

THE LANCET

Supplementary webappendix

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Webappendix: Modeling Maternal Mortality

1. Introduction

There are particular challenges in modeling maternal mortality over time. At least four aspects of the dataset require special consideration: the available covariates explain only a moderate component of the variance; data are missing for many years; non-sampling error can be large in some settings such as India; and there is marked variation in temporal trends across countries. In the appendix figures, a number of countries such as Kazakhstan or Singapore show how the MMR can accelerate or decelerate; Yemen illustrates a country case where there are only two observations in the 29 year period from 1980 to 2008.

Our general modeling strategy bears some similarity to that used by Rajaratnam et al.¹ for adult mortality. The general model for the expected mortality rate from maternal causes is of the form:

$$\ln(\mu_{a,i,t}) = \beta x_{a,i,t} + M_{a,i,t} + e$$

Where $\mu_{a,i,t}$ is the maternal death rate for age a in country i for year t . $x_{a,i,t}$ is a vector of covariates that explain variation in maternal mortality rates across all countries. Substantial variation in the maternal mortality rate is not explained by these covariates, and the unexplained component, $M_{a,i,t}$ varies systematically over time and across countries. e is the stochastic error in the maternal mortality rate due to sampling and to unmeasured factors that are not correlated in time and space.

Estimation of this general model can be divided into two steps. We call for convenience the estimation of $\beta x_{a,i,t}$ the linear model and estimation of $M_{a,i,t}$ the spatial-temporal local regression component.

2. Linear Model Estimation

There are three important steps in the development of the linear model: type of model, choice of covariates, and transformation of the covariates into the appropriate functional form. The data on maternal mortality from the various sources discussed in the main body of the paper can be expressed as either maternal mortality rates or counts of maternal deaths. We have tested both the use of count models and log death rate models. The advantage of count models is that due to small numbers in some vital registration data or in survey data, zero maternal deaths may be observed.

Because of the assumption of the poisson model that the rate of the event count is also the variance of the count, this model does not fit the maternal mortality data. The negative binomial, which allows for the rate of the event count to be overdispersed, is more appropriate. Moreover, since in maternal mortality the degree of overdispersion appears to be related to age, the most relevant count model is the generalized negative binomial, which we have implemented. As a second family of models, we estimated directly the relationship between the log of the maternal mortality rate and the explanatory variables. Because of zeros and many outliers, we tested a range of robust regression methods including Huber-White, Tukey, median regression and also OLS. All the robust regression methods yielded nearly identical estimates of the betas.

Based on the literature and the set of factors that might plausibly be related to maternal mortality, we considered the following covariates: total fertility rate, GDP per capita, HIV seroprevalence, neonatal mortality, age-specific female education, skilled birth attendance and indicators for 5-year age groups 15-19, 20-24, 25-29, 30-34, 35-39, 40-44, 45-49. We examined the relationship between each of these covariates and the log of the maternal mortality rate. This suggested that the appropriate transformations of the independent variables were the log of the total fertility, the log of the distributed lag of GDP per capita, and the inclusion of HIV-squared as well as HIV sero-prevalence in the model. Because of high co-linearity between skilled birth attendance, neonatal mortality and GDP per capita and the fact that SBA was only available for 1986-2008 and not for the entire interval, we did not include this variable in the final model. We also used predictive validity to compare the performance of models including SBA and excluding SBA and found that including SBA did not improve model fit over a version of the model that included neonatal mortality.

Webtable 2 provides the regression coefficients for three models: OLS, Generalized Negative Binomial and robust regression. The values of the betas on the covariates are quite similar across models. It is interesting to note that

the count model yields similar results to the robust regression models with zero values dropped, because they cannot be transformed into log rates. Based on the similarity of results and out-of-sample predictive validity tests, we have more extensively evaluated the performance of the generalized negative binomial and robust regression method.

3. Spatial-Temporal Local Regression

Examination of the residuals from the first stage linear models shows clear patterns of serial auto-correlation as well as correlation across countries within regions. The purpose of spatial-temporal regression methods is to capture the information in these spatial and temporal correlation patterns to improve prediction of the quantity of interest. Variants of these methods are widely used in the geospatial literature.²⁻⁶ We capture this systemic pattern in the residuals by running a local fixed effects regression where the weights on the data for each country-year regression are a function of distance in time, space and age. Loess regression, used in many global health applications,^{7,8} is an example of temporal local regression. We add to the temporal relatedness, spatial and age-group relatedness. Our time weights are similar to standard loess weights and take the form:

$$w_t = \left[1 - \left(\frac{|r_t - r_{est}|}{1 + \argmax_t |r_t - r_{est}|} \right)^\lambda \right]^3$$

Spatial relatedness is only allowed between countries within a GBD region. The relative weight of data points from outside a country compared to the weight on observations from within a country is controlled by the parameter ζ which is the fraction of the total weight that is assigned to within country observations. Sub-national observations are counted as within country observations, but are given a weight compared to national observations that is only 0.2 times the national weight for the equivalent distance in time or age.

Because the determinants of maternal mortality that are not captured in the linear model but vary systematically across space and time are likely to affect more than one maternal age-group, we also estimate the local regression putting weights on adjacent age-groups. The form of the weights are a simple exponential decay such that the weight on the observation in the adjacent age-group is controlled by the parameter ω in an exponential function. The final weight on all observations is the product of time weights, spatial weights and age weights. Based on in-sample fit tests, we have chosen the time weighting parameter λ to be 0.5, ζ to be 0.8 and Ω to be 1.0. For small countries, we increase λ to equal 1.0 because of increased stochastic signal in the data; similarly, we increase λ to 2.0 for countries with no data available.

4. Predictive Validity

Given the range of options for the modeling strategy and the variation in in-sample fit, it is essential to objectively evaluate model performance. In-sample fit measures, such as the fraction of the variance explained by the predicted values, are extremely high with the addition of the spatial-temporal local regression component. But with this type of model which can track the data very closely, high in-sample fit does not necessarily mean improved predictions for years without data, or for the 21 countries with no data, or for backcasting or forecasting from the most recent observation to generate a complete time series for 1980-2008. For this reason, we have undertaken extensive predictive validity testing.

Four different types of predictive validity tests were undertaken: a) holding out a random sample of 20% of country-years of data; b) holding out all data from a random sample of 20% of countries; c) holding out the first 20% of years of data for all countries; d) holding out the last 20% of years for all countries. For each of these knock-out datasets, we estimate our model including the linear and spatial-temporal local regression components and compare predictions to the real data in the 20% of the sample held out. We repeat the 20% of countries and 20% of country-years tests 30 times to make sure our results are not an artifact of a given random sample of the data being withheld.

We examine four measures of predictive validity: root mean squared error, root median squared error, average relative error and median relative error. The RMSE and average relative error are influenced by outliers while the root median squared error and median relative error are robust to the performance on outliers. Webtable 3 provides for the generalized negative binomial and robust regression with and without the second stage spatial-temporal predictive validity measures for the four different types of tests. In all tests, the results are remarkably consistent. For the linear model alone, predictive validity is better for robust regression than the generalized negative binomial

particularly for backcasting, forecasting and for predicting for countries with no data. Both models have median relative errors in excess of 40% and average relative errors which are at best 55% and extend as high as 94.5% for the negative binomial. Addition of the spatial-temporal component of the model substantially improves out-of-sample performance. In all metrics and all tests, the predictive validity analysis demonstrates that there is tremendous information content captured in the patterns of the residuals from the linear model over time and space. Median relative errors drop substantially to around 20% for forecasting, backcasting and to 16% for country-years. The most difficult test relevant to the 21 countries with no data shows that predictive validity is not as good with a median relative error of 36%. The average relative errors are higher, but still demonstrate substantial improvements over the linear model alone. The predictive validity tests confirm that the spatial-temporal component of the model is essential for improved performance.

In addition to the out-of-sample predictive validity tests above, we calculated in-sample performance. The absolute median relative error is just 12% in sample, while the average relative error is 25%. The root mean squared error and the root median squared error are 76.98 and 8.16, respectively.

5. Uncertainty Analysis

Depending on the analysis, uncertainty intervals may be computed for the expected value of the quantity of interest or for the observation or realization of the quantity of interest. In our case, we are interested in estimating the uncertainty in the expected value of the maternal death rate, MMR or maternal death numbers. Uncertainty in the expected value of an estimated quantity of interest can come from five sources. Most studies capture only one or two of these sources. In global health publications, there is marked variation across studies in practices about uncertainty; at the extreme some studies report no uncertainty intervals for descriptive measurements or use subjective intervals with no grounding in statistical theory such as reported by Hill et al for the 2005 maternal mortality estimates.

We outline the five potential sources of uncertainty in the expected value of the MMR or the number of maternal deaths. Not all of these sources can be propagated into the final uncertainty intervals of the expected value of the quantity of interest due to both data limitations and methodological challenges. The five sources are:

1. Uncertainty in the model parameters related to the uncertainty in the input dataset used in statistical estimation due to stochastic variance. Since each study, whether a vital registration data point or a survey data point, has stochastic measurement uncertainty associated with it, this means that there is greater uncertainty in the parameter estimates of the model than if there was no uncertainty in these measurements. In this study, we capture this source of uncertainty by simulating 100 draws from a binomial distribution for each study with the observed maternal cause fraction as π and the number of trials as the total number of deaths observed in the study for that maternal age-group. This uncertainty is then propagated through each step of the study to generate an uncertainty distribution around the log maternal death rates used in the statistical model.
2. Uncertainty in the model parameters related to uncertainty in the input dataset that arises from non-sampling error. This non-sampling error could be due to biases that appear in different data systems due to survey implementation, misclassification, interviewer training and a myriad other problems. While in selected countries with multiple observations, we observe that the variance at a given time is far greater than expected on the basis of sampling alone, we have found no generalized method for this dataset to estimate the non-sampling variance.
3. Uncertainty in the covariates used in the model. In some developing countries, there is likely to be considerable uncertainty in estimates of GDP per capita, educational attainment, neonatal mortality, HIV sero-prevalence and other potential covariates for maternal mortality. Uncertainty in independent variables, called errors in-variables in the econometric literature, also leads to biased estimation, which for causal modeling is an important but largely unresolved issue. As most producers of development data (UNAIDS being an important exception) do not report uncertainty intervals for their measurements, it is in practice not possible to capture this source of uncertainty in the estimation of the parameters of the model.

4. Uncertainty in model parameters related to estimation. Estimation of a statistical model yields uncertainty in the parameters of the model. Standard simulation methods have been developed and widely applied to capture parameter uncertainty in a predicted quantity of interest. We include in this study, estimation uncertainty using simulation methods both for the linear model and the spatial temporal model.
5. Uncertainty in the prediction of the expected value of the quantity of interest that is related to systematic variation not explained by the model. The size of this component of the model is related to how well the model explains the observed variation in the data. It can be large or small depending on the quantity being studied and the model that has been developed. This is the most challenging and perhaps important source of uncertainty to capture. We discuss the challenges and our approach to uncertainty estimation of this fundamental uncertainty below.

The main issue for category 5 is how to estimate the systematic variation not explained by the model. We can easily compute the variation in the dependent variable that is unexplained by the spatial-temporal regression model. The dependent variable, however, is not the expected value of the maternal death rate but the observation or realization of the maternal death rate in a study which includes both stochastic variance and non-sampling variance. Thus, the unexplained residual variance in the study observations is substantially larger than the systematic variance in the expected value of the maternal death rate that is unexplained by the model. The residual variance from the spatial-temporal regression model therefore includes three components: systematic variation, stochastic variation and non-sampling variation.

If one is willing to assume that each of these components in a large dataset is normally distributed, it is possible to estimate the systematic variance by subtracting an estimate of the stochastic and non-sampling variances from the total residual variance. The remaining variance is then the systematic unexplained variance in the expected value of the maternal death rate. However, while the stochastic variance can be identified using simulation methods, it is not possible to estimate the contribution of non-sampling variance to the residual variance. Rather than underestimate uncertainty by not capturing systematic variance unexplained by the model, we have chosen to include both impact of non-sampling variance and systematic variation in the expected value not captured by the model. It is important to note that this quantity is a marked overestimate of the systematic variation not explained by the model because non-sampling variance in the studies of maternal mortality appears to be large. Comparison of multiple national sources of data for India at a given time, demonstrates huge variance which is not explained by stochastic variance. We have, however, not found an effective method for these data sources to decompose the remaining variance into non-sampling variance and systematic variance.

Because we observe that stochastic variance will vary by type of data collection mechanism, we have undertaken the simulations and computations of the variances separately for countries with VR data alone and all other countries. To avoid the impact of outliers on the estimation of the standard deviation of the residuals and the stochastic variance, we use robust estimators of the standard deviation. For the 21 countries with no data from 1980-2008, we use the observed relationship from the predictive validity studies; this demonstrated that the standard deviation of the residuals for countries without any data is 1.7 times larger than for countries with data. We therefore scale the estimated standard deviation of the non-sampling variance plus systematic variance by this constant.

In summary, we propagate uncertainty from four sources into our final estimates for each country and year: sampling uncertainty in the underlying studies, parameter uncertainty in the linear model, parameter uncertainty in the spatial temporal local regressions and an estimate of the fundamental uncertainty unexplained by the estimation model. Sampling uncertainty is generated through randomly sampling from the binomial distribution using the observed fraction of deaths due to maternal causes as π and the total number of deaths as the number of trials. We generate 100 datasets by drawing from the binomial distribution of each observation. For each dataset, we compute the linear model and draw from the variance-covariance matrix of the betas of the regression 5 times. For each of the 500 draws of the sampling uncertainty and the parameter uncertainty, we then estimate the complete set of local regressions. For each variance-covariance matrix of each of the local regressions, we sample 5 times.

We estimate the systematic component of the unexplained variance in two steps. First, we compute a robust estimate of the stochastic uncertainty using the bootstrap samples described above. Second, we subtract this estimate of stochastic variance from the total observed variance of the residuals. This yields an estimate of the combination of variance due to non-sampling error and systematic variation in the expected value of the maternal death rate.

Although this quantity is an over-estimate of the systematic variance, we nevertheless use it for the final stage of the uncertainty analysis.

This procedure generates 2,500 predictions of each MMR and number of maternal deaths. We use the full distribution of these values to compute all quantities of interest such as global, regional or national deaths and MMRs and rates of change. For uncertainty in rates of change, we use a robust estimate of the remaining autocorrelation in the distribution of the residuals at any two points in time.

Reference List

- (1) Rajaratnam JK, Marcus JR, Levin-Rector A, Chalupka AN, Wang H, Dwyer L, et al. Worldwide mortality in women and men aged 15-59 from 1970-2010: a systematic review. *Lancet* 2010. In press.
- (2) Hengl T, Heuvelink GBM, Stein A. A generic framework for spatial prediction of soil variables based on regression-kriging. *Geoderma* 2004;**120**:75-93.
- (3) Hudson G, Wackernagel H. Mapping temperature using kriging with external drift: theory and an example from Scotland. *Int J Climatol* 1994;**14**:77-92.
- (4) Knotters M, Brus DJ, Oude Voshaar JH. A comparison of kriging, co-kriging and kriging combined with regression for spatial interpolation of horizon depth with censored observations. *Geoderma* 1995;**67**:227-46.
- (5) Lado LR, Polya D, Winkel L, Berg M, Hegan A. Modelling arsenic hazard in Cambodia: A geostatistical approach using ancillary data. *Appl Geochem* 2008;**23**:3010-8.
- (6) Minasny B, McBratney AB. Spatial prediction of soil properties using EBLUP with the Matern covariance function. *Geoderma* 2007;**140**:324-36.
- (7) Murray CJ, Laakso T, Shibuya K, Hill K, Lopez AD. Can we achieve Millennium Development Goal 4? New analysis of country trends and forecasts of under-5 mortality to 2015. *Lancet* 2007;**370**:1040-54.
- (8) Masanja H, de Savigny D, Smithson P, Schellenberg J, John T, Mbuya C, et al. Child survival gains in Tanzania: analysis of data from demographic and health surveys. *Lancet* 2008;**371**:1276-83.

Webtable 1. Correlation matrix of covariates included in the linear model

	ln(TFR)	ln(GDP per capita)	Neonatal mortality	Education	HIV	HIV²
ln(TFR)	1					
ln(GDP per capita)	-0.7544	1				
Neonatal mortality	0.7720	-0.7649	1			
Education	-0.8273	0.7393	-0.7686	1		
HIV	0.1600	-0.1835	0.0940	-0.0684	1	
HIV²	0.0675	-0.0809	0.0277	0.0022	0.9127	1

Webtable 2. Model regression coefficients for 3 forms of the linear model (Ordinary Least Squares, Generalized Negative Binomial, & Robust Regression)

	Ordinary Least Squares Regression		Generalized Negative Binomial Regression		Robust Regression	
	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error
Intercept	5.044	0.107	-6.334	0.110	5.107	0.105
ln(TFR)	1.921	0.023	1.904	0.024	1.884	0.023
ln(GDP per capita)	-0.532	0.011	-0.514	0.011	-0.536	0.010
Neonatal mortality	13.777	0.757	11.568	0.796	13.994	0.741
Education	-0.102	0.003	-0.106	0.003	-0.101	0.003
HIV	0.116	0.005	0.144	0.005	0.119	0.005
HIV²	-0.002	0.000	-0.003	0.000	-0.002	0.000
Age 15-19	-1.264	0.021	-1.174	0.020	-1.235	0.021
Age 20-24	-0.412	0.021	-0.360	0.020	-0.406	0.020
Age 25-29	-0.078	0.020	-0.091	0.021	-0.082	0.020
Age 35-39	-0.175	0.021	-0.153	0.024	-0.173	0.020
Age 40-44	-0.628	0.021	-0.543	0.026	-0.633	0.021
Age 45-49	-1.354	0.025	-1.302	0.029	-1.394	0.025

Webtable 3. Predictive validity for robust regression and generalized negative binomial regression:

Out-of-sample model performance measured by root mean squared error (SE), root median SE, mean relative error (RE) and median RE for the following hold-out scenarios: (i) withholding all information for 20% of countries; (ii) withholding the first 20% of years of data for every country; (iii) withholding the last 20% of years of data for every country; and (iv) withholding 20% of all datapoints.

Robust Regression: 20% of Countries				
Regression	Root Mean SE*	Root Median SE	Mean RE**	Median RE
Linear	214.84	27.00	0.604	0.417
Spatio-Temporal	189.27	25.34	0.521	0.357

Robust Regression: First 20% of Country Years				
Regression	Root Mean SE	Root Median SE	Mean RE	Median RE
Linear	208.28	22.04	0.702	0.437
Spatio-Temporal	129.32	11.92	0.392	0.199

Robust Regression: Last 20% of Country Years				
Regression	Root Mean SE	Root Median SE	Mean RE	Median RE
Linear	158.86	13.23	0.538	0.421
Spatio-Temporal	104.08	7.46	0.284	0.213

Robust Regression: Random 20% of Country Years				
Regression	Root Mean SE	Root Median SE	Mean RE	Median RE
Linear	215.44	24.22	0.619	0.419
Spatio-Temporal	125.34	10.36	0.286	0.165

Generalized Negative Binomial Regression: 20% of Countries				
Regression	Root Mean SE	Root Median SE	Mean RE	Median RE
Linear	241.59	27.67	0.783	0.472
Spatio-Temporal	183.57	25.57	0.518	0.355

Generalized Negative Binomial Regression: First 20% of Country Years				
Regression	Root Mean SE	Root Median SE	Mean RE	Median RE
Linear	235.84	26.88	0.945	0.567
Spatio-Temporal	124.93	10.72	0.384	0.206

Generalized Negative Binomial Regression: Last 20% of Country Years				
Regression	Root Mean SE	Root Median SE	Mean RE	Median RE
Linear	221.62	12.30	0.74	0.443
Spatio-Temporal	113.99	7.73	0.293	0.220

Generalized Negative Binomial Regression: Random 20% of Country Years				
Regression	Root Mean SE	Root Median SE	Mean RE	Median RE
Linear	256.72	24.73	0.820	0.480
Spatio-Temporal	123.81	10.11	0.284	0.163

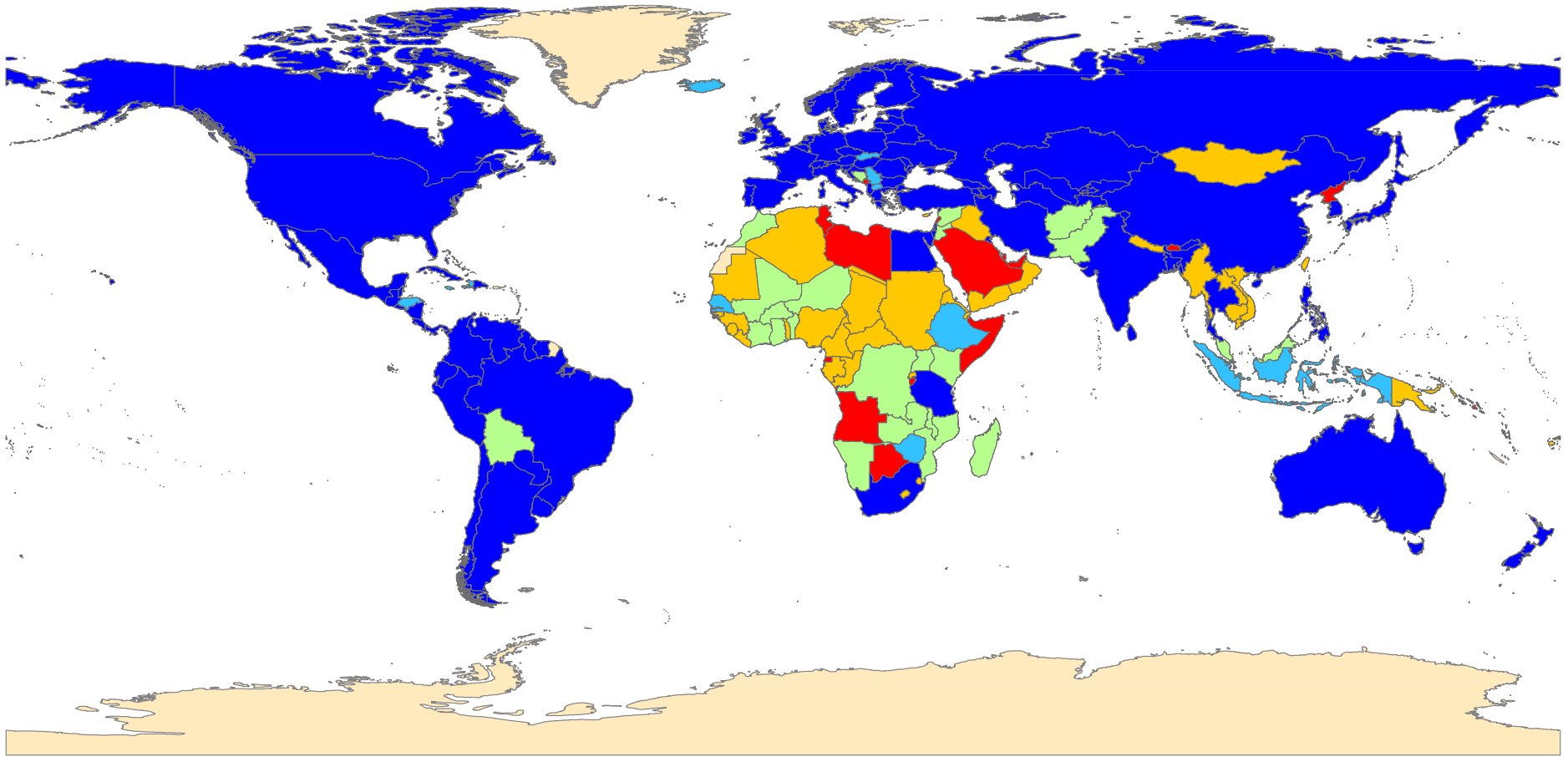
* SE = Squared Error

** RE = Relative Error

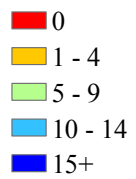
Webtable 4. Number and proportion of maternal deaths and live births for top 21 countries, 2008

Order	Country	Deaths in 1000s (UI)	Deaths (%)	Cumulative %	Births (%)	Cumulative %
1	India	68.3 (41.6-106.2)	19.9	19.9	19.7	19.7
2	Nigeria	36.7 (22.4-57.0)	10.7	30.6	4.4	24.1
3	Pakistan	20.1 (12.3-31.3)	5.9	36.5	3.9	28.0
4	Afghanistan	20.0 (7.5-43.1)	5.8	42.3	0.9	28.9
5	Ethiopia	18.2 (11.1-28.8)	5.3	47.6	2.3	31.2
6	Congo, the Democratic Republic of the	15.4 (9.0-24.7)	4.5	52.1	2.1	33.3
7	Bangladesh	11.6 (6.7-18.7)	3.4	55.5	2.5	35.8
8	Indonesia	9.6 (5.6-16.0)	2.8	58.3	3.1	38.9
9	Tanzania, United Republic of	8.0 (4.8-12.8)	2.3	60.6	1.3	40.2
10	China	7.3 (6.4-8.3)	2.1	62.7	13.3	53.5
11	Malawi	6.8 (4.0-10.9)	2.0	64.7	0.4	53.9
12	Côte d'Ivoire	6.8 (4.1-10.8)	2.0	66.7	0.5	54.4
13	Kenya	6.2 (3.6-10.2)	1.8	68.5	1.1	55.5
14	Chad	5.3 (3.3-8.2)	1.5	70.0	0.4	55.9
15	Mozambique	5.2 (3.1-8.4)	1.5	71.5	0.6	56.5
16	Uganda	5.2 (3.1-8.2)	1.5	73.0	1.1	57.6
17	Cameroon	5.0 (2.8-8.1)	1.4	74.4	0.5	58.1
18	Niger	4.7 (3.0-7.3)	1.4	75.8	0.6	58.7
19	Angola	4.6 (1.8-9.9)	1.3	77.1	0.6	59.3
20	Sudan	4.0 (2.5-6.0)	1.2	78.3	0.9	60.2
21	Mali	3.6 (2.3-5.5)	1.1	79.4	0.4	60.6
	All other countries (160)	70.3 (43.0-112.2)	20.5	100.0	39.3	100.0
	Total	342.9	100.0	100.0	100.0	100.0

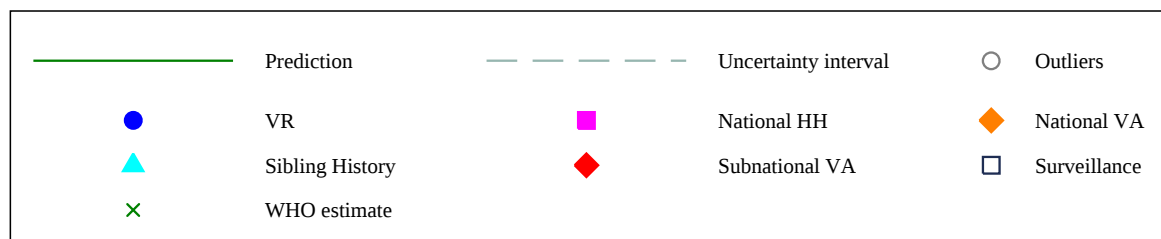
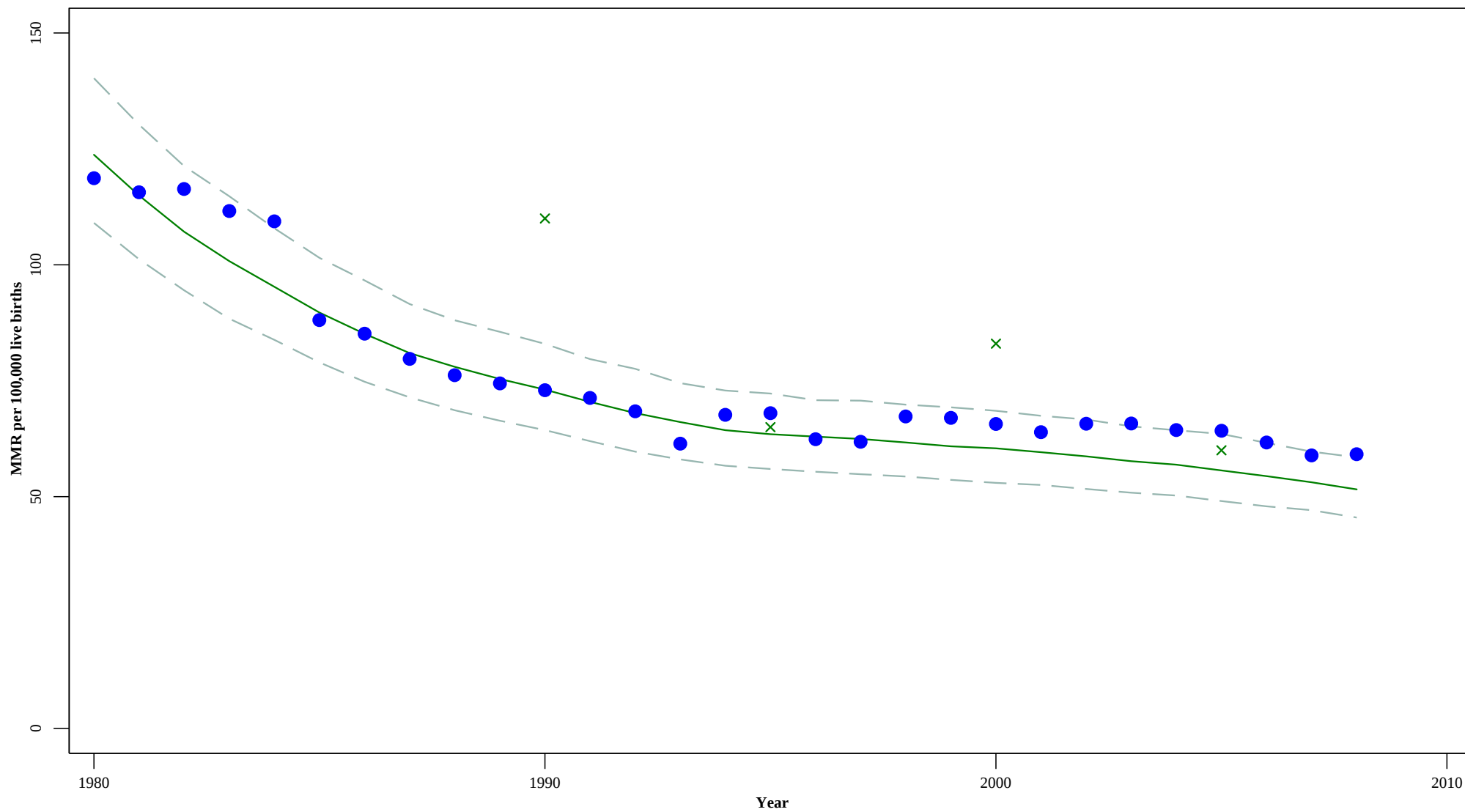
Webfigure 1. Density of Site-Years of Observation, 1980 to 2008



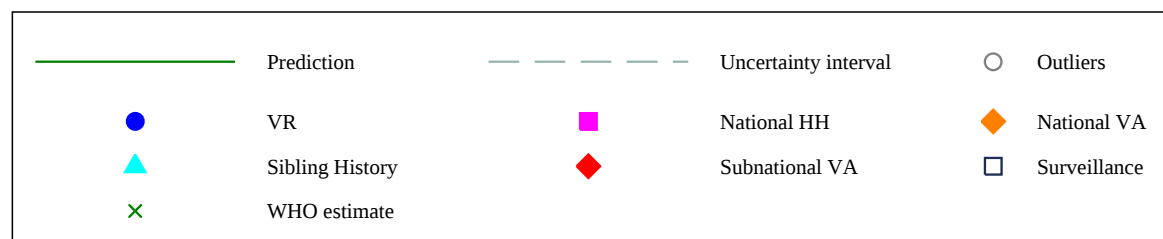
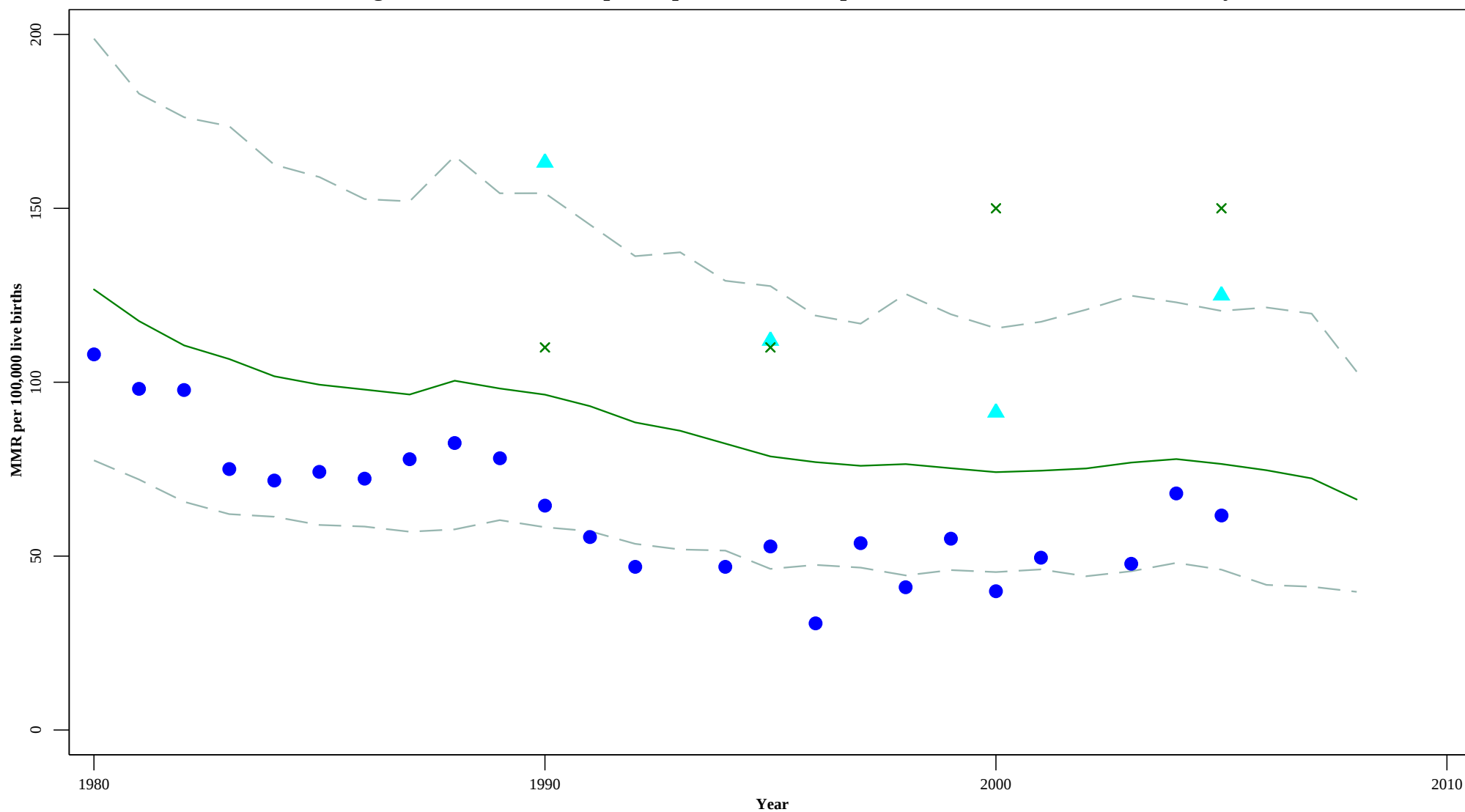
Number of Site-Years of Observation



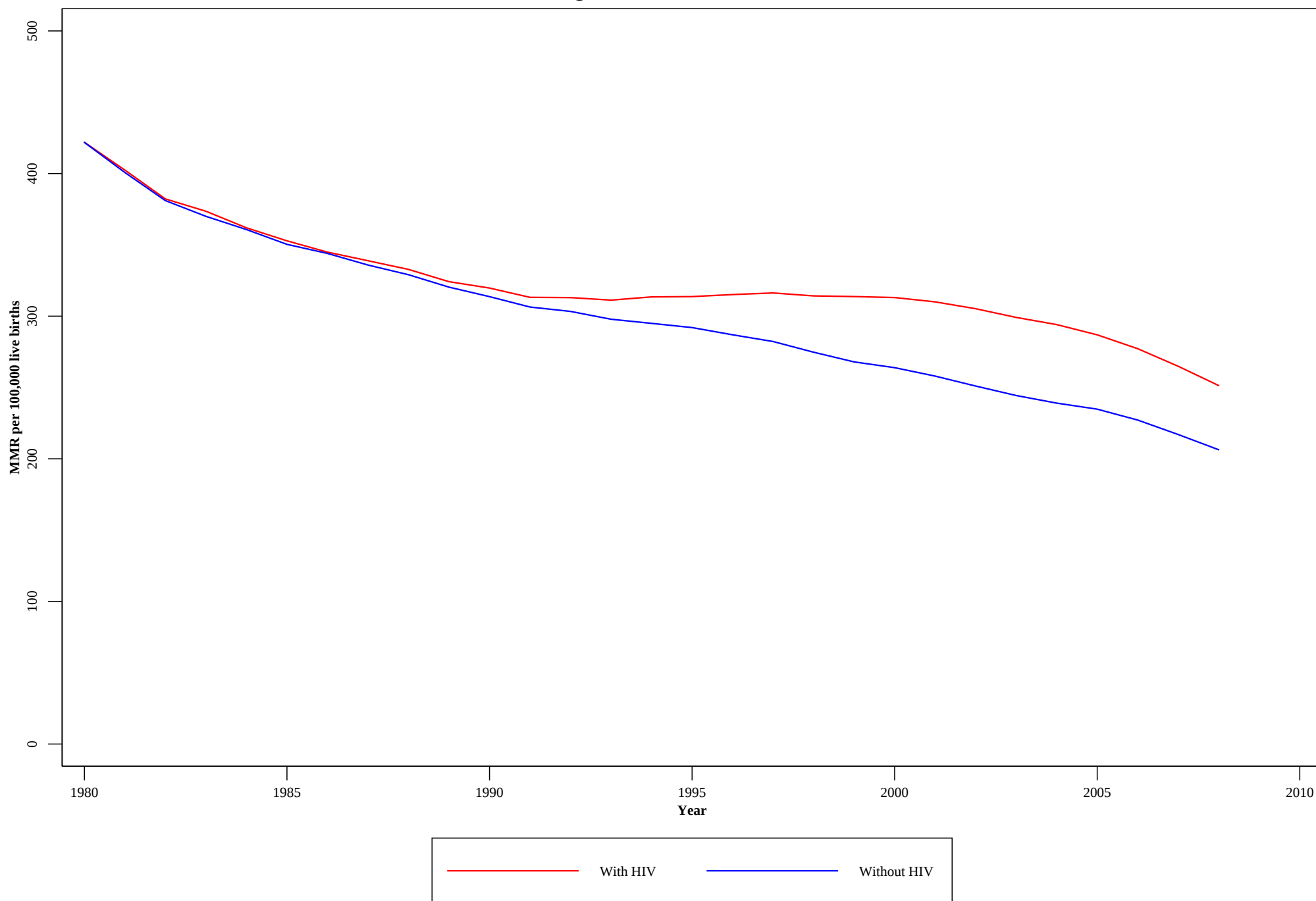
Webfigure 2a. Mexico predicted MMR per 100,000 live births with uncertainty



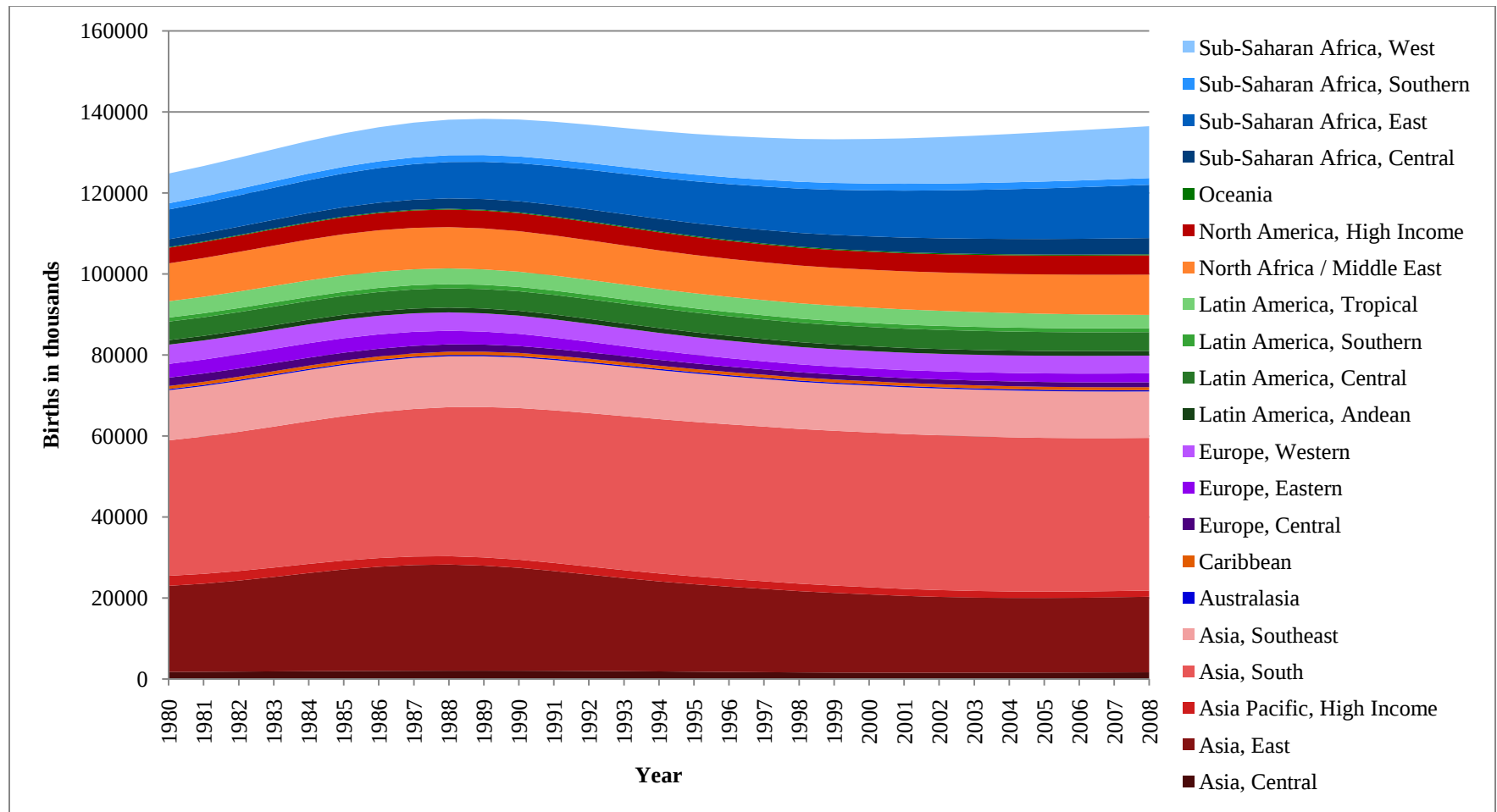
Webfigure 2b. Dominican Republic predicted MMR per 100,000 live births with uncertainty



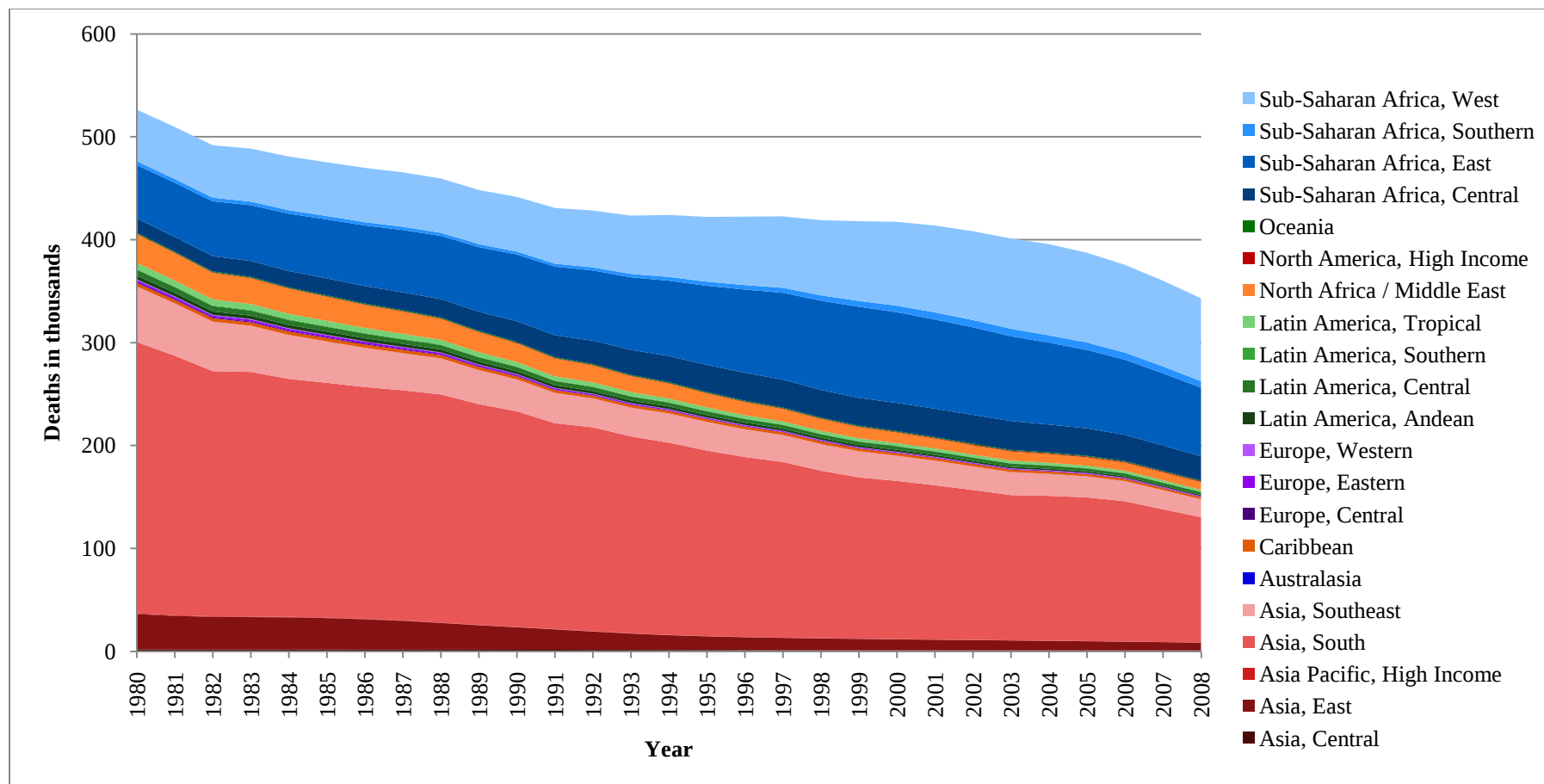
Webfigure 3. Global MMR, 1980–2008



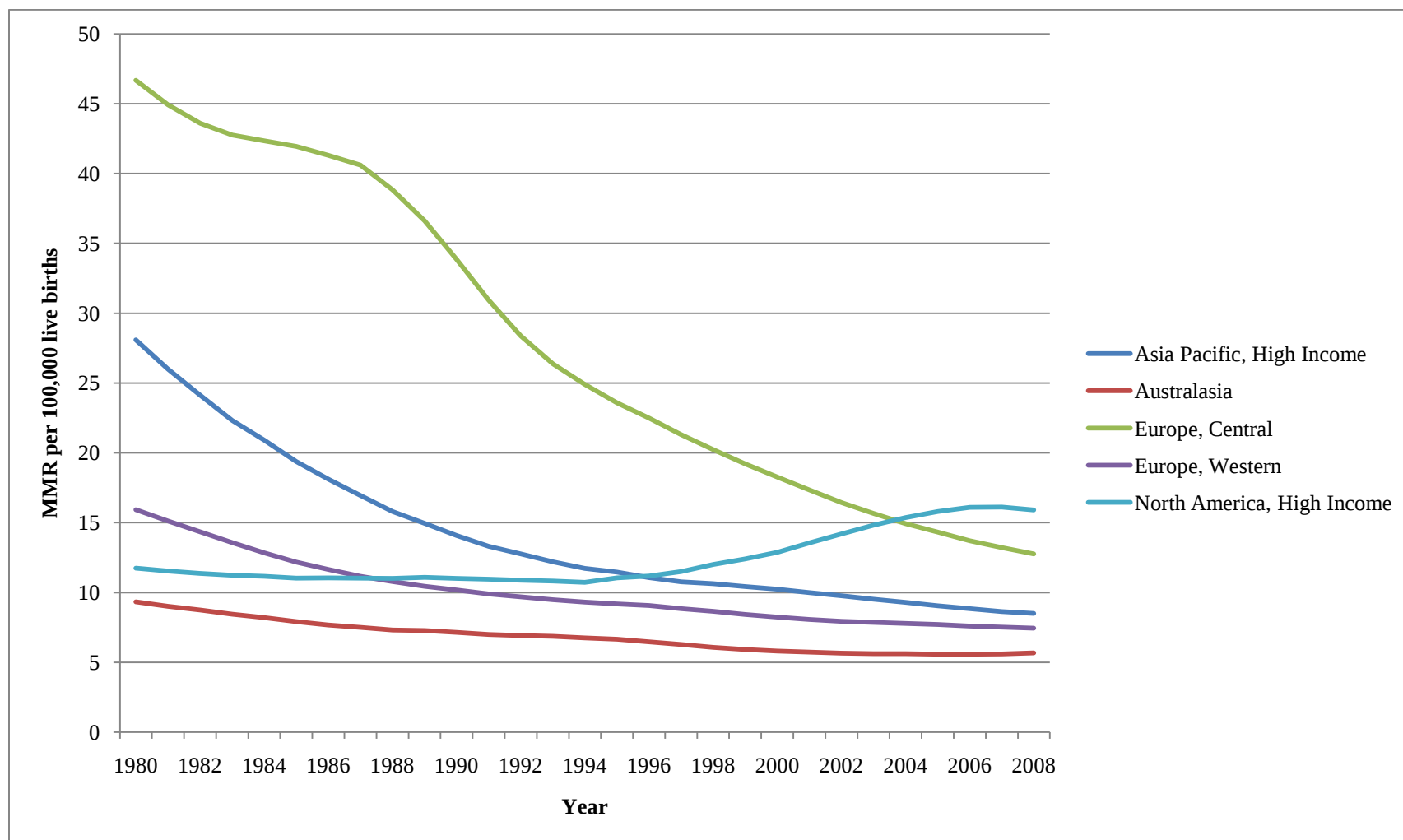
Webfigure 4. Births by Region, 1980-2008



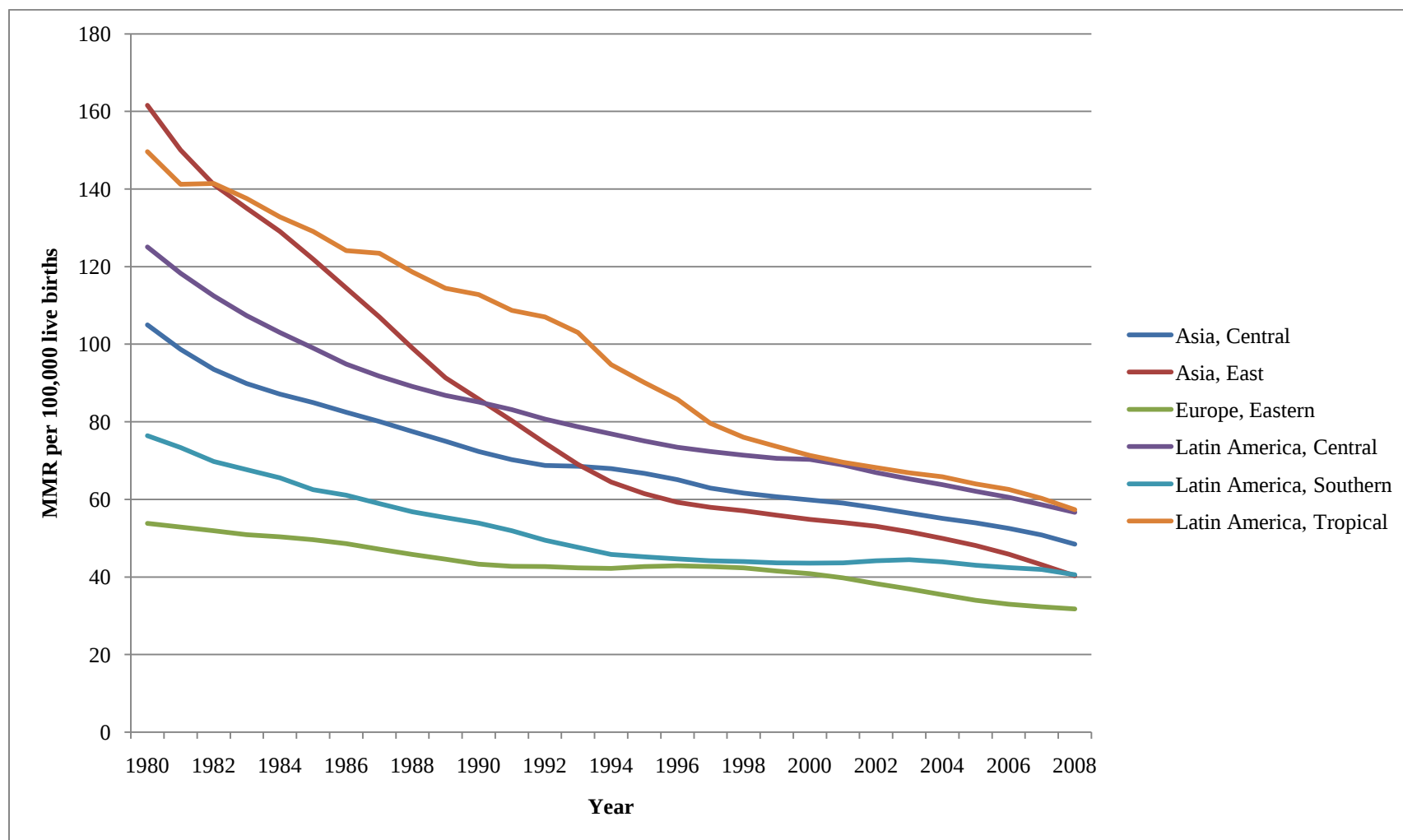
Webfigure 5. Maternal Deaths by Region, 1980-2008



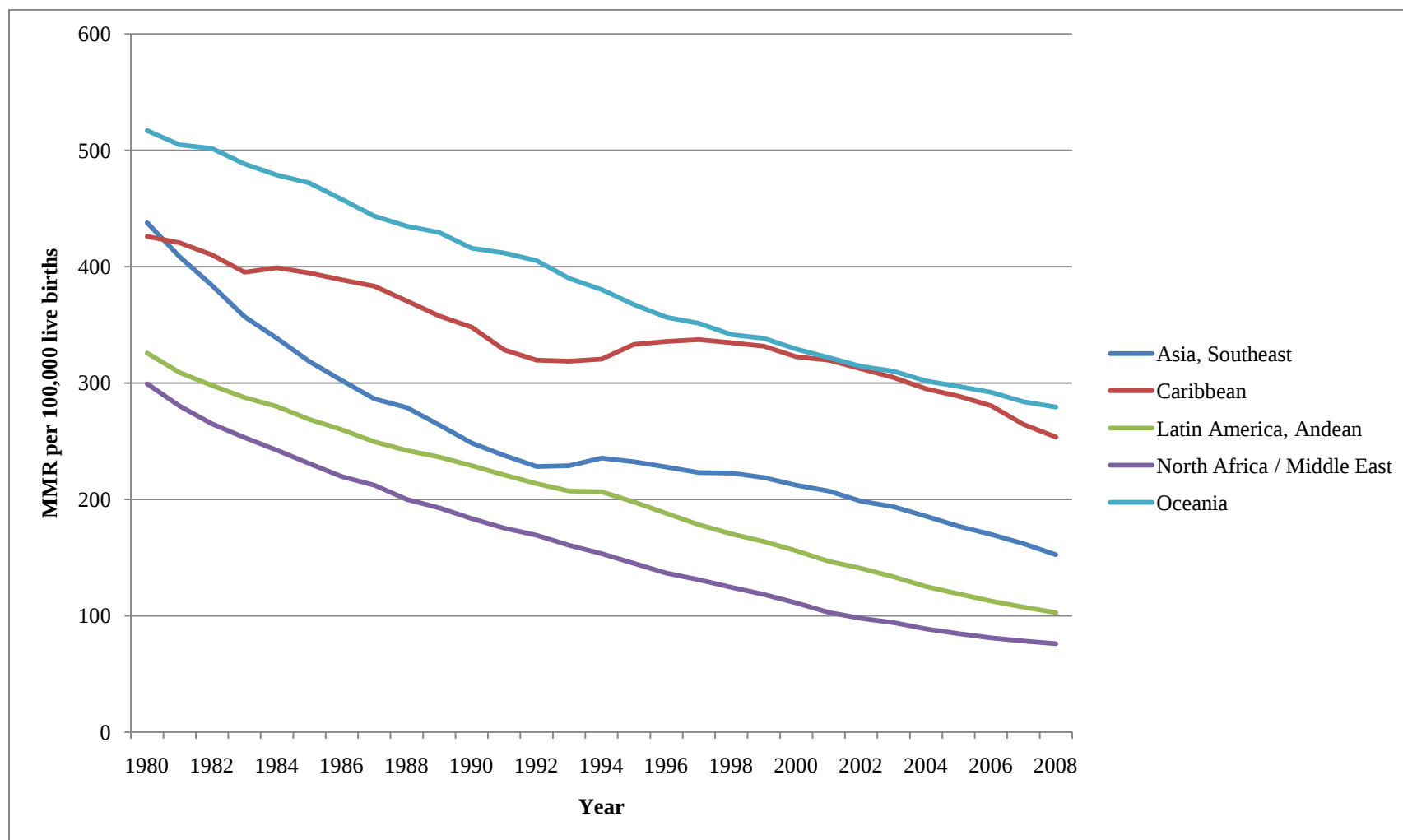
Webfigure 6a. Maternal mortality ratio (MMR) per 100, 000 live births, low MMR regions



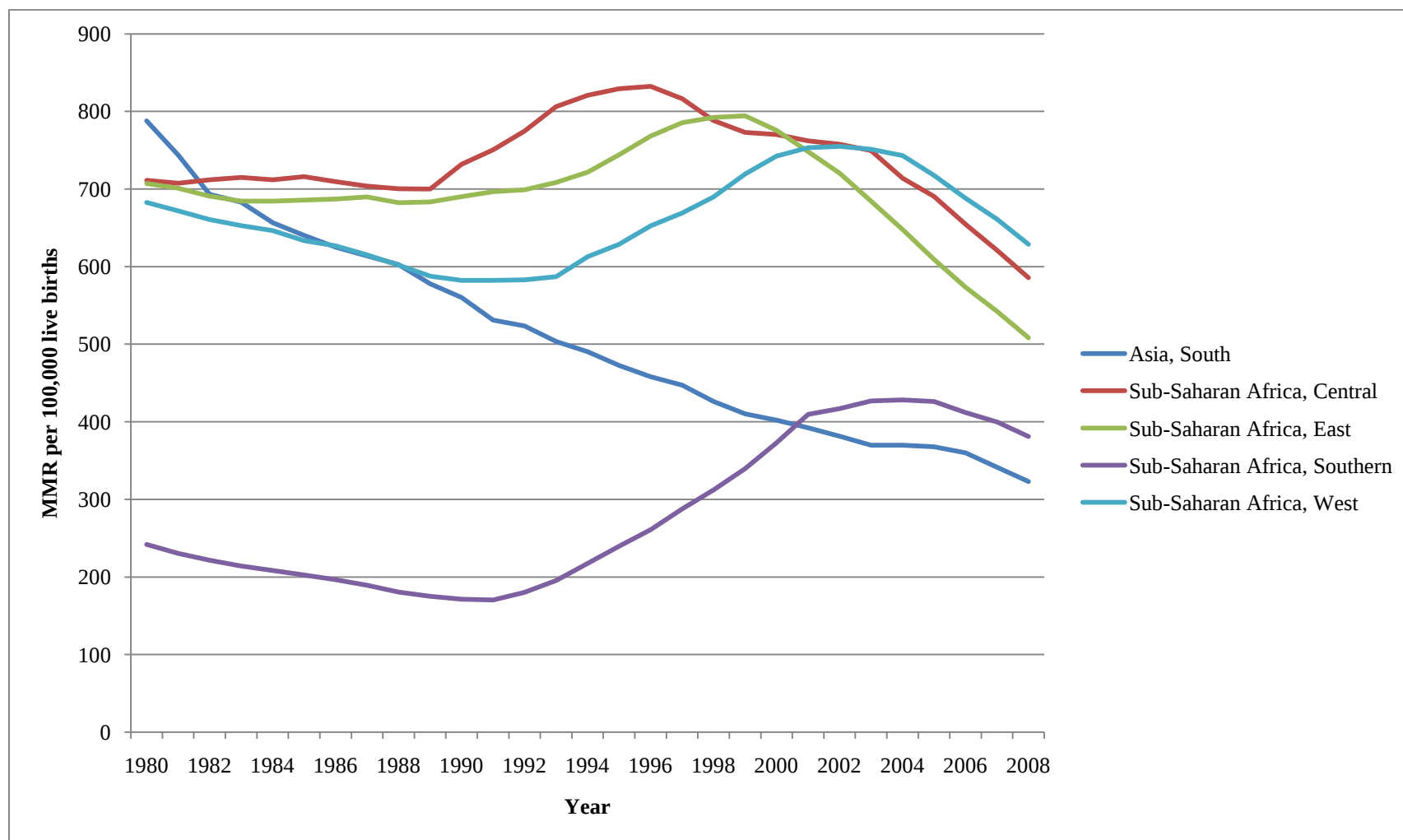
Webfigure 6b. Maternal mortality ratio (MMR) per 100,000 live births, moderate MMR regions



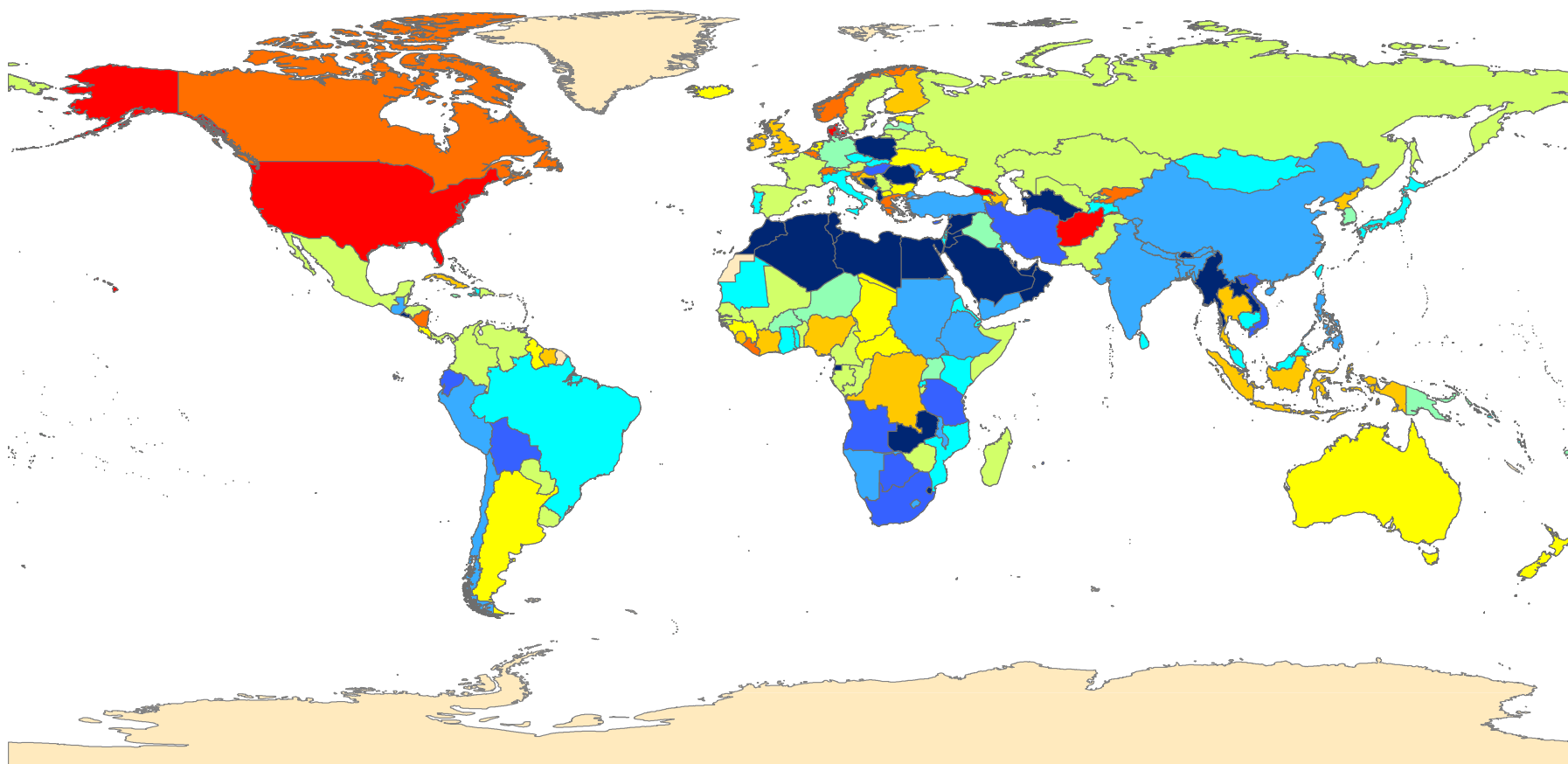
Webfigure 6c. Maternal mortality ratio (MMR) per 100, 000 live births, high MMR regions



Webfigure 6d. Maternal mortality ratio (MMR) per 100,000 live births, very high MMR regions



Webfigure 7. Annualized Rate of Decline in MMR, excluding HIV, 1990 to 2008

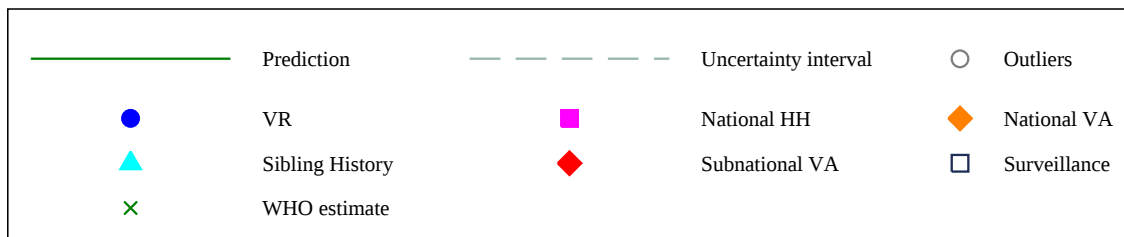
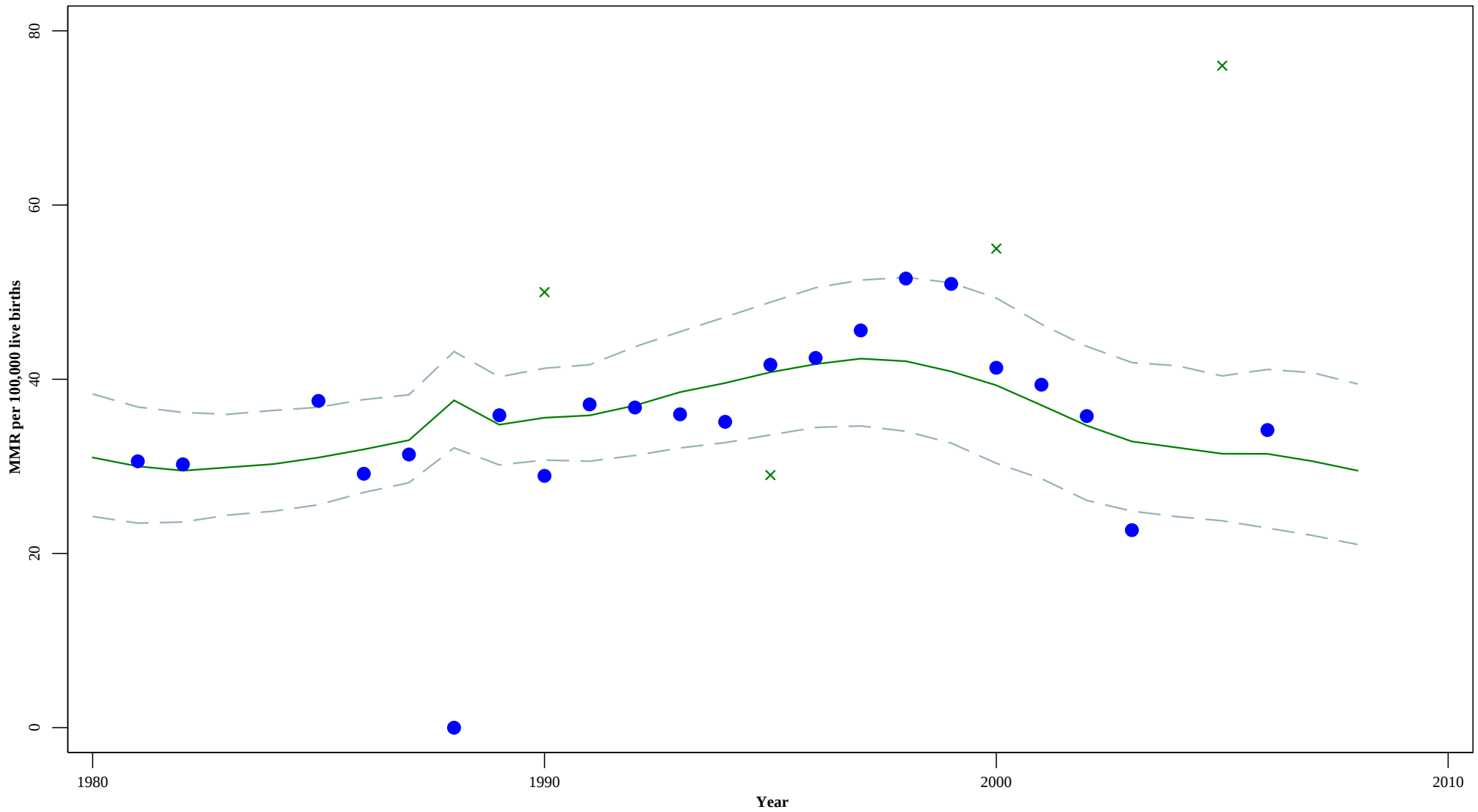


Annualized percent rate of decline in MMR (%)

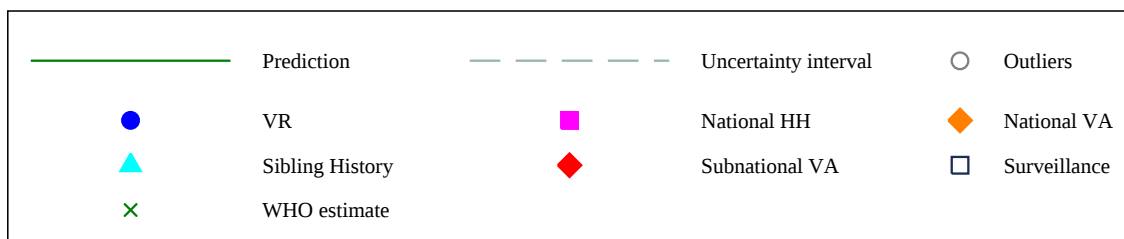
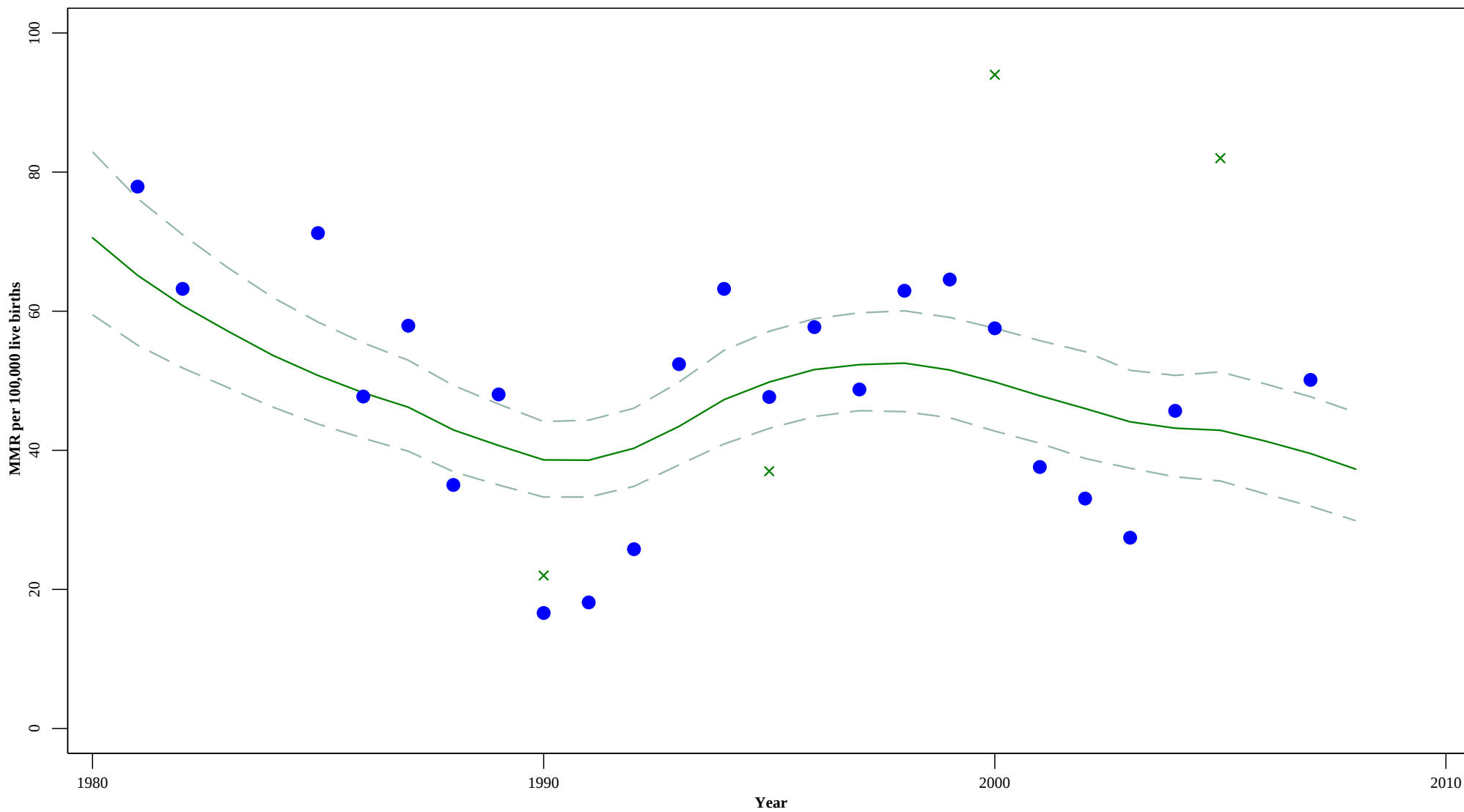


Webfigure 8. Predicted MMR per 100,000 live births with uncertainty by country

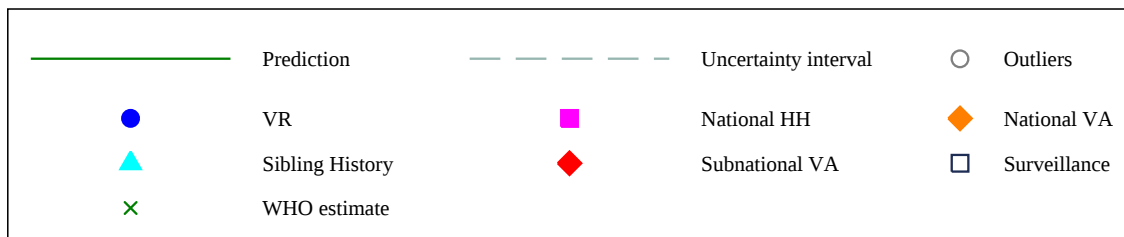
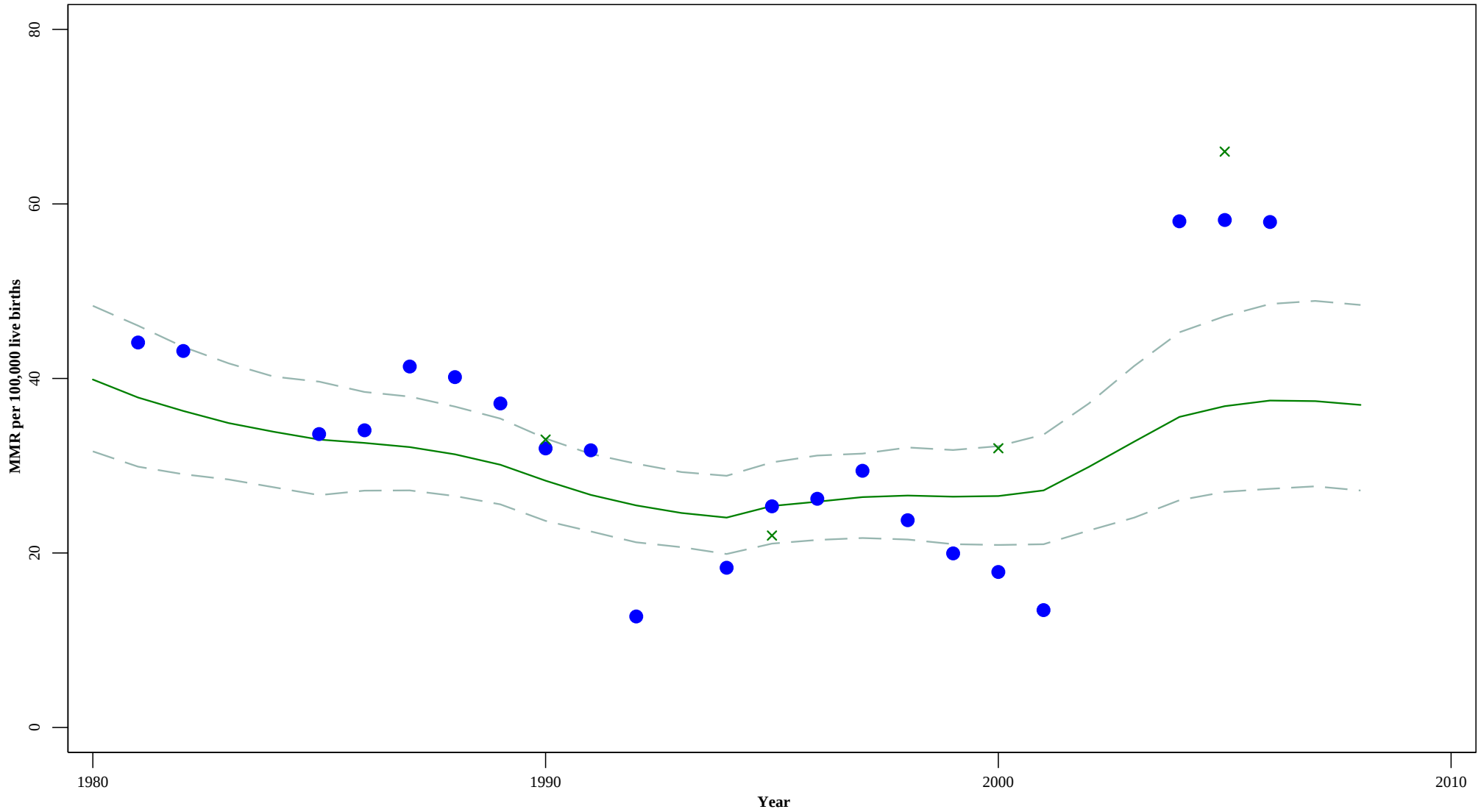
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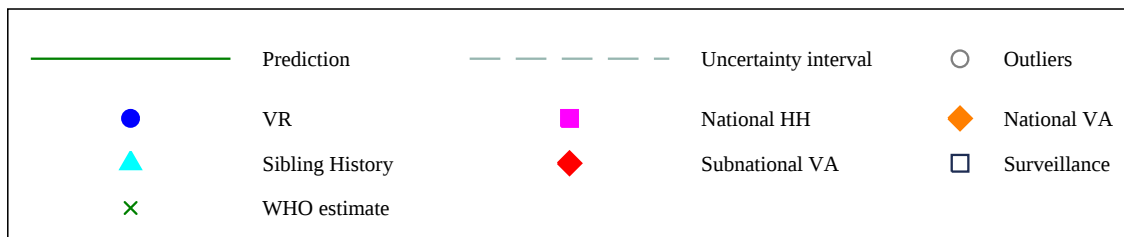
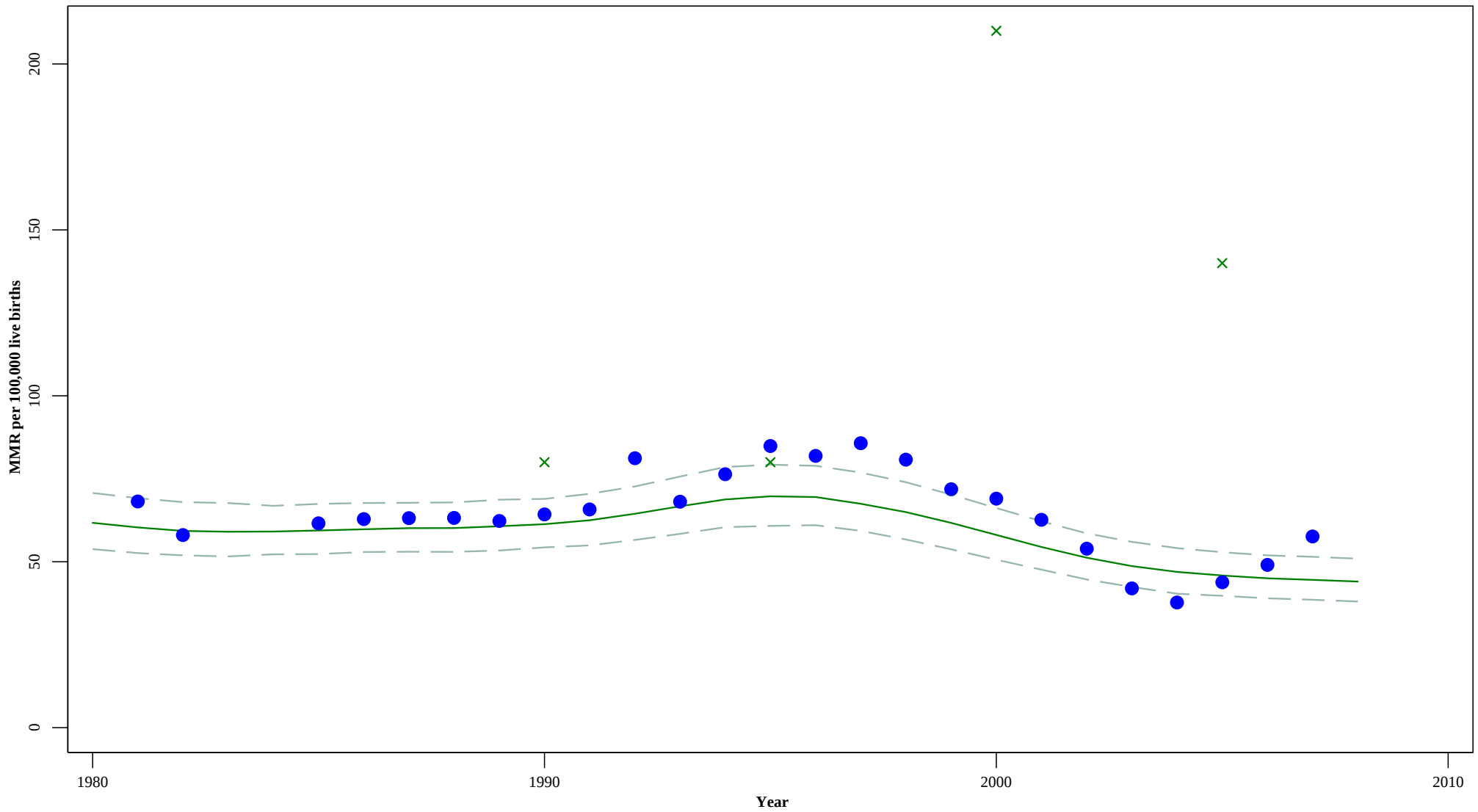
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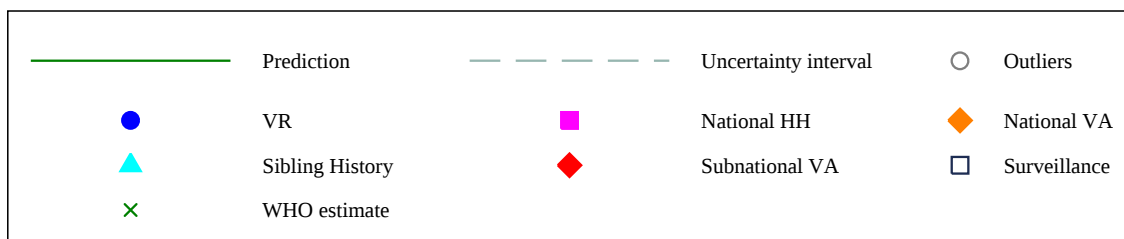
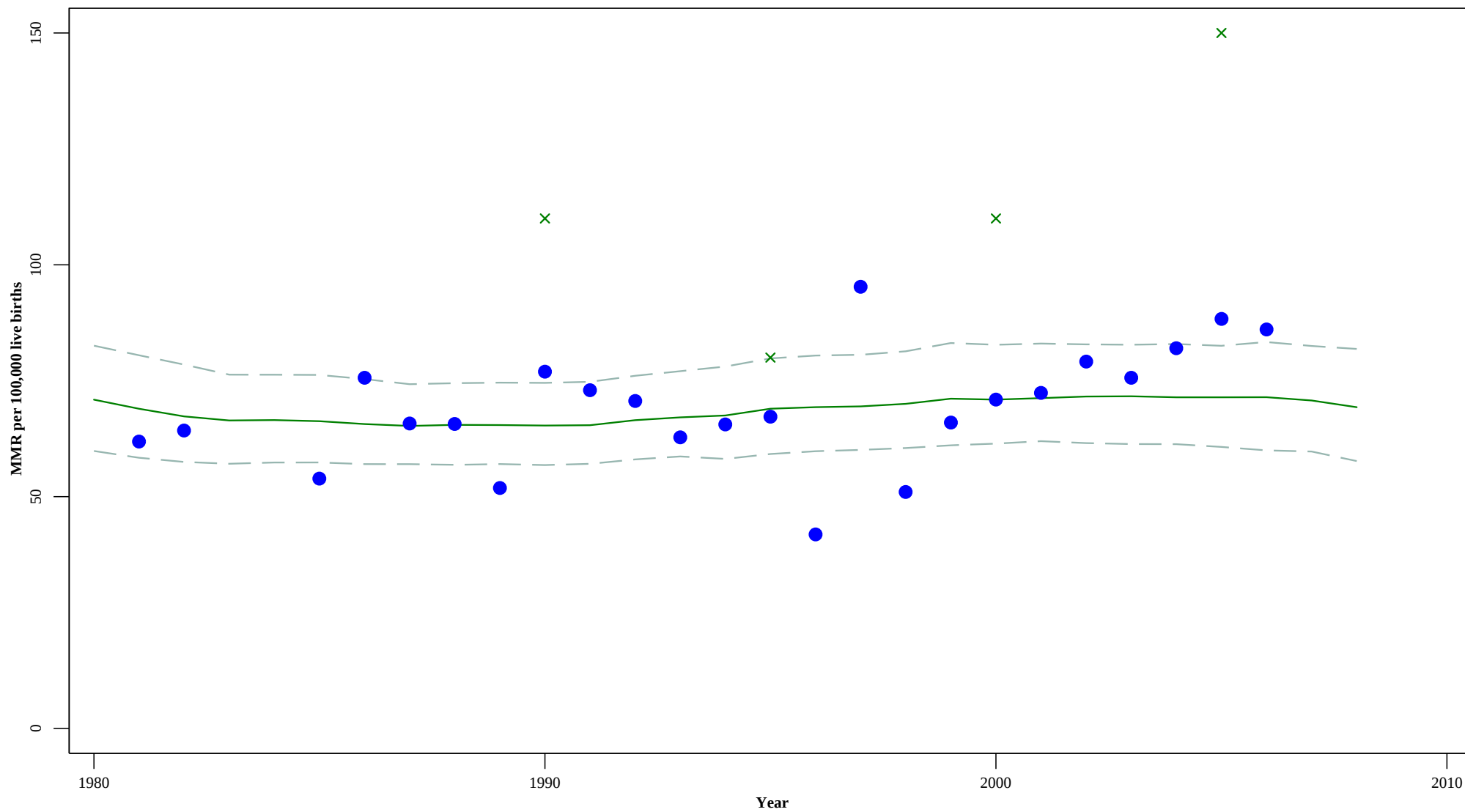
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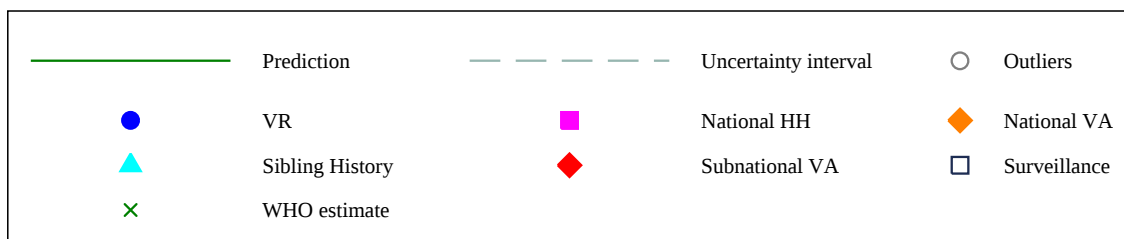
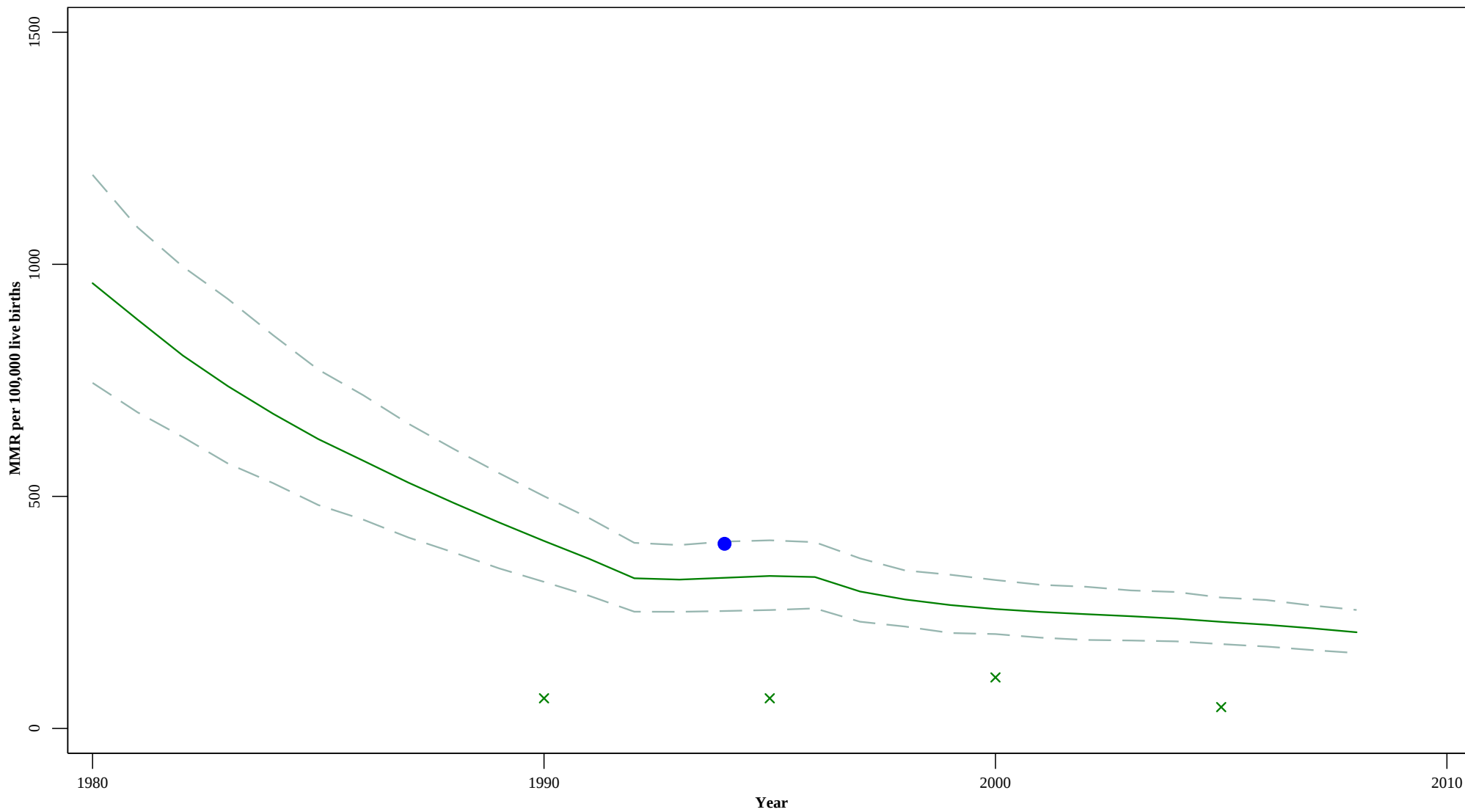
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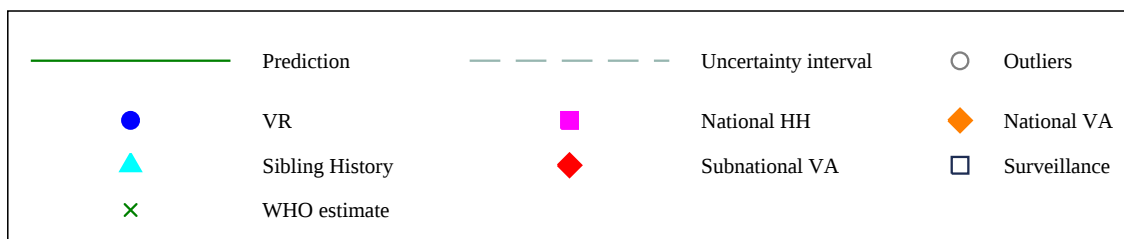
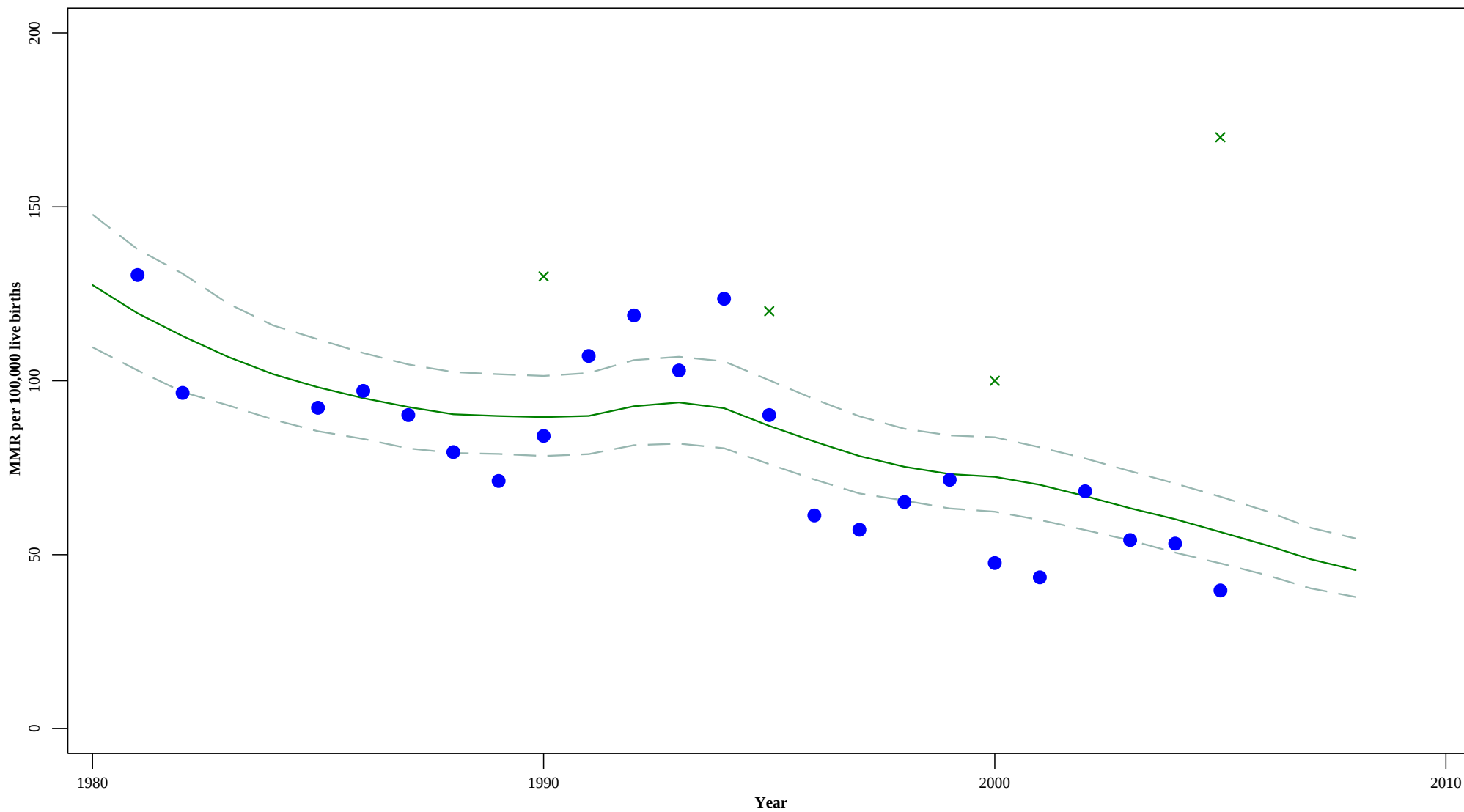
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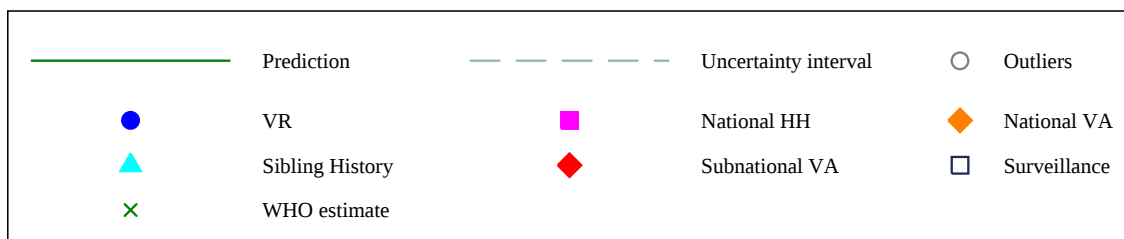
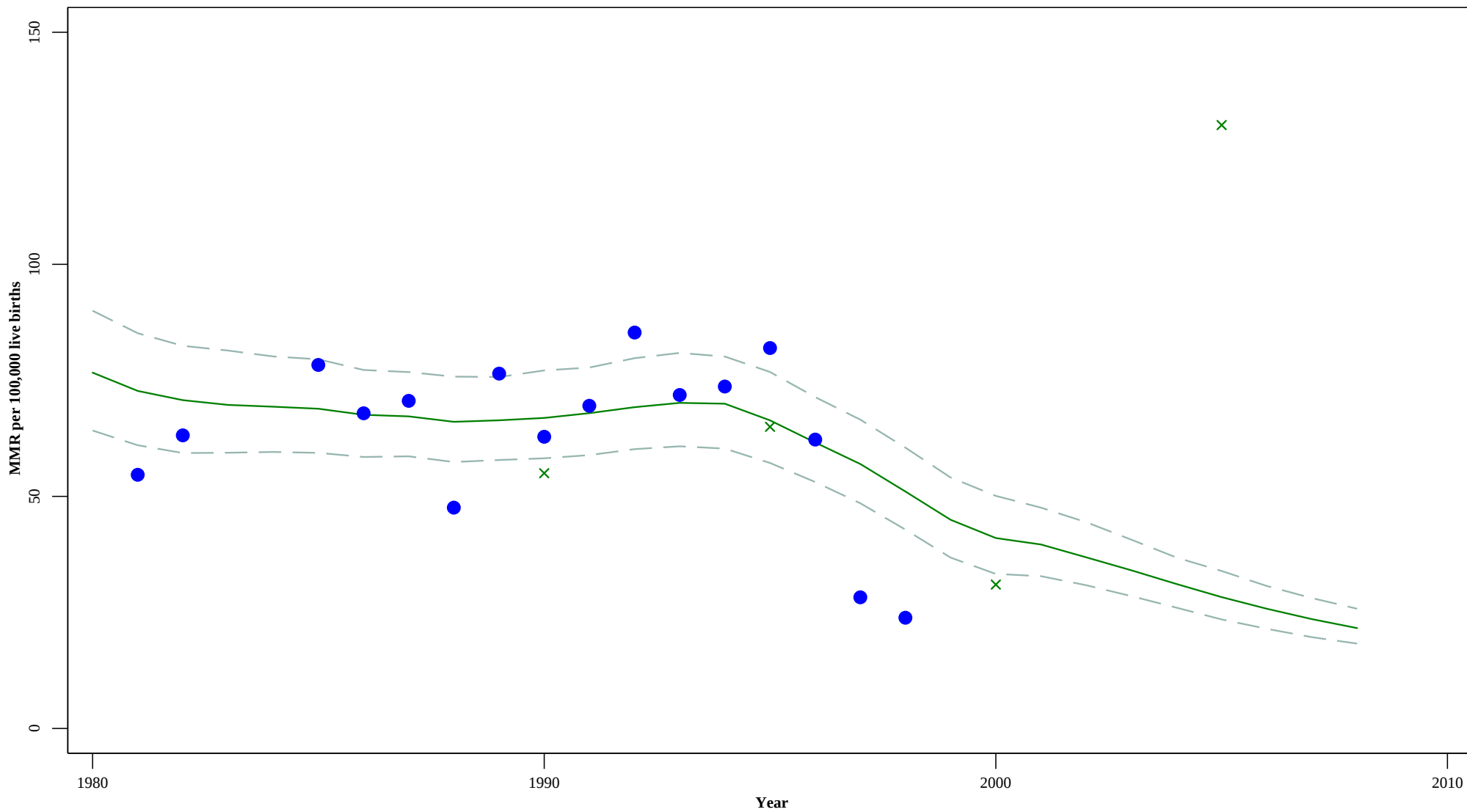
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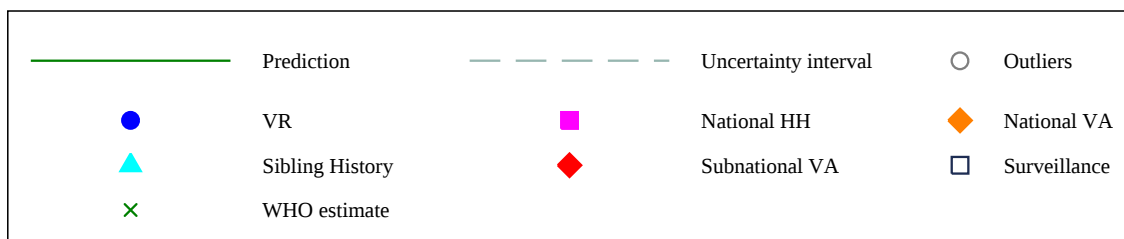
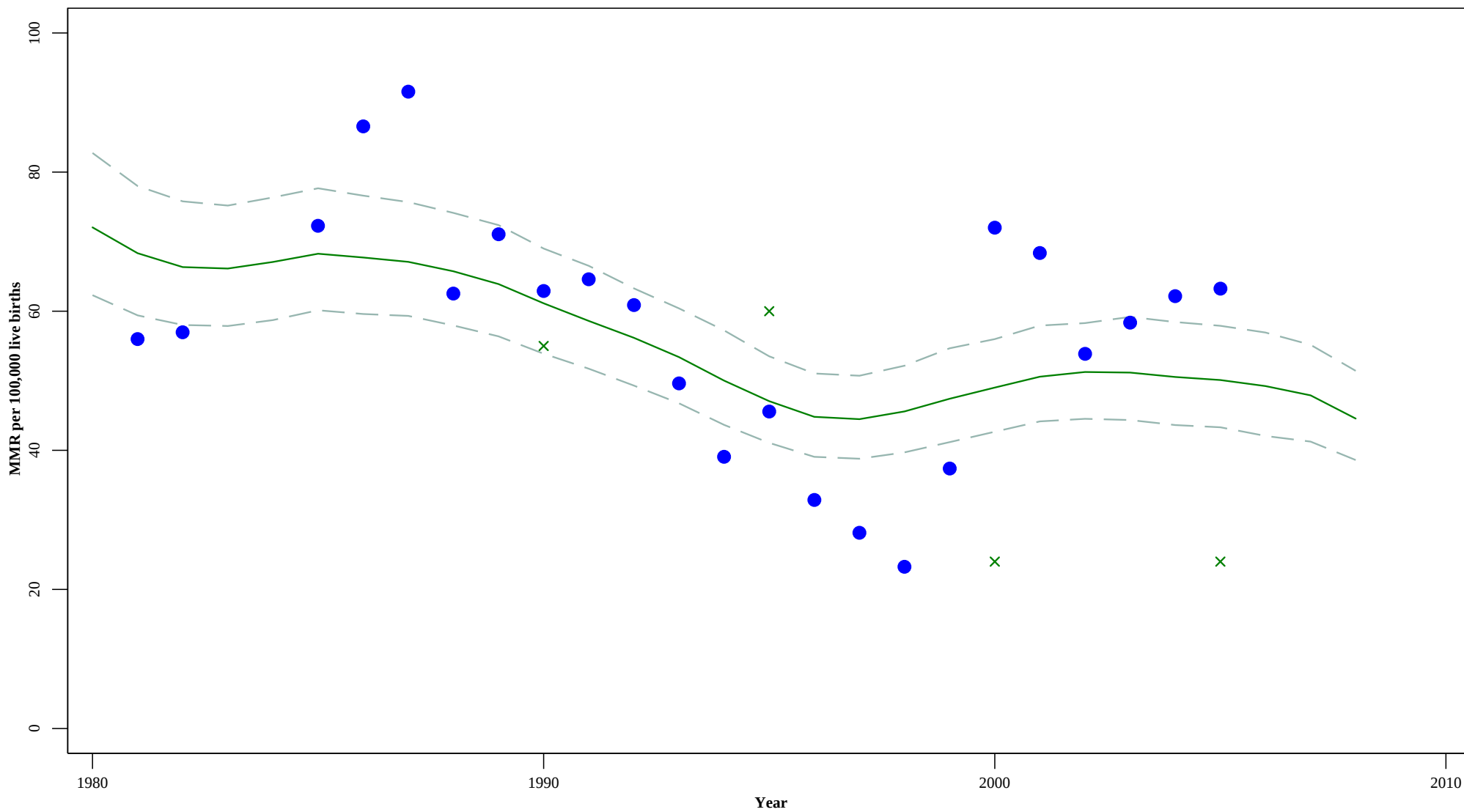
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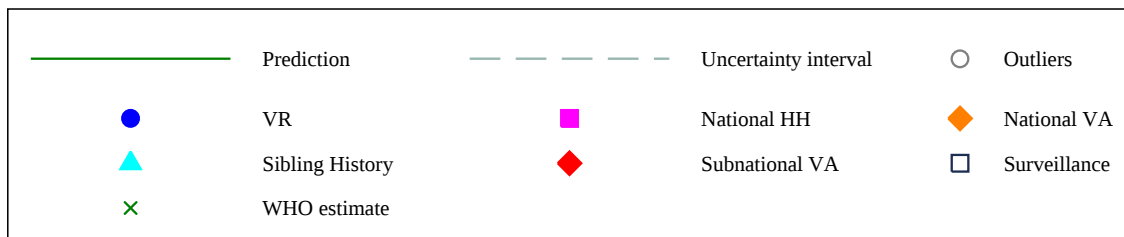
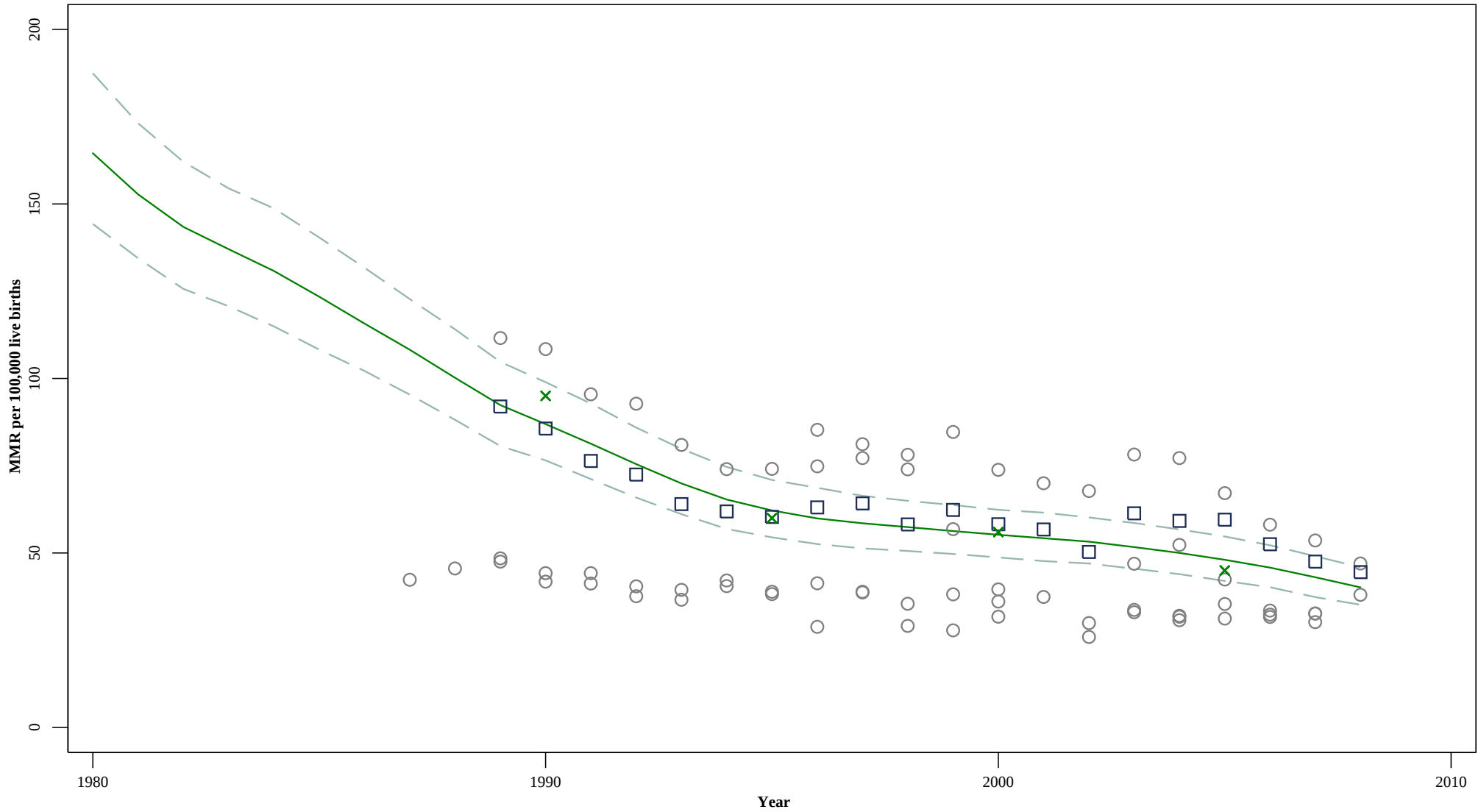
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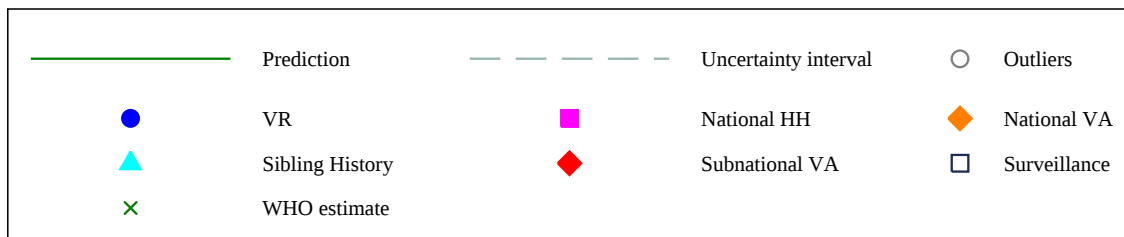
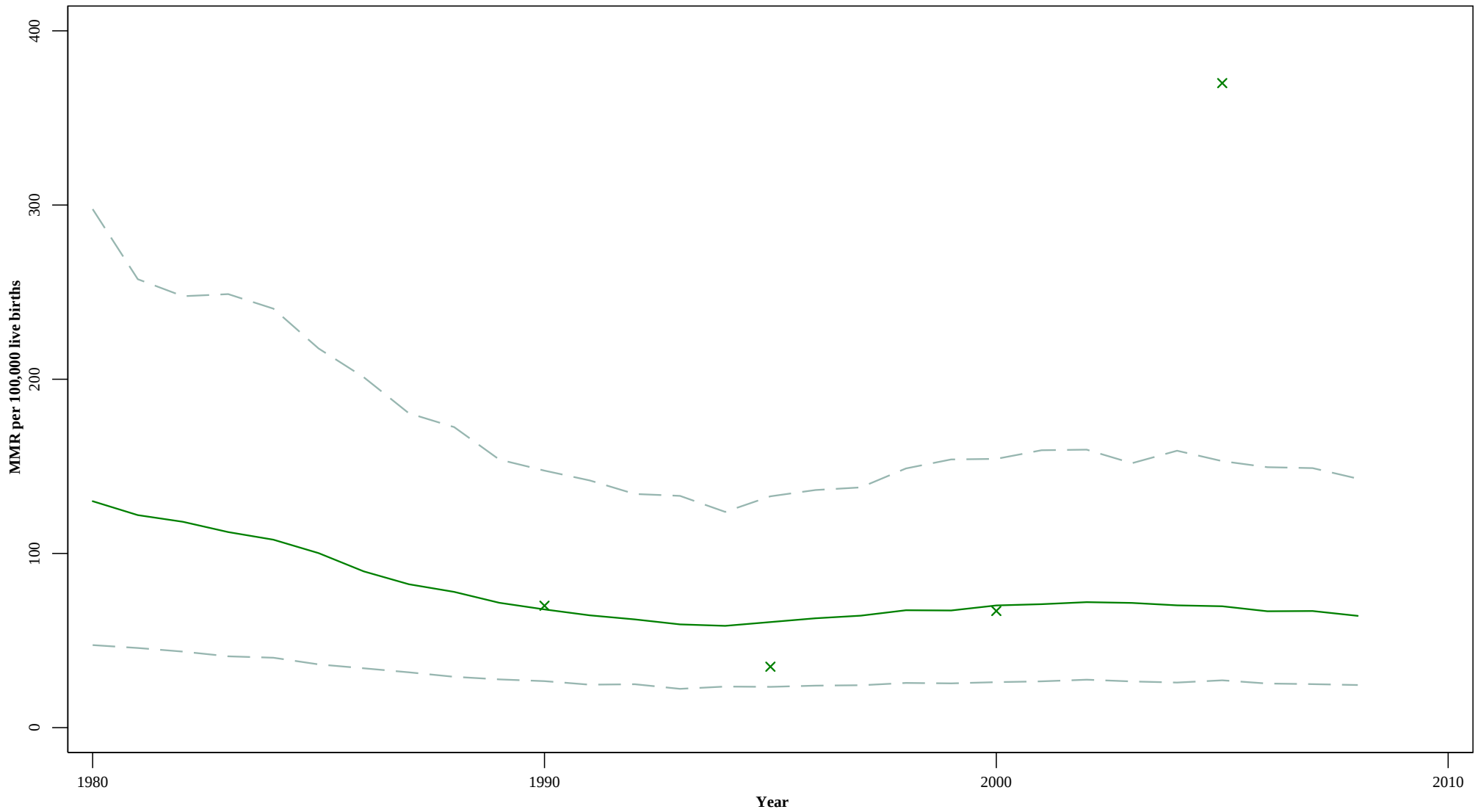
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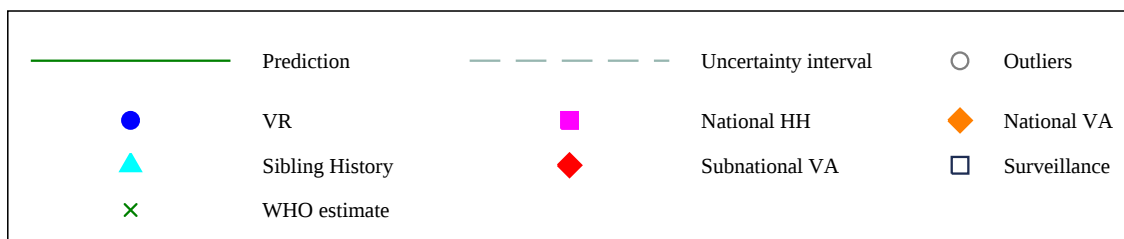
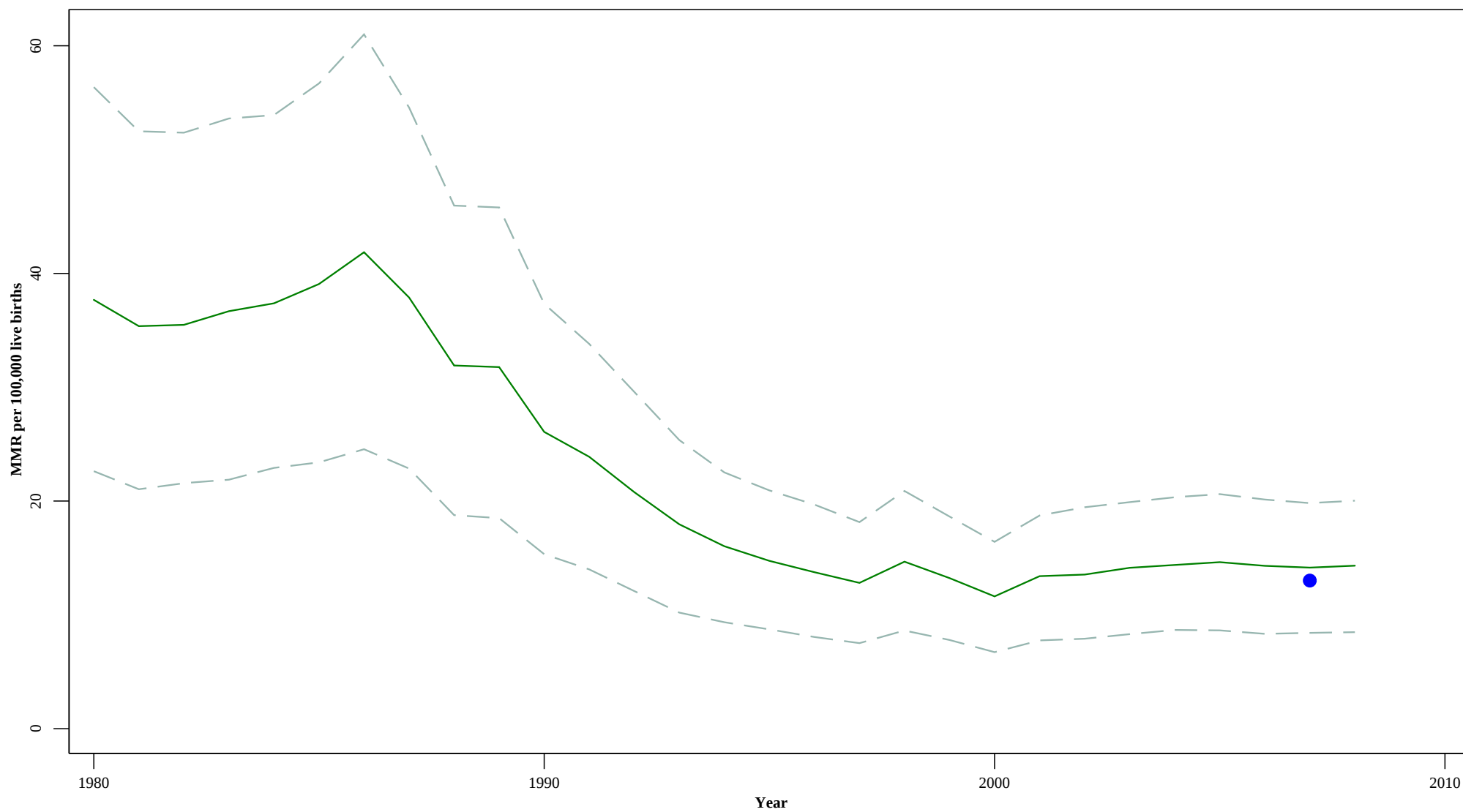
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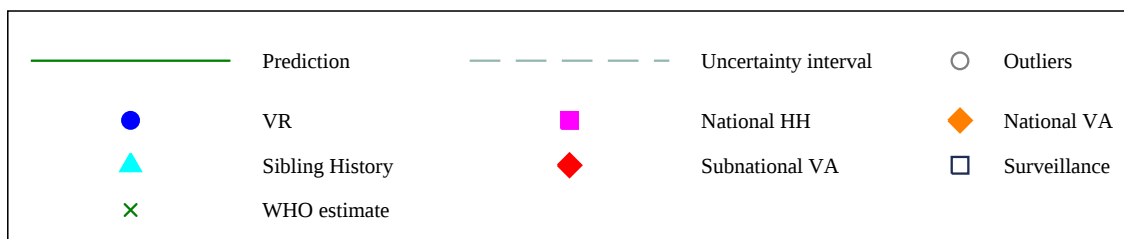
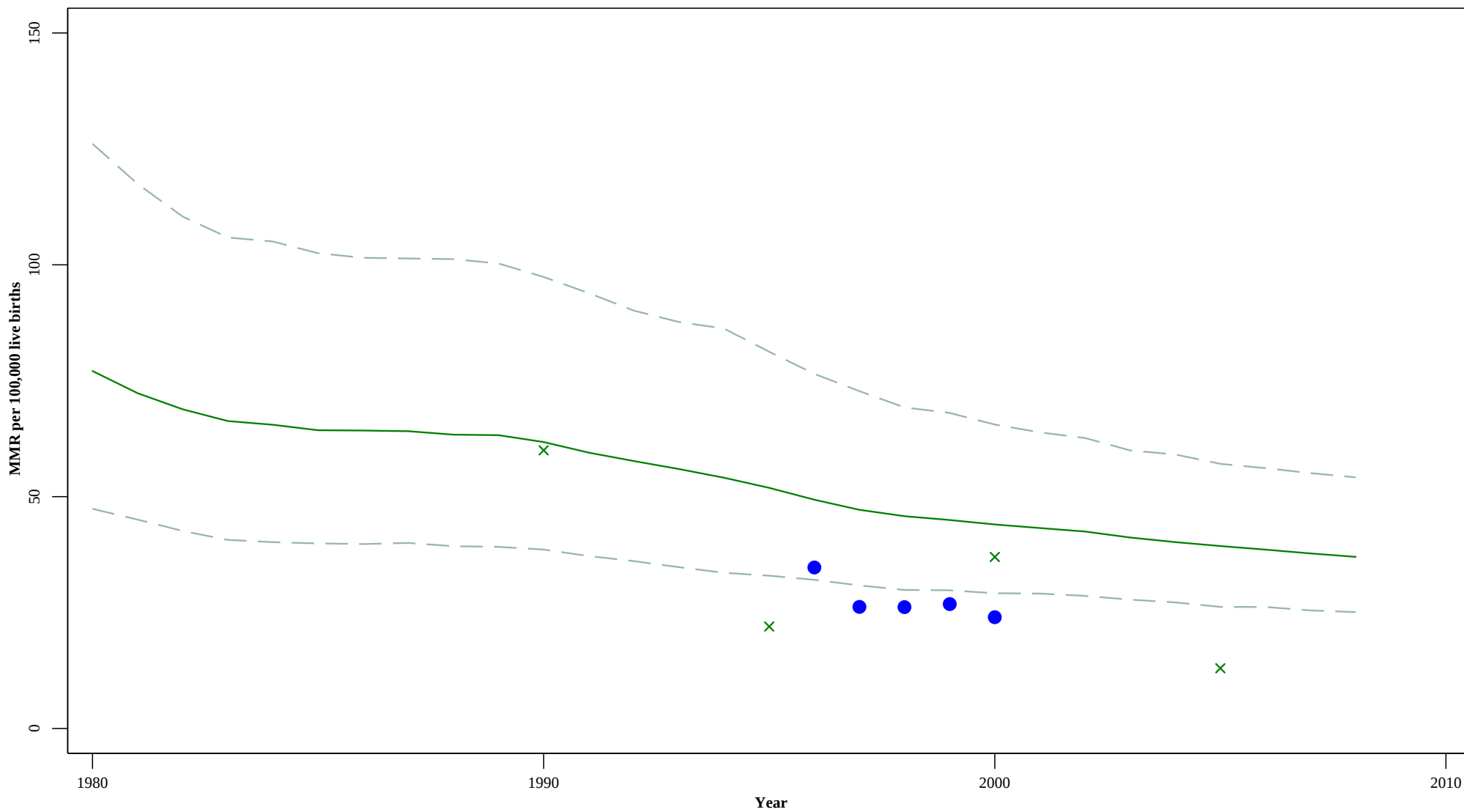
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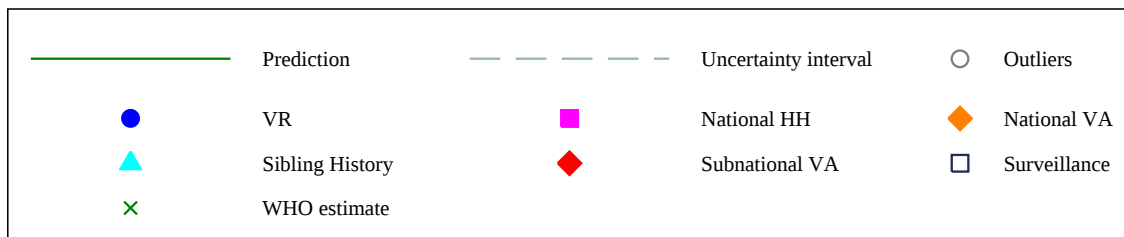
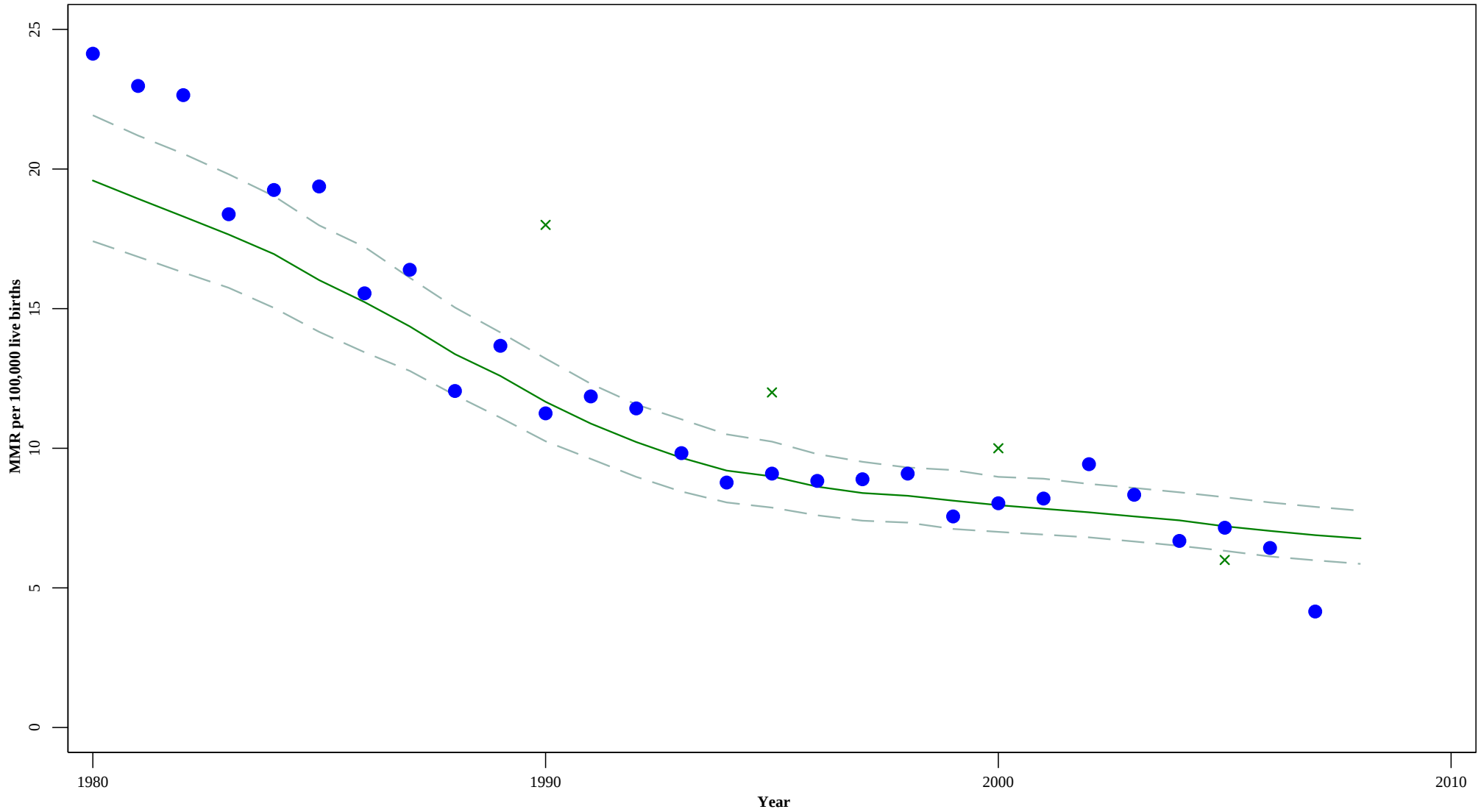
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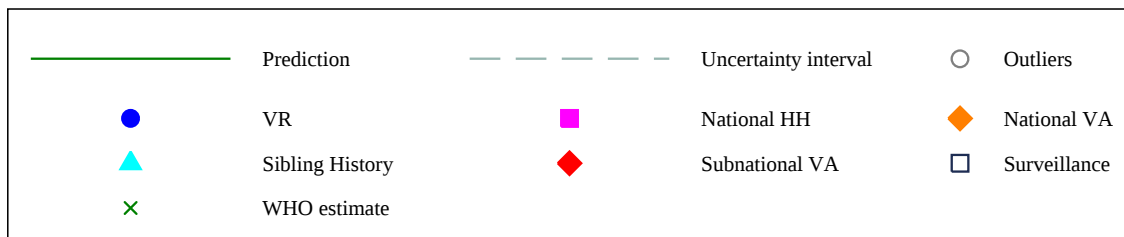
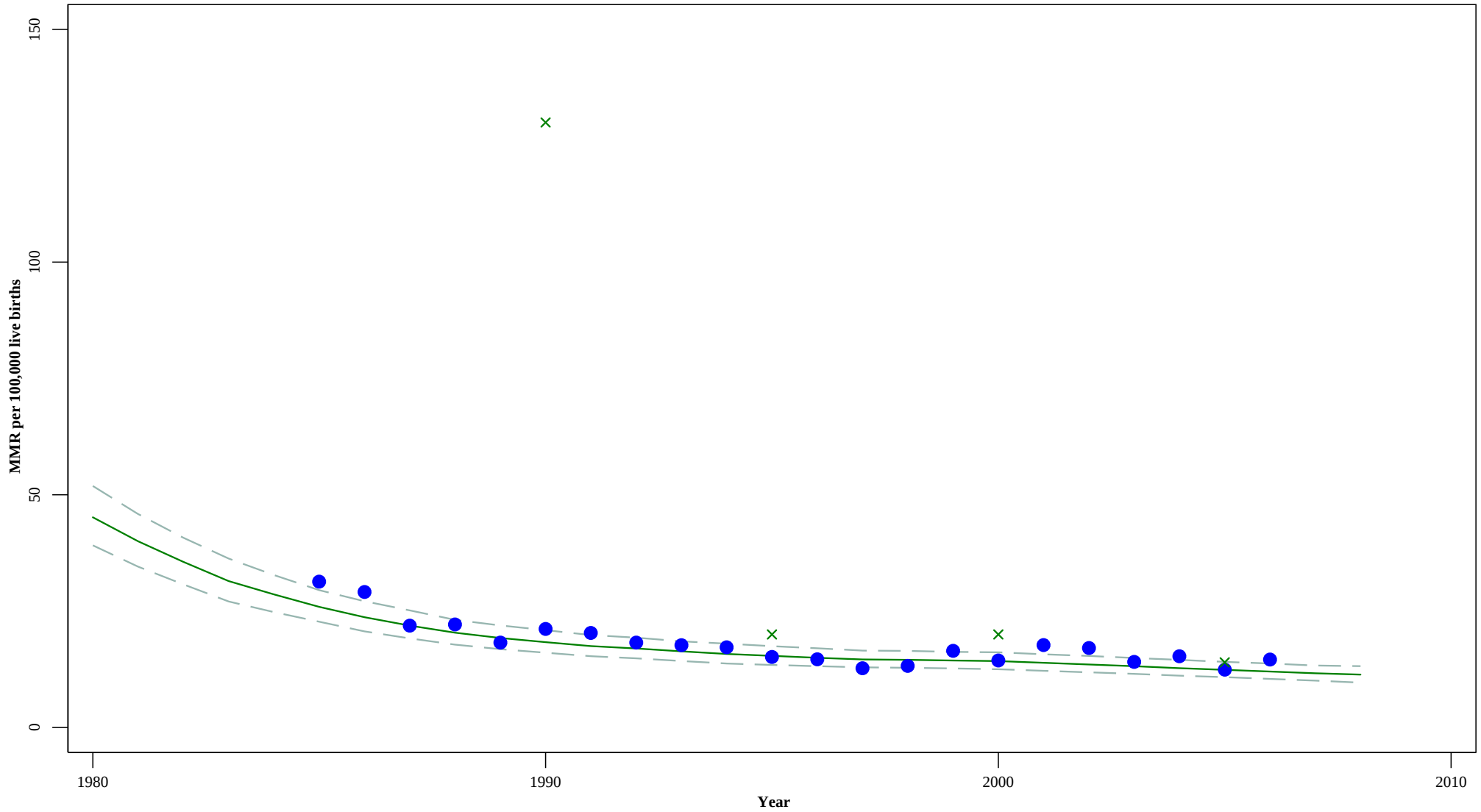
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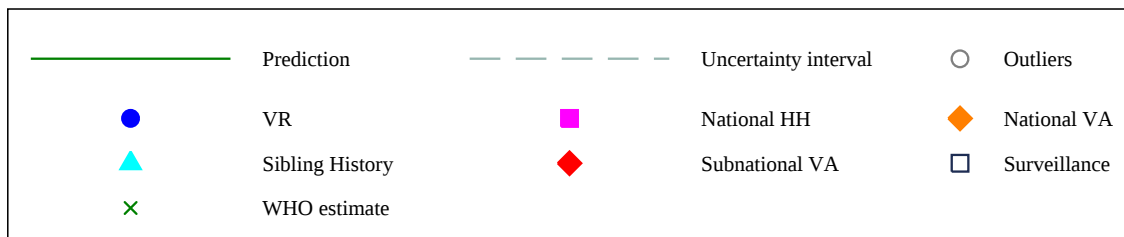
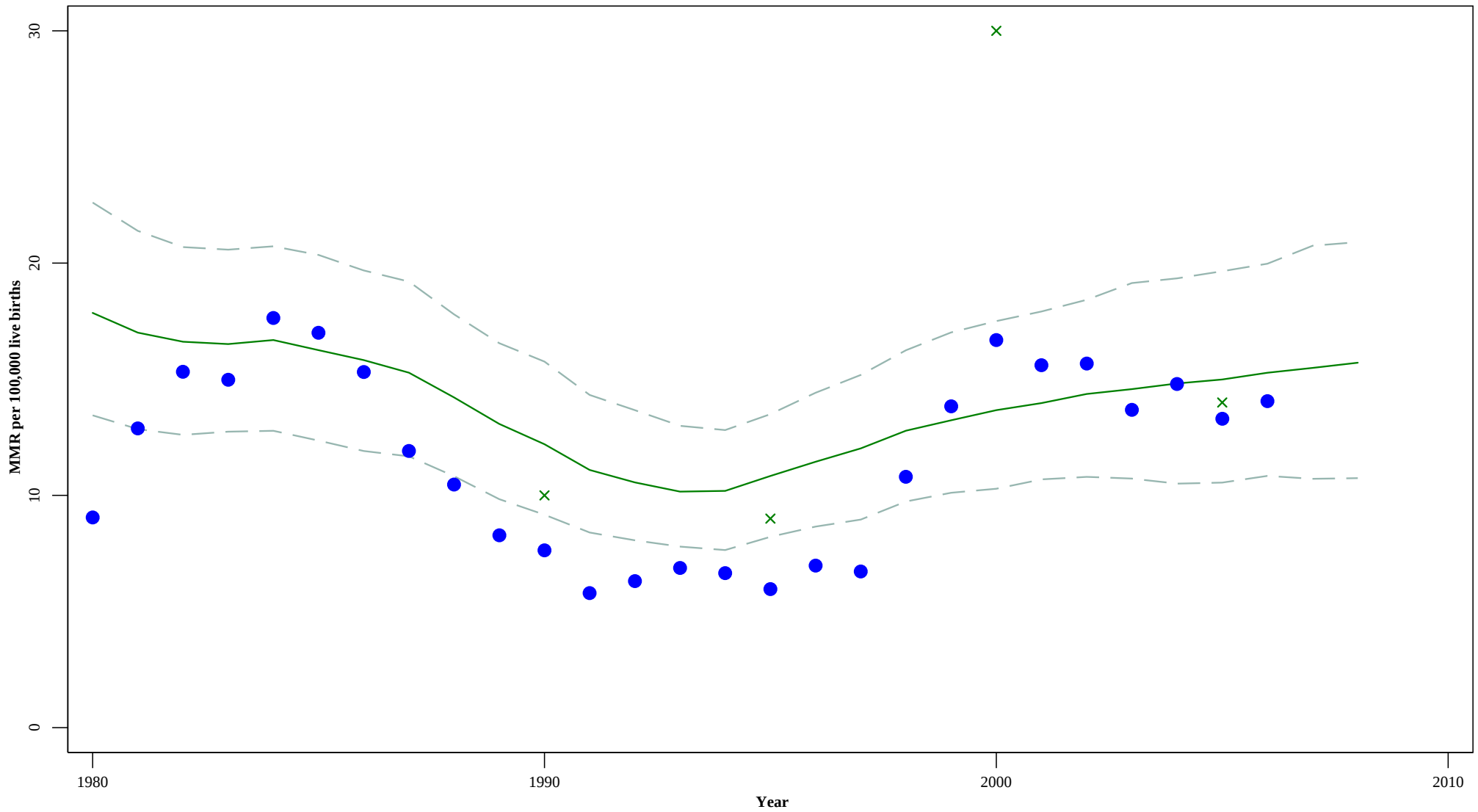
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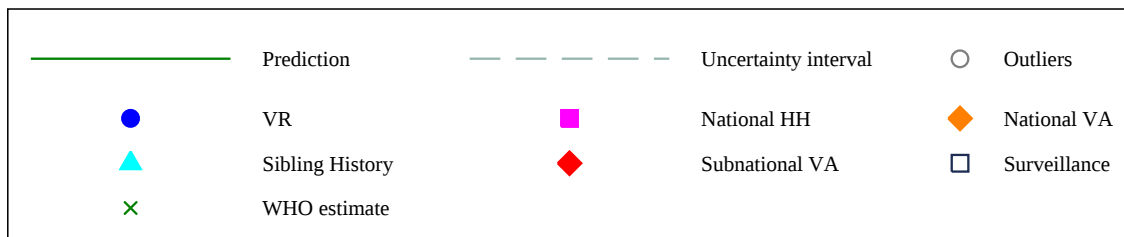
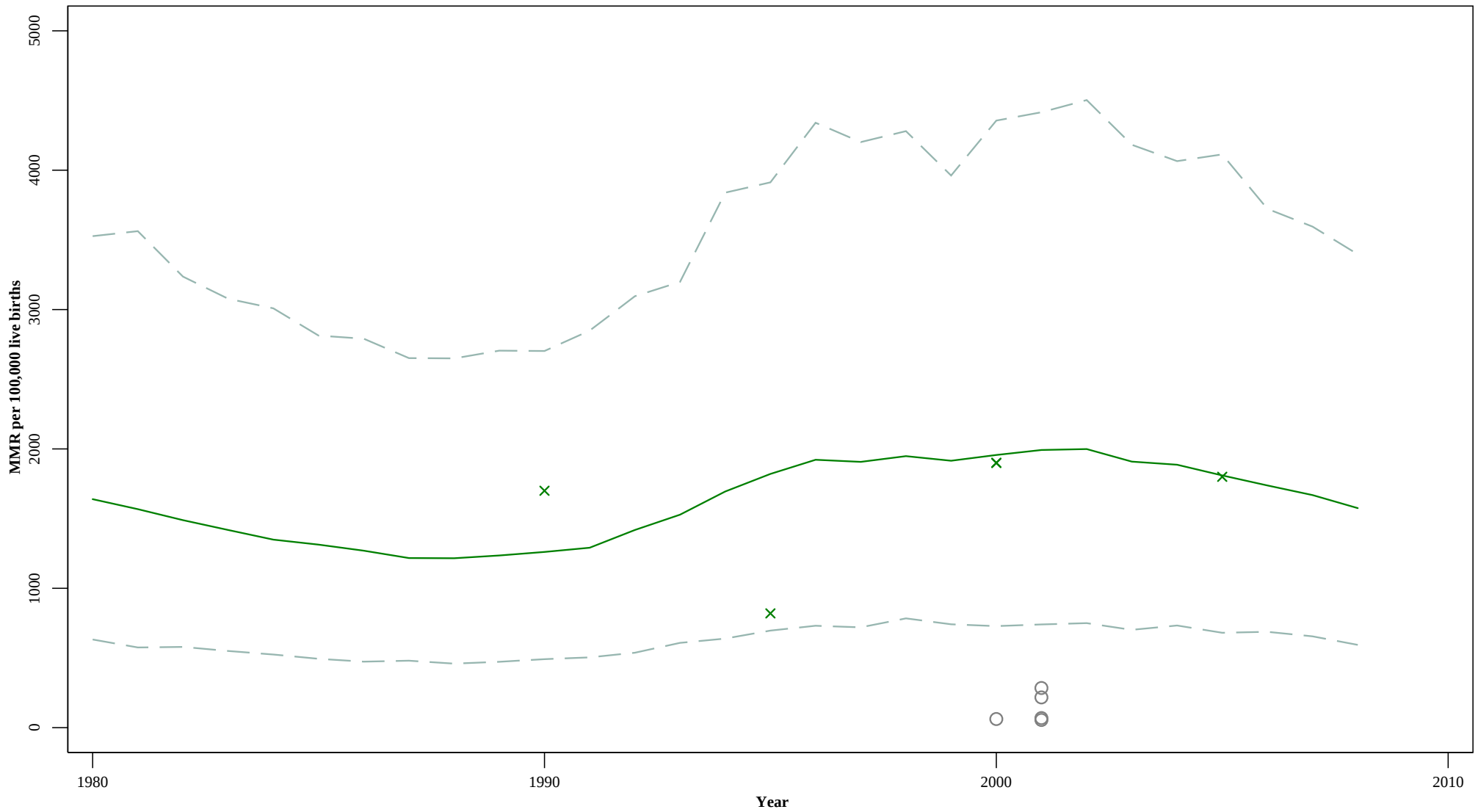
Korea, Republic of



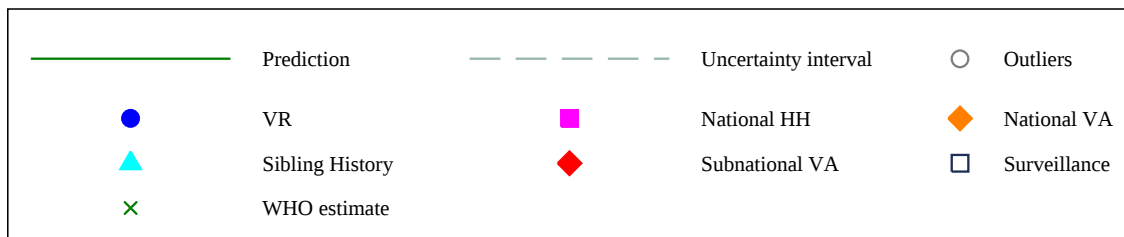
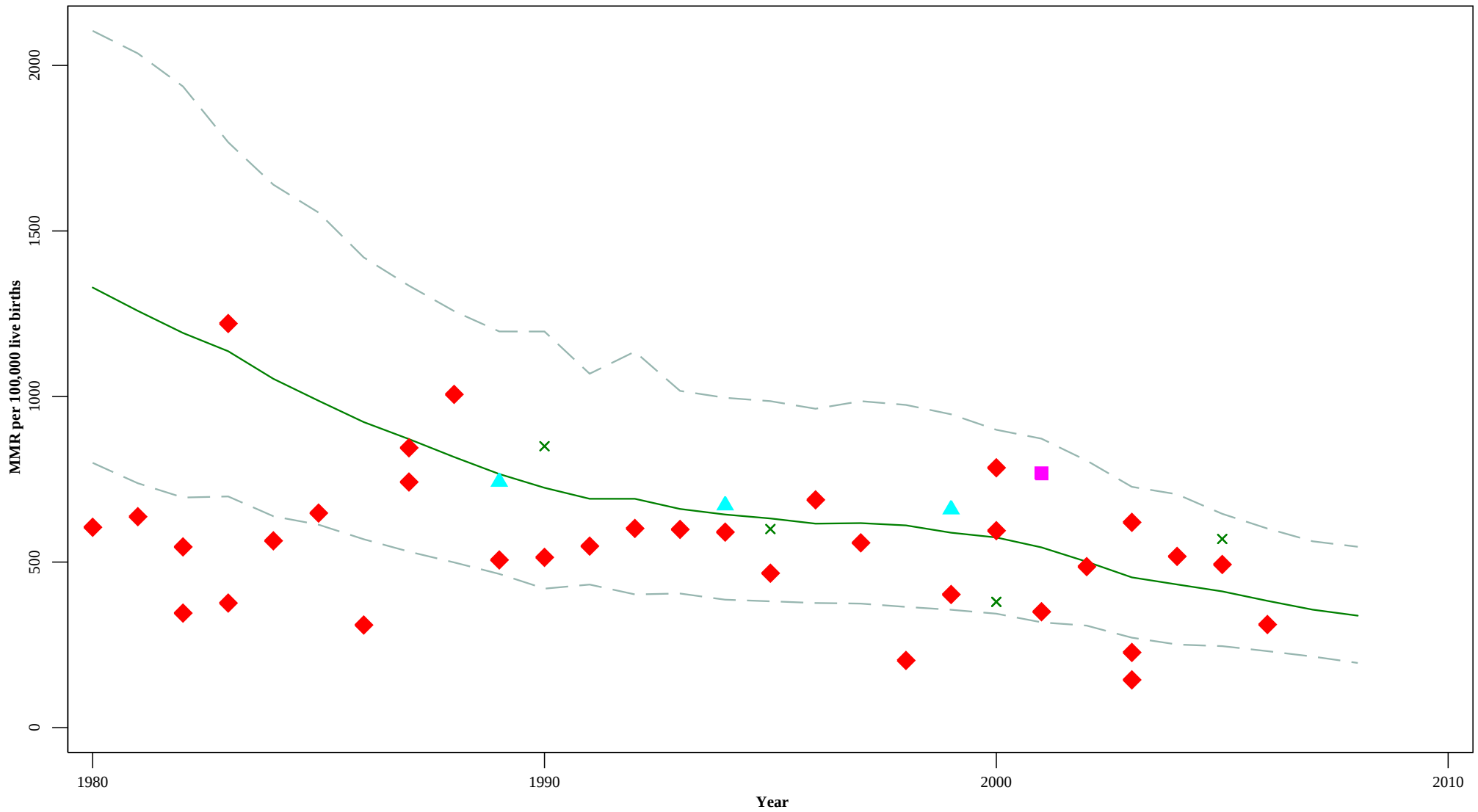
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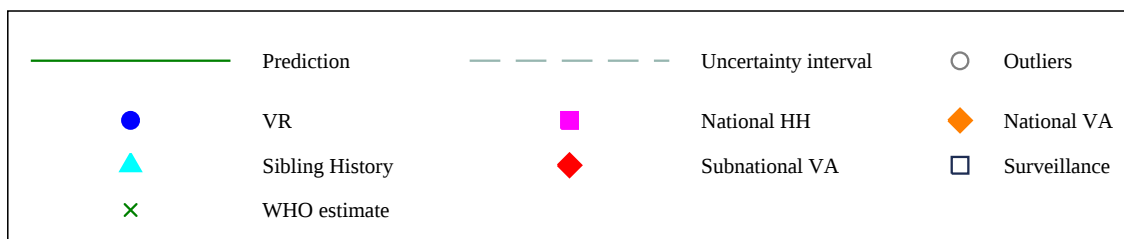
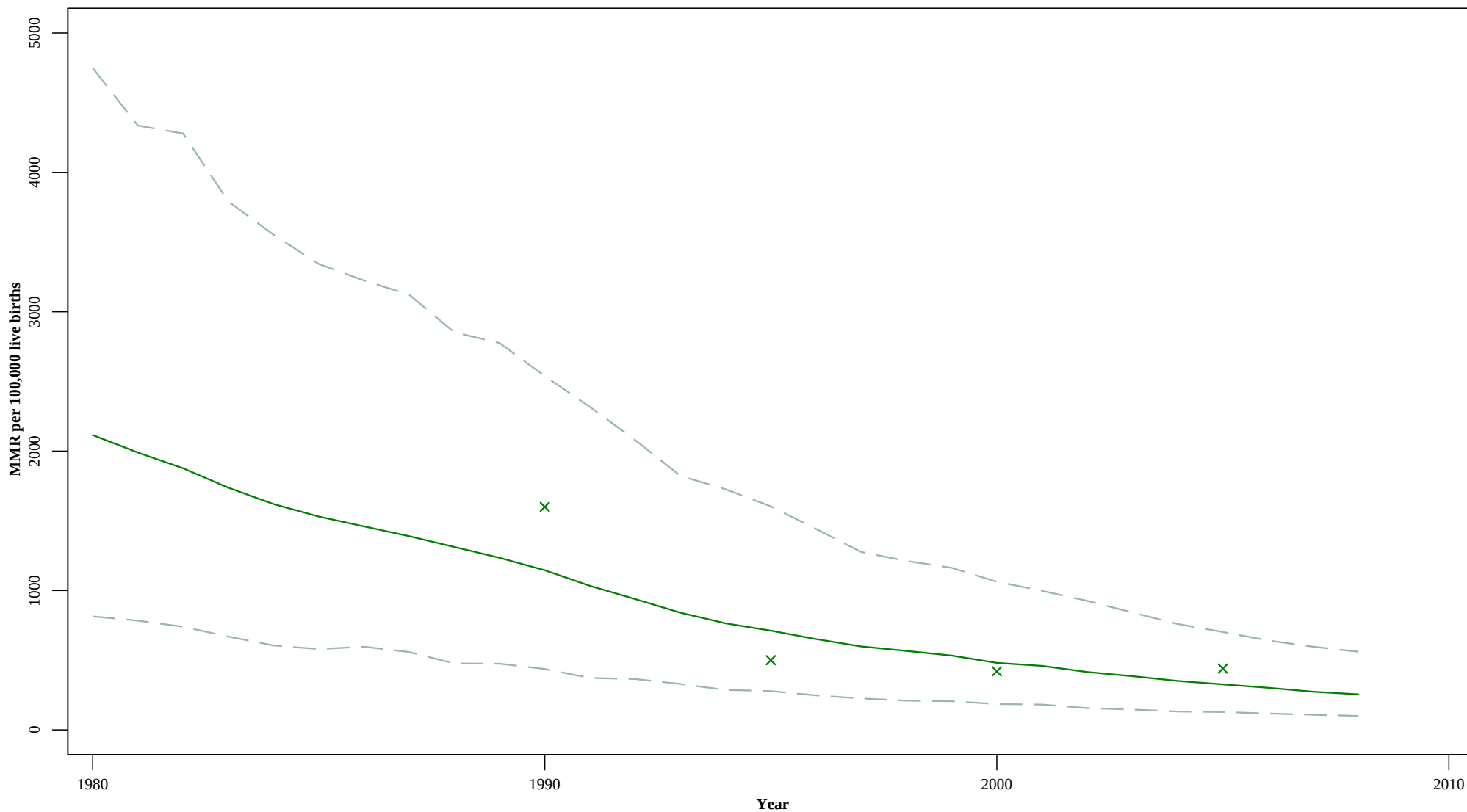
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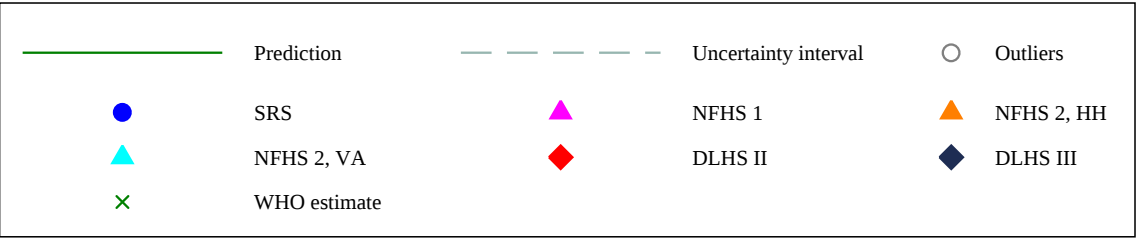
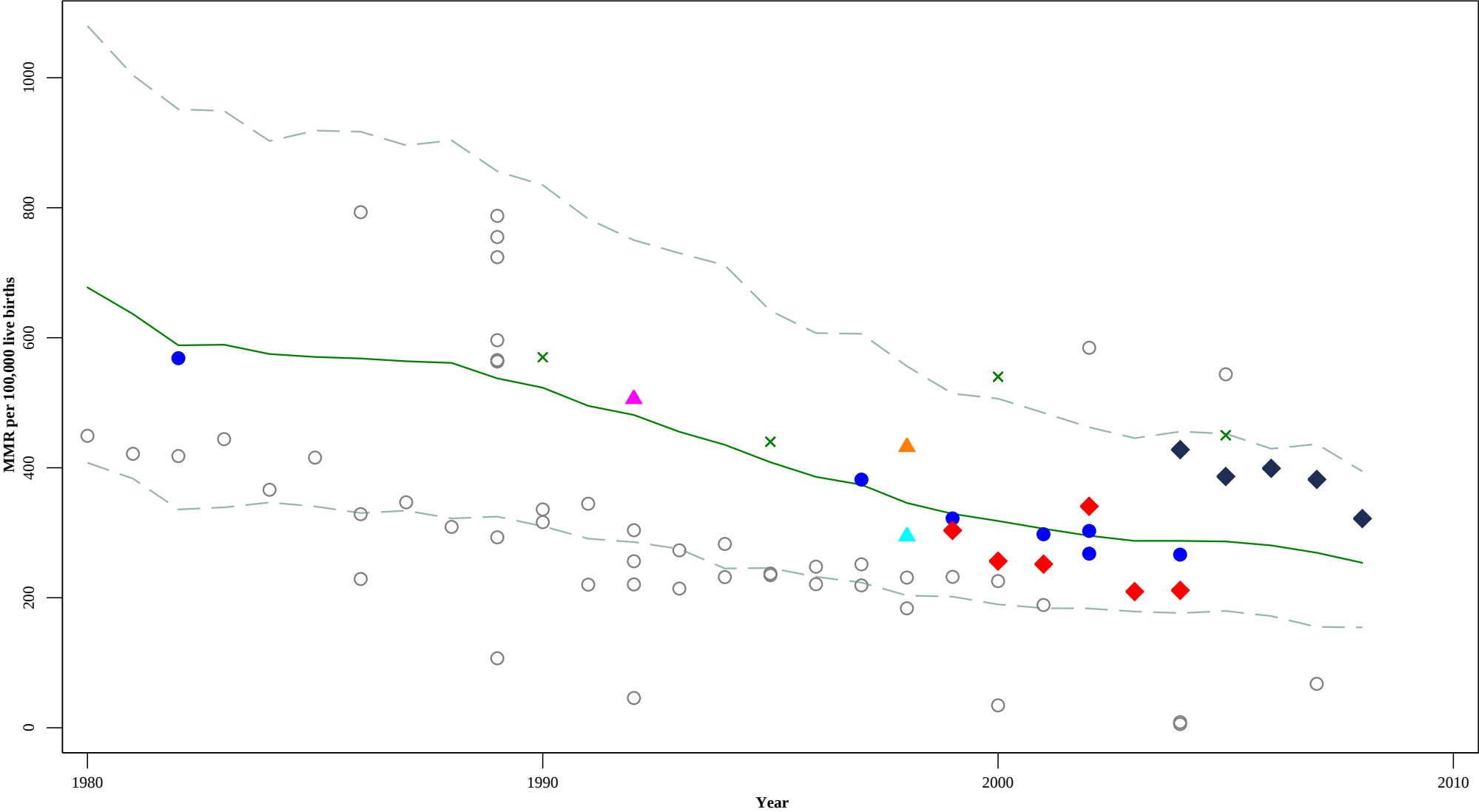
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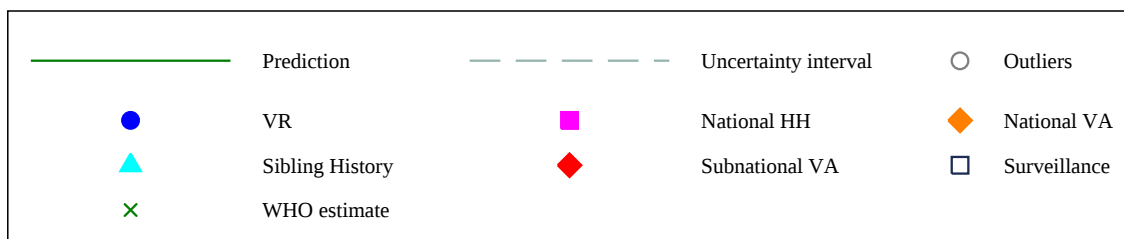
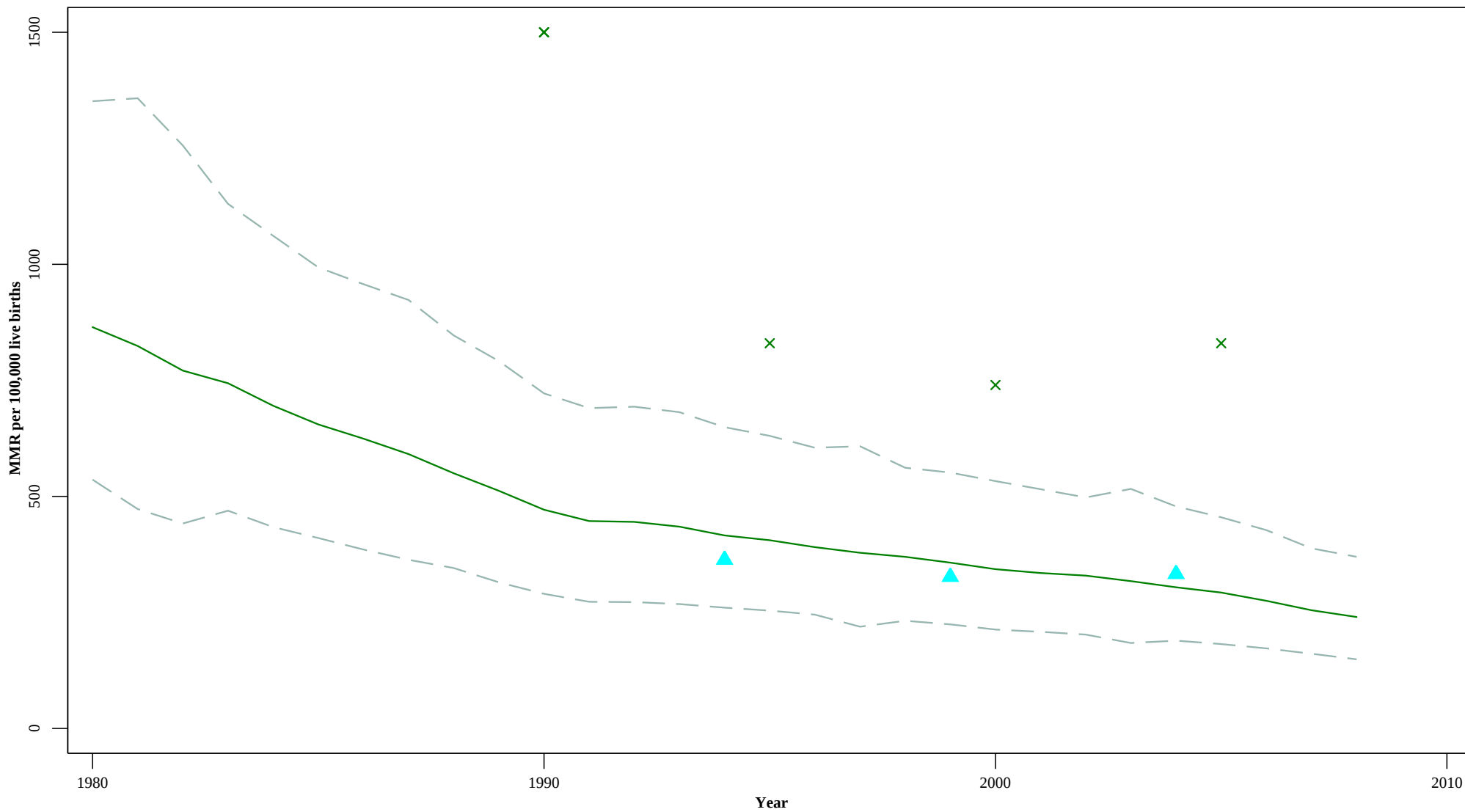
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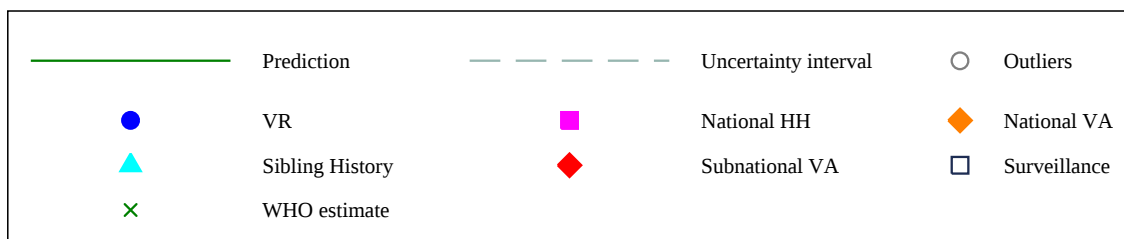
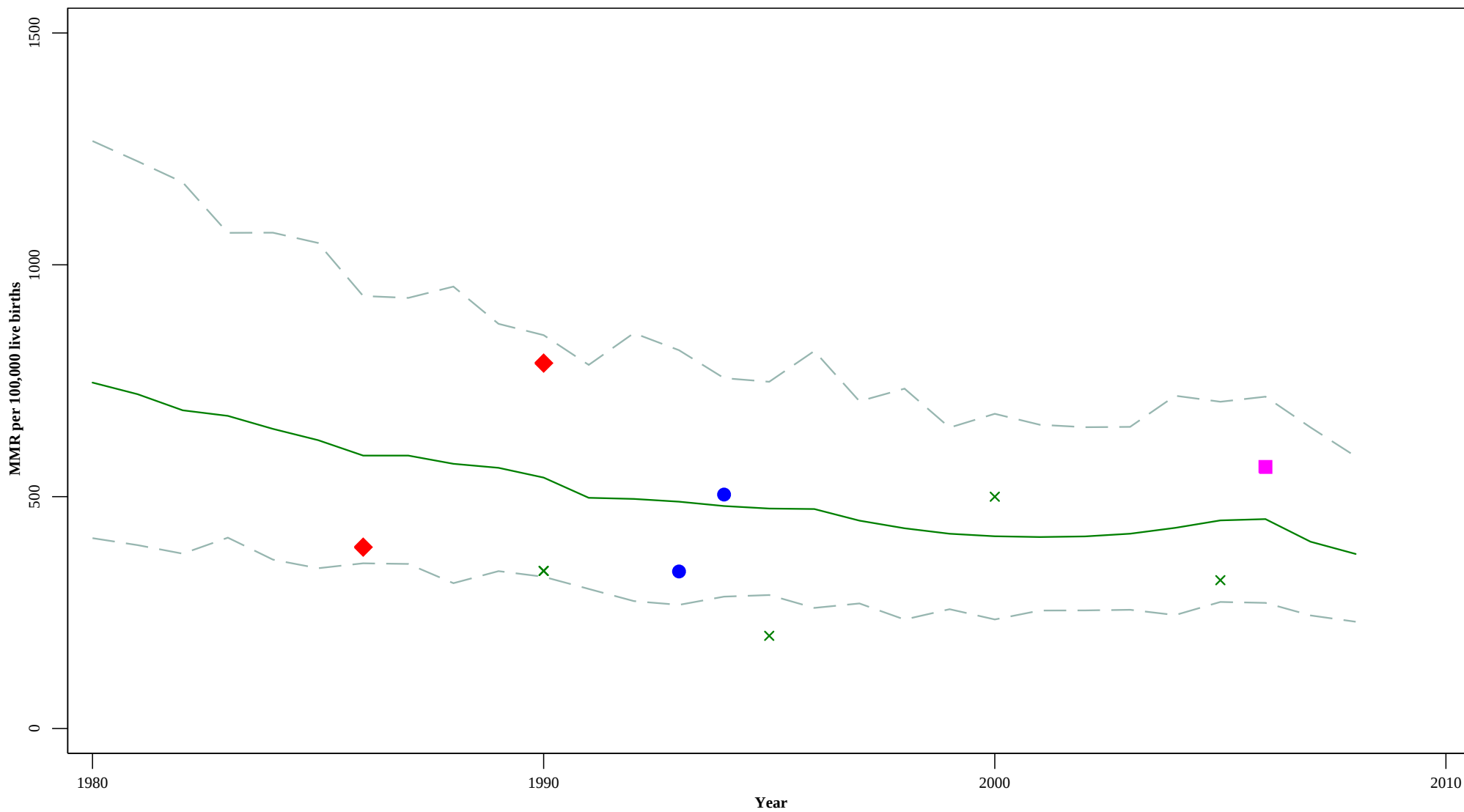
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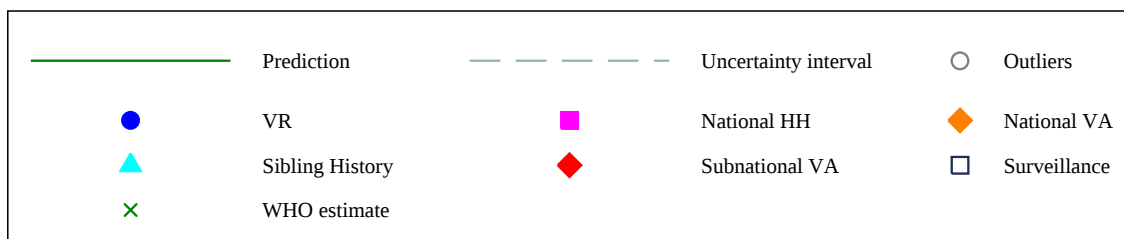
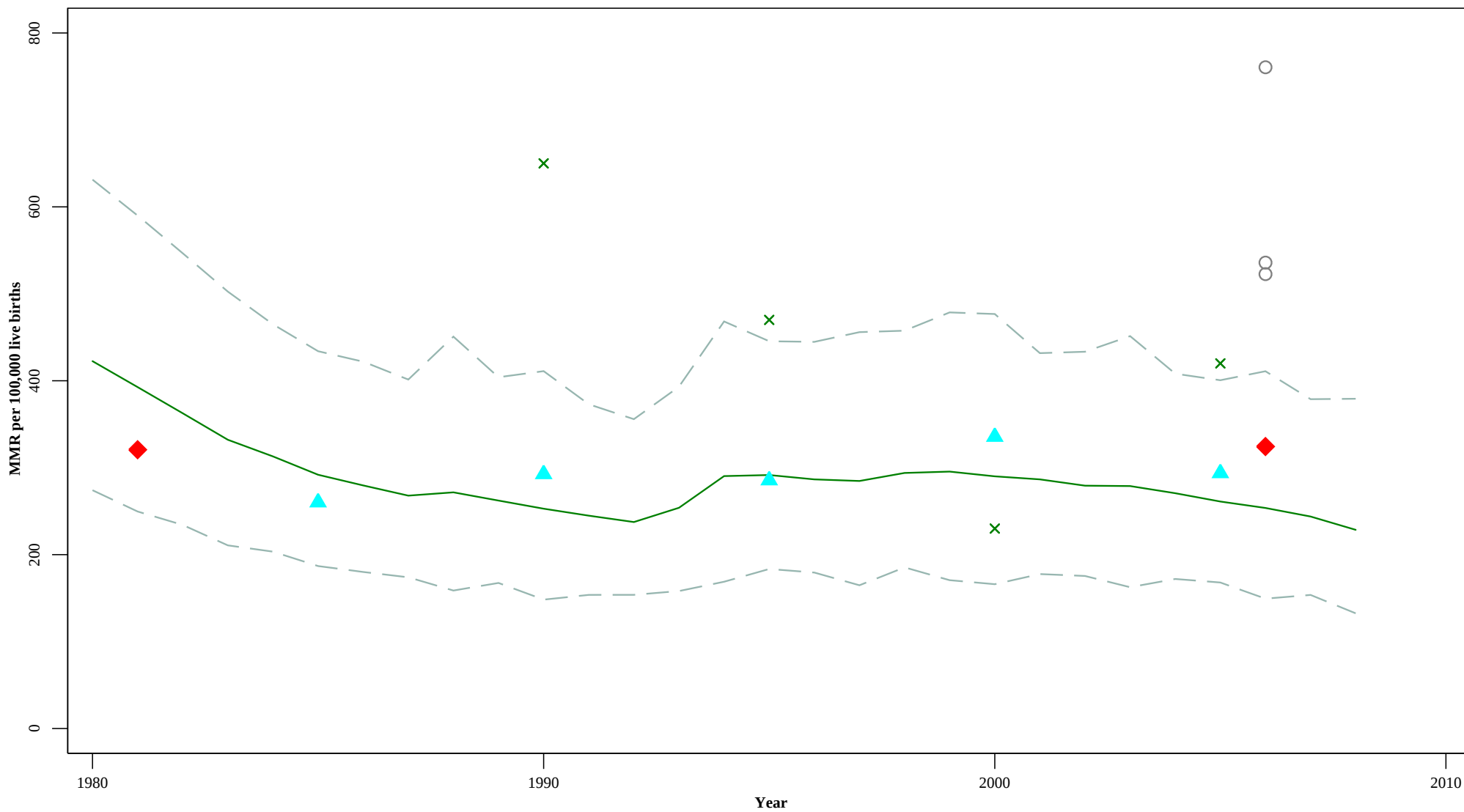
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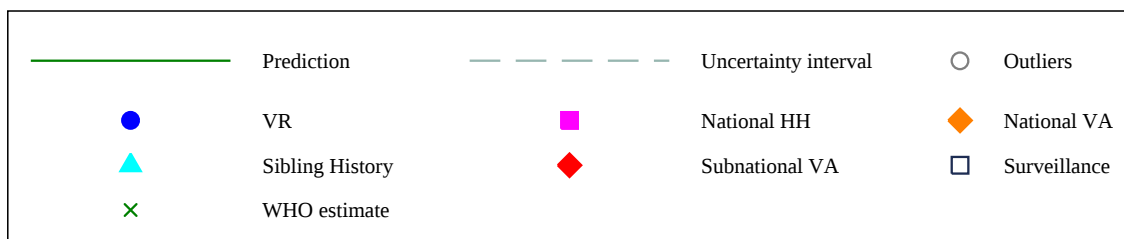
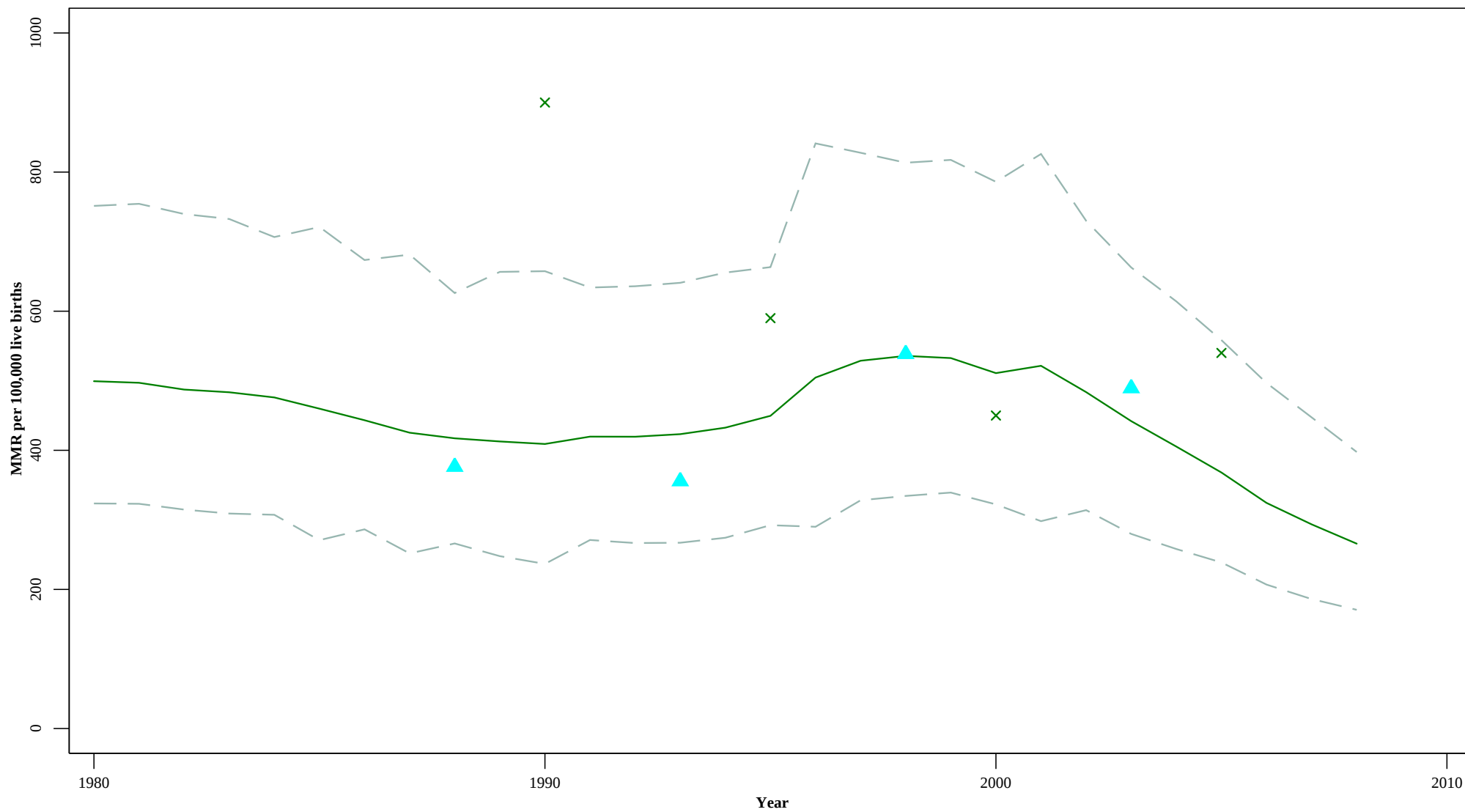
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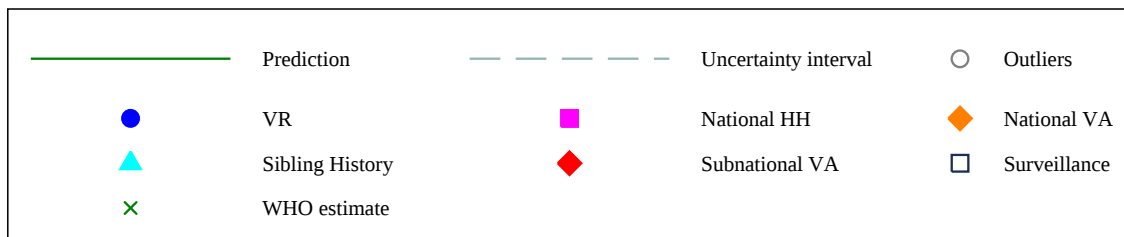
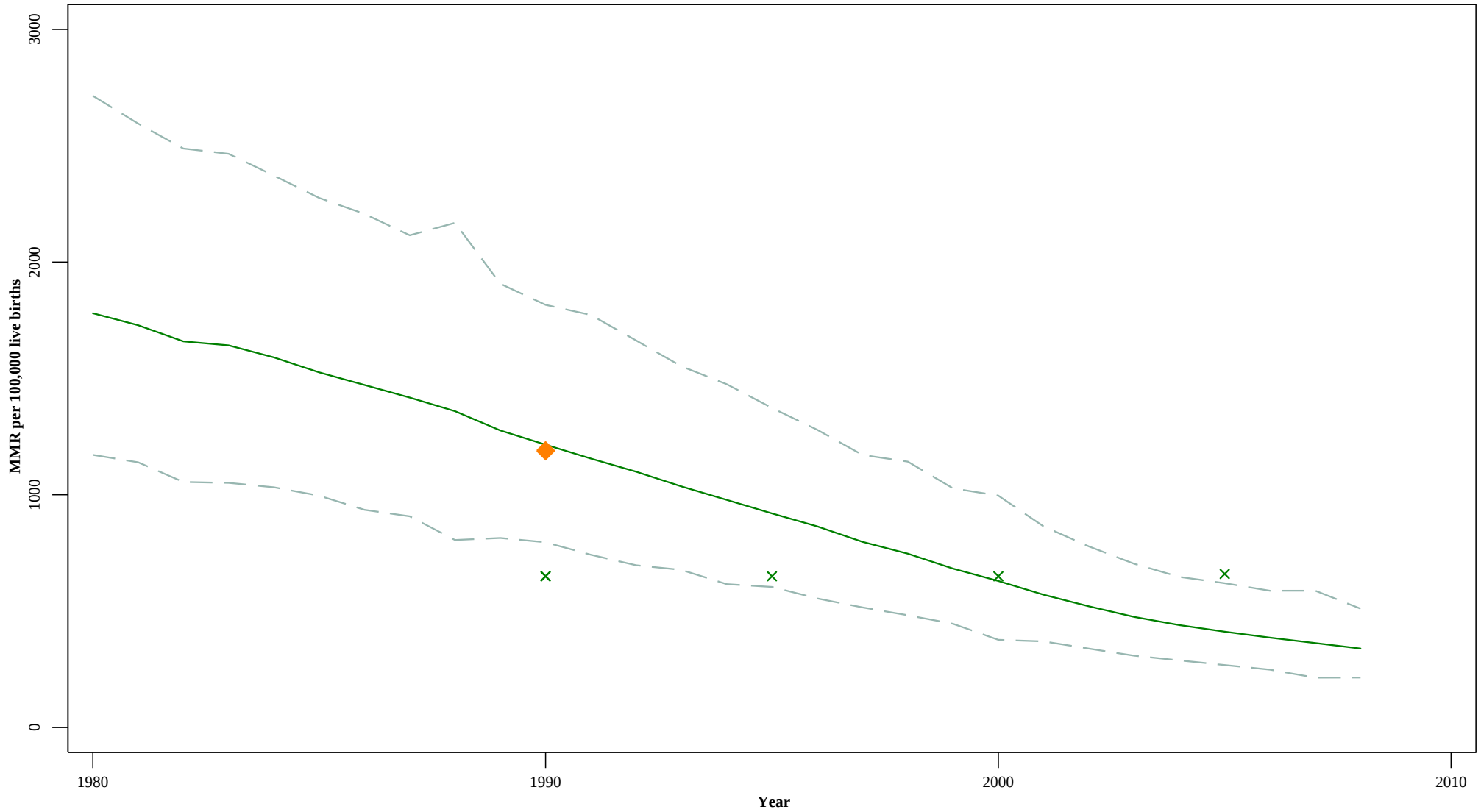
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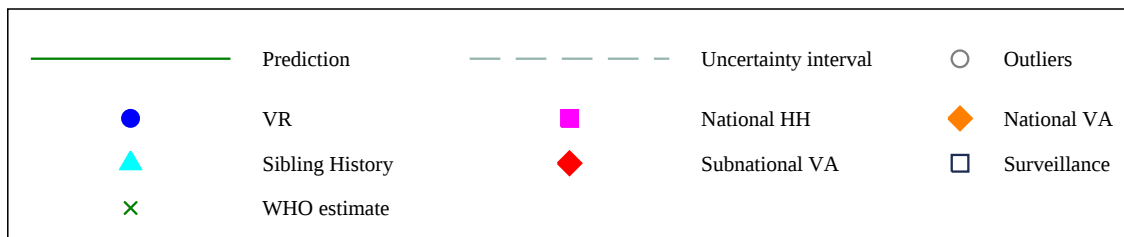
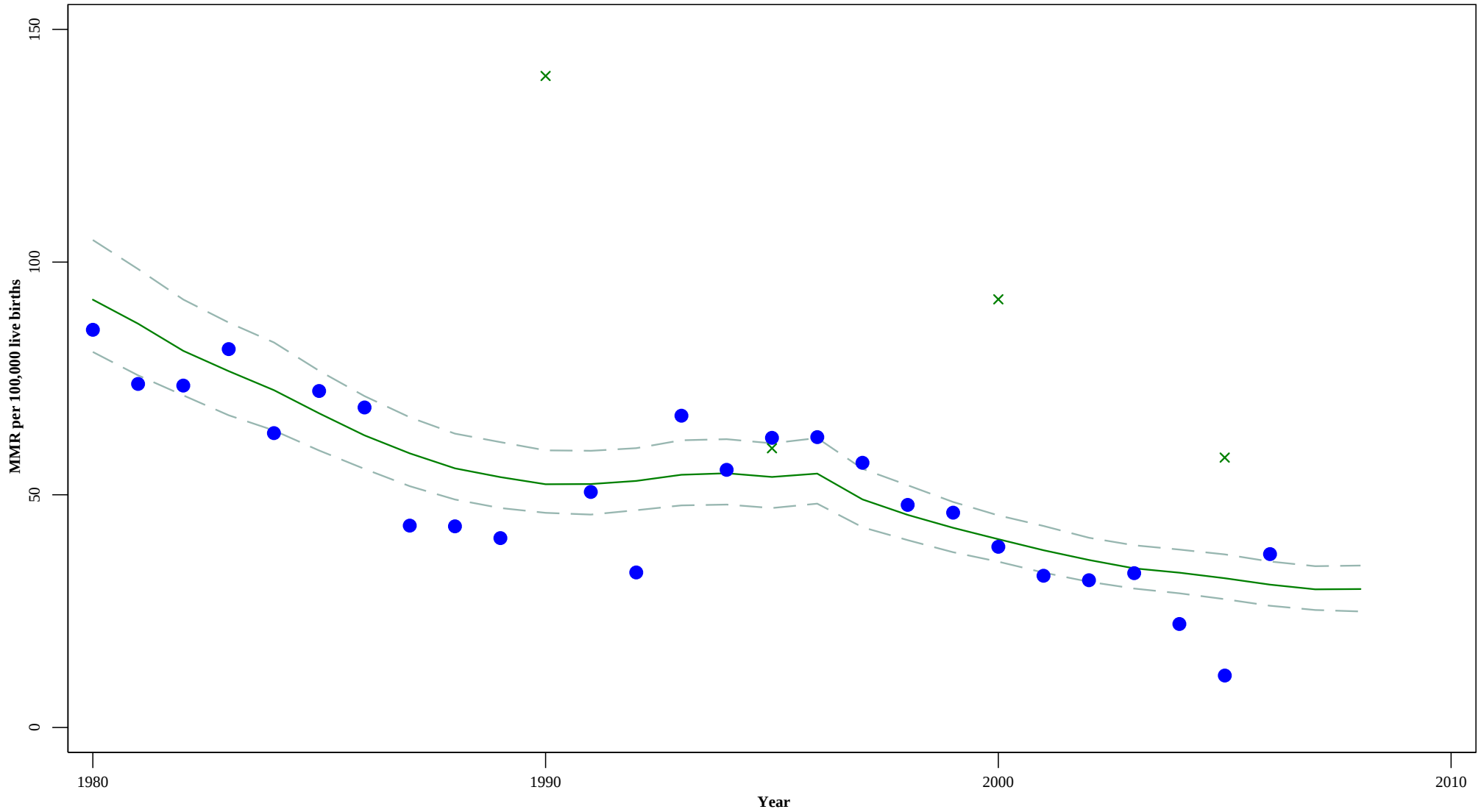
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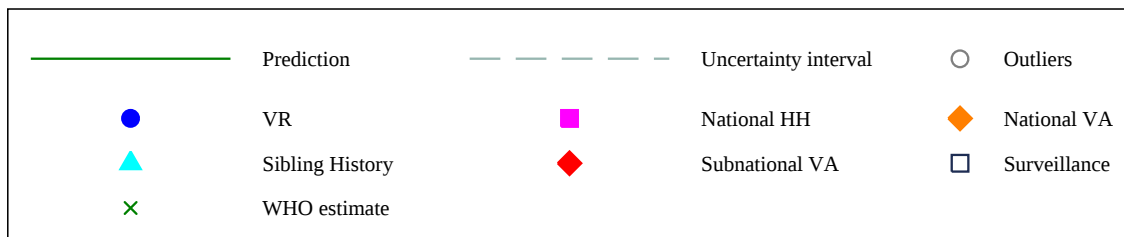
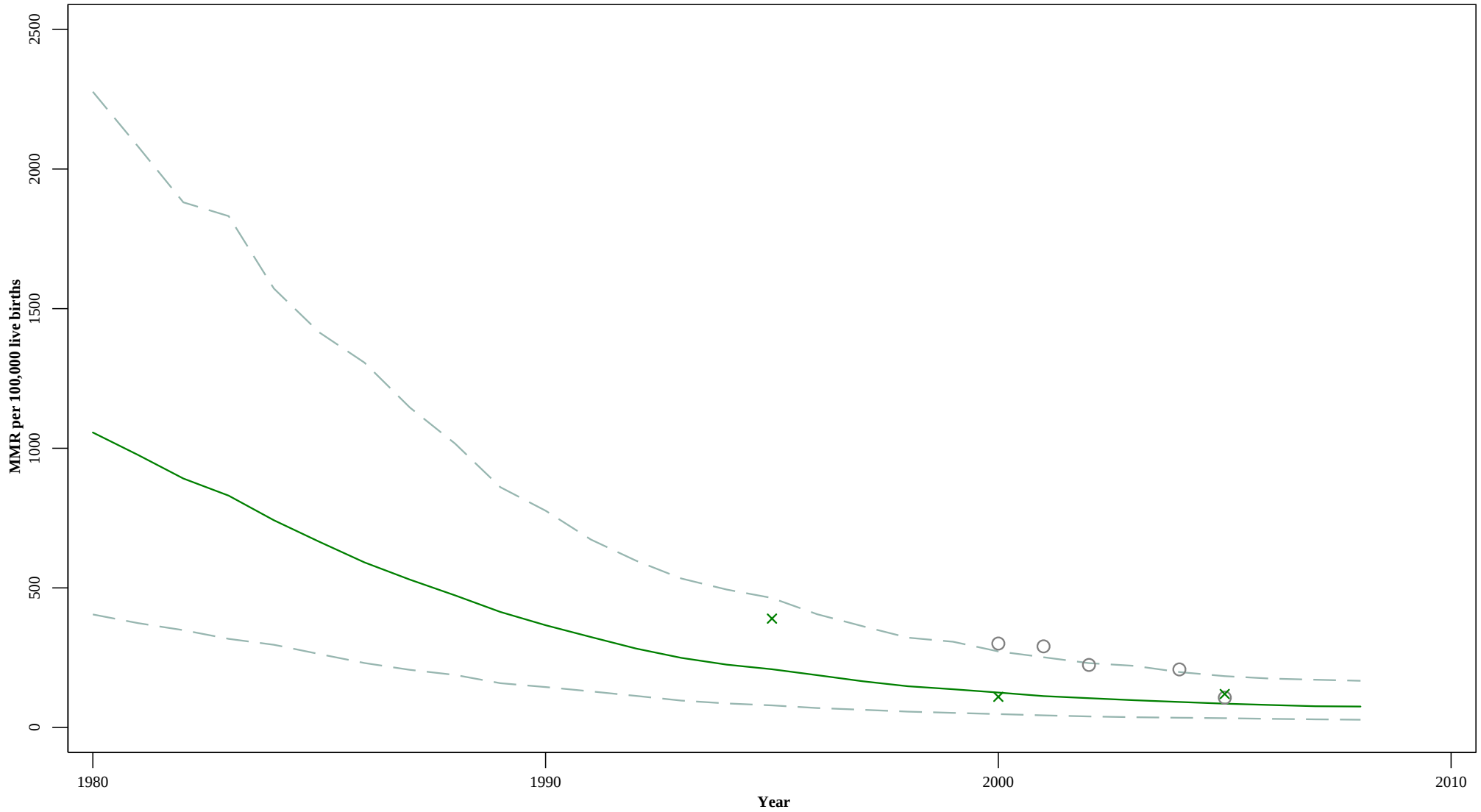
Lao People's Democratic Republic



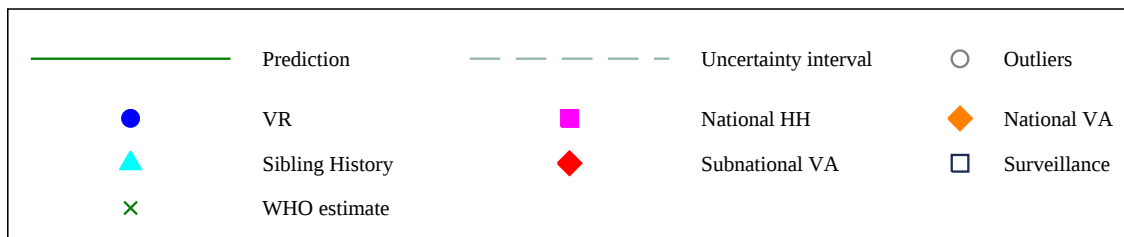
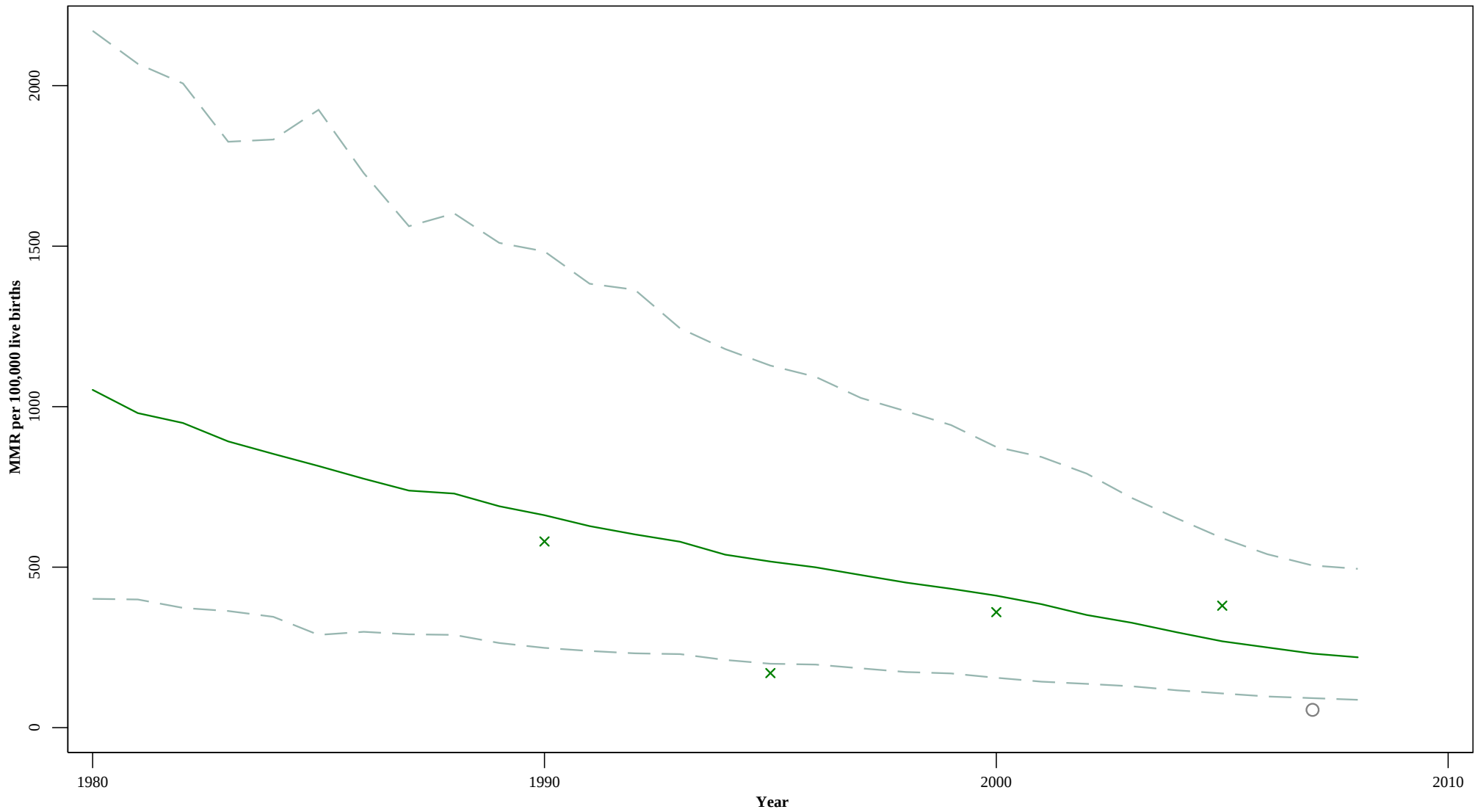
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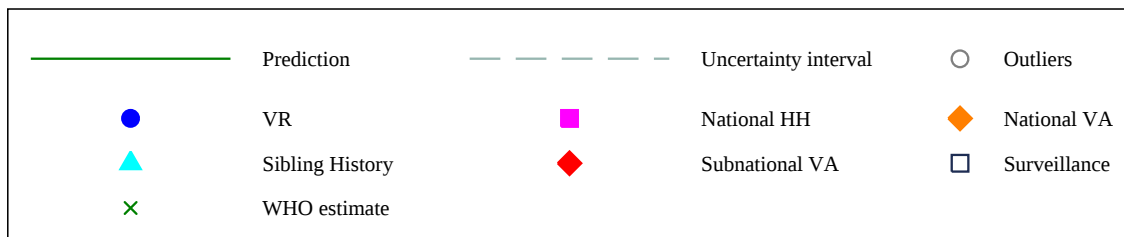
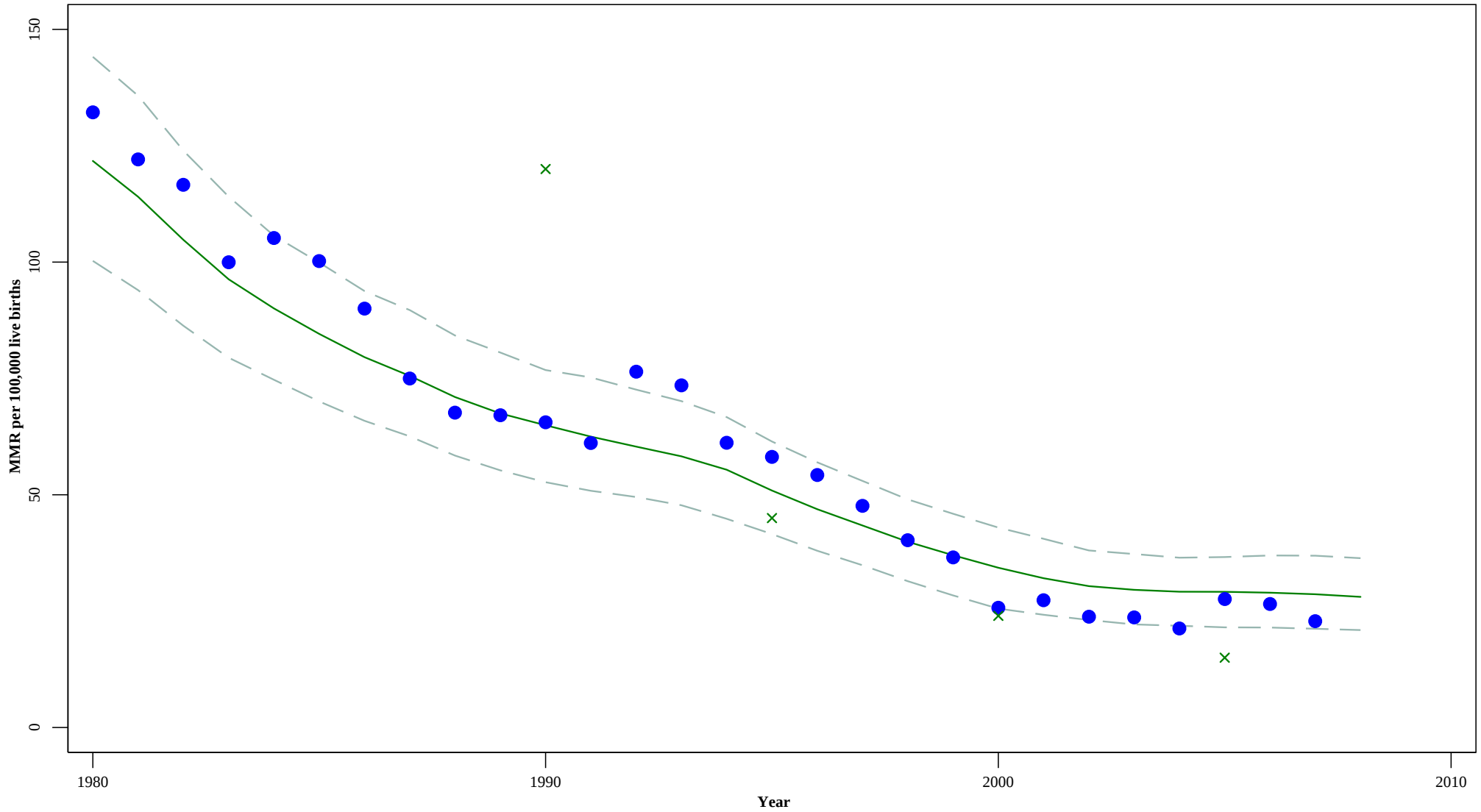
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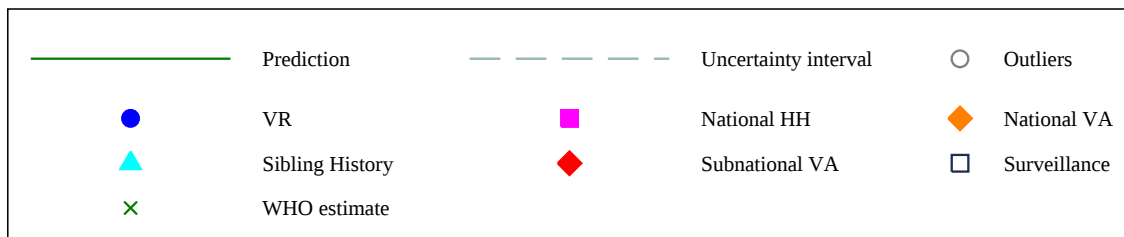
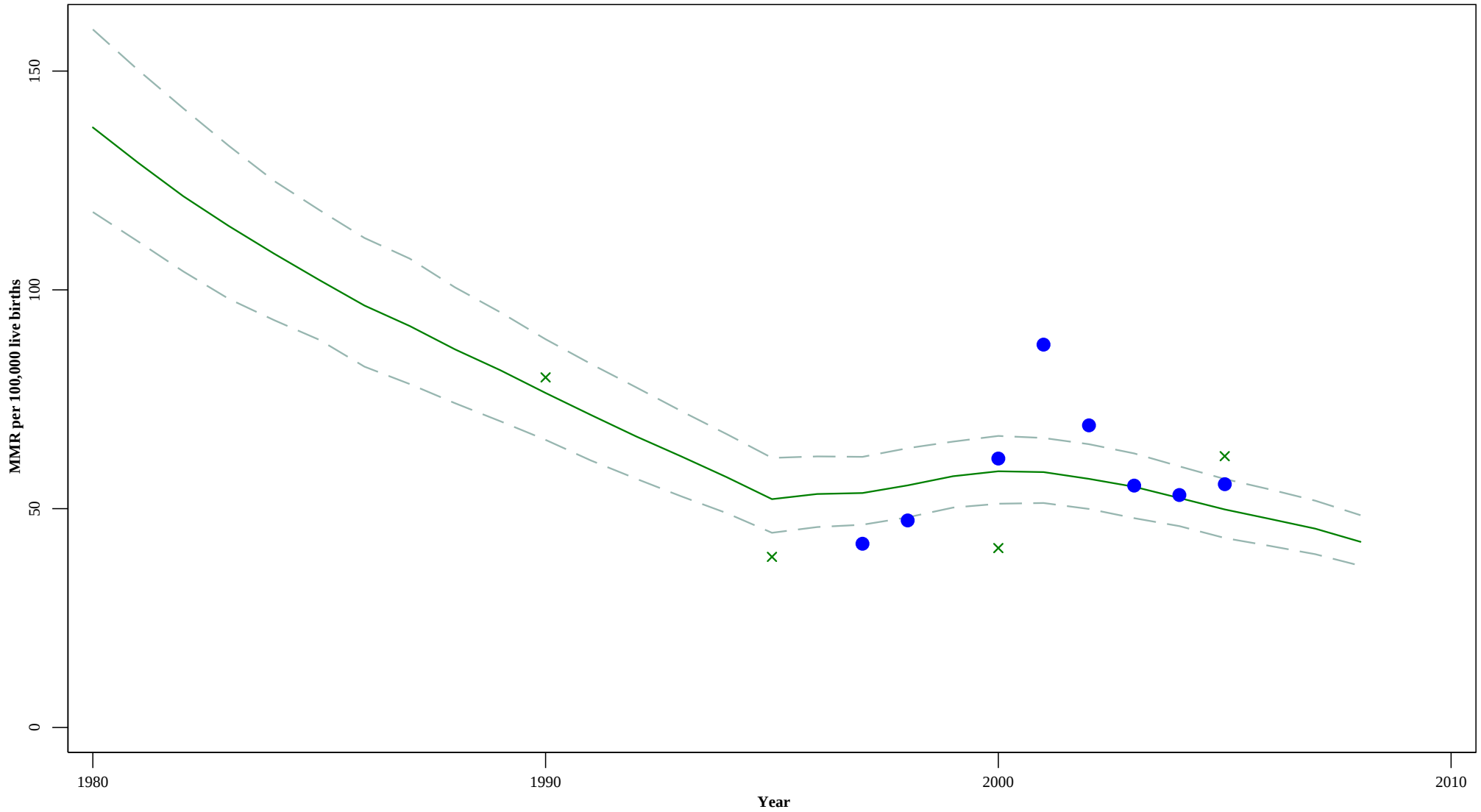
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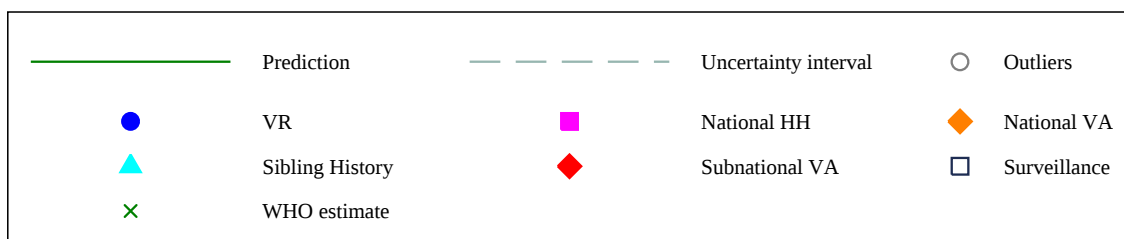
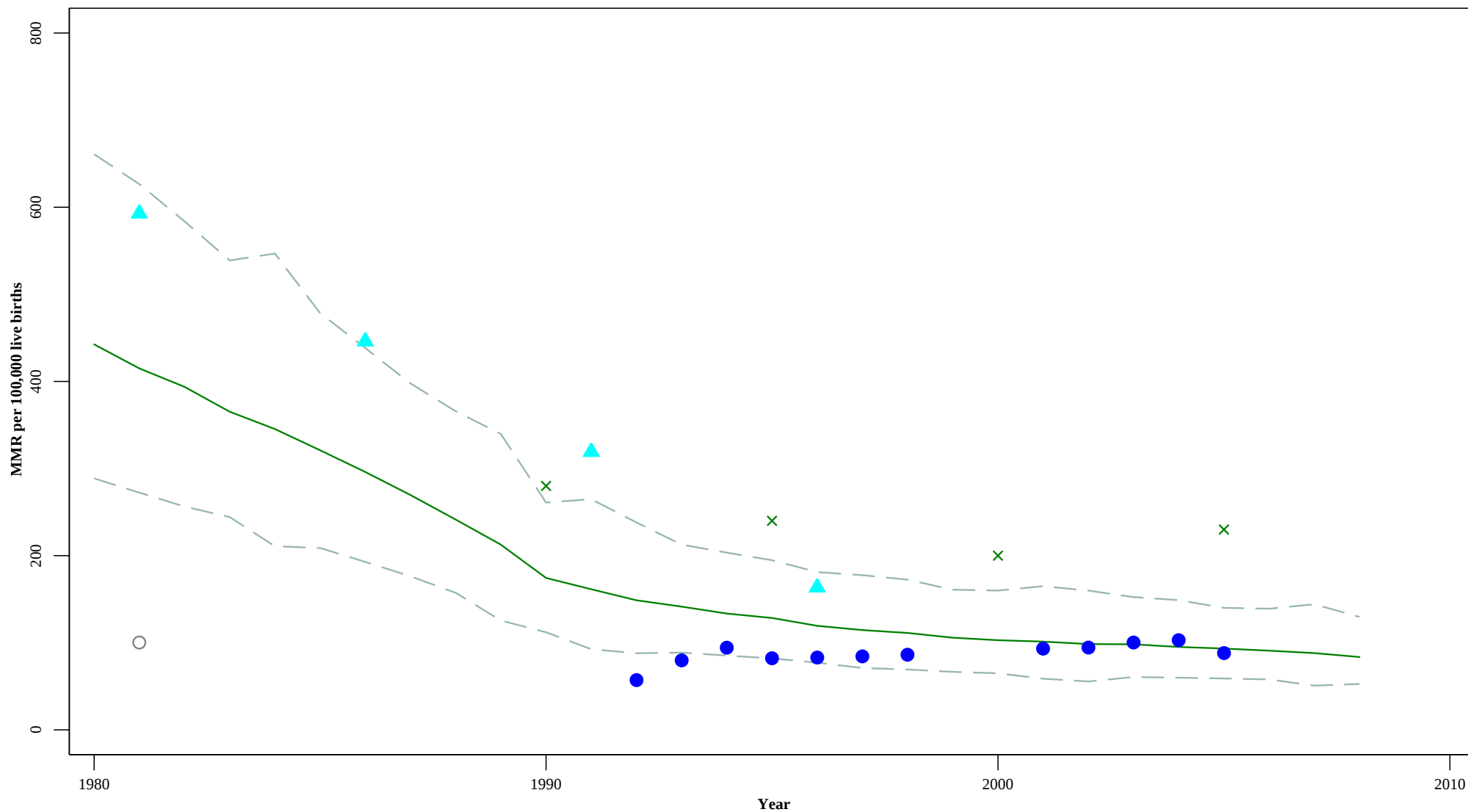
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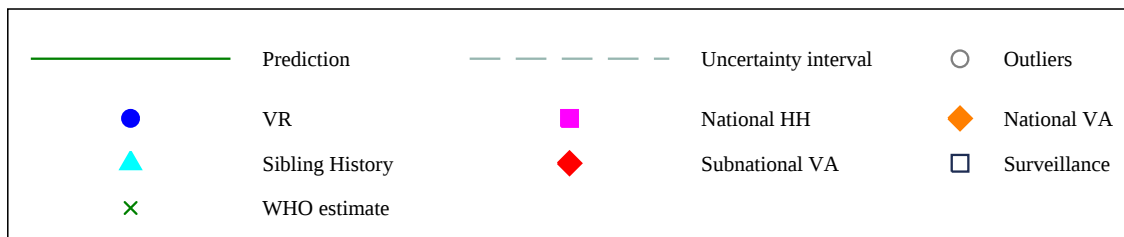
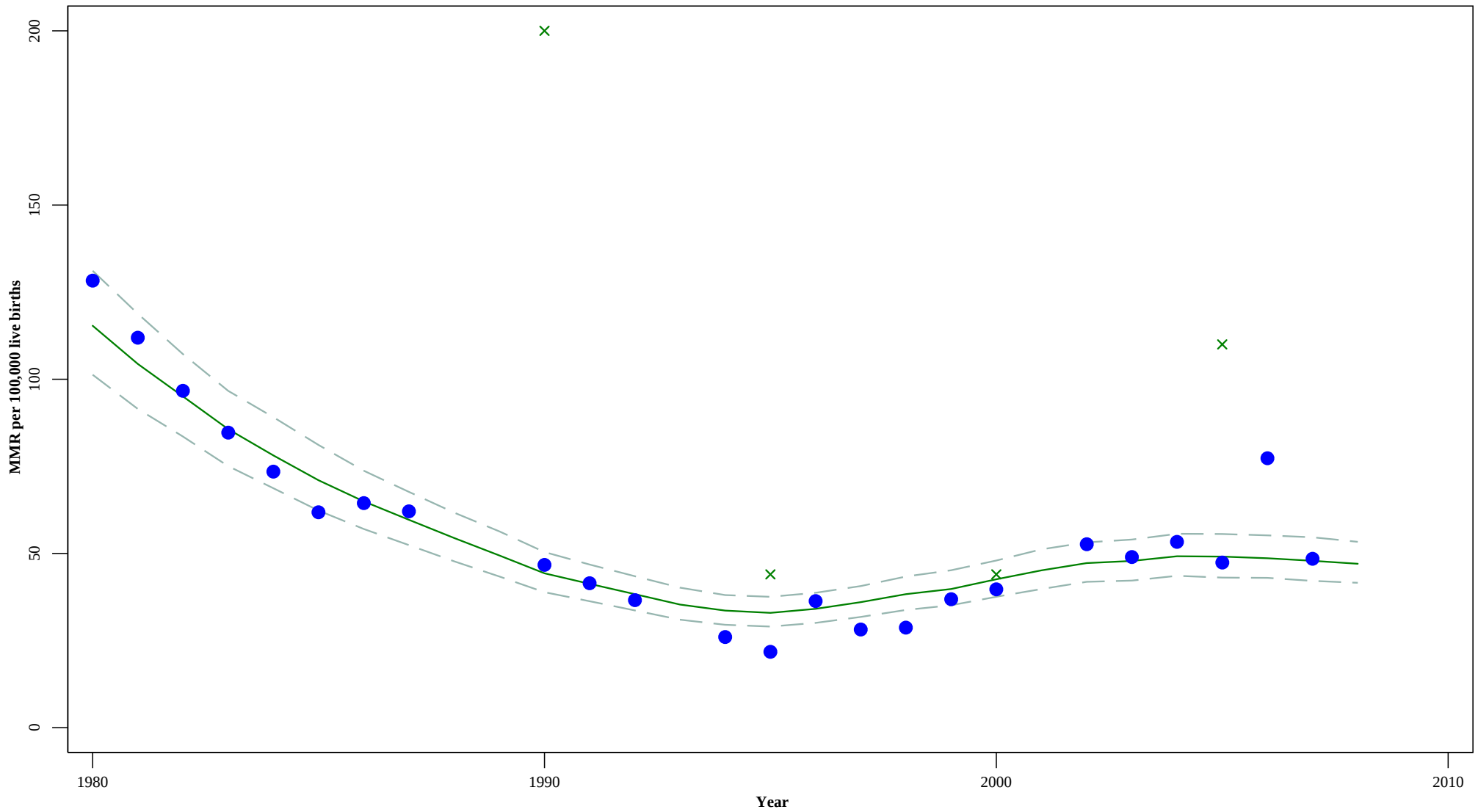
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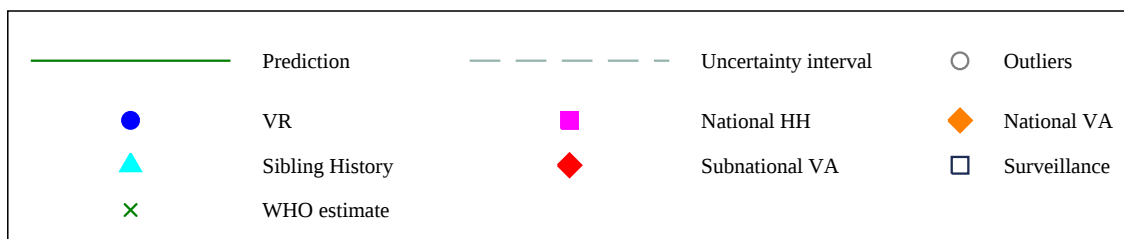
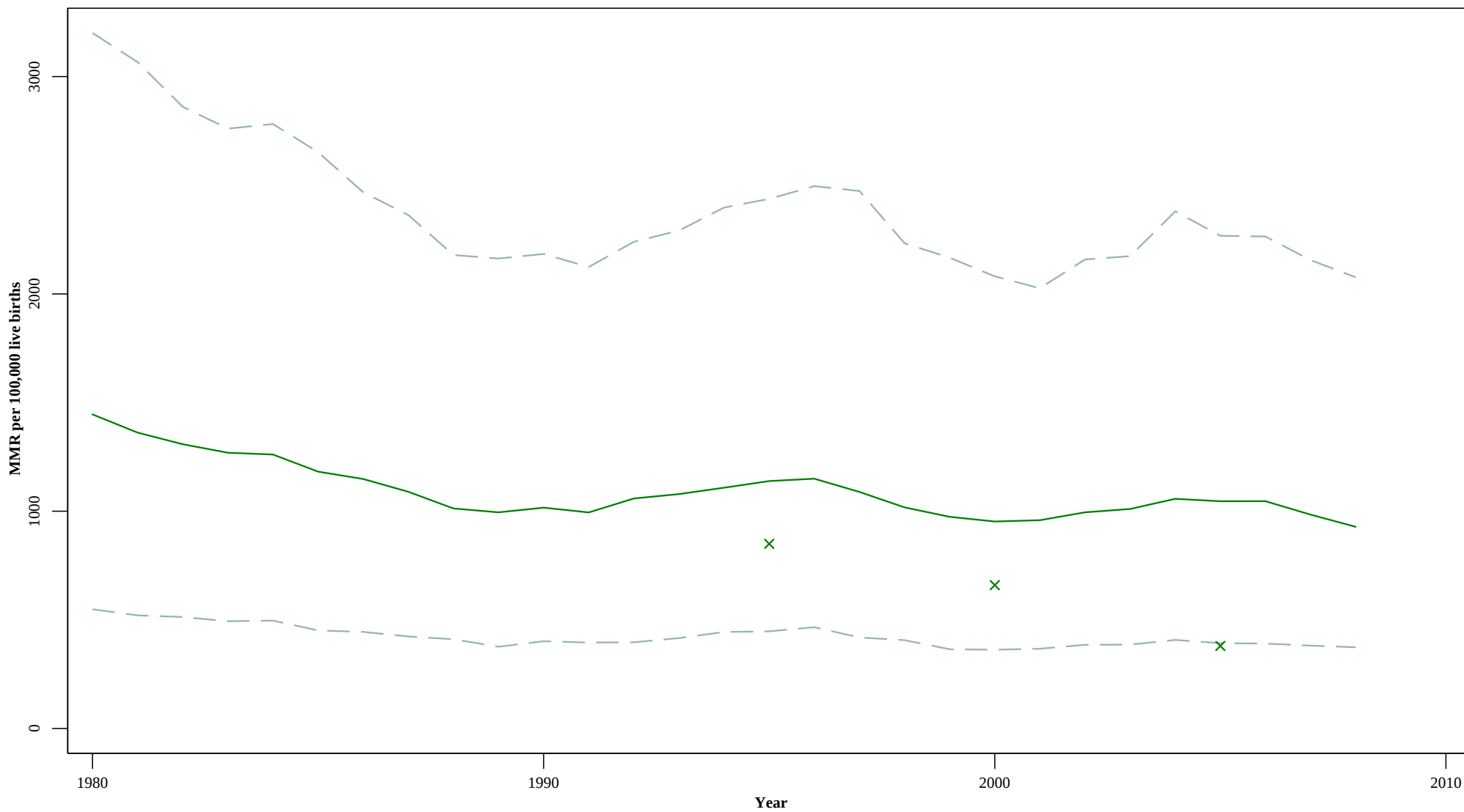
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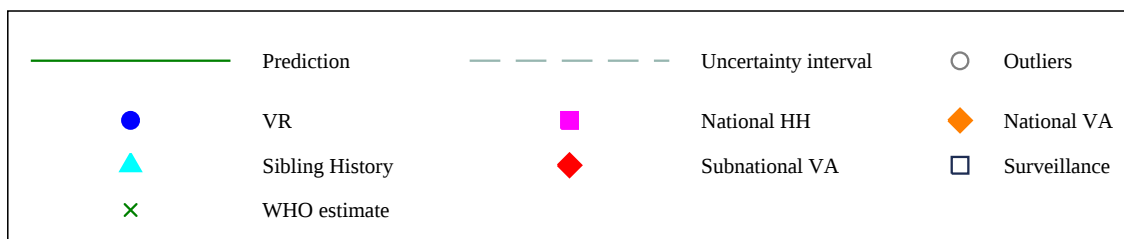
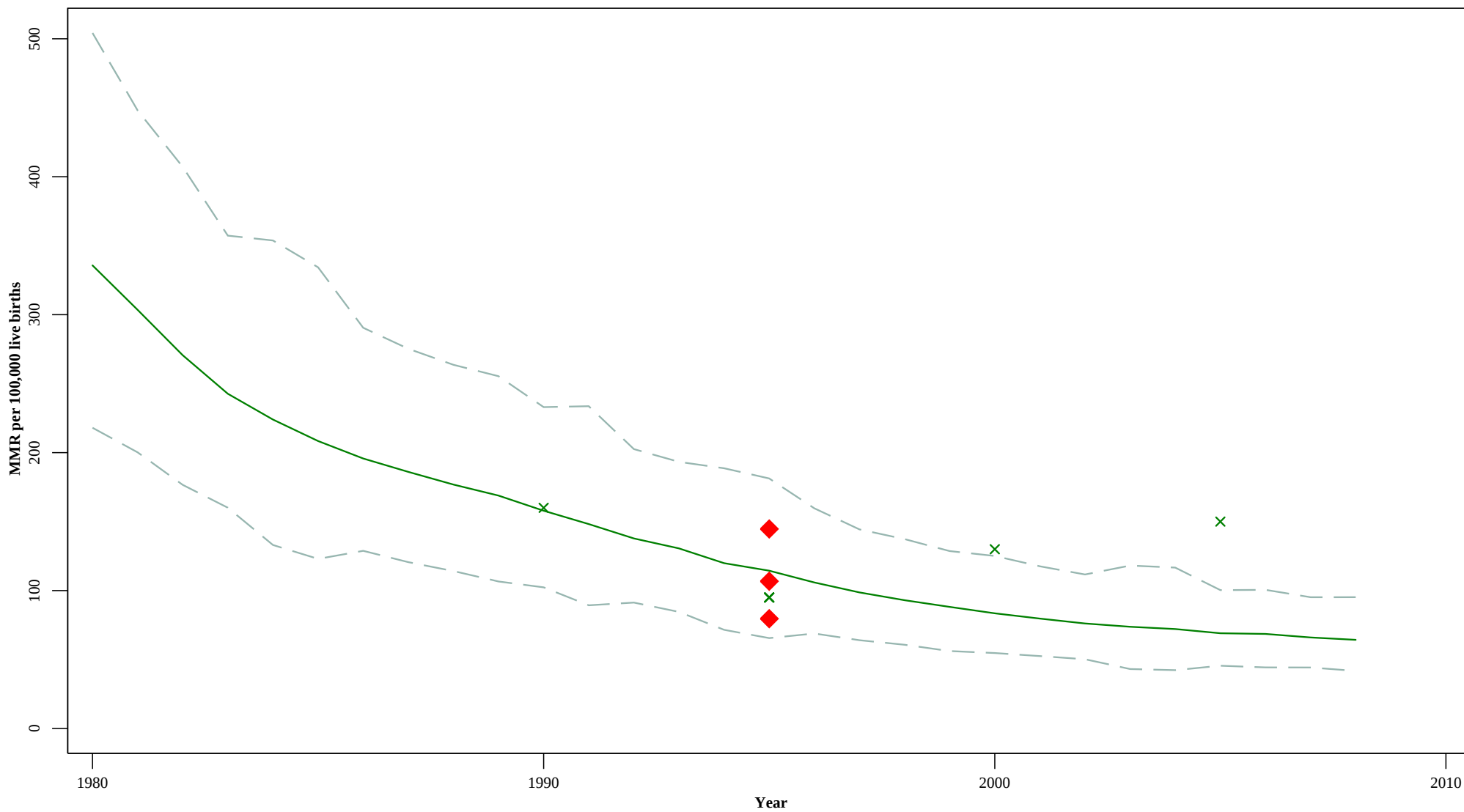
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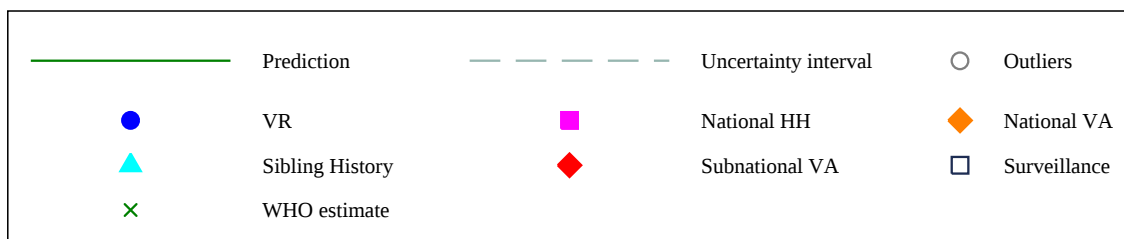
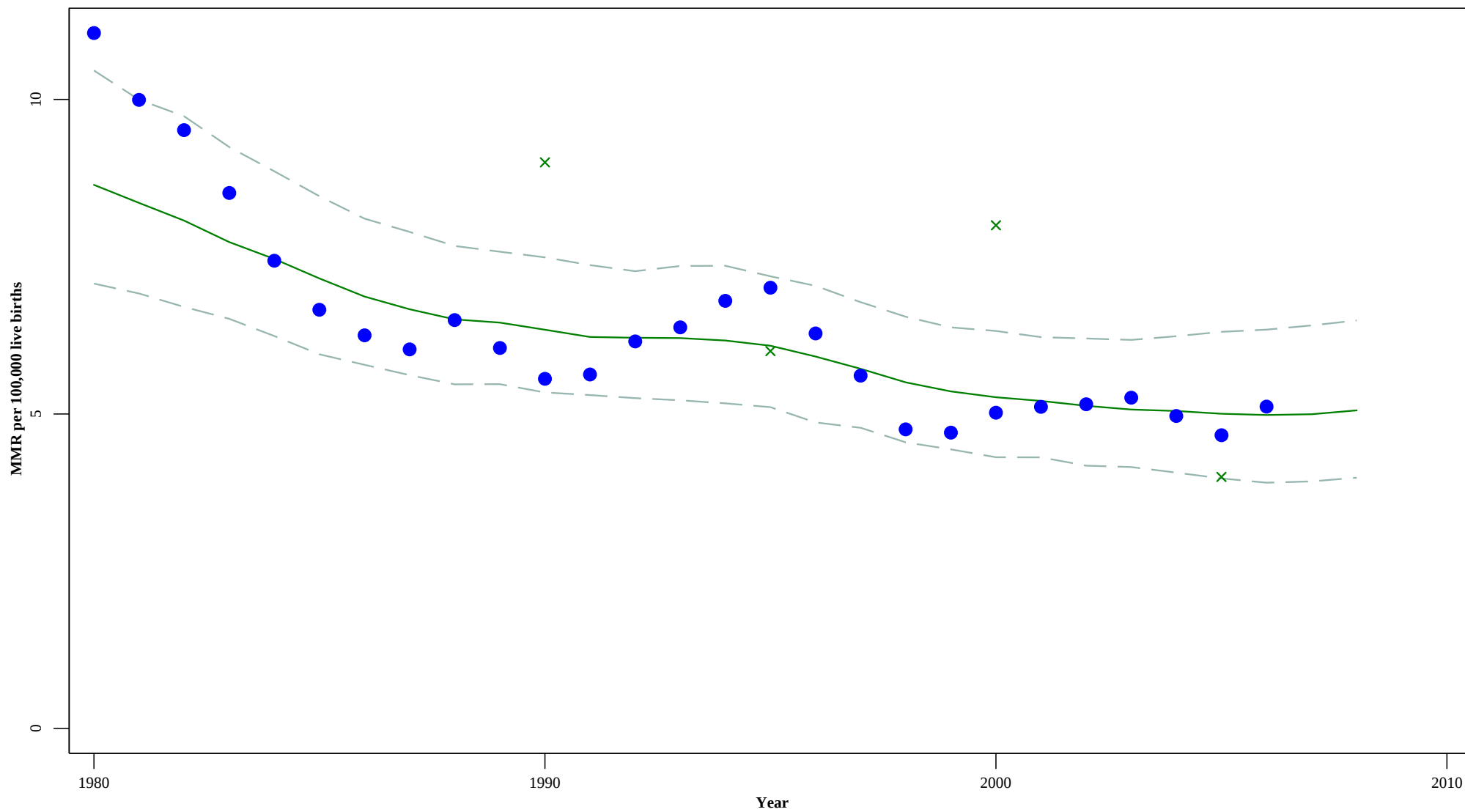
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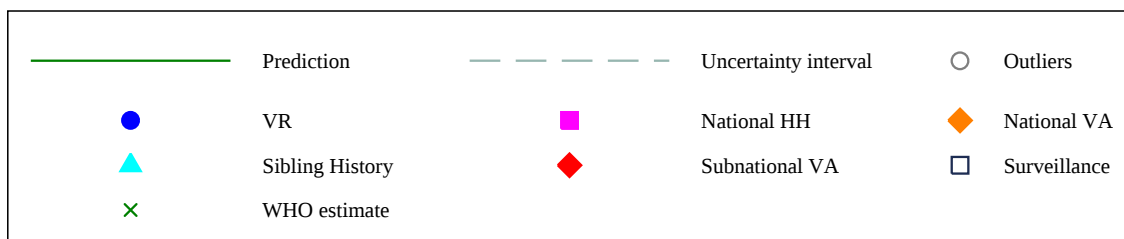
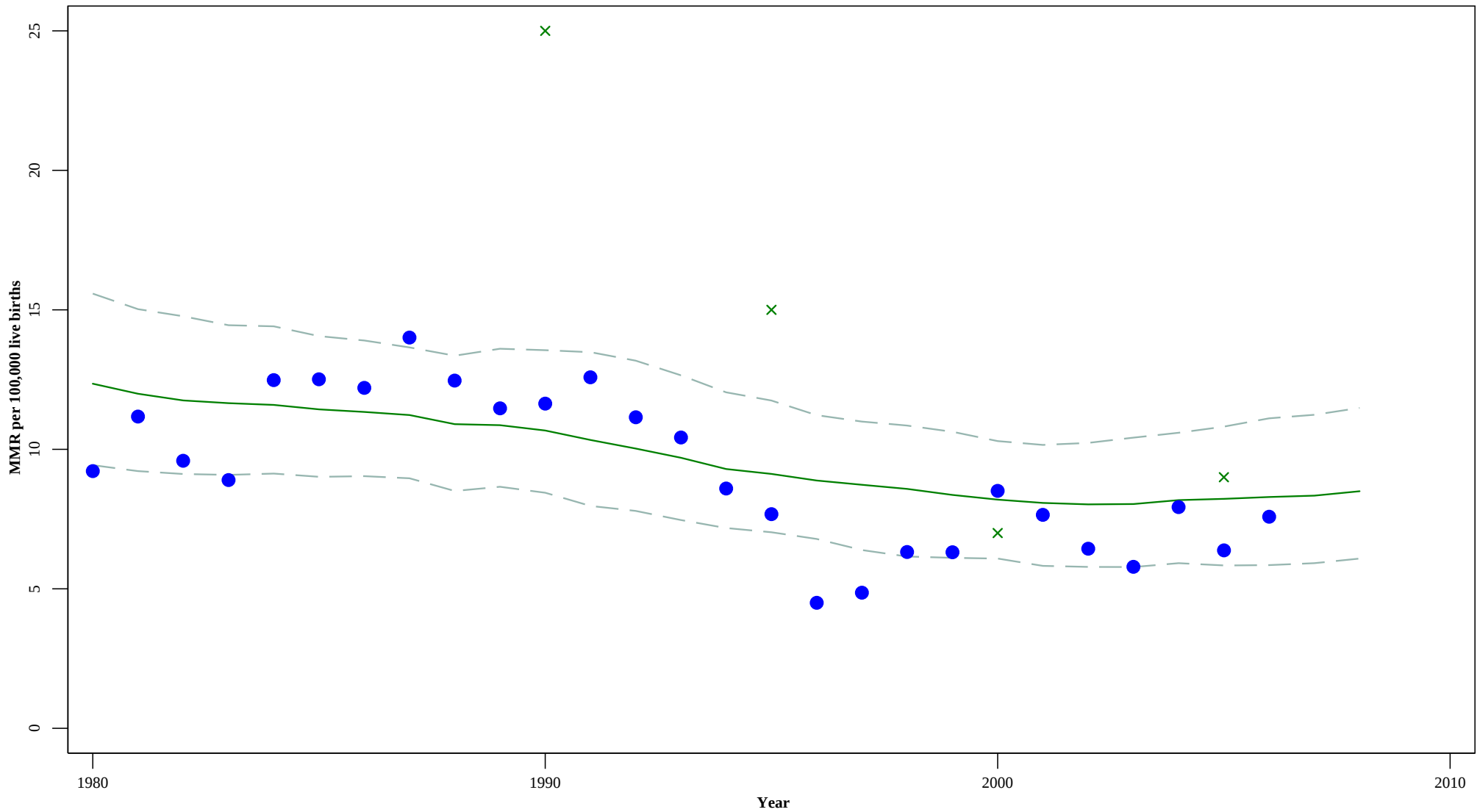
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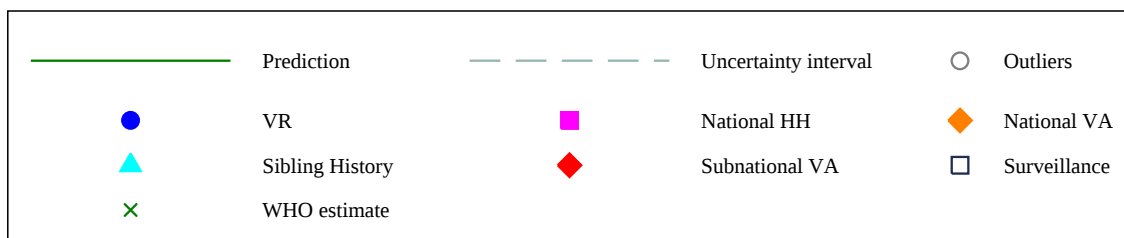
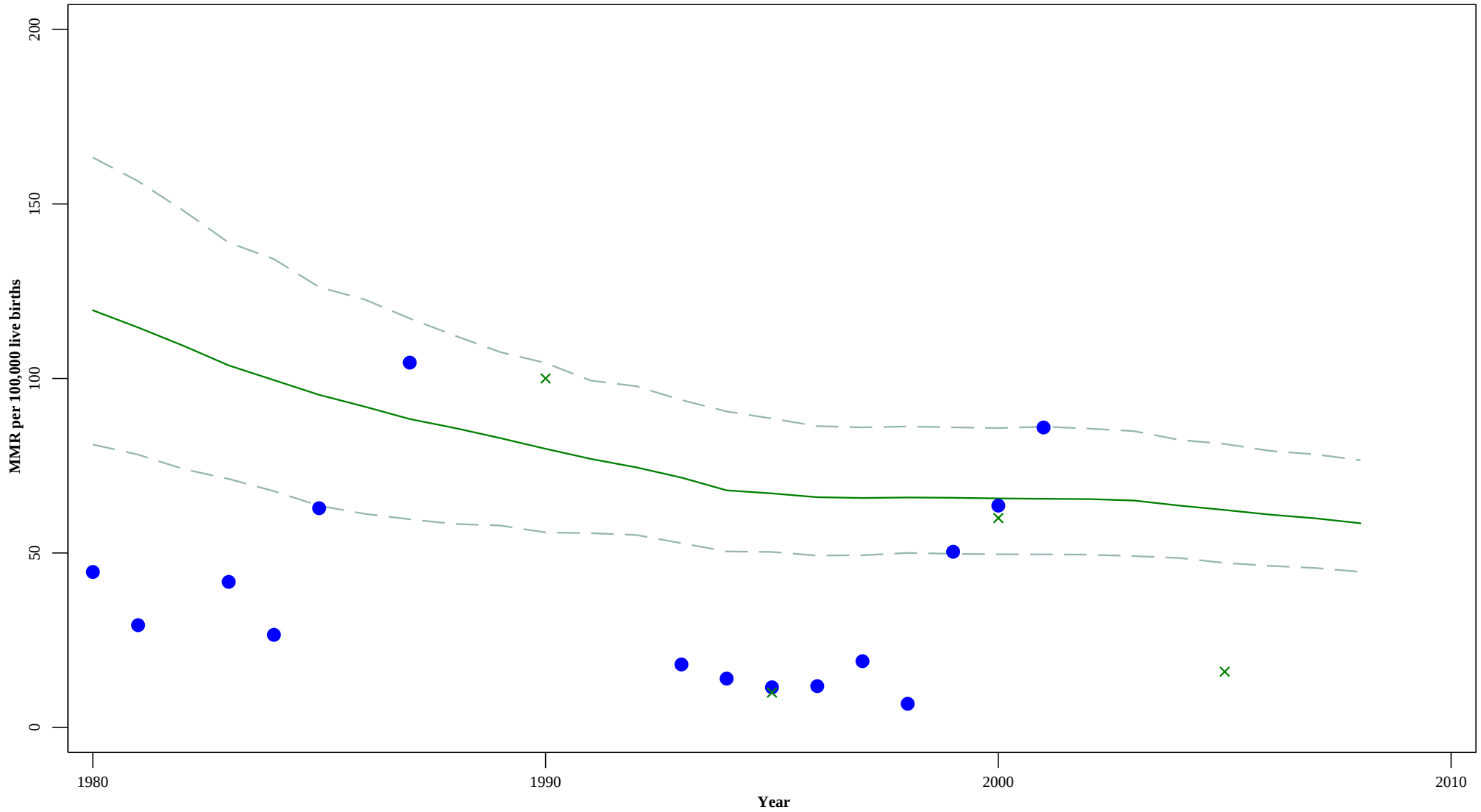
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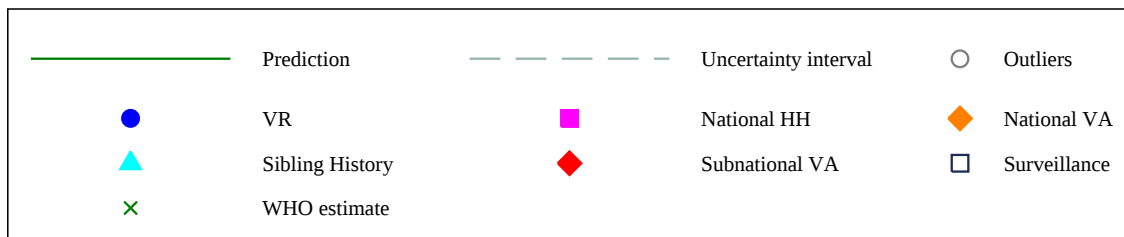
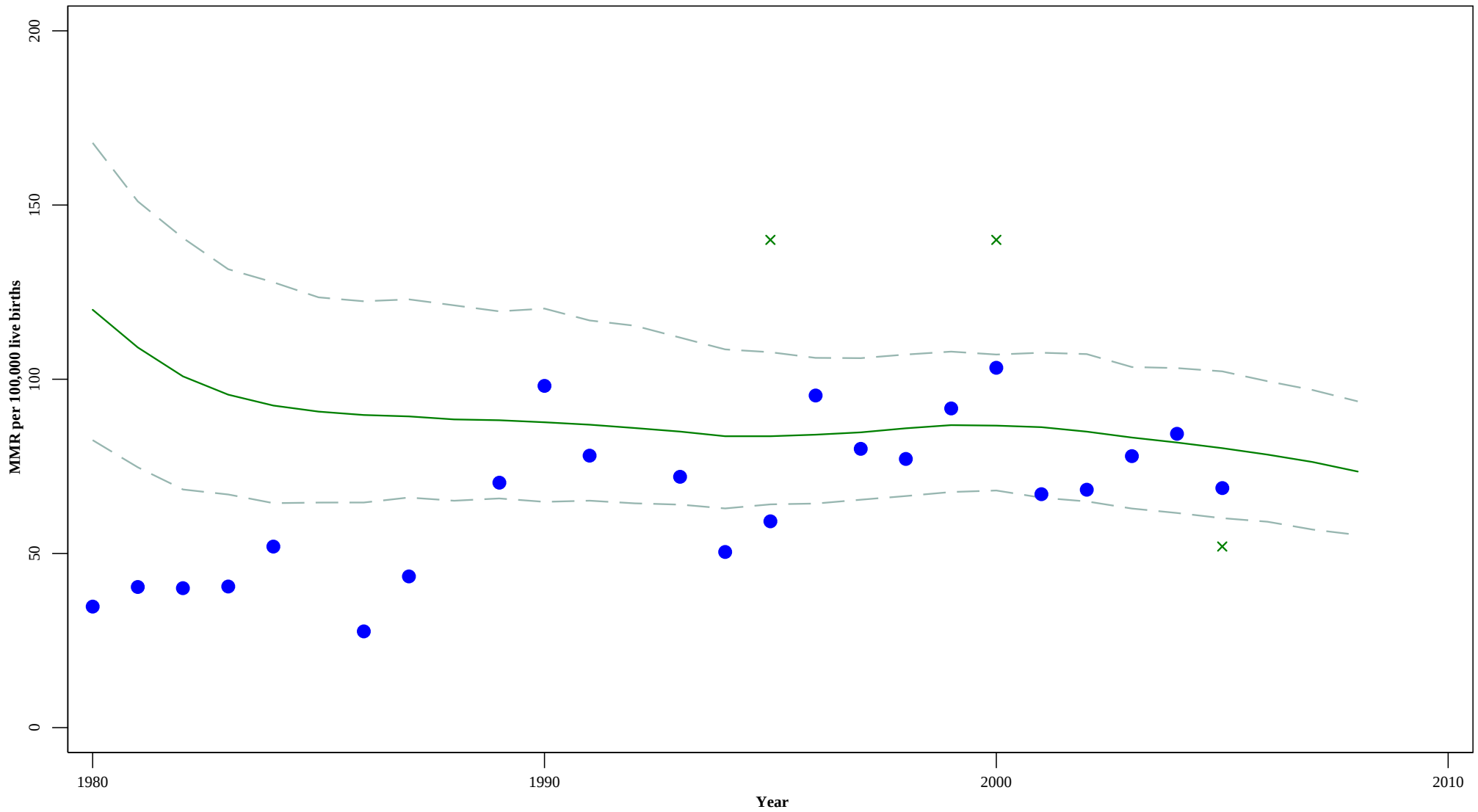
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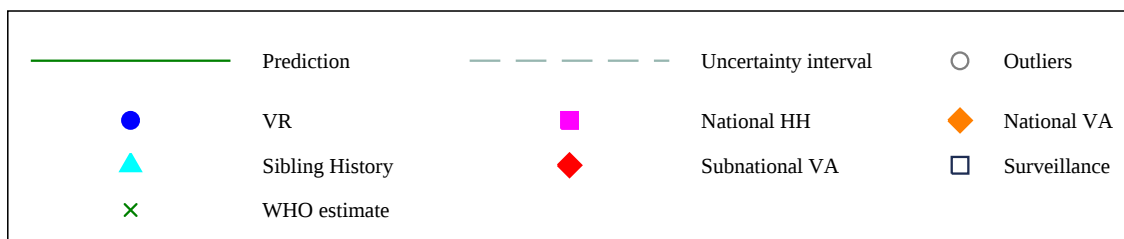
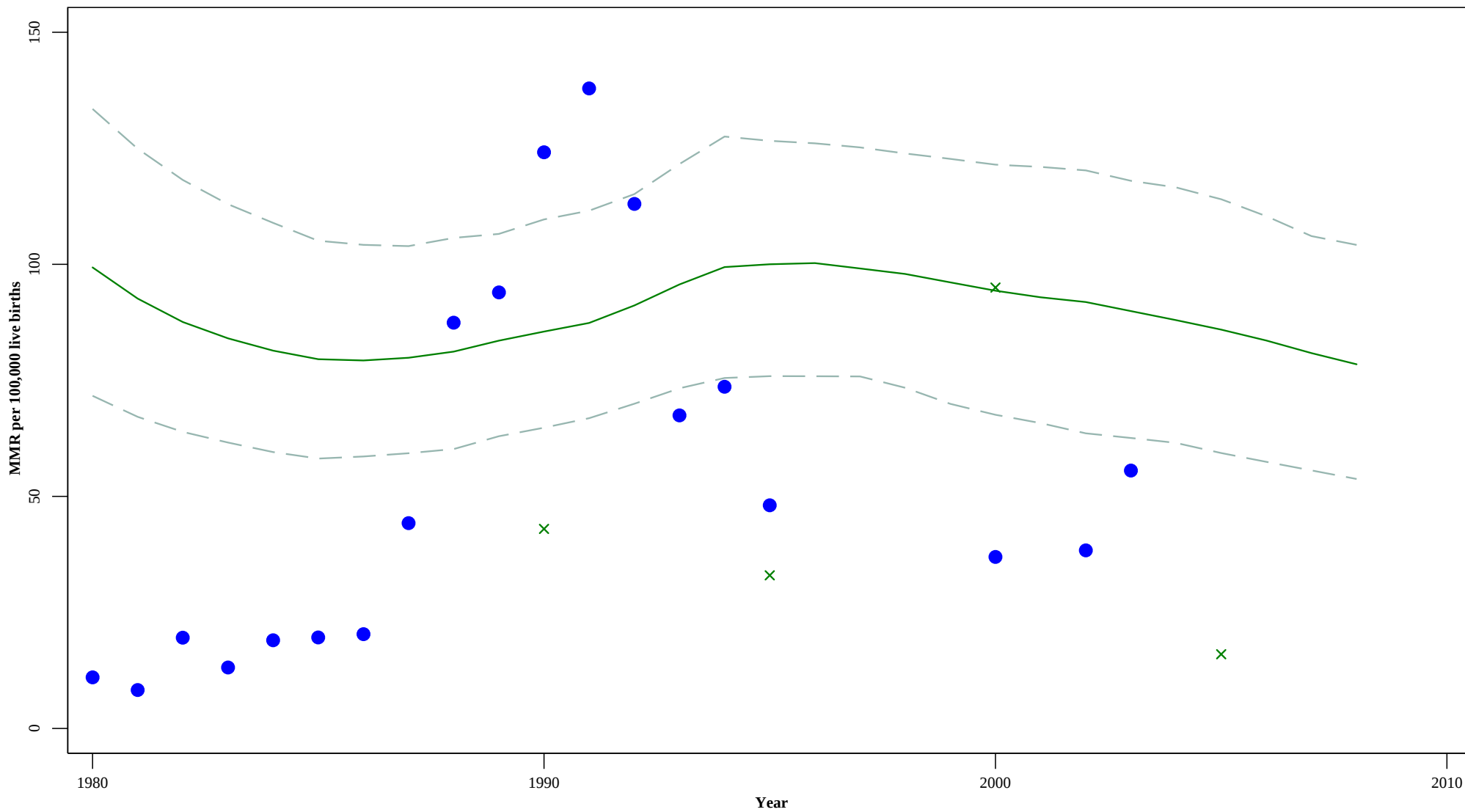
Bahamas



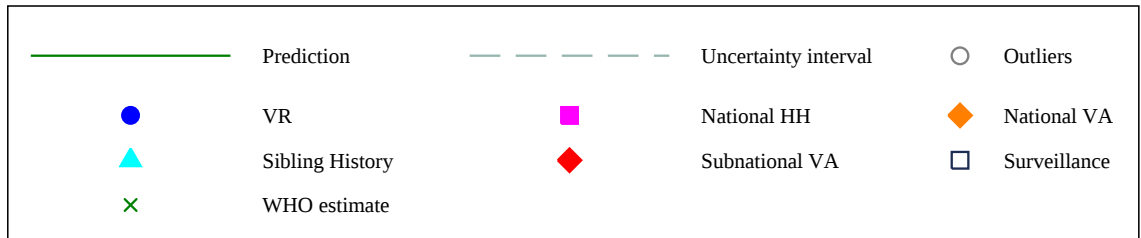
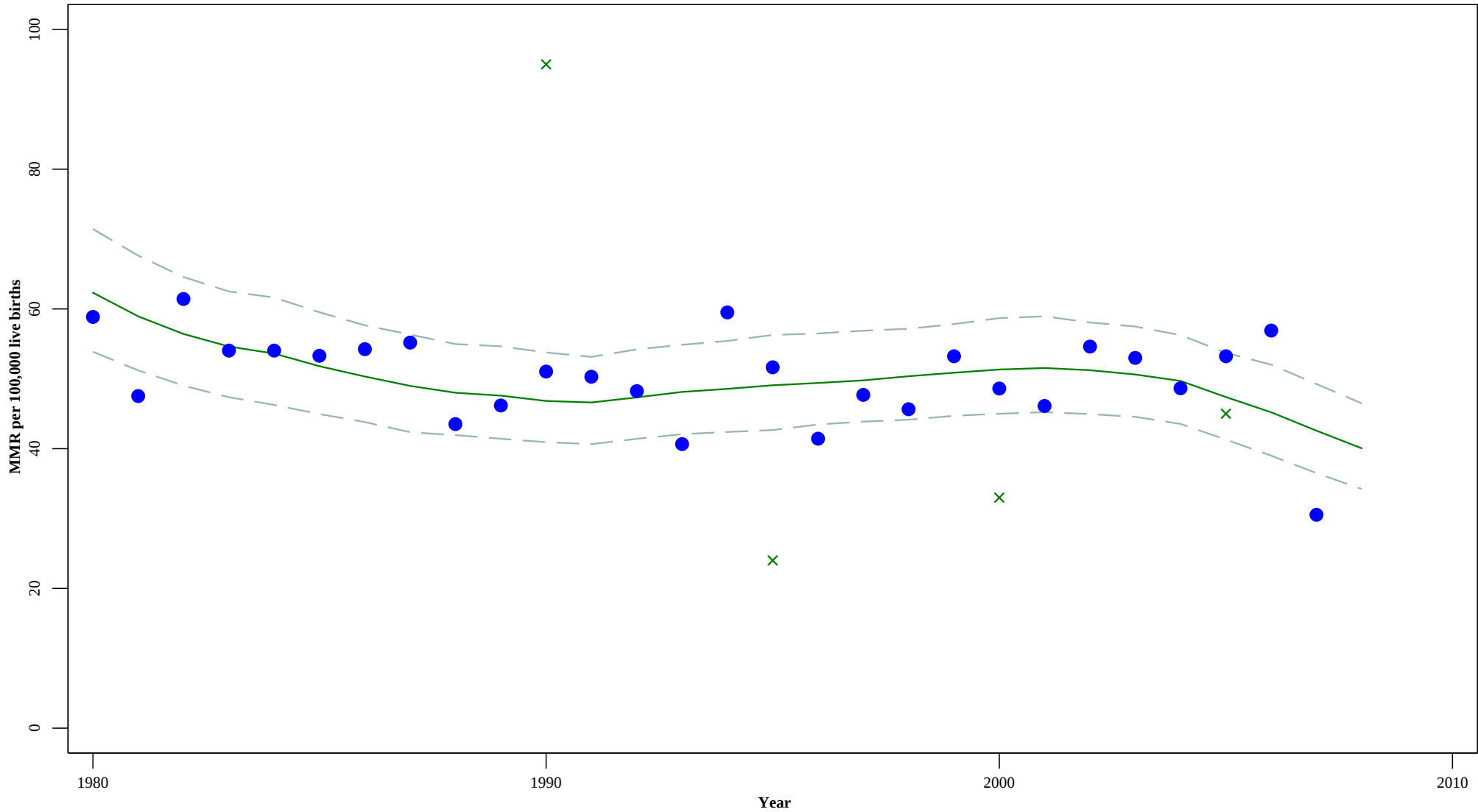
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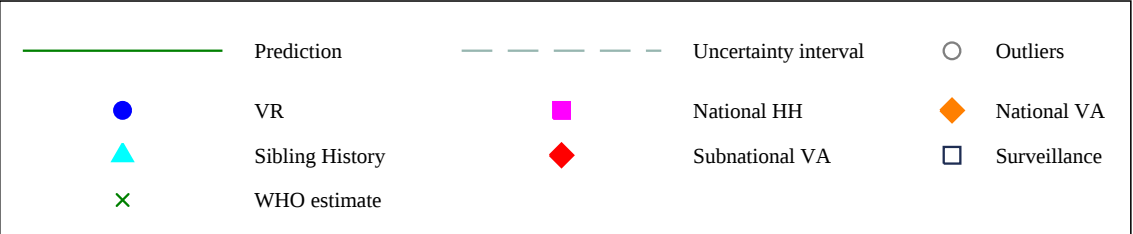
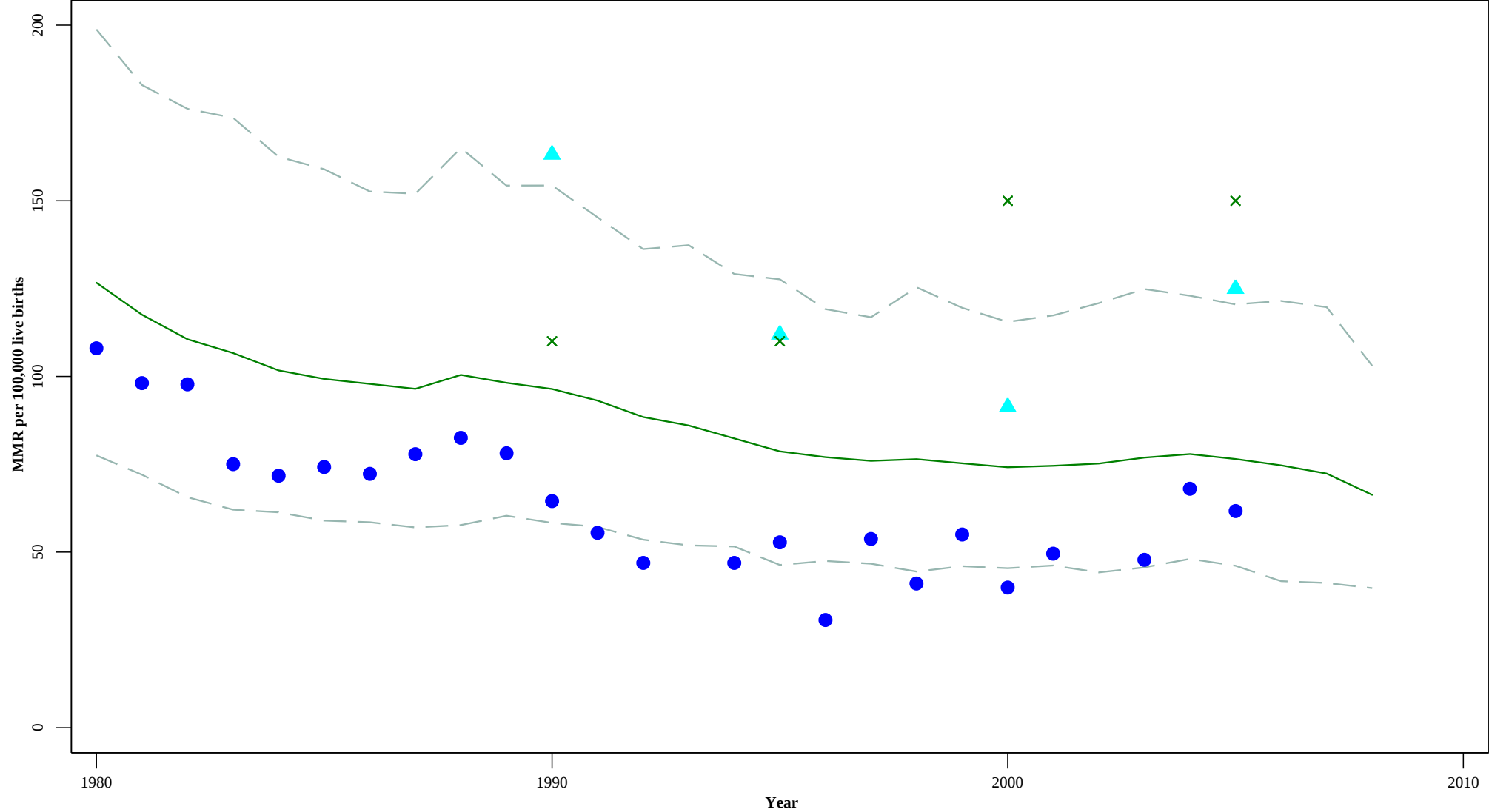
Barbados



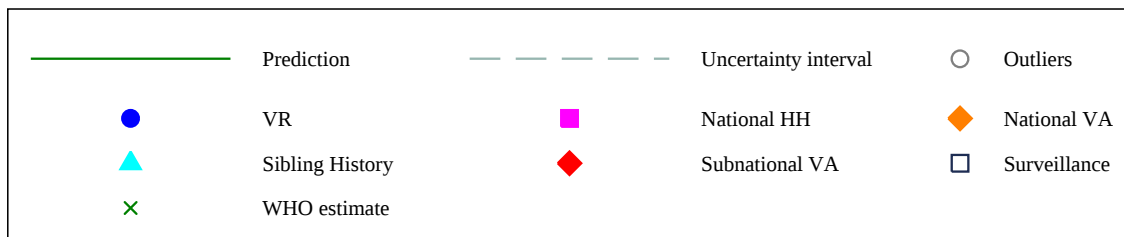
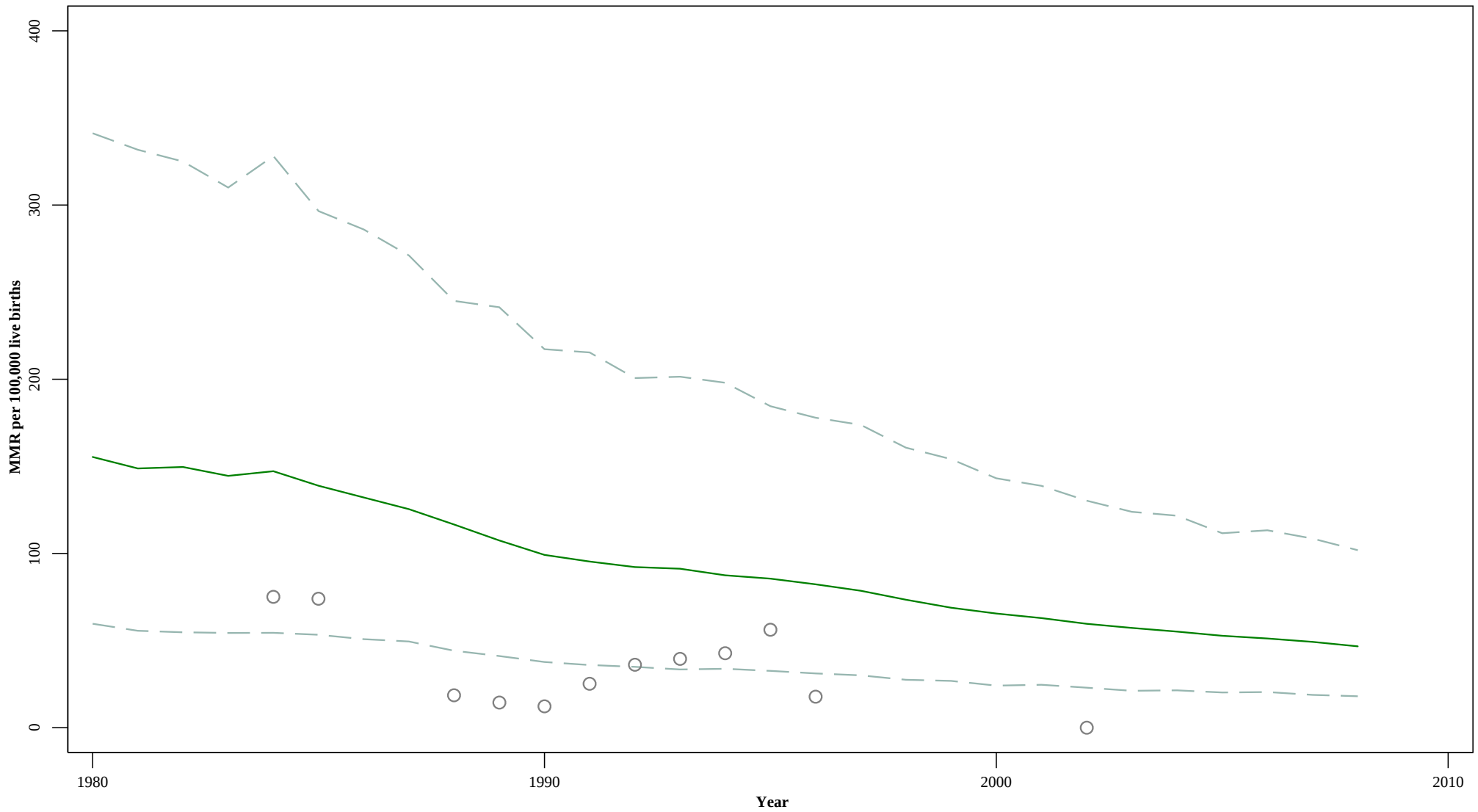
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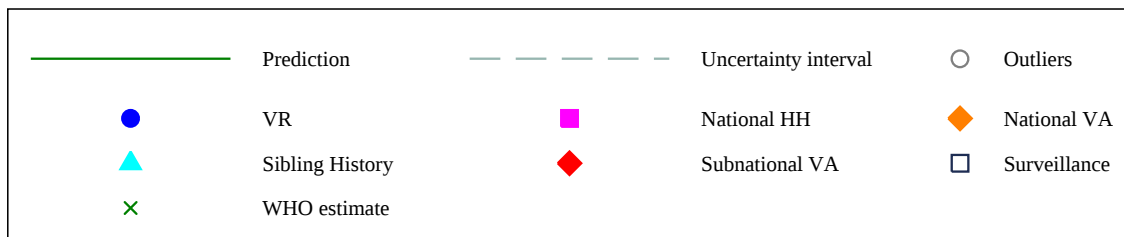
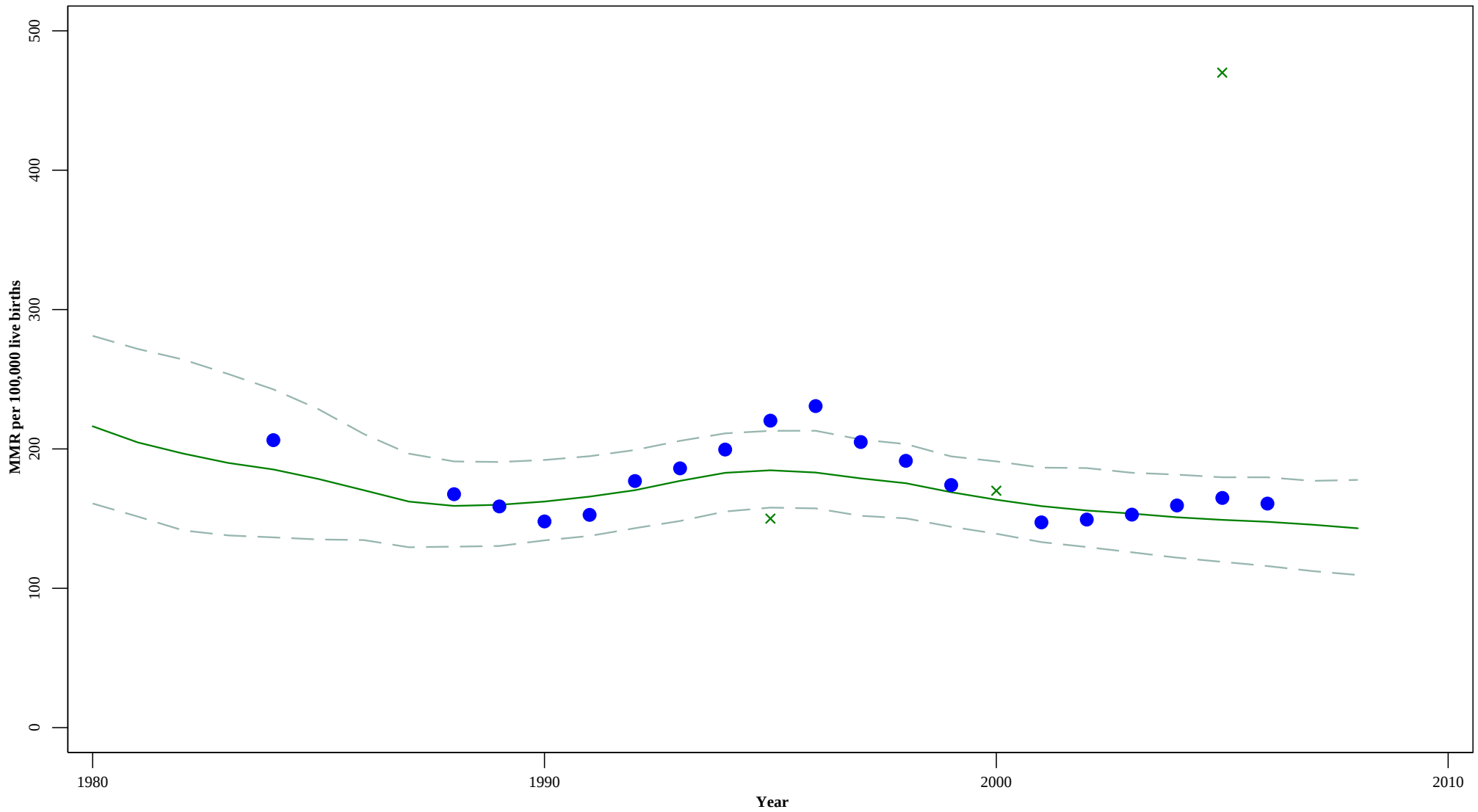
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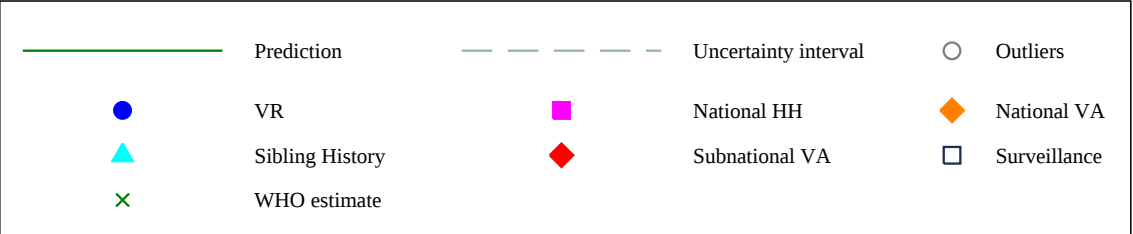
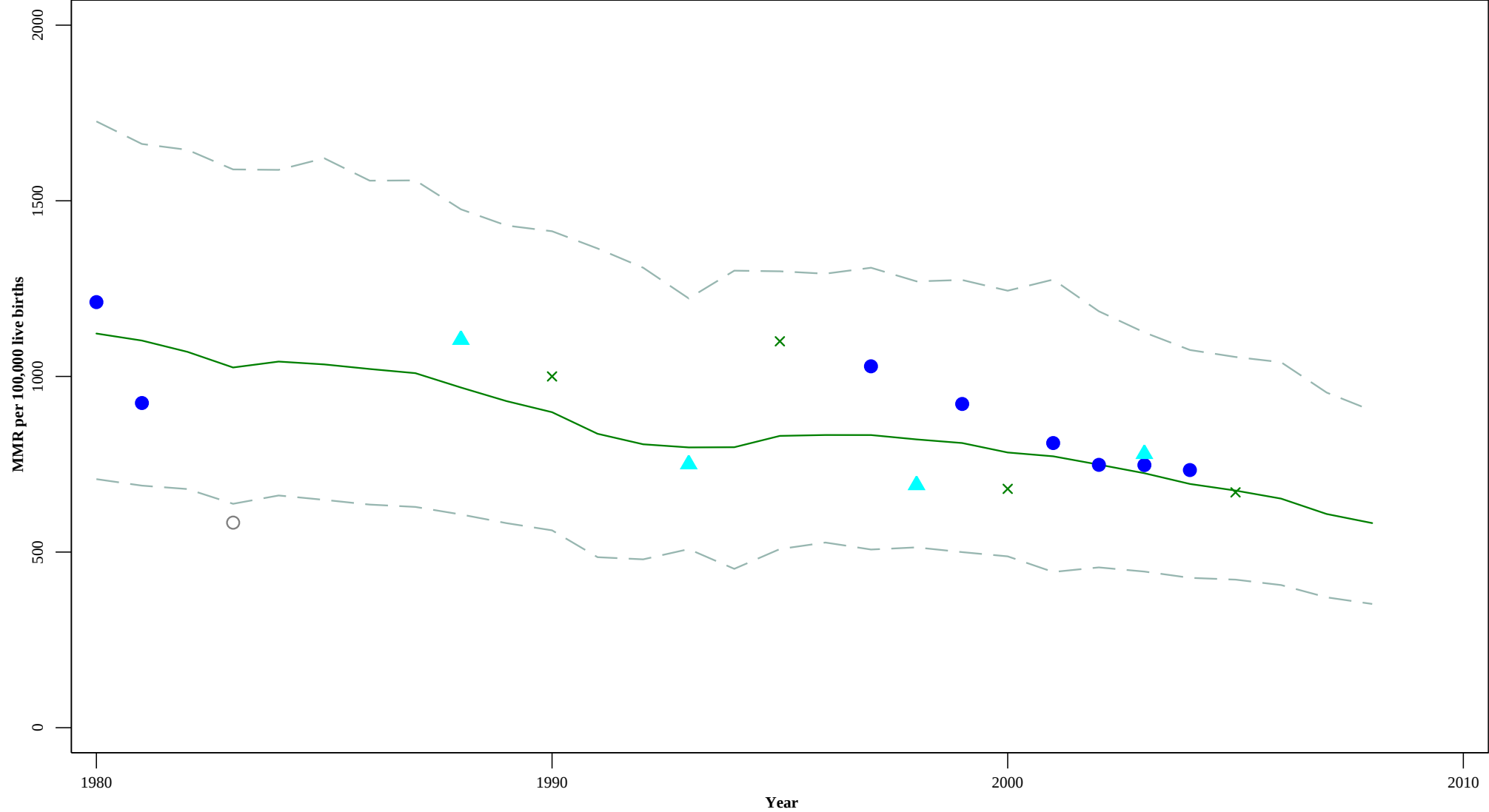
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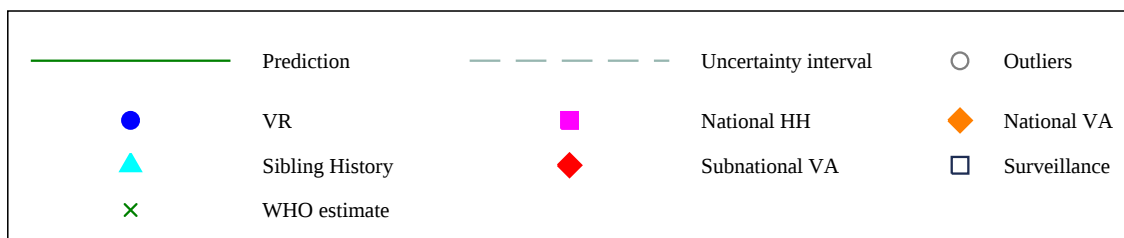
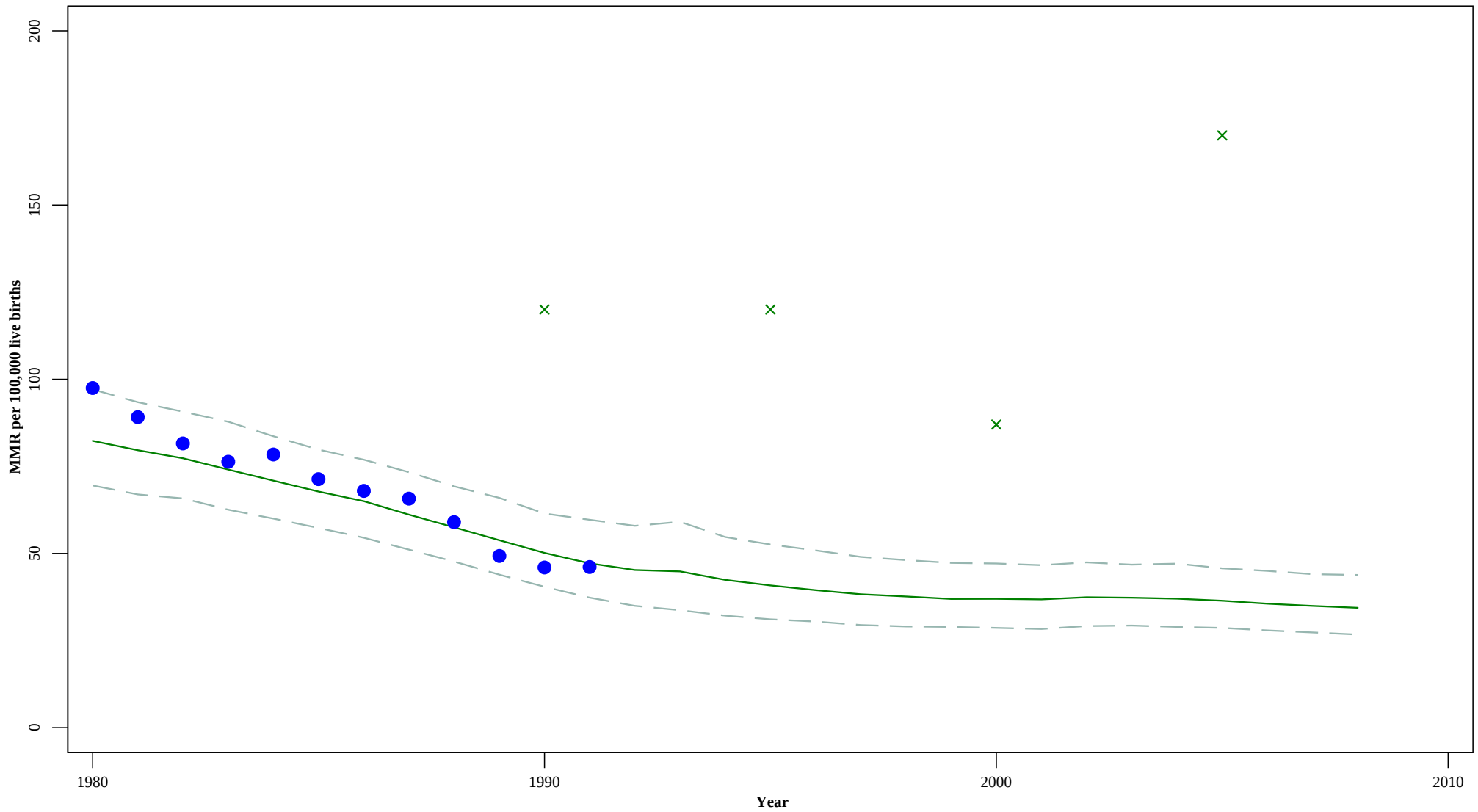
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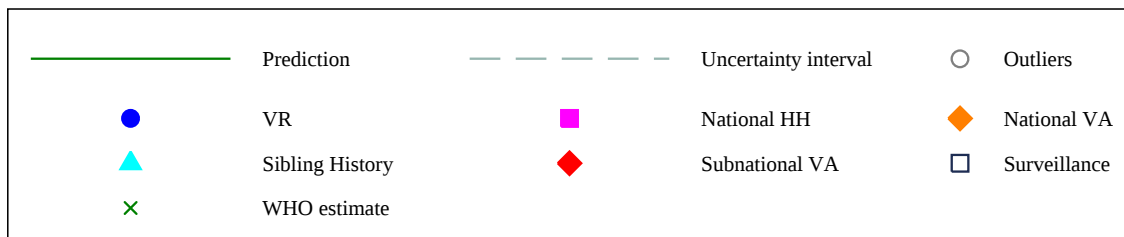
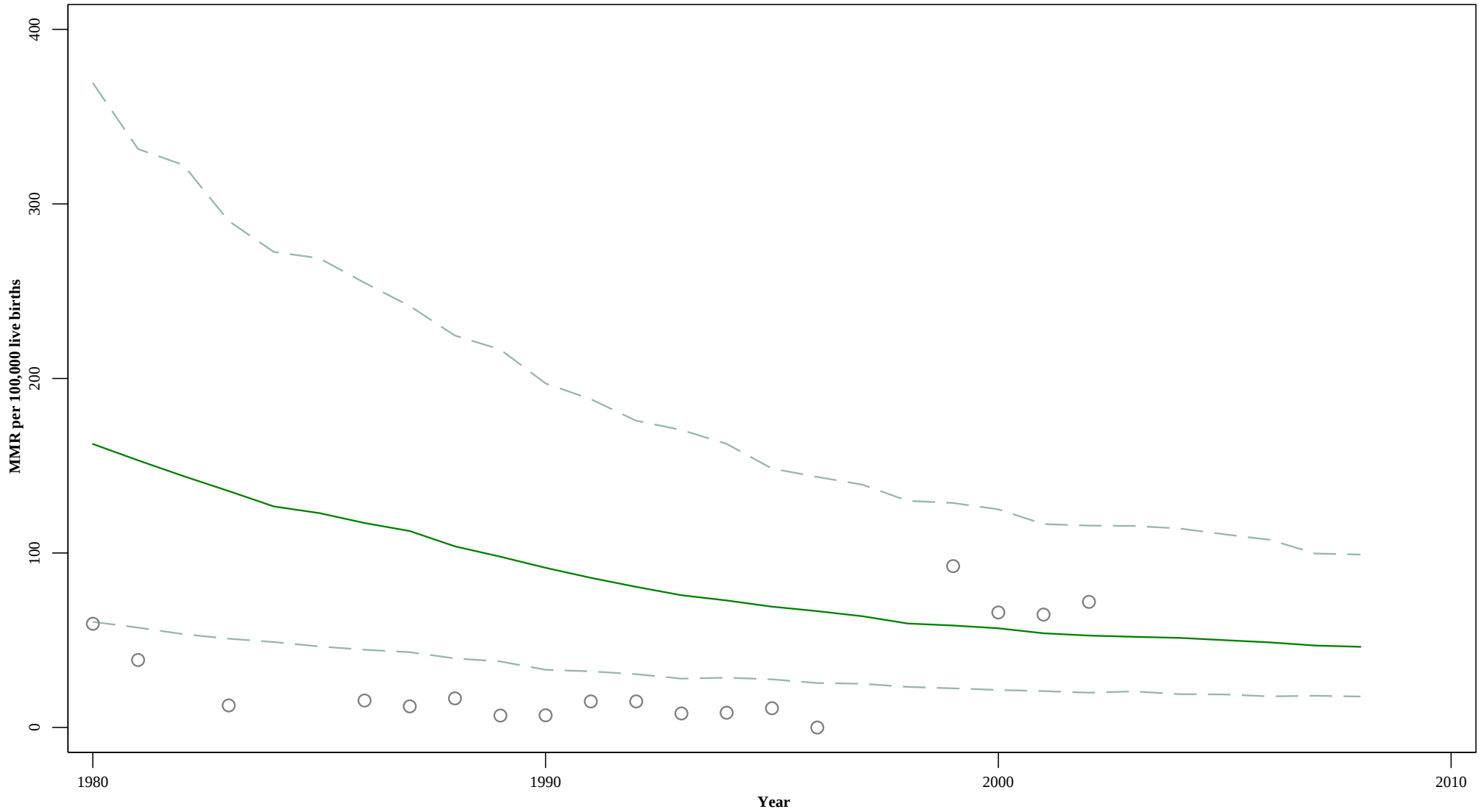
Haiti



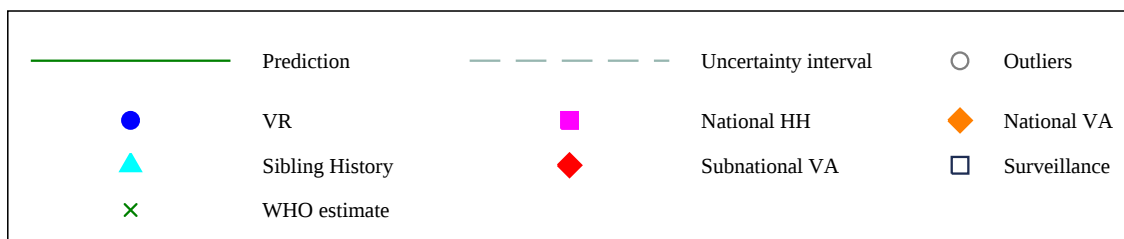
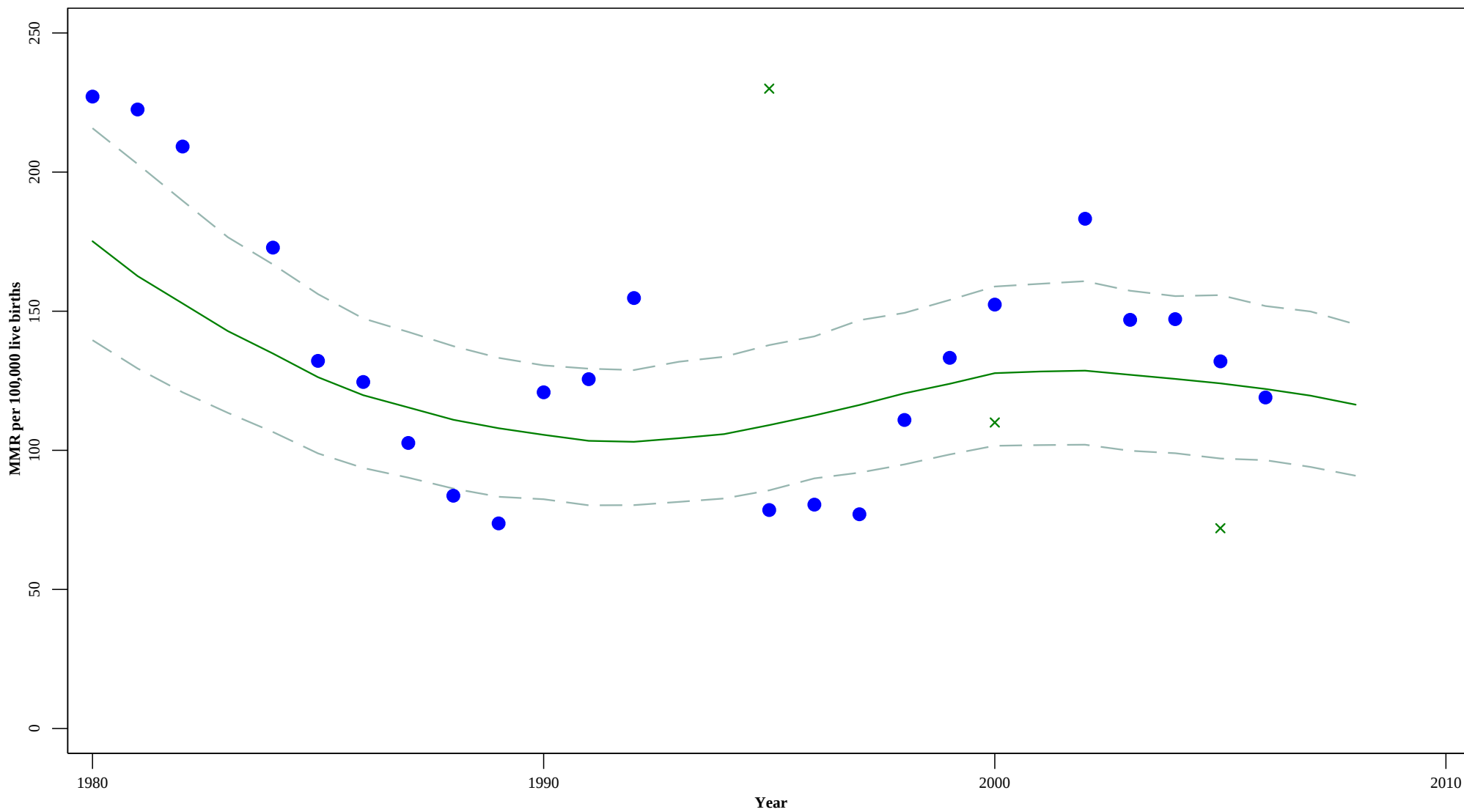
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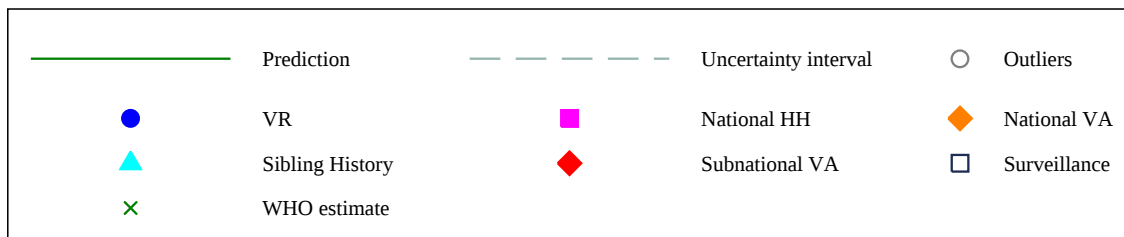
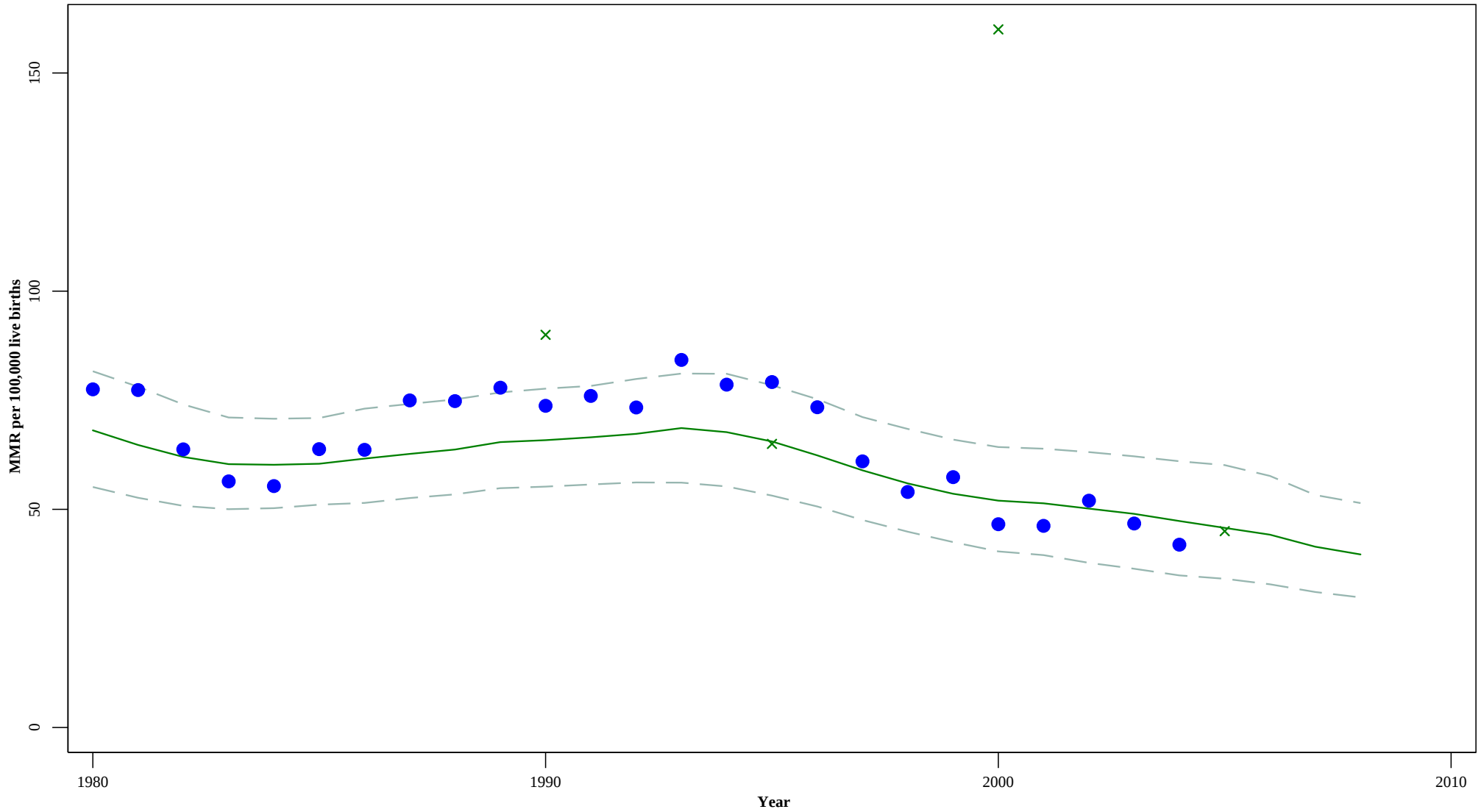
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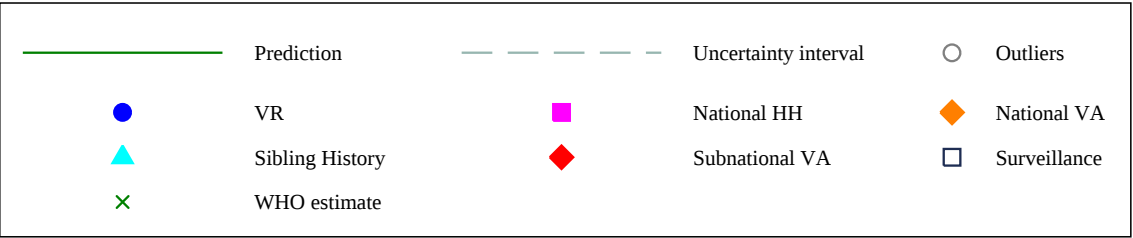
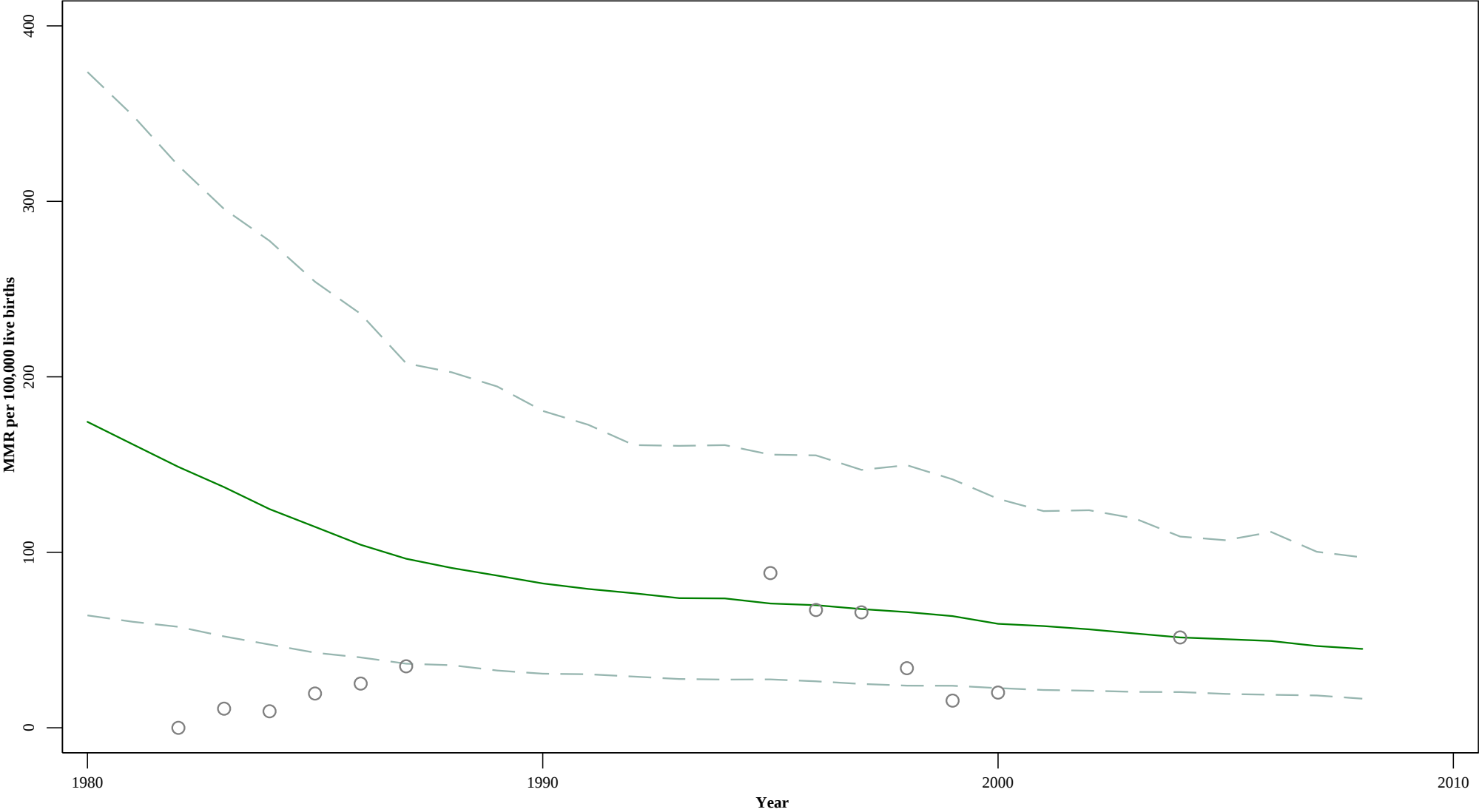
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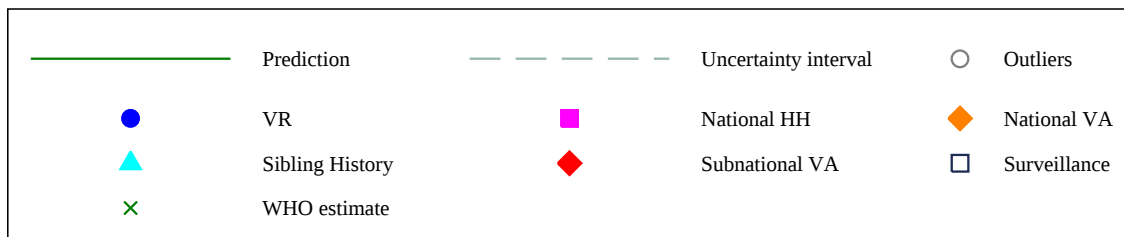
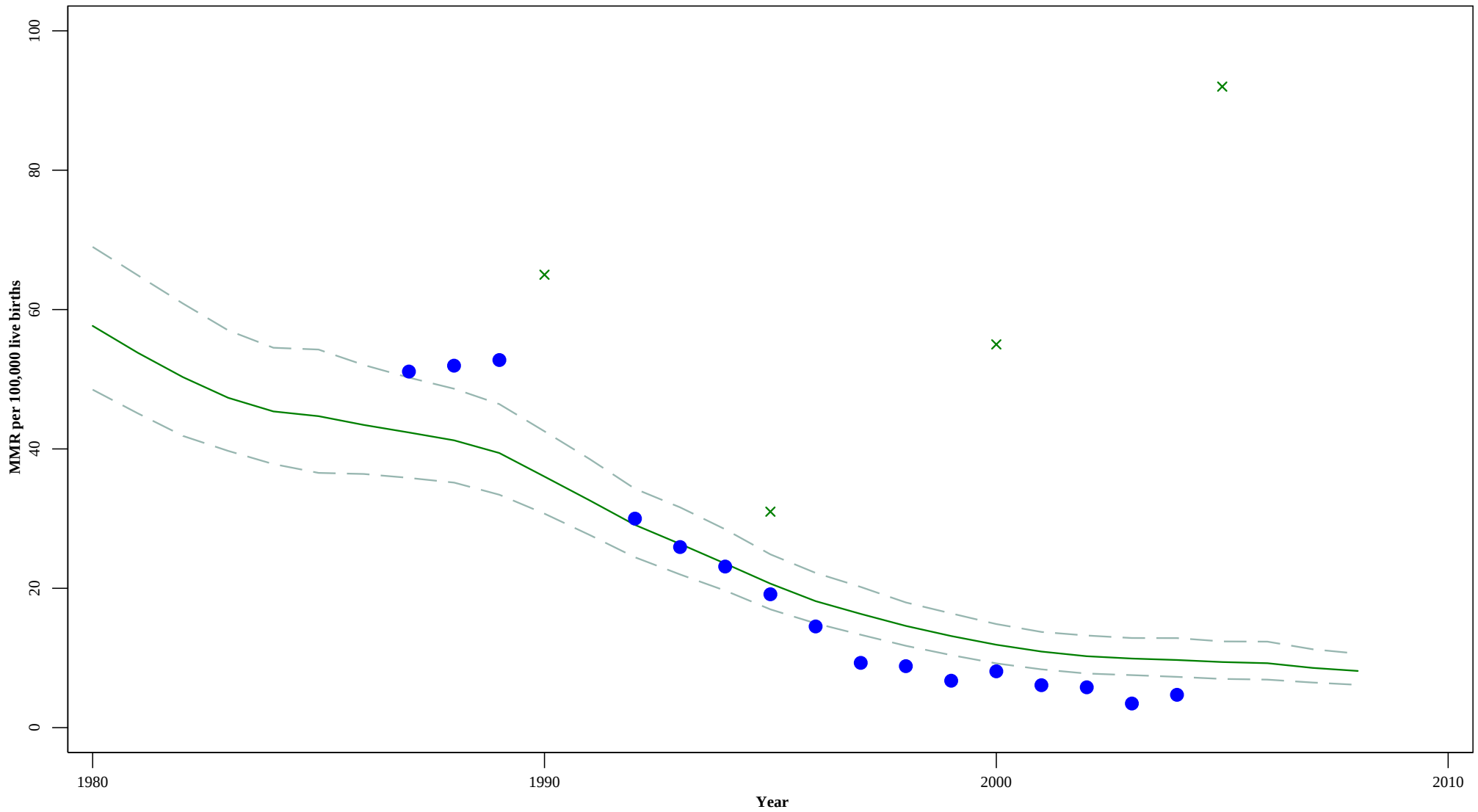
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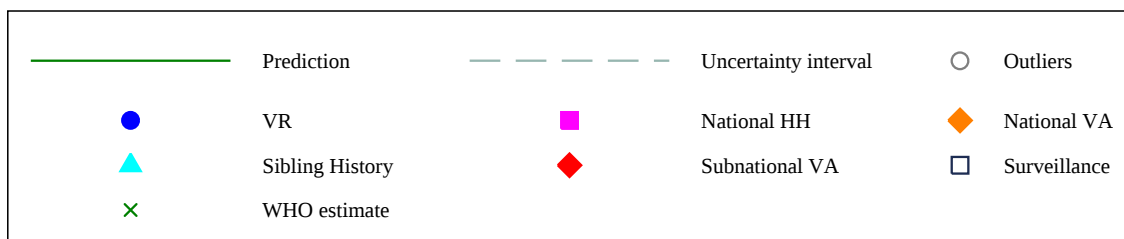
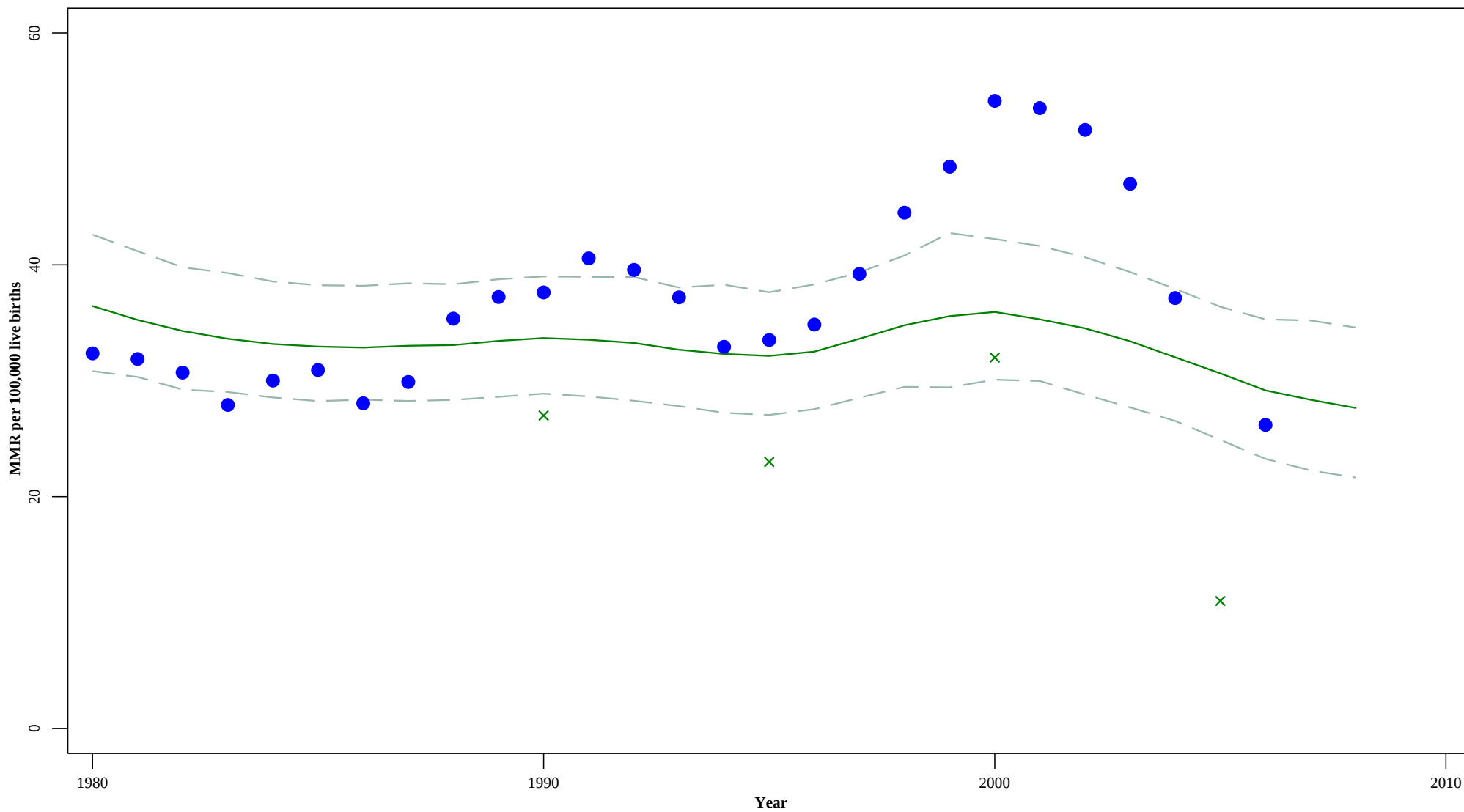
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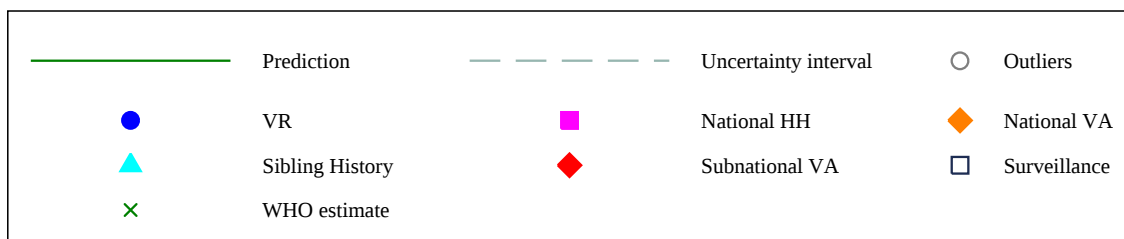
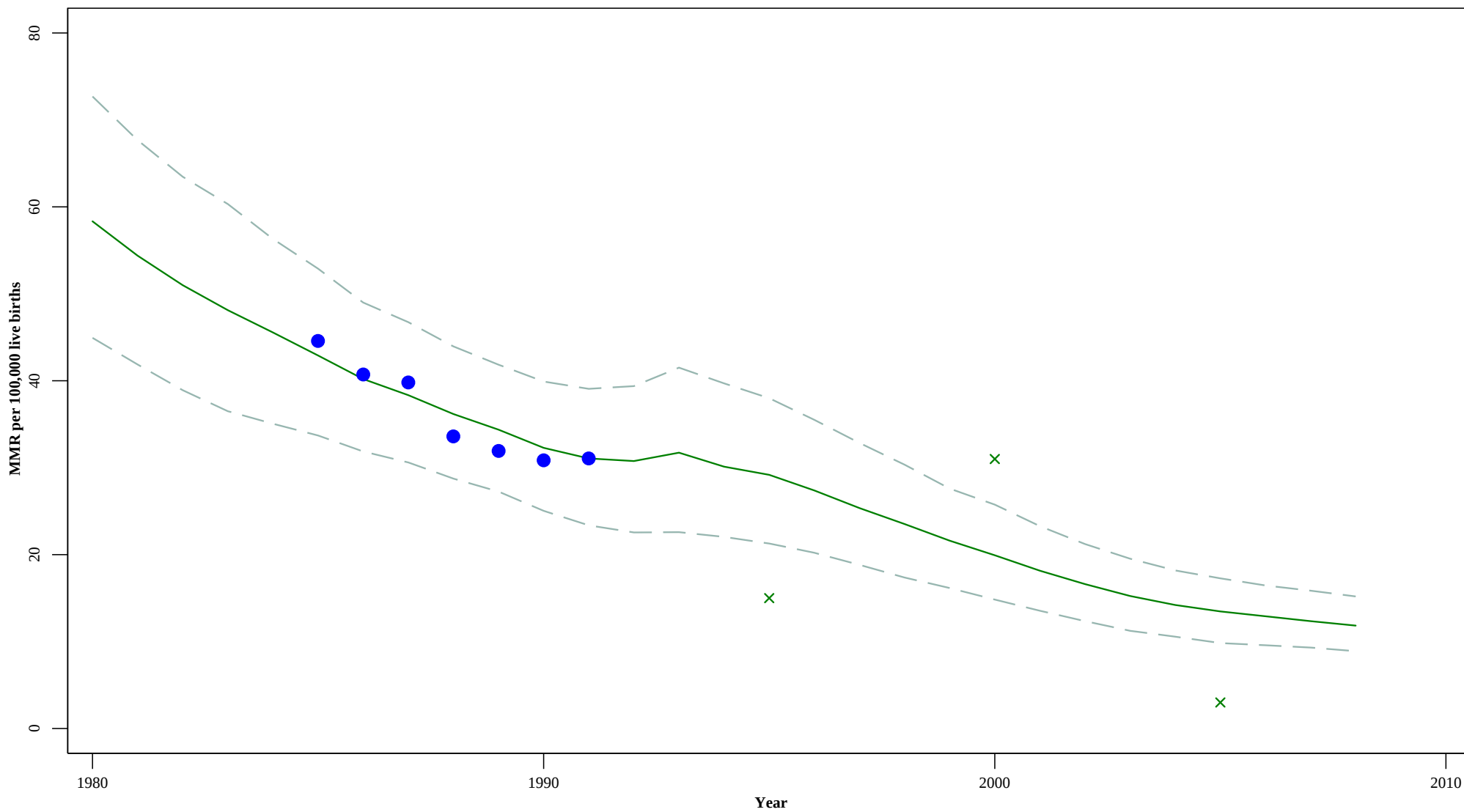
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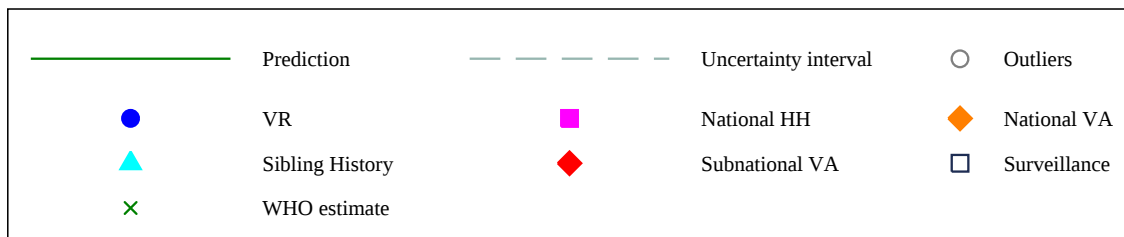
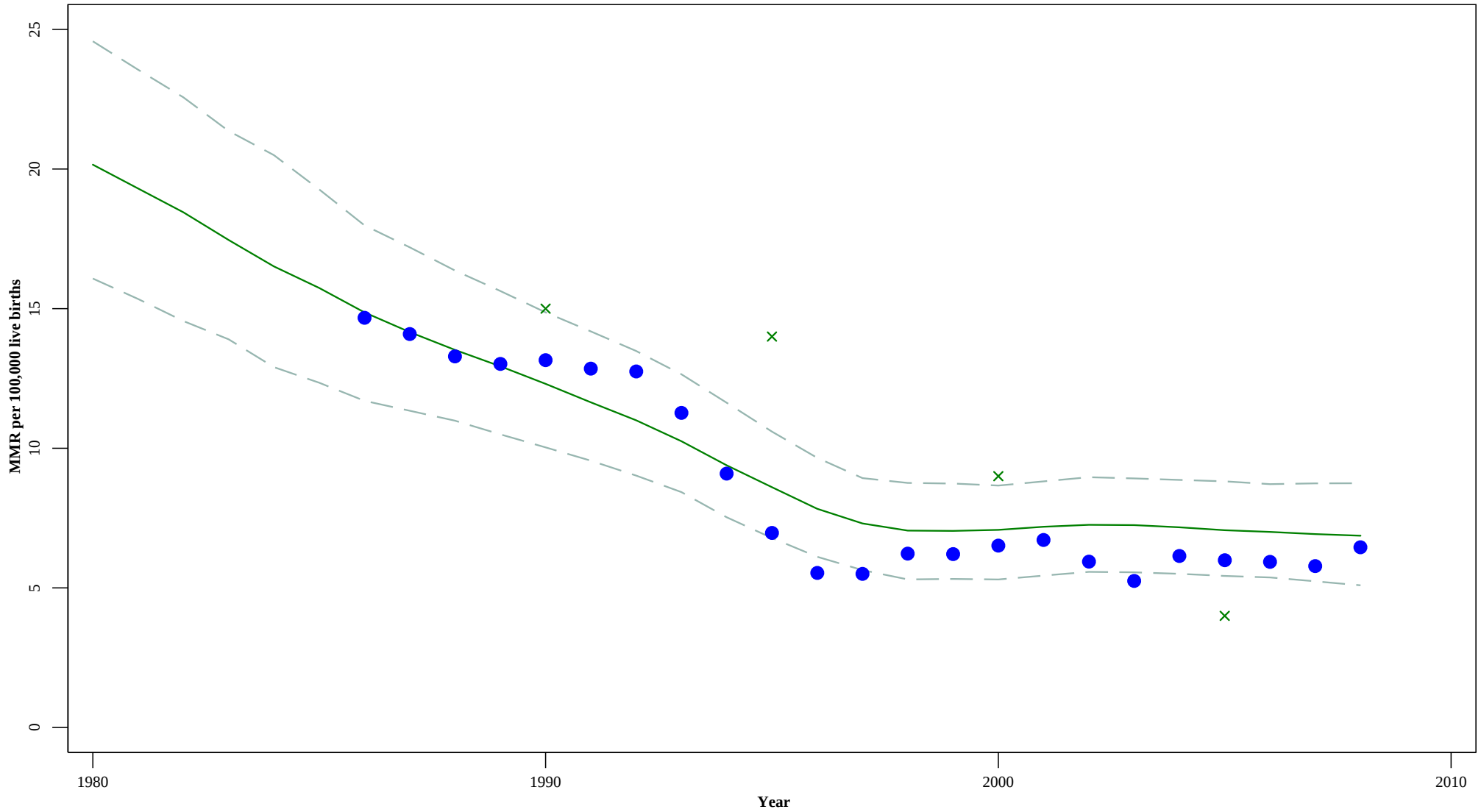
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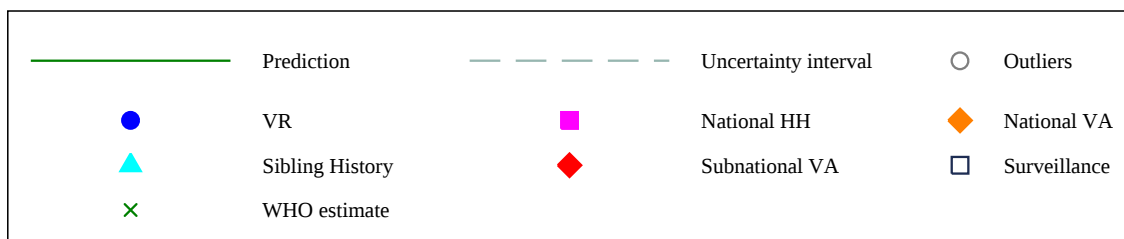
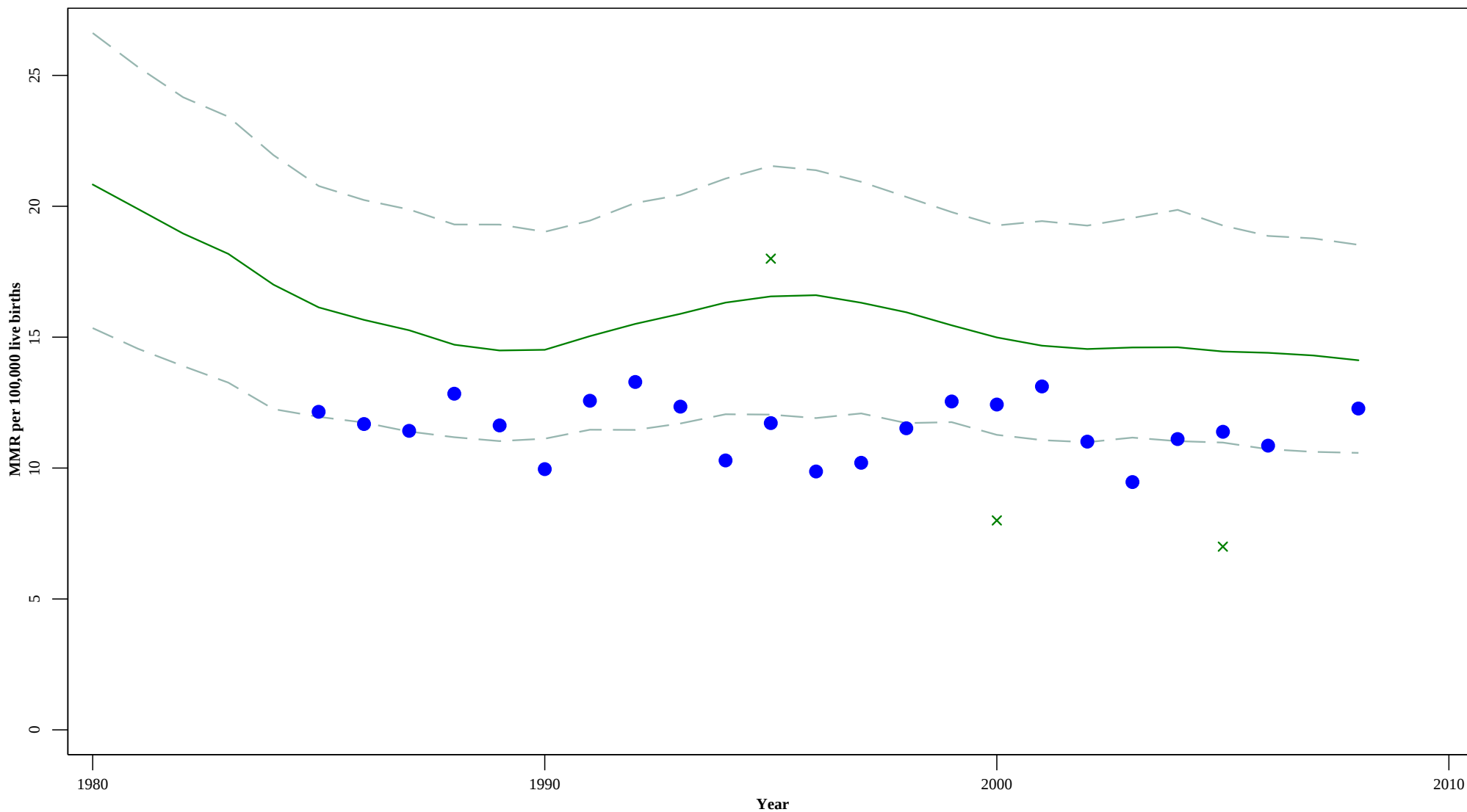
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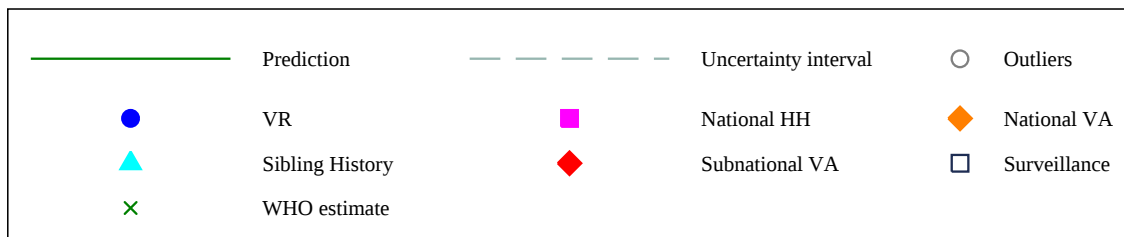
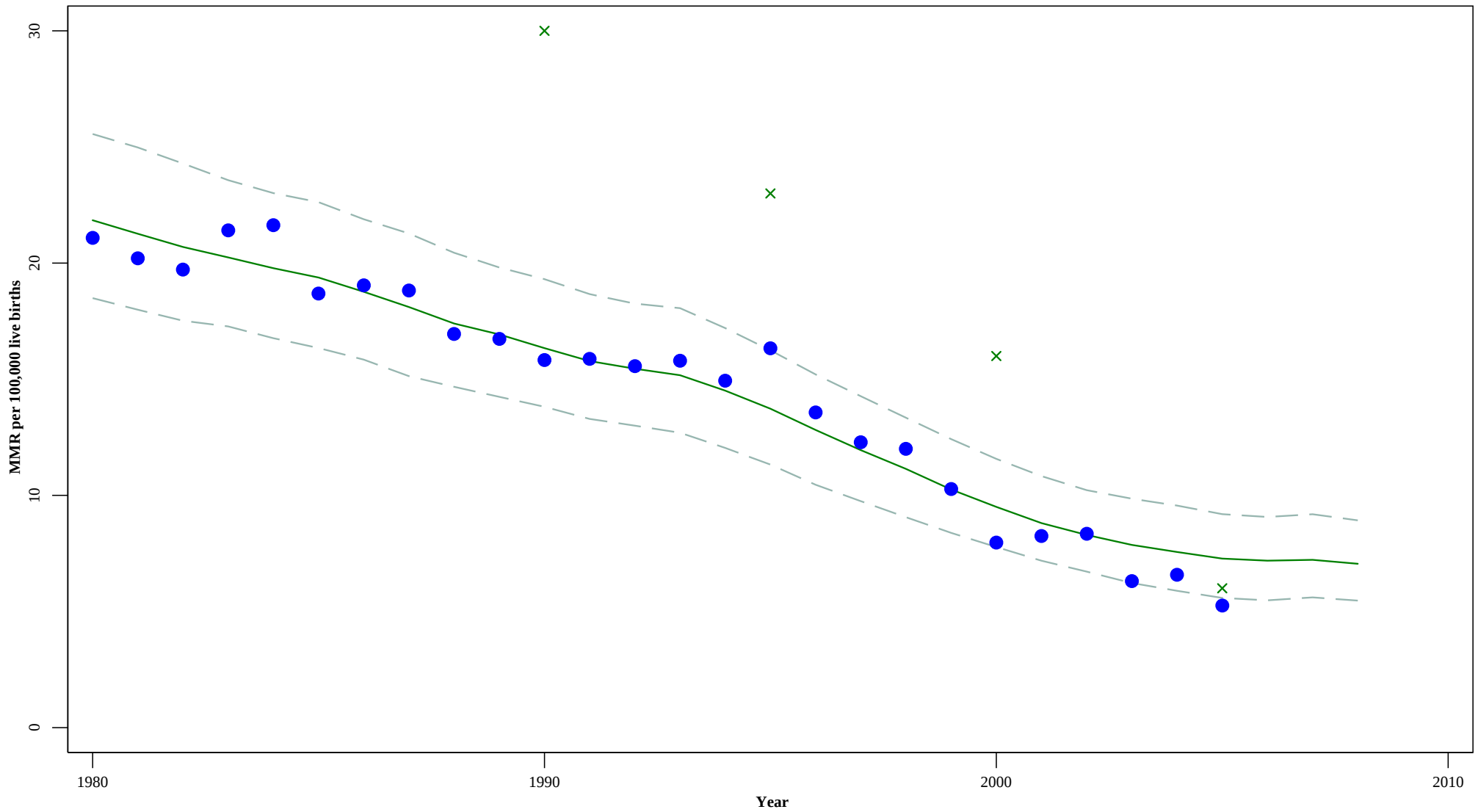
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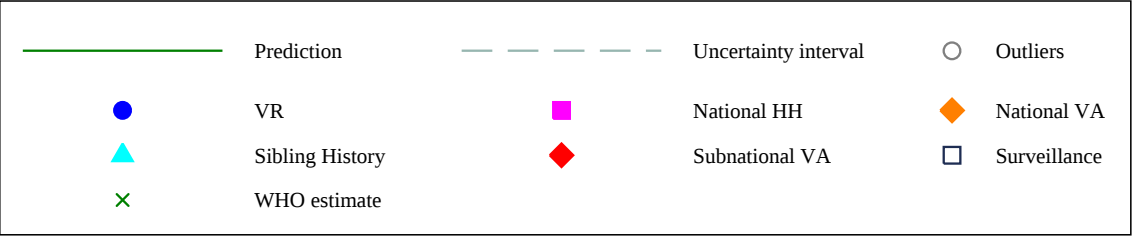
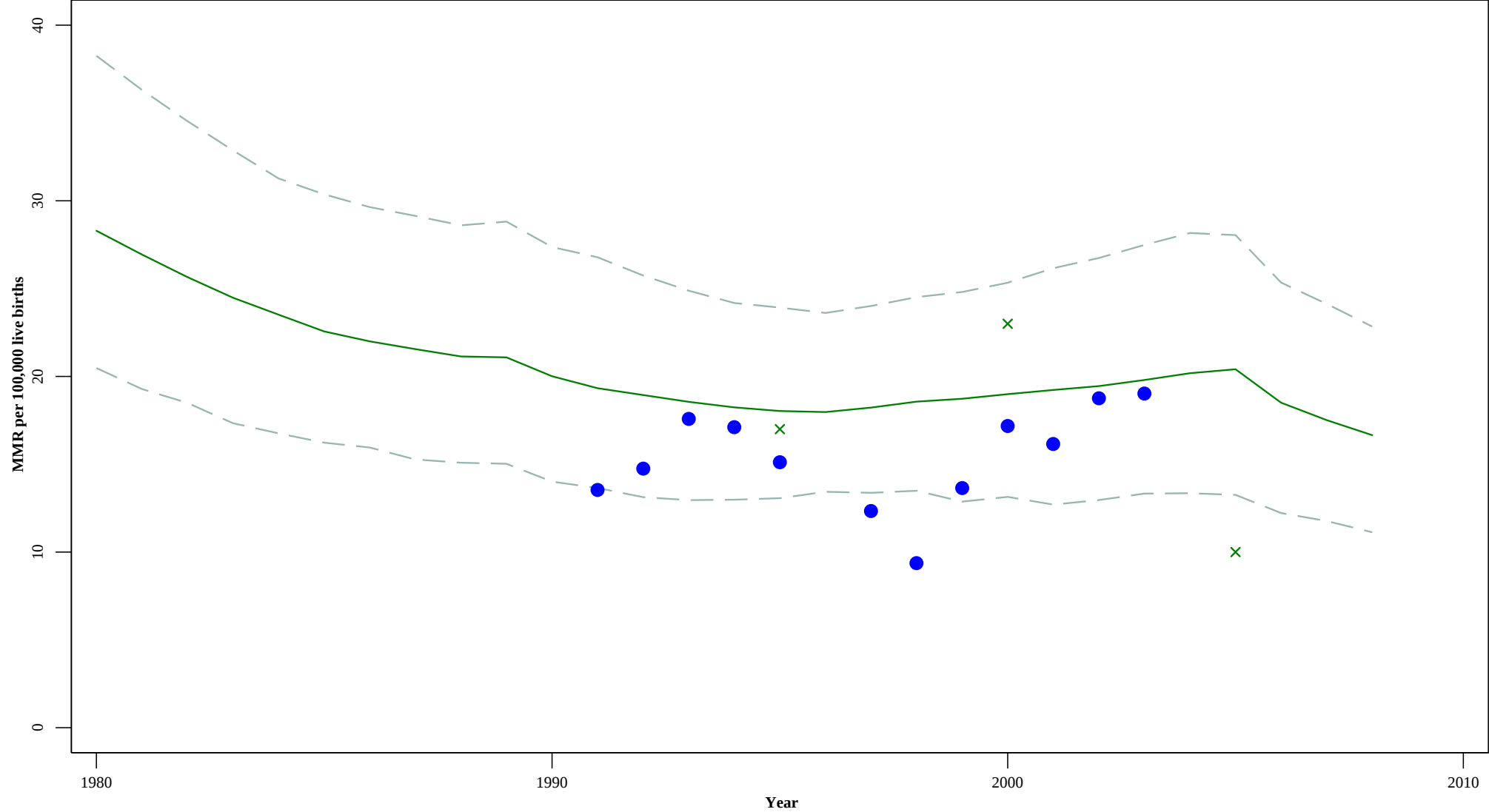
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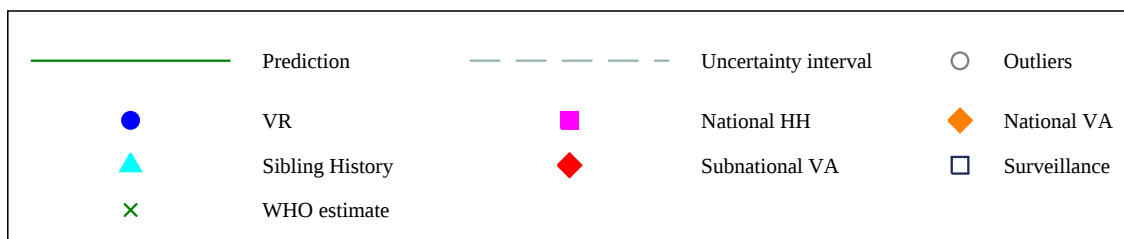
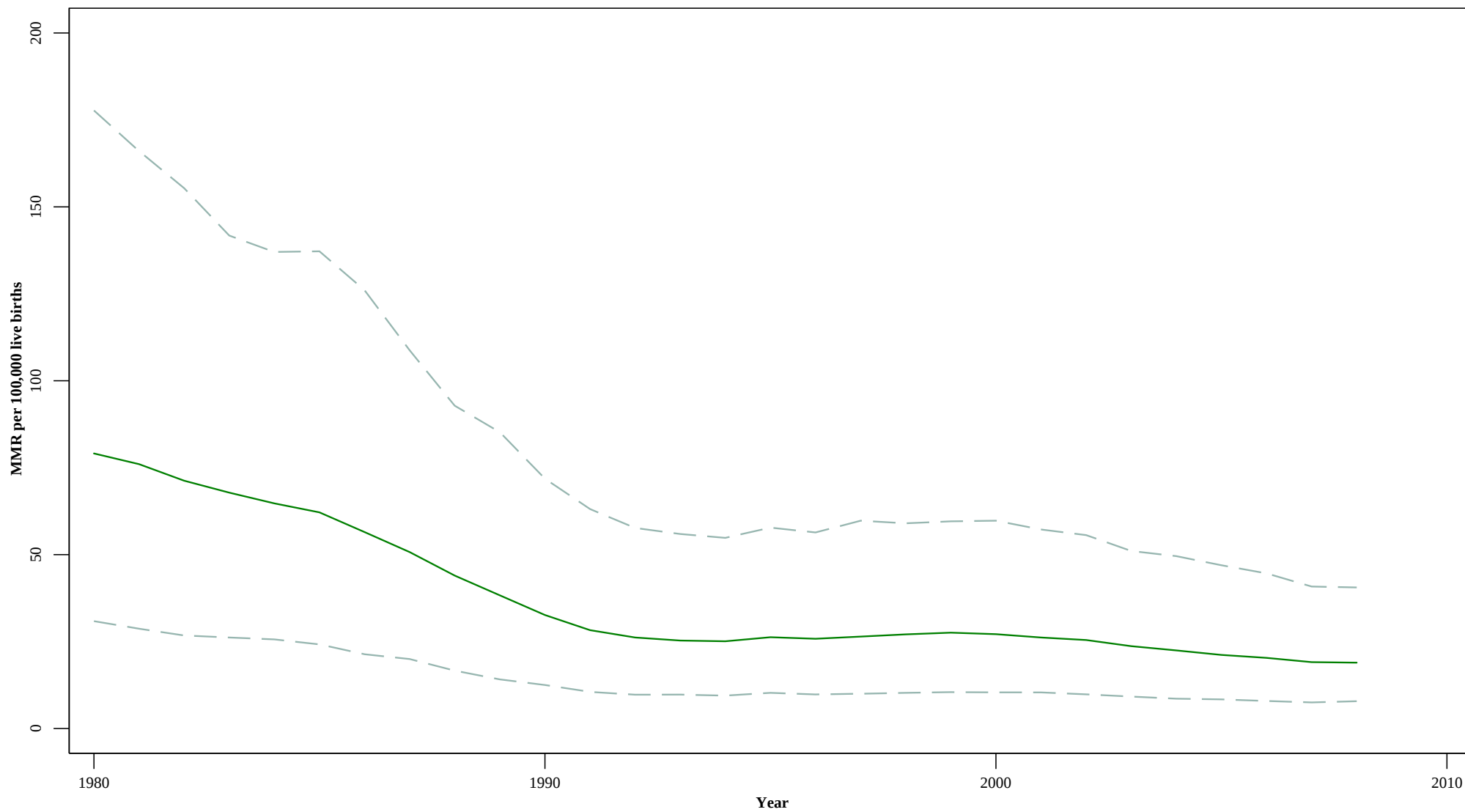
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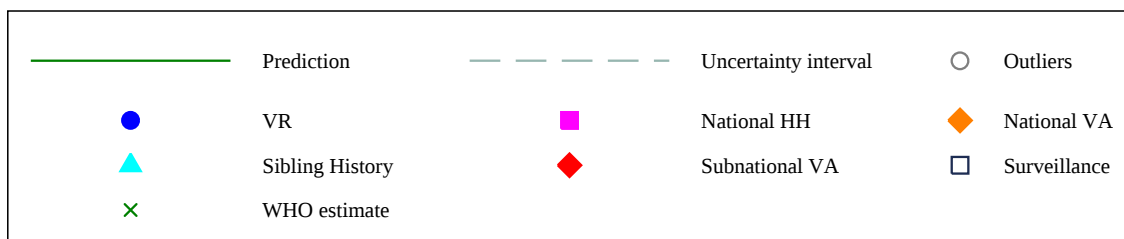
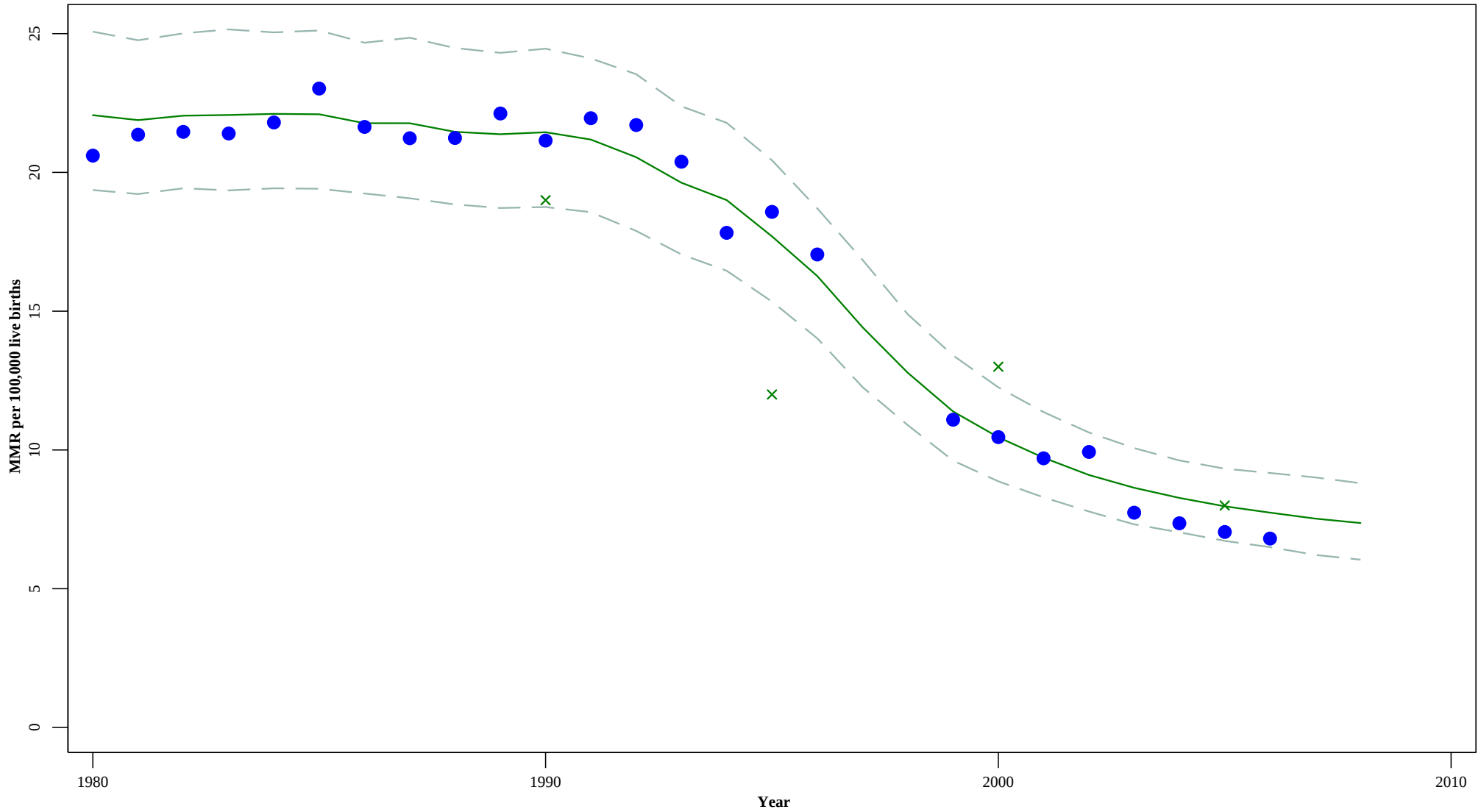
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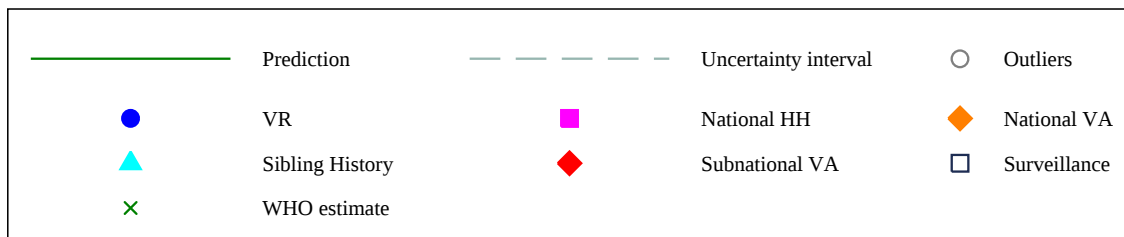
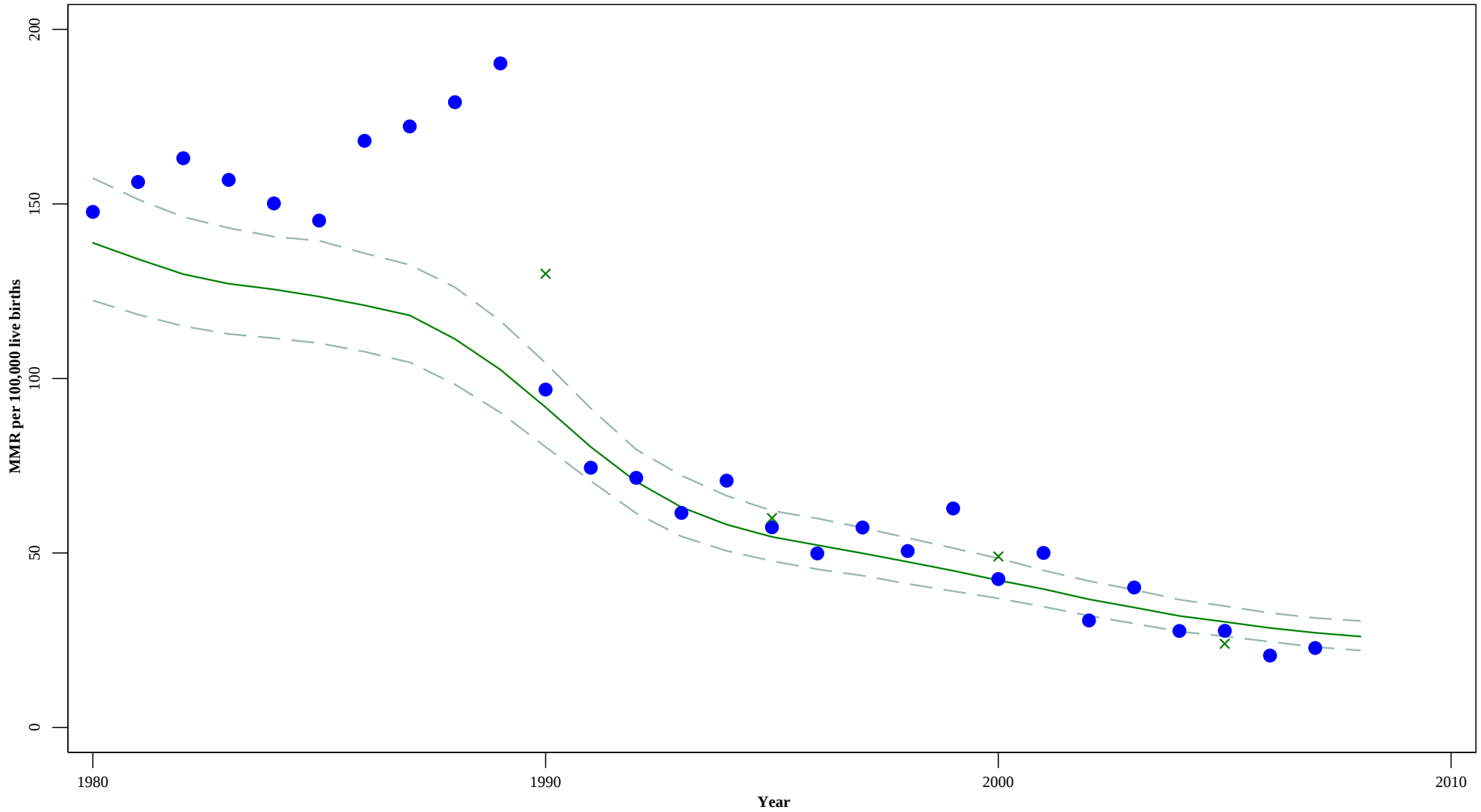
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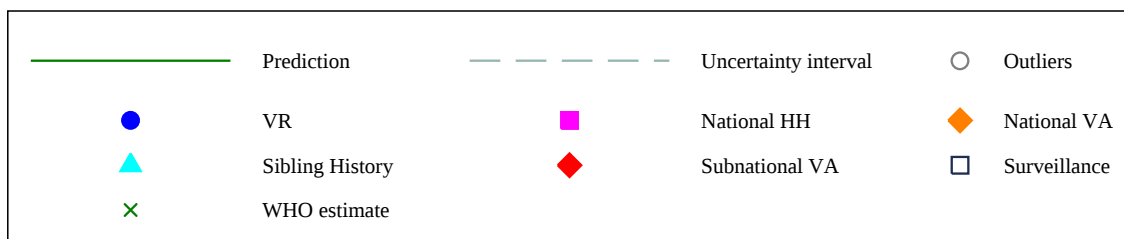
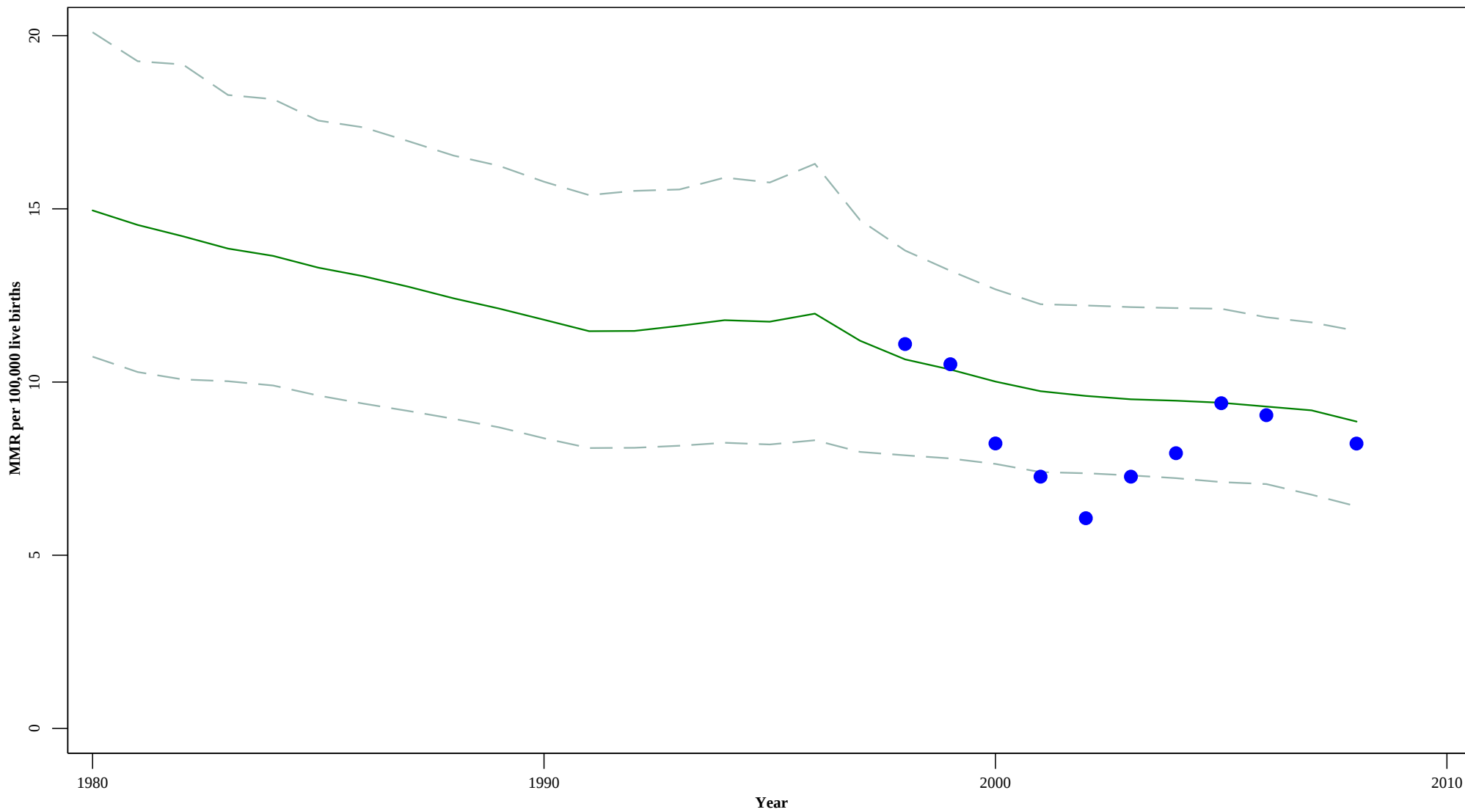
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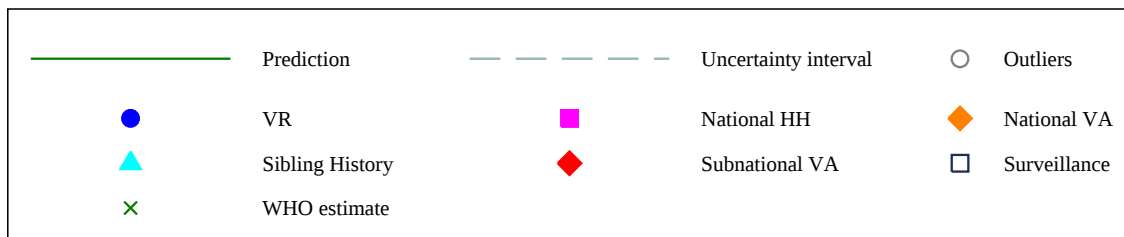
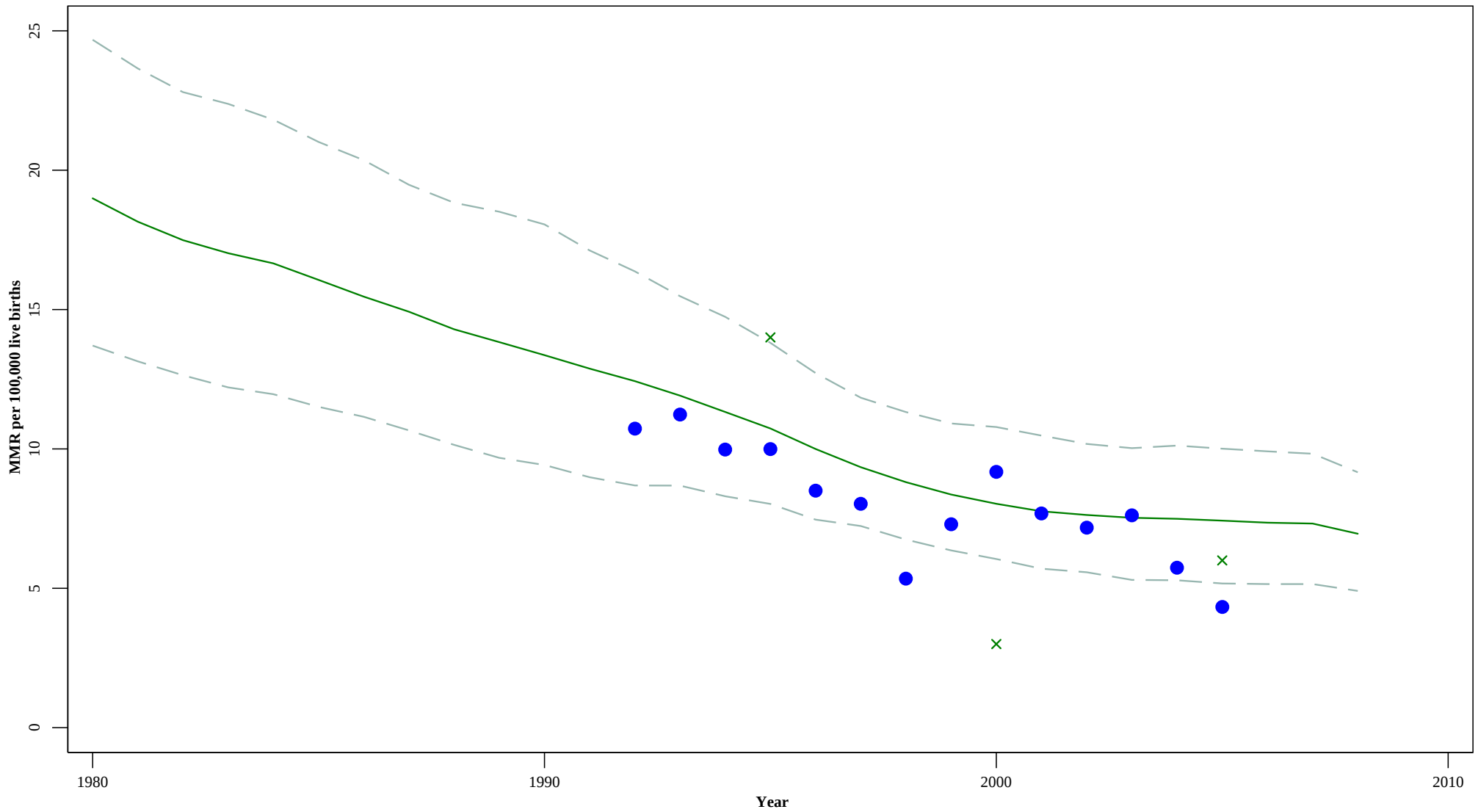
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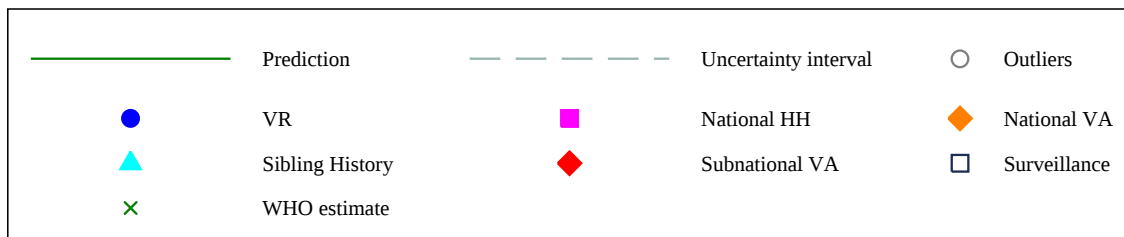
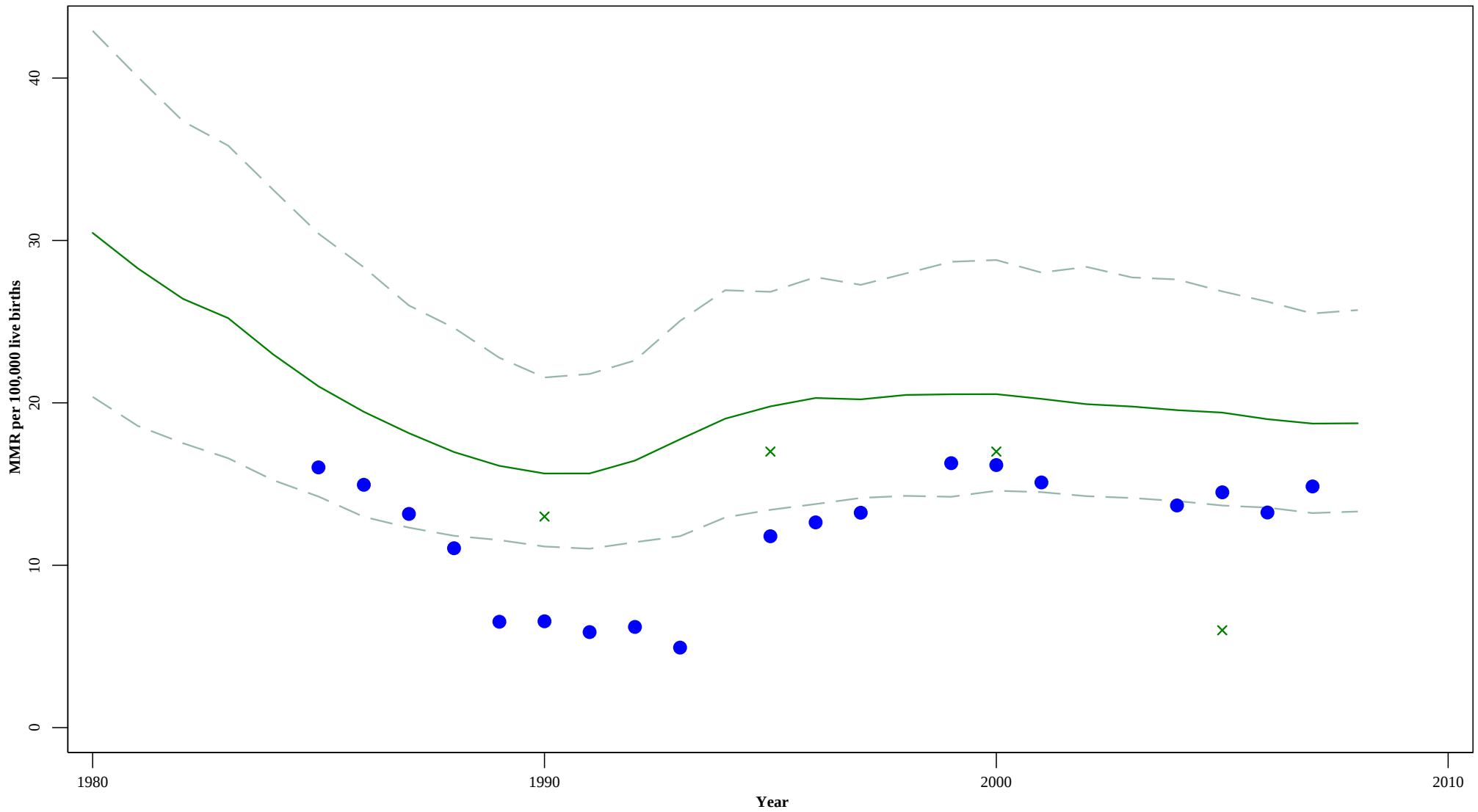
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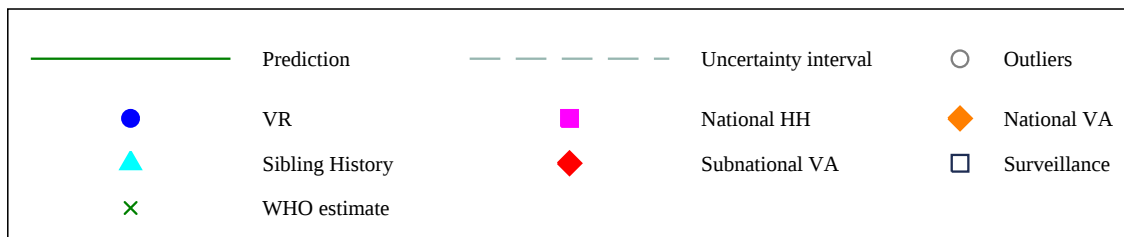
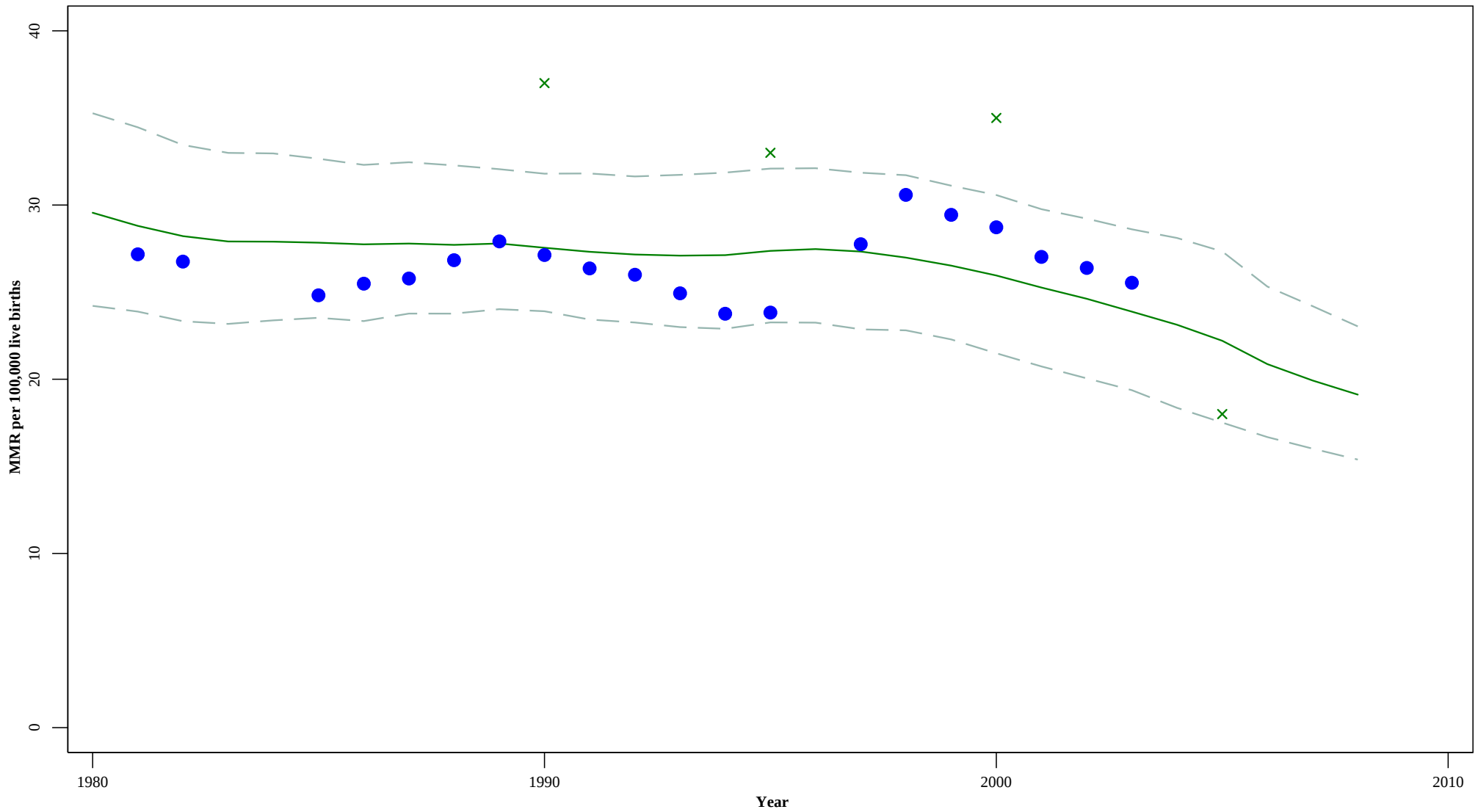
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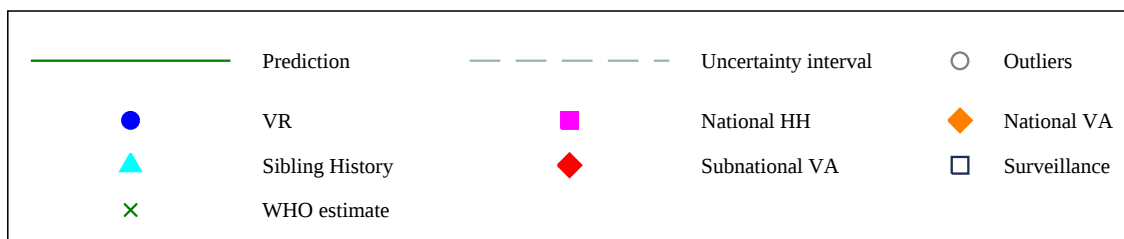
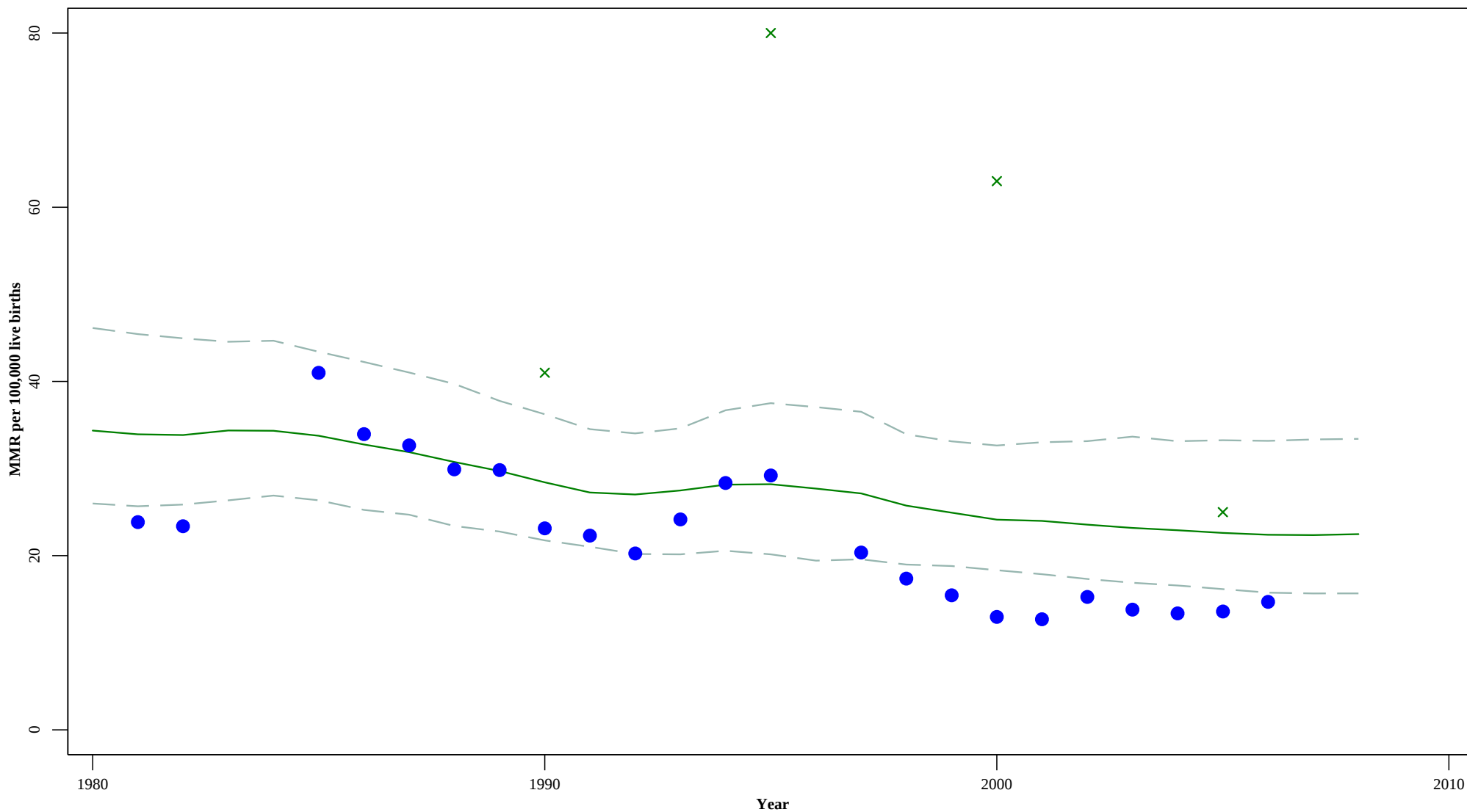
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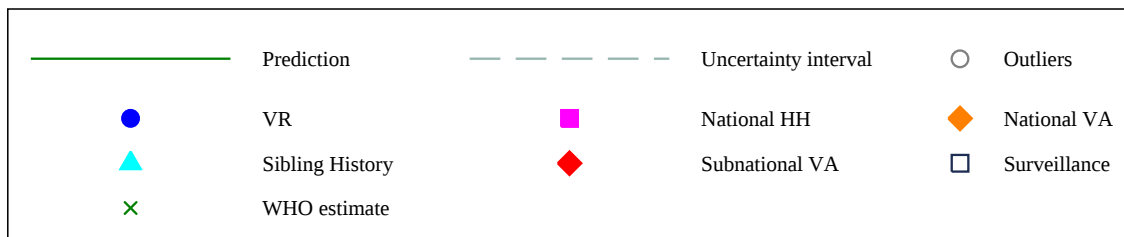
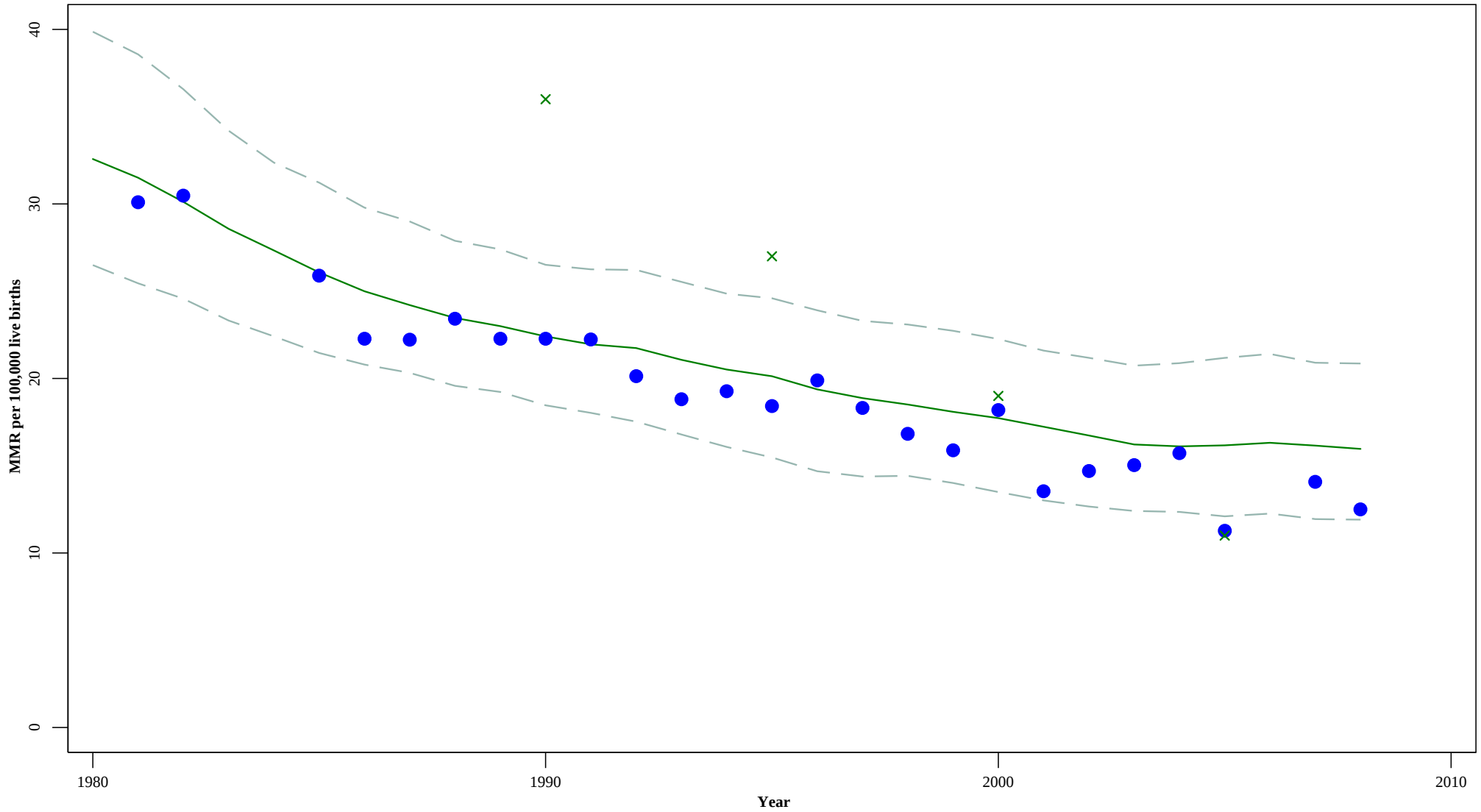
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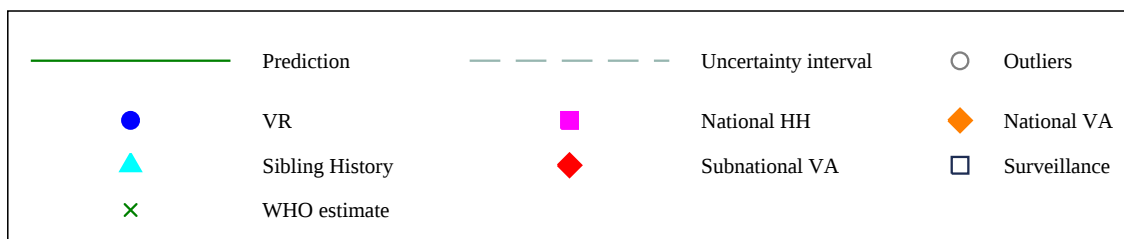
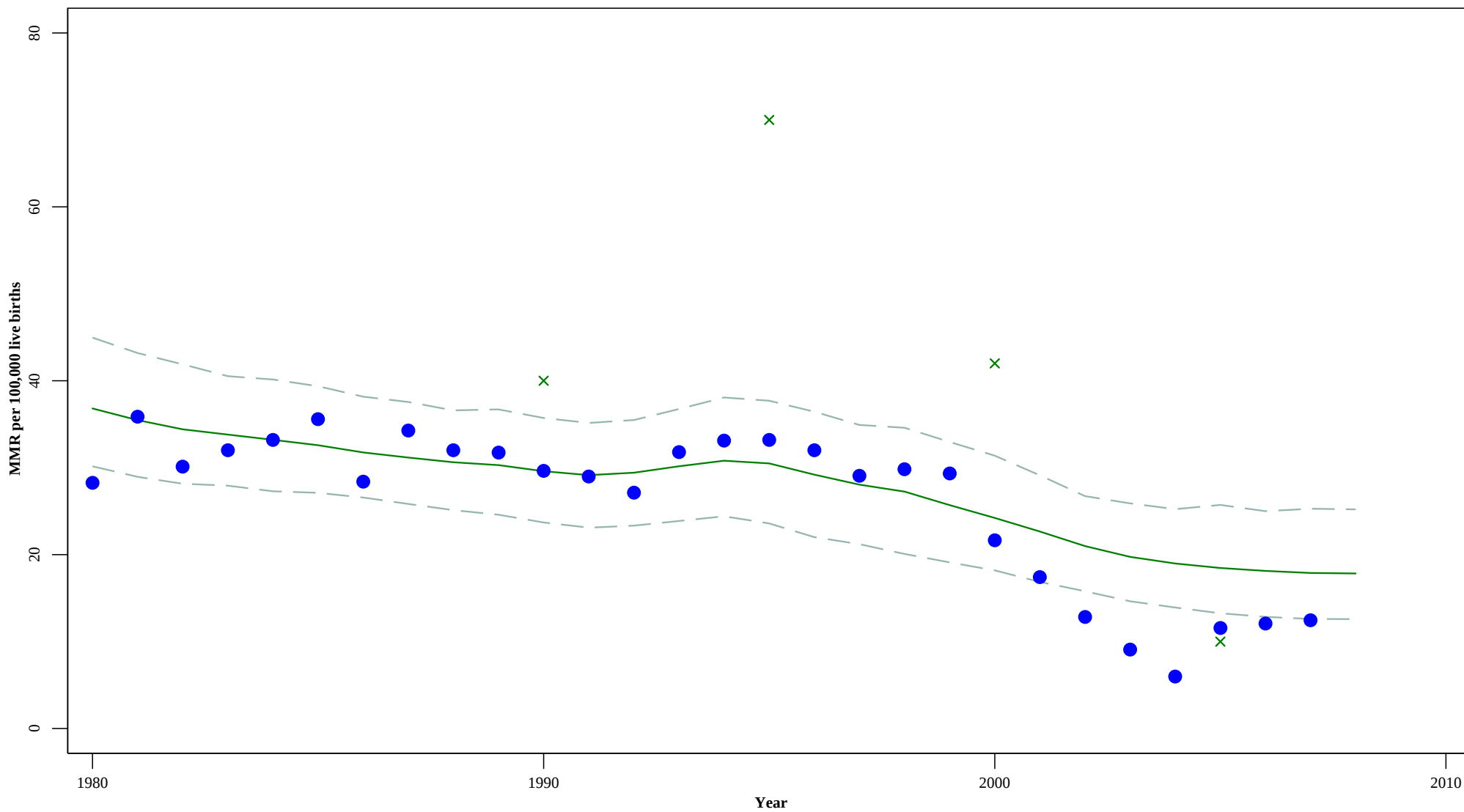
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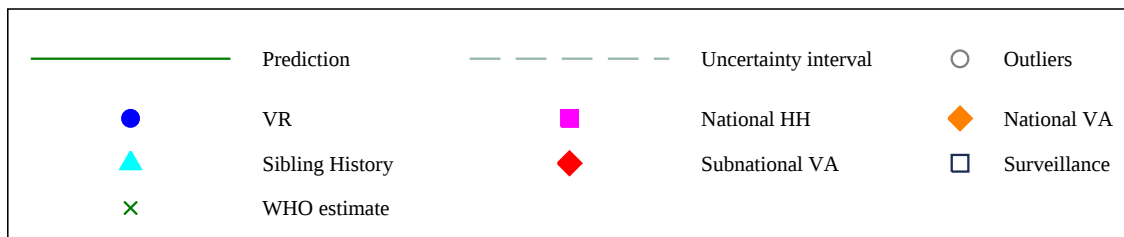
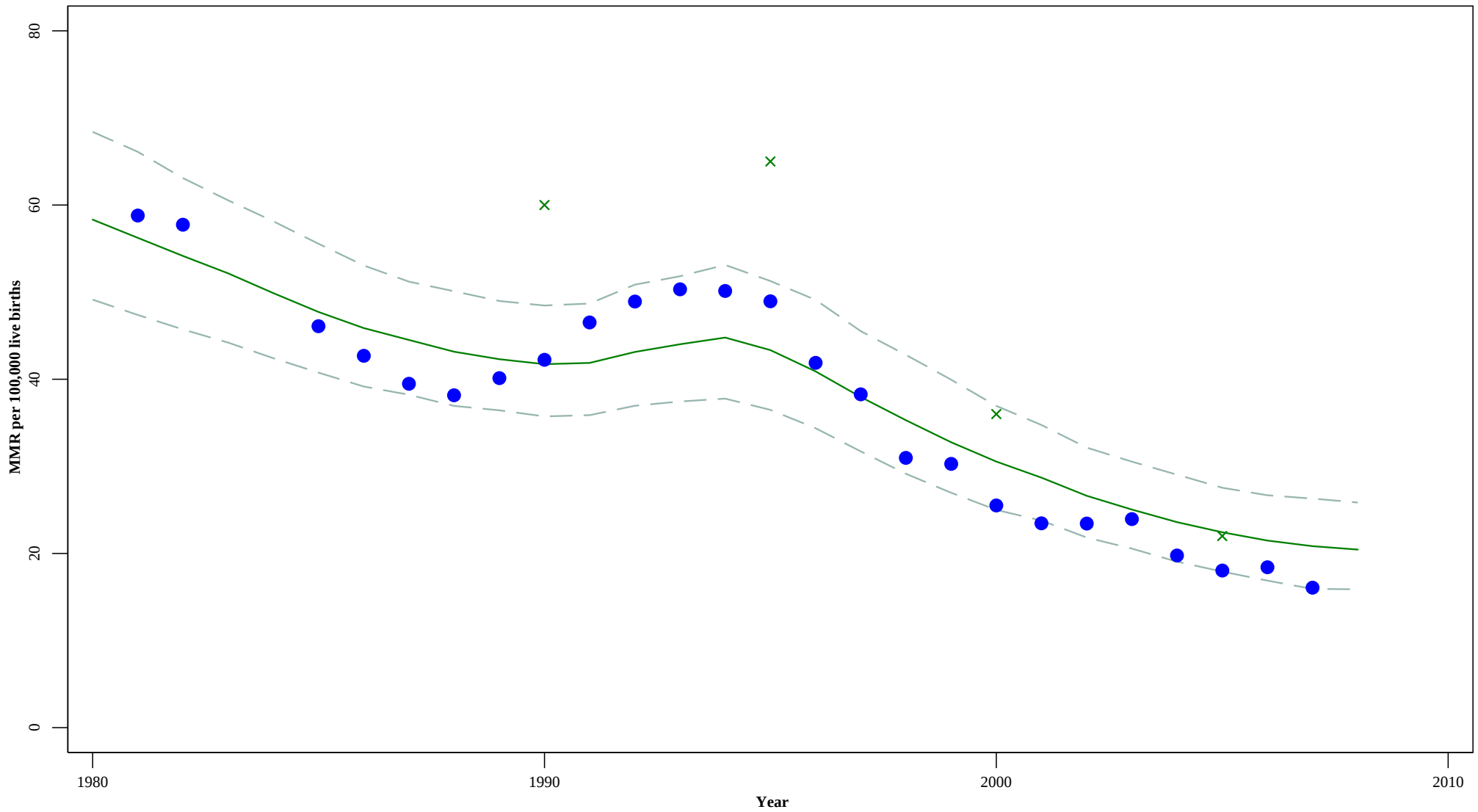
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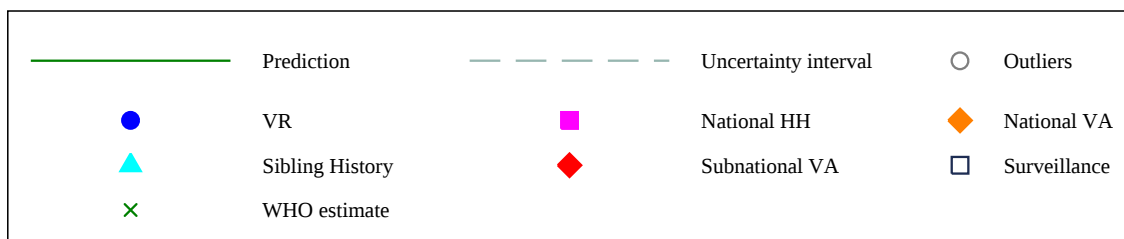
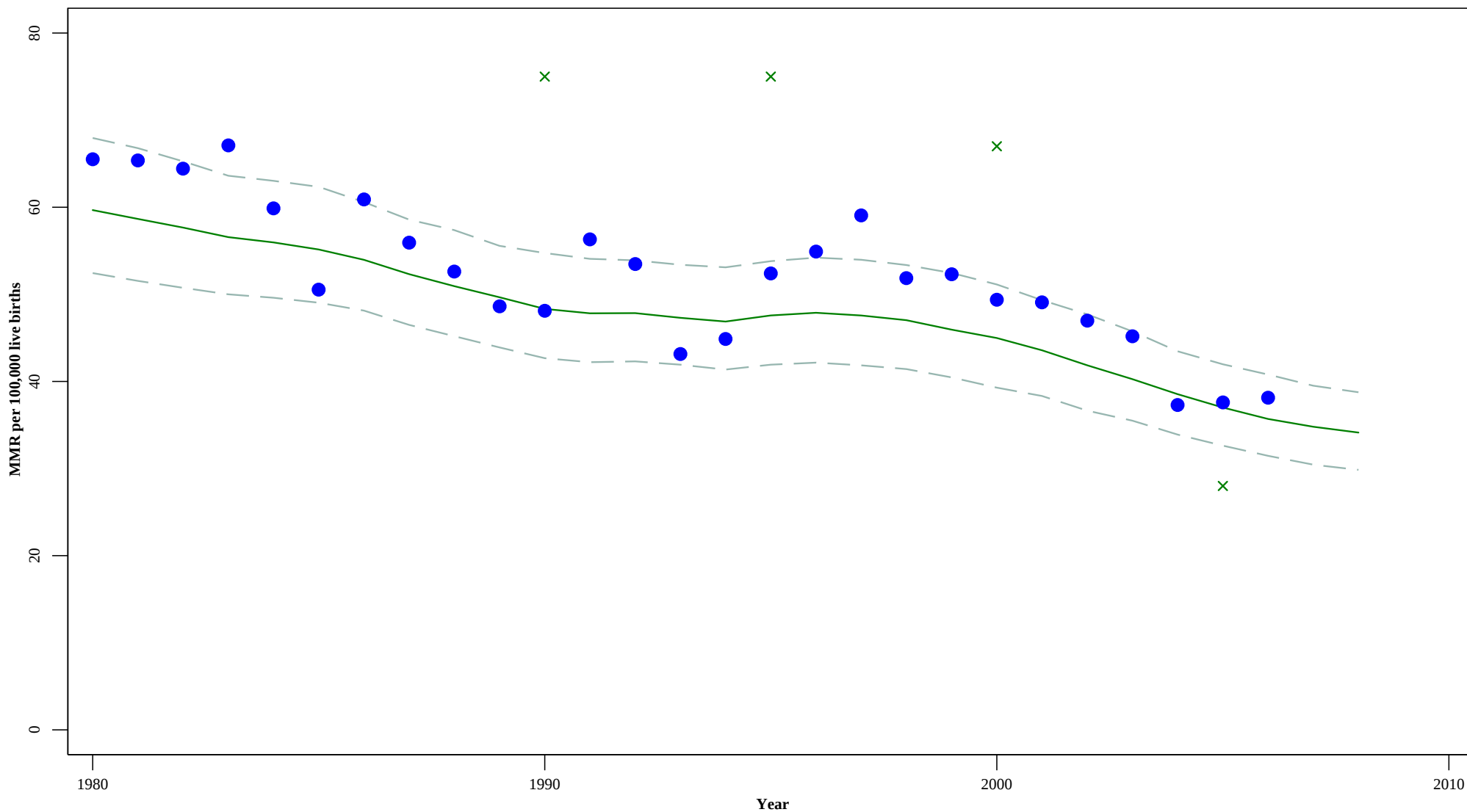
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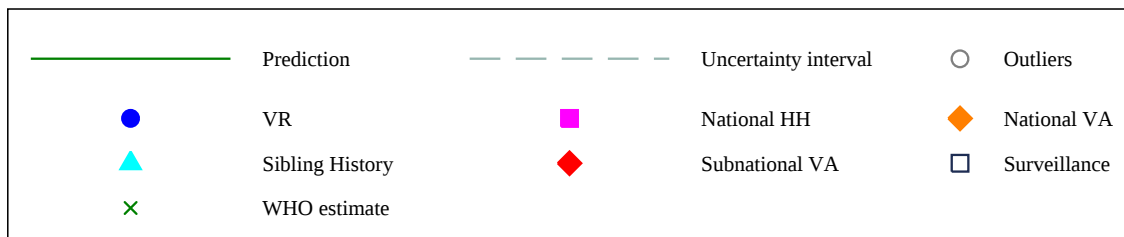
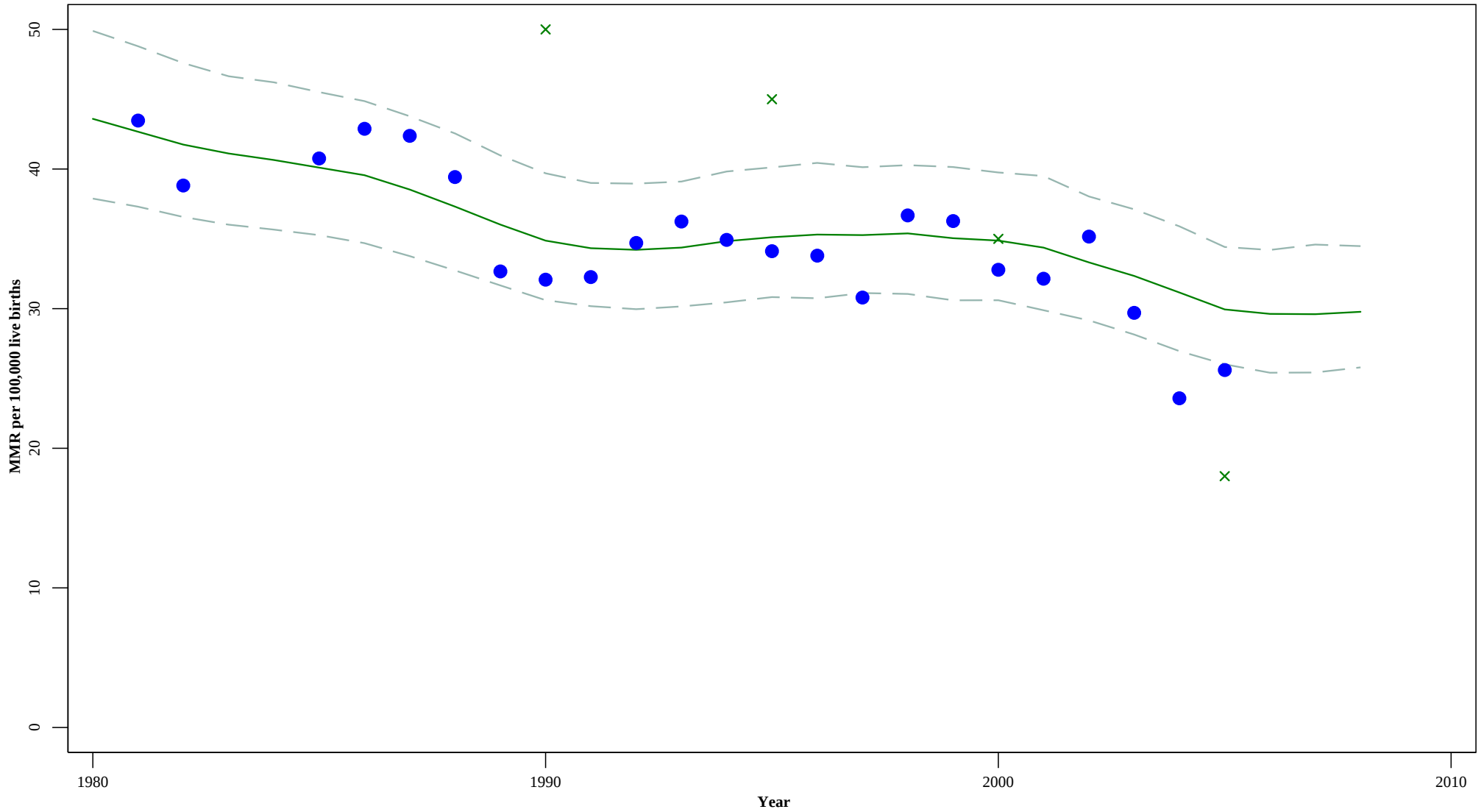
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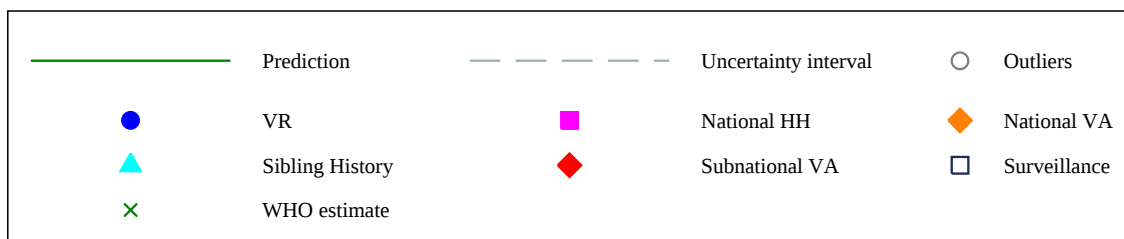
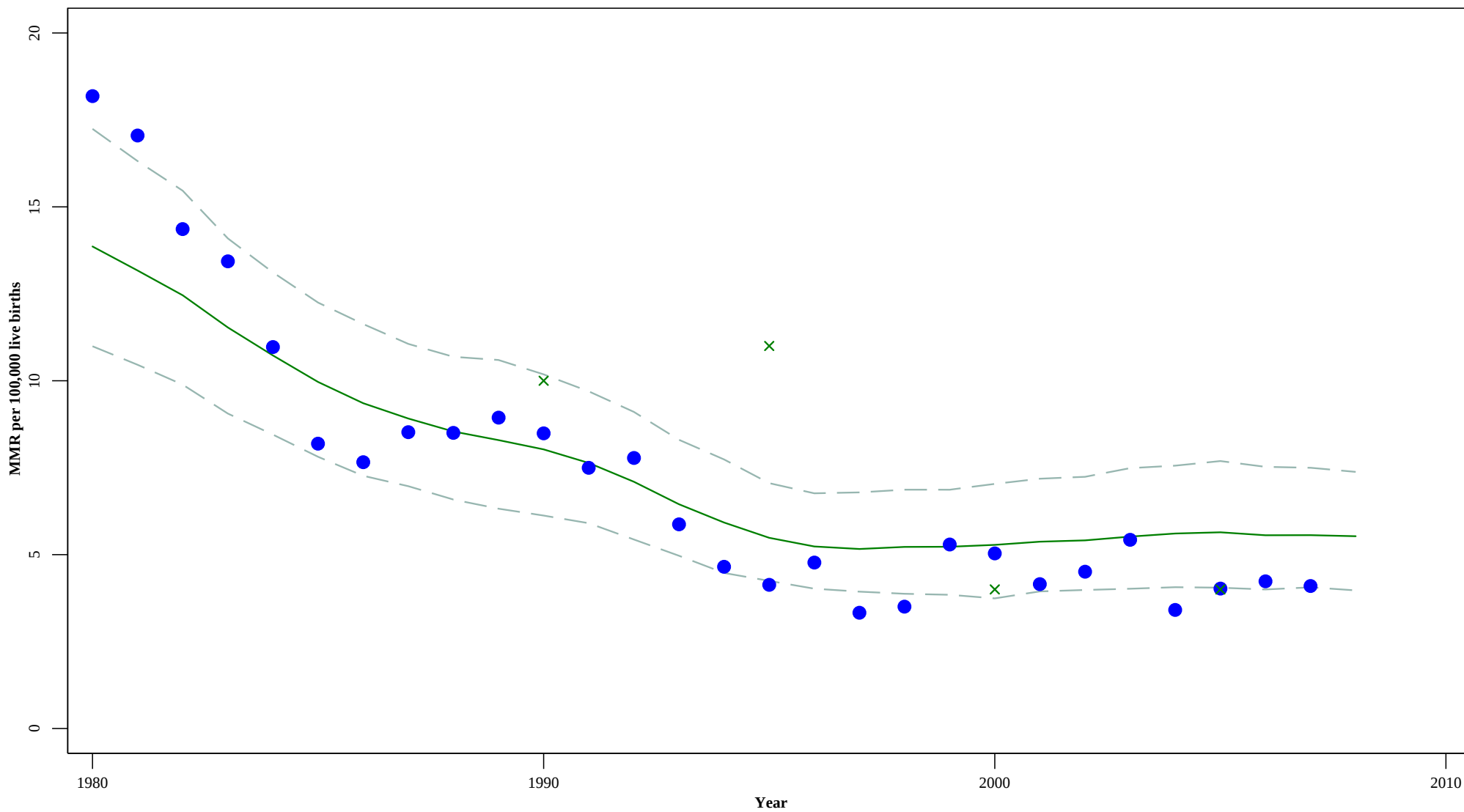
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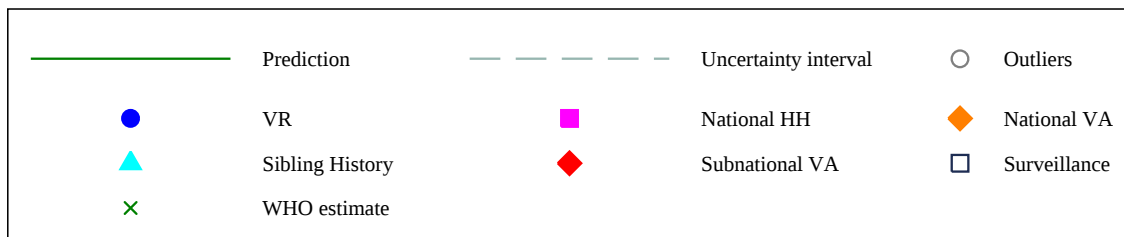
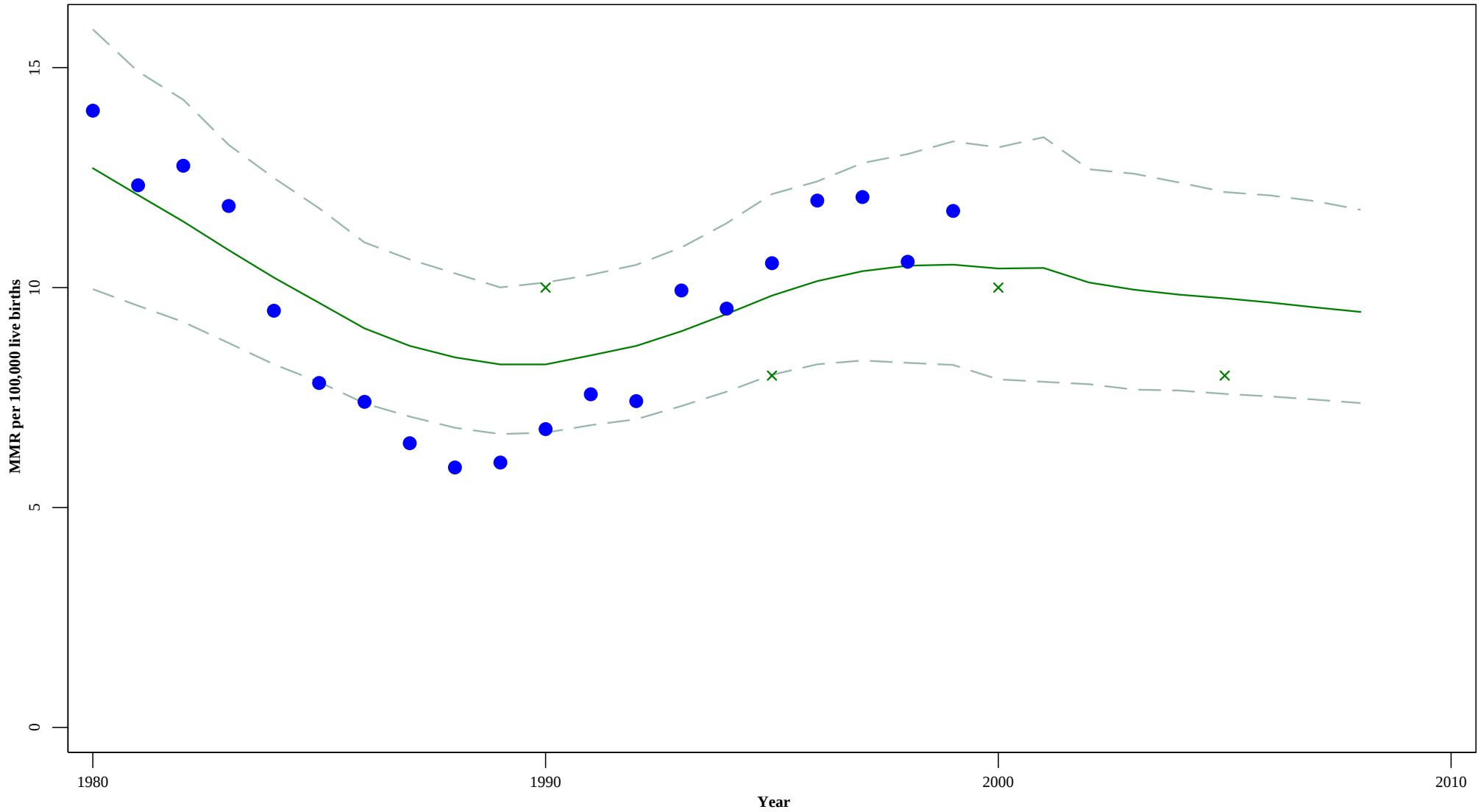
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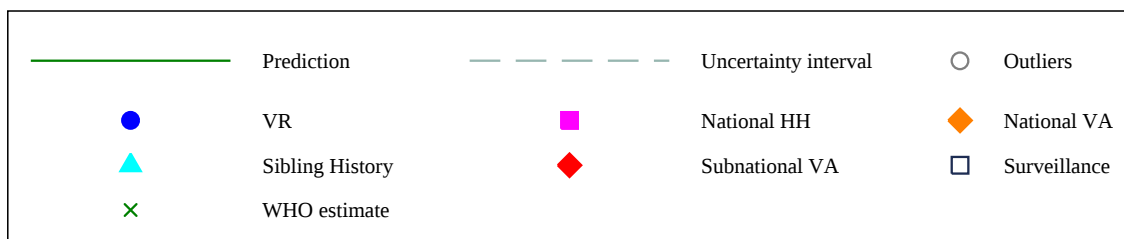
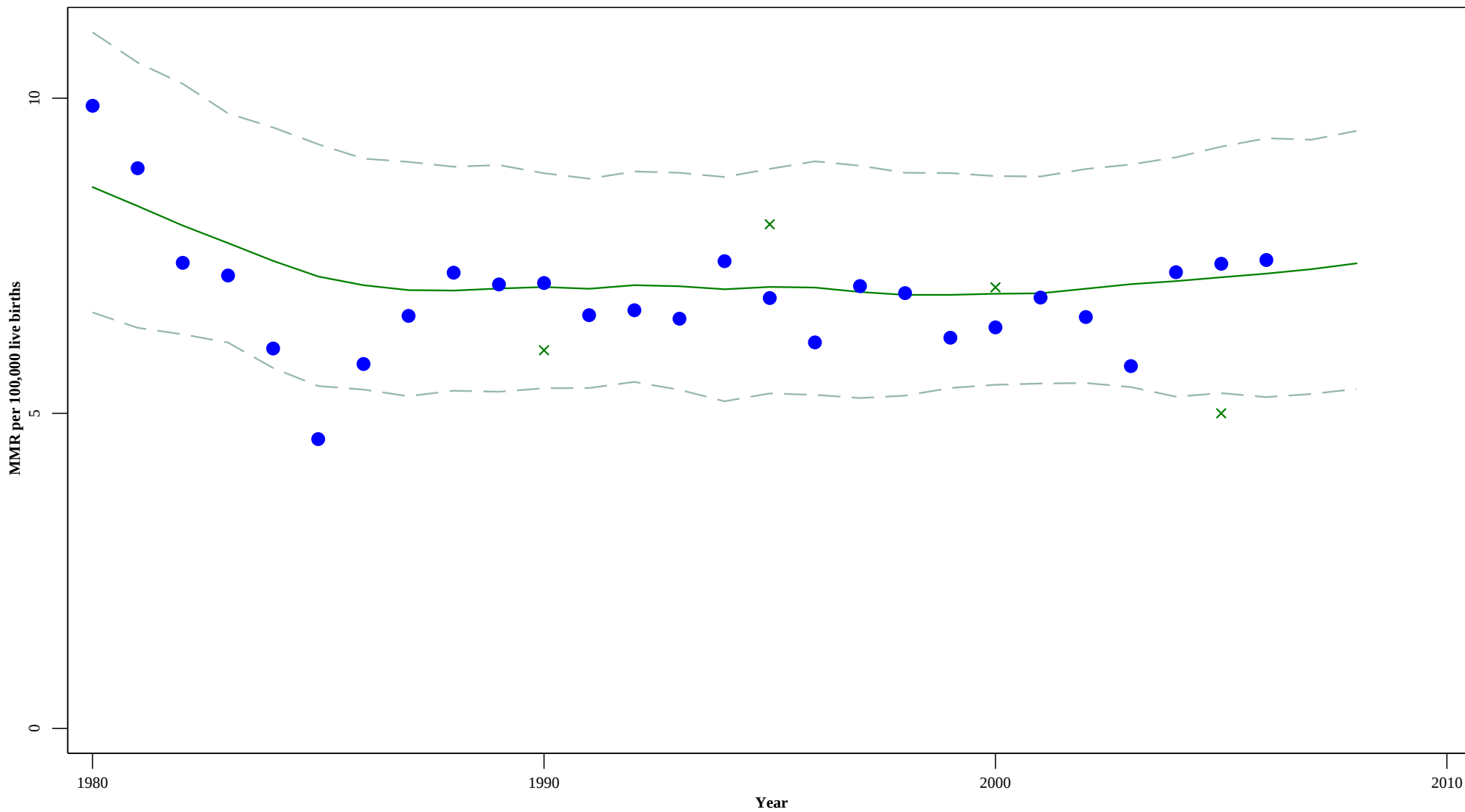
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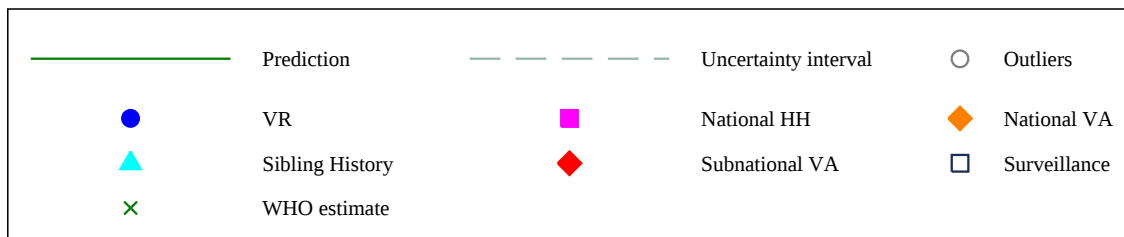
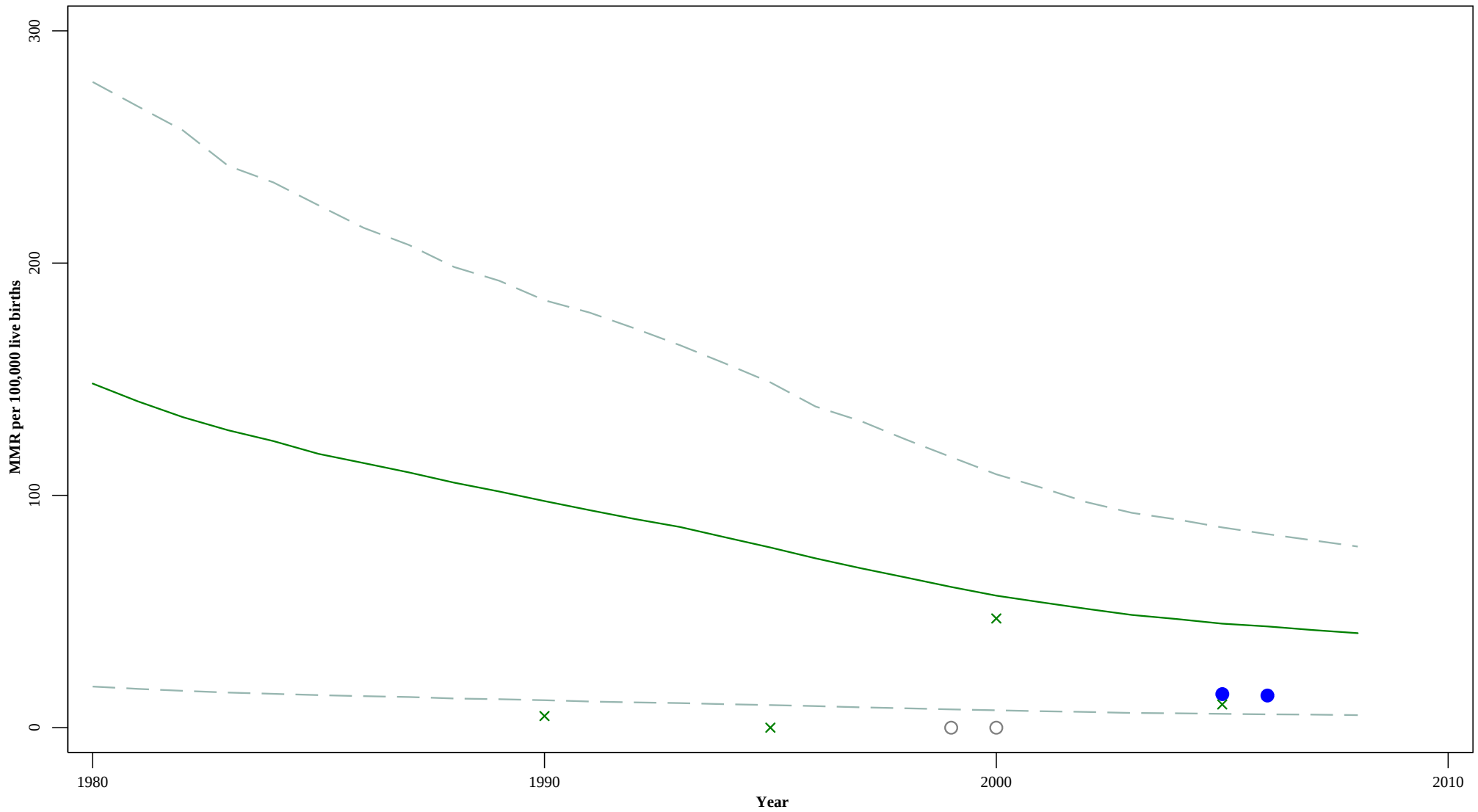
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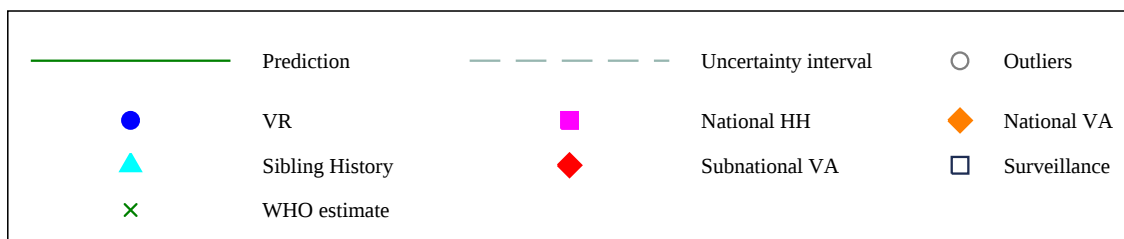
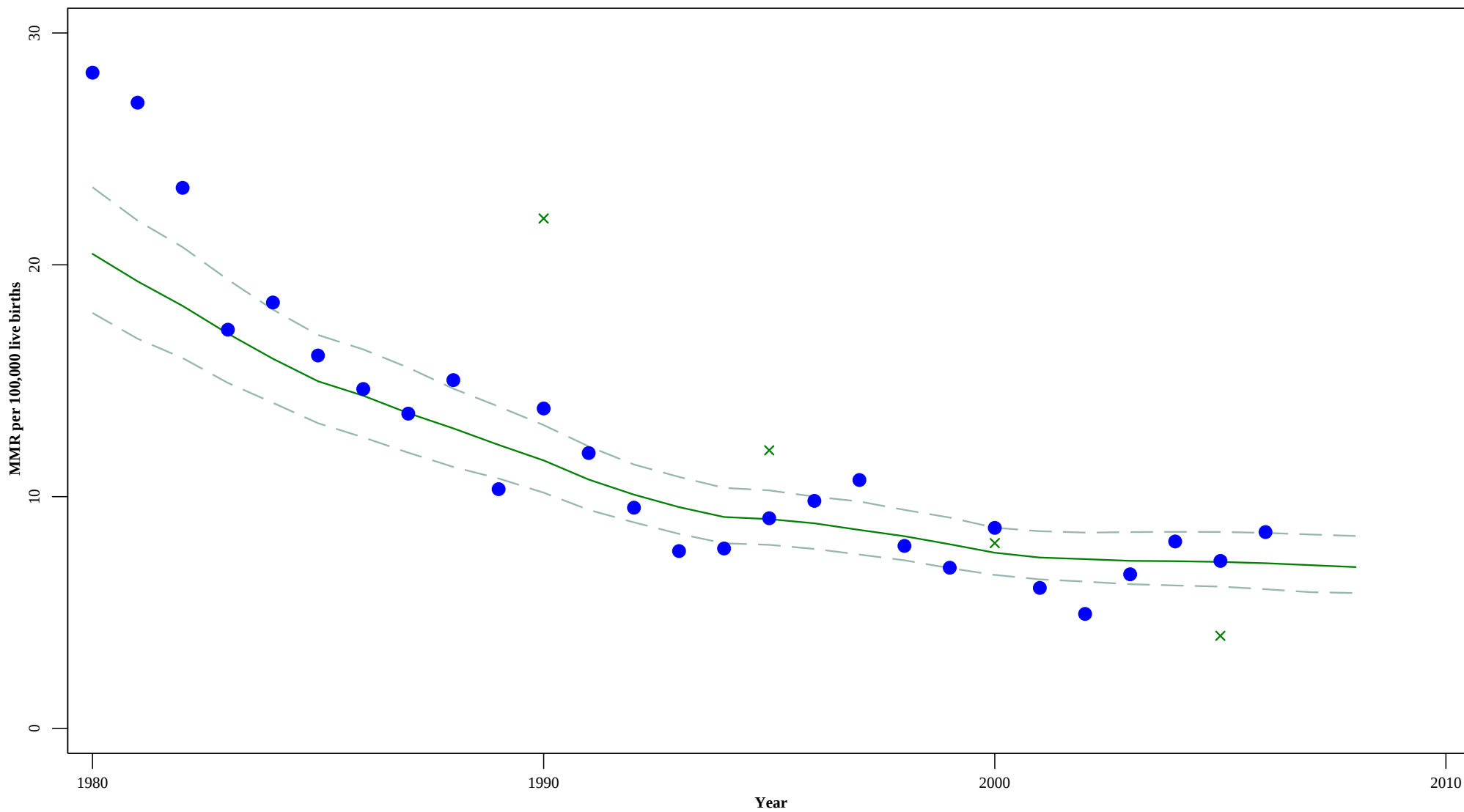
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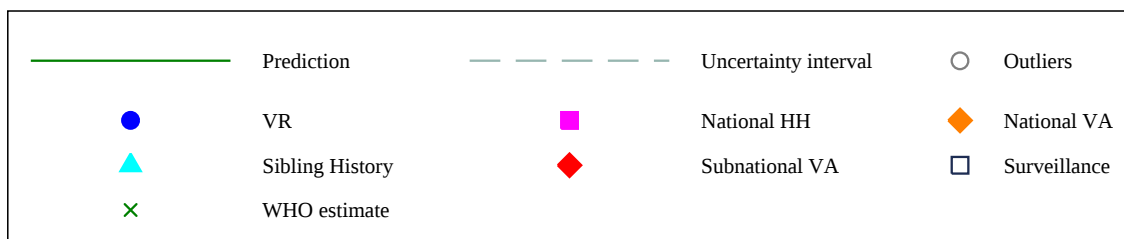
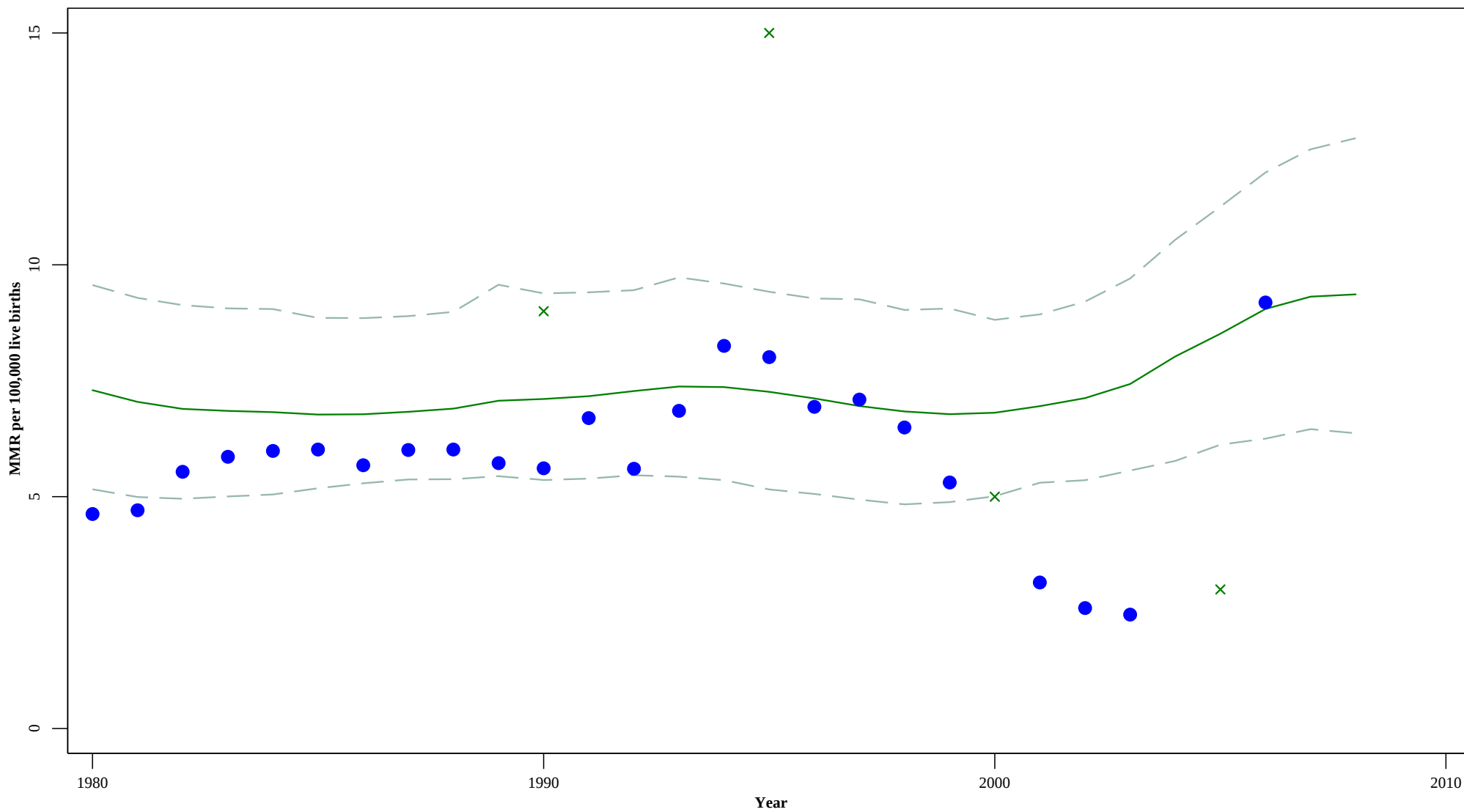
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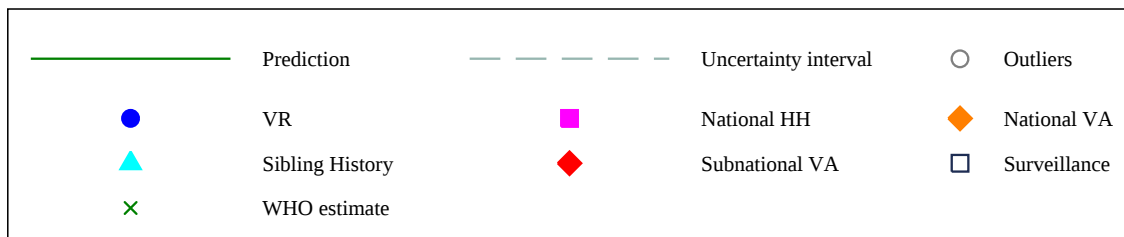
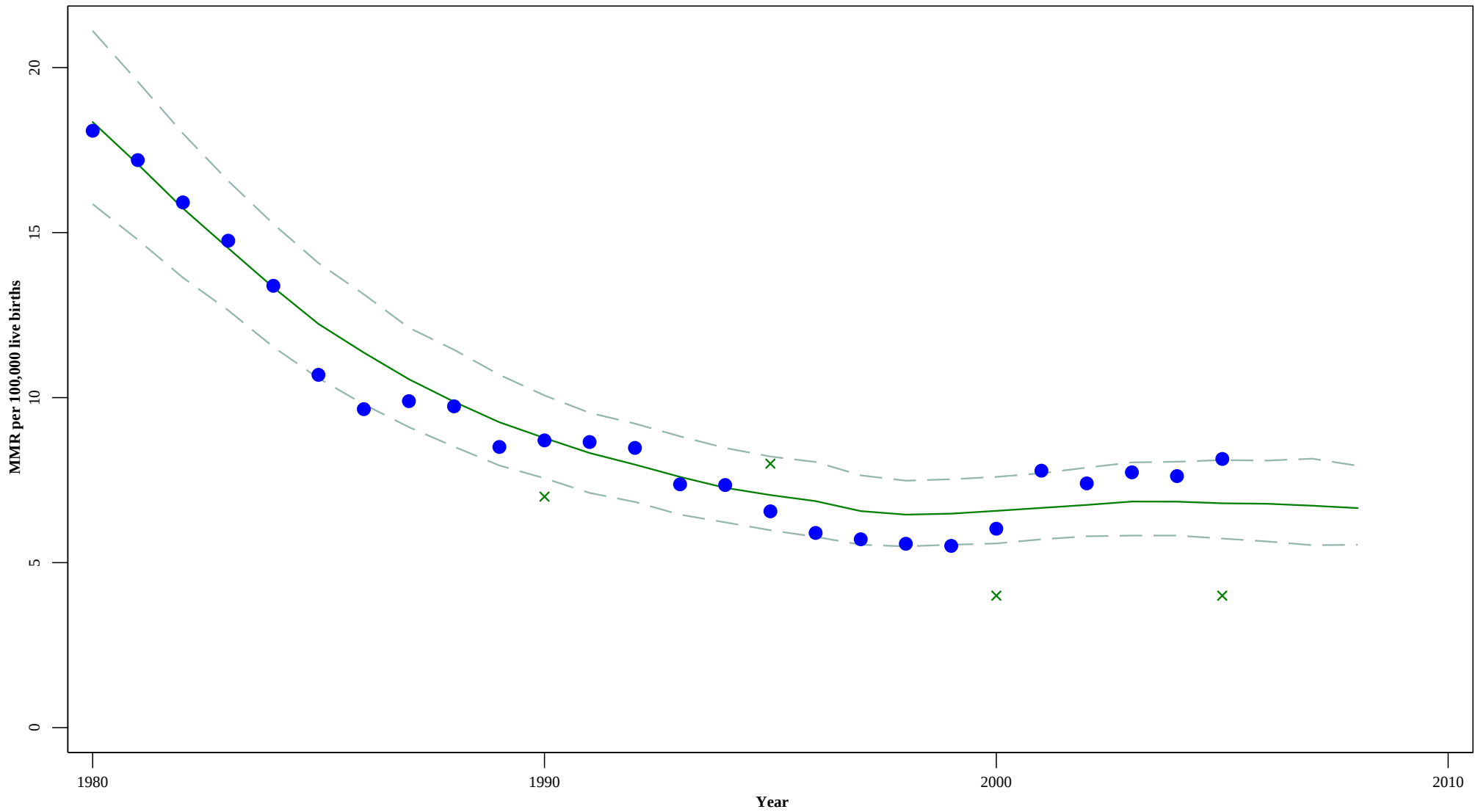
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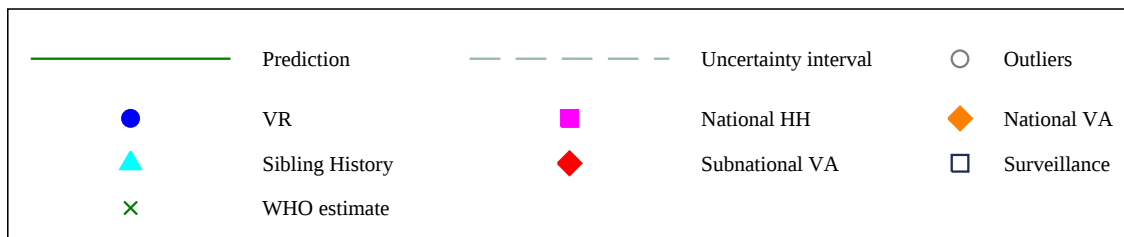
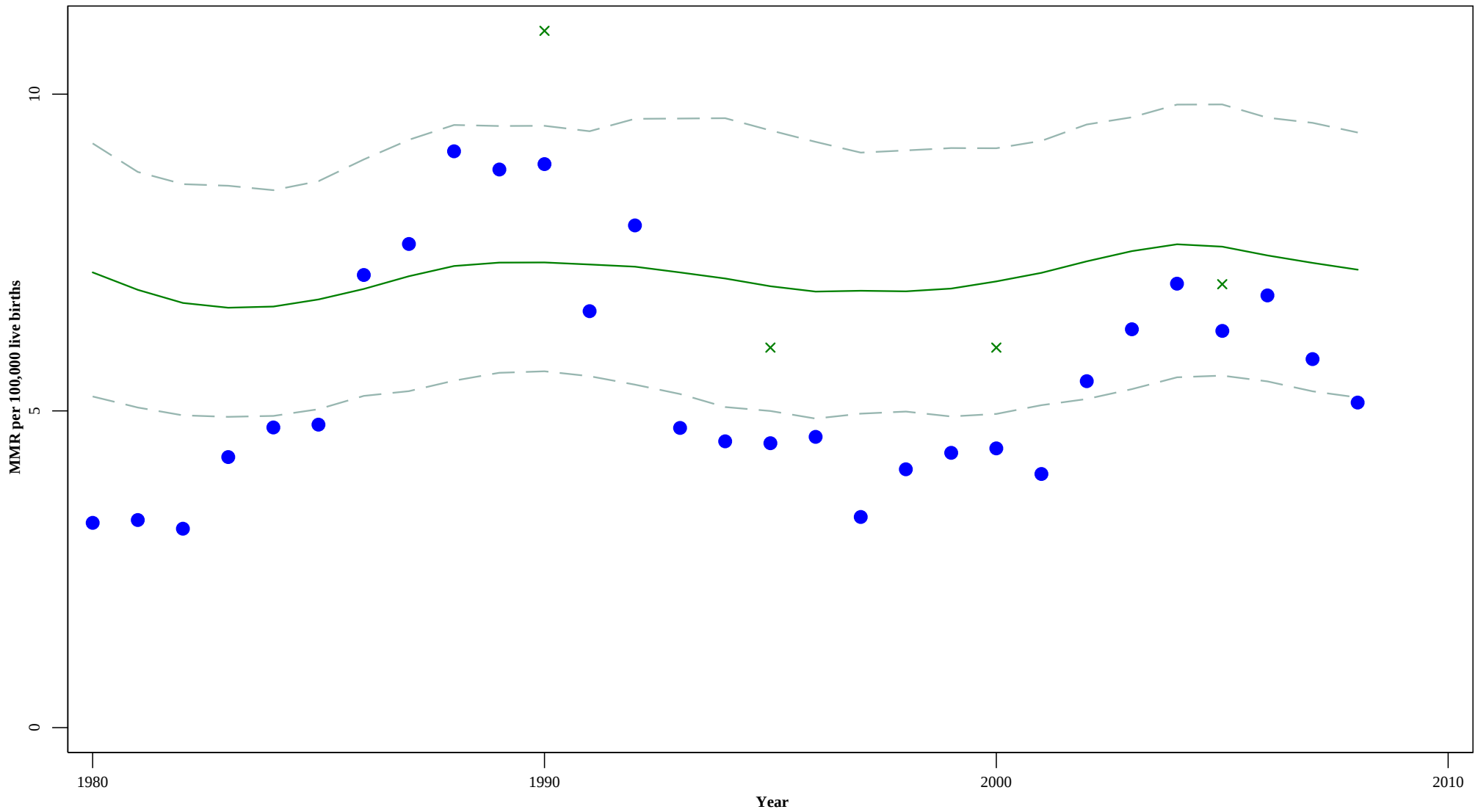
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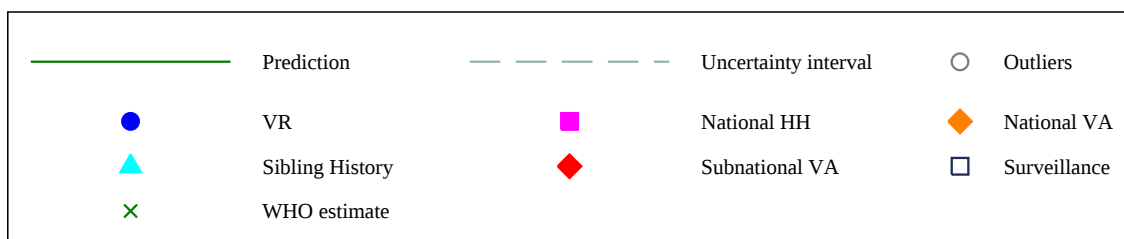
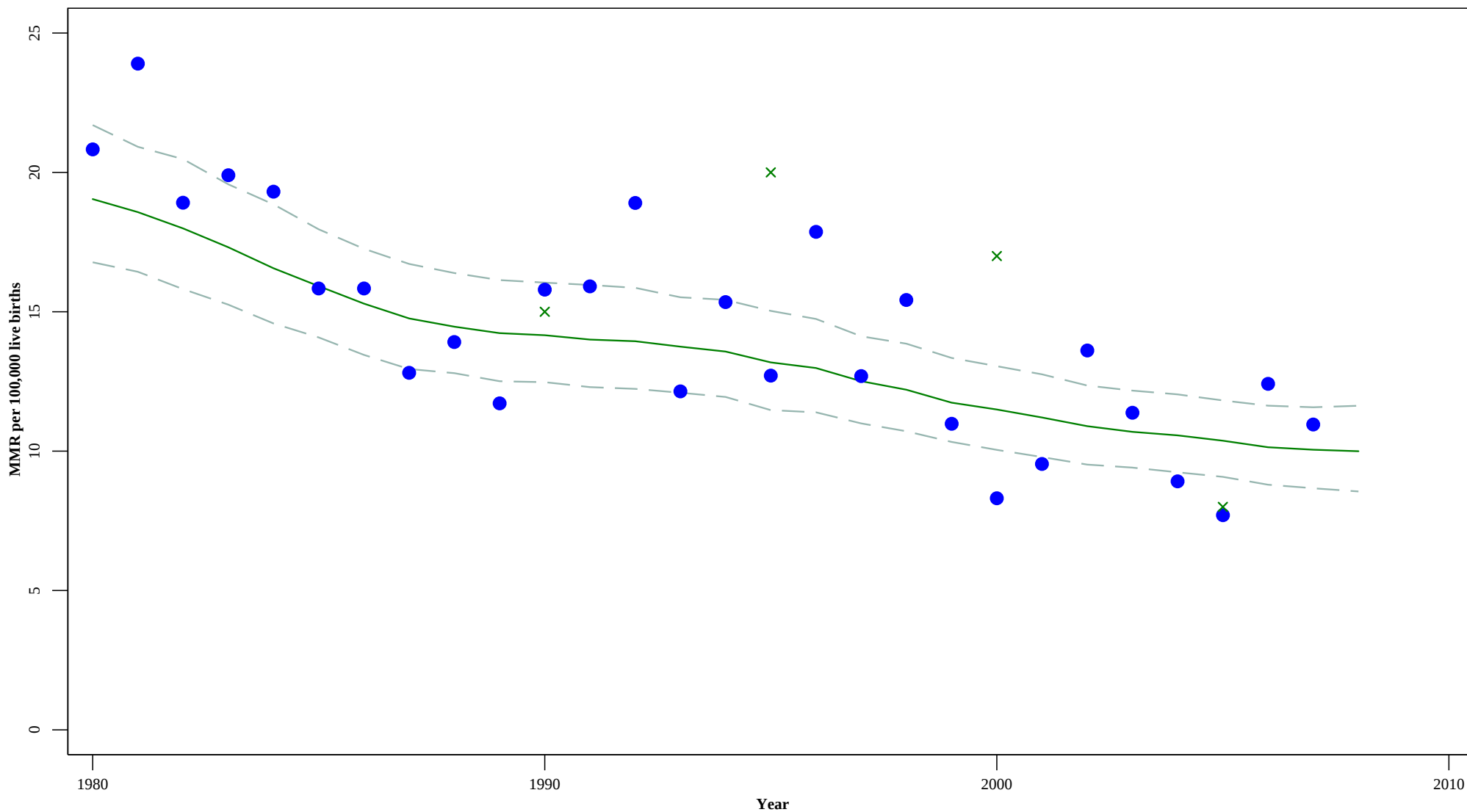
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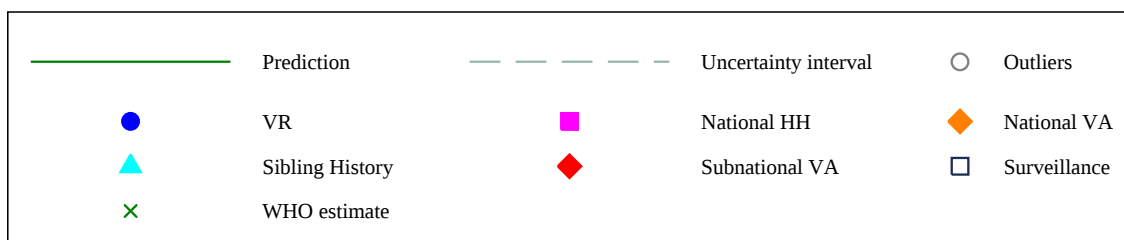
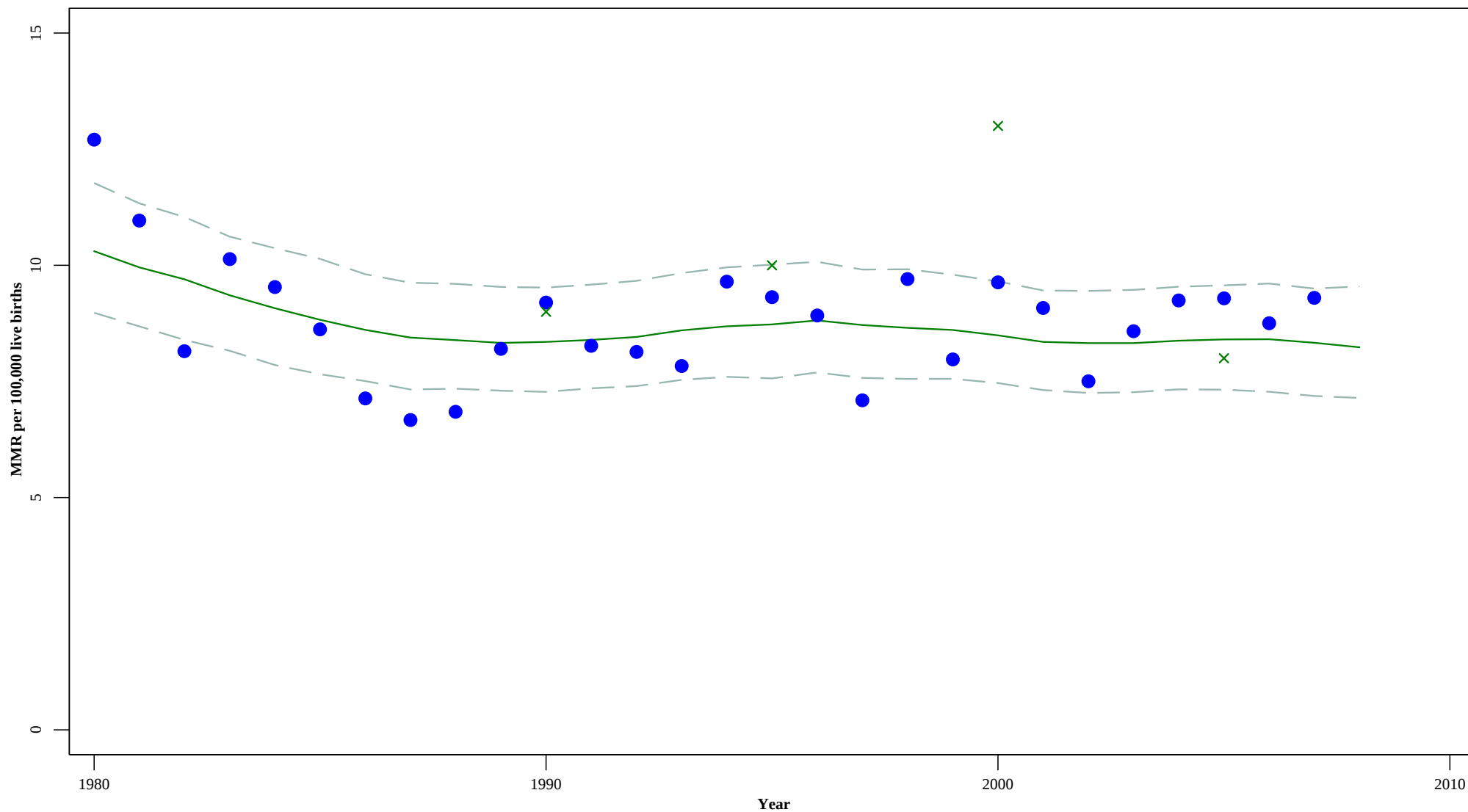
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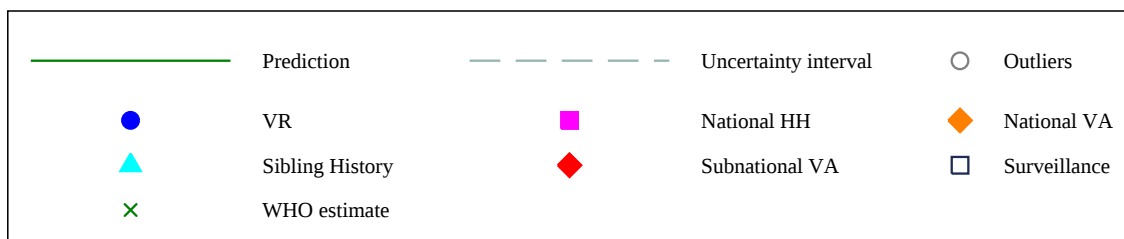
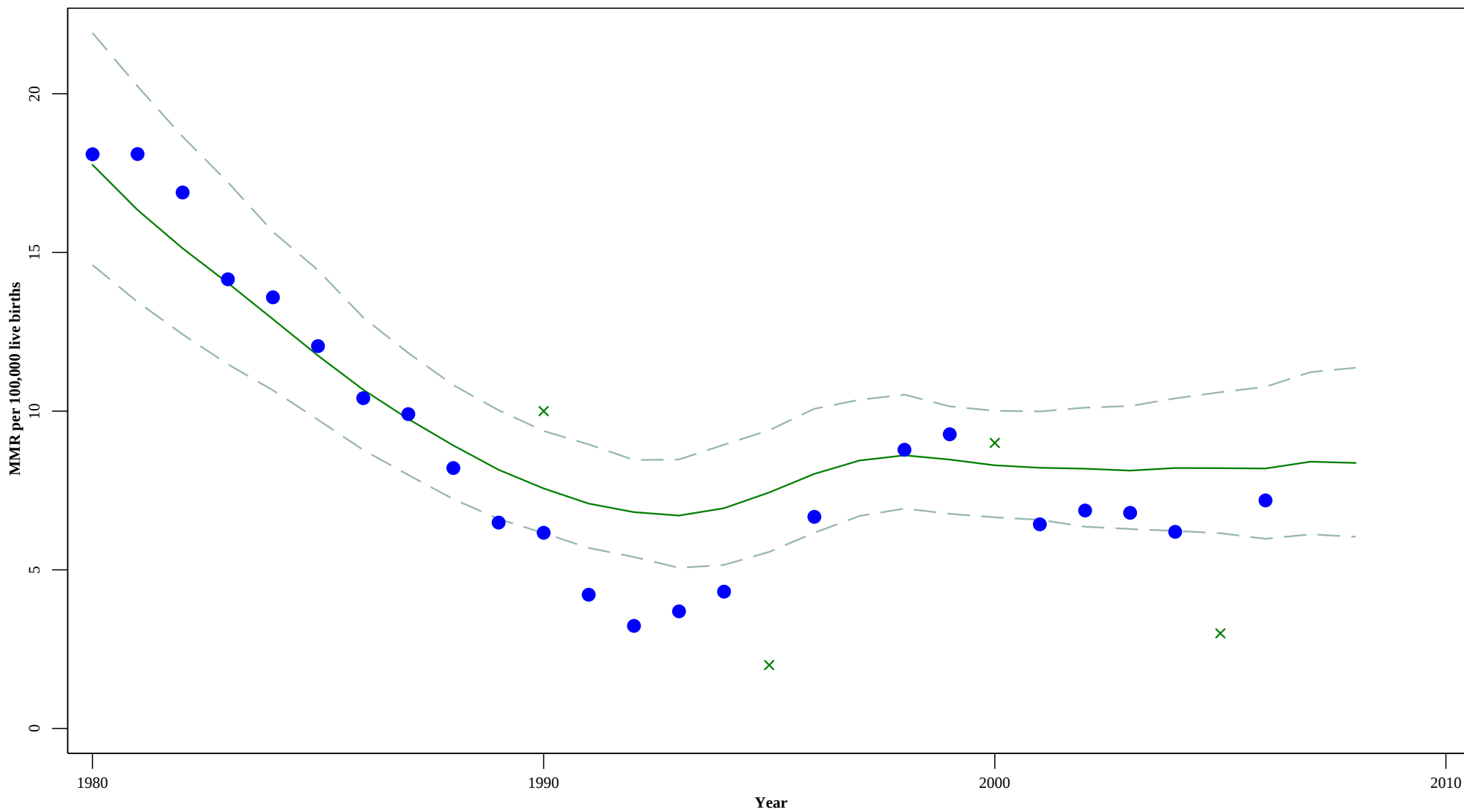
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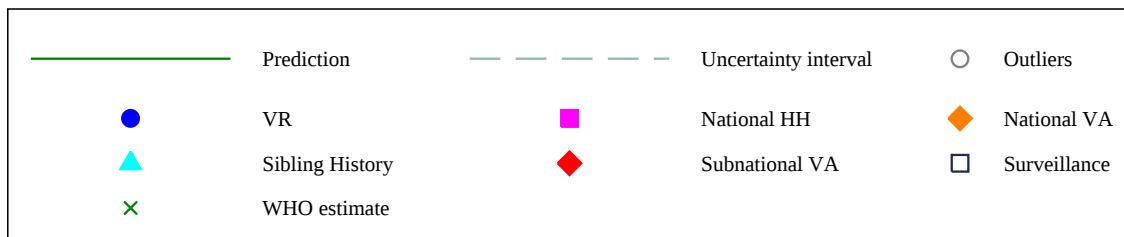
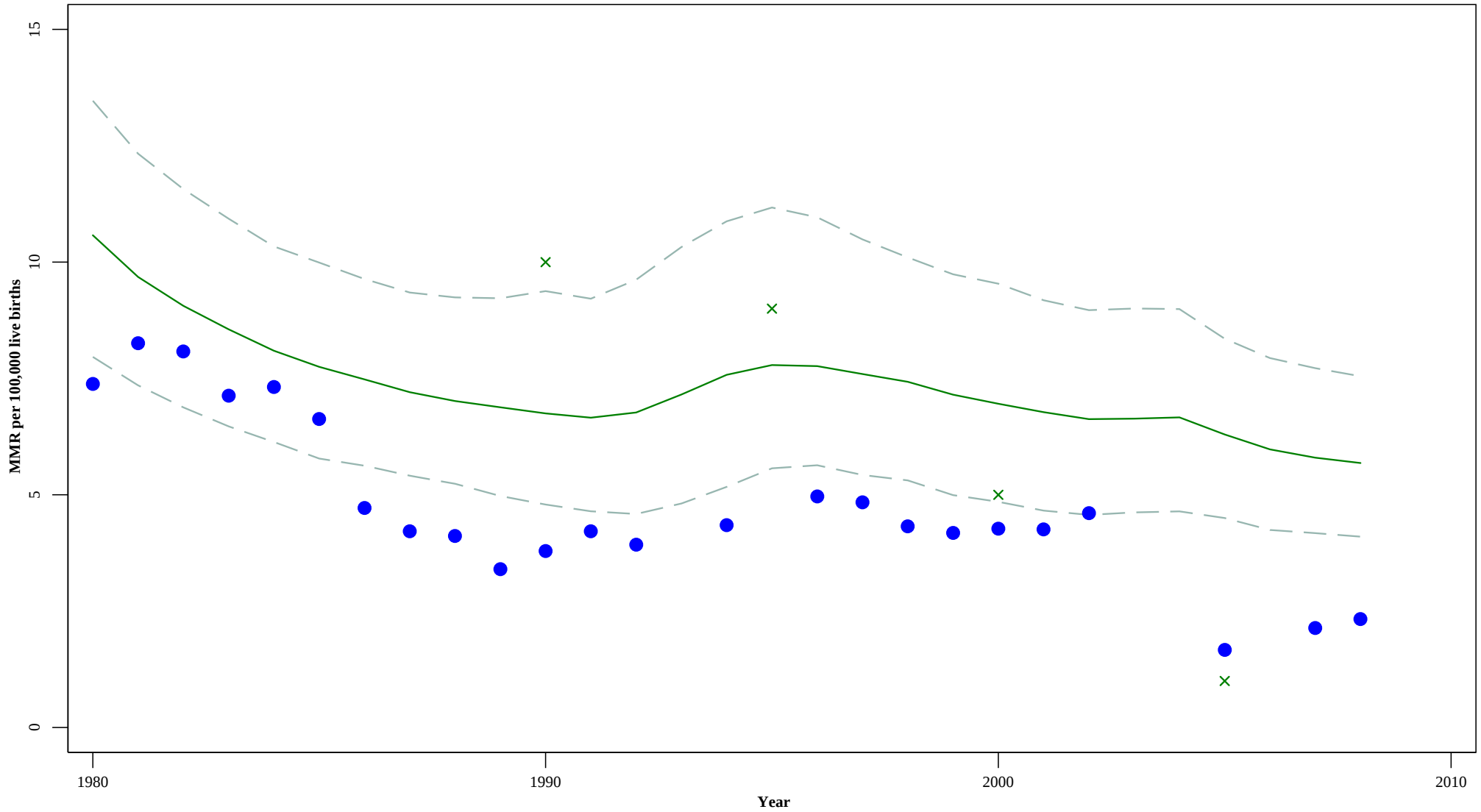
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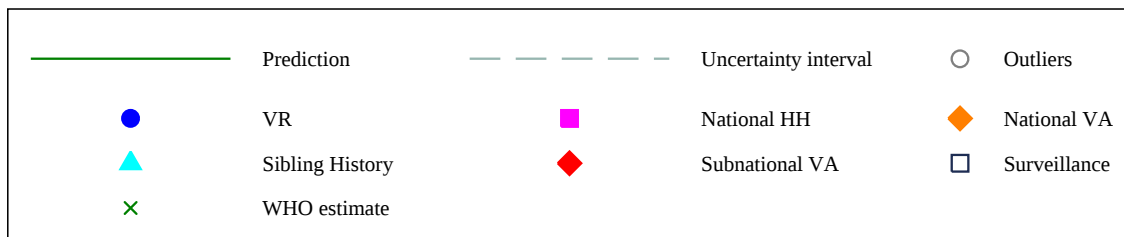
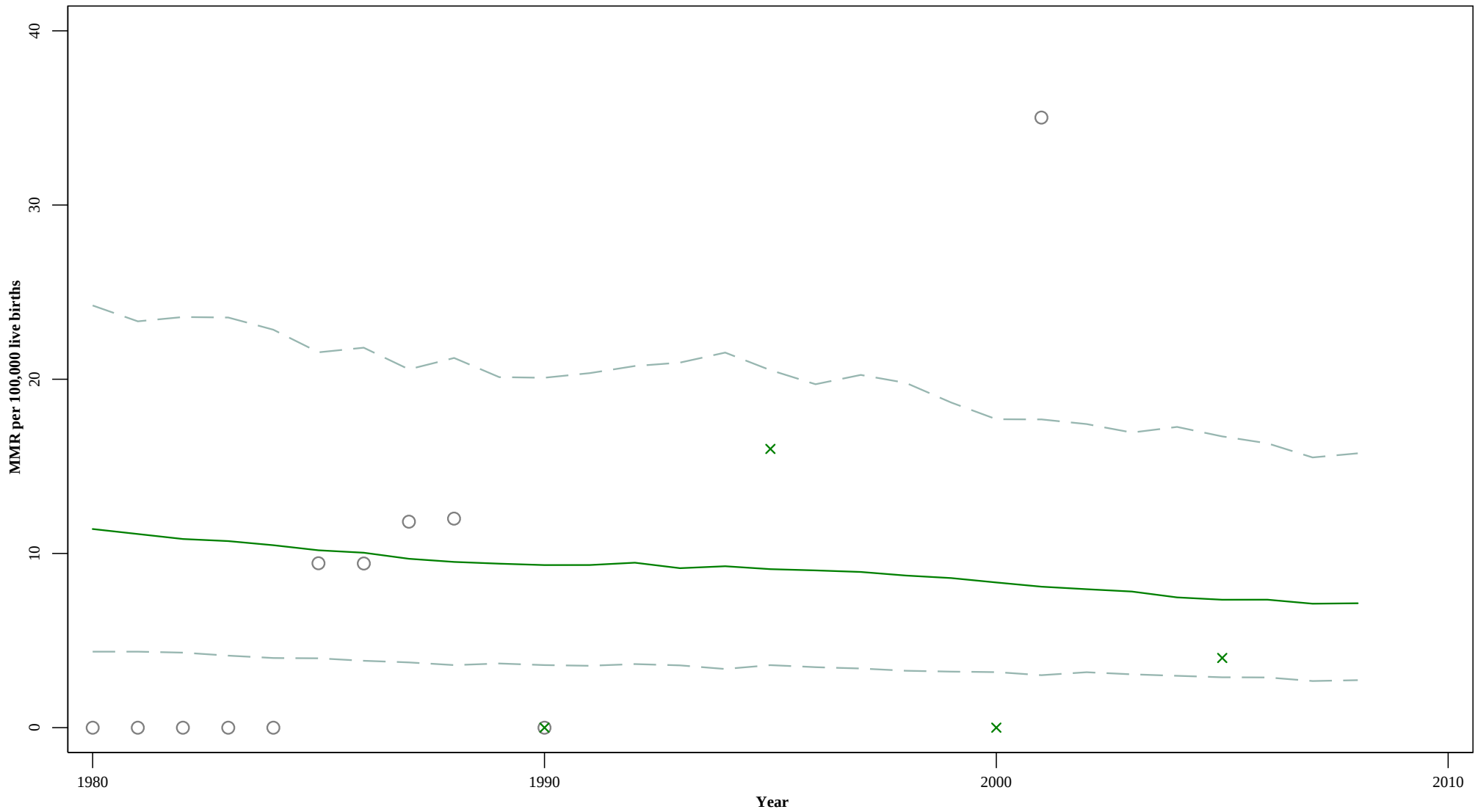
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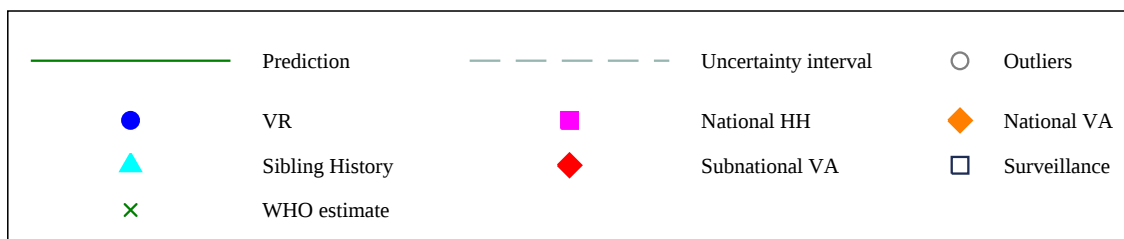
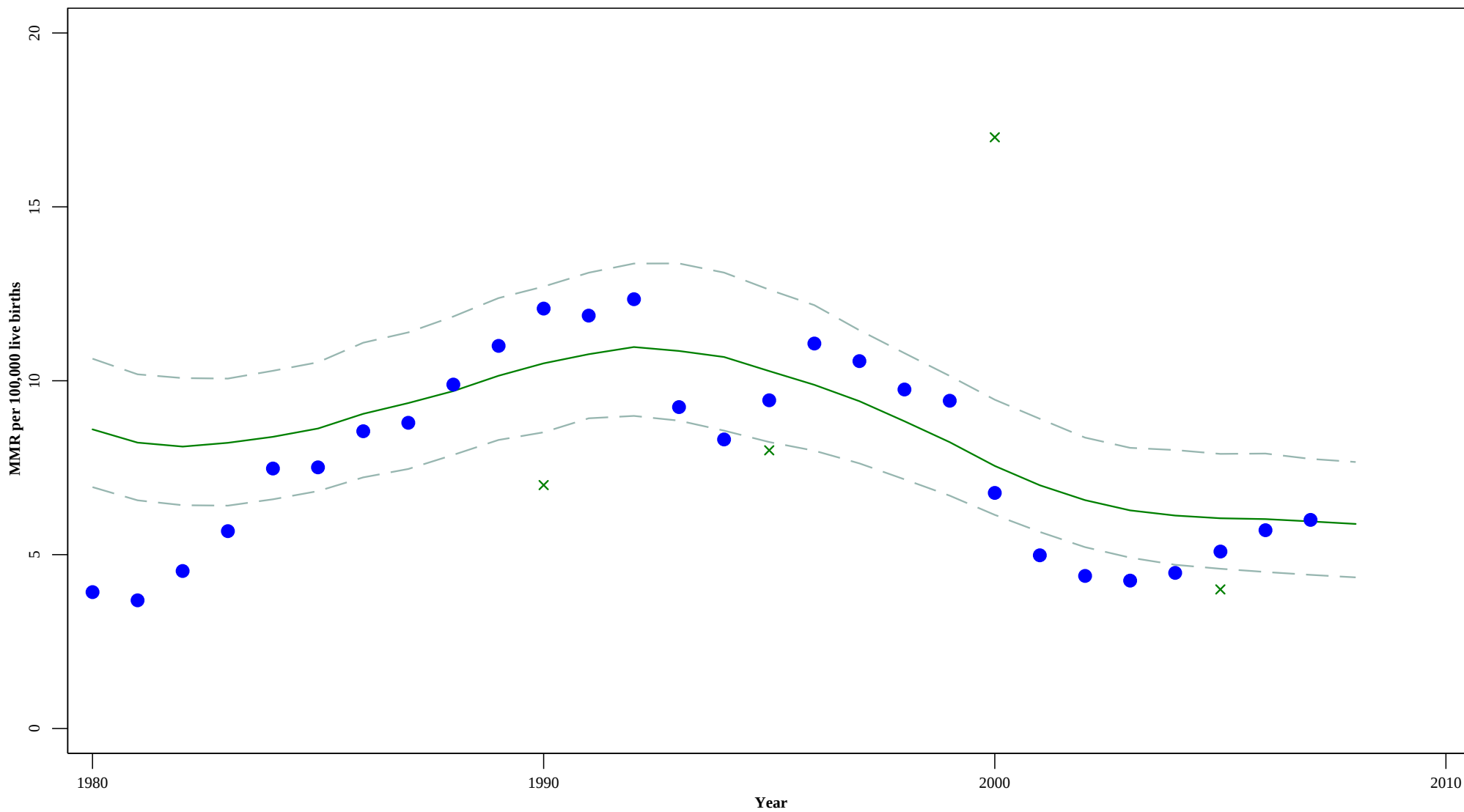
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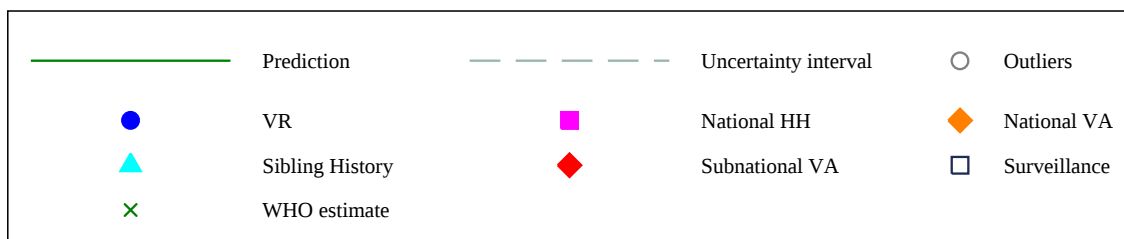
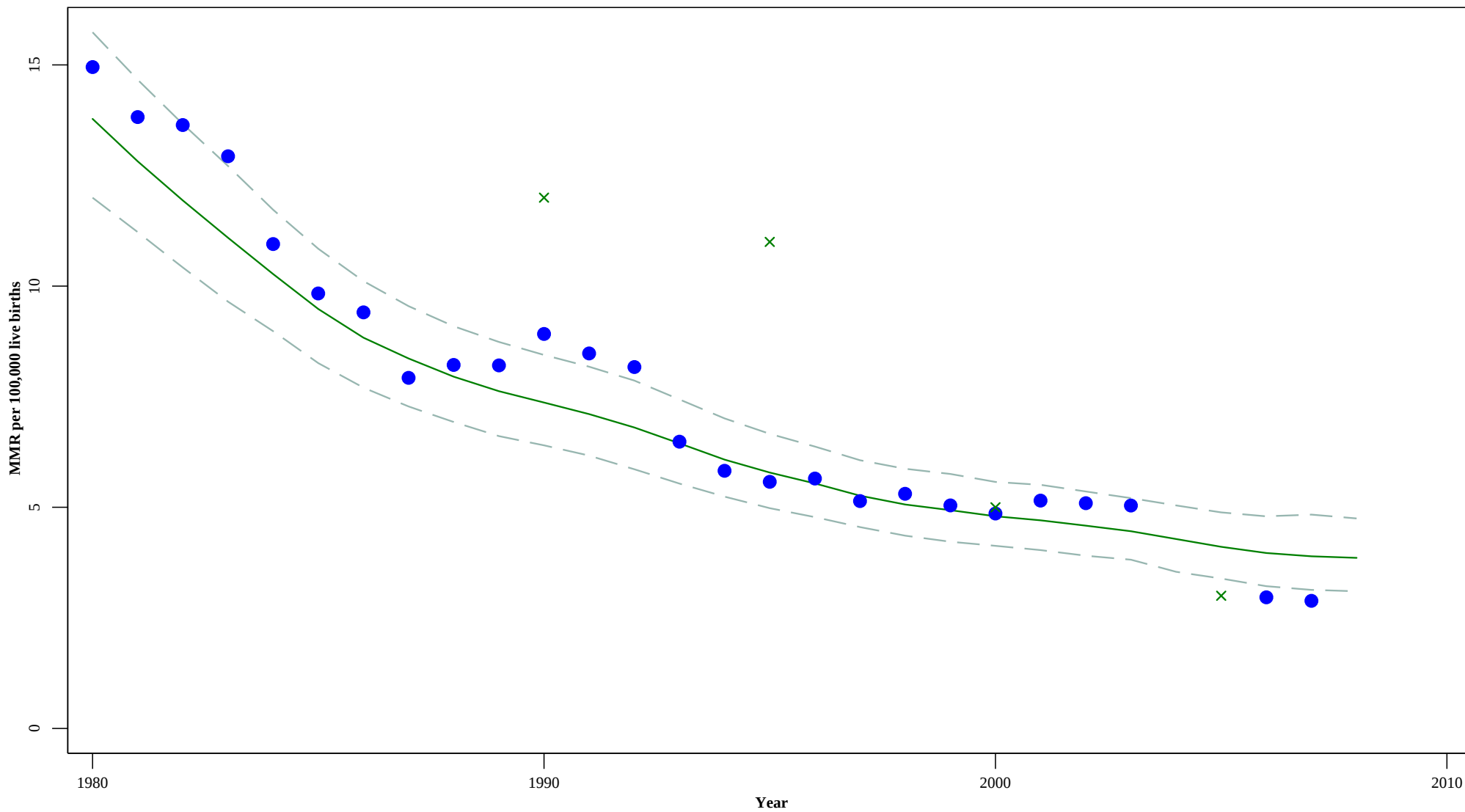
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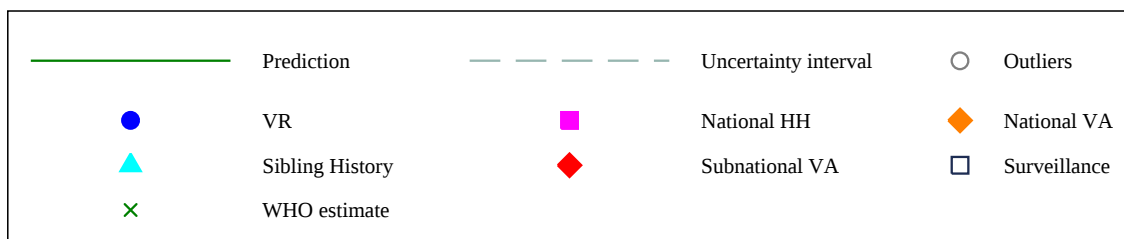
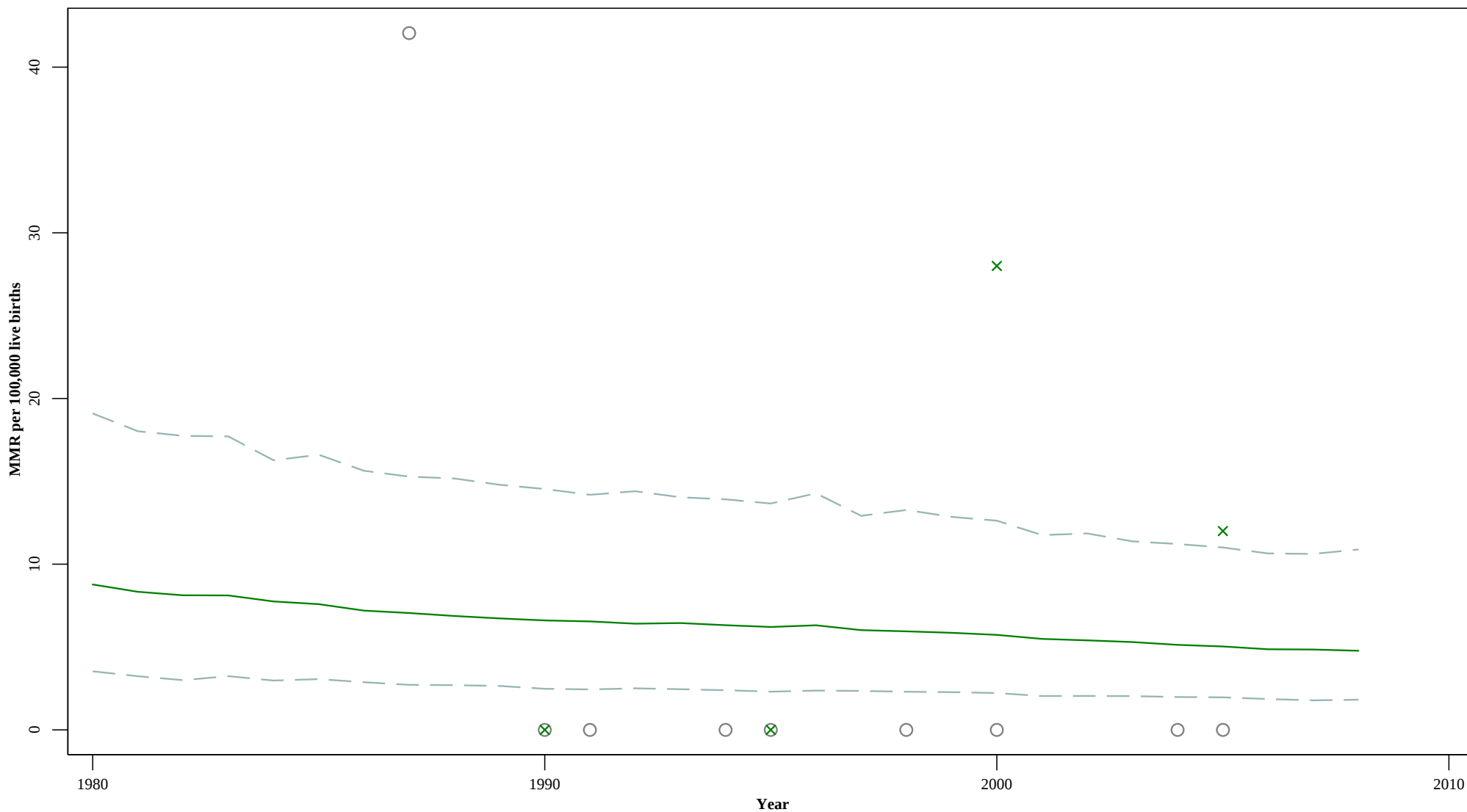
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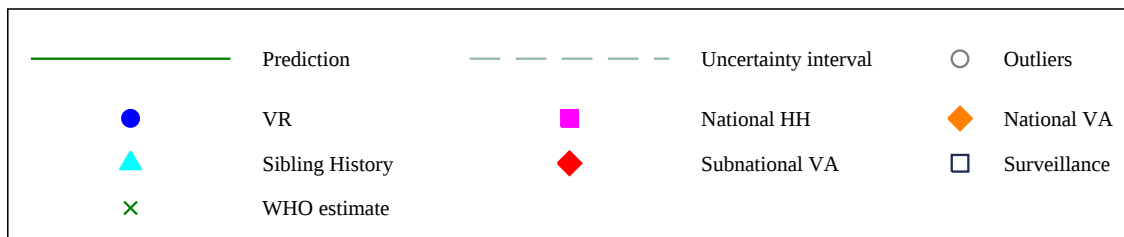
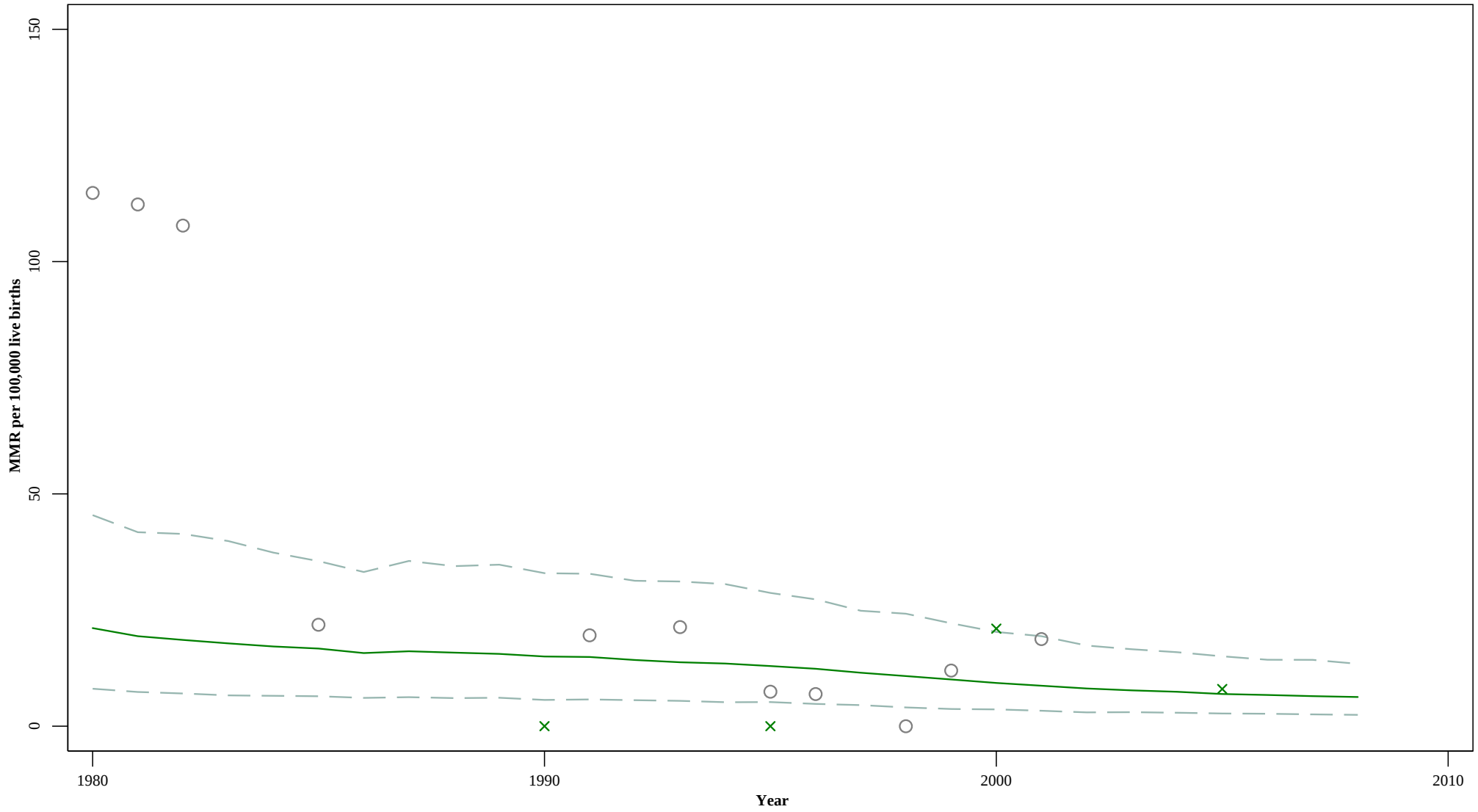
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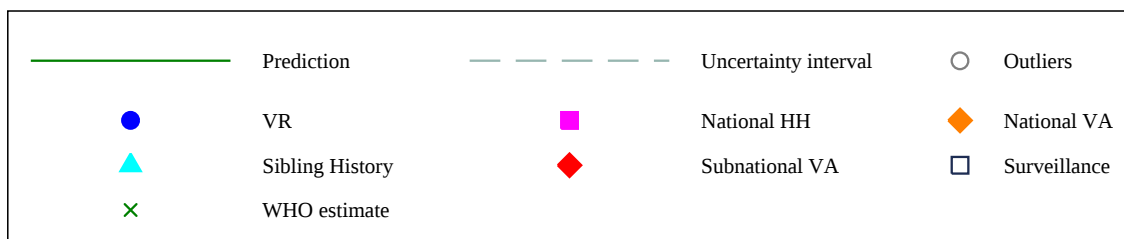
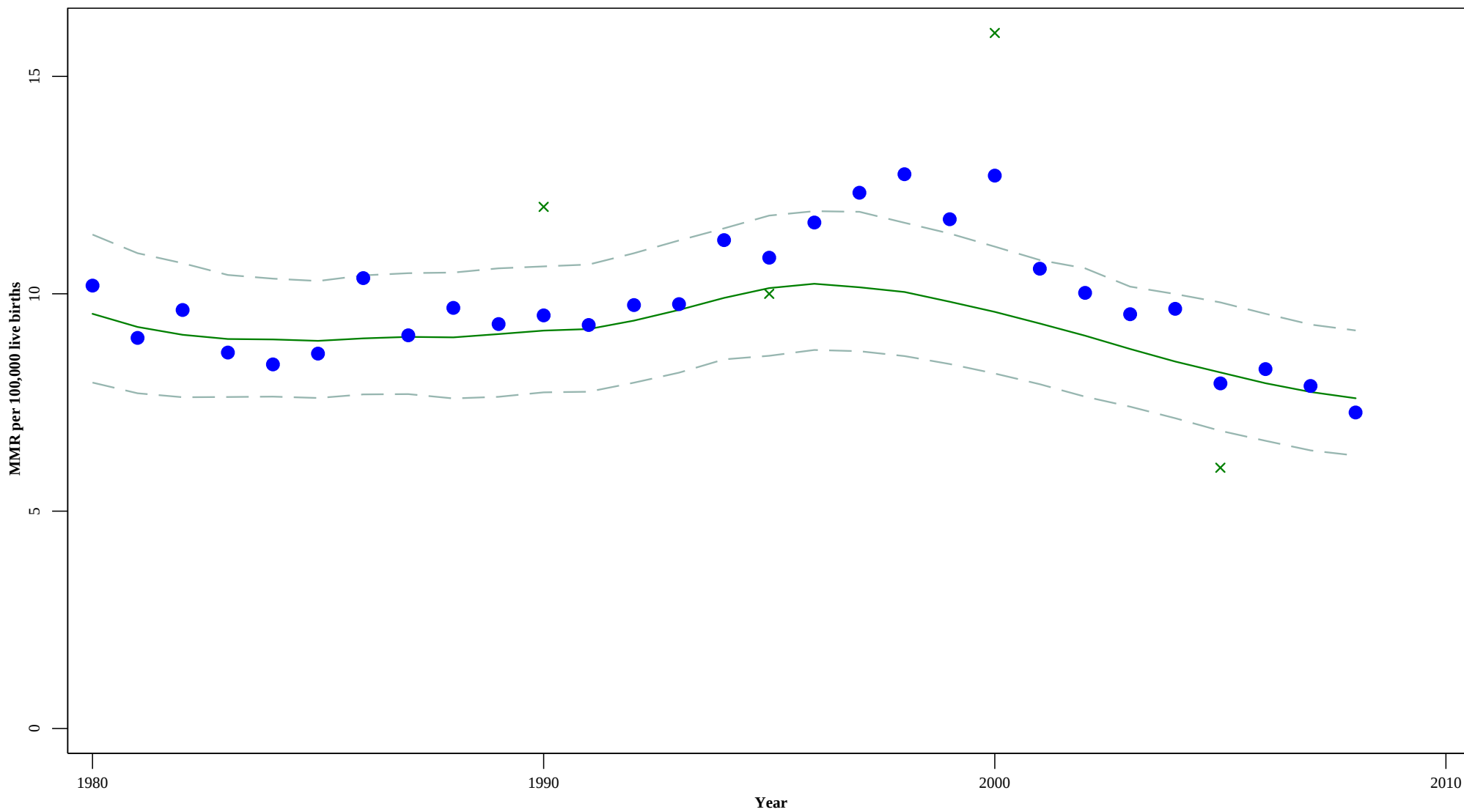
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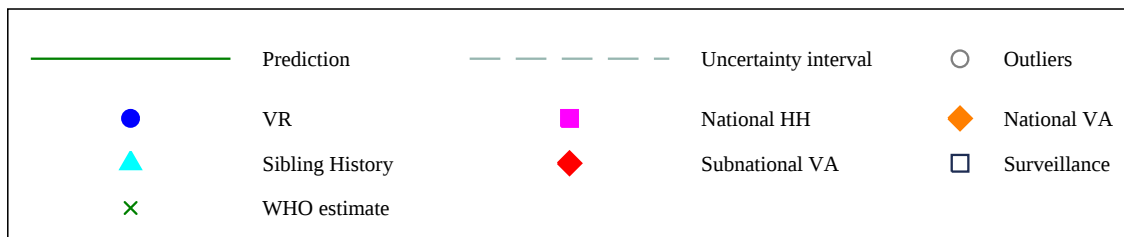
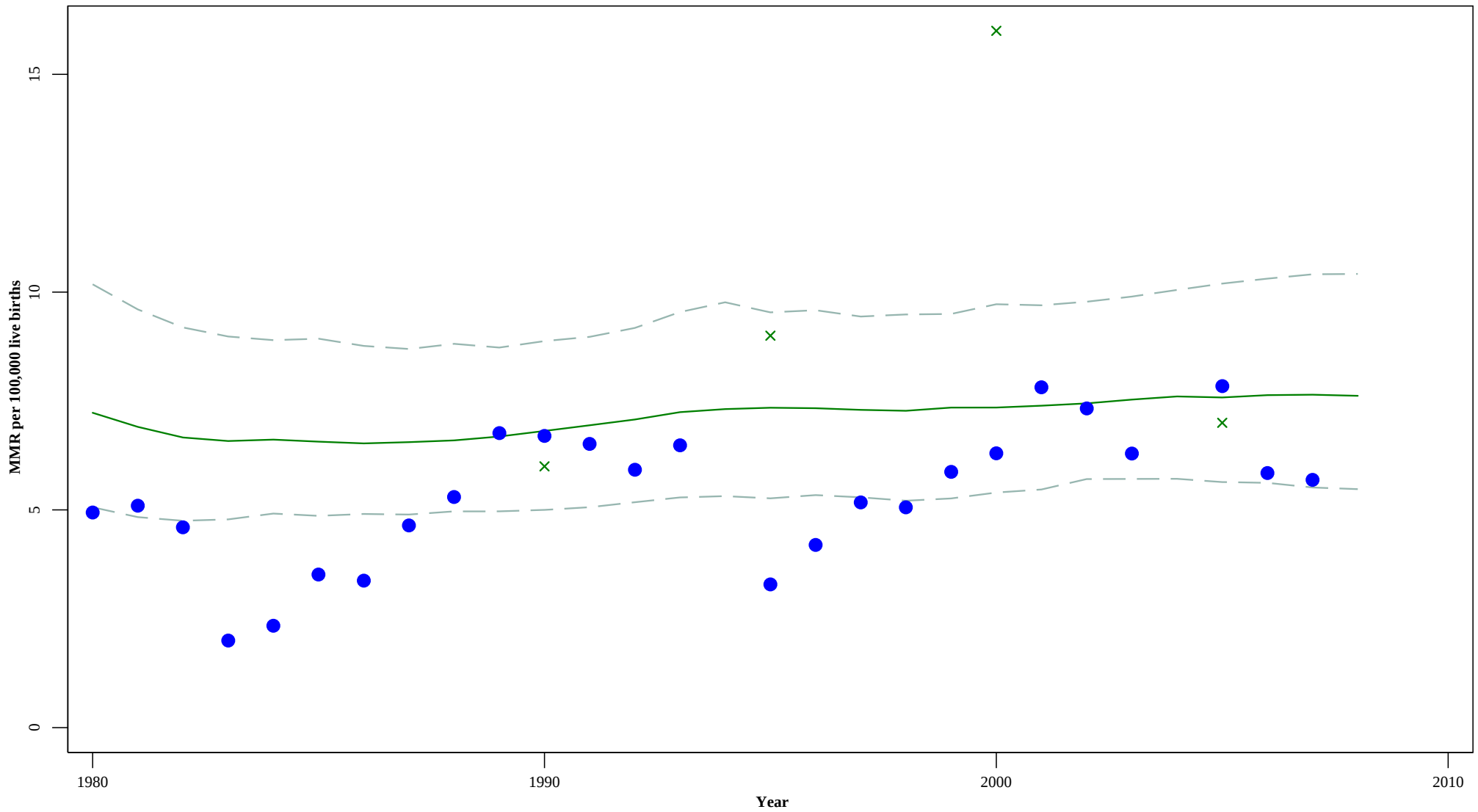
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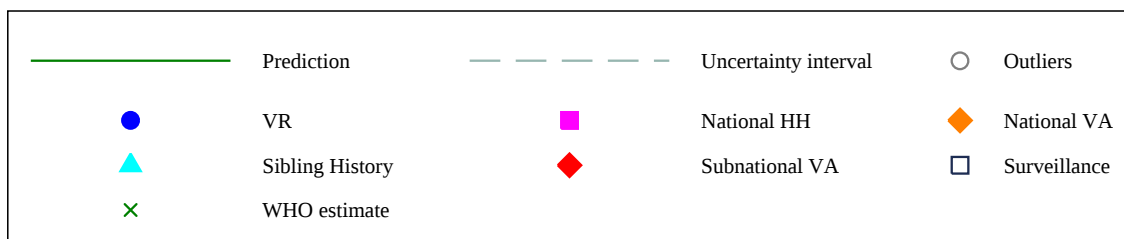
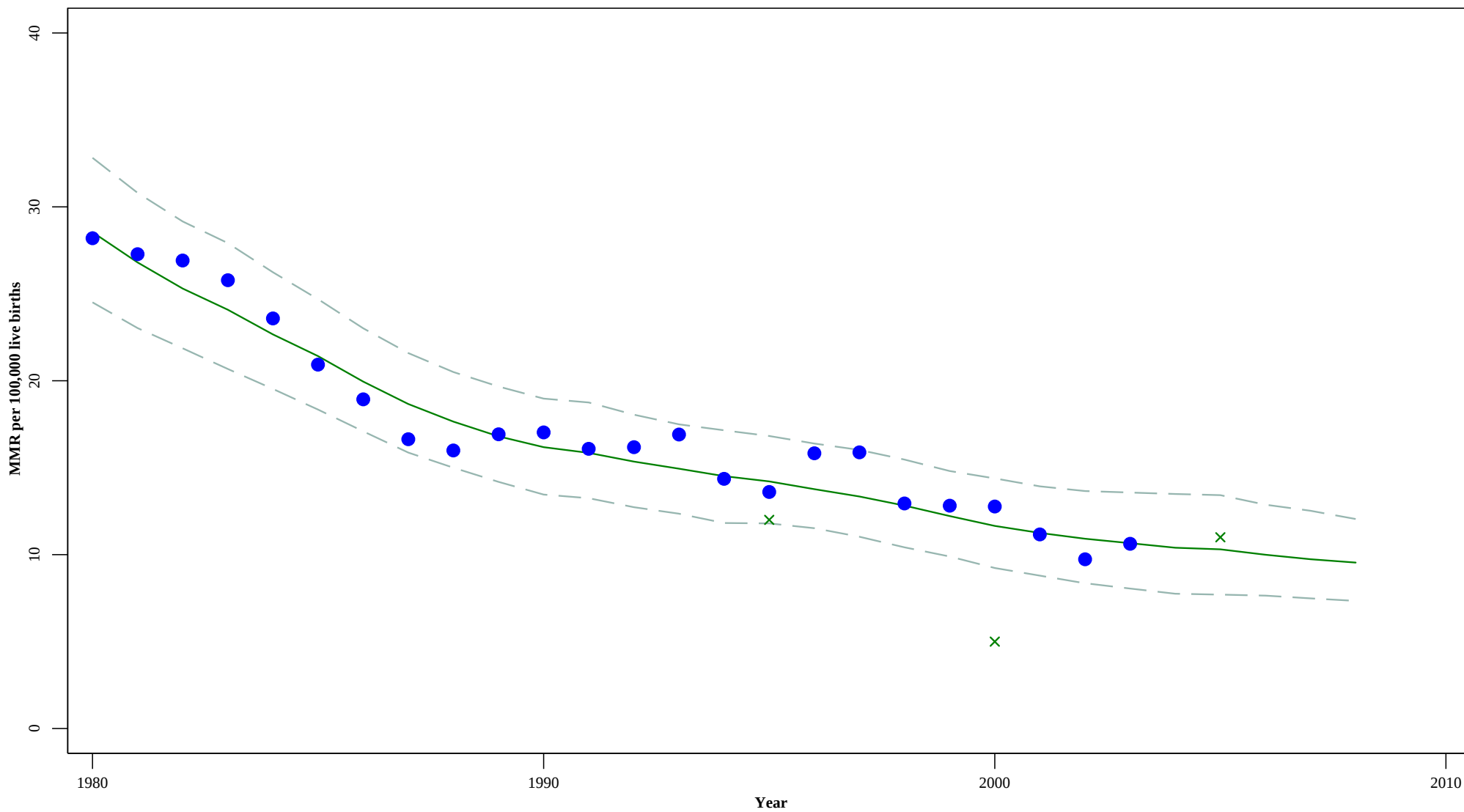
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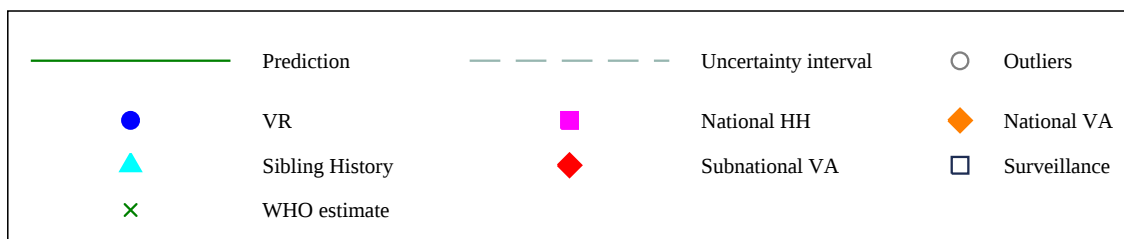
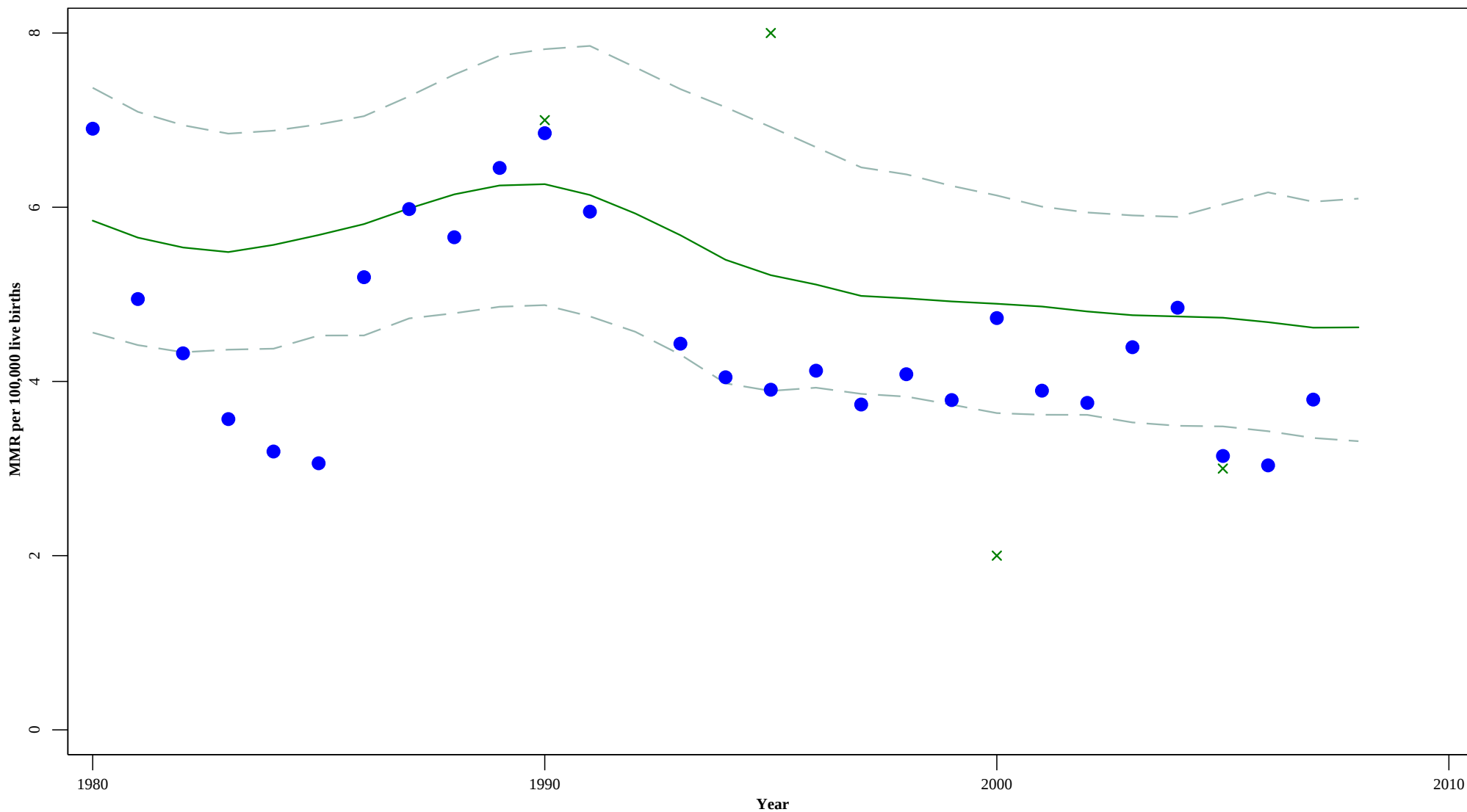
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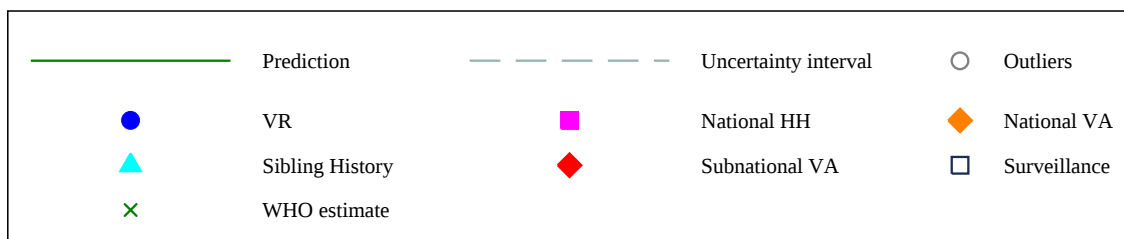
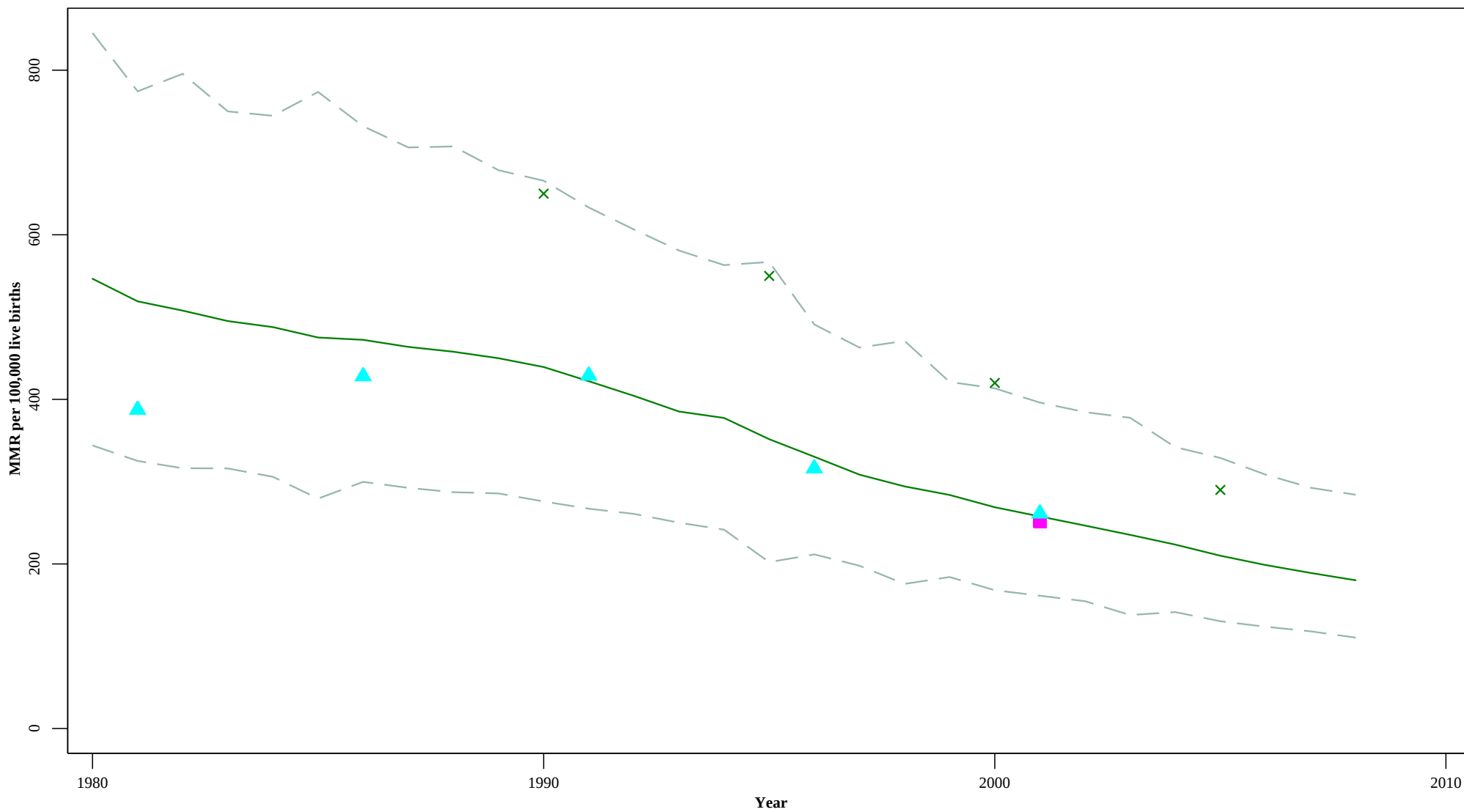
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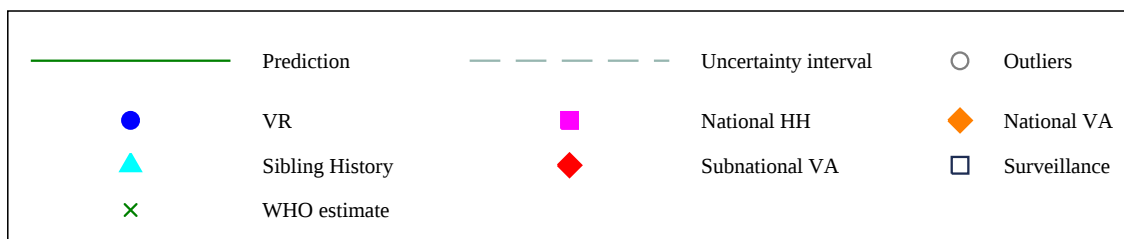
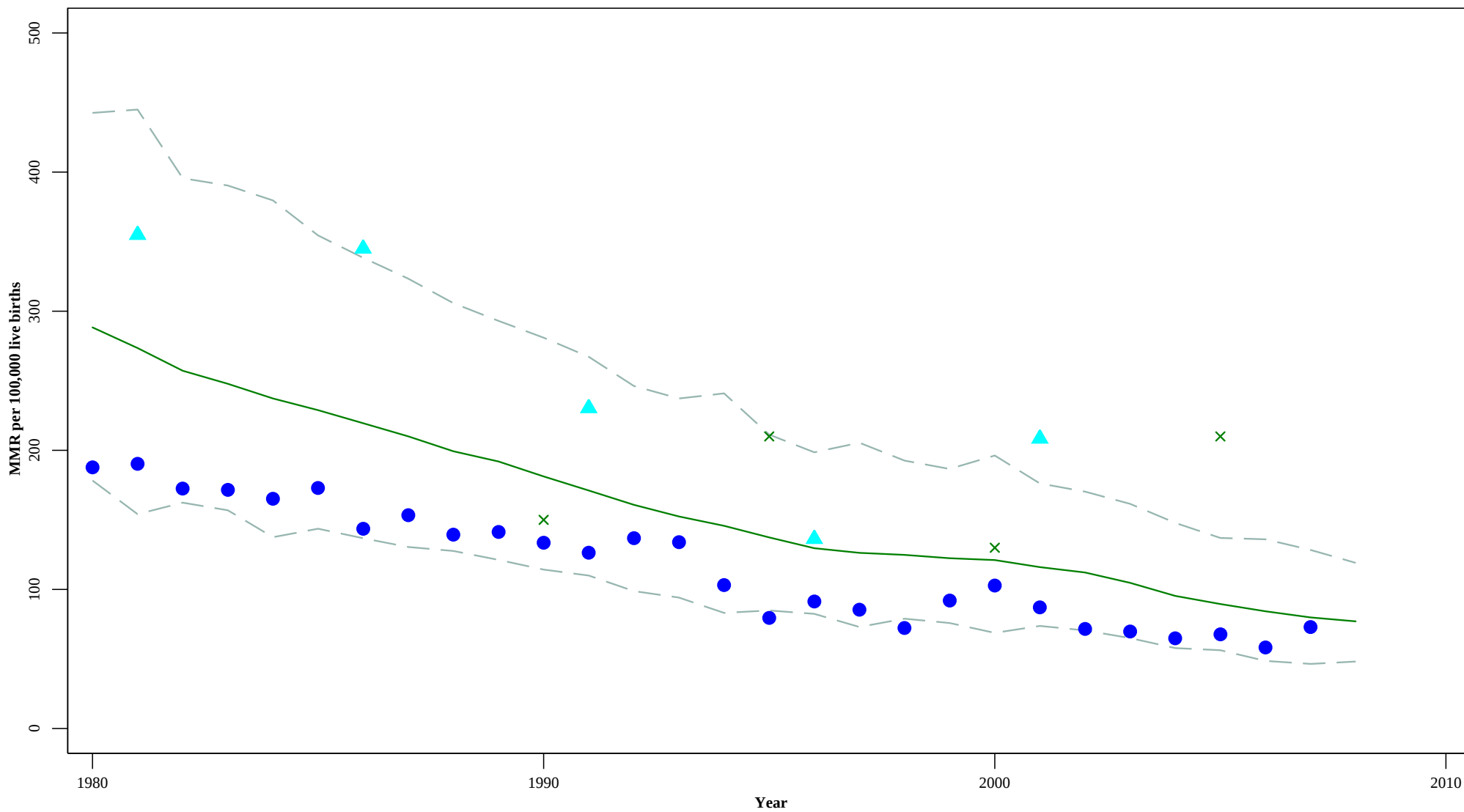
Sweden



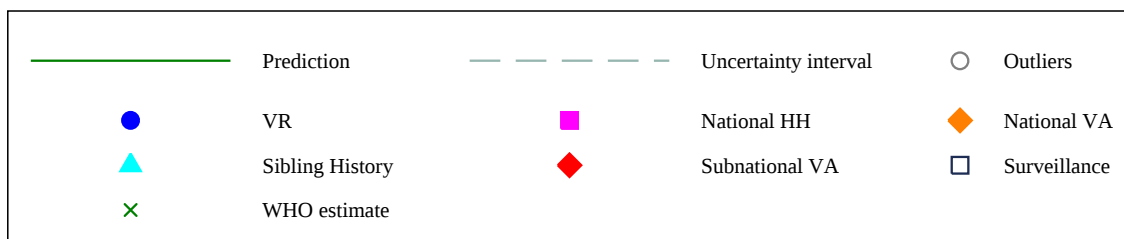
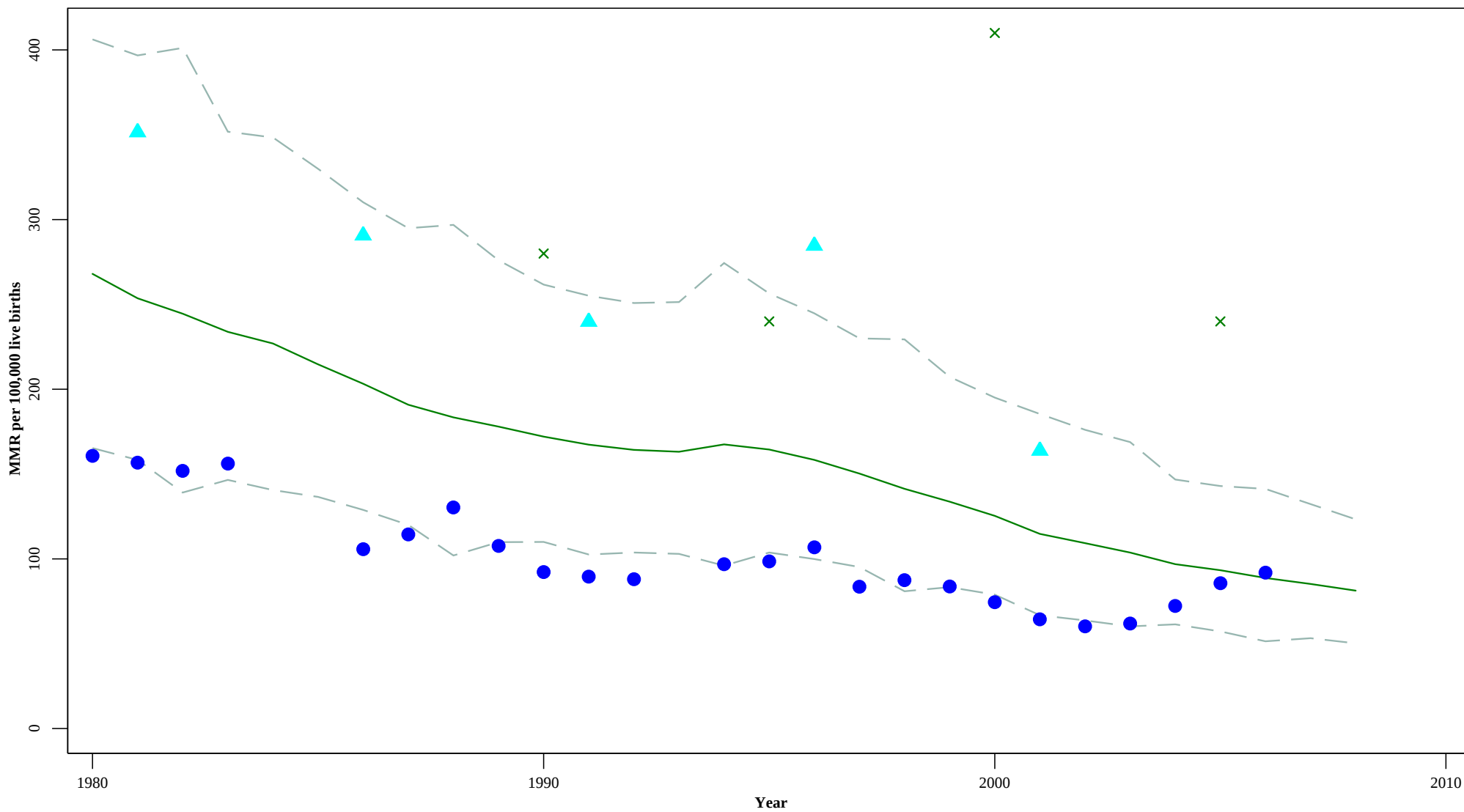
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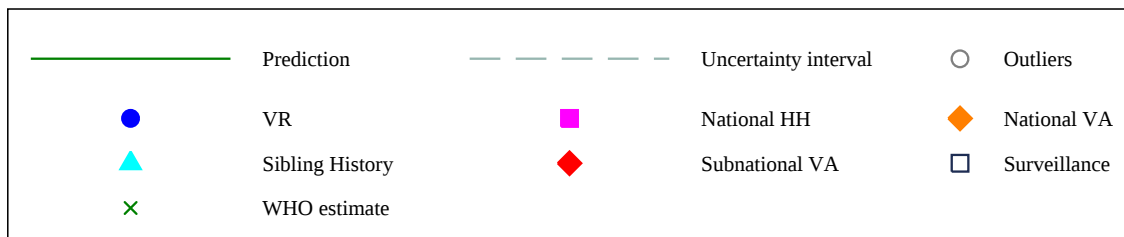
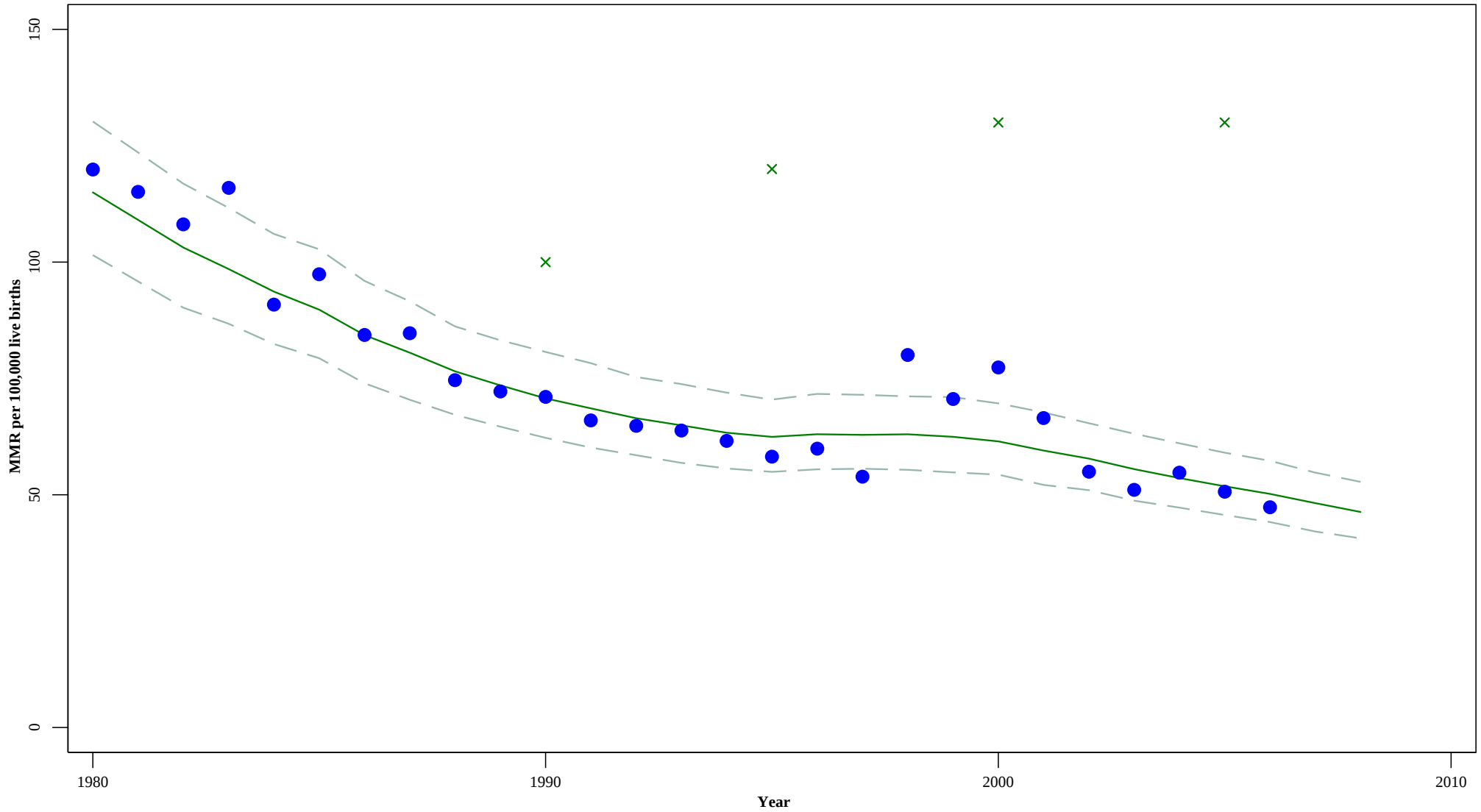
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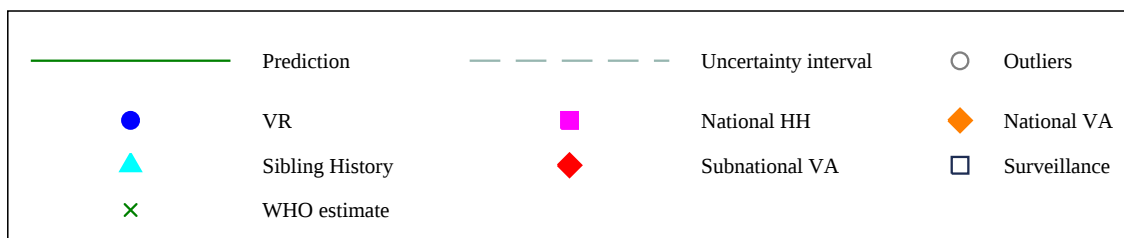
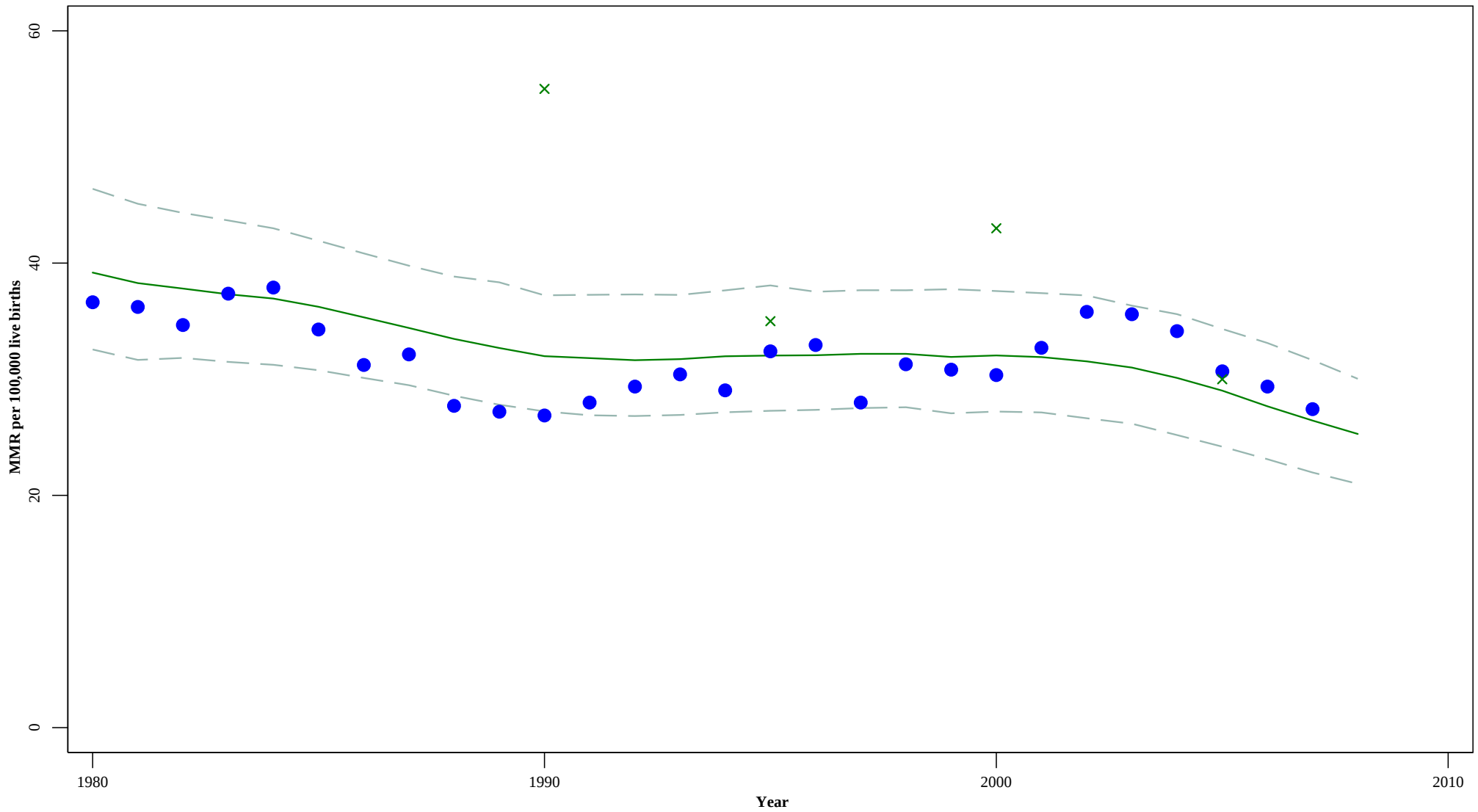
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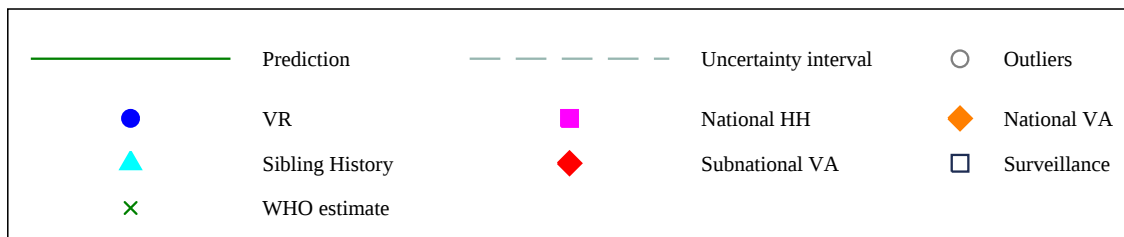
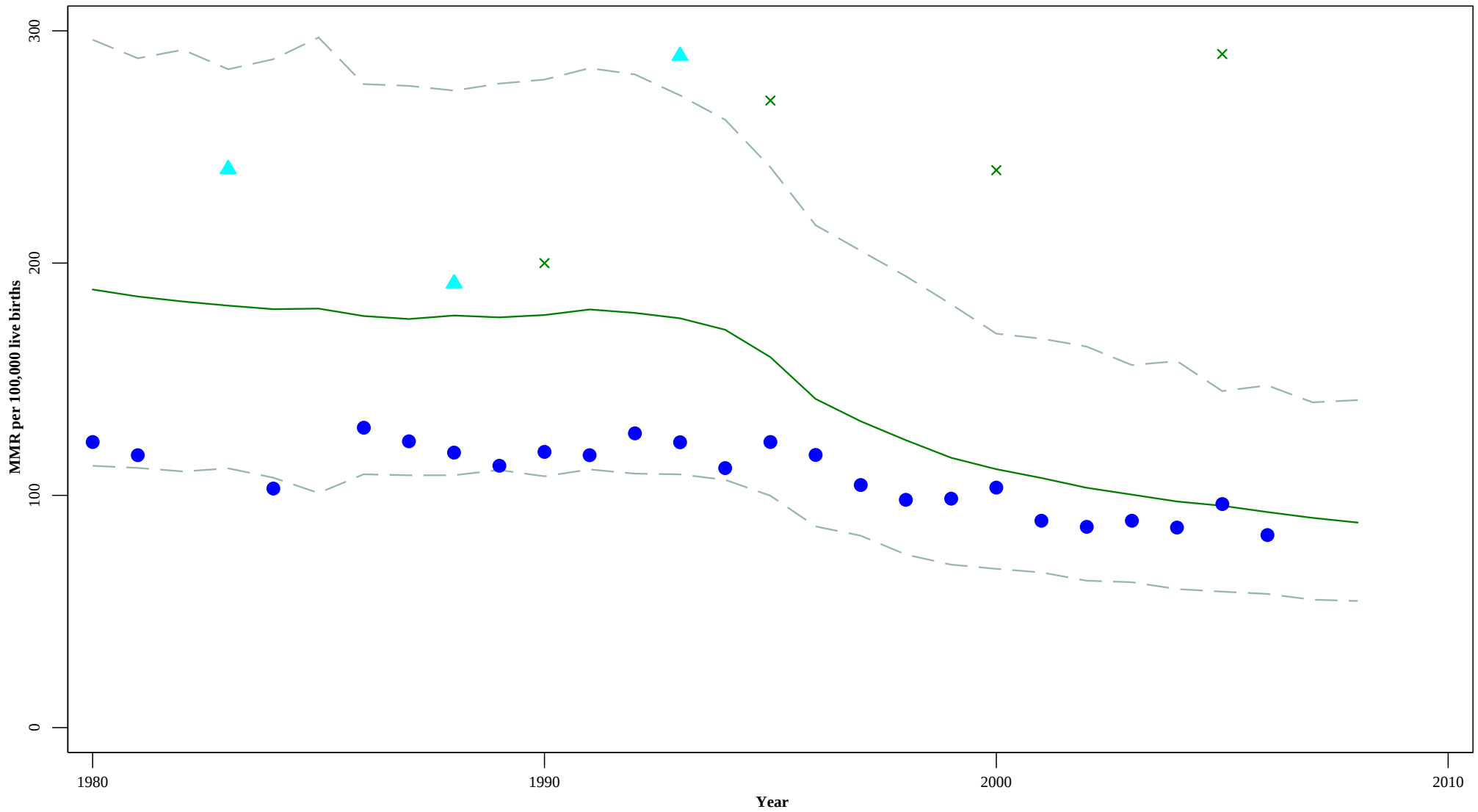
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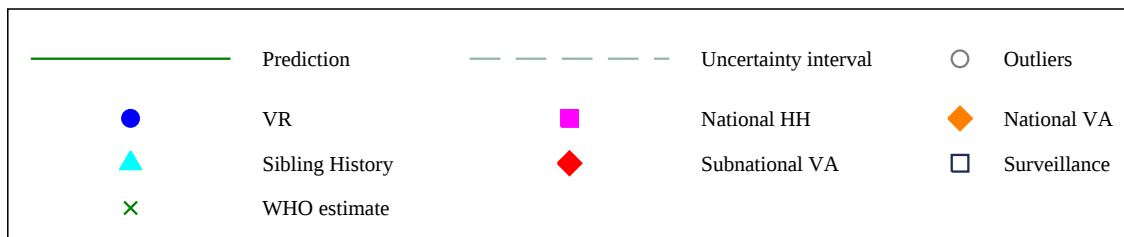
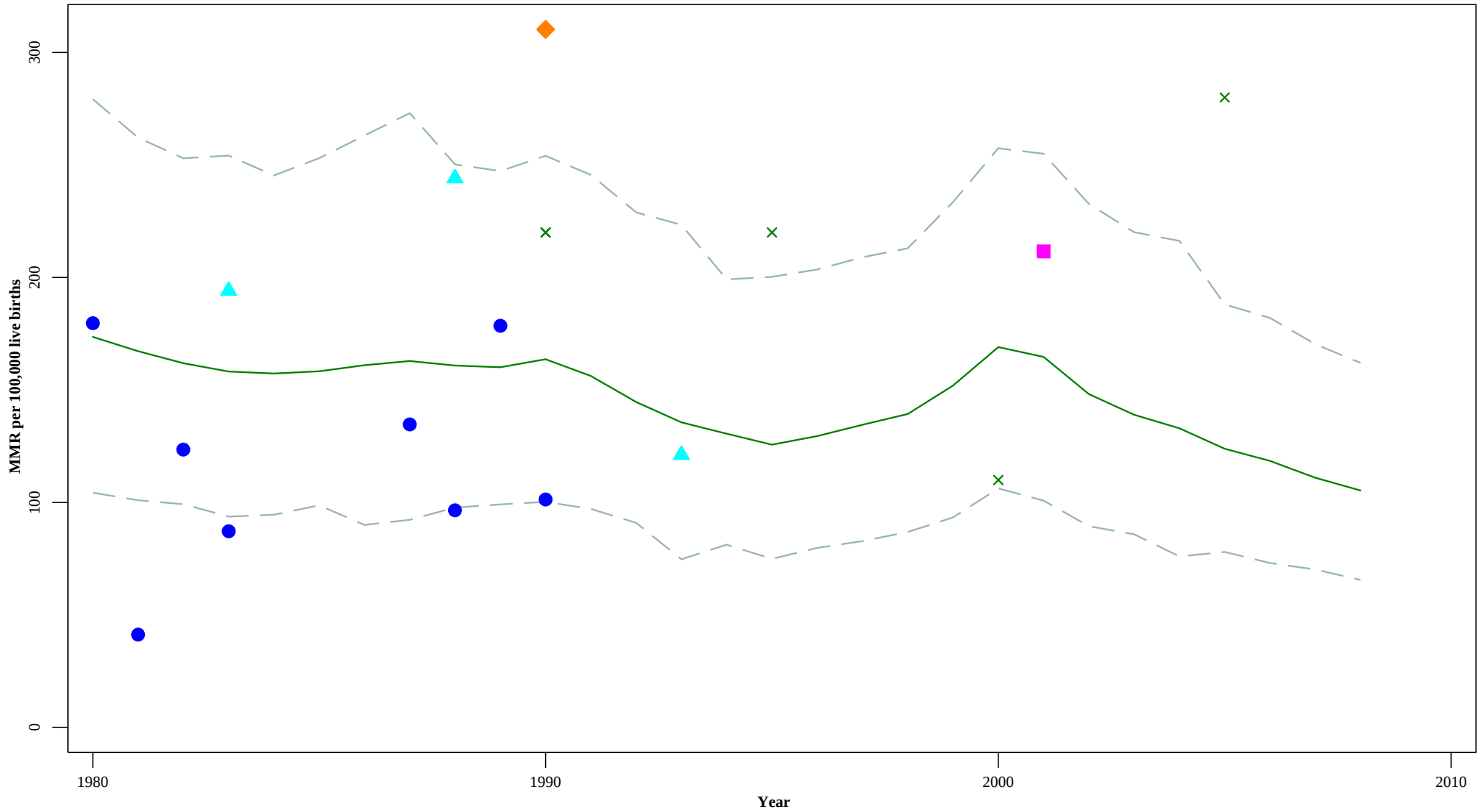
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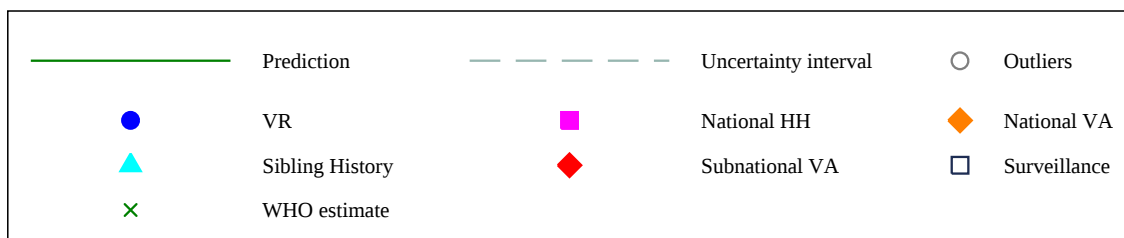
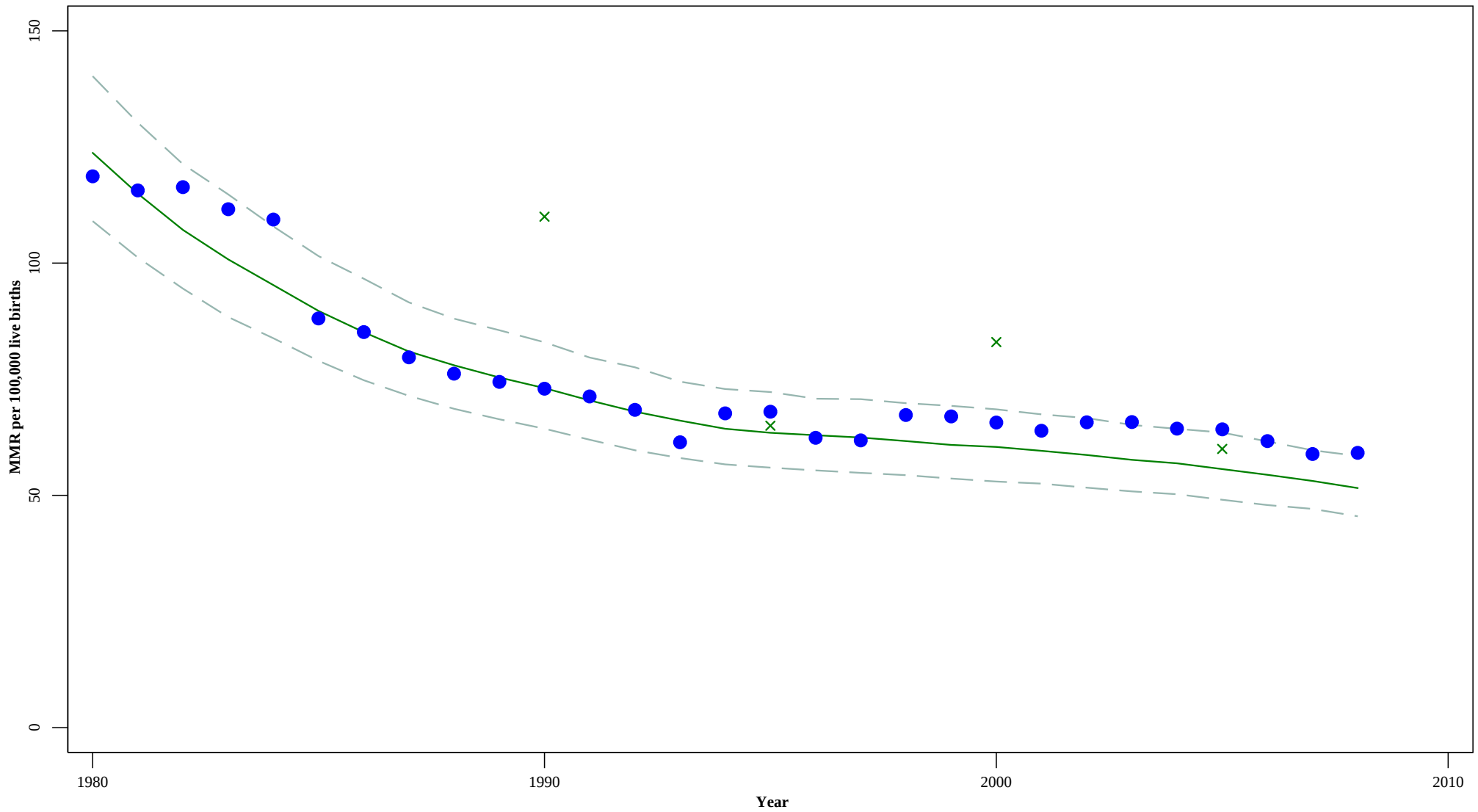
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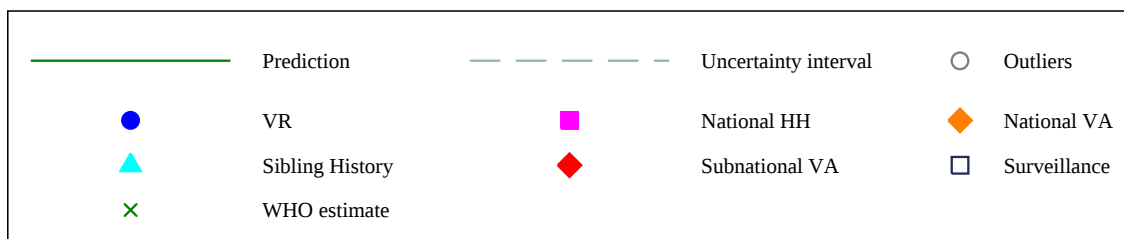
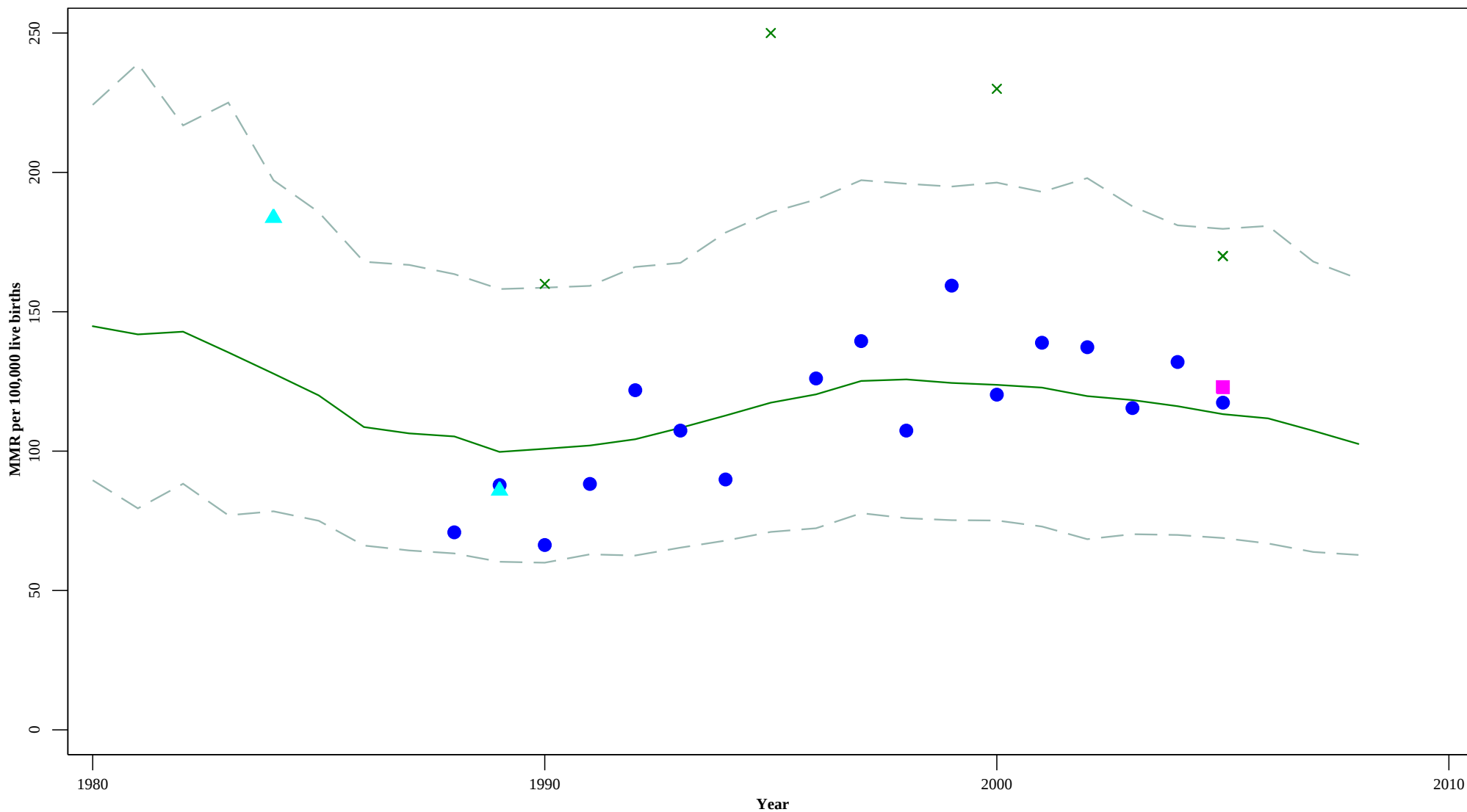
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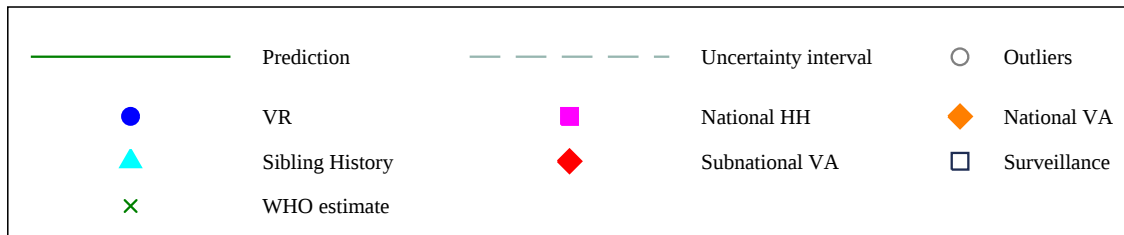
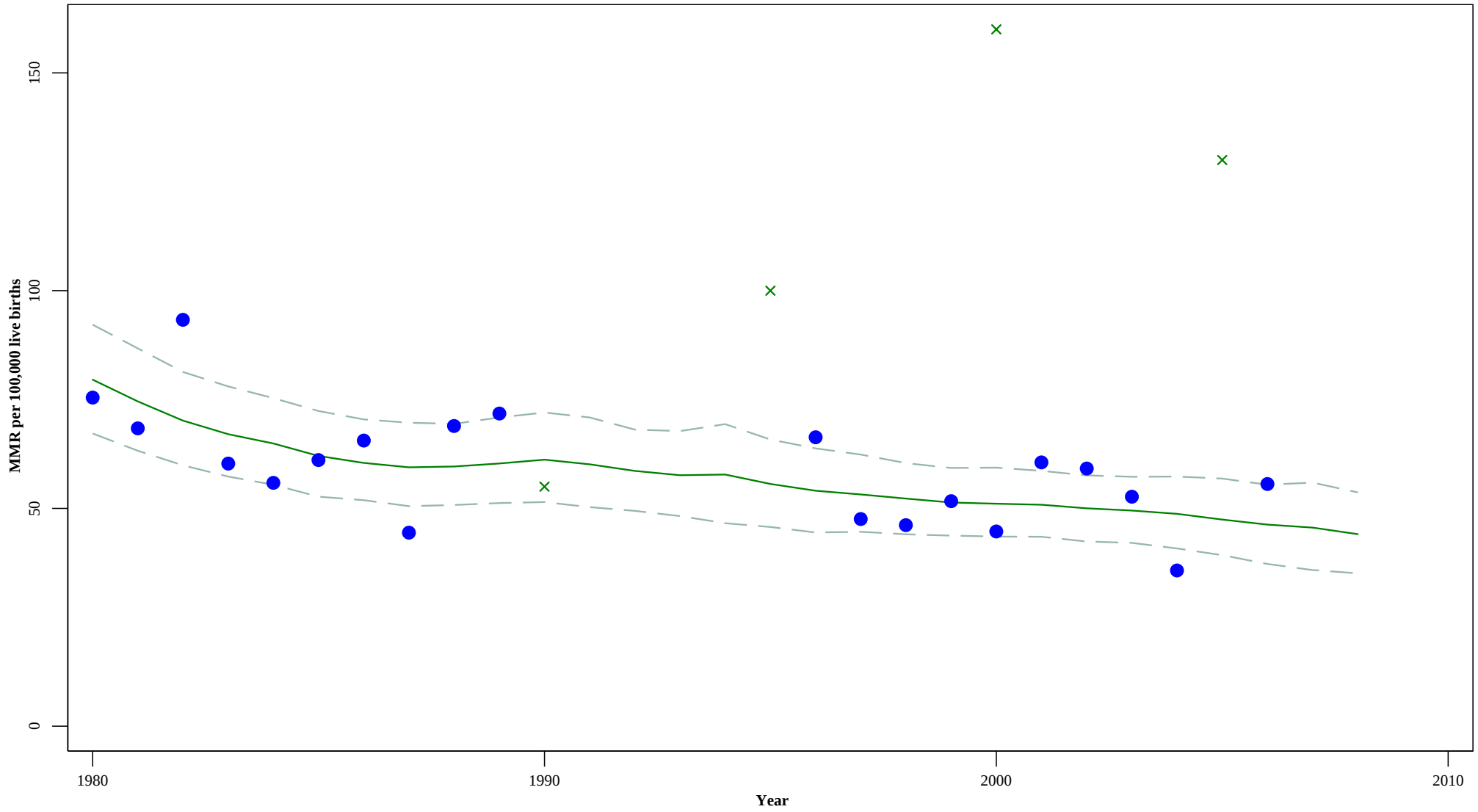
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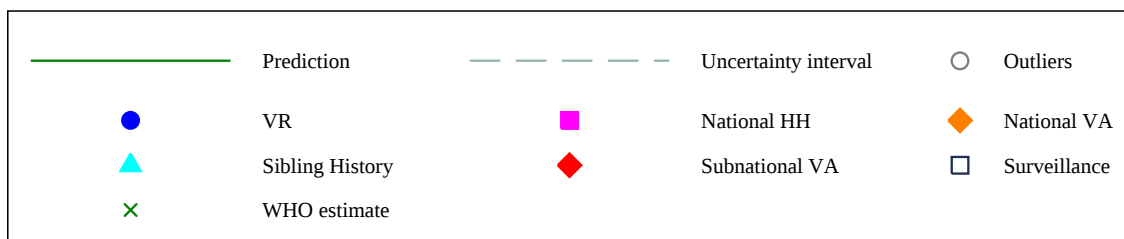
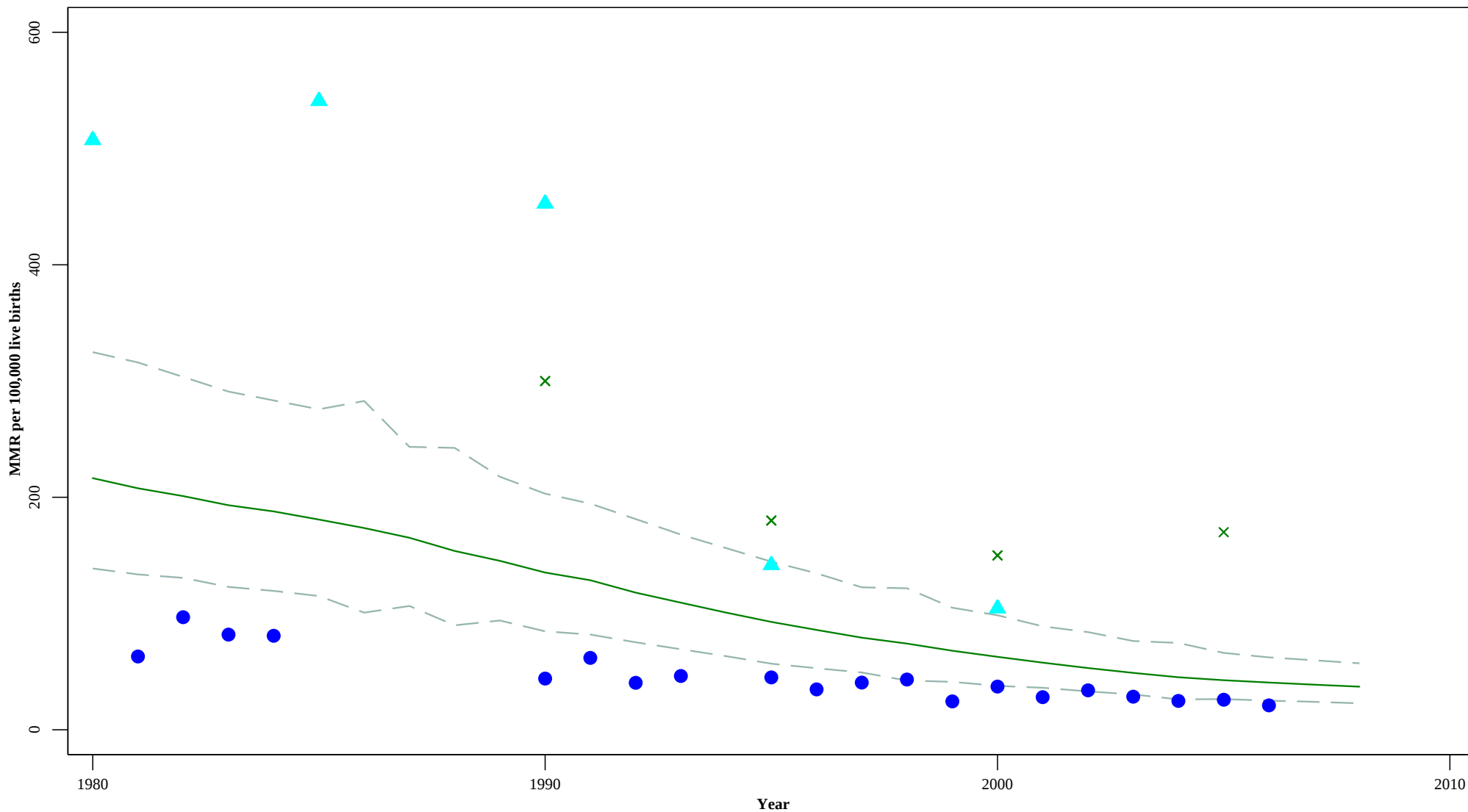
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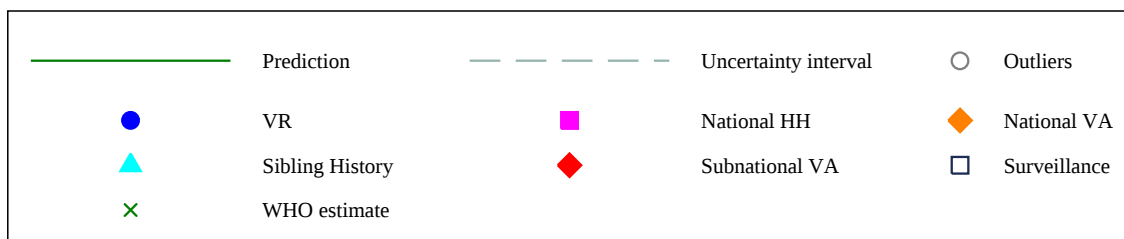
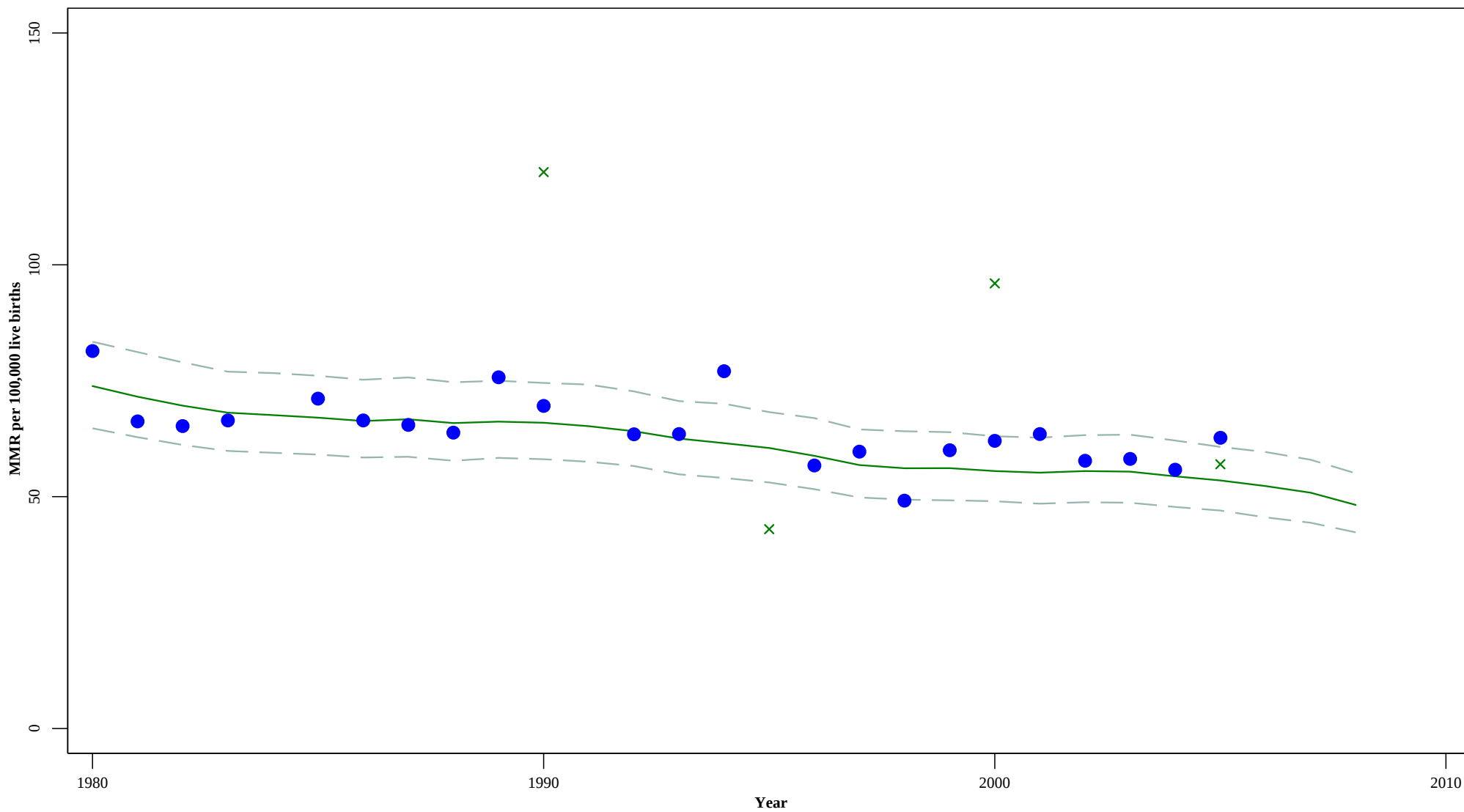
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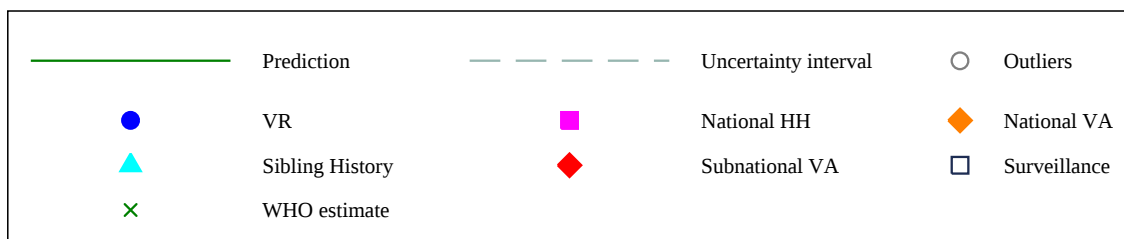
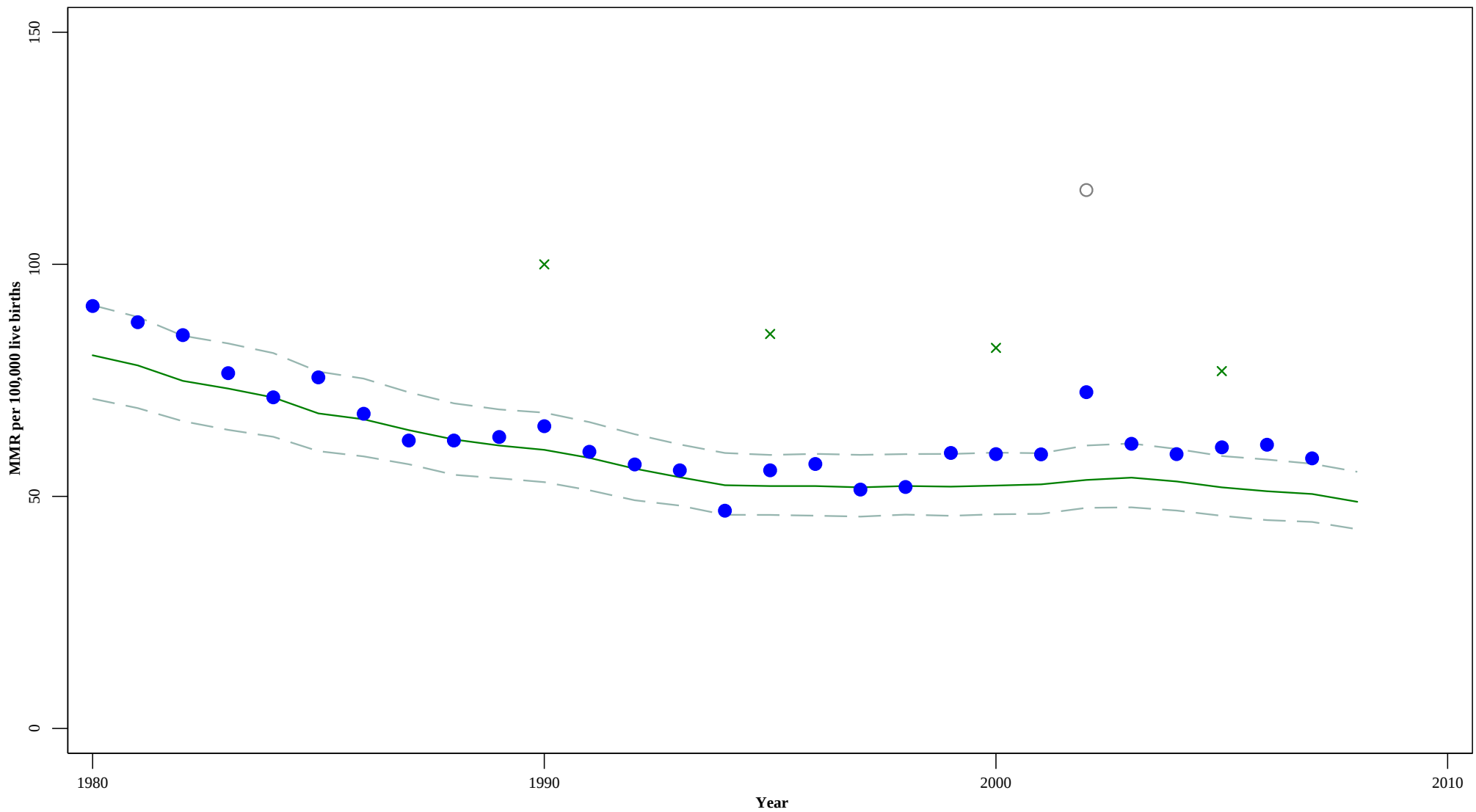
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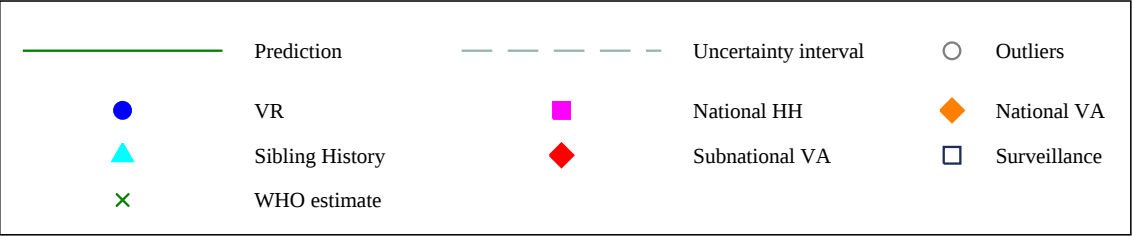
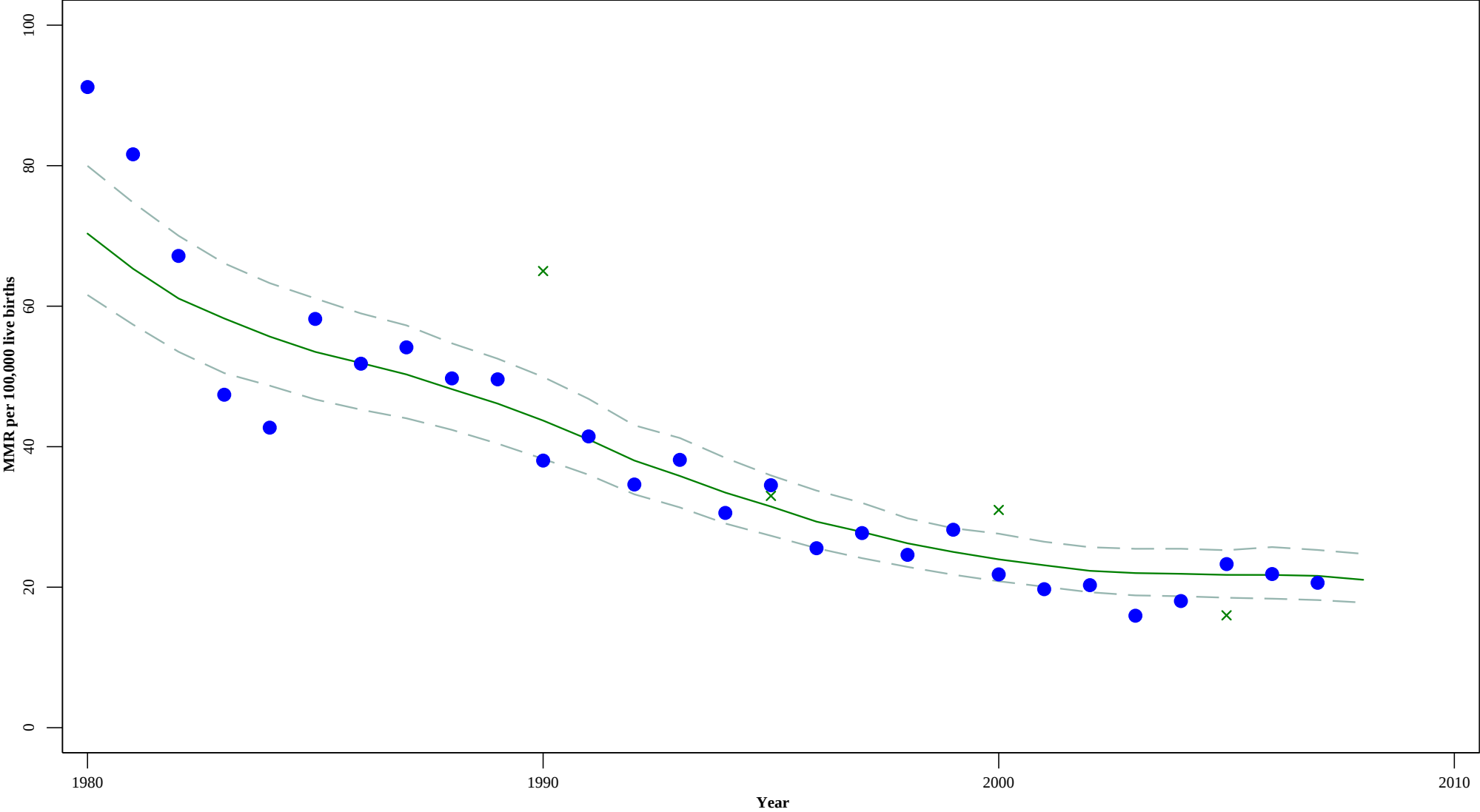
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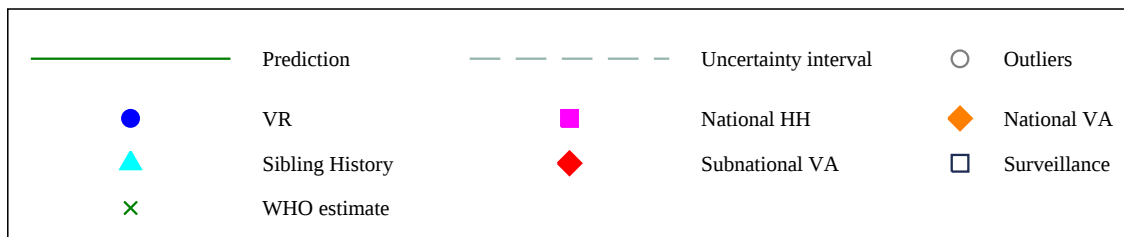
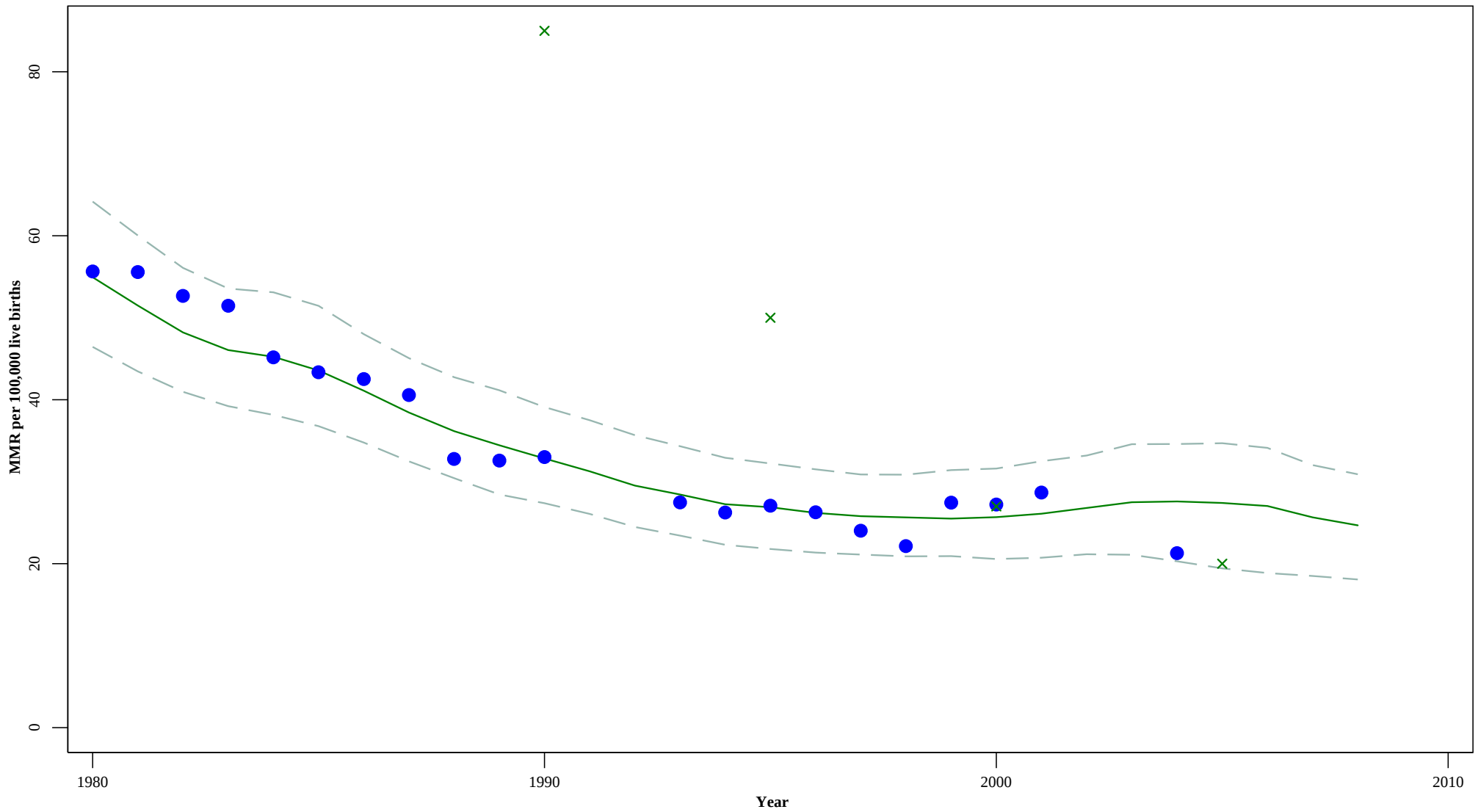
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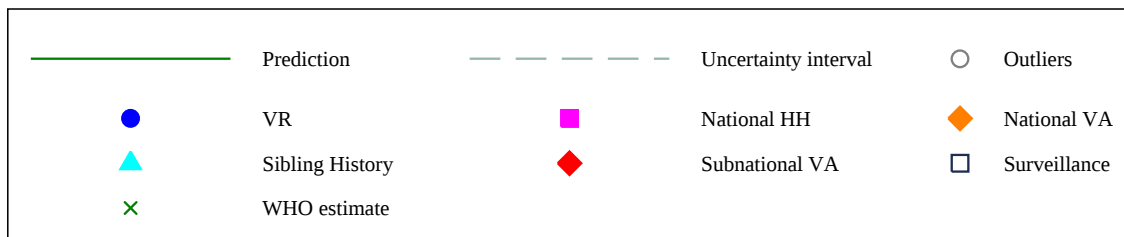
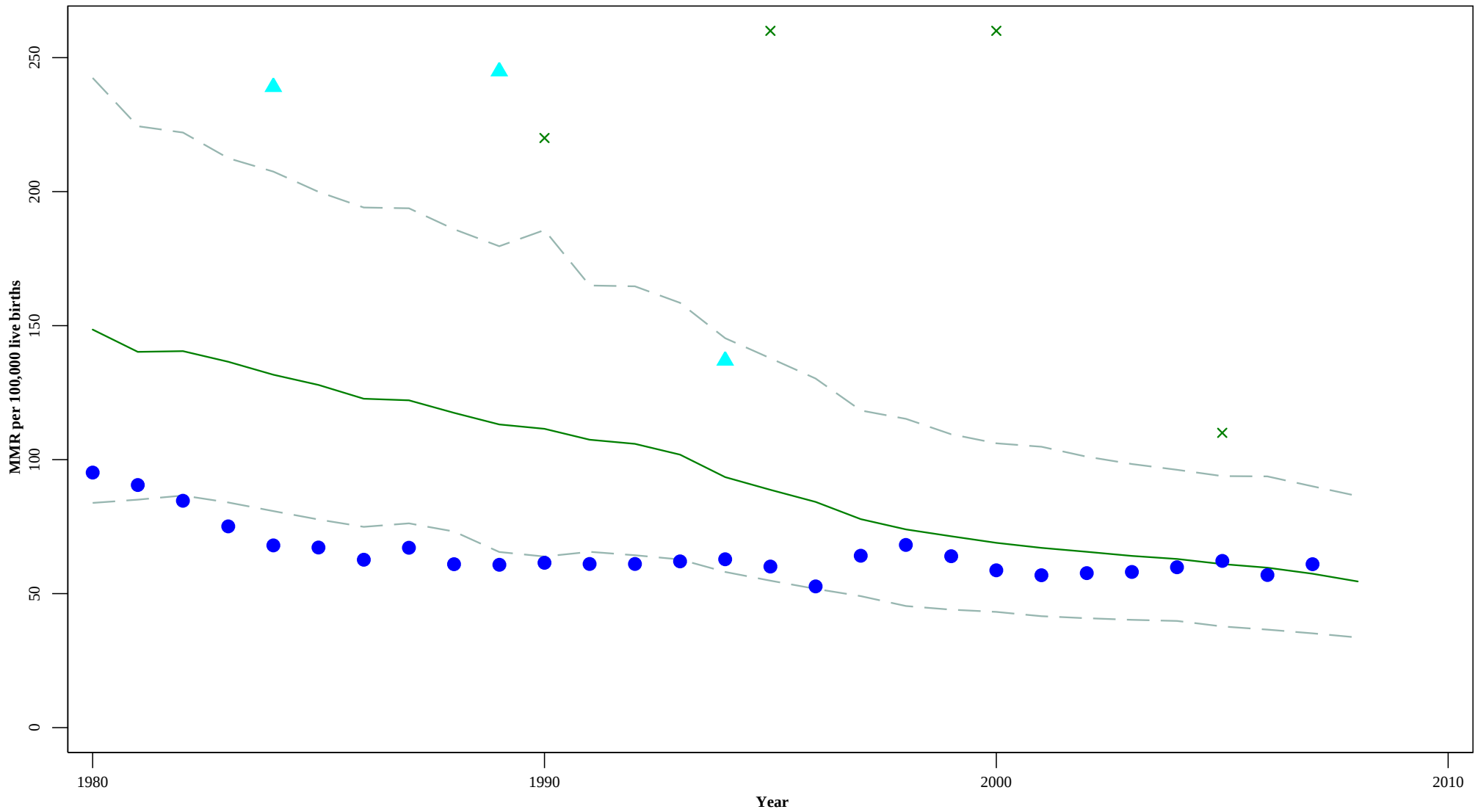
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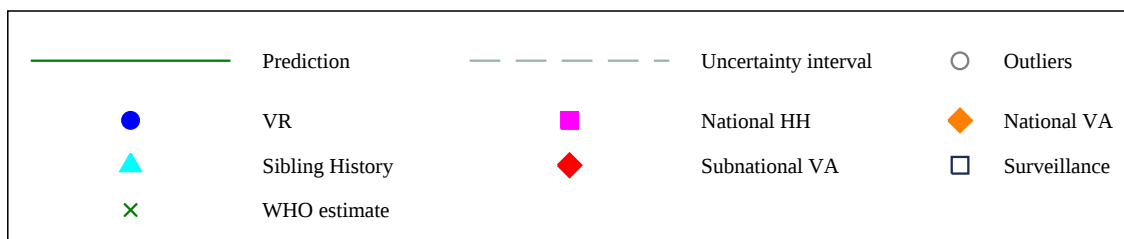
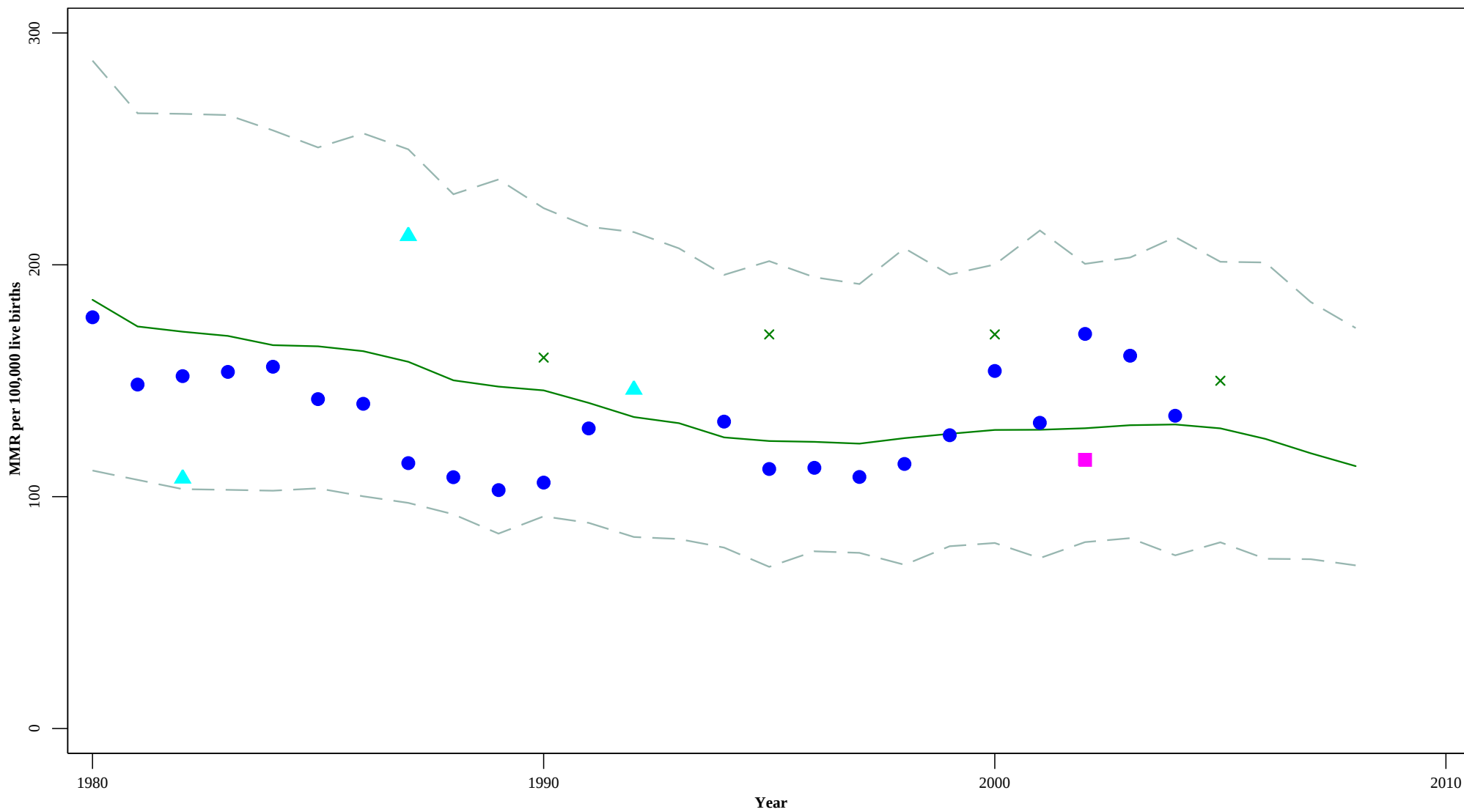
Uruguay



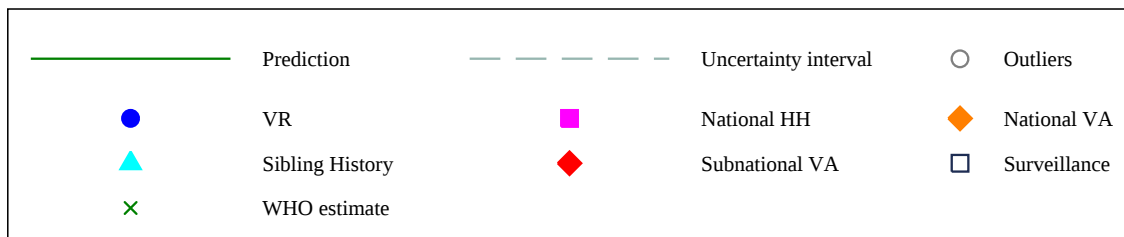
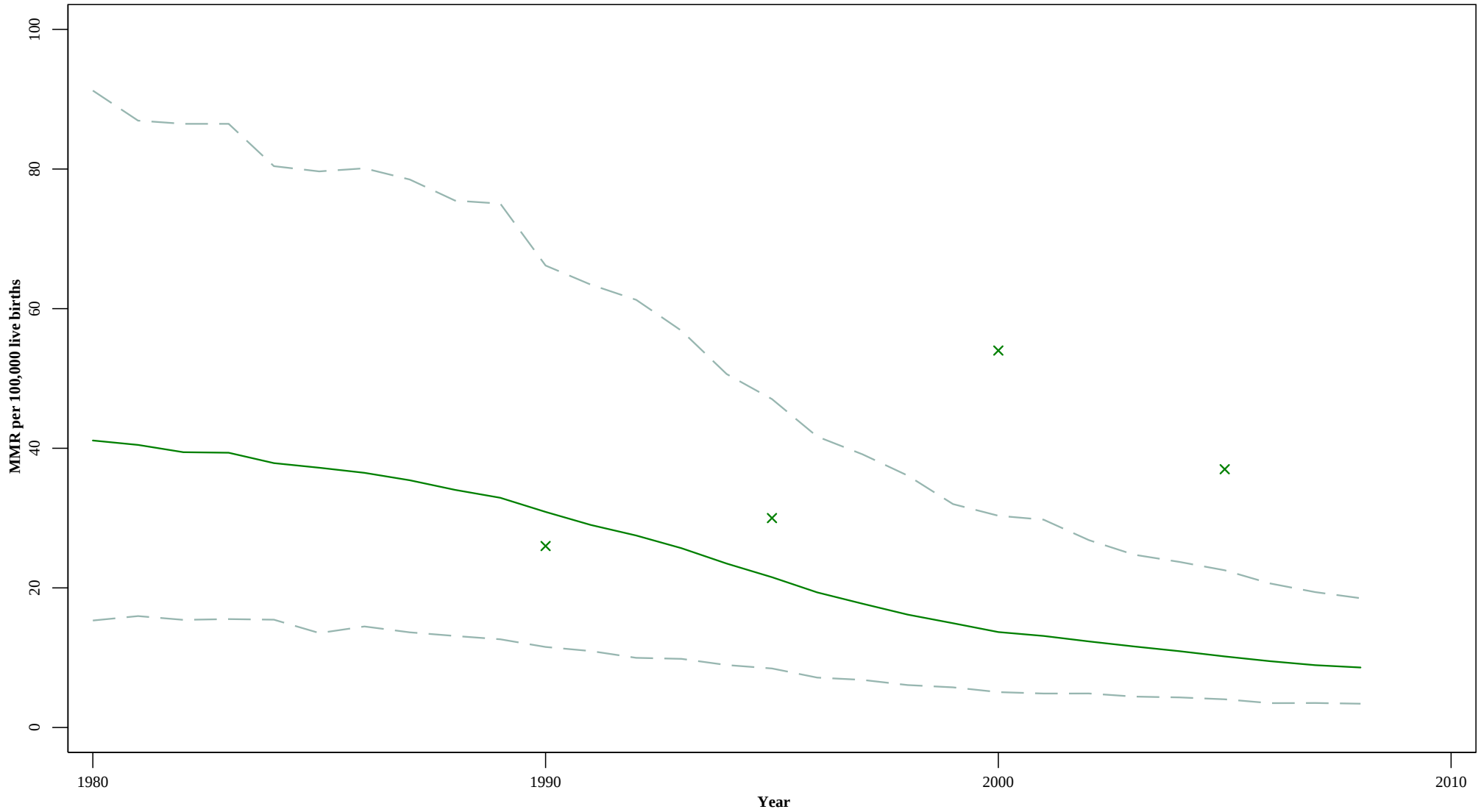
Brazil



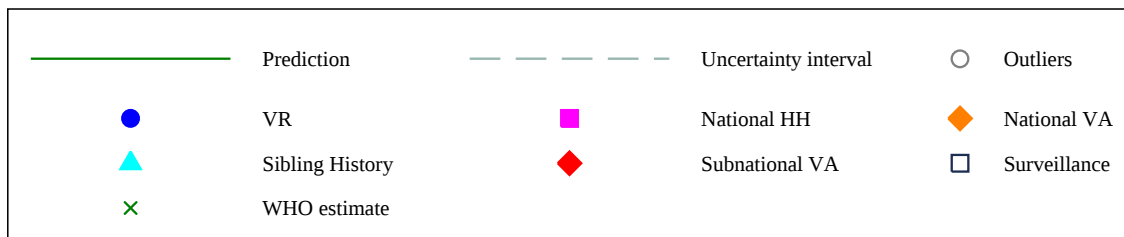
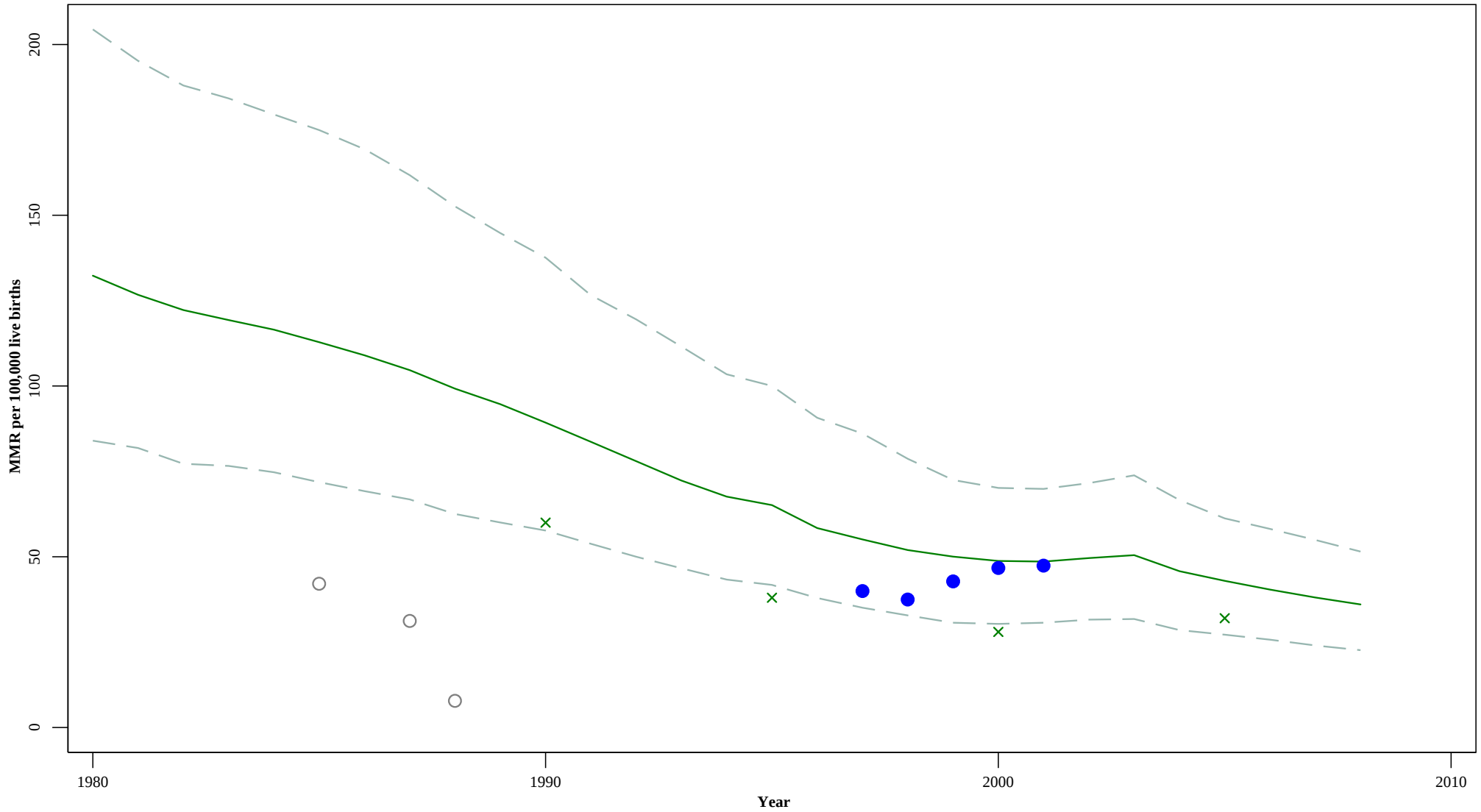
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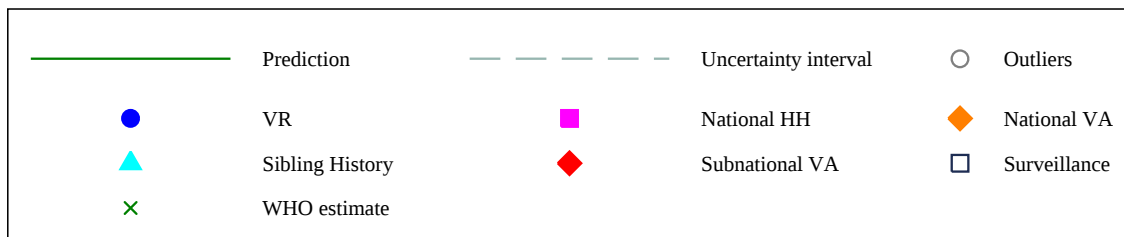
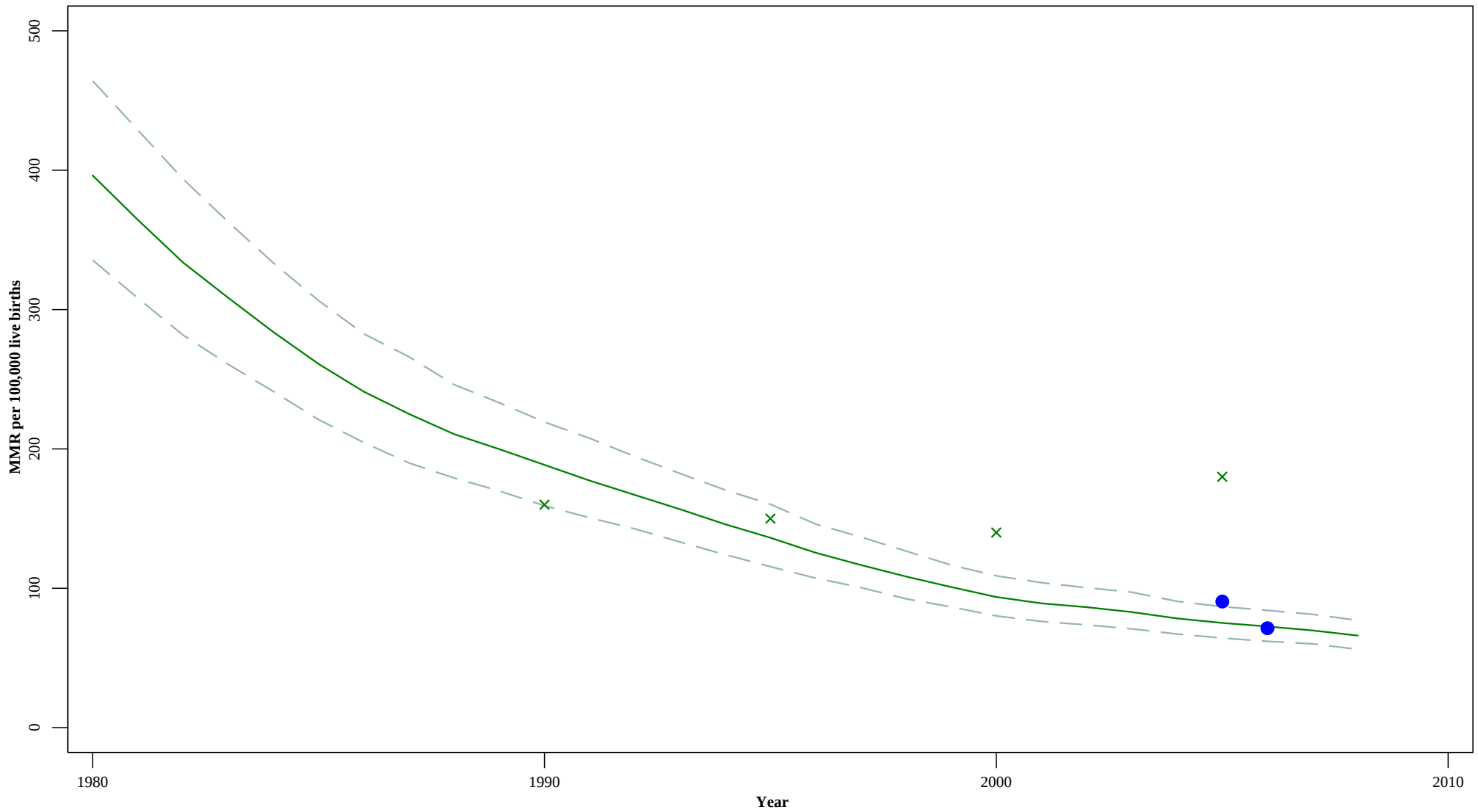
United Arab Emirates



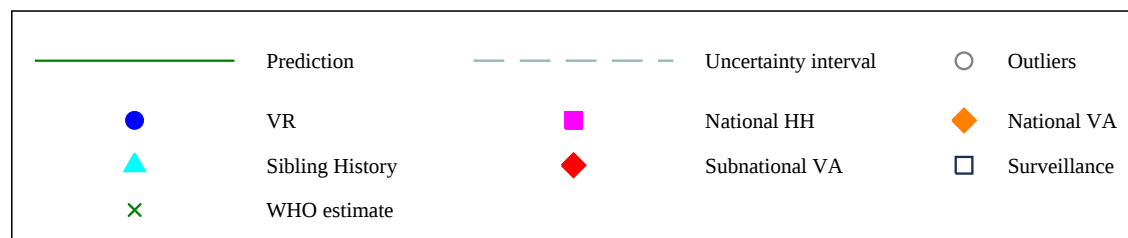
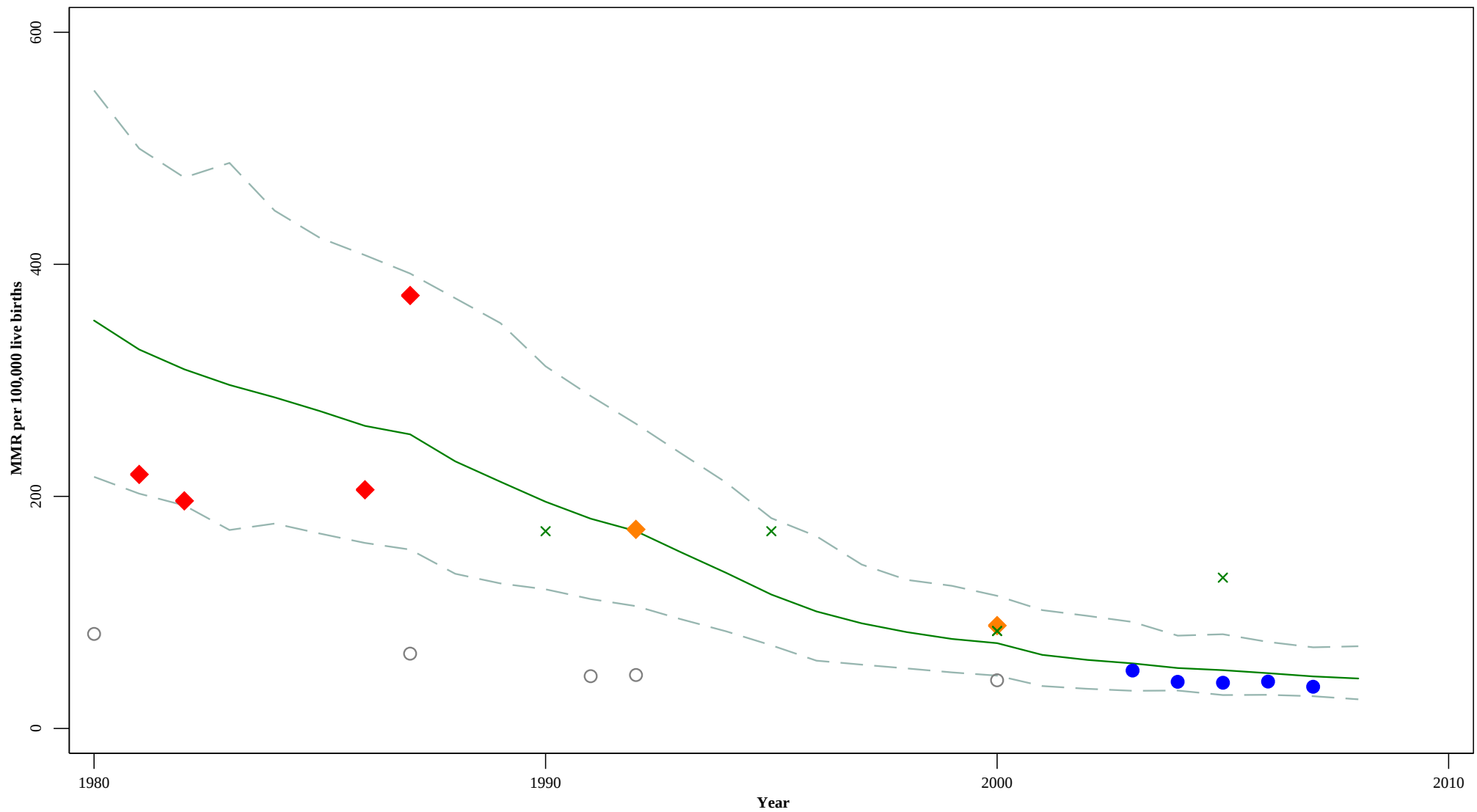
Bahrain



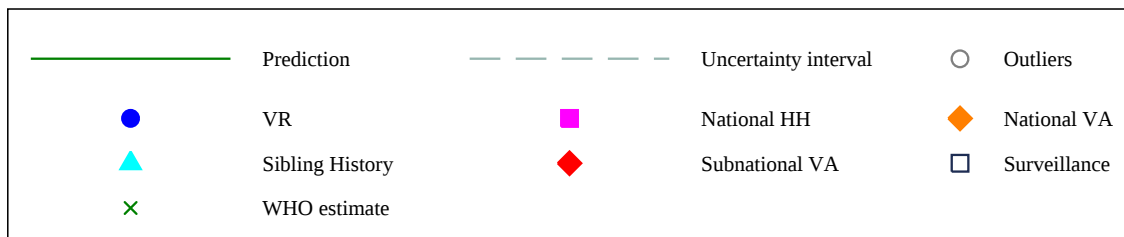
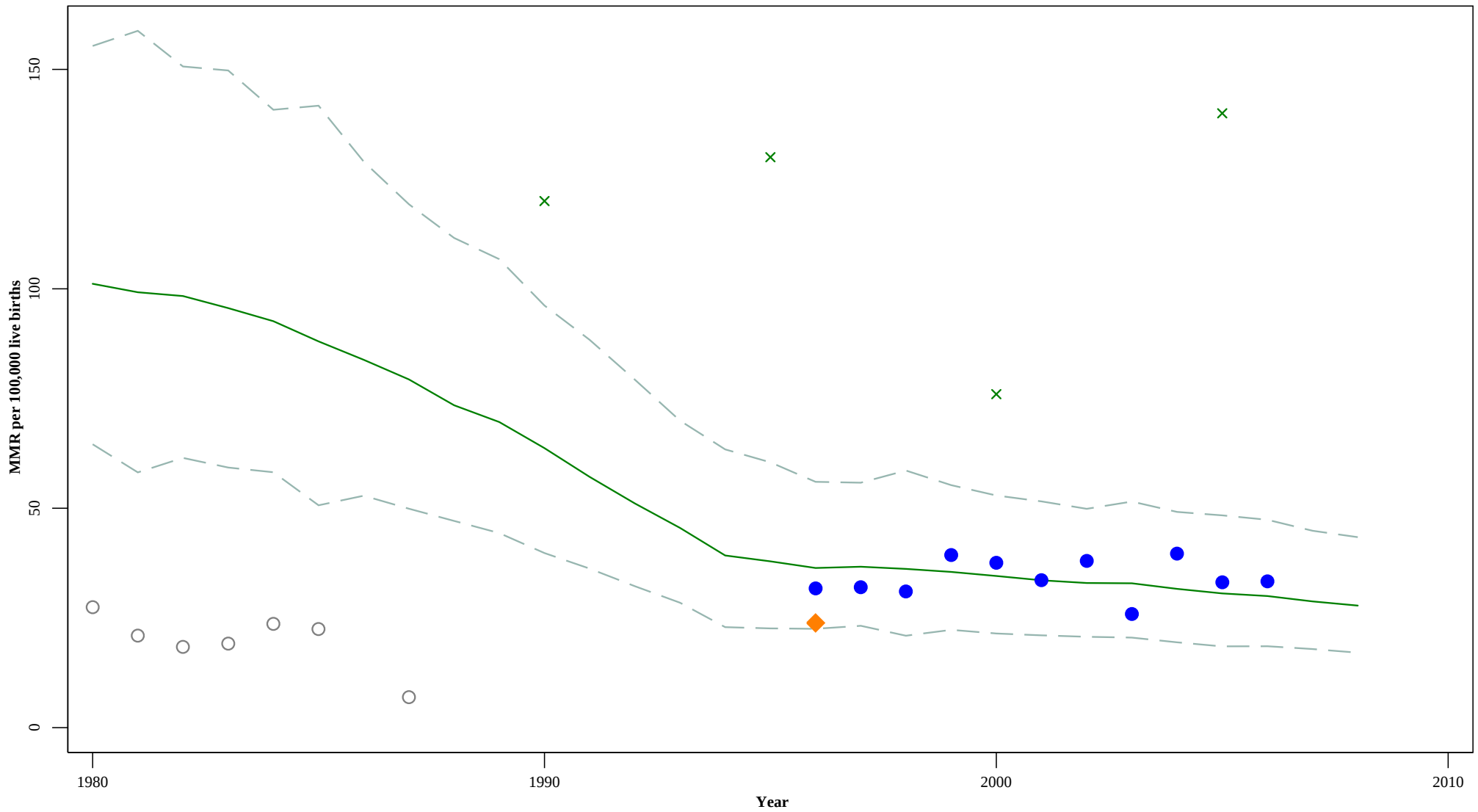
Algeria



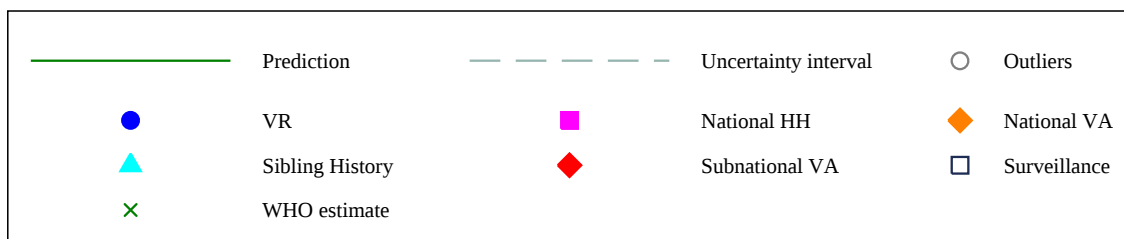
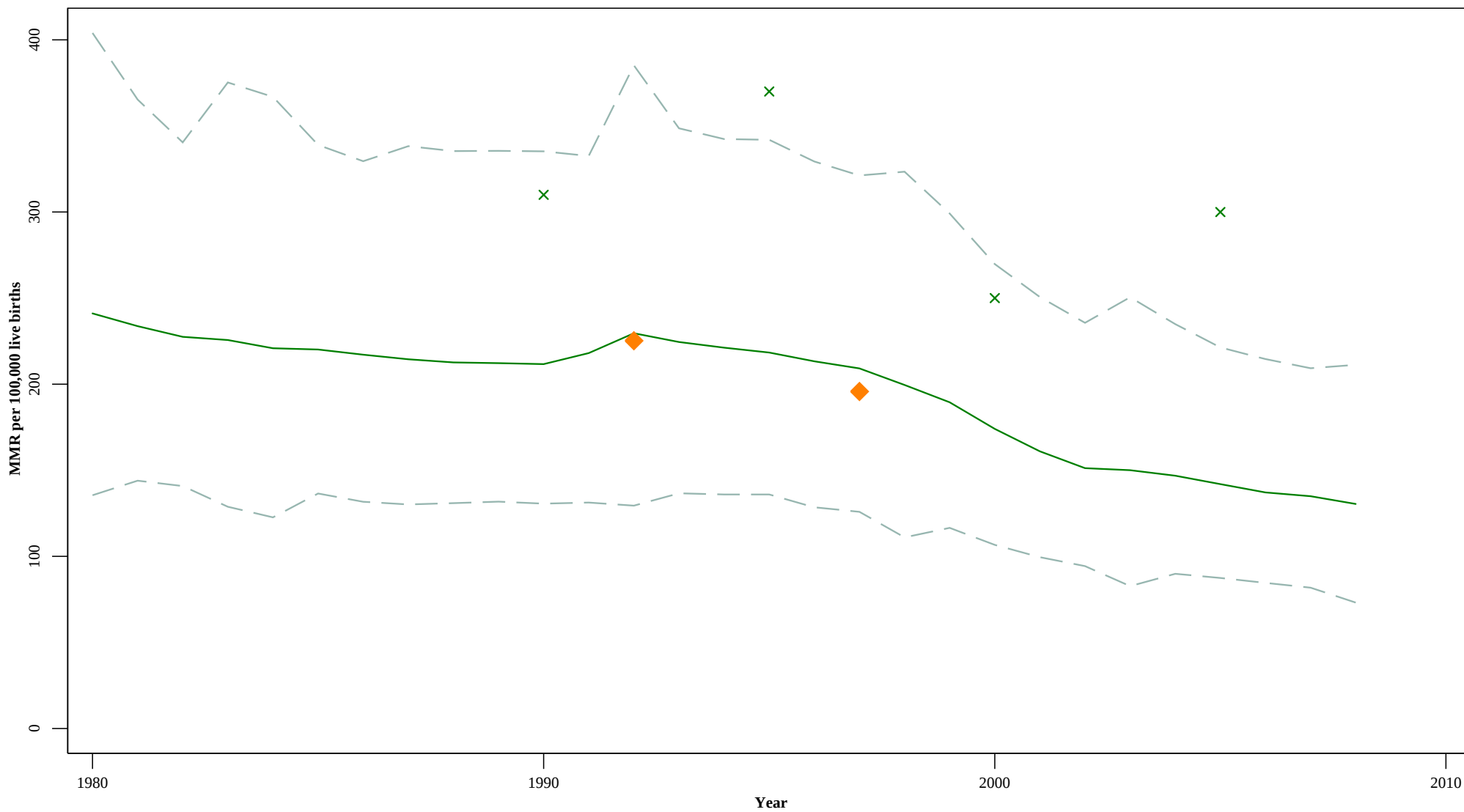
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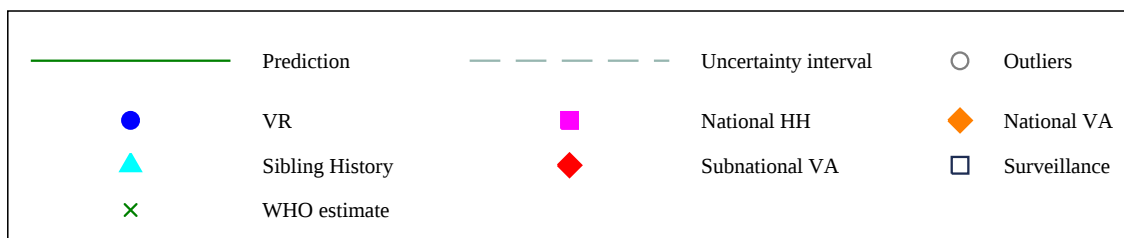
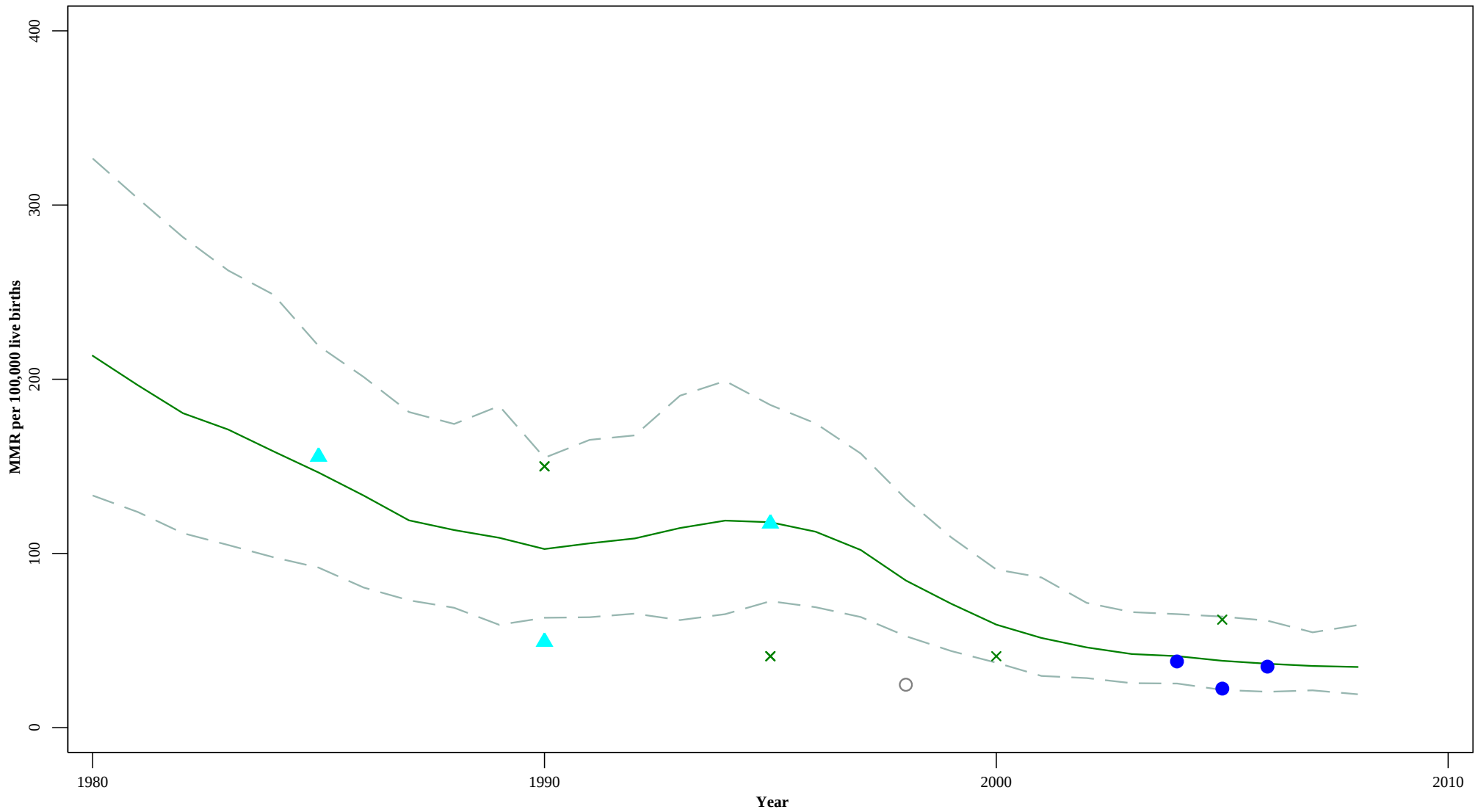
Iran, Islamic Republic of



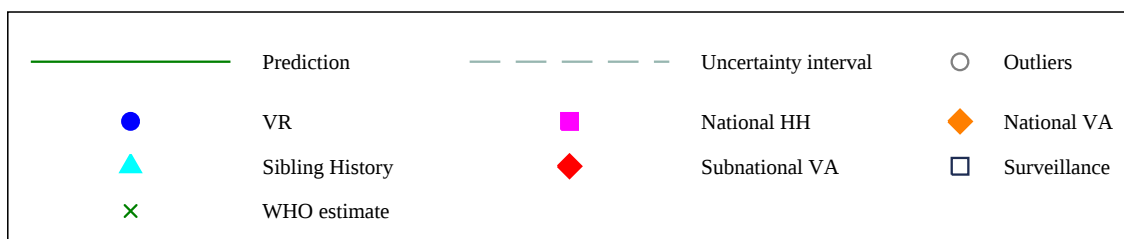
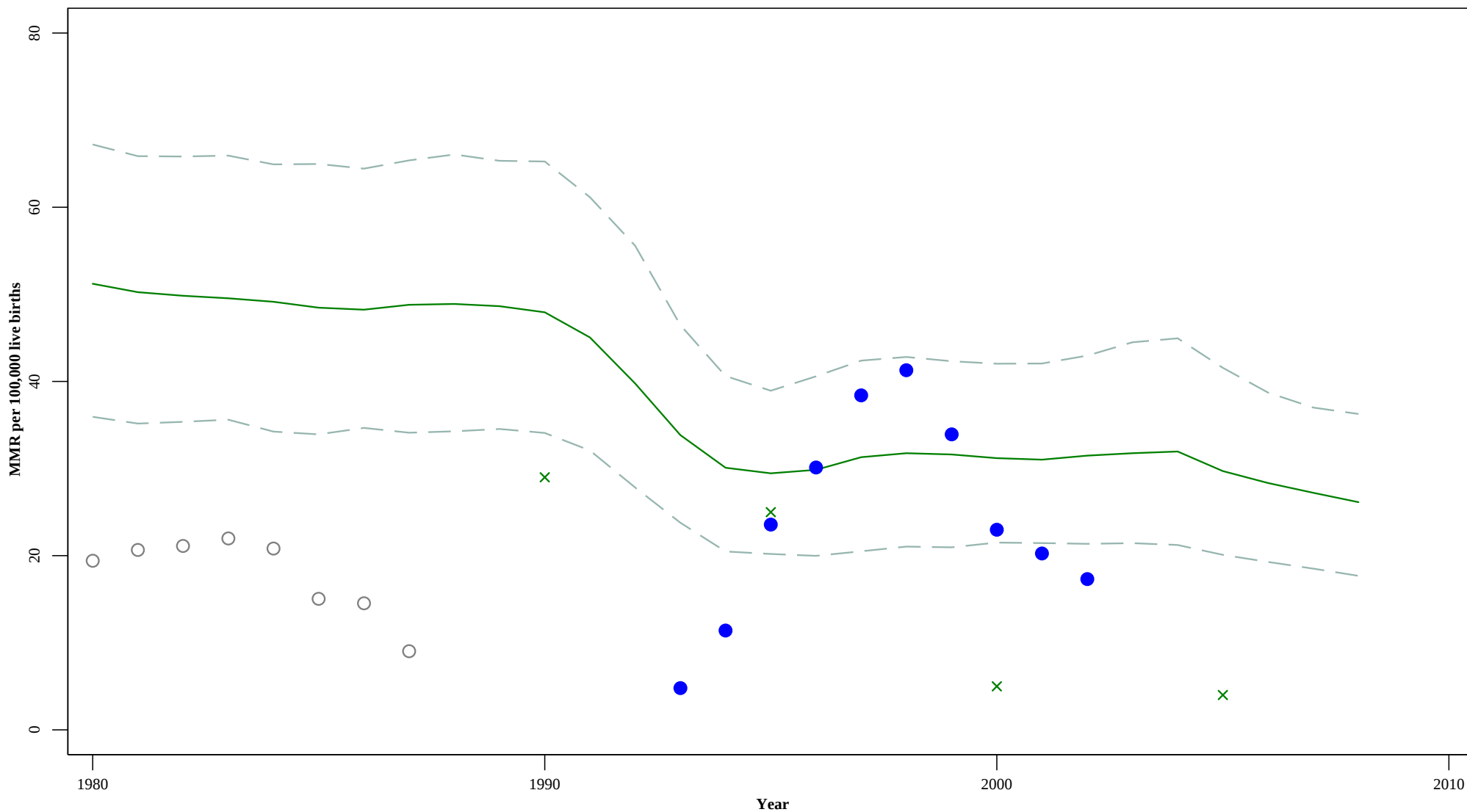
Iraq



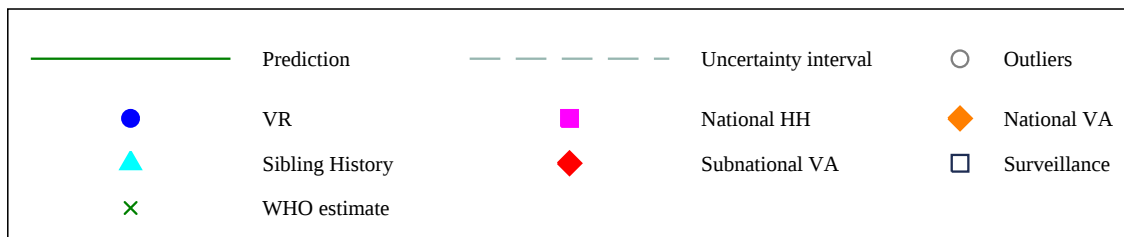
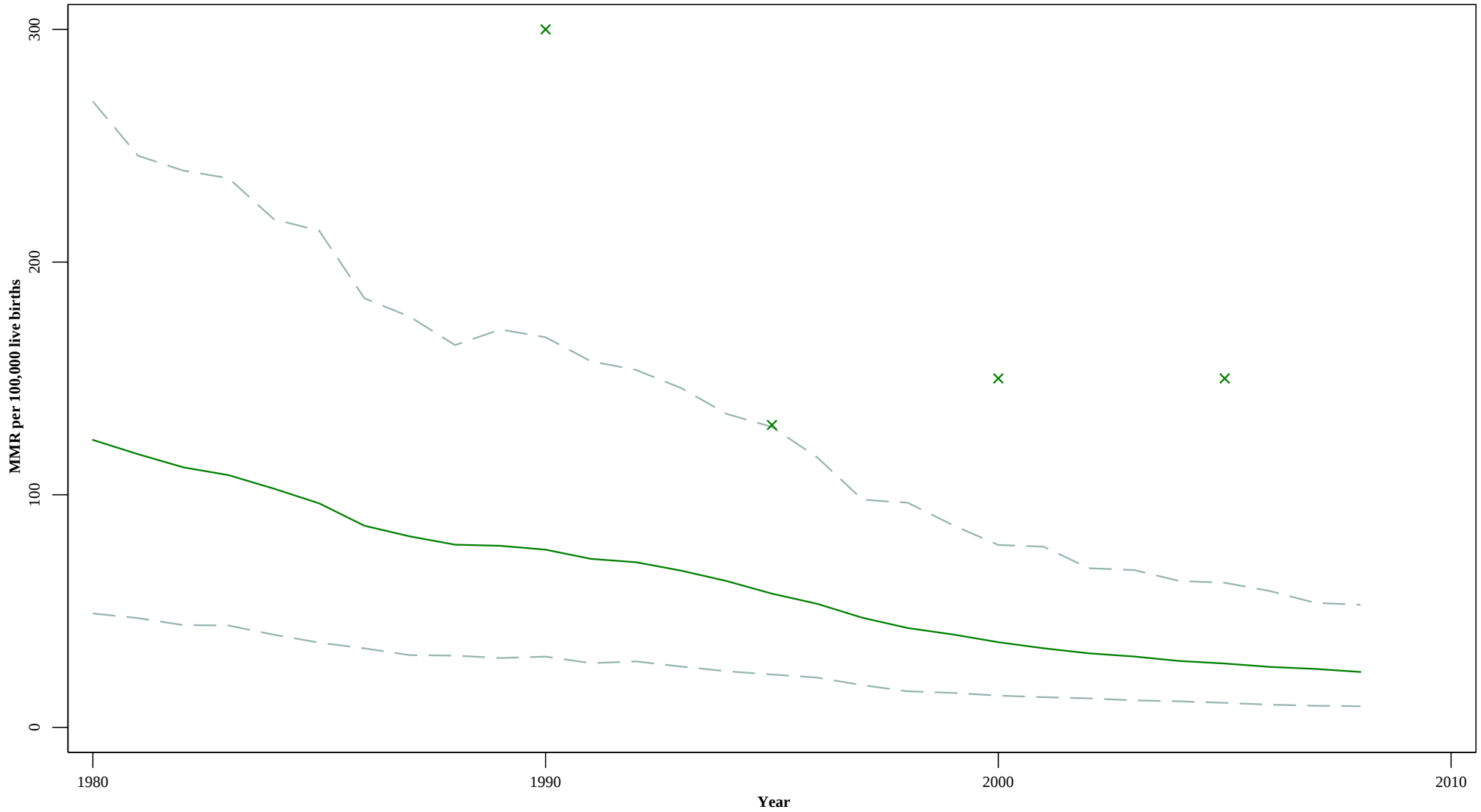
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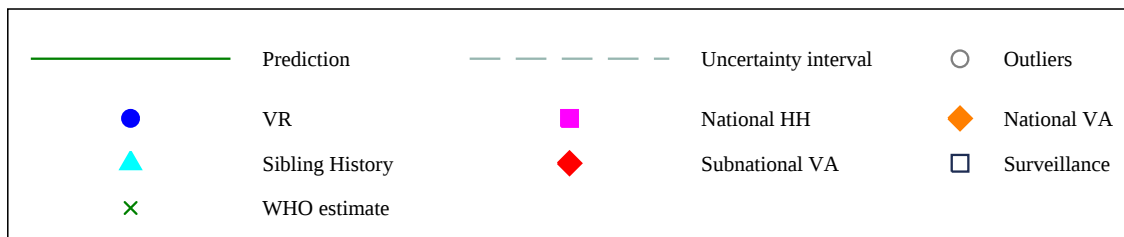
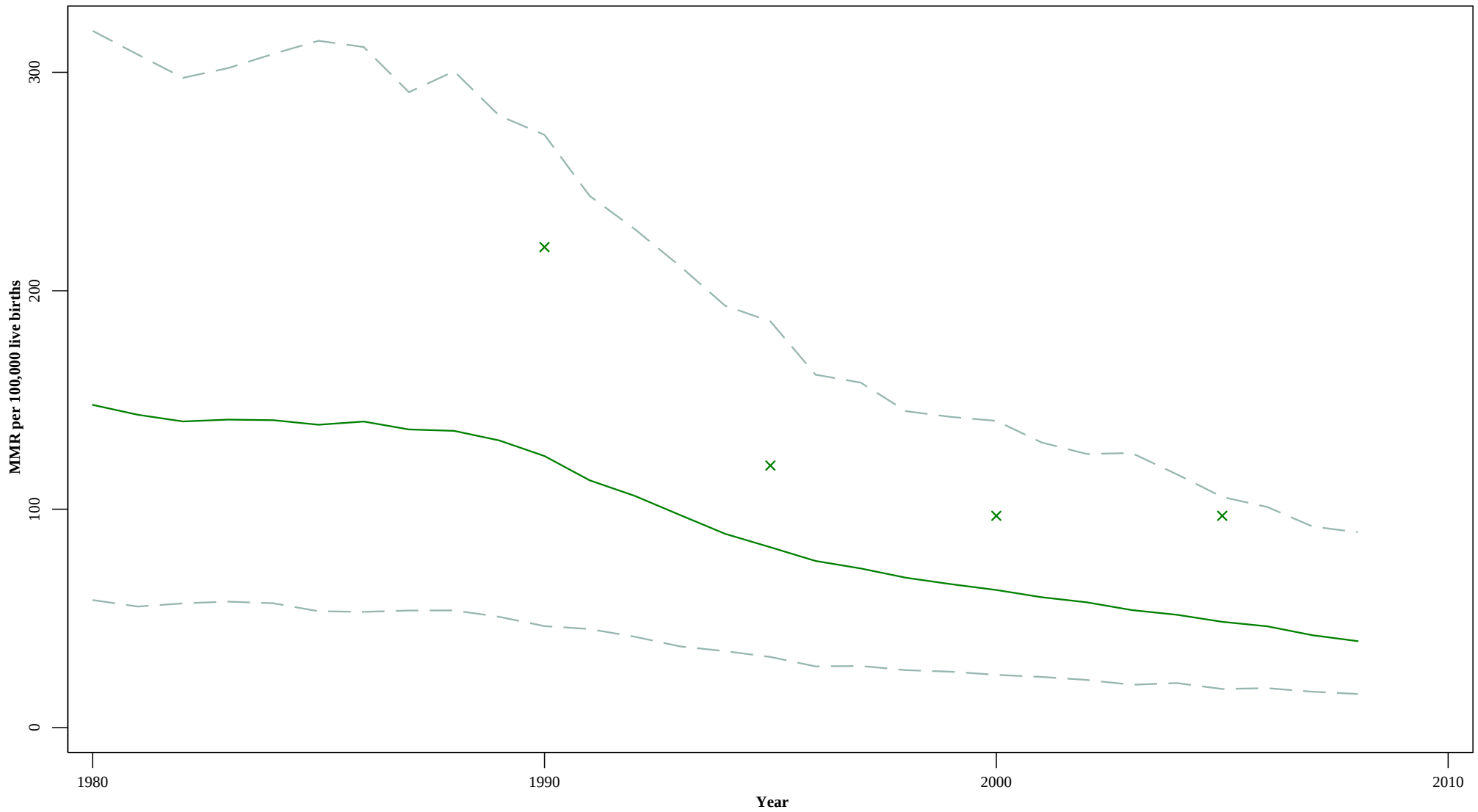
Kuwait



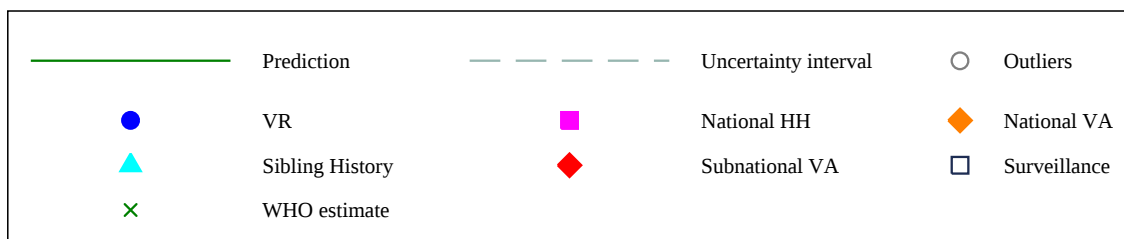
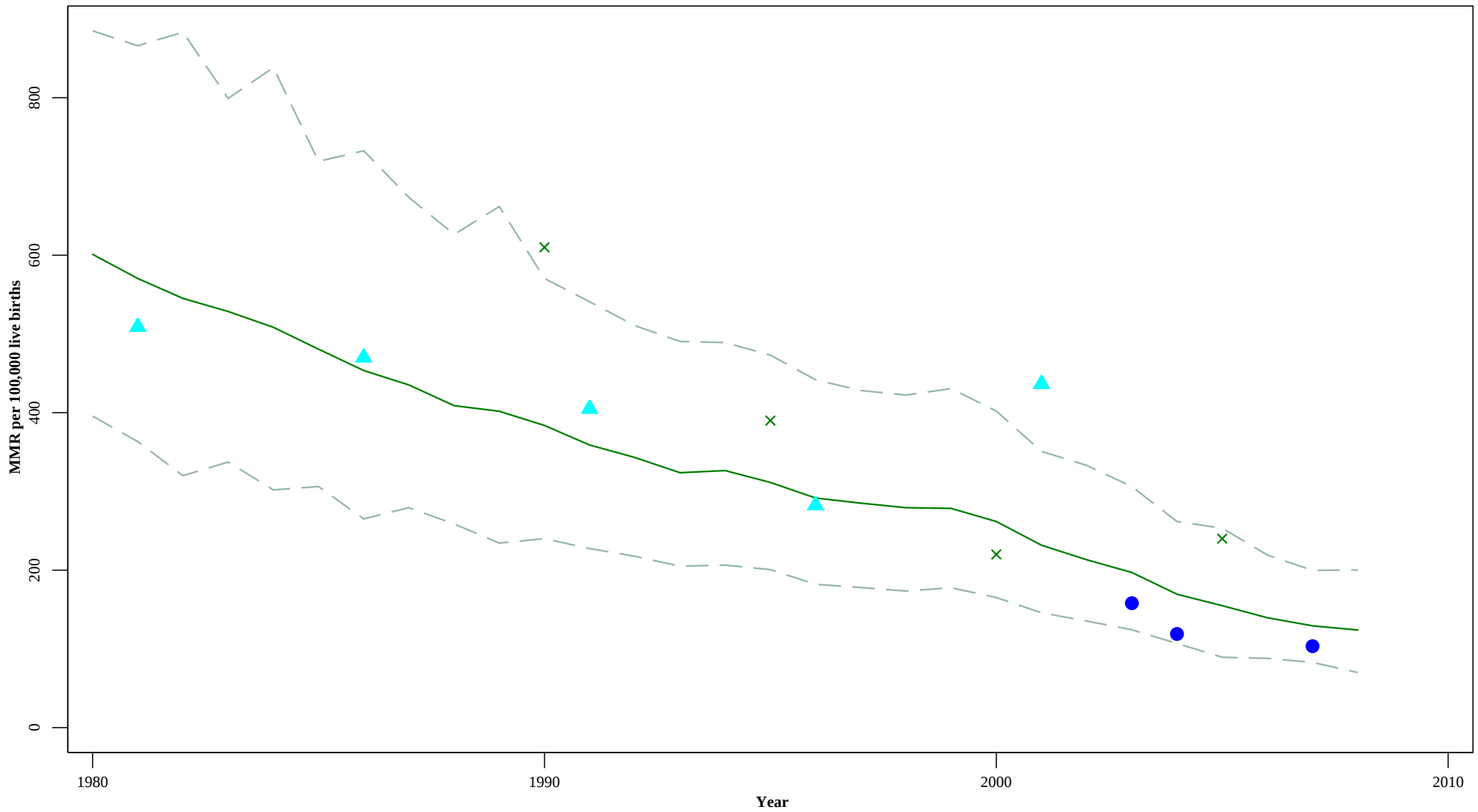
Lebanon



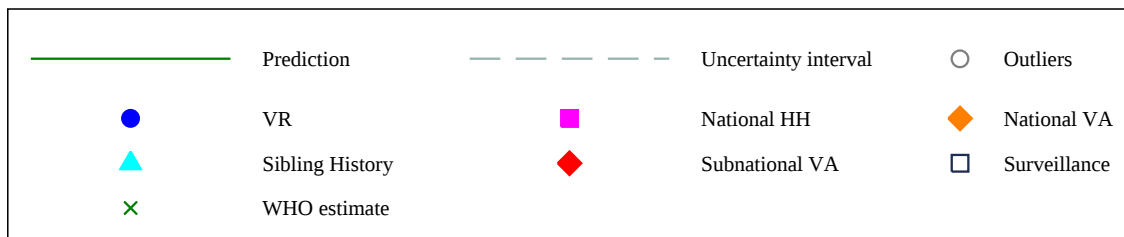
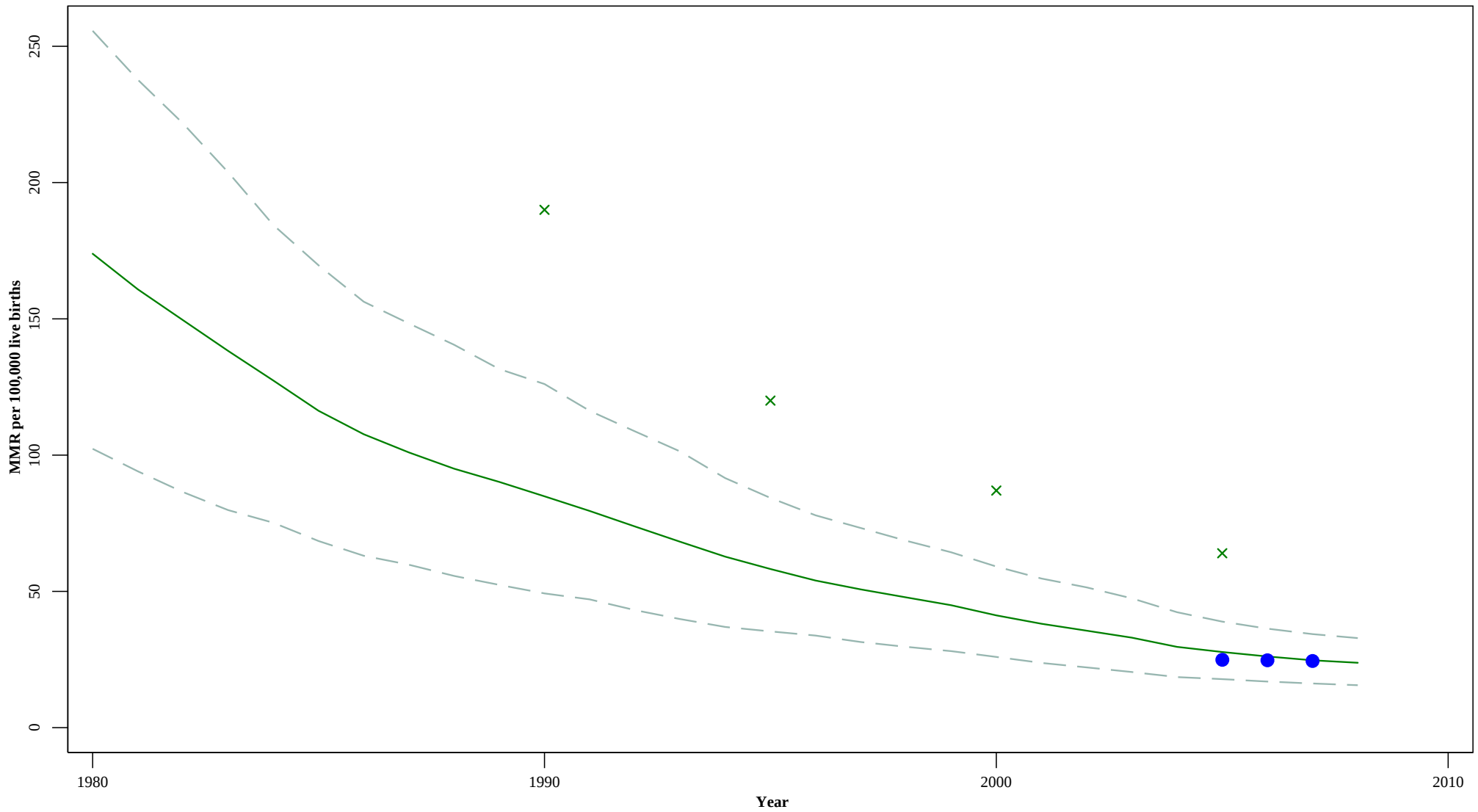
Libyan Arab Jamahiriya



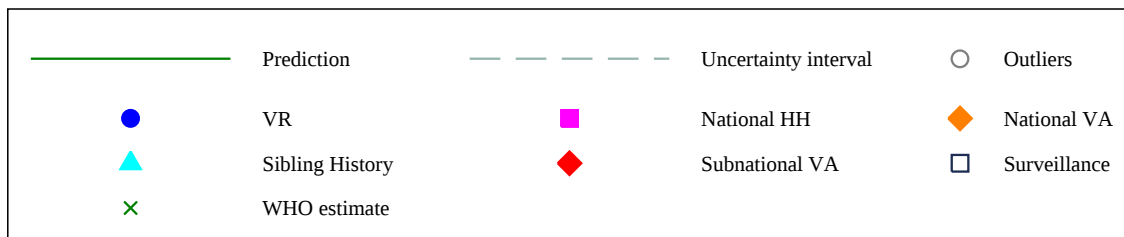
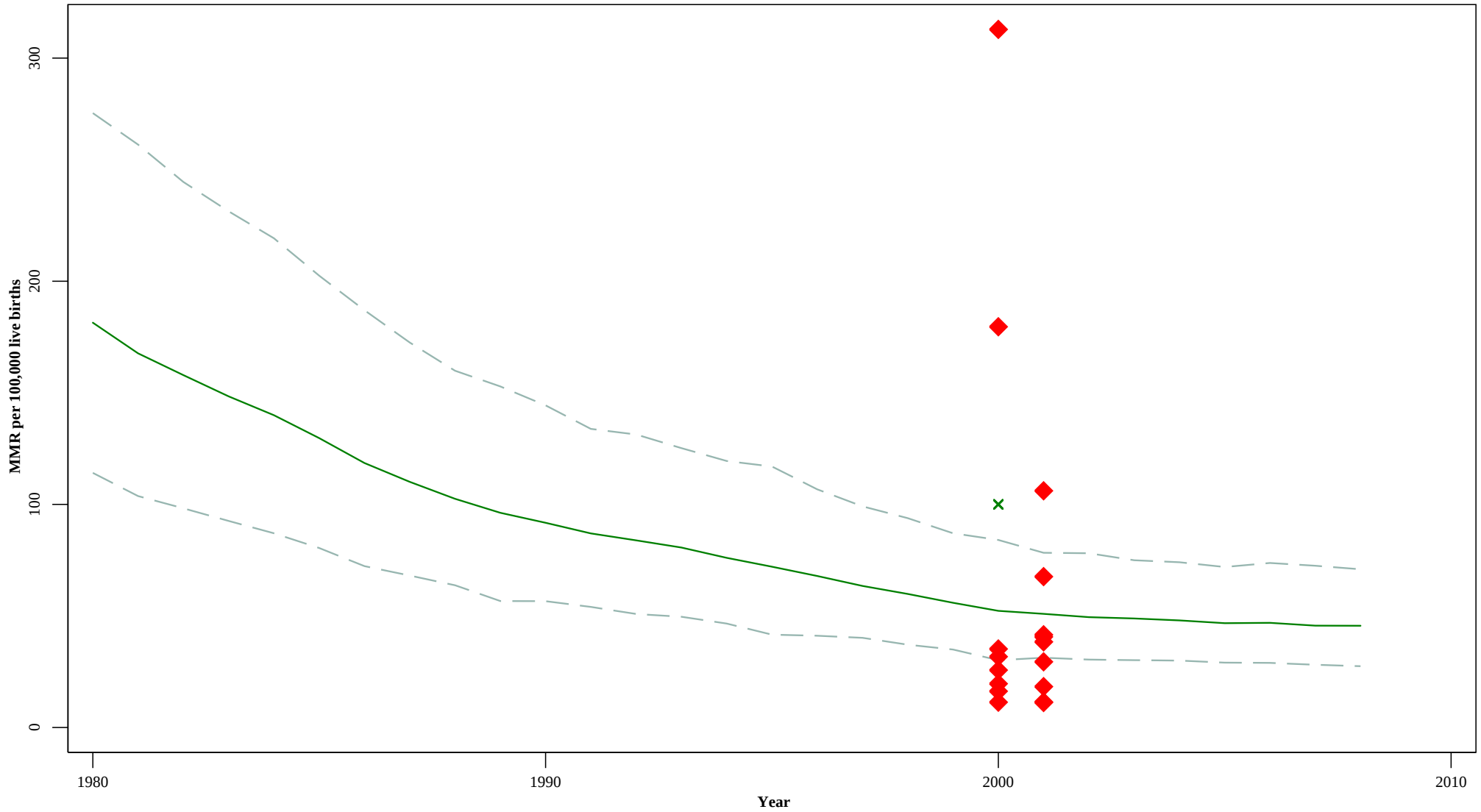
Morocco



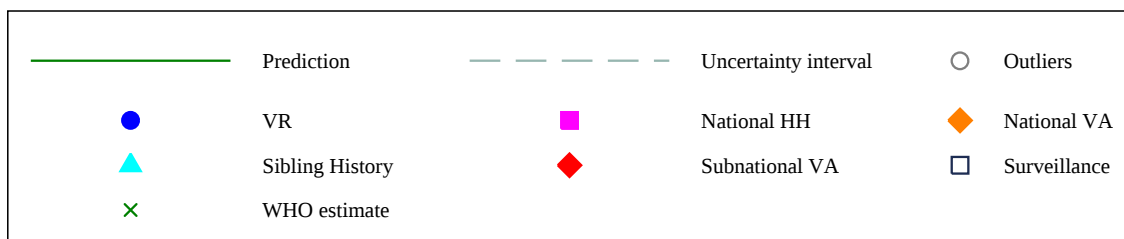
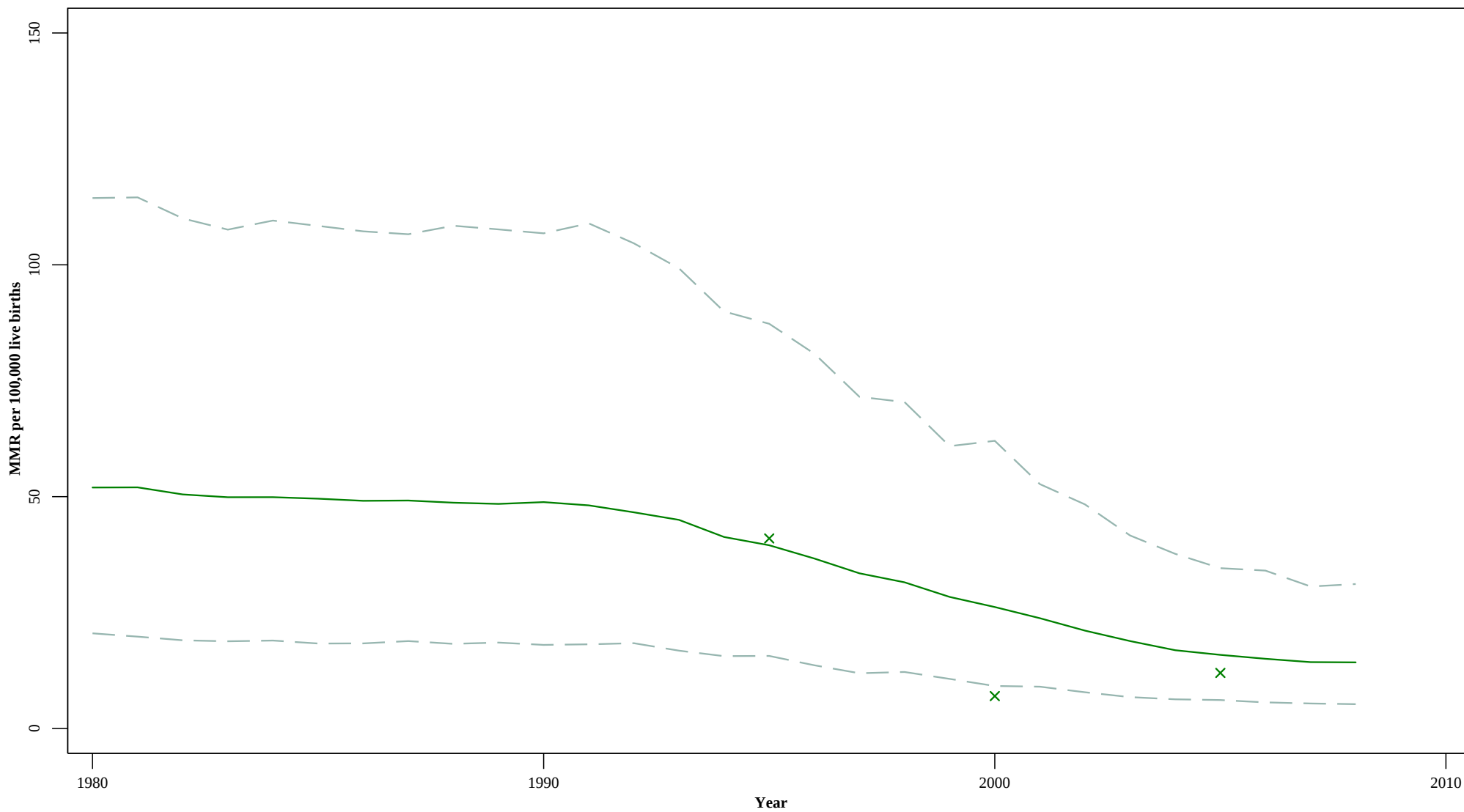
Oman



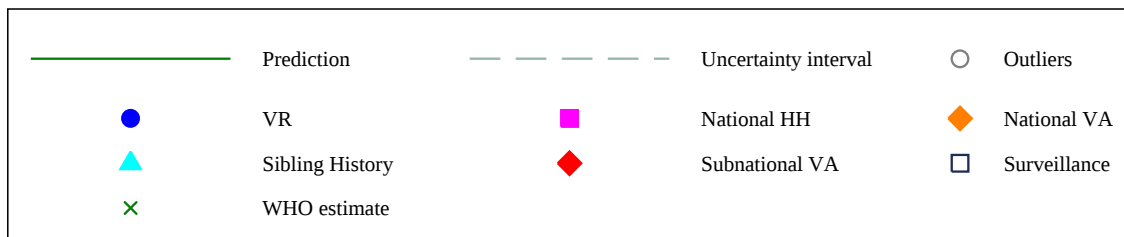
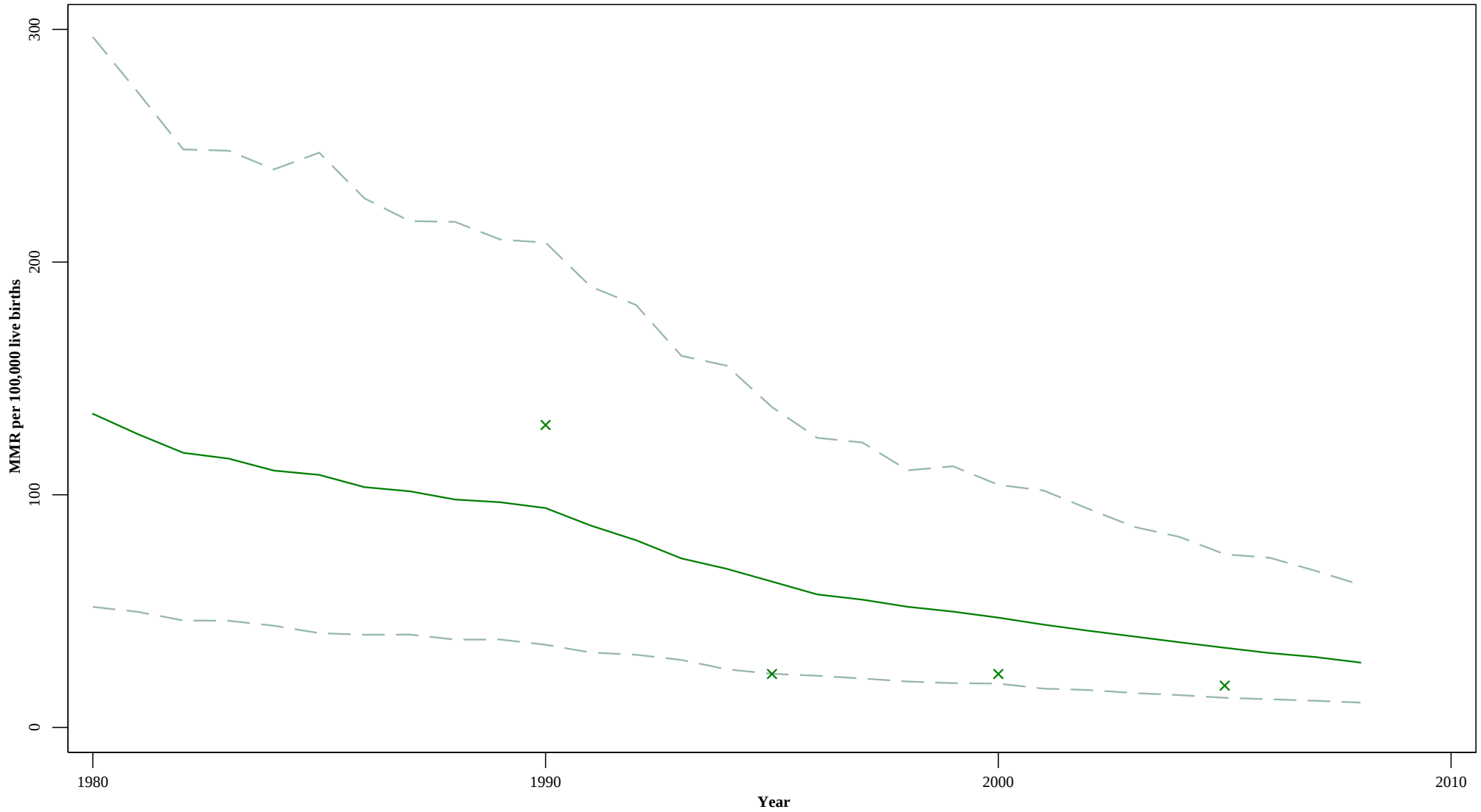
Occupied Palestinian Territory



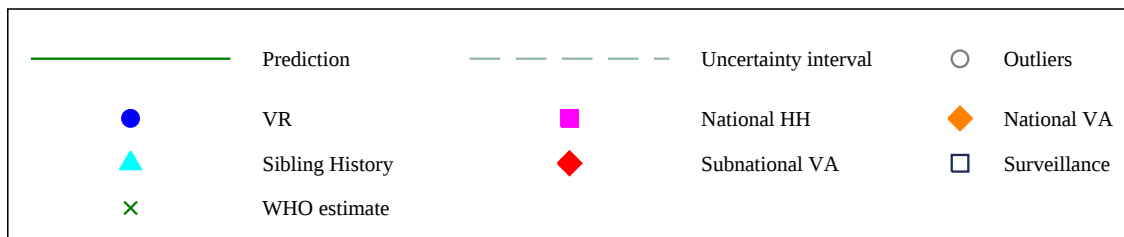
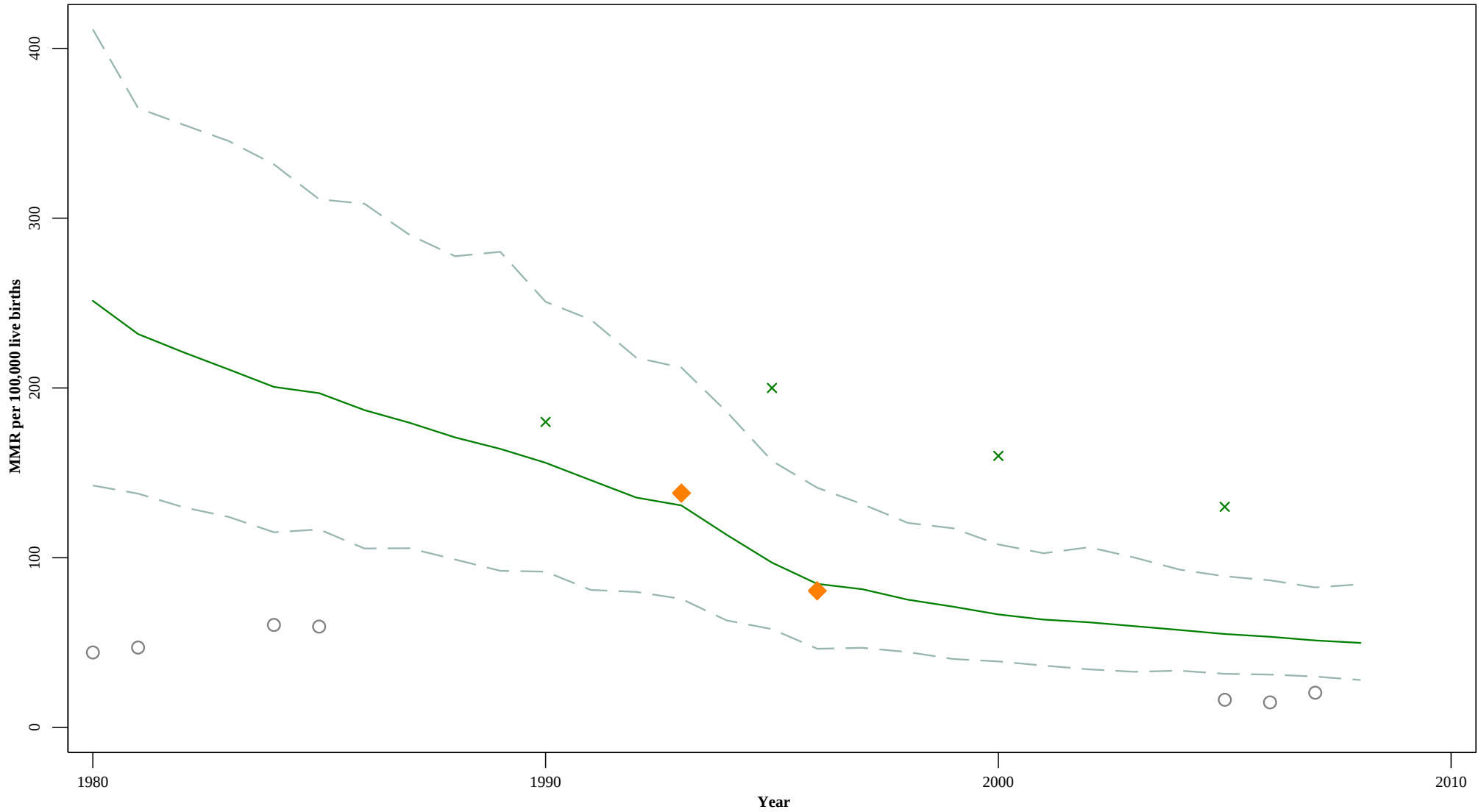
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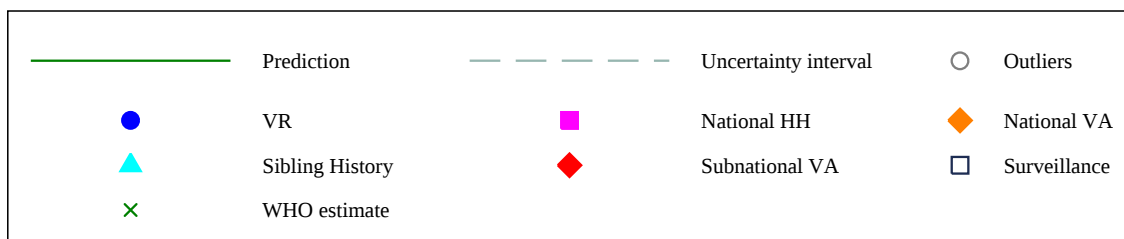
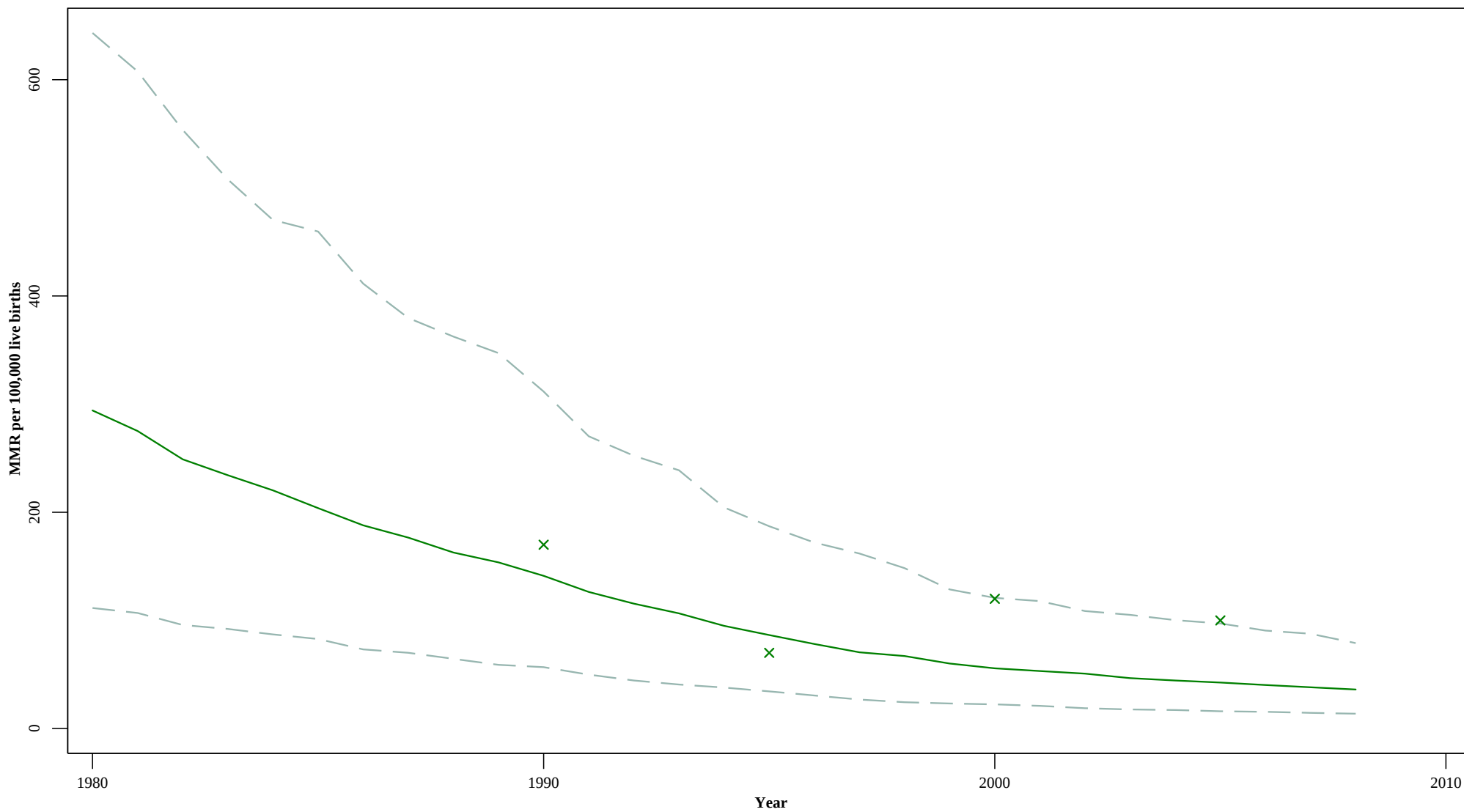
Saudi Arabia



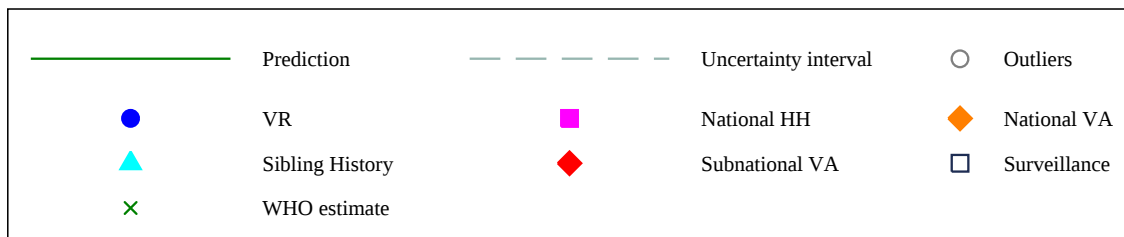
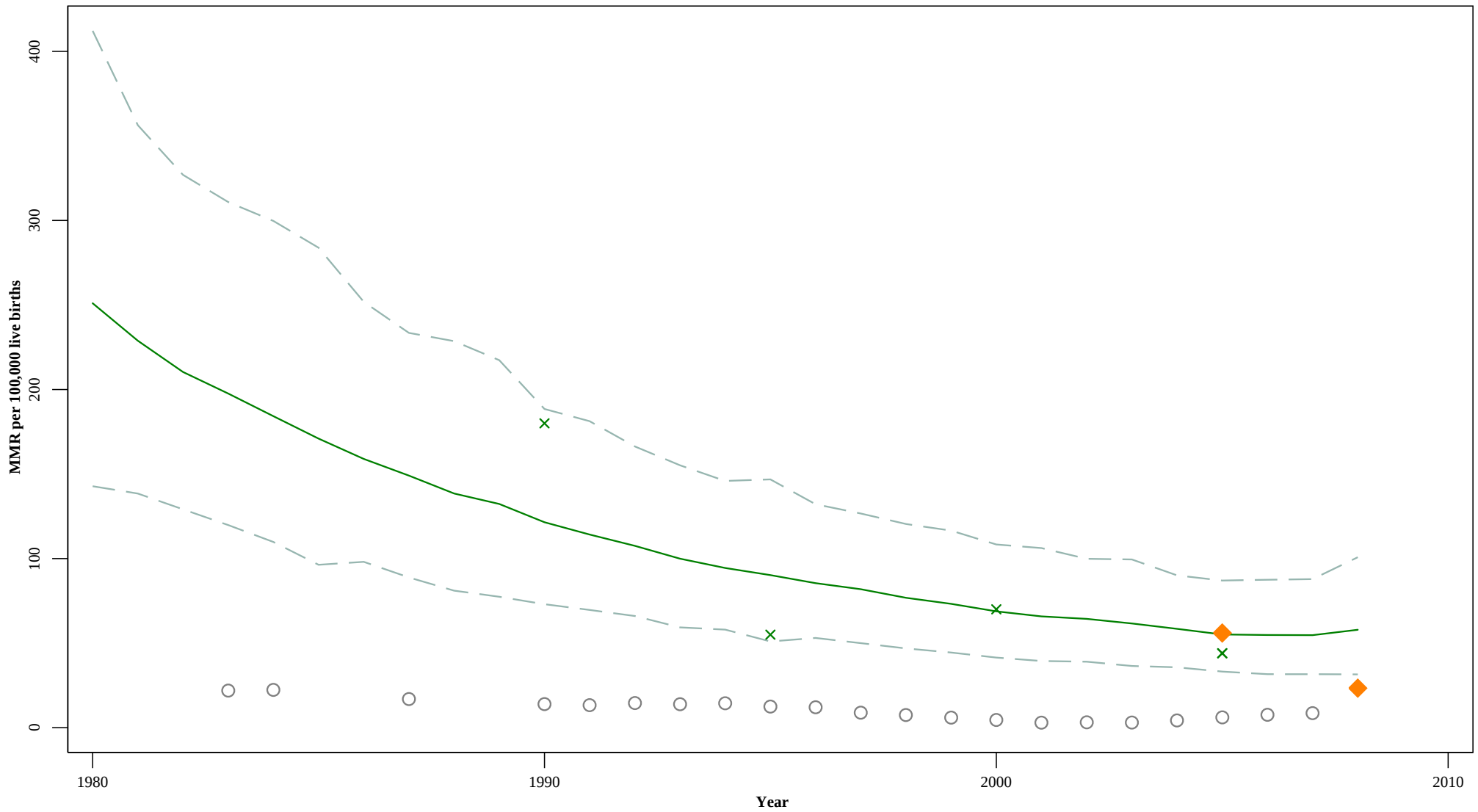
Syrian Arab Republic



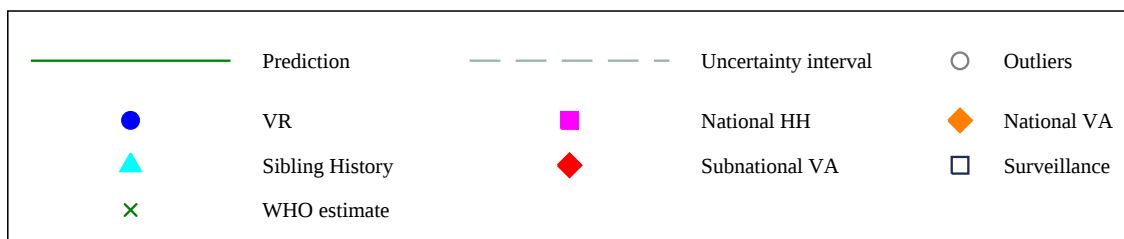
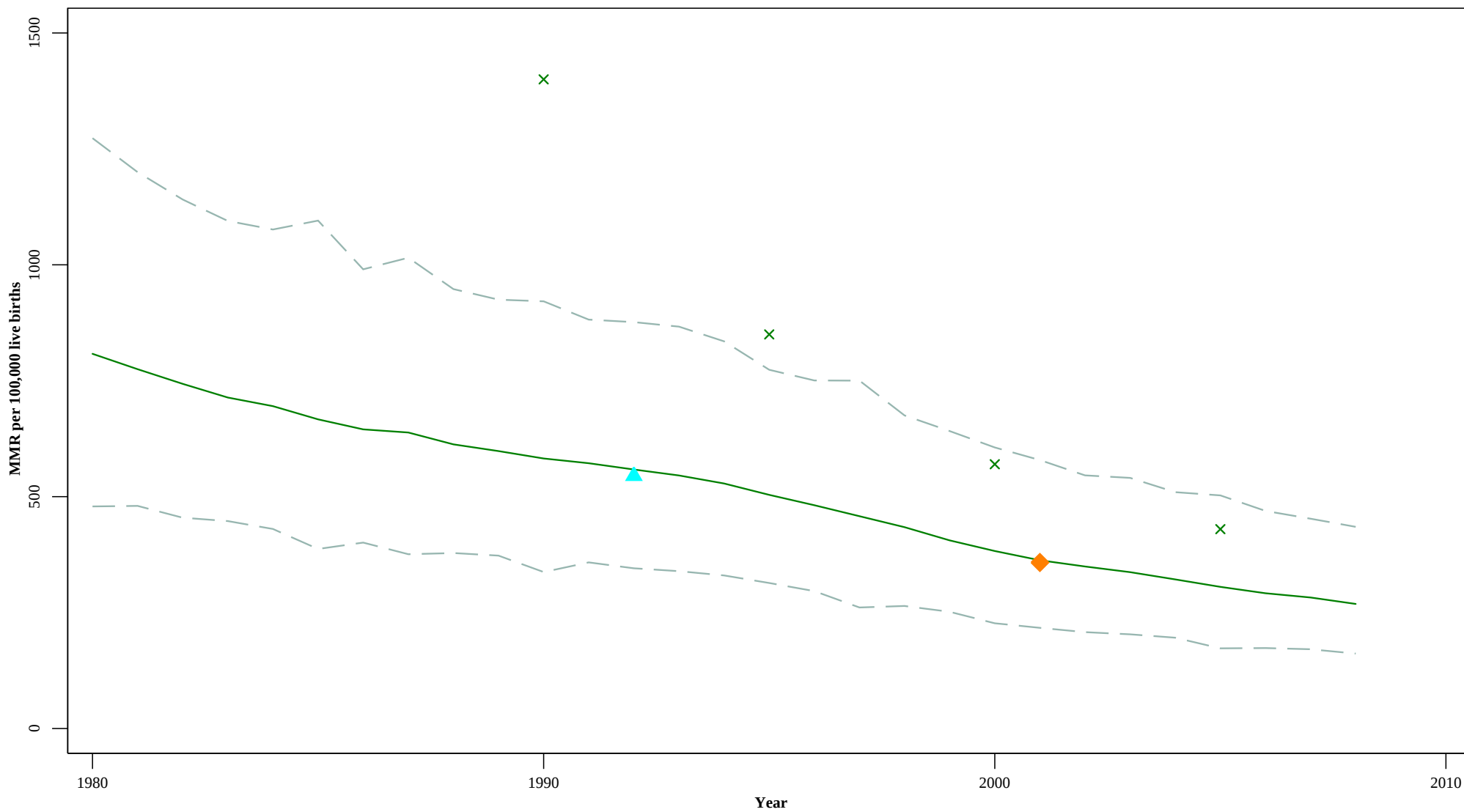
Tunisia



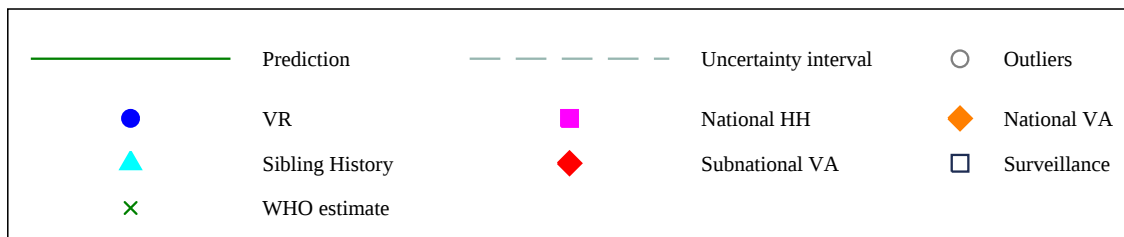
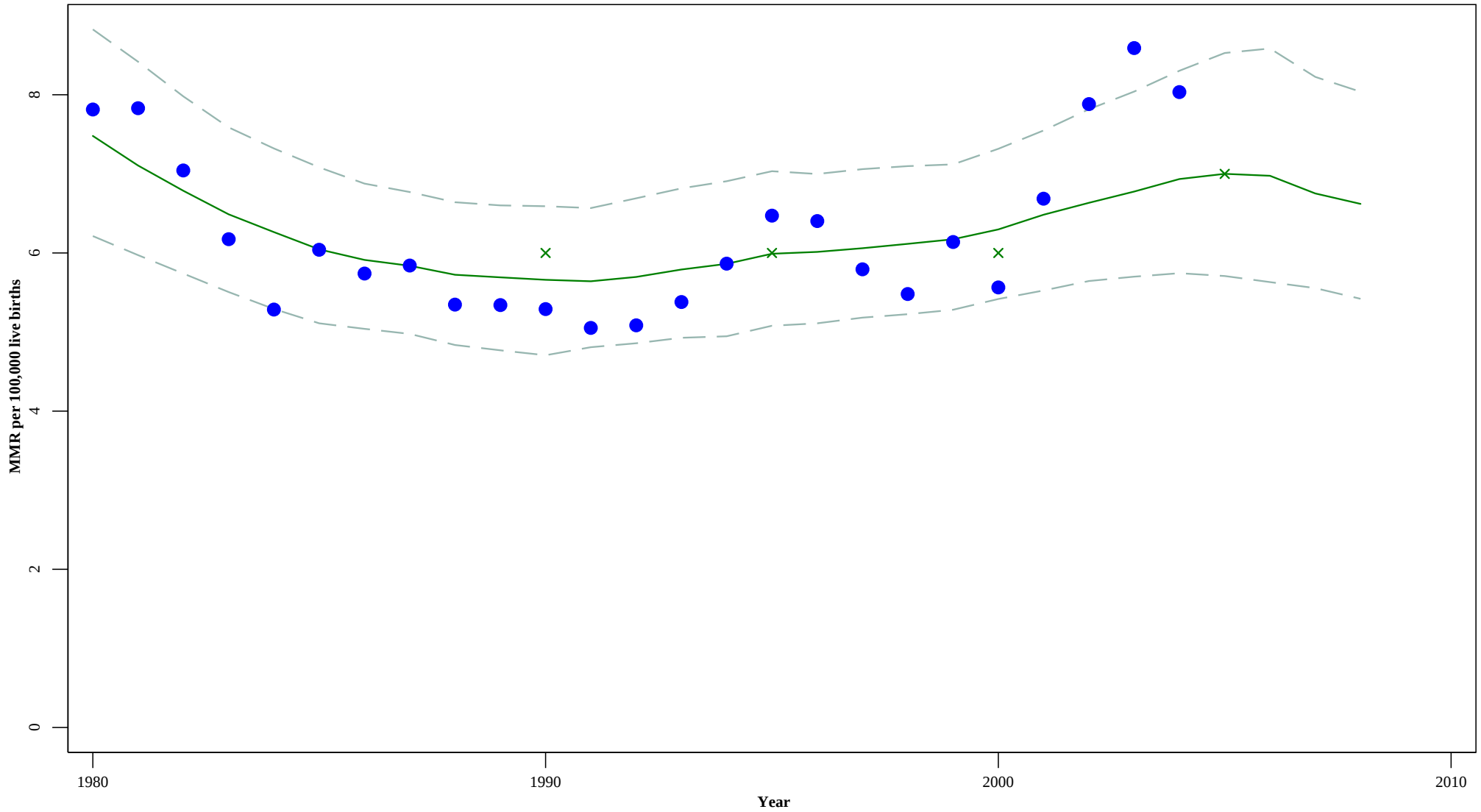
Turkey



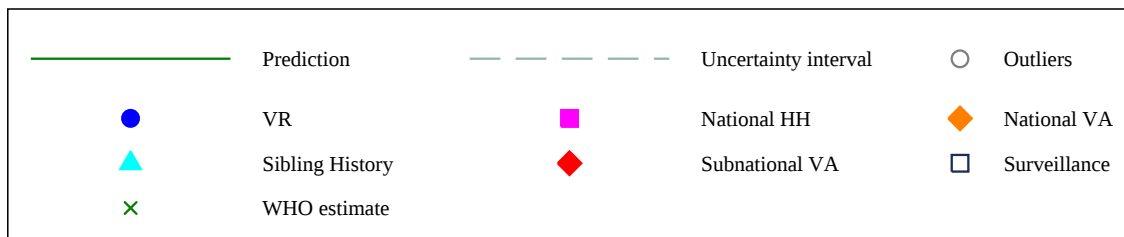
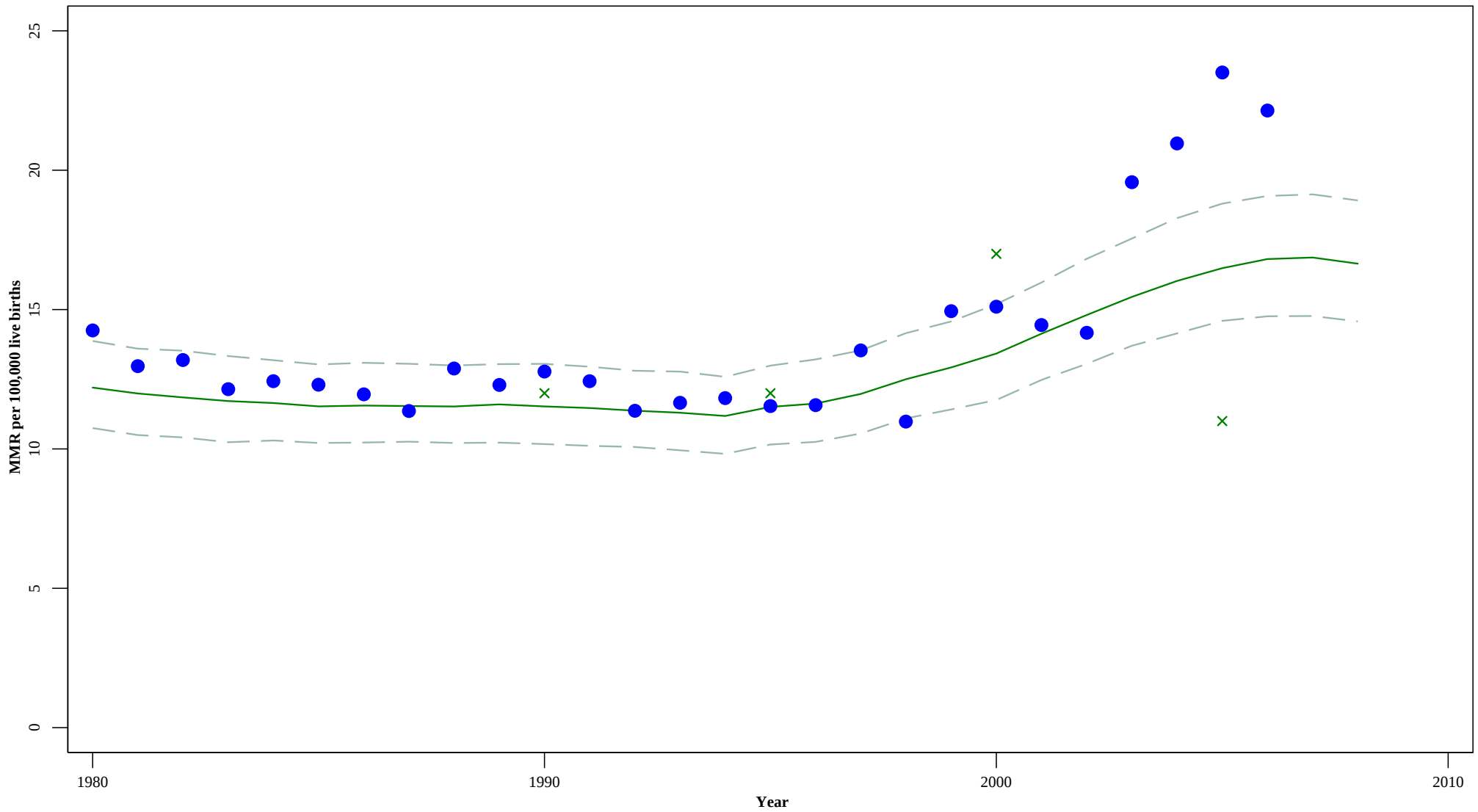
Yemen



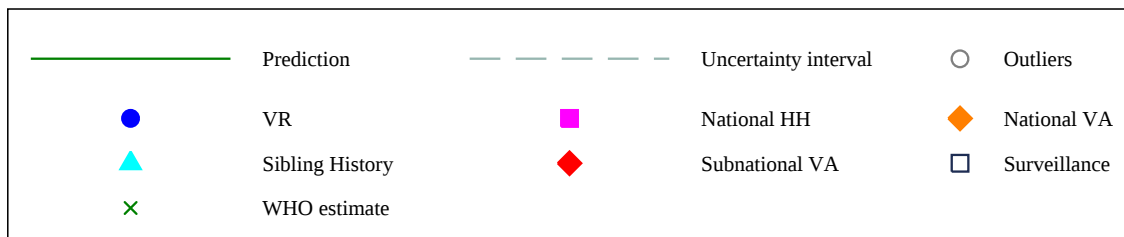
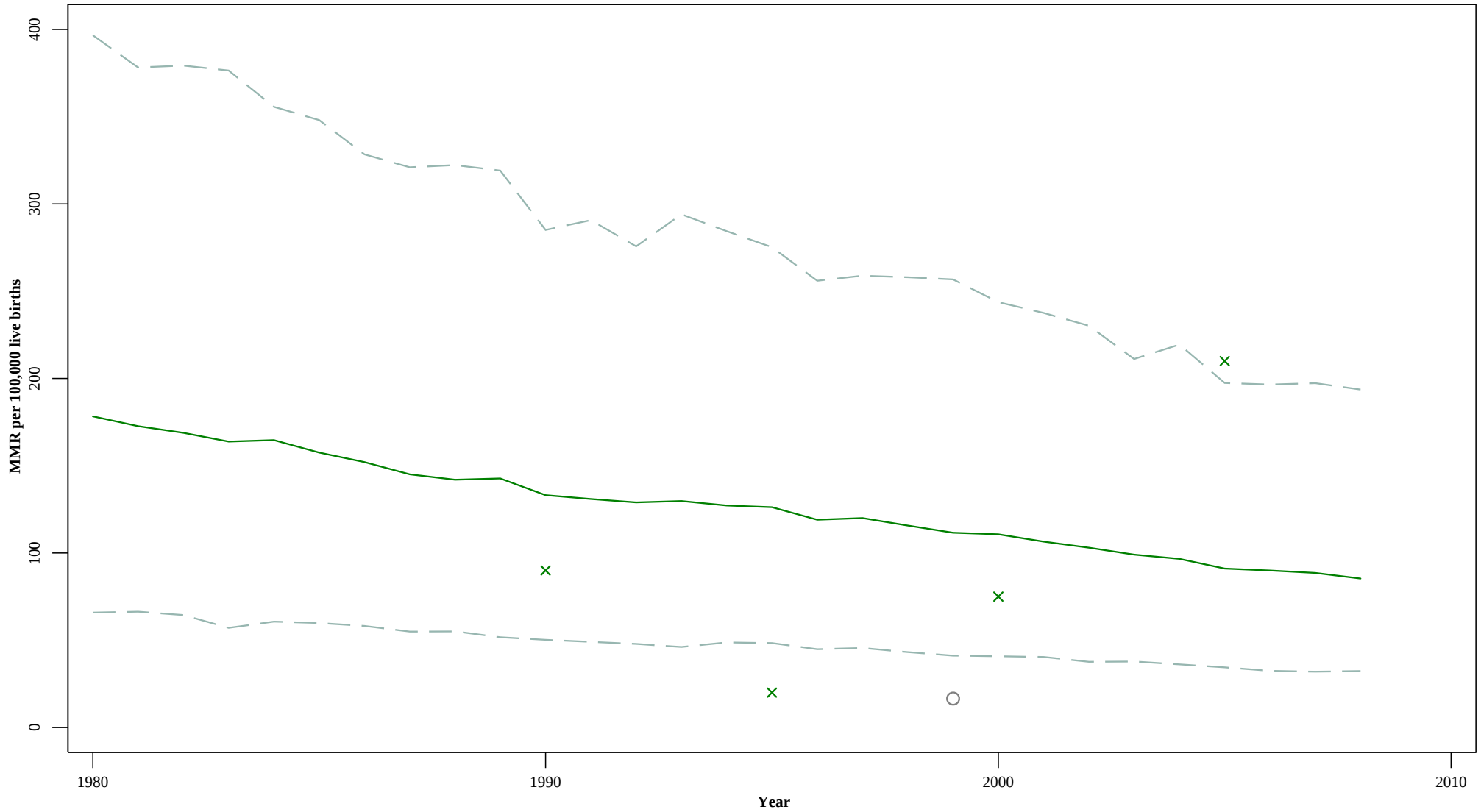
Canada



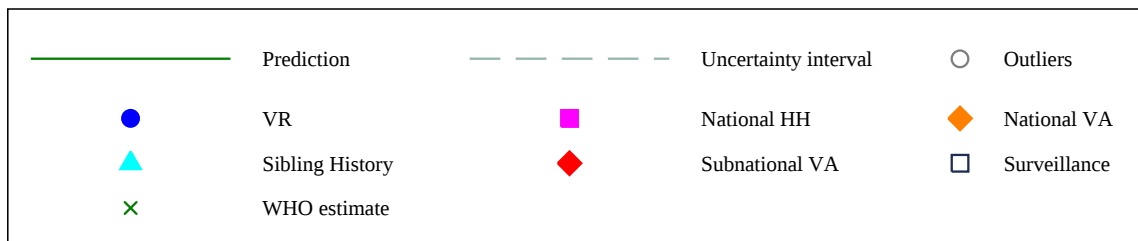
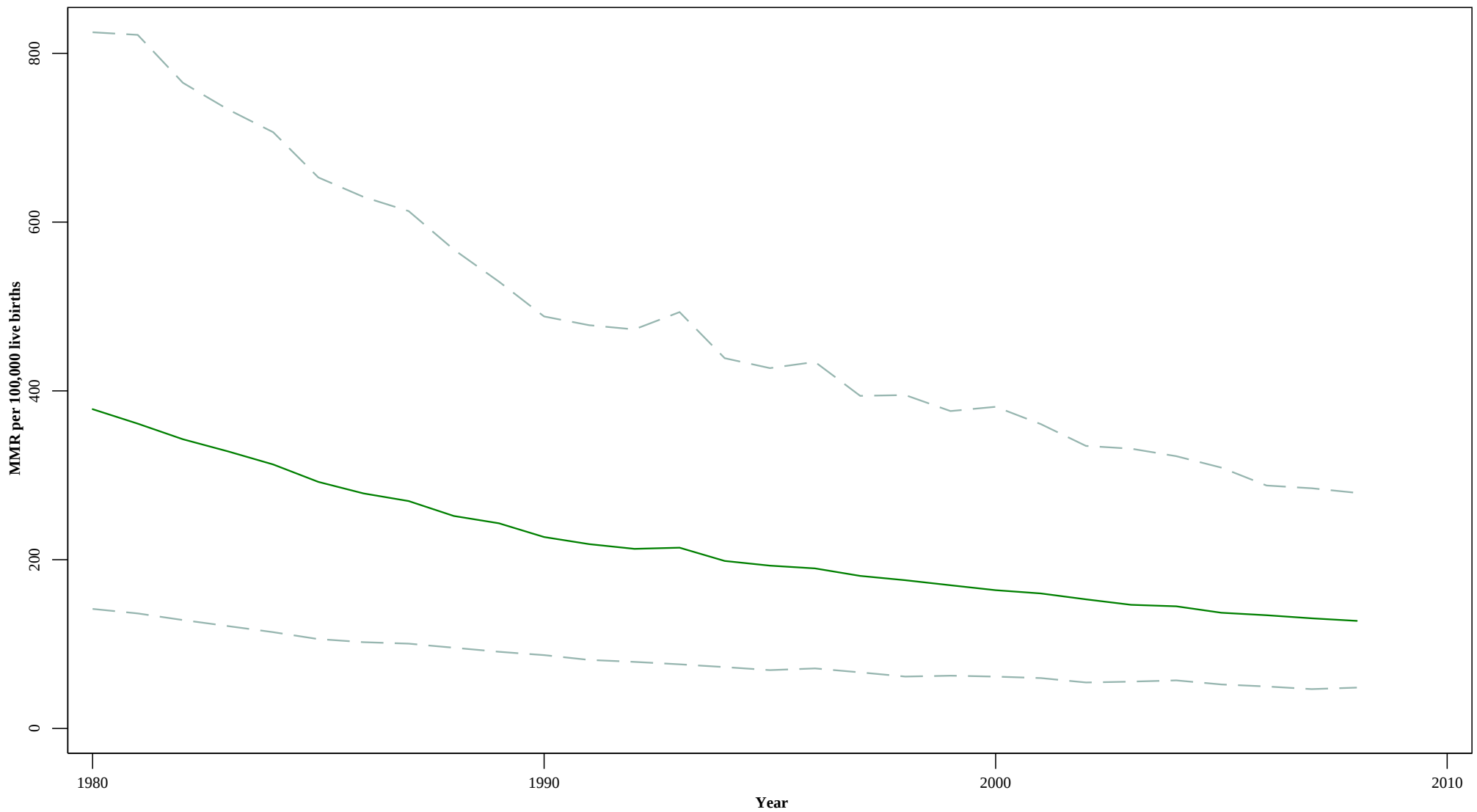
United States



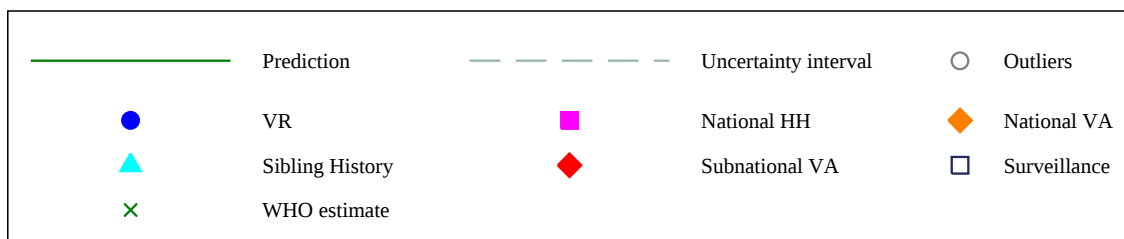
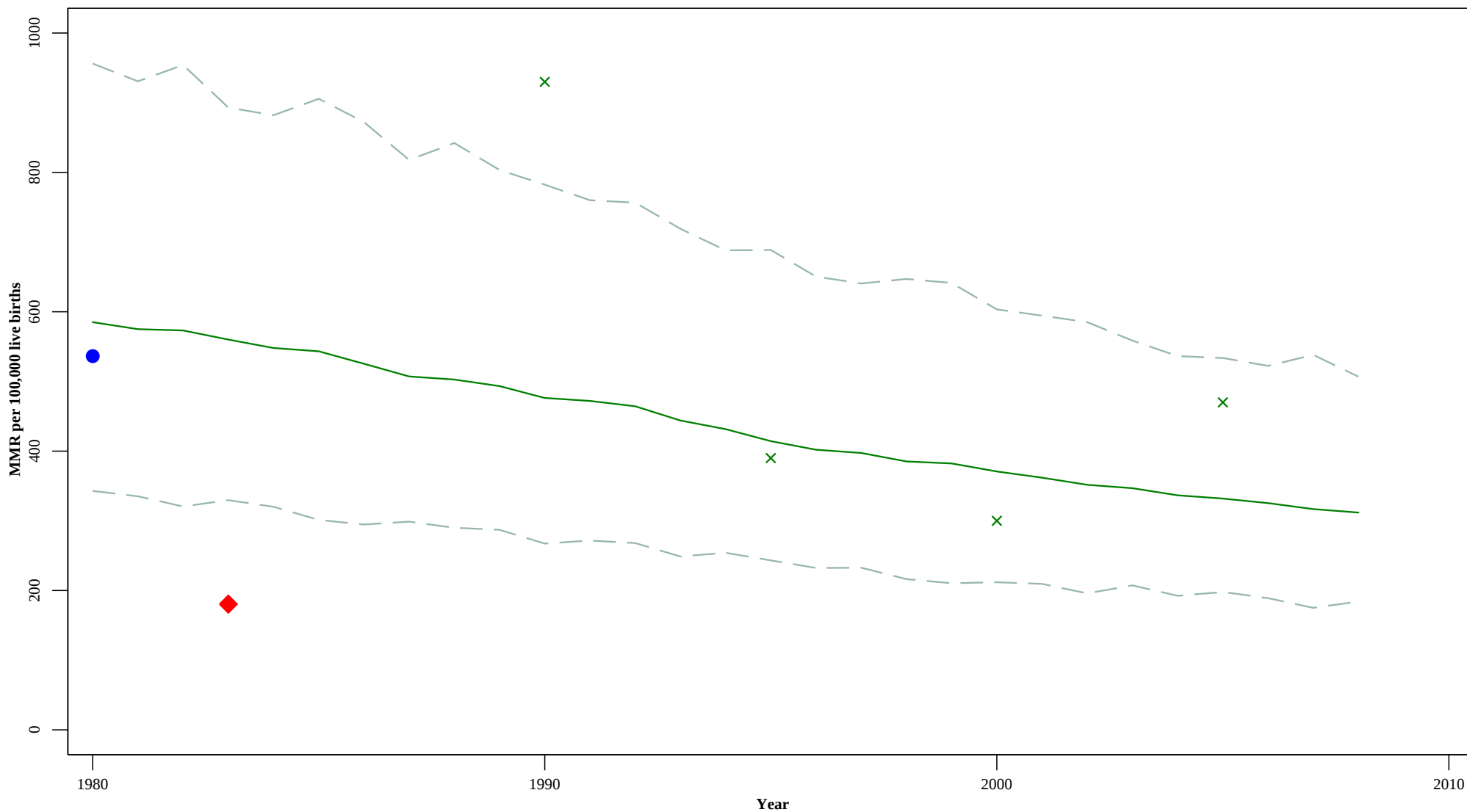
Fiji



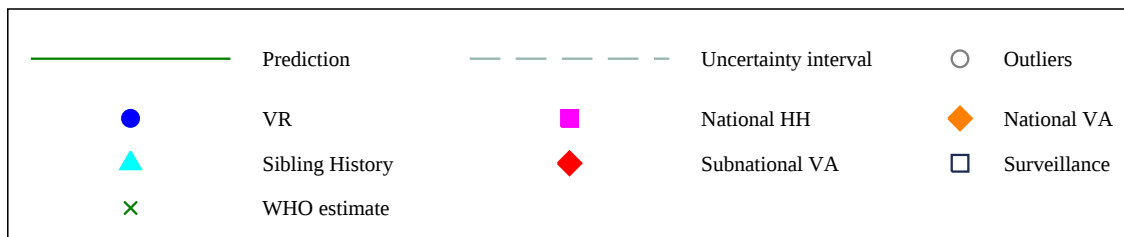
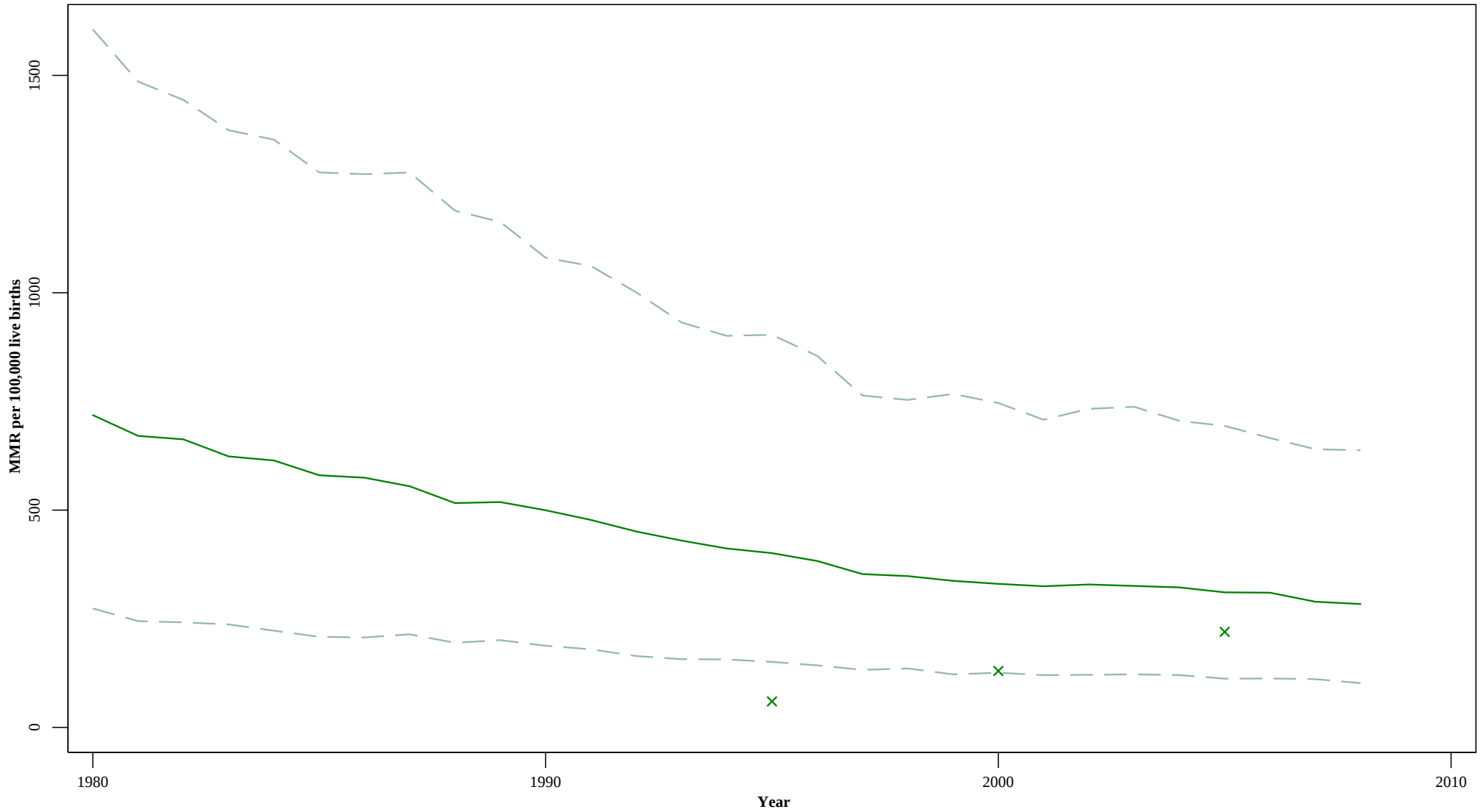
Micronesia, Federated States of



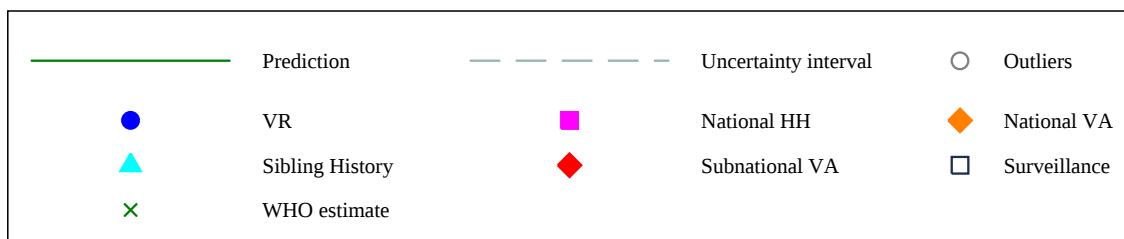
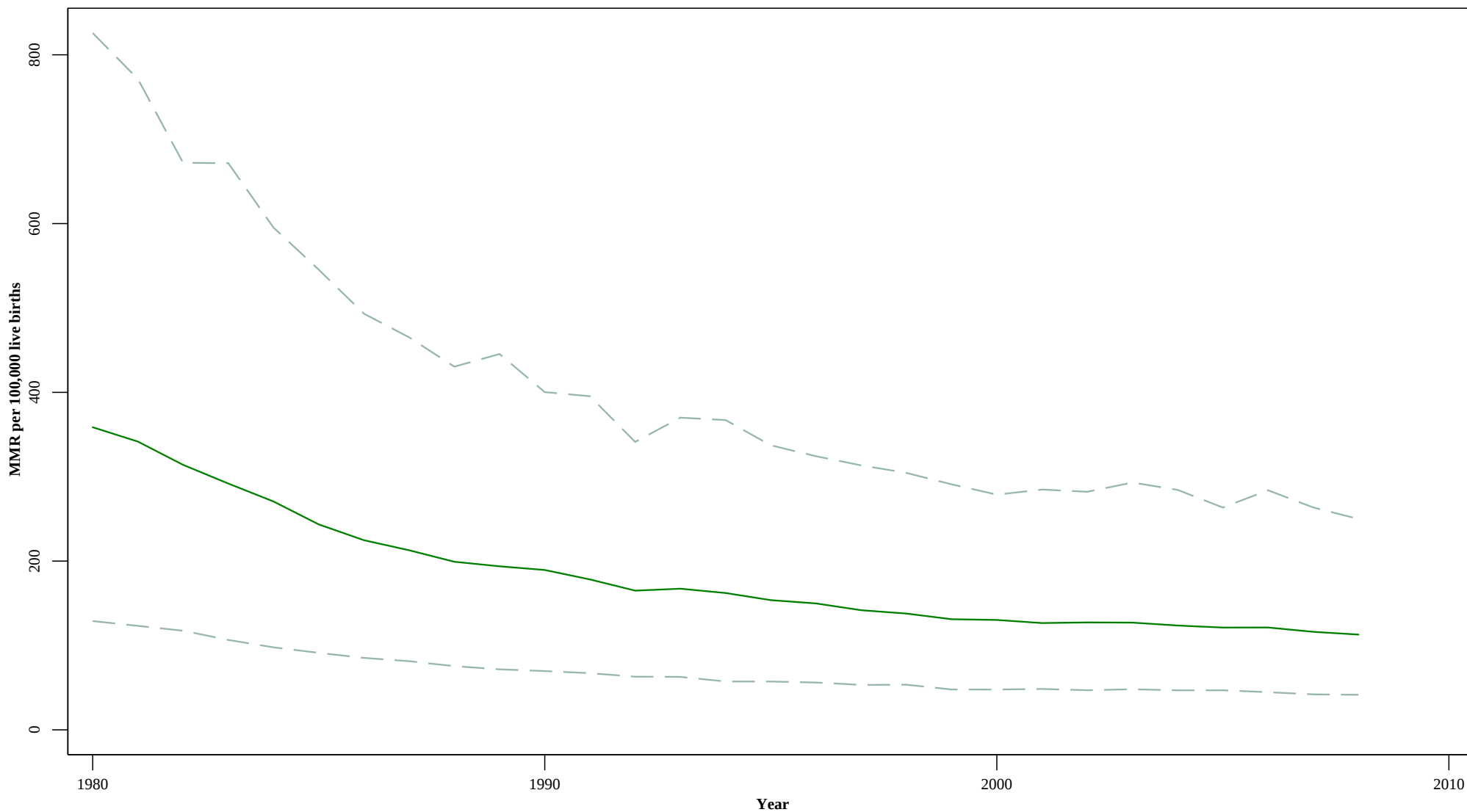
Papua New Guinea



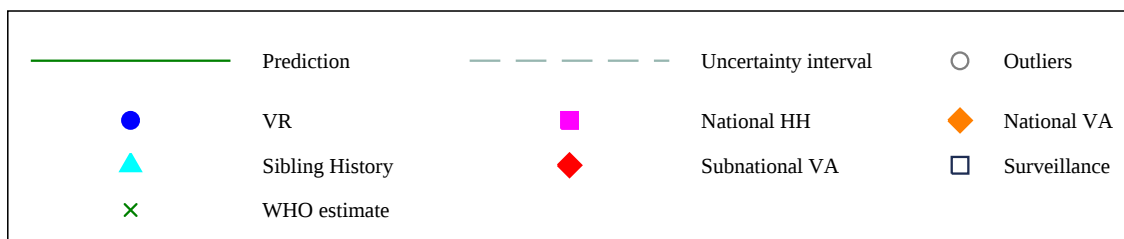
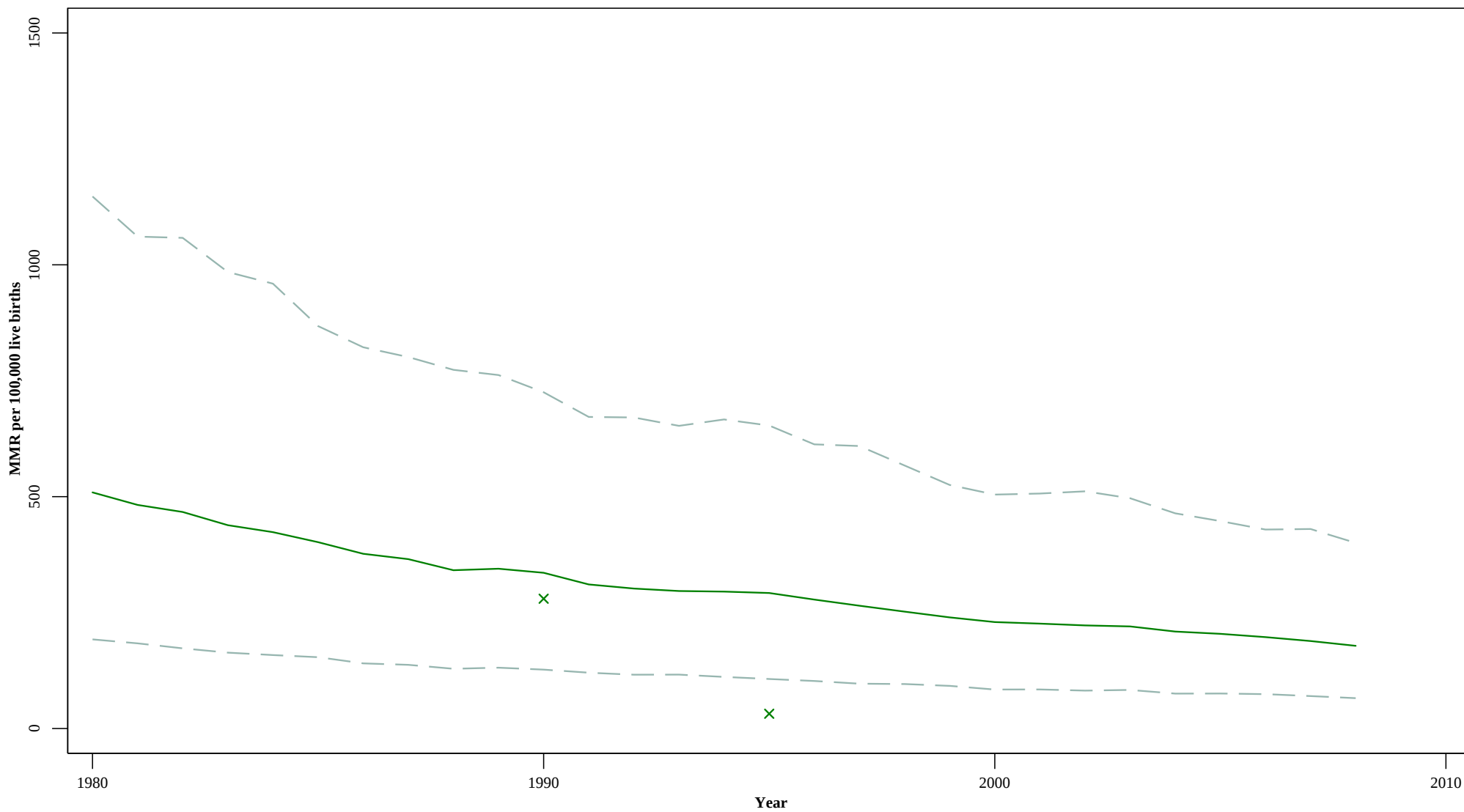
Solomon Islands



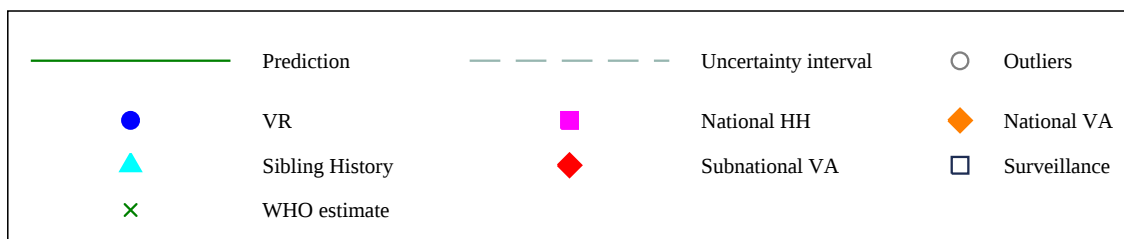
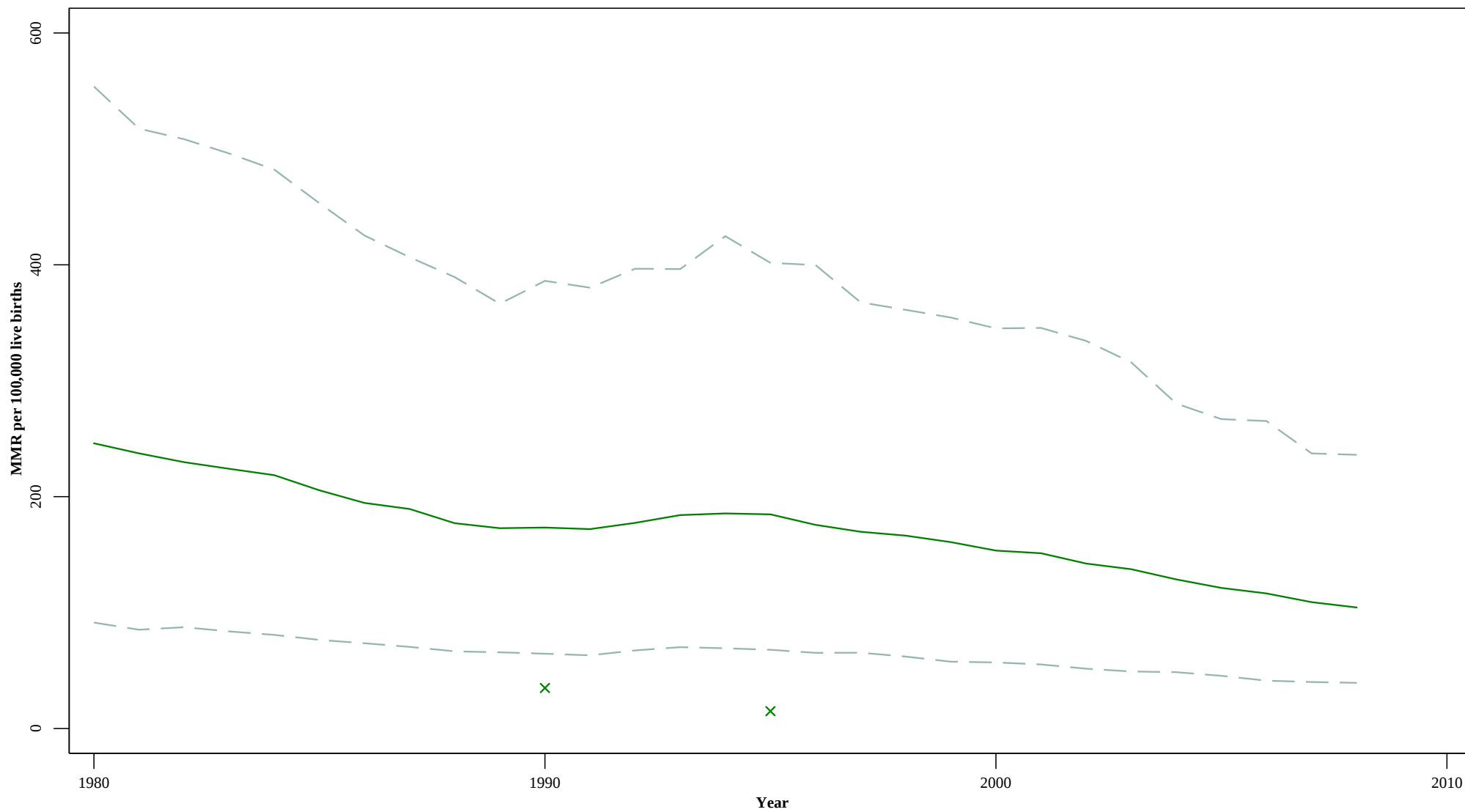
Tonga



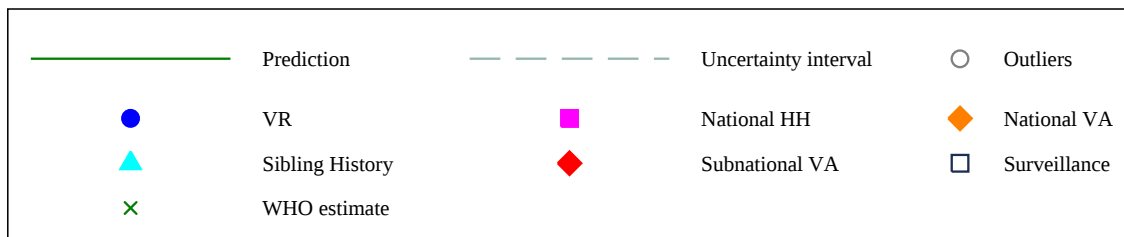
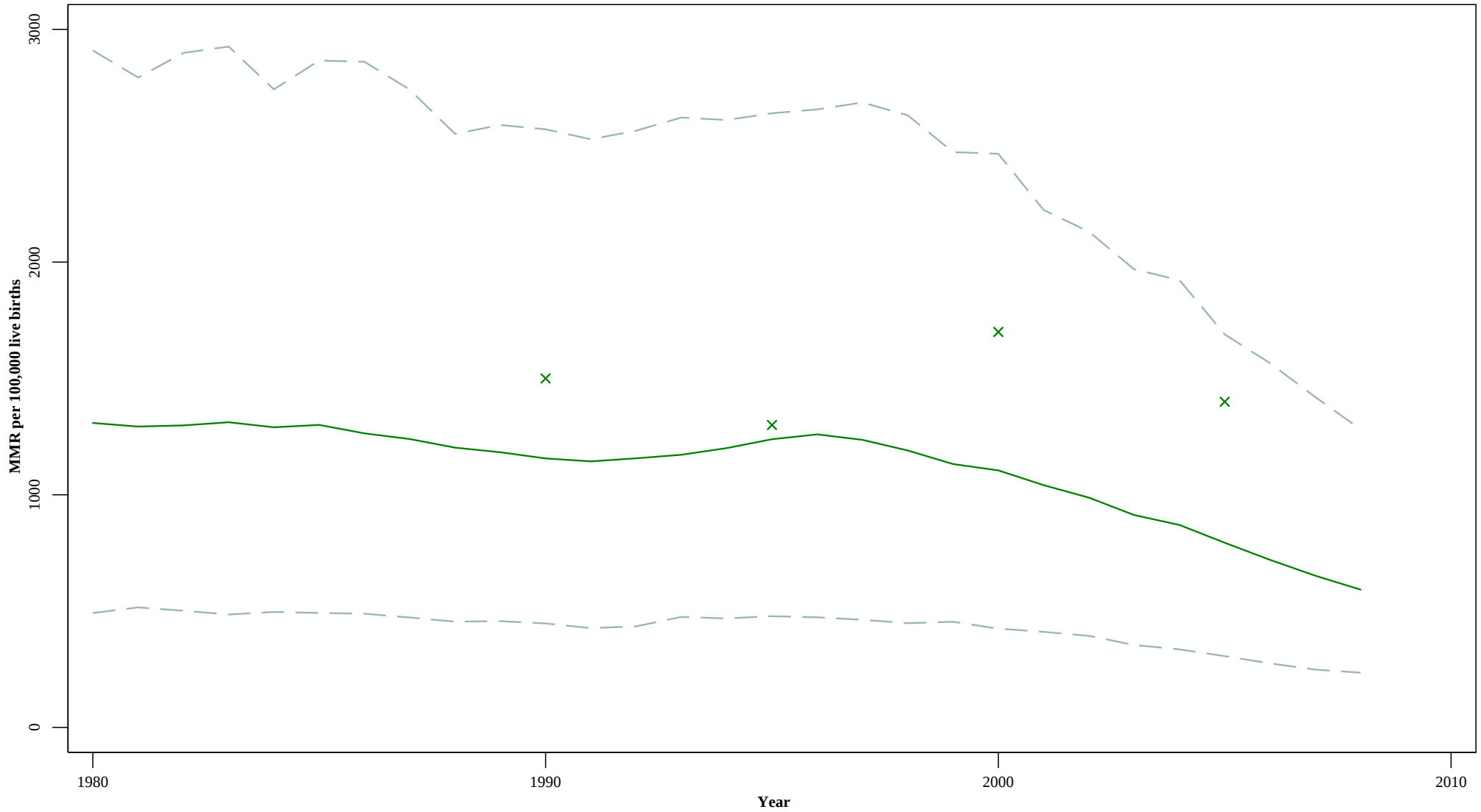
Vanuatu



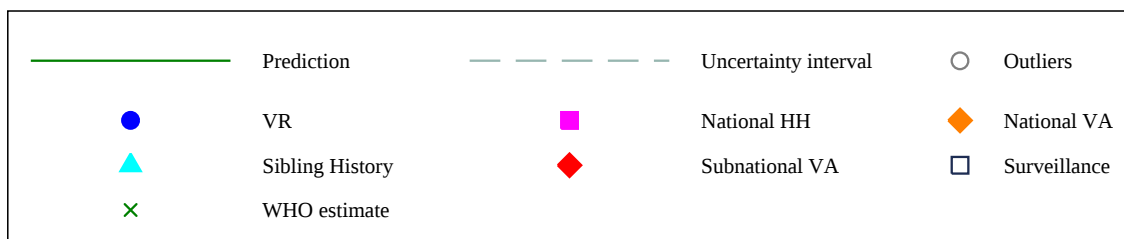
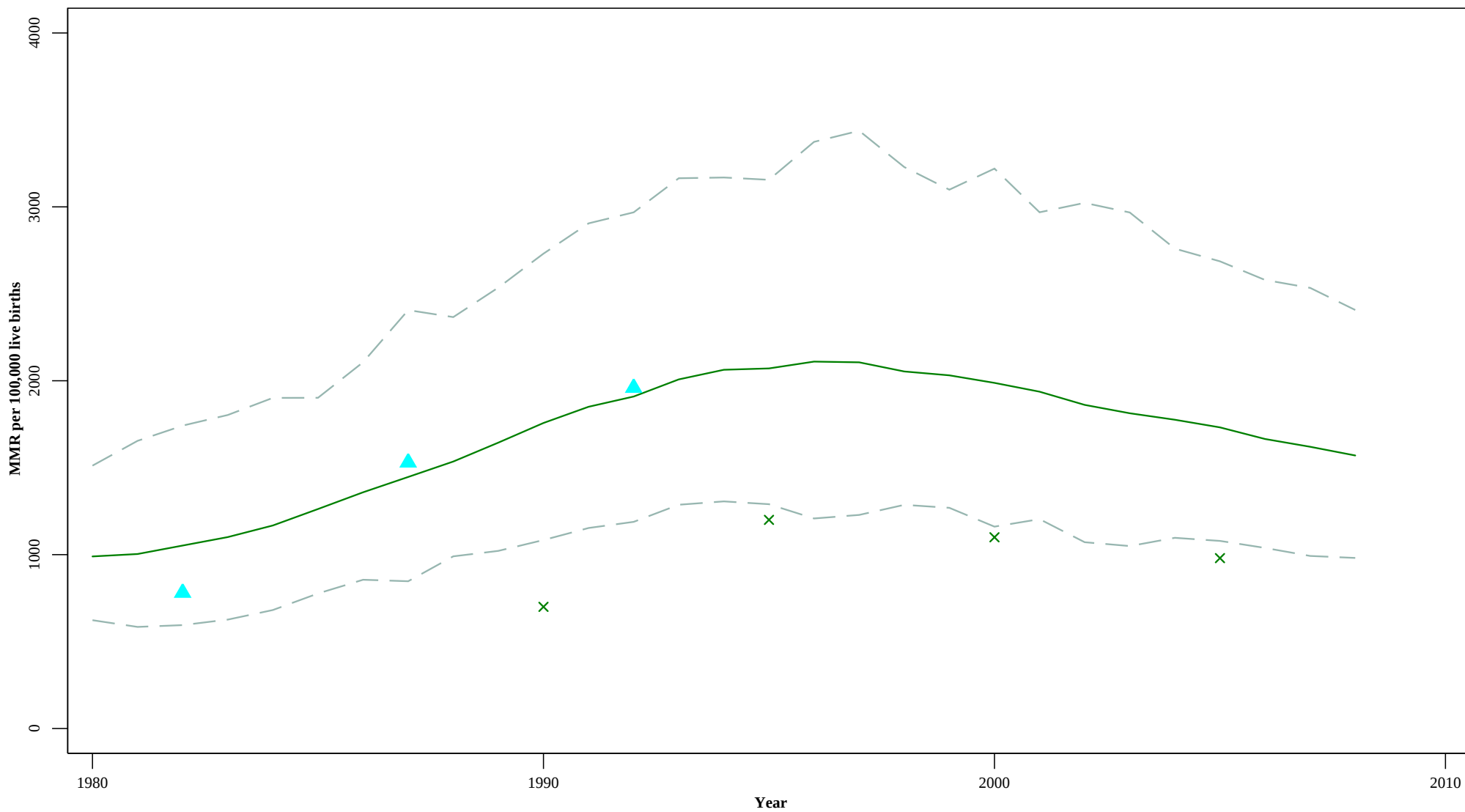
Samoa



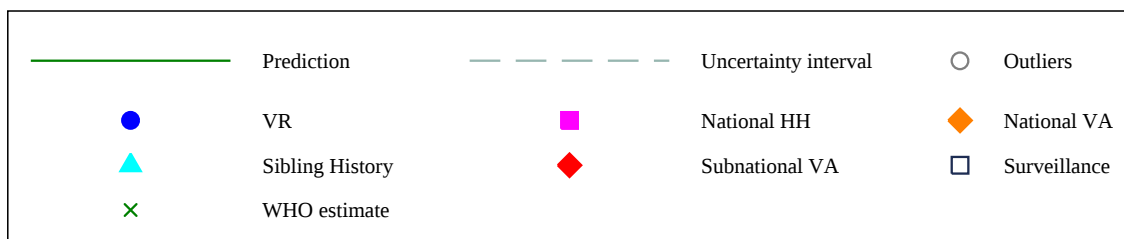
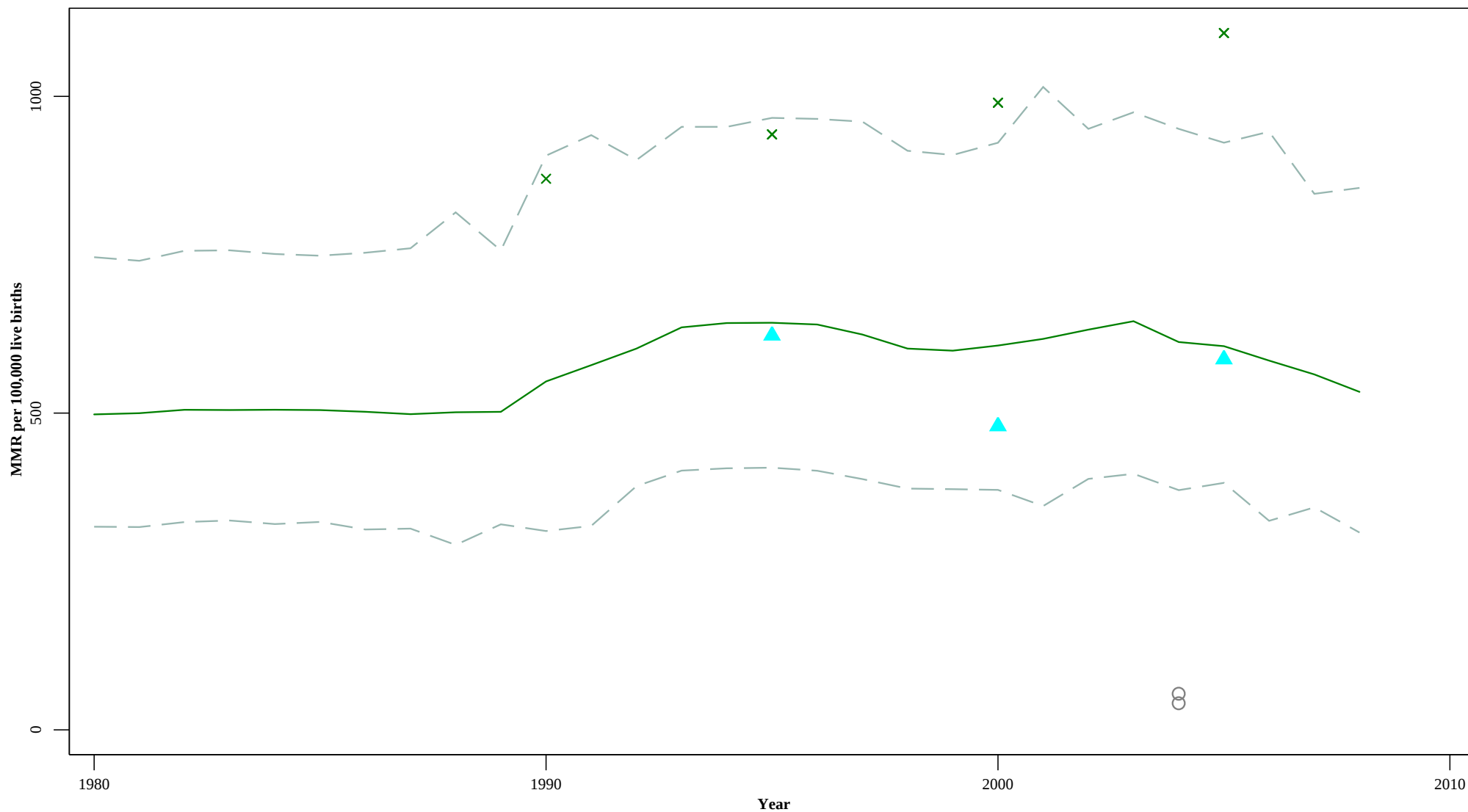
Angola



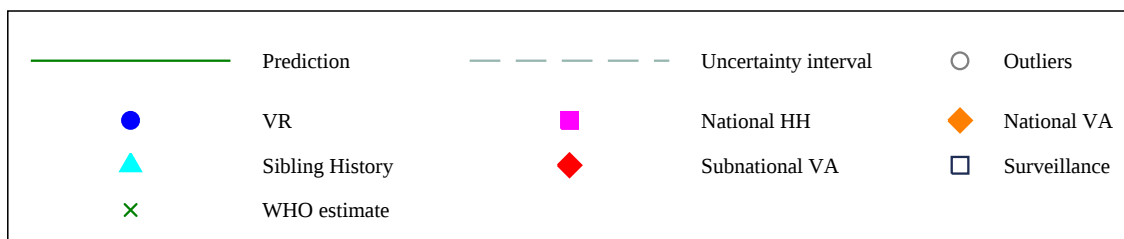
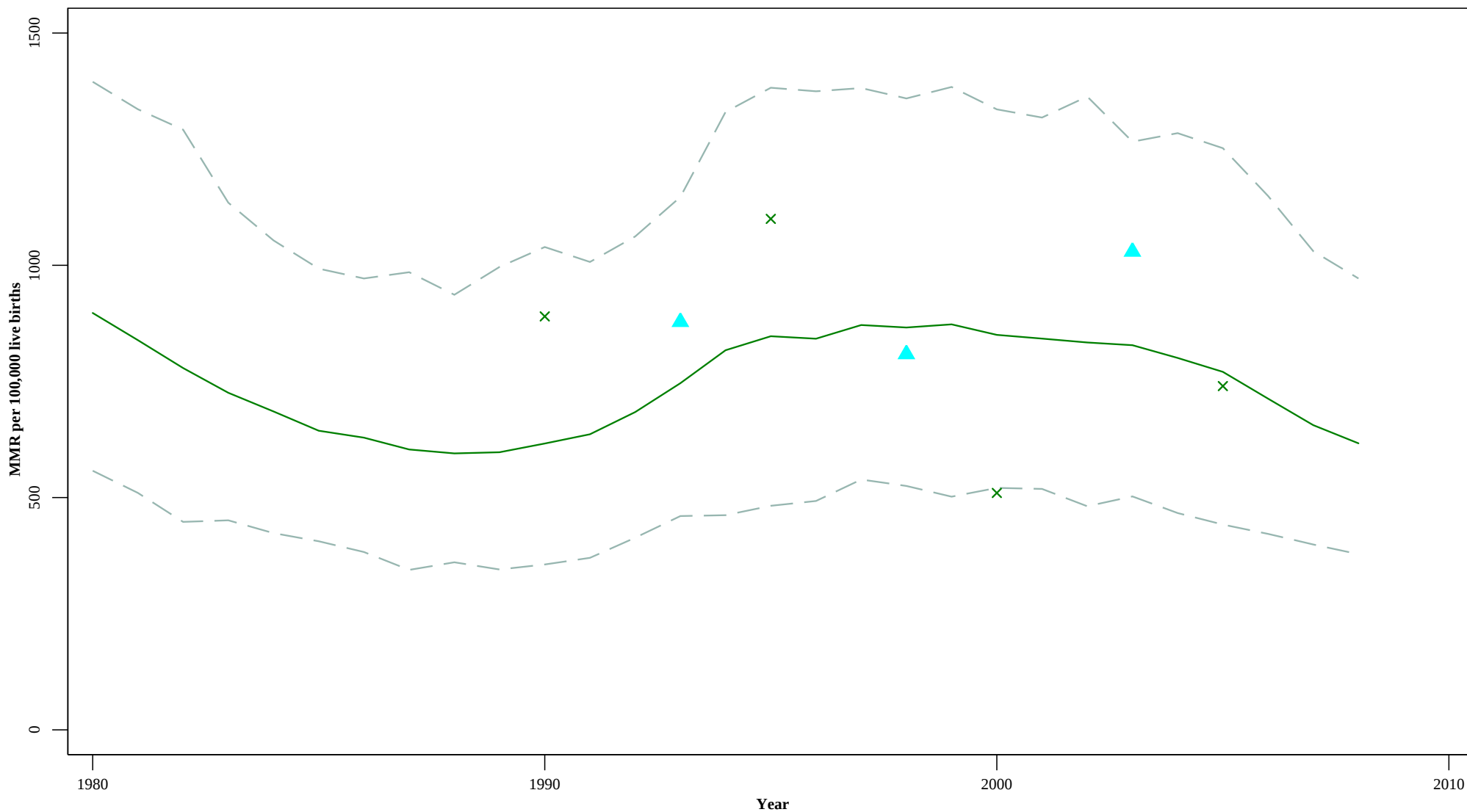
Central African Republic



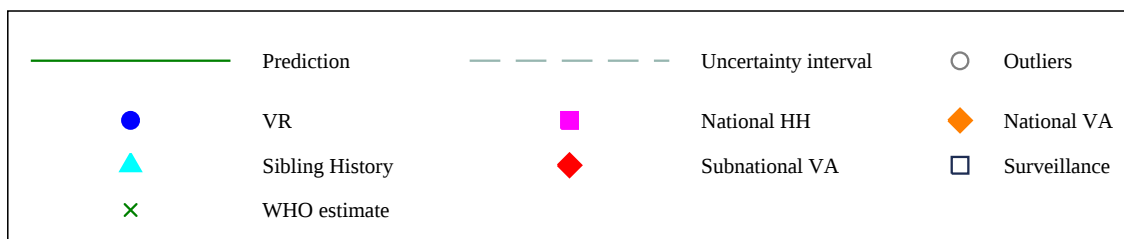
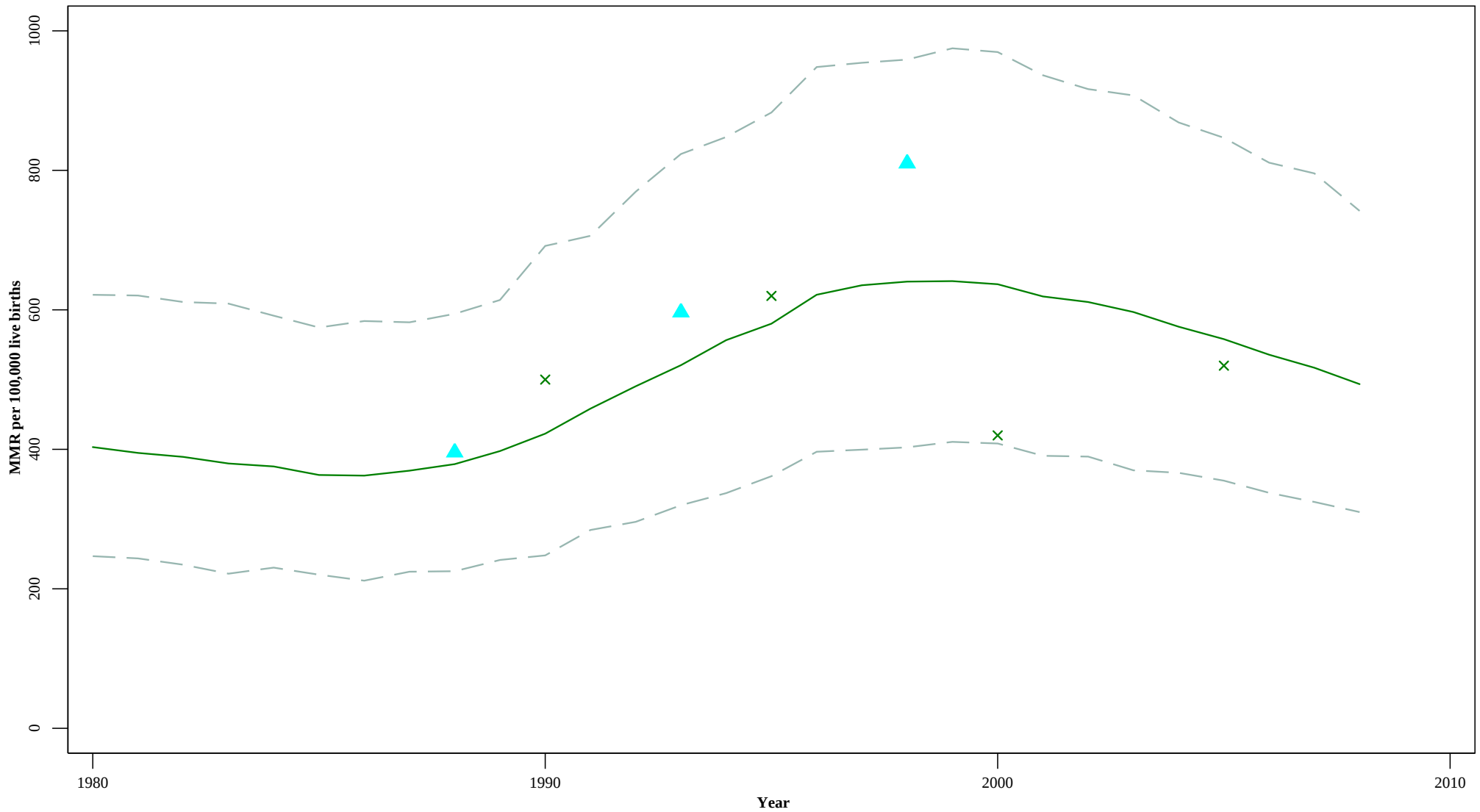
Congo, the Democratic Republic of the



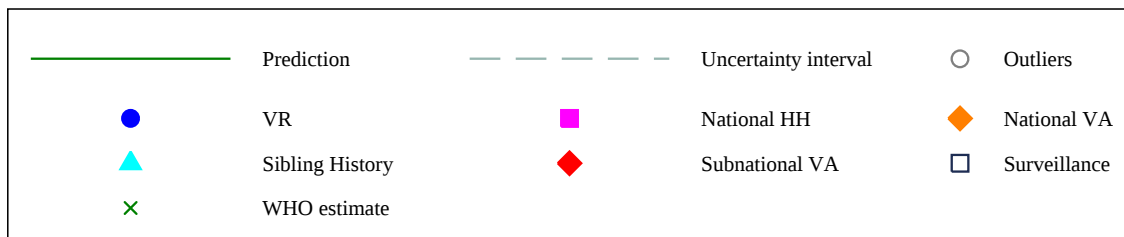
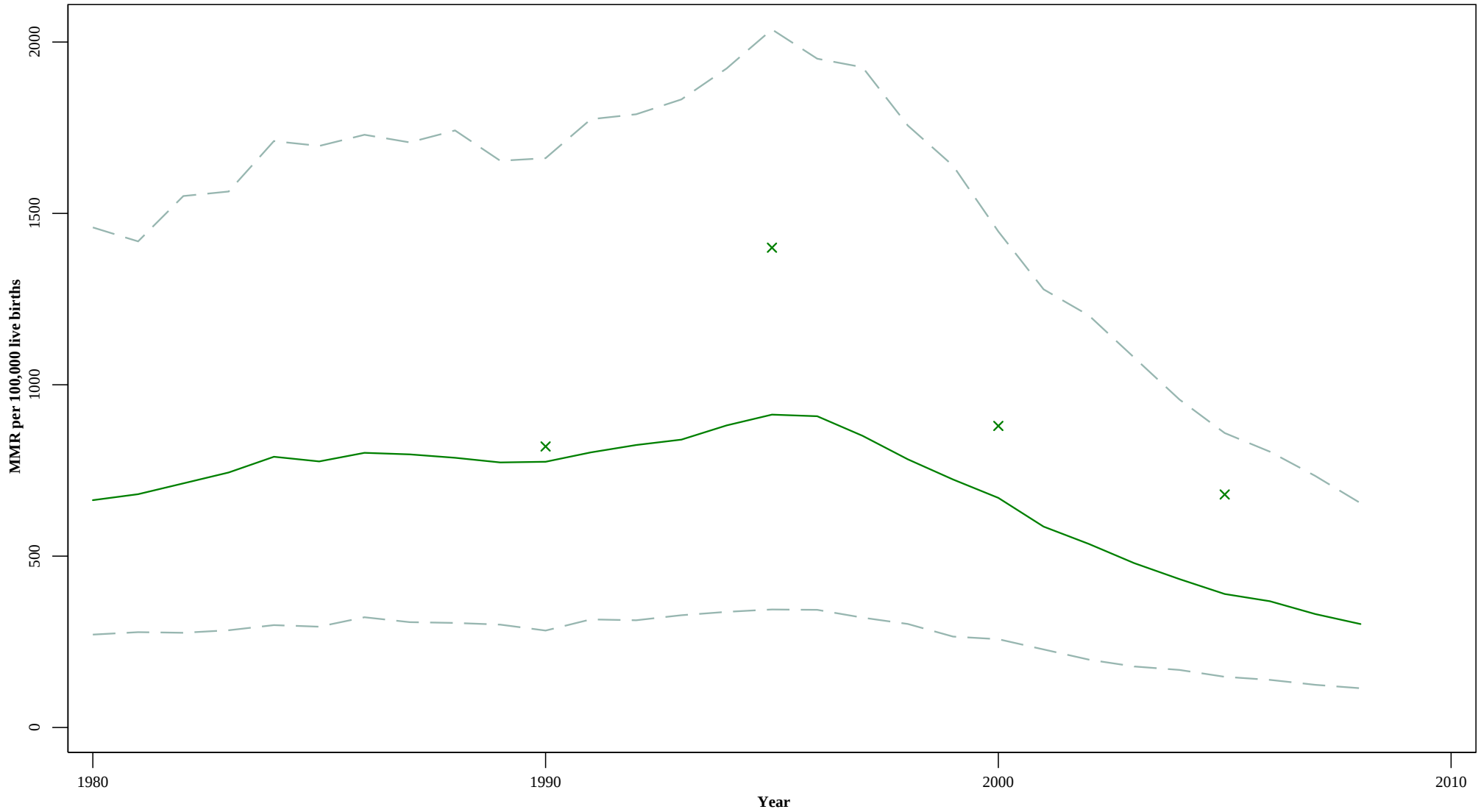
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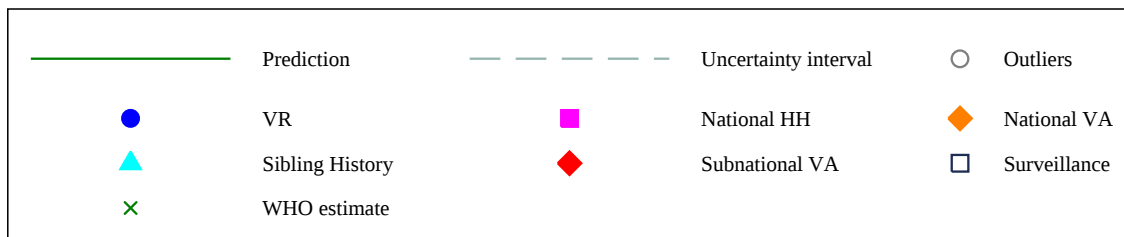
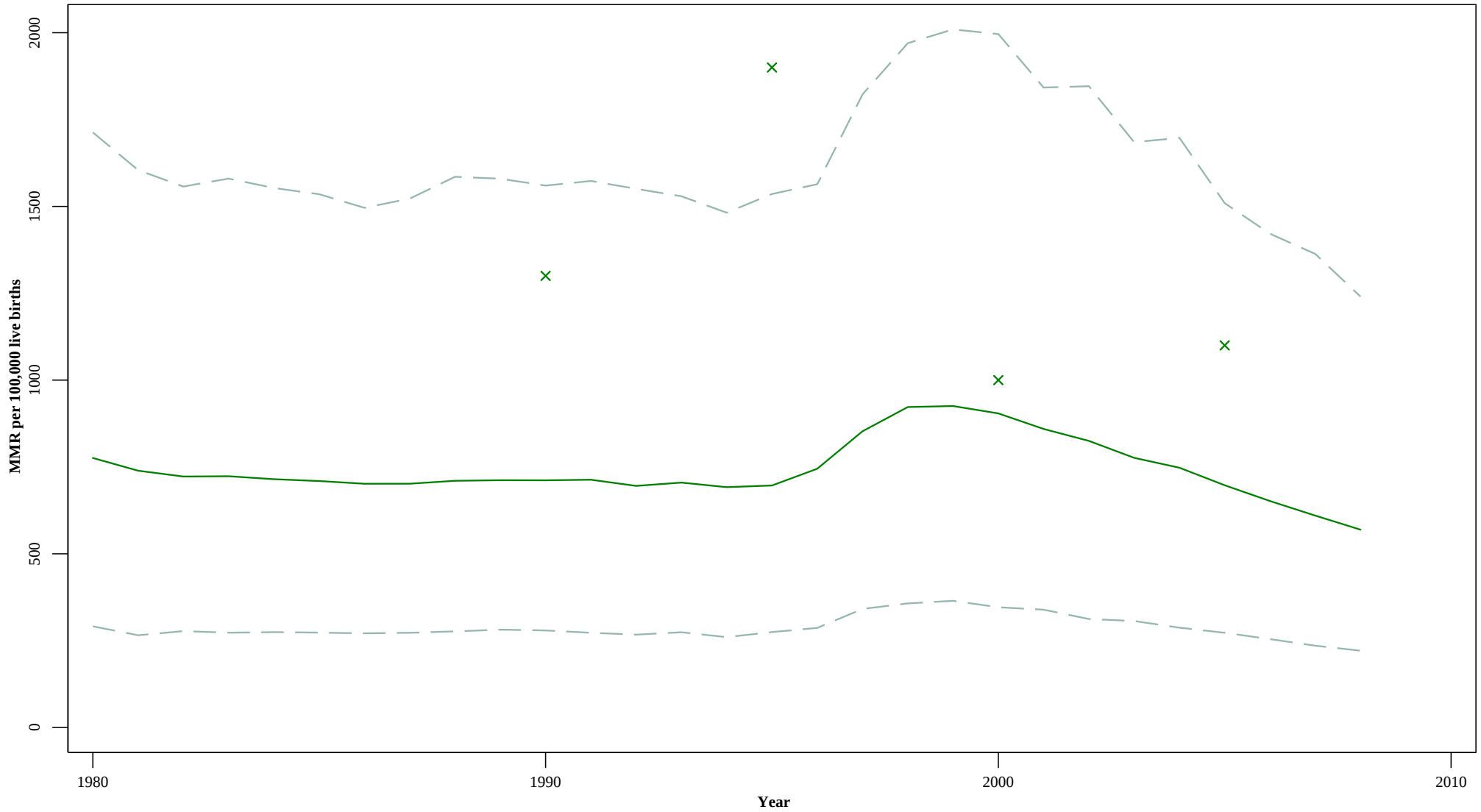
Gabon



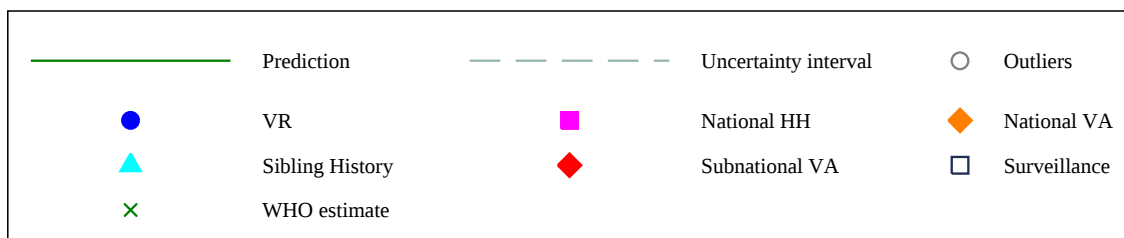
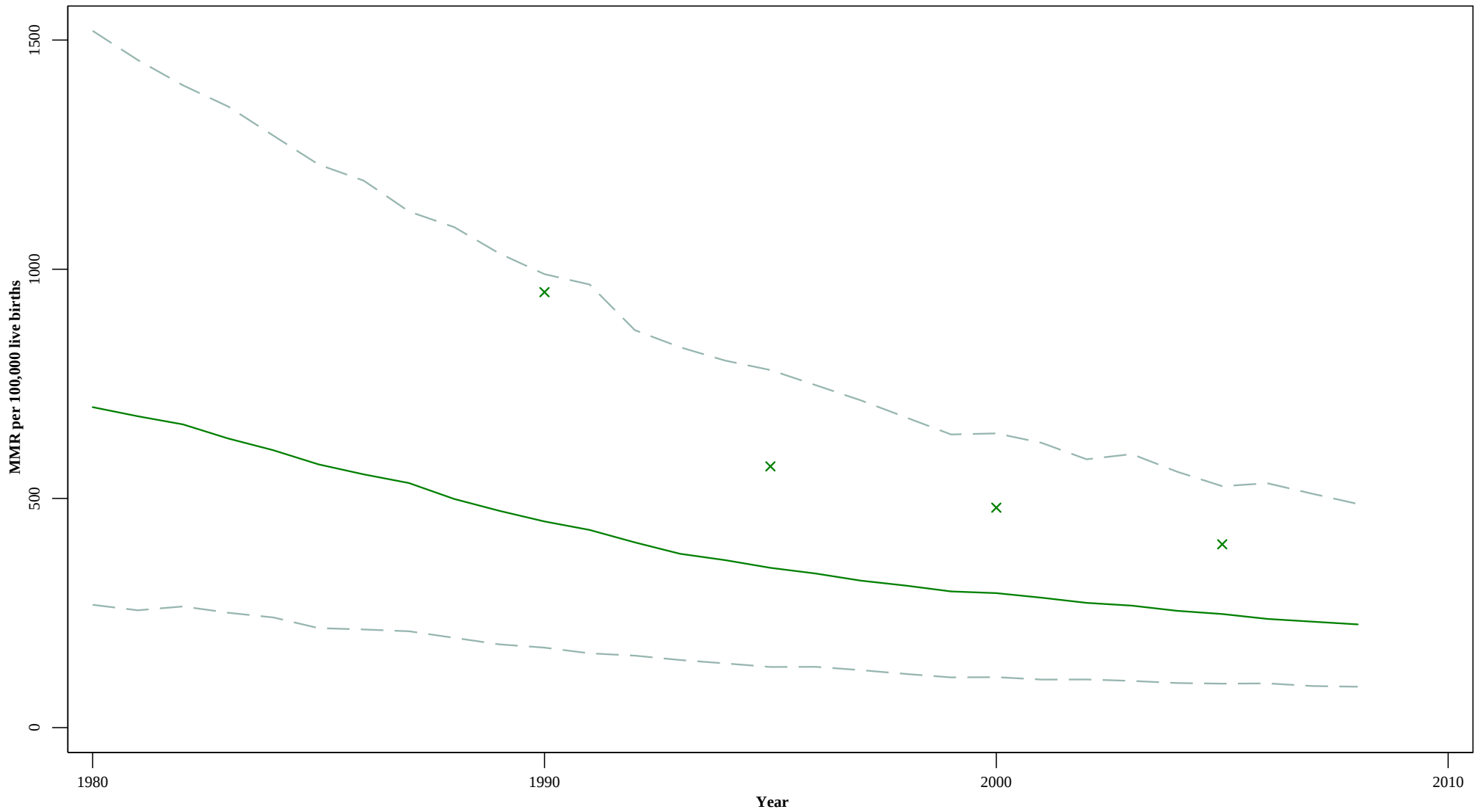
Equatorial Guinea



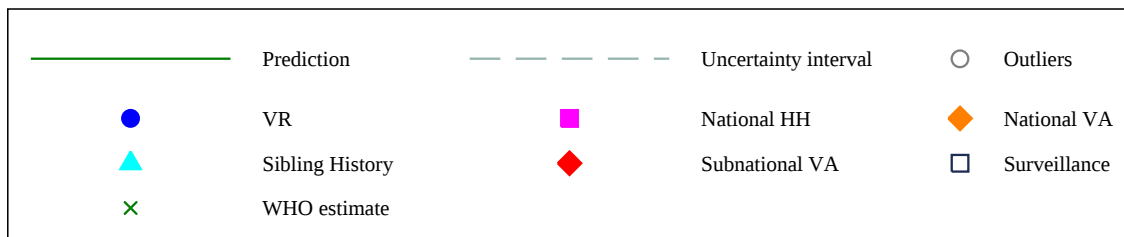
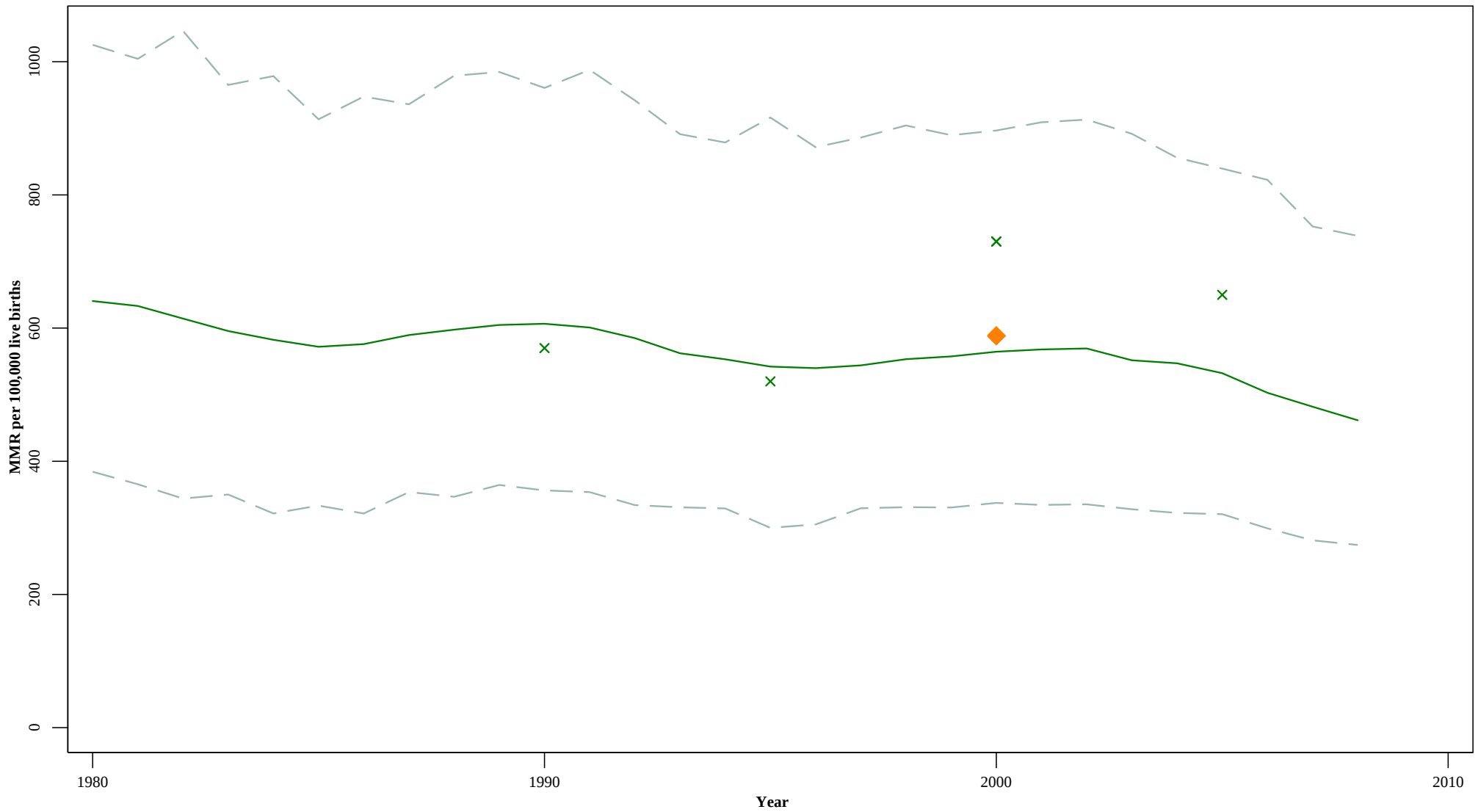
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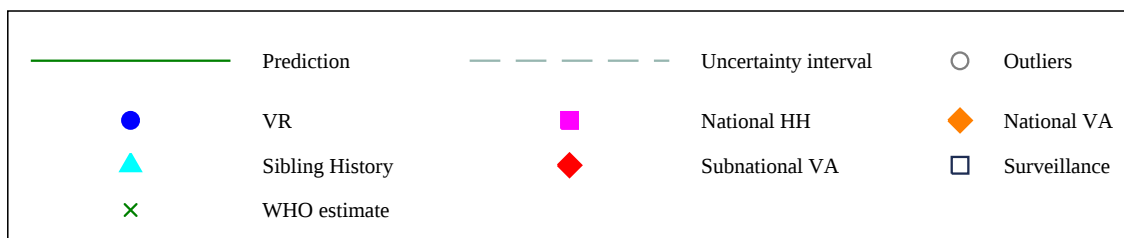
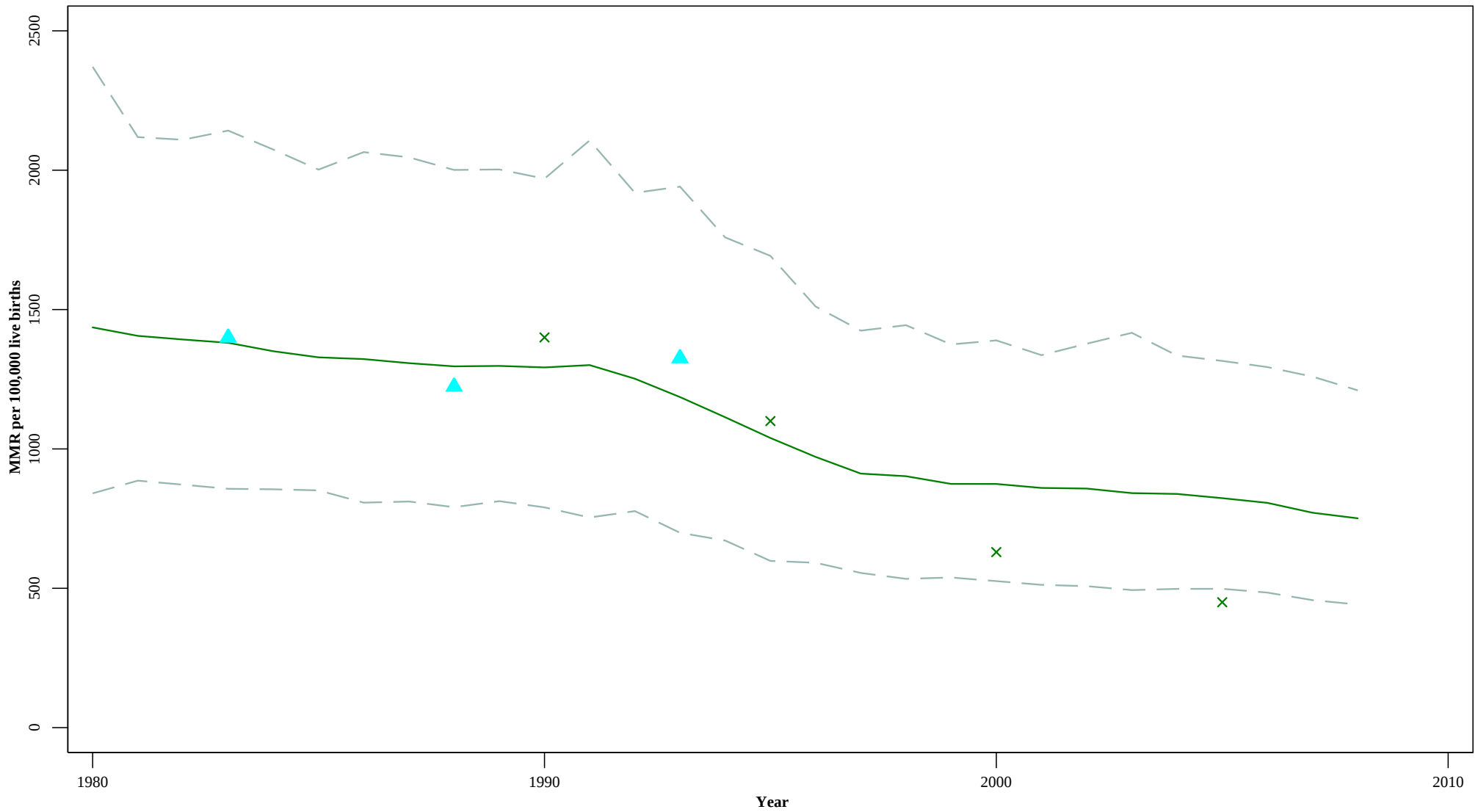
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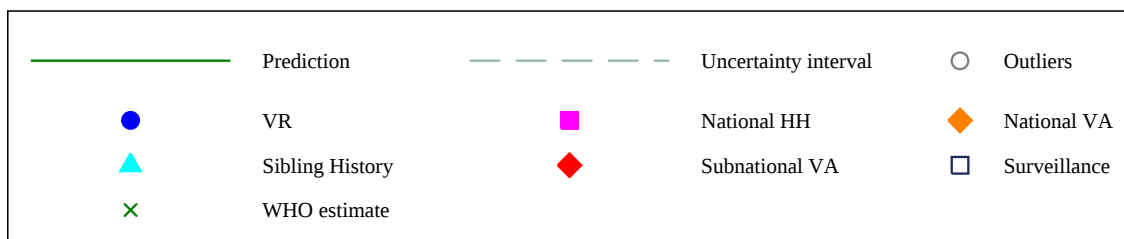
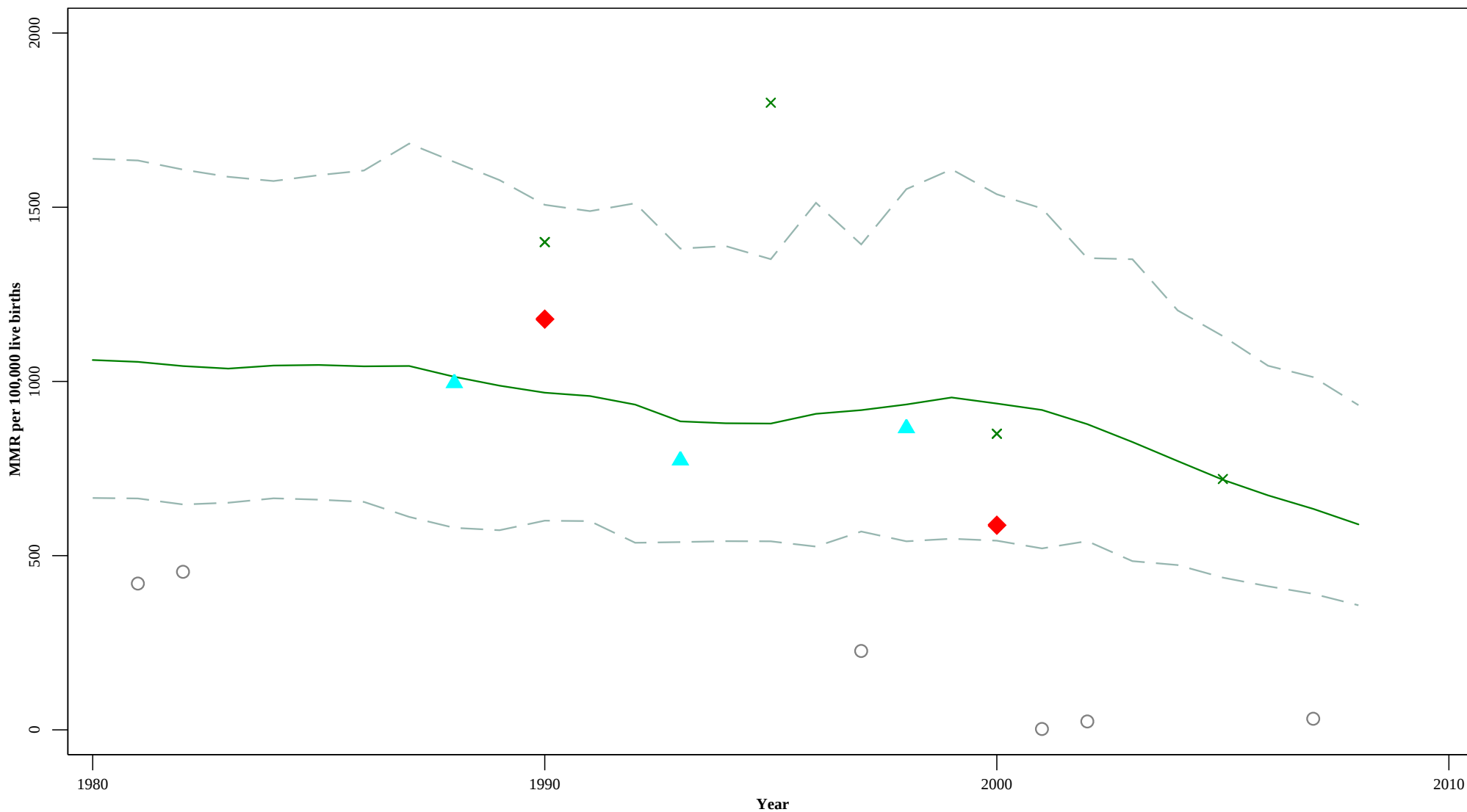
Djibouti



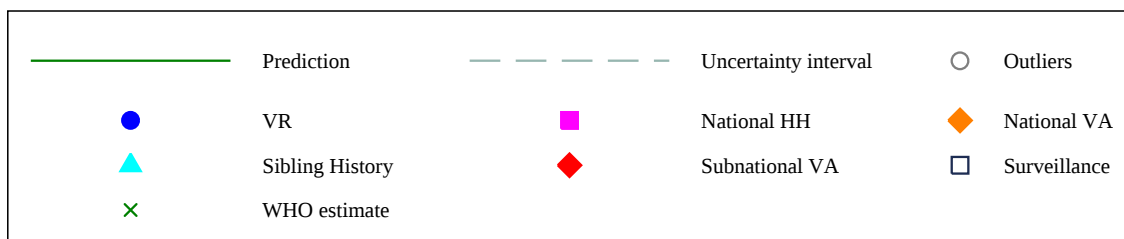
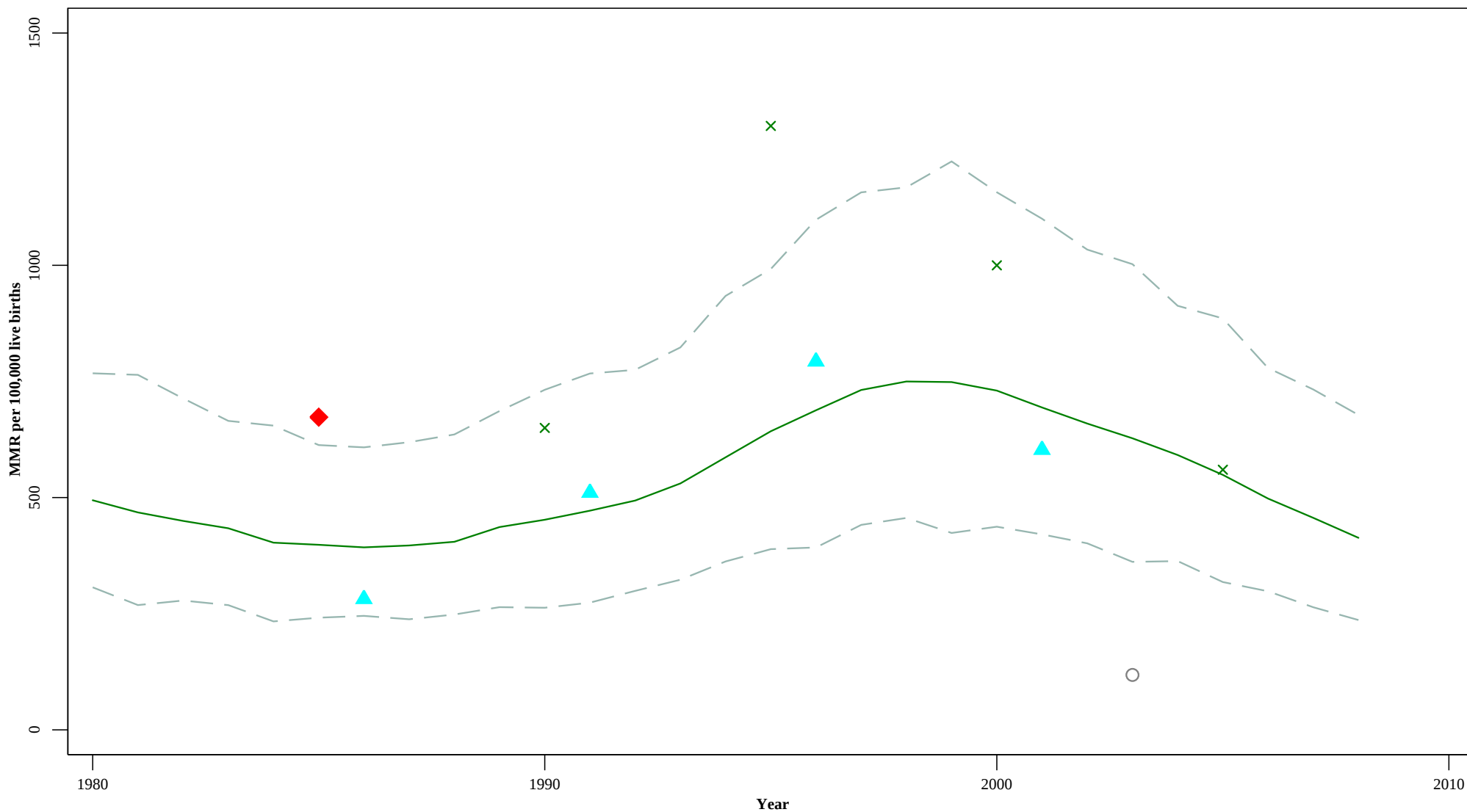
Eritrea



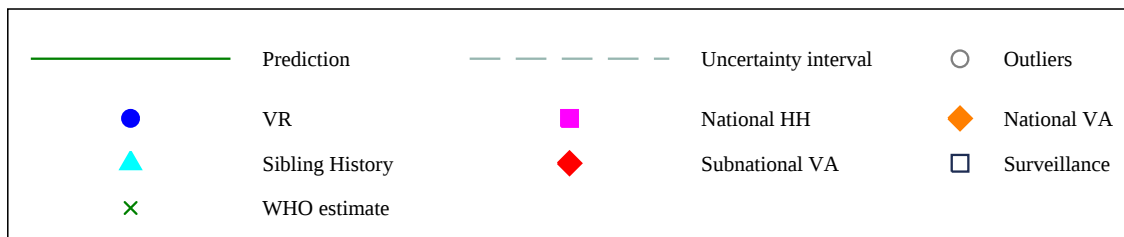
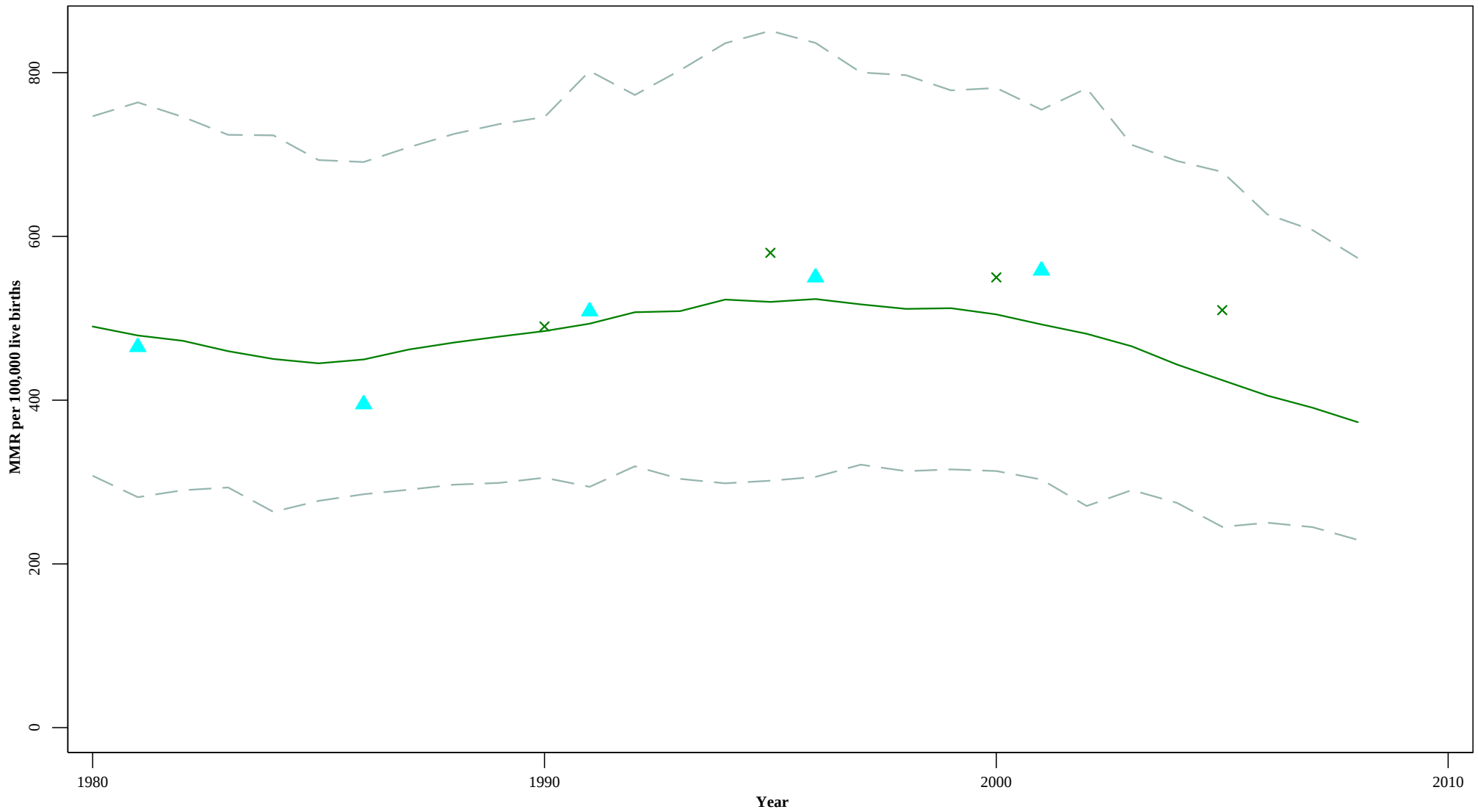
Ethiopia



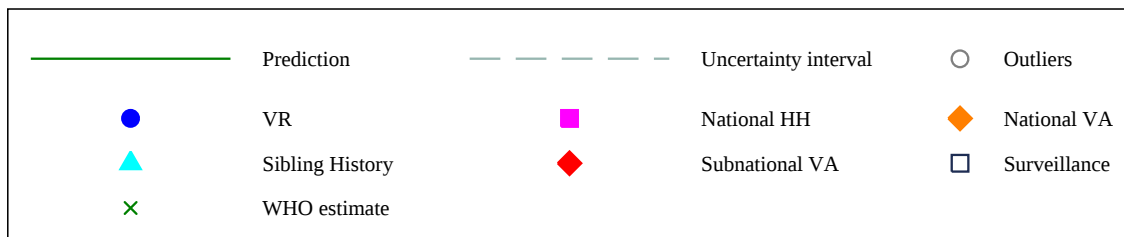
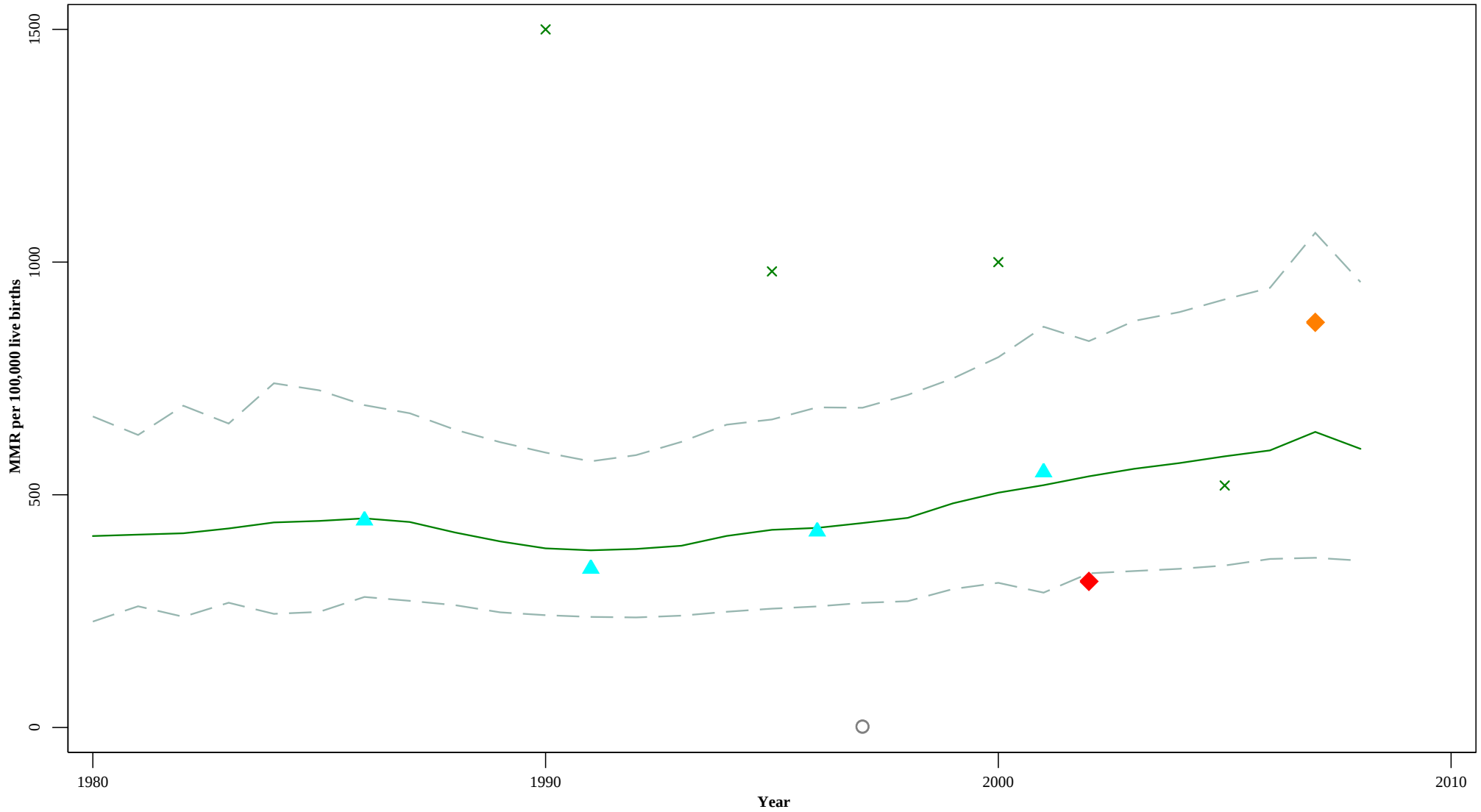
Kenya



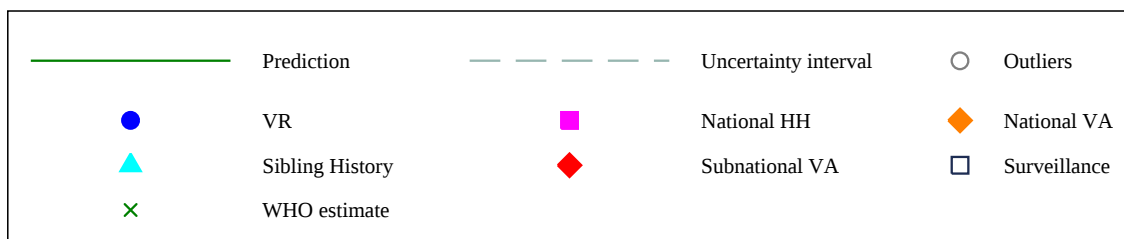
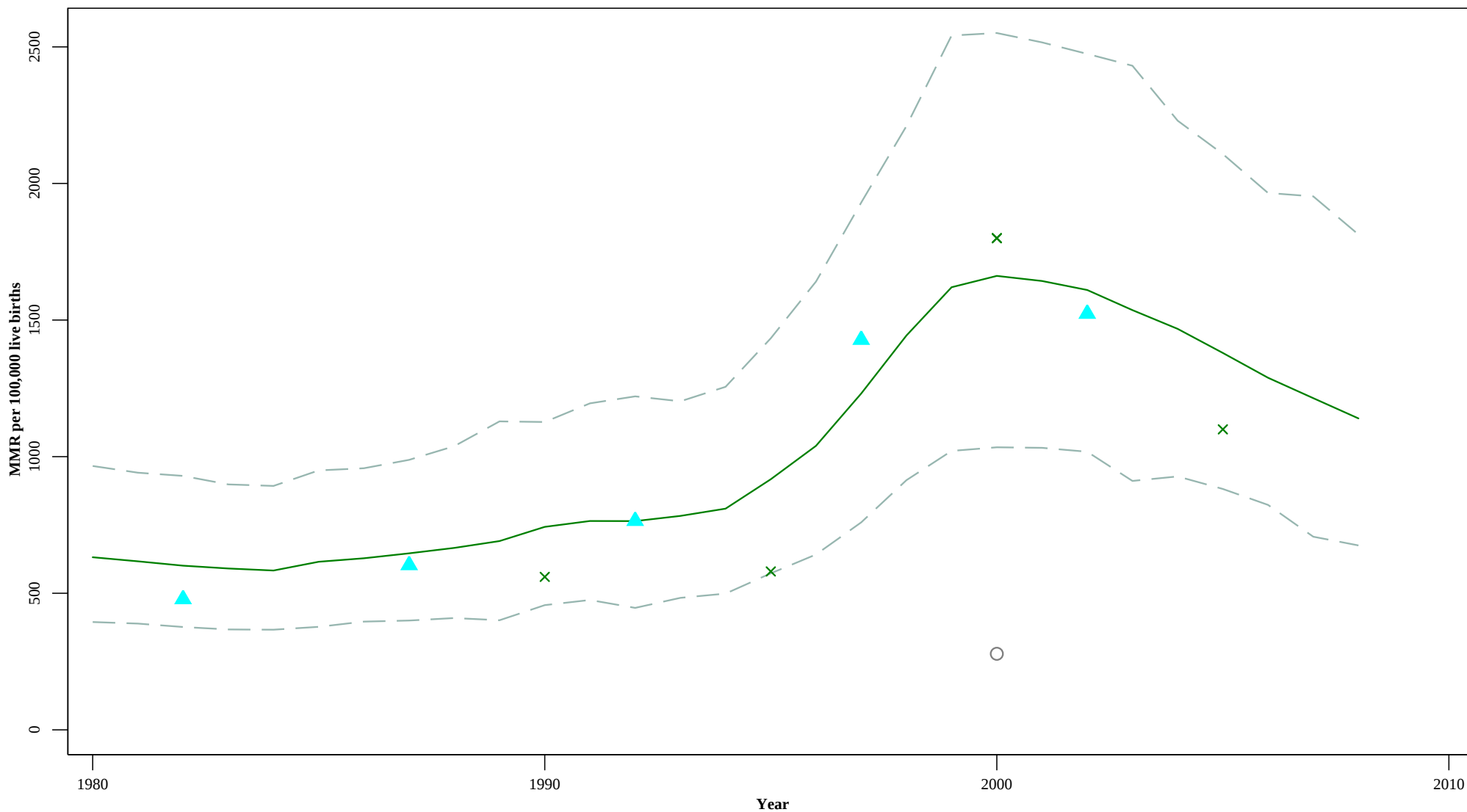
Madagascar



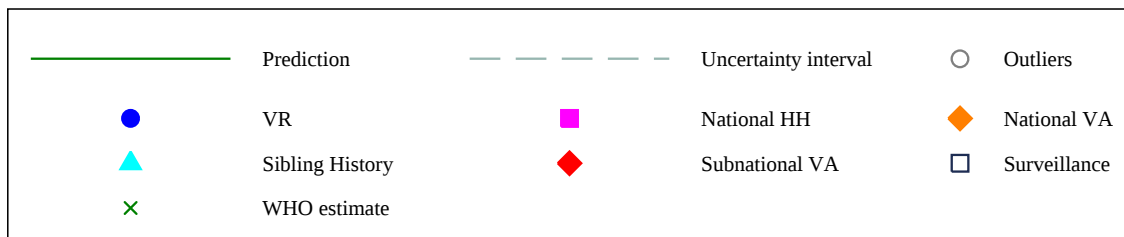
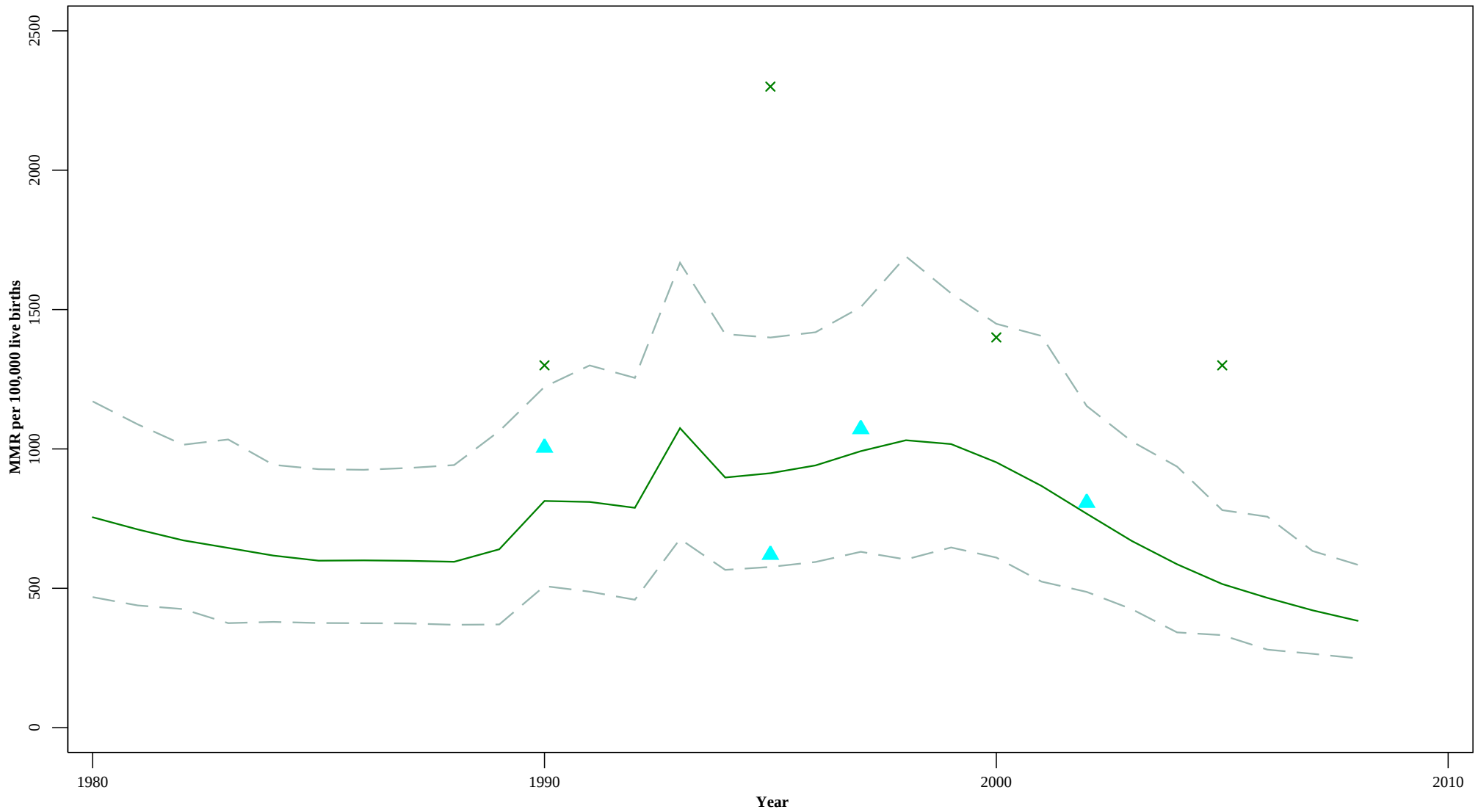
Mozambique



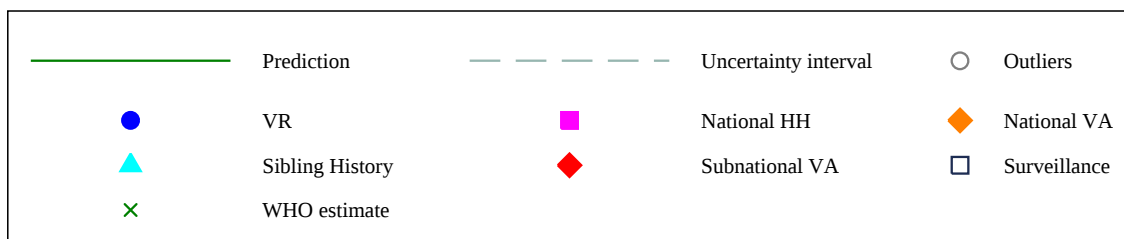
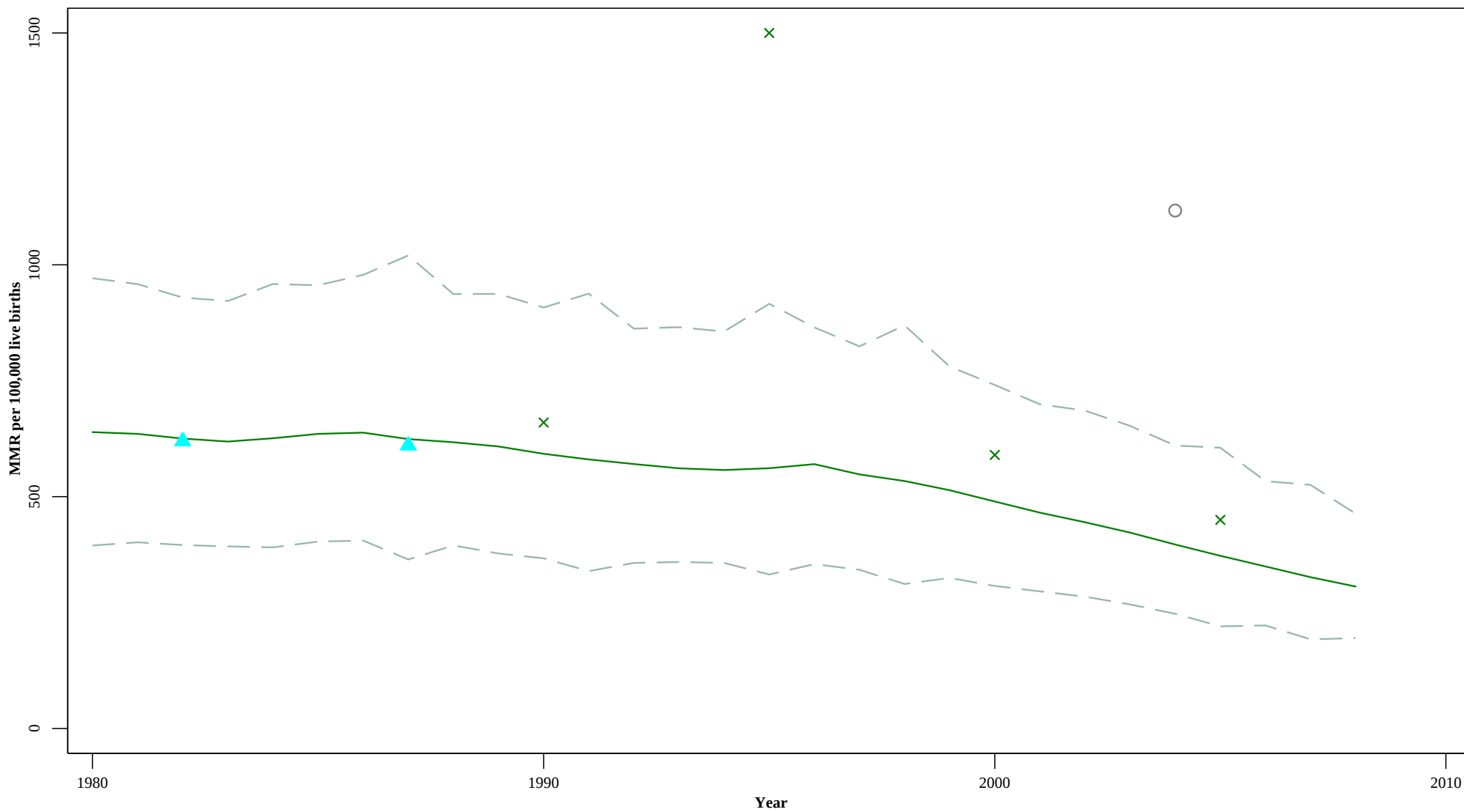
Malawi



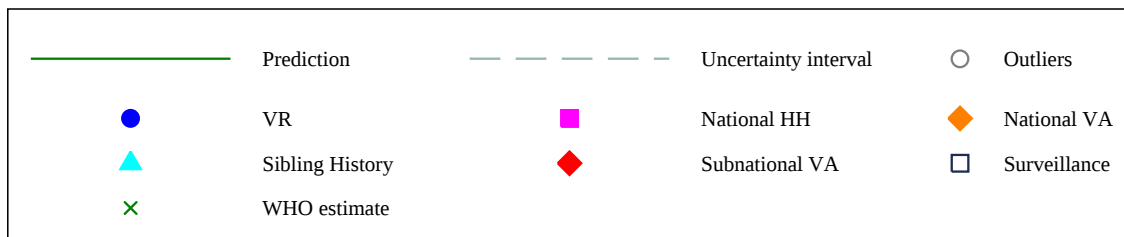
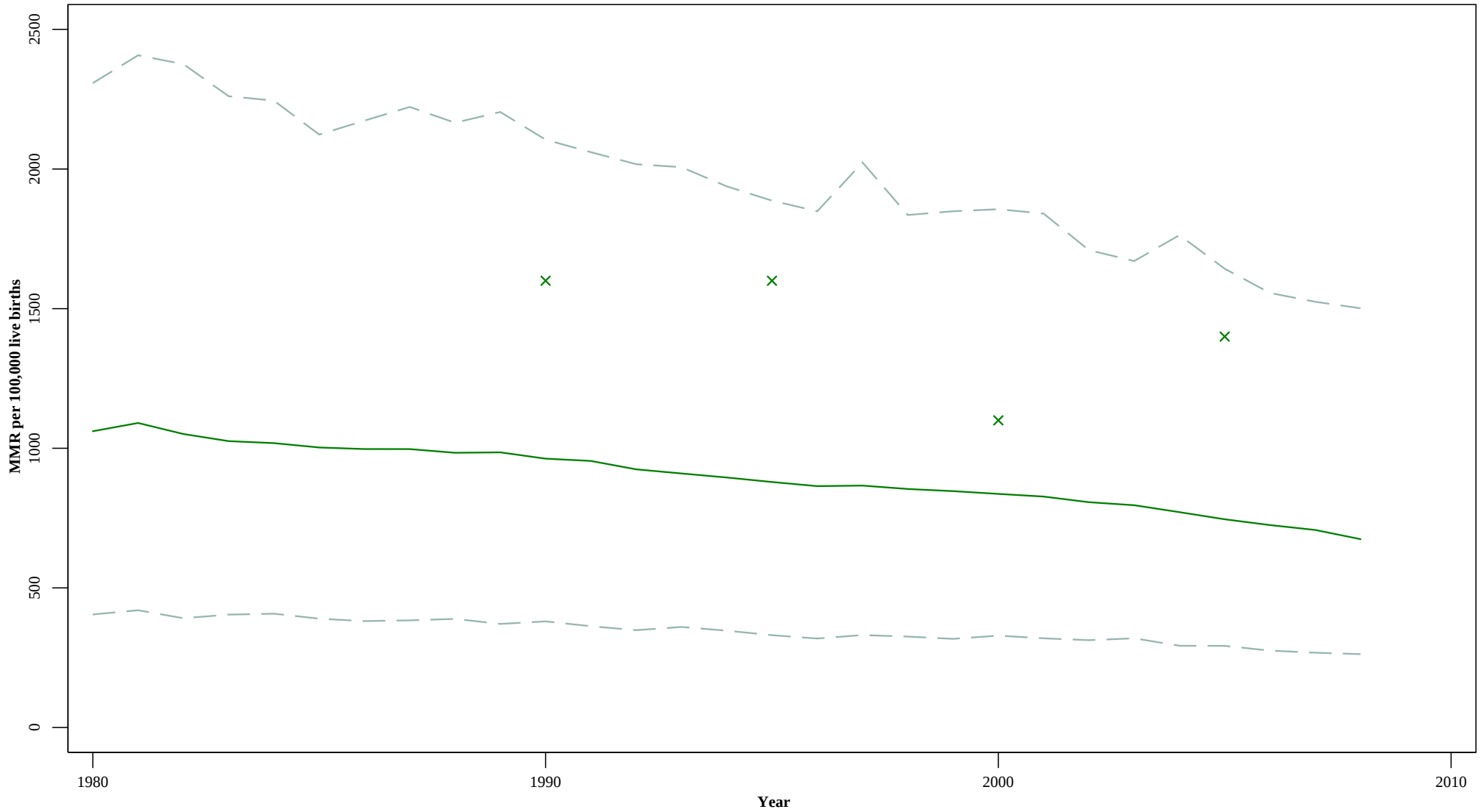
Rwanda



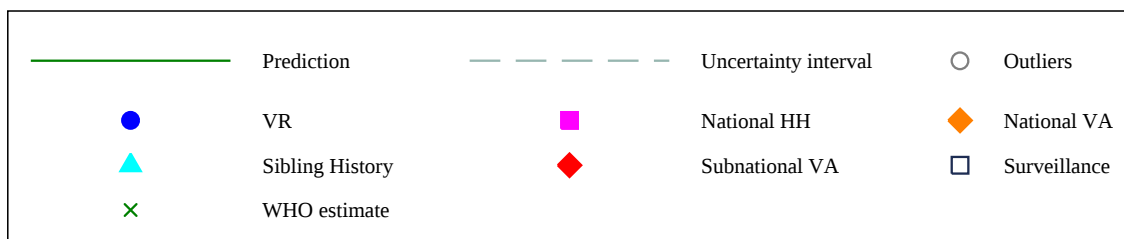
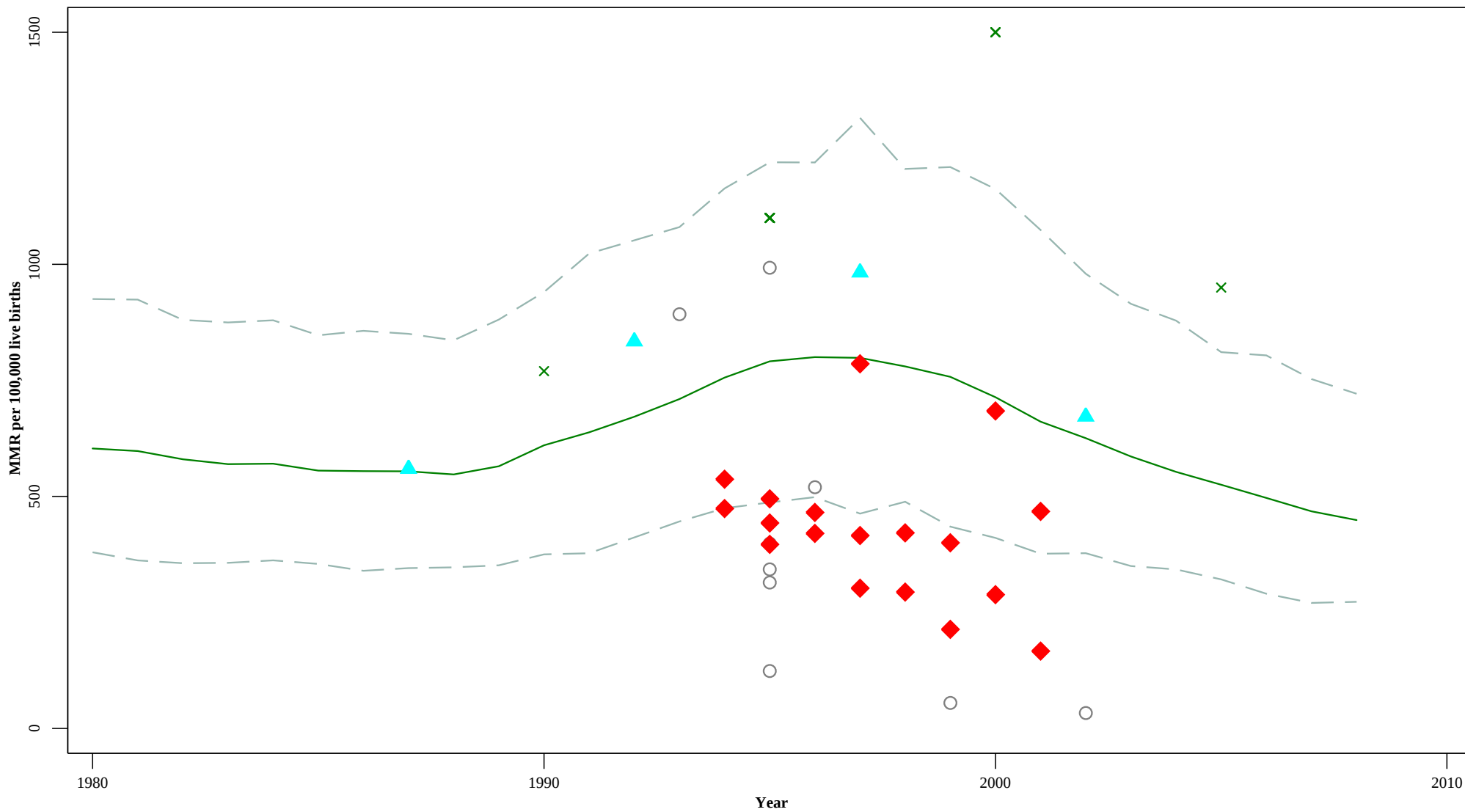
Sudan



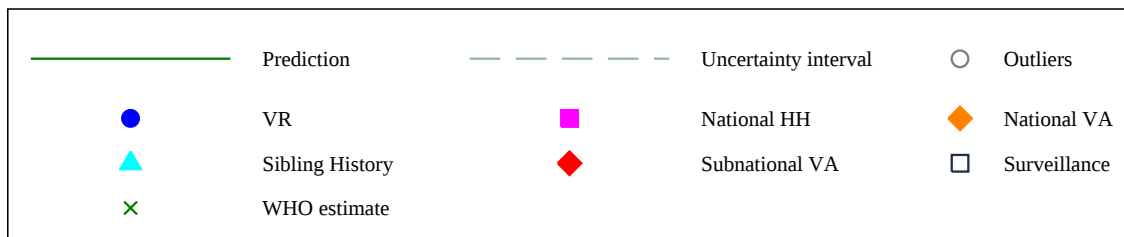
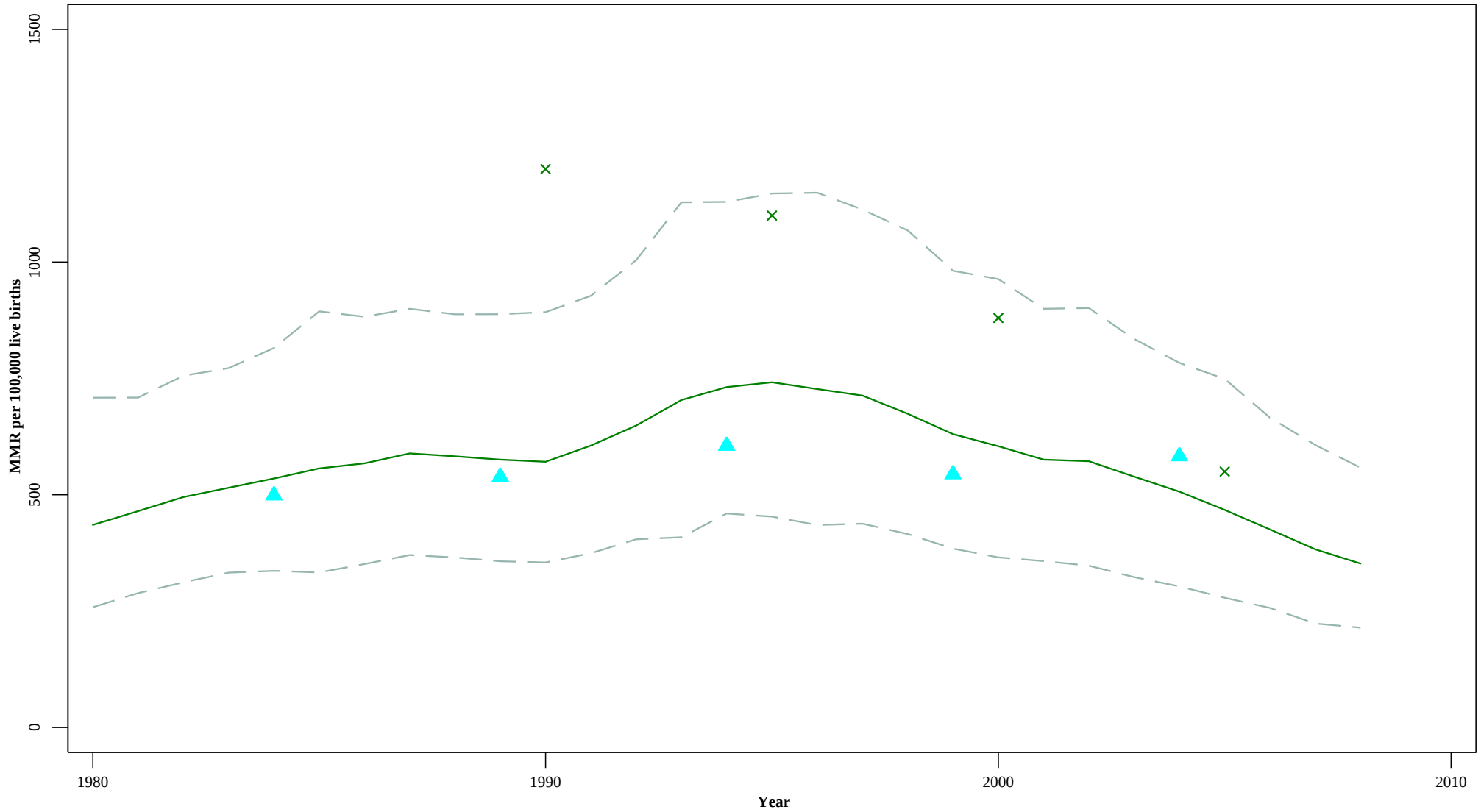
Somalia



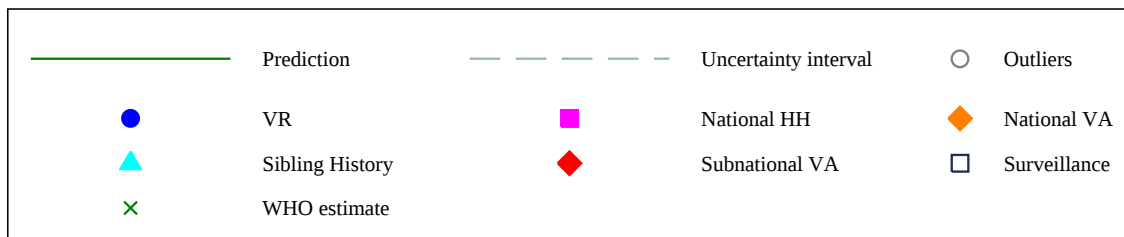
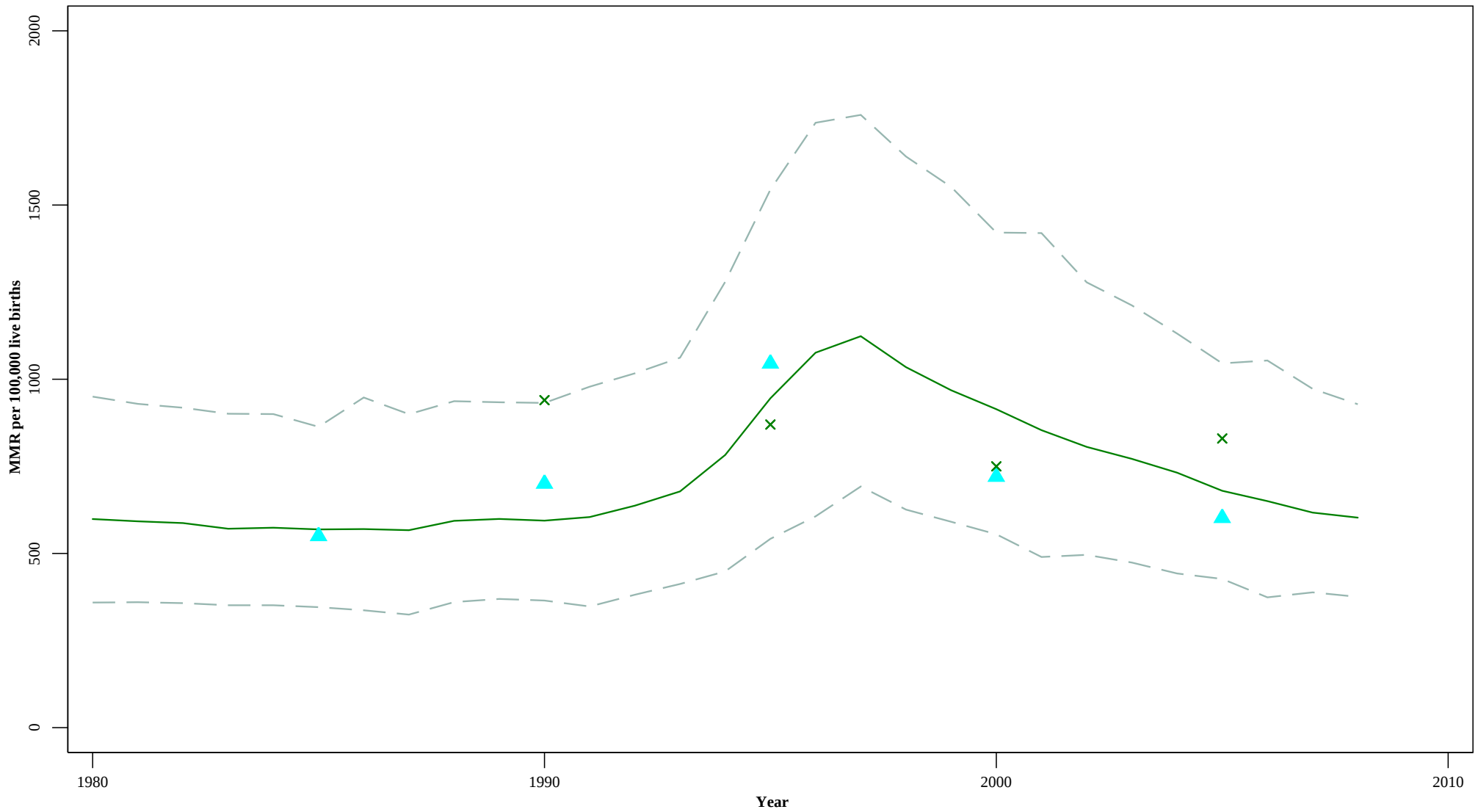
Tanzania, United Republic of



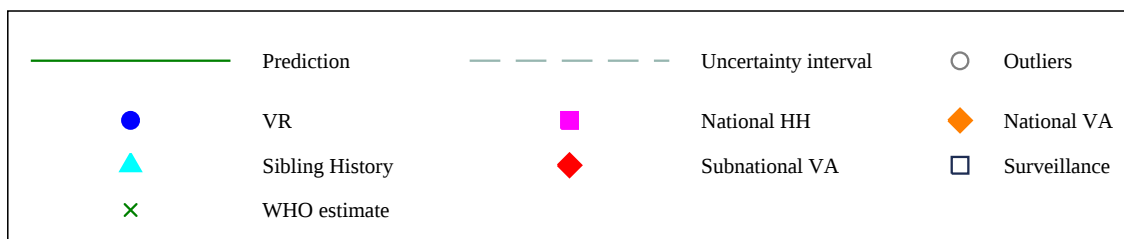
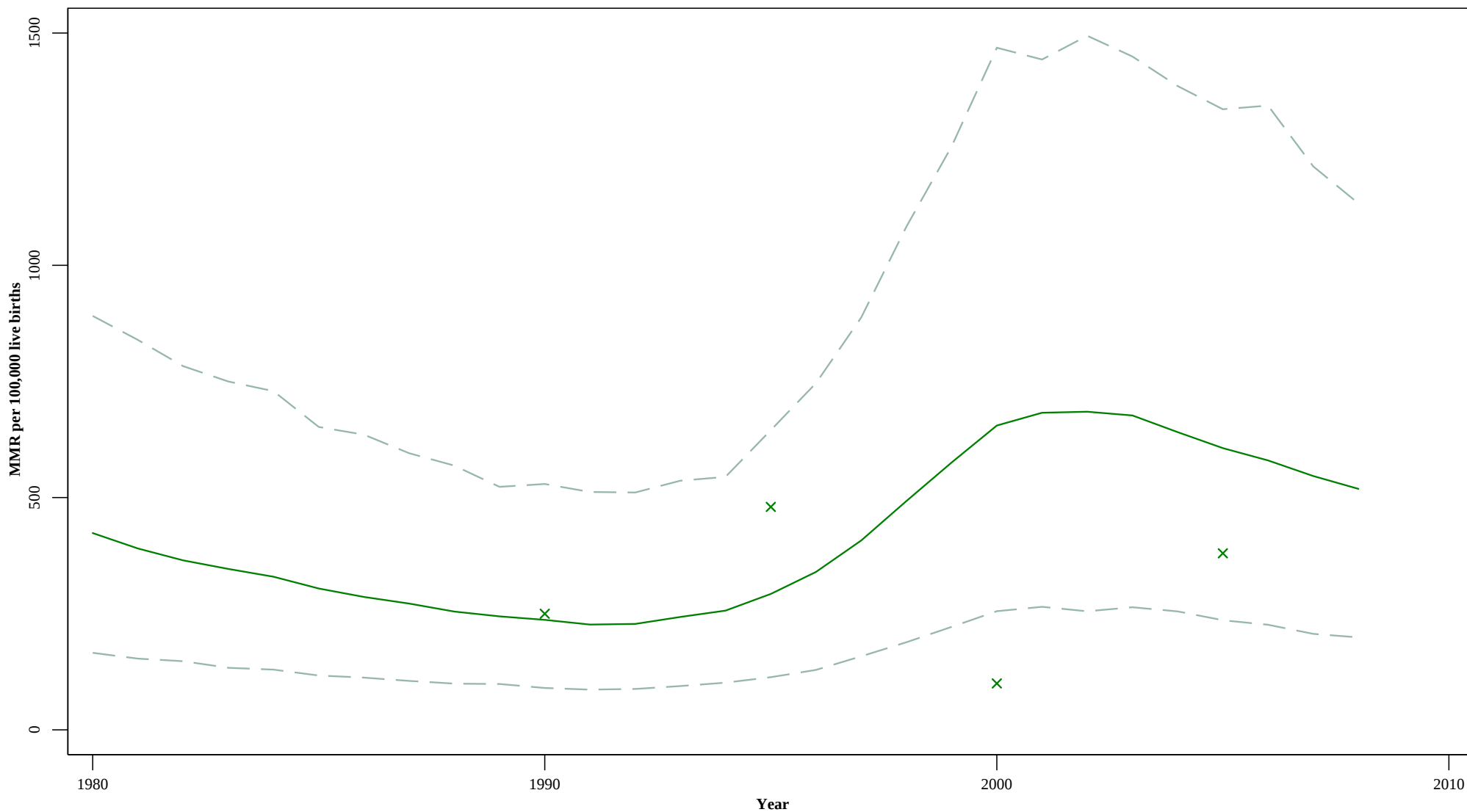
Uganda



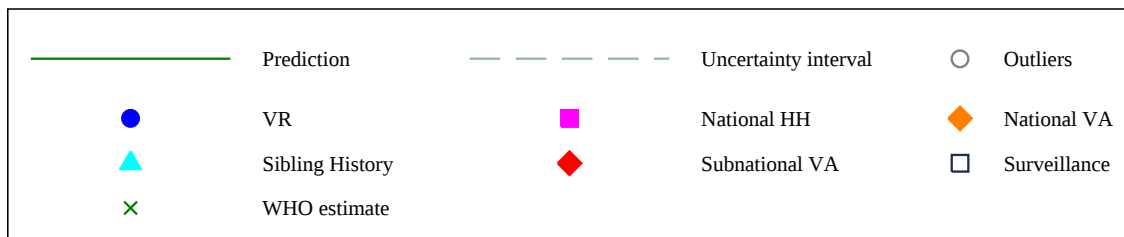
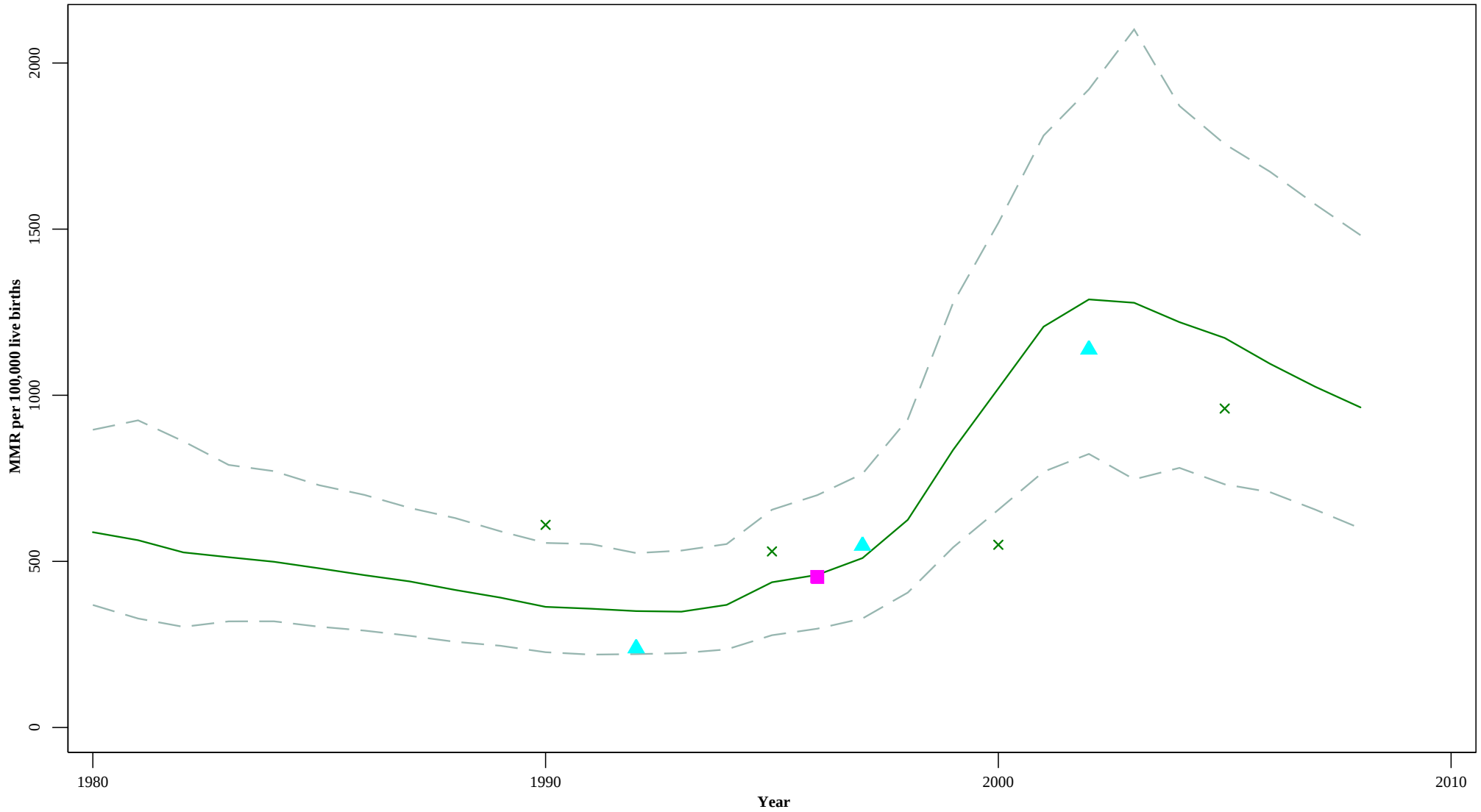
Zambia



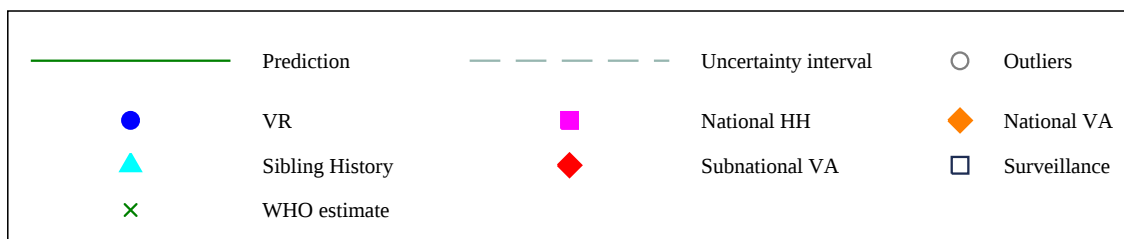
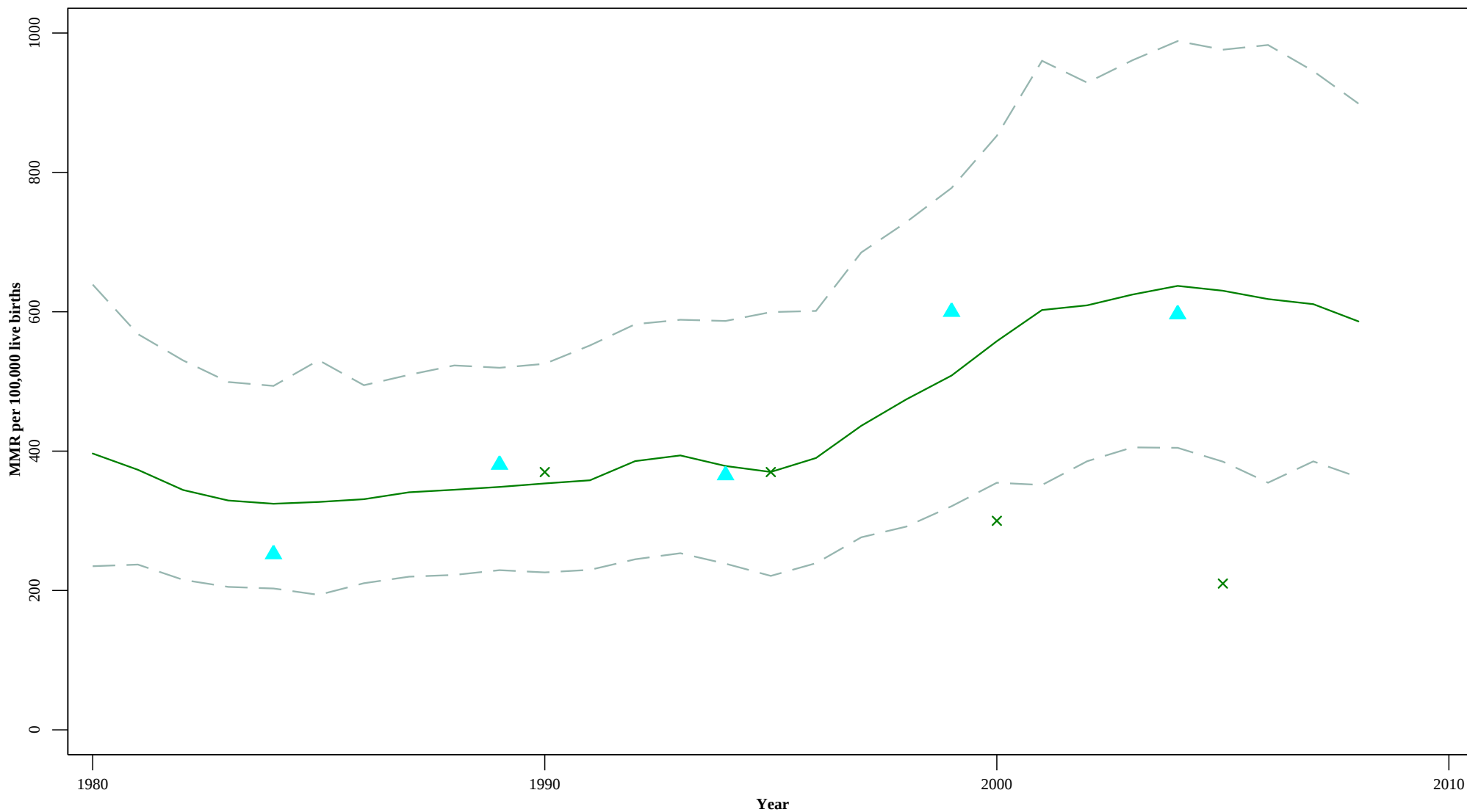
Botswana



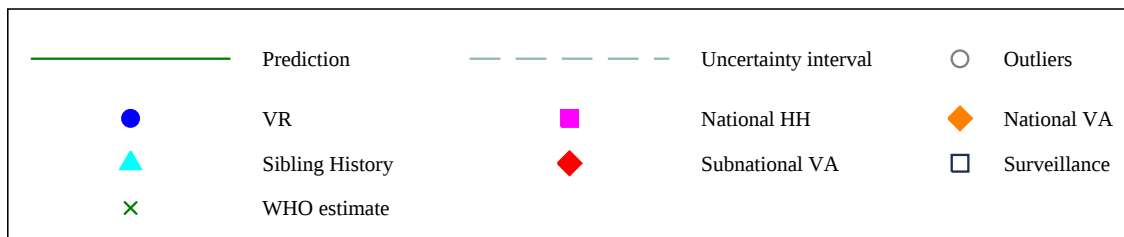
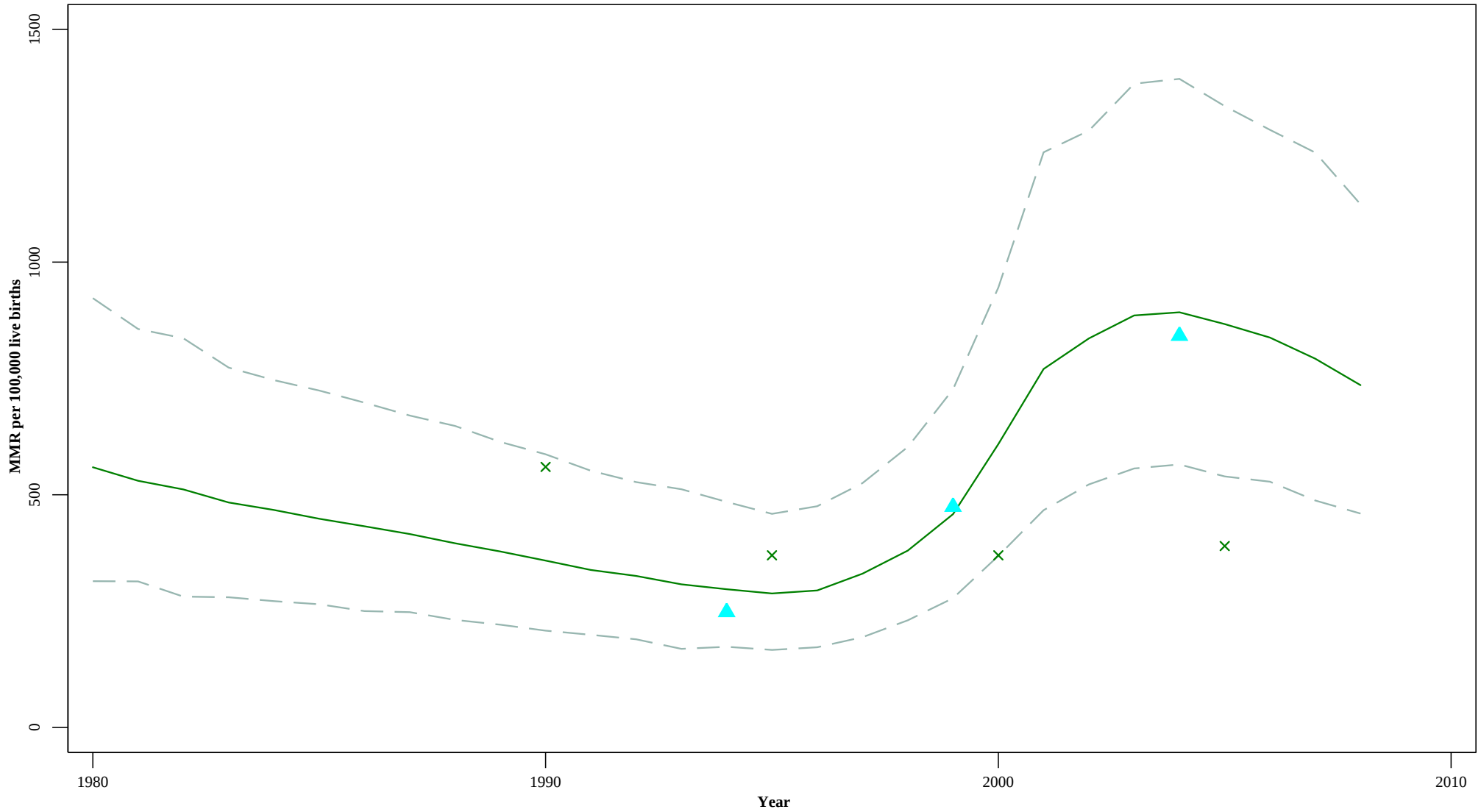
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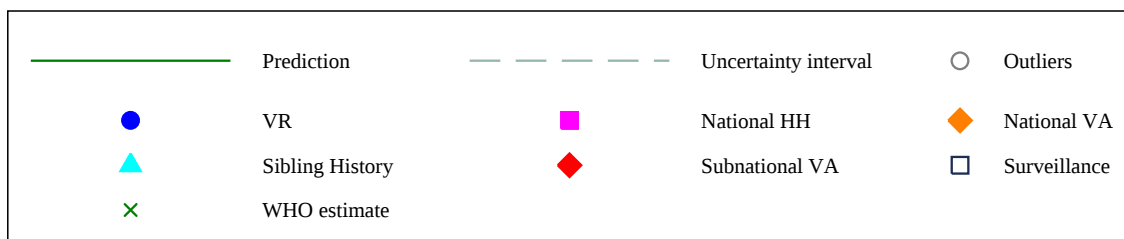
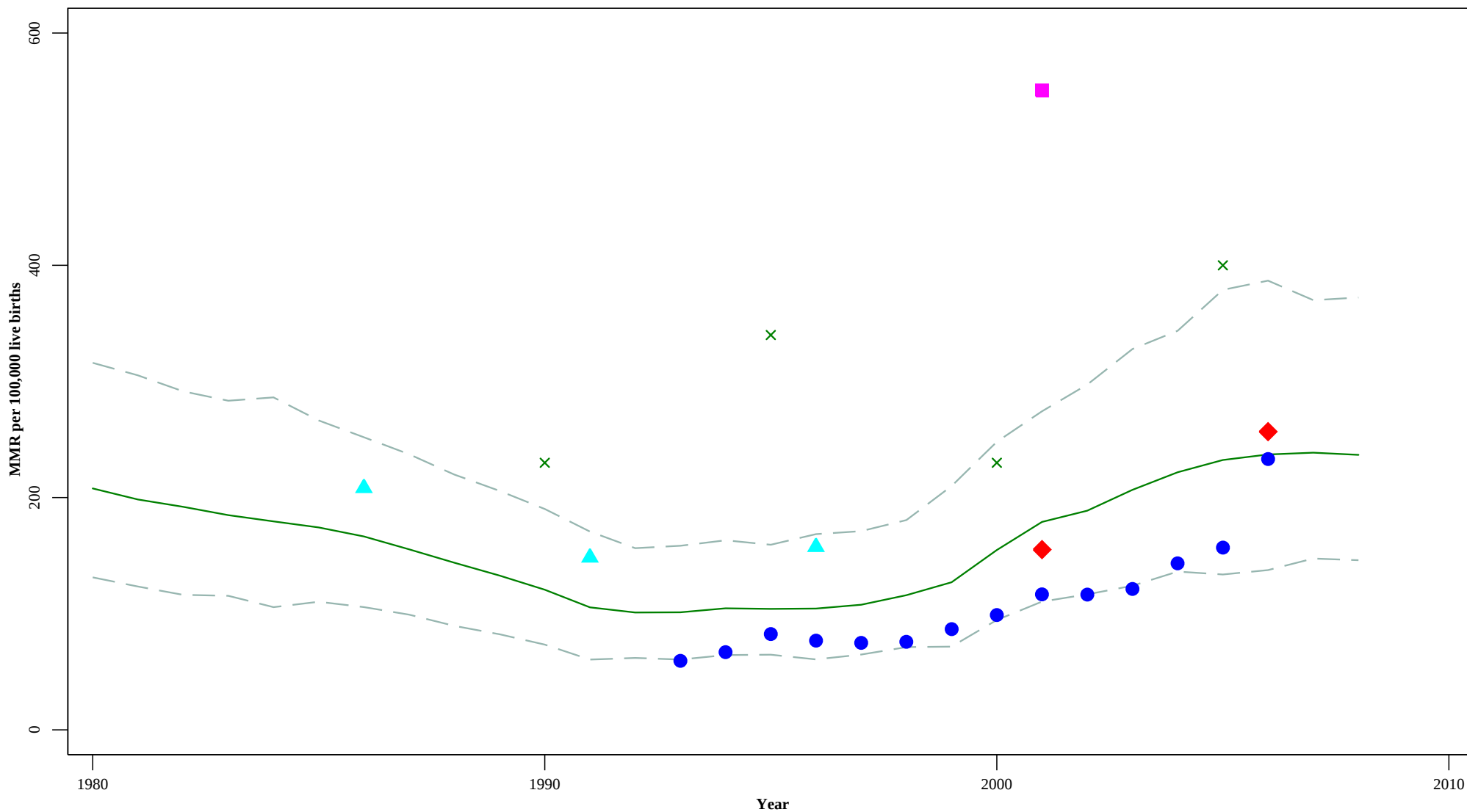
Namibia



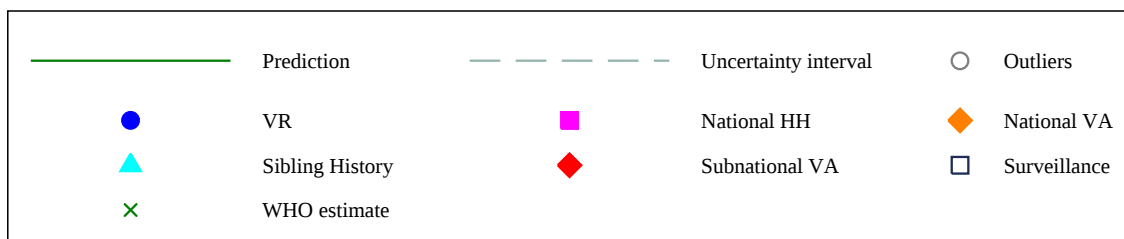
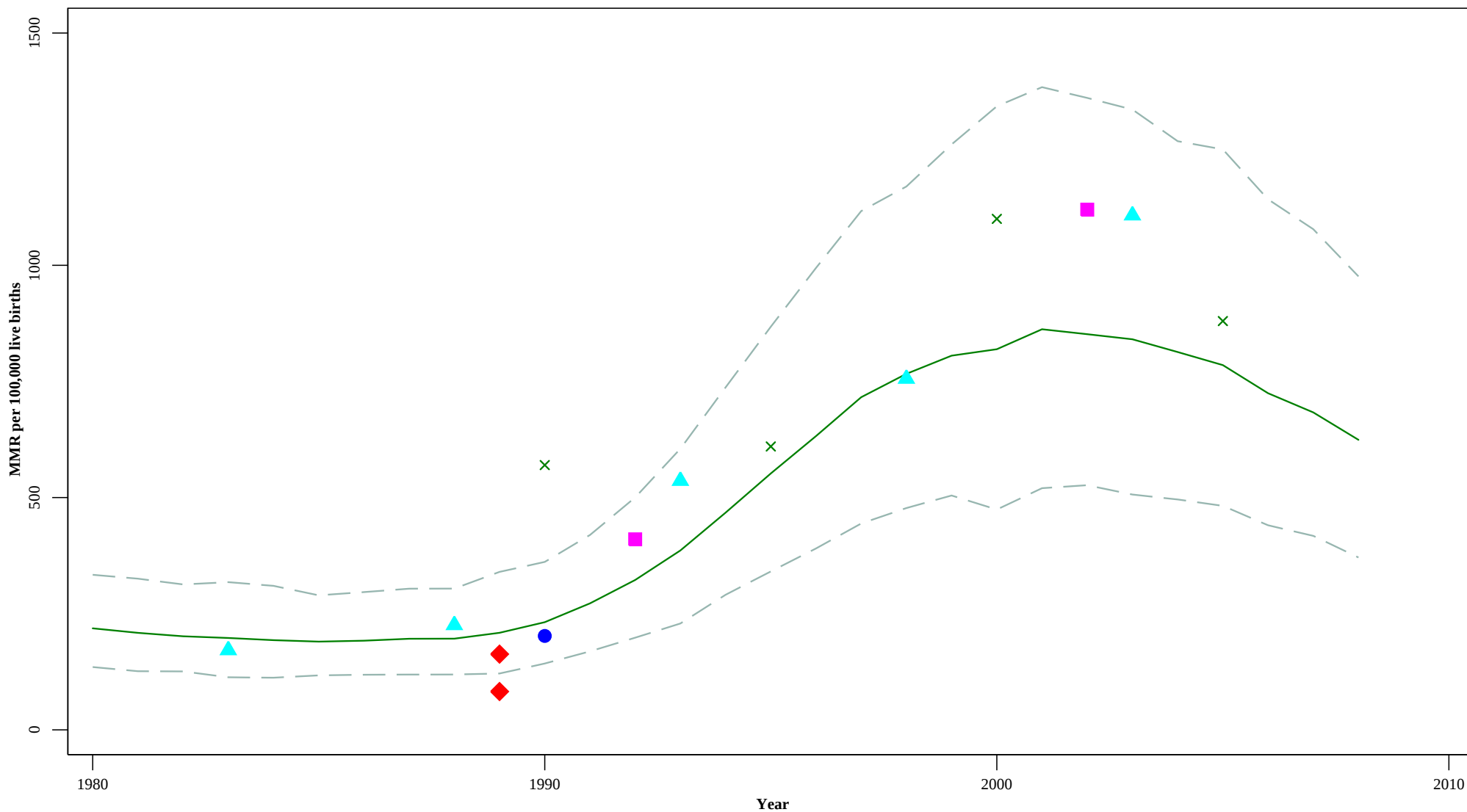
Swaziland



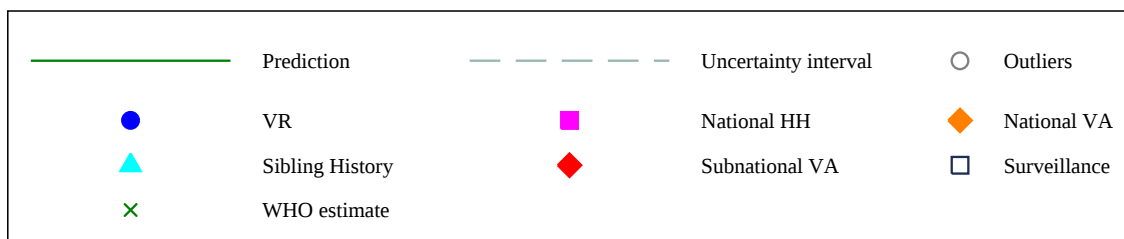
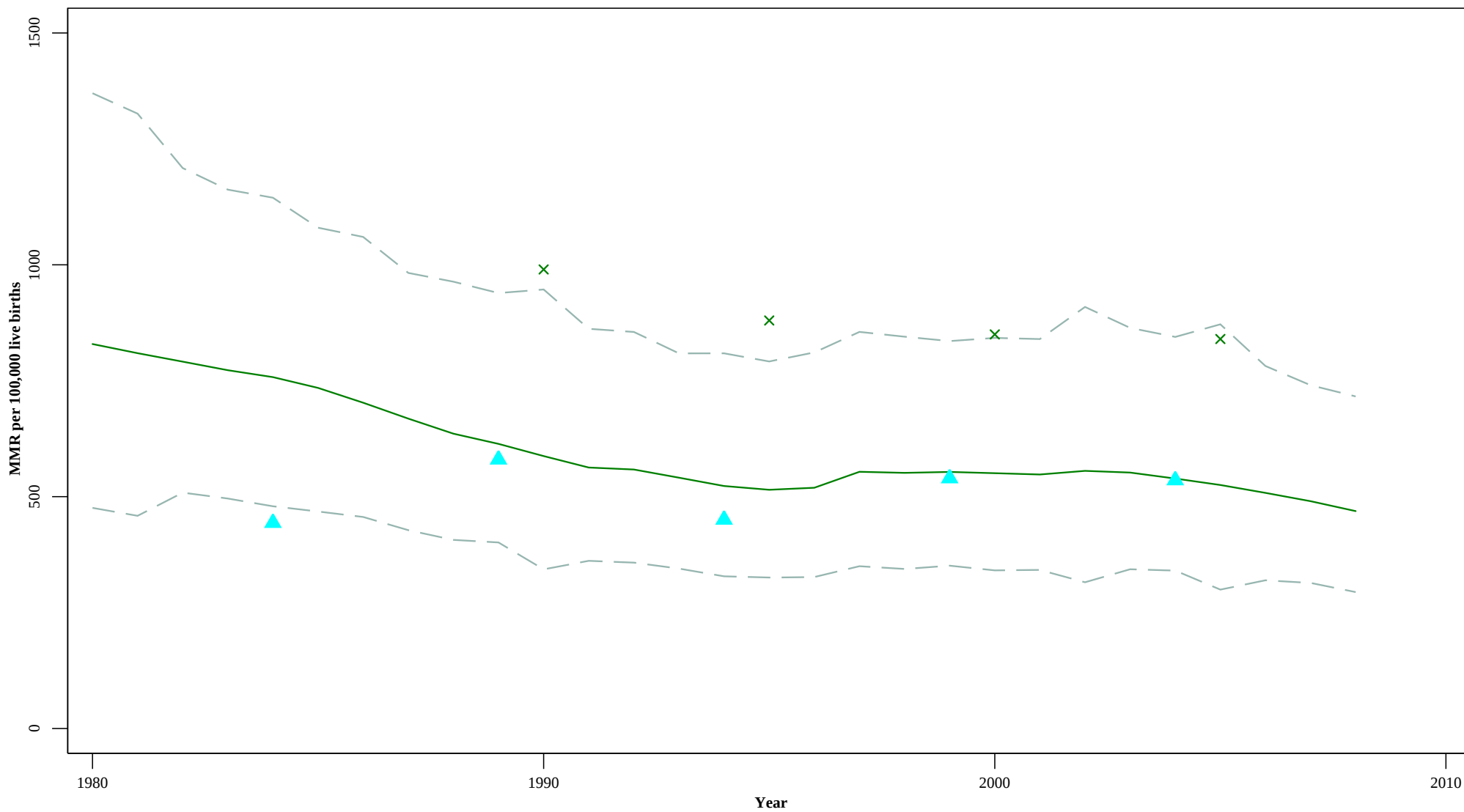
South Africa



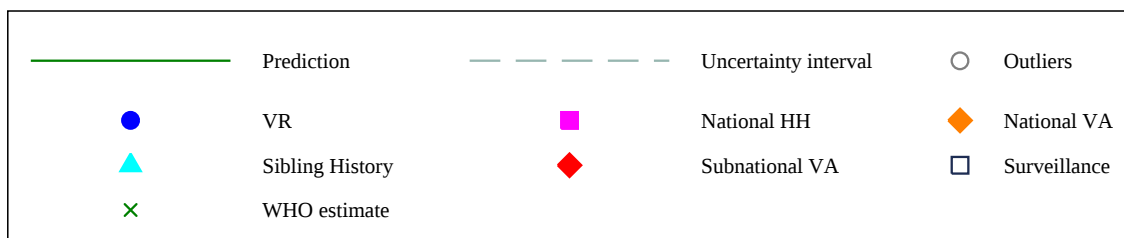
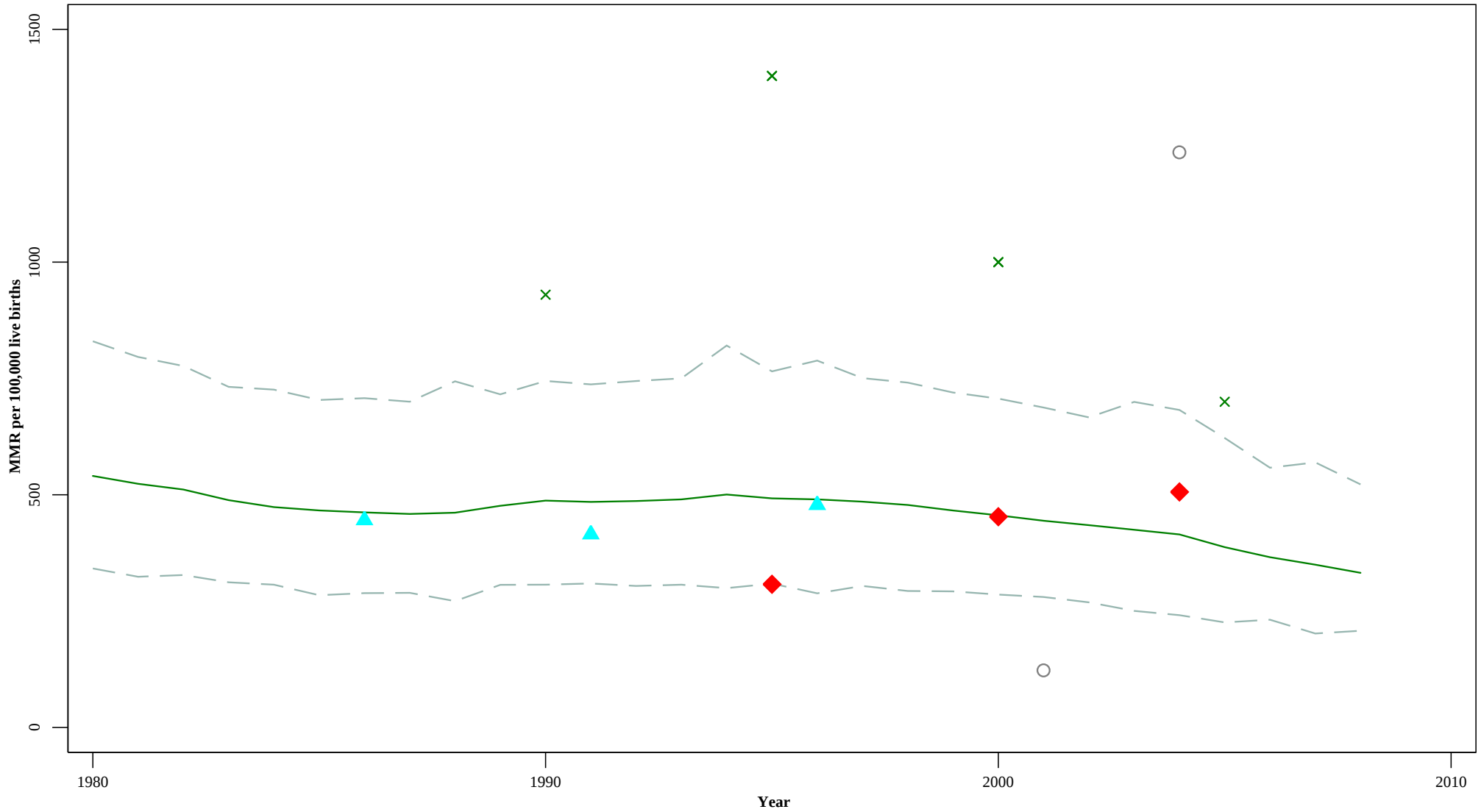
Zimbabwe



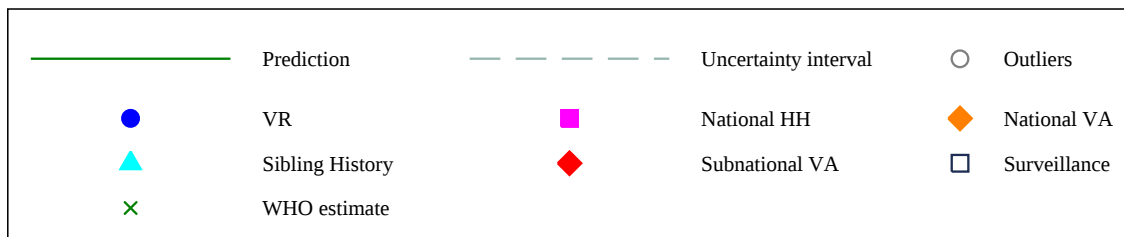
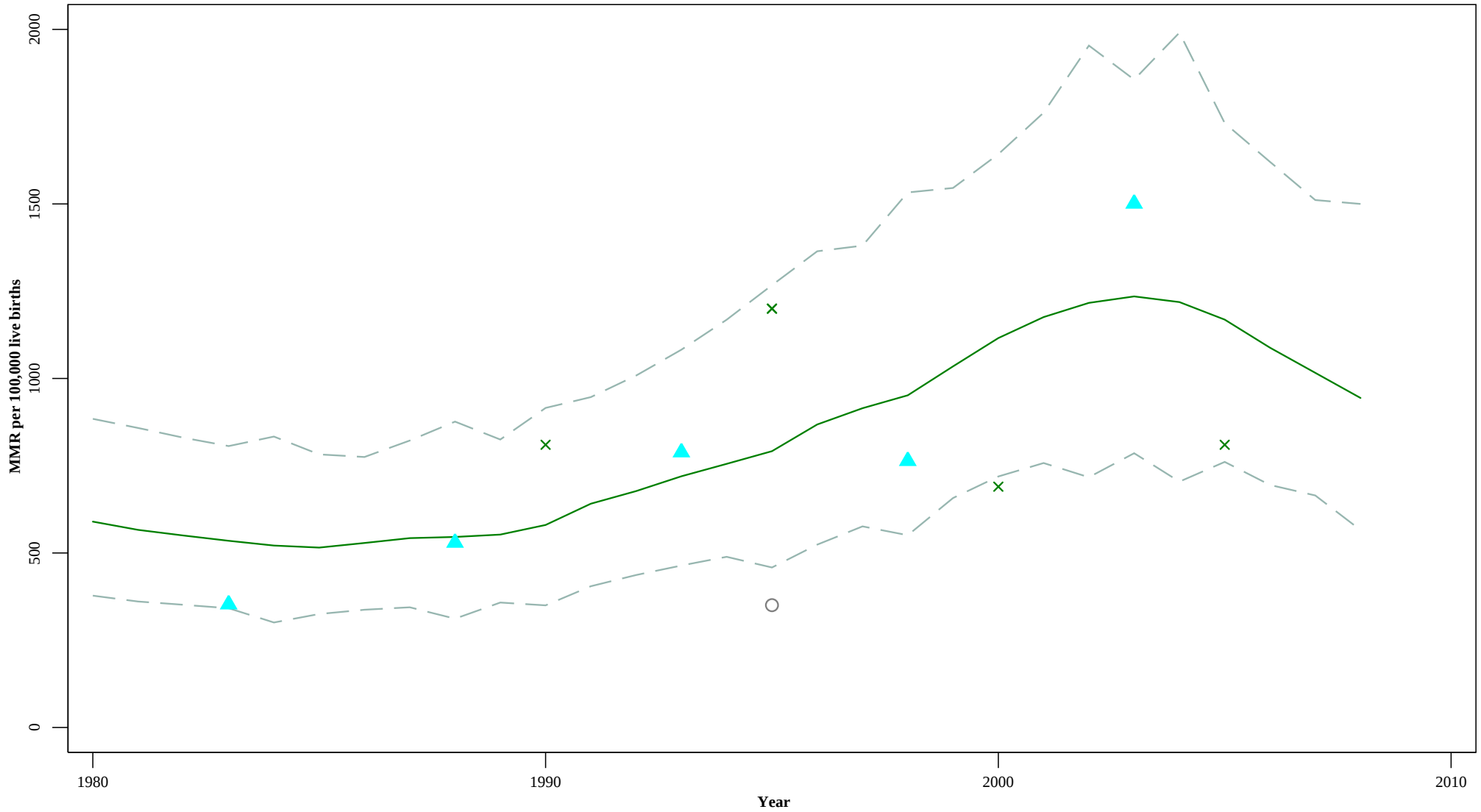
Benin



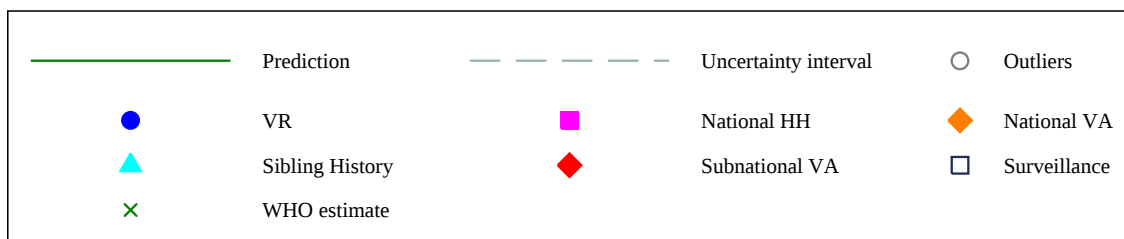
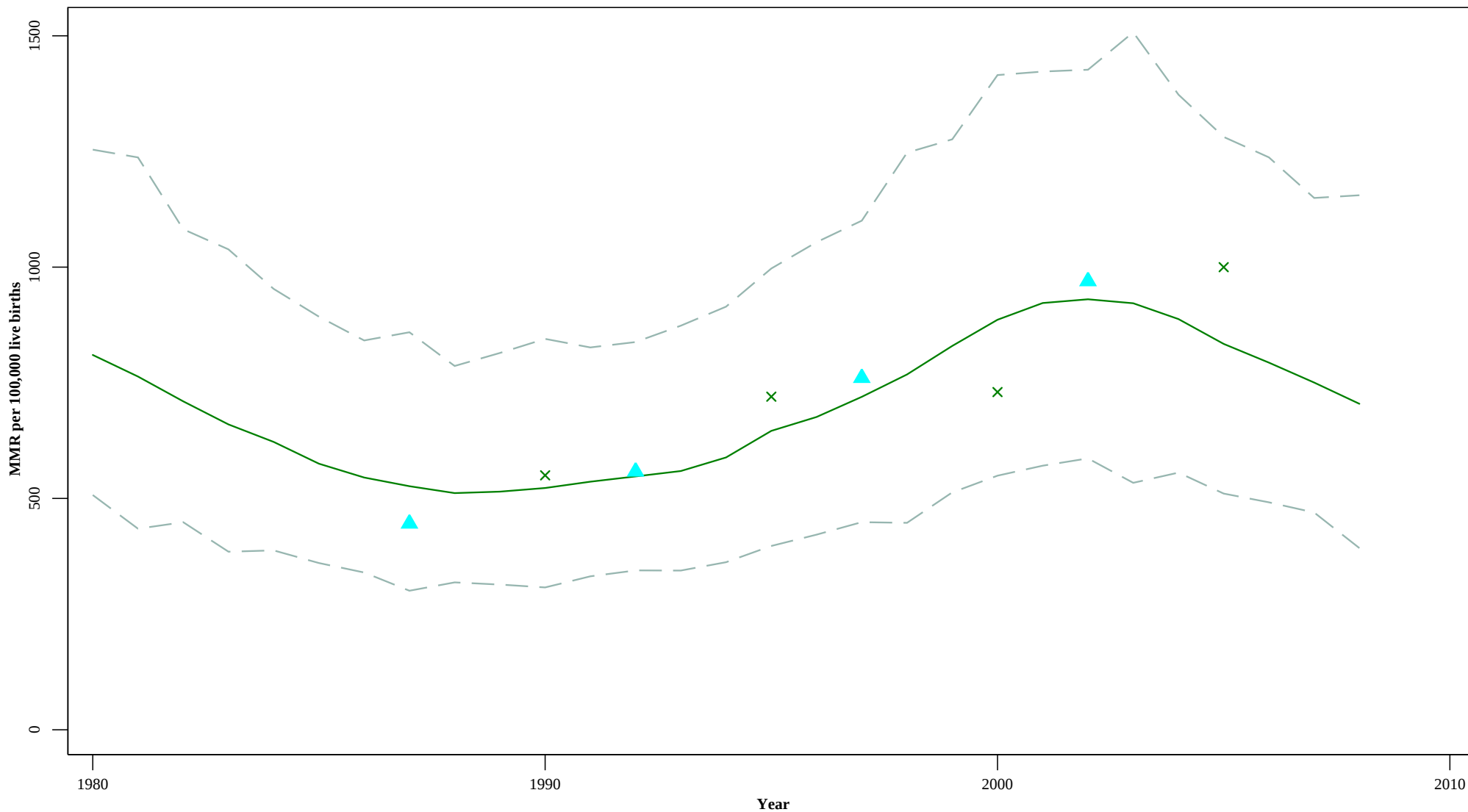
Burkina Faso



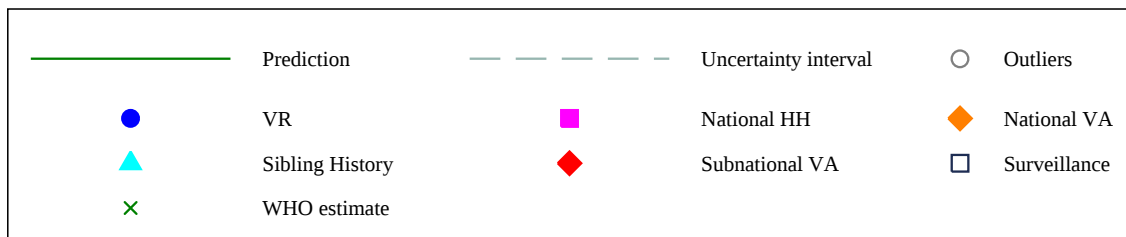
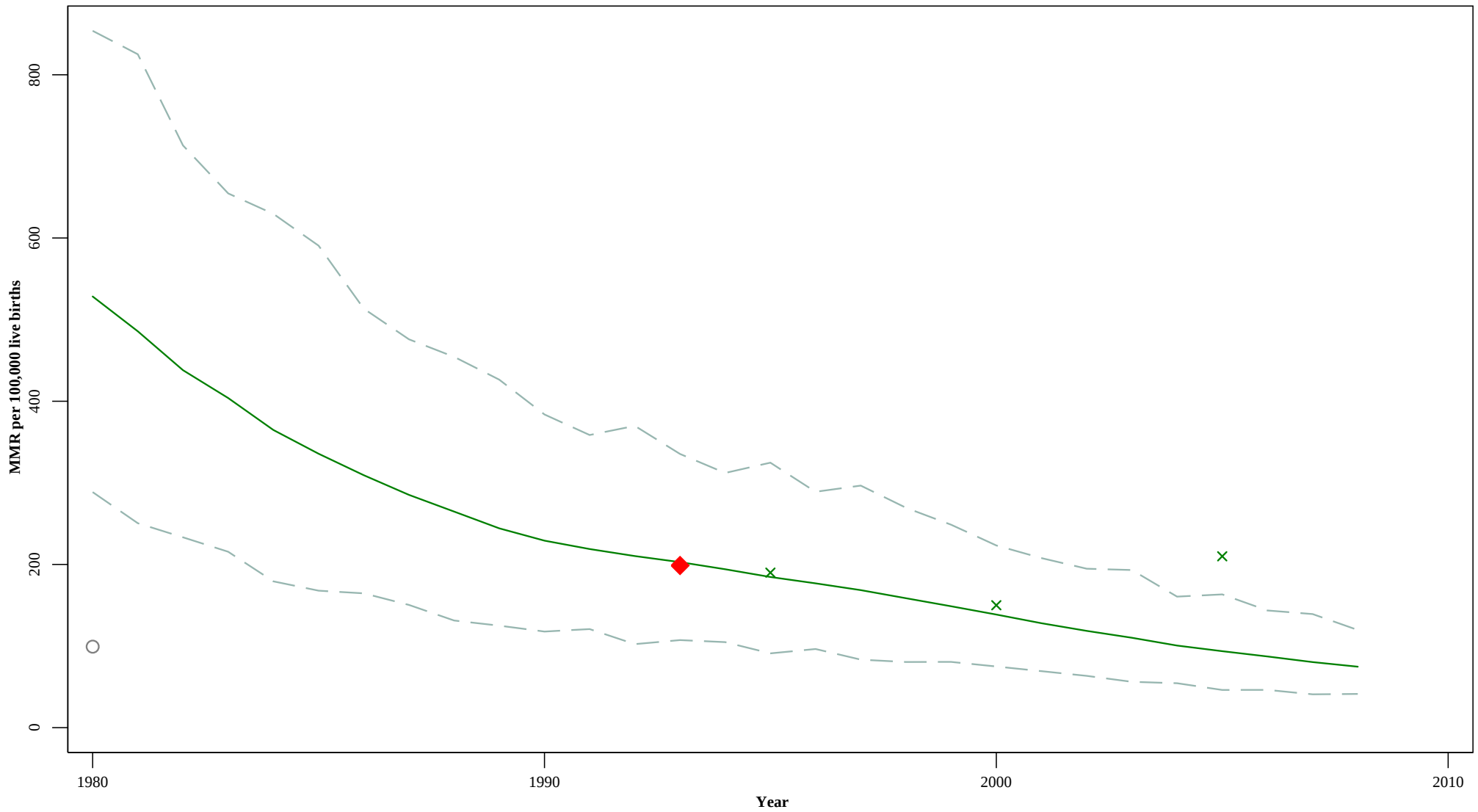
Côte d'Ivoire



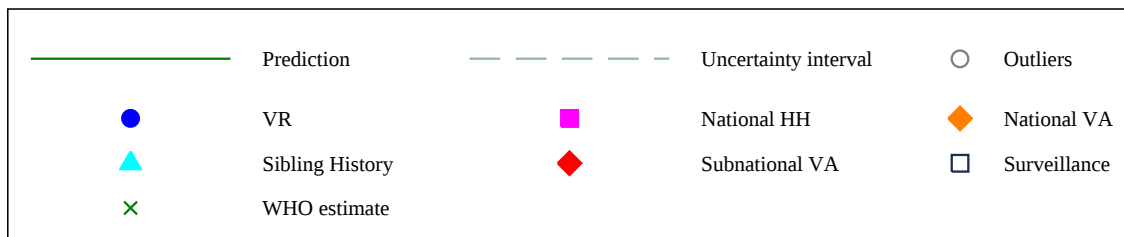
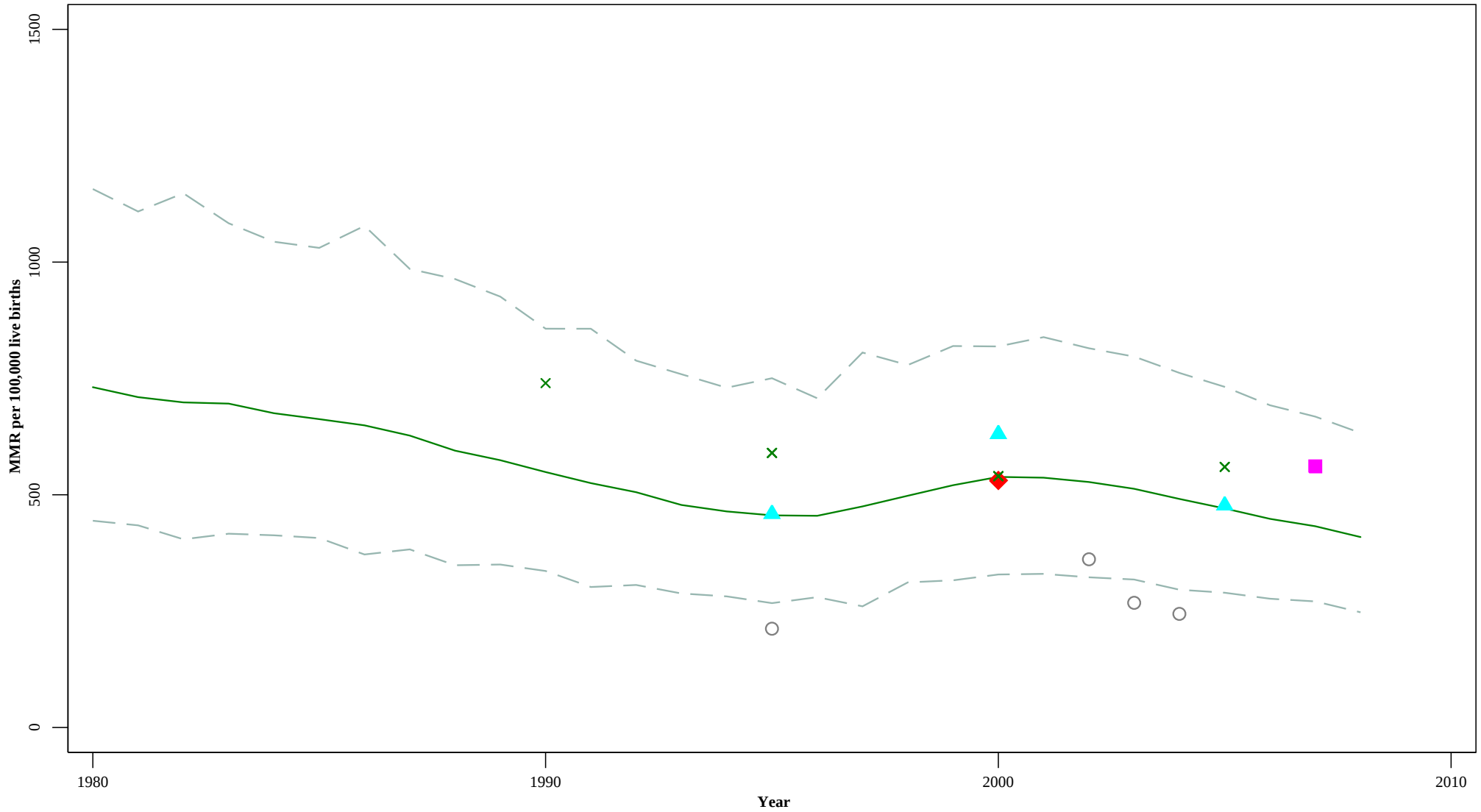
Cameroon



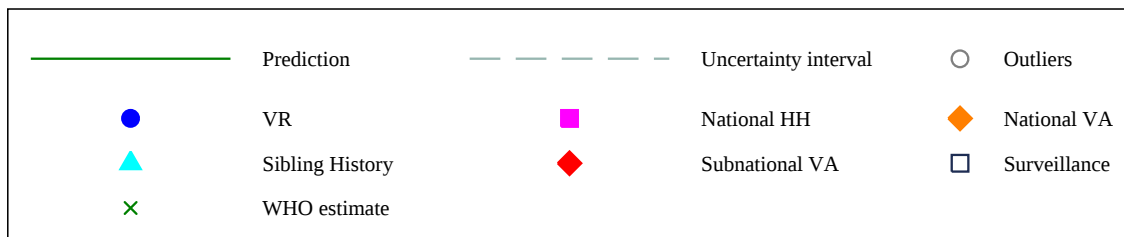
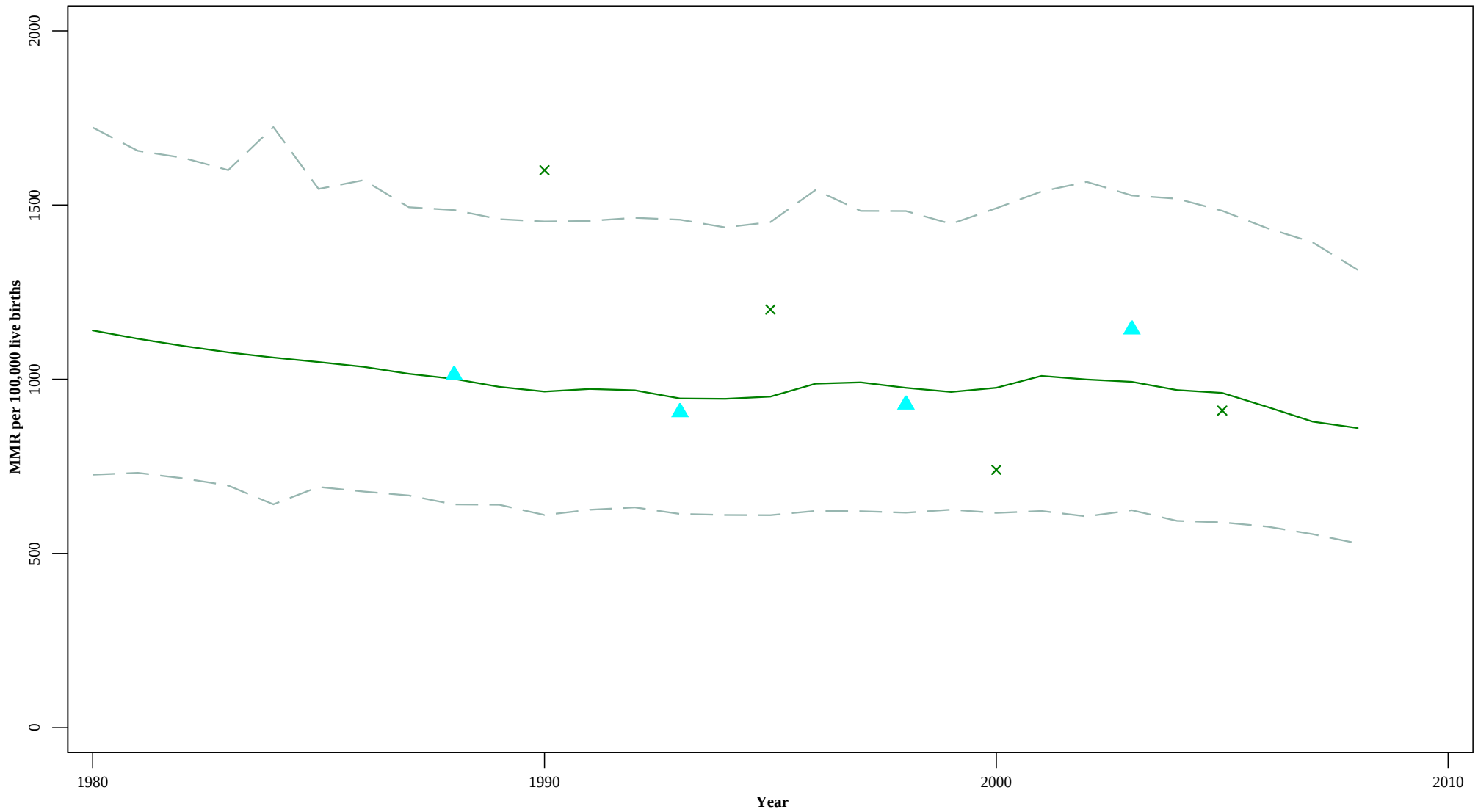
Cape Verde



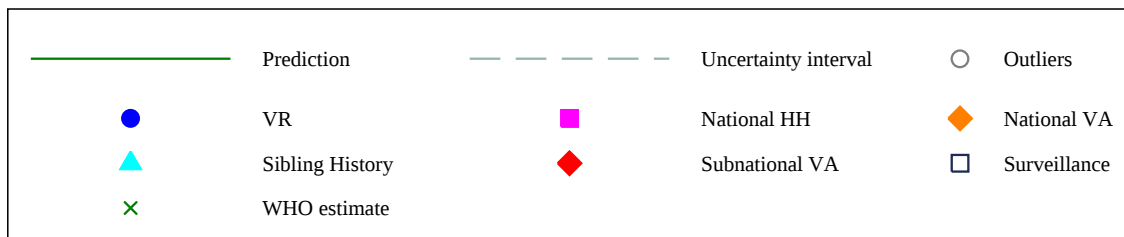
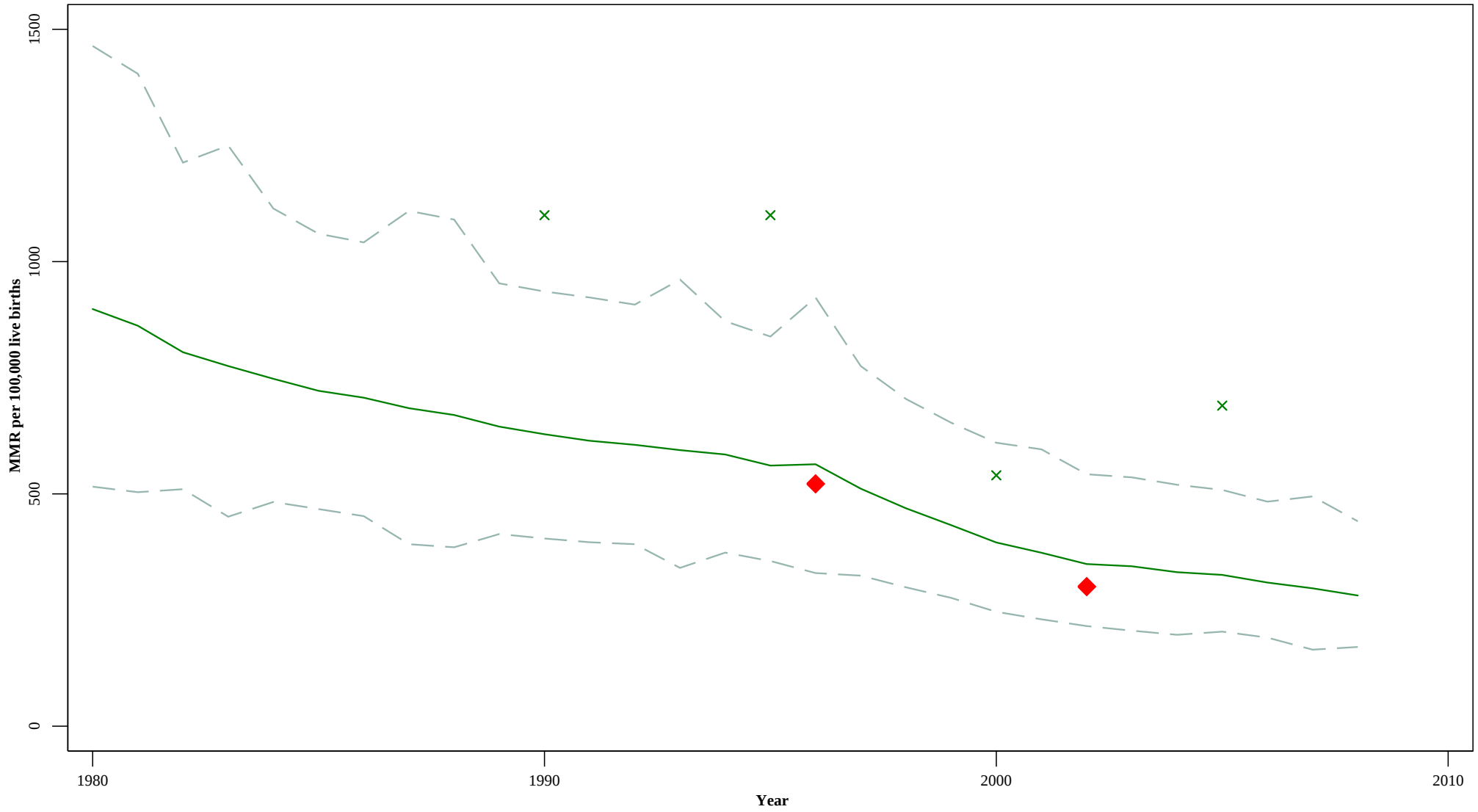
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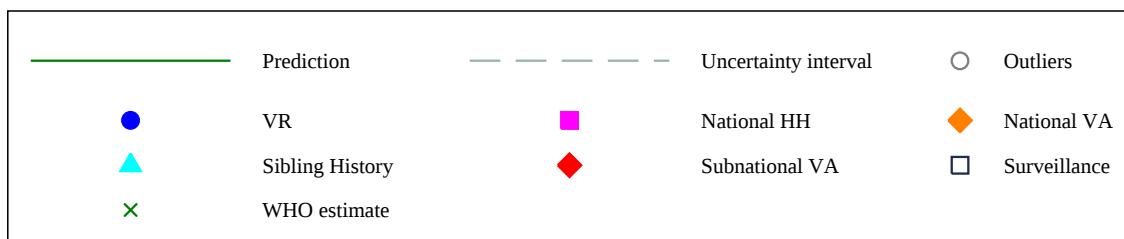
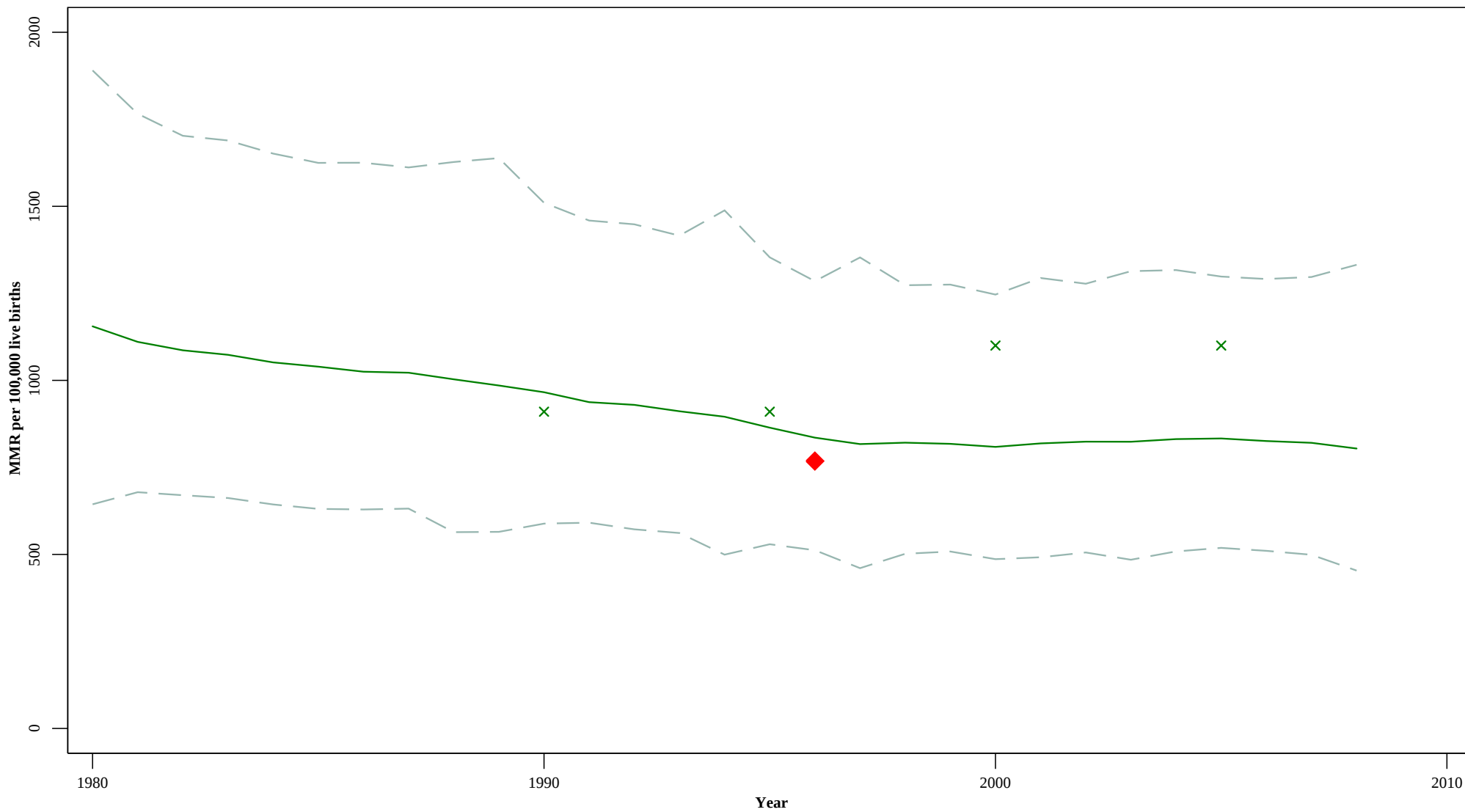
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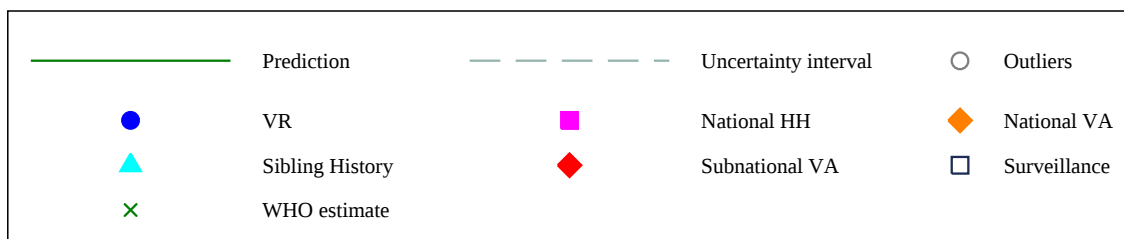
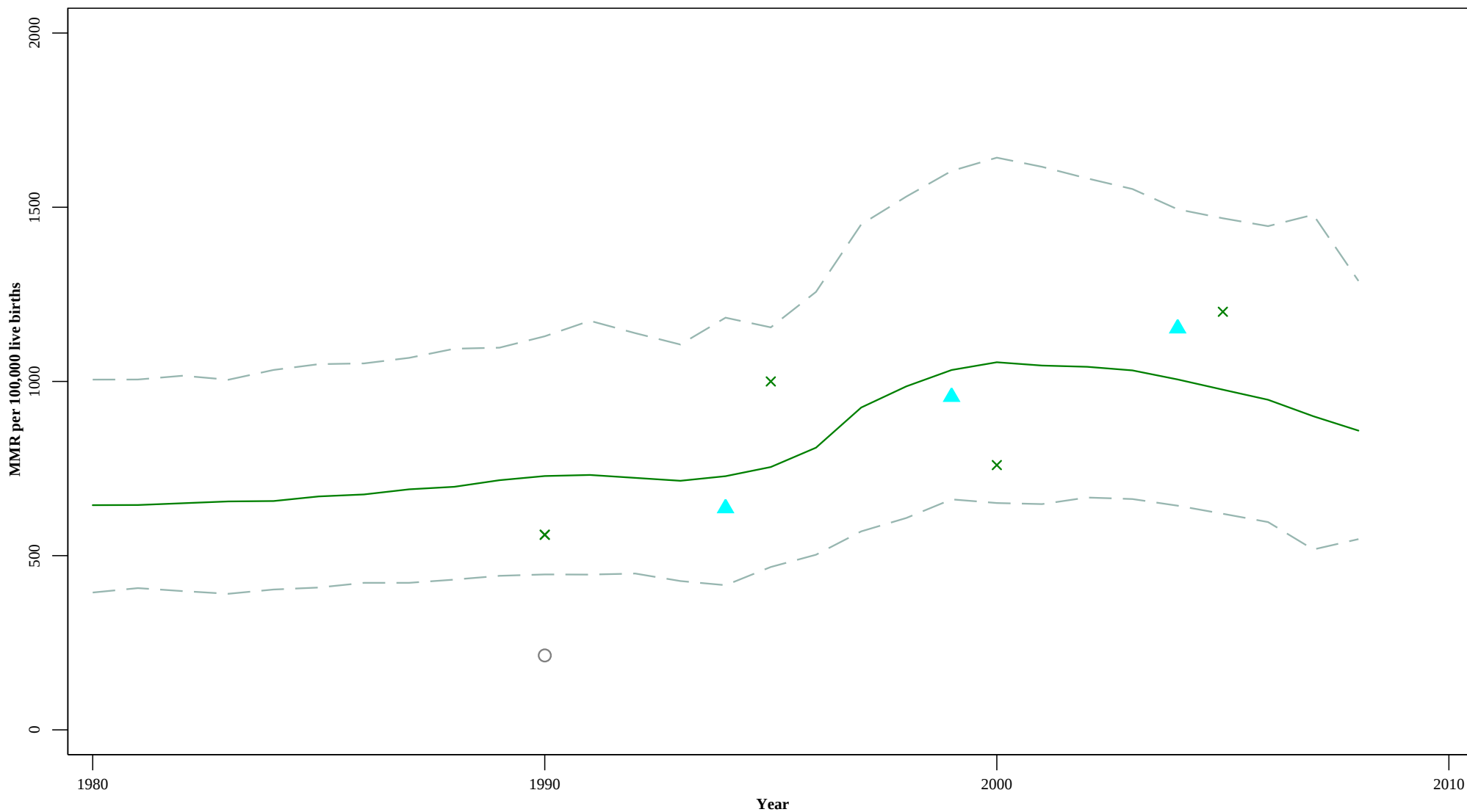
Gambia



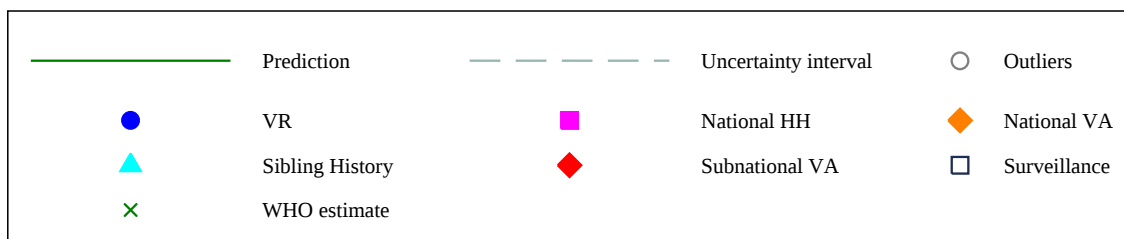
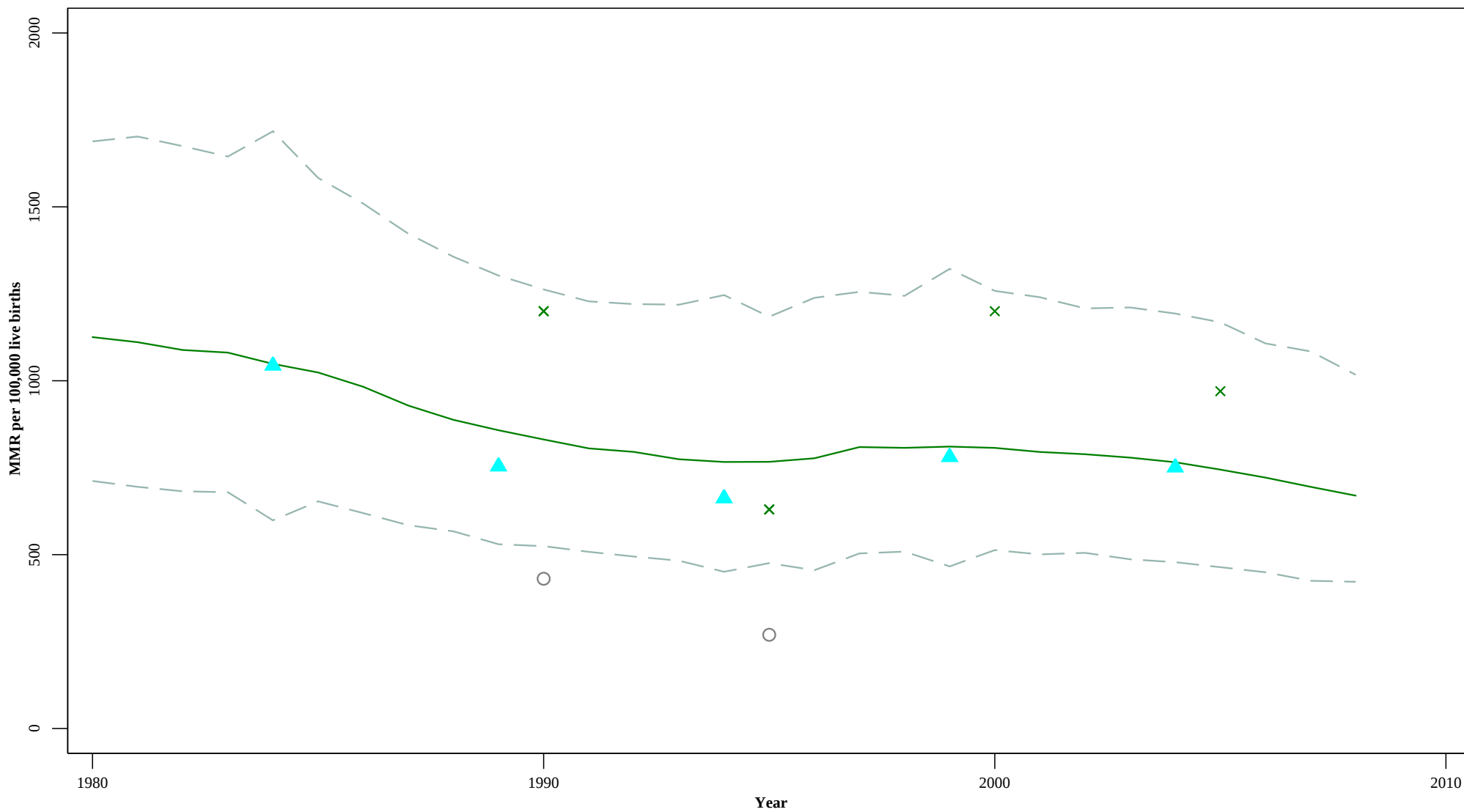
Guinea-Bissau



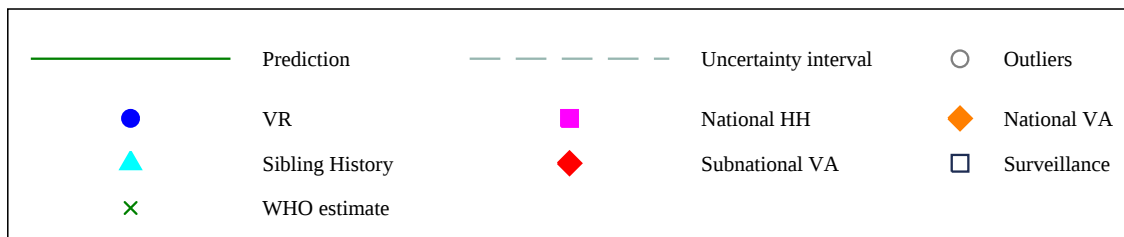
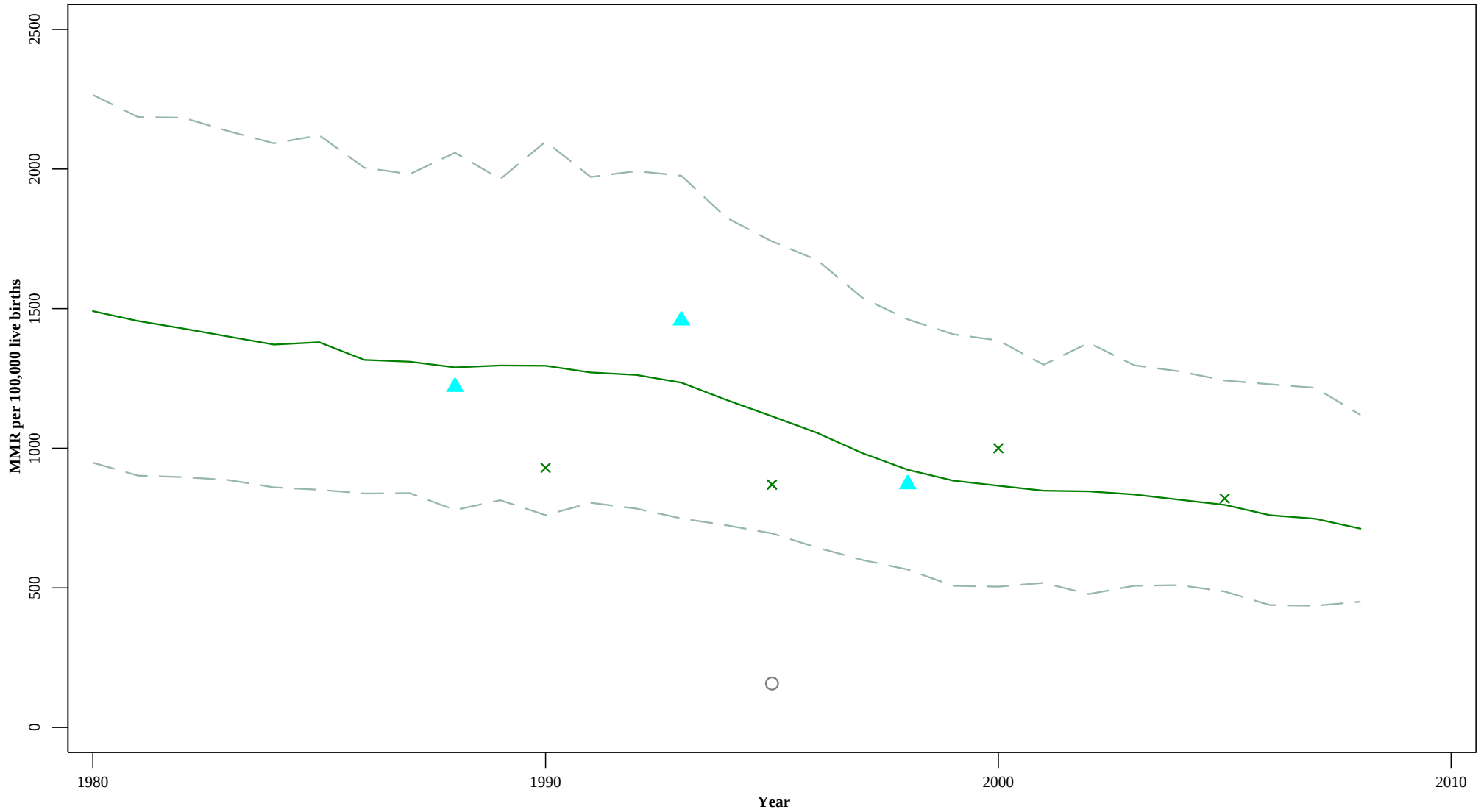
Liberia

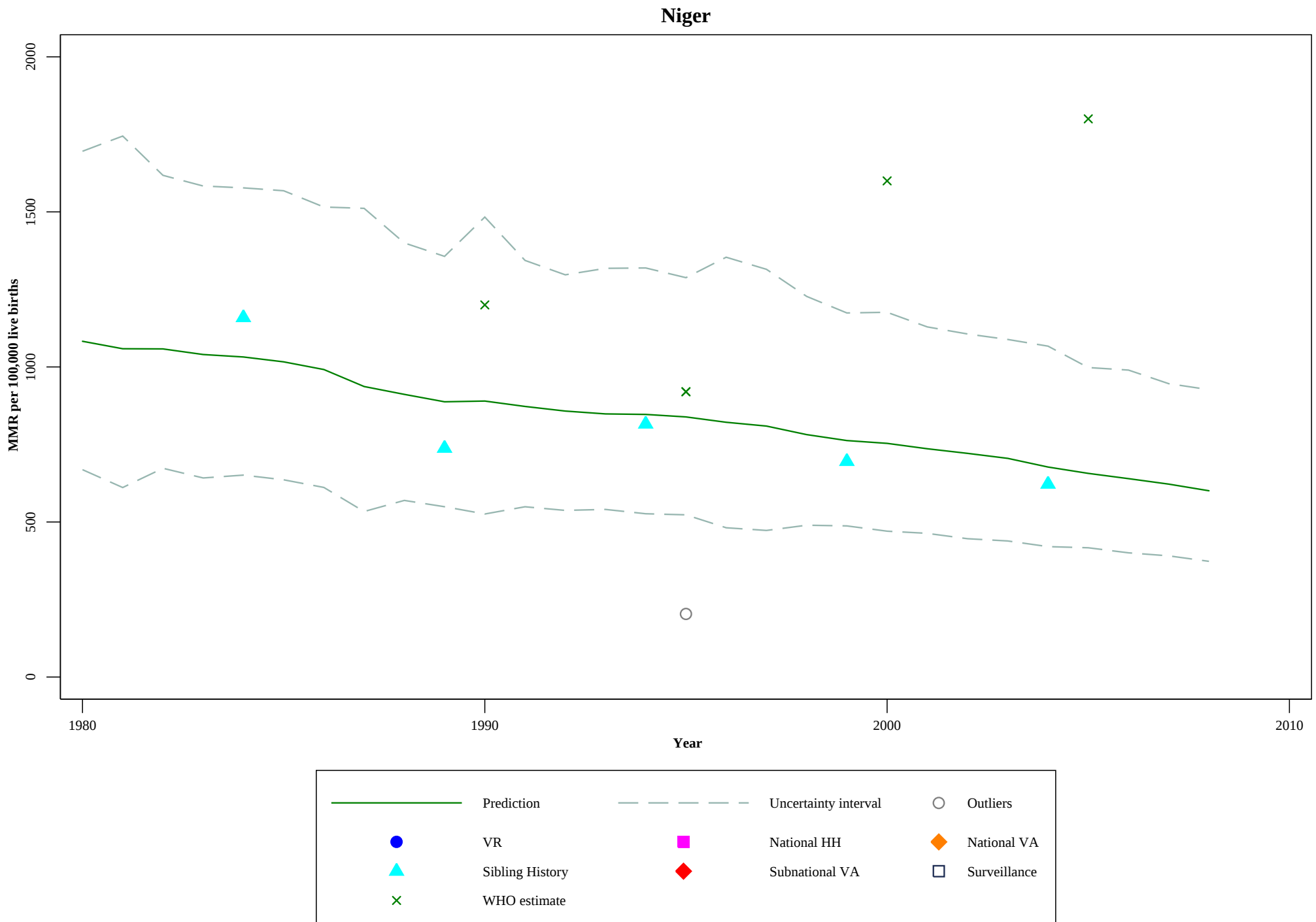


Mali

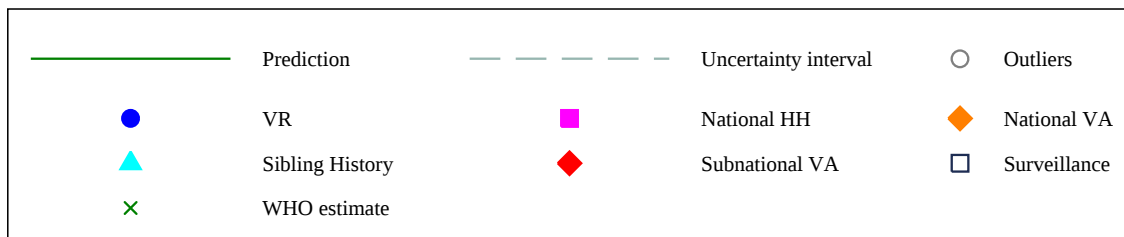
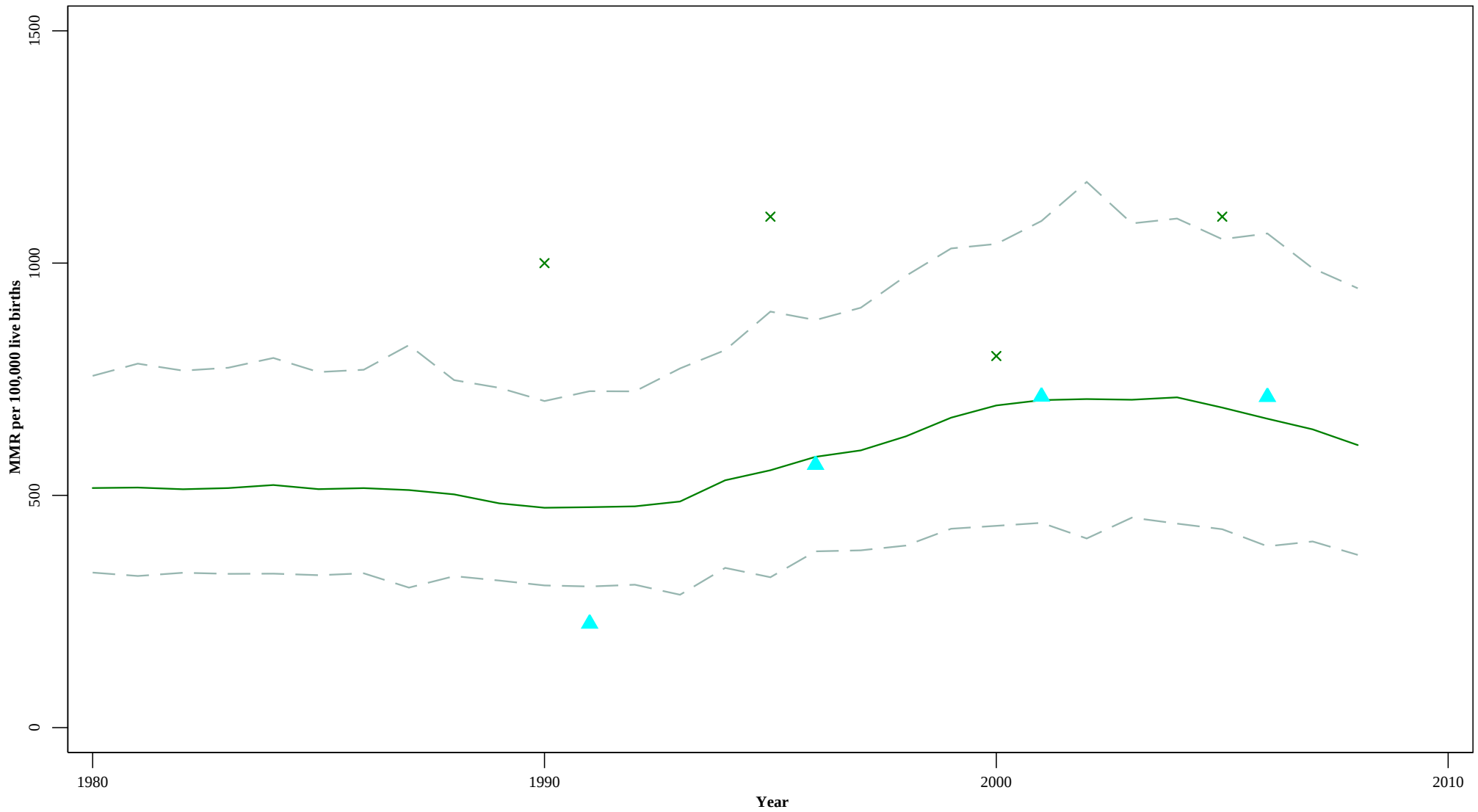


Mauritania

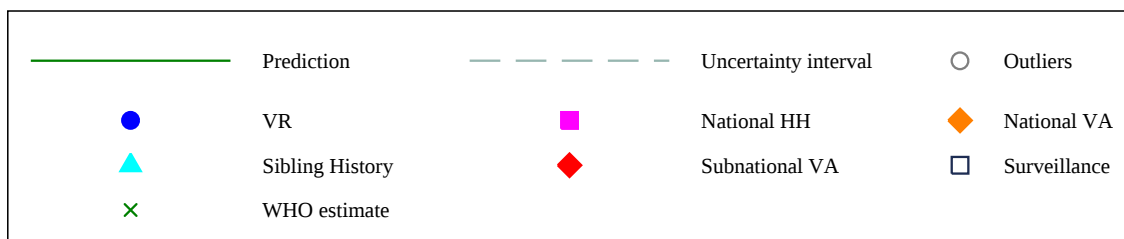
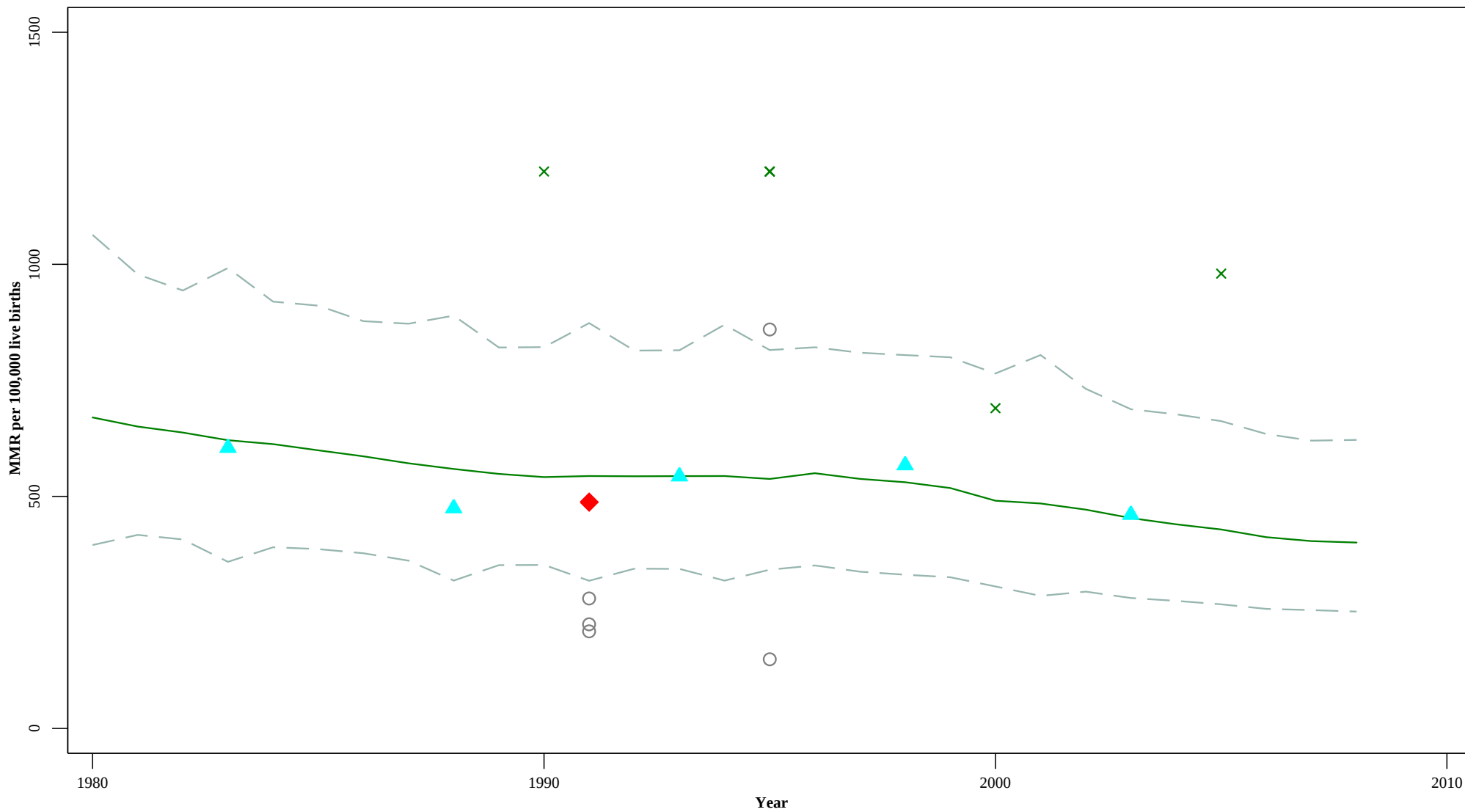




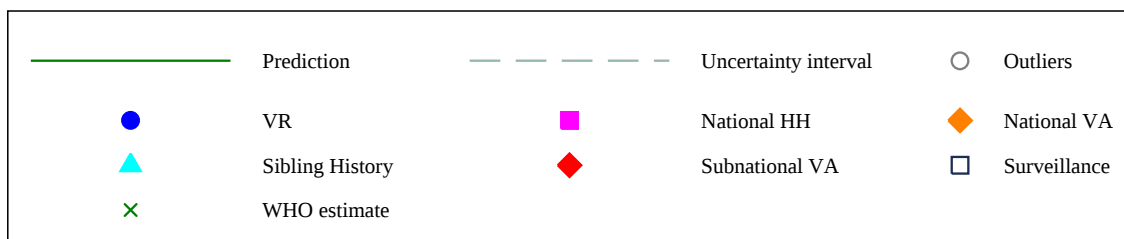
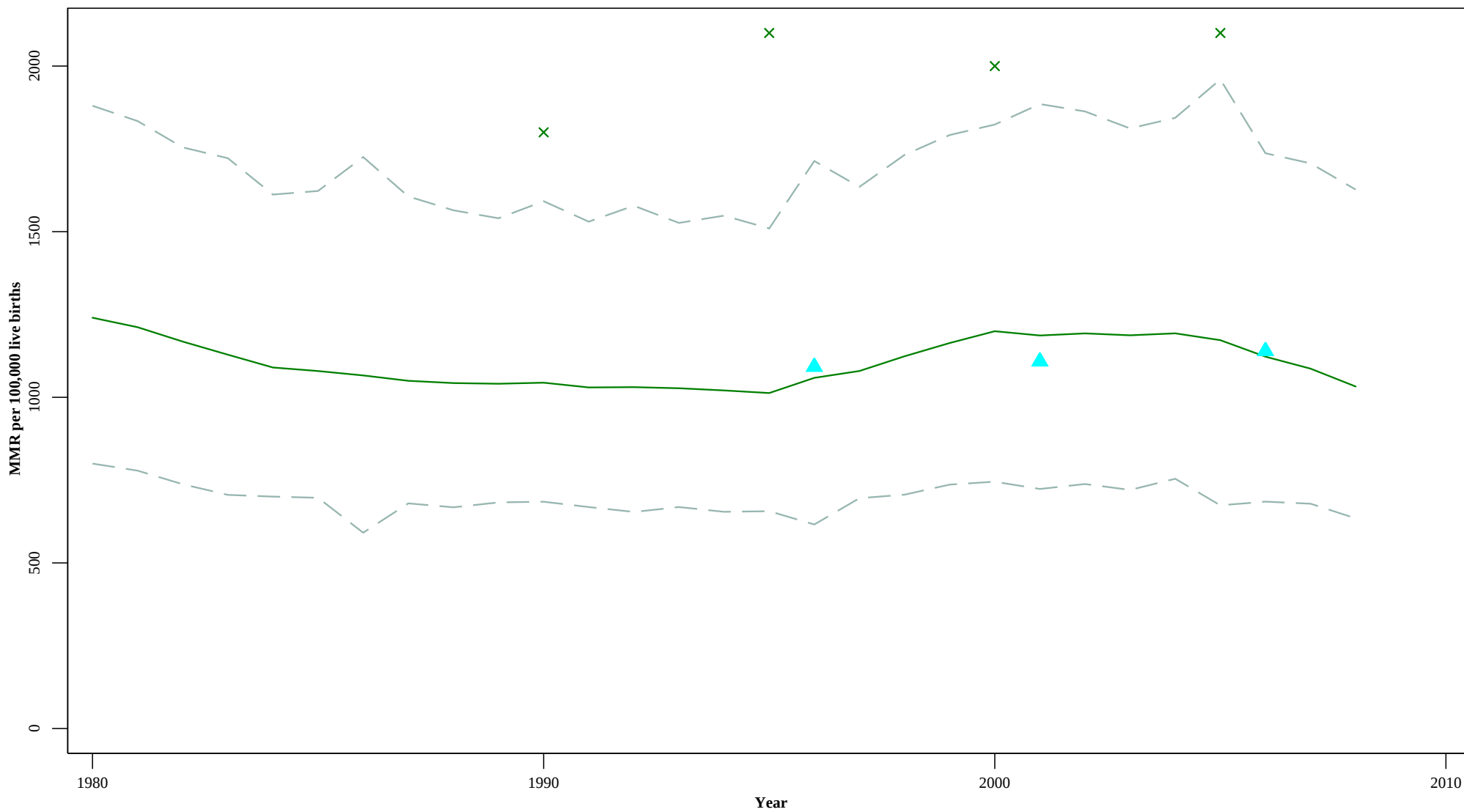
Nigeria



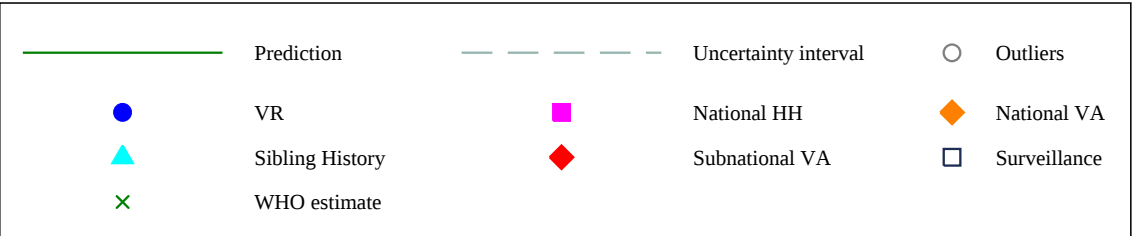
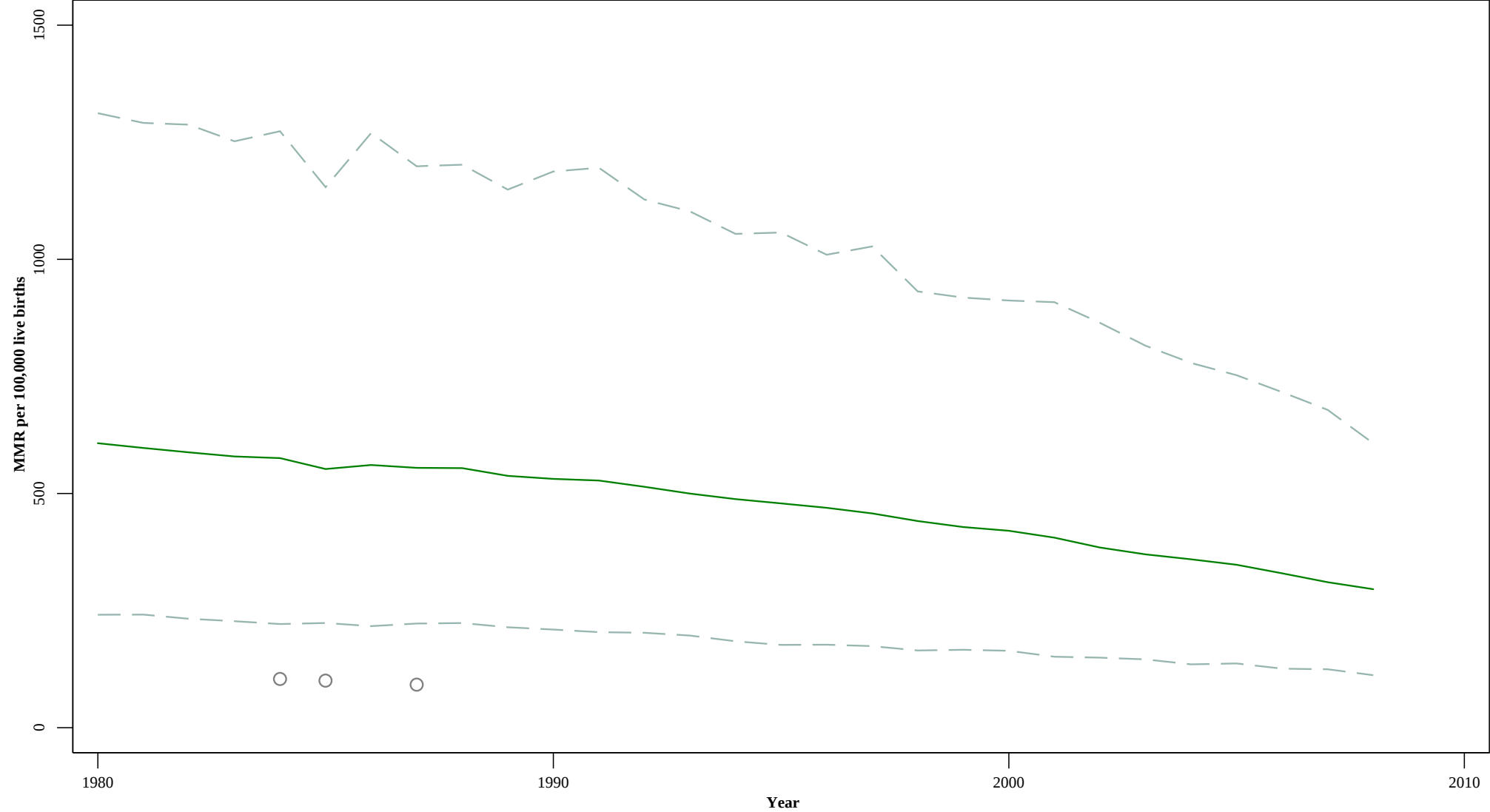
Senegal



Sierra Leone



Sao Tome and Principe



Chad

