quad (5)$$

$$Y_{it} \sim Poisson(\lambda_{it}) \quad (6)$$

$$\theta_i \sim N(0, \sigma_\theta) \quad (7)$$

$$\eta_t \mid \eta_{t-1} \sim N(\rho\eta_{t-1}, \sigma_\eta) \quad (8)$$

$$\eta_t = c + \rho\eta_{t-1} + \varepsilon_t \quad (9)$$

$$\varepsilon_t \sim N(0, \sigma_t) \quad (10)$$

η_t is the temporal random effect term and follows autoregressive model of order 1. θ_i is the extra Poisson variation. t is the time point, $t = 1, 2, 3, \ldots$ and c is the intercept term. The remaining parameters are defined identically to those in the spatial model.

3 RESULTS

This section discuss the results obtained from applying our proposed spatial and spatial-temporal models to claim frequency data. We first examined the evolutionary spatial correlations of claim frequency in Ontario and southern Ontario. The results are presented in Figures 1 and 2. These Figures provide insights into the spatial distribution of claim frequency for each accident half-year. Within each map, the similar colour indicates a similar level of relative claim frequency. On the other hand, the similar patterns among different maps reveal temporal correlations spanning the accident half years. Notably, the maps exhibit lighter colours across Ontario during the pandemic, suggesting a decreasing claim frequency. This observation strengthens our commitment to expanding the scope of our analysis beyond spatial dependencies and integrating temporal dynamics into our models.

We use the Global Moran's I statistics to quantify the spatial auto-correlation of the claim frequency across different neighbouring FSAs. The Global Moran's I take values from -1 to 1, and the proximity to 1 signifies a positive autocorrelation, while -1 denotes a negative autocorrelation. The proximity to 0 implies no spatial autocorrelation. In this study, Moran's I test results yielded compelling evidence of spatial auto-correlation in claim frequency across Ontario. The estimated Moran's I values are all positive, and the p-values are less than 2.2 e-16. The spatial auto-correlation was estimated to be around 0.5, indicating a pronounced positive spatial auto-correlation of claim frequency throughout Ontario. This implies that each FSA shares approximately a similar number of claim frequencies with its neighbouring areas. This finding suggests that analyzing the spatial clus-

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Table 1: Five number summary statistics and mean of claim frequency values under different methods, including empirical, Besag, and BYM models, by different accident half years.

Quantiles for Claim Frequency in 2018-2022							
Time	Parameters	Minimum	Q1	Median	Q3	Maximum	Mean
201801	CF	0.0479	0.08387	0.10252	0.11556	0.15152	0.10056
	cf_{Besag}	0.05204	0.08563	0.1031	0.11506	0.1479	0.10058
	cf_{BYM}	0.05246	0.08535	0.10315	0.11499	0.1484	0.1006
201802	CF	0.04589	0.08431	0.0989	0.1132	0.15938	0.09963
	cf_{Besag}	0.05005	0.08476	0.09943	0.11327	0.15634	0.09968
	cf_{BYM}	0.04994	0.0848	0.09946	0.11318	0.15684	0.09969
201901	CF	0.04847	0.08411	0.10016	0.11209	0.15647	0.09912
	cf_{Besag}	0.05385	0.08515	0.10076	0.11253	0.1504	0.09916
	cf_{BYM}	0.05361	0.08518	0.10068	0.11251	0.15086	0.09918
201902	CF	0.04365	0.08627	0.10155	0.11559	0.15959	0.10142
	cf_{Besag}	0.04914	0.08649	0.10152	0.11553	0.15408	0.10138
	cf_{BYM}	0.0489	0.08636	0.10163	0.1155	0.15376	0.10141
202001	CF	0.02791	0.05637	0.06436	0.07257	0.10888	0.06492
	cf_{Besag}	0.03377	0.05641	0.06449	0.07233	0.10237	0.06495
	cf_{BYM}	0.03436	0.05651	0.0645	0.0723	0.10241	0.06497
202002	CF	0.03706	0.06334	0.0708	0.07912	0.12124	0.07128
	cf_{Besag}	0.04153	0.0638	0.07067	0.07833	0.10999	0.07125
	cf_{BYM}	0.04272	0.06384	0.07073	0.07829	0.11084	0.07129
202101	CF	0.02468	0.04977	0.05705	0.0656	0.09817	0.05802
	cf_{Besag}	0.02634	0.05045	0.05709	0.06527	0.09455	0.05804
	cf_{BYM}	0.02699	0.05054	0.0571	0.06534	0.09423	0.05806
202102	CF	0.04135	0.07157	0.08178	0.09112	0.12538	0.08131
	cf_{Besag}	0.04614	0.07143	0.08179	0.09028	0.12066	0.08131
	cf_{BYM}	0.0459	0.07154	0.08184	0.09015	0.1206	0.08134
202201	CF	0.04247	0.0748	0.08517	0.09582	0.12529	0.08508
	cf_{Besag}	0.04681	0.07518	0.08561	0.09527	0.12089	0.08504
	cf_{BYM}	0.04742	0.07521	0.08561	0.09521	0.12084	0.08506
202202	CF	0.03958	0.07561	0.08824	0.10055	0.14336	0.08815
	cf_{Besag}	0.04136	0.07584	0.08863	0.09997	0.1322	0.08814
	cf_{BYM}	0.04171	0.07589	0.08843	0.09991	0.13241	0.08816

tering of claim frequencies could serve as another important aspect in exploring patterns of insurance claim frequency.

Figures 3 and 4 described the relative claim frequency for each FSA region and the average value of the relative claim frequency of its neighbours. All these plots show that most of the points are laid around the off-diagonal lines, which means FSA regions have similar values to their neighbours. This could imply that areas with high claim frequency are surrounded by other areas with high claim frequency, and areas with low claim frequency are surrounded by other areas with low claim frequency. The presence of clustering could be attributed to various factors such as similar driving conditions, local infrastructure, traffic patterns, or socio-economic characteristics. This positive spatial auto-correlation identified through Global Moran's I can be integrated into the modelling of claim frequency. This spatial pattern suggests that the spatial auto-correlation can be incorporated into the predictive model that we select to further refine the understanding of how both spatial and temporal factors contribute to insurance claim frequency variations.

The identification of positive spatial auto-correlation holds considerable significance, prompting the adoption of a spatial modelling approach, specifically, the Besag-York-Mollié model, to effectively address this spatial dependence. The estimate for the structured random effect (γ) effectively captures spatial patterns and dependencies within the claim frequency data. The impact of neighbouring regions on each FSA is substantial. The fitted results under the BYM model are illustrated in Figures 5 and 6, revealing similar clustered patterns compared to Figures 1 and 2, respectively. Notice that, the Greater Toronto Area (GTA) exhibits the highest claim frequency values, a spatial pattern attributed to the ur-

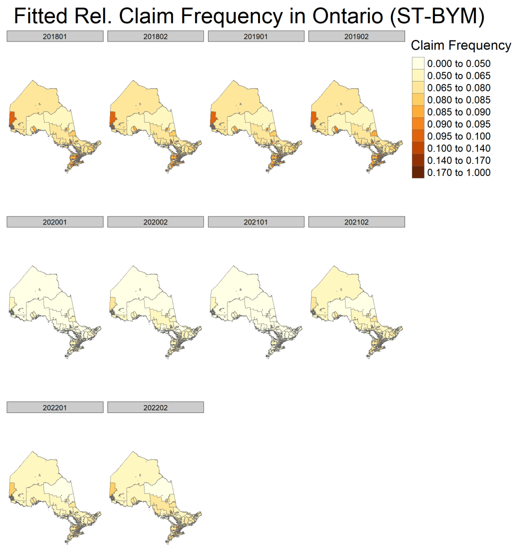

Figure 7: Fitted relative claim frequency maps for spatio-temporal BYM model using the entire Ontario loss data.

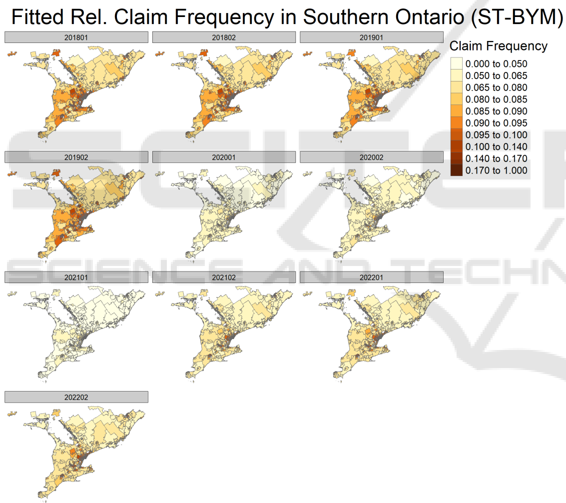

Figure 8: Fitted relative claim frequency maps for spatio-temporal BYM model using the southern Ontario loss data only.

ban nature of the GTA. Factors such as high population density, increased vehicular presence, and unique driving behaviours contribute to elevated claim frequencies. Moreover, there is a noticeable increase in claim frequency as one moves southward. The close alignment between the fitted values by the spatial BYM model and the actual values underscores the model's accuracy. This spatial analysis emphasizes the importance of considering geographical information in insurance risk assessment, particularly the significant influence of territory risk on claim frequency trends. The insights gained from this analysis provide valuable guidance for insurers, aiding in refining risk assessment strategies and pricing models across diverse regions within the studied area.

In this research, the selection of a suitable spatio-temporal model emerged as a natural progression, leading us to focus on the auto-regressive model with an order of 1 for the temporal term. By opting for the auto-regressive model, we aimed to holistically understand the interplay of spatial and temporal factors in shaping claim frequency dynamics. This approach culminated in the development of a comprehensive spatio-temporal Besag York Mollié model, incorporating both spatial and temporal considerations. The observed decline in fitted claim frequency during 2020 and 2021, as illustrated in Figures 7 and 8, can be attributed to the widespread changes in driving behaviour and mobility patterns induced by the COVID-19 pandemic. Individuals reduced outdoor activities and travel during this period, resulting in a proportional reduction in insurance claim frequency. The spatial trends depicted in Figure 6 reveal a consistent pattern of fitted claim frequency gradually increasing from north to south. This spatial gradient signifies a spatially varying risk that the model effectively captures. Additionally, the temporal pattern indicating a lower frequency of claims during the pandemic years (2020–2021) compared to other years aligns with the results presented in Figures 7 and 8. Our spatio-temporal BYM model not only effectively captures the spatial and temporal dynamics of claim frequency but also highlights the impact of the COVID-19 pandemic on driving behaviours and subsequent insurance claims. The observed trends provide valuable insights for insurers, aiding in the refinement of risk assessment methodologies and the development of strategies to adapt to dynamic changes in spatial and temporal domains.

The fitted results, presented in Table 1, encompass various model configurations and accident half-years. This table synthesizes the five-number summary statistics, providing a comparative analysis between the empirical estimates and the outcomes yielded by different models. The findings show a remarkable consistency across diverse model setups, with minimal variability observed in the estimates. The relative claim frequency values show notable discrepancies before, during, and after the pandemic, indicating a substantial influence of the COVID-19 pandemic on auto insurance claims.

4 CONCLUSION

In this work, we model auto insurance claim frequency data using spatial and spatio-temporal models to uncover the impact of COVID-19 pandemic on auto insurance risk. Moran's I estimates show that there is spatial auto-correlation in the frequency of claims throughout Ontario, suggesting the impact of geographic factors. We used a spatio-temporal BYM model to explain these spatial and temporal dynamics, and it was successful in capturing the complex linkages. The model demonstrated how the frequency of claims gradually decreased in 2020 and 2021, in keeping with the impacts of COVID-19 pandemic. Our findings were supported by the temporal pattern of decreasing claims throughout the pandemic years and the spatial trend of increasing claims from north to south.

This analysis emphasizes how crucial it is to take spatial and temporal information into account when evaluating insurance risk. In the end, the spatio-temporal model helps insurers make better decisions and manage risk across spatial and temporal domains by providing insightful information on how to improve risk assessment techniques and pricing models. The acknowledgment of an evaluated decline in claim frequency during the pandemic years (2020–2021) is crucial for both insurers and regulators. This information can influence how insurers assess and price risks during future events similar to the COVID-19 pandemic. Understanding the temporal patterns allows insurers to adjust their pricing models to reflect the changing risk landscape. This also may impact insurance companies' reserving practices and financial planning. Understanding these patterns allows insurers to better estimate the potential financial impact and allocate reserves accordingly.

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