EVALUATION OF DATA ASSIMILATION METHODS AT URBAN SCALE WITH THE SIRANE MODEL

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INTRODUCTION

Air quality modelling is widely used by local and national authorities to evaluate population exposure, to locate concentration thresholds exceedances, to investigate the relationships between air pollution and health effects or to quantify the impact of urban and traffic planning. Compared to the ground point measurements, numerical models are less accurate but their spatial resolution is better, in particular when using urban air quality models, which can describe the pollution with a resolution of a few meters.

In order to reduce errors in modeling, data assimilation techniques can be applied, which consists in a combination of modelling and measurements. They are widely used with models at the regional scale (e.g. Wang et al., 2011) but according to our knowledge, only Tilloy and al. (2013), and Denby (2007) have applied these methods with an atmospheric dispersion model at urban scale. The aim of this study is to evaluate the performance of the data assimilation, using the Best Linear Unbiased Estimator method (BLUE), using the SIRANE urban atmospheric dispersion model (Soulhac et al., 2012, 2011).

BEST LINEAR UNBIASED ESTIMATOR (BLUE)

In the BLUE theory, the best estimation, called analysis state vector, is estimated with the equation 1, where y is the observation state vector, x^b is the background state vector (prior estimate), x^a is the analysis state vector, H is the observation operator which maps from the background to the observation space, and K is the Kalman gain matrix. The Kalman gain matrix which minimize the analysis variance error is given by the equation 2, where B and R are respectively the background and the observation error covariance matrix.

$$x^a = x^b + K\left(y - Hx^b\right) \quad (1) \qquad K = BH^T\left(HBH^T + R\right)^{-1} \quad (2)$$

MODELISATION OF THE BACKGROUND ERROR COVARIANCE MATRIX

Generally, B is modelled with a spatial approach which suppose that closer two points are, more correlated the background errors are. The first model (M1) used is the one proposed by Tilloy et al. (2013) which is function of the variable d_{ij} which is the shorter distance between the points s_i and s_j along the road network and of the variable P_i which is the distance from the point s_i to the closer road (equation 3). The parameters v_0, L_d, L_p, and α are respectively a characteristic variance, a characteristic distance along the road, a characteristic projection distance and a scaling coefficient.

$$B_{ij} = v_0 \exp\left(-\frac{d_{ij}}{L_d}\right)\exp\left(-\frac{\left|P_i - P_j\right|}{L_p + \alpha \min\left(P_i, P_j\right)}\right) \quad (3)$$

The second model (M2) used is inspired by Blond et al. (2003). This model takes into account the variable ρ_{ij} which is the correlation between the background concentrations of the points s_i and s_j and the variable var_i which is the variance of the background concentrations of the point s_i.

The parameters ρ_0, L_p, and β are respectively a characteristic correlation, a characteristic correlation distance and a scaling coefficient (equation 4). This model assume that more correlated the concentrations are, more correlated the errors are. In this case the diagonal of the matrix is modelled with the equation 5.

$$B_{ij(i\neq j)} = \rho_0 \exp\left(\frac{\rho_{ij} - 1}{L_p}\right)\sqrt{B_{ii}B_{jj}} \quad (4) \qquad B_{ii} = \beta var_i \quad (5)$$

The third model (M3) implemented in this study is a combination of the two first model (equation 6). Also in this case, the diagonal of the matrix is modelled with the equation 5.

$$B_{ij(i\neq j)} = \rho_0 \exp\left(-\frac{d_{ij}}{L_d}\right)\exp\left(-\frac{\left|P_i - P_j\right|}{L_p + \alpha \min\left(P_i, P_j\right)}\right)\exp\left(\frac{\rho_{ij} - 1}{L_p}\right)\sqrt{B_{ii}B_{jj}} \quad (6)$$

MODELISATION OF THE OBSERVATION ERROR COVARIANCE MATRIX

European Directive relative to air quality stipulate that the maximal incertitude for the measurements must be of 15 %. Moreover, Tilloy et al. (2013) indicates that the observation errors are dependent of the measured concentrations. We assume in this study that the probability distribution of the observation error is a Gaussian and that 95% of the errors are inferior to 15% of the mean measured concentrations. So, the diagonal R matrix is estimated with the equation 7.

$$R = I\left(\frac{0.15\bar{y}}{1.96}\right)^2 \quad (7)$$

APPLICATION

The BLUE method has been implemented to estimate NO_2 hourly concentrations on Lyon city (France) in 2008, where 16 measurements stations are available. In this study, the background state vector is provided by the SIRANE urban atmospheric dispersion model. To evaluate the performances of the assimilation, we realize a leave-one-out cross-validation and we calculate the statistical indices (SI) defined in the table 1, where the C and σ represent respectively the concentration and the concentration standard deviation (the subscripts m and p refer respectively to measured data and to predicted data).

Bias	RE (Relative Error)	RMSE (Root Mean Square Error)	Corr (Correlation coefficient)
$\overline{C_m - C_p}$	$\overline{\left(\frac{\left\|C_m - C_p\right\|}{C_m}\right)}$	$\sqrt{\overline{\left(C_m - C_p\right)^2}}$	$\frac{\overline{\left(C_m - \overline{C_m}\right)\left(C_p - \overline{C_p}\right)}}{\sigma_m \sigma_p}$

Table 1: Statistical indices used to evaluate the method performances

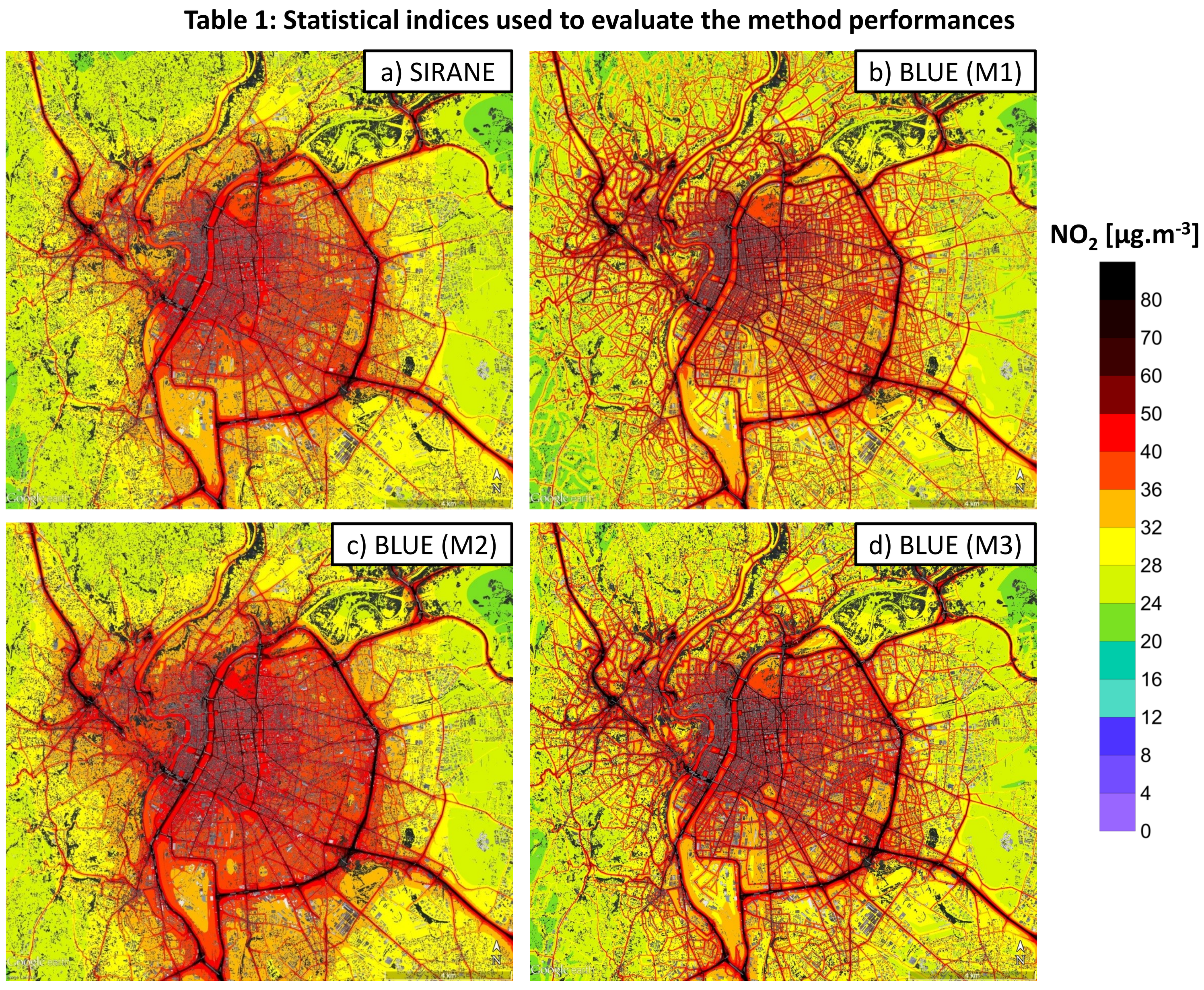

Figure 1: NO_2 annual mean concentration on Lyon city in 2008 estimated with the SIRANE model (a) and the BLUE method (b, c, and d)

The global performances (table 2) indicate that the BLUE method improves the SIRANE estimations for all statistical indices. The three background error covariance model lead to an improvement of about 20% for the RE and the RMSE indices, and an improvement superior to 50% and 10% for the bias and the Corr indices. We can note that the performances are slightly better for the model M3. The figure 1 shows the NO_2 annual mean concentration estimated with SIRANE and the BLUE method. Locally, the BLUE method also improve the RMSE and the Corr indices (figure 2). However, the bias and the RE are sometimes much worse after assimilation.

Method	Bias [µg.m^{-3}]	ER	RMSE [µg.m^{-3}]	Corr
SIRANE	3.51	0.48	22.31	0.73
BLUE (M1)	1.41 (59%)	0.38 (20%)	17.68 (20%)	0.83 (13%)
BLUE (M2)	0.73 (79%)	0.39 (18%)	18.11 (18%)	0.82 (12%)
BLUE (M3)	1.04 (70%)	0.36 (25%)	17.22 (22%)	0.84 (15%)

Table 2: SIRANE and BLUE global performances (improvement quantification are in brackets)

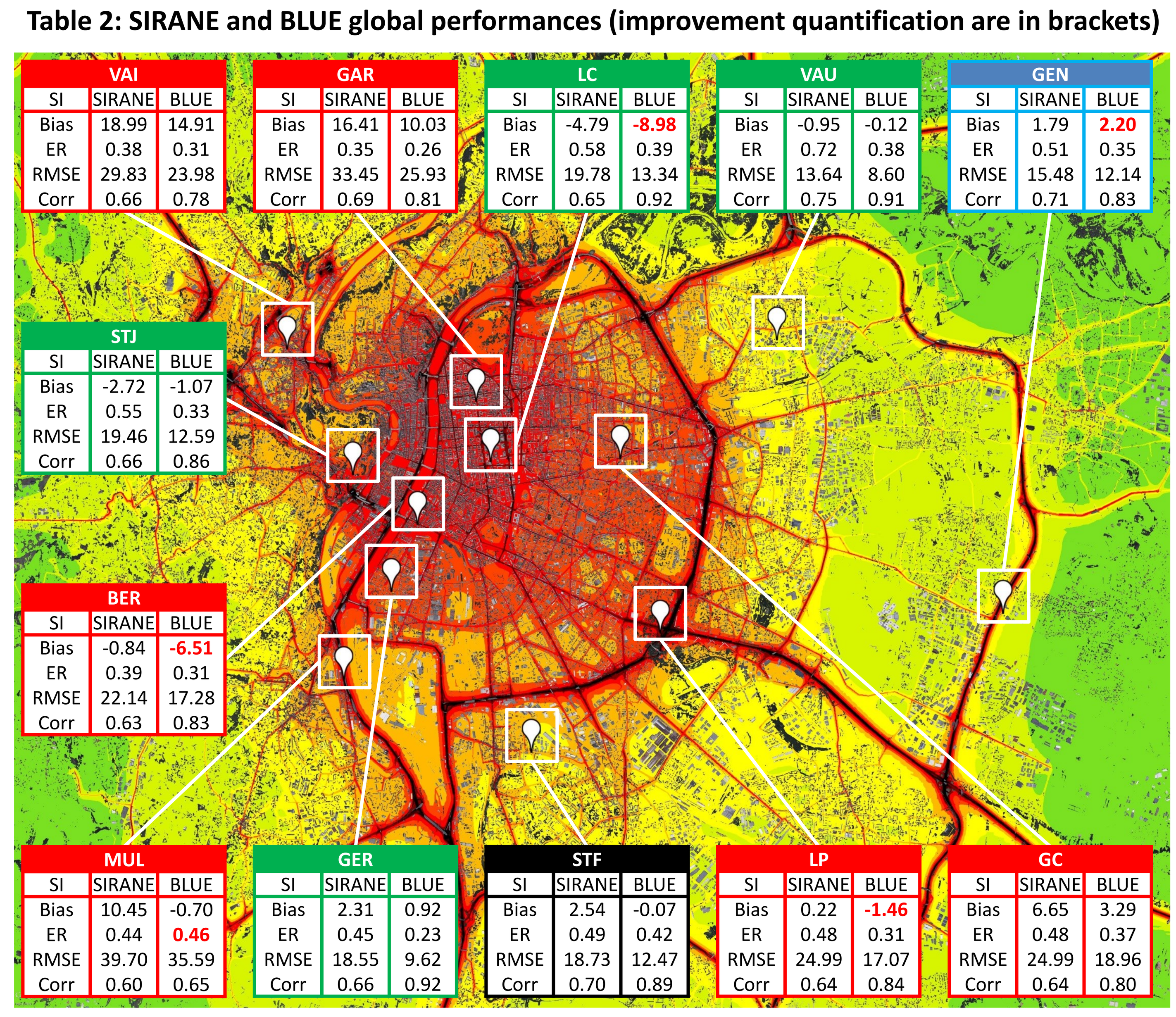

Figure 2: SIRANE and BLUE (M3) local performances (red: traffic station; green: urban station; black: industrial station; blue: background station; red value: worse performance after assimilation)

CONCLUSION

In this work, we have evaluated the performances of the BLUE method with three background error covariance models to estimate the NO_2 hourly concentrations in the Lyon city in 2008.

The results indicates that the BLUE method improve the global estimation of the SIRANE urban atmospheric dispersion model for the bias, the RE, the RMSE, and the Corr statistical indices. However, locally the results are sometimes much worse for the bias and the RE indices.

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