Assimilation scenario for long-term deposition of ^{137}Cs

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I. Introduction

In the current state of development is software system HARP capable to model atmospheric dispersion of radioactive pollutants and subsequent dose distributions and health effects in the exposed population. Main objective is to improve reliability of the model predictions via advanced statistical techniques of assimilation of model results with observations from terrain. The aim is to develop modeling, simulation and educational tool with unified user-friendly graphical interface for utilization in radiation protection.

II. HARP system

The HARP system consists of three main parts: Atmospheric dispersion model (ADM), Dose model (DOS) and Food-chain model (FCM), more in [1]. In recent development of HARP were numerical algorithms modified from deterministic to their probabilistic versions, see [2]. Probabilistic version enables for sensitivity analysis, uncertainty analysis and also for statistical estimate of error covariance structure of generated data. The block diagram of system architecture is in the Fig. (1).

1. Assimilation submodule

Assimilation submodule offers comfortable graphical user interface for interactive insertion of data and its maintenance and evaluation. Numerical and assimilation subsystem have direct binding to visualization submodule (see Fig. (1)), so both modeled data and measurements can be easily visualized on relevant scalable map background. Evaluation of results is also supported by data tables and comparative graphs. Also access to ORACLE database of meteorological forecasts and measurement stations included in Radiation Monitoring Network of the Czech Republic is established there. In the current state of the art are implemented following assimilation algorithms: Interpolation procedures, successive corrections method, optimal interpolation and Kalman filter.

2. Atmospheric dispersion model

ADM in HARP is based on segmented Gaussian plume model (SGPM). The segmentation allows us to use different set of input parameters for each of the segments. In the current state of development the model has more than hundred input parameters and the most significant of them $P_1 - P_{12}$ (resulting from sensitivity analysis) are listed in Table (2.). In the table are distributions of random parameters multiplicatively applied to nominal values of input parameters in order to obtain probability distributions of those. Parameter distributions are expert-based estimates supplemented by measurements. The influence of the rest of model input parameters on variation of model output is assumed to be unimportant and these parameters are on input set to their best estimate values.

We divide the parameters into to groups: Local and global. The global parameters don't vary through the segments and remains same for all of them. Values of local parameters vary in time and/or with spatial location. SGPM enables to take into account realistic weather forecasts hourly provided by the Czech Hydro-Meteorological Institute. ADM also accounts for many factors affecting the plume

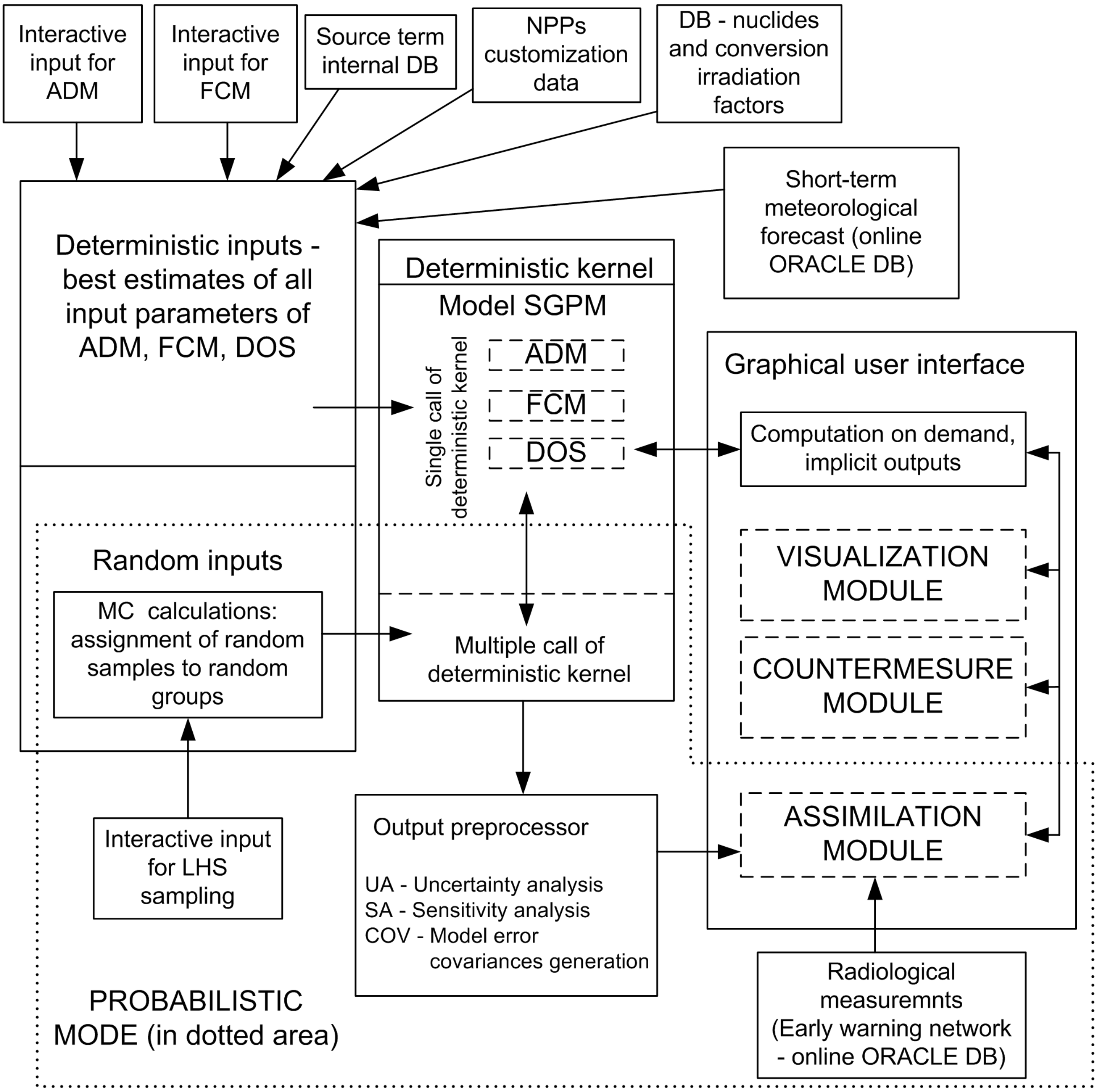

Figure 1: The architecture of the HARP system. Deterministic numerical kernel is interconnected to visualization and assimilation submodule via graphical user interface.

Table 1: The most significant parameter of ADM and distribution of multiplicative factors used for their generating from nominal values.

Variable	**G/L**	**Min**	**Mean**	**Max**	**Distribution**	σ
P_1 - intensity of release	G		1.0		normal	0.20
P_2 - horiz. dispersion	G		1.0		normal	0.13
P_3 - horiz. fluct. of wind dir.	L	-5	0	5	disc. uniform	
P_4 - dry deposition of elem.	G	0.41	1.0	1.6	uniform	
P_5 - dry deposition of aero.	G	0.41	1.0	1.6	uniform	
P_6 - elution of elem. iodine	G	0.2	1.0	5.0	log-uniform	
P_7 - elution of aero.	G	0.2	1.0	5.0	log-uniform	
P_8 - advection speed of plume	L	-1.0	0.0	1.0	uniform	
P_9 - wind profile	G	0.5	1.0	1.5	uniform	
P_{10} - vertical dispersion	G		1.0		normal	0.13
P_{11} - mixing layer height	G	0.6	1.175	1.75	uniform	
P_{12} - heat flux	G	0.0	0.5	1.0	uniform	

depletion (dry/wet deposition, influence of terrain type etc.).

III. Scenario for long-term deposition of ^{137}Cs over terrain

The plume moving over the terrain leaves behind a radioactive trace due to dry and wet activity deposition. Movement of a plume over observed area lasts usually few hours. When the plume leaves observed area, the trace represents an initial condition for prediction of further evolution of radiological situation on terrain. Our analyzed scenario starts just after the plume leaves the observed terrain. An emphasis is laid on prediction of long term evolution of radiological situation in time horizon of years up to tens of years. This knowledge is important for planning of long-term countermeasures relating to food-chain model, which is also a part of the HARP system.

The only nuclide assumed in this scenario is ^{137}Cs. As half-time to decay of ^{137}Cs is approximately 30 years, it is one of most significant and dominant source of radioactivity in long term scenarios.

Initial conditions (background field) for assimilation is given by the ADM when the radioactive plume is gone. As s model of radiation situation evolution is used the relation according to Eq. (3) from the OSCAAR model. The crucial task is to estimate error covariance structure of the model and the background field. As a first attempt, we are trying to estimate error covariance structure by Monte-Carlo approach as a sample covariance of a drawn sample of size $N \approx 10^3$. The sample was generated according to given probability distributions, see Table (1.).

Alternative way of estimation of error covariance structure could be a spatial filter widely used in meteorology because of high dimensionality of problems solved there. Spatial filters are based on assumption: The bigger distance between two points the smaller correlation between modeled/measured values in these points. This assumption is rather unrealistic and physically inexact and also denies one of major advantages of assimilation methods - embodying of physical information. Spatial filters for determination of correlation between points i and j proposed by Bergthorson and Doos are as follows:

$$\mathbf{P}_{ij}^f = exp\left[-\frac{r_{ij}^2}{L}\right] \tag{1}$$

$$\mathbf{P}_{ij}^f = (1 + \frac{r_{ij}}{L})exp\left[-\frac{r_{ij}}{L}\right] \tag{2}$$

where r_{ij} is the distance between the points and L is a chosen constant called radius of influence.

1. OSCAAR model

Abbreviation OSCAAR stands for Off-Site Consequence Analysis code for Atmospheric Releases in reactor accidents and it has been developed within the research activities on probabilistic safety assessment at the Japan Atomic Research Institute [3]. OSCAAR consists of a series of interlinked modules and that are used to calculate the atmospheric dispersion and deposition of selected radionuclides. In this work are adopted formulae and principles used in OSCAAR for prediction of dose rate due to long-term groundshine. It can be expressed by the Eq. (3).

$$D_s(t) = SD_k \cdot R(t) \cdot E(t) \cdot DF_g \cdot L \cdot \sum_i f_i \cdot (OF_i^{out} + OF_i^{in} \cdot SF) \tag{3}$$

The interpretation of terms in Eq. (3) is in the Table (2). The following exponential functions represent

Table 2: Interpretation of term in Eq. (3)

$D_g(t)$	dose rate on day t after deposition of a radionuclide ($Sv\ s^{-1}$)
SD_k	total deposition of the radionuclide at place k ($Bq\ m^{-2}$)
$R(t)$	factor to account for radioactive dacay occuring between the deposition and t
$E(t)$	factor to account for the environmental dacay of groundshine ($Sv\ s^{-1}\ perBq\ m^{-2}$)
DF_g	dose-rate conversion factor for groundshine
L	geometric factor ($\%$)
f_i	fraction of i-th occupation group ($\%$)
OF_i^{out}	outdoor occupancy factor for i-th occupation group ($\%$)
OF_i^{in}	indoor occupancy factor for i-th occupation group ($\%$)
SF	shielding factor for wooden of brick house ($\%$)

the two factors of $R(t)$ and $E(t)$ as a functions of time. The experiments had shown that the mitigation of groundshine due to environmental decay follows relation given by superposition of two exponentials (Eq. (5), (6)).

$$R(t) = exp(-ln2 \cdot \frac{t}{T_y}) \tag{4}$$

$$E(t) = d_f \cdot exp(-ln2 \cdot \frac{t}{T_{sf}}) + d_s \cdot exp(-ln2 \cdot \frac{t}{T_{ss}}) \tag{5}$$

where

$$d_f + d_s = 1 \tag{6}$$

Ground deposition model formulae are semi-empirical, it means that some of equation parameters are determined empiricaly upon measurements and the parameter values depend on the local conditions in the place of model application (soil type etc.). The dose conversion factor was calculated by the method of Kocher (1980) in which the exposed individual was assumed to stand on a smooth, infinite plane surface with uniform concentration of source of radioactivity. Data used in the groundshine dose calculations are given in Table (1.). The parameter distributions were determined for ^{137}Cs from Chernobyl disaster. The appropriate data for other elements are not available but it is assumed that the long-term influence of most of them is not significant. For elements with high half-time to decay are assumed the same equations of groundshine mitigation as for ^{137}Cs. As in the HARP, the approach used in OSCAAR adopted probabilistic methodology and it allows us to determine error covariance structure of the model. It is a necessary condition for application of advanced assimilation techniques to the model (Kalman filter, 4DVAR).

Table 3: Parameter values used for ground exposure calculations in OSCAAR model.

Variable	Mean	Min	Max	Distribution	Units
d_s	0.52	0.40	0.71	Uniform	-
T_{sf}	1.1	0.41	1.4	Uniform	y
T_{ss}	28	24.3	29.4	Uniform	y
L	0.45	0.2	0.7	Uniform	-
SF(wood)	0.52	0.26	0.78	Uniform	-
SF(brick)	0.2	0.1	0.3	Uniform	-
DF_g	5.86×10^{-16}	-	-		$Sv\, s^{-1}/Bq\, m^{-2}$

IV. Data assimilation

The goal of data assimilation is to provide an analysis which relies on measurements and so called background field from a model forecast. Other inputs to data assimilation process can be physical constraints on the problem or any additional prior knowledge not included in the model. Merging of these contending sources of information had shown to be very promising in many branches of contemporary Earth sciences like meteorology and oceanography.

In data assimilation we try to adjust model according to measured values what represents research effort to move from isolated model prediction forward reality. An automatic procedure for bringing observations into the model is called objective analysis. The major progress of the objective analysis was achieved in the field of meteorological forecasting techniques that represents efficient tool in struggle with tendency to chaotic destruction of physical knowledge, see [4]. Advanced assimilation methods are capable to take into account measurements and model errors in form of error covariance matrices.

In the Fig. (2) we can see the schematic of two stage assimilation process. In the first stage called data update step are modeled values adjusted according to all measurements available in certain time step. This part of data assimilation process is often called intermittent assimilation. This step allows us to get new and hopefully better initial conditions for time update step which performs the prediction of evolution of an analyzed quantity. Advanced assimilation algorithms also enables for prediction of evolution of model errors. Without data update step we could get a prediction substantially diverging from the true evolution.

1. Kalman filter

The Kalman filter ([5]) has long been regarded as the optimal solution to many tracking and data prediction tasks. The purpose of filtering is to extract the required information from a signal, ignoring everything else. Kalman described his filter using state space technique which enables filter to be used as either a smoother, a filter or a predictor. In this paper is presented exploitation of Kalman filtering method in a special assimilation scenario.

As was already stated in previous paragraph, initial condition for the task of prediction of radiological situation evolution is given as a result of ADM when the plume is gone. Reliability of this initial value $\mathbf{x}_f$ (often called background field) can be improved by assimilation process. If there are available some measurements $\mathbf{y}_o^t$ at time t which we assume to be more reliable then the model, we can adjust the model according to their values with respect to physical information contained in the model. Error covariance structure is expressed in form of error covariance matrices of model $\mathbf{P}_f^t$ and measurements $\mathbf{R}^t$. The result of this process in time t is a new better initial condition $\mathbf{x}_a^t$ called analysis (Eq. (7), Eq. (8)) and information on its error covariance structure $\mathbf{P}_a^t$ (Eq. (9)). $\mathbf{H}$ is a linear operator for transformation of points from space of model into the space of measurements. This process is called data update step of Kalman Filter.

$$\mathbf{x}_a^t = \mathbf{x}_f^t + \mathbf{K}^t(\mathbf{y}_o^t - \mathbf{H}\mathbf{x}_f^t) \tag{7}$$

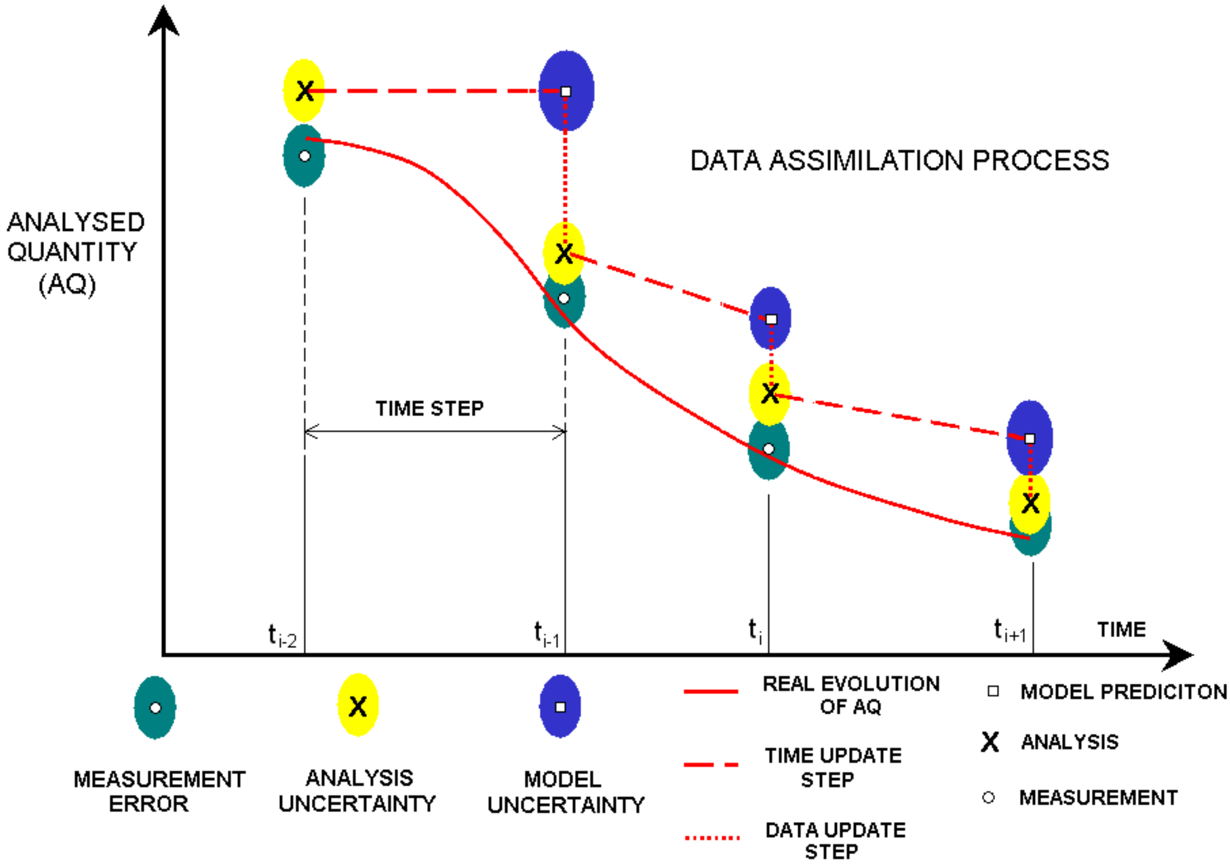

Figure 2: The schematic of data assimilation process.

$$\mathbf{K}^t = \mathbf{P}_f^t \mathbf{H}^T (\mathbf{R}^t + \mathbf{H}\mathbf{P}_f^t \mathbf{H}^T)^{-1} \tag{8}$$

$$\mathbf{P}_a^t = (\mathbf{I} - \mathbf{K}^t \mathbf{H}) \mathbf{P}_f^t \tag{9}$$

The second step is called time update and in this step is performed time evolution of an analyzed quantity via linear model $\mathbf{M}$ (Eq. (10)) and also evolution of its error covariance structure (Eq. (11)). Output of second step of Kalman filter is prediction $\mathbf{x}_f^{t+1}$ and information on error of this prediction $\mathbf{P}_f^{t+1}$.

$$\mathbf{x}_f^{t+1} = \mathbf{M}\mathbf{x}_a^t \tag{10}$$

$$\mathbf{P}_f^{t+1} = \mathbf{M}\mathbf{P}_a^t \mathbf{M}^T + \mathbf{Q} \tag{11}$$

This two steps can be iteratively repeated as long as new measurements are available.

V. Results and Conclusion

In assumed scenario no shielding was assumed, so shielding coefficients were set to 1. Because of lack of real measurements testing of an assimilation process was performed with simulated measurements sampled from the same numerical model using perturbed input parameters. Early results presented in oral part of presentation show that this task can be successfully solved via two step data assimilation process, but there are still some problems especially with estimation of error covariance structure (ECS) and its propagation forward in time.

The achieved results had shown so far that the differentiation of ADM input parameters to local and global introduced in paragraph II.2 substantially influences ECS of the model. Choice of parameters to vary in order to estimate error covariance structure is important part of assimilation process. The presented results can be seen in the Fig (3). We can see there a visualization of ECS for certain point of polar network (Fig (3a)). The ECS was an input to the assimilation procedure, which was used to adjust nominal value of numerical model (Fig (3b)) according to measurements (Fig (3c)). The assimilated value of the model was used as a new better initial condition for further prediction of evolution of ^{137}Cs on terrain (Fig (3d)).

The results from spatial filter (Eq. (1), (2)) could by used for weighing of statistical estimate of error covariance structure and to mitigate the influence of global vs. local property of certain input parameter.

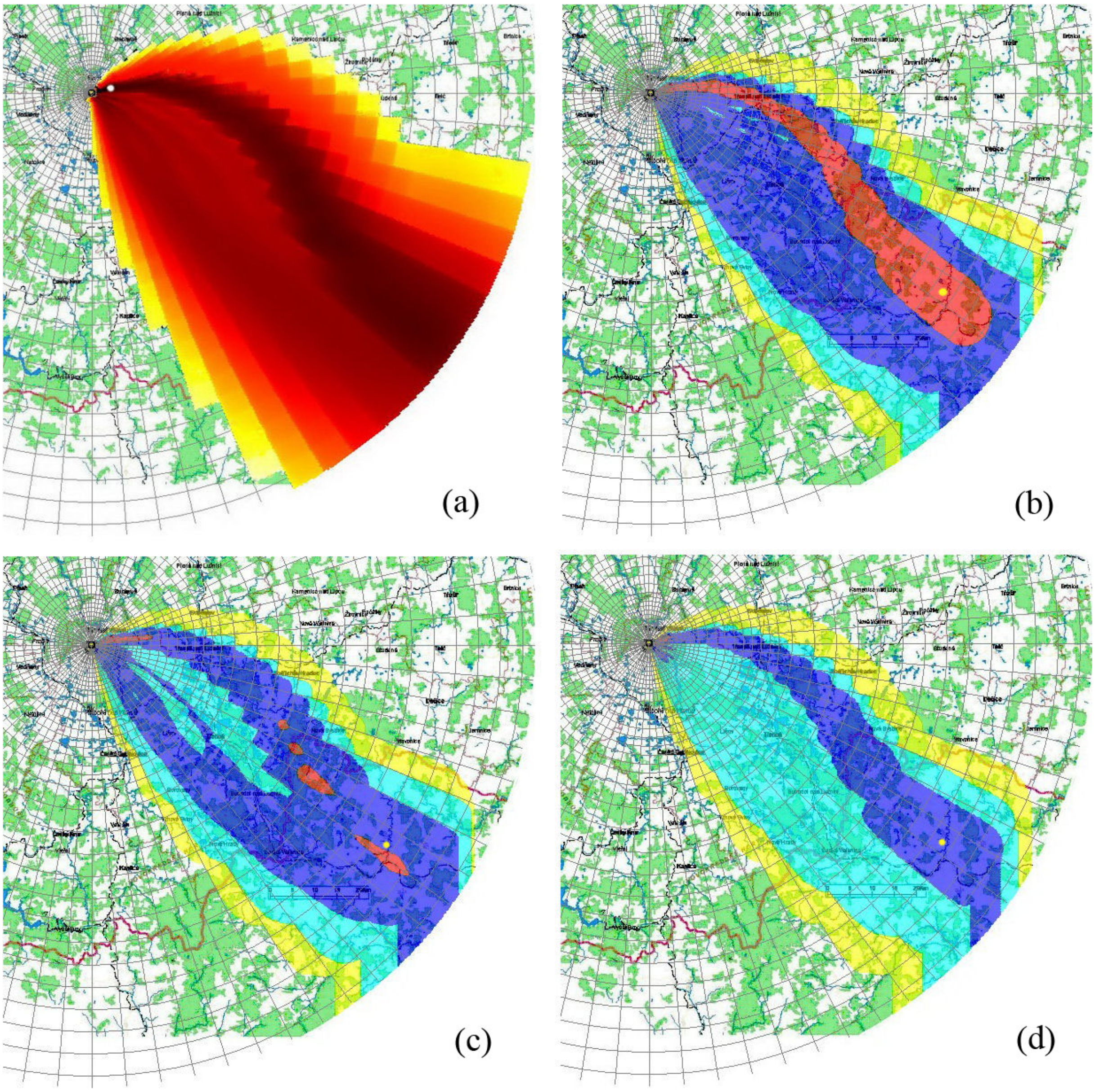

Figure 3: (a) Visualization of ECS for certain point (white point). (b) Background field from ADM. (c) BF after assimilation with the only measurement (yellow point). (d) Prediction of an evolution after 10 years.

In the next development of assimilation methodology and HARP system is intended to implement some other advanced assimilation methods based on Bayesian approach.

Acknowledgement

This work is part of the grant project GAČR No. 102/07/1596, which is funded by Grant Agency of the Czech Republic. A lot of useful knowledge has been also acquired during RODOS customization procedure for the Czech territory

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