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Bayesian spatial methods for small-area injury analysis: a study of geographical variation of falls in older people in the Wellington–Dufferin–Guelph health region of Ontario, Canada

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ABSTRACT

Objectives To examine falls in older people in the Wellington–Dufferin–Guelph (WDG) health region of Ontario, Canada, and to identify areas with excess RR and associated risk factors, particularly those related to private dwellings.

Methods Cases of hospitalisation following falls among older people in the WDG health region between 2002 and 2006 were geocoded to the dissemination area level and used in the spatial analysis. The falls data and covariates from the 2006 Canadian census were analysed using Poisson log-linear models with (spatial and non-spatial) random effects at the dissemination area level. A Bayesian approach with Markov chain Monte Carlo simulation allowed the spatial random effects models to be fitted. Map decomposition was used to visualise the results.

Results The percentage of occupied private dwellings requiring repairs and median income were significantly associated with falls in older people in the WDG health region. Twenty-six dissemination areas with high RR of falls in older people in the WDG health region were identified. Map decomposition revealed that RR were also driven by unknown factors that have spatial patterns.

Conclusions This research identified an association between falls in older people and housing conditions; the higher the percentage of dwellings requiring repairs in an area, the higher its risk of falls in older people. Bayesian spatial modelling accounts for measurement errors and unobserved or unknown risk factors that have spatial patterns. The findings have the potential to contribute to future research in reducing falls in older people and generate more interest in using Bayesian spatial modelling approaches in injury and public health research.

Falls among older people (persons aged 65 years and over) are a common and growing concern in research on injury-related hospitalisations in Canada. Falls account for almost 80% of injury-related hospitalisations among older people, making falls the leading cause of injury-related hospitalisation for older people.[1] The rate of fall-related injuries is nine times greater among older people than the rest of the population, and one-third of community-dwelling older people experience one fall a year.[1 2] The problem of falls in older people will only become more prominent because they are the fastest growing population group in Canada.

Injuries sustained in a fall can be devastating, resulting in bone fractures, but adverse health outcomes caused by a fall are often more severe for older people, and may even result in death.[2 3] Even if a fall does not result in injury, older people may become fearful of falling, thereby affecting their quality of life. Furthermore, fall-related injuries among older people account for more than $C1 billion in healthcare costs in Canada annually.[4] Public health research to identify risk factors for falls in older people can play an important role in preventing falls and reducing their associated burden of illness.

The causes of falls in older people are multifactorial in nature. They involve biological, behavioural, environmental and socioeconomic factors. However, they can be grouped into two categories for non-syncopal falls (unintentional movements to the floor not related to passing out, blacking out, or losing consciousness):[5] intrinsic and extrinsic factors. Intrinsic factors are factors within the individual, including factors such as poor vision, poor balance and impairments in cognition. Extrinsic factors are factors within the individual's physical (built) and socioeconomic environment such as home hazards, inadequate housing and low income.[2 5 6] Unlike intrinsic factors, which have been shown to be effective as predictors of falls, evidence is not consistent between the causal association of extrinsic factors and falls in older people.[2 5 7 8]

Reducing falls by means of older people's built environment could be an effective strategy because it offers potential long-term benefits.[9] The built environment includes spaces that are created and modified by people such as homes and all buildings; the location and density of housing is also considered.[10] Many studies on the built environment and falls in older people focus on environmental hazards in the home caused by the interior decoration, such as the arrangement of furniture.[5–8 11] This is not surprising as over half (57%) of falls among older people occur in their home.[12] However, there is little evidence showing a clear association between falls in older people and the built environment, in particular their housing condition, using small-area analyses.

Based on a recent report from the Ontario Ministry of Health and Long-Term Care, the fall-related hospitalisations among older people in the Wellington–Dufferin–Guelph (WDG) health region, in the province of Ontario, Canada, was higher than the average rate in Ontario.[13] The objective of this study was to examine falls in older people in the WDG health region, to identify areas with an excess risk of falls among older people and risk factors associated with the built environment in the WDG health region, specifically in private dwellings, and to provide an example of the application of Bayesian spatial methods in injury research.

METHODS

Data source

Data on hospitalisation due to falls (International Classification of Disease codes W00–19) among older people (aged 65 years and over) in the WDG health region during the period 2002–6 inclusively (N=2712) were obtained from Wellington–Dufferin–Guelph Public Health (WDGPH), as extracted from the Ontario provincial health planning database. Falls among older people were analysed at the census dissemination area level; the dissemination area is the smallest standard census geographical unit covering all of Canada, with a population of no more than 700. Counts of hospitalisation between 2002 and 2006 were aggregated to minimise potential small number problems that could arise as counts of falls in dissemination areas in 1 year can be very small, and estimates of risks would lack precision.[14] The geographical boundary file provided by WDGPH consisted of 308 dissemination areas. Some source dissemination areas (N=313) were merged to ensure a more stable representation of all spatial units over time.

Covariates from the 2006 census were used to test their associations with falls in older people.[15] Box 1 lists the covariates retrieved from the census that were associated with demographics, private dwellings and socioeconomic status.

Box 1 Covariates from the 2006 Canadian census tested for statistical significance of risk factors of falls in older people

Demographic covariates

Population density—total population divided by land area

Socioeconomic covariates

Median income of population aged 15 years and over before tax
Percentage of older people with low education (no certificate, diploma, or degree)
Percentage of older people living alone
Percentage of people who have spent any number of hours providing unpaid care or assistance to older people

Private dwelling covariates

Percentage of occupied private dwellings requiring repairs
Percentage of occupied private dwellings that were originally constructed before 1946
Percentage of occupied private dwellings that were originally constructed before 1960
Percentage of occupied private dwellings that were originally constructed before 1980
Percentage of apartment buildings among occupied private dwellings
Percentage of rented occupied private dwellings

Population

The WDG health region boundary includes the counties of Wellington (including the city of Guelph) and Dufferin, located approximately 100 km west of Toronto, Ontario. The WDG health region serves a population of 254 860 in an area of 4242 km^2, which is 2.1% of the population and 0.5% of the land area in Ontario. Older people comprise 12.5% of the WDG population. Between 2001 and 2006, the total population of the WDG health region increased by approximately 7%, and the percentage of older people in the region increased by approximately 13%. Individuals 85 years of age and older represent 12% of the older population in the WDG health region.[16]

Geocoding method

The geocoding procedure was carried out by WDGPH. Statistics Canada's postal code conversion file+ version 5D (PCCF+) was used initially to assign dissemination areas to all falls-related hospitalisations among older people using recorded postal code and municipality of residence. When a postal code overlapped multiple dissemination areas or did not correspond to the recorded municipality of residence, records were assigned to eligible dissemination areas using a random, population-weighted method.[17] Approximately 14.5% of the records were assigned to eligible dissemination areas using this method by WDGPH.

Analysis

We modelled raw counts of falls in older people with (non-spatial and spatial) random effects to adjust for potential over-dispersion that can be caused by unknown risk factors of falls in older people, clustering of cases within and across dissemination areas, and heterogeneity of individual-level risk factors at the scale of the dissemination area level.[18]

As the number of cases in each dissemination area is small, the observed counts were assumed to be Poisson distributed with parameter λ_i. The model, which has been commonly used for small-area analysis,[19 20] is a Poisson log-linear model with two random effects terms.

$$\log[\lambda_i] = \log[E_i] + \beta_0 + \beta_1 X_{1,i} + \ldots + \beta_k X_{k,i} + U_i + S_i \quad i = 1 \ldots n$$

The parameter λ_i of the Poisson distribution is the expected value of the number of hospitalisations following falls among older people in the ith dissemination area. It is given by the multiplication of E_i and r_i, where r_i is the unknown area-specific RR of hospitalisations due to falls in older people in area i. E_i defines the expected number of falls for area i, given the size of the population and its age and sex composition in area i. Log$[E_i]$ is an offset term, a quantitative variable in which its regression coefficient is 1. Log[] denotes log to the base of e. β_0 is a constant term. $X_1,\ldots,X_k$ is a set of covariates for area i, and $\beta_1,\ldots,\beta_k$ the corresponding regression parameters. U_i and S_i are two Gaussian random effects terms. The U_i term allows for random effects that do not have a spatial pattern. The S_i term accounts for

Table 1 Descriptive statistics for the significant covariates (repairs required and median income)

	Repairs required (%)	Median income ($C)
Mean	34.17	29 915
Median	34.21	29 682
Minimum	4.55	17 350
Maximum	71.43	47 163
Standard deviation	11.92	5809

Table 2 Comparison of the results of the Poisson log-linear models with and without the two significant covariates (repairs required and median income)

	Models*			
	Model 1 without covariates	Model 2 repairs required	Model 3 median income	Model 4 repairs required and median income
DIC	1553.500	1551.300	1551.590	1549.510
Posterior means of regression coefficients (95% CI)				
Alpha (β_0)	−0.171 (−0.300 to −0.048)	−0.584 (−0.866 to −0.282)	−0.165 (−0.289 to −0.044)	−0.579 (−0.883 to −0.272)
Repairs required	N/A	1.241 (0.431 to 1.978)	N/A	1.234 (0.408 to 2.041)
Median income	N/A	N/A	0.018 (0.001 to 0.035)	0.019 (0.003 to 0.035)

*All of the four Poisson log-linear models include spatial and non-spatial random effects.
DIC, deviance information criterion.

spatial dependence (ie, neighbouring areas might have similar counts of falls) via an intrinsic conditional autoregression model. It acts as a surrogate for missing covariates or measurement errors that have a spatial pattern.[21 22]

We derived E_i, the expected number of falls in each area, using indirect (internal) standardisation for age and sex, a common approach in small-area analysis that accounts for risks in different age groups and sex.[22–24] Population data for older people, at the dissemination area level, from the 2001 census were used to calculate the expected counts for 2002 and 2003, and population data from the 2006 census were used to calculate the expected counts for 2004, 2005 and 2006.[15] The age groups used in the analysis include ages 65–69, 70–74, 75–79, 80–84 and 85 years and older.

In the Bayesian approach, information from the data (eg, observed counts of falls in older people) and previous information about the parameters of interest (eg, regression coefficients follow a normal distribution) are combined to produce the joint posterior distributions of the parameters. Often, the mean or median of the posterior distribution is used to summarise the estimated value of a parameter. The Bayesian approach allows the spatial model to be fitted using Markov chain Monte Carlo simulation. The model, which contains a spatial random effects term, is difficult to fit using standard (frequentist) approaches, but can be fitted more straightforwardly using a Bayesian simulation approach with WinBUGS.[25] Each of the fitted models was run using two chains with differing initial values to assess convergence. Convergence was checked by a visual inspection of the iterative series and by using the Gelman–Rubin diagnostic. The first 10 000 iterations were discarded as burn-in, and the next 10 000 iterations were used as samples. Vague priors reflecting prior ignorance were used for the regression coefficients. Prior information specified for both coefficients is a normal distribution with an expected mean of 0 and a precision of 0.00001. Details for specifications and the fitting of this model have been discussed extensively in the literature.[21 26] The deviance information criterion (DIC) is a generalisation of the Akaike information criterion, compares the performance of Bayesian models that contain different sets of covariates. In comparing models, the DIC (output from WinBUGS) takes into account both model fit and model complexity. The model that gives the smallest DIC is the best model.[22]

We used probability mapping (that maps the statistical significance of risks rather than the risks themselves) to present the proportion of simulations, in which a dissemination area has a RR of hospitalisation following falls among older people in the WDG health region greater than 1.[21] Map decomposition was used to visualise the results of the final model.[21 22] Based on the Poisson log-linear model, the RR of falls in older people in area i was decomposed into four main components: $\exp[\beta_0]$, $\exp[\beta_k X_{k,i}]$, $\exp[U_i]$, $\exp[S_i]$. Maps with the posterior means of the parameters were drawn using ArcMap 9.3.[27] They display areas with high RR of falls in older people, and inform whether the covariate(s), non-spatial, or spatial random effects contributed most to the RR for each area.

RESULTS

The average annual rate of hospitalisation due to falls among older people is 1838 per 100 000 population, which is slightly higher than the 2007 rate provided by the Ontario Ministry of Health and Long-Term Care.[13] Consistent with previous reports, the majority of these cases were women (1946, 71.8%) versus men (766, 28.2%).[2 3] The number of falls in older people was higher in older population groups. People 85 years of age and older comprised 37.9% of the cases of falls among older people.

Analytical results from the model fitted with each of the covariates shown in box 1 revealed that the percentage of occupied private dwellings requiring repairs (hereinafter referred to as 'repairs required') and the median income of the population aged 15 years and over before tax (hereinafter referred to as 'median income') were significantly associated with falls in older people at a 95% credible interval (interval in which

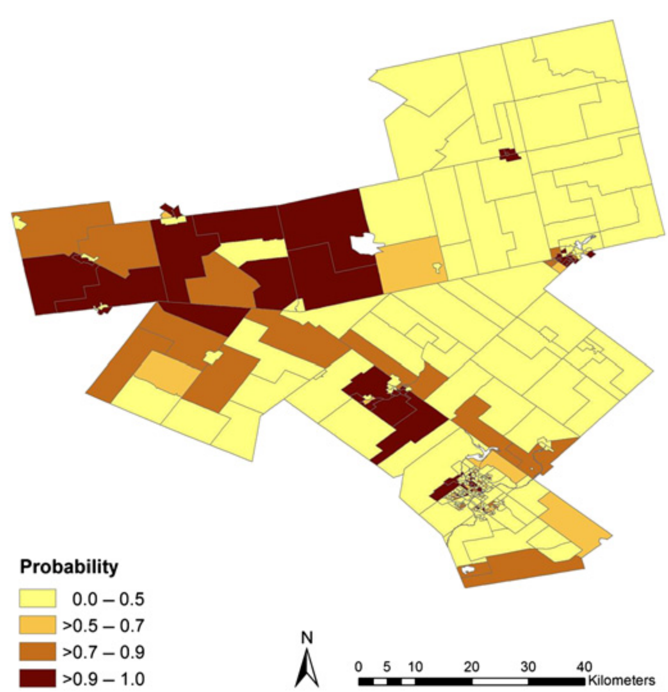

Figure 1 Probability mapping of the proportion of simulations when a DA has a relative risk of hospitalisation following falls among older people in the WDG health region greater than 1.

the probability under the posterior distribution is 0.95).[21] A summary of statistics of these two variables is presented in table 1. Three models (comprising different sets of covariates in the Poisson model) based on repairs required and median income were then compared with the model without any covariates (β_0 only) to identify the best model. As shown in table 2, model 1 contains no covariate; model 2 contains the covariate of repairs required; model 3 contains the covariate of median income; and model 4 contains the covariates of repairs required and median income. The DIC for model 4 is the smallest and thus was selected as the best model.

Figure 1 presents the estimated probabilities of dissemination areas with RR of hospitalisation greater than 1 using the final model. There are 109 dissemination areas with probabilities of over 0.5, and more than 50 dissemination areas with probabilities of or close to 1. As shown in figure 2, 26 dissemination areas had high RR of falls in older people of more than 2, and the highest RR is 7. An area with three neighbouring dissemination areas in the Wellington County had RR over 3. Map decomposition of the final model indicates that while repairs required and median income explained some of the RR of hospitalisation following falls among older people, risks are also affected by unmeasured factors (figure 2). These factors have spatial patterning, whose effects are reflected in the spatial random effect terms.[21 22]

DISCUSSION

This study identified an association between the percentage of occupied private dwellings requiring repairs and hospitalisation due to falls among older people after controlling for the median income of the population aged 15 years and over before tax in

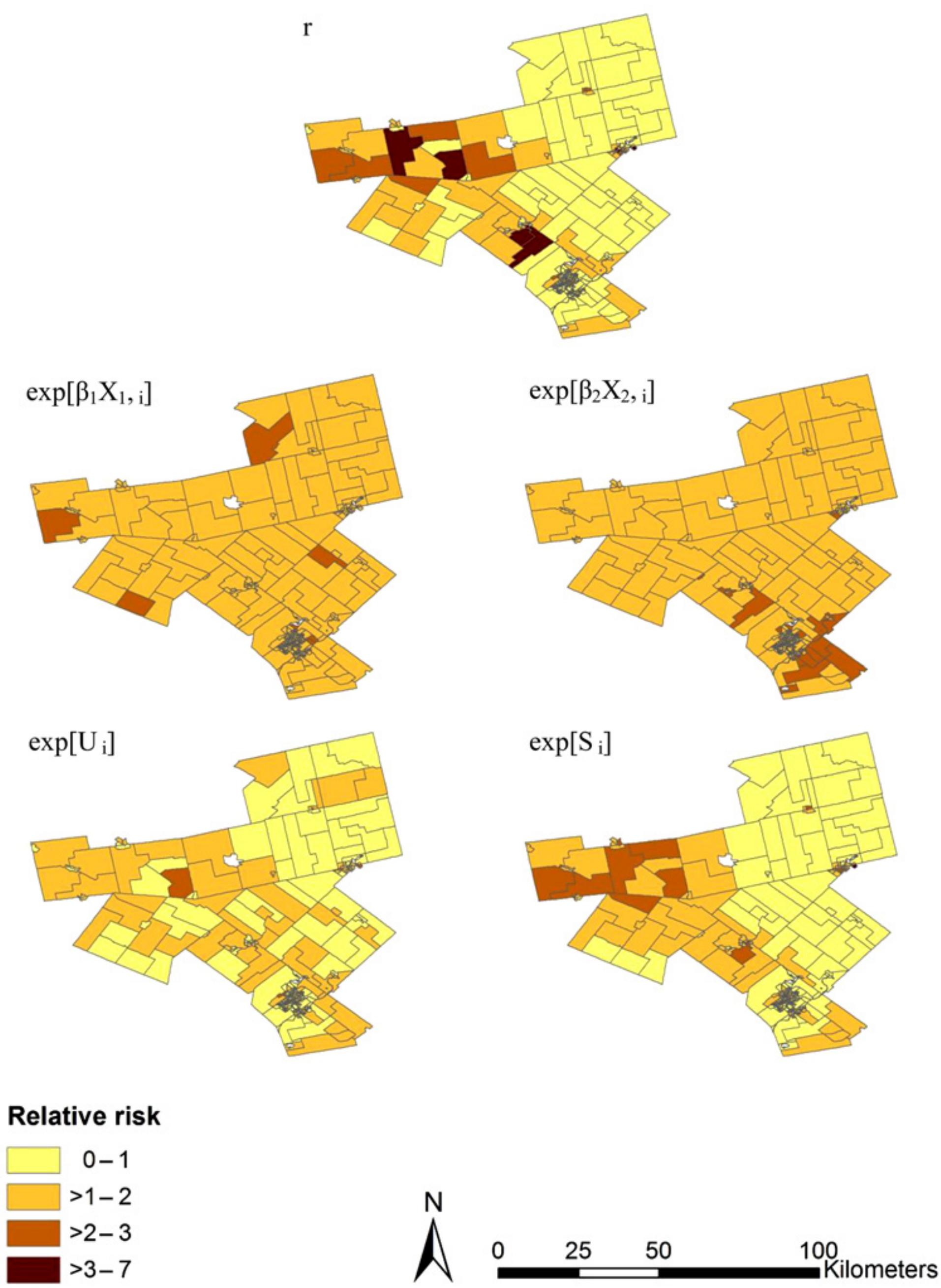

Figure 2 Map decomposition of the relative risk (r) of falls in older people into the components associated with repairs required (exp[β1X1, i]), median income (exp[β2X2, i]), spatial random effects (exp[S i]), and non-spatial random effects (exp[U i]) of the final model (Model 4).

the WDG health region. The covariate repairs required refers to repair of defective electrical wiring or plumbing, structural repairs to walls, floors, or ceilings, and repair of missing or loose floor tiles, bricks or shingles, defective steps, railing or siding.[15] This excludes desirable remodelling or additions. Housing that requires repairs implies the presence of environmental hazards that may lead to falls. In general, older people spend only half as much on home maintenance as younger home owners of similar housing.[28] Older people living in housing that requires repairs may not be spending money to remove the environmental hazards at their home, especially if they are financially constrained. Home hazard modification is an important part of multifaceted strategies to prevent falls and falls-related injuries among older people.[9] Older people living in housing that requires repairs may be a useful indicator to include in falls prevention research and initiatives for older people. Further research that covers other regions and study periods is warranted to investigate the risk of falls among older people living in housing that requires repairs. This study also identified a number of dissemination areas with a high RR of falls in older people in the WDG health region, including an area with three neighbouring dissemination areas in the Wellington County. Additional investigation, such as site visits to these areas and conversations with the local health and social security agencies, can be helpful in exploring whether older people living in these dissemination areas do have a higher risk of falls.

While repairs required and median income are both shown to be associated with falls in older people, results from map decomposition show that the risk of falls among older people in the WDG health region is still affected by some random effects. These random effects may be due to measurement errors or the multifactorial nature of non-syncopal falls—intrinsic and extrinsic factors may interact in their effects on the risk of falls. An environmental feature that may be hazardous for some older people may not be so for others, as a result of differences in physical and cognitive abilities.[7 8] For this study, covariates related to intrinsic factors of falls among older people were not available and therefore could not be included to explore the impact of intrinsic factors on extrinsic factors of falls in older people. Our analysis is exploratory. Further study controlling for extrinsic as well as intrinsic factors at the individual level is warranted.

There are several limitations to this study. As the indicator for repairs required is expressed in terms of dwellings rather than individuals, the extent to which individual older people are affected by such defects in housing conditions is unknown. Also, the variable repairs required is a self-reported variable from the census; the definition of housing requiring repairs may differ between individuals. While hospitalisation data are a good indicator of the prevalence of falls among older people, not all older people who fall seek medical attention at the hospital, and less severe cases would not be captured. The hospitalisation data were requested by WDGPH from the Ontario provincial health planning database, and not all variables were requested, including the location of occurrence of individual cases. Therefore, there is no information on the location of the fall, and it is assumed that the incident happened at the older person's residence. Data on the location of nursing and old people's homes were not included in the study. However, such data will be obtained from WDGPH for further research to account for varying numbers of nursing and old people's homes in each area. The problem of re-hospitalisation may exist because data were provided at the record level and were not patient specific, and this may inflate some of the case counts in certain dissemination areas. We attempted to minimise this problem by calculating the expected falls on a yearly basis; that is, we assumed that no older person was hospitalised due to a fall more than once in a year. It was also found that the geocoding method used by WDGPH produced different results compared with those relying solely on Statistics Canada's PCCF+ as a basis for assigning dissemination areas to the cases. PCCF+ is a commonly used geocoding method, but like the geocoding method used by WDGPH, it has its limitations. It is beyond the scope of this paper to evaluate geocoding methods used in Canada.

Some of the work in this study will be useful to injury and public health research. The spatial model, which can be fit using a Bayesian approach, to account for overdispersion and missing or unknown covariates, can be applied to future studies. The results of models fitting by Bayesian methods enable the application of map decomposition, displaying which components contribute most to areas with high RR. Probability mapping addresses the small number problems in small-area analysis by mapping the statistical significance of risks rather than the risks themselves. It utilises the information on the entire posterior distribution of the probabilities, which provides further information on the relationship between each dissemination area, and whether a specific dissemination area has risks of hospitalisation following falls among older people that are significantly higher than the population risk. The analysis of raw counts instead of calculated rates of health outcome minimised the small-area problem and yielded more reliable results.

To the best of our knowledge, there has not been a study that identified an association between falls in older people and occupied private dwellings requiring repairs. The association remains significant after controlling for income. Our findings have the potential to contribute to future research in reducing falls in older people. We hope that this study will generate interest in using Bayesian spatial modelling approaches in injury and public health research.

What is already known on the subject

- Fall-related hospitalisations among older people is a growing concern.
- Risk factors related to older people's built environment and socioeconomic status are associated with falls in older people.
- Housing and income are recognised as determinants of health, but there is limited research that studies the relationship between falls and these determinants.

What this study adds

- A potential association between occupied private dwellings requiring repairs and falls in older people after controlling for median income.
- Demonstrated the use of Bayesian spatial modelling approaches in injury research, especially on falls in older people, and how to apply these methods in local public health units.

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Competing interests None.

Contributors WCC, JL, and PS conceived the idea of the study. PS provided the geocoded data for the study. JL designed the statistical models and analysis strategy, and supervised the study. WCC performed the literature review and most of the statistical analyses, and wrote the first draft. All authors read, edited and approved the final version of the paper.

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