

Title: Comparing lagged impacts of mobility changes and environmental factors on COVID-19 waves in rural and urban India: a Bayesian spatiotemporal modelling study

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1 **Abstract**

2 Previous research in India has identified urbanisation, human mobility and population
3 demographics as key variables associated with higher district level COVID-19 incidence.
4 However, the spatiotemporal dynamics of mobility patterns in rural and urban areas in India,
5 in conjunction with other drivers of COVID-19 transmission, have not been fully investigated.
6 We explored travel networks within India during two pandemic waves using aggregated and
7 anonymized weekly human movement datasets obtained from Google, and quantified changes
8 in mobility before and during the pandemic compared with the mean baseline mobility for the
9 8-week time period at the beginning of 2020. We fit Bayesian spatiotemporal hierarchical
10 models coupled with distributed lag non-linear models (DLNM) within the integrated nested
11 Laplace approximate (INLA) package in R to examine the lag-response associations of drivers
12 of COVID-19 transmission in urban, suburban, and rural districts in India during two pandemic
13 waves in 2020-2021. Model results demonstrate that recovery of mobility to 99% that of pre-
14 pandemic levels was associated with an increase in relative risk of COVID-19 transmission
15 during the Delta wave of transmission. This increased mobility, coupled with reduced
16 stringency in public intervention policy and the emergence of the Delta variant, were the main
17 contributors to the high COVID-19 transmission peak in India in April 2021. During both
18 pandemic waves in India, reduction in human mobility, higher stringency of interventions, and
19 climate factors (temperature and precipitation) had 2-week lag-response impacts on the R_t of
20 COVID-19 transmission, with variations in drivers of COVID-19 transmission observed across
21 urban, rural and suburban areas. With the increased likelihood of emergent novel infections
22 and disease outbreaks under a changing global climate, providing a framework for
23 understanding the lagged impact of spatiotemporal drivers of infection transmission will be
24 crucial for informing interventions.

25

26 **Keywords:** COVID-19; human mobility; non-pharmaceutical interventions; travel restriction;
27 climate; INLA; DLNM; Bayesian spatiotemporal model; lag-response; India.

28

29 **Introduction**

30 The COVID-19 pandemic highlighted the intrinsic role of human movement, along with
31 demographics and environmental factors, in the dispersal of human pathogens in a highly
32 connected, mobile and globalised society.¹⁻³ As the global climate changes and environmental
33 and extreme weather events increase in frequency, emergence of novel zoonotic diseases and
34 outbreaks of bacterial, parasitic and viral infections are likely to become more frequent⁴.
35 Effective and efficient responses to future outbreaks and epidemics require a thorough
36 understanding of the infection transmission drivers that contributed to different COVID-19
37 pandemic waves. Furthermore, it is essential to develop a framework for examining the
38 spatiotemporal variations in transmission drivers across urban, suburban, and rural areas.

39 In India, the initial wave of COVID-19 was contained by a nationwide lockdown, which
40 extended from March 31st to May 31st, 2020,⁵ with a subsequent phased lockdown for
41 containment zones in effect until June 30th, 2020.⁶ The first wave of COVID-19 transmission
42 in India was characterised by mild clinical infection and a relatively low mortality rate of less
43 than 3%.⁵ Several serosurveys carried out following the initial pandemic wave in India
44 determined a high proportion of asymptomatic infections⁷⁻¹⁰, leading to speculation as to the
45 reasons for lower incidence of severe clinical cases including population demographics and
46 innate population immunity.^{11,12}

47 In March 2021, India experienced a severe second wave of COVID-19 transmission
48 with a high proportion of infection associated mortality.¹³ The Delta variant, or B.1.617
49 lineage, dominant during the second transmission wave was first identified in Maharashtra in
50 late 2020¹⁴ before quickly spreading throughout India and to at least 90 other countries.¹⁵

51 Compared with the initial pandemic wave in India, the Delta wave was characterised by high
52 morbidity and mortality, even among a younger age cohort, overwhelming health systems
53 across the country.^{16,17} On April 26th 2021, India recorded 360,960 new cases, at the time the
54 highest number of daily new SARS-CoV-2 infections recorded worldwide,¹⁸ and by mid-June
55 2021 more than 29 million cases of COVID-19 had been confirmed.¹⁹ During the second
56 pandemic wave, the number of COVID-related deaths in India ranked third globally with an
57 estimated 2.7 million COVID-19-related deaths occurring between April and July 2021.²⁰

58 Although reasons for the second wave of transmission were unclear, it was speculated
59 that the surge in case numbers was attributed to the circulation of the B.1.617 lineage of SARS-
60 CoV-2 (Delta variant), which had a more effective transmission capability, shorter incubation
61 period and was more pathogenic than previous lineages.^{17,21,22} Prior to this surge in
62 transmission, adherence to COVID-19 preventative behaviours in India was less stringent,
63 likely due to pandemic fatigue, economic necessity and complacency due to the perception
64 that clinical case infections in India were mild relative to other populations.^{16,23} Population
65 mobility, which had begun to increase relative to mobility during national lockdown
66 interventions, including rural-urban-rural migration to mass election rallies and social and
67 religious gatherings such as Kumbh Mela (approximately 7 million people), was also likely to
68 be a primary driver of the second wave of SARS-CoV-2 in India.^{13,15}

69 Previous research has explored the relationship between human mobility in response to
70 government interventions and COVID-19 transmission during the early stages of the pandemic
71 ^{24,25,26}, or state level associations between human mobility and COVID-19 transmission during
72 the Delta pandemic wave.²⁷ However, no previous research has compared mobility patterns, or
73 inter-district movement across both pandemic waves, relative to pre-pandemic mobility levels,
74 and associated impact on COVID-19 transmission. The contribution of district level
75 urbanisation,^{28,29} population density and demographics,^{30,31} climate^{32,33} and stringency of

76 government interventions²⁴ to COVID-19 transmission in India has also previously been
77 investigated. However methodological approaches have included simple correlation^{24,30} or
78 regression analyses³⁴ and, to the best of our knowledge, no spatiotemporal modelling approach
79 has been used to explore the urban-rural district level associations of human mobility,
80 stringency of government intervention, and climate to transmission risk across both pandemic
81 waves in India.

82 In this study, we quantified changes in mobility patterns and travel networks across
83 India, before and during the COVID-19 pandemic, using spatially resolved, aggregated and
84 anonymized weekly human movement datasets obtained from Google. We used a Bayesian
85 spatiotemporal hierarchical framework, coupled with distributed lag non-linear models
86 (DLNM) to examine the lag-response associations between the transmission dynamics of
87 COVID-19 and drivers of transmission during the initial wave (July to November 2020) and
88 Delta wave (March to July 2021) of SARS-CoV-2 in India. We also compared the lagged
89 impacts of mobility metrics, climate covariates, and stringency of government interventions on
90 the transmission of SARS-CoV-2 lineages between both pandemic waves, and across urban,
91 suburban and rural delineated districts.

92 **Methods**

93 **Data sources**

94 *Covid-19 incidence data*

95 In India, administrative units are divided in state (36 including eight union territories), district
96 and township, corresponding to spatial administrative levels I, II and III, respectively (**SI**
97 **Figure S1**). The daily number of confirmed COVID-19 cases at country level were obtained
98 from the Data Repository assembled by the Centre for Systems Science and Engineering
99 (CSSE) at Johns Hopkins University³⁵. We also obtained COVID-19 data at district (admin II)
100 level for the period from 26 April 2020 to 31 October 2021 for 666 districts from

101 www.covid19india.org, a volunteer driven, crowdsourced tracker for COVID-19 cases in
102 India.³⁶ COVID-19 data were available in 666 district units, as in some cases, depending on
103 testing capacity and guidelines in each federal state, data were aggregated to state level only or
104 case incidence estimated by state pool.³⁶

105 Administrative level I and II shapefiles for India, corresponding with state and district
106 level, were obtained from the Database of Global Administrative Areas (GADM version 3.6)
107 (<https://gadm.org/>). Since the last national census of population in India in 2011, new districts
108 have been created by splitting and rearranging some administrative boundaries.³⁰ COVID-19
109 data aggregated to current district boundaries were merged with 2011 administrative level II
110 units according to the best spatial alignment of current and previous district boundaries. For
111 the purpose of spatial modelling, the islands in Lakshadweep and the Andaman Islands have
112 been unified as discrete spatial areas and treated as distinct districts. The authors remain neutral
113 with regard to jurisdictional claims in maps used in this study.

114 ***Google COVID-19 Aggregated Mobility Research Dataset***

115 Aggregated and anonymized weekly human movement datasets were obtained from Google to
116 measure the changes of mobility across and within regions from November 10, 2019, to
117 December 31, 2021, and to assess their impacts on COVID-19 transmission in India. The
118 Google mobility dataset contains anonymized mobility flows aggregated over users who have
119 turned on the Location History setting, which is off by default. This is similar to the data used
120 to show how busy certain types of places are in Google Maps — helping to identify when a
121 local business tends to be the most crowded. The dataset aggregates flows of people between
122 S2 cells, which here is further aggregated by district of origin and destination. Each S2 cell
123 represents a quadrilateral on the surface of the planet and allows for efficient indexing of
124 geographical data.

125 To produce this dataset, machine learning was applied to log data to automatically
126 segment data into semantic trips.^{37,38} To provide strong privacy guarantees, all trips were
127 anonymized and aggregated using a differentially private mechanism to aggregate flows over
128 time (see <https://policies.google.com/technologies/anonymization>). This research is done on
129 the resulting heavily aggregated and differentially private data. No individual user data was
130 ever manually inspected, only heavily aggregated flows of large populations were handled. All
131 anonymized trips are processed at aggregate level to extract their origin, destination, location
132 and time. For example, if users travelled from location a to location b within time interval t,
133 the corresponding cell (a, b, t) in the tensor would be $n\bar{F}err$, where err is Laplacian noise. The
134 automated Laplace mechanism adds random noise drawn from a zero mean Laplace
135 distribution and yields (ϵ, δ) -differential privacy guarantee of $\epsilon = 0.66$ and $\delta = 2.1 \times 10^{-29}$. The
136 parameter ϵ controls the noise intensity in terms of its variance, while δ represents the deviation
137 from pure ϵ -privacy. The closer they are to zero, the stronger the privacy guarantees. Each user
138 contributes at most one increment to each partition. If they go from a region A to another region
139 B multiple times in the same week, they only contribute once to the aggregation count.

140 The summed weekly domestic mobility inflows and outflows of each district were then
141 divided by the number of origin S2 cells (each was calculated only once) that contained data
142 between November 10, 2019 and December 31, 2021. Any potential bias that might be
143 introduced by discarding the increasing number of S2 cells in order to protect privacy due to
144 the decreasing number of travellers under travel restrictions was accounted for. For
145 comparability of changes in mobility across districts, aggregated flows were further
146 standardised using pre-pandemic mean baseline levels of mobility for the first eight weeks of
147 2020 (December 29, 2019 – February 22, 2020) (**SI Figure S2 – S4 & Figure S29**). This
148 dataset was analysed by researchers at the University of Southampton, UK as per the terms of

149 the data sharing agreement. Production of this anonymized and aggregated dataset has been
150 detailed in previous studies.^{3,37-39}

151 *Stringency of COVID-19 Intervention*

152 Stringency Index of COVID-19 intervention policy in India data were obtained from the
153 Oxford COVID-19 Government Response Tracker (OxCGRT) project at state level and daily
154 temporal resolution (**SI Figure S5 & S30**). The Stringency Index is a composite index of
155 government responses to the COVID-19 pandemic compiled by OxCGRT based on data
156 collected from publicly available sources such as news articles, and government press releases
157 and briefings from 1 January 2020.^{40,41} The project tracks national government policies and
158 interventions across a standardized series of indicators and creates a suite of composite indices
159 to measure the extent of these responses to understand how government responses evolved over
160 the course of the pandemic.⁴¹ The Stringency Index was calculated as a composite score of 18
161 indicators of closure and containment, health, and economic policy.^{24,40} Scores were created
162 using an additive unweighted approach, taking the ordinal value and adding a weighted
163 constant if the policy was general rather than targeted. The maximum values were rescaled to
164 create a score ranging from 0 to 100, with higher scores indicating stricter measures.⁴⁰
165 Stringency index data for India were obtained from 27th April 2020 to 25th July 2021.

166 *Climate data*

167 Three-dimensional Network Common Data Form (NetCDF) climate data were obtained from
168 the Copernicus Climate Data online repository (Copernicus Climate Change Service, Climate
169 Data Store, (2023): ERA5 hourly data on single levels from 1940 to present. Copernicus
170 Climate Change Service (C3S) Climate Data Store (CDS), DOI: [10.24381/cds.adbb2d47](https://doi.org/10.24381/cds.adbb2d47)
171 (Accessed on 19-05-2023). Data were ERA5 daily reanalysis global climate data obtained for
172 January 2019 to March 2021, gridded to 0.25 degrees of latitude and longitude. Variables
173 obtained were mean temperature of air (°C at 2m above the surface of land, sea or inland

174 waters), accumulated precipitation (metres), relative humidity (%) and downward ultraviolet
175 (UV, KJ/m^2 per hour) radiation at the Earth's surface (**SI Figures S6-S9 & S31 – S34**).

176 ERA5 data is the fifth generation of European Centre for Medium-Range Weather
177 Forecasts (ECMWF) reanalysis for the global climate and weather for the past 4 to 7 decades.
178 Reanalysis is a method of combining model data with global observations for producing
179 complete and consistent datasets for a large number of atmospheric, ocean-wave and land-
180 surface quantities. Reanalysis works in the same way as the principle of data assimilation which
181 combines previous forecasts with newly available observations on a 12-hour basis to produce
182 new best estimates of atmospheric measures.⁴² Climate data were extracted from NetCDF files
183 using the `ncdf4`^{40,43} and `RNetCDF`⁴⁴ packages in R statistical software version 4.1.0 and
184 aggregated to district level using Quantum Geographic Information Systems (QGIS)
185 software.⁴⁵

186 ***Urban and rural classification***

187 Data on the degree of urban, rural and suburban spatial area within each district (administrative
188 level II) were derived from the Global Human Settlement Layer (GHSL)⁴⁶ using the Degree of
189 Urbanisation – Territorial units classifier (GHS-DU-TUC) tool. The GHS-DU-TUC tool
190 classifies local units from a settlement classification grid according to the Degree of
191 Urbanisation (DEGURBA). It operationalises the method recommended by the 51st Session of
192 the United Nations Statistical Commission to delineate cities, urban and rural areas (stage
193 2, units classification) as defined by the Degree of Urbanisation Level 1 and 2. Categorized
194 variables for each degree of urbanisation (DEGURBA_L1_1 to DEGURBA_L1_3) were
195 generated for degree of urban vs. rural spatial area in each district area in accordance with
196 methods for implementation of INLA models outlined in Lezama-Ochoa *et al.* 2020.⁴⁷

197 Degree of urbanisation was categorised as follows: (1) Rural (mostly thinly populated
198 areas), (2) Suburban (mostly intermediate density areas), and (3) Urban (mostly densely

199 populated areas). Population data for 2020 were obtained at 100m spatial resolution from the
200 WorldPop online repository (<https://www.worldpop.org/>) and aggregated to calculate
201 population density per km² for each district. Data on public holidays time periods were
202 obtained from the National Portal of India online repository (<https://www.india.gov.in/>). Public
203 holidays, which included the date of public holiday and one day before and after, were assigned
204 a value of 1. All other days were given a value 0.

205 **Data analysis**

206 *Exploring changes in mobility in India during the pandemic*

207 To gain a better understanding of travel networks and connectivity across India, we explored
208 the overall patterns in domestic travel by rural, semi-urban and urban delineated areas in India,
209 using weekly Google mobility data from November 10, 2019, to December 31, 2021. The
210 relative levels of mobility across regions (regions are defined as six zones comprising different
211 states in India defined under the States Reorganisation Act 1956⁴⁸) and weeks were further
212 calculated for each type of flow, relative to the mean level of pre-pandemic baseline in each
213 region from December 29, 2019, to February 22, 2020. We also defined mobility reductions
214 and communities of population movements between administrative level II units, i.e. districts,
215 across the country for five periods (**SI Figure S2 - S3**): 1)

216 Pre-pandemic period (15 weeks) from November 10, 2019 to February 22, 2020; 2)
217 First lockdown (6 weeks), from March 22 to May 2, 2020, that included strict travel restrictions,
218 stay-at home orders and closure of many businesses; 3) Pre-second lockdown period (8 weeks)
219 from January 31 to March 27, 2021; 4) Second lockdown (6 weeks) for the Delta wave, from
220 April 18 to May 29, 2021; 5) post-second lockdown period (8 weeks), from November 7 to
221 December 31, 2021, after travel restrictions for COVID-19 had been lifted in India. In the
222 context of travel networks, a community refers to a group of areas that are more closely
223 connected internally than with other areas in the network.^{49,50} Community structures were

224 detected using the Louvain algorithm, a method of extracting communities from large
225 networks.⁴⁹ We mapped the communities identified to highlight distinct geographic groupings
226 of districts in terms of movements across periods.

227 ***Reproduction number***

228 To account for variations in the transmissibility of COVID-19, we estimated the instantaneous
229 reproduction number (R_t) for each district of the country with available case data (**SI Figure**
230 **S10 & S35**). First, the number of daily new COVID-19 cases at district level were smoothed
231 using a Gaussian smoothing approach over a 7-day rolling window.⁵¹ Second, the mean
232 incidence of cases at day t was assumed following the Poisson distribution that is defined as:

$$233 \quad E(I_t) = R_t \sum_{k=1}^t I_{t-k} w_k$$

234
235 where I_{t-k} is the incidence at time $t - k$, w_k is the infectivity profile which depends on the
236 serial interval of COVID-19 (5.2, 95%CI: 4.9–5.5).⁵² The serial interval represents the time
237 between onset of the primary case to onset of the secondary case. Last, we estimated the daily
238 R_t for each district with a 7-day sliding window, using the EpiEstim package⁵³ in R statistical
239 software version 4.1.0.⁵⁴

240 In order to account for changing transmissibility of COVID-19 caused by different
241 variants in the modelling, we also estimated the instantaneous basic reproduction number (R_0)
242 over time to capture the intrinsic transmission capability of the virus without interventions. We
243 first assembled data of the biweekly proportion of sequences of six main SARS-CoV-2
244 variants, including lineages B.1.1.7 (VOC Alpha), B.1.351 (Beta), P.1 (Gamma), B.1.617.2
245 (Delta), B.1.525 (Eta), and B.1.617.1 (Kappa), based on SARS-CoV-2 sequence data in the
246 Global Initiative on Sharing All Influenza Data (GISAID),⁵⁵ as of 25 October 2021. Using an
247 approach described by Ge *et al.*,⁵⁶ we then calculated a weighted average of basic reproduction

248 numbers of the six variants mentioned above and the SARS-CoV-2 strain in circulation before
249 VOCs became predominant (seven coronavirus variants in total).

250 *Models for examining lag-response associations between COVID-19 transmission and*
251 *different factors*

252 We built spatiotemporal Bayesian hierarchical models which consisted of weekly changes in
253 the R_t of COVID-19 transmission for 665 India districts where data were available during 17
254 weeks from March 7 to July 3, 2021 (Delta wave) and during the 19 weeks between July 19th
255 2020 and November 29th 2020 (wave 1). We assumed that R_t adjusted by R_0 , denoted as ΔR_t
256 $= R_t/R_0$, conformed to the Gamma distribution, $\Delta R_t | \mu_t \sim \text{Gamma}(\frac{\mu_t}{0.5}, 0.5)$, where μ_t was
257 the corresponding distribution expectation (or mean), reflecting the shape-rate parameterisation
258 of the Gamma distribution used by the INLA package. Spatial and temporal fixed effects were
259 accounted for in the model by incorporating terms for district and week, representing the spatial
260 resolution of the data, and time scale during which data was collected. Spatiotemporal random
261 effects were included to account for unobserved and unmeasured sources of variation in
262 transmission and spatial and temporal dependency structures. First, for the expectation of ΔR_t
263 within each city i , we constructed a base model below with two spatiotemporal random effects,
264 r_t and b_i , and a fixed effect $v_{i,t}$

265
$$\mu_{i,t} = 1 + r_t + b_i + v_{i,t}$$

266 where $\Delta r_t = r_t - r_{t-1} \sim N(0, \tau^{-1})$ is a random walk model of order 1 (rw1), used to account
267 for data temporality; b_i is a modified Besag-York-Mollie (BYM2) model for space, used to
268 account for spatial variation across districts in the data; and the fixed effect $v_{i,t}$ of the
269 cumulative infection rate among population was also included in the base model, as it might
270 be related to herd immunity acquired by natural infection in previous waves before mass
271 vaccination.

272 Second, as the evolution of COVID-19 is a complex process, and factors mentioned
273 above might not be the only explanatory variables for the observed changes in transmission,
274 we further examined the duration of public holidays as a fixed effect in models. All covariates
275 obtained at daily temporal resolution were averaged by week. To account for multicollinearity
276 of factors, we calculated pair-wise Pearson correlations for these variables and the variance
277 inflation factor (VIF) for candidate variables in linear regressions for the whole country (**SI**
278 **Figure S11 & S36**). In order to account for any non-normally distributed data, we also
279 calculated Kendall rank coefficients between explanatory variables in our model as a non-
280 parametric exploration of multicollinearity (**SI Figure S12 & S37**). Estimations of
281 multicollinearity were broadly similar using Pearson and Kendall rank correlation coefficients,
282 with weaker associations found using Kendall rank coefficients. Collinear variables were
283 therefore excluded based on the more conservative Pearson correlation coefficients. Variables
284 with the highest VIF score and Pearson correlation coefficients of 0.5 which were excluded
285 included relative humidity and UV, and only variables with a VIF score of less than 2.5 were
286 retained. The relative impacts of remained factors, thus, was defined as the contributed
287 percentage change in ΔR_t .

288 We built models of increasing complexity by systematically incorporating
289 combinations of mobility, temperature, precipitation, stringency of intervention policy and
290 public holidays covariates into our base model. Model goodness of fit was assessed using the
291 deviance information criterion (DIC) and logarithmic score (logscore), consistent with
292 previous studies⁵⁷, and final models for each pandemic wave selected. DIC balances model
293 accuracy against complexity by estimating the number of effective parameters, while the
294 logarithmic scores measure the predictive power of the model when excluding one data point
295 at a time, with smaller values for each denoting better fitting models.

296 Third, we used the distributed lag non-linear models (DLNMs) formulation by defining
297 lagged model covariates and a cross-basis matrix and incorporating the resulting cross-basis
298 functions into our Bayesian spatiotemporal modelling framework. Using this approach we
299 explored exposure-lag response associations between the relative risk (RR) of increase R_t in
300 COVID-19 transmission, and changes in mobility, meteorological variations, and Stringency
301 Index of intervention policy. DLNMs are a family of models that describe the lagged
302 relationship between exposure and response variables in a model across both spatial and
303 temporal dimensions.⁵⁸ DLNM models incorporate cross-basis functions that combine a lag-
304 response function of variables at the temporal dimension and an exposure-response function to
305 present the potential non-linear relationship along with the change of one factor. The resulting
306 bi-dimensional exposure-lag-response function flexibly estimates the intensity of factors at
307 varying time-lags after exposure.⁵⁸

308 Given the common delays from infection to diagnosis and reporting, the lag-response
309 impact of different factors on COVID-19 transmission were assessed by 0-3 weeks, with
310 natural cubic splines selected for both the exposure and the lag dimensions. Last, we tested 18
311 candidate models of increasing complexity (with regard to input variables and model structure)
312 with DLNMs for the whole country, and rural, suburban, and urban areas, respectively (**SI**
313 **Table S2**). DLNM cross-basis functions were built using R packages ‘dlnm’ and ‘splines’ and
314 model parameters were estimated using the Integrated Nested Laplace Approximation (INLA)
315 approach in R version 4.1.0.^{54,60} INLA approaches include a wide and flexible class of models
316 ranging from generalized linear mixed models to spatial and spatiotemporal models that are
317 less computationally intensive therefore avoiding problems with model convergence.⁵⁹⁻⁶¹

318 Finally, as no informed prior distribution estimates were available at the time of
319 analyses, we explored the sensitivity of the best fit model to a range of uninformative priors.
320 We specified a range of priors around the hyperparameters, i.e., τ , θ_1 , and θ_2 , in our base

321 model. Prior distributions were investigated for the best fit model using data for the Delta wave
322 time period (**SI Table S4**) and for the wave 1 time period (**Tables S7**) using the deviance
323 information criterion (DIC). The choice of prior distributions applied to best fit models using
324 data from both waves was found to elicit only negligible measurable differences in model
325 hyperparameters and DIC. Therefore, the prior used in this study was a penalized complexity
326 prior with the precision $t = 1 / \sigma^2$, so that $\Pr(1/\sqrt{t} > 0.5) = 0.01$.

327 ***Model performance and validation***

328 Model goodness-of-fit was assessed using DIC scores to compare model performances
329 and identify the best-fitting model for the whole country, and rural, suburban, and urban areas,
330 respectively. We also calculated the difference in mean absolute error (MAE) between the
331 baseline model and the final selected model for each pandemic wave in order to identify the
332 proportion of districts in different regions of India for which a more complex data-driven model
333 improved model fit. Cross-validations using a leave-one-week-out and leave-one-state out
334 approach were conducted to refit the selected model. This approach excluded one week or one
335 state, respectively, from the fitting process during each cross-validation model iteration.
336 Comparisons were made between observations and out-of-sample posterior predictive R_t for
337 state and each week of both pandemic waves investigated. In order to validate DLNM model
338 results, based on the findings of lag-response associations from analyses above, we
339 incorporated lag-adjusted covariates into our spatiotemporal Bayesian hierarchical modelling
340 and compared results with observations obtained from Bayesian spatiotemporal models
341 incorporating DLNM models built using cross-basis functions.

342 **Results**

343 ***Spatiotemporal heterogeneity of mobility changes in India during the pandemic***

344 Compared with baseline mean mobility patterns during the first 8 weeks of 2020, domestic
345 travel within India dropped dramatically after the COVID-19 pandemic was declared by the

346 WHO and the country implemented its first lockdown for transmission containment (**Figure**
347 **1**). The lowest mobility level for domestic travel (26.9% of the pre-pandemic mean level) was
348 observed at week 15 of 2020 (April 5 – 11, 2020). In June 2020, restrictions on opening
349 shopping centres, religious places, hotels, and restaurants were lifted [32], coinciding with
350 increased population flows and an increase in infection cases. Overall, mobility gradually
351 recovered from mid-May 2020 to early March 2021, even during the first wave of COVID-19
352 in the second half of 2020.

353 Following a surge in transmission in March 2021, and concern about increased
354 infections and deaths caused by the Delta variant, another lockdown was implemented across
355 the country from mid-April to early June 2021. Domestic mobility during the second lockdown
356 reduced significantly from an average level of 90.5% in the 8 weeks between January 31 –
357 March 27, 2021, reaching its lowest level (54.6%) at week 20 of 2021 (May 16 – 22). However,
358 the stringency, compliance and duration of mobility reductions were less strict and shorter than
359 those of the first wave. Additionally, changes in mobility between rural, suburban and urban
360 districts of India displayed similar temporal patterns (**Figures 1C**), but travel in urban areas
361 (73.9%) was more affected by the pandemic compared with mobility in semi-urban (91.7%)
362 and rural (94.4%) areas in 2020 – 2021. In terms of geographic groupings of districts in
363 connected travel networks, there was also apparent spatiotemporal heterogeneity in response
364 to efforts to mitigate the varying scale of transmission across districts at different time periods
365 (**Figure 2**). During the pre-pandemic period from November 10, 2019, to February 22, 2020,
366 districts highly connected with each other formed 23 communities, with the 13 largest
367 communities containing 94.4% of districts in the country, ranging in size from 23 to 97 districts
368 per community.

369 Connections between districts in terms of travel were disrupted to mitigate transmission
370 during the first lockdown in 2020 (**SI Figure S3A**), and more isolated communities (n=79)

371 were formed with 54.4% (43) of them containing only one district. However, due to the fewer
372 reductions in mobility (**SI Figure S3C**), connections between districts (31 communities) during
373 the second lockdown were not as sparse as during the first lockdown. A total of 13 major
374 communities contained 93.8% of districts, with a similar geographical range during the pre-
375 pandemic period, except for some remote rural and semi-urban areas. Following the recovery
376 of travel in November – December 2021 across the country (**SI Figure S3D**), connections
377 between districts formed 22 communities, a pattern closely resembling that of pre-pandemic
378 connected district communities.

379

380 **Fig 1. COVID-19 cases, reproduction numbers and mobility changes in India during the**
381 **pandemic.** (A) Number of daily new confirmed COVID-19 cases reported in India from March 15,
382 2020, to December 25, 2021. (B) Estimated mean and 95% confidence interval (CI) of the basic
383 reproduction number (R_0) and instantaneous reproduction rate (R_t). (C) Relative weekly mobility of
384 domestic travel by rural, suburban and urban areas in India as measured by the aggregated Google
385 COVID-19 mobility research dataset. Relative mobility levels were standardized by the overall mean
386 level of each type of flow in each region during the first 8 weeks of 2020. The red and grey vertical
387 dashed lines indicate the date of the COVID-19 pandemic being declared by the WHO and the first date
388 of each year, respectively.

389

390

391 **Fig 2. Changes in community domestic travel networks of Indian districts across four time periods**
392 **in 2019-2021).** (A) Communities (n=23) of domestic travel at district level during the pre-pandemic
393 period from November 10, 2019, to February 22, 2020*. (B) Communities (n=79) of domestic travel
394 during the first lockdown on March 22 - May 2, 2020*. (C) Communities (n=31) of domestic travel
395 during the second lockdown on April 18 - May 29, 2021*. (D) Communities (n=22) of domestic travel
396 post-second lockdown period (8 weeks), from November 7 to December 31, 2021, after travel
397 restrictions for COVID-19 had been lifted in India. In each panel, geographically adjacent areas of the
398 same colour represent an internally and closely connected community in terms of human movement in
399 India. The community structure was detected using the Louvain algorithm. Circle size represents the
400 relative volume of outbound travellers. The bigger the circle, the higher the level of outflow.* Based on
401 aggregated Google COVID-19 mobility research dataset.

402

403

404 *Nonlinear and lag-response impacts of mobility and other factors on the Delta wave*

405 Upon initial exploratory analysis using baseline Bayesian spatiotemporal models for India, we
406 found that population density as a fixed effect was not statistically associated with ΔR_t for
407 COVID-19 transmission (DIC = 4756; **SI Table S2**). Humidity and UV were removed due to

408 a higher VIF and potential multicollinearity. We then included DLNMs for mobility,
409 temperature, precipitation and Stringency Index, lagged between 0 and 3 weeks, including the
410 holiday variable as a fixed effect in different candidate models (**SI Table S2**). The inclusion of
411 mobility, temperature, precipitation and Stringency Index as DLNMs (Model 4.1) for the whole
412 country and urban areas resulted in a greater reduction in the DIC and mean logarithmic score
413 compared with the baseline model (**SI Figure S18**).

414 However, models which included DLNMs for mobility, temperature, and Stringency
415 Index (Model 3.1) had the smallest DIC and logarithmic score in semi-urban areas. The best
416 fitting model for rural areas only contained Stringency Index as DLNMs, which might be due
417 to the smaller reductions in mobility in rural districts. The posterior predictive results from the
418 best fitting model by cross validation showed that the model had a robust performance
419 compared to observed data (**SI Figure S13 - S16**). The spatial random effects and the fitted R_t
420 for the whole country were also presented in Supplementary (**SI Figures S17 - S20**). Based on
421 results of the best fitting models for the whole country, overall, the recovery of mobility to 99%
422 of the pre-pandemic level and the decrease of intervention stringency below 68 significantly
423 increased the RR (>1) of COVID-19 transmission in India during the study period (**Figures 3A**
424 **and 3J**). The increase of weekly precipitation ($>0.15\text{m}$) and cold weather ($<27.2^\circ\text{C}$) were also
425 associated with a higher risk of transmission ($\text{RR}>1$), but the variation in RRs in response to
426 precipitation was small and the impact of temperature below 0°C was not significant (**Figures**
427 **3D and 3G**).

428
429 **Fig 3. The lagged impact of different factors and scenarios on COVID-19 transmission during the**
430 **Delta wave in 2021.** (A) The overall association between mobility changes and COVID-19
431 transmission dynamics under 0- to 3-week lags. The red/blue lines show RR under the scenario of
432 mobility below/above the overall mean level (0.99). The histogram with the secondary y-axis shows
433 the frequency of data under different levels. (B) Contour plot of the association between mobility and
434 relative risk (RR) of COVID-19 transmission. The deeper the shade of purple, the greater the increase
435 in RR of transmission, while the deeper the shade of green, the greater the decrease in RR. (C) COVID-
436 19 lag-response association for mobility level at 0.6, 0.8, 1.25, relative to the overall pre-pandemic
437 mean level (1). The mean and 95% CI were presented. (D) – (F) Lag-response association between
438 COVID-19 transmission and temperature (Temp) for cool (10°C), warm (20°C), and hot (30°C)

439 weather, relative to the overall mean of 27.2°C. (G) – (I) COVID-19 lag-response association for
440 precipitation (Prec) at 0.05, 0.5, and 1m, relative to the overall mean of 0.15m. (J) – (L) Lag-response
441 association between COVID-19 transmission and the stringency of intervention policy at low (40),
442 medium (60), and high (80), relative to the overall mean Stringency Index (68.2). Results are for the
443 best fitting model with DLNMs (base model + mobility + temperature + precipitation + intervention
444 policy; see SI Table S2) across the whole country.
445

446
447 **Fig 4. The lag-response association between COVID-19 transmission and different factors in**
448 **urban, suburban, and rural districts.** (A) – (D) COVID-19 lag-response association for different
449 levels of mobility, temperature (Temp), precipitation (Prec) and the stringency of intervention policy in
450 urban areas, relative to the overall mean level. Results are for the best fitting model with DLNMs (base
451 model + mobility + temperature + precipitation + intervention policy) in urban districts. (E) – (G) Lag-
452 response association between the risk of COVID-19 transmission and different levels of mobility,
453 temperature (Temp), and the stringency of intervention policy in semi-urban areas, based on the best
454 fitting model with DLNMs (base model + mobility + temperature + intervention policy; see SI Table
455 S2) in suburban districts. (H) COVID-19 lag-response association for the Stringency Index of
456 intervention policy at low (40), medium (60), and high (80), based on the best fitting model with
457 DLNMs (base model + intervention policy) in rural districts. The mean and 95% CI of RR for each
458 level were presented.
459

460 In addition, given the reporting delays of cases after exposure (i.e. incubation period
461 plus the lags from illness onset, diagnosis to reporting, normally 10 days with an interquartile
462 range of 8 – 11 days,⁶² we found that the introduction of DLNMs improved model adequacy
463 statistics compared with the inclusion of factors with no lags, which proved the rationality and
464 necessity of considering the lag-response effects in the modelling. The maximum associations
465 of mobility reductions (**Figure 3B**; relative mobility >0.5 times baseline mobility associated
466 with RR of <0.8)) and intervention policy (**Figure 3K**; Stringency Index <30 associated with
467 RR <0.95) with changes in R_t of COVID-19 transmission were found at a lag of 2 weeks with
468 precipitation having an apparent maximum impact at a 1 to 2-week lag. However, we also
469 found an increasing/decreasing risk of transmission under cool/hot weather at one 1-week lag
470 (**Figure 3F**; temperature of <20°C associated with RR >1).

471 Similar lag-response patterns between COVID-19 transmission and covariates at
472 different levels were also found in urban, suburban, and rural districts (**Figure 4**). Mobility of
473 <0.8 times that of baseline was associated with a decrease in RR <1 at a 0 and 1-week lag in

474 urban delineated districts (**Figure 4A**). Association of stringency of government interventions
475 with COVID-19 RR exhibited some heterogeneity between urban, suburban and rural areas
476 however, with a Stringency Index of <40 associated with a $RR > 1$ in urban areas at a 1-week
477 lag (Figure 4D), but exhibiting a 2-week lagged response in suburban and rural areas (**Figures**
478 **4G & H**). Based on findings and methods described above, we re-tested models (without
479 DLNMs) using all covariates with a 2-week lag, i.e. two weeks before cases reported and R_t
480 observed (**SI Table S3**). We found that the best fitting model at country level was similar to
481 the previous Model 4.1 with DLNMs, but precipitation was replaced by UV radiation due to
482 potential multicollinearity. The results from leave-one-week-out cross-validation showed the
483 best fitting 2-week lag-response model could further improve the prediction of dynamics in R_t
484 of COVID-19 transmission across India (**SI Figures S23-S27**).

485 *Comparing lag-response impacts of different factors between waves*

486 We also ran Bayesian spatiotemporal models with DLNMs and data for the wave in 2020 (19th
487 July to 29th November 2020) to compare drivers of transmission during both pandemic waves
488 in 2020 (initial transmission wave) and 2021 (Delta wave). Results of DLNMs exploring
489 drivers of COVID-19 transmission during the first wave were consistent with those exploring
490 associations of COVID-19 transmission during the Delta wave in India. Humidity and UV were
491 removed from the analyses due to multicollinearity ascertained by higher VIF statistics (≥ 2.5).
492 Based on best fit model statistics (lowest DIC and mean logarithmic score compared to baseline
493 model) DLNMs which best fit the data were models which included mobility, temperature,
494 precipitation and Stringency Index (Model 4.1; **SI Table S3**). Consistent with model validation
495 using data for the Delta wave, cross validation showed robust model results when posterior
496 predictive results for the wave in 2020 were compared with observed data (**SI Figure S38 –**
497 **S41**).

498

499 **Fig 5. The lagged impact of different factors and scenarios on COVID-19 transmission during the**
500 **initial wave of COVID-19 transmission in the second half of 2020.** (A) The overall association
501 between mobility changes and COVID-19 transmission dynamics under 0- to 3-week lags. The red/blue
502 lines show RR under the scenario of mobility below/above the overall mean level (0.99). The histogram
503 with the secondary y-axis shows the frequency of data under different levels. (B) Contour plot of the
504 association between mobility and relative risk (RR) of COVID-19 transmission. The deeper the shade
505 of purple, the greater the increase in RR of transmission, while the deeper the shade of green, the greater
506 the decrease in RR. (C) COVID-19 lag–response association for mobility level at 0.8, 1.2, 1.4 relative
507 to the overall pre-pandemic mean level (1). The mean and 95% CI were presented. (D) – (F) Lag-
508 response association between COVID-19 transmission and temperature (Temp) for cool (10°C), warm
509 (20°C), and hot (30°C) weather, relative to the overall mean of 25°C. (G) – (I) COVID-19 lag-response
510 association for precipitation (Prec) at 0.5, 1.5, and 2.5m, relative to the overall mean of 0.24m. (J) –
511 (L) Lag-response association between COVID-19 transmission and the stringency of intervention
512 policy at three different measures of stringency: 70, 75, and 80, relative to the overall mean Stringency
513 Index (76.5). Results are for the best fitting model with DLNMs (base model + mobility + temperature
514 + precipitation + intervention policy; see SI Table S2) across the whole country.
515
516

517 Model results using data for the whole country found that a rebound in mobility to 1.2
518 and 1.4 times the mobility of pre-pandemic levels results in an increase in RR (>1) with a lag-
519 time of between one and two weeks (**Figure 5C**). A high Stringency Index (80) was found to
520 be associated with a lower RR with a two-and-a-half-week lag (**Figure 5L**) with a reduction in
521 RR (<1) observed over a Stringency Index of 75 (**Figure 5J**). Cold weather (10°C & 20°C)
522 was associated with a higher RR with a decrease in RR observed at higher temperatures (30°C)
523 (**Figures 5D and 5F**). An increase in weekly precipitation (>0.2m) was also associated with
524 an increase in transmission risk (**Figure 5G**) with a lag-time increase of between 1 and 2 weeks,
525 although higher levels of weekly precipitation (>2.5m) were associated with a decrease again
526 in RR (<1) at a 2 to 3-week lag.

527

528 **Discussion**

529 Using a de-identified and aggregated Google COVID-19 mobility research dataset, derived
530 from time- and space-explicit mobile phone data, our study identified connected communities
531 of travel networks, and quantified changes in population movements across rural and urban
532 districts in India over the course of the pandemic. Our modelling results showed that mobility

533 changes, together stringency of government interventions and climate factors had lagged-
534 response impacts on the risk of COVID-19 transmission. The first nationwide lockdown
535 between March and June 2020, together with a reduction in population mobility, appear to have
536 been the main drivers for a relatively low transmission wave of COVID-19 in India during the
537 first half of 2020.^{21,63} Although the announcement of the lockdown had initially resulted in an
538 increase in population mobility, with workers mostly representing informal sectors travelling
539 interstate to return home,⁶⁴ the majority of people travelling were not infected and this
540 population mobility therefore had little impact on transmission.⁵

541 In early 2021, NPI restriction measures such as social distancing and mask-wearing had
542 been gradually eased due to a sense of COVID-19 clinical infections being mild,^{8,65} and inter-
543 state and rural to urban human mobility was seen to be increasing.^{21,65} This included mass
544 attendance of political rallies and religious festivals, such as the Hindu festival Kumbh Mela
545 in India's most populous state of Uttar Pradesh where hundreds of thousands of people gathered
546 at the banks of the River Ganges.^{21,23,65} The modelling results presented here indicate that this
547 recovery of mobility in early 2021 to 99% that of pre-pandemic levels, together with lower
548 stringency of government interventions and emergence of the more transmissible Delta variant,
549 contributed to higher transmission of COVID-19 infection during the Delta pandemic wave.
550 This is consistent with previously published research which attributed the surge of COVID-19
551 in April 2021 to the emergence of the more transmissible Delta variant (B.1.617 lineage) and
552 dominance as the main circulating strain, as well as relaxation of non-pharmaceutical
553 interventions.^{13,21,66}

554 The second lockdown with reduced travel frequency and contact rates among
555 populations also played a significant role in mitigating COVID-19 spread across districts and
556 transmission in communities in the country. Mobility patterns were inversely associated with
557 the national Stringency Index, with a relative drop in mobility below 50% associated with a

558 Stringency Index of 80, consistent with previous research which found that community
559 mobility, based on Google location data, drastically fell after the lockdown was instituted.
560 However, the impacts of mobility changes were not fully synchronized between rural and urban
561 areas, and the effects of travel restrictions and other interventions in slowing down COVID-19
562 transmission hinged on the intensity of these measures in reducing R_t of new variants with a
563 higher transmissibility. Model results showed differences in lagged associations of COVID-19
564 RR with Stringency Index between rural, semi-urban and urban districts²⁴ and this was
565 reflected in urban vs. rural transmission dynamics between both pandemic waves. During the
566 first wave of COVID-19 in India, transmission was higher in urban rather than rural settings
567 and cases were spatially clustered throughout metropolitan areas and peri-urban areas.^{34,67,68}
568 Conversely, during the Delta pandemic wave in India, cases were observed to be spreading
569 more in rural areas where access to healthcare can be more limited than in urban areas.¹⁸

570 Climate covariates (temperature and precipitation) were also found to have lag-
571 response associations with COVID-19 transmission, although these effects appear to be very
572 limited in terms of relative risk. Modelling results for the Delta pandemic wave found a
573 decrease in temperature ($<20^\circ\text{C}$) was associated with an increased relative risk, consistent with
574 previous modelling studies exploring climate impacts on COVID-19 transmission in India³³,
575 and an increase in precipitation ($>2.5\text{m}$) associated with a decreased relative risk, with a 1 to
576 2-week lagged impact. This is consistent with wave 1 modelling results which found a 1 to 2-
577 week lagged association between cold weather and precipitation on an increase in RR of
578 COVID-19 transmission. Previous studies have also observed significant associations between
579 COVID-19 transmission and temperature, dew point, humidity, and wind speed (Spearman's
580 correlation)⁶⁹; a 1°C rise in mean temperature associated with increase in the daily number of
581 COVID-19 confirmed cases when mean temperature was below 3°C (GAM)⁵¹; a positive
582 correlation between the number of infections with long-term climatic records of temperature,

583 wind speed, solar radiation³²; average temperature correlated with COVID-19 based on
584 Spearman's correlation⁴⁰; and minimum temperature and average temperature correlated with
585 the spread of COVID-19 in New York city (Spearman's correlation).⁷⁰ These previous
586 approaches most commonly used correlation analyses however, and spatiotemporal analyses
587 had not been used to examine such associations prior to the research we present here.

588 The work we have presented therefore builds upon previous research exploring the
589 driving factors that led to the surge in COVID-19 transmission during the Delta pandemic wave
590 in India ^{15,23,27}, while also presenting a number of novel factors not previously presented in the
591 literature. Firstly, to our knowledge this is the first study to explore inter-district mobility
592 patterns in India during the initial and Delta waves of COVID-19 transmission, relative to pre-
593 pandemic levels, delineated by urban, suburban and rural location. By investigating these
594 changes in human mobility using fine spatial resolution Google COVID-19 Aggregated
595 Mobility Research data we have demonstrated that a surge in population movement, together
596 with an easing of NPIs were the main contributors to the surge in transmission during the Delta
597 pandemic wave. We have also explored the spatiotemporal heterogeneities in drivers of
598 transmission at district level accounting for urbanisation, building upon previous research
599 exploring the association between state level urbanisation and COVID-19 transmission.²⁹

600 Additionally, the Bayesian hierarchical modelling approach we used provides a flexible
601 framework for quantifying heterogeneities in spatiotemporal drivers of transmission during
602 both pandemic waves while allowing complex and nonlinear relationships within the data to
603 be captured⁶⁰. The ability for Bayesian models to incorporate spatial and temporal
604 dependencies in the models is particularly useful in regions such as India with substantial
605 divergence between urban and rural areas^{71,72}. Integrating novel DLNM models into the
606 Bayesian framework allowed us to quantify lagged, nonlinear associations of drivers of

607 transmission with COVID-19 incidence, to account for the incubation period from infection to
608 onset of clinical infection and delays in reporting of infection.

609 While our findings represent a comprehensive understanding of the drivers of
610 transmission during the initial and Delta waves of COVID-19 transmission in India, these
611 results should be interpreted in light of several important limitations. First, the Google mobility
612 data is limited to smartphone users who have opted into Google's Location History feature,
613 which is off by default. These data may not be representative of the population as whole, and
614 furthermore their representativeness may vary by location. Importantly, these limited data are
615 only viewed through the lens of differential privacy algorithms, specifically designed to protect
616 user anonymity and obscure fine detail. However, comparisons between mobility datasets have
617 shown good agreement with Google Location History data and other commonly used mobility
618 data sources for capturing population-level mobility patterns⁷³. Moreover, comparisons across
619 rather than within locations are only descriptive since these regions can differ in substantial
620 ways.

621 Second, the accuracy of our models relied on accurate estimates of R_t derived from
622 reported case data, and R_0 estimates were proportional to the contact rate and might vary
623 according to the local situation. The quality of reported data likely differed across districts due
624 to varying case definitions, testing and surveillance capacity across the country, with various
625 underreporting rate and reporting delays. Third, the Stringency Index data at state level used in
626 spatiotemporal analyses for districts was formulated to assess lockdown strictness and measure
627 the political commitment and strictness of governmental policies. These data did not measure
628 the effectiveness of a country's response or provide information on how well policies were
629 enforced. A higher value of Stringency Index did not necessarily mean that a country's
630 response was better than that of those with lower values.^{24,40} Fourth, many other factors (e.g.

631 vaccination and prior infections) might also contribute to COVID-19 transmission, but our
632 models did not specify the contributions of these factors.

633 To our knowledge, this is the first study to combine human mobility data with
634 Stringency Index and climate data within a Bayesian spatiotemporal framework to compare
635 drivers of transmission by urban, suburban and rural district over the course of the pandemic
636 in India, and quantify the lagged impact of these drivers on COVID-19 transmission risk. With
637 the frequency of emerging infection outbreaks likely to increase in an increasingly urbanised
638 global society, with more extreme weather events and pronounced changes in climate, the
639 spatiotemporal modelling approach presented here provides a valuable framework for
640 understanding drivers of infection transmission.^{74,75} Based on our approach, examining how
641 the lagged impact of human mobility, interventions and climate vary by urban and rural
642 environment in their contribution to infection transmission can provide valuable insights into
643 the intervention strategies in the future.

644

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655

656 **Data Availability Statement:** The code and data used for the analysis described in this study
657 is available at the following GitHub repository: [https://github.com/e3cleary/COVID-19-](https://github.com/e3cleary/COVID-19-INDIA.git)
658 [INDIA.git](https://github.com/e3cleary/COVID-19-INDIA.git). The Google COVID-19 Aggregated Mobility Research Dataset used for this study
659 is available with permission from Google LLC. Ethical clearance for collecting and using
660 secondary data in this study was granted by the institutional review board of the University of
661 Southampton (No. 61865). All data were supplied and analysed in an anonymous format,
662 without access to personal identifying information.

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Supporting information

Figure S1. Regions in India investigated by this study and the number and density of population at district level (administrative level II) in 2020. Areas shaded in grey are areas for which no data is available.

Figure S2. Five periods for travel network modularity analysis (A): 1) Pre-pandemic period (15 weeks) from November 10, 2019 to February 22, 2020; 2) First lockdown (6 weeks), from March 22 to May 2, 2020, that included strict travel restrictions, stay-at-home orders and closure of many businesses; 3) Pre-

second lockdown period (8 weeks) from January 31 to March 27, 2021; 4) Second lockdown (6 weeks) for the Delta wave, from April 18 to May 29, 2021; 5) post-second lockdown period (8 weeks), from November 7 to December 31, 2021, after travel restrictions for COVID-19 had been lifted in India.

Fig S3. Relative changes of outbound travel from districts across India during the pandemic compared with average pre-pandemic levels during the 12 weeks from November 10, 2019, to February 22, 2020. (A) Reductions of outbound flows under the first lockdown during the 6-week period from March 22 to May 2, 2020. (B) Changes in outflow during the 8-week period from January 31 to March 27, 2021, before the second lockdown. (C) Reductions of outflows during the 6-week second lockdown from April 18 to May 29, 2021. (D) Changes in outflow during the 8-week period from November 7 to December 31, 2021. Sub-division maps at administrative level I (state) and II (district) were obtained from the GADM version 3.6 (<https://gadm.org/>). Regions in which outflow data are not available are those represented in green. Areas shaded in grey are areas for which no data is available.

Table S1. Summary Statistics for data used for wave 1 and Delta wave spatiotemporal models

SI Delta Wave

Table S2. Wave 2: Adequacy results for models with DLNMs and increasing complexity.

Table S3. Wave 2: Adequacy results for models (without DLNMs) using 2-week lag covariates with increasing complexity.

Table S4. Model hyperparameters using a range of prior distributions in best fit model 4.1 for Delta Wave

Figure S4. Relative intra-district mobility during the Delta wave in India, standardised by pre-pandemic mean baseline levels of mobility for the first eight weeks of 2020 (December 29, 2019 – February 22, 2020) for each district. The weeks in 2021 investigated are numbered in maps. Areas shaded in grey are areas for which no data is available.

Figure S5. Stringency Index of COVID-19 intervention policy implemented during the Delta wave in India. The weeks in 2021 investigated are numbered in maps. Areas shaded in grey are areas for which no data is available.

Figure S6. Mean temperature at 2m above the surface during the Delta wave in India. The weeks in 2021 investigated are numbered in maps. Areas shaded in grey are areas for which no data is available.

Figure S7. Accumulated weekly precipitation (metres) during the Delta wave in India. The weeks in 2021 investigated are numbered in maps. Areas shaded in grey are areas for which no data is available.

Figure S8. Relative humidity during the Delta wave in India. The weeks in 2021 investigated are numbered in maps. Areas shaded in grey are areas for which no data is available.

Figure S9. Downward ultraviolet (UV) radiation (KJ/m² per hour) during the Delta wave in India. The weeks in 2021 investigated are numbered in maps. Areas shaded in grey are areas for which no data is available.

Figure S10. Weekly Rt derived from COVID-19 cases reported during the Delta wave in India. The weeks in 2021 investigated are numbered in maps. Areas shaded in grey are areas for which no data is available.

Figure S11. Pairwise Pearson correlations between weekly means of variables at district level during the Delta wave in India, 2021. R0: basic reproduction number. Rt: instantaneous reproduction number. ln_R: $\log(Rt/R0)$. Cases_rate: new COVID-19 cases reported per 1000 people. Cases_accu_rate: cumulative cases per 1000 people reported since the first week of the wave. mean_intra: intra-district relative mobility. d2m: relative humidity. t2m: mean temperature of air (°C at 2m above the surface of land, sea or inland waters). tp: precipitation (metres). uv: downward ultraviolet radiation. Stringency: index of COVID-19 intervention stringency. Holiday: days of public holidays in a week. pop_sum: total population of each district. pop_density: population number per km² of each district.

Figure S12. Kendall rank correlations between weekly means of variables at district level during the Delta wave in India, 2021. R0: basic reproduction number. Rt: instantaneous reproduction number. ln_R: $\log(Rt/R0)$. Cases_rate: new COVID-19 cases reported per 1000 people. Cases_accu_rate: cumulative cases per 1000 people reported since the first week of the wave. mean_intra: intra-district relative mobility. d2m: relative humidity. t2m: mean temperature of air (°C at 2m above the surface of land, sea or inland waters). tp: precipitation (metres). uv: downward ultraviolet radiation. Stringency: index of COVID-19 intervention stringency. Holiday: days of public holidays in a week. pop_sum: total population of each district. pop_density: population number per km² of each district.

Figure S13. Posterior predictive mean Rt during the Delta wave in India, 2021, derived from the best fitting model (model 4.1) at country level using leave-one-week-out cross-validation approach. The weeks in 2021 investigated are numbered in maps. Areas shaded in grey are areas for which no data is available.

Figure S14. Standard deviation (SD) of posterior predictive R_t during the Delta wave in India, 2021, derived from the best fitting model (model 4.1 without DLNMs) at country level using a leave-one-week-out cross-validation approach. Areas shaded in grey are areas for which no data is available.

Figure S15. Posterior predictive mean R_t during the Delta wave in India, 2021, derived from the best fitting model (model 4.1) at country level using leave-one-state-out cross-validation approach. The weeks in 2021 investigated are numbered in maps. Areas shaded in grey are areas for which no data is available.

Figure S16. Standard deviation (SD) of posterior predictive R_t during the Delta wave in India, 2021, derived from the best fitting model (model 4.1 without DLNMs) at country level using a leave-one-state-out cross-validation approach. Areas shaded in grey are areas for which no data is available.

Figure S17. Contribution of spatial random effects to estimates of R_t changes in the base model. Areas shaded in grey are areas for which no data is available.

Figure S18. Improvement by using the best fitting model across the country, compared to baseline model. Difference between mean absolute error (MAE) for the baseline model (weekly random effects, spatial random effects and population density) and MAE for the best fitting model (model 4.1 with DLNMs). Districts with positive values (pink) suggest that capturing the nonlinear and delayed impacts of mobility, climate information and intervention stringency, improves the model in these areas. Districts with negative values (blue) suggest that mobility, intervention and climate information did not improve the model fit and other unexplained factors might dominate space-time dynamics in these areas. The MAE of the selected model was smaller than the baseline model for 385 of the 665 (57.9%) districts in India, with the results of model performance provided by geo-political regions in the Table. Areas shaded in grey are areas for which no data is available.

Figure S19. Observed versus posterior fitted R_t in the capital district of each state using the best fitting model (model 4.1 with DLNMs) at country level. Graphs with a log scale at y-axis show the observed R_t derived from reported case data, and corresponding mean and 95% confidence interval (CI, shaded pink area) of fitted R_t , derived from the best fitting model (model 4.1 with DLNMs) at country level. States are ordered by their geographical location.

Figure S20. Observed versus posterior predictive R_t in the capital district of each state, using leave-one-week-out cross-validation approach. Graphs with a log scale at y-axis show the observed R_t derived from reported case data, and corresponding posterior predictive mean and 95% prediction interval (CI, shaded pink area), derived from the best fitting model (model 4.1 with DLNMs) at country level. States are ordered by their geographical location.

Figure S21. Contribution of spatial random effects to estimates of R_t changes in the base model. Areas shaded in grey are areas for which no data is available.

Figure S22. Improvement of using the best fitting model with 2-week lag covariates (no DLNMs), compared to baseline model with the same lag. Difference between mean absolute error (MAE) for the baseline model and MAE for the best fitting model (Model 4.1). Districts with positive values (pink) suggest that capturing the 2-week lag impacts of mobility, temperature, UV and intervention stringency, improves the model in these areas. Districts with negative values (blue) suggest that mobility, intervention and climate information did not improve the model fit and other unexplained factors might dominate space-time dynamics in these areas. The MAE of the selected model was smaller than the baseline model for 428 of the 665 (64.4%) districts in India, and further improved the best fitting model with DLNMs (Figure S12). Results of model performance are provided by geo-political regions in the Table. Areas shaded in grey are areas for which no data is available.

Figure S23. Posterior predictive mean R_t during the Delta wave in India, 2021, derived from the best fitting model (model 4.1 without DLNMs) at country level using 2-week lag covariates and leave-one-week-out cross-validation approach. Areas shaded in grey are areas for which no data is available.

Figure S24. Standard deviation (SD) of posterior predictive R_t during the Delta wave in India, 2021, derived from the best fitting model (model 4.1 without DLNMs) at country level using 2-week lag covariates and leave-one-week-out cross-validation approach. Areas shaded in grey are areas for which no data is available.

Fig S25. Observed versus posterior predictive R_t in the capital district of each state. Graphs with a log scale at y-axis show the observed R_t derived from reported case data, and corresponding posterior predictive mean and 95% prediction interval (CI, shaded pink area), derived from the best fitting model without DLNMs at country level (model 4.1: base model + mobility + temperature + UV + intervention policy; see SI Table S2), using 2-week lag covariates and leave-one-week-out cross-validation approach. States are ordered by their geographical location.

Figure S26. Posterior predictive mean R_t during the Delta wave in India, 2021, derived from the best fitting model (model 4.1 without DLNMs) at country level using 2-week lag covariates and leave-one-state-out cross-validation approach. Areas shaded in grey are areas for which no data is available.

Figure S27. Standard deviation (SD) of posterior predictive R_t during the Delta wave in India, 2021, derived from the best fitting model (model 4.1 without DLNMs) at country level using 2-week lag

covariates and leave-one-state-out cross-validation approach. Areas shaded in grey are areas for which no data is available.

SI Wave 1

Table S5. Wave 1: Adequacy results for models with DLNMs and increasing complexity.

Table S6. Wave 1: Adequacy results for models (without DLNMs) using 2-week lag covariates with increasing complexity.

Table S7. Model hyperparameters using a range of prior distributions in best fit model 4.1 for Wave 1

Figure S28. COVID-19 cases reported by district each week during wave 1 in India. The weeks in 2020 investigated are numbered in maps. Areas shaded in grey are areas for which no data is available.

Figure S29. Relative intra-district mobility during wave 1 in India, standardised by pre-pandemic mean baseline levels of mobility for the first eight weeks of 2020 (December 29, 2019 – February 22, 2020) for each district. The weeks in 2020 investigated are numbered in maps. Areas shaded in grey are areas for which no data is available.

Figure S30. Stringency Index of COVID-19 intervention policy implemented during wave 1 in India. The weeks in 2020 investigated are numbered in maps. Areas shaded in grey are areas for which no data is available.

Figure S31. Mean temperature at 2m above the surface during wave 1 in India. The weeks in 2020 investigated are numbered in maps. Areas shaded in grey are areas for which no data is available.

Figure S32. Accumulated weekly precipitation (metres) during wave 1 in India. The weeks in 2020 investigated are numbered in maps. Areas shaded in grey are areas for which no data is available.

Figure S33. Relative humidity during wave 1 in India. The weeks in 2020 investigated are numbered in maps. Areas shaded in grey are areas for which no data is available.

Figure S34. Downward ultraviolet (UV) radiation (KJ/m² per hour) during wave 1 in India. The weeks in 2020 investigated are numbered in maps. Areas shaded in grey are areas for which no data is available.

Figure S35. Weekly R_t derived from COVID-19 cases reported during the wave 1 in India. The weeks in 2020 investigated are numbered in maps. Areas shaded in grey are areas for which no data is available.

Figure S36. Pairwise Pearson correlations between weekly means of variables at district level during the wave 1 in India, 2020. R_0 : basic reproduction number. R_t : instantaneous reproduction number. \ln_R : $\log(R_t/R_0)$. $Cases_rate$: new COVID-19 cases reported per 1000 people. $Cases_accu_rate$: cumulative cases per 1000 people reported since the first week of the wave. $mean_intra$: intra-district relative mobility. $d2m$: relative humidity. $t2m$: mean temperature of air ($^{\circ}C$ at 2m above the surface of land, sea or inland waters). tp : precipitation (metres). uv : downward ultraviolet radiation. Stringency: index of COVID-19 intervention stringency. Holiday: days of public holidays in a week. pop_sum : total population of each district. $pop_density$: population number per km^2 of each district.

Figure S37. Kendall rank correlations between weekly means of variables at district level during the wave 1 in India, 2020. R_0 : basic reproduction number. R_t : instantaneous reproduction number. \ln_R : $\log(R_t/R_0)$. $Cases_rate$: new COVID-19 cases reported per 1000 people. $Cases_accu_rate$: cumulative cases per 1000 people reported since the first week of the wave. $mean_intra$: intra-district relative mobility. $d2m$: relative humidity. $t2m$: mean temperature of air ($^{\circ}C$ at 2m above the surface of land, sea or inland waters). tp : precipitation (metres). uv : downward ultraviolet radiation. Stringency: index of COVID-19 intervention stringency. Holiday: days of public holidays in a week. pop_sum : total population of each district. $pop_density$: population number per km^2 of each district.

Figure S38. Posterior predictive mean R_t during wave 1 in India, 2020, derived from the best fitting model (model 4.1) at country level using leave-one-week-out cross-validation approach. The weeks in 2020 investigated are numbered in maps. Areas shaded in grey are areas for which no data is available.

Fig S39. Standard deviation (SD) of posterior predictive R_t during wave 1 in India, 2020, derived from the best fitting model (model 4.1) at country level leave-one-week-out cross-validation approach. Areas shaded in grey are areas for which no data is available.

Figure S40. Posterior predictive mean R_t during wave 1 in India, 2020, derived from the best fitting model (model 4.1) at country level using leave-one-district-out cross-validation approach. The weeks in 2020 investigated are numbered in maps. Areas shaded in grey are areas for which no data is available.

Fig S41. Standard deviation (SD) of posterior predictive R_t during wave 1 in India, 2020, derived from the best fitting model (model 4.1) at country level leave-one-district-out cross-validation approach. Areas shaded in grey are areas for which no data is available.

Figure S42. Contribution of spatial random effects to estimates of R_t changes in the base model. Areas shaded in grey are areas for which no data is available.

Figure S43. Improvement by using the best fitting model across the country, compared to baseline model. Difference between mean absolute error (MAE) for the baseline model (weekly random effects, spatial random effects and population density) and MAE for the best fitting model (model 4.1 with DLNMs). Districts with positive values (pink) suggest that capturing the nonlinear and delayed impacts of mobility, climate information and intervention stringency, improves the model in these areas. Districts with negative values (blue) suggest that mobility, intervention and climate information did not improve the model fit and other unexplained factors might dominate space-time dynamics in these areas. The MAE of the selected model was smaller than the baseline model for 430 of the 661 (65.17%) districts in India, with the results of model performance provided by geo-political regions in the Table. Areas shaded in grey are areas for which no data is available.

Figure S44. Observed versus posterior fitted R_t in the capital district of each state using the best fitting model (model 4.1 with DLNMs) at country level. Graphs with a log scale at y-axis show the observed R_t derived from reported case data, and corresponding mean and 95% confidence interval (CI, shaded pink area) of fitted R_t , derived from the best fitting model (model 4.1 with DLNMs) at country level. States are ordered by their geographical location.

Figure S45. Observed versus posterior predictive R_t in the capital district of each state, using leave-one-week-out cross-validation approach. Graphs with a log scale at y-axis show the observed R_t derived from reported case data, and corresponding posterior predictive mean and 95% prediction interval (CI, shaded pink area), derived from the best fitting model (model 4.1 with DLNMs) at country level. States are ordered by their geographical location.

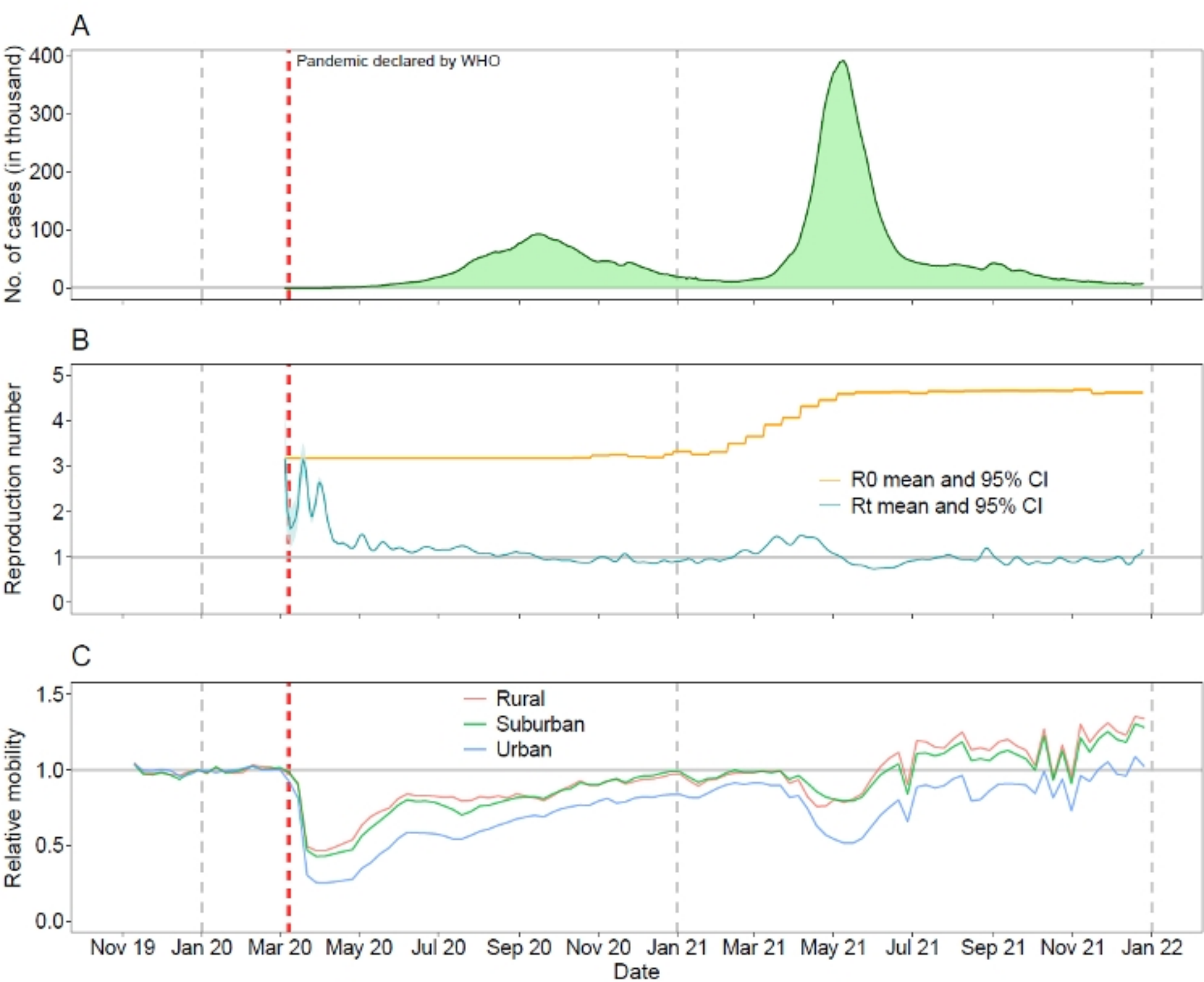
Figure S46. Posterior predictive mean R_t during the wave 1 in India, 2020, derived from the best fitting model (model 4.1 without DLNMs) at country level using 2-week lag covariates and leave-one-week-out cross-validation approach. Areas shaded in grey are areas for which no data is available.

Fig S47. Standard deviation (SD) of posterior predictive R_t during wave 1 in India, 2020, derived from the best fitting model (model 4.1 without DLNMs) at country level using 2-week lag covariates and

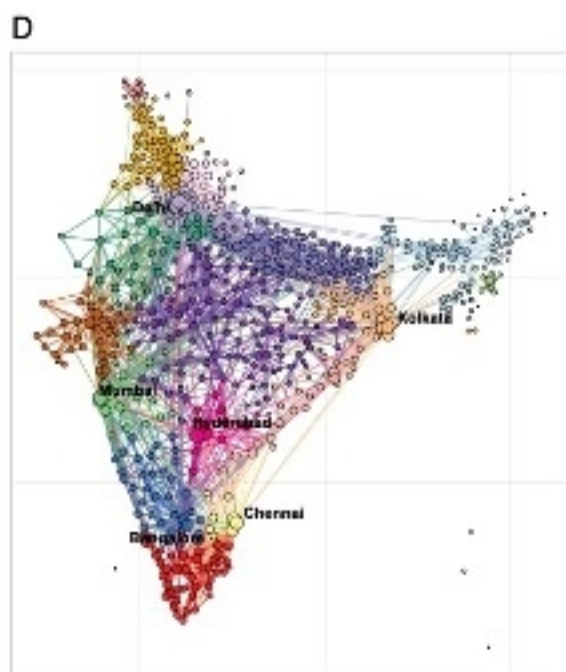
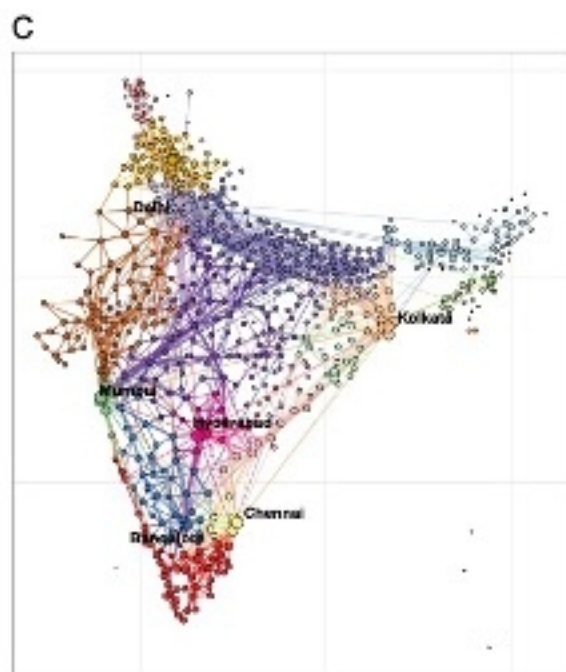
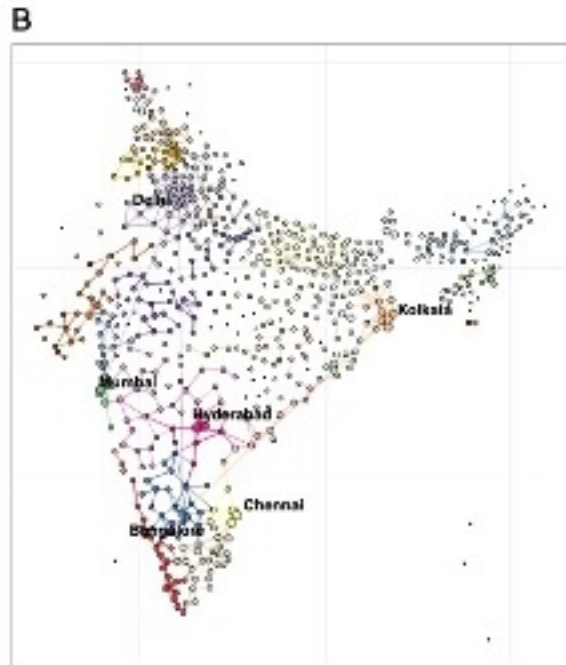
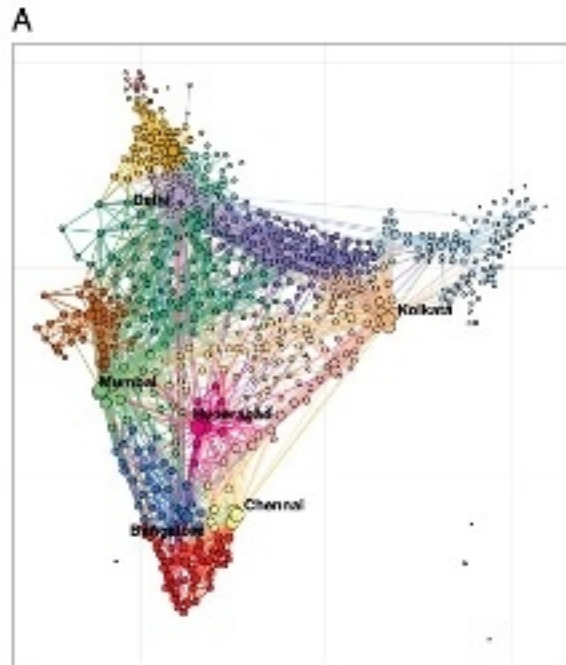
leave-one-week-out cross-validation approach. Areas shaded in grey are areas for which no data is available.

Figure S48. Posterior predictive mean R_t during the wave 1 in India, 2020, derived from the best fitting model (model 4.1 without DLNMs) at country level using 2-week lag covariates and leave-one-district-out cross-validation approach. Areas shaded in grey are areas for which no data is available.

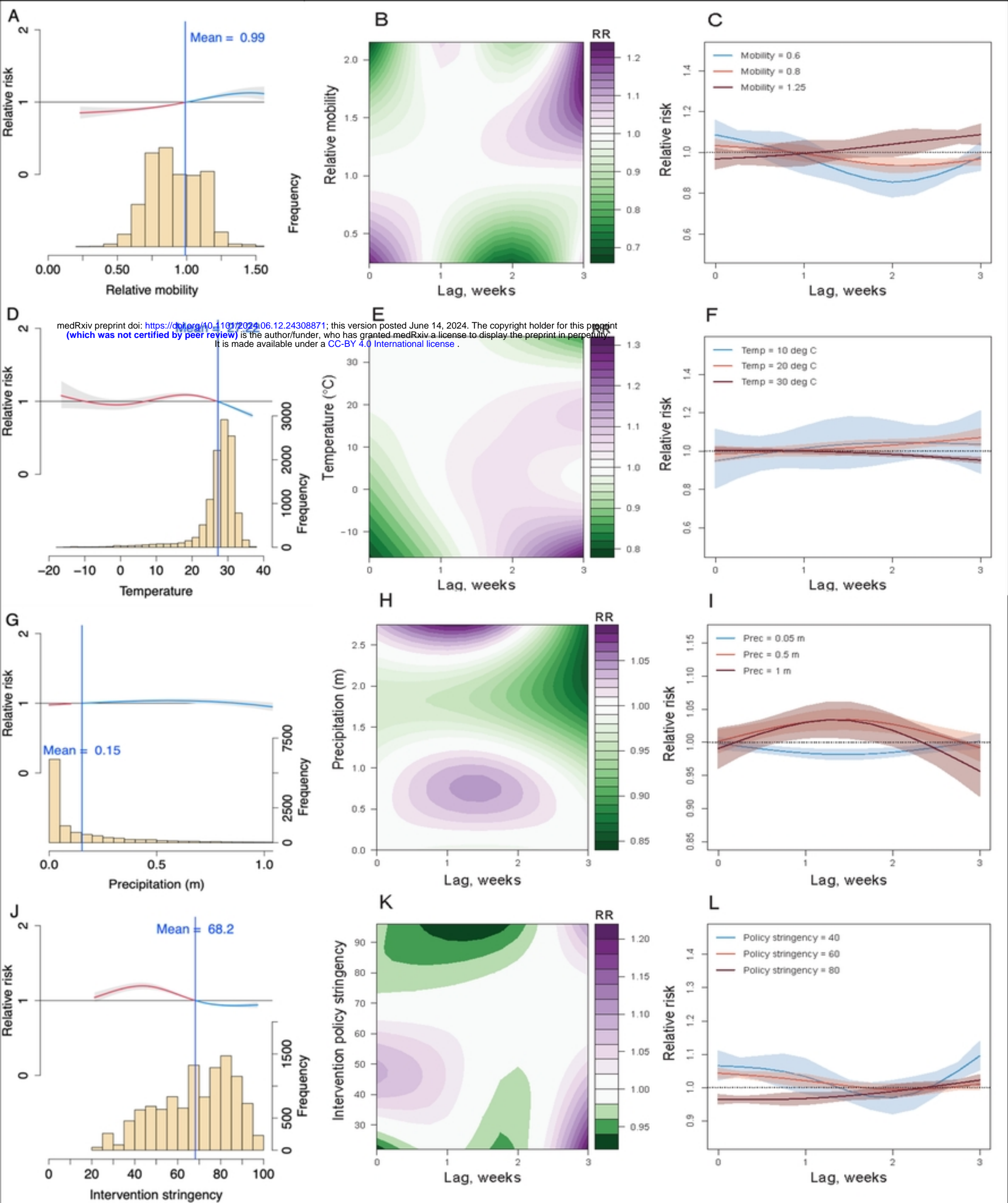
Fig S49. Standard deviation (SD) of posterior predictive R_t during wave 1 in India, 2020, derived from the best fitting model (model 4.1 without DLNMs) at country level using 2-week lag covariates and leave-one-district-out cross-validation approach. Areas shaded in grey are areas for which no data is available.



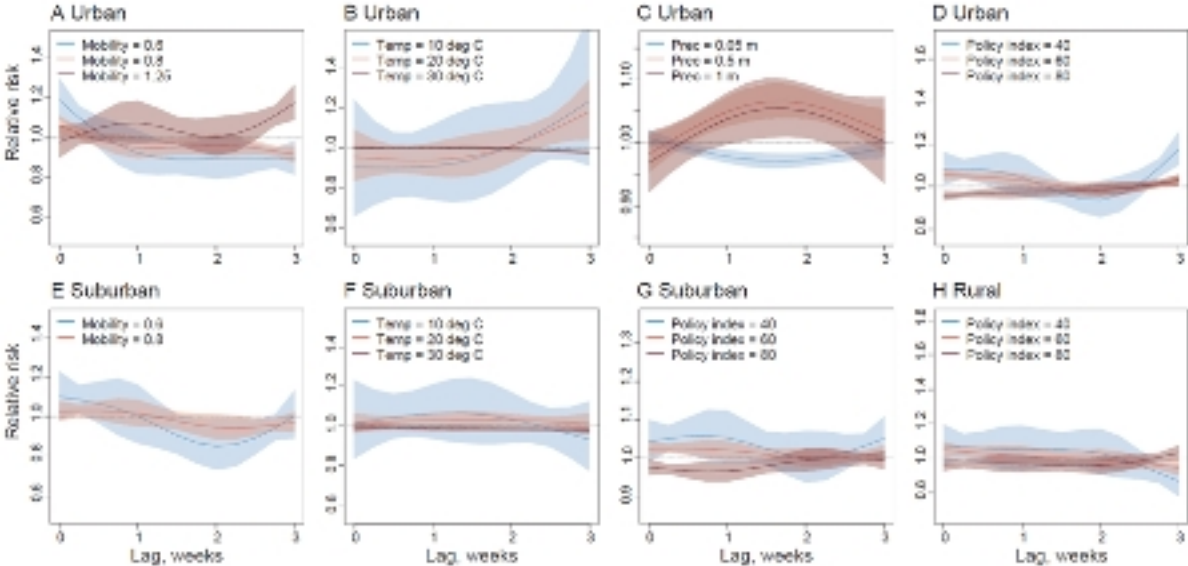
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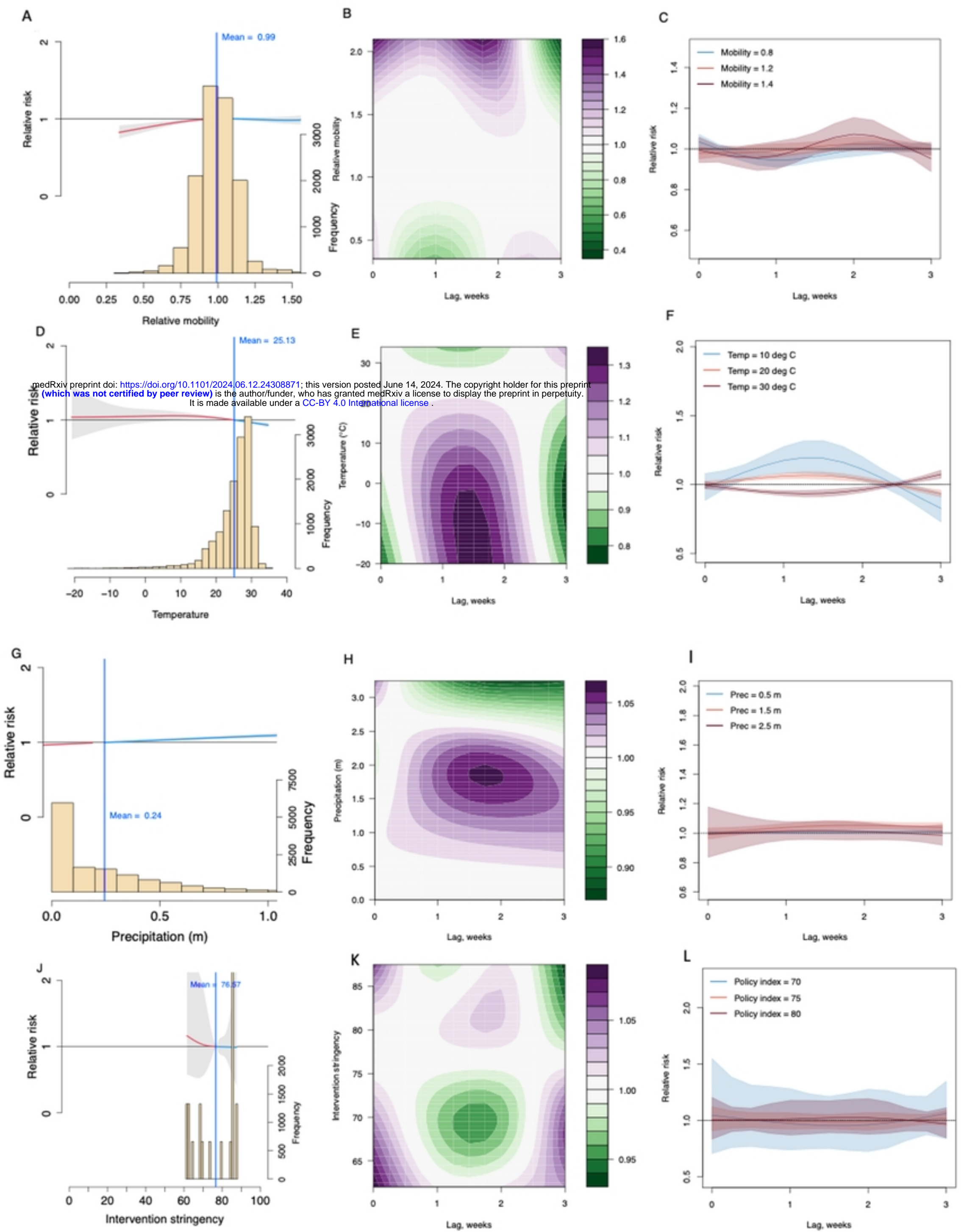
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