Field calibration and performance evaluation of low-cost sensors

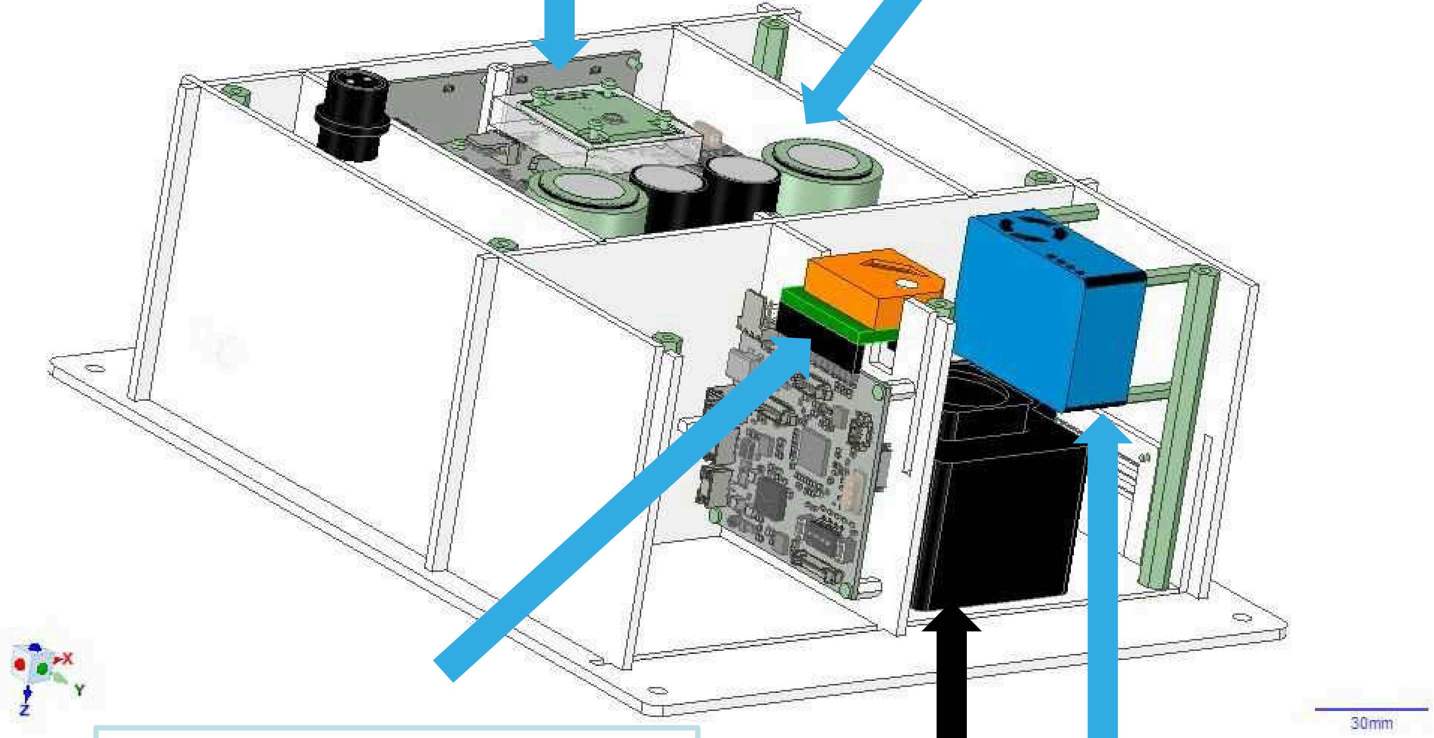
Sinan Yatkin[1], Michel Gerboles[1], Annette Borowiak[1], Silvije Davila[2], Alena Bartonova[3], Franck Dauge[3], Philipp Schneider[3], Martine Van Poppel[4], Jan Peters[4], Christina Matheeussen[5], and Marco Signorini[6]

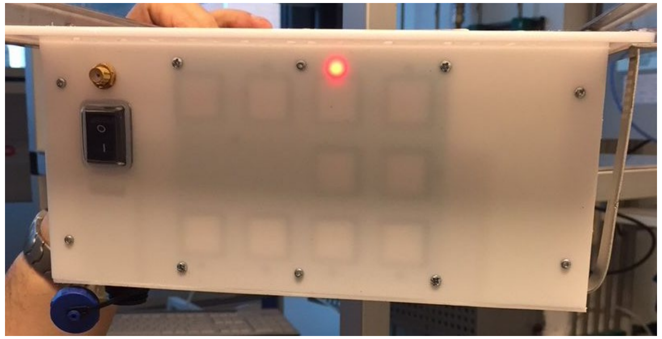
[1] European Commission, Joint Research Centre (JRC), Via E. Fermi, 21027 Ispra, Italy
[2] Institute for Medical Research and Occupational Health, Ksaverska cesta 2, Zagreb, Croatia
[3] Norwegian Institute for Air Research, PO Box 100, 2027 Kjeller, Norway
[4] Flemish Institute for Technological Research (VITO), Boeretang 200, 2400 Mol, Belgium
[5] Flanders Environment Agency, Dokter De Moorstraat 24-26, 9300 Aalst, Belgium
[6] Liberaintentio Srl, Malnate 21046, Italy

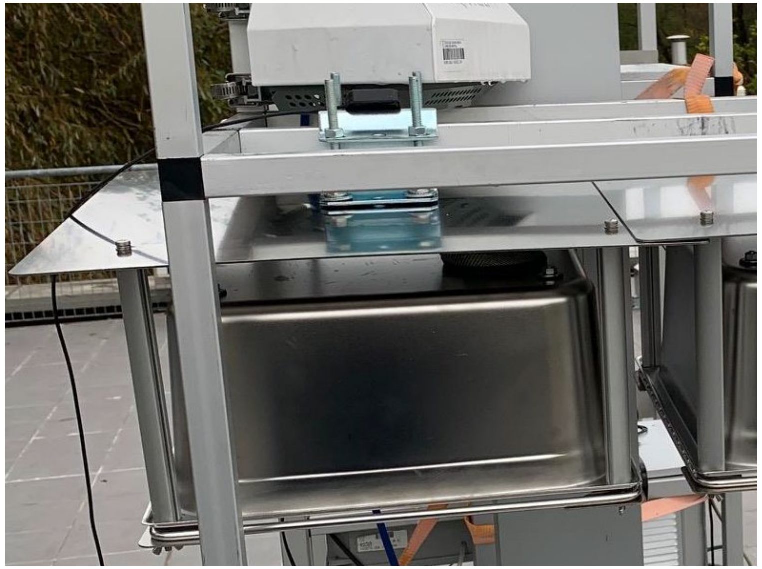
Low-cost sensors system (AirSensEUR by JRC)

T & RH: Sensirion SHT31
Pressure: Bosch BMP280

Alphasense ECS
CO (CO-A4)
NO (NO-B4)
NO_2 (NO2-B43F)
O_3 (OX-A431)







CO_2: ELT D-300G

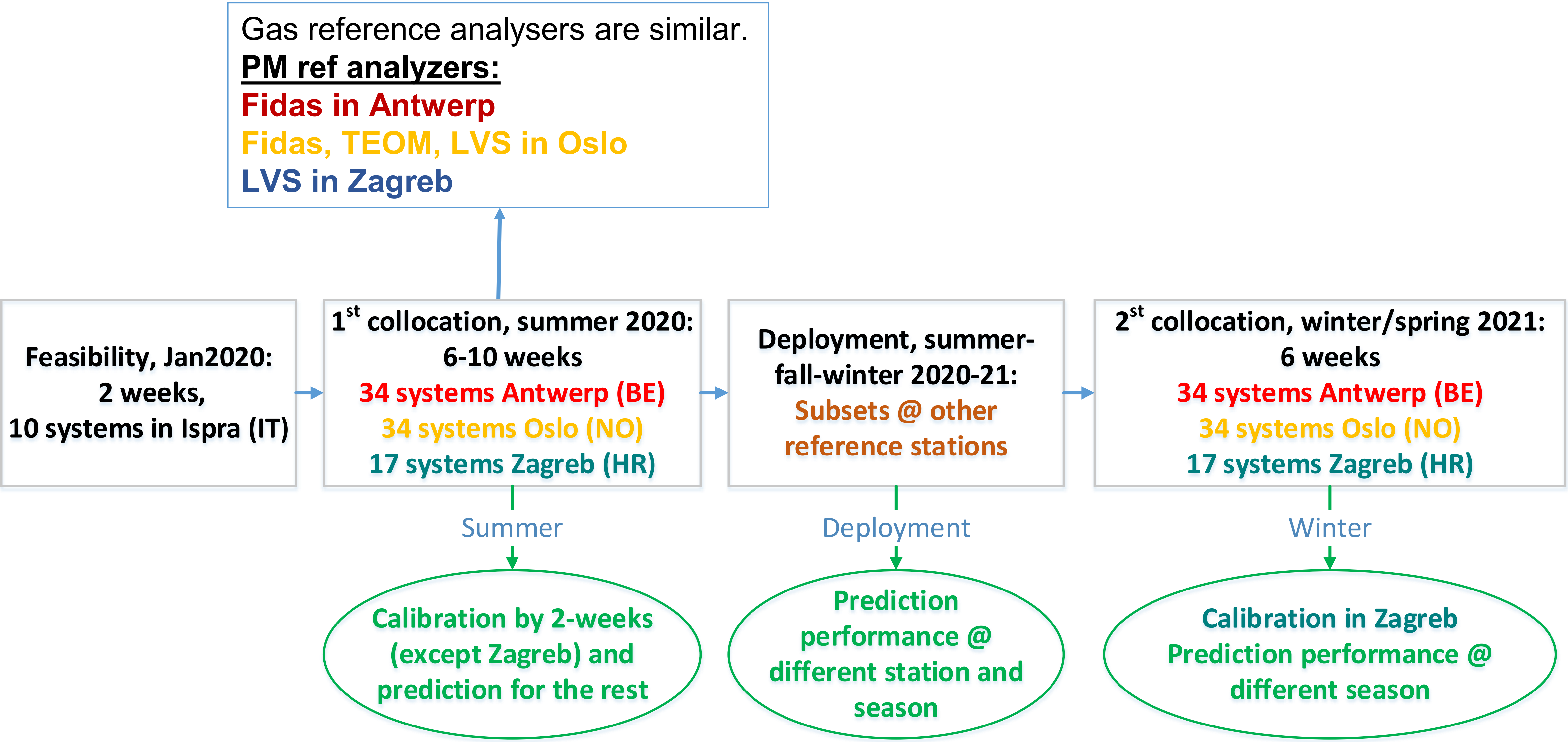
PM
PMS5003: Plantower
OPC-N3: Alphasense

European Commission

Integrating smart sensors and modelling for air quality monitoring in cities (Antwerp (BE), Oslo (NO) and Zagreb (HR))

1. Developing a traceable field calibration methodology;
2. Performance evaluation of sensors to measure air pollution (prediction);
   - Uncertainty meeting data quality objectives in EU directive,
   - Linear reg btw modelled and reference data,
3. Evaluating the effects of site characteristics and season on calibration;
4. Evaluating sensor relocation and season on prediction.

Scope and timeline



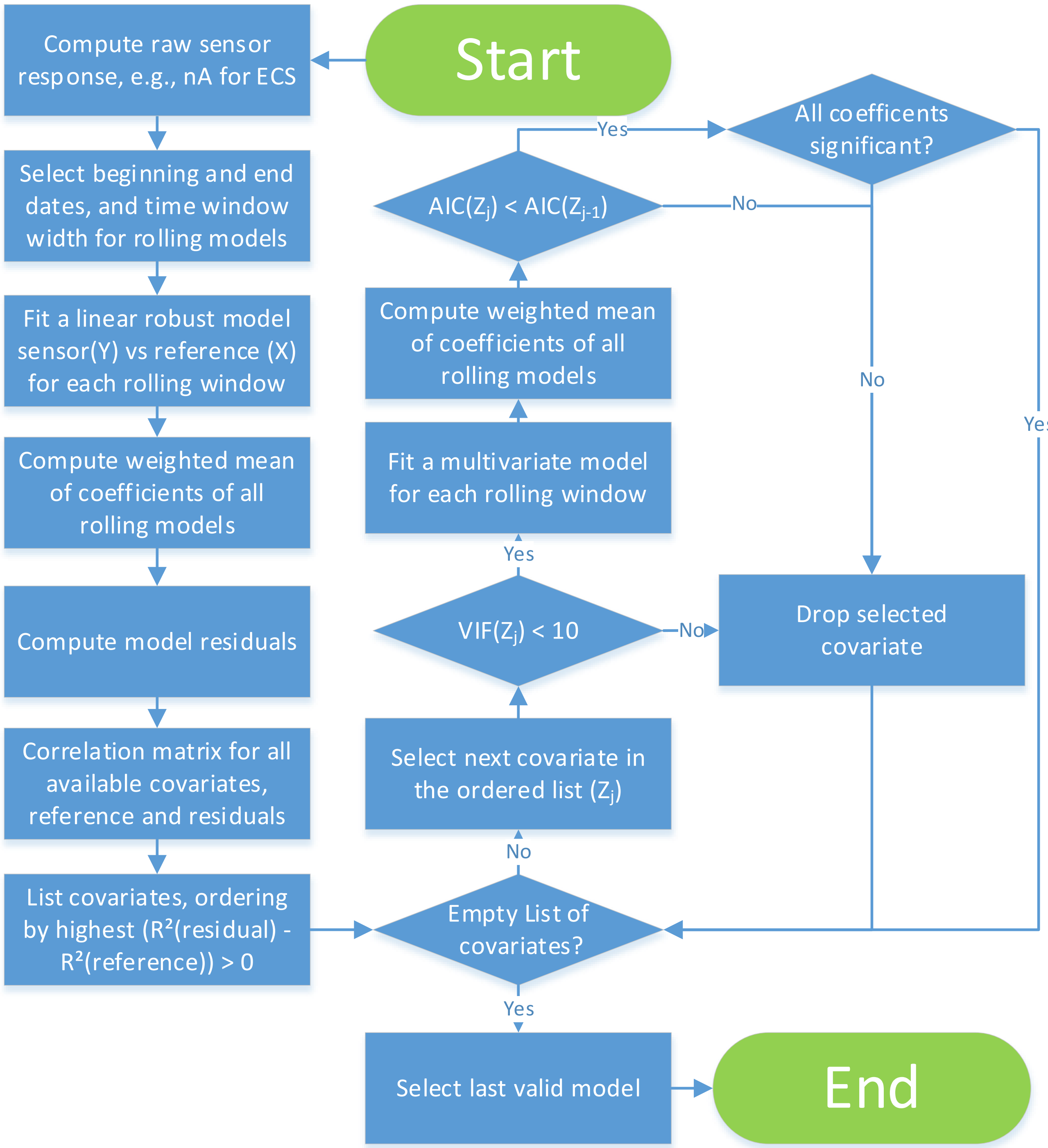
Calibration methodology

All data are <u>in 1 min resolution</u>

$$\underbrace{\underbrace{Y = a_0 + a_1 X}_{\text{Linear robust (LR) model}} + \sum_{j=3}^{n} a_{j-1} Z_j^{m_j} + \varepsilon}_{\text{Multilinear (ML) model}}$$

Y : the raw sensor response in raw units;
X : the reference data;
a_0, a_1 and a_{j-1} : the coefficients;
Z_j : the variables having an effect on sensor response at specific degree of m_j (so-called covariates);
n : the number of coefficients
ε : the error component (residual)

VIF: Variance Inflation Factor for collinearity of independent covariates
AIC: Akaike Information Criterion to check whether the last added covariate improves calibration model



Calibration methodology

Exponential calibration model for NO sensors: based on Faraday law

$$Y_{NO} = a_0 + a_1\ NO_{ref} + a_2 e^{kT} + \ \varepsilon = a_0 + a_1\ NO_{ref} + e^{kT+ln(a_2)} + \ \varepsilon$$

T: Ambient or internal temperature, in ^{0}C

k is fitted by Levenberg-Marquardt algorithm

Kohler correction for PM sensors

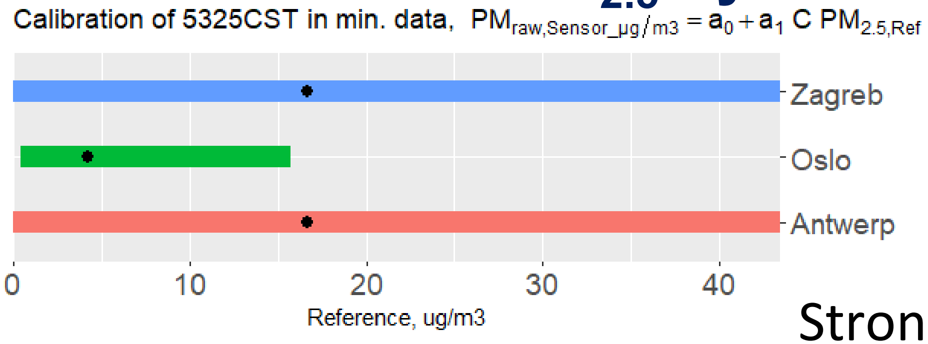
$$Y_{PMsen} = \ C\ PM_{ref}$$

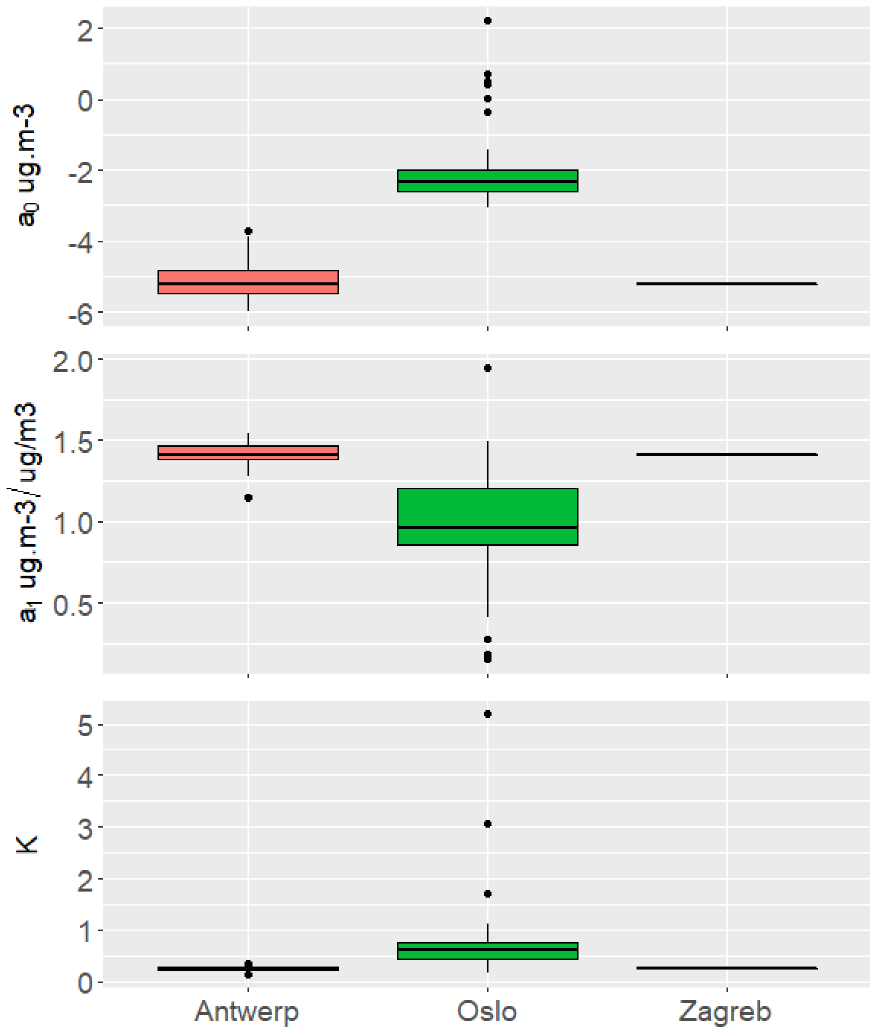
$$C = 1 + \frac{K/\rho}{-1 + 1/a_w}$$

ρ : particle density (1.65 g cm^{-3})
a_w : water activity, RH/100
K is fitted by Levenberg-Marquardt algorithm

$$Y_{PMsens} = a_0 + a_1\ C\ PM_{ref}$$

$PM_{2.5}$ by PMS5003: Calibration and prediction





Strong city effect:

- Antwerp ref from Fidas (similar to PMS)
- Oslo ref: transformation between LVS vs Fidas

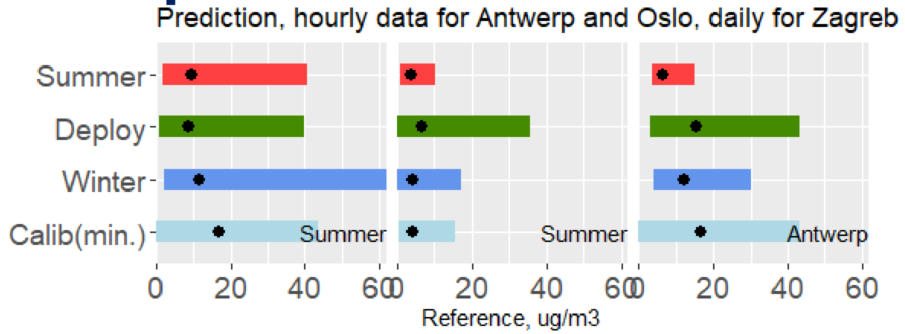
➢ U < DQO at LV

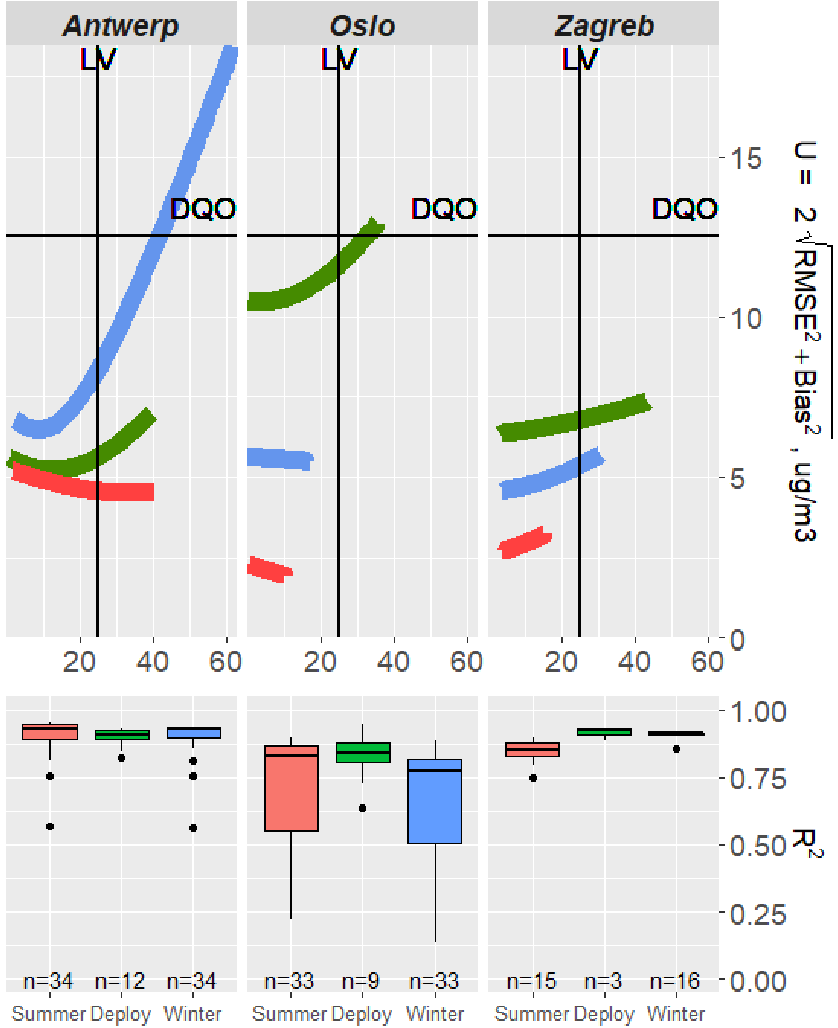
➢ No significant drift

➢ Antwerp model worked well in Zagreb (daily data)

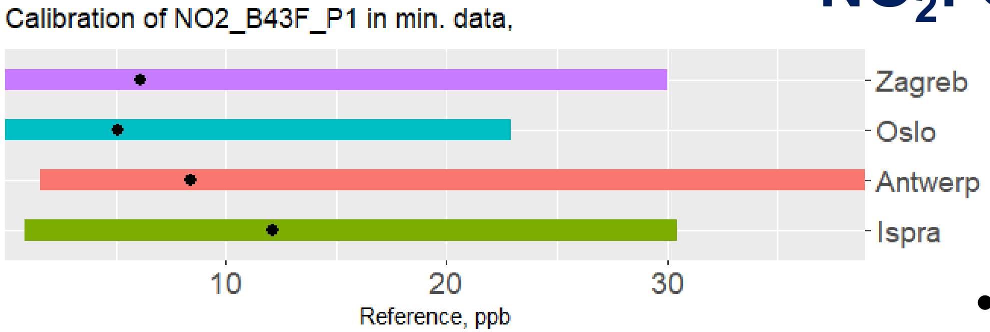
➢ Prediction performances decrease with size:

$U_{PM10} > U_{PM2.5} > U_{PM1}$





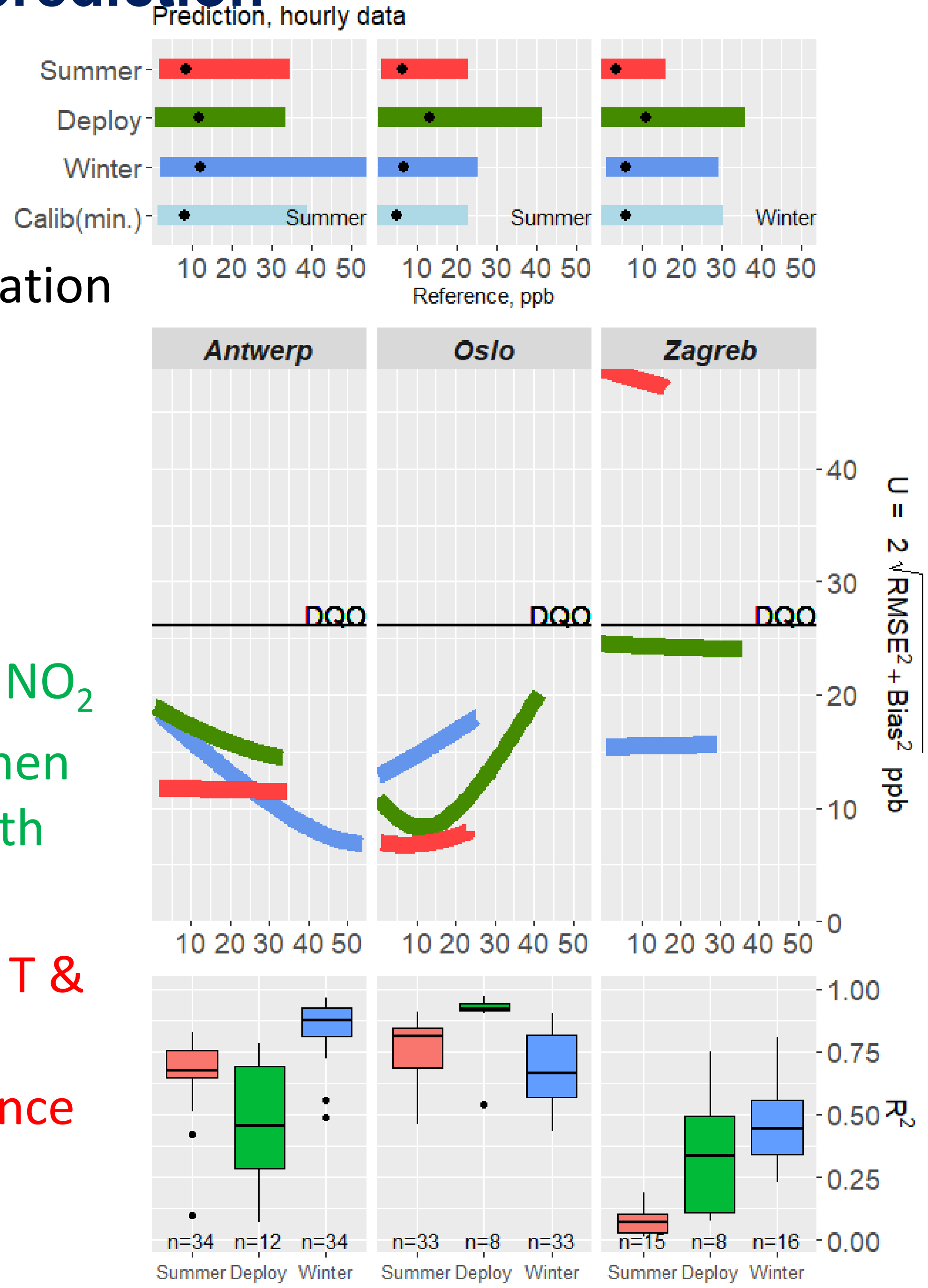
NO_2: Calibration and prediction



First_Co	Second_Co	Third_Co	N
Absolute_humidity	Temperature_int		17
Td_deficit			17
Absolute_humidity	OX_A431		11
Absolute_humidity			11
Relative_humidity	OX_A431		8
Temperature_int	Td_deficit		6
OX_A431	Td_deficit		4
Relative_humidity			4
Relative_humidity	Temperature_int		3
Temperature_int	OX_A431		3
			3
Absolute_humidity	Temperature_int	OX_A431	2
Temperature_int	OX_A431	Td_deficit	2
Temperature_int			2
Absolute_humidity	OX_A431	Td_deficit	1

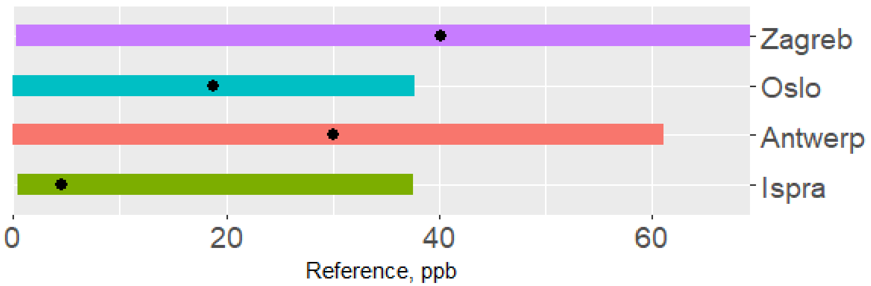
- No common calibration model

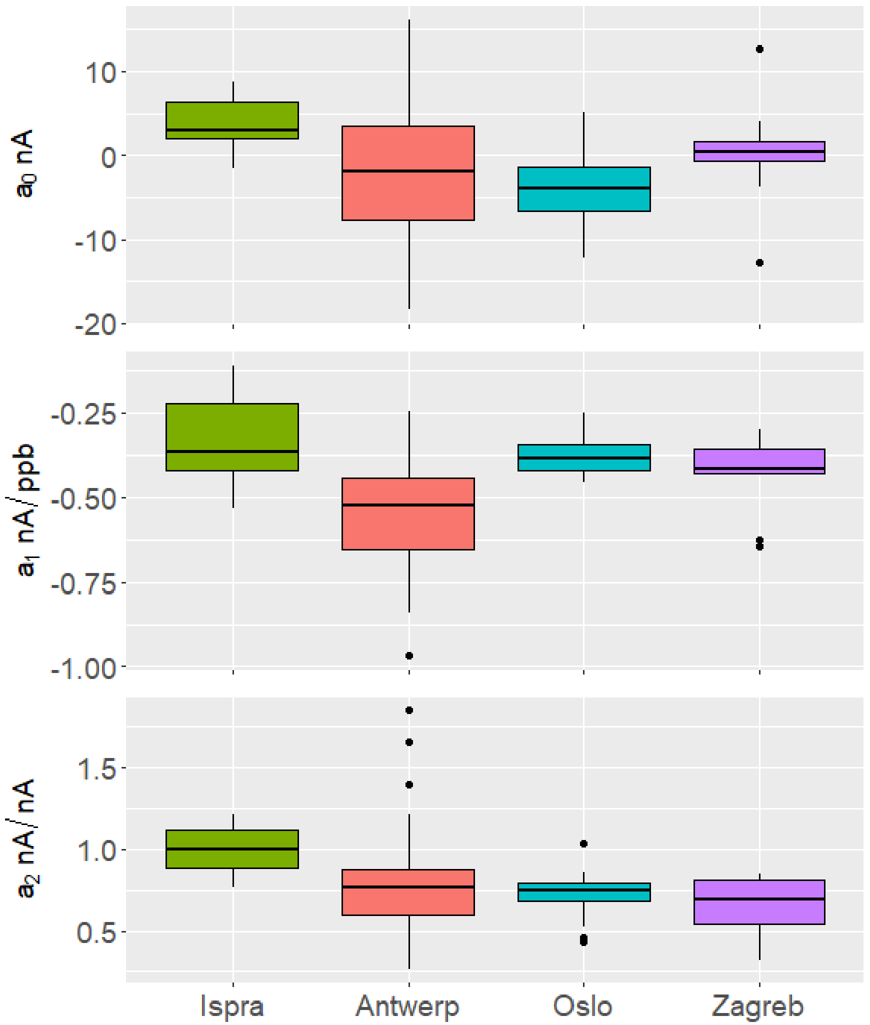
- Mostly U < DQO
- Prediction highly dependent on T & NO_2
- Poor prediction when high T **together** with low NO_2 & high O_3
- Calibration at high T & low NO_2 did not improve performance
- No significant drift



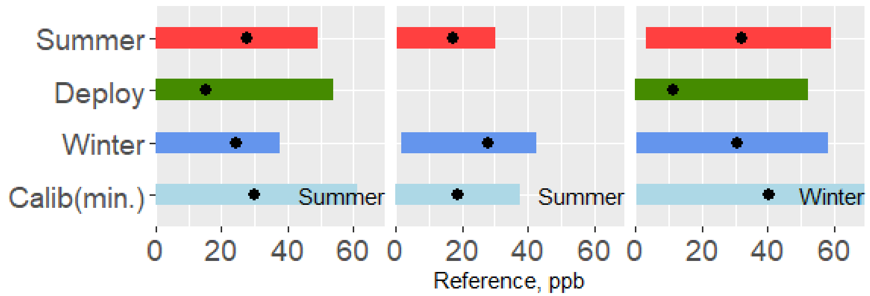
O_3: Calibration and prediction

Calibration of OX_A431_P1 in min. data, $O_{3,Sensor\_nA} = a_0 + a_1\, O_{3,Ref} + a_2\, NO_{2,Sensor}$





Prediction, hourly data

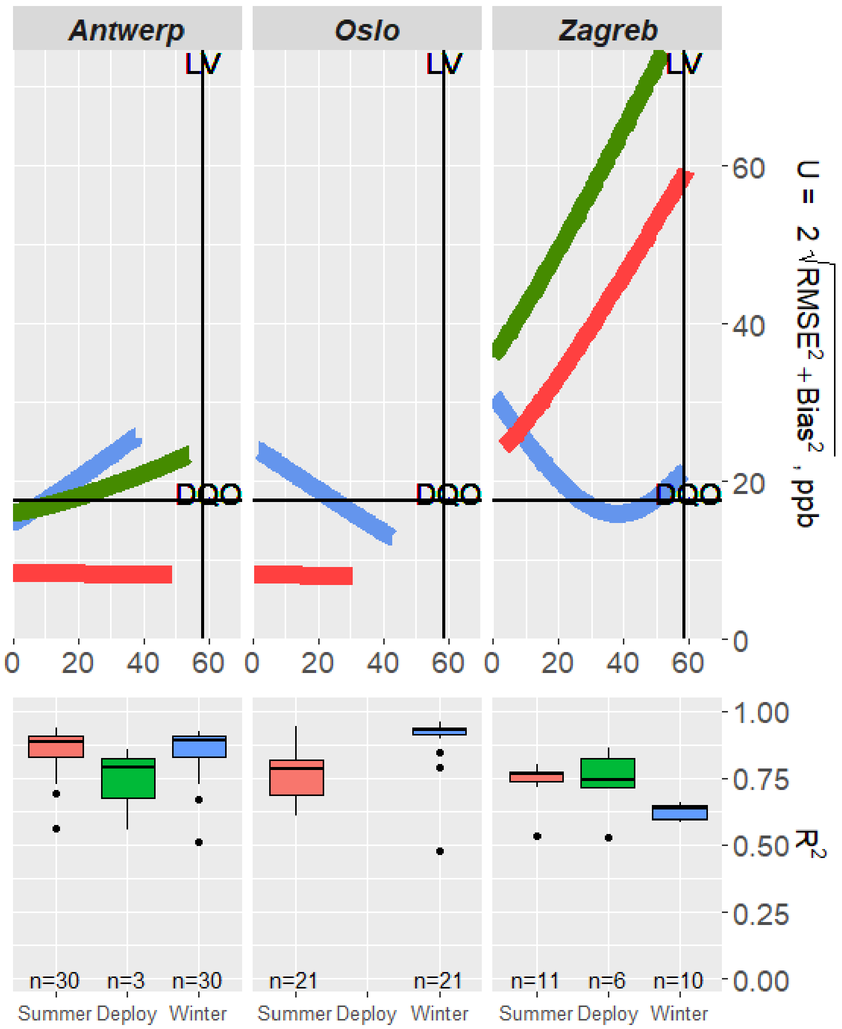


- 75% of ML only with NO_2
- Low city & seasonality effects

➢ Strong seasonality effect

➢ Or, drifted over a year: Requires frequent calibration, e.g., every 6 months

➢ Mostly U < DQO



Conclusions

- PMS $PM_{2.5}$ Kohler models predicted well, even in another city
- NO_2 models predicted well when conditions were similar to calibration time
- ML O_3 models with NO_2 predicted well with important seasonality effect: requires seasonal calibration
- Gas sensors except for O_3 were affected from extreme ambient T: NO and NO_2 the most, CO much less
- Relocation within a city did not significantly affect sensor performances
- All sensors except for O_3 did not significantly drift over a year
- Tests are required for O_3 drifting: due to aging or mis-calibration

Thank you!!!

Evaluation of prediction : expanded uncertainty

$$Y_i = b_0 + b_1 X_i$$

Y_i : LCS final (modelled) data for period of i
X_i : reference data

$$U(Y_i) = k\left(\underbrace{\frac{\mathrm{RSS}}{N-2} - u^2(bs,RM) + u^2(bs,s)}_{\text{Random error}} + \underbrace{[b_0 + (b_1 - 1)X_i]^2}_{\text{Bias}}\right)^{1/2}$$

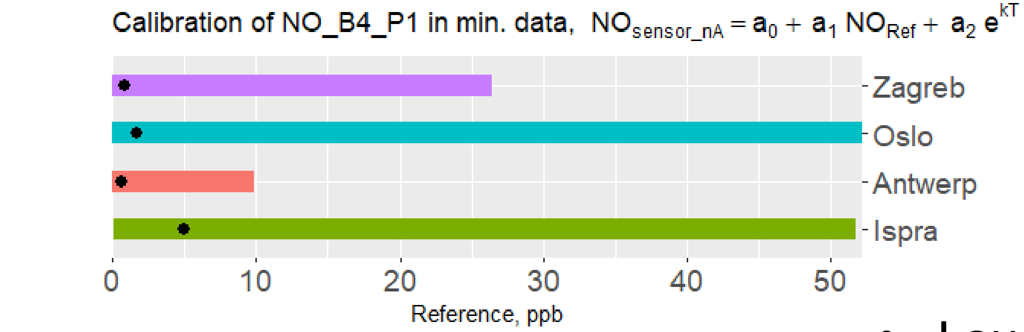
k : coverage factor, 2
RSS: sum squared residuals
N: number of data pairs
u(bs,s): btw LCS unc. (optional)
u(bs,RM): btw reference method std. unc. (from validation testing in literature)

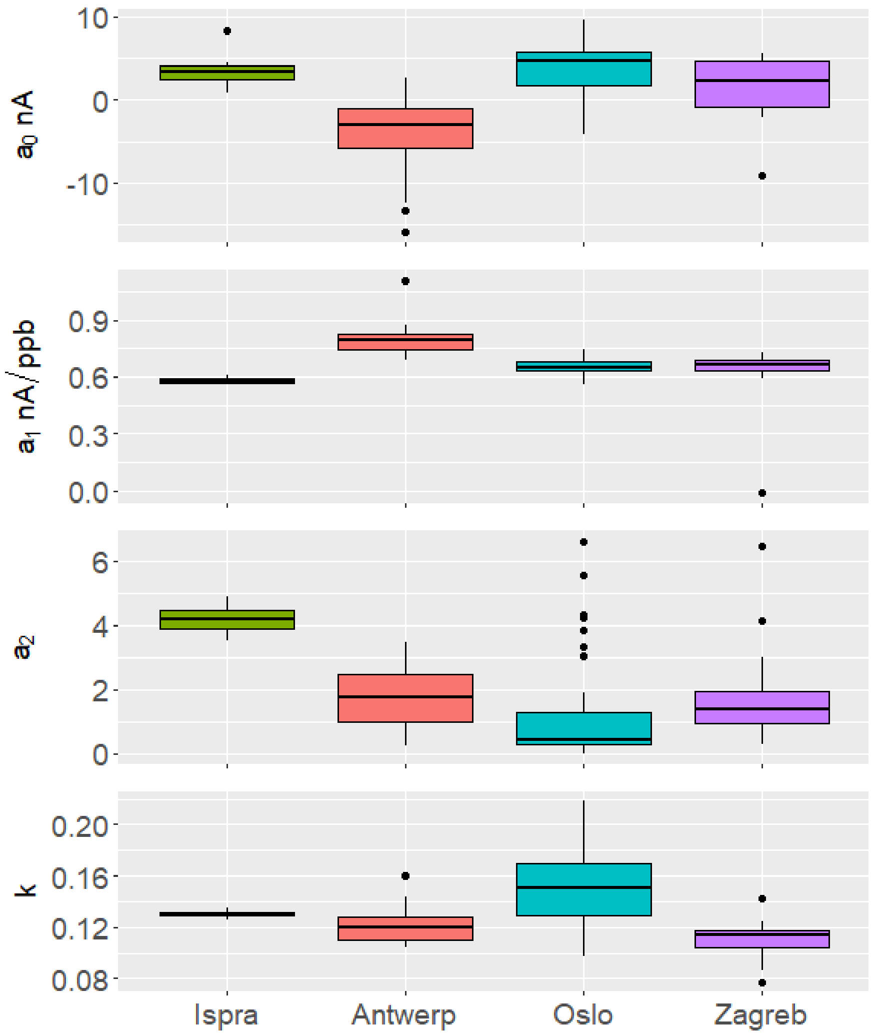
$$\mathrm{RSS} = \sum_{i=1}^{N} [Y_i - (b_0 + b_1 X_i)]^2$$

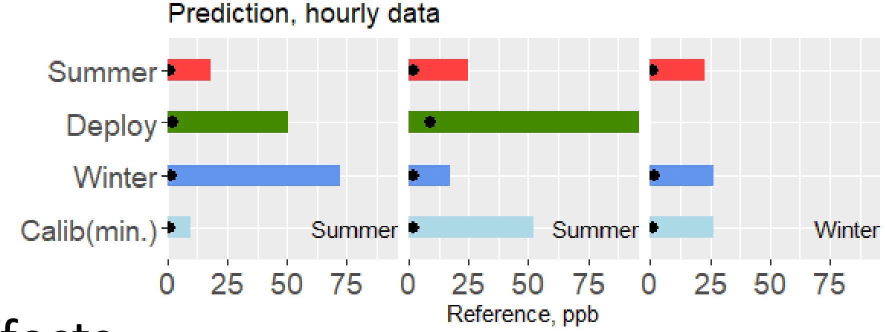
$$U(Y_i) \leq \mathit{Data\ Quality\ Objective\ (DQO)\ at\ limit\ value\ (LV)}$$

	Averaging time	LV	DQO of indicative meas.
		µg/m³	%
CO	8 h	10 (mg/m³)	25
O_3	8 h	120	30
NO_2 & NO	1 h	200	25
PM_{10}	24 h/1 h	50	50
$PM_{2.5}$	24 h/1 h	25	50

NO: Calibration and prediction







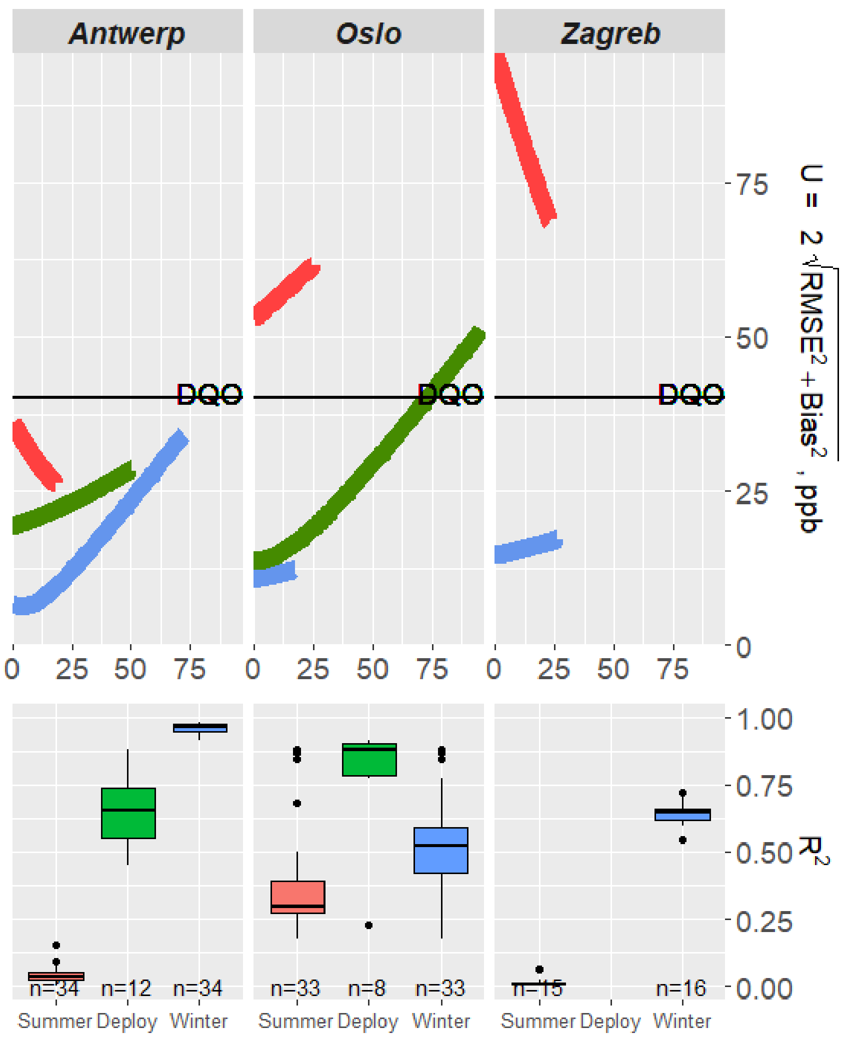
- Low city/seasonality effects

➢ Mostly U < DQO

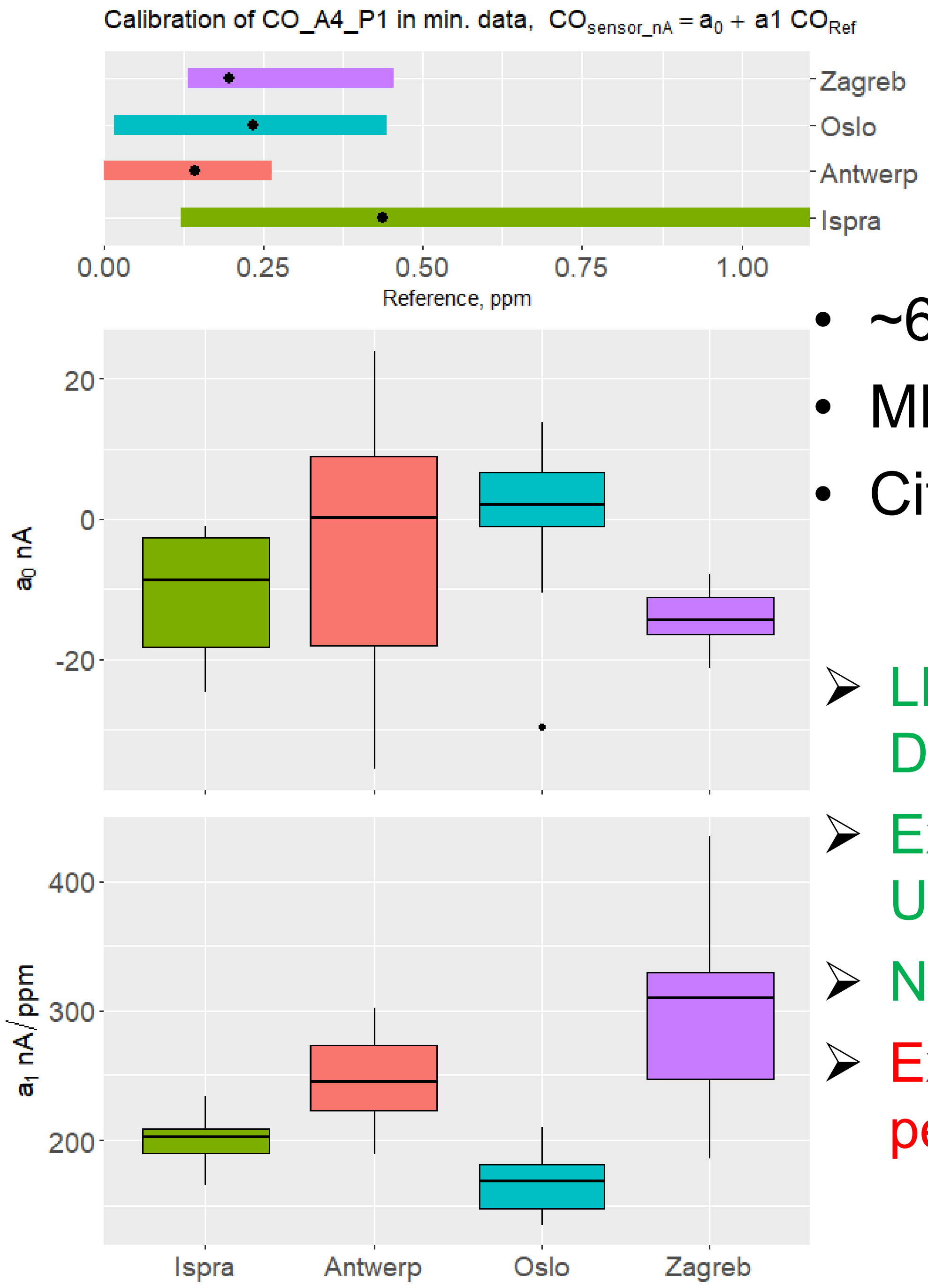
➢ Prediction highly dependent on T and NO

➢ Poor prediction when high T **together** with low NO

➢ Calibration at high T & low NO did not improve



CO: Calibration and prediction



- ~60% with Linear Robust
- ML not improved predict.
- City & seasonality effects

➢ LR predicts well. U < DQO **although CO << LV**

➢ Extrapolations increase U, particularly in Zagreb

➢ No significant drift

➢ Extreme T decreased performance slightly