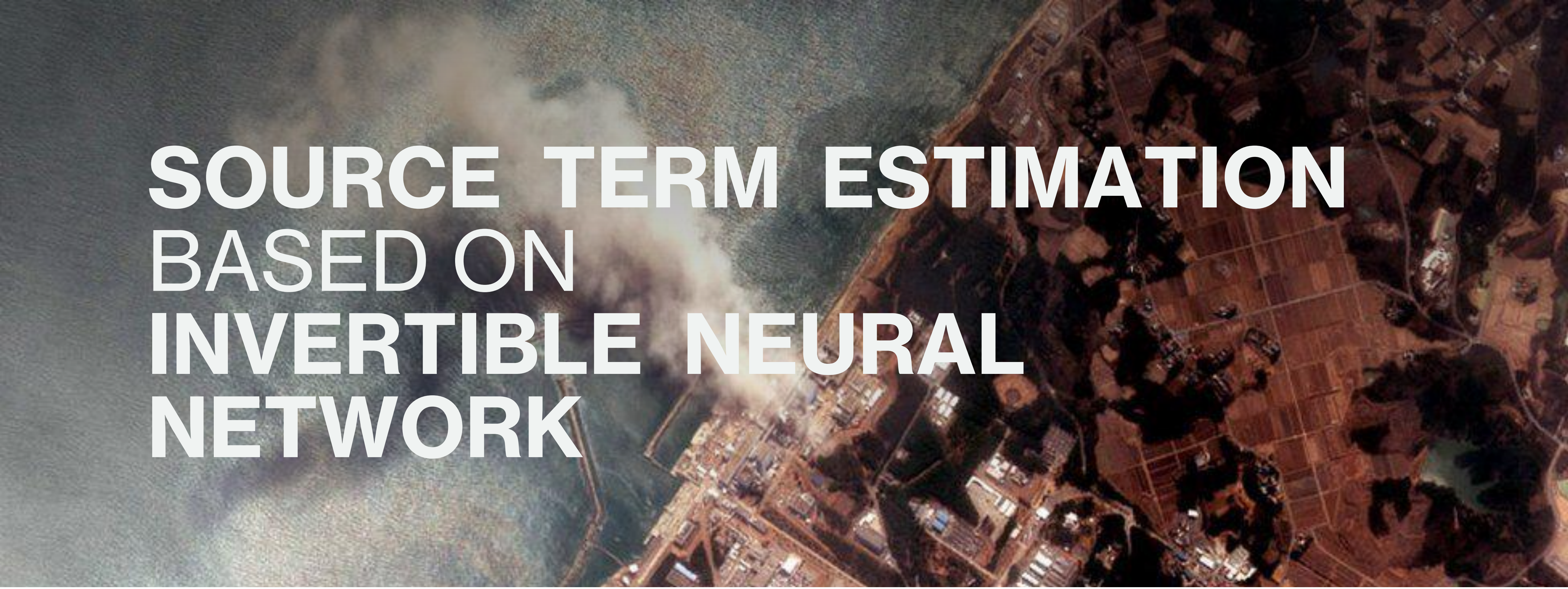


SOURCE TERM ESTIMATION BASED ON **INVERTIBLE NEURAL NETWORK**

2024 KNS Spring

Suhyeon Kim (Speaker), Siho Jang, Eung Soo Kim

Seoul National University

NUCLEAR ENERGY SYSTEM LAB

Intro

Lesson from Fukushima

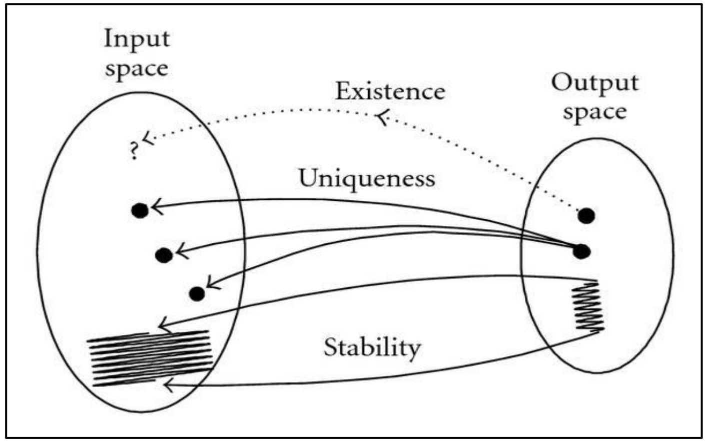
- ***Internal monitoring systems could fail in case of severe accident.***

  Indirectly estimating the state with external environmental monitoring data becomes essential.

- ***Conservative emergency response had price*****.**

  Giving appropriate information for decision making is crucial.

Intro



How to estimate Source Term

- ***Radionuclides' concentration data has time delay.***

  Despite giving accurate radionuclides' activity, it is inappropoirate for emergency response.

- ***Gamma dose rate gives real time but limited information***

  Estimating source term with gamma dose rate is "ill- posed problem."

Previous Study

Researcher	**Forward** Model	**Inverse Model**	**Radionuclide**
V. Tsiouri, et. al. (2011)	DIPCOT*	Variational Data Assimilation	1 radionuclide: Ar-41
Genki Katata, et. al. (2012)	WSPEEDI-II*	Reverse Estimation methods	5 radionuclides: I-131, I-132, Te-132, Cs-134, Cs-137
O. Saunier, et. al. (2013)	Eulerian 1dX	Inverse modeling: Tikhonov regularization with the isotopic ratios	8 radionuclides: Cs-134, Cs-137, Cs-136, Ba-137m, I-131, I-132, Te-132, Xe-133
Ond rei Tichý, et. al. (2017)	FLEXPART	Bayesian method for recovery of the Source term: using Variational Bayes methodology	16 radionuclides: Cs-136, Cs-134, Cs-137, I-133, I-131, I-135, I-132, I-134, Kr-85m, Kr-88, Kr-87, Sr-90, Sr-89, Te-132, Xe-135, Xe-133
C. V. Srinivas, et. al. (2017)	SPEEDI	ASTER	1 radionuclide: Ar-41
Xiaole Zhang, et. al. (2017)	JRODOS*	Sequential Estimation method: Source-receptor relationship & Tikhonov regularization & Suppression of negative estimation	5 radionuclides: 1-131, Cs-137, Te-132, La-140, Xe-133
Xinpena Li, et. al. 2019)	RASCAL, RIMPUFF*	Inverse modeling: Weighted additive model(consider priors from different mechanisms) Ensemble Kalman Filter	4 radionuclides: 1-131, Cs-137, Cs-134, Te-132
Hiroaki Terada, et. al. (2020)	WSPEEDI-I - GEARN (LDM)	Ensemble meteorological calculations & Bayesian inference method	2 radionuclides: Cs-137, I-131
Yongsheng Ling, et. al. (2021)	InterRAS*	Recurrent Neural Networks(RNN)	6 radionuclides: Sr-91, La-140, Te-132, Xe-133, I-131, Cs-137
Yongsheng Ling, et. al. (2022)	InterRAS	Temporal Convolution Network(TCN, Sequential CNN)	7 radionuclides: Kr-88, Te-132, I-131, Xe-133, Cs-137, Ba-140, Ce-144
K. S. Tollose, et. al. (2022)	DERMA*	Bayesian Inversion and Sampling Method: Inverse method for probabilistic source term estimation	11 radionuclides: Kr-88, Xe-133, Xe-135, Xe-135m, Cs-134, Cs-137, I-131, I-132, I-133, I-135, Te-132
Yongsheng Ling, et. al. (2023)	InterRAS	Fusion of TCN and 2D-CNN	7 radionuclides: Kr-88, Te-132, I-131, Xe-133, Cs-137, Ba-140, Ce-144
Siho Jang, et. al. (2024)		Gaussian Plume Ensemble Kalman Inversion(EKI)	11 radionuclides: Kr-88, Xe-133, I-131, Cs-137, Te-132, Sr-91, Mo-99, Ba-140, La-140, La-140, Ce-144, Sb-129
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Previous Study

Classical approach

+ Gives relatively precise prediction.
- Need forward computation.
- Sequential algorithm makes *solution unscalable.*
- Vulnerable to observation error.

AI based approach

+ No need forward computation.
+ Parallel computation makes *scalable solution.*
- Gives relatively unprecise prediction.
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Previous Study

Inverse Problem Solving
with point prediction

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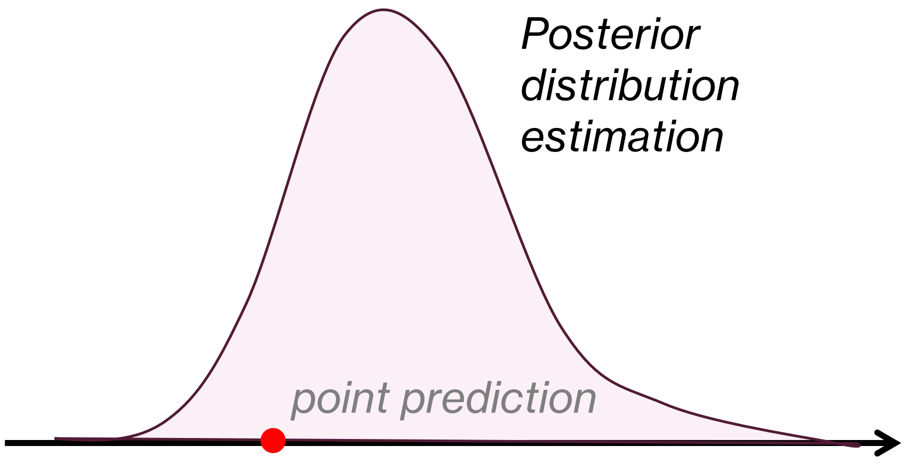


What has been done in this research

Bayesian Inverse Problem Solving
with posterior distribution estimation

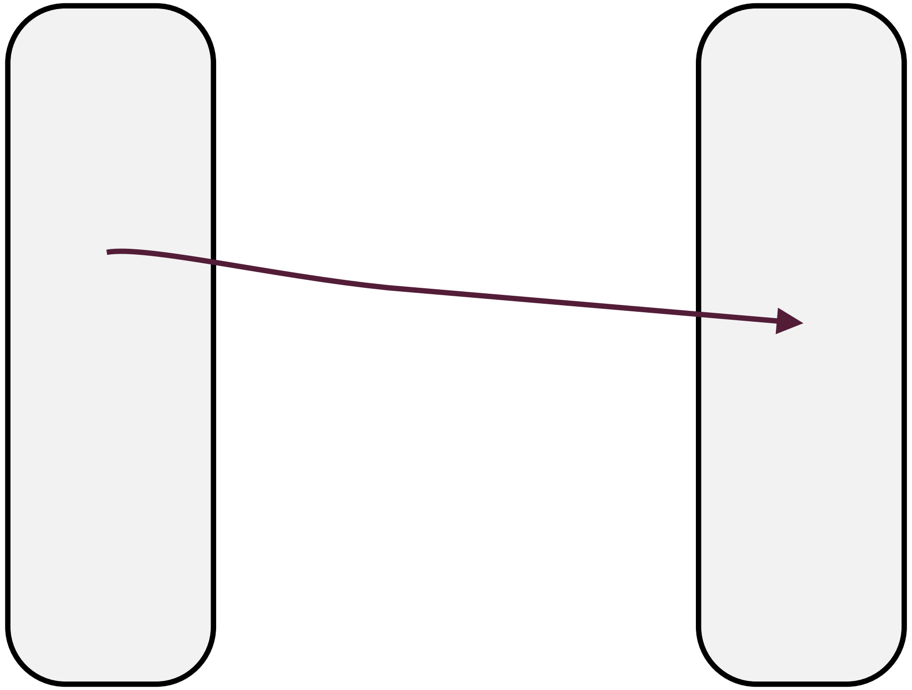
Invertible Neural Network based approach

+ No need forward computation.
+ Parallel computation makes *scalable*
+ Gives true posterior distribution.
+ Model considering observation error.

Research Objective

Source Term
release rate
$\boldsymbol{x}$

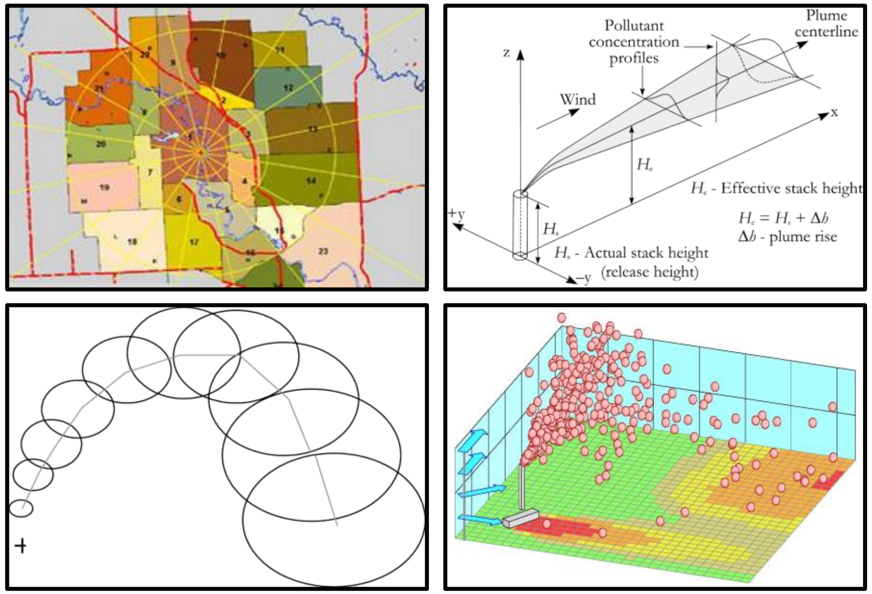
Atmospheric
γ ray at receptors
$\boldsymbol{y}$



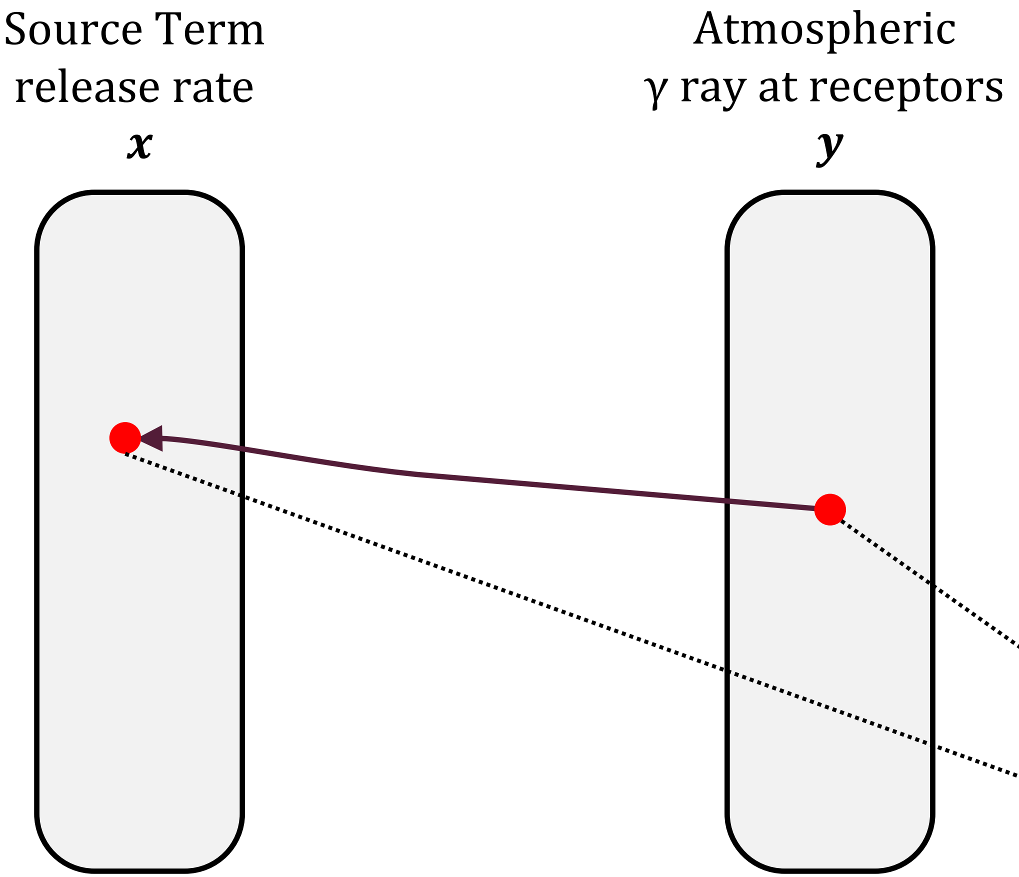
Foward Process: $y = f(x)$

Atmospheric Dispersion

- *Various LV3PSA code*
- *Gaussian Plume Model*
- *Gaussian Puff Model*



Research Objective



Inverse Problem: $x = f^{-1}(y)$

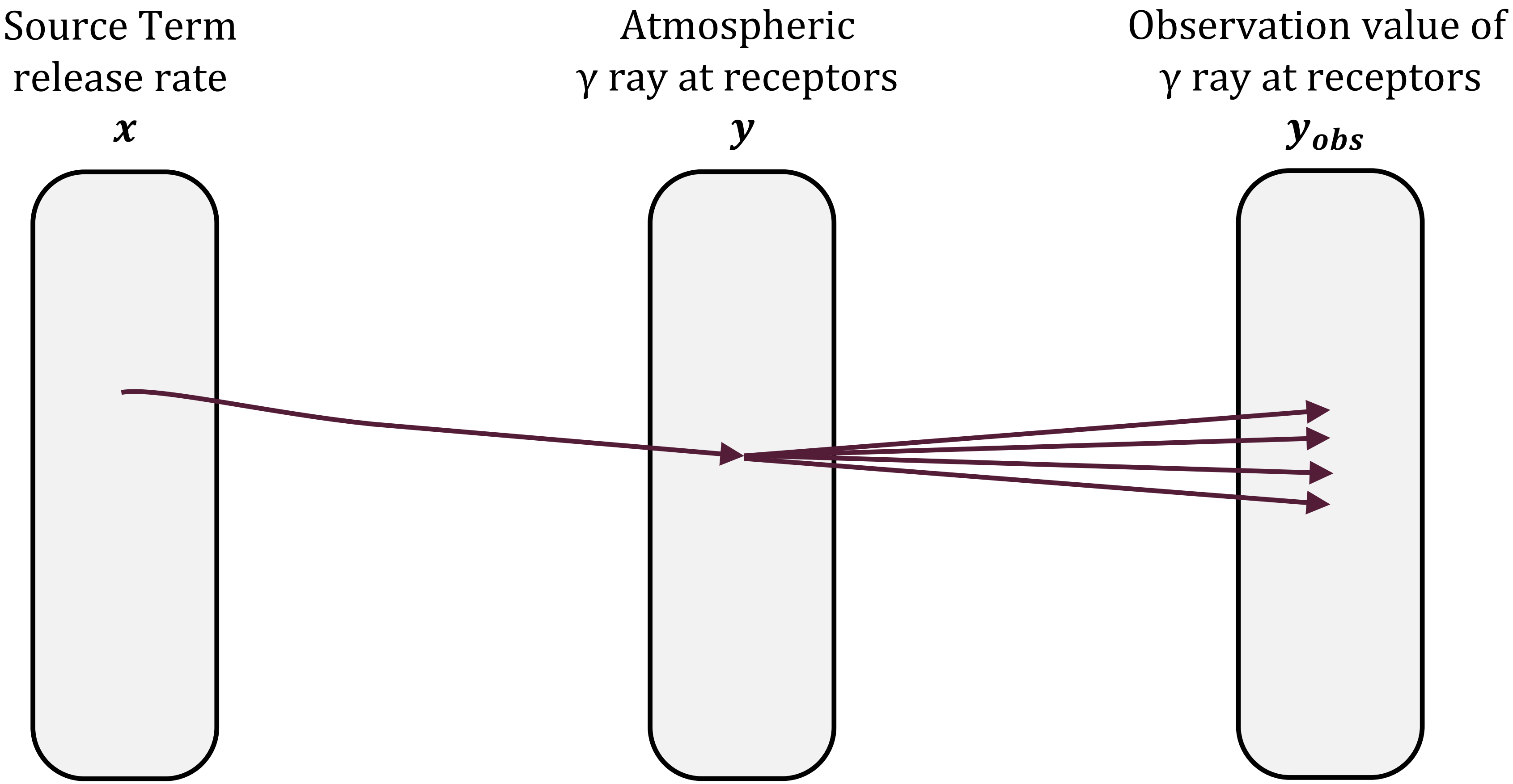
Inverse Problem Solving
with point prediction

- *Classical Optimization*
- *AI based Inverse function*
- *Reverse Estimation*

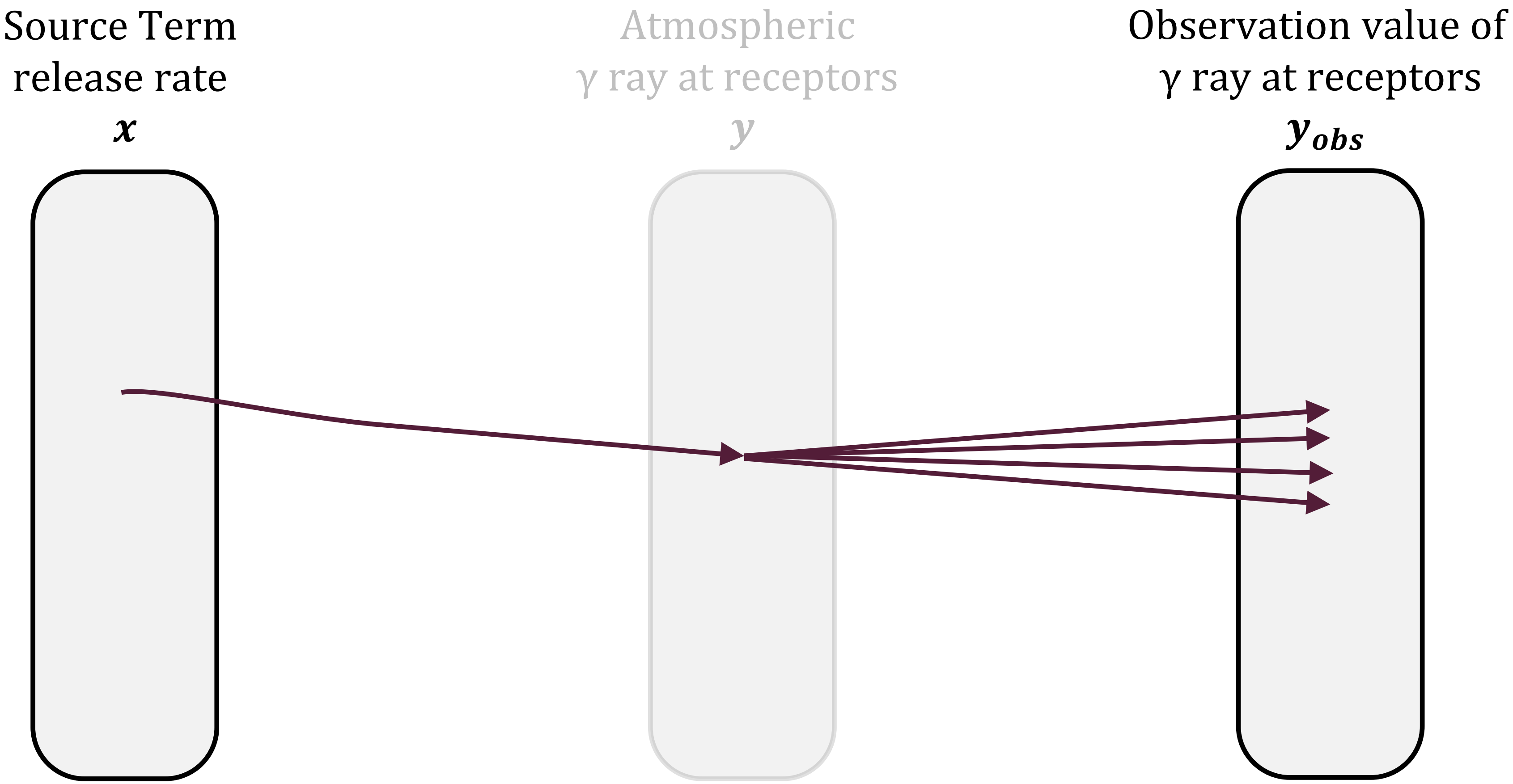
With given γ dose values of receptors,

We can get source term release rate.

Research Objective

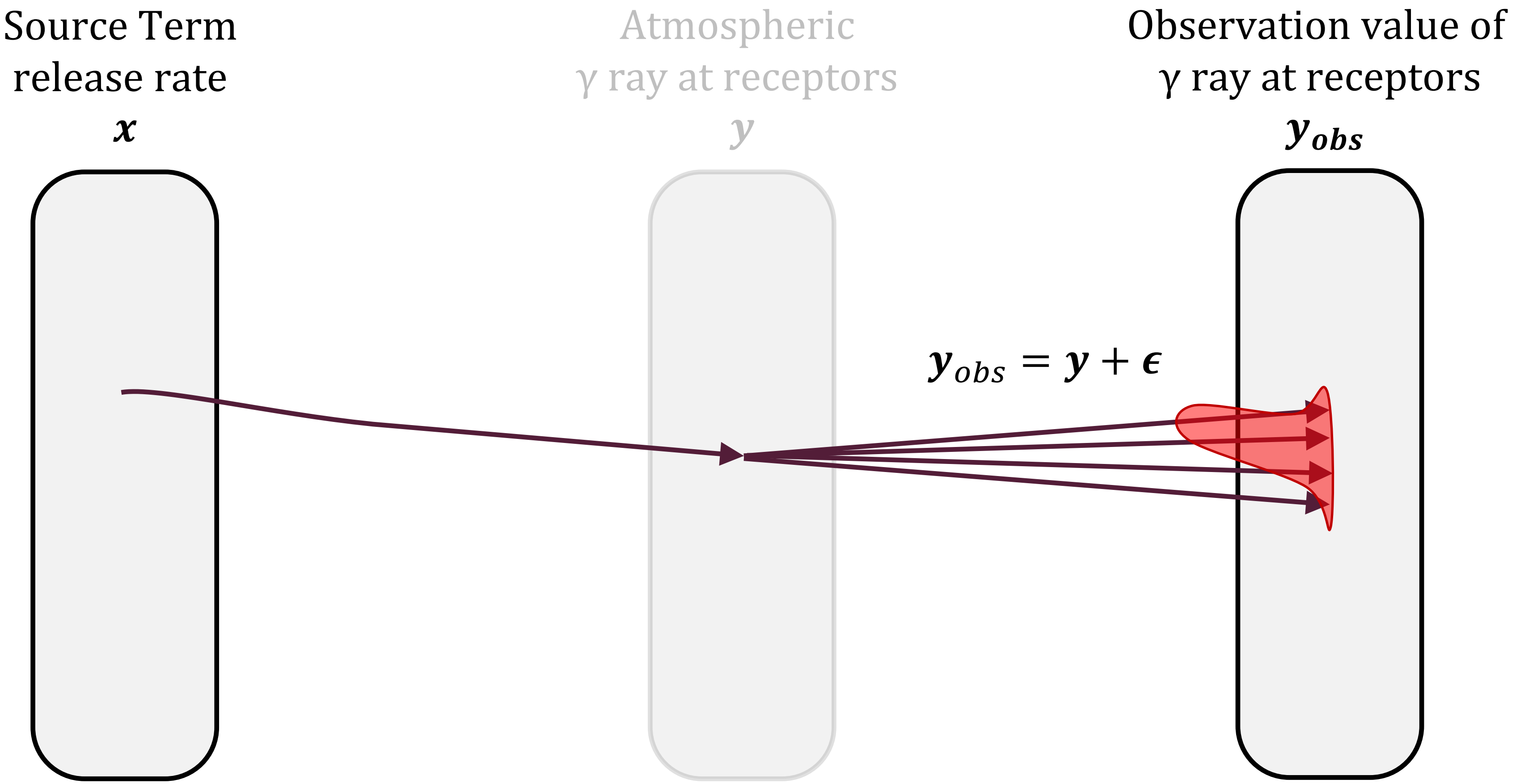


Research Objective



In reality, We **can not access to actual value** of Atmospheric gamma dose.

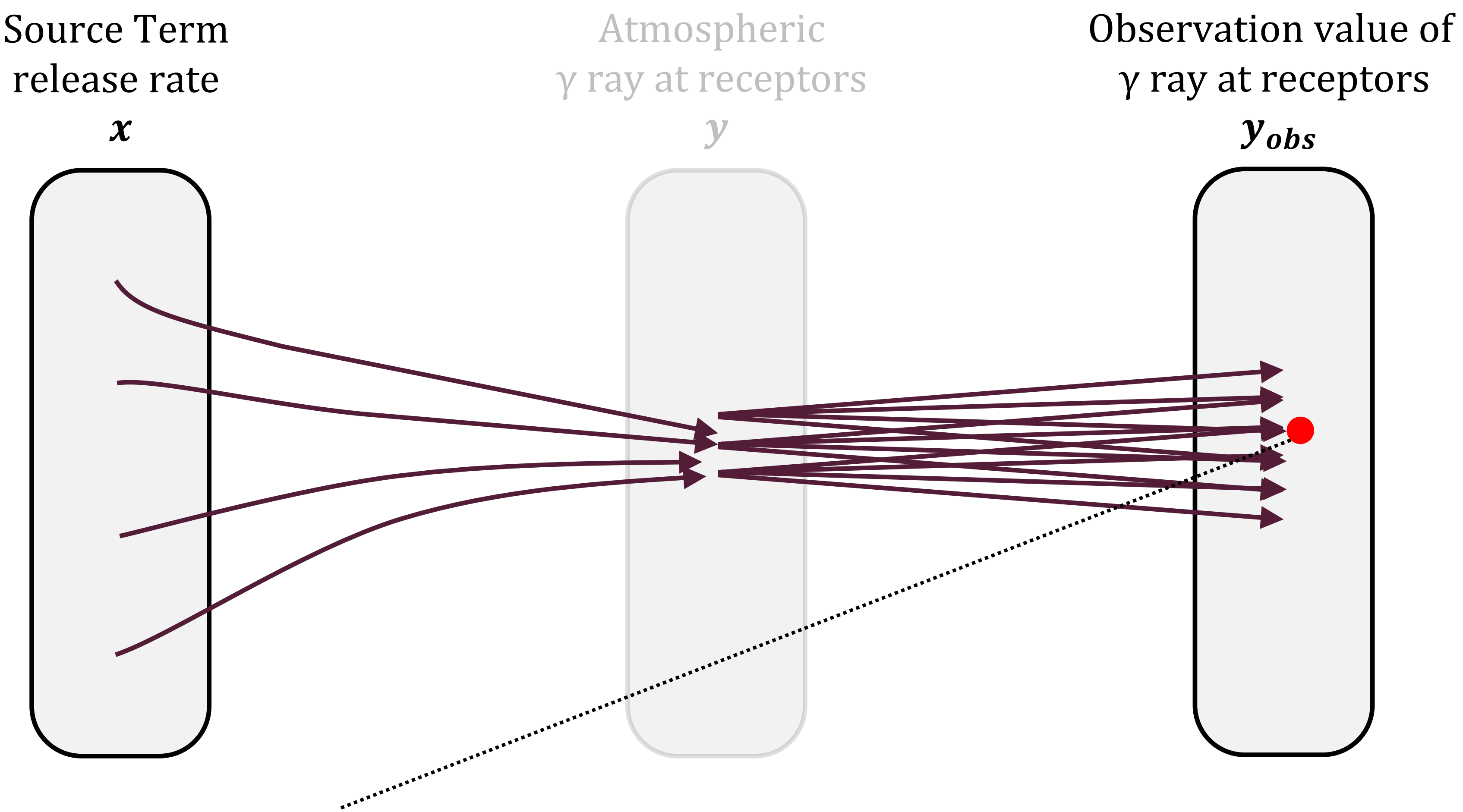
Research Objective



In reality, We **can not access to actual value** of Atmospheric gamma dose.

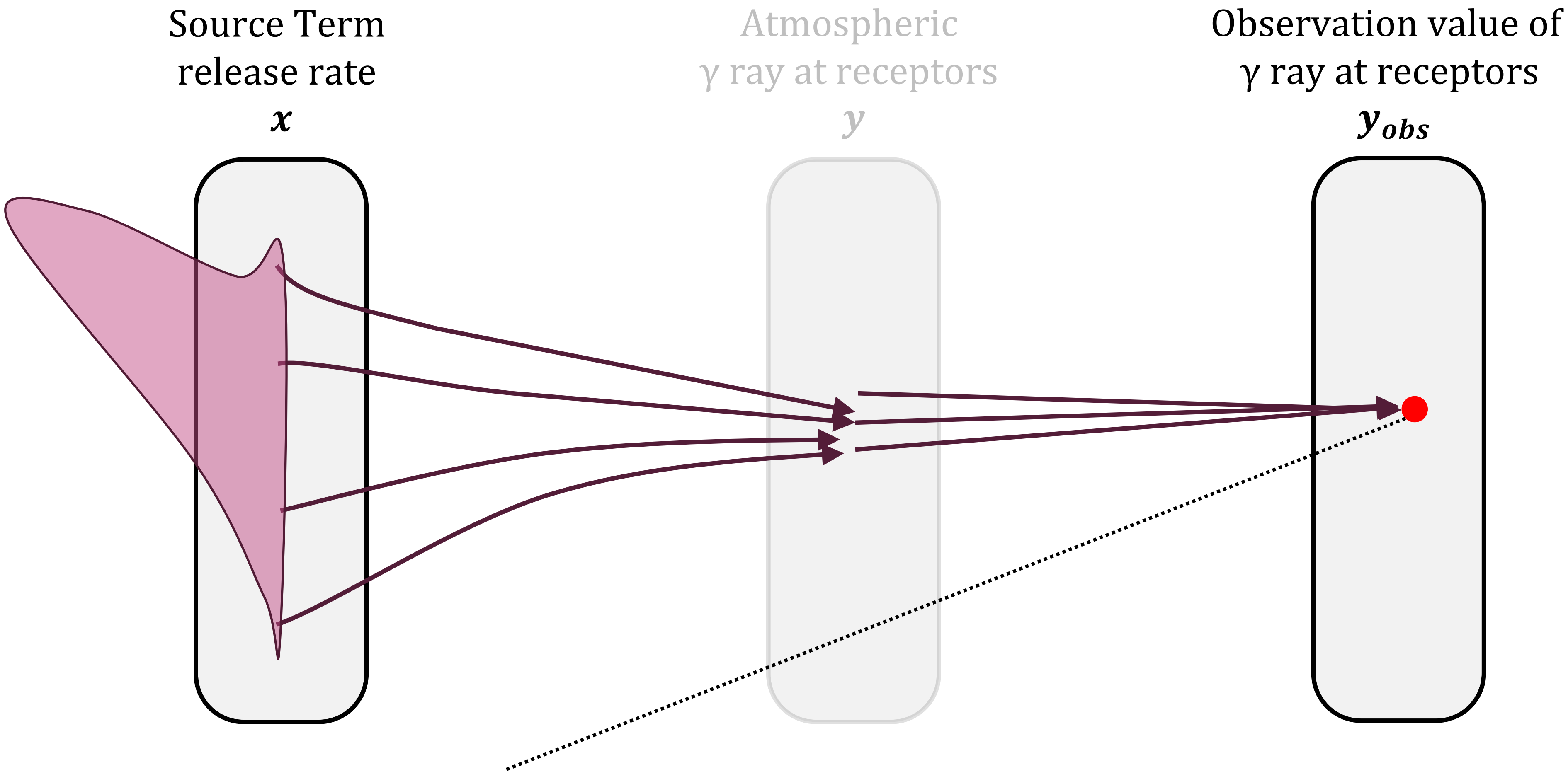
Instead, We **can access** to **noisy observation value** of Atmospheric gamma dose.

Research Objective



Therefore, with given γ dose observation,

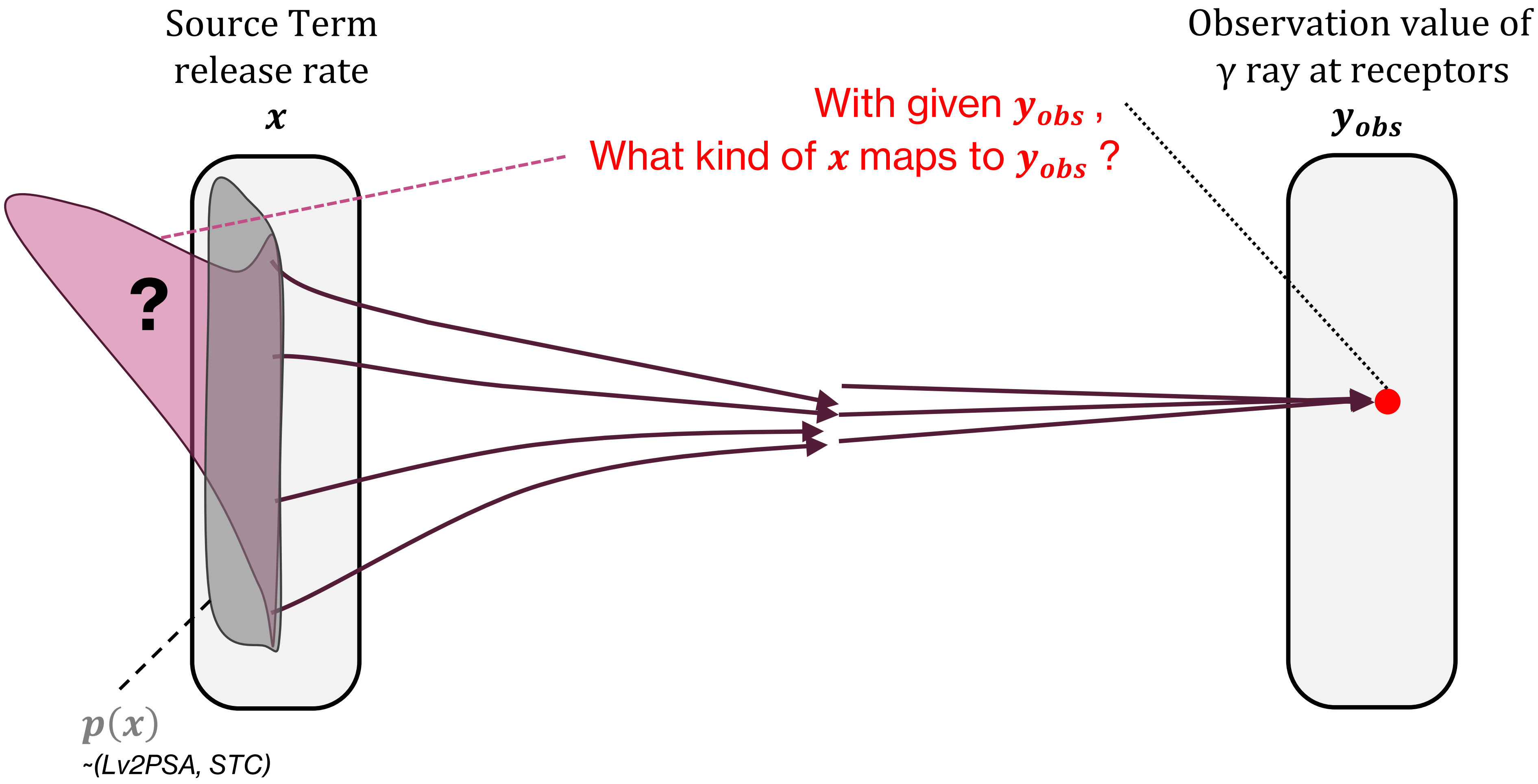
Research Objective



Therefore, with given γ dose observation, ***true information we can get is posterior distribution*** $p(x \mid y_{obs})$

Research Objective

Research Objective



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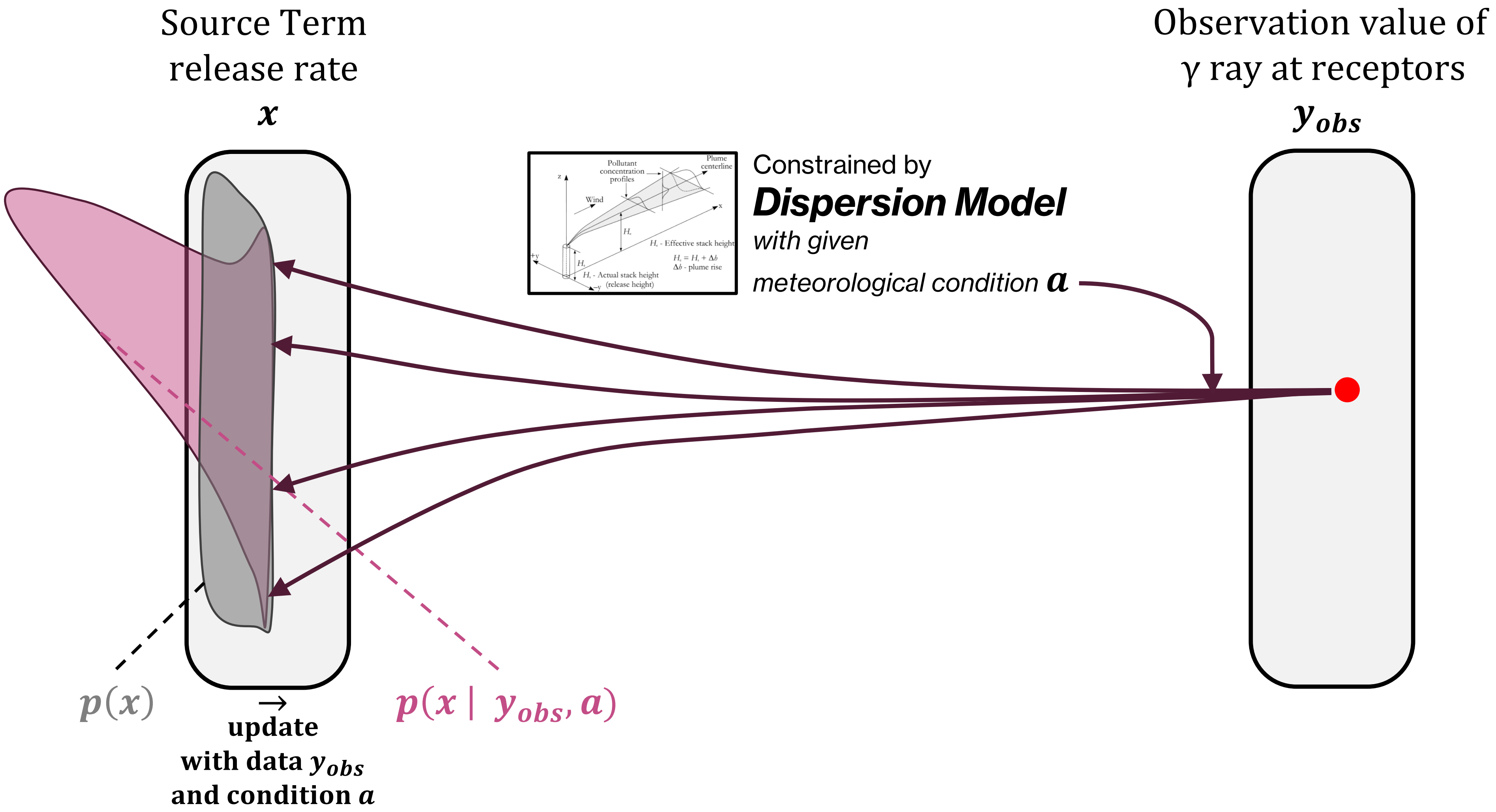

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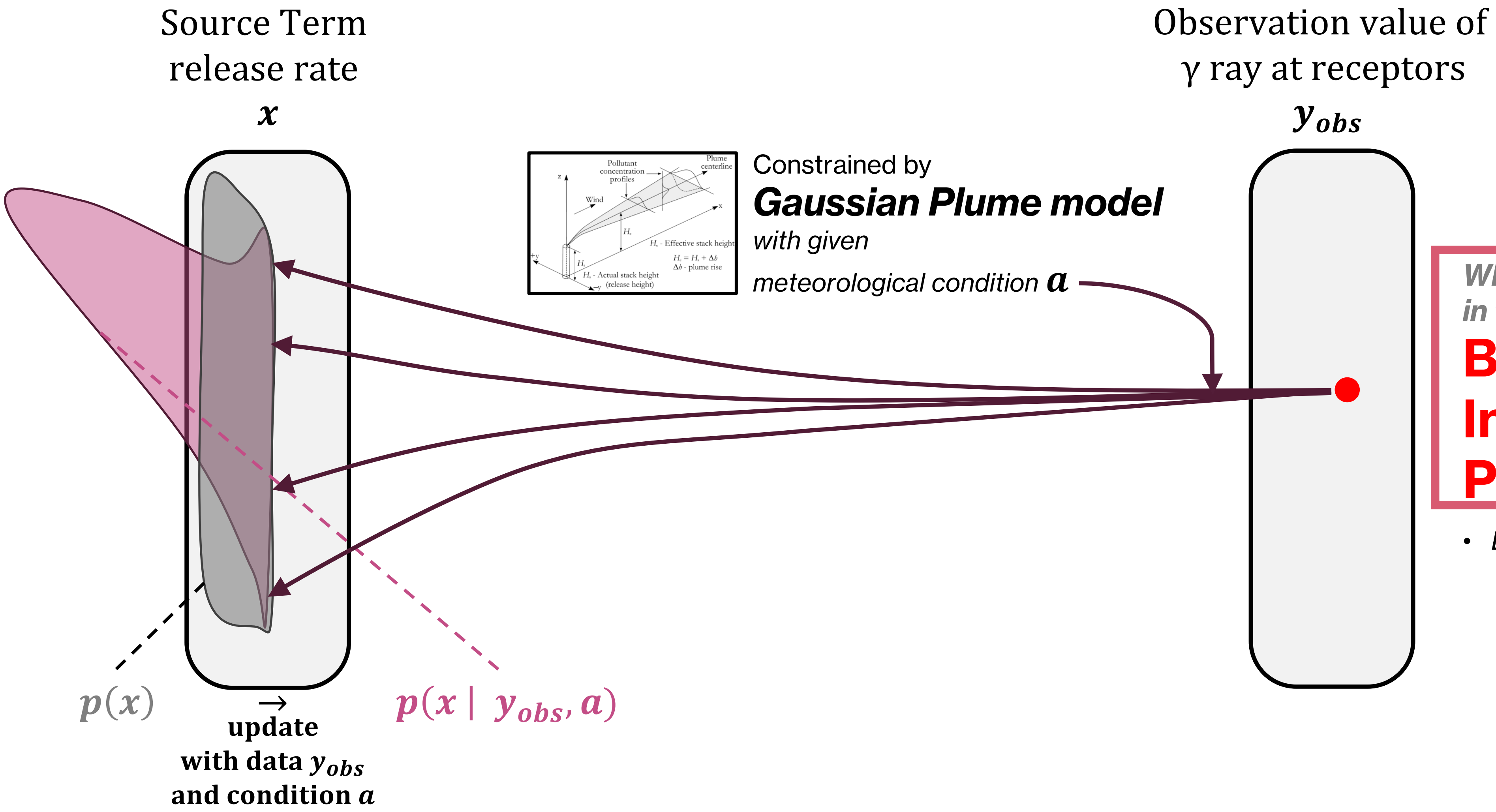


What has been done
in this research

Bayesian Inverse Problem Solving

- *Based on Generative AI*

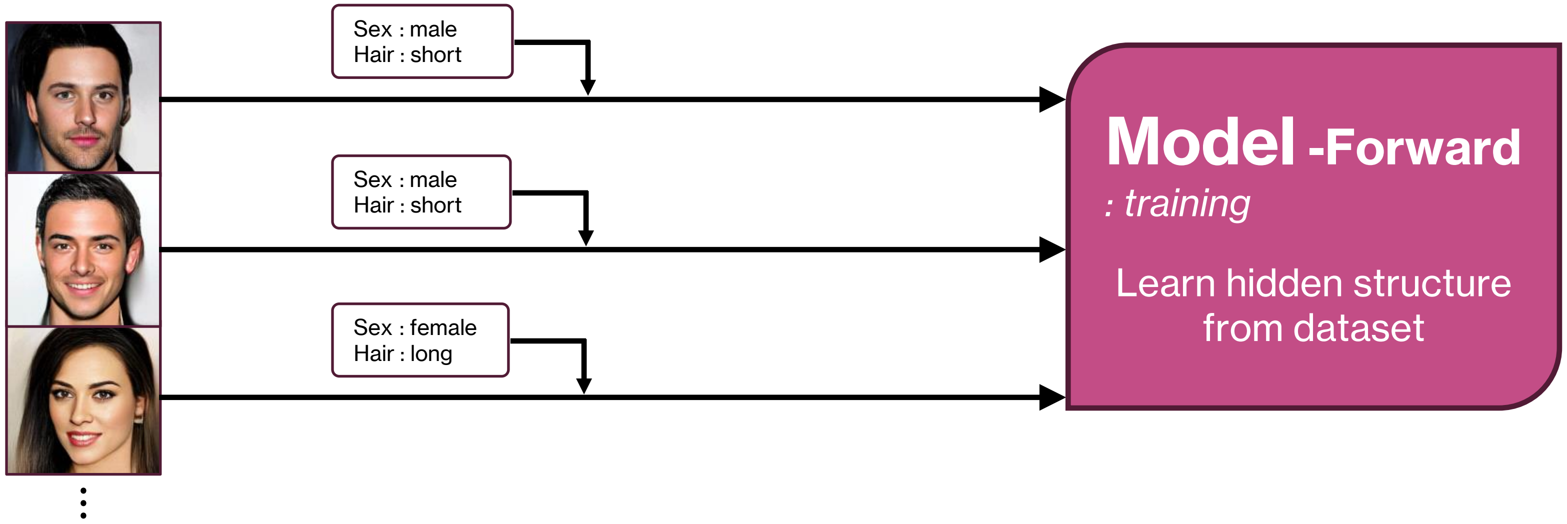
Methodology

How to grant posterior distribution $p(x \mid y_{obs}, a)$?

Invertible Neural Network

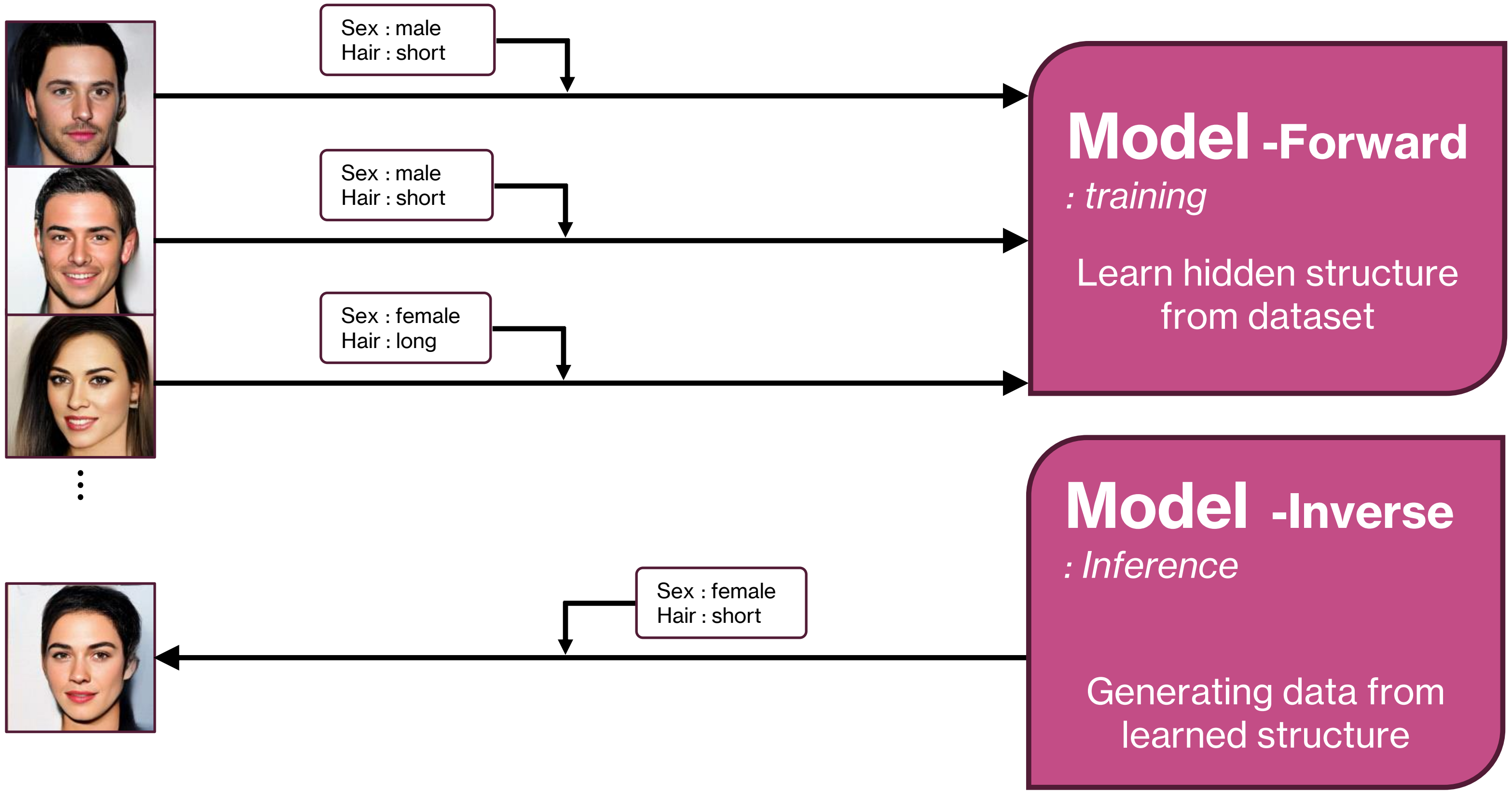
Methodology :
Invertible Neural Network

INN(Invertible Neural Network) is based on **Generative AI architecture.**



Methodology :
Invertible Neural Network

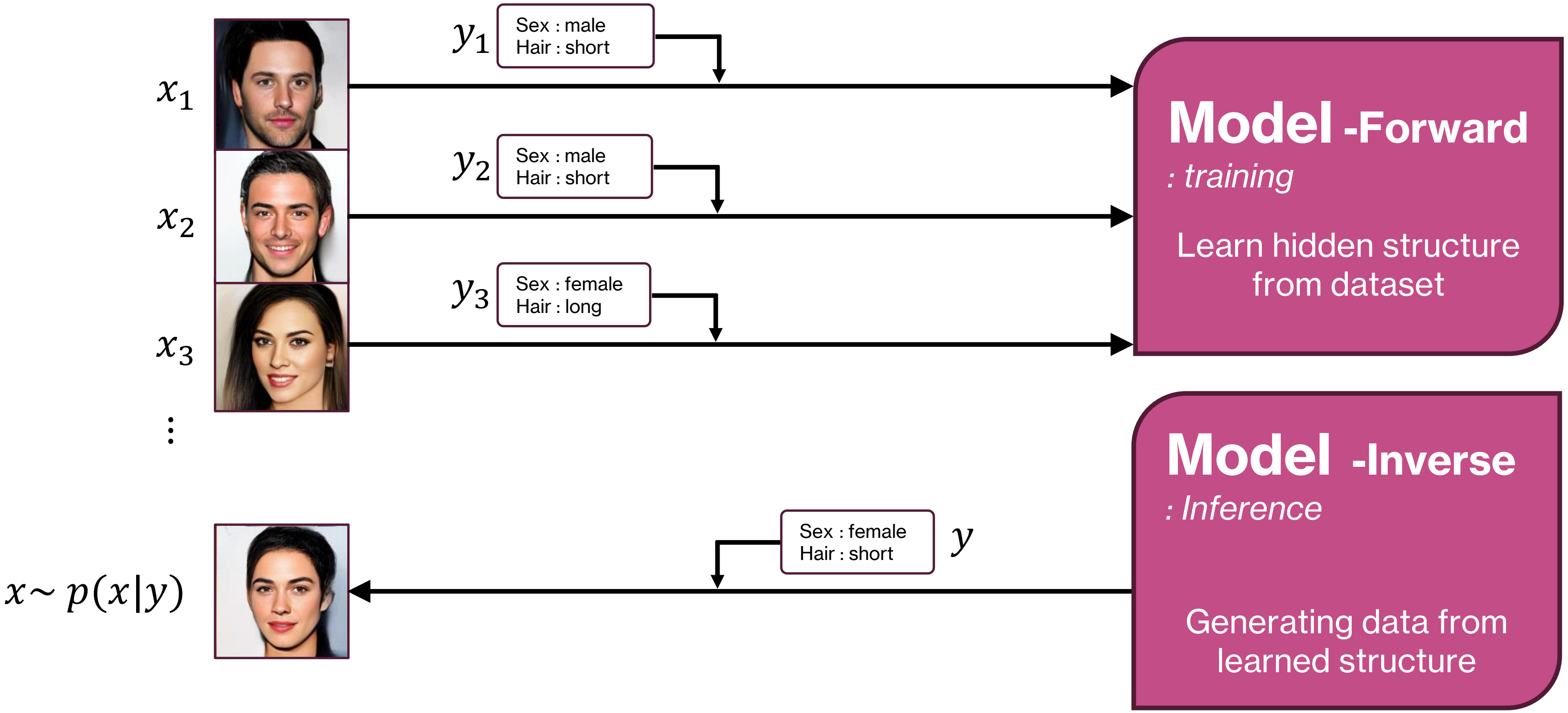
INN(Invertible Neural Network) is based on **Generative AI architecture.**



Methodology :

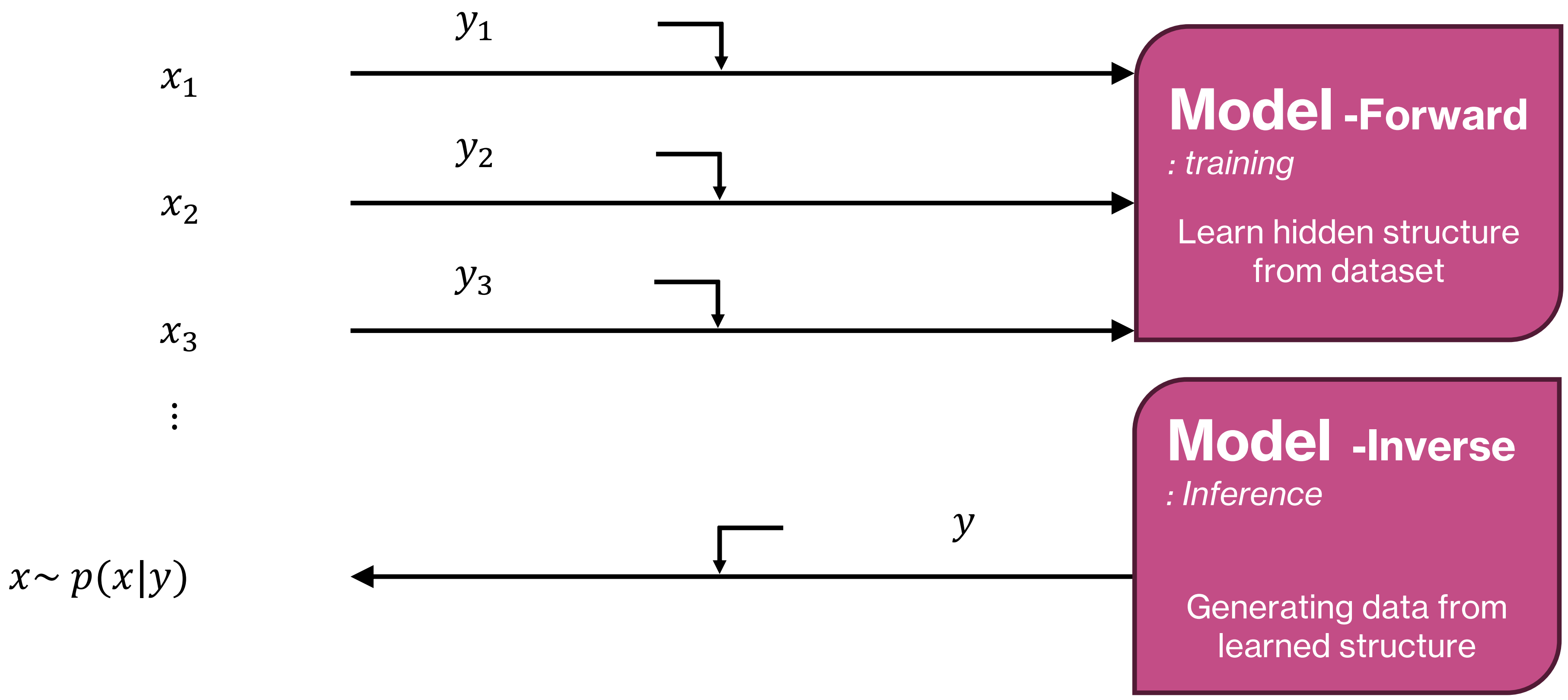
Invertible Neural Network

INN(Invertible Neural Network) can be used for Bayesian Inverse Problem.



Methodology :
Invertible Neural Network

INN(Invertible Neural Network) can be used for Bayesian Inverse Problem.



Methodology :
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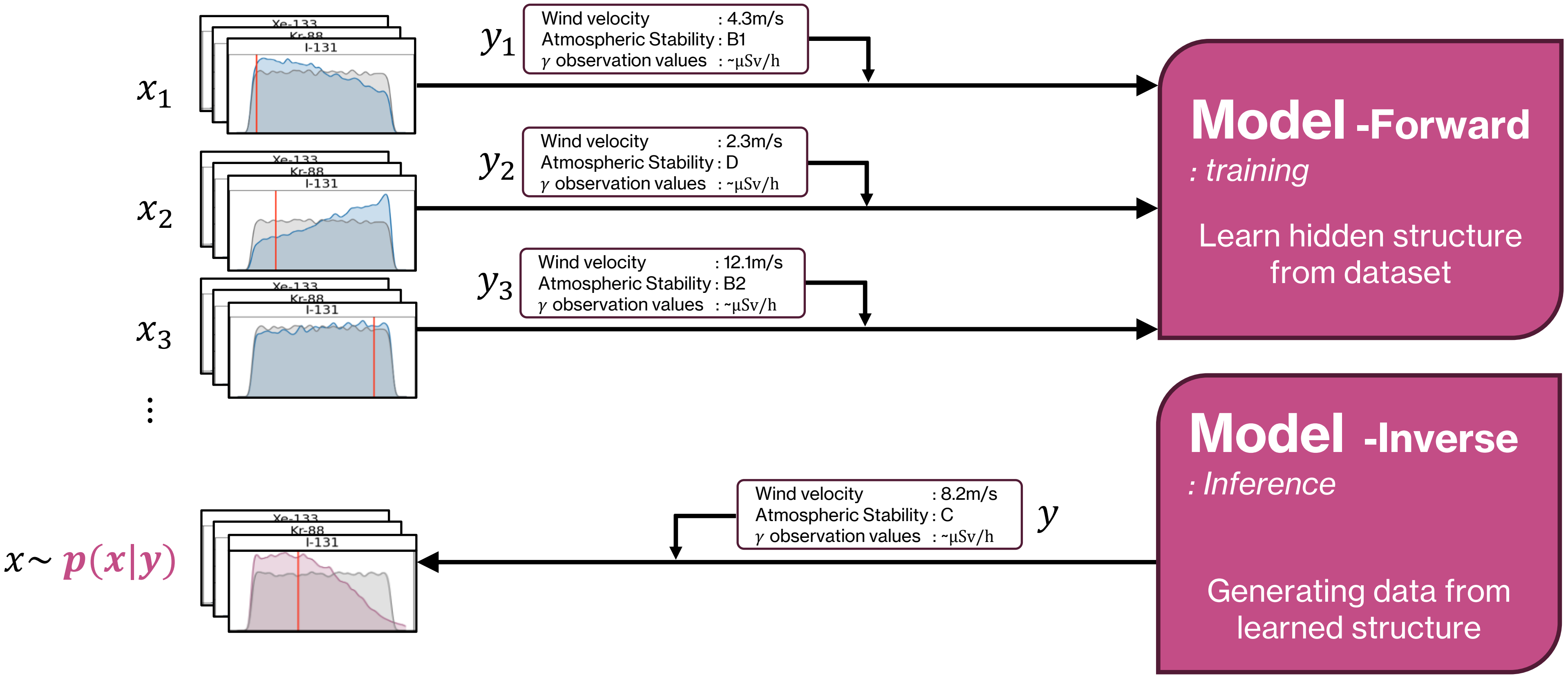
INN(Invertible Neural Network) can be used for Bayesian Inverse Problem.



Methodology

How to grant posterior distribution $p(x \mid y_{obs}, a)$?

Invertible Neural Network

Methodology

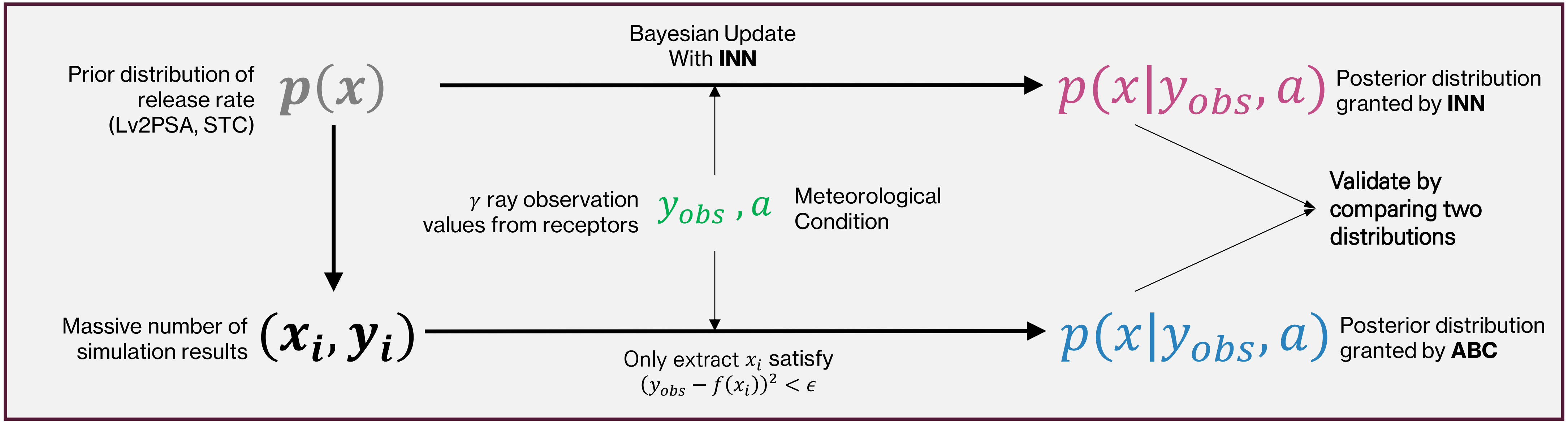
How to grant posterior distribution $p(x \mid y_{obs}, a)$? Invertible Neural Network

How to validate output $p(x \mid y_{obs}, a)$ of **INN** ? **Approximate Bayesian Computation**

Methodology

How to grant posterior distribution $p(x \mid y_{obs}, a)$? Invertible Neural Network

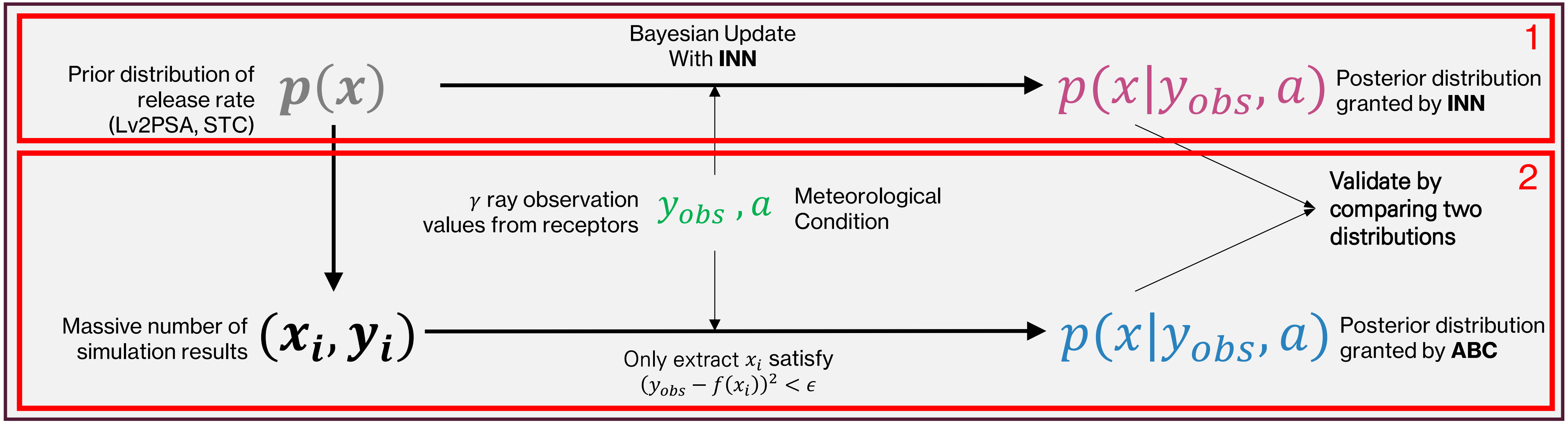
How to validate output $p(x \mid y_{obs}, a)$ of **INN** ? **A**pproximate **B**ayesian **C**omputation



Methodology

1 How to grant posterior distribution $p(x \mid y_{obs}, a)$? **Invertible Neural Network**

2 How to validate output $p(x \mid y_{obs}, a)$ of **INN** ? **Approximate Bayesian Computation**

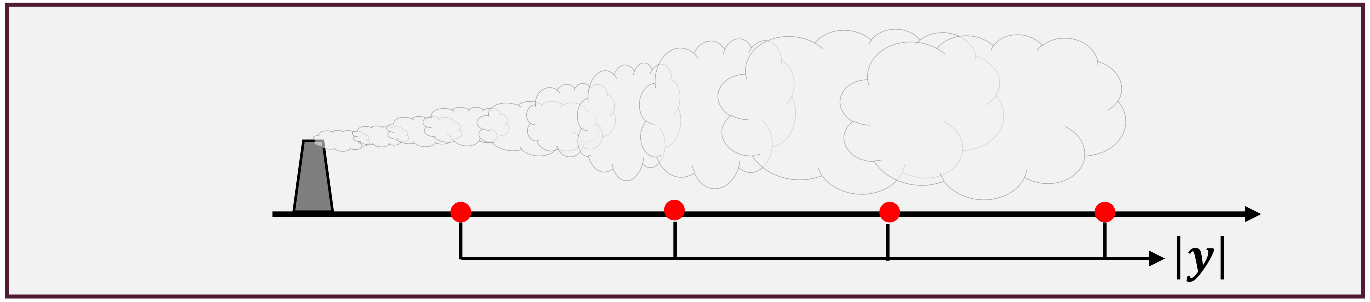


Result

Validation with ABC(Approximate Bayesian Computation) is composed of two cases.

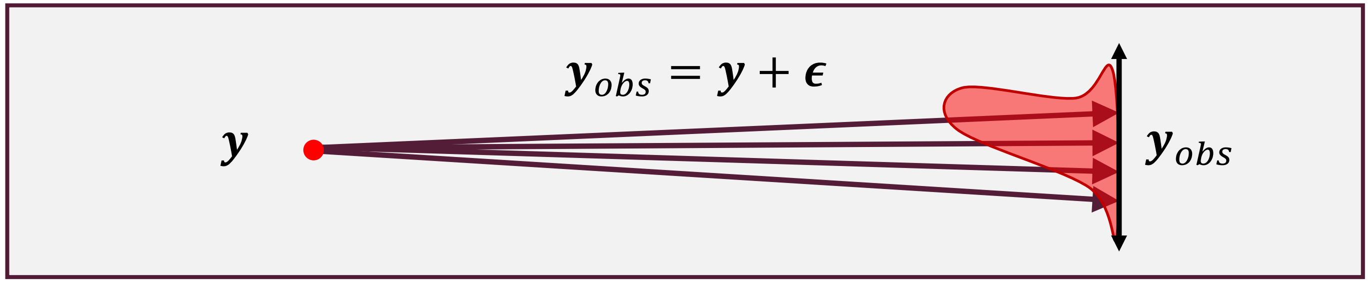
Output and validate of posterior probability distribution $\boldsymbol{p}(\boldsymbol{x}|\boldsymbol{y})$ according to…

1. Changes in the **# of $\boldsymbol{\gamma}$-dose measurement station** $|\boldsymbol{y}|$.



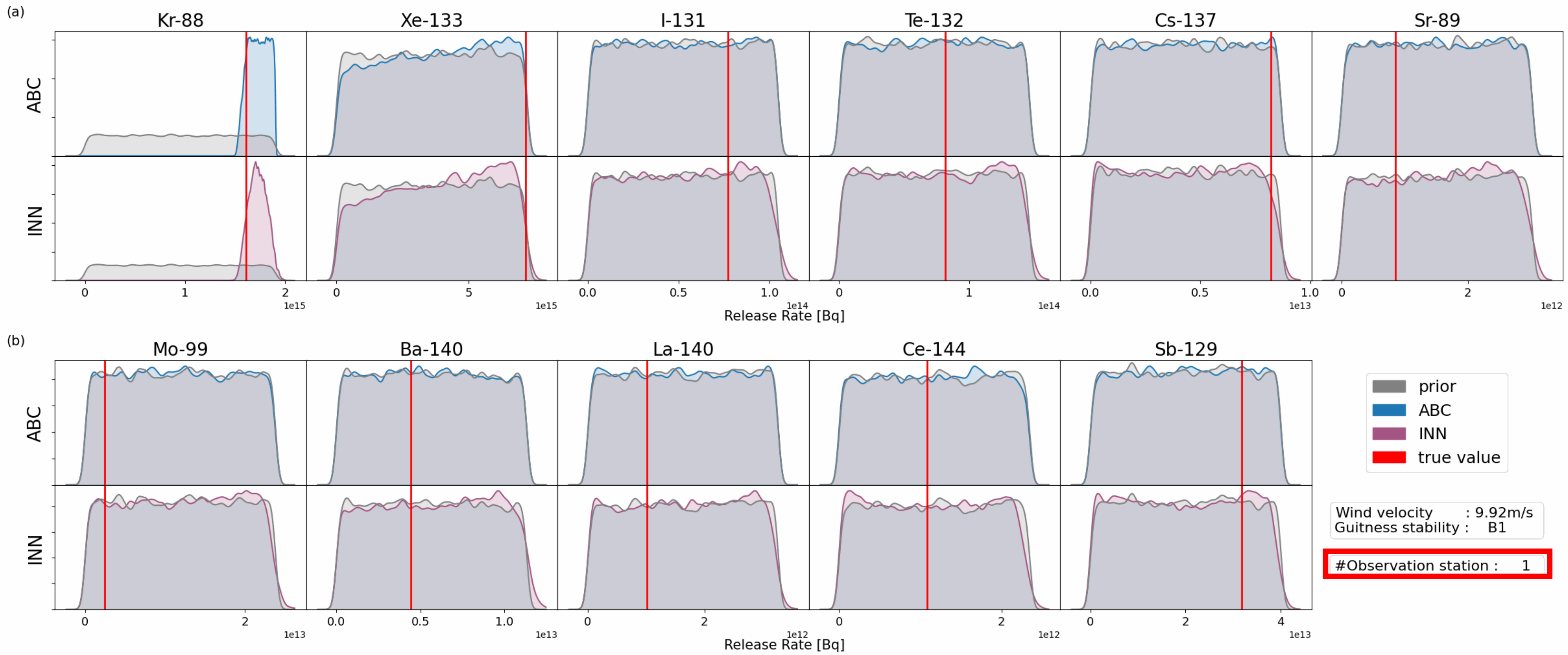
$|\boldsymbol{y}|$
$1 \sim 40$

2. Changes in the **observation uncertainty $\boldsymbol{\epsilon}$ of $\boldsymbol{\gamma}$-dose measurement**.



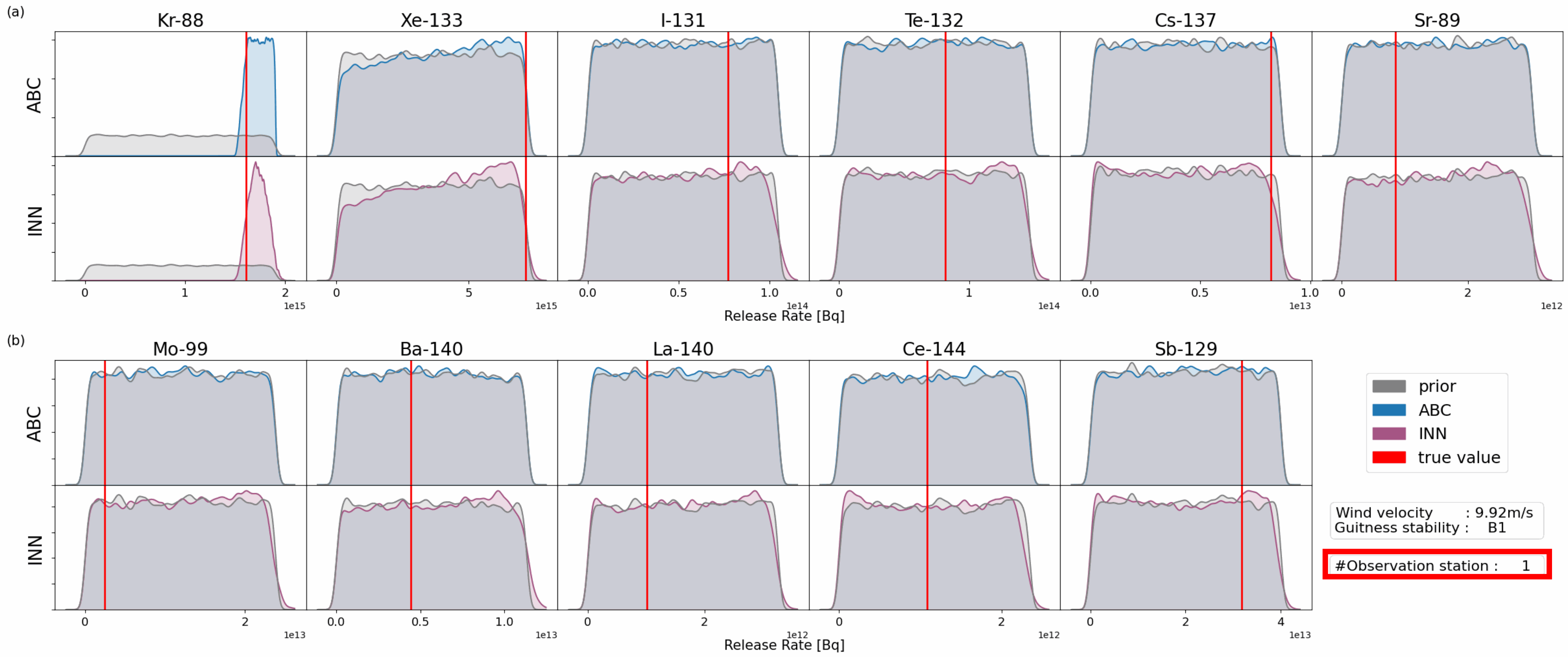
$\boldsymbol{\epsilon}$
$0.5\% \sim 20\%$

Result : # of observation $|y|$ variation



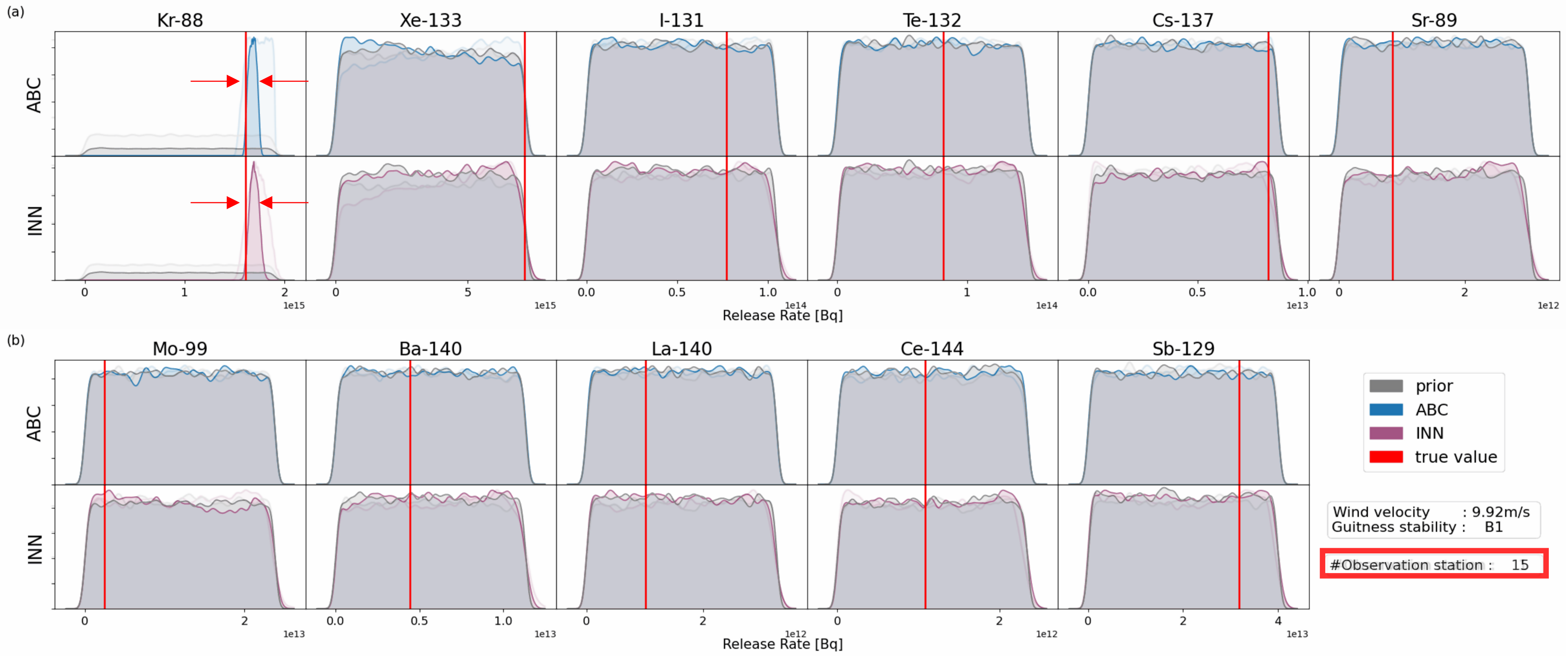
Compare ABC generated $p(x|y_{obs}, a)$ and INN generated $p(x|y_{obs}, a)$

Result : *# of observation* $|y|$ *variation*



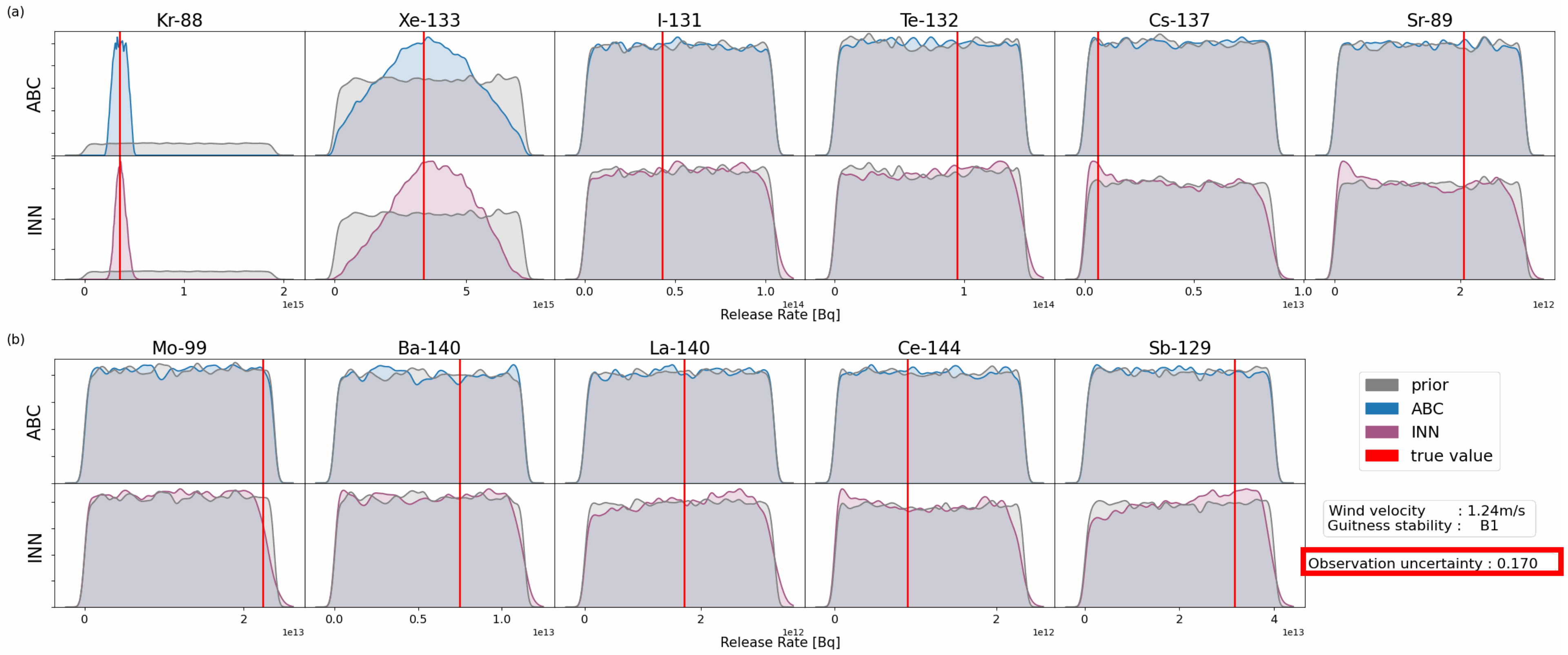
As *# of observation* $|y|$ get bigger,

Result : *# of observation* $|\boldsymbol{y}|$ *variation*



As *# of observation* $|\boldsymbol{y}|$ get bigger, posterior distribution $p(x|y_{obs}, a)$ shrink!

Result : *observation uncertainty ϵ variation*



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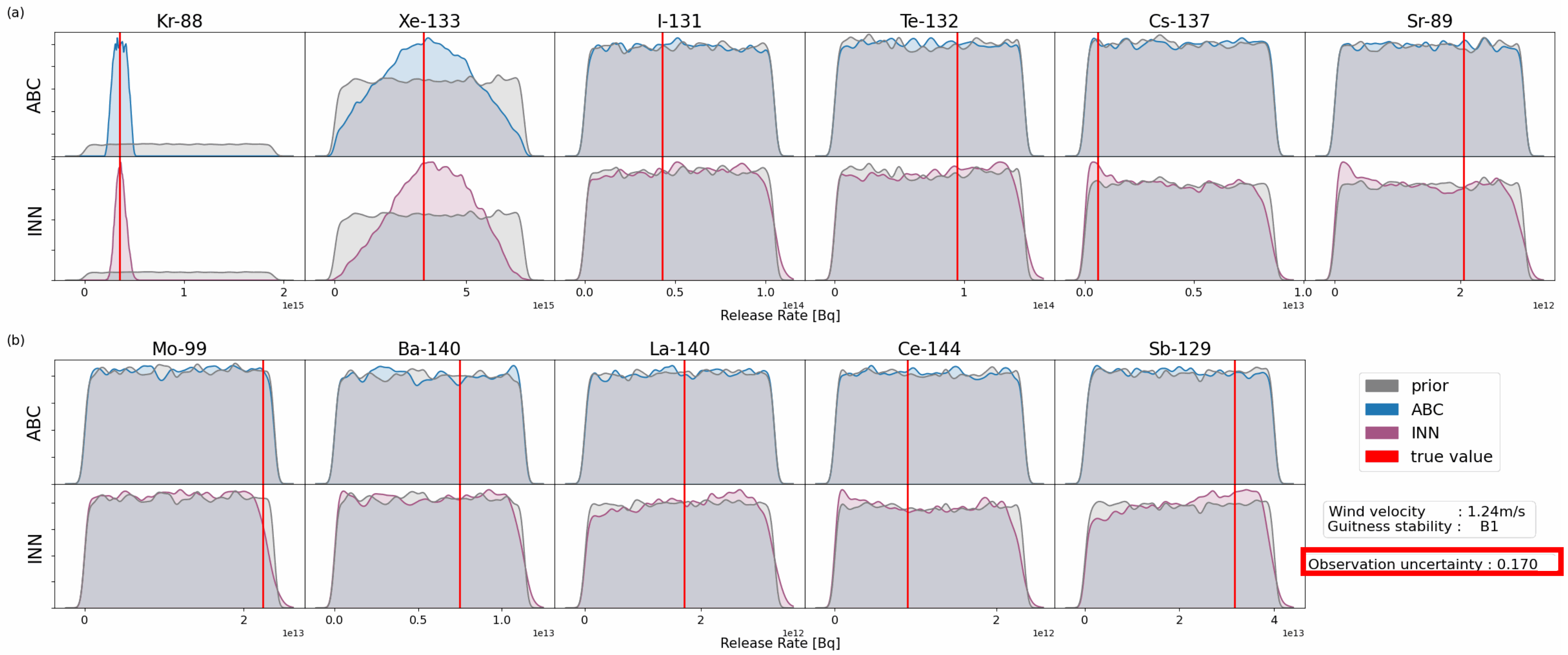
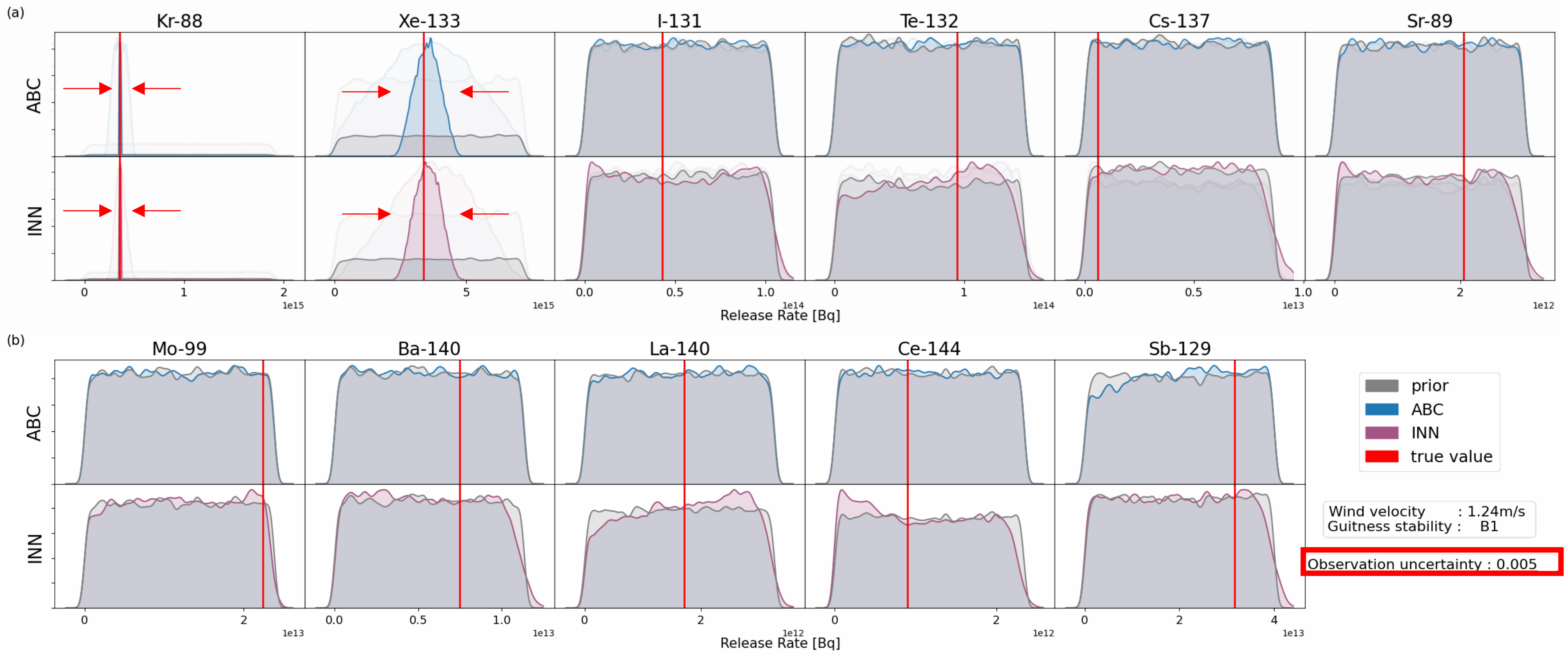


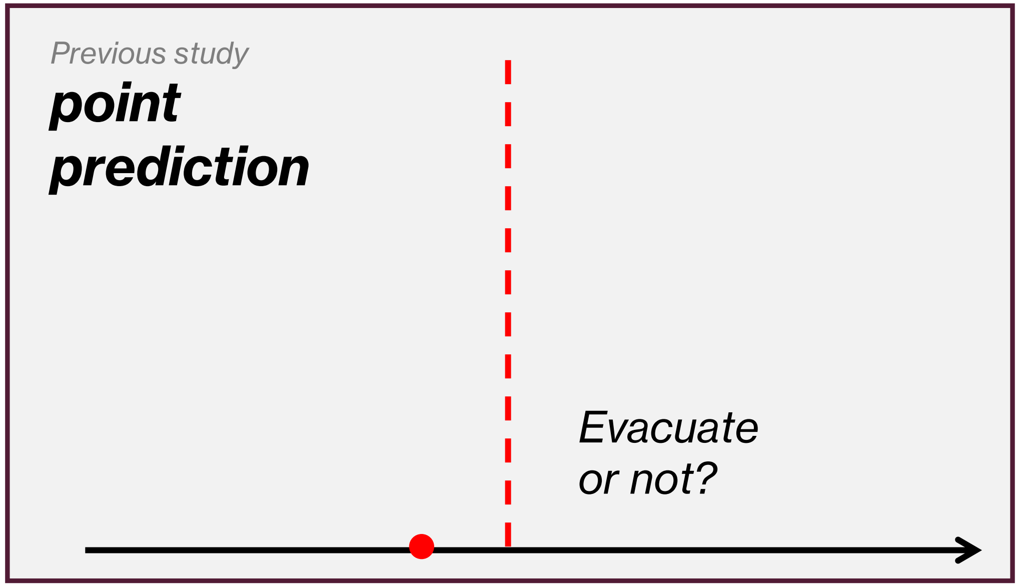
As *observation uncertainty ϵ* get smaller,

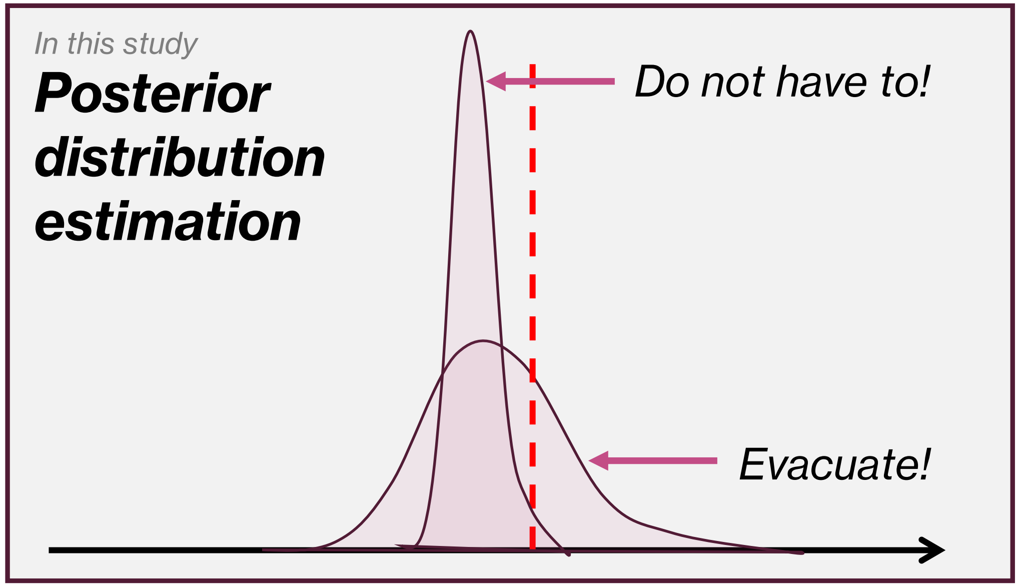
Result : *observation uncertainty ϵ variation*



As *observation uncertainty ϵ* get smaller, posterior distribution $p(x|y_{obs}, a)$ shrink!

Conclusion



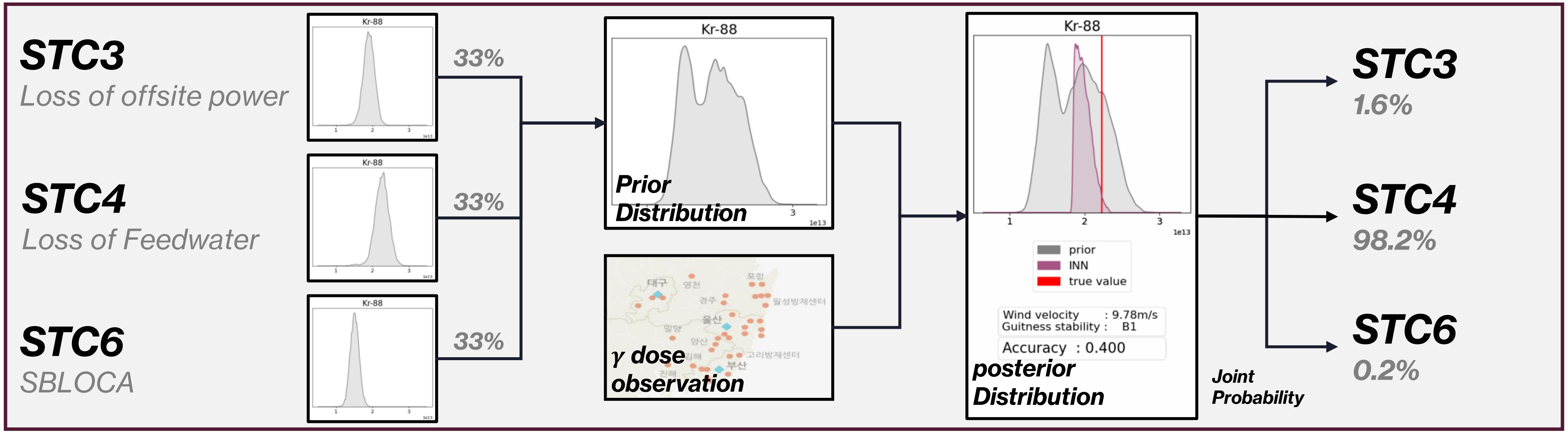


1. Offering probability distribution as a result.

   - **Gives true posterior** without any approximation or regularization

   - **Much more realistic and applicable in case of emergency**

Conclusion



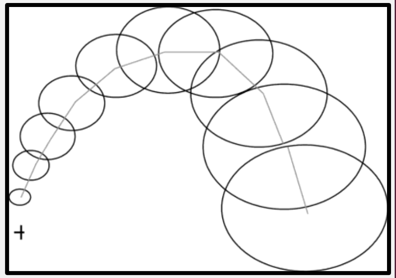
2. Successful modeling of Bayesian inverse problem considering observation error.

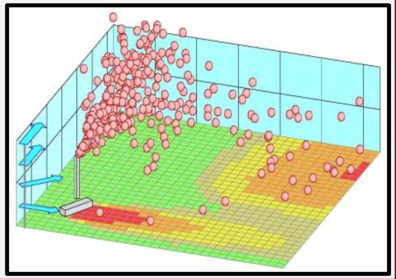
   - **Can be used for determining accident status** (ex STC, CFVS status…)

   - Gives **reliable data** for further PSA analysis

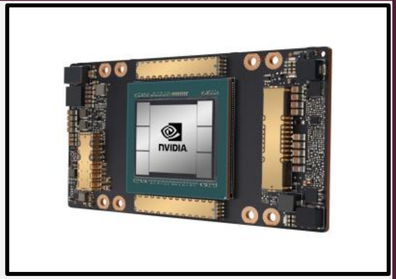
Conclusion

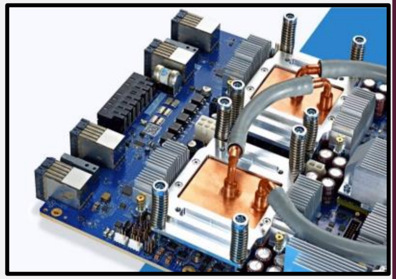
Sophisticated and Intensive Forward Simulation





Modern Computing and Computer technology





3. INN is scalable solution

- Can be applicable to **Gaussian puff model** and **Largrangian dispersion model**
- Fully works in GPU, harnessing advantage of modern-computing technology

THANK YOU

2024 KNS Spring
Suhyeon Kim (Speaker), Siho Jang, Eung Soo Kim

Seoul National University

Appendix :
Invertible Neural Network training

Training scheme is as followed.

We want to make,

$$\underset{\text{prior distribution}}{p(\cdot)} \quad \xrightarrow[\text{Update with data } \boldsymbol{y_{obs}} \text{ and condition } \boldsymbol{a}]{} \quad \underset{\text{posterior distribution}}{p(\cdot \mid \boldsymbol{y_{obs}}, \boldsymbol{a})}$$

Thanks to invertible architecture of INN(RealNVP),
it is possible to emulate a specific distribution as following manner.

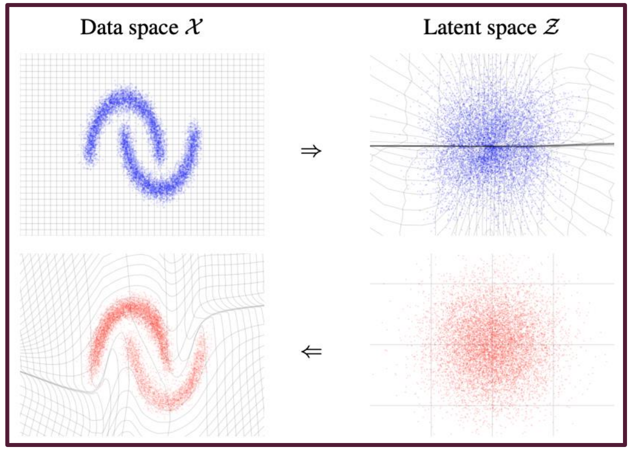
with $\boldsymbol{x} \sim p(\cdot), \boldsymbol{y} = f(\boldsymbol{x}; \boldsymbol{a})$
if $NN^F(\boldsymbol{x};\ \boldsymbol{y}, \boldsymbol{a}) \sim N(0, 1)$,
then with sampled, $\boldsymbol{z} \sim N(0, 1)$,
$NN^I(\boldsymbol{z};\ \boldsymbol{y}, \boldsymbol{a}) \sim p(\boldsymbol{x} \mid \boldsymbol{y}, \boldsymbol{a})$

In conclusion, whole training process of INN for
Bayesian inverse problem is summarized as followed.

Given training data
$[\boldsymbol{x_i}, \boldsymbol{a_i}, \boldsymbol{y_i}]$ with $y_i = f(\boldsymbol{x_i}; \boldsymbol{a_i})$,

$$\underset{\boldsymbol{\theta}}{\textbf{minimize}}\, \boldsymbol{D}\left\{ \boldsymbol{p}_{\mathrm{NN}_{\boldsymbol{\theta}}^{F}(\boldsymbol{x_i}; \boldsymbol{y_i}, \boldsymbol{a_i})}(\cdot), \mathbf{N}(\mathbf{0}, \mathbf{1}) \right\}$$

$$NN^F(\boldsymbol{x}; \boldsymbol{y}, \boldsymbol{a}) = \boldsymbol{z}$$



$$NN^I(\boldsymbol{z}; \boldsymbol{y}, \boldsymbol{a}) = \boldsymbol{x}$$