

## Appendix

### Short-term Association among Meteorological Variation, Outdoor Air Pollution and Acute Bronchiolitis in Children in a Subtropical Setting

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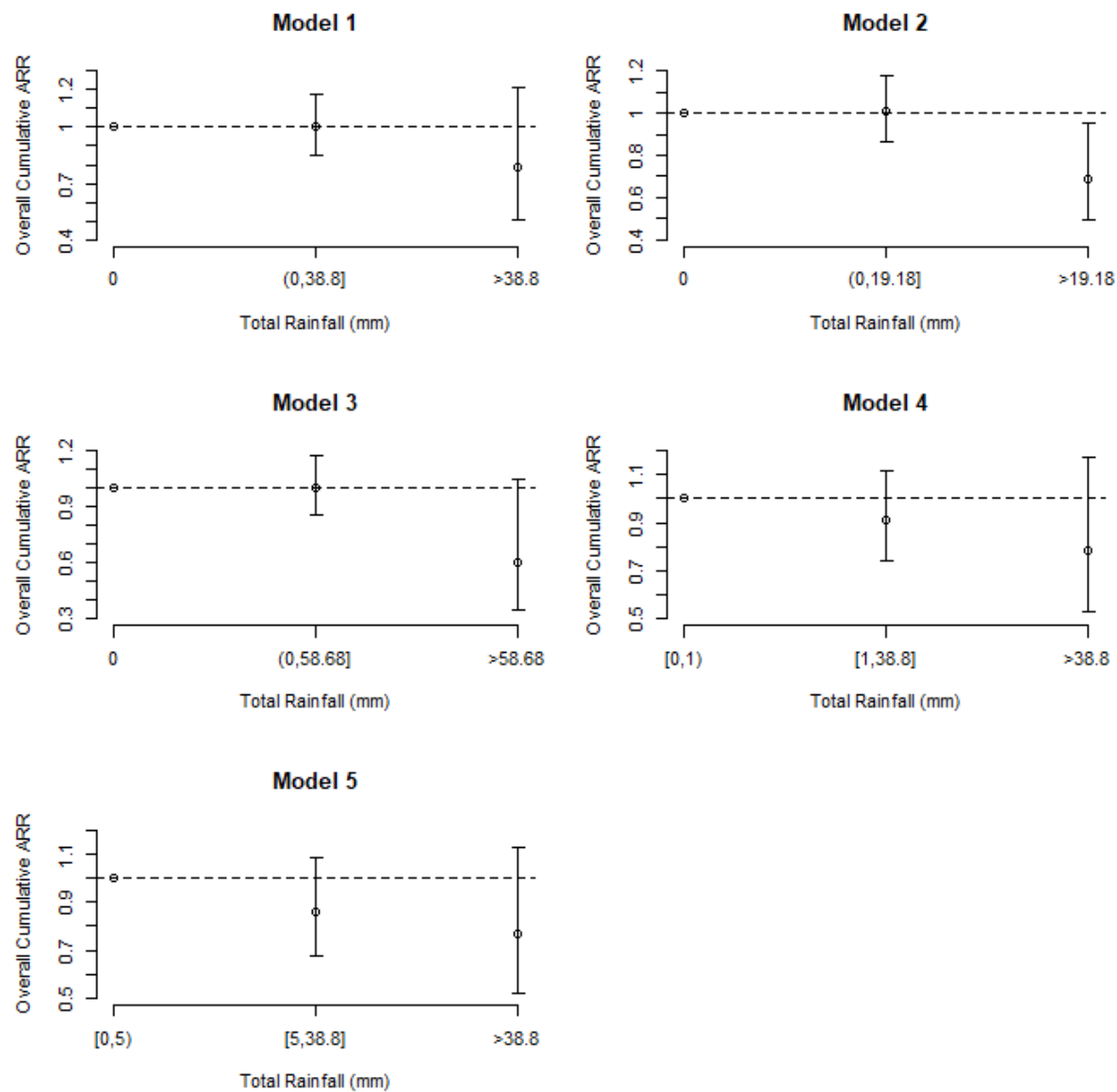
- A. Pearson correlation coefficient between the meteorological factors and pollutants during the study period (2008 - 2017)
- B. Sensitivity Analysis: Cumulative adjusted relative risks (ARRs) of rainfall using different sets of cutoffs
- C. Sensitivity Analysis: Cumulative adjusted relative risks (ARRs) of meteorological parameters at different parameter settings
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- E. R outputs of the modelling analysis

**A. Pearson correlation coefficient between the meteorological factors and pollutants during the study period (2008 - 2017)**

	<b>Ambient Temperature</b>	<b>Apparent Temperature</b>	<b>Relative Humidity</b>	<b>Vapour Pressure</b>	<b>Rainfall</b>	<b>NO<sub>2</sub></b>	<b>log(SO<sub>2</sub>)</b>	<b>O<sub>3</sub></b>	<b>log(PM<sub>10</sub>)</b>
<b>Ambient Temperature</b>		0.973	0.227	0.942	0.121	-0.337	0.023	-0.093	-0.468
<b>Apparent Temperature</b>			0.281	0.939	0.105	-0.250	0.097	-0.199	-0.476
<b>Relative Humidity</b>				0.506	0.352	-0.329	-0.384	-0.439	-0.515
<b>Vapour Pressure</b>					0.239	-0.439	-0.095	-0.277	-0.619
<b>Rainfall</b>						-0.133	-0.150	-0.191	-0.309
<b>NO<sub>2</sub></b>							0.576	0.191	0.697
<b>log(SO<sub>2</sub>)</b>								-0.068	0.417
<b>O<sub>3</sub></b>									0.566
<b>log(PM<sub>10</sub>)</b>									

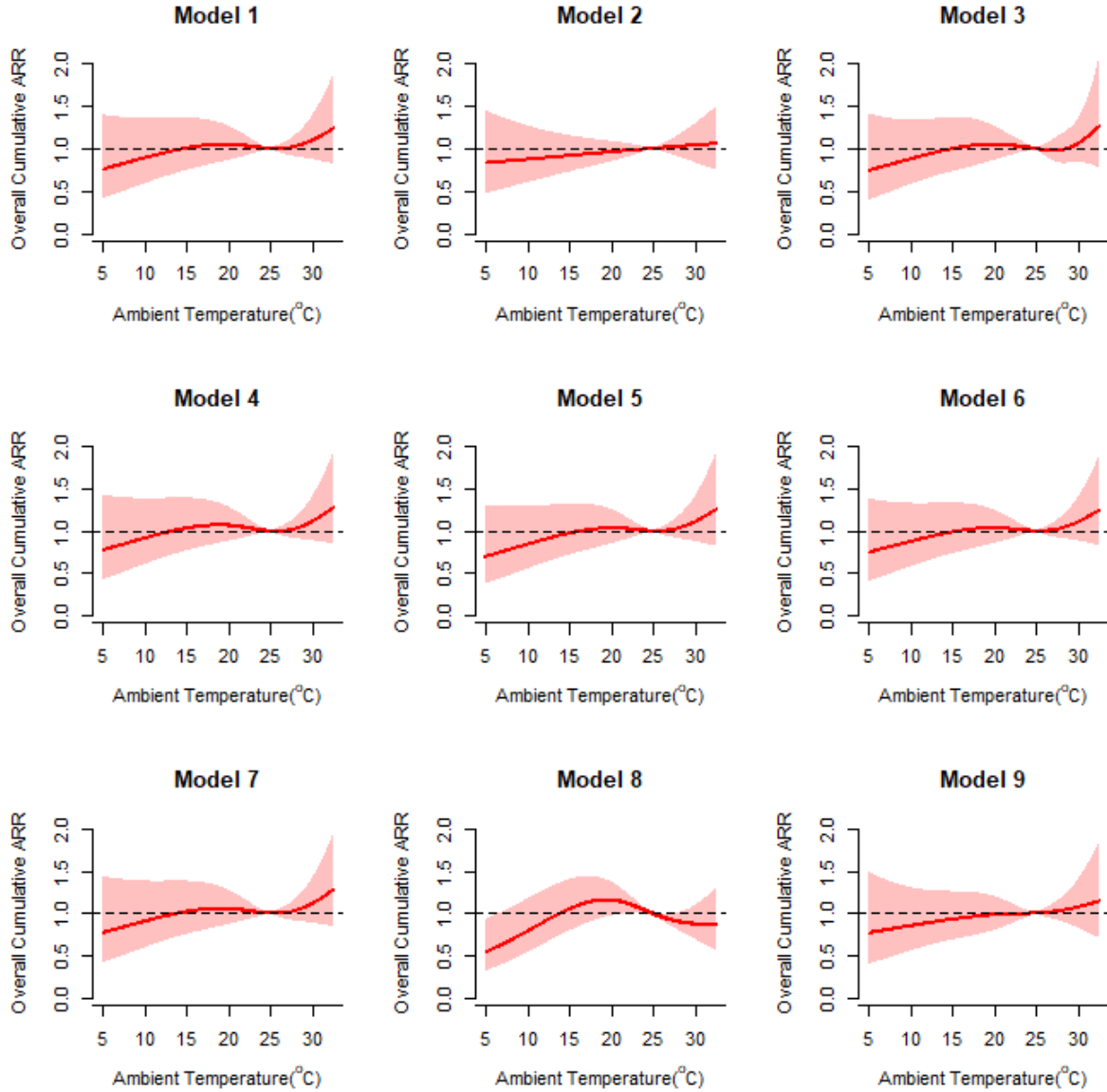
## B. Sensitivity Analysis: Cumulative adjusted relative risks (ARRs) of rainfall using different sets of cutoffs

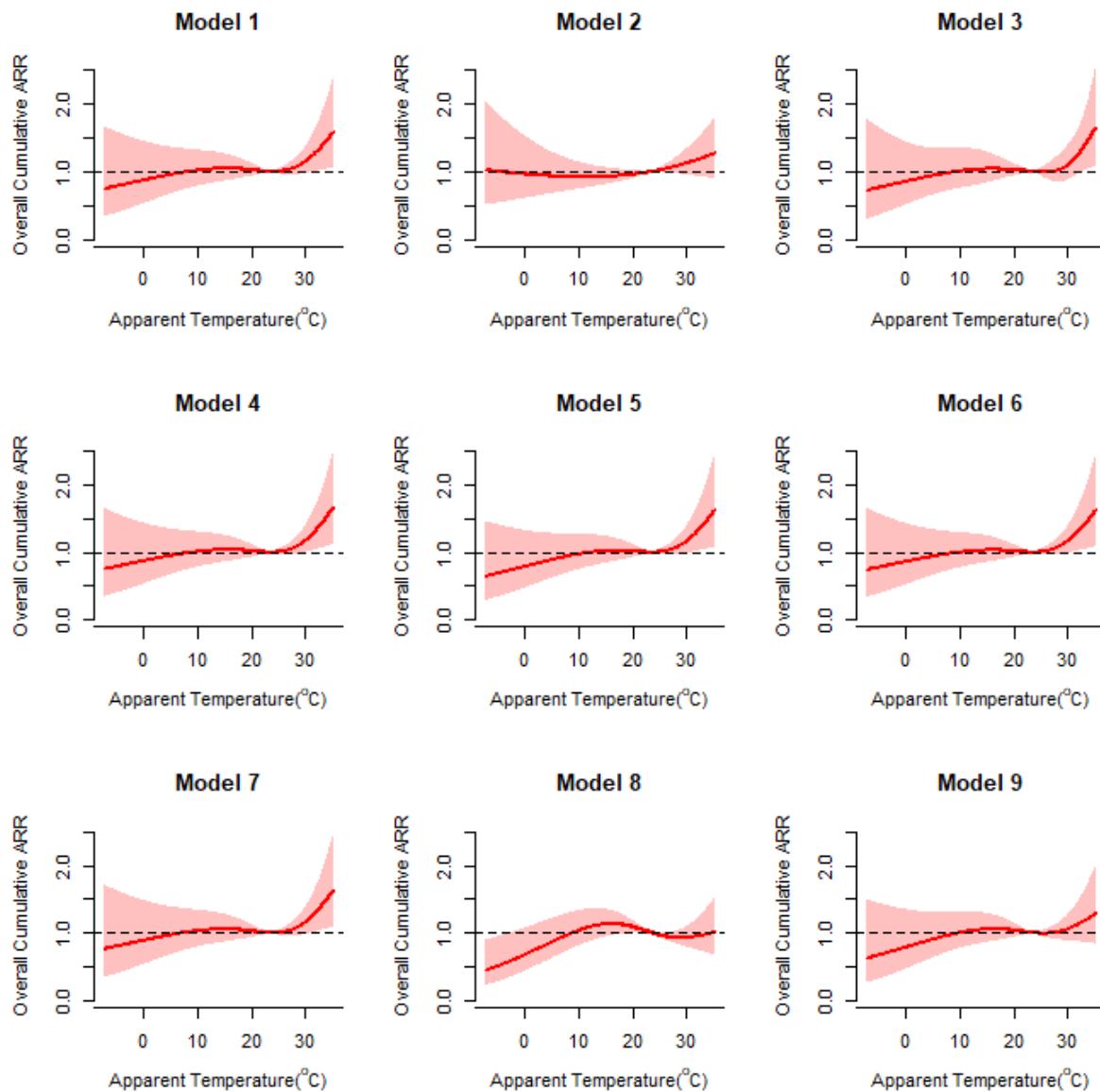
- **Model 1:** (i) Rainfall = 0; (ii)  $0 < \text{Rainfall} \leq 95^{\text{th}}$  percentile; and (iii) Rainfall  $> 95^{\text{th}}$  percentile
- **Model 2:** (i) Rainfall = 0; (ii)  $0 < \text{Rainfall} \leq 90^{\text{th}}$  percentile; and (iii) Rainfall  $> 90^{\text{th}}$  percentile
- **Model 3:** (i) Rainfall = 0; (ii)  $0 < \text{Rainfall} \leq 97.5^{\text{th}}$  percentile; and (iii) Rainfall  $> 97.5^{\text{th}}$  percentile
- **Model 4:** (i)  $0 \leq \text{Rainfall} \leq 1$ ; (ii)  $1 < \text{Rainfall} \leq 97.5^{\text{th}}$  percentile; and (iii) Rainfall  $> 97.5^{\text{th}}$  percentile
- **Model 5:** (i)  $0 \leq \text{Rainfall} \leq 5$ ; (ii)  $5 < \text{Rainfall} \leq 97.5^{\text{th}}$  percentile; and (iii) Rainfall  $> 97.5^{\text{th}}$  percentile

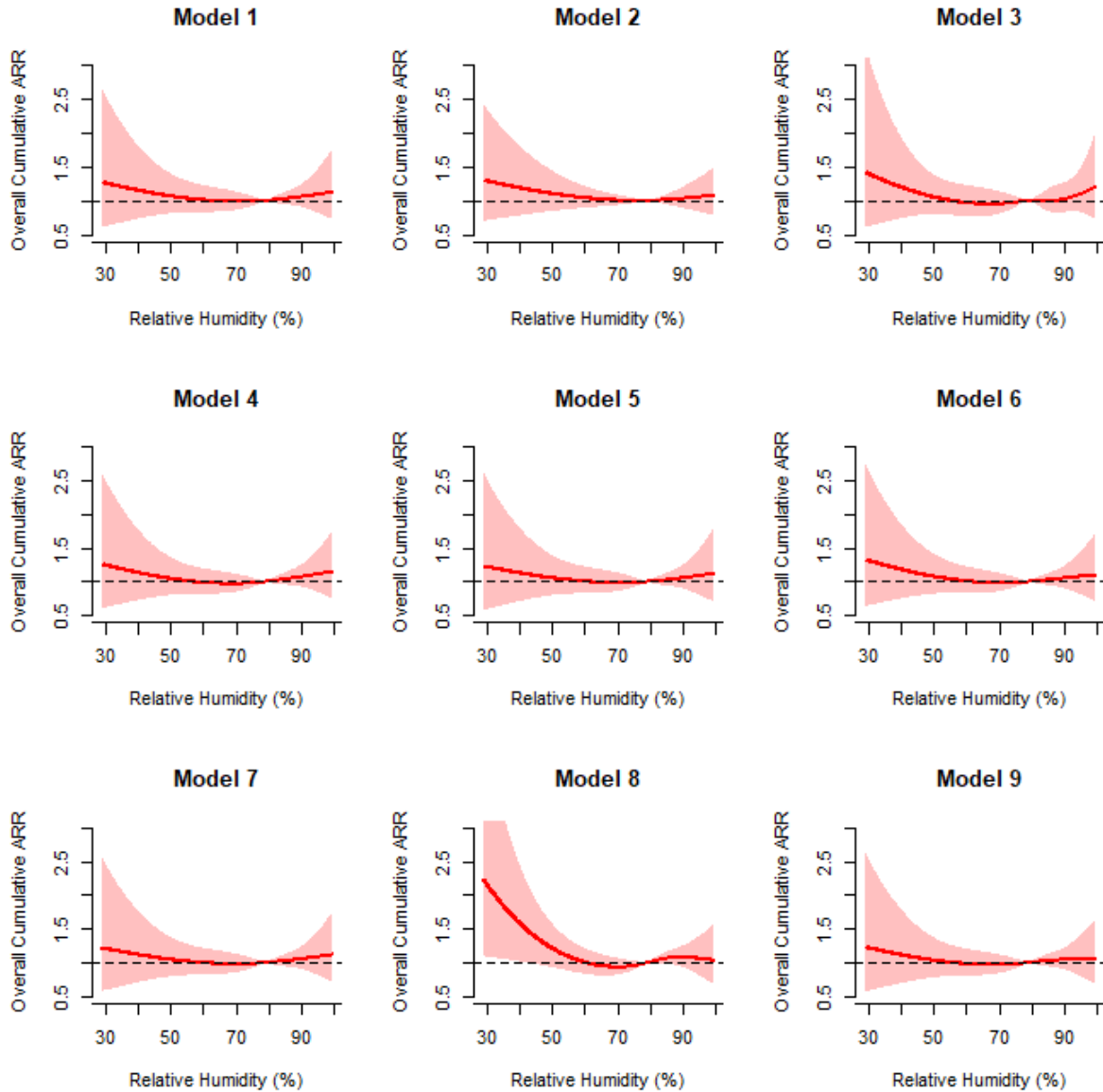


**C. Sensitivity Analysis: Cumulative adjusted relative risks (ARRs) of meteorological parameters: (a) ambient temperature, (b) apparent temperature, (c) relative humidity, (d) vapour pressure, and (e) total rainfall at different parameter settings**

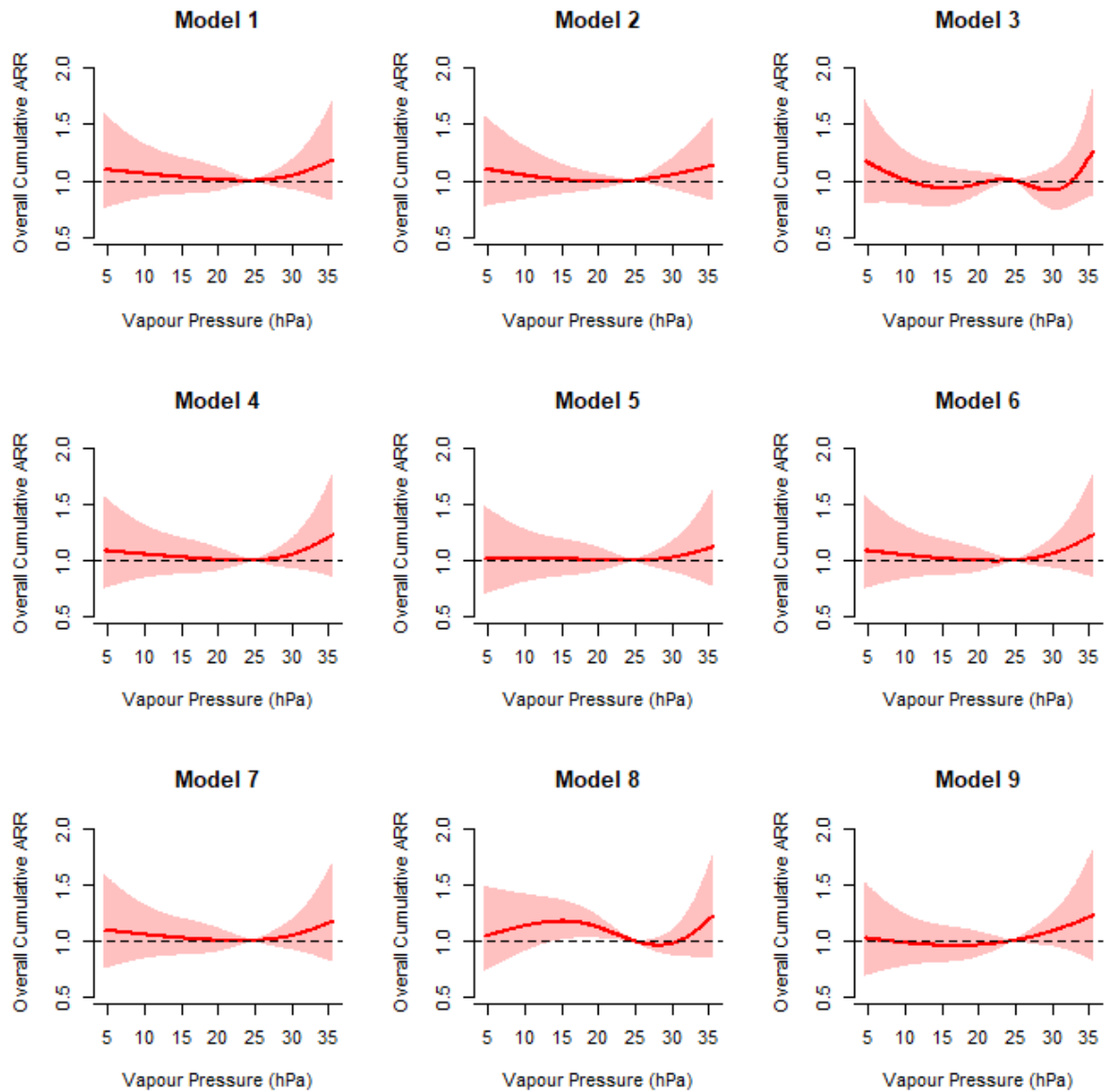
- **Model 1:** df for the meteorological parameters = 3; df for the pollutants = 4; df for lag = 4, df for day of study per year = 7
- **Model 2:** df for the meteorological parameters = 2; df for the pollutants = 4; df for lag = 4, df for day of study per year = 7
- **Model 3:** df for the meteorological parameters = 5; df for the pollutants = 4; df for lag = 4, df for day of study per year = 7
- **Model 4:** df for the meteorological parameters = 3; df for the pollutants = 3; df for lag = 4, df for day of study per year = 7
- **Model 5:** df for the meteorological parameters = 3; df for the pollutants = 5; df for lag = 4, df for day of study per year = 7
- **Model 6:** df for the meteorological parameters = 3; df for the pollutants = 4; df for lag = 3, df for day of study per year = 7
- **Model 7:** df for the meteorological parameters = 3; df for the pollutants = 4; df for lag = 5, df for day of study per year = 7
- **Model 8:** df for the meteorological parameters = 3; df for the pollutants = 4; df for lag = 4, df for day of study per year = 6
- **Model 9:** df for the meteorological parameters = 3; df for the pollutants = 4; df for lag = 4, df for day of study per year = 8

**(a) Ambient Temperature (ref. = 24.8°C)**

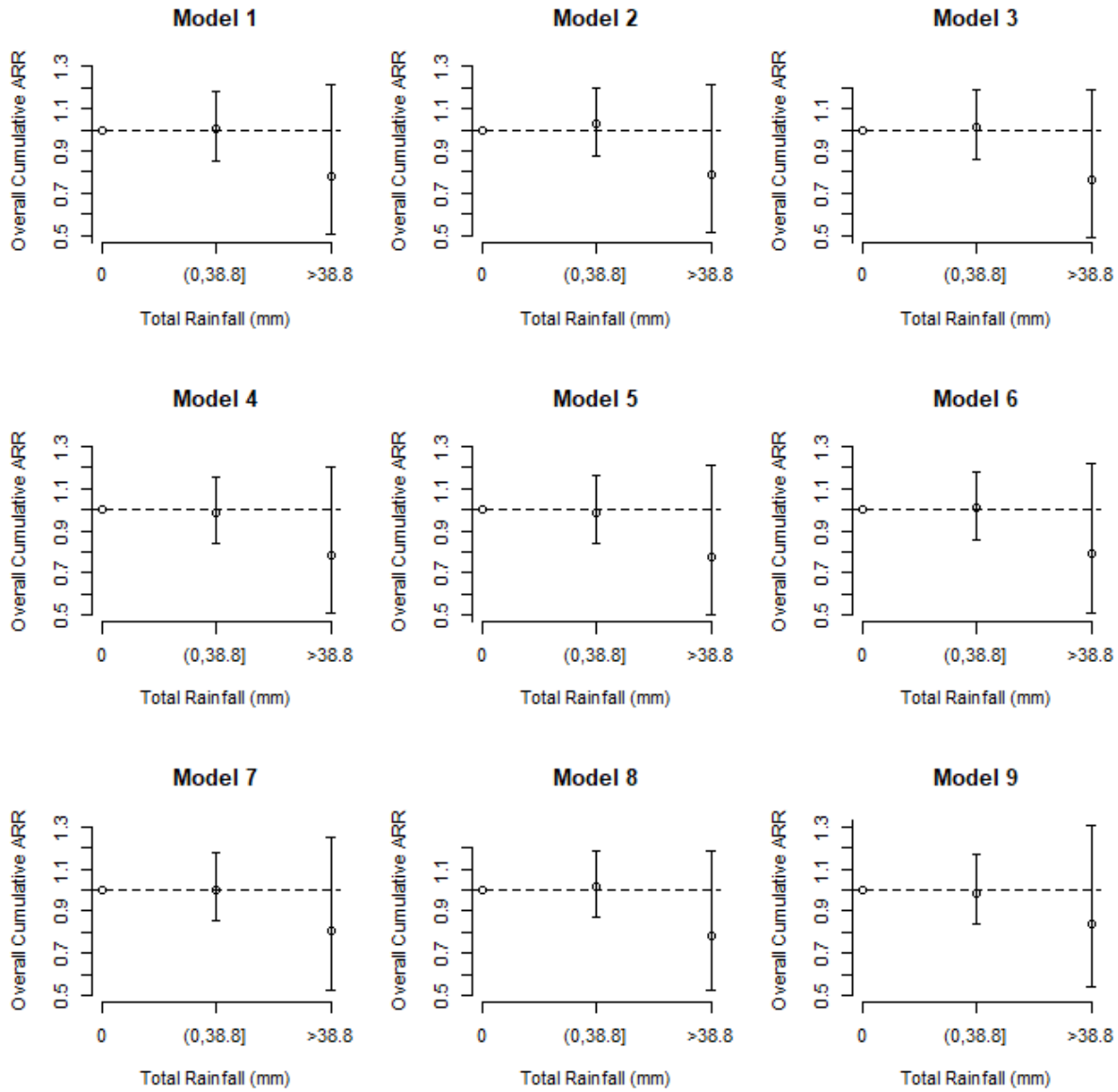
**(b) Apparent Temperature (ref. = 23.6°C)**

**(c) Relative Humidity (ref. = 79.0%)**



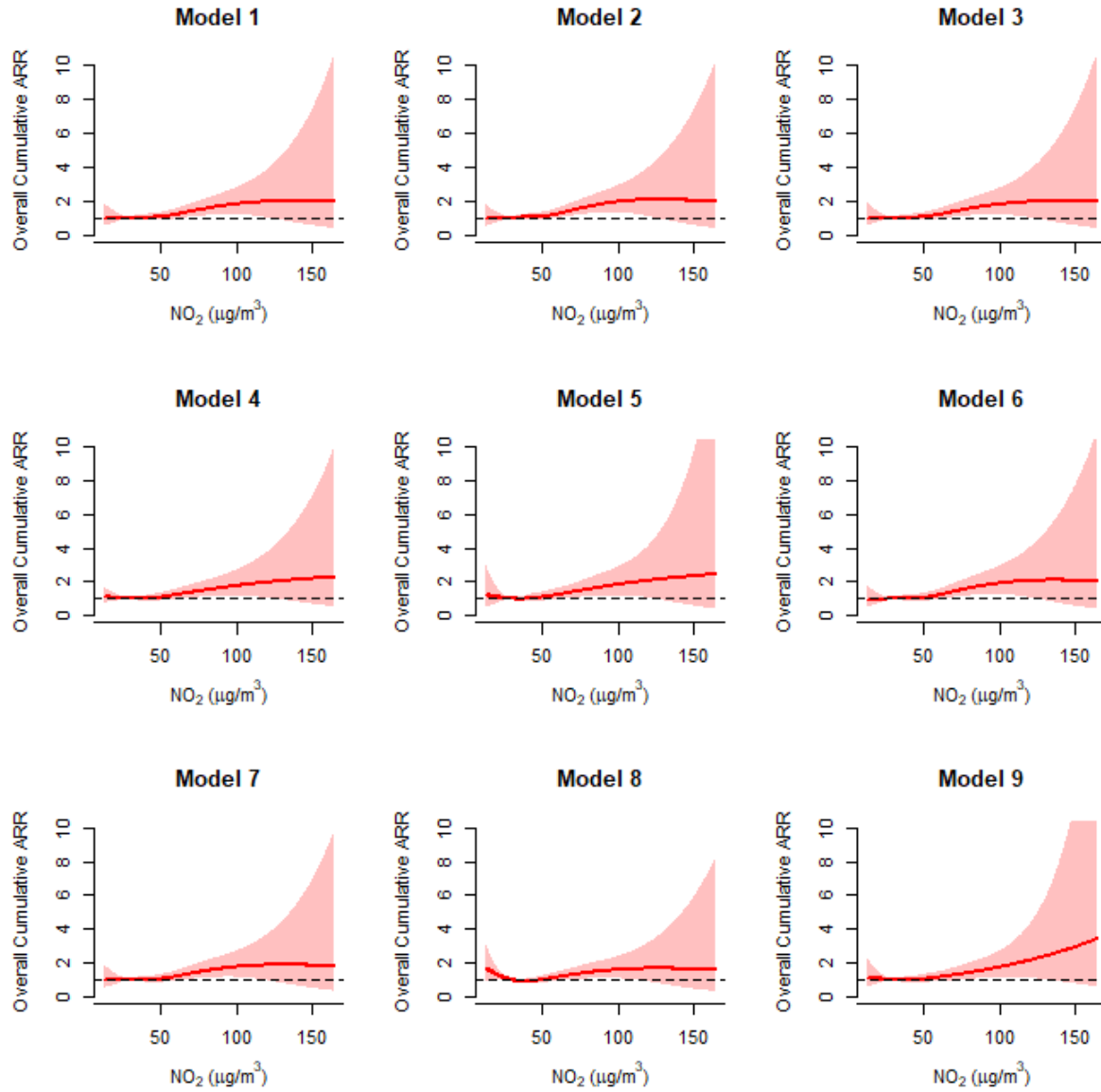
**(d) Vapour Pressure (ref. = 24.7 hPa)**

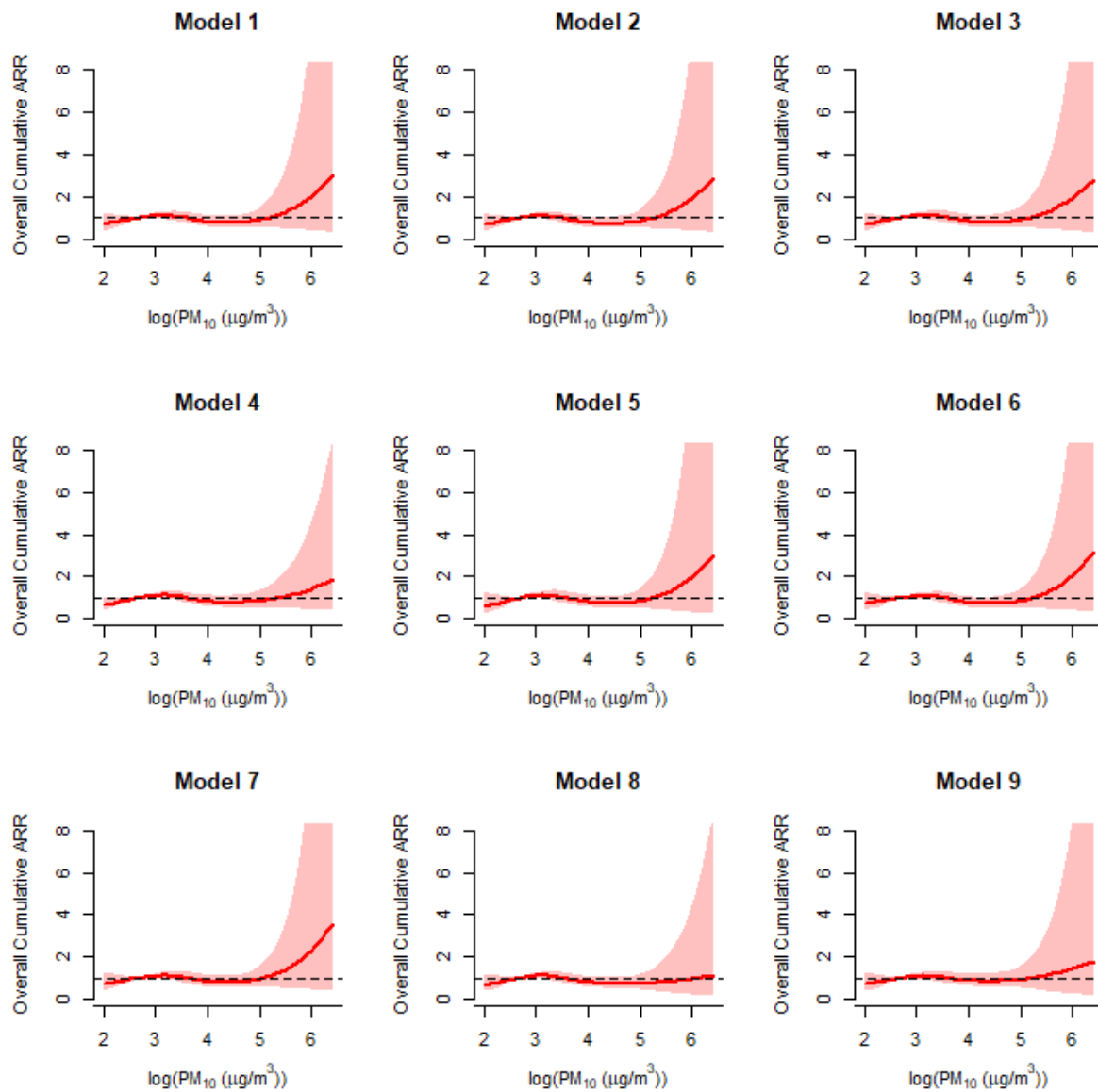
(e) Rainfall (ref. = 0)

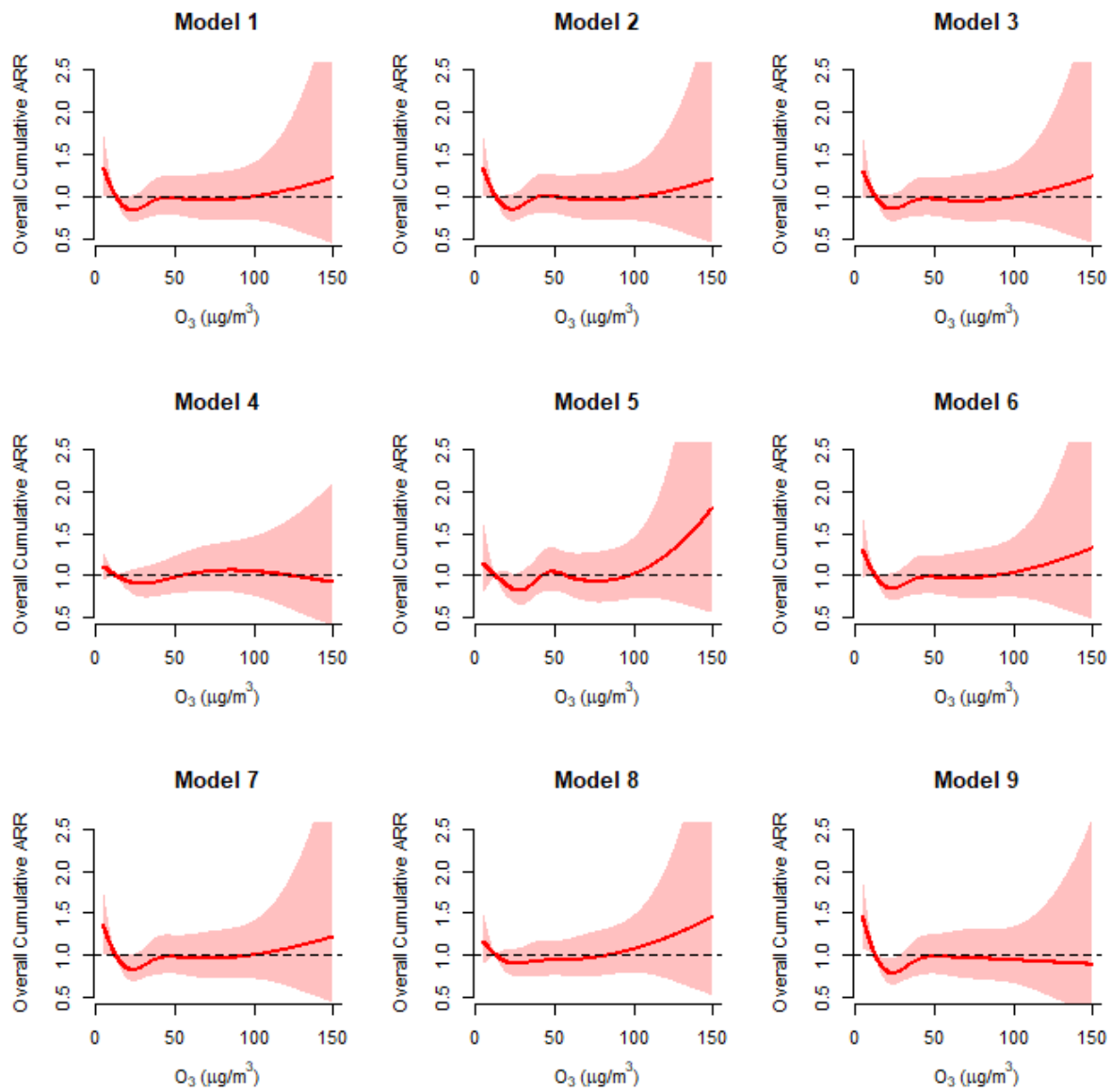


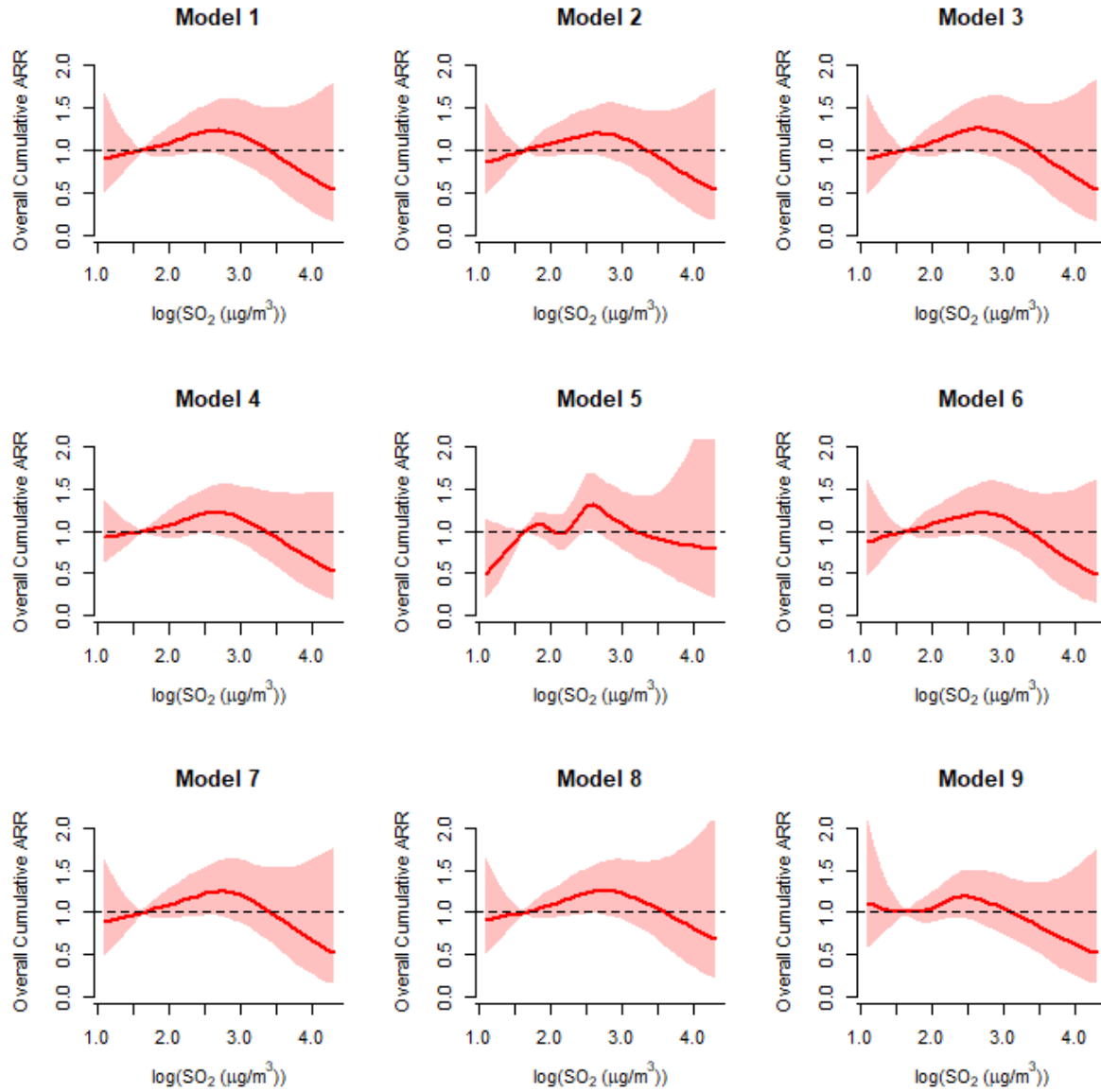
**D. Sensitivity Analysis: Cumulative adjusted relative risks (ARRs) of pollutants: (a) NO<sub>2</sub>, (b) PM<sub>10</sub>, (c) O<sub>3</sub>, and (d) SO<sub>2</sub> at different parameter settings**

- **Model 1:** df for the meteorological parameters = 3; df for the pollutants = 4; df for lag = 4, df for day of study per year = 7
- **Model 2:** df for the meteorological parameters = 3; df for the pollutants = 4; df for lag = 4, df for day of study per year = 7
- **Model 3:** df for the meteorological parameters = 5; df for the pollutants = 4; df for lag = 4, df for day of study per year = 7
- **Model 4:** df for the meteorological parameters = 3; df for the pollutants = 3; df for lag = 4, df for day of study per year = 7
- **Model 5:** df for the meteorological parameters = 3; df for the pollutants = 5; df for lag = 4, df for day of study per year = 7
- **Model 6:** df for the meteorological parameters = 3; df for the pollutants = 4; df for lag = 3, df for day of study per year = 7
- **Model 7:** df for the meteorological parameters = 3; df for the pollutants = 4; df for lag = 5, df for day of study per year = 7
- **Model 8:** df for the meteorological parameters = 3; df for the pollutants = 4; df for lag = 4, df for day of study per year = 6
- **Model 9:** df for the meteorological parameters = 3; df for the pollutants = 4; df for lag = 4, df for day of study per year = 8

(a) NO<sub>2</sub> (ref. = 29.0 µg/m<sup>3</sup>)

**(b)  $\log(\text{PM}_{10})$  (ref. =  $\log(15.0 \mu\text{g}/\text{m}^3)$ )**

(c) O<sub>3</sub> (ref. = 12.6 µg/m<sup>3</sup>)

**(d)  $\log(\text{SO}_2)$  (ref. =  $\log(5.2 \mu\text{g}/\text{m}^3)$ )**

## E. R outputs of the modelling analysis

**1. Primary model:**  $\log[E(Y_t)] = \alpha + \text{cb}(\text{temperature}_t) + \text{cb}(\text{relative humidity}_t) + \text{cb}(\text{factor}(\text{rainfall}_t)) + \text{cb}(\text{NO}_{2_t}) + \text{cb}(\log(\text{SO}_{2_t})) + \text{cb}(\text{O}_{3_t}) + \text{cb}(\log(\text{PM}_{10_t})) + \text{cb}(\text{factor}(\text{Holiday}_t)) + \text{ns}(\text{DOS}_t, \text{df} = 7 \text{ per year}) + \text{factor}(\text{DOW}_t) + s(\sqrt{\text{influenza}_t}, k = 7)$

Family: quasipoisson

Link function: log

Formula:

```
ad ~ temp.cb + humid.cb + rainfall.cb + o3.cb + so2.cb + no2.cb +
      pm10.cb + holiday.cb + factor(dow) + ns(dos, df = 10 * trend_df) +
      s(sqrt(influ), k = 7)
```

Parametric coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	1.4512548	0.7160001	2.027	0.042750 *
temp.cbv1.11	0.0439784	0.0418318	1.051	0.293187
temp.cbv1.12	-0.0878345	0.0390152	-2.251	0.024430 *
temp.cbv1.13	0.0446216	0.0618343	0.722	0.470570
temp.cbv1.14	-0.0034920	0.0423107	-0.083	0.934228
temp.cbv2.11	0.1231761	0.1142025	1.079	0.280852
temp.cbv2.12	-0.1643616	0.1065041	-1.543	0.122864
temp.cbv2.13	0.1794677	0.1601544	1.121	0.262540
temp.cbv2.14	-0.0698977	0.1133739	-0.617	0.537590
temp.cbv3.11	0.0137331	0.0511297	0.269	0.788258
temp.cbv3.12	-0.1119861	0.0500760	-2.236	0.025394 *
temp.cbv3.13	0.0684730	0.0706839	0.969	0.332752
temp.cbv3.14	0.0674186	0.0498300	1.353	0.176153
humid.cbv1.11	-0.0266661	0.0328741	-0.811	0.417331
humid.cbv1.12	0.0259349	0.0323173	0.803	0.422314
humid.cbv1.13	0.0136069	0.0448957	0.303	0.761849
humid.cbv1.14	-0.0470236	0.0330892	-1.421	0.155373
humid.cbv2.11	-0.0812557	0.1074348	-0.756	0.449505
humid.cbv2.12	0.1865052	0.1062710	1.755	0.079349 .
humid.cbv2.13	-0.0743799	0.1565142	-0.475	0.634655
humid.cbv2.14	-0.1123834	0.1107212	-1.015	0.310171
humid.cbv3.11	-0.0198497	0.0412145	-0.482	0.630106
humid.cbv3.12	0.0941500	0.0406179	2.318	0.020511 *
humid.cbv3.13	-0.0571965	0.0556244	-1.028	0.303899
humid.cbv3.14	0.0217260	0.0391004	0.556	0.578488
rainfall.cbv1.11	-0.0022131	0.0110607	-0.200	0.841422
rainfall.cbv1.12	-0.0047411	0.0115397	-0.411	0.681211
rainfall.cbv1.13	0.0032760	0.0145790	0.225	0.822220
rainfall.cbv1.14	0.0045150	0.0105962	0.426	0.670061
rainfall.cbv2.11	-0.0104598	0.0280257	-0.373	0.709005
rainfall.cbv2.12	-0.0495716	0.0304926	-1.626	0.104106
rainfall.cbv2.13	0.0254501	0.0361916	0.703	0.481977
rainfall.cbv2.14	-0.0359519	0.0268185	-1.341	0.180151
o3.cbv1.11	0.0345359	0.0298613	1.157	0.247540
o3.cbv1.12	-0.0307839	0.0298265	-1.032	0.302099
o3.cbv1.13	-0.0591781	0.0410856	-1.440	0.149856
o3.cbv1.14	0.0178601	0.0293947	0.608	0.543494
o3.cbv2.11	0.0179539	0.0389989	0.460	0.645280
o3.cbv2.12	0.0066618	0.0398056	0.167	0.867098
o3.cbv2.13	-0.0294685	0.0524620	-0.562	0.574350
o3.cbv2.14	-0.0338190	0.0377101	-0.897	0.369880
o3.cbv3.11	0.0729922	0.0746161	0.978	0.328026
o3.cbv3.12	-0.0630899	0.0762029	-0.828	0.407773
o3.cbv3.13	-0.1670266	0.0999883	-1.670	0.094919 .
o3.cbv3.14	0.0555581	0.0730619	0.760	0.447053
o3.cbv4.11	0.1574924	0.0703358	2.239	0.025210 *
o3.cbv4.12	-0.1800452	0.0740213	-2.432	0.015052 *
o3.cbv4.13	-0.0433764	0.0938465	-0.462	0.643963
o3.cbv4.14	0.1376333	0.0706558	1.948	0.051503 .
so2.cbv1.11	0.0134665	0.0521547	0.258	0.796266
so2.cbv1.12	0.0984224	0.0509775	1.931	0.053602 .



so2.cbv1.13	0.0114321	0.0712974	0.160	0.872620
so2.cbv1.14	-0.0912327	0.0503946	-1.810	0.070326 .
so2.cbv2.11	0.0464193	0.0474932	0.977	0.328445
so2.cbv2.12	0.0811822	0.0475452	1.707	0.087824 .
so2.cbv2.13	-0.0280440	0.0639681	-0.438	0.661120
so2.cbv2.14	-0.0241849	0.0459626	-0.526	0.598792
so2.cbv3.11	0.0549618	0.1204914	0.456	0.648313
so2.cbv3.12	0.2331202	0.1208678	1.929	0.053847 .
so2.cbv3.13	-0.1215267	0.1657625	-0.733	0.463524
so2.cbv3.14	-0.1651787	0.1167885	-1.414	0.157352
so2.cbv4.11	0.0026564	0.0769013	0.035	0.972447
so2.cbv4.12	0.0560959	0.0811260	0.691	0.489319
so2.cbv4.13	-0.0973958	0.1074898	-0.906	0.364949
so2.cbv4.14	-0.0658722	0.0757302	-0.870	0.384455
no2.cbv1.11	-0.0616957	0.0527942	-1.169	0.242642
no2.cbv1.12	0.0017939	0.0542495	0.033	0.973623
no2.cbv1.13	-0.0009991	0.0715642	-0.014	0.988862
no2.cbv1.14	0.1019180	0.0538348	1.893	0.058420 .
no2.cbv2.11	0.0188803	0.0511363	0.369	0.711990
no2.cbv2.12	-0.0198304	0.0538109	-0.369	0.712508
no2.cbv2.13	0.0673643	0.0691143	0.975	0.329787
no2.cbv2.14	0.0877127	0.0512704	1.711	0.087210 .
no2.cbv3.11	-0.1785233	0.1212393	-1.472	0.140980
no2.cbv3.12	0.1512279	0.1246071	1.214	0.224969
no2.cbv3.13	0.0090424	0.1643940	0.055	0.956138
no2.cbv3.14	0.2665555	0.1212167	2.199	0.027944 *
no2.cbv4.11	-0.0688453	0.1023508	-0.673	0.501221
no2.cbv4.12	0.1026636	0.1061544	0.967	0.333554
no2.cbv4.13	0.0079176	0.1451105	0.055	0.956490
no2.cbv4.14	0.1460566	0.1029970	1.418	0.156262
pm10.cbv1.11	-0.0236306	0.0549739	-0.430	0.667330
pm10.cbv1.12	-0.0261759	0.0527177	-0.497	0.619553
pm10.cbv1.13	0.1661722	0.0743066	2.236	0.025395 *
pm10.cbv1.14	-0.1381865	0.0528898	-2.613	0.009021 **
pm10.cbv2.11	-0.0436518	0.0515316	-0.847	0.397004
pm10.cbv2.12	-0.0538285	0.0513311	-1.049	0.294411
pm10.cbv2.13	0.0703806	0.0739057	0.952	0.341010
pm10.cbv2.14	-0.1381750	0.0517831	-2.668	0.007658 **
pm10.cbv3.11	0.0970854	0.1293034	0.751	0.452804
pm10.cbv3.12	-0.2039492	0.1259097	-1.620	0.105365
pm10.cbv3.13	0.3679024	0.1741204	2.113	0.034679 *
pm10.cbv3.14	-0.2342362	0.1248315	-1.876	0.060682 .
pm10.cbv4.11	0.0010267	0.1237157	0.008	0.993379
pm10.cbv4.12	-0.0726563	0.1305394	-0.557	0.577847
pm10.cbv4.13	0.2272455	0.1722491	1.319	0.187162
pm10.cbv4.14	0.0032430	0.1298638	0.025	0.980079
holiday.cbv1.11	0.0195226	0.0139753	1.397	0.162523
holiday.cbv1.12	-0.0377211	0.0125888	-2.996	0.002751 **
holiday.cbv1.13	-0.0213359	0.0183454	-1.163	0.244904
holiday.cbv1.14	-0.0291242	0.0132594	-2.196	0.028123 *
factor(dow)2	-0.0587772	0.0221779	-2.650	0.008080 **
factor(dow)3	-0.0737656	0.0235202	-3.136	0.001726 **
factor(dow)4	-0.0442848	0.0237874	-1.862	0.062731 .
factor(dow)5	-0.0751847	0.0237134	-3.171	0.001535 **
factor(dow)6	-0.0899525	0.0235340	-3.822	0.000135 ***
factor(dow)7	-0.0397347	0.0228790	-1.737	0.082524 .
ns(dos, df = 10 * trend_df)1	0.8616721	0.3091919	2.787	0.005351 **
ns(dos, df = 10 * trend_df)2	-0.0458647	0.4184533	-0.110	0.912729
ns(dos, df = 10 * trend_df)3	0.9980103	0.3923718	2.544	0.011017 *
ns(dos, df = 10 * trend_df)4	0.3362908	0.4123966	0.815	0.414868
ns(dos, df = 10 * trend_df)5	0.4138532	0.3848843	1.075	0.282331
ns(dos, df = 10 * trend_df)6	-0.2839202	0.4000807	-0.710	0.477965
ns(dos, df = 10 * trend_df)7	-0.0838325	0.3579476	-0.234	0.814841
ns(dos, df = 10 * trend_df)8	1.2097265	0.3573797	3.385	0.000720 ***
ns(dos, df = 10 * trend_df)9	-0.8398919	0.4148958	-2.024	0.043012 *
ns(dos, df = 10 * trend_df)10	-0.1715906	0.4126791	-0.416	0.677585
ns(dos, df = 10 * trend_df)11	-0.1609482	0.4416006	-0.364	0.715533
ns(dos, df = 10 * trend_df)12	0.6232963	0.3867686	1.612	0.107152
ns(dos, df = 10 * trend_df)13	-0.5633256	0.3747890	-1.503	0.132918
ns(dos, df = 10 * trend_df)14	1.3810768	0.3554162	3.886	0.000104 ***
ns(dos, df = 10 * trend_df)15	0.7007377	0.3546676	1.976	0.048262 *

```

ns(dos, df = 10 * trend_df)16 0.0950378 0.3999787 0.238 0.812200
ns(dos, df = 10 * trend_df)17 -0.7546348 0.4165587 -1.812 0.070136 .
ns(dos, df = 10 * trend_df)18 0.3153634 0.4294361 0.734 0.462775
ns(dos, df = 10 * trend_df)19 0.3169441 0.3761137 0.843 0.399465
ns(dos, df = 10 * trend_df)20 0.9033308 0.3660175 2.468 0.013635 *
ns(dos, df = 10 * trend_df)21 -0.1041196 0.3738877 -0.278 0.780662
ns(dos, df = 10 * trend_df)22 1.1412016 0.3575339 3.192 0.001426 **
ns(dos, df = 10 * trend_df)23 0.1288197 0.3916974 0.329 0.742270
ns(dos, df = 10 * trend_df)24 0.7538852 0.3893076 1.936 0.052891 .
ns(dos, df = 10 * trend_df)25 0.9750480 0.4100772 2.378 0.017474 *
ns(dos, df = 10 * trend_df)26 0.1975424 0.3802096 0.520 0.603402
ns(dos, df = 10 * trend_df)27 -0.4322074 0.3771566 -1.146 0.251890
ns(dos, df = 10 * trend_df)28 0.6356608 0.3621247 1.755 0.079286 .
ns(dos, df = 10 * trend_df)29 1.0673142 0.3595173 2.969 0.003011 **
ns(dos, df = 10 * trend_df)30 0.1287451 0.4219465 0.305 0.760292
ns(dos, df = 10 * trend_df)31 0.1093384 0.3945192 0.277 0.781687
ns(dos, df = 10 * trend_df)32 0.5879758 0.4081295 1.441 0.149771
ns(dos, df = 10 * trend_df)33 0.5000772 0.3804599 1.314 0.188798
ns(dos, df = 10 * trend_df)34 0.6856981 0.3469802 1.976 0.048213 *
ns(dos, df = 10 * trend_df)35 1.1784024 0.3723688 3.165 0.001566 **
ns(dos, df = 10 * trend_df)36 0.0960919 0.3497702 0.275 0.783541
ns(dos, df = 10 * trend_df)37 0.2188771 0.4076512 0.537 0.591356
ns(dos, df = 10 * trend_df)38 1.1243102 0.3909058 2.876 0.004050 **
ns(dos, df = 10 * trend_df)39 0.5472236 0.4055893 1.349 0.177359
ns(dos, df = 10 * trend_df)40 0.3836715 0.3869929 0.991 0.321551
ns(dos, df = 10 * trend_df)41 -0.0475495 0.3874454 -0.123 0.902332
ns(dos, df = 10 * trend_df)42 -0.5383873 0.3875989 -1.389 0.164913
ns(dos, df = 10 * trend_df)43 1.5538601 0.3523201 4.410 1.06e-05 ***
ns(dos, df = 10 * trend_df)44 0.4011037 0.4129479 0.971 0.331458
ns(dos, df = 10 * trend_df)45 0.1423757 0.4001527 0.356 0.722010
ns(dos, df = 10 * trend_df)46 0.1128887 0.4155741 0.272 0.785911
ns(dos, df = 10 * trend_df)47 0.4619514 0.3811831 1.212 0.225638
ns(dos, df = 10 * trend_df)48 0.1630531 0.3813022 0.428 0.668953
ns(dos, df = 10 * trend_df)49 -0.2127009 0.3906294 -0.545 0.586127
ns(dos, df = 10 * trend_df)50 0.6608814 0.3591247 1.840 0.065816 .
ns(dos, df = 10 * trend_df)51 0.2155257 0.4203650 0.513 0.608186
ns(dos, df = 10 * trend_df)52 0.1086832 0.4229558 0.257 0.797224
ns(dos, df = 10 * trend_df)53 0.6313049 0.3956350 1.596 0.110653
ns(dos, df = 10 * trend_df)54 0.3613383 0.4008369 0.901 0.367407
ns(dos, df = 10 * trend_df)55 0.5361872 0.3478824 1.541 0.123338
ns(dos, df = 10 * trend_df)56 0.9130877 0.3846419 2.374 0.017657 *
ns(dos, df = 10 * trend_df)57 0.6538293 0.3522626 1.856 0.063527 .
ns(dos, df = 10 * trend_df)58 0.8777681 0.4292818 2.045 0.040956 *
ns(dos, df = 10 * trend_df)59 0.2278709 0.4058652 0.561 0.574531
ns(dos, df = 10 * trend_df)60 0.1307263 0.4172703 0.313 0.754080
ns(dos, df = 10 * trend_df)61 0.6635502 0.3857125 1.720 0.085463 .
ns(dos, df = 10 * trend_df)62 0.6422523 0.3559697 1.804 0.071282 .
ns(dos, df = 10 * trend_df)63 0.4363803 0.3762755 1.160 0.246236
ns(dos, df = 10 * trend_df)64 1.1266372 0.3555550 3.169 0.001545 **
ns(dos, df = 10 * trend_df)65 0.0357018 0.4227793 0.084 0.932707
ns(dos, df = 10 * trend_df)66 0.5818062 0.4249520 1.369 0.171054
ns(dos, df = 10 * trend_df)67 1.0917789 0.4220827 2.587 0.009732 **
ns(dos, df = 10 * trend_df)68 0.5217567 0.3044827 1.714 0.086695 .
ns(dos, df = 10 * trend_df)69 0.5761929 0.7550888 0.763 0.445468
ns(dos, df = 10 * trend_df)70 -0.0060447 0.1776860 -0.034 0.972864

```

```

---
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

Approximate significance of smooth terms:

```

      edf Ref.df      F p-value
s(sqrt(influ)) 1.259 1.482 9.878 0.000315 ***

```

```

---
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

```

R-sq.(adj) = 0.474  Deviance explained = 47.9%
GCV = 1.0821  Scale est. = 0.98661  n = 3632

```

**2. Secondary model 1:**  $\log[E(Y_t)] = \alpha + \text{cb}(\text{Apparent Temperature}_t) + \text{cb}(\text{Relative Humidity}_t) + \text{cb}(\text{factor}(\text{Rainfall}_t)) + \text{cb}(\text{NO}_{2t}) + \text{cb}(\log(\text{SO}_{2t})) + \text{cb}(\text{O}_{3t}) + \text{cb}(\log(\text{PM}_{10t})) + \text{cb}(\text{factor}(\text{Holiday}_t)) + \text{ns}(\text{DOS}_t, \text{df} = 7 \text{ per year}) + \text{factor}(\text{DOW}_t) + s(\sqrt{\text{Influenza}_t}, k = 7)$

Family: quasipoisson

Link function: log

Formula:

ad ~ AT.cb + humid.cb + rainfall.cb + o3.cb + so2.cb + no2.cb + pm10.cb + holiday.cb + factor(dow) + ns(dos, df = 10 \* trend\_df) + s(sqrt(influ), k = 7)

Parametric coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	1.6660412	0.7586414	2.196	0.028155 *
AT.cbv1.l1	0.0552618	0.0477023	1.158	0.246754
AT.cbv1.l2	-0.1034158	0.0444522	-2.326	0.020054 *
AT.cbv1.l3	0.0631939	0.0685733	0.922	0.356829
AT.cbv1.l4	-0.0334739	0.0473336	-0.707	0.479496
AT.cbv2.l1	0.2376932	0.1459218	1.629	0.103427
AT.cbv2.l2	-0.2115769	0.1356748	-1.559	0.118987
AT.cbv2.l3	0.1915229	0.2004322	0.956	0.339369
AT.cbv2.l4	-0.1378967	0.1445228	-0.954	0.340076
AT.cbv3.l1	0.0423648	0.0472982	0.896	0.370479
AT.cbv3.l2	-0.0966215	0.0457569	-2.112	0.034793 *
AT.cbv3.l3	0.1121366	0.0661026	1.696	0.089903
AT.cbv3.l4	-0.0018263	0.0468047	-0.039	0.968877
humid.cbv1.l1	-0.0218804	0.0356452	-0.614	0.539365
humid.cbv1.l2	0.0224829	0.0347639	0.647	0.517850
humid.cbv1.l3	-0.0009628	0.0477471	-0.020	0.983914
humid.cbv1.l4	-0.0370310	0.0348635	-1.062	0.288234
humid.cbv2.l1	-0.0646684	0.1164570	-0.555	0.578728
humid.cbv2.l2	0.1329434	0.1113794	1.194	0.232716
humid.cbv2.l3	-0.0641735	0.1653667	-0.388	0.697990
humid.cbv2.l4	-0.0963373	0.1162263	-0.829	0.407234
humid.cbv3.l1	-0.0068002	0.0432011	-0.157	0.874933
humid.cbv3.l2	0.0665029	0.0423867	1.569	0.116753
humid.cbv3.l3	-0.0534840	0.0575815	-0.929	0.353040
humid.cbv3.l4	0.0285791	0.0404871	0.706	0.480312
rainfall.cbv1.l1	-0.0031316	0.0115235	-0.272	0.785827
rainfall.cbv1.l2	-0.0049700	0.0121226	-0.410	0.681846
rainfall.cbv1.l3	0.0040544	0.0150196	0.270	0.787220
rainfall.cbv1.l4	0.0053266	0.0109031	0.489	0.625197
rainfall.cbv2.l1	-0.0105060	0.0292174	-0.360	0.719184
rainfall.cbv2.l2	-0.0421359	0.0321307	-1.311	0.189816
rainfall.cbv2.l3	0.0412199	0.0378669	1.089	0.276433
rainfall.cbv2.l4	-0.0502319	0.0282973	-1.775	0.075965
o3.cbv1.l1	0.0348665	0.0295563	1.180	0.238217
o3.cbv1.l2	-0.0416967	0.0294356	-1.417	0.156711
o3.cbv1.l3	-0.0463252	0.0409948	-1.130	0.258546
o3.cbv1.l4	0.0248903	0.0290758	0.856	0.392031
o3.cbv2.l1	0.0227358	0.0387075	0.587	0.556992
o3.cbv2.l2	0.0025551	0.0397889	0.064	0.948801
o3.cbv2.l3	-0.0224234	0.0527896	-0.425	0.671032
o3.cbv2.l4	-0.0292102	0.0378654	-0.771	0.440512
o3.cbv3.l1	0.0649870	0.0744233	0.873	0.382613
o3.cbv3.l2	-0.0755945	0.0759536	-0.995	0.319676
o3.cbv3.l3	-0.1363626	0.1003953	-1.358	0.174474
o3.cbv3.l4	0.0494855	0.0731764	0.676	0.498929
o3.cbv4.l1	0.1564937	0.0718709	2.177	0.029519 *
o3.cbv4.l2	-0.1974352	0.0761727	-2.592	0.009585 **
o3.cbv4.l3	-0.0179600	0.0957428	-0.188	0.851213
o3.cbv4.l4	0.1257924	0.0725845	1.733	0.083180
so2.cbv1.l1	0.0167104	0.0541531	0.309	0.757662
so2.cbv1.l2	0.0831071	0.0531672	1.563	0.118118
so2.cbv1.l3	0.0001811	0.0739389	0.002	0.998046
so2.cbv1.l4	-0.0649959	0.0516835	-1.258	0.208634
so2.cbv2.l1	0.0512144	0.0489616	1.046	0.295632
so2.cbv2.l2	0.0676012	0.0492383	1.373	0.169864
so2.cbv2.l3	-0.0380584	0.0660353	-0.576	0.564428
so2.cbv2.l4	-0.0034456	0.0473060	-0.073	0.941941

so2.cbv3.11	0.0512808	0.1243337	0.412	0.680040
so2.cbv3.12	0.1955869	0.1250029	1.565	0.117758
so2.cbv3.13	-0.1419627	0.1713154	-0.829	0.407355
so2.cbv3.14	-0.1093854	0.1195790	-0.915	0.360387
so2.cbv4.11	-0.0021016	0.0774203	-0.027	0.978345
so2.cbv4.12	0.0148940	0.0813678	0.183	0.854773
so2.cbv4.13	-0.1435432	0.1088079	-1.319	0.187182
so2.cbv4.14	-0.0180096	0.0761196	-0.237	0.812985
no2.cbv1.11	-0.0651355	0.0527155	-1.236	0.216693
no2.cbv1.12	0.0240398	0.0527676	0.456	0.648722
no2.cbv1.13	-0.0233851	0.0722192	-0.324	0.746104
no2.cbv1.14	0.0724792	0.0537295	1.349	0.177440
no2.cbv2.11	0.0133337	0.0507296	0.263	0.792692
no2.cbv2.12	0.0124311	0.0529264	0.235	0.814321
no2.cbv2.13	0.0291712	0.0688185	0.424	0.671676
no2.cbv2.14	0.0585159	0.0513353	1.140	0.254420
no2.cbv3.11	-0.1983282	0.1208347	-1.641	0.100826
no2.cbv3.12	0.2152031	0.1223656	1.759	0.078722
no2.cbv3.13	-0.0379806	0.1657823	-0.229	0.818806
no2.cbv3.14	0.2064575	0.1214117	1.700	0.089135
no2.cbv4.11	-0.0736111	0.1029959	-0.715	0.474845
no2.cbv4.12	0.1499224	0.1062928	1.410	0.158496
no2.cbv4.13	0.0300032	0.1462432	0.205	0.837460
no2.cbv4.14	0.1414452	0.1034423	1.367	0.171598
pm10.cbv1.11	-0.0413979	0.0564995	-0.733	0.463785
pm10.cbv1.12	-0.0148565	0.0534441	-0.278	0.781043
pm10.cbv1.13	0.1699841	0.0763136	2.227	0.025984 *
pm10.cbv1.14	-0.1356220	0.0539619	-2.513	0.012008 *
pm10.cbv2.11	-0.0655134	0.0532196	-1.231	0.218409
pm10.cbv2.12	-0.0535008	0.0528486	-1.012	0.311449
pm10.cbv2.13	0.0908371	0.0754894	1.203	0.228942
pm10.cbv2.14	-0.1419105	0.0531216	-2.671	0.007590 **
pm10.cbv3.11	0.0621278	0.1325245	0.469	0.639242
pm10.cbv3.12	-0.1970264	0.1281867	-1.537	0.124382
pm10.cbv3.13	0.3798868	0.1784794	2.128	0.033372 *
pm10.cbv3.14	-0.2472232	0.1270476	-1.946	0.051750 .
pm10.cbv4.11	0.0051321	0.1264202	0.041	0.967621
pm10.cbv4.12	-0.0879770	0.1327344	-0.663	0.507501
pm10.cbv4.13	0.2528895	0.1743678	1.450	0.147063
pm10.cbv4.14	-0.0317103	0.1314118	-0.241	0.809334
holiday.cbv1.11	0.0229240	0.0140656	1.630	0.103241
holiday.cbv1.12	-0.0384166	0.0127883	-3.004	0.002684 **
holiday.cbv1.13	-0.0271741	0.0184173	-1.475	0.140180
holiday.cbv1.14	-0.0262329	0.0133766	-1.961	0.049950 *
factor(dow)2	-0.0649037	0.0225217	-2.882	0.003979 **
factor(dow)3	-0.0786969	0.0238626	-3.298	0.000984 ***
factor(dow)4	-0.0522564	0.0241511	-2.164	0.030556 *
factor(dow)5	-0.0788882	0.0240608	-3.279	0.001054 **
factor(dow)6	-0.0962840	0.0238861	-4.031	5.68e-05 ***
factor(dow)7	-0.0411008	0.0231921	-1.772	0.076455 .
ns(dos, df = 10 * trend_df)1	0.9348702	0.3096874	3.019	0.002557 **
ns(dos, df = 10 * trend_df)2	-0.0803316	0.4164357	-0.193	0.847047
ns(dos, df = 10 * trend_df)3	1.0230267	0.3934626	2.600	0.009362 **
ns(dos, df = 10 * trend_df)4	0.2611783	0.4190711	0.623	0.533175
ns(dos, df = 10 * trend_df)5	0.4308111	0.3930425	1.096	0.273117
ns(dos, df = 10 * trend_df)6	-0.3433589	0.4087290	-0.840	0.400932
ns(dos, df = 10 * trend_df)7	-0.0118598	0.3584741	-0.033	0.973610
ns(dos, df = 10 * trend_df)8	1.1995473	0.3593351	3.338	0.000852 ***
ns(dos, df = 10 * trend_df)9	-0.9221487	0.4106954	-2.245	0.024812 *
ns(dos, df = 10 * trend_df)10	-0.1866354	0.4136076	-0.451	0.651848
ns(dos, df = 10 * trend_df)11	-0.2841876	0.4413071	-0.644	0.519641
ns(dos, df = 10 * trend_df)12	0.6536305	0.3931383	1.663	0.096487 .
ns(dos, df = 10 * trend_df)13	-0.5691370	0.3824402	-1.488	0.136800
ns(dos, df = 10 * trend_df)14	1.3880733	0.3552156	3.908	9.50e-05 ***
ns(dos, df = 10 * trend_df)15	0.7389734	0.3566781	2.072	0.038359 *
ns(dos, df = 10 * trend_df)16	0.0195143	0.3967728	0.049	0.960777
ns(dos, df = 10 * trend_df)17	-0.7927040	0.4170666	-1.901	0.057432 .
ns(dos, df = 10 * trend_df)18	0.2183160	0.4275896	0.511	0.609683
ns(dos, df = 10 * trend_df)19	0.3343548	0.3729369	0.897	0.370026
ns(dos, df = 10 * trend_df)20	0.9254000	0.3714831	2.491	0.012783 *
ns(dos, df = 10 * trend_df)21	-0.1336946	0.3742418	-0.357	0.720934

```

ns(dos, df = 10 * trend_df)22 1.1972173 0.3591861 3.333 0.000868 ***
ns(dos, df = 10 * trend_df)23 0.0118967 0.3885849 0.031 0.975578
ns(dos, df = 10 * trend_df)24 0.7251224 0.3867721 1.875 0.060907 .
ns(dos, df = 10 * trend_df)25 0.8458428 0.4134686 2.046 0.040862 *
ns(dos, df = 10 * trend_df)26 0.2569205 0.3719087 0.691 0.489729
ns(dos, df = 10 * trend_df)27 -0.4461225 0.3833977 -1.164 0.244669
ns(dos, df = 10 * trend_df)28 0.6629031 0.3611692 1.835 0.066530 .
ns(dos, df = 10 * trend_df)29 1.0391171 0.3682964 2.821 0.004810 **
ns(dos, df = 10 * trend_df)30 0.1485589 0.4257700 0.349 0.727173
ns(dos, df = 10 * trend_df)31 0.0513062 0.3928524 0.131 0.896100
ns(dos, df = 10 * trend_df)32 0.4906748 0.4061067 1.208 0.227040
ns(dos, df = 10 * trend_df)33 0.5155347 0.3745580 1.376 0.168796
ns(dos, df = 10 * trend_df)34 0.7009934 0.3520285 1.991 0.046530 *
ns(dos, df = 10 * trend_df)35 1.1763850 0.3748126 3.139 0.001712 **
ns(dos, df = 10 * trend_df)36 0.1230499 0.3514770 0.350 0.726291
ns(dos, df = 10 * trend_df)37 0.1355332 0.4026633 0.337 0.736446
ns(dos, df = 10 * trend_df)38 1.1019279 0.3907503 2.820 0.004830 **
ns(dos, df = 10 * trend_df)39 0.4670187 0.4022368 1.161 0.245703
ns(dos, df = 10 * trend_df)40 0.3887944 0.3783013 1.028 0.304148
ns(dos, df = 10 * trend_df)41 -0.0256821 0.3917498 -0.066 0.947734
ns(dos, df = 10 * trend_df)42 -0.5588517 0.3885952 -1.438 0.150490
ns(dos, df = 10 * trend_df)43 1.5858538 0.3556713 4.459 8.52e-06 ***
ns(dos, df = 10 * trend_df)44 0.3081121 0.4151729 0.742 0.458061
ns(dos, df = 10 * trend_df)45 0.0408652 0.4048381 0.101 0.919603
ns(dos, df = 10 * trend_df)46 -0.0130057 0.4174507 -0.031 0.975148
ns(dos, df = 10 * trend_df)47 0.4410692 0.3781409 1.166 0.243530
ns(dos, df = 10 * trend_df)48 0.1638694 0.3867899 0.424 0.671837
ns(dos, df = 10 * trend_df)49 -0.2254507 0.3913279 -0.576 0.564575
ns(dos, df = 10 * trend_df)50 0.6883038 0.3620310 1.901 0.057358 .
ns(dos, df = 10 * trend_df)51 0.1323519 0.4167186 0.318 0.750804
ns(dos, df = 10 * trend_df)52 -0.0167819 0.4269387 -0.039 0.968648
ns(dos, df = 10 * trend_df)53 0.5195820 0.3981041 1.305 0.191935
ns(dos, df = 10 * trend_df)54 0.3275957 0.3929122 0.834 0.404474
ns(dos, df = 10 * trend_df)55 0.5389357 0.3528137 1.528 0.126723
ns(dos, df = 10 * trend_df)56 0.8693710 0.3848434 2.259 0.023946 *
ns(dos, df = 10 * trend_df)57 0.7022714 0.3553213 1.976 0.048187 *
ns(dos, df = 10 * trend_df)58 0.7339430 0.4301806 1.706 0.088078 .
ns(dos, df = 10 * trend_df)59 0.1534584 0.4069458 0.377 0.706125
ns(dos, df = 10 * trend_df)60 0.0042170 0.4202259 0.010 0.991994
ns(dos, df = 10 * trend_df)61 0.6576398 0.3811990 1.725 0.084586 .
ns(dos, df = 10 * trend_df)62 0.6332635 0.3593769 1.762 0.078142 .
ns(dos, df = 10 * trend_df)63 0.3733542 0.3790214 0.985 0.324672
ns(dos, df = 10 * trend_df)64 1.1305471 0.3587700 3.151 0.001641 **
ns(dos, df = 10 * trend_df)65 -0.0773355 0.4220216 -0.183 0.854613
ns(dos, df = 10 * trend_df)66 0.5305942 0.4265496 1.244 0.213616
ns(dos, df = 10 * trend_df)67 0.8842477 0.4293260 2.060 0.039513 *
ns(dos, df = 10 * trend_df)68 0.5238019 0.2922416 1.792 0.073166 .
ns(dos, df = 10 * trend_df)69 0.5981283 0.7591184 0.788 0.430797
ns(dos, df = 10 * trend_df)70 -0.0693098 0.1784268 -0.388 0.697708

```

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:

```

      edf Ref.df      F p-value
s(sqrt(influ)) 1.47  1.833 6.815 0.00122 **

```

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) = 0.48 Deviance explained = 48.6%  
GCV = 1.0847 Scale est. = 0.98601 n = 3507

**3. Secondary model 2:**  $\log[E(Y_t)] = \alpha + \text{cb}(\text{Vapour Pressure}_t) + \text{cb}(\text{factor}(\text{Rainfall}_t)) + \text{cb}(\text{NO}_{2t}) + \text{cb}(\log(\text{SO}_{2t})) + \text{cb}(\text{O}_{3t}) + \text{cb}(\log(\text{PM}_{10t})) + \text{cb}(\text{factor}(\text{Holiday}_t)) + \text{ns}(\text{DOS}_t, \text{df} = 7 \text{ per year}) + \text{factor}(\text{DOW}_t) + s(\sqrt{\text{Influenza}_t}, k = 7)$

Family: quasipoisson

Link function: log

Formula:

ad ~ VP.cb + rainfall.cb + o3.cb + so2.cb + no2.cb + pm10.cb + holiday.cb + factor(dow) + ns(dos, df = 10 \* trend\_df) + s(sqrt(influ), k = 7)

Parametric coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	1.3553095	0.5661917	2.394	0.016731 *
VP.cbv1.l1	-0.0051677	0.0275582	-0.188	0.851264
VP.cbv1.l2	-0.0370730	0.0268103	-1.383	0.166819
VP.cbv1.l3	0.0166116	0.0390717	0.425	0.670749
VP.cbv1.l4	-0.0001894	0.0271655	-0.007	0.994437
VP.cbv2.l1	0.0736201	0.0682986	1.078	0.281147
VP.cbv2.l2	-0.1653748	0.0687627	-2.405	0.016224 *
VP.cbv2.l3	0.0694318	0.0948159	0.732	0.464047
VP.cbv2.l4	-0.0303909	0.0677348	-0.449	0.653694
VP.cbv3.l1	0.0501825	0.0367864	1.364	0.172606
VP.cbv3.l2	-0.0702289	0.0341507	-2.056	0.039815 *
VP.cbv3.l3	-0.0011149	0.0510029	-0.022	0.982561
VP.cbv3.l4	0.0573688	0.0354223	1.620	0.105417
rainfall.cbv1.l1	-0.0089060	0.0095426	-0.933	0.350734
rainfall.cbv1.l2	0.0117857	0.0097057	1.214	0.224713
rainfall.cbv1.l3	0.0042138	0.0131819	0.320	0.749243
rainfall.cbv1.l4	0.0049149	0.0094476	0.520	0.602940
rainfall.cbv2.l1	-0.0185781	0.0234733	-0.791	0.428733
rainfall.cbv2.l2	-0.0031497	0.0254193	-0.124	0.901395
rainfall.cbv2.l3	0.0097602	0.0311368	0.313	0.753949
rainfall.cbv2.l4	-0.0329604	0.0236611	-1.393	0.163703
o3.cbv1.l1	0.0350348	0.0279724	1.252	0.210480
o3.cbv1.l2	-0.0471171	0.0278681	-1.691	0.090980
o3.cbv1.l3	-0.0414443	0.0393413	-1.053	0.292206
o3.cbv1.l4	0.0141358	0.0277313	0.510	0.610266
o3.cbv2.l1	0.0324395	0.0363703	0.892	0.372497
o3.cbv2.l2	-0.0195819	0.0370433	-0.529	0.597102
o3.cbv2.l3	-0.0096331	0.0501870	-0.192	0.847797
o3.cbv2.l4	-0.0289869	0.0358466	-0.809	0.418780
o3.cbv3.l1	0.0665267	0.0717748	0.927	0.354053
o3.cbv3.l2	-0.0888793	0.0732998	-1.213	0.225386
o3.cbv3.l3	-0.1384151	0.0969419	-1.428	0.153435
o3.cbv3.l4	0.0581507	0.0704800	0.825	0.409390
o3.cbv4.l1	0.1555801	0.0703260	2.212	0.027013 *
o3.cbv4.l2	-0.1850006	0.0742172	-2.493	0.012724 *
o3.cbv4.l3	-0.0411989	0.0938417	-0.439	0.660670
o3.cbv4.l4	0.1450825	0.0711142	2.040	0.041413 *
so2.cbv1.l1	0.0192957	0.0464112	0.416	0.677615
so2.cbv1.l2	0.0453044	0.0455387	0.995	0.319876
so2.cbv1.l3	0.0652402	0.0636952	1.024	0.305786
so2.cbv1.l4	-0.0983907	0.0451572	-2.179	0.029410 *
so2.cbv2.l1	0.0575265	0.0423461	1.358	0.174398
so2.cbv2.l2	0.0219654	0.0425749	0.516	0.605940
so2.cbv2.l3	0.0162539	0.0574158	0.283	0.777124
so2.cbv2.l4	-0.0230780	0.0414628	-0.557	0.577840
so2.cbv3.l1	0.0597653	0.1104291	0.541	0.588398
so2.cbv3.l2	0.1164419	0.1119523	1.040	0.298365
so2.cbv3.l3	-0.0011307	0.1518771	-0.007	0.994060
so2.cbv3.l4	-0.1620714	0.1076844	-1.505	0.132400
so2.cbv4.l1	-0.0106711	0.0716659	-0.149	0.881640
so2.cbv4.l2	-0.0269358	0.0756726	-0.356	0.721898
so2.cbv4.l3	-0.0254380	0.1003181	-0.254	0.799840
so2.cbv4.l4	-0.0690957	0.0707578	-0.977	0.328881
no2.cbv1.l1	-0.0544867	0.0501652	-1.086	0.277490
no2.cbv1.l2	0.0321086	0.0505383	0.635	0.525255
no2.cbv1.l3	-0.0337680	0.0679432	-0.497	0.619218
no2.cbv1.l4	0.1157413	0.0508129	2.278	0.022799 *
no2.cbv2.l1	0.0281539	0.0492771	0.571	0.567807

no2.cbv2.12	0.0265271	0.0510940	0.519	0.603667
no2.cbv2.13	0.0314189	0.0663276	0.474	0.635749
no2.cbv2.14	0.1039874	0.0496052	2.096	0.036128 *
no2.cbv3.11	-0.1666180	0.1183115	-1.408	0.159132
no2.cbv3.12	0.2087022	0.1203854	1.734	0.083075 .
no2.cbv3.13	-0.0291471	0.1604221	-0.182	0.855837
no2.cbv3.14	0.2799515	0.1178405	2.376	0.017571 *
no2.cbv4.11	-0.0545403	0.1007962	-0.541	0.588477
no2.cbv4.12	0.1379325	0.1043397	1.322	0.186270
no2.cbv4.13	-0.0173810	0.1432889	-0.121	0.903460
no2.cbv4.14	0.1642793	0.1012649	1.622	0.104836
pm10.cbv1.11	-0.0407622	0.0533743	-0.764	0.445095
pm10.cbv1.12	-0.0517256	0.0510717	-1.013	0.311224
pm10.cbv1.13	0.2054219	0.0720623	2.851	0.004389 **
pm10.cbv1.14	-0.1512313	0.0515482	-2.934	0.003371 **
pm10.cbv2.11	-0.0694038	0.0512745	-1.354	0.175961
pm10.cbv2.12	-0.0543270	0.0506952	-1.072	0.283956
pm10.cbv2.13	0.0810566	0.0727806	1.114	0.265480
pm10.cbv2.14	-0.1532471	0.0514432	-2.979	0.002912 **
pm10.cbv3.11	0.0800839	0.1273213	0.629	0.529397
pm10.cbv3.12	-0.2573946	0.1233464	-2.087	0.036983 *
pm10.cbv3.13	0.4379224	0.1715185	2.553	0.010716 *
pm10.cbv3.14	-0.2506877	0.1233479	-2.032	0.042193 *
pm10.cbv4.11	0.0507315	0.1222589	0.415	0.678203
pm10.cbv4.12	-0.1276988	0.1284987	-0.994	0.320402
pm10.cbv4.13	0.2442471	0.1718410	1.421	0.155304
pm10.cbv4.14	-0.0219763	0.1290729	-0.170	0.864814
holiday.cbv1.11	0.0216149	0.0139777	1.546	0.122103
holiday.cbv1.12	-0.0389137	0.0126002	-3.088	0.002029 **
holiday.cbv1.13	-0.0243269	0.0182945	-1.330	0.183692
holiday.cbv1.14	-0.0253565	0.0132018	-1.921	0.054853 .
factor(dow)2	-0.0593118	0.0221940	-2.672	0.007566 **
factor(dow)3	-0.0739103	0.0235176	-3.143	0.001688 **
factor(dow)4	-0.0438628	0.0237731	-1.845	0.065114 .
factor(dow)5	-0.0746431	0.0237100	-3.148	0.001657 **
factor(dow)6	-0.0892264	0.0235227	-3.793	0.000151 ***
factor(dow)7	-0.0417234	0.0228870	-1.823	0.068387 .
ns(dos, df = 10 * trend_df)1	1.0053188	0.3018644	3.330	0.000876 ***
ns(dos, df = 10 * trend_df)2	-0.0733716	0.4172199	-0.176	0.860415
ns(dos, df = 10 * trend_df)3	1.0199234	0.3882061	2.627	0.008645 **
ns(dos, df = 10 * trend_df)4	0.3463243	0.4060638	0.853	0.393784
ns(dos, df = 10 * trend_df)5	0.4701391	0.3666328	1.282	0.199818
ns(dos, df = 10 * trend_df)6	-0.2401648	0.3955762	-0.607	0.543807
ns(dos, df = 10 * trend_df)7	-0.0260474	0.3533197	-0.074	0.941236
ns(dos, df = 10 * trend_df)8	1.2971209	0.3541993	3.662	0.000254 ***
ns(dos, df = 10 * trend_df)9	-0.8712522	0.3967492	-2.196	0.028160 *
ns(dos, df = 10 * trend_df)10	-0.1775152	0.4185246	-0.424	0.671486
ns(dos, df = 10 * trend_df)11	-0.1639397	0.4219056	-0.389	0.697618
ns(dos, df = 10 * trend_df)12	0.6751854	0.3725418	1.812	0.070015 .
ns(dos, df = 10 * trend_df)13	-0.5013254	0.3614264	-1.387	0.165508
ns(dos, df = 10 * trend_df)14	1.3977460	0.3488010	4.007	6.27e-05 ***
ns(dos, df = 10 * trend_df)15	0.8347699	0.3524784	2.368	0.017925 *
ns(dos, df = 10 * trend_df)16	0.0515214	0.3942280	0.131	0.896029
ns(dos, df = 10 * trend_df)17	-0.7347354	0.4198475	-1.750	0.080206 .
ns(dos, df = 10 * trend_df)18	0.2638040	0.4153546	0.635	0.525386
ns(dos, df = 10 * trend_df)19	0.4053899	0.3674312	1.103	0.269970
ns(dos, df = 10 * trend_df)20	0.9291309	0.3633743	2.557	0.010602 *
ns(dos, df = 10 * trend_df)21	-0.1141378	0.3633280	-0.314	0.753430
ns(dos, df = 10 * trend_df)22	1.2252529	0.3535204	3.466	0.000535 ***
ns(dos, df = 10 * trend_df)23	0.0883765	0.3766806	0.235	0.814518
ns(dos, df = 10 * trend_df)24	0.7963751	0.3922070	2.030	0.042382 *
ns(dos, df = 10 * trend_df)25	0.9461921	0.3956940	2.391	0.016845 *
ns(dos, df = 10 * trend_df)26	0.2515012	0.3644274	0.690	0.490161
ns(dos, df = 10 * trend_df)27	-0.3910095	0.3693294	-1.059	0.289810
ns(dos, df = 10 * trend_df)28	0.6571490	0.3495717	1.880	0.060210 .
ns(dos, df = 10 * trend_df)29	1.2016442	0.3569473	3.366	0.000770 ***
ns(dos, df = 10 * trend_df)30	0.0220232	0.4114475	0.054	0.957316
ns(dos, df = 10 * trend_df)31	0.1566382	0.3897626	0.402	0.687796
ns(dos, df = 10 * trend_df)32	0.5486411	0.3934679	1.394	0.163294
ns(dos, df = 10 * trend_df)33	0.5550475	0.3643537	1.523	0.127756
ns(dos, df = 10 * trend_df)34	0.7738539	0.3409383	2.270	0.023282 *

```

ns(dos, df = 10 * trend_df)35 1.1660641 0.3613343 3.227 0.001262 **
ns(dos, df = 10 * trend_df)36 0.2220552 0.3445922 0.644 0.519359
ns(dos, df = 10 * trend_df)37 0.1518120 0.4031203 0.377 0.706500
ns(dos, df = 10 * trend_df)38 1.1555986 0.3847944 3.003 0.002691 **
ns(dos, df = 10 * trend_df)39 0.4897097 0.4063586 1.205 0.228240
ns(dos, df = 10 * trend_df)40 0.4762154 0.3646694 1.306 0.191679
ns(dos, df = 10 * trend_df)41 -0.0188192 0.3872195 -0.049 0.961240
ns(dos, df = 10 * trend_df)42 -0.5647915 0.3723370 -1.517 0.129387
ns(dos, df = 10 * trend_df)43 1.7093045 0.3491602 4.895 1.03e-06 ***
ns(dos, df = 10 * trend_df)44 0.3305572 0.3981937 0.830 0.406516
ns(dos, df = 10 * trend_df)45 0.1669668 0.4079098 0.409 0.682328
ns(dos, df = 10 * trend_df)46 0.0622764 0.4056984 0.154 0.878010
ns(dos, df = 10 * trend_df)47 0.5551462 0.3660050 1.517 0.129415
ns(dos, df = 10 * trend_df)48 0.1556012 0.3755963 0.414 0.678696
ns(dos, df = 10 * trend_df)49 -0.1621871 0.3828264 -0.424 0.671842
ns(dos, df = 10 * trend_df)50 0.7622711 0.3517725 2.167 0.030307 *
ns(dos, df = 10 * trend_df)51 0.1223278 0.4180436 0.293 0.769830
ns(dos, df = 10 * trend_df)52 0.1600776 0.4078557 0.392 0.694723
ns(dos, df = 10 * trend_df)53 0.5942923 0.3955386 1.502 0.133062
ns(dos, df = 10 * trend_df)54 0.3892705 0.3768845 1.033 0.301740
ns(dos, df = 10 * trend_df)55 0.6049207 0.3440421 1.758 0.078789 .
ns(dos, df = 10 * trend_df)56 0.8654396 0.3735774 2.317 0.020582 *
ns(dos, df = 10 * trend_df)57 0.8190290 0.3483579 2.351 0.018773 *
ns(dos, df = 10 * trend_df)58 0.7551938 0.4116690 1.834 0.066670 .
ns(dos, df = 10 * trend_df)59 0.2679309 0.4124670 0.650 0.516006
ns(dos, df = 10 * trend_df)60 0.0836855 0.4071016 0.206 0.837143
ns(dos, df = 10 * trend_df)61 0.6969491 0.3738524 1.864 0.062373 .
ns(dos, df = 10 * trend_df)62 0.7025813 0.3536095 1.987 0.047014 *
ns(dos, df = 10 * trend_df)63 0.4321847 0.3711280 1.165 0.244295
ns(dos, df = 10 * trend_df)64 1.2265577 0.3530616 3.474 0.000519 ***
ns(dos, df = 10 * trend_df)65 -0.0542336 0.4122271 -0.132 0.895338
ns(dos, df = 10 * trend_df)66 0.6087704 0.4147462 1.468 0.142245
ns(dos, df = 10 * trend_df)67 1.0404031 0.4240504 2.453 0.014197 *
ns(dos, df = 10 * trend_df)68 0.6124457 0.2615844 2.341 0.019273 *
ns(dos, df = 10 * trend_df)69 0.5883909 0.7494997 0.785 0.432481
ns(dos, df = 10 * trend_df)70 0.0603472 0.1696749 0.356 0.722114

```

```

---
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

Approximate significance of smooth terms:

```

      edf Ref.df      F p-value
s(sqrt(influ)) 1.03 1.059 14.78 9.19e-05 ***

```

```

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Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

```

R-sq.(adj) = 0.472   Deviance explained = 47.6%
GCV = 1.081   Scale est. = 0.98971   n = 3632

```