European Commission

Results of the 3rd ATM-Challenge 2019

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Environment and Climate Change Canada
Environnement et Changement climatique Canada

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ORAL PRESENTATION

ZAMG

Results of the 3rd ATM-Challenge 2019

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1. The 16 participants of the 3rd ATM-Challenge and their model set-ups

Main aims:
Investigate the added of:
1) stack emission data

and

2) training an optimum ensemble

Name	Institution	ATM	Meteorology	Simulation length	Minor emitters included
Kihyun Park (Korea)	KAERI	LADAS	UM-GDAPS (KMA)	6 months	Yes
Arnaud Quérel (France)	IRSN	IdX-C3X (Eulerian)	ARPEGE (Météo France)	6 months	No (ZAMG's)
Akiko Furuno (Japan)	JAEA	WSPEEDI-II (WRF+GEARN)	GPV- Global (JMA)	3 months	No (ZAMG's)
Alain Malo (Canada)	CMC	MLDP	GDPS (CMC)	6 months	Yes
Donald Lucas (USA)	LLNL	LODI	NCEP-GFS/ADAPT	6 months	Yes
Paul Eslinger (USA)	PNNL	HYSPLIT	NCEP-GDAS	6 months	Yes
Yuichi Kijima (Japan)	JAEA	HYSPLIT	NCEP-GDAS	3 months	No (ZAMG's)
Rich Britton (UK)	UK-NDC/AWE	HYSPLIT	NCEP-GDAS	6 months	Yes
Blake Orr (Australia)	ARPANSA	HYSPLIT	ACCESS-G (BoM)	6 months	No (ZAMG's)
Alice Crawford (USA)	NOAA-ARL	HYSPLIT (-GEM)	NCEP-GDAS & ERA5	6 months	Yes
Anders Axelsson (Sweden)	FOI	HYSPLIT	NCEP-GDAS	6 months	Yes
Jolanta Kusmierczyk-Michulec (CTBTO)	CTBTO/IDC	FLEXPART 9.3.2	ECMWF-IFS	6 months	Yes
Christian Maurer (Austria)	ZAMG	FLEXPART 10.3	ECMWF-IFS	6 months	Yes
Michael Schoeppner (CTBTO)	CTBTO/OSI	FLEXPART 9.3.2	ECMWF-IFS	3 months	Yes
Petra Seibert (Austria)	BOKU	FLEXPART	ECMWF-IFS	6 months	Yes
Pham Kim Long (Vietnam)	VINATOM	FLEXPART	NCEP-GFS	6 months	Yes

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2. A first glimpse on important statistics

What is the average benefit (over all four investigated stations CAX17, DEX33, SEX63, USX75 and all samples for June to December 2014 and all submitted runs) of:

- using *actual historic daily stack emission*[1] versus *average literature emission* data for IRE and CNL facilities?
- including rough *estimates for NPPs' & and other facilities'* emissions?

$$\text{Rank} = R^2 + \left(1 - \frac{|\text{FB}|}{2}\right) + \text{F5} + \text{ACC}$$

1) „Rank" according to 2nd ATM-Challenge („R_2nd_Challenge"; 4 metrics combined)
2) „Rank" amended by distribution metric („R_KS"; 5 metrics combined)
3) „Seibert's Skill Score („SS"; 4 metrics combined)

Rank[2]	Actual daily stack emissions	Average literature emissions
NPP emissions included	**2.33 [1.45,2.70]**; 3.08 [2.01,3.56]; 0.46 [0.20,0.61]	**2.39 [1.47,2.73]**; 3.17 [2.04,3.62]; 0.45 [0.19,0.60]
NPP emissions not included	**1.92 [0.91,2.45]**; 2.56 [1.37,3.21]; 0.35 [0.07,0.58]	**2.09 [1.08,2.59]**; 2.78 [1.56, 3.39]; 0.39 [0.09,0.59]

[1] accessed via vDEC
[2] Reviewed IMS data set accessed via vDEC + DEX33 altitude correction applied

Answers:

- No average benefit from daily stack data over all samples, independent of the score used
- Indication of a positive impact of roughly estimated emissions of NPPs and other facilities
- that adds up to ~20%

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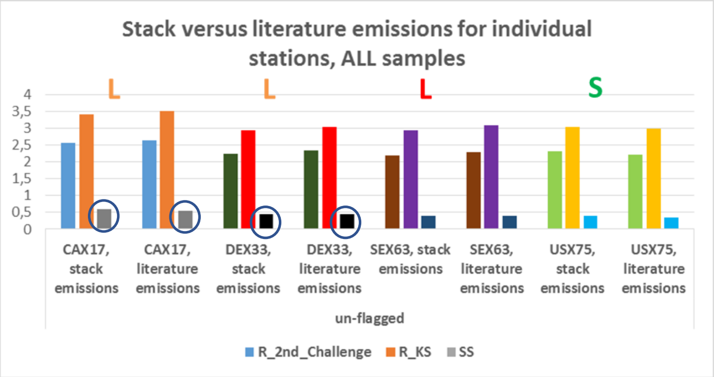
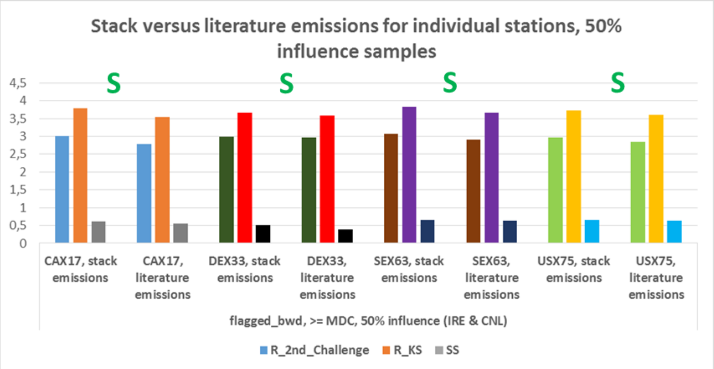
3. Statistics per station – flagging main emitters‘ influence based on ATM

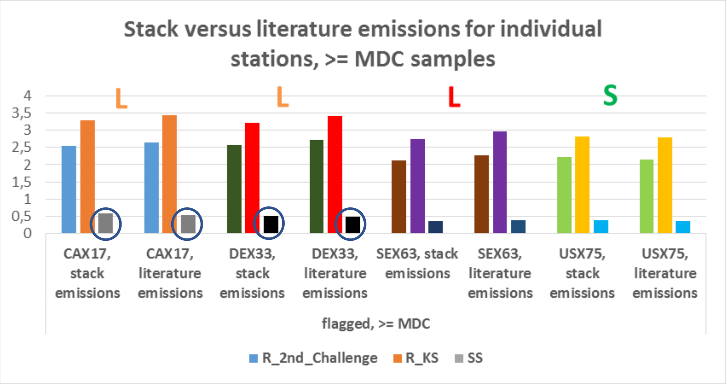


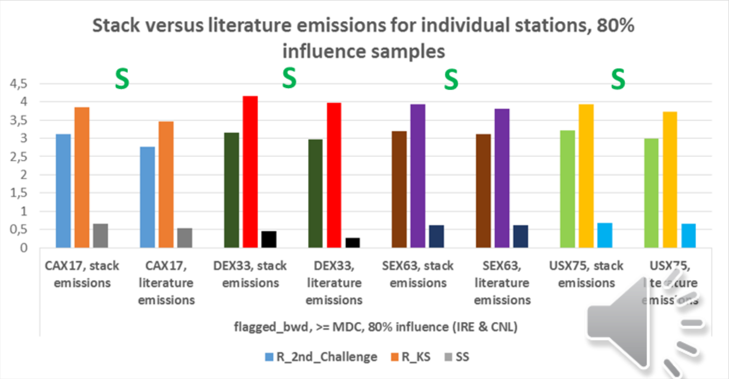


S: stack emissions outperform literature emissions based on all metrics

L: literature emissions outperform stack emissions based on Rank, but not on SS

L: literature emissions outperform stack emissions based on all metrics





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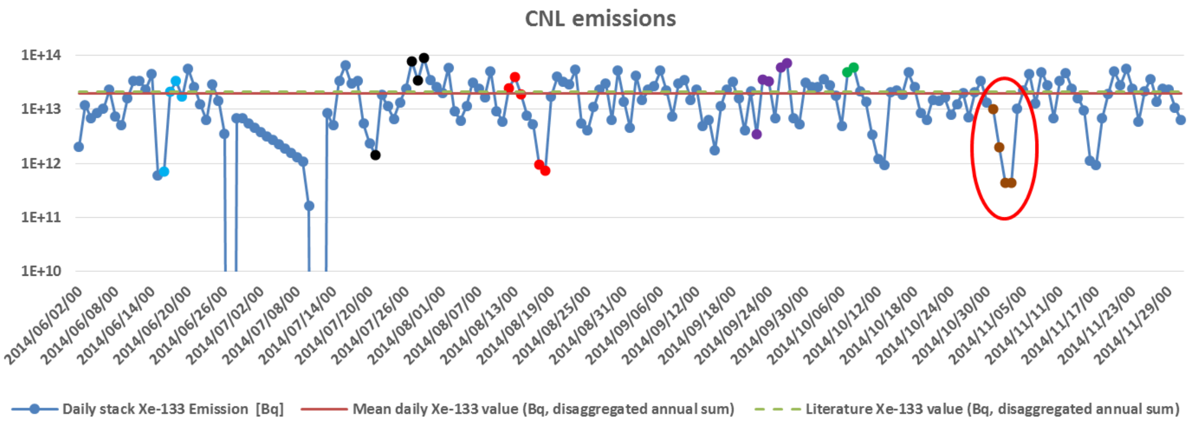
4.1 A different perspective: Selecting samples based on the emission profile: CNL-USX75



- In 2/3 of the cases the CNL contribution alone does not explain the signal -> *Something is missing!*
- NPPs+NRRs+other facilities‘ contributions are always and up to two orders of magnitude smaller than CNL stack emission based contributions -> *CNL is the driving force*
- *Stack data are beneficial in 2/3 of the cases*

USX75

Collection start [UTC]	Measured value [mBq/m3]	MIPFs contribution stack	MIPFs contribution literature	NPPs+NRRs+other facilites	Sum stack	Sum literature
20141102160000	0,53	0,88	20,70 S!	0,36 S!	1,24	21,06
20140802160000	*18,51*	3,92	1,07 S?	0,09 S	4,01	1,16
20140620160000	*5,63*	4,82	3,57 S?	0,13 S	4,95	3,71
20140820160000	*0,80*	0,17	0,23 L?	0,10 L	0,27	0,33
20141001160000	4,80	6,85	2,61 L	0,67 L	7,52	3,28
20141014160000	*0,95*	0,38	0,15 S?	0,05 S	0,43	0,2

Disclaimer: The views expressed on this presentation are those of the author and do not necessarily reflect the view of the CTBTO

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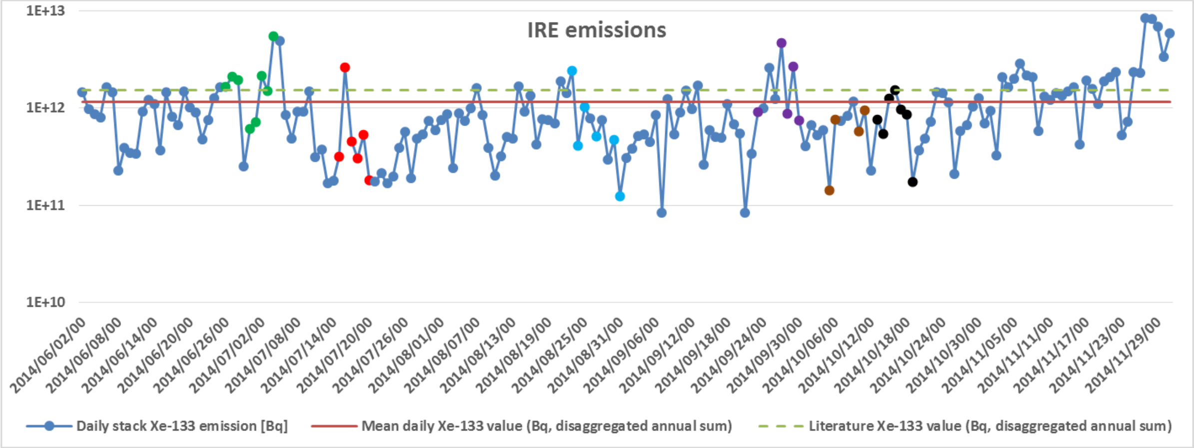
4.2 A different perspective: Selecting samples based on the emission profile: IRE-SEX63



- For all cases the IRE (+CNL) contribution alone does not explain the signal -> *Something is missing!*
- NPPs+NRRs+other facilities' contributions are in 2/3 of the cases and up to two orders of magnitude bigger than IRE stack emission based contributions -> *IRE is not the driving force for these samples*
- *Stack data are beneficial in 2/3 of the cases*

SEX63

Collection start [UTC]	Measured value [mBq/m3]	MIPFs contribution stack	MIPFs contribution literature	NPPs+NRRs+other facilites		Sum stack	Sum literature
20140707000000	*1,71*	0,16	0,09 S?	0,11 S		0,27	0,20
20140727000000	*0,60*	0,05	0,08 L?	0,54 S		0,60	0,62
20140903000000	*0,41*	0,12	0,41 S?	0,29 S		0,42	0,70
20141024000000	*1,36*	0,02	0,03 L?	1,02 L		1,04	1,05
20141003000000	*1,01*	0,30	0,34 L?	1,52 S	CNL influence!	1,82	1,8[illegible]
20141013000000	*0,72*	0,19	0,48 L?	0,15 L		0,33	0,62

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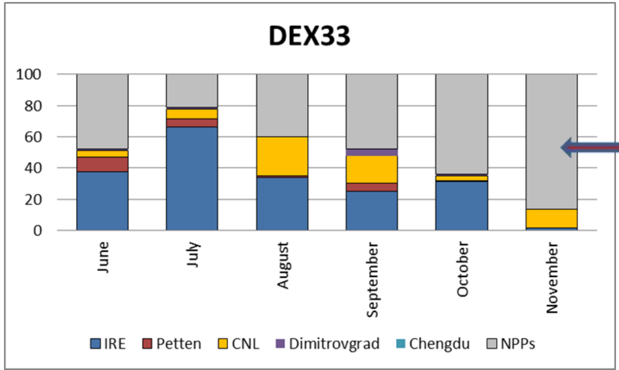
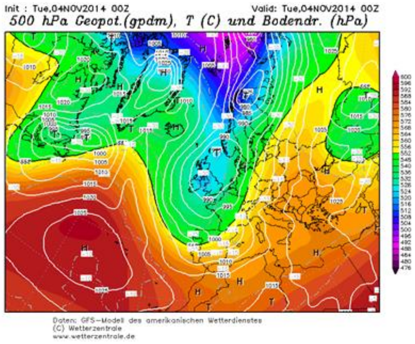
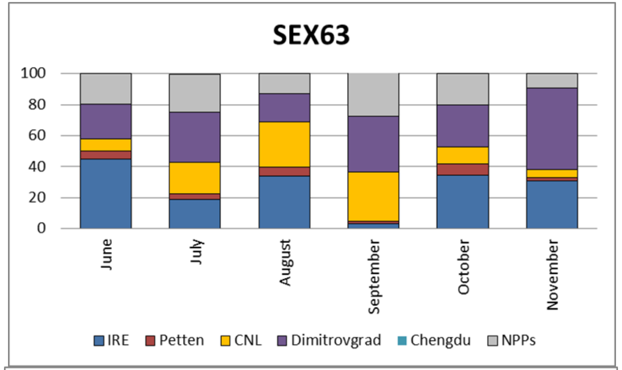
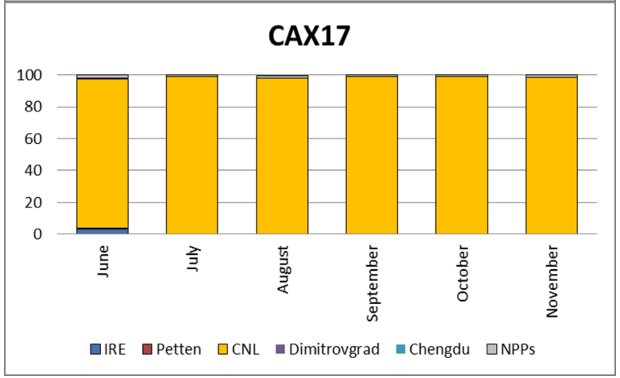
5. To remember: Monthly Xe-background in 2014 (PTS pilot study)





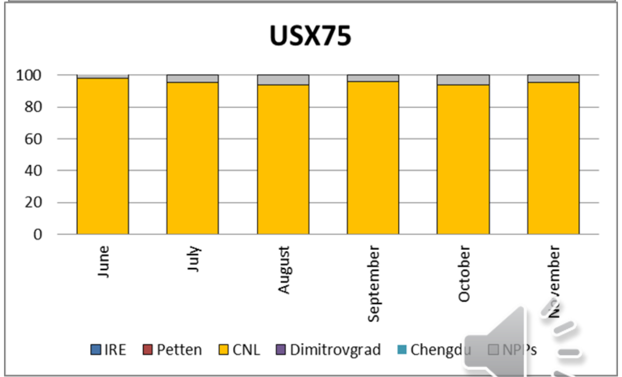




Gueibe et al. (2017):
IRE: 2E15 Bq/y
CNL: 1.5E16 Bq/y

- **CNL had highest annual values!**
- **Knowing exact IRE emissions is clearly not enough for DEX33 and SEX63!**

Percentage values are based on actual concentrations in Bq/m3



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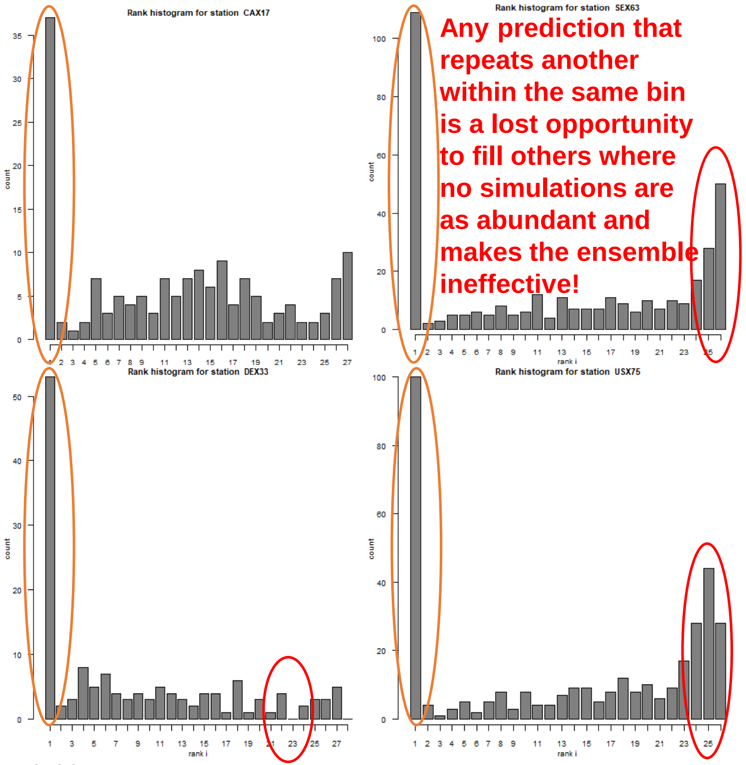
6. Redundancy of the ensemble



Any prediction that repeats another within the same bin is a lost opportunity to fill others where no simulations are as abundant and makes the ensemble ineffective!

<u>Prominent Features</u>:

- **High redundancy within the ensemble: Talagrand diagram is not evenly populated!**
- Ensemble is highly overpredictive for very small concentrations. Likely due to setting below MDC concentrations to 0.

<u>Number of effective members (that are sufficient to cover the variability of the observations):</u>

- Define metric $d = e_m - R * MME$; e_m: error of model m, R: Pearson correlation coefficient between multi-model average error MME and error e_m of model m
- Calculate eigenvalues λ of $corr(d_i, d_j)$ with $i, j = 1 \dots N$ ensemble members
- Calculate $N_{eff} = \frac{\left(\sum_{i=1}^{N} \lambda_i\right)^2}{\sum_{i=1}^{N} \lambda_i^2}$ for period 20140601-20141201
- **3.5 (out of 26 models) for CAX17**
- **2.5 (out of 27 models) for DEX33**
- **3.5 (out of 25 models) for SEX63**
- **1.7 (out of 25 models) for USX75**
- **But not necessarily the very same 2 to 4 members at every station!**

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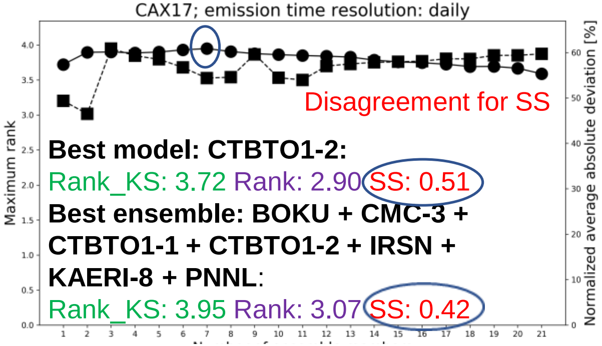
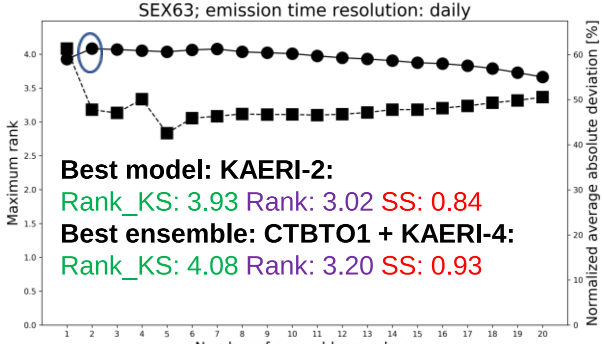
7. A first outlook on optimized ensemble results

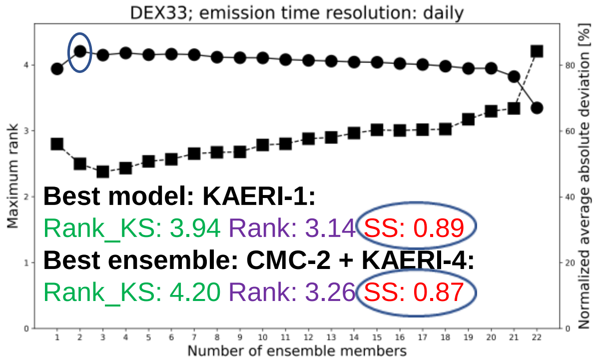


Disagreement for SS

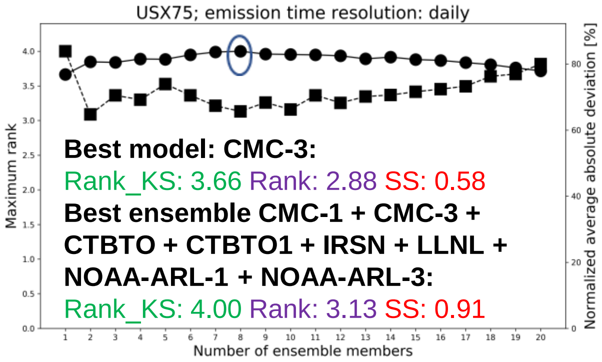
Best model: CTBTO1-2:
Rank_KS: 3.72 Rank: 2.90 SS: 0.51
Best ensemble: BOKU + CMC-3 + CTBTO1-1 + CTBTO1-2 + IRSN + KAERI-8 + PNNL:
Rank_KS: 3.95 Rank: 3.07 SS: 0.42



Best model: KAERI-2:
Rank_KS: 3.93 Rank: 3.02 SS: 0.84
Best ensemble: CTBTO1 + KAERI-4:
Rank_KS: 4.08 Rank: 3.20 SS: 0.93



Best model: KAERI-1:
Rank_KS: 3.94 Rank: 3.14 SS: 0.89
Best ensemble: CMC-2 + KAERI-4:
Rank_KS: 4.20 Rank: 3.26 SS: 0.87



Best model: CMC-3:
Rank_KS: 3.66 Rank: 2.88 SS: 0.58
Best ensemble CMC-1 + CMC-3 + CTBTO + CTBTO1 + IRSN + LLNL + NOAA-ARL-1 + NOAA-ARL-3:
Rank_KS: 4.00 Rank: 3.13 SS: 0.91

A sophisticated analysis performed by the Joint Research Center is currently on its way.

Optimum ensemble outperforms full ensemble for all stations according to all metrics within training period (20140701-20140901)

Evaluation period (20140901-20141001):

CAX17:
Best/full ensemble: Rank_KS: 4.06/4.00 Rank: 3.13/3.11 SS: 0.47/0.60
DEX33:
Best/full ensemble: Rank_KS: 3.19/2.53 Rank: 2.61/2.20 SS: 0.41/0.23
SEX63:
Best/full ensemble: Rank_KS: 3.78/3.73 Rank: 2.96/2.90 SS: 0.24/0.21
USX75:
Best/full ensemble: Rank_KS: 4.02/4.10 Rank: 3.23/3.27 SS: 0.54/0.54

8.1 Conclusions

- A **huge data pool** of modelling results has been created. Please request it from ZAMG/CTBTO (i.e., contact christian.maurer@zamg.ac.at and jolanta.kusmierczyk-michulec@ctbto.org). A **more thorough statistical analysis** (Phd?) would be **desirable**.

- It seems to be **important to select samples appropriately to demonstrate an – on average – small added value of stack emissions from IRE and CNL alone.** However, there is **considerable benefit from these stack data for individual samples.**

- It is interesting to note that **the mere selection of samples partly** (at least to 50%) **or predominantly** (at least to 80%) **influenced by IRE and/or CNL pushes the scores up most**. The relative **increase in scores** on average adds up to **~15%** when **switching from all above MDC samples to those with 50% or 80% IRE and/or CNL influence using literature emissions** compared to **7% when additionally switching from literature to stack emissions for 50% or 80% influence samples**. This demonstrates that 1) **knowing a large emitter and its location** as well as 2) **a proper average emission** is **more important than** knowing the **exact emission profile**. Implicitly suppressing samples with overprediction > 50% or 20% in the sample selection process (via an absolute difference metric) can further enhance the scores which demonstrates the effects of the transport error on scores.

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8.2 Conclusions II

- **Simulating the radioxenon background at CAX17 without selecting samples according to CNL influence** seems to be **especially promising** since CAX17 is a remote station with (at the time of 2014) dominating CNL influence.

- It seems to be **very important to gain more knowledge about non IRE- and CNL-related emissions** (for 2014). These **emissions may be small** individually (but can also be big, see MIPF Dimtrovgrad for SEX63), **but** in any case their **sum** (e.g., for DEX33) – **depending on the predominant synoptic situation – is a decisive factor** in accurately predicting the radioxenon background at IMS stations.

- The existent, **full ensemble is highly redundant**. If individual members cannot be made more diverse, **a few submissions are good enough to forecast the Xe-133 background**. This characteristic is related, e.g., to dominating transport models (FLEXPART & HYSPLIT), dominant meteorological input (ECMWF-IFS, NCEP-GFS) or to the fact that meteorological input consists of analyses concatenated with short-term forecasts thus reducing forecast uncertainty. **The effective ensemble size is below five**, however, depending on the station investigated, the time period considered and the individual members involved.

- A preliminary study shows that a **reduced, optimized ensemble at each station has slightly higher skill compared to the full ensemble also for an independent evaluation period**.

5. References

- P.W. Eslinger, T.W. Bowyer, P. Achim, T. Chai, B. Deconninck, K. Freeman, S. Generoso, P. Hayes, V. Heidmann, I. Hoffman, Y. Kijima, M. Krysta, A. Malo, C. Maurer, F. Ngan, P. Robins, J.O. Ross, O. Saunier, C. Schlosser, M. Schoeppner, B.T. Schrom, P. Seibert, A.F. Stein, K. Ungar, J. Yi (2016): International challenge to predict the impact of radioxenon releases from medical isotope production on a comprehensive nuclear test ban treaty sampling station*. Journal of Environmental Radioactivity* **157**, 41-51, https://doi.org/10.1016/j.jenvrad.2016.03.001

- C. Maurer, J. Baré, J. Kusmierczyk-Michulec, A. Crawford, P.W. Eslinger, P. Seibert, B. Orr, A. Philipp, O. Ross, S. Generoso, P. Achim, M. Schoeppner, A. Malo, A. Ringbom, O. Saunier, D. Quèlo, A. Mathieu, Y. Kijima, A. Stein, T. Chai, F. Ngan, S.J. Leadbetter, P. De Meutter, A. Delcloo, R. Britton, A. Davies, L.G. Glascoe, D.D. Lucas, M.D. Simpson, P. Vogt, M. Kalinowski, T.W. Bowyer (2018): International challenge to model the long-range transport of radioxenon released from medical isotope production to six Comprehensive Nuclear Test-Ban Treaty monitoring stations. *Journal of Environmental Radioactivity* **192**, 667 – 686, https://doi:10.1016/j.jenvrad.2018.01.030

- vDEC-Virtual Data Exploitation Centre. CTBTO, https://www.ctbto.org/specials/vdec/

THANK YOU FOR YOUR ATTENTION!

Auxiliary material

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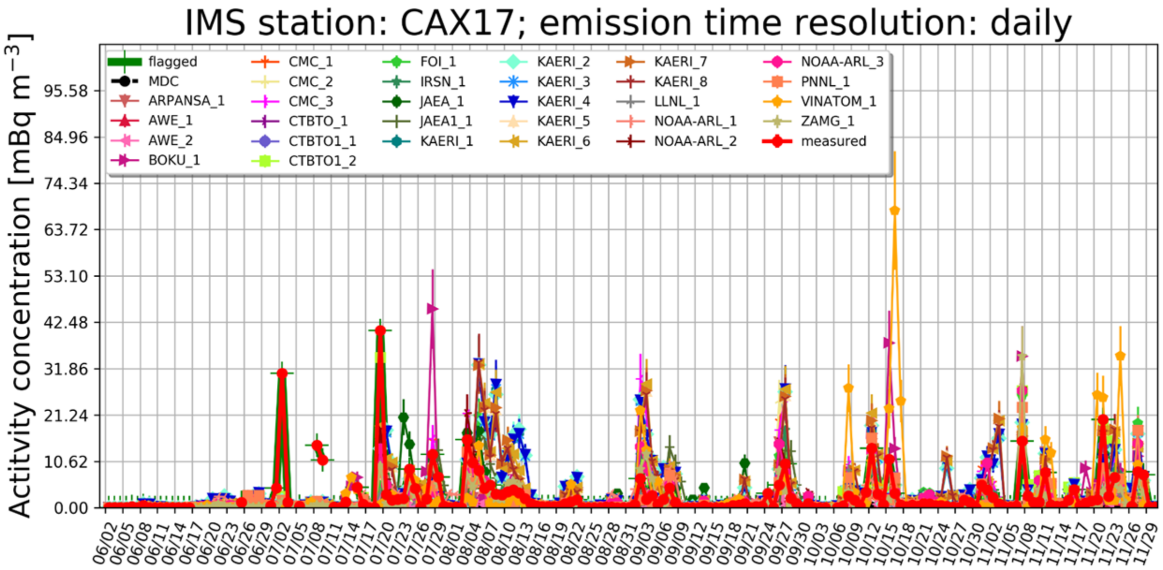
An example: Time series for CAX17

- A lot of valuable data for half a year
- 28 to 31 runs per station (CAX17, DEX33, SEX63 & USX75)



- **Ensemble approach** has started: Appropriate files were sent to S. Galmarini (JRC, ensemble expert). **Results will demonstrate how much independent and redundant information is inherent in the runs.**

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Correcting DEX33 results to STP conditions

- CTBTO-IMS Xe-measurements are valid with respect to STP (standard temperature and pressure, T = 288.15 K, p =1013.25 hPa)
- All but BOKU and VINATOM submissions were referenced to ambient conditions -> simulations at DEX33 (~1200 m a.s.l.) are biased low due to reduced air density.
- Rough correction of activity concentrations via multiplying with the density quotient of STP density and average ambient density in the respective output layer.
- Average ambient density in the output layer calculated according to:

$$\rho = \rho_0 (T_0/(T_0 + \gamma h))^{(1+g_0 M/R\gamma)} \qquad (1)$$

$\rho_0 = 1.225\ \mathrm{kg/m^3}$, $T_0 = 288.15\ \mathrm{K}$, $\gamma =$ -0.0065 K/m, $R = 8.314\ \mathrm{kg\,m^2/K\,mol\,s^2}$,
$M = 0.029\ \mathrm{kg/mol}$, $g_0 = 9.81\ \mathrm{m/s^2}$

- **Correction on average improves scores just slightly (7% for one metric).**
- Not unexpected, a positive effect is only pronounced for those runs, where upper output layers were sampled (e.g., ZAMG and CMC runs) and not just the first 100 or 200 m above model topography.

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Different approaches for selecting samples

Hypothesis: Benefit of stack emission data depends on the samples selected

Selection methods applied:

- (1) $\frac{|\,measurement - MIPFs' \; contribution|}{measurement} \leq 50\% \; or \; 80\%$

or (1a) $\frac{measurement - MIPFs' \; contribution}{measurement} \leq 50\% \; or \; 80\%$

Contributions are calculated based on (A1) FLEXPART V9 bwd runs or a (B1 & B1a) FLEXPART V9-CTBTO fwd run and (A1) 1° or (B1 & B1a) 0.5° meteorological input and output resolution (operational CTBTO/IDC set-up as of 2014 or set-up for 3rd ATM-Challenge 2019).

- (2) $\frac{NPPs' + NRRs' + other \; facilities' \; contributions}{simulated \; value} \leq 50\% \; or \; 80\%$

Contributions are calculated based on a FLEXPART V9-CTBTO fwd run and 0.5° meteorological input and output resolution (set-up for 3rd ATM-Challenge 2019).

- (3) Select subjectively a few outstanding daily stack emissions (outstanding with respect to the mean daily value as deduced from disaggregating the annual sum) and related samples predicted by the CTBTO fwd run.

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A detailed look on the scores: all stations

Table 1: Average statistics per institution over all stations over all and for individual run-IDs ordered by Rank

Institution	R	FB	F5 [%]	RMSE	NMSE	KS [%]	ACC [%]	NAAD [%]	CRmax ($\hat{t}$)	Rank	Rank KS	SS
AWE-1	0.18	-1.07	30	5.17	40	47	51	99	0.18 (-1)	**1.30**	**1.83**	**0.19**
AWE	0.16	-0.63	36	7.01	31	44	58	294	0.18 (-1)	**1.45**	**2.01**	**0.20**
AWE-2	0.14	-0.18	41	8.84	22	40	65	489	0.19 (-1)	**1.59**	**2.19**	**0.22**
LLNL	0.35	-0.51	63	4.52	11	33	66	92	0.35 (0)	**2.09**	**2.77**	**0.27**
FOI	0.36	-0.20	60	4.81	9	28	67	108	0.36 (-1)	**2.15**	**2.88**	**0.39**
VINATOM	0.27	0.48	56	11.80	18	21	70	181	0.27 (0)	**2.16**	**2.95**	**0.46**
PNNL	0.35	-0.20	60	4.61	8	34	69	100	0.35 (0)	**2.18**	**2.84**	**0.40**
JAEA	0.40	-0.15	61	4.37	6	25	65	101	0.40 (0)	**2.19**	**2.93**	**0.45**
CTBTO	0.47	-0.57	65	2.79	5	31	66	76	0.49 (0)	**2.25**	**2.94**	**0.45**
ARPANSA-1	0.41	-0.55	68	4.58	10	24	68	76	0.44 (-1)	**2.28**	**3.04**	**0.37**
ARPANSA	0.47	-0.57	70	3.90	9	25	67	74	0.49 (-1)	**2.33**	**3.09**	**0.35**
BOKU	0.32	-0.12	69	5.29	9	17	72	98	0.32 (0)	**2.38**	**3.21**	**0.58**
KAERI-6	0.39	0.34	67	5.71	7	24	75	132	0.41 (-1)	**2.40**	**3.17**	**0.62**
KAERI-5	0.37	0.30	68	5.76	7	22	75	126	0.40 (-1)	**2.42**	**3.21**	**0.62**
ZAMG	0.48	-0.44	70	4.19	8	25	71	70	0.48 (0)	**2.45**	**3.20**	**0.49**
KAERI-8	0.40	0.23	69	5.73	8	19	74	117	0.43 (-1)	**2.46**	**3.27**	**0.61**
KAERI-7	0.39	0.27	69	5.69	7	21	75	119	0.42 (-1)	**2.46**	**3.26**	**0.62**
JAEA1	0.45	0.05	71	4.10	4	18	73	108	0.54 (0)	**2.47**	**3.30**	**0.55**
NOAA-ARL-1	0.41	-0.00	69	4.76	6	28	76	91	0.42 (0)	**2.51**	**3.23**	**0.50**
NOAA-ARL	0.44	-0.23	71	4.56	8	24	75	79	0.46 (-1)	**2.52**	**3.28**	**0.49**
NOAA-ARL-3	0.47	-0.39	73	4.44	9	23	75	71	0.49 (-1)	**2.52**	**3.29**	**0.45**
KAERI	0.43	0.25	70	5.24	6	20	77	111	0.44 (-1)	**2.52**	**3.32**	**0.61**
NOAA-ARL-2	0.45	-0.30	72	4.49	8	22	75	74	0.49 (-2)	**2.53**	**3.31**	**0.52**
ARPANSA-2	0.70	-0.67	74	1.18	4	28	65	65	0.70 (0)	**2.56**	**3.28**	**0.26**
CTBTO1-1	0.48	0.07	72	5.20	11	16	78	100	0.49 (0)	**2.56**	**3.41**	**0.47**
CMC-3	0.43	0.03	76	4.47	6	21	78	92	0.43 (0)	**2.59**	**3.38**	**0.55**
KAERI-2	0.47	0.25	72	4.77	5	22	78	103	0.47 (0)	**2.60**	**3.38**	**0.60**
KAERI-4	0.48	0.19	72	4.75	5	19	79	98	0.48 (0)	**2.61**	**3.42**	**0.58**
KAERI-3	0.47	0.21	72	4.75	5	19	79	99	0.47 (0)	**2.61**	**3.42**	**0.60**
KAERI-1	0.47	0.19	73	4.73	5	18	79	96	0.47 (0)	**2.62**	**3.44**	**0.61**
CMC	0.48	-0.09	78	4.35	6	17	80	79	0.48 (0)	**2.68**	**3.51**	**0.56**
CTBTO1	0.51	0.03	74	4.34	8	15	79	89	0.52 (0)	**2.69**	**3.54**	**0.60**
IRSN	0.53	-0.36	77	4.00	7	14	78	66	0.53 (0)	**2.70**	**3.56**	**0.48**
CMC-1	0.50	-0.03	77	4.20	5	18	80	79	0.50 (0)	**2.72**	**3.54**	**0.60**
CMC-2	0.49	-0.28	80	4.38	7	12	81	67	0.49 (0)	**2.74**	**3.61**	**0.55**
CTBTO1-2	0.58	-0.05	78	2.63	3	13	82	69	0.58 (0)	**2.94**	**3.81**	**0.86**
Average over all institutions	**0.40**	**-0.20**	**66**	**4.99**	**10**	**24**	**71**	**108**	**0.42 (-1)**	**2.33**	**3.08**	**0.46**
Median over all institutions	**0.44**	**-0.20**	**69**	**4.44**	**8**	**24**	**70**	**95**	**0.45 (0)**	**2.35**	**3.14**	**0.47**
Maximum over all institutions	**0.53**	**0.48**	**78**	**11.80**	**31**	**44**	**80**	**294**	**0.54 (0)**	**2.70**	**3.56**	**0.61**
Minimum over all institutions	**0.16**	**-0.63**	**36**	**2.79**	**4**	**14**	**58**	**66**	**0.18 (-1)**	**1.45**	**2.01**	**0.20**

Ranking according to one metric does not necessarily do justice to the submissions!

Average Rank of **2nd ATM-Challenge** was **2.06**.
However, the **metrics of the two Challenges should not be compared** because of different:

- participants, model set-ups (uniform vs. non-uniform output grid!), model versions
- coverage of seasons, hemispheres
- number of samples above MDC for the 2nd Challenge (very low)

Results of the 3rd ATM-Challenge 2019

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A detailed look on the scores: CAX17

Table 2: Average statistics and individual statistics for station CAX17 per institution over all run-IDs and for individual run-IDs ordered by Rank

Institution	R	FB	F5 [%]	RMSE	NMSE	KS [%]	ACC [%]	NAAD [%]	CRmax ($\hat{t}$)	Rank	Rank KS	SS
AWE-1	0.42	-1.46	23	5.25	25	46	54	86	0.42 (0)	**1.22**	**1.76**	**0.12**
AWE	0.43	-1.41	28	5.21	23	45	58	85	0.43 (0)	**1.33**	**1.89**	**0.13**
AWE-2	0.44	-1.37	32	5.17	20	43	61	83	0.44 (0)	**1.44**	**2.01**	**0.13**
JAEA1	0.12	-0.04	52	6.99	5	7	68	112	0.44 (-1)	**2.19**	**3.12**	**0.74**
LLNL	0.47	-0.89	74	4.87	9	29	78	69	0.47 (0)	**2.29**	**3.00**	**0.24**
VINATOM	0.23	0.03	54	8.04	9	21	74	111	0.23 (0)	**2.32**	**3.11**	**0.77**
CTBTO	0.48	-0.74	71	5.63	7	22	79	69	0.48 (0)	**2.36**	**3.14**	**0.25**
JAEA	0.42	-0.08	59	5.89	4	7	73	87	0.42 (0)	**2.45**	**3.38**	**0.79**
KAERI-4	0.43	0.46	69	6.38	4	14	88	125	0.43 (0)	**2.51**	**3.37**	**0.50**
KAERI-1	0.43	0.46	69	6.32	4	14	87	124	0.43 (0)	**2.52**	**3.38**	**0.51**
KAERI-3	0.43	0.46	70	6.32	4	14	87	124	0.43 (0)	**2.52**	**3.38**	**0.51**
KAERI-2	0.44	0.47	70	6.32	4	14	87	125	0.44 (0)	**2.52**	**3.38**	**0.50**
KAERI	0.45	0.42	71	6.22	4	13	87	118	0.45 (0)	**2.57**	**3.45**	**0.53**
KAERI-6	0.47	0.41	71	6.25	4	11	87	114	0.47 (0)	**2.60**	**3.49**	**0.54**
FOI	0.48	-0.34	75	4.79	5	16	80	69	0.48 (0)	**2.61**	**3.45**	**0.57**
PNNL	0.59	-0.53	70	4.31	5	18	83	63	0.59 (0)	**2.62**	**3.44**	**0.45**
KAERI-5	0.46	0.37	72	6.10	4	11	88	111	0.46 (0)	**2.62**	**3.51**	**0.57**
BOKU	0.37	-0.12	73	6.19	6	11	82	90	0.37 (0)	**2.63**	**3.52**	**0.77**
KAERI-7	0.47	0.37	72	6.09	4	11	88	111	0.47 (0)	**2.63**	**3.52**	**0.57**
ZAMG	0.53	-0.42	79	4.58	5	20	80	64	0.53 (0)	**2.66**	**3.46**	**0.52**
KAERI-8	0.46	0.34	73	5.98	4	11	89	109	0.46 (0)	**2.66**	**3.55**	**0.59**
ARPANSA	0.59	-0.39	78	4.28	4	13	83	65	0.59 (0)	**2.76**	**3.63**	**0.54**
NOAA-ARL-3	0.60	-0.31	79	4.24	4	12	84	63	0.60 (0)	**2.84**	**3.72**	**0.61**
NOAA-ARL-1	0.63	-0.08	70	4.11	3	26	79	72	0.63 (0)	**2.85**	**3.59**	**0.72**
NOAA-ARL	0.62	-0.20	76	4.16	3	17	83	66	0.62 (0)	**2.87**	**3.71**	**0.69**
NOAA-ARL-2	0.64	-0.21	79	4.12	3	12	84	63	0.64 (0)	**2.94**	**3.82**	**0.74**
CMC-2	0.56	-0.13	87	4.45	3	6	89	64	0.56 (0)	**3.01**	**3.95**	**0.80**
IRSN	0.62	-0.20	84	4.09	3	5	89	59	0.62 (0)	**3.02**	**3.97**	**0.71**
CMC-3	0.56	0.03	87	4.85	3	6	91	71	0.56 (0)	**3.07**	**4.01**	**0.89**
CMC	0.57	-0.03	88	4.59	3	5	91	68	0.57 (0)	**3.09**	**4.04**	**0.86**
CTBTO1-1	0.74	-0.15	79	3.53	2	11	87	58	0.74 (0)	**3.13**	**4.02**	**0.83**
CTBTO1	0.74	-0.12	79	3.53	2	10	87	58	0.74 (0)	**3.15**	**4.05**	**0.86**
CMC-1	0.60	0.01	90	4.47	3	3	93	68	0.60 (0)	**3.17**	**4.14**	**0.90**
CTBTO1-2	0.75	-0.09	79	3.53	2	9	88	58	0.75 (0)	**3.18**	**4.09**	**0.89**
Average over all institutions	**0.48**	**-0.32**	**69**	**5.21**	**6**	**16**	**80**	**78**	**0.50 (-1)**	2.56	3.40	0.59
Median over all institutions	**0.48**	**-0.20**	**74**	**4.83**	**5**	**15**	**81**	**69**	**0.48 (0)**	2.61	3.45	0.63
Maximum over all institutions	**0.74**	**0.42**	**88**	**8.04**	**23**	**45**	**91**	**118**	**0.74 (0)**	3.15	4.05	0.86
Minimum over all institutions	**0.12**	**-1.41**	**28**	**3.53**	**2**	**5**	**58**	**58**	**0.23 (-1)**	1.33	1.89	0.13

However, the highest Ranks tend to come with high „Seibert Scores“

Results of the 3rd ATM-Challenge 2019

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A detailed look on the scores: DEX33

Table 3: Average statistics and individual statistics for station DEX33 per institution over all run-IDs and for individual run-IDs ordered by Rank

Institution	R	FB	F5 [%]	RMSE	NMSE	KS [%]	ACC [%]	NAAD [%]	CRmax ($\hat{t}$)	Rank	Rank_KS	SS
AWE-2	-0.17	1.79	10	16.44	22	90	63	1682	-0.07 (-3)	**0.87**	**0.97**	**0.04**
AWE	-0.13	0.99	34	9.03	13	61	64	903	-0.08 (-2)	**1.51**	**1.90**	**0.28**
VINATOM	-0.02	1.02	48	4.08	8	32	64	296	-0.02 (0)	**1.61**	**2.29**	**0.16**
FOI	0.16	0.72	45	3.01	6	29	57	213	0.16 (0)	**1.69**	**2.40**	**0.27**
PNNL	0.10	0.71	55	2.01	3	50	65	176	0.10 (0)	**1.85**	**2.35**	**0.36**
CMC-3	0.25	0.72	59	1.97	3	47	66	159	0.25 (0)	**1.95**	**2.48**	**0.39**
KAERI-6	0.45	0.98	58	2.78	4	48	66	223	0.45 (0)	**1.95**	**2.47**	**0.30**
LLNL	0.08	0.47	60	1.79	3	30	64	145	0.08 (0)	**2.01**	**2.71**	**0.41**
KAERI-5	0.39	0.87	62	2.98	5	36	69	203	0.39 (0)	**2.02**	**2.66**	**0.27**
JAEA	0.46	-0.71	65	1.60	4	39	59	70	0.46 (0)	**2.10**	**2.71**	**0.30**
ARPANSA-1	0.42	-0.55	66	1.31	4	19	58	81	0.42 (0)	**2.14**	**2.95**	**0.29**
AWE-1	-0.10	0.18	58	1.62	3	32	64	123	-0.10 (0)	**2.14**	**2.82**	**0.52**
CTBTO1-1	0.36	0.77	72	4.48	13	16	74	167	0.37 (3)	**2.20**	**3.04**	**0.17**
KAERI-7	0.47	0.78	68	2.70	5	33	69	174	0.47 (0)	**2.20**	**2.87**	**0.30**
KAERI-8	0.50	0.71	68	3.02	6	25	65	169	0.50 (0)	**2.22**	**2.97**	**0.27**
KAERI	0.55	0.70	63	2.10	3	38	67	153	0.55 (0)	**2.26**	**2.88**	**0.41**
BOKU	0.30	0.33	70	1.93	4	16	64	121	0.30 (0)	**2.26**	**3.10**	**0.55**
CMC-1	0.49	0.43	61	1.34	2	38	69	110	0.49 (0)	**2.32**	**2.94**	**0.51**
KAERI-2	0.63	0.66	60	1.43	2	50	66	129	0.63 (0)	**2.34**	**2.84**	**0.50**
ARPANSA	0.56	-0.61	70	1.24	4	24	62	73	0.56 (0)	**2.35**	**3.11**	**0.27**
CMC	0.44	0.34	67	1.48	2	31	72	111	0.44 (0)	**2.39**	**3.09**	**0.54**
KAERI-3	0.64	0.56	62	1.34	1	39	68	113	0.64 (0)	**2.43**	**3.04**	**0.53**
NOAA-ARL-1	0.54	0.37	65	1.23	2	49	68	104	0.54 (0)	**2.43**	**2.94**	**0.44**
CTBTO1	0.38	0.38	74	3.11	9	17	75	123	0.39 (1)	**2.45**	**3.28**	**0.50**
KAERI-4	0.65	0.53	62	1.31	1	37	67	109	0.65 (0)	**2.45**	**3.08**	**0.54**
KAERI-1	0.63	0.47	64	1.25	1	36	68	103	0.63 (0)	**2.49**	**3.13**	**0.56**
NOAA-ARL	0.55	0.15	64	1.19	2	36	68	89	0.55 (0)	**2.54**	**3.18**	**0.65**
ARPANSA-2	0.70	-0.67	74	1.18	4	28	65	65	0.70 (0)	**2.56**	**3.28**	**0.26**
NOAA-ARL-2	0.54	0.06	63	1.17	2	29	67	83	0.54 (0)	**2.57**	**3.28**	**0.75**
CTBTO	0.34	-0.11	78	1.64	2	21	73	84	0.34 (0)	**2.58**	**3.37**	**0.74**
ZAMG	0.50	-0.25	74	1.28	3	18	73	71	0.50 (0)	**2.59**	**3.41**	**0.65**
IRSN	0.51	-0.25	75	1.21	3	7	73	70	0.51 (0)	**2.61**	**3.54**	**0.53**
NOAA-ARL-3	0.55	0.03	65	1.16	2	31	69	80	0.55 (0)	**2.63**	**3.32**	**0.75**
CTBTO1-2	0.41	-0.01	77	1.73	4	17	76	79	0.41 (0)	**2.69**	**3.52**	**0.84**
JAEA1	0.61	-0.23	86	1.37	2	23	72	61	0.61 (0)	**2.83**	**3.60**	**0.71**
CMC-2	0.60	-0.14	81	1.12	2	7	81	64	0.60 (0)	**2.91**	**3.84**	**0.72**
Average over all institutions	**0.34**	**0.23**	**64**	**2.38**	**4**	**29**	**67**	**172**	**0.34 (-1)**	**2.23**	**2.93**	**0.46**
Median over all institutions	**0.41**	**0.33**	**66**	**1.71**	**3**	**30**	**66**	**116**	**0.42 (0)**	**2.31**	**3.09**	**0.46**
Maximum over all institutions	**0.61**	**1.02**	**86**	**9.03**	**13**	**61**	**75**	**903**	**0.61 (1)**	**2.83**	**3.60**	**0.74**
Minimum over all institutions	**-0.13**	**-0.71**	**34**	**1.19**	**2**	**7**	**57**	**61**	**-0.08 (-2)**	**1.51**	**1.90**	**0.16**

Results of the 3rd ATM-Challenge 2019

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A detailed look on the scores: SEX63

Table 4: Average statistics and individual statistics for station SEX63 per institution over all run-IDs and for individual run-IDs ordered by Rank

Institution	R	FB	F5 [%]	RMSE	NMSE	KS [%]	ACC [%]	NAAD [%]	CRmax ($\hat{t}$)	**Rank**	**Rank KS**	**SS**
AWE-1	0.17	-1.63	19	2.22	63	61	38	91	0.17 (0)	**0.78**	**1.17**	**0.03**
AWE	0.12	-0.90	41	2.26	35	35	51	95	0.17 (0)	**1.48**	**2.14**	**0.31**
LLNL	0.19	-0.88	65	2.14	15	40	60	76	0.19 (0)	**1.84**	**2.44**	**0.15**
CTBTO	0.50	-0.89	61	0.93	4	42	51	73	0.60 (1)	**1.93**	**2.51**	**0.29**
FOI	0.17	-0.74	66	2.16	13	34	65	78	0.17 (0)	**1.97**	**2.63**	**0.21**
PNNL	0.17	-0.63	65	2.17	12	32	64	78	0.17 (0)	**2.00**	**2.68**	**0.25**
ARPANSA	0.19	-0.67	73	2.17	12	31	65	77	0.19 (0)	**2.09**	**2.78**	**0.26**
ZAMG	0.21	-0.57	72	2.17	11	30	66	75	0.21 (0)	**2.14**	**2.84**	**0.31**
JAEA	0.38	-0.44	63	0.99	3	27	59	80	0.38 (0)	**2.15**	**2.88**	**0.49**
AWE-2	0.08	-0.16	62	2.31	8	8	64	98	0.17 (1)	**2.18**	**3.10**	**0.59**
VINATOM	0.21	0.13	64	2.91	10	18	68	120	0.21 (0)	**2.30**	**3.12**	**0.72**
BOKU	0.17	-0.26	73	2.30	9	19	71	89	0.17 (2)	**2.34**	**3.15**	**0.54**
NOAA-ARL-1	0.22	-0.45	78	2.07	9	15	78	68	0.22 (0)	**2.38**	**3.23**	**0.22**
IRSN	0.22	-0.49	80	2.14	10	20	78	69	0.22 (0)	**2.38**	**3.18**	**0.32**
NOAA-ARL-3	0.23	-0.56	84	2.08	10	21	78	67	0.23 (0)	**2.40**	**3.19**	**0.21**
NOAA-ARL	0.21	-0.50	82	2.10	9	18	78	68	0.21 (-2)	**2.40**	**3.22**	**0.24**
NOAA-ARL-2	0.18	-0.48	83	2.14	10	18	79	70	0.19 (-4)	**2.41**	**3.23**	**0.29**
CMC-2	0.25	-0.44	81	2.06	9	16	77	66	0.25 (0)	**2.43**	**3.27**	**0.30**
CMC-3	0.24	-0.33	78	2.09	8	14	78	69	0.24 (0)	**2.46**	**3.32**	**0.41**
CMC	0.25	-0.35	80	2.08	8	14	78	68	0.25 (0)	**2.46**	**3.31**	**0.39**
CMC-1	0.25	-0.29	79	2.09	8	13	78	69	0.25 (0)	**2.49**	**3.36**	**0.44**
JAEA1	0.49	-0.45	79	0.89	2	19	69	65	0.49 (0)	**2.49**	**3.30**	**0.50**
CTBTO1	0.16	0.26	79	3.82	15	8	82	104	0.20 (-1)	**2.50**	**3.42**	**0.52**
KAERI-7	0.18	-0.01	74	2.42	8	11	75	93	0.18 (0)	**2.52**	**3.41**	**0.78**
KAERI-8	0.18	-0.02	75	2.42	8	13	76	93	0.18 (0)	**2.53**	**3.40**	**0.78**
KAERI-5	0.19	-0.01	75	2.36	7	12	76	92	0.19 (0)	**2.54**	**3.42**	**0.77**
KAERI-6	0.18	0.01	75	2.42	8	10	77	93	0.18 (0)	**2.55**	**3.45**	**0.78**
KAERI	0.19	0.01	77	2.33	7	10	79	89	0.19 (0)	**2.59**	**3.49**	**0.76**
KAERI-1	0.20	0.03	78	2.25	6	7	82	86	0.20 (0)	**2.63**	**3.56**	**0.74**
KAERI-3	0.19	0.02	79	2.25	6	7	82	85	0.19 (0)	**2.64**	**3.57**	**0.74**
KAERI-4	0.19	0.03	79	2.26	6	8	82	86	0.19 (0)	**2.64**	**3.56**	**0.74**
KAERI-2	0.20	0.03	80	2.24	6	8	83	85	0.20 (0)	**2.65**	**3.57**	**0.74**
Average over all institutions	**0.24**	**-0.46**	**70**	**2.10**	**11**	**25**	**68**	**82**	**0.25 (0)**	2.19	2.94	0.39
Median over all institutions	**0.20**	**-0.49**	**73**	**2.16**	**10**	**24**	**67**	**77**	**0.21 (0)**	2.23	3.00	0.32
Maximum over all institutions	**0.50**	**0.26**	**82**	**3.82**	**35**	**42**	**82**	**120**	**0.60 (2)**	2.59	3.49	0.76
Minimum over all institutions	**0.12**	**-0.90**	**41**	**0.89**	**2**	**8**	**51**	**65**	**0.17 (-2)**	1.48	2.14	0.15

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A detailed look on the scores: USX75

Table 5: Average statistics and individual statistics for station USX75 per institution over all run-IDs and for individual run-IDs ordered by Rank

Institution	R	FB	F5 [%]	RMSE	NMSE	KS [%]	ACC [%]	NAAD [%]	CRmax ($\hat{t}$)	**Rank**	**Rank_KS**	**SS**
AWE-1	0.21	-1.39	21	11.60	71	50	48	95	0.21 (-1)	**1.04**	**1.54**	**0.09**
AWE	0.22	-1.19	40	11.53	54	34	61	94	0.22 (-1)	**1.46**	**2.12**	**0.10**
AWE-2	0.23	-0.99	58	11.45	37	18	73	93	0.23 (0)	**1.87**	**2.69**	**0.12**
JAEA	0.36	0.64	55	8.98	13	28	69	167	0.36 (0)	**2.05**	**2.77**	**0.22**
ARPANSA	0.45	-0.58	56	10.54	19	32	65	83	0.55 (-4)	**2.12**	**2.80**	**0.39**
CTBTO	0.54	-0.52	49	2.96	5	37	60	78	0.54 (0)	**2.13**	**2.76**	**0.51**
NOAA-ARL-2	0.43	-0.58	62	10.55	19	28	69	80	0.59 (-4)	**2.21**	**2.93**	**0.32**
NOAA-ARL-3	0.51	-0.71	63	10.26	21	28	69	74	0.57 (-4)	**2.22**	**2.94**	**0.22**
LLNL	0.66	-0.72	52	9.28	17	32	64	78	0.66 (0)	**2.24**	**2.92**	**0.29**
PNNL	0.52	-0.34	52	9.96	13	35	64	84	0.52 (0)	**2.26**	**2.91**	**0.53**
NOAA-ARL	0.40	-0.38	62	10.81	17	25	72	91	0.48 (-2)	**2.27**	**3.02**	**0.39**
BOKU	0.42	-0.43	61	10.75	17	22	71	94	0.42 (0)	**2.28**	**3.06**	**0.46**
FOI	0.60	-0.43	54	9.28	13	31	65	72	0.63 (-1)	**2.35**	**3.04**	**0.49**
JAEA1	0.56	0.91	67	7.16	6	22	84	193	0.61 (1)	**2.37**	**3.15**	**0.25**
NOAA-ARL-1	0.26	0.15	62	11.62	11	20	77	120	0.28 (2)	**2.38**	**3.18**	**0.62**
VINATOM	0.67	0.75	59	32.17	45	12	73	195	0.67 (0)	**2.39**	**3.27**	**0.20**
KAERI-8	0.44	-0.11	59	11.52	14	27	67	96	0.57 (-1)	**2.41**	**3.14**	**0.80**
ZAMG	0.67	-0.49	56	8.72	12	32	66	70	0.67 (0)	**2.42**	**3.10**	**0.47**
CTBTO1	0.67	-0.58	57	8.96	14	28	70	69	0.67 (0)	**2.42**	**3.14**	**0.38**
KAERI-7	0.45	-0.05	62	11.56	13	27	69	98	0.55 (-2)	**2.49**	**3.22**	**0.84**
KAERI-5	0.45	-0.04	62	11.62	13	27	69	99	0.55 (-2)	**2.50**	**3.23**	**0.85**
KAERI-6	0.45	-0.04	62	11.40	13	25	71	98	0.53 (-1)	**2.52**	**3.27**	**0.85**
CMC-2	0.56	-0.40	72	9.88	14	20	77	74	0.56 (0)	**2.60**	**3.40**	**0.36**
KAERI	0.54	-0.13	70	10.30	12	21	74	86	0.59 (-1)	**2.67**	**3.46**	**0.73**
IRSN	0.76	-0.48	71	8.56	11	24	73	64	0.76 (0)	**2.78**	**3.54**	**0.37**
CMC	0.64	-0.32	76	9.26	11	19	78	71	0.64 (0)	**2.79**	**3.61**	**0.46**
KAERI-4	0.65	-0.27	78	9.04	10	16	78	72	0.65 (0)	**2.84**	**3.68**	**0.54**
KAERI-3	0.63	-0.20	79	9.08	10	16	78	74	0.63 (0)	**2.86**	**3.70**	**0.63**
KAERI-1	0.63	-0.20	79	9.09	10	16	78	74	0.63 (0)	**2.86**	**3.70**	**0.63**
KAERI-2	0.63	-0.16	79	9.09	9	15	78	74	0.63 (0)	**2.88**	**3.73**	**0.68**
CMC-3	0.67	-0.29	78	8.98	10	18	79	69	0.67 (0)	**2.88**	**3.70**	**0.50**
CMC-1	0.68	-0.26	77	8.92	10	18	79	70	0.68 (0)	**2.90**	**3.72**	**0.53**
Average over all institutions	**0.54**	**-0.27**	**58**	**10.58**	**17**	**27**	**69**	**99**	**0.56 (-1)**	**2.31**	**3.04**	**0.39**
Median over all institutions	**0.55**	**-0.43**	**57**	**9.28**	**13**	**28**	**69**	**84**	**0.60 (0)**	**2.31**	**3.05**	**0.39**
Maximum over all institutions	**0.76**	**0.91**	**76**	**32.17**	**54**	**37**	**84**	**195**	**0.76 (1)**	**2.79**	**3.61**	**0.73**
Minimum over all institutions	**0.22**	**-1.19**	**40**	**2.96**	**5**	**12**	**60**	**64**	**0.22 (-4)**	**1.46**	**2.12**	**0.10**

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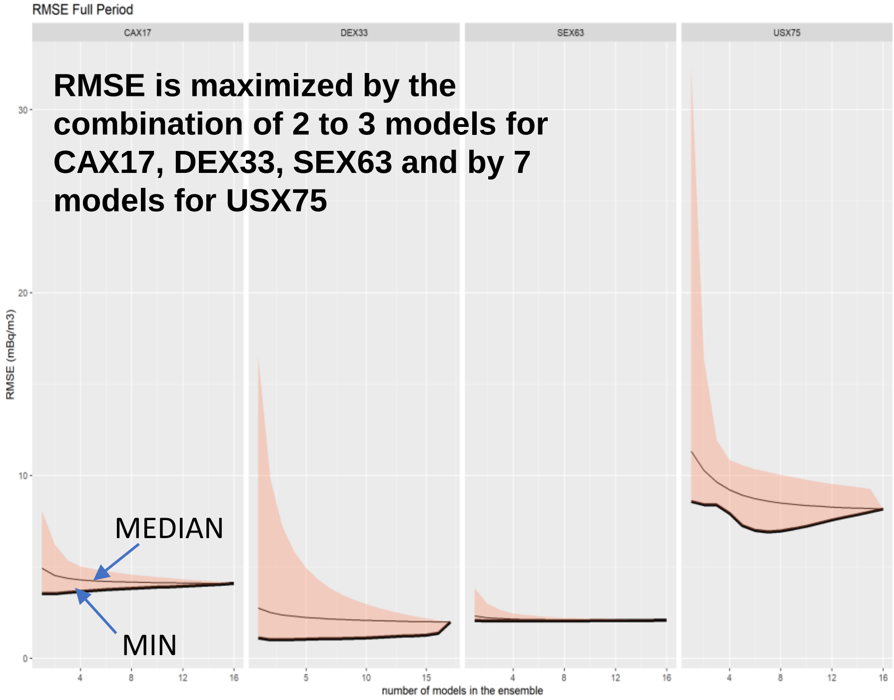
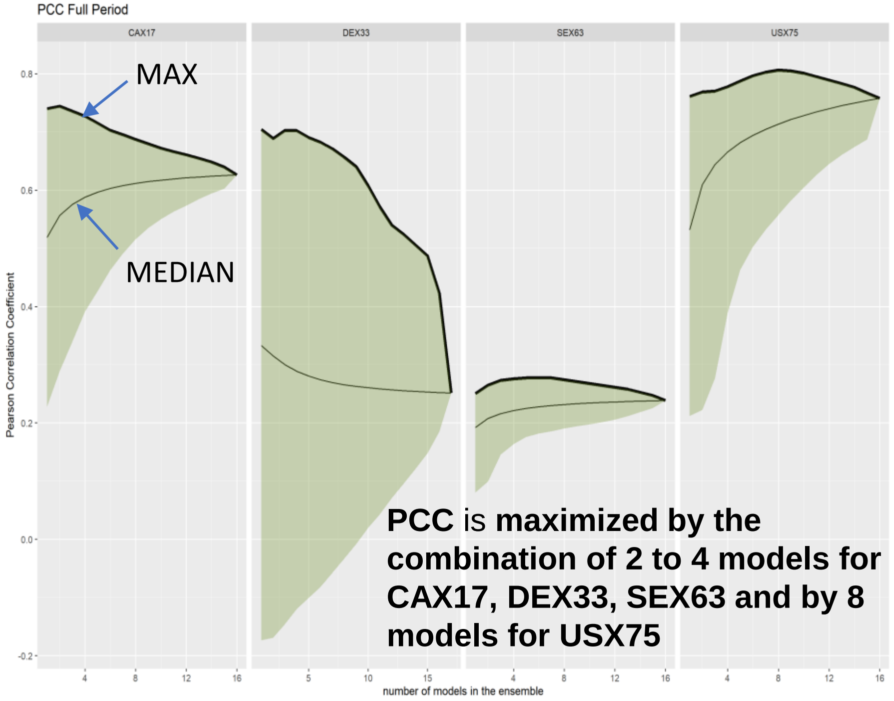
Ensemble optimisation based on RMSE and Pearson‘s correlation coefficient (PCC)





Analysis valid for the period 20140601 to 20141201. Number of involved members N reduced to 16 (one per participating institution) due to computational limitations. Given N members, there are G=N!/(r!(N-r)!) possible groups of r elements!

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Details on statistical metrics

Given N predictions P_j and measurements M_i at times t_j and t_i with mean values $\overline{P}$ and $\overline{M}$ as well as minimum detectable concentrations MDC_j and MDC_i the statistical scores in subsection 2.8 are formally defined as:

$$\mathrm{FB} = 2\frac{(\overline{P} - \overline{M})}{(\overline{P} + \overline{M})} \tag{A.1}$$

$$R = \frac{\sum (M_i - \overline{M})(P_i - \overline{P})}{\sqrt{(M_i - \overline{M})^2 (P_i - \overline{P})^2}} \tag{A.2}$$

Let T denote the number of fractions satisfying:

$$0.2 \le \frac{P_i}{M_{i|M_i > 0.0}} \le 5.0 \tag{A.7}$$

and Q the number of pairs with $P_{i|P_i \geq MDC_i}$ and/or $M_{i|M_i \geq MDC_i}$ then F5 is defined as:

$$\mathrm{F5} = \frac{T}{Q}100 \tag{A.8}$$

Given the number of correctly forecasted above MDC values A (true positives) and below MDC values B (true negatives) as well as the number of not correctly forecasted above MDC values (false positives) C and below MDC values D (false negatives), the Accuracy is given as:

$$\mathrm{ACC} = \frac{A + B}{A + B + C + D}100 \tag{9}$$

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Details on statistical metrics

The *Kolmogorov-Smirnov parameter* (KSP) is defined as:

$$\mathrm{KSP} = Max|D(M_k) - D(O_k)| * 100\% \tag{A.7}$$

where D is the cumulative distribution of the predicted and measured (or other predicted) concentrations over the range of k values such that D is the probability that the concentration will not exceed M_k or O_k. The score measures the ability of the model to reproduce the measured (or another predicted) concentration distribution regardless of space and time. The maximum difference between any two distributions cannot be more than 100%.

Further visual evaluations in Kioutsioukis and Galmarini [19] are based on comparing *Cumulative Density Functions (cdf)* of the models and the observations or on showing *Taylor diagrams* (i.e, a combination of correlation coefficient, root mean square error and standard deviation, Figure 2). The distance between the reference (black point in Figure 2) and model points in a Taylor diagram is then the BC_RMSE. According to Taylor [42] model standard deviation, BC_RMSE and R can be combined into a single skill score S_r.

$$S_r = 2(1+R)\left(\frac{\sigma_m}{\sigma_o} + \frac{\sigma_o}{\sigma_m}\right)^{-2} \tag{20}$$

with σ_m and σ_o being the standard deviations of predictions and observations.

The correlation contribution becomes important for large values of BC_RMSE. If one wants to include also the relative bias FB into the skill score, Seibert [34] suggests:

$$S_b = \frac{1}{1 + bFB^2} \tag{21}$$

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Details on statistical metrics

A value of $b = 10$ appears to give a relationship fulfilling Seibert's [34] subjective idea about such a skill score. Finally, both skill scores can be combined into a total skill score S:

$$S = \alpha S_r + (1 - \alpha) S_b \tag{22}$$

The value of α is rather arbitrary and would depend on the application. $\alpha = 0.5$ might be acceptable. An additive and not multiplicative combination of the two scores is suggested because a model that has skill either in reproducing the mean or in reproducing the patterns should be attributed some total skill; the product of the two scores would be zero with one of the factors being zero. In any case, data sets with strongly non-normal distributions might better be transformed before applying any of the measures.