

# Fractional Gaussian Fields for Modeling and Rendering of Spatially-Correlated Media

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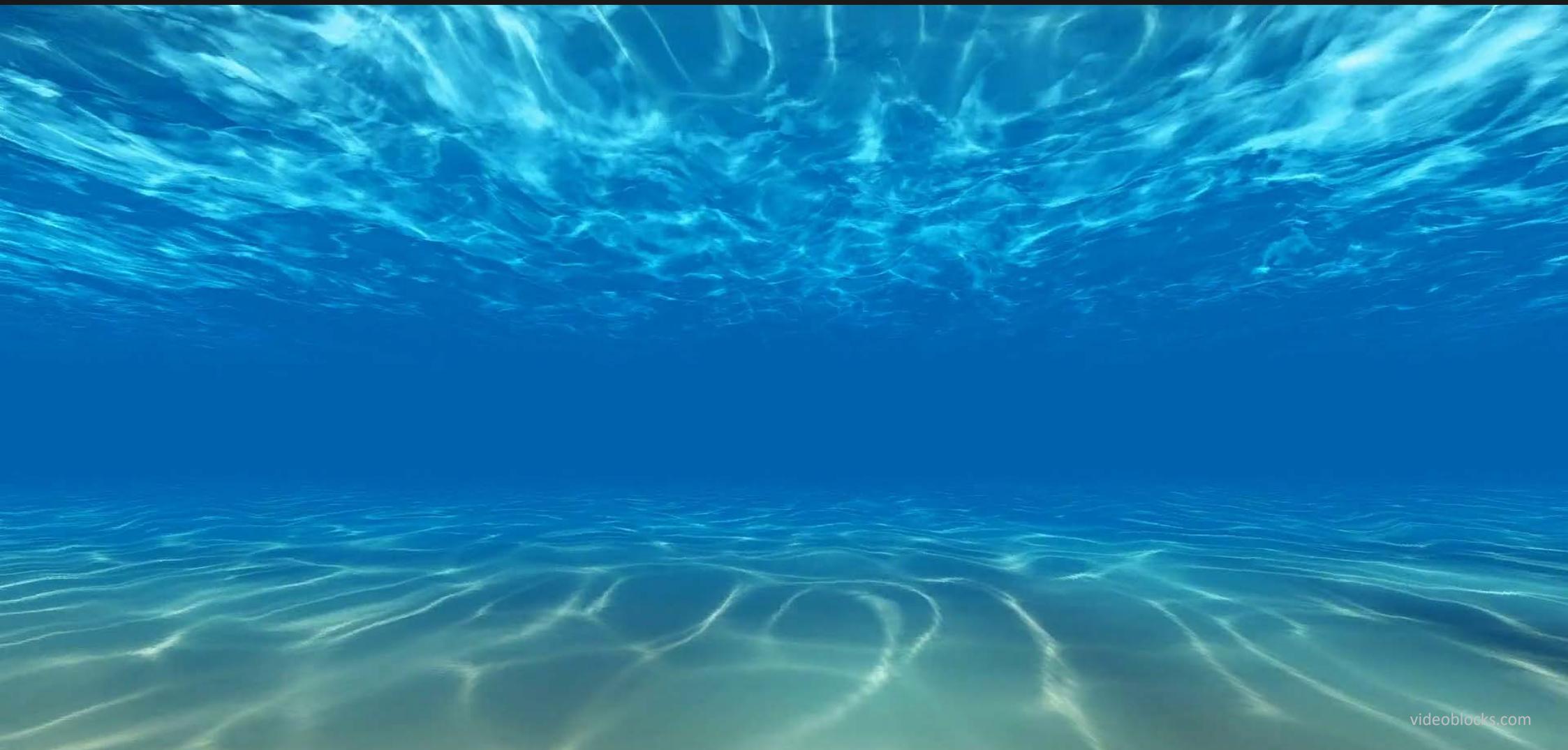
<sup>2</sup>University of California, Santa Barbara



# Participating Media



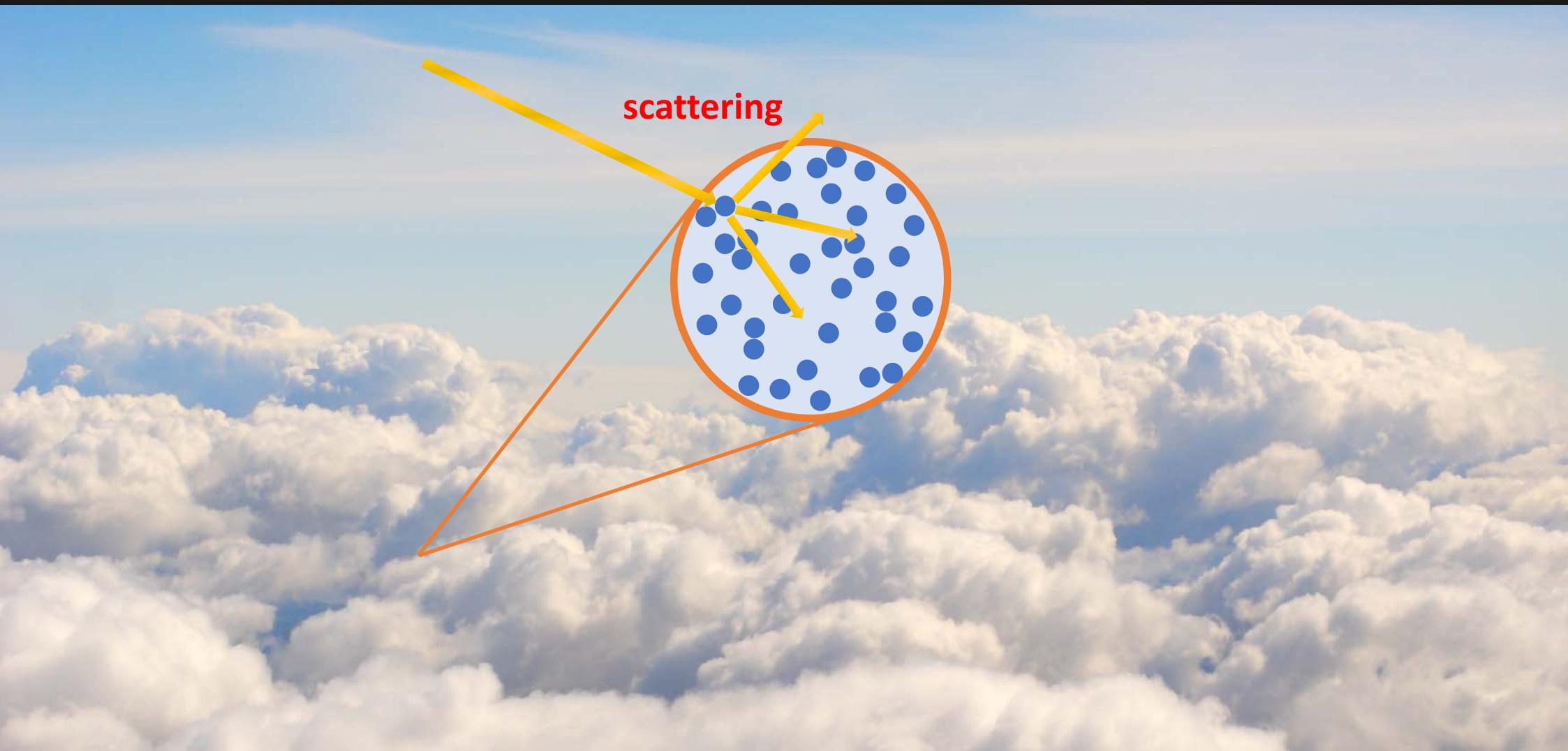
# Participating Media



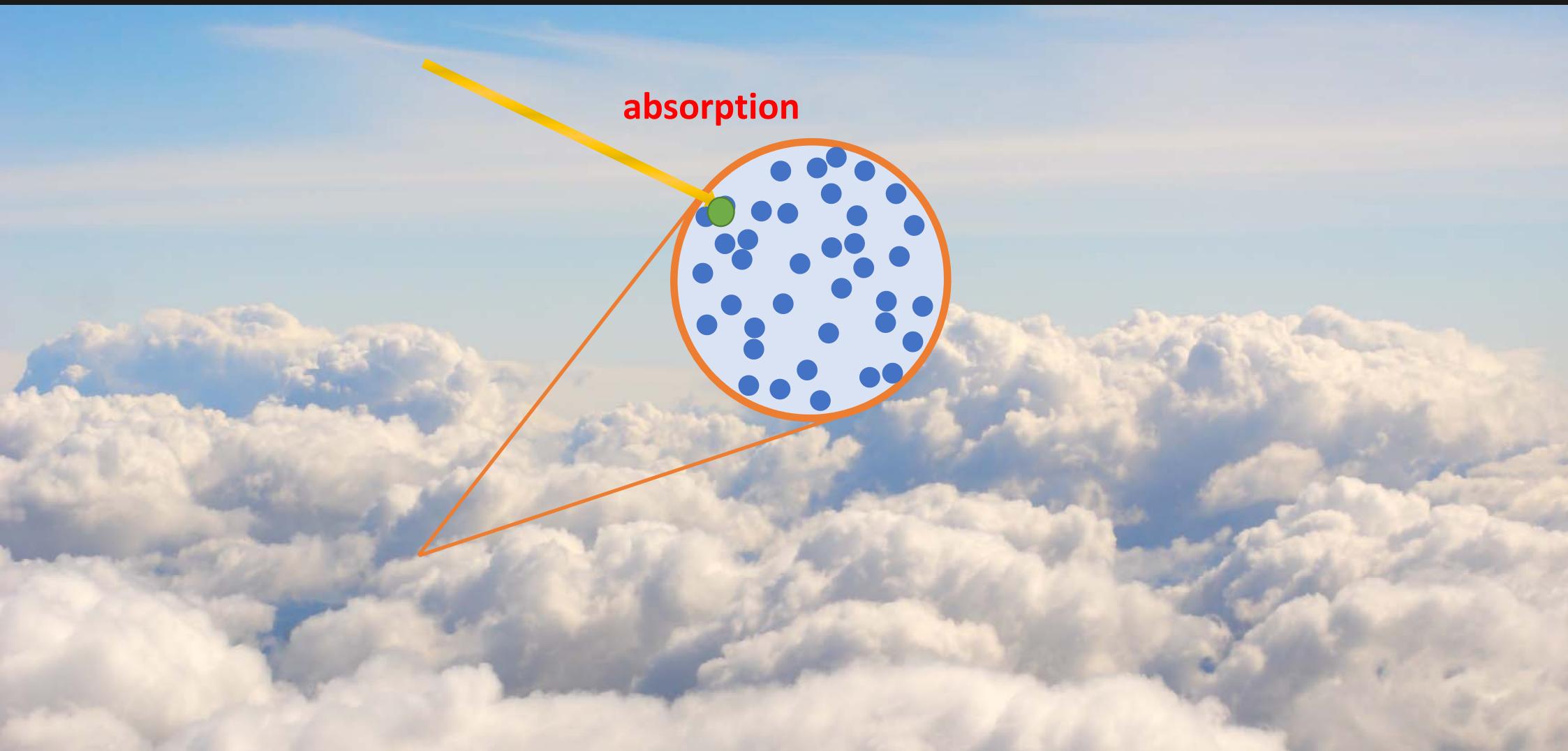
# Participating Media



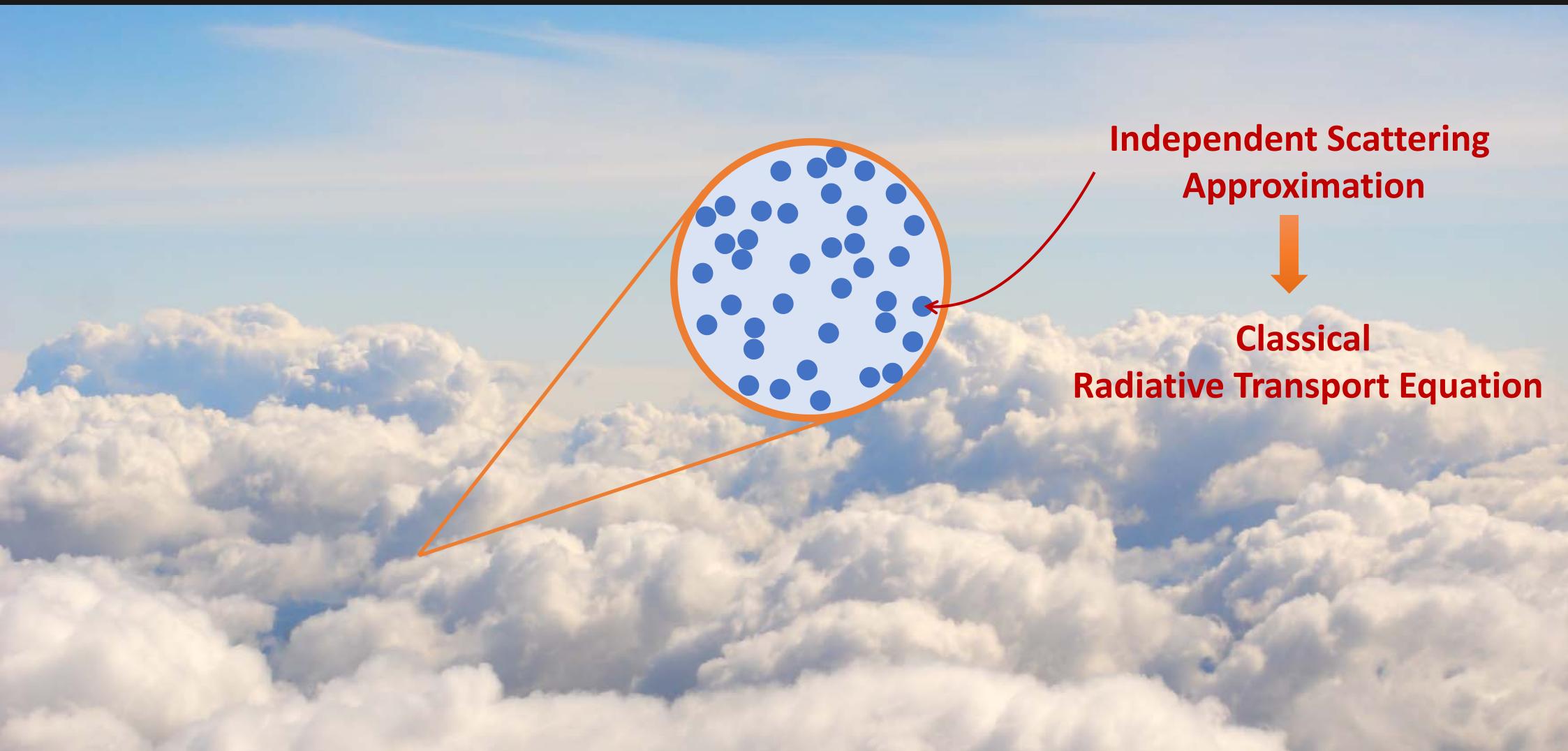
# Participating Media



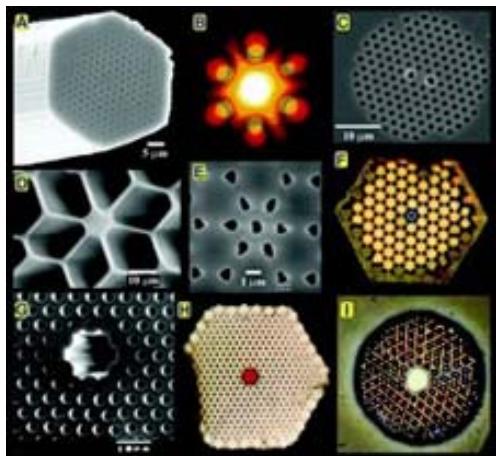
# Participating Media



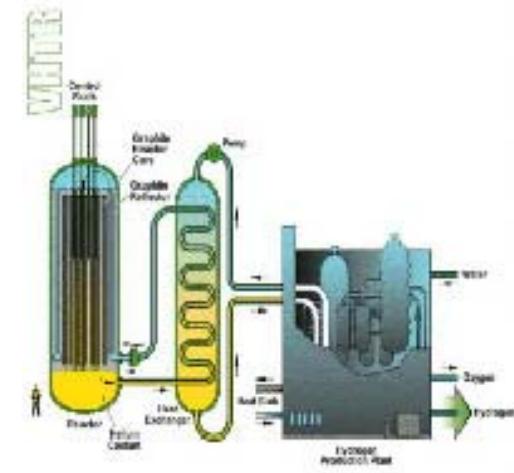
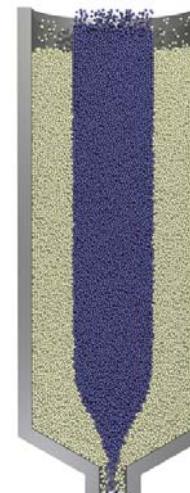
# Participating Media



# Related Work



(But, a lot of works have observed  
**correlations** in particle distribution)



# Related Work



# Related Work



[Meng et al. 2015]



[Müller et al. 2016]

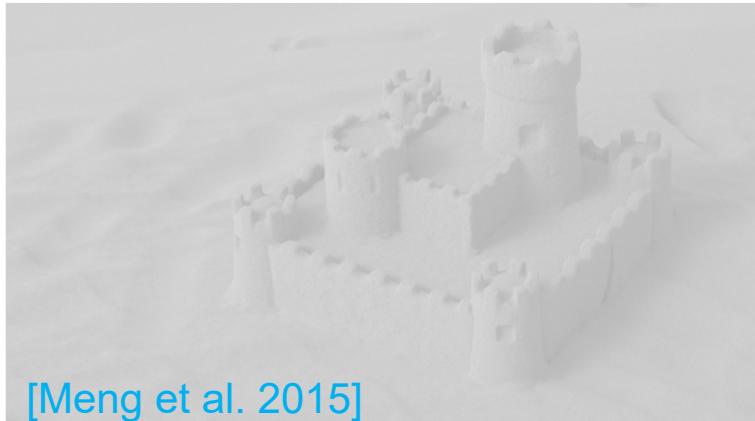


[Jarabo et al. 2018]



[Bitterli et al. 2018]

# Related Work



[Meng et al. 2015]



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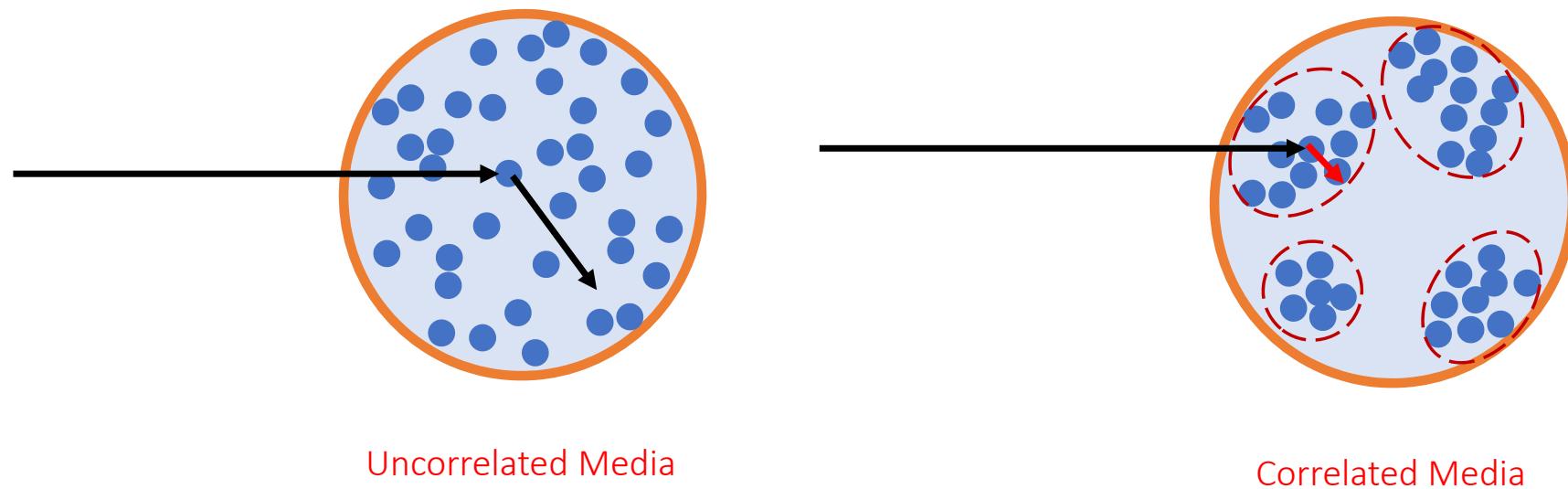


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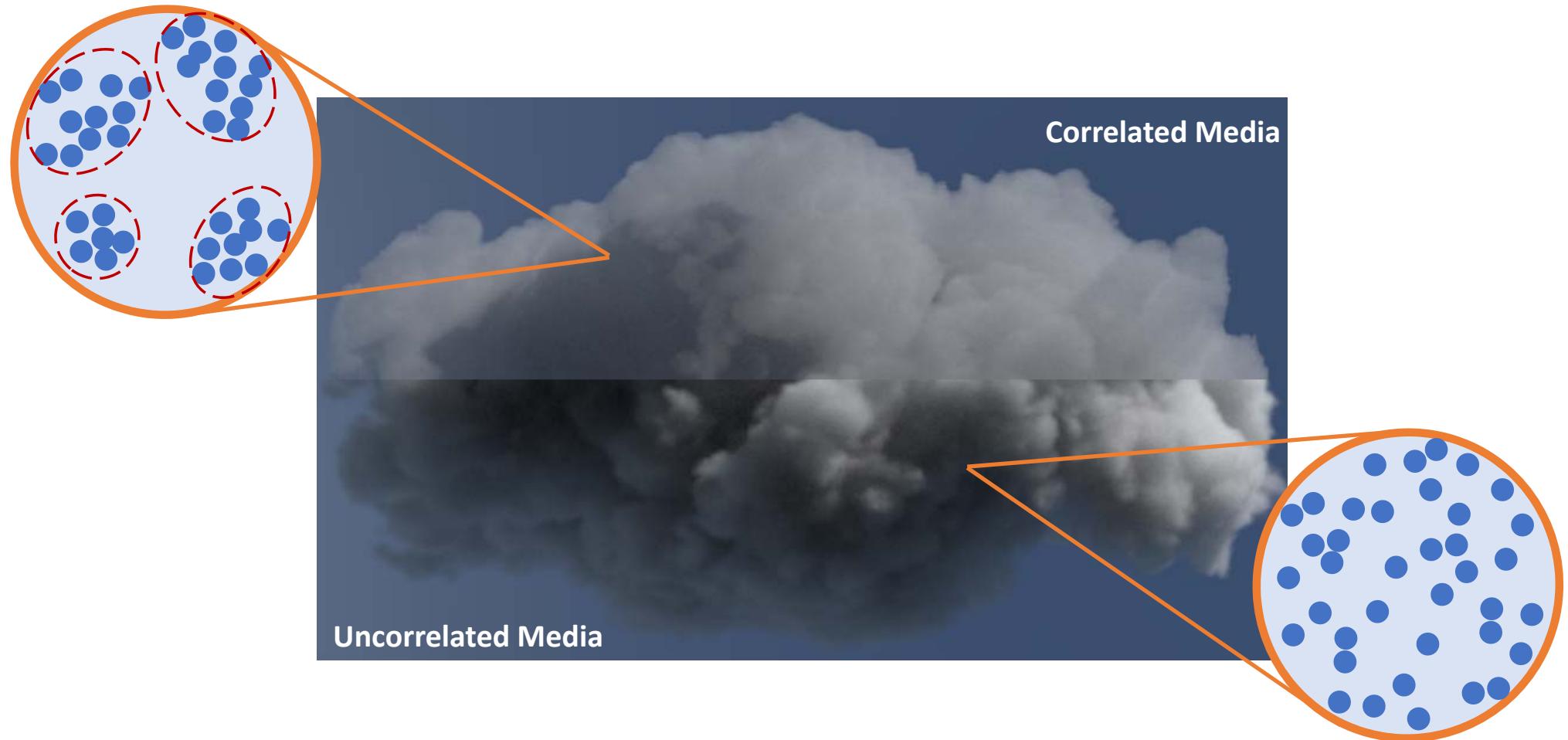
## Our method

- ✓ General media
- ✓ Heterogeneity
- ✓ Long-range correlations

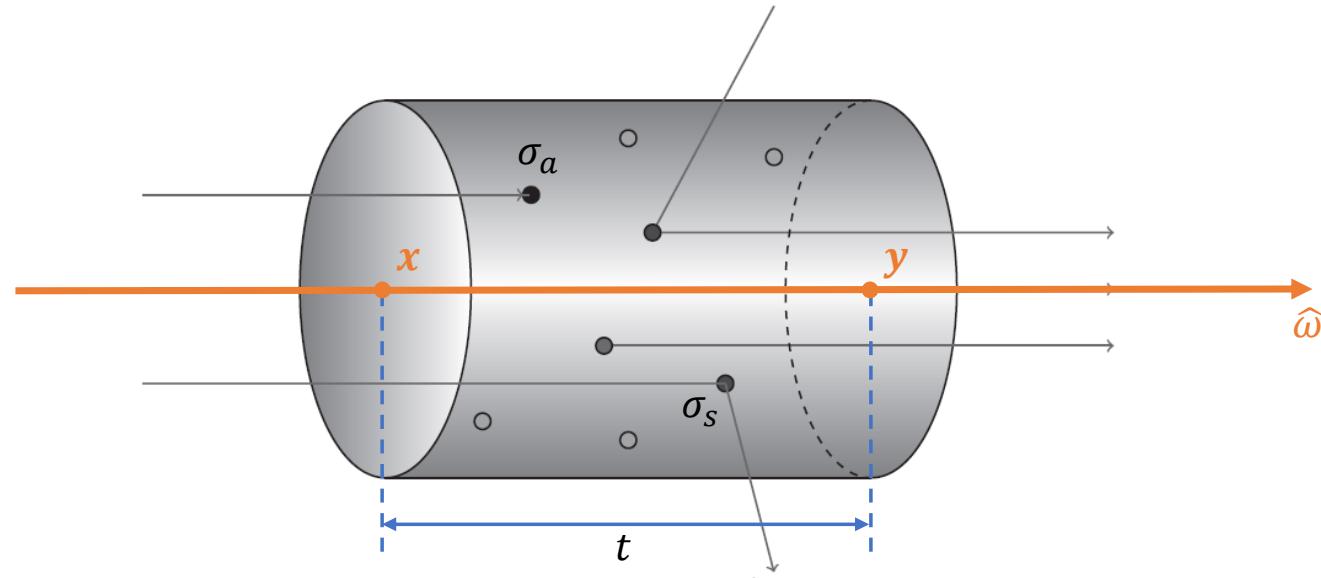
# Spatially-Correlated Media



# Spatially-Correlated Media



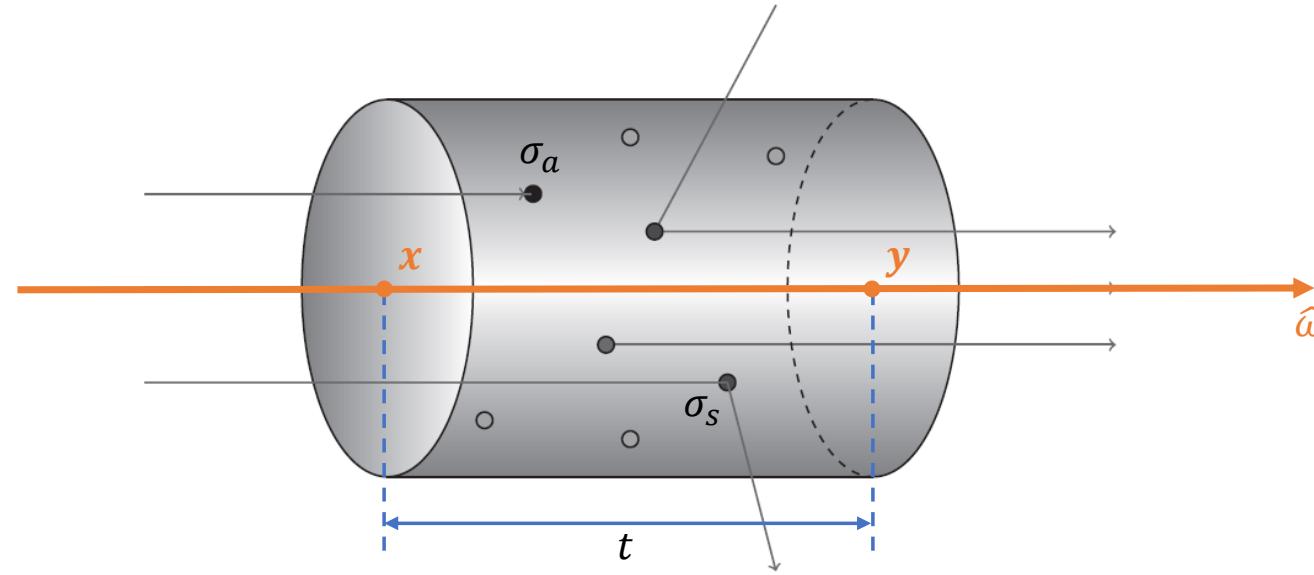
# Spatially-Correlated Media



$$\textbf{Transmittance: } T(x, y) = e^{- \int_0^t \sigma_t(x + s\hat{\omega}) ds} = e^{-\tau(x, t)}$$

$$\textbf{Extinction field: } \sigma_t(x) = \sigma_a(x) + \sigma_s(x)$$

# Spatially-Correlated Media



$$\textbf{Transmittance: } T(x, y) = e^{- \int_0^t \sigma_t(x + s\hat{\omega}) ds} = e^{-\tau(x, t)}$$

$$\textbf{Extinction field: } \sigma_t(x) = \sigma_a(x) + \sigma_s(x)$$

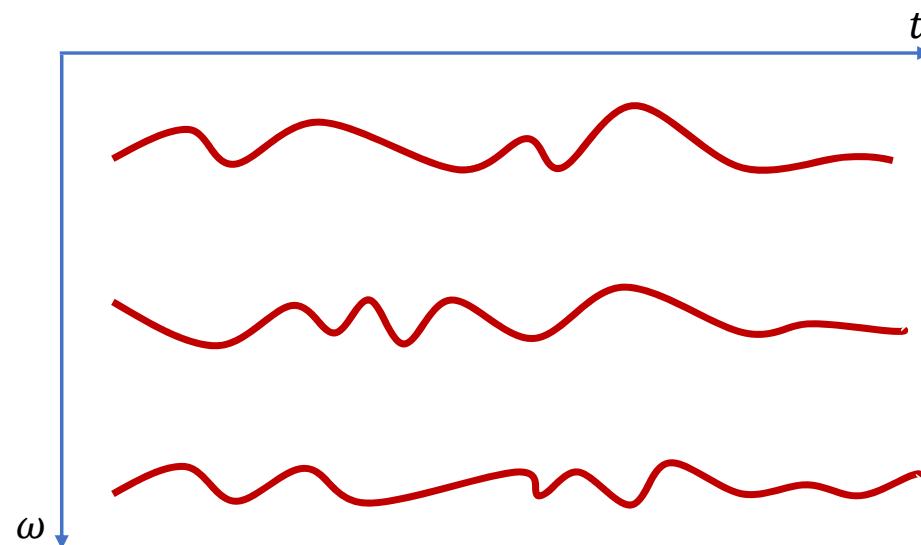
We model  $\sigma_t$  as a  
**Fractional Gaussian Field (FGF)**

# Fractional Gaussian Fields

## Random field

A collection of random variables:

$$X = \{X(t, \omega), t \in \mathbb{R}^d, \omega \in \Omega\}$$

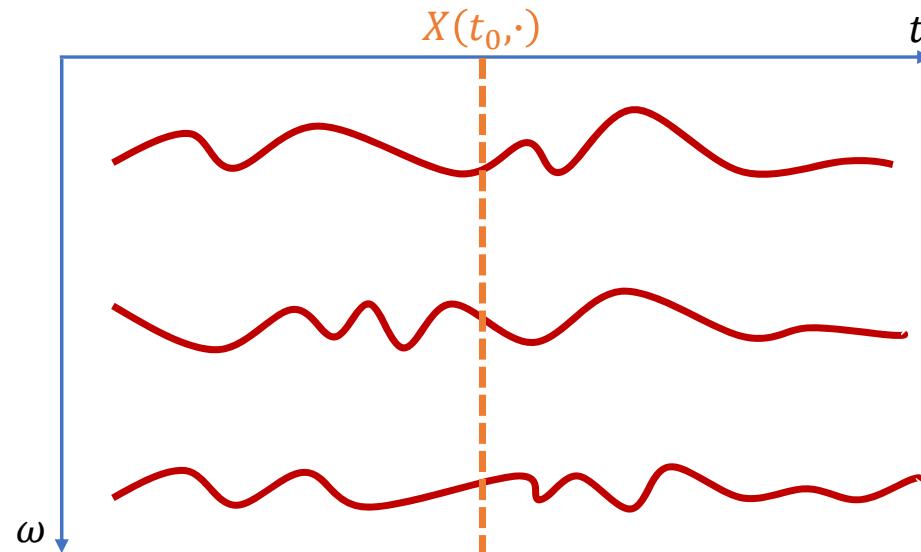


# Fractional Gaussian Fields

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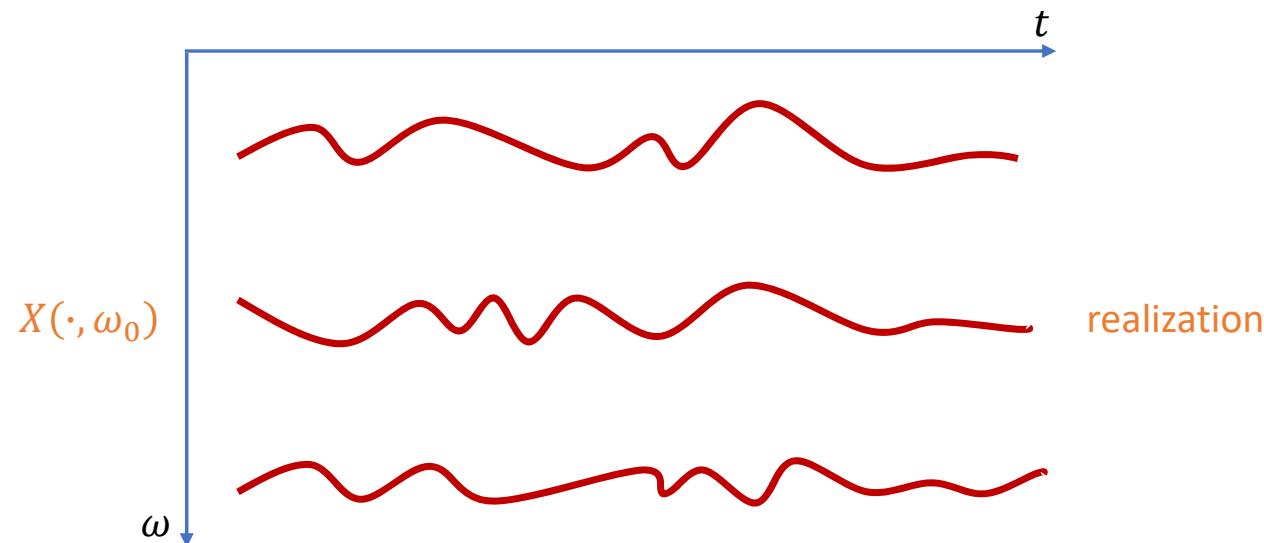


# Fractional Gaussian Fields

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# Fractional Gaussian Fields

## Random field

A collection of random variables:

$$X = \{X(t, \omega), t \in \mathbb{R}^d, \omega \in \Omega\}$$

## Gaussian (random) field

A collection of **Gaussian-distributed** random variables.



# Fractional Gaussian Fields

Then what is “**fractional**”?

Let  $I$  be the *integral operator*

$$I[1] = x \quad I^2[1] = x^2/2 \quad \sqrt{I}[x] = ?$$

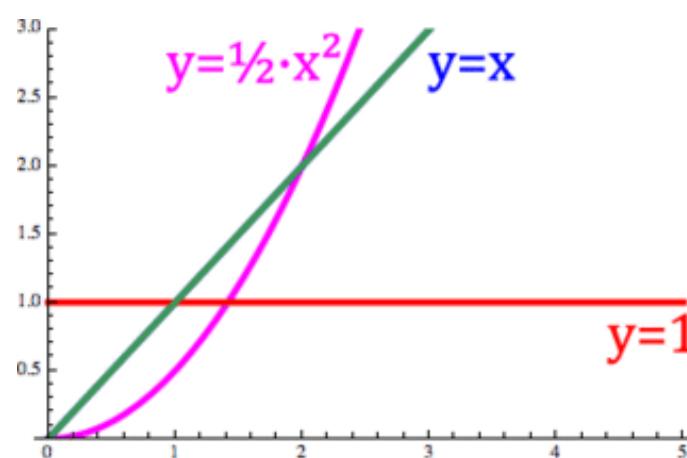
$$I^\alpha[x] = ?, \alpha > 0$$

# Fractional Gaussian Fields

Then what is “**fractional**”?

Let  $I$  be the *integral operator*

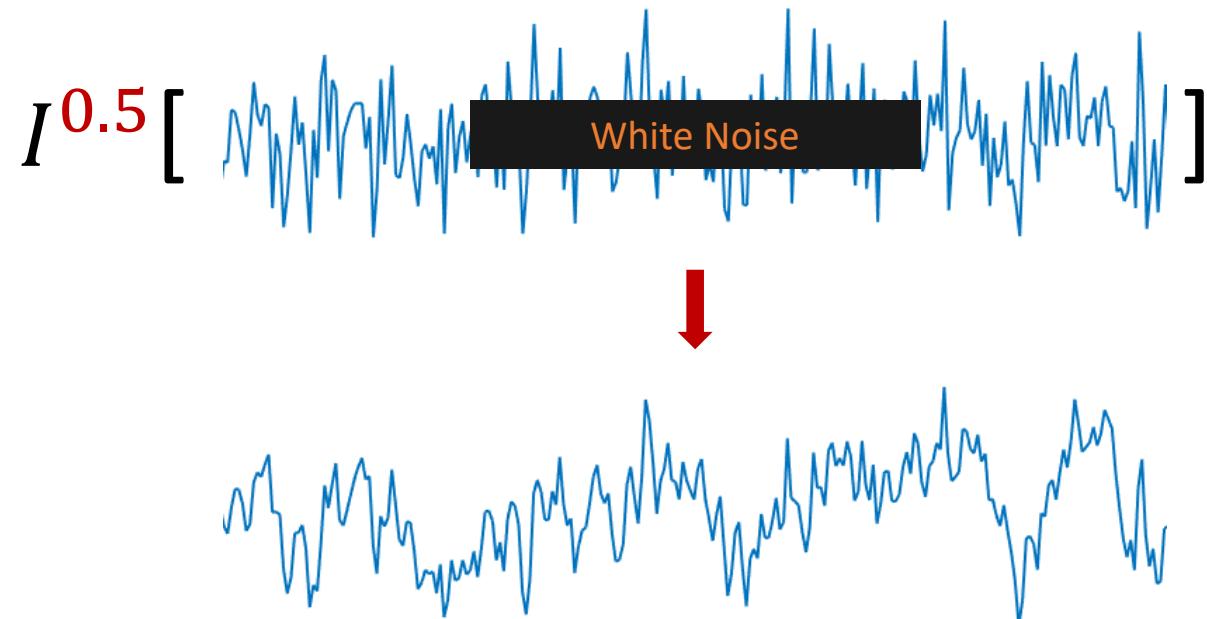
$$I[1] = x \quad I^2[1] = x^2/2 \quad \sqrt{I}[x] = ?$$



$$I^a[x] = ?, a > 0$$

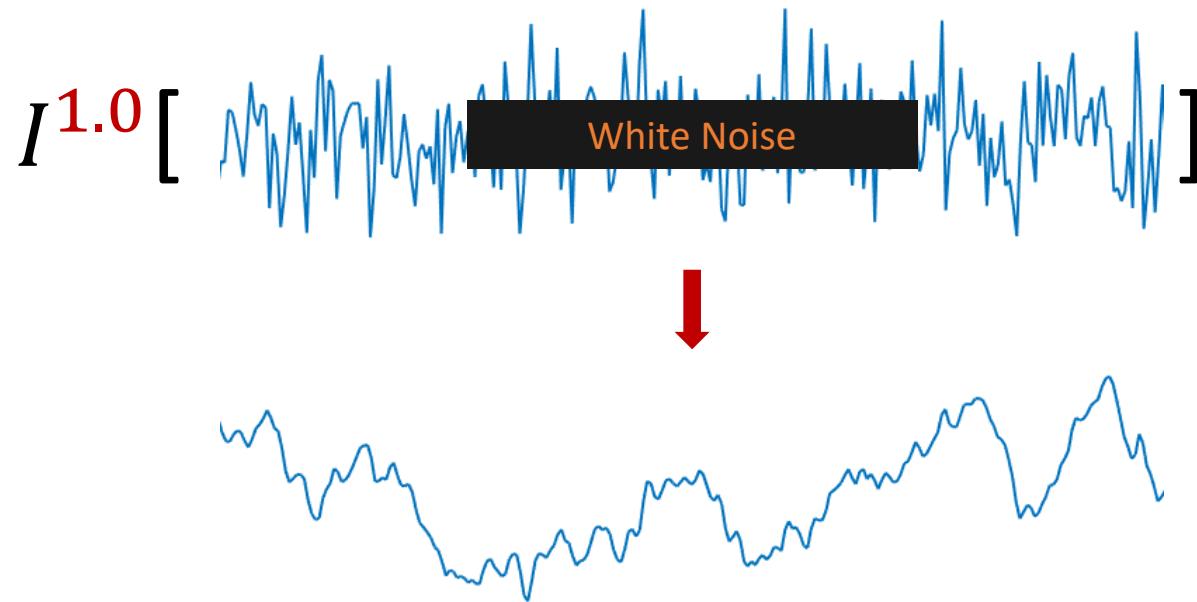
# Fractional Gaussian Fields

With the *fractional integral operator*  $I^\alpha$



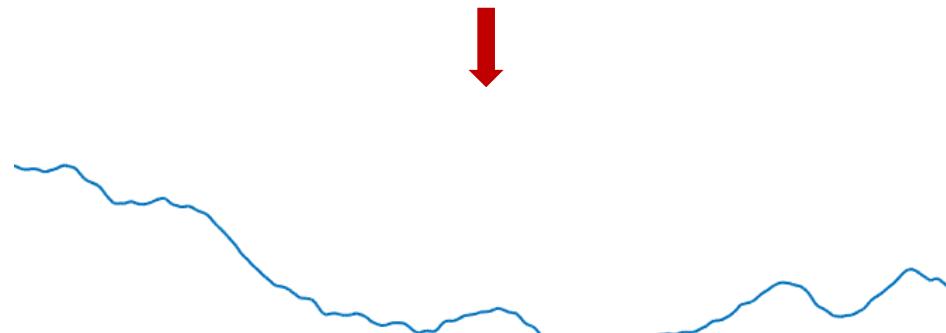
# Fractional Gaussian Fields

With the *fractional integral operator*  $I^a$

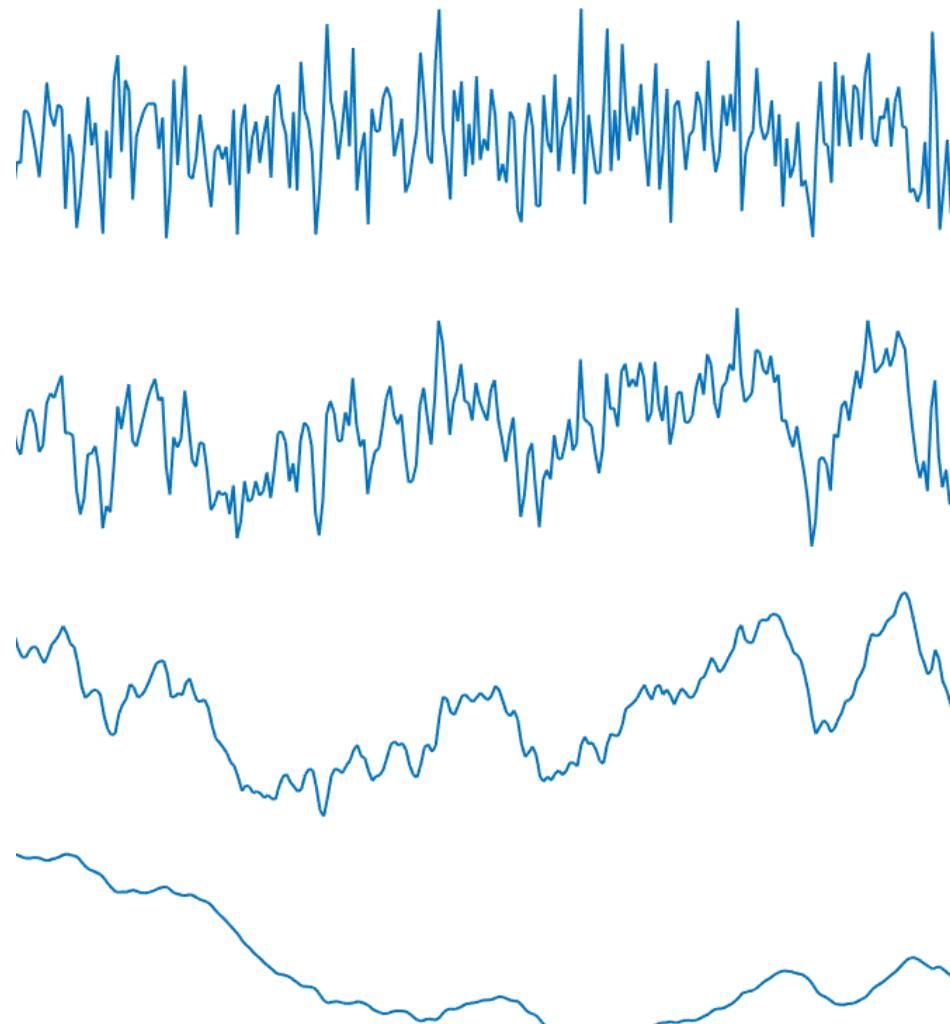


# Fractional Gaussian Fields

With the *fractional integral operator*  $I^a$



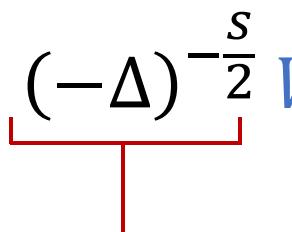
# Fractional Gaussian Fields



Fractional Gaussian Fields

# Fractional Gaussian Fields

$$d\text{-dimensional FGF: } M = (-\Delta)^{-\frac{s}{2}} W \quad W: \text{white noise}$$

  
fractional Laplacian

The FGF family

$$s = 0$$

white noise

$$s = 1, d = 1$$

Brownian motion

$$\frac{1}{2} < s < \frac{3}{2}, d = 1$$

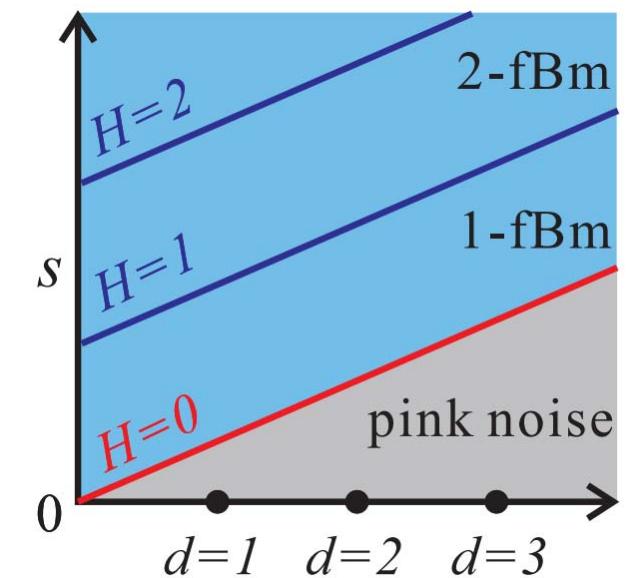
fractional Brownian motion  
(fBm)

# Fractional Gaussian Fields

$d$ -dimensional FGF:  $M = (-\Delta)^{-\frac{s}{2}} W$   $W$ : white noise

Hurst parameter  $H = s - \frac{d}{2}$

$H$  ↗ Correlation ↗



# Autocovariance Function

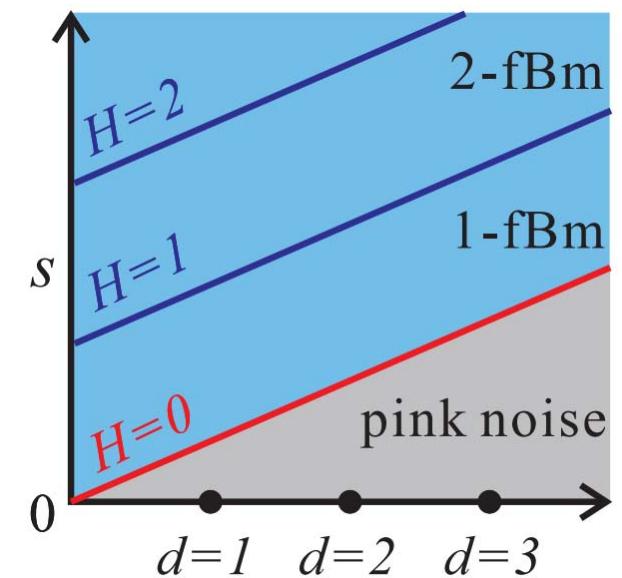
$d$ -dimensional FGF:  $M = (-\Delta)^{-\frac{s}{2}} W$   $W$ : white noise

Autocovariance function of **pink noise**:

$$\text{cov}(\mathbf{x}, \mathbf{y}) = C(H, d) S_w |\mathbf{x} - \mathbf{y}|^{2H}$$

$C(H, d)$  Scaling term

$S_w$  Power spectral density of white noise

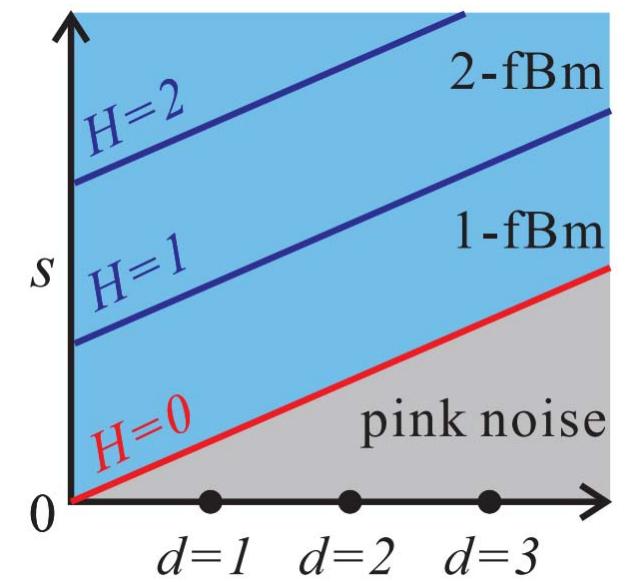


# Autocovariance Function

$d$ -dimensional FGF:  $M = (-\Delta)^{-\frac{s}{2}} W$   $W$ : white noise

Autocovariance function of **k-fBm**:

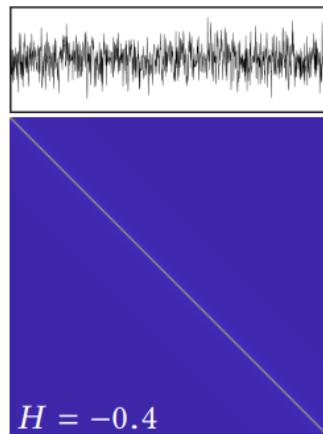
$$\text{cov}(\mathbf{x}, \mathbf{y}) = C(H, d) S_w \left\{ |x - y|^{2H} - \sum_{j=0}^{k-1} (-1)^j \binom{2H}{j} \cdot \left[ \left( \frac{|x|}{|y|} \right)^j |y|^{2H} + \left( \frac{|y|}{|x|} \right)^j |x|^{2H} \right] \right\}$$



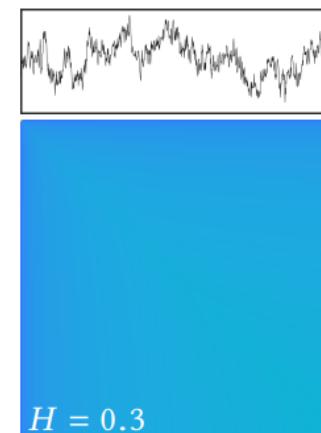
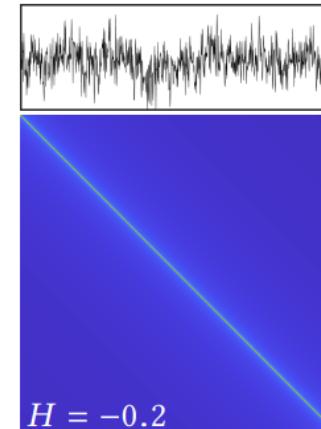
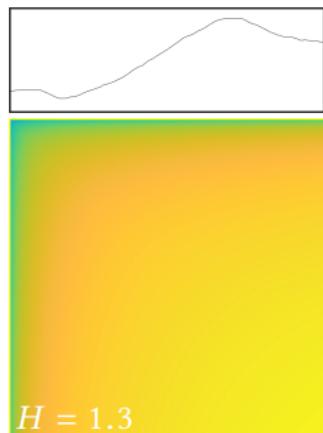
# Autocovariance Function

covariance matrix  
(1D)

Pink noise  
( $H < 0$ )



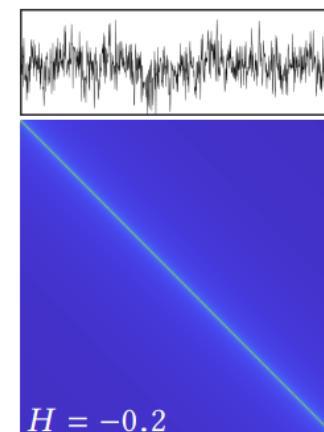
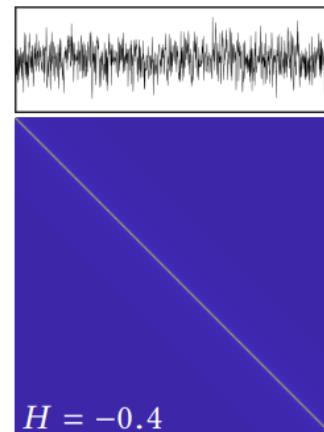
k-fBm  
( $H > 0$ )



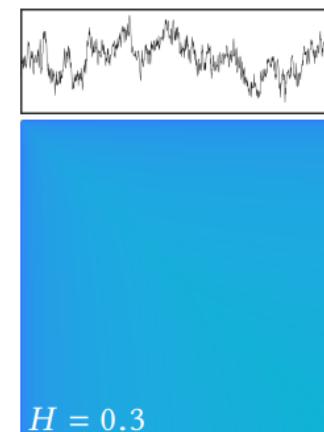
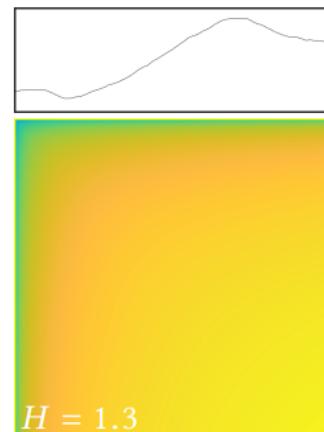
# Autocovariance Function

covariance matrix  
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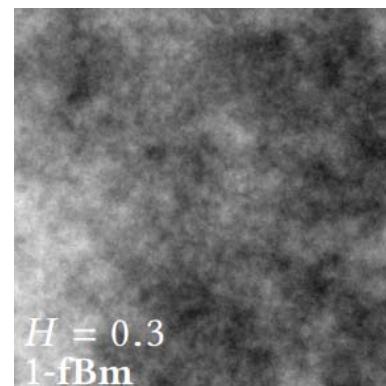
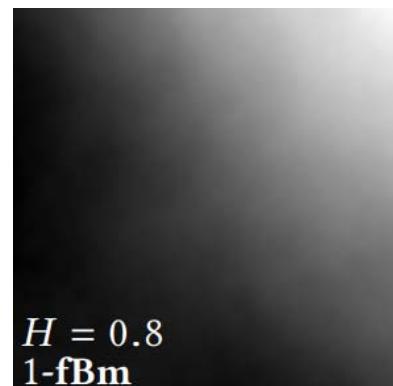
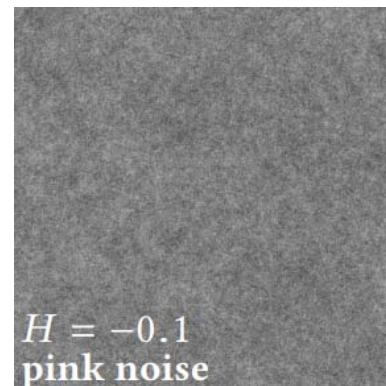
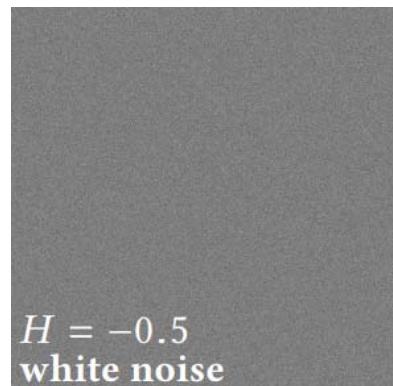


k-fBm

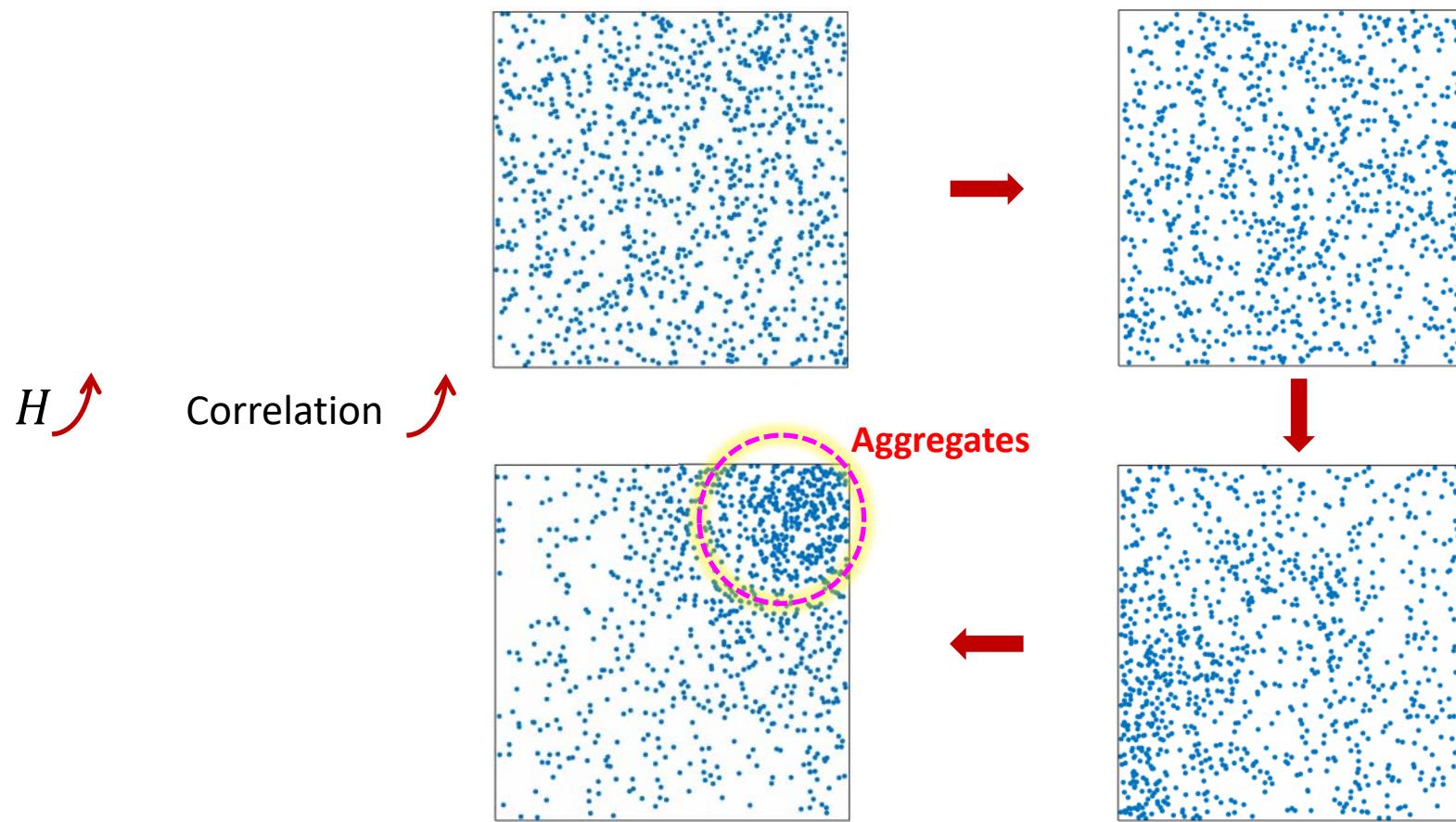


Long-range  
correlation

# 2D Fractional Gaussian Fields



# 2D Fractional Gaussian Fields



# Extinction Field

We model  $\sigma_t$  as a **FGF** :

$$\sigma_t(x) = \sigma_m + \sigma_u(x)$$

Macro-scale: **Constant**

Micro-scale: **FGF**

$$\text{var}[\sigma_t(x)] = ?$$

Fixing  $x$ ,  $\sigma_t(x)$  is a random variable with mean  $\sigma_m$  and its variance is controlled by the FGF

# Extinction Field

We model  $\sigma_t$  as a **FGF** :

The *line-averaged extinction*  $\bar{\sigma}_t(x) = \frac{\int_0^t \sigma_t(x+s\hat{\omega})ds}{t} = \frac{\tau(x,t)}{t}$  is a **Gaussian-distributed** random variable.

$$\text{var}[\bar{\sigma}_t] = \frac{1}{t^2} (\langle \tau(x,t)^2 \rangle - \langle \tau(x,t) \rangle^2) = \frac{1}{t^2} \int_0^t \int_0^t \boxed{\text{cov}(x', x'')} dt' dt''$$

autocovariance function of the  
**FGF**

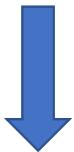
# Extinction Field

Pink noise  
( $H < 0$ )

$$\text{cov}(\mathbf{x}, \mathbf{y}) = C(H, d) S_w |\mathbf{x} - \mathbf{y}|^{2H}$$



$$\text{var}[\bar{\sigma}_t] = \frac{1}{t^2} (\langle \tau(x, t)^2 \rangle - \langle \tau(x, t) \rangle^2) = \frac{1}{t^2} \int_0^t \int_0^t \text{cov}(x', x'') dt' dt''$$



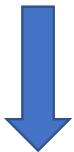
$$\text{var}_p[\bar{\sigma}_t] = -2C(H + 1)S_w t^{2H}$$

# Extinction Field

k-fBm  
(H>0)

$$\text{cov}(\mathbf{x}, \mathbf{y}) = C(H, d) S_w \left\{ |\mathbf{x} - \mathbf{y}|^{2H} - \sum_{j=0}^{k-1} (-1)^j \binom{2H}{j} \cdot \left[ \left( \frac{|\mathbf{x}|}{|\mathbf{y}|} \right)^j |\mathbf{y}|^{2H} + \left( \frac{|\mathbf{y}|}{|\mathbf{x}|} \right)^j |\mathbf{x}|^{2H} \right] \right\}$$

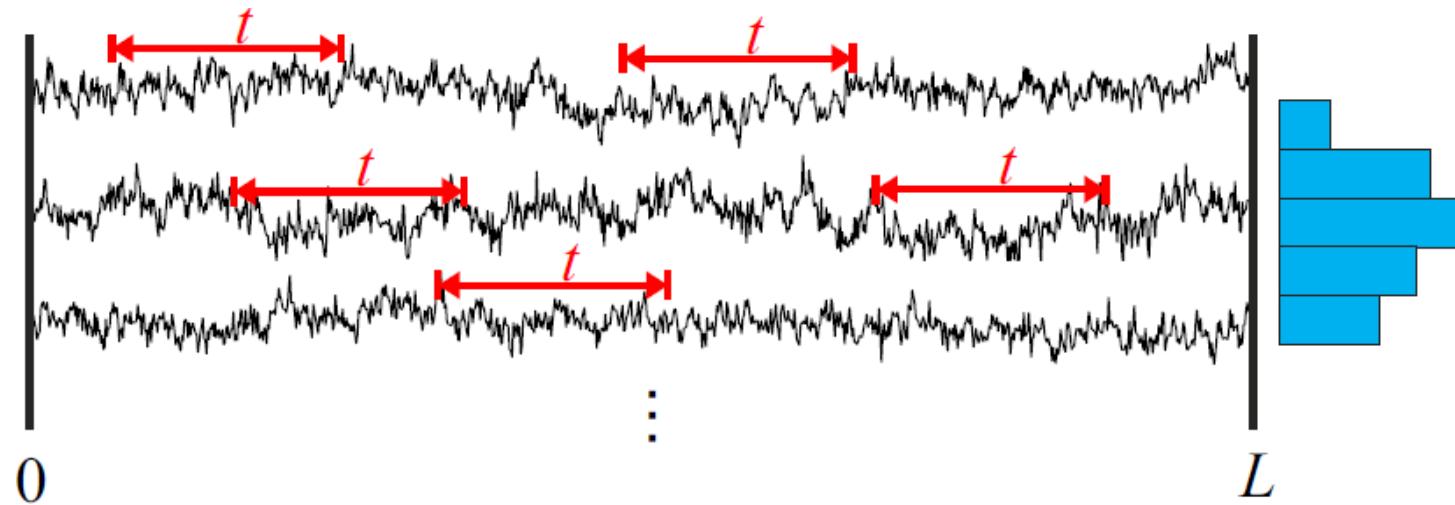
$$\text{var}[\bar{\sigma}_t] = \frac{1}{t^2} (\langle \tau(\mathbf{x}, t)^2 \rangle - \langle \tau(\mathbf{x}, t) \rangle^2) = \frac{1}{t^2} \int_0^t \int_0^t \text{cov}(\mathbf{x}', \mathbf{x}'') dt' dt''$$



$$\text{var}_{kf}[\bar{\sigma}_t] = \frac{2C(H)S_w(-1)^k}{2H+1} \binom{2H-1}{k-1} L^{2H}$$

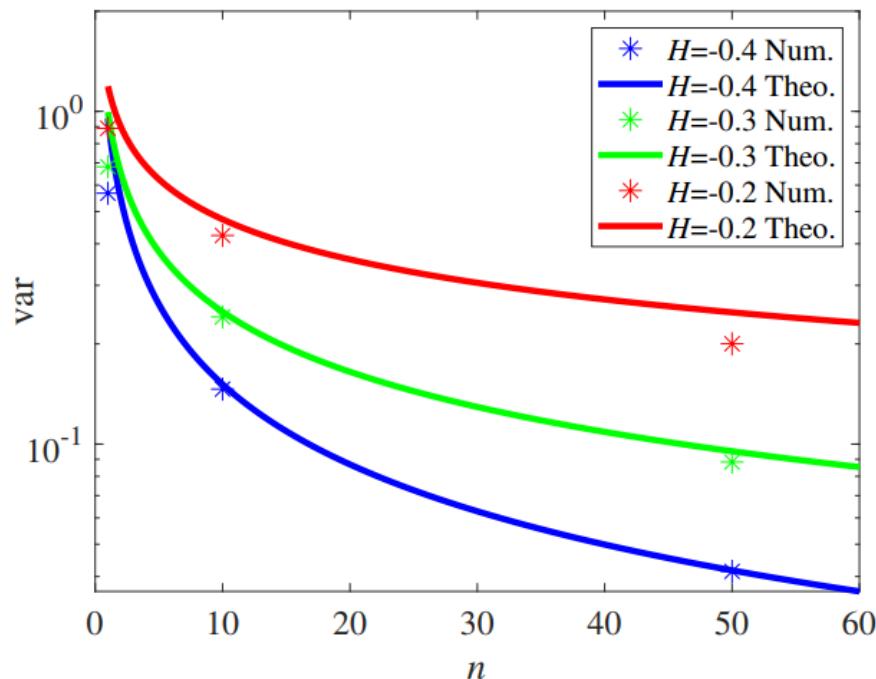
# Extinction Field

Numerical verification:

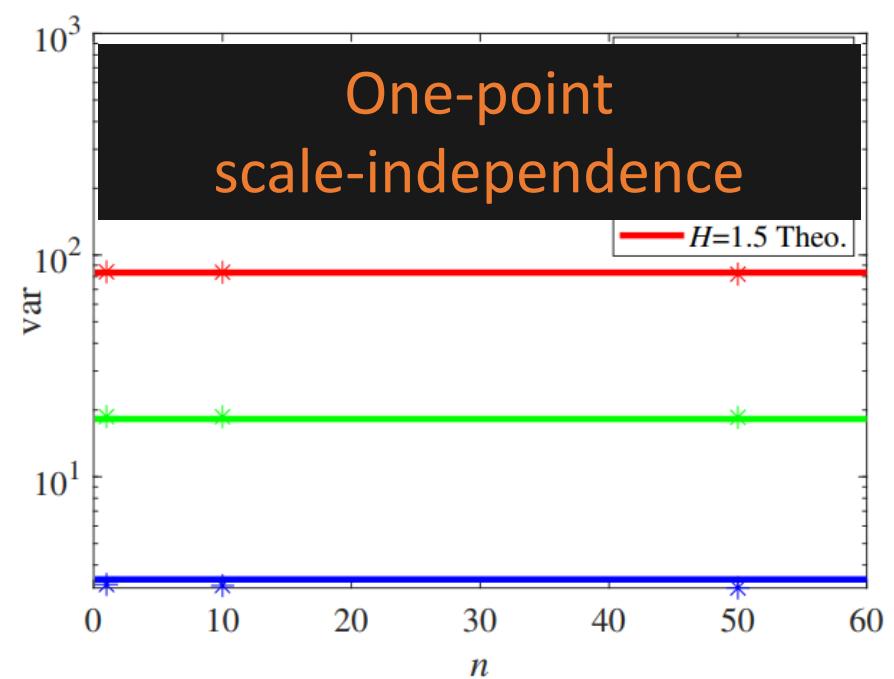


# Extinction Field

Numerical verification:



Pink noise

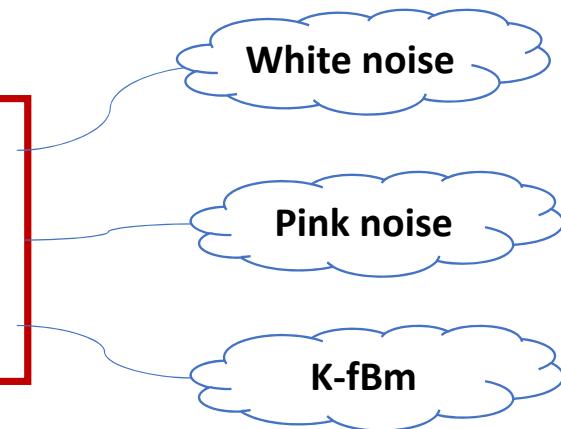


k-fBm

# Extinction Field

The variance of  $\bar{\sigma}_t(x)$ :

$$\text{var}[\bar{\sigma}_t] = \begin{cases} S_w t^{-1} & H = -1/2 \\ S_p(H) t^{2H} & H \in (-1/2, 0) \\ S_{kf}(H) L^{2H} & H \in (k-1, k) \end{cases}$$



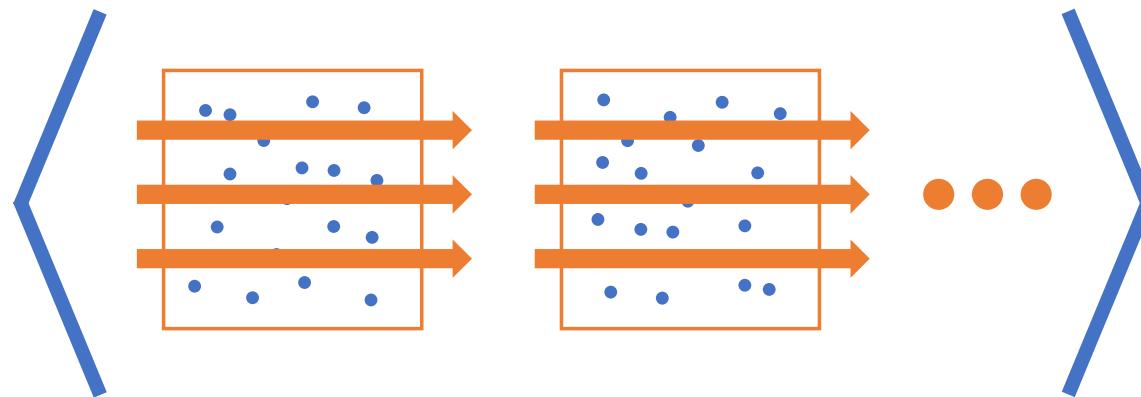
$$S_p(H) = \frac{S_w}{\Gamma(2H+3)|\sin(\pi H)|}$$

$$S_{kf}(H) = \frac{S_w}{\Gamma(2H+2)|\sin(\pi H)|} \binom{2H-1}{k-1}$$

# Transmittance

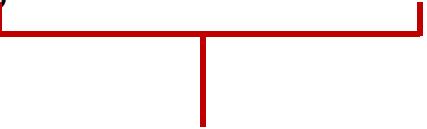
Ensemble-averaged transmittance

$$\langle \text{Tr}(t) \rangle = \langle e^{-t\bar{\sigma}_t} \rangle = \int_0^{\infty} e^{-t\bar{\sigma}_t} \text{pdf}(\bar{\sigma}_t) d\bar{\sigma}_t$$



# Transmittance

Ensemble-averaged transmittance

$$\langle \text{Tr}(t) \rangle = \langle e^{-t\bar{\sigma}_t} \rangle = \int_0^{\infty} e^{-t\bar{\sigma}_t} pdf(\bar{\sigma}_t) d\bar{\sigma}_t$$


characteristic function  $\varphi_{\bar{\sigma}_t}(it)$

$$\bar{\sigma}_t \sim \Gamma\left(\frac{\langle \bar{\sigma}_t \rangle^2}{\text{var}[\bar{\sigma}_t]}, \frac{\langle \bar{\sigma}_t \rangle}{\text{var}[\bar{\sigma}_t]}\right)$$

Use gamma distribution for non-negative extinction

# Transmittance

Ensemble-averaged transmittance

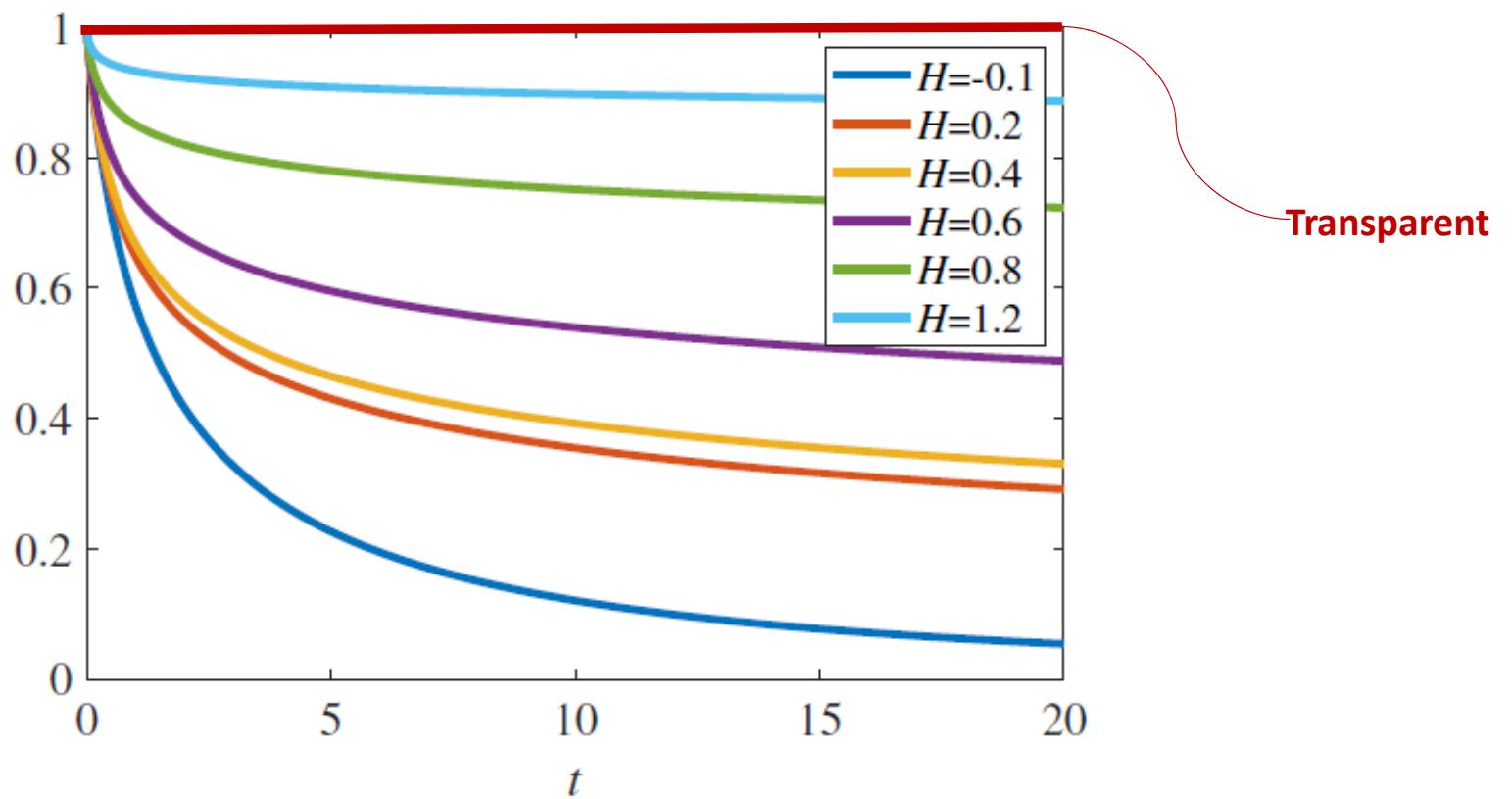
$$\langle \text{Tr}(t) \rangle = \langle e^{-t\bar{\sigma}_t} \rangle = \int_0^{\infty} e^{-t\bar{\sigma}_t} pdf(\bar{\sigma}_t) d\bar{\sigma}_t$$



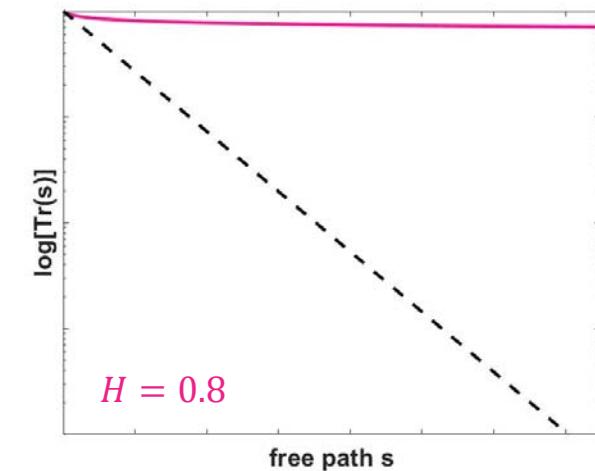
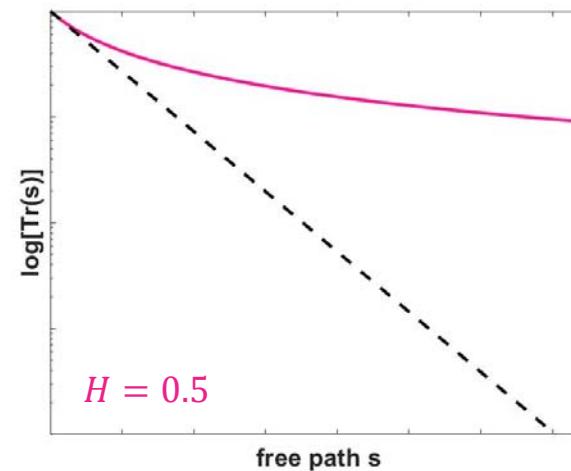
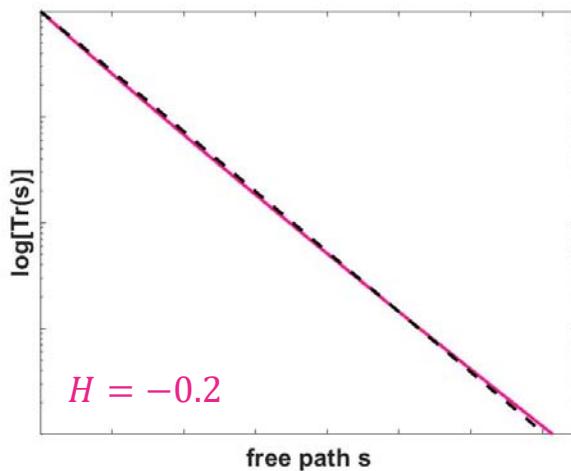
$$\text{Tr}(t) = \varphi_{\bar{\sigma}_t}(it) = \left(1 + \frac{\langle \bar{\sigma}_t \rangle}{\alpha(t)} t\right)^{-\alpha(t)}$$

$$\alpha(t) = \frac{\langle \bar{\sigma}_t \rangle^2}{\text{var}[\bar{\sigma}_t]}$$

# Transmittance



# Transmittance



# Rendering Techniques

## Energy-Conserving Volumetric Rendering Equation

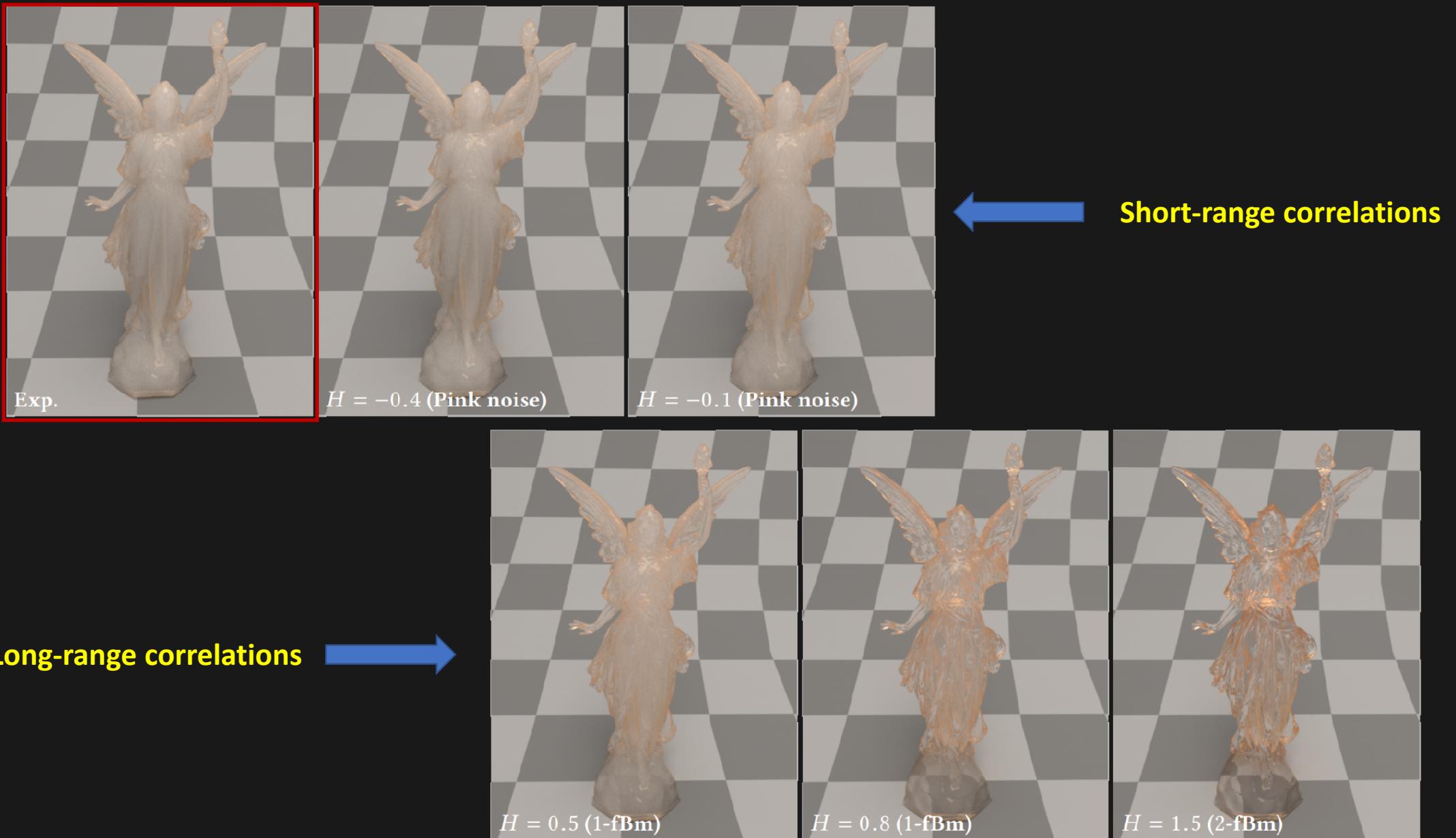
$$L_o(\mathbf{x}, \boldsymbol{\omega}) =$$

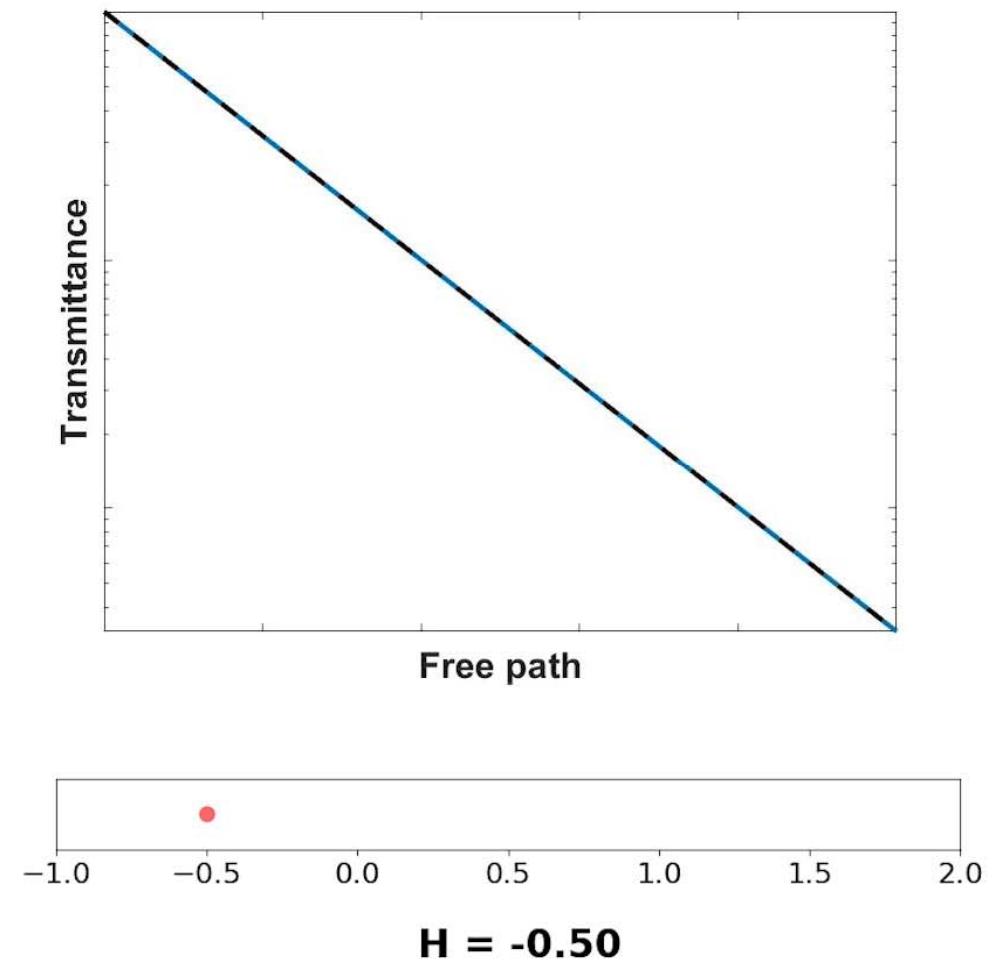
$$\int_0^t T(\mathbf{x}, \mathbf{x}') \Lambda \sigma_t(\mathbf{x}') L_i(\mathbf{x}', \boldsymbol{\omega}) dt' + T(\mathbf{x}, \mathbf{x}_s) L_s(\mathbf{x}_s, \boldsymbol{\omega})$$

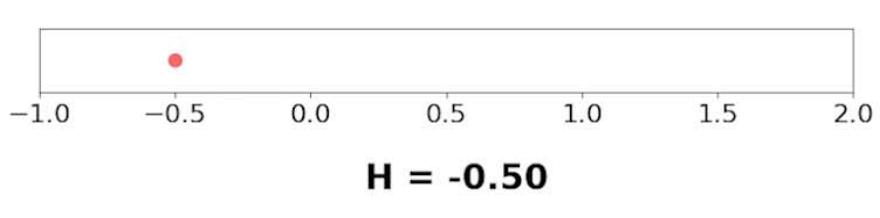
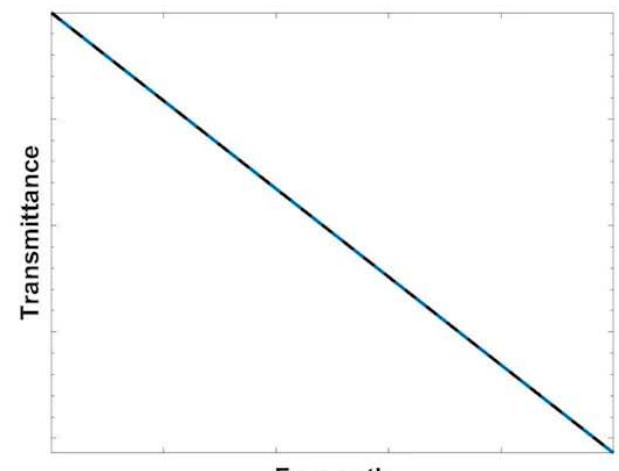
**Transport kernel:**  $T(\mathbf{x}, \mathbf{x}') = \begin{cases} \text{Tr}(\mathbf{x}, \mathbf{x}') & \text{if } \mathbf{x}' \text{ on surface} \\ -\frac{1}{\sigma_t(\mathbf{x}')} \frac{\partial \text{Tr}(\mathbf{x}, \mathbf{x}')}{\partial t} & \text{if } \mathbf{x}' \text{ in media.} \end{cases}$

$$\frac{\partial \text{Tr}(t)}{\partial t} = \text{Tr}(t) \left[ -\frac{\partial \alpha(t)}{\partial t} \ln \beta(t) - \frac{\partial \beta(t)}{\partial t} \frac{\alpha(t)}{\beta(t)} \right]$$

# Results







**Side lighting**



**Exp.**



$H = 0.2$  (1-fBm)



$H = -0.1$  (Pink noise)



$H = 1.2$  (2-fBm)

Side lighting

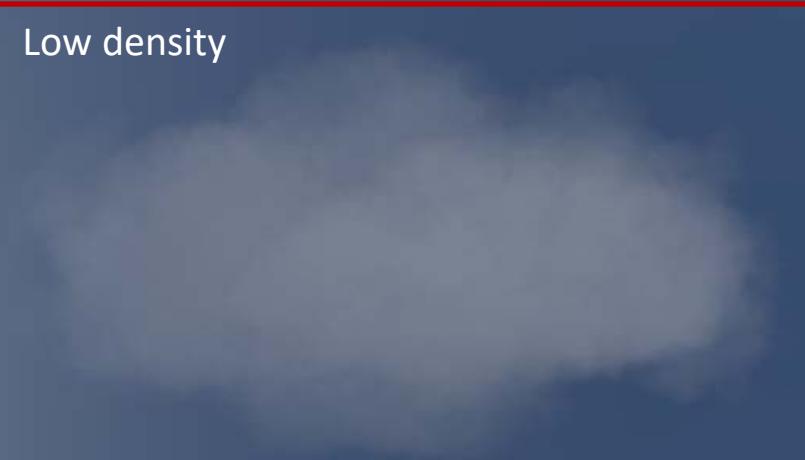


Exp.



$H = -0.1$  (Pink noise)

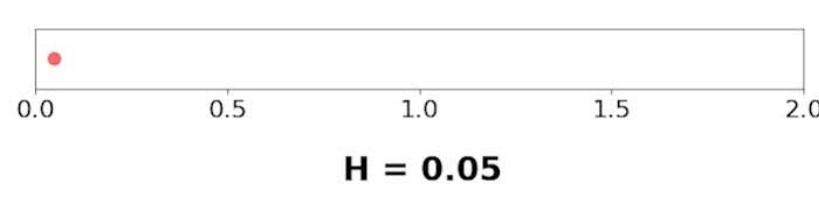
Low density



Exp.



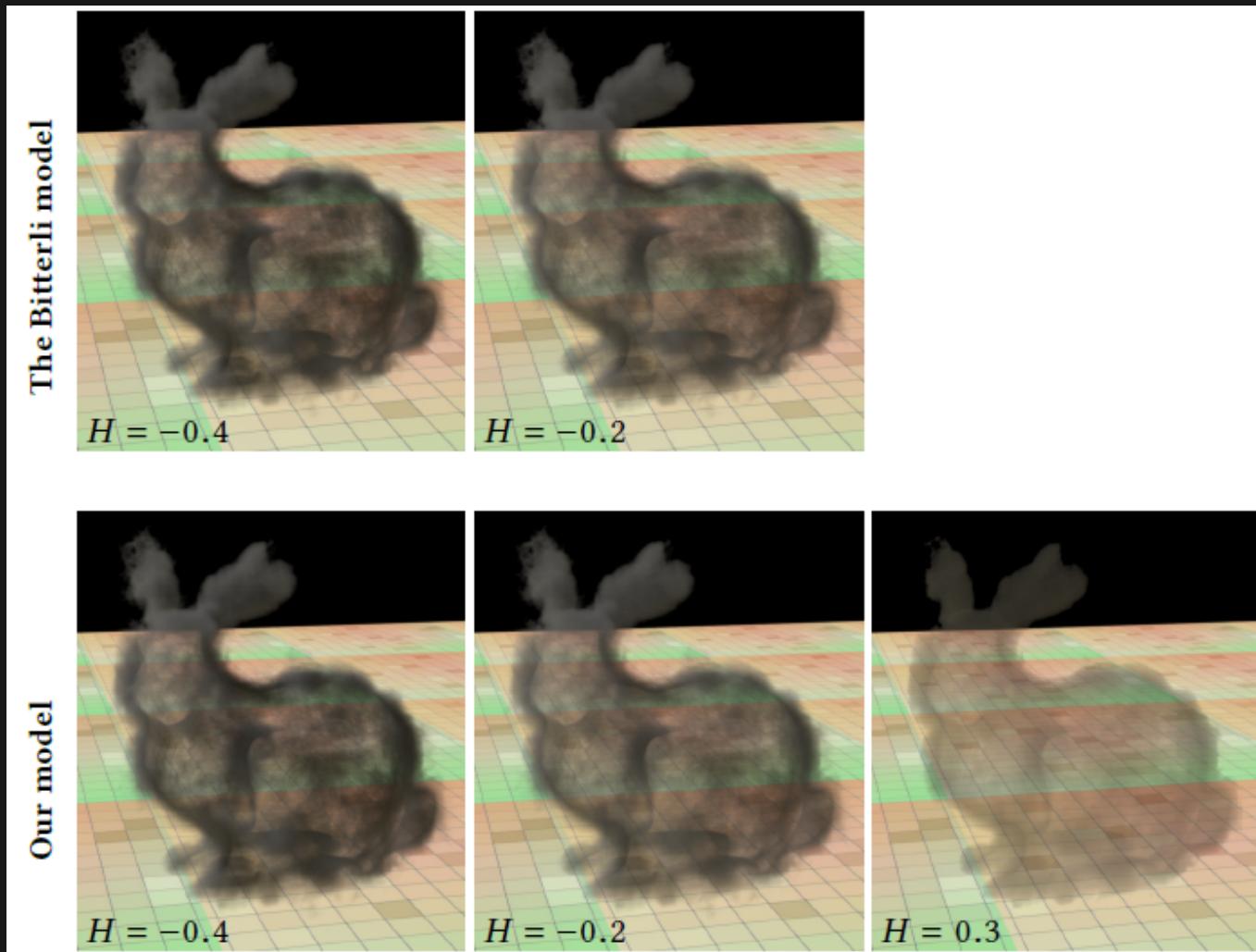
$H = 1.2$  (2-fBm)



Comparing to the GBE [Jarabo et al. 2018]



## Comparing to the Bitterli model [Bitterli et al. 2018]



## Uncorrelated media



## Correlated media



# Conclusion

- A mathematical tool for physically-based modeling spatial correlations in random media.
- Using k-th order fBm to generate long-range correlations.
- The usage of the non-exponential transmittance functions in an energy-conserving RTE framework.



Thank you!  
Q&A

H=0.2

H=-0.4

H=1.8

H=1.2

H=0.85