

Application of EULAG for stochastic event reconstruction in urban areas

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EULAG

EULAG is an all-scale numerical hydrodynamic solver. It uses both, Eulerian and LAGrangian framework. EULAG was created to provide its users with a solver with high effectiveness and confidence in simulation results. It is a perfect tool for calculating the geophysical flows.

EULAG has been already used in urban flow modelling and its effectiveness has been proved. In this work, urban flows and hazardous substances dispersion in atmosphere is being calculated by EULAG for solving the event reconstruction problem, related to the release of hazardous substance. Currently EULAG is provided with forward in time schemes but doesn't seem to have the reversed schemes. Therefore stochastic event reconstruction has been proposed for solving inverse problem.

Stochastic event reconstruction

In this work, EULAG is being used as forward model calculated multiple times with different release parameters. This will lead to finding the parameters closest to the real release parameters, like coordinates or release quality.

For stochastic event reconstruction, Bayes theorem can be written as follows:

$$P(M|D) \propto P(D|M)P(M)$$

To estimate the unknown source parameters M , the posterior distribution $P(M|D)$ is sampled by MCMC technique with the Metropolis–Hastings algorithm. $P(D|M)$ quantifies the likelihood of a set of measurements D given the source parameters M . A measure indicating the quality of the current state of Markov chain is expressed in terms of a likelihood function. This function compares model's predictions and observed data at the sensor locations as:

$$\ln[P(D|M)] = \ln[\lambda(M)] = -\frac{\sum_i^N [\log(C_i^M) - \log(C_i^E)]^2}{2\sigma_{rel}^2}$$

where λ is the likelihood function, C_i^M are the predicted by the forward model (in this case EULAG) concentrations at the sensor locations i , C_i^E are the sensor measurements, σ_{rel}^2 is an error parameter chosen accordingly to expected errors in the observations and predictions. After calculating value of the likelihood function for the proposed state its acceptance is performed as follows:

$$\frac{\ln(\lambda_{prop})}{\ln(\lambda)} \geq RND(0,1)$$

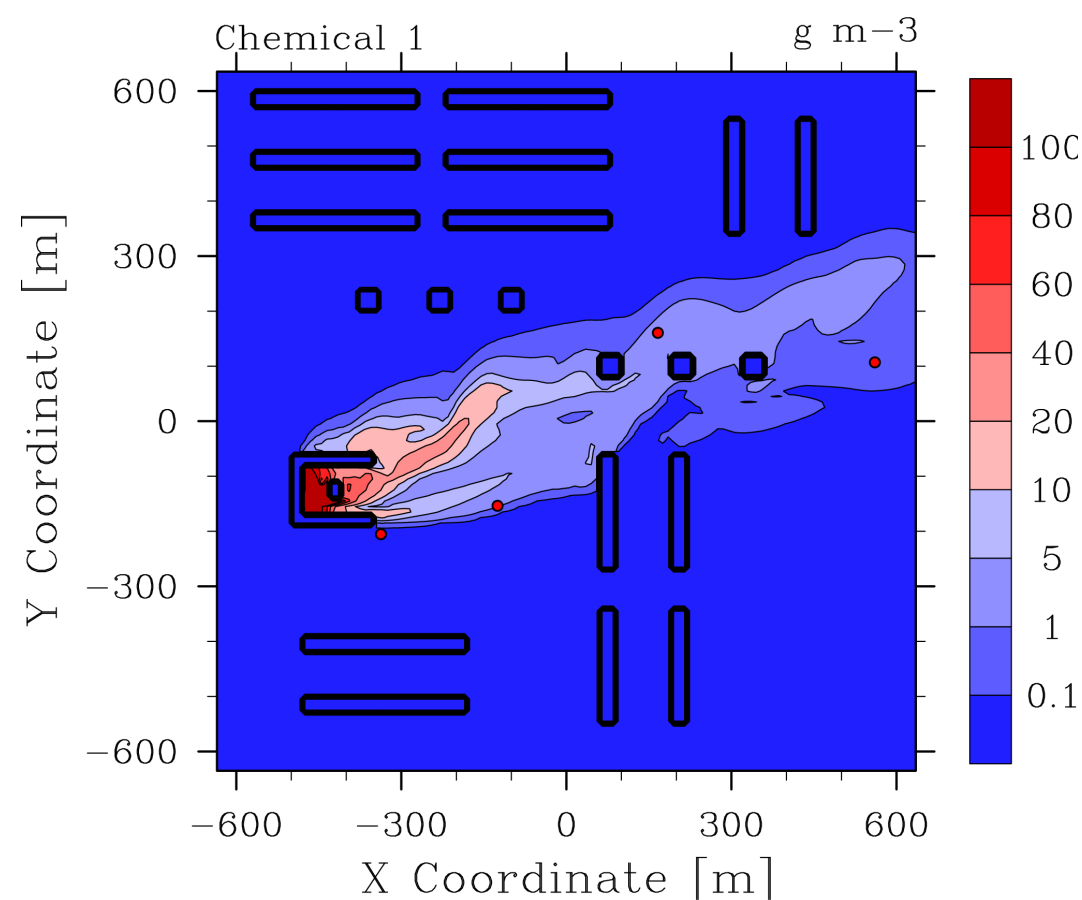


Figure 1: Chemical substance concentration

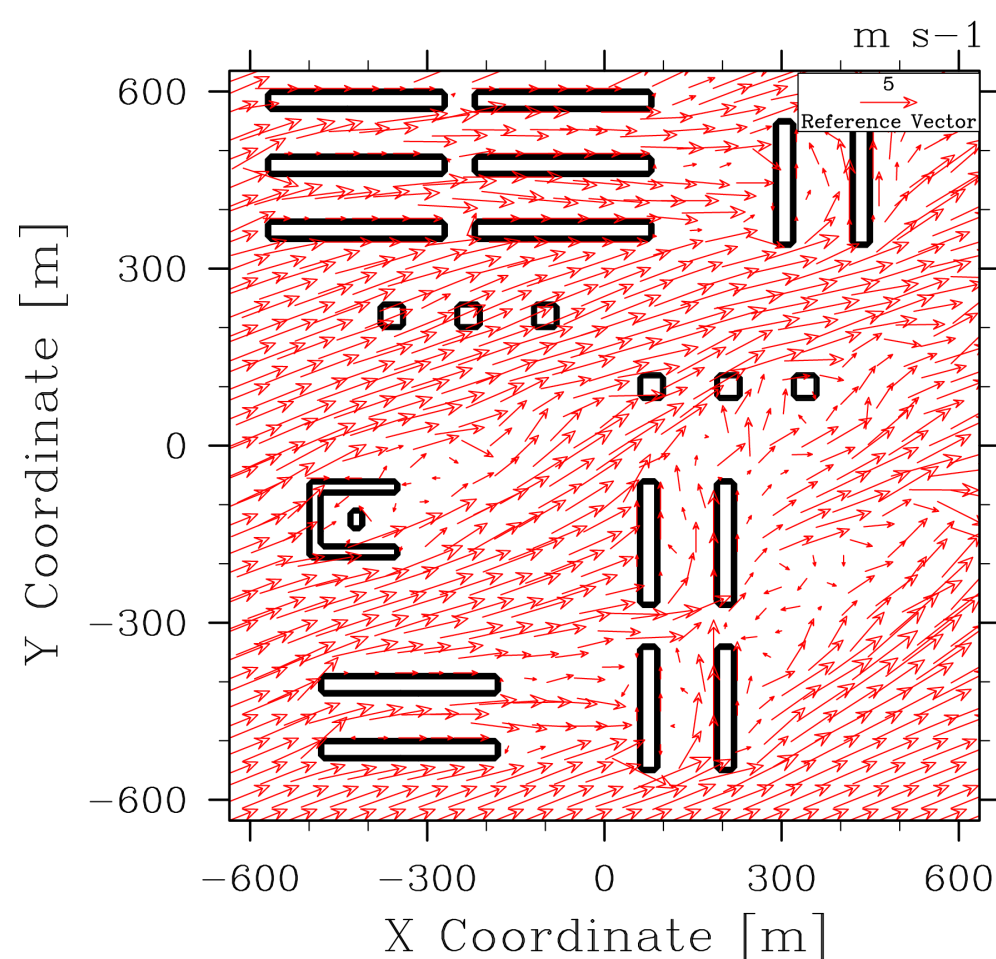


Figure 2: Velocity field

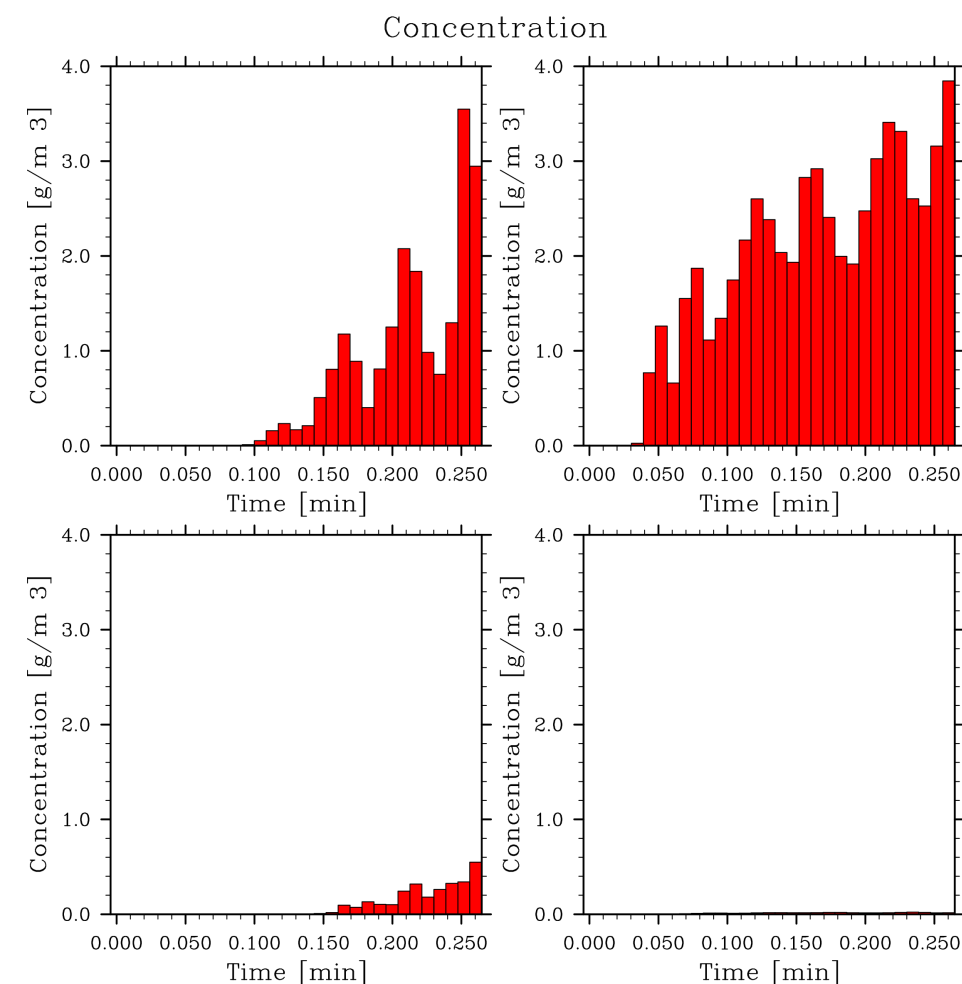


Figure 3: Sensors records

which represents the probability of a particular model configuration giving the results matching the observations at sensor locations. Above equation is a sum over the entire Markov chain of length n of all the sampled values M_i . Thus $\delta(M_i - M) = 1$ when $M_i = M$ and 0 otherwise. If a Markov chain spends several iterations at the same location value of $P(M|D)$ is increased through the summation (increasing the probability for those source parameters). The algorithm is represented in figure 4

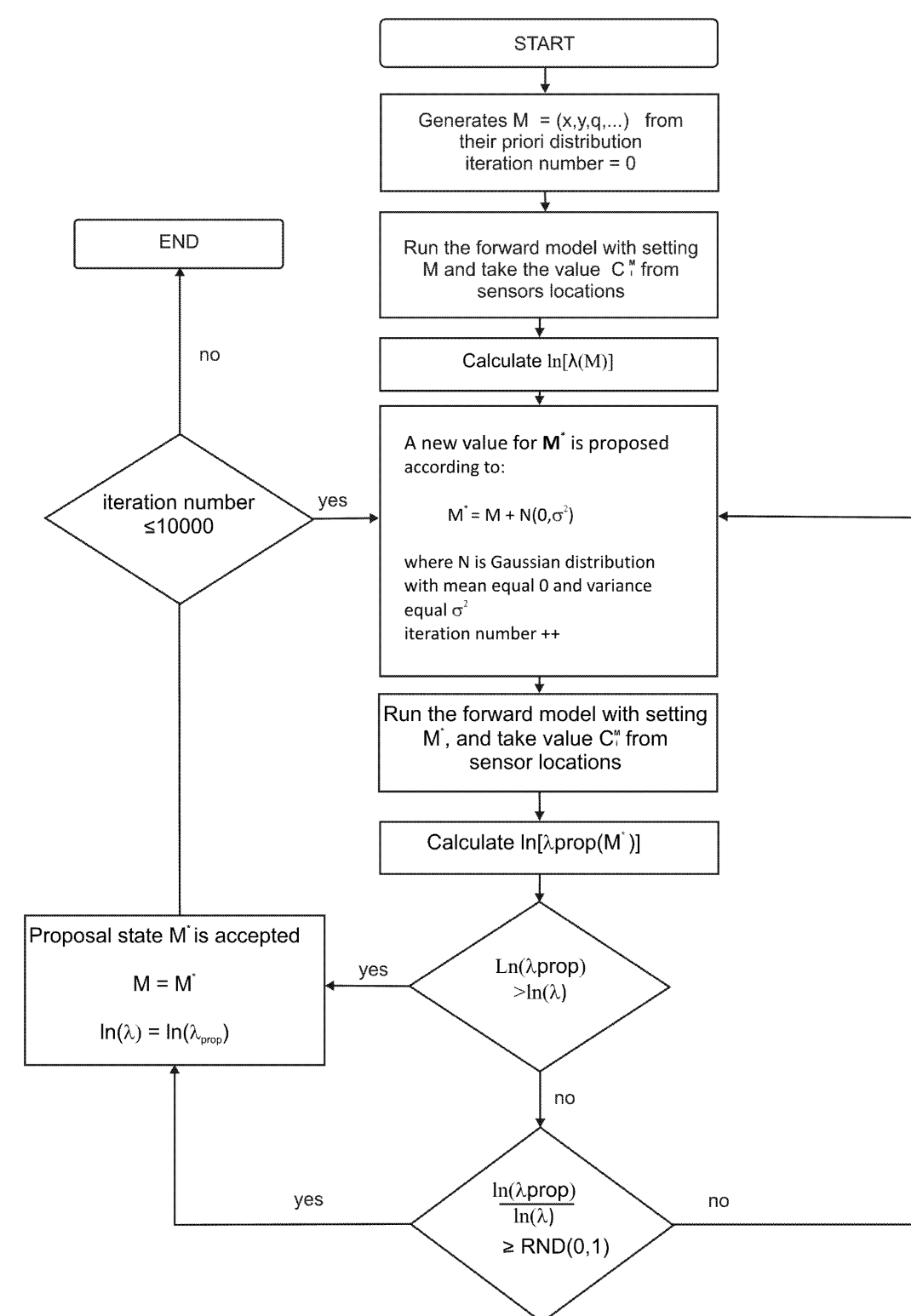


Figure 4: Space scanning algorithm

the domain. These records are represented in figure 3. Released passive tracer has the same temperature as environment. Simulation with these settings and many more, is being performed by EULAG as the forward model by algorithm represented by figure 4 for locating the release coordinates, its quality and possibly other parameters which are unknown.

Acknowledgments

Our team would like to thank Mr. A. Wyszogrodzki for his help with mastering EULAG.

where λ_{prop} is the likelihood value of the proposal state, λ is the previous likelihood value, and $RND(0, 1)$ is a random number generated from a uniform distribution in the interval $(0, 1)$.

The posterior probability distribution is computed directly from the resulting Markov chain paths defined by the algorithm described in figure 4 and is estimated as:

$$P(M|D) = \frac{1}{n} \sum_{i=1}^N \delta(M_i - M)$$

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Simulation details

Simulation of urban flow, was performed in Cartesian coordinate system with orthogonal grid. Grids dimensions was $dx=dy=dz=10.0m$. Timestep was set to $dt=0.25$ sec to avoid stability issues. Chemical release was set in a single gridbox to a constant in time quality of $1000g/m^3/s$. Boundary conditions of wind were set to $U = 5m/s$ and $V = 2m/s$. Buildings were placed in simulation as immersed boundary. Figures 1 and 2 represent a wind field and chemical dispersion on layer 10 meters above the ground.

Simulation gave the reading from virtual sensors placed within

