



# FOG Library for SENSORS SIMULATION

## MODELLING & USE in ANSYS AD SOLUTIONS

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**Confidentiality** None

\*Augmented information displayed as examples



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## I. CONTEXT & PRESENTATION

### I.1. Fog Library deliverables

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The present document describes the modelling of a Fog library from wave optics law, discusses the limitations & validity range, and provides analysis of sensors perceptions in fog environment. We deliver a fog library defined by their Volume Optical Properties for the following fogs (see next section for “vis” definition).

- ArtificialFog\_vis15m
- ArtificialFog\_vis30m
- ArtificialFog\_vis50m
- ArtificialFog\_vis100m
- ArtificialFog\_vis150m

The library is defined for ANSYS SPEOS simulations of Optical sensors from [400nm – 16microns]. Therefore the library is compatible with

- Visible camera simulation

- NIR camera simulation
- Lidar simulation
- Thermal simulation

## 1.2. Fog in driving conditions

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Fog is known to impair the driving condition by inducing strong light scattering in visible wavelength range. The scattering shortens visibility and reduces objects detection capabilities of both humans' eyes and automated algorithms.

To model the effect of fog on driving conditions using ANSYS SPEOS, let's take a closer loop at the fog composition. Microscopically, fog is a distribution of size-varying spherical water droplets, see Fig 1 - right.

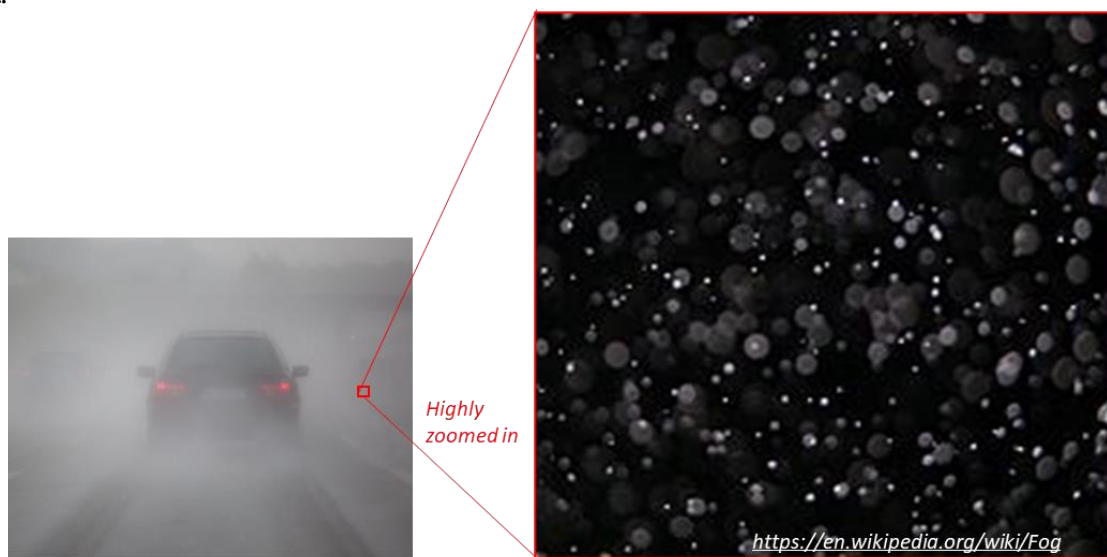


Figure 1 Left : Example of Fog in driving conditions. Right : Closed view on fog unveiling water droplets suspended in air.

Such distribution, varying in time, position, and altitude, is the fingerprint of the fog. Several mechanisms generate various type of fog [1] ranging from Radiation, Ground, Advection, Evaporation.

### I.3. Fog classification

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It is convenient to describe the fog by its visibility  $v$  (also names Meteorological Optical Range) defined by the distance through a fog at which a beam has lost 95% of its intensity.

$v$ : distance where  $T(v) = \frac{I(v)}{I_0} = 5\%$  [defined in the visible range].

Using such metric, one can classified different fogs, mist and haze using the visibility (see. Fig 2)



Figure 2 - visibility to classify fog, mist & haze. [ref Wikipedia]]

### I.4. Disclaimer & Limit of liability

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1. ANSYS assumes neither warranty, nor guarantee nor any other liability of any kind for the contents and correctness of the provided data.
2. The data has been generated with highest diligence but may not represent the complete possible variation range of all component parameters as they are based on measurements on few physical sample components of the ANSYS partners.
3. Therefore, in certain cases a deviation between the real optical, thermal, electrical behaviour and the characteristics which are encoded in the provided data could occur.
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## 2. MODELLING

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Modelling of the Fog relies on 3 steps:

- (i) Identify or derive fog Particles Size Distribution (PSD),
- (ii) Compute each droplet scattering & absorption ( $\sigma_{abs}, \sigma_{scatt}, f(\theta)$ )
- (iii) Sum over the PSD distribution and derive Volume Optical Properties ( $\mu_{abs}, \mu_{scatt}, f(\theta)$ )

### 2.1. Fog particle size distribution

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In this study, we resort to the Particles Size Distribution that are provided and discussed in the following articles:

*Duthon2019 : **Artificial fog** - Duthon, P.; Colomb, M.; Bernardin, F. *Light Transmission in Fog: The Influence of Wavelength on the Extinction Coefficient*. Appl. Sci. 2019, 9, 2843.*

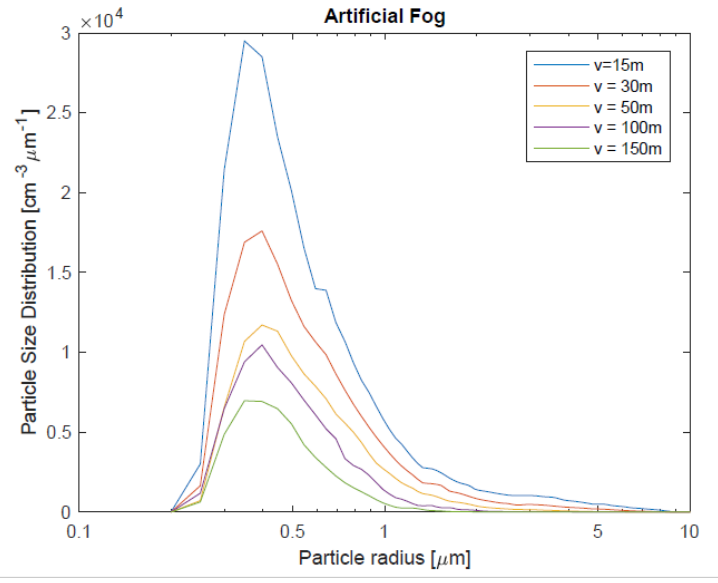


Figure 3. Particle size distribution adapted from Duthon2019. The PSD is presented for different particles radius in Log scale. PSD are defined for different fogs described by their visibility  $v$ .

## 2.2. Theory: Mie theory for dilute emulsions.

- For a single sphere described by its radius  $r$ , its complex refractive index  $n$ , surrounded by air (refractive index=1) and illuminated by a plane wave with wavelength  $\lambda$ . The particle cross sections (absorption & scattering)  $\sigma$  [usually  $\mu m^2$ ] are computed by the Mie Theory. Interested readers may refer to the book of Bohren & Huffman for further information.

$$[\sigma_{abs}(\lambda), \sigma_{scatt}(\lambda), f(\theta, \lambda)] = \text{Mie}(n(\lambda), r, \lambda)$$

- Now let's consider a small volume  $dV$  containing  $N$  particles with radius  $r$  randomly located in the volume; the density is defined by  $\rho = \frac{N}{dV}$ . Computing the statistical mean volume optical properties requires to solve Maxwell equations of large ensemble of particles, currently not feasible in practice; even with HPC.
- Nonetheless, when  $\rho \ll 1\%$ , particles can be supposed far from each other's and non-interacting. In the volume  $dV$ , light may be scattered by one particle, but it is statistically improbable that multiple scattering occurs. Under the dilute regime, (or single scattering regime), the mean volume properties absorption & scattering coefficients scale linearly with the particle's density and one has

$$\left\{ \begin{array}{l} \mu_{abs}(\lambda) = \rho \sigma_{abs}(\lambda) \\ \mu_{scatt}(\lambda) = \rho \sigma_{scatt}(\lambda) \end{array} \right\} (1)$$

In case of polydispersed (different size of particles), described by a Particle Size Distribution (PSD), the coefficients become

$$\left\{ \begin{array}{l} \mu_{abs}(\lambda) = \int_0^\infty \sigma_{abs}(r, \lambda) \cdot PSD(r) dr \\ \mu_{scatt}(\lambda) = \int_0^\infty \sigma_{scatt}(r, \lambda) \cdot PSD(r) dr \\ f(\theta, \phi, \lambda) = \frac{1}{\mu_{scatt}(\lambda)} \int_0^\infty f(\theta, \phi, \lambda, r) \cdot \sigma_{scatt}(r, \lambda) \cdot PSD(r) dr \end{array} \right\} (2)$$

- SPEOS uses discrete particle density  $\rho$  (with unit:  $mm^{-3}$ ) and rotationally  $\phi$  symmetric diagram thus it computes :

$$\left\{ \begin{array}{l} \mu_{abs}(\lambda) = \sum_k \sigma_{abs}(r_k, \lambda) \cdot \rho(r_k) \\ \mu_{scatt}(\lambda) = \sum_k \sigma_{scatt}(r_k, \lambda) \cdot \rho(r_k) \\ f(\theta, \lambda) = \frac{1}{\mu_{scatt}(\lambda)} \sum_k f(\theta, \lambda, r) \cdot \sigma_{scatt}(r_k, \lambda) \cdot \rho(r_k) \end{array} \right\}$$

With  $f(\theta, \lambda, r) = \langle f(\theta, \phi, \lambda, r) \rangle_\phi$

### 2.3. Inputs of the modelling

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- PSD described in section 2.1.
- Air refractive index is taken as = 1. (error <1‰ over the 0.4-20 $\mu$ m range)
- Water (complex) refractive index is extracted from [refractiveIndex.info](https://refractiveindex.info)

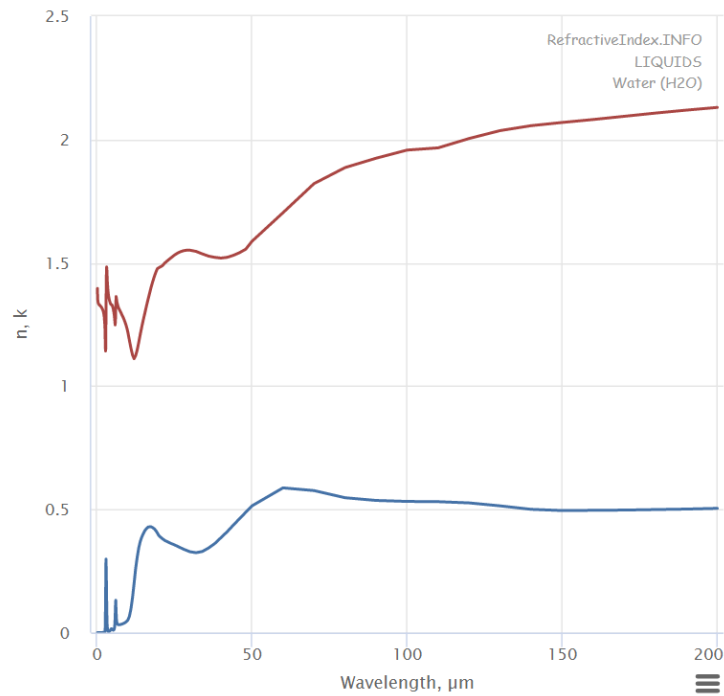


Figure 4 Water spectral refractive index. Real (in red) & imaginary (in blue) parts.

### 2.4. Validity & Limitations

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- ✓ Assumption of pure water and pure air.
- ✓ Droplets are considered as spherical.
- ✓ Single Scattering [Mie theory](#) applied to many spheres is accurate provided the dispersion is diluted. Volume fraction of water <<1%

### 3. RESULTING OPTICAL PROPERTIES

#### 3.1. Scattering & Absorption coefficients

Applying the theory described in section 2, one can estimate the absorption & scattering coefficients of any fog, provided its PSD is known. Fig.5 show a typical fog volume optical properties. The coefficients are computed and presented from 0.4micron to 15microns in a log-x scale to highlight VISIBLE, NIR and LWIR spectral ranges behavior.

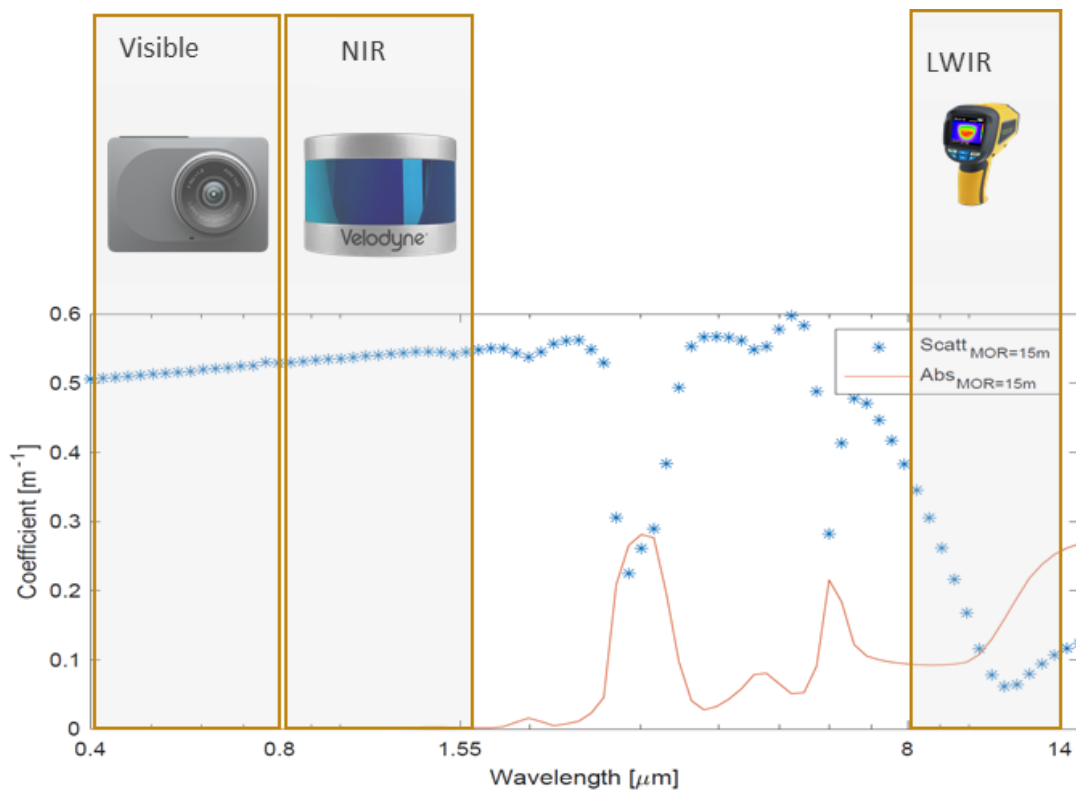


Figure 5 Absorption (red) & Scattering (blue) coefficients (m<sup>-1</sup>) of an artificial fog from Duthon 2019 with visibility  $v = 15m$ .

In the visible & near Infrared (NIR) range, the scattering largely dominates over the absorption which is close to null. On the contrary, when reaching thermal emission range (8-14microns), scattering drops to 5x less scattering. The drawback is a significant increase of absorption up to dominate over scattering at 10microns; mainly due to water absorption.

Similar observation holds for all types of fog, see next figure.



### 3.2. Scattering diagram

The scattering angular distribution  $f(\theta)$  (i.e. the phase function) varies with the wavelength and with each FOG PSD. Bottom figure shows the phase function of the Artificial fog and shows that

- Fog is dominantly forward scattering at any wavelength
- Visible & NIR frequencies have very similar phase function
- As the wavelength increases, the scattering becomes more & more isotropic
- Fog has a retroreflective “lobe”
- The higher the visibility (i.e. lower density), the more isotropic is the phase function

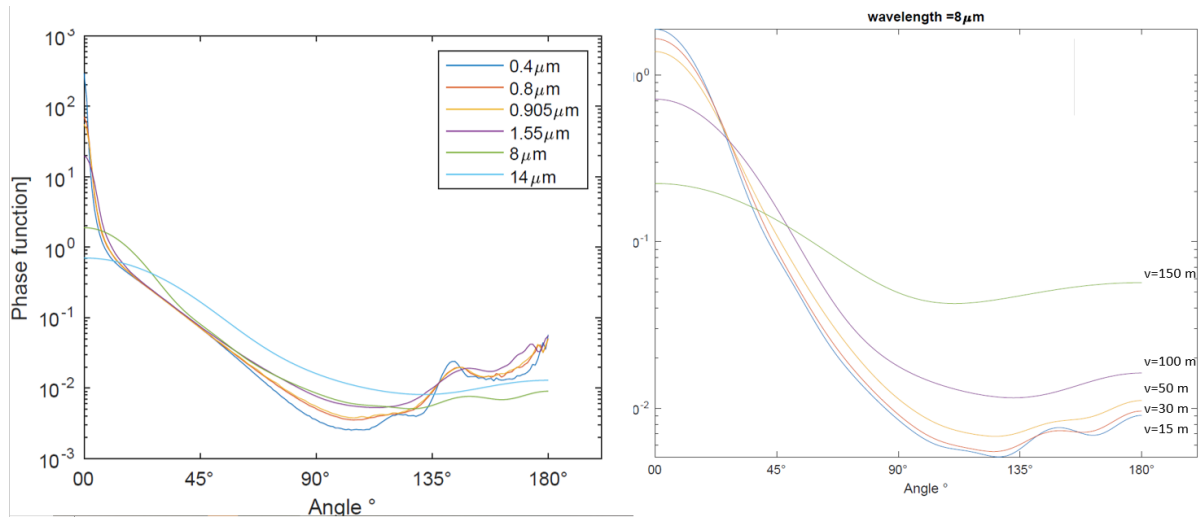


Figure 6 - Fog phase function (in log-scale) computed for a 15m-visibility fog from Duthon2019 at various wavelength (left) and fixed wavelength with varying visibility in the LWIR range (right).

### 3.3. Sensors detection through Fog

#### 3.3.1. Spectral visibility

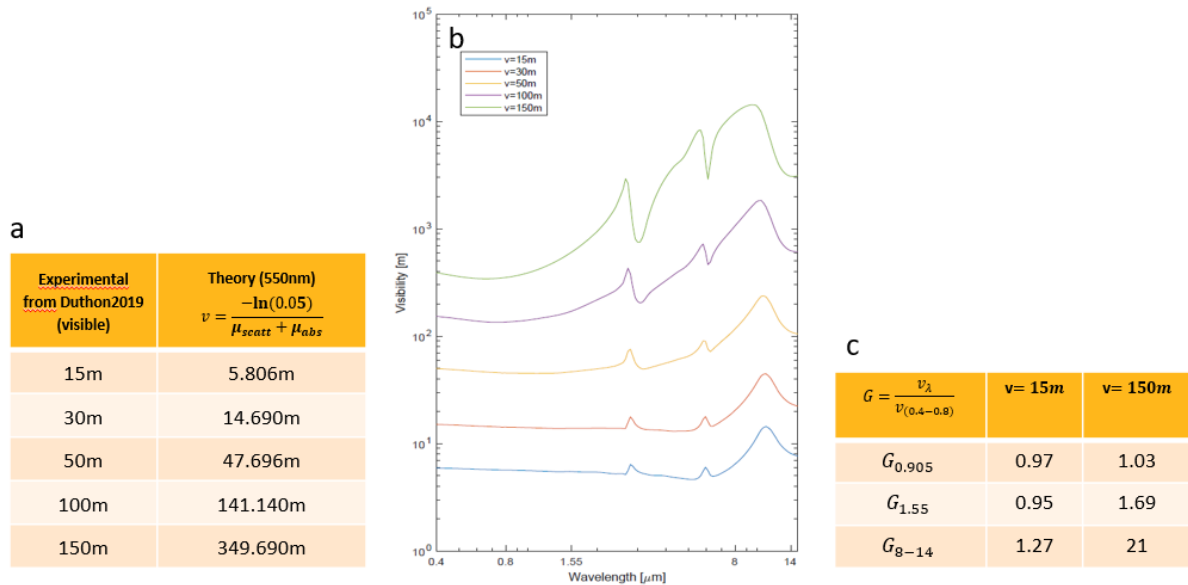
Below table (a) compares the experimental visibility results from the article with the theoretical visibility computed from visibility equation (Beer-Lambert) in section 1.3, and show some qualitative agreement.

To analyze how the sensor spectral range would affect the sensor capabilities to see through fog, figure (b) presents the visibility spectral variation for all fog type. The log-scale highlights that the visibility:

- increases with decreasing fog density (i.e. increasing fog visibility)
- increases with wavelength, with a maximum in the LWIR around 10microns.
- exhibits “holes” around 3 & 6microns, signatures of atmospheric air absorption bands.

Finally, one can estimate the spectral visibility gain  $G$ , from the curves in b.

Results are summarized in (c) for most used sensors spectral range (Lidar 905nm and 1.55microns & thermal camera sensitive in the 8-14microns) and predict a significant gain for thermal camera and light fogs.



In conclusion, sensors operating around the thermal emission range are the less affected by fog.

### 3.3.2. SPEOS Model

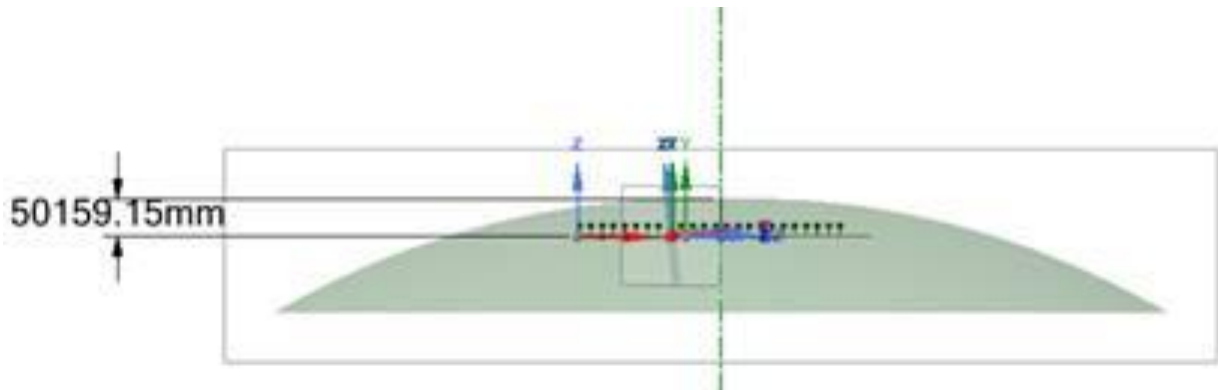
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- Daylight use-case

When modelling day-driving fog scene, the ambient lighting comes from an “infinitely far away” HDRI emissive surface, therefore applying an ambient diffusive/absorbing material would result to no light reaching the sensor.

To overcome this effect, we model a finite fog dome-shaped (in green in the bottom scheme) and position the ground at a fixed distance from the top of the dome.

Typical fog has a 10 to 300m thickness range.



### 3.3.3. Visible camera sensor

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- Visible camera simulation of day-driving use-case in fog.



Figure 7 Ansys SPEOS simulation of pedestrian detection by a camera through fog. Fog is defined by a dome of 26m height and visibility  $v=150\text{m}$  from Duthon2019.

- Influence of fog visibility on pedestrian visibility.

As demonstrated by below simulations of the camera, ANSYS SPEOS can predict the distance at which a pedestrian (at 53m from camera) becomes visible depending on the fog “visibility” properties.

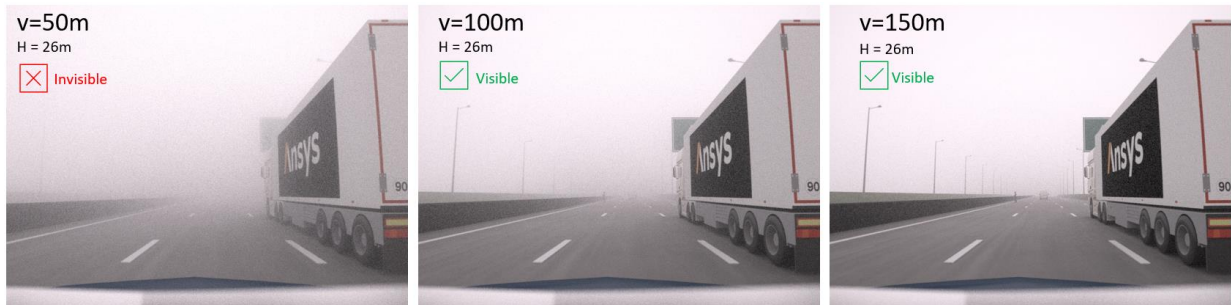


Figure 8 Influence of fog visibility (i.e. inversely proportional to the density) on pedestrian visible simulations. Fog of vertical thickness  $H=26m$ .

- Influence of fog thickness on pedestrian visibility

Remarkably increasing the dome (i.e. the fog) thickness does not influence the results, but simply increases the computational cost. We suspect that this conclusion does not hold for very (vertical) thin fog.



Figure 9 Influence of fog thickness on Camera visible simulations. Fog of visibility 50m.