A functionalized Monte Carlo 3D radiative transfer model: Radiative effects of clouds over reflecting surfaces

Najda Villefranque and Howard Barker

LMD, CNRS/Sorbonne Université, Paris, France
Environment and Climate Change Canada, Toronto, Canada

Simulated cloud field (ARM-Cumulus at 8 m resolution) rendered using a Monte Carlo path-tracing model (htrdr, Villefranque et al. 2019)

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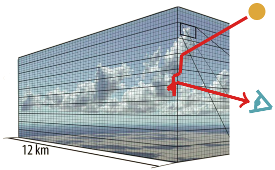
Challenges in understanding, modelling and observing radiation in cloudy atmospheres

How can we think through light propagation at the cloud field scale?
How do radiative fluxes depend on the cloud field properties?
How can we interpret radiance measurements in the presence of clouds?

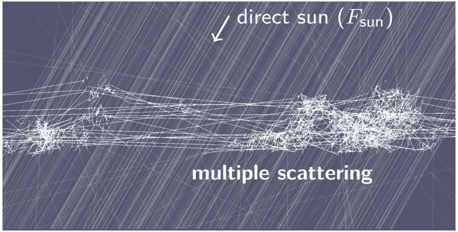
Simulated cloud field (ARM-Cumulus at 8 m resolution) rendered using a Monte Carlo path-tracing model (htrdr, Villefranque et al. 2019)

Monte Carlo (MC) methods: input description of the medium π, sample optical paths Γ by simulating radiative processes at the photon scale.



Standard MC: estimate radiative quantity F_π as the mean sampled-path weight.
(e.g. upward flux is the average of reflected path weights F_{sun} and non reflected path weights 0)

$$F_\pi = \int_{\Omega_\Gamma} \underbrace{d\gamma \; p_\Gamma(\gamma;\pi)}_{\text{probability of path } \gamma} \; \underbrace{w_\gamma(\pi)}_{\text{path weight}}$$



Solar paths sampled in a heterogeneous cumulus cloud field

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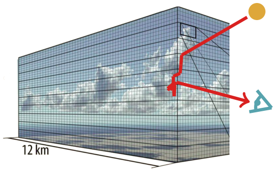

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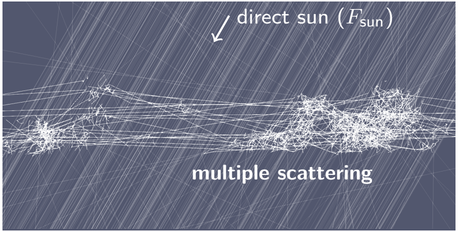
Much more information is contained in the sampled paths!
How to extract it? How to synthesize it?

Proposition $\Rightarrow$ **Symbolic (or Functionalized) MC**:
use the sampled paths to estimate a functional $F(\pi)$
Dunn, 1981; Galtier et al., 2017; Maanane et al., 2020



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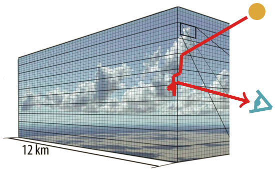

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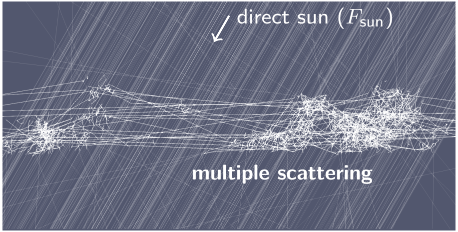
Linear Symbolic MC (trivial) $\quad p_\Gamma(\gamma;\pi) \perp \pi$

Path probability is not affected by the parameter
(e.g. π is the amount of incoming solar radiation)



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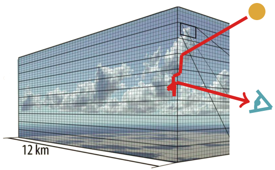

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Linear Symbolic MC (trivial) $p_\Gamma(\gamma;\pi) \perp \pi$

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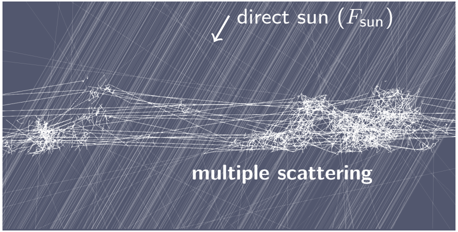
Non-linear Symbolic MC $p_\Gamma(\gamma;\pi) \not\perp \pi$

Path probability is affected by the parameter
(e.g. π is the surface albedo or cloud droplet effective radius)

$\Rightarrow$ use importance sampling to go back to linear, and apply weight-correction *offline*!



Solar paths sampled in a heterogeneous cumulus cloud field

$$F(\pi) = \int_{\Omega_\Gamma} \mathrm{d}\gamma\ p_\Gamma(\gamma;\hat{\pi})\ w_\gamma(\hat{\pi}) \frac{p_\Gamma(\gamma;\pi)}{p_\Gamma(\gamma;\hat{\pi})}$$

Illustration with the albedo α of a Lambertian surface as "symbolic" parameter, homogeneous slabs

1. Write the radiative transfer equation with $\hat{\alpha}$ an arbitrary value for α

$$F(\alpha) = \sum_{k=0}^{\infty} F_{k|\hat{\alpha}} \left(\frac{\alpha}{\hat{\alpha}}\right)^k$$

2. Estimate $F_{k|\hat{\alpha}}$ as the mean weight of the paths that have been reflected k times (as in e.g. Barker and Davies 1992)

$$F_{k|\hat{\alpha}} \approx \overline{\boldsymbol{F}}_{\boldsymbol{k|\hat{\alpha}}} = \frac{1}{N_{k|\hat{\alpha}}} \sum_{i=1}^{N_{k|\hat{\alpha}}} w_{i,k}$$

3. Evaluate $\overline{\boldsymbol{F}}_{\hat{\boldsymbol{\alpha}}}(\boldsymbol{\alpha}) = \sum_{k=0}^{K_{\max}} \overline{F}_{k|\hat{\alpha}} \left(\frac{\alpha}{\hat{\alpha}}\right)^k$

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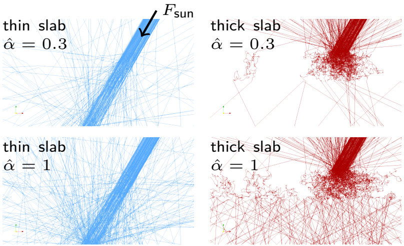
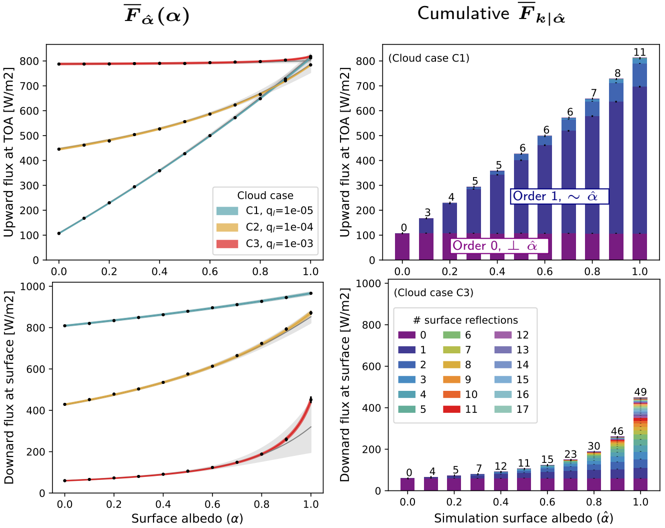




● = one standard MC simulation

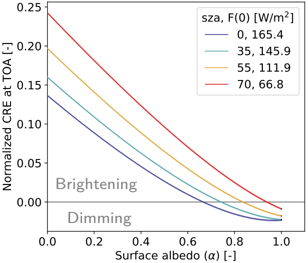
— = one Symbolic MC simulation (colored $\Rightarrow \hat{\alpha} = 1$; gray $\Rightarrow \hat{\alpha} = 0.3$)

Illustration with the albedo α of a Lambertian surface as "symbolic" parameter, complex cloud field

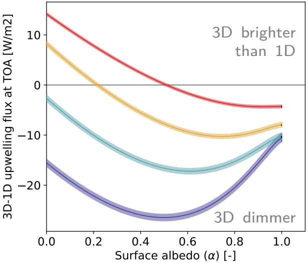
3 SMC simulations per solar zenith angle: 3D, 1D, clear sky; $\overline{F}_{\hat{\alpha}=1}(\alpha) = \sum_{k=0}^{K_{\max}} \overline{F}_{k|\hat{\alpha}=1}\alpha^k$

Input cloud field
40 km x 21 km domain
250 m horizontal res
Cloud cover 0.83

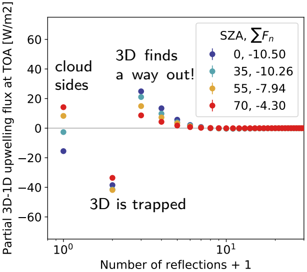
Cloud Radiative Effect = all sky - clear sky



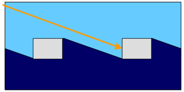
3D effects = 3D - 1D

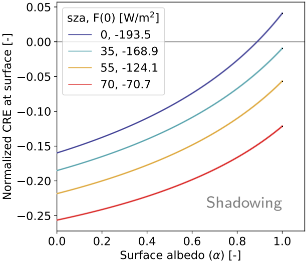


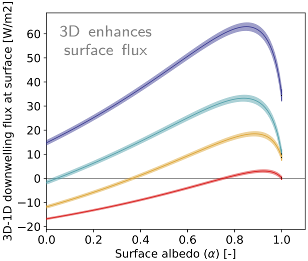
Contribution of order k to 3D effects

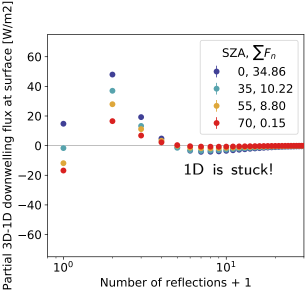


Low sun = more reflective clouds, even more so in 3D because of cloud side interception

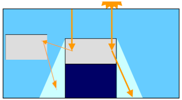






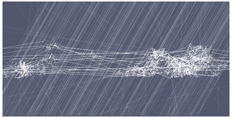


At all sun angles: 3D flows from cloud sides towards the surface or is intercepted by other clouds on its way back up to space

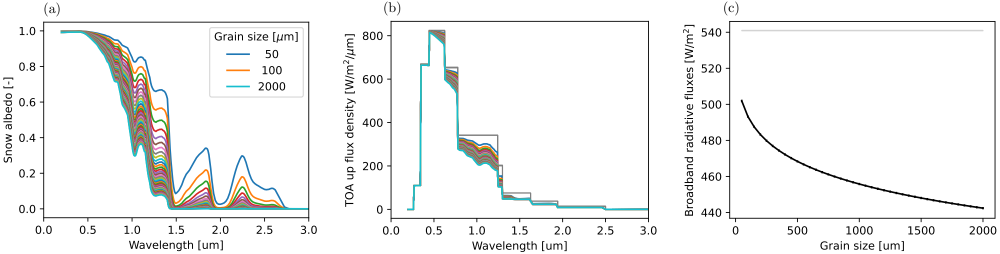


(schematics adapted from Sophia Schäfer's thesis)

Summary and outlook



- A **formal framework** for extracting information from sampled paths
- Useful for analysis of complex propagation, e.g. **3D effects** of heterogeneous clouds
- and for parameter identification and uncertainty propagation



- Geometrical parameters are more challenging (cf Galtier et al. talk)
- Also challenging: large number of parameters (e.g. 3D fields?)
- Towards parameterization for lage-scale models?

Thanks!

Small albedo = large uncertainties in the large albedo region,
Large albedo = increase computation time
Symbolic might be a bit more expensive (larger arrays to manage, not optimized here)
Multiple scattering dominates