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Original Research Article

Air conditioning and heat-related mortality: a multi-country longitudinal study

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ABSTRACT

Background

Air conditioning has been proposed as one of the key factors explaining reductions of heat-related mortality risks observed in the last decades. However, direct evidence is still limited.

Methods

We used a multi-country, multi-city, longitudinal design to quantify the independent role of air conditioning in reported attenuation in risk. We collected daily time series of mortality, mean temperature, and yearly air conditioning prevalence for 311 locations in Canada, Japan, Spain, and the USA between 1972 and 2009. For each city and sub-period, we fitted a quasi-Poisson regression combined with distributed lag non-linear models to estimate summer-only temperature–mortality associations. At the second stage, we used a novel multilevel, multivariate spatio-temporal meta-regression model to evaluate effect modification of air conditioning on heat–mortality associations. We computed relative risks and fractions of heat-attributable excess deaths under observed and fixed air conditioning prevalences.

Results

Results show an independent association between increased air conditioning prevalence and lower heat-related mortality risk. Excess deaths due to heat decreased during the study periods from 1.40% to 0.80% in Canada, 3.57% to 1.10% in Japan, 3.54% to 2.78% in Spain, and 1.70% to 0.53% in the US. However, increased air conditioning explains only part of the observed attenuation, corresponding to 16.7% in Canada, 20.0% in Japan, 14.3% in Spain, and 16.7% in the US.

Conclusions

Our findings are consistent with the hypothesis that air conditioning represents an effective heat adaptation strategy, but suggests that other factors have played an equal or more important role in increasing the resilience of populations.

Keywords: air conditioning; temperature; adaptation; longitudinal; meta-analysis; multilevel.

INTRODUCTION

Epidemiologic studies in various countries have provided evidence of a decrease in mortality risks associated to exposure to heat over the last decades.[1,2] Several mechanisms have been suggested as potential drivers of such attenuation, including physiologic (referred to as acclimatization), behavioral (e.g., clothing), infrastructural (green spaces), and technological (heat warning system).[2-4] However, evidence is still limited, and an appropriate characterization of factors responsible for the attenuation of heat-related risks is still lacking. This information is nonetheless critical for planning effective public health and climate policies.[1-3]

Air conditioning is one of the most straightforward strategies to reduce heat stress, and previous investigations have assessed its role in modifying mortality risks associated to exposure to high temperature using both individual- or aggregated-level designs, although with conflicting results.[5-13] These studies adopted either a cross-sectional and/or longitudinal design, comparing risks at different air conditioning prevalence between individuals/locations or at different times. However, they faced a number of methodologic challenges. Analyses based on the cross-sectional comparison of subjects or cities with different air conditioning use and prevalence are prone to bias, as other characteristics, such as socio-economic or climatic conditions, can be responsible for differences in health risks. Longitudinal designs can address this issue, but they need data consistently collected over a long period of time to allow for substantial variation in air conditioning use within each location. More importantly, these studies can be affected by temporal confounding due to concurrent changes in other modifying factors, such as infrastructural changes and access to health care. Finally, the complexity of exposure–response relationships, characterised by non-linearity and temporally delayed effects, presents additional problems in modelling temperature–mortality associations. A recent investigation by Nordio and colleagues[10] partly addressed these issues by comparing estimates from several USA cities over five decades, while using flexible exposure–response functions and adjusting for underlying trends. However, that study was performed in a single country, and its estimates of the role of air conditioning can be affected by the lack of separation between spatial and temporal contrasts.

In this contribution, we extend the assessment to a multi-country setting and adopting sophisticated longitudinal designs to control for spatial and temporal confounding. Specifically, the analysis makes use of a unique dataset with time series data from 331 locations in four countries (US, Japan, Canada, and Spain) in the period 1972-2019, and applies novel two-stage methods based on multilevel multivariate spatio-temporal meta-regression models.

METHODS

Data

We collated data on mortality, temperature, and air conditioning prevalence from multiple locations in the four countries (see eTable 1). For each location the data consist of daily counts of all-cause (Canada, Japan, and Spain) or non-accidental (US) mortality and temperature series in summer months (June to September), and air conditioning prevalence from survey data in multiple years within the study period. Table 1 lists the study locations, the observation period as well as the air conditioning variable and surveys used to derive air conditioning prevalences in the four countries included in this study. Across countries air conditioning prevalence data comes from different surveys with different frequency of reporting (see eAppendix). More detailed information on the data collected in each country are reported in the eAppendix.

Statistical methods

The analytical strategy was based on three steps, briefly summarized here and described in detail below. In the first step, each country-specific study interval was split into multiple periods. Then, we fitted separate regression models to obtain estimates of heat–mortality associations for each location and period. In addition, we reconstructed location-specific air conditioning trends and assigned prevalence estimates to each location or period unit. In the second step, we pooled the set of coefficients defining the associations to evaluate changes in heat-related mortality risks by calendar year and air conditioning prevalence, accounting for both within- and between-city variations. Finally, in the third and last step, we used the coefficients of the meta-regression models to derive trends in relative risk (RR) and attributable fractions (AF%) predicted using observed and alternative scenarios of air conditioning prevalence trends.

Step 1: Estimating location and period-specific air conditioning prevalence and risks

In the first step, for each location, we divided the observation time was divided into specific time intervals. The number and the different periods for each country are reported in eTable 2. Time intervals have a length of 4 or 5 years. The length of time intervals was chosen a priori in order to provide enough statistical power to derive period-specific estimates, and enough time points to detect changes over time. For each country and locations, using the original air conditioning data, which was assessed intermittently, we estimated the air conditioning prevalence for each period, as described in the eAppendix. Briefly, for the US, Canada, and Spain, we fitted a linear mixed-effects model with a B-spline parameterization of the time variable (years), and city as grouping level. We used best linear unbiased prediction estimates were used to predict yearly air conditioning prevalence in mid-summer (1st of July) in each city of the three countries. For Japan, we used the original yearly data, and assigned it to mid-summer. To assessed if changes in reporting air conditioning prevalence over time affected the predicted trends we performed a sensitivity analysis including an indicator that defines pre- and post-periods corresponding to implementation of the new reporting methods (see eAppendix).

We estimated the location and period-specific temperature–mortality associations through quasi-Poisson regression[14] with distributed lag non-linear models (DLNMs).[15] Based on previous work[16], we specified the cross-basis function of daily mean temperature using a quadratic B-spline function for the temperature dimension, with two internal knots at the 50th and 90th percentiles of the location and period-specific summer temperature distributions, and unconstrained parameterization over lag 0-2. To control for long-term trends and residual seasonality, we included interaction terms between a natural cubic B-spline function with 4 degrees of freedom (df) of the day of the year and indicators of year, along with an indicator of day of the week. We tested these modelling choices in a sensitivity analysis.

Step 2: modelling spatial and temporal variation in risk

The location and period-specific estimates obtained from the quasi-Poisson model in Step 1 were then combined using multilevel multivariate spatio-temporal models that consider possible non-independence of estimates within each location.[17] For each location $i = 1, \dots, m$ and year $t = 1, \dots, T_i$ (defined as mid-points of periods), we obtained a $k = 4$ length column vector of spline coefficients θ_{it} representing the temperature–mortality association cumulated over lag 0-2 in location *i* and period t, and associated $k \times k$ estimated (co)variance matrix S_{it}. The multilevel multivariate spatio-temporal meta-regression model for the multivariate vector response θ_{it} can be written as:

$$\theta_{it} = X_{it}\beta + Z_i b_i + \varepsilon_{it} \qquad (1)$$

with $b_i \sim N(0, \Psi_1)$, and $\varepsilon_{it} \sim N(0, S_{it})$.

The matrix X_{it} in the meta-regression model in (1) included fixed-effect predictors, represented by indicators of country, calendar year, period specific average and interquartile range (IQR) of daily mean temperature, in addition to air conditioning prevalence. Temperature variables were selected following previous evidence of their role in modifying heat-related mortality risks, while a linear term for calendar year was included to control for underlying variations in risk unrelated to air conditioning use. We compared the role of different fixed-effect predictors through likelihood ratio (LR) test in models fitted with a maximum likelihood (ML) estimator. We included random terms at city or prefecture level, represented by indicators Z_i with random coefficients b_i. The random coefficients have unstructured (co)variance matrices Ψ_1. The term S_{it} represents the estimation error within location/period combinations. A restricted maximum likelihood estimator was used for the final model.

This modeling approach allows investigation of the independent effect of changes over time in air conditioning prevalence on the temperature–mortality association, while adjusting for country and location-specific trends. Using random terms at location level allows the use of information both within and between locations.

Step 3: quantifying heat-related risks and AC contribution

The estimated fixed-effects coefficients $\hat{\beta}$ from the multilevel multivariate spatio-temporal meta-regression model (1) fitted in Step 2 can be used to predict a set of spline coefficients $\hat{\theta}_{ct}$ that represent pooled heat–mortality association curves for any combination of country, year, and air conditioning prevalence. Specifically, associations were predicted longitudinally or at the end of country-specific study periods, either using observed values of meta-predictors or under specific scenarios of air conditioning prevalence. Results were first reported in terms of country-averaged relative risk (RR), using country-specific temperature distributions and minimum mortality temperature as references. In addition, we also derived summaries corresponding to estimated mortality fractions (in percentage) attributed to summer heat for each country/sub-period, following a procedure described elsewhere.[18] In brief, we computed the mortality attributable to heat first by summing the temperature-related deaths occurring in days with temperatures higher than the location specific 50th percentile of the summer distribution, and then by dividing this excess by the total number of deaths. We calculated empirical standard error (SE) using Monte Carlo simulations, assuming a multivariate normal distribution of the fixed-effects coefficients estimated in Step 2.[18]

RESULTS

Data description

During the study period, more than 23 million deaths were registered in the 331 locations assessed in the four countries. On average, air conditioning prevalence increased in all countries (Figure 1), with the highest prevalence at the end of the study period observed in Japan (89.2%), followed by the USA (82.8%), Canada (48.8%), and Spain (26.9%).

Multilevel multivariate spatio-temporal meta-regression model

The results of meta-regression models with different fixed-effects specifications are shown in eTable 3. In the final specification of the multilevel multivariate spatio-temporal meta-regression model, air conditioning prevalence shows an independent association with heat-related risks (p-value = 0.011), while accounting for country-specific trends and adjusting also by locations and period-specific average and interquartile range of mean temperature. We did not find strong evidence of a differential effect of air conditioning prevalence between countries (p-value = 0.084). Inspection of distribution of the residuals and their scatter plot versus time and air conditioning prevalence suggested a good fit of the model (see eFigure 3).

Quantification of the heat-related risk and its trend

Figure 2 represents the changes in the heat–mortality association curves predicted by spatio-temporal meta-regression, at the beginning and end of the study periods in the four countries. Japan showed a strong attenuation in risk, with a decline of the RRs across almost all the summer temperature range. The US and Spain also displayed a decrease in risk, although more evident at highest temperature percentiles. Canada showed little evidence of a reduction in heat-related RR over the observed period.

Table 2 presents air conditioning prevalence, estimated RR at 99th percentile of the temperature distribution versus minimum mortality temperature, and estimated excess mortality by country and calendar year. The trend is consistent with the attenuation in risk, especially in Japan where the RR declined from 1.32 to 1.08 during the period 1975-2007. In the same period, the heat-related excess deaths reduced from 3.57% to 1.10%. A reduction in RR is also evident in the USA and Spain, with a reduction of excess deaths due to heat from 0.54% to 2.78% in Spain, and 1.70% to 0.53% in the USA. In Canada, there was no evidence of reduction of the RR corresponding to the 99th temperature percentile, but we observed a decrease in mortality fraction attributable to heat, from 1.40% to 0.80%, due to an attenuation in risk at lower temperature percentiles (90th and 50th), as shown in eFigure 2.

Temporal changes in temperature-related risks are generated by both variation in air conditioning prevalence and underlying trends due to other factors. In order to quantify the role of air conditioning, we fixed the calendar year at the end of the study period and calculated the RR at 99th temperature percentile and heat-related mortality fraction for different levels of air conditioning prevalence (Table 3). Results indicate that increasing the AC prevalence from 30% to 80% would be associated with important reduction in heat-related death: 30.2% in the US, 24.9% in Canada, 20.3% in Japan, and 8.8% in Spain.

Finally, in order to separate and quantify the contribution of air conditioning prevalence from other time-varying factors in attenuating heat-related risks, we compared the excess mortality under scenarios of observed increase or no change in air conditioning prevalence

(Figure 3). The dark and light blue bars represent the excess mortality fraction calculated at the beginning and at the end of the study periods, using the actual air conditioning prevalences, with figures reported in Table 2. The middle blue bar represent instead the excess mortality fraction at the end of study period assuming no change in air conditioning prevalence: the comparison indicates that an increased air conditioning prevalence is responsible for only part of the observed attenuation, corresponding approximately to 16.7% in Canada, 20.0% in Japan, 14.3% in Spain, and 16.7% in the US. These results suggest that other adaptation factors can be equally and, in some cases, more important for explaining the decreasing trend (see eTable 4).

DISCUSSION

Our results on air conditioning prevalence in Japan, the US, Canada, and Spain are consistent with the hypothesis that air conditioning reduces heat-related mortality. This reduction occurs on top of variations in heat-related health risks possibly associated with planned and unplanned adaptation processes other than air conditioning use. These independent adaptation pathways were quantified and compared using alternative scenarios of air conditioning prevalence and underlying temporal trends. These scenarios indicate that while the increase in air conditioning use is associated with a reduction in heat-related mortality, this only explains a part of the decline in risk experienced in some countries, and other adaptation pathways have had a more important role in reducing the health burden.

Our results are consistent with published epidemiological investigations that have reported a substantial attenuation of heat-related health risk.[1,2,19] In particular, similar declining trends were observed in the US[6,7,10,16,20-24], Japan[8,9,25], Spain[26], and Canada[16]. Similar declining trends were also observed in Sweden[27], Austria[28], UK[29,30], Netherlands[31], nine European cities[32], and Korea[33,34], but not in China.[35]

Previous studies have evaluated the protective effect of air conditioning on heat-related risks. Some assessments used cohort[12] and case–control study designs[13], and suggested a role of AC in reducing the heat-related mortality risks in the USA. These studies were followed by two-stage studies in which the first-stage estimates obtained through case-only[11] or time-series analyses[5] in multiple cities were combined using meta-regression models with air conditioning prevalence as a contextual variable. These studies confirmed the protective effect of air conditioning in the USA, but were prone to ecologic confounding as the selected cities can differ by other unmeasured characteristics (e.g., demographic, socio-economic, and infrastructural) related to health risk. More recent studies in the US and Japan used a longitudinal design to disentangle the effect of air conditioning as behavioural adaptive measure. In the US, two studies found an independent protective effect of air conditioning[5,6], but Bobb and colleagues observed no evidence of protective effect.[7] The longitudinal study of Nordio and colleagues[10] reported independent protective effects of air conditioning while controlling for region, time trend, and mean summer temperature, using spline models in individual cities and a meta-regression approach. The two longitudinal studies conducted in Japan did not find evidence consistent with an independent protective effect of air conditioning over the declining heat-related risk trend.[8,9] Differences on previous studies results can be partly explained by low statistical power, as these investigations were conducted in a single country and/or the temperature–mortality curve was summarized using simplified indices. Moreover, these studies did not jointly consider the longitudinal and spatial structure of the data, and the non-independence of the observations within locations.

Our study has several strengths. First, we used distributed lag non-linear modeling techniques to estimate the heat–mortality association. This modeling framework helps avoid biases due to simplification of the exposure–response association and considers possible lagged effects of heat on mortality.[15] Second, we were able to collect mortality, temperature and air conditioning data for 331 locations in four countries for a period of four decades. This provided large variability in air conditioning prevalence both within and across locations, offering sufficient statistical power to isolate the impact on modifying heat–mortality relationships. Third, we used a study design based on both spatial and longitudinal comparison, reducing the chance of ecologic bias and temporal confounding due to concurrent changes in other modifying factors, such as socio-economic conditions and access to health care. The spatial component provides increased variability in response and exposure, while the longitudinal design compares variations in risk within a location. Finally, we used novel multilevel multivariate spatio-temporal meta-regression models that allow disentangling of the reduction in heat-related risk associated to the increase in air conditioning prevalence from underlying trends due to other adaptation pathways, while at the same time correctly accounting for correlations between repeated measures taken within the same location.[17]

We must acknowledge some limitations. First, the results of our study refer to developed countries with predominantly temperate or continental climates. Caution should be used when extrapolating results to low-income countries, which are characterized by different climatic, socio-demographic, and development conditions, and where technology based adaptation measures, such as increasing air conditioning use, may be problematic as many low-income countries already experience chronic shortages of power.[2] Second, we reconstructed air conditioning prevalence along the past decades by applying smoothing techniques to irregular survey data from multiple sources. However, additional analyses described in the eAppendix show that results are robust to this filling-up procedure. The results of the sensitivity analysis suggest that the smoothing process could have introduced some error, although it is unlikely that this is correlated with the estimated period-specific risk, and therefore can probably be assumed as random. Third, our air conditioning variable is defined as presence of air conditioning units or central air conditioning at home, but does not capture its actual use. Moreover, this measure is not informative about air conditioning use in other environments, such as on public transport, stores, workplaces, and public areas. This may induce some additional problems in the interpretation of the results.

The analysis of factors related to changes in susceptibility to temperature-related mortality is critical to inform health and climate policies. Air conditioning is a solution to regulate ambient indoor temperatures and lower the heat stress imposed on the human thermoregulatory function[36], and it represents one of the most cited behavioural adaptation strategy to climate change.[37] The results of our analysis confirm that air conditioning is an effective adaptive measure and have contributed to reduce the burden of heat-related mortality. According to our estimates in the USA and Japan, nearly 0.09% and 0.32% of deaths during summer months were delayed by increasing the air conditioning prevalence level to more than 80%, respectively. In these countries, the air conditioning market seems to have reached a plateau, but the heat-related mortality is still substantial. However, the quantitative comparison of the contribution of increase in air conditioning prevalence, and the independent attenuation of the risk reported in Figure 3, suggest that other adaptation pathways can be equally or even more effective in reducing the health burden. In Spain and Canada, the delayed deaths during summer months were both 0.05%, suggesting a further margin on reduction of heat-related mortality, especially in Spain where the reported air conditioning prevalence reaches only 30% in 2009. In addition, increasing air conditioning use has also important negative consequences, including capital and energy cost, carbon and pollution-generating energy demand, and contribution to the heat-island effect.[2] However, the current rapid transition of electricity generation to carbon zero sources is likely to ameliorate the pollution impact in the next few decades. A quantitative assessment of health and economic impacts of this and other adaptive changes is critical for generating plausible scenarios of potential mitigation and adaptation benefit and costs.

In conclusion, in this study we found a reduction over time of the heat-related health risk in Japan, the USA, and Spain. Air conditioning prevalence was factor that independently explained part of the decrease in heat-related deaths, although we estimated that other adaptive strategies accounted for a larger proportion of the attenuation. These results can be used to inform policy measures based at individual, community, and international level, and to improve and extend projections of future heat impacts on human health.

FIGURES

Figure 1. Air conditioning (AC) prevalence (%) by year in Canada, Japan, Spain and the US.

Figure 2. Country-average exposure–response curves (in relative risk, RR) predicted at the beginning and end of the study periods in Canada, Japan, Spain, and the US. The x-axis represents relative temperatures in percentiles, but rescaled using the average distribution of absolute temperature across cities in each country.

Figure 3. Excess mortality associated to heat reported as attributable fraction (AF%) estimated at the beginning (Baseline, dark blue) and end of the study period assuming no change (End-Study period with fixed air conditioning, medium blue) or with the observed change (End-Study period, light blue) in air conditioning (AC) prevalence.

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TABLES

Table 1. Geographical boundaries, observation period, and definition of air conditioning prevalence in each country.

Country	Locations	Period	Air conditioning variable	Survey
Canada	20 census metropolitan areas + city of Hamilton	1991-2009	Proportion of dwellings with an air conditioning system (central or with a window or room mounted air conditioning system)	-Survey of Household & Energy Use (SHEU)[1] -Households and Environment Survey (HES)[2]
Japan	47 prefectures	1972-2009	Proportion of households with two or more occupants with air conditioning	-Regional statistics database[3]
Spain	52 capital cities	1990-2009	Proportion of family homes with “refrigeration"; and from 2007 Proportion of "homes with air conditioning"	-Population and Housing Census[4] -“Life Conditions" Survey[5]
USA	211 metropolitan areas	1973-2006	Proportion of households in each metropolitan area with central air conditioning	-Census of Population[6] -American Housing Survey (AHS)[7] - Residential Energy Consumption Survey[8]

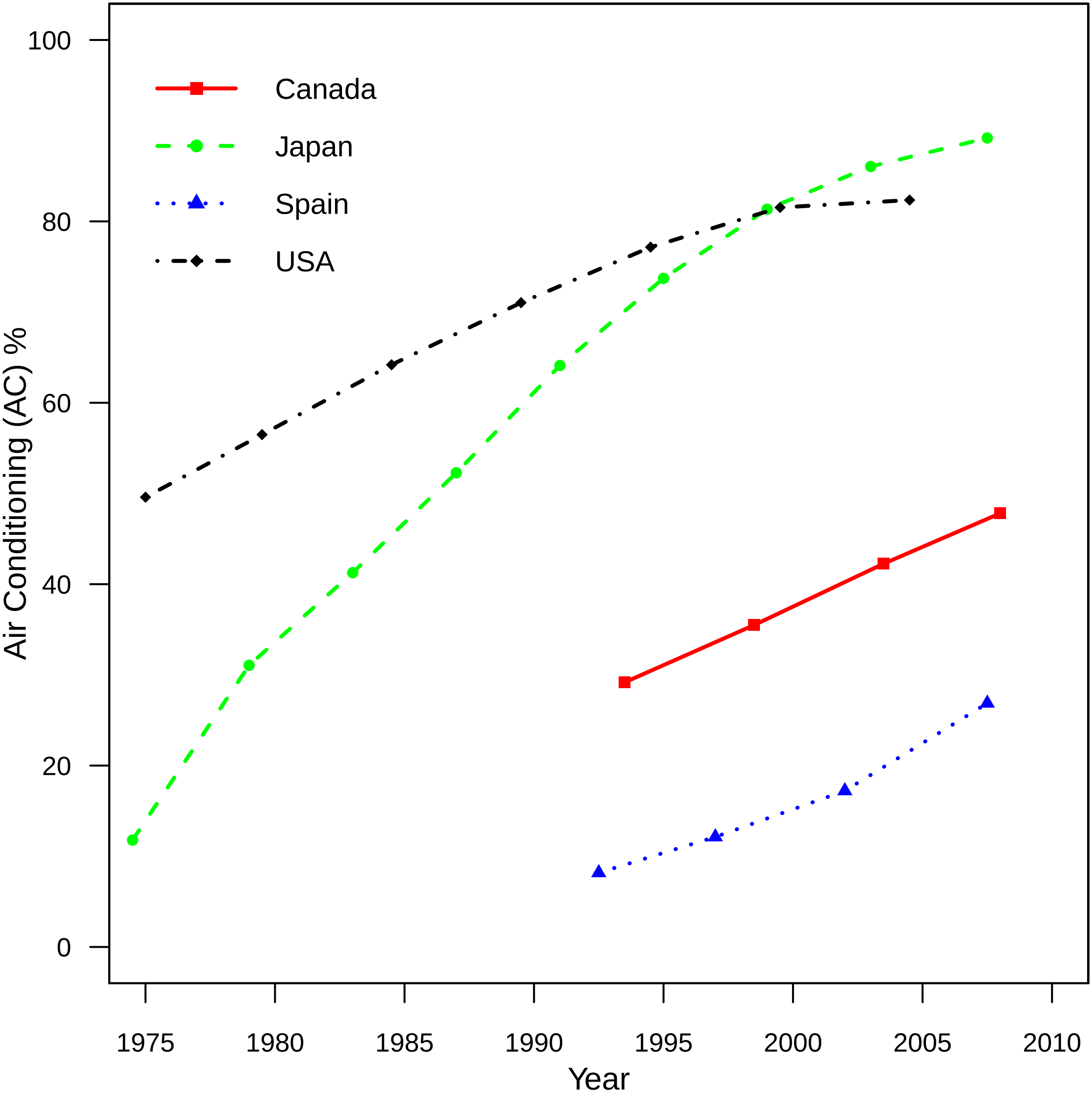
[1] Estimates at regional level in years 1993, 1997, 2003
[2] Estimates at city level in years 2006, 2007, 2009
[3] Asahi Newspaper Publishing.2015
[4] Estimates at city level in years 1991 and 2001
[5] Estimates at regional level in 2007
[6] Estimates before 1985 at city level
[7] AHS use a rotation sampling of cities; data available yearly from 1985
[8] Used to estimate air conditioning prevalence in northern New England cities

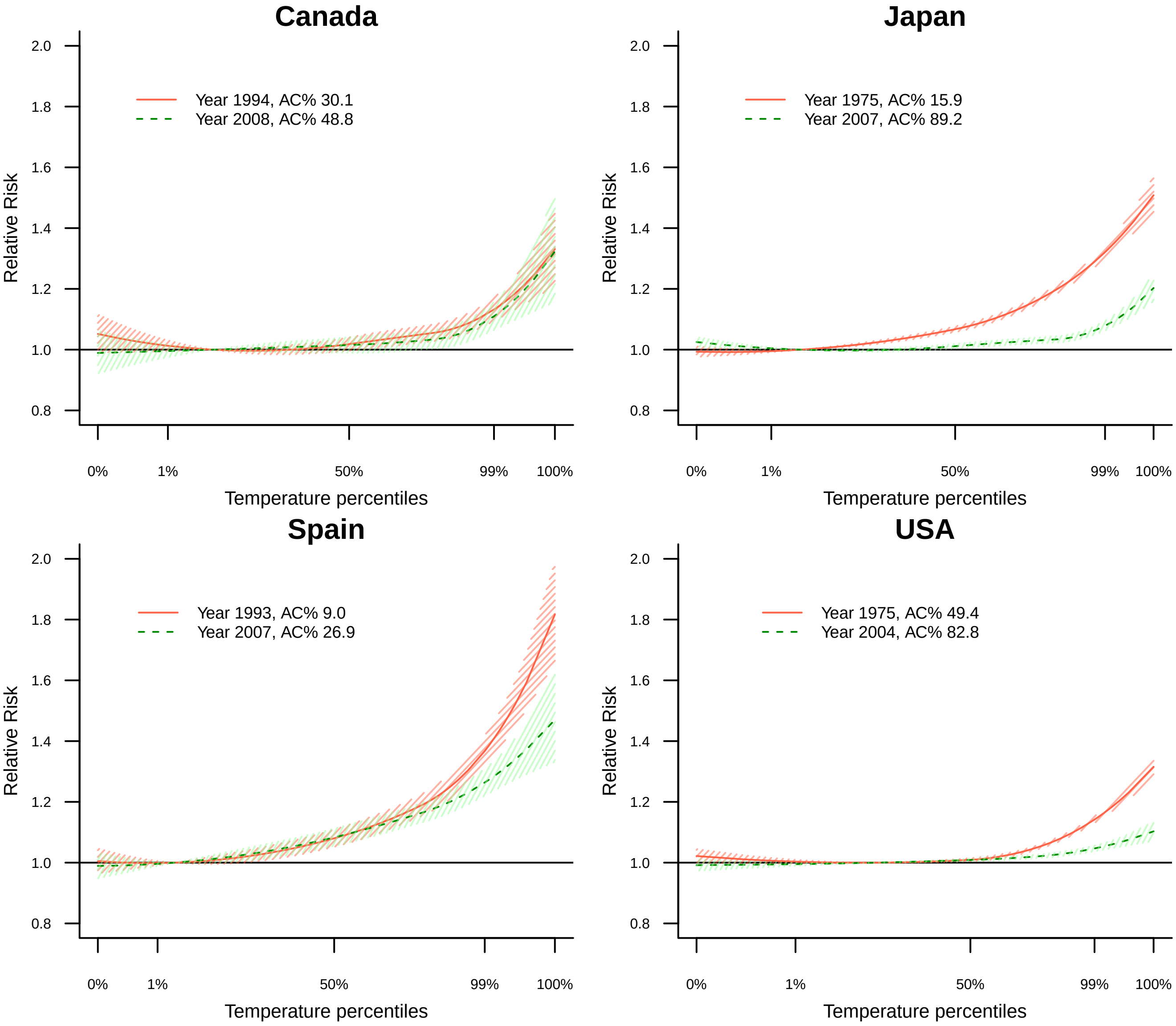
Table 2. Reconstructed air conditioning (AC) prevalence, relative risk (RR) at 99th percentile of the temperature distribution versus minimum mortality temperature, and attributed mortality fraction AF% by country and year.

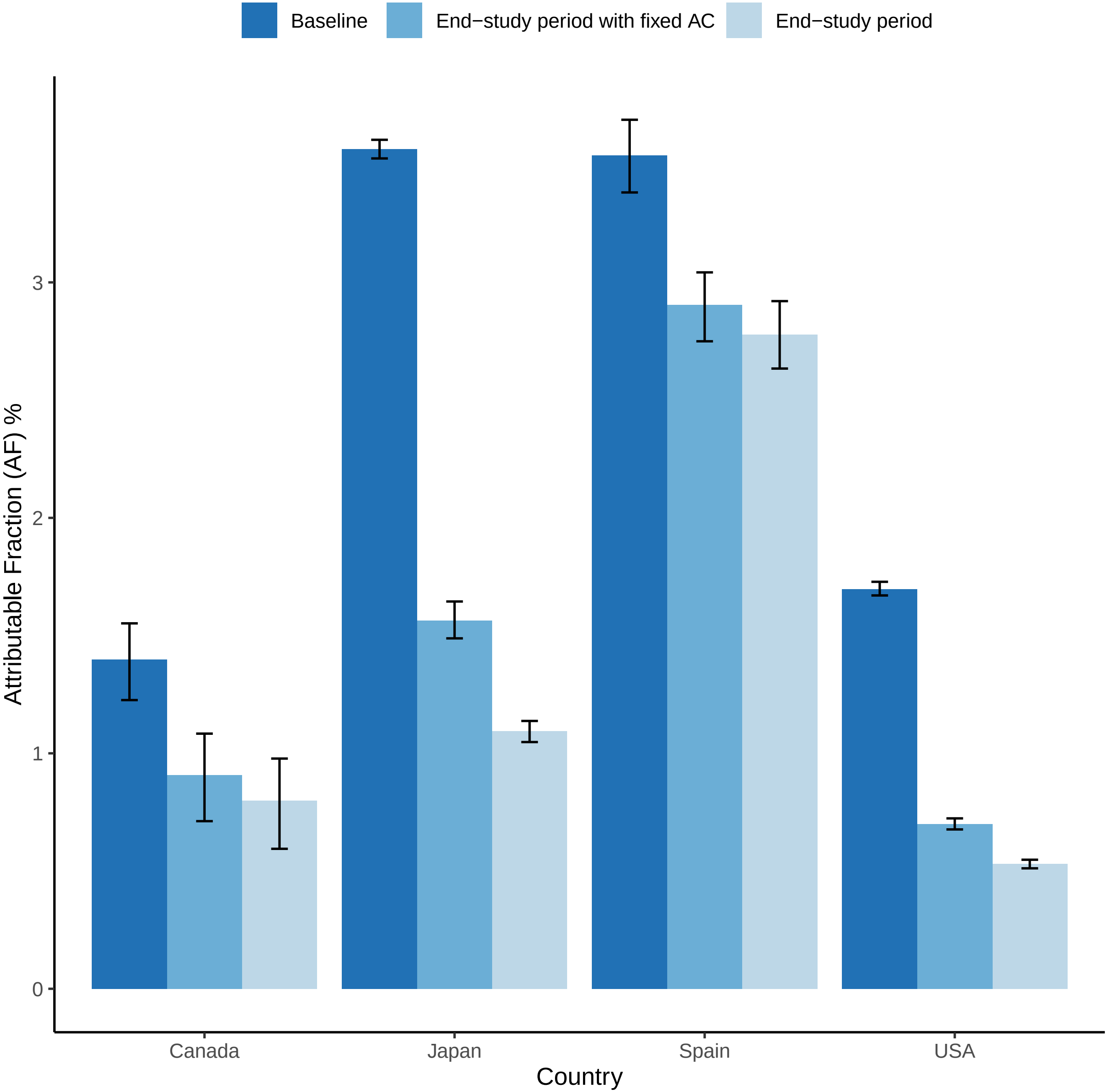
Country	Year	AC%	99th RR 95%CI	AF% 95%CI
Canada	1994	30.1	1.13 (1.09, 1.17)	1.40 (1.23 ;1.55)
	1998	35.5	1.12 (1.08; 1.16)	1.33 (1.20; 1.44)
	2003	41.9	1.11 (1.08; 1.14)	1.22 (1.05; 1.38)
	2008	48.8	1.11 (1.07; 1.16)	0.80 (0.59; 0.98)
Japan	1975	15.9	1.32 (1.29; 1.34)	3.57 (3.53; 3.61)
	1979	31.1	1.28 (1.26; 1.30)	3.13 (3.10; 3.17)
	1983	41.3	1.24 (1.23; 1.26)	2.83 (2.79; 2.86)
	1987	52.3	1.21 (1.19; 1.22)	2.52 (2.49; 2.56)
	1991	64.1	1.18 (1.16; 1.19)	2.24 (2.20; 2.28)
	1995	73.7	1.15 (1.13; 1.16)	1.90 (1.86; 1.94)
	1999	81.3	1.12 (1.11; 1.14)	1.70 (1.66; 1.75)
	2003	86.0	1.10 (1.08; 1.11)	1.43 (1.39; 1.46)
	2007	89.2	1.08 (1.06; 1.10)	1.10 (1.05; 1.14)
Spain	1993	9.0	1.37 (1.32; 1.42)	3.54 (3.38; 3.69)
	1998	12.9	1.42 (1.37; 1.46)	3.54 (3.42; 3.65)
	2003	19.2	1.35 (1.32; 1.39)	3.51 (3.41; 3.60)
	2007	26.9	1.26 (1.22; 1.31)	2.78 (2.63; 2.92)
USA	1975	49.4	1.14 (1.13; 1.15)	1.70 (1.67; 1.73)
	1979	56.5	1.13 (1.12; 1.14)	1.56 (1.54; 1.58)
	1984	64.1	1.11 (1.10; 1.12)	1.32 (1.30; 1.33)
	1989	71.0	1.09 (1.08; 1.10)	1.09 (1.07; 1.10)
	1994	76.8	1.08 (1.07; 1.09)	0.88 (0.87; 0.90)
	1999	80.7	1.06 (1.05; 1.07)	0.67 (0.65; 0.68)
	2004	82.8	1.05 (1.04; 1.06)	0.53 (0.51; 0.55)

Table 3. Predicted relative risk (RR) at 99th temperature percentile, and attributed mortality fraction (AF%) with 95% confidence intervals (CI) calculated at the end of the study period for four scenarios of air conditioning prevalence levels (30%, 55%, 80% and 100%) in Canada, Japan, Spain, and the USA

Country; Year	AC%	RR	AF%
Canada (2008)	30%	1.12 (1.07; 1.17)	0.93 (0.75; 1.10)
	55%	1.11 (1.06; 1.15)	0.82 (0.63; 1.00)
	80%	1.09 (1.05; 1.14)	0.70 (0.51; 0.89)
	100%	1.08 (1.03; 1.13)	0.61 (0.40; 0.80)
Japan (2007)	30%	1.12 (1.09; 1.14)	1.48 (1.41; 1.54)
	55%	1.10 (1.08; 1.12)	1.33 (1.28; 1.37)
	80%	1.08 (1.07; 1.10)	1.18 (1.13; 1.22)
	100%	1.07 (1.06; 1.09)	1.06 (1.01; 1.10)
Spain (2007)	30%	1.26 (1.22; 1.31)	2.86 (2.70; 2.99)
	55%	1.24 (1.20; 1.29)	2.73 (2.58; 2.87)
	80%	1.23(1.18; 1.28)	2.61 (2.45; 2.77)
	100%	1.21 (1.16; 1.27)	2.50 (2.32; 2.66)
USA (2004)	30%	1.07 (1.05; 1.09)	0.82 (0.79; 0.84)
	55%	1.06 (1.05; 1.07)	0.69 (0.67; 0.71)
	80%	1.05 (1.04; 1.06)	0.57 (0.55; 0.59)
	100%	1.04 (1.03; 1.05)	0.47 (0.45; 0.49)


100
80
60
40
20
0
Air Conditioning (AC) %
Canada
Japan
Spain
USA
1975
1980
1985
1990
1995
2000
2005
2010
Year


Canada
Year 1994, AC% 30.1
Year 2008, AC% 48.8
Relative Risk
2.0
1.8
1.6
1.4
1.2
1.0
0.8
0%
1%
50%
99%
100%
Temperature percentiles
Japan
Year 1975, AC% 15.9
Year 2007, AC% 89.2
Relative Risk
2.0
1.8
1.6
1.4
1.2
1.0
0.8
0%
1%
50%
99%
100%
Temperature percentiles
Spain
Year 1993, AC% 9.0
Year 2007, AC% 26.9
Relative Risk
2.0
1.8
1.6
1.4
1.2
1.0
0.8
0%
1%
50%
99%
100%
Temperature percentiles
USA
Year 1975, AC% 49.4
Year 2004, AC% 82.8
Relative Risk
2.0
1.8
1.6
1.4
1.2
1.0
0.8
0%
1%
50%
99%
100%
Temperature percentiles


Baseline
End−study period with fixed AC
End−study period
Attributable Fraction (AF) %
0
1
2
3
Canada
Japan
Spain
USA
Country

Additional information on data collection

Japan

We collected data for each of the 47 prefectures in Japan in the period 1972-2009. (1) Daily counts of deaths from all causes were extracted from a computerised death certificate database maintained by the Ministry of Health, Labour and Welfare of Japan. We derived daily mean temperature by averaging hourly measurements provided by the Japan Meteorological Agency for a single weather station in the capital city of each prefecture. We obtained prefecture-specific prevalence data of AC for households with two or more occupants in each year from a regional statistics database. (1)

USA

We collected data for 211 metropolitan areas in the USA with a nationwide geographic distribution in the period 1973-2006. (2) Metropolitan areas were composed of single or multiple counties. All cause daily mortality excluding any death from accidental causes (ICD-code 10th revision: V01-Y98, ICD-code 9th revision: 001-799) were calculated from individual mortality data obtained from the National Center for Health Statistics (NCHS). Daily mean temperature was obtained from the airport weather station nearest to each city (National Oceanic and Atmospheric Administration [NOAA]). We estimated percentage of households in each city with central air conditioning (AC) by combining county-level or metropolitan area-level data. For years in 1970's and 1980's, county-level AC data were gathered from the USA Census of Population. For later years, we used metropolitan area data from the American Housing Survey (AHS). As the AC prevalence shows a strong (north to south) geographical pattern in the USA, for cities not included in the AHS we used the nearest metropolitan area with available data. For northern New England cities, we used regional level data from the "US Energy Information Administration, Office of Energy Consumption Residential Energy Consumption Survey".

Canada

We collected data from 20 census metropolitan areas (CMA) and the city of Hamilton in the period 1986-2009. All-cause daily mortality was obtained from Statistics Canada through access to the Canadian Mortality Database. Mean daily temperature, computed as the 24-hour average based on hourly measurements, were obtained from Environment Canada. A single weather station was selected for each city using the airport monitoring station located closest to the CMA centre. Proportion of dwellings with an air conditioning system (central or with a window or room mounted air conditioning system) was available for years 1993, 1997, 2003, 2006, 2007, 2009. The information is available at regional level until 2003 (Survey of household & energy use (SHEU)), and from 2006 at city level (Households and environment survey (HES)).

Spain

We collected data from the 52 capital cities in the period 1990-2014. All-cause daily mortality was obtained from Spain National Institute of Statistics. Mean daily temperature, computed as the 24-hour average based on hourly measurements, was obtained from Spain National Meteorology Agency. A single weather station, located within the urban area or at the near airport, was selected for each city. Single-day missing values were imputed as the average of the days before and after. For periods longer than two days, no imputation was done. AC prevalence data were available for three years, in 1991, 2001 and 2007. Data for 1991 and 2001 available at city level come from the National Population and housing census and refers to number of family homes with “refrigeration". Data for year 2007 available at regional level (17 Regions) comes from “Life conditions" survey and refers to "homes with air conditioning".

Derivation of AC trends

For each country and location, using the original AC data, we estimated the AC prevalence for each sub-period. Briefly, for the USA, Canada and Spain we fitted a linear mixed-effects model with a B-spline parametrisation of the time variable (years), and city as grouping level. (3) The B-spline variables were used as fixed and random effects, borrowing information across locations, and allowing the random terms to model city-specific deviations in the trend. Best linear unbiased prediction (BLUP) estimates were used to predict yearly AC prevalence in mid-summer (1st of July) in each city of the three countries. For Japan, we used the original yearly data, and assigned it to mid-summer.

The original prevalence data for each country, location and sub-period for all the four countries, together with the estimated smoothed trends, are reported in eFigures 1 (a)-(d).

Sensitivity Analyses

Across countries AC prevalence data comes from different surveys with different frequency of reporting. To assess if changes in how AC prevalence was collected and reported affect our results we performed a sensitivity analysis in the linear mixed-effects models fitted for deriving trends in US and Canada. In particular we added an indicator that defines pre/post periods corresponding to implementation of the new reporting methods, using as threshold the year 1980 for US (transition from census (counties) to AHS survey (metropolitan areas), and the year 2003 for Canada (transition from regional to city level data). The parameters for these indicators are not significant at 95% (p=0.11 and p=0.10, and indeed their inclusion results in negligible changes in predicted AC prevalence).

AC data from cities in the USA come from different sources (USA Census of Population, American Housing Survey (AHS) and Residential Energy Consumption Survey), which were collected with different designs and frequency. We performed a sensitivity analysis to assess if the effect of AC in USA was different in cities with (n = 105) and without (n = 106) AHS data. Briefly, we applied multilevel multivariate meta-analytic model with calendar year, AC prevalence, average and range of mean temperature as fixed effects and city as random term. An indicator variable was introduced to represent cities with and without AHS data with an interaction term with AC prevalence to assess the AC effect is modified by the two group of cities. The results of this analysis show that the AC effect is not modified (p=0.529) by the group of cities.

1. Chung Y, Yang D, Gasparrini A, et al. Changing Susceptibility to Non-Optimum Temperatures in Japan, 1972-2012: The Role of Climate, Demographic, and Socioeconomic Factors. *Environ Health Perspect* 2018;126(5):057002.
2. Nordio F, Zanobetti A, Colicino E, et al. Changing patterns of the temperature–mortality association by time and location in the US, and implications for climate change. *Environment international* 2015;81:80-6.
3. Ruppert D, Wand MP, Carroll RJ. *Semiparametric regression*. Cambridge university press; 2003.

Additional tables

eTable 1(a). Total number of deaths during summer months, daily mean temperature (Celsius degree) and average AC prevalence by 21 study locations in Canada during the study period 1986-2009.

City	Deaths	Daily Mean Temperature	Average AC prevalence
Abbotsford	7838	17.0	16.8
Calgary	38533	14.3	13.4
Edmonton	45066	15.4	11.3
Halifax	20661	16.9	7.8
Hamilton	33352	18.8	67.0
Kingston	11469	18.8	61.8
Kitchener-Waterloo	20230	17.9	64.0
London Ontario	28166	18.8	65.8
Montreal	80028	18.9	32.0
Ottawa	39664	18.7	64.3
Regina	14581	16.3	31.1
Saint John NB	12648	15.3	31.7
Saskatoon	16794	15.8	55.5
St. John's NFL	15741	13.9	7.4
Sudbury	12019	16.7	7.5
Thunder Bay	10529	15.3	53.0
Toronto	198640	19.4	66.5
Vancouver	94778	16.8	10.5
Victoria	24457	15.8	11.3
Windsor	18810	21.0	69.8
Winnipeg	49069	17.1	34.3

eTable 1(b). Total number of deaths during summer months, daily mean temperature (Celsius degree) and average AC prevalence by 47 study locations in Japan during the study period 1972-2009.

Prefecture	Deaths	Daily Mean Temperature	Average AC prevalence
Aichi	452427	25.0	74.7
Akita	124440	21.7	30.3
Aomori	138564	20.1	18.5
Chiba	353653	24.0	63.7
Ehime	145620	25.2	62.1
Fukui	73010	24.2	68.1
Fukuoka	390851	25.5	70.5
Fukushima	189597	22.5	33.6
Gifu	167354	25.2	62.1
Gunma	163532	23.7	59.4
Hiroshima	238543	25.1	69.8
Hokkaido	467270	19.2	6.0
Hyogo	429740	25.2	73.8
Ibaraki	226688	22.4	53.4
Ishikawa	99811	24.0	63.4
Iwate	131879	20.4	20.0
Kagawa	95519	25.3	74.8
Kagoshima	185235	26.4	53.6
Kanagawa	479908	24.0	66.1
Kochi	90113	25.3	58.2
Kumamoto	168999	25.8	61.3
Kyoto	210622	25.4	79.0
Mie	156597	24.8	68.8
Miyagi	170173	21.3	33.3
Miyazaki	104213	25.6	55.0
Nagano	197618	22.3	27.7
Nagasaki	146701	25.5	59.6
Nara	104561	24.2	76.0
Niigata	228737	23.4	58.2
Oita	119665	24.9	56.4
Okayama	174873	25.4	71.5
Okinawa	78148	27.8	57.9
Osaka	625918	26.0	83.4
Saga	83179	25.5	66.6
Saitama	382546	24.0	73.7
Shiga	94724	24.2	67.8
Shimane	83086	23.9	56.5
Shizuoka	279169	24.6	58.5
Tochigi	158398	22.9	55.0

Tokushima	83947	25.2	66.3
Tokyo	839158	24.7	74.2
Tottori	60834	24.1	59.6
Toyama	104314	23.5	63.4
Wakayama	108623	25.5	70.5
Yamagata	124152	21.9	38.8
Yamaguchi	155872	24.6	62.0
Yamanashi	75953	24.0	42.1

eTable 1(c). Total number of deaths during summer months, daily mean temperature (Celsius degree) and average AC prevalence by 52 study locations in Spain during the study period 1990-2014.

City	Deaths	Daily Mean Temperature	Average AC prevalence
A Coruna	16435	18.9	4.6
Albacete	7657	23.1	15.0
Alicante	17524	24.8	23.2
Almeria	9622	25.2	26.2
Avila	3293	19.0	5.7
Badajoz	7356	24.7	28.2
Bilbao	25981	19.8	6.1
Barcelona	119966	23.1	19.4
Burgos	10884	18.1	3.0
Cadiz	9221	23.8	18.0
Caceres	4585	24.5	29.3
Ciudad Real	4078	24.7	21.8
Ceuta	3668	23.3	8.4
Cordoba	18015	26.4	39.8
Castellon	8906	24.4	20.3
Cuenca	3405	21.7	12.2
Guadalajara	3780	21.6	17.5
Girona	4579	22.1	19.3
Granada	15302	23.7	26.4
Huelva	8310	24.6	19.7
Huesca	3506	22.3	16.6
Jaen	6148	25.2	35.7
Leon	9530	18.2	3.0
Logrono	8150	21.4	7.2
Lleida	7641	23.5	22.0
Lugo	6118	17.5	3.2
Malaga	32155	24.9	21.5
Madrid	194623	23.7	21.6
Melilla	3100	24.6	11.7

Murcia	19671	26.1	35.1
Ourense	7223	21.5	4.1
Oviedo	14887	18.1	5.0
Palmas G. Canaria	20947	23.9	3.9
Palma Mallorca	20727	23.7	22.6
Palencia	5697	19.5	3.9
Pamplona	11776	20.1	7.6
Pontevedra	4520	19.6	3.7
Segovia	3706	20.3	4.1
Salamanca	10890	19.8	4.7
San Sebastian	12657	18.5	6.5
Santander	13103	19.3	6.3
Soria	2366	18.7	3.8
Sevilla	42071	26.9	42.5
Teruel	2328	20.4	15.1
Tenerife	11999	24.7	6.3
Toledo	3927	24.8	27.5
Tarragona	6777	25.1	19.0
Vitoria	11886	18.1	6.0
Valladolid	18921	20.7	6.0
Valencia	51853	24.8	28.1
Zamora	4517	21.1	2.8
Zaragoza	42089	23.8	21.2

eTable 1(d). Total number of deaths during summer months, daily mean temperature (Celsius degree) and average AC prevalence by 211 study locations in USA during the study period 1973-2006.

City	Deaths	Daily Mean Temperature	Average AC prevalence
AUGUSTA (GA)	16328	25.4	85.6
AKRON (OH)	50880	20.3	54.6
ALBANY (NY)	28663	19.7	59.2
ALBUQUERQUE (NM)	29823	23.6	61.6
ALLENTOWN (PA)	27587	21.3	73.2
ANCHORAGE (AK)	5904	13.5	1.0
ANAHEIM (CA)	137811	22.6	47.7
ANN ARBOR (MI)	14962	20.3	64.7
ANNANDALE (VA)	24150	23.7	92.9
AUSTIN (TX)	29496	27.6	94.8
ATLANTIC CITY (NJ)	23639	21.9	61.1
ATLANTA (GA)	133722	24.4	84.5
AZTEC (NM)	3051	21.7	76.7
BATH (NY)	7696	19.2	42.5
BUFFALO (NY)	102555	19.7	32.4
BAKERSFIELD (CA)	37912	27.1	73.7
BOULDER (CO)	10504	21.4	40.9
BALTIMORE (MD)	151409	23.3	79.6
BANGOR (ME)	12045	17.9	33.0
BOISE CITY (ID)	10125	20.9	50.2
PATERSON (NJ)	112797	22.4	81.0
BURLINGTON (VT)	7828	19.1	36.4
BIRMINGHAM (AL)	80149	25.1	84.2
BARNSTABLE (MA)	22275	20.1	50.7
BROWNSVILLE (TX)	15246	28.2	78.1
BOSTON (MA)	230062	20.8	58.0
BATON ROUGE (LA)	27480	26.4	92.9
CEDAR RAPIDS (IA)	12886	20.8	81.0
CHICAGO (IL)	543251	22.3	76.3
CHARLOTTE (NC)	34665	24.2	83.5
CHARLESTON (SC)	21786	26.0	86.5
CHATTANOOGA (TN)	27278	24.3	90.1
CHARLESTON (WV)	23102	21.8	77.9
COLUMBUS (OH)	73424	21.7	75.4
COLORADO SPRINGS (CO)	21173	19.0	39.0
CLEVELAND (OH)	192411	21.8	58.5
CINCINNATI (OH)	83233	22.5	78.9
CANTON (OH)	35823	20.2	58.8

COLUMBIA (SC)	32946	25.4	91.0
CARLISLE (PA)	16529	22.3	62.9
CORPUS CHRISTI (TX)	20657	27.9	84.9
LAYTON (UT)	7228	21.4	50.1
DALLAS (TX)	116462	28.3	95.4
DENVER (CO)	81168	20.4	43.0
BEAVER DAM (WI)	5773	19.7	60.5
DOVER (DE)	8362	22.8	75.9
DURHAM (NC)	14200	23.8	83.3
DES MOINES (IA)	25279	22.1	85.6
DETROIT (MI)	348759	21.6	63.1
DAVENPORT (IA)	25669	21.5	84.1
DAYTONA BEACH (FL)	44885	26.4	91.3
DAYTON (OH)	50614	21.8	78.1
EL CENTRO (CA)	6978	32.2	54.3
ELKHART (IN)	11791	22.3	73.7
EL PASO (TX)	30456	26.7	72.6
ELIZABETH (NJ)	46629	23.1	77.6
ERIE (PA)	25514	20.0	37.5
ESSEX (MA)	62360	20.5	58.2
EUGENE (OR)	22396	17.7	27.7
EVANSVILLE (IN)	17643	23.7	85.9
EVERETT (WA)	28599	17.0	6.0
FARGO (ND)	6372	19.1	48.7
FLINT (MI)	34774	19.7	51.1
FRESNO (CA)	44191	26.1	83.0
FORT LAUDERDALE (FL)	133746	28.2	93.6
FORT MYERS (FL)	34326	27.3	94.1
FORT PIERCE (FL)	26163	27.1	85.6
FORT WORTH (TX)	74381	27.9	96.0
FORT WAYNE (IN)	23452	21.0	76.6
FAYETTEVILLE (NC)	14727	25.2	85.7
GARY (IN)	42247	22.4	76.0
GREEN BAY (WI)	13173	18.9	60.8
GREENSBURG (PA)	39408	22.3	54.9
GRAND HAVEN (MI)	11578	19.4	56.3
GRAND JUNCTION (CO)	6151	23.1	49.6
GRAND RAPIDS (MI)	36477	19.9	55.3
GREENSBORO (NC)	29000	23.3	84.8
GREENVILLE (SC)	24980	24.8	82.5
GAINESVILLE (FL)	11380	25.9	87.1
GETTYSBURG (PA)	5058	22.7	56.9
HICKORY (NC)	9600	23.2	75.4
HOLLAND (MI)	5255	19.4	56.3

HONOLULU (HI)	36742	26.6	30.9
HARRISBURG (PA)	23678	22.3	61.7
HARTFORD (CT)	71541	21.4	60.4
HOUSTON (TX)	161273	27.3	94.4
INDIANAPOLIS (IN)	70216	22.2	81.8
IOWA CITY (IA)	3434	21.0	85.0
JACKSONVILLE (FL)	55432	26.9	89.1
JERSEY CITY (NJ)	52656	19.5	66.6
KLAMATH FALLS (OR)	4132	17.1	27.3
KALAMAZOO (MI)	15947	21.3	61.6
KENOSHA (WI)	10620	20.2	64.2
KANSAS CITY (KS)	100016	24.8	87.2
KNOXVILLE (TN)	36093	23.6	87.8
LAFAYETTE (IN)	8821	21.9	79.8
LAFAYETTE (LA)	10644	26.6	89.5
LAKE CHARLES (LA)	14017	27.4	88.6
LAKELAND (FL)	39449	27.8	79.7
LANCASTER (PA)	35226	22.5	78.9
LANSING (MI)	17190	19.6	53.4
LOGAN (UT)	2466	20.0	39.6
LOUISVILLE (KY)	65088	23.8	83.0
LA PORTE (IN)	9585	20.9	74.0
LOS ANGELES (CA)	585151	21.5	49.3
LAS VEGAS (NV)	60738	30.8	94.5
LITTLE ROCK (AR)	29271	25.9	92.4
MACON (GA)	15179	25.6	83.3
MCALLEN (TX)	20083	28.9	77.7
MIDDLESEX (NJ)	48927	22.8	86.1
MIDDLETOWN (OH)	21954	22.3	78.7
MEDFORD (OR)	13963	20.6	37.7
MADISON (IL)	21823	24.7	80.0
MODESTO (CA)	26730	25.8	49.9
MADISON (WI)	21529	19.8	62.4
MIAMI (FL)	173549	27.9	87.7
MELBOURNE (FL)	34939	27.3	89.3
MILWAUKEE (WI)	109839	20.2	64.7
MEMPHIS (TN)	70069	26.3	94.1
TOMS RIVER (NJ)	103364	23.0	78.4
MINNEAPOLIS (MN)	113123	20.6	75.9
MONTGOMERY (AL)	18371	27.3	87.2
MOBILE (AL)	32427	27.0	91.4
MONROE (LA)	11976	26.3	86.9
MERCER (PA)	12730	19.8	52.6
UPPER MARLBORO (MD)	33827	23.0	90.6

MUSKEGON (MI)	14426	19.4	55.2
MUNCIE (IN)	10741	22.4	74.6
MYRTLE BEACH (SC)	12073	25.6	83.4
NAMPA (ID)	4082	20.6	47.1
NASHUA (NH)	22925	21.5	47.9
MELVILLE (NY)	217220	21.4	73.4
NILES (MI)	14168	20.8	62.2
NORFOLK (VA)	69980	24.5	87.9
NASHVILLE (TN)	44063	24.5	94.8
NEWBURGH (NY)	23313	20.6	58.5
NEW HAVEN (CT)	72842	21.7	59.5
NEW LONDON (CT)	18931	20.6	54.1
NEW ORLEANS (LA)	88199	27.6	89.0
NEWARK (NJ)	107048	23.1	71.1
NEW YORK (NY)	691188	19.5	61.4
OCALA (FL)	21980	26.0	81.9
OKLAHOMA CITY (OK)	52741	25.7	93.7
OAKLAND (CA)	145642	16.9	31.0
OMAHA (NE)	33423	22.4	92.7
ORLANDO (FL)	65320	26.8	91.0
OTTAWA (IL)	11733	21.3	74.2
PHILADELPHIA (PA)	427954	22.6	78.0
PHOENIX (AZ)	152406	33.2	88.4
PALM BEACH (FL)	94124	27.3	89.5
PLYMOUTH (MA)	34916	20.2	56.5
PENSACOLA (FL)	21640	26.8	90.4
PORTLAND (OR)	94919	18.7	28.9
PROVO (UT)	11373	21.8	46.1
PORT ARTHUR (TX)	23927	26.9	90.1
PORTAGE (IN)	8380	22.4	78.8
PORTLAND (ME)	21078	18.3	36.1
PROVIDENCE (RI)	118928	20.7	50.4
PITTSBURGH (PA)	154655	21.1	57.4
RICHMOND (VA)	40673	23.8	86.4
ROCHESTER (NY)	60756	19.6	48.3
ROCKVILLE (MD)	38423	24.5	92.0
READING (PA)	32927	22.2	71.2
RENO (NV)	18059	20.6	71.0
RALEIGH (NC)	24517	23.9	89.2
RIVERSIDE (CA)	177334	23.3	79.6
SACRAMENTO (CA)	72377	22.1	89.2
SCRANTON (PA)	71109	19.9	47.2
SAN DIEGO (CA)	158466	21.3	34.0
SAN FRANCISCO (CA)	118777	16.9	7.2

SALT LAKE CITY (UT)	39245	22.8	50.9
SAN JOSE (CA)	79032	21.8	32.2
SANTA BARBARA (CA)	25352	18.2	38.1
SAN ANTONIO (TX)	81165	28.1	86.3
SPOKANE (WA)	31111	18.8	45.4
SPRINGFIELD (MA)	44171	21.1	61.9
SPRINGFIELD (MO)	18837	23.3	81.1
SPARTANBURG (SC)	19782	24.2	77.3
SARASOTA (FL)	62363	27.7	93.3
STEUBENVILLE (OH)	11219	21.5	58.6
ST. CHARLES (MO)	11185	24.4	88.9
STOCKTON (CA)	35179	23.5	84.1
EAST ST. LOUIS (IL)	23205	24.5	85.0
SOUTH BEND (IN)	22463	20.8	70.5
ST. LOUIS (MO)	131259	24.7	88.4
STAMFORD (CT)	66789	20.6	72.8
ST. PETERSBURG (FL)	68483	28.5	90.8
STATE COLLEGE (PA)	7171	19.7	55.5
SEATTLE (WA)	102243	16.0	7.3
SIOUX CITY (IA)	7325	21.5	83.5
TACOMA (WA)	41570	17.1	8.2
TAMPA (FL)	68483	27.3	89.9
TUCSON (AZ)	52297	29.1	60.8
TALLAHASSEE (FL)	10497	26.1	88.9
TOLEDO (OH)	44939	21.3	66.0
TOPEKA (KS)	14340	23.7	89.3
TRENTON (NJ)	27141	22.5	86.2
TERRE HAUTE (IN)	11482	22.2	80.6
TULSA (OK)	42061	26.1	92.6
VISALIA (CA)	22014	25.4	44.5
VANCOUVER (WA)	15616	18.6	8.6
VENTURA (CA)	37298	18.8	43.4
WICHITA (KS)	30425	24.9	92.4
OGDEN (UT)	10926	23.5	47.6
WILMINGTON (DE)	34130	22.7	81.6
WINSTON-SALEM (NC)	22695	24.2	80.4
WORCESTER (MA)	62512	18.8	46.6
WASHINGTON (DC)	67541	24.3	87.3
WASHINGTON (PA)	22831	20.7	54.5
YOUNGSTOWN (OH)	41226	19.6	56.9
YORK (PA)	28005	22.0	71.6

eTable 2. Country specific sub-periods, and period specific averagre daily mean temperature (Celsisus degree).

Country	Sub-period	Average daily mean temperature
Canada	[1991; 1995]	16.7
Canada	[1996; 2000]	17.1
Canada	[2001; 2005]	17.4
Canada	[2006; 2009]	17.0
Japan	[1972; 1976]	23.5
Japan	[1977; 1980]	24.0
Japan	[1981; 1984]	23.6
Japan	[1985; 1988]	23.9
Japan	[1989; 1992]	24.3
Japan	[1993; 1996]	24.1
Japan	[1997; 2000]	24.7
Japan	[2001; 2004]	24.6
Japan	[2005; 2009]	24.7
Spain	[1990; 1994]	22.0
Spain	[1995; 1998]	21.8
Spain	[1999; 2004]	22.5
Spain	[2005; 2009]	22.4
USA	[1973; 1976]	22.4
USA	[1977; 1981]	23.0
USA	[1982; 1986]	22.7
USA	[1987; 1991]	23.2
USA	[1992; 1996]	23.0
USA	[1997; 2001]	22.9
USA	[2002; 2006]	23.0

eTable 3. Multivariate multilevel meta-regression models with different fixed-effects specification and related p-values of Wald tests.

	Model 1	Model 2	Model 3	Model 4
Country*year interaction		<0.0001	<0.0001	<0.0001
Air Conditioning (%)			<0.0001	0.011
Average summer mean temperature °C				0.740
Interquartile range of mean temperature °C				<0.0001
I^2	35.0%	22.5%	22.1%	20.5%

Model 1: Intercept
Model 2: Intercept, country*year interaction
Model 3: Intercept, country*year interaction, AC
Model 4: Intercept, country*year interaction, AC, average mean temperature, interquartile range of mean temperature

eTable 4. Attributable fractions (AF%), Attributable deaths by country and sub periods calculated under observed air conditioning prevalence (Scenario 1) and under Scenario 2 on which, in each country, air conditioning prevalence is set at the level observed at the beginning of the observational period. Delayed deaths were calculated as difference between attributable deaths calculated between scenario 2 and scenario 1.

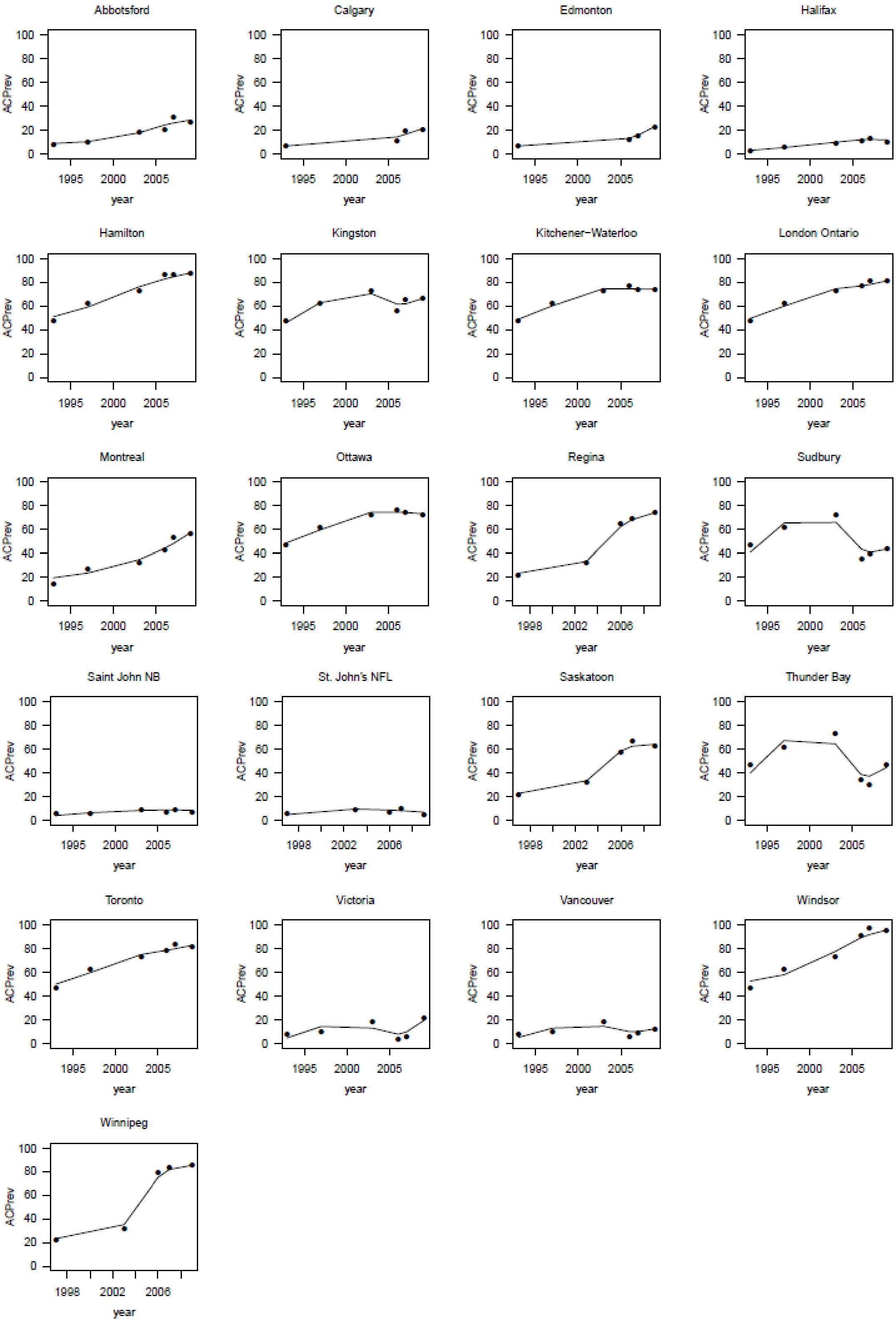
		Scenario 1. Observed air conditioning prevalence				**Scenario 2: Air conditioning prevalence set at the level observed at the beginning of the observational period**				
		AF%		**Attributable deaths**		**AF%**		**Attributable deaths**		**Delayed deaths**
Country	Period	**Point estimate**	**95%CI**	**Point estimate**	**95%CI**	**Point estimate**	**95%CI**	**Point estimate**	**95%CI**	
Canada	[1991; 1995]	1.4	(1.2; 1.6)	2366.4	(2070.9; 2642)	1.4	(1.2; 1.6)	2381.2	(2108.8; 2647)	14.8
	[1996; 2000]	1.3	(1.2; 1.5)	2284.4	(2047.4; 2506)	1.4	(1.2; 1.5)	2345.4	(2116.8; 2571.2)	61.0
	[2001; 2005]	1.2	(1.1; 1.4)	1928.1	(1663.4; 2191.7)	1.3	(1.2; 1.5)	2095.6	(1835.9; 2336.4)	167.5
	[2006; 2009]	0.8	(0.6; 1)	1002.3	(758.8; 1230.7)	0.9	(0.7; 1.1)	1136.8	(903.6; 1357.2)	134.5
									Delayed deaths	377.8
									Total deaths	793073
									Delayed AF%	0.05

Japan	[1972; 1976]	3.6	(3.5; 3.6)	37131.7	(36735.3; 37554.5)	3.6	(3.5; 3.6)	37293.1	(36862.9; 37678.3)	161.4
	[1977; 1980]	3.1	(3.1; 3.2)	26476.9	(26182.5; 26761.1)	3.3	(3.2; 3.3)	27486.9	(27206.4; 27779.2)	1010.0
	[1981; 1984]	2.8	(2.8; 2.9)	24687.3	(24383.1; 24972.6)	3.0	(3; 3.1)	26287.2	(25940.6; 26652.8)	1599.9
	[1985; 1988]	2.5	(2.5; 2.6)	23182.0	(22867.4; 23527.1)	2.8	(2.7; 2.8)	25453.3	(25014.1; 25890.6)	2271.3
	[1989; 1992]	2.2	(2.2; 2.3)	22402.2	(21979.9; 22798.3)	2.6	(2.5; 2.6)	25862.9	(25263.2; 26440.4)	3460.7
	[1993; 1996]	1.9	(1.9; 1.9)	20218.4	(19799.2; 20665.7)	2.3	(2.2; 2.4)	24519.9	(23831; 25203.5)	4301.5
	[1997; 2000]	1.7	(1.7; 1.7)	18937.1	(18452.2; 19409.5)	2.2	(2.1; 2.2)	24118.4	(23288.9; 24930.7)	5181.3
	[2001; 2004]	1.4	(1.4; 1.5)	17090.7	(16617; 17538)	1.9	(1.8; 2)	22989.7	(22051.7; 23992.8)	5899.0
	[2005; 2009]	1.1	(1; 1.1)	18268.8	(17422.3; 19040.2)	1.6	(1.5; 1.6)	26097.9	(24791.5; 27415.1)	7829.1
									Delayed deaths	31714.2
									Total deaths	9764534
									Delayed AF%	0.32
Spain	[1990; 1994]	3.5	(3.4; 3.7)	6055.3	(5791.6; 6306.5)	3.5	(3.4; 3.7)	6061.7	(5805.7; 6314.6)	6.4
	[1995; 1998]	3.5	(3.4; 3.7)	5005.7	(4848; 5179.8)	3.6	(3.5; 3.7)	5050.4	(4888.5; 5214.7)	44.7
	[1999; 2004]	3.5	(3.4; 3.6)	7775.2	(7545.3; 7997.1)	3.6	(3.5; 3.7)	7929.4	(7713.4; 8149.7)	154.2
	[2005; 2009]	2.8	(2.6; 2.9)	5201.3	(4919.3; 5455.6)	2.9	(2.8; 3)	5438.9	(5178.8; 5707.5)	237.6
									Delayed deaths	442.9
									Total deaths	918076

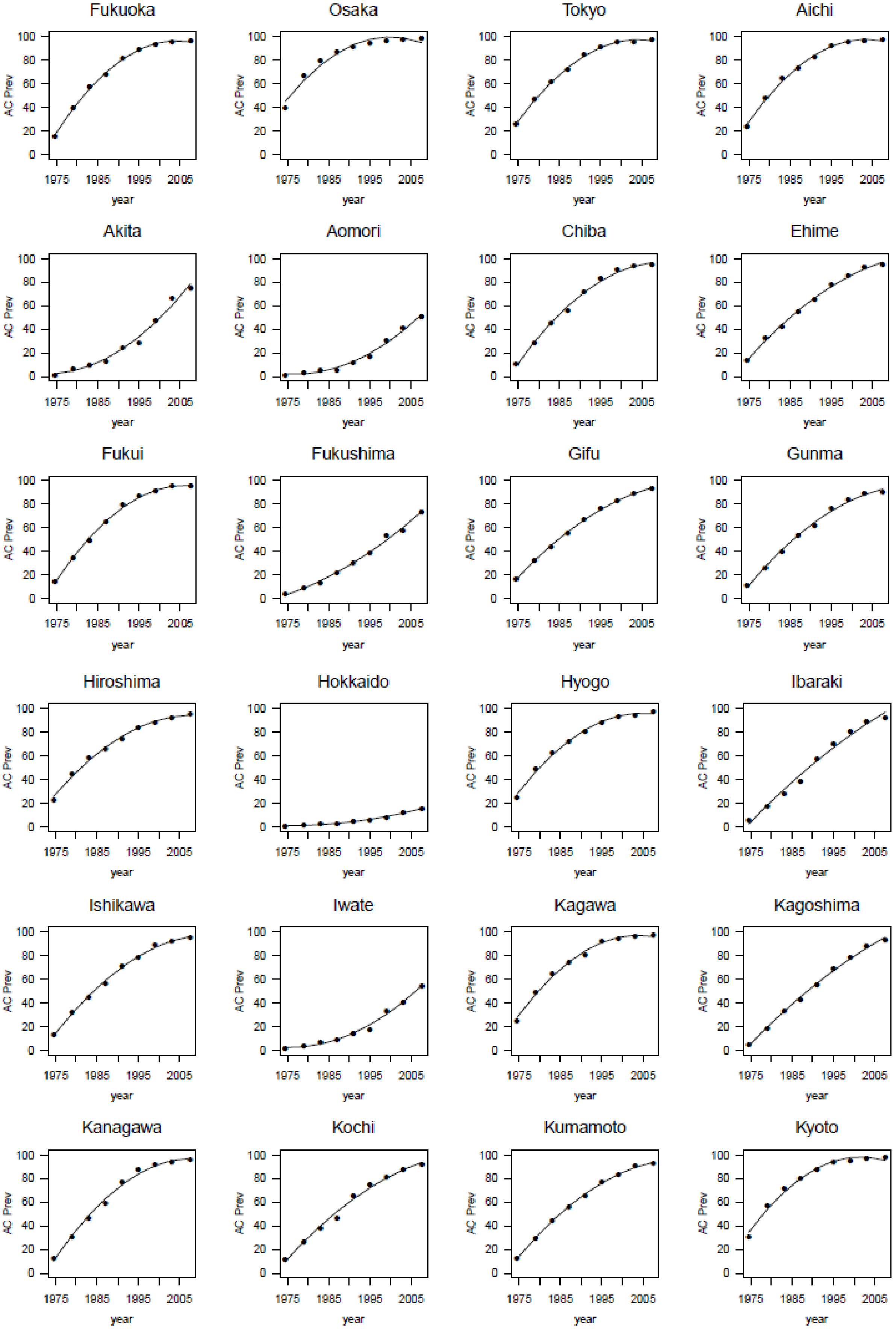
									Delayed AF%	0.05
USA	[1973; 1976]	1.7	(1.7; 1.7)	20659.3	(20327.1; 20967.7)	1.7	(1.7; 1.7)	20540.2	(20216.1; 20847.5)	-119.1
	[1977; 1981]	1.6	(1.5; 1.6)	23776.4	(23459.7; 24106.6)	1.6	(1.6; 1.6)	24229.1	(23923.3; 24518.9)	452.7
	[1982; 1986]	1.3	(1.3; 1.3)	21885.6	(21570.6; 22164.5)	1.4	(1.4; 1.4)	22920.2	(22655.3; 23188)	1034.6
	[1987; 1991]	1.1	(1.1; 1.1)	19344.4	(19079.4; 19619.4)	1.2	(1.2; 1.2)	21177.6	(20864.3; 21486.1)	1833.2
	[1992; 1996]	0.9	(0.9; 0.9)	16215.0	(15896.4; 16528.2)	1.0	(1; 1)	18368.7	(18049.8; 18680.7)	2153.7
	[1997; 2001]	0.7	(0.7; 0.7)	12353.9	(12062; 12604.9)	0.8	(0.8; 0.8)	15016.5	(14666.6; 15358.6)	2662.6
	[2002; 2006]	0.5	(0.5; 0.5)	10037.1	(9680.4; 10355.1)	0.7	(0.7; 0.7)	13255.1	(12815.9; 13693.2)	3218.0
									Delayed deaths	11235.7
									Total deaths	11839659
									Delayed AF%	0.09

Additional figures

eFigure 1(a). Location specific air conditioning prevalence with the estimated smoothed trends. Canada, 21 locations, period 1986-2009.



eFigure 1(b). Location specific air conditioning prevalence with the estimated smoothed trends. Japan, 47 locations, period 1972-2009.



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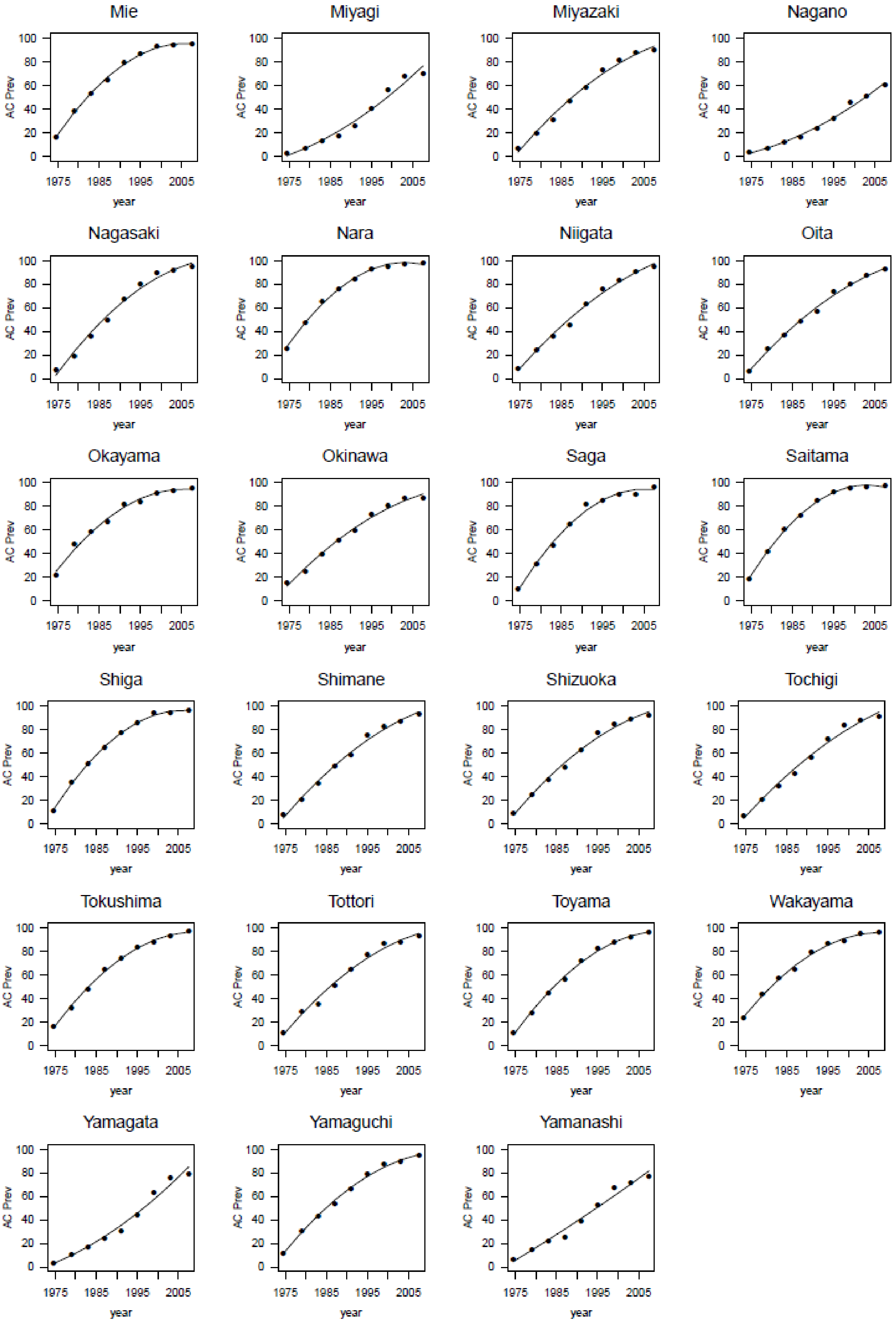

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Nagasaki Nara Niigata Oita

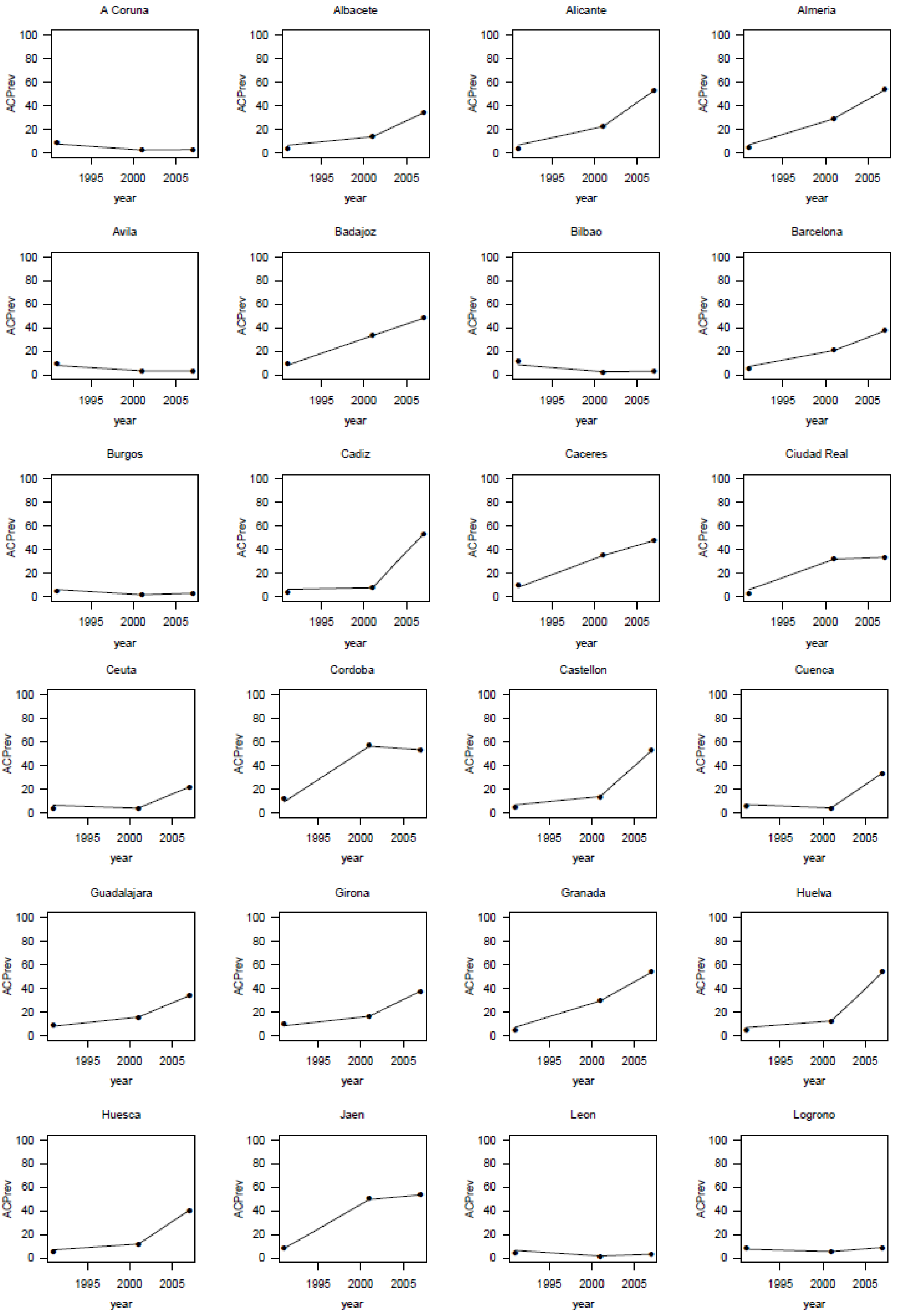
Okayama Okinawa Saga Saitama

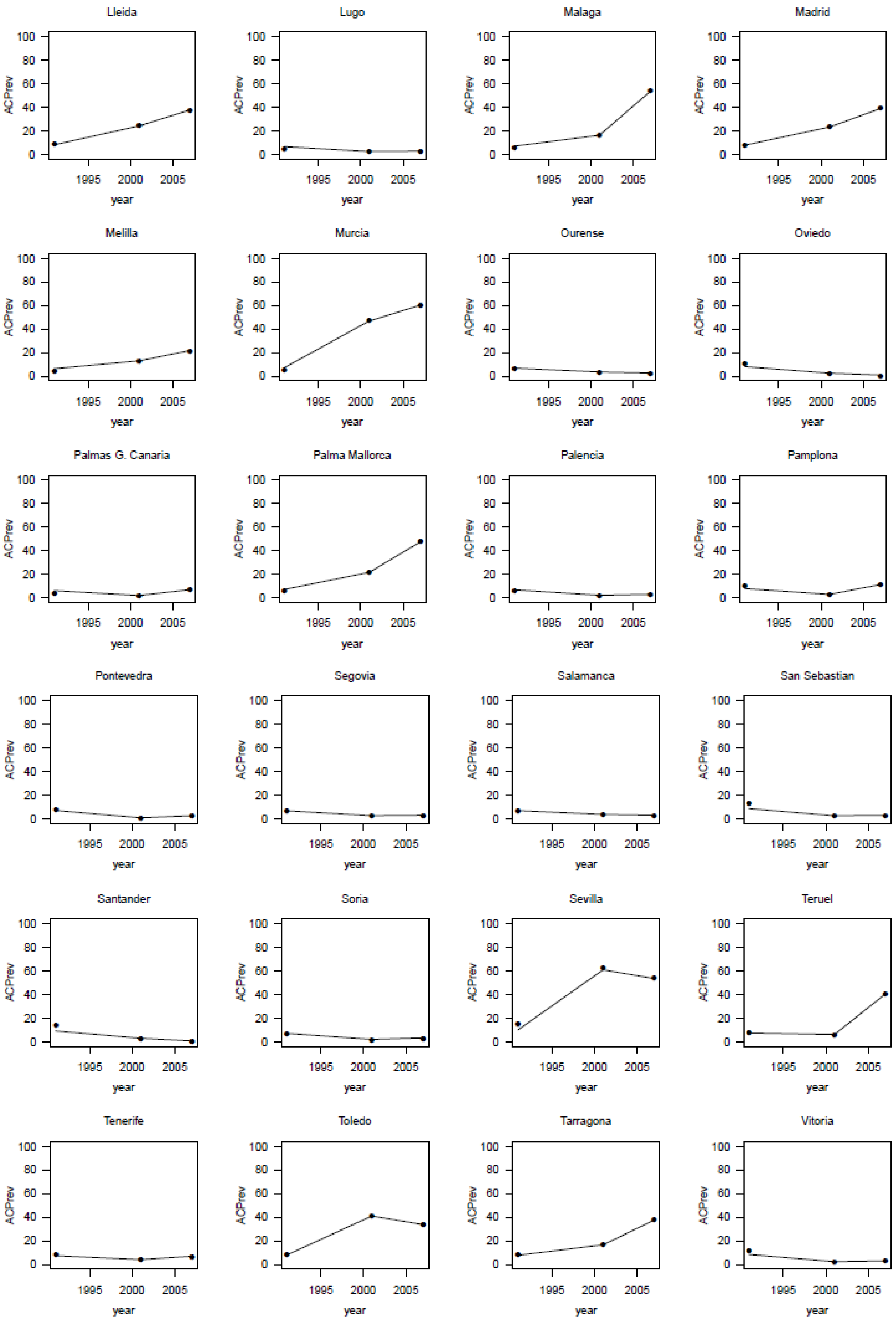
Shiga Shimane Shizuoka Tochigi

Tokushima Tottori Toyama Wakayama

Yamagata Yamaguchi Yamanashi

eFigure 1(c). Location specific air conditioning prevalence with the estimated smoothed trends. Spain, 52 locations, period 1990-2014.

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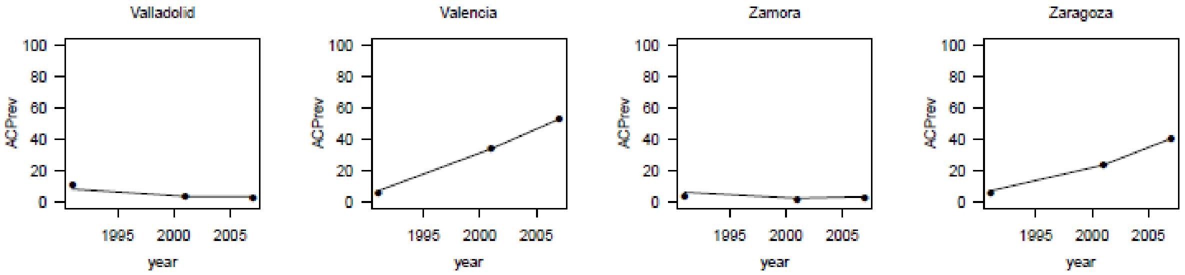
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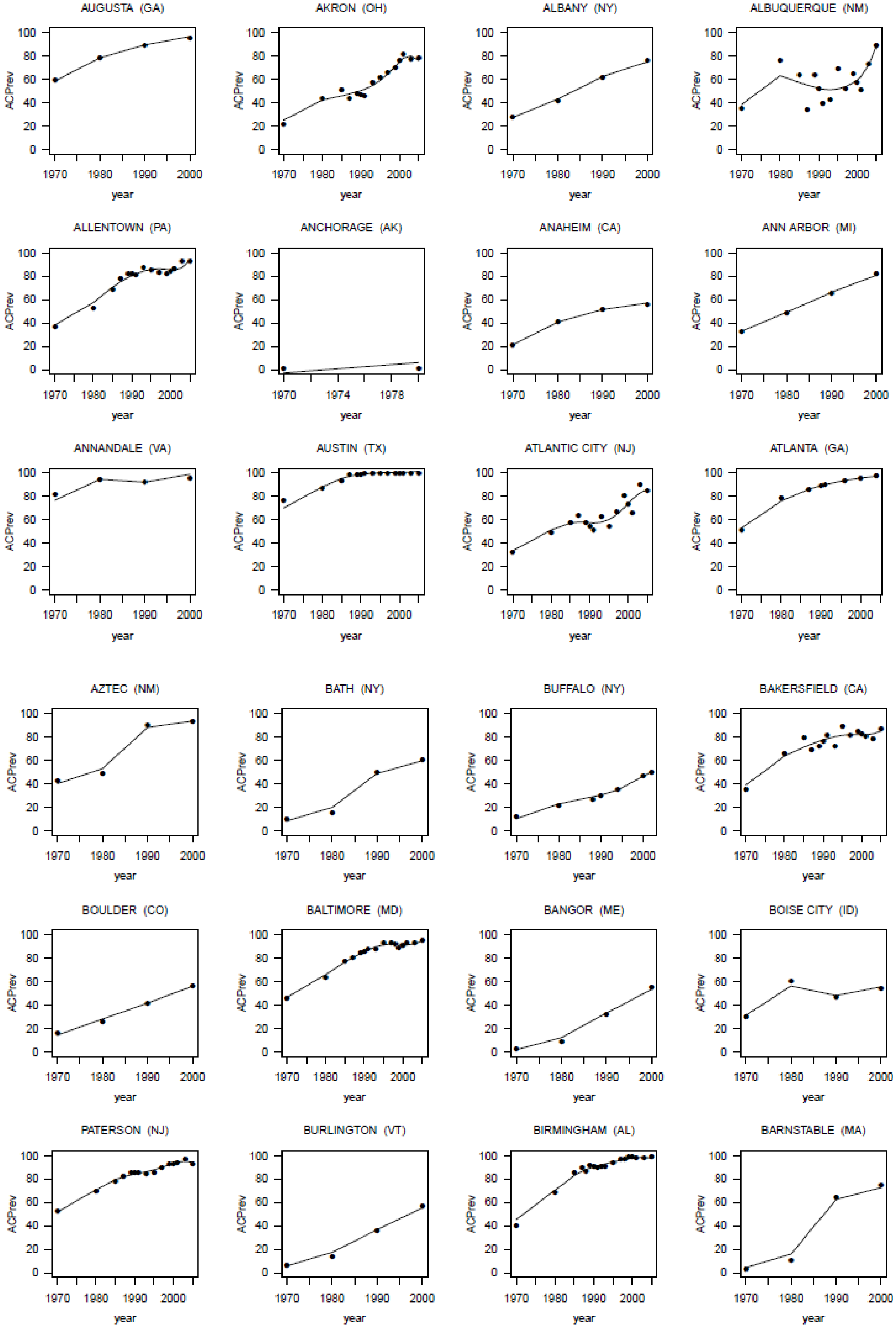
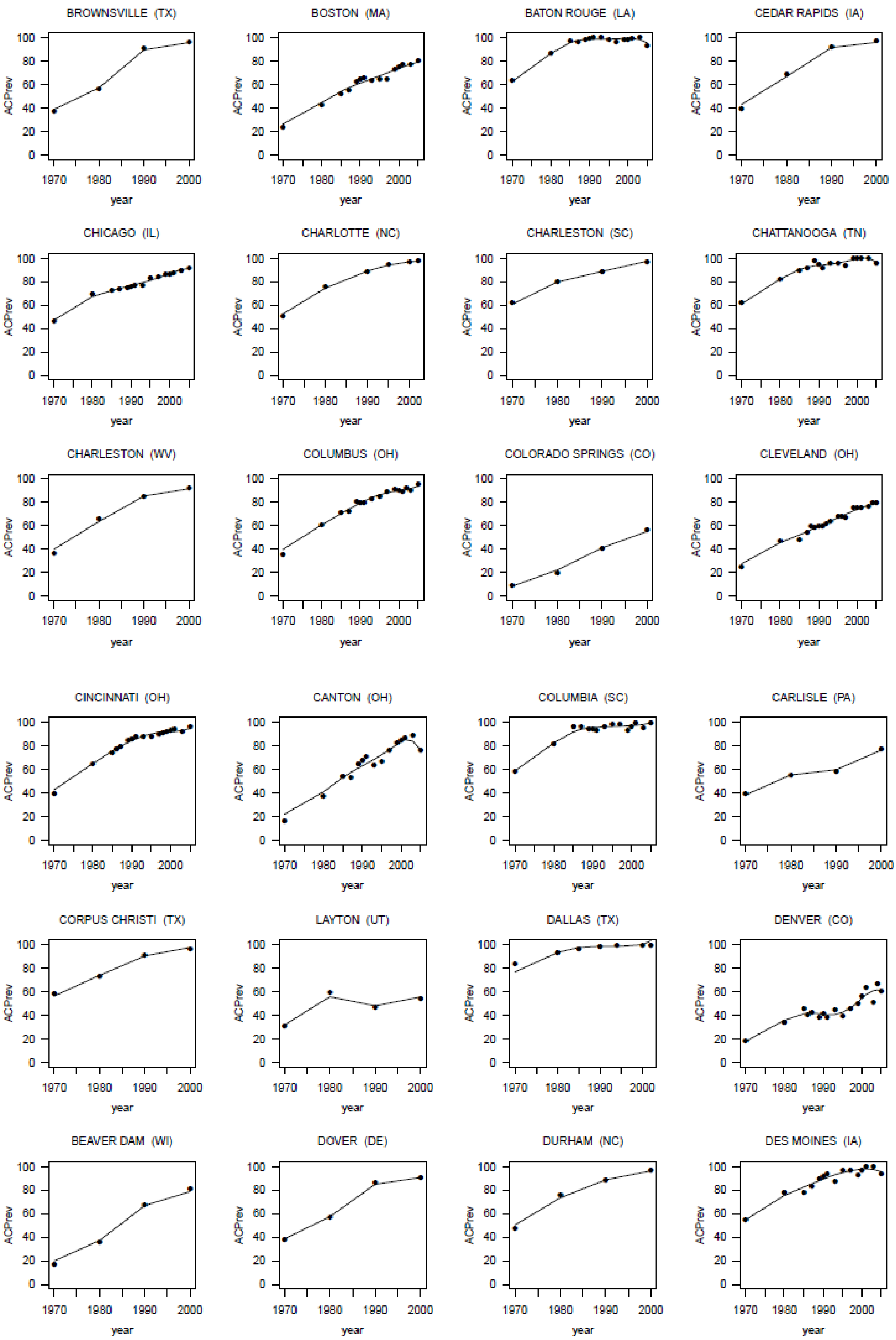
eFigure 1(d). **Location specific air conditioning prevalence with the estimated smoothed trends. USA, 211 locations, period 1973-2006.**

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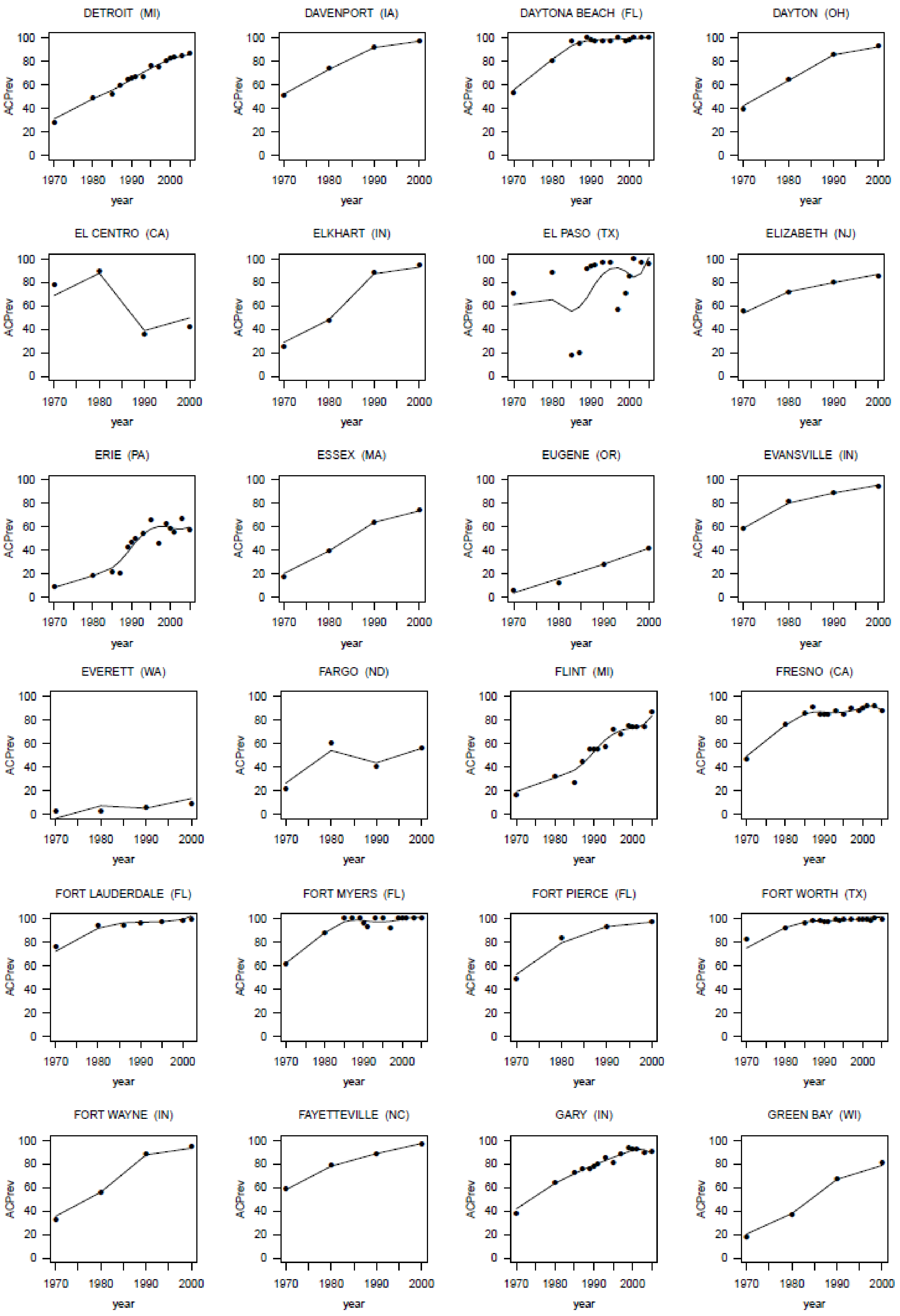
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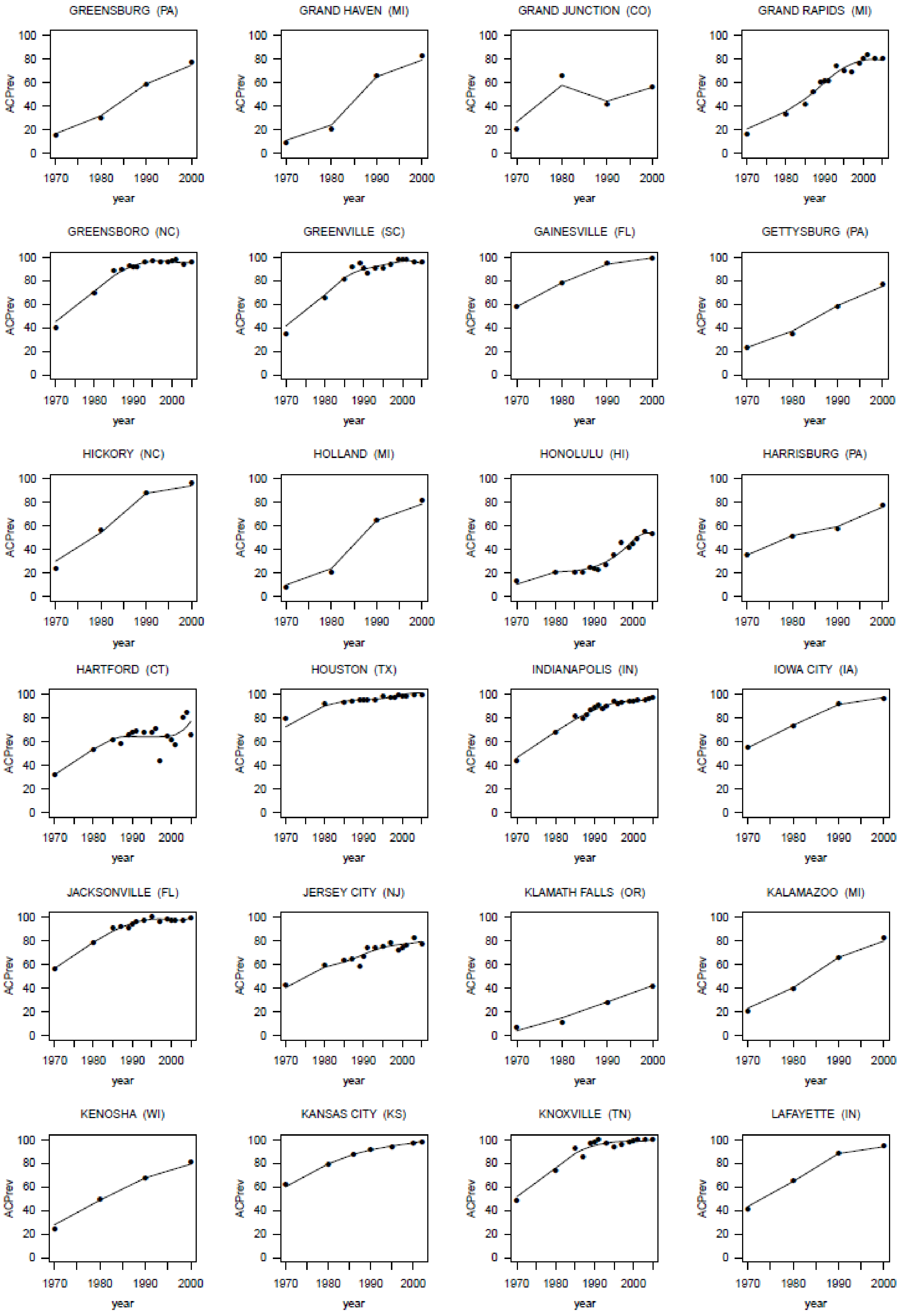
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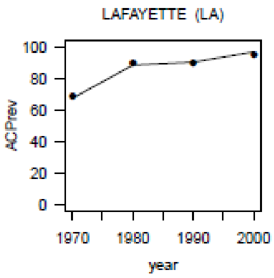
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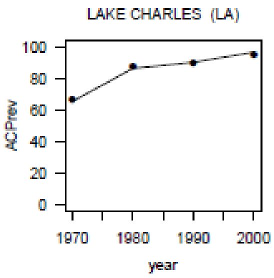
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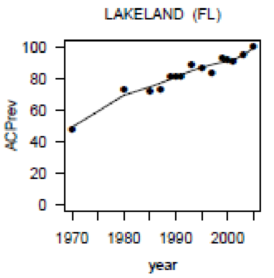
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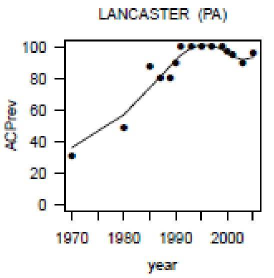
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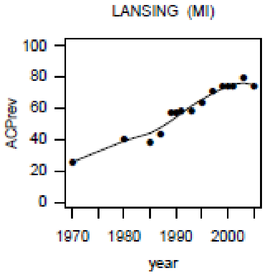
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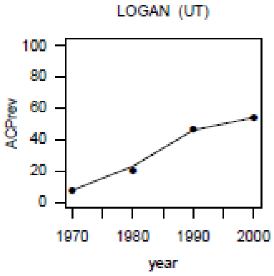
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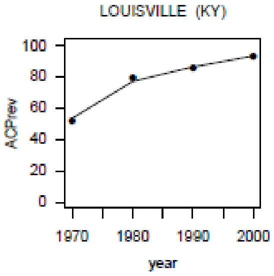
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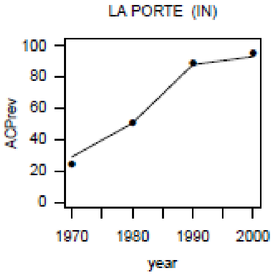
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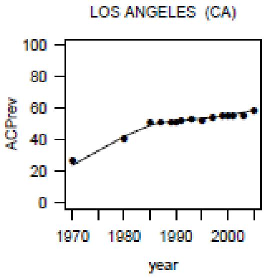
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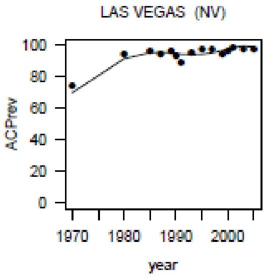
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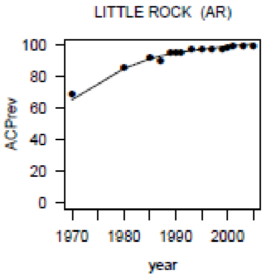
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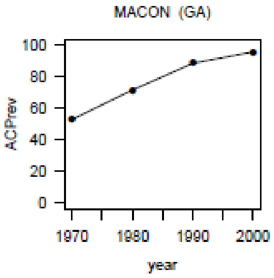
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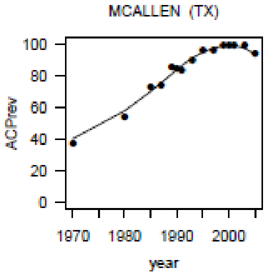
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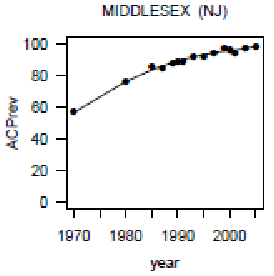
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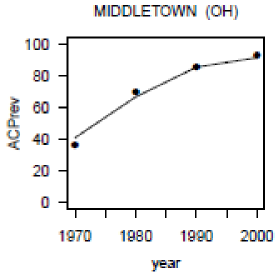
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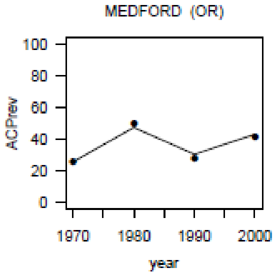
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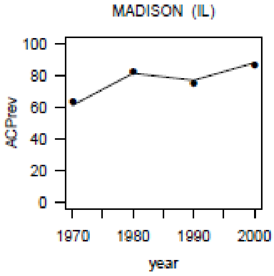
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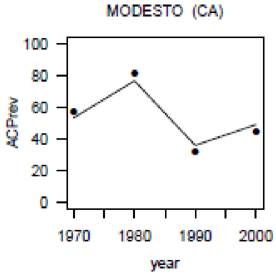
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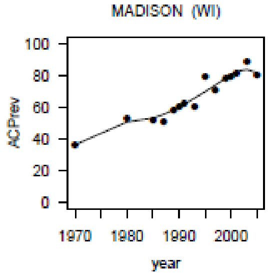
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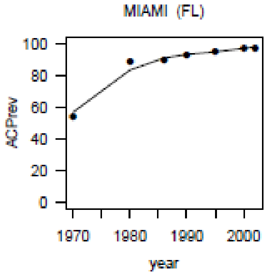
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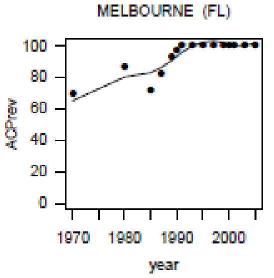
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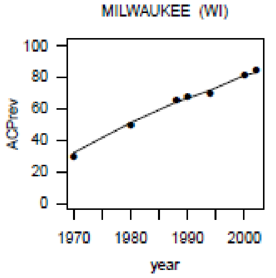
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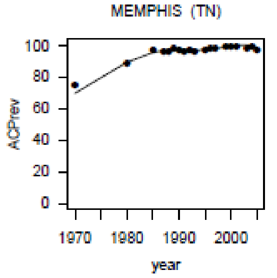
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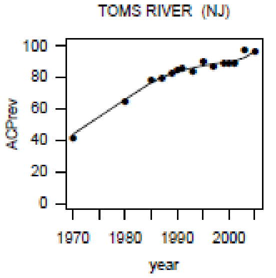
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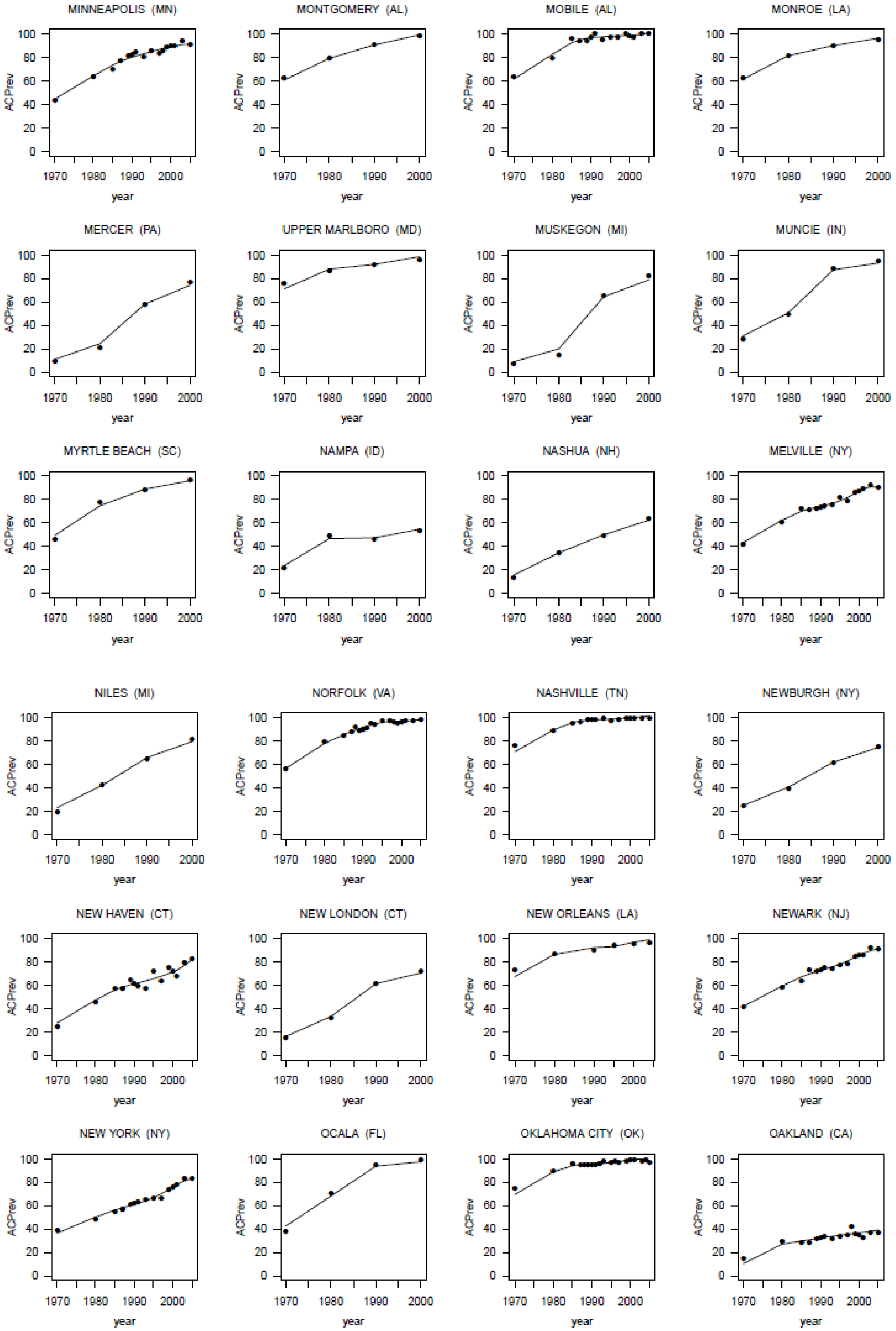
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MUNCIE (IN)
MYRTLE BEACH (SC)
NAMPA (ID)
NASHUA (NH)
MELVILLE (NY)
NILES (MI)
NORFOLK (VA)
NASHVILLE (TN)
NEWBURGH (NY)
NEW HAVEN (CT)
NEW LONDON (CT)
NEW ORLEANS (LA)
NEWARK (NJ)
NEW YORK (NY)
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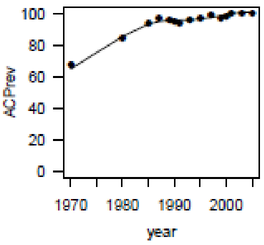
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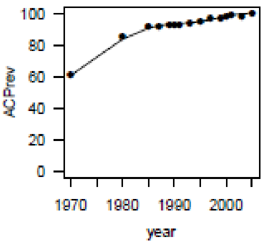
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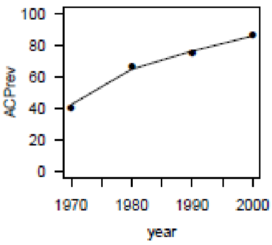
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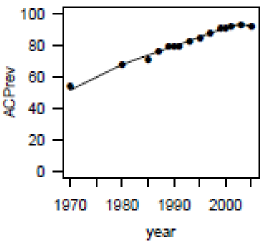
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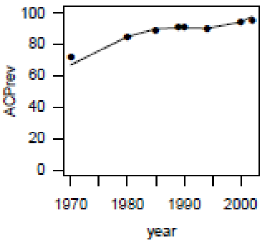
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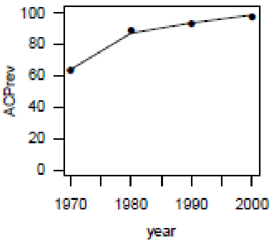
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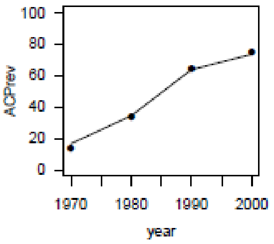
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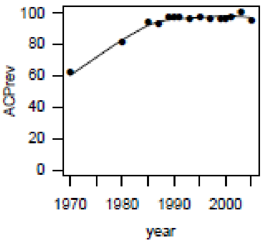
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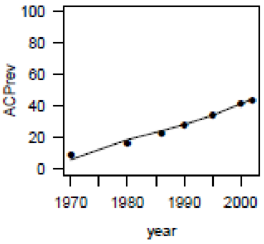
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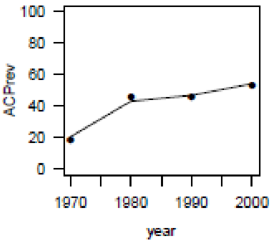
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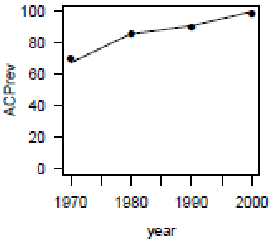
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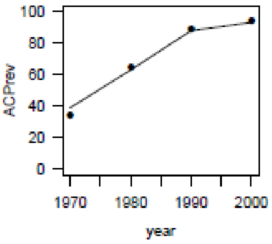
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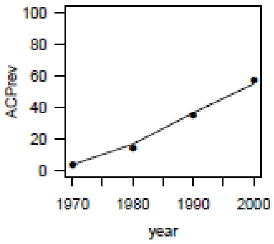
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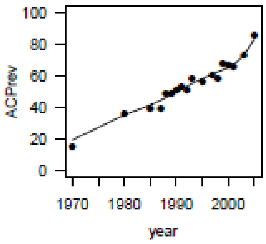
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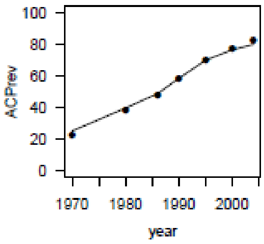
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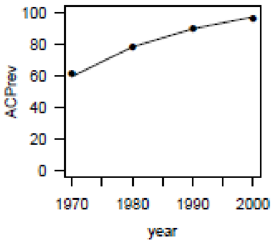
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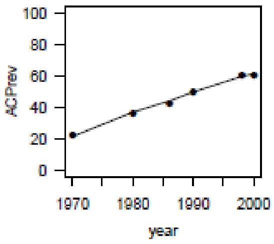
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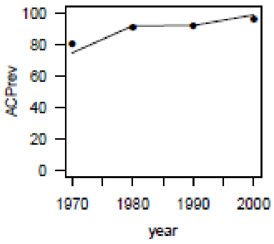
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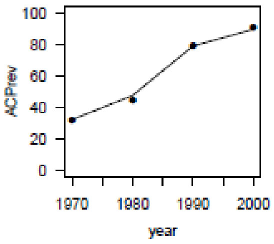
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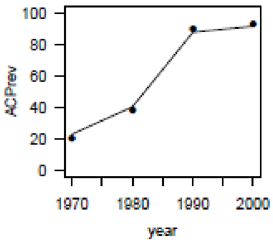
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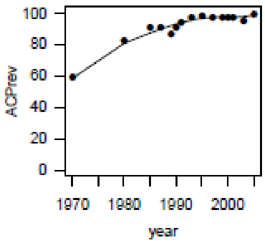
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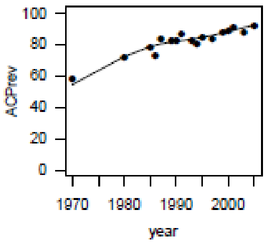
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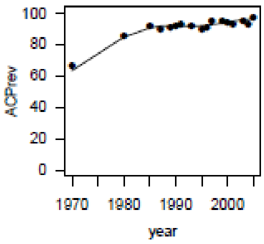
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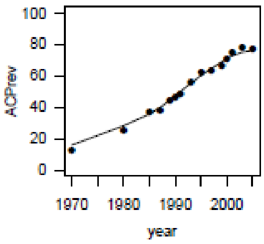
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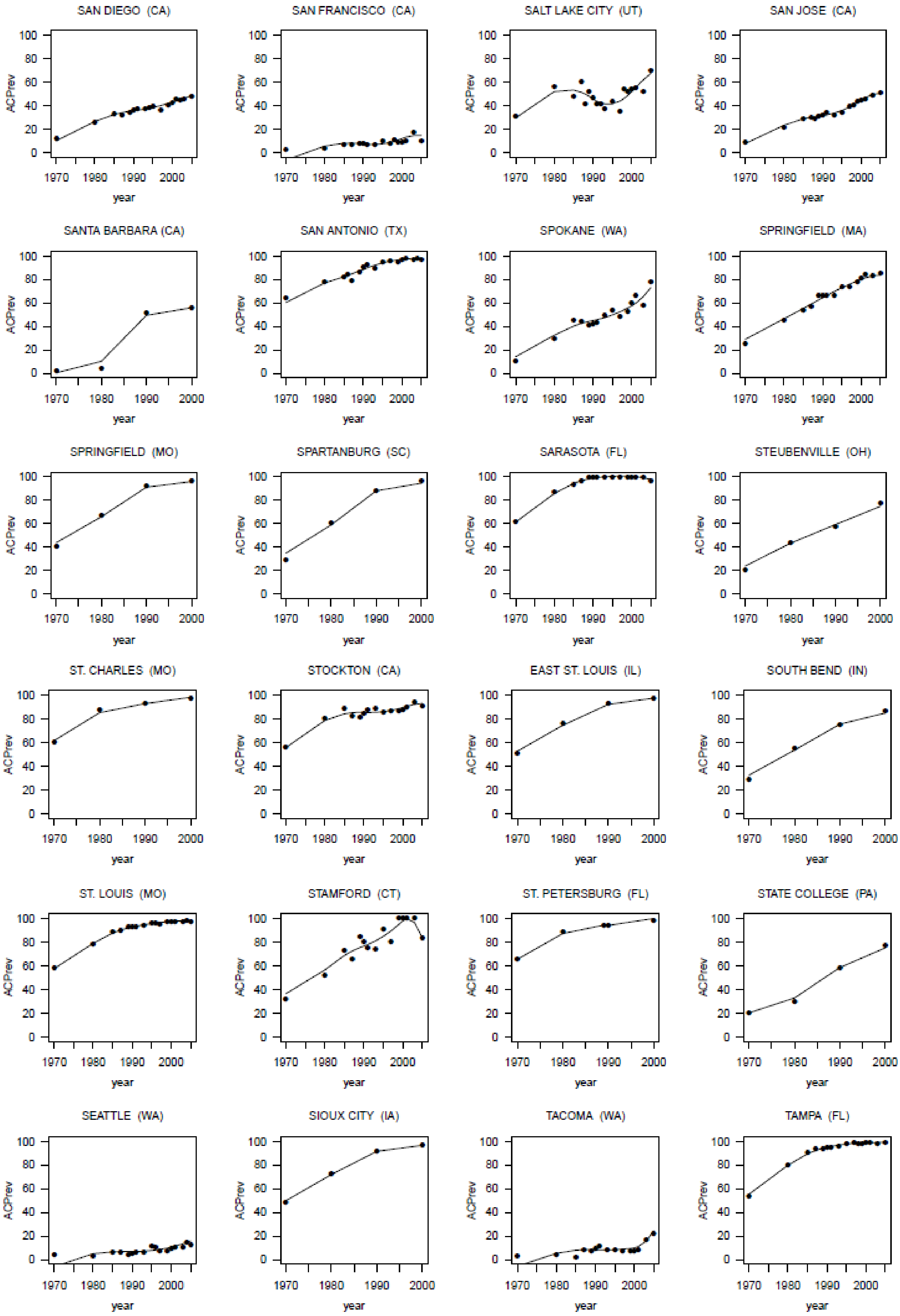
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SPRINGFIELD (MA)
SPRINGFIELD (MO)
SPARTANBURG (SC)
SARASOTA (FL)
STEUBENVILLE (OH)
ST. CHARLES (MO)
STOCKTON (CA)
EAST ST. LOUIS (IL)
SOUTH BEND (IN)
ST. LOUIS (MO)
STAMFORD (CT)
ST. PETERSBURG (FL)
STATE COLLEGE (PA)
SEATTLE (WA)
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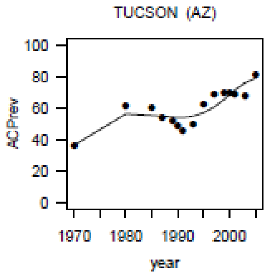
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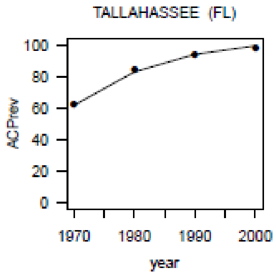
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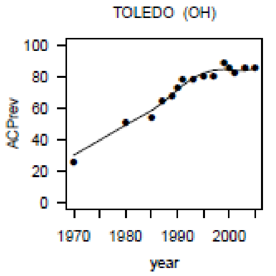
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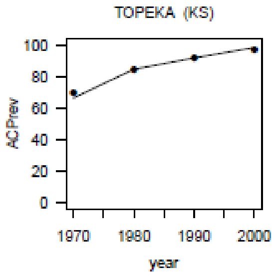
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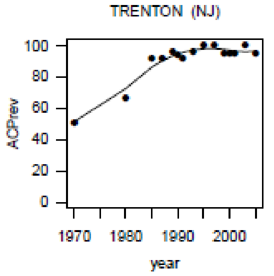
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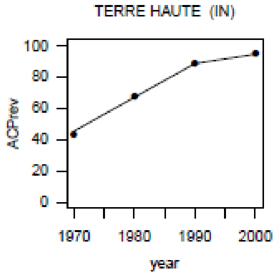
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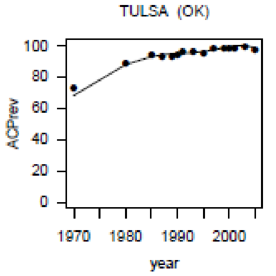
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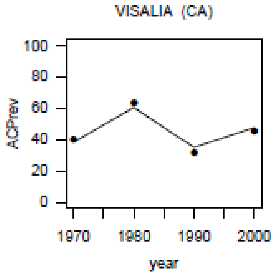
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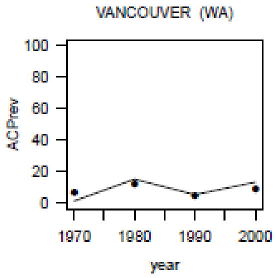
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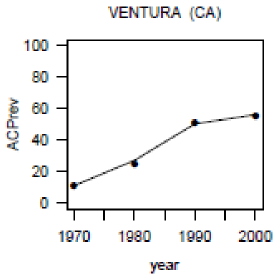
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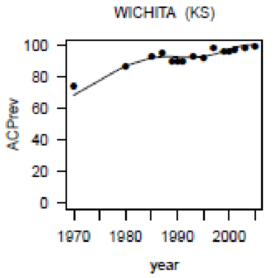
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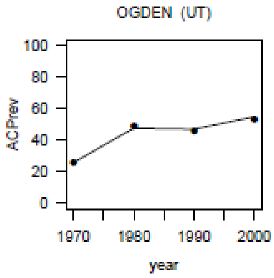
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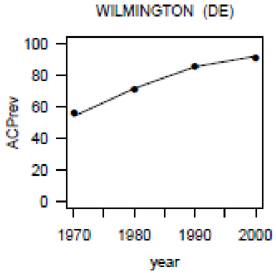
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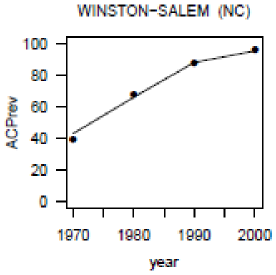
WINSTON-SALEM (NC)
ACPrev
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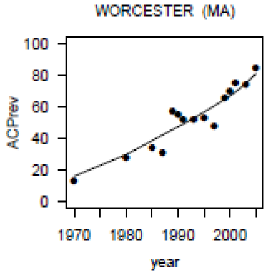
WORCESTER (MA)
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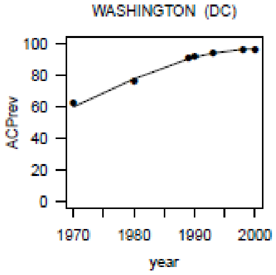
WASHINGTON (DC)
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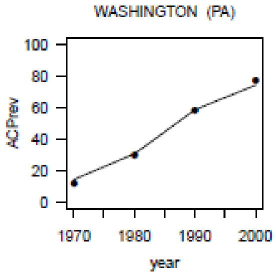
WASHINGTON (PA)
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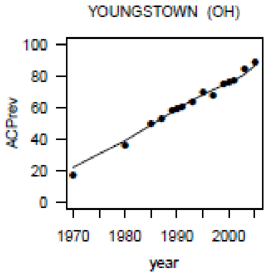
YOUNGSTOWN (OH)
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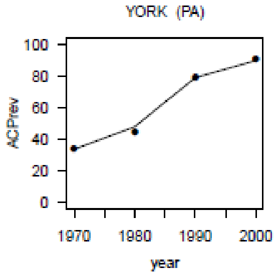
YORK (PA)
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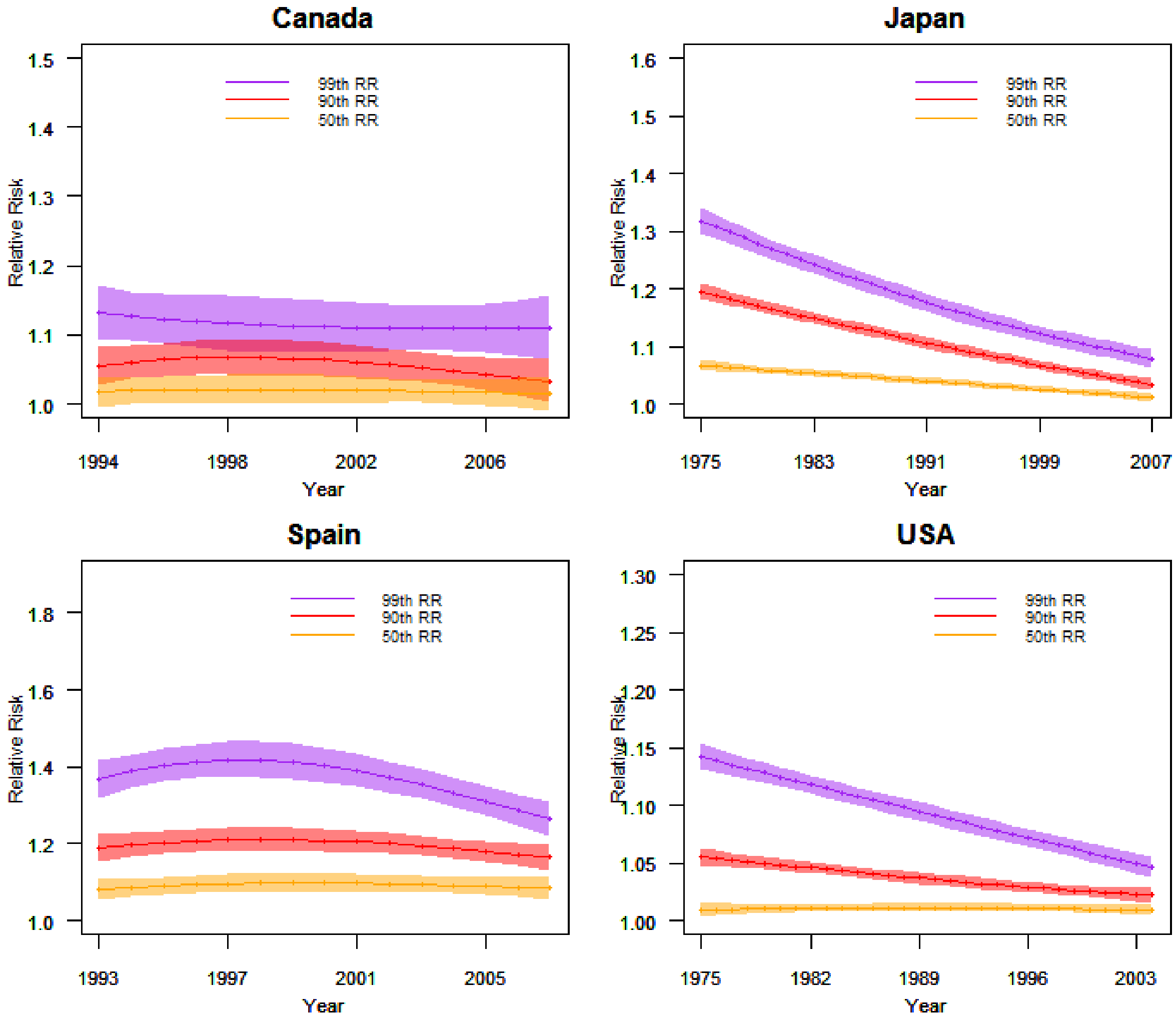
eFigure 2. Country specific trends of relative risks calculated at 90th, 95th and 99th percentile of the country specific mean temperature distribution in summer months.



eFigure 3. Analysis of the raw residuals of the multivariate multilevel meta-analysis model. For each outcome (spline coefficient) are shown the histogram of the residuals, and the scatterplot of the residuals (y axis) versus AC prevalence (%) and calendar year (x axes).