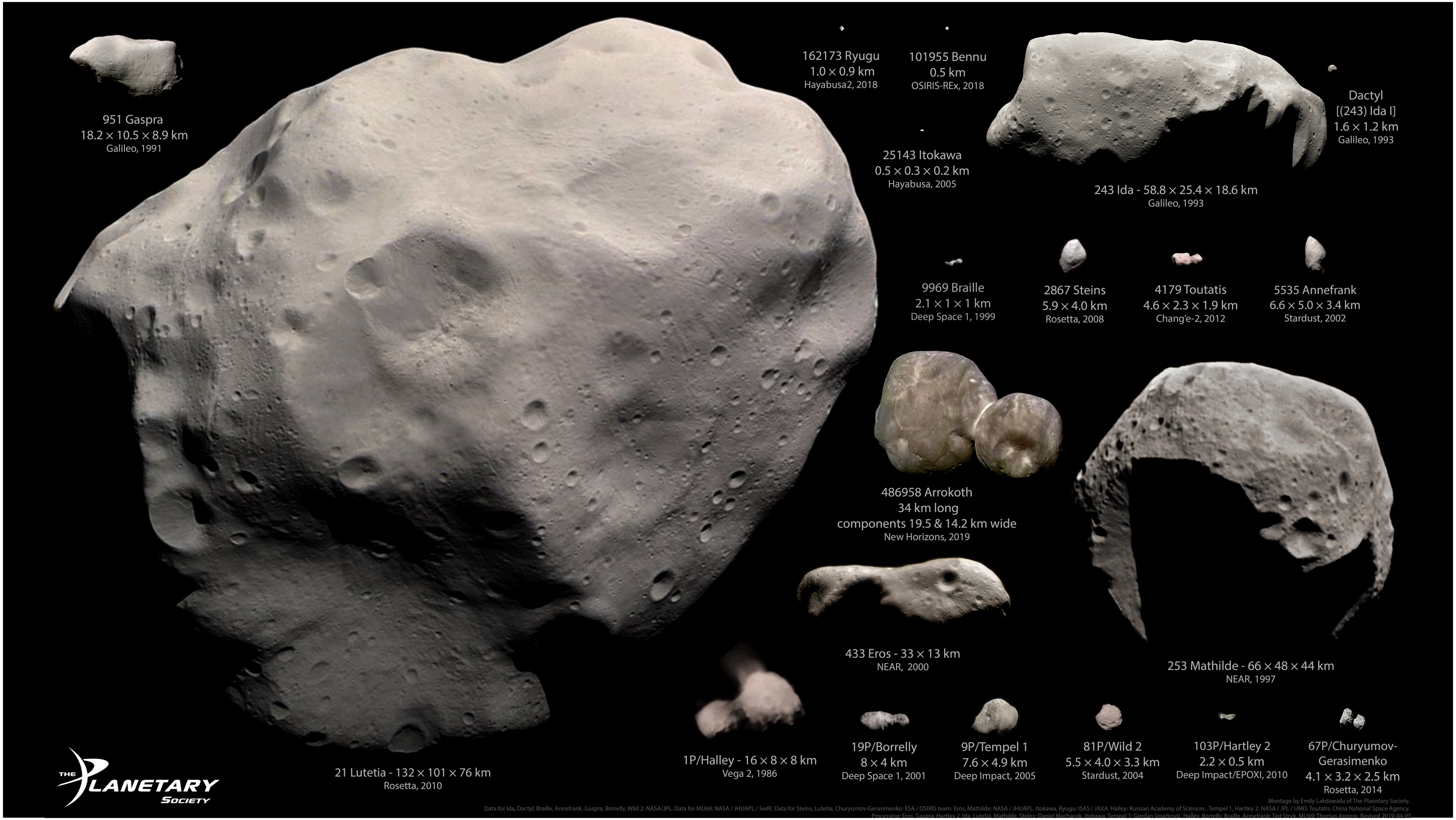
Astronomical Institute of the Romanian Academy Scientific Seminar | 30/04/2025

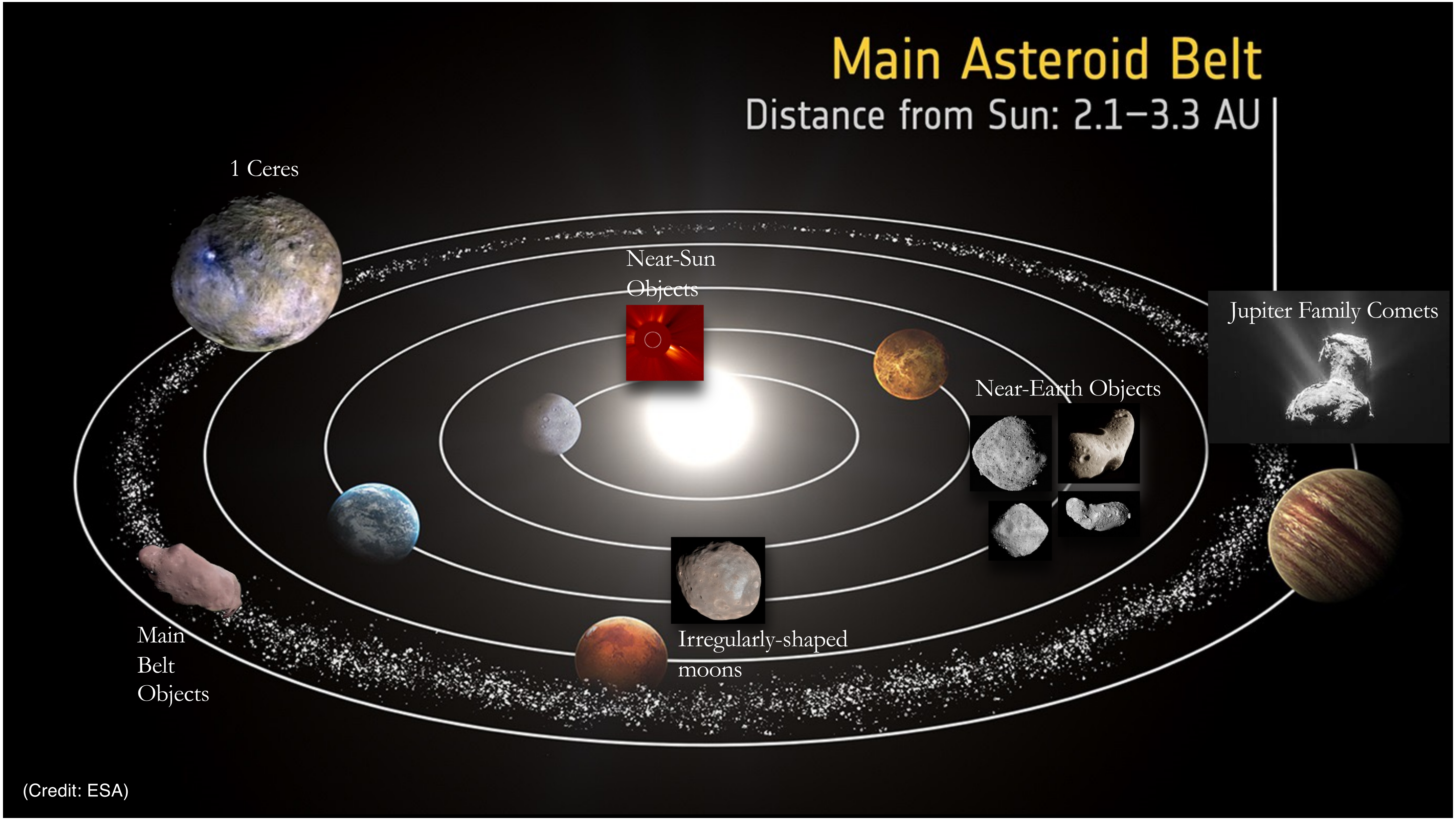
AI-driven Thermophysical Modelling for Small Solar System Bodies

Xian Shi

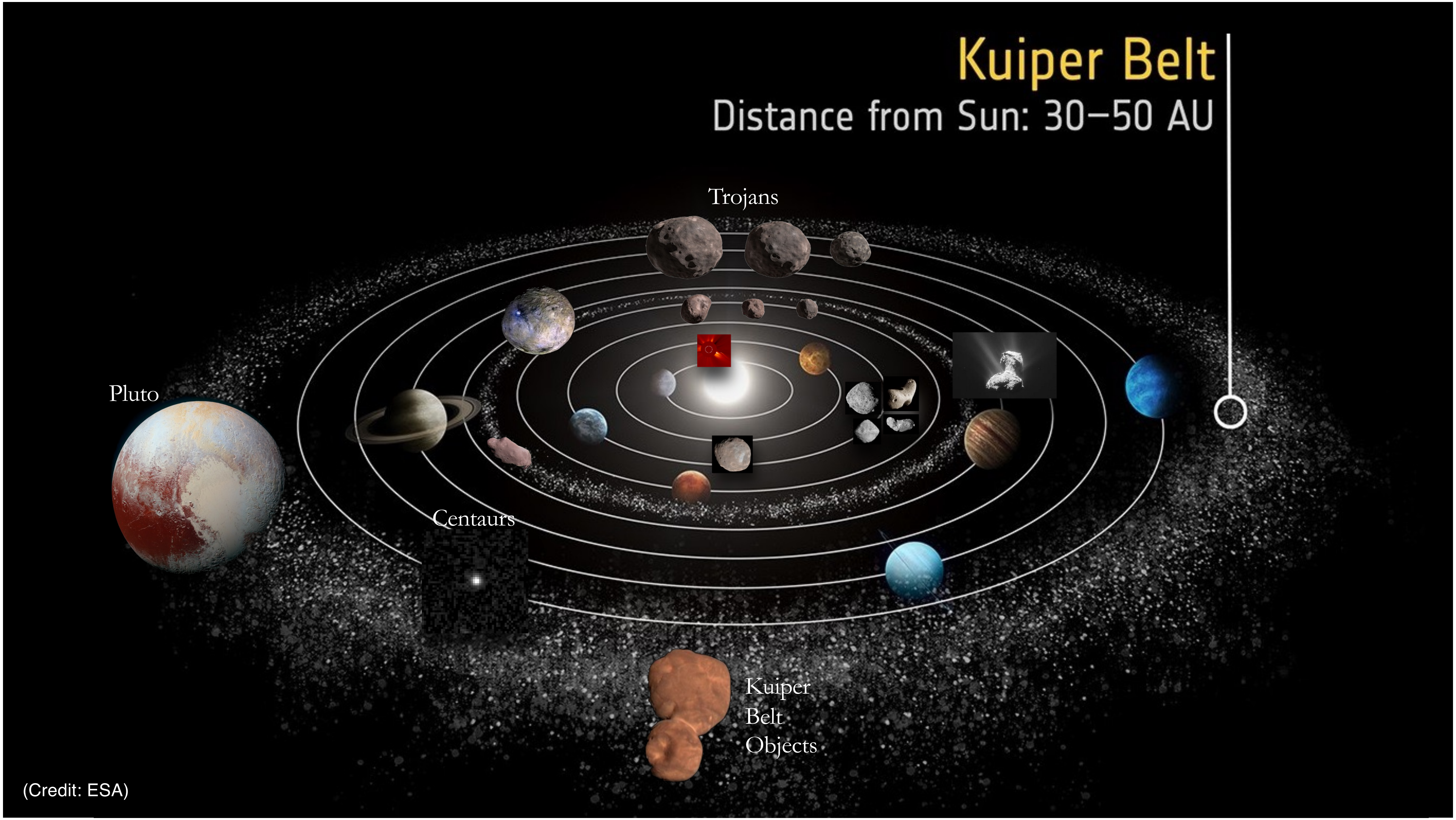
Shanghai Astronomical Observatory, Chinese Academy of Sciences

Team: Shunjing Zhao (SHAO/NJU), Hanlun Lei(NJU), Man-To Hui (SHAO), et al.

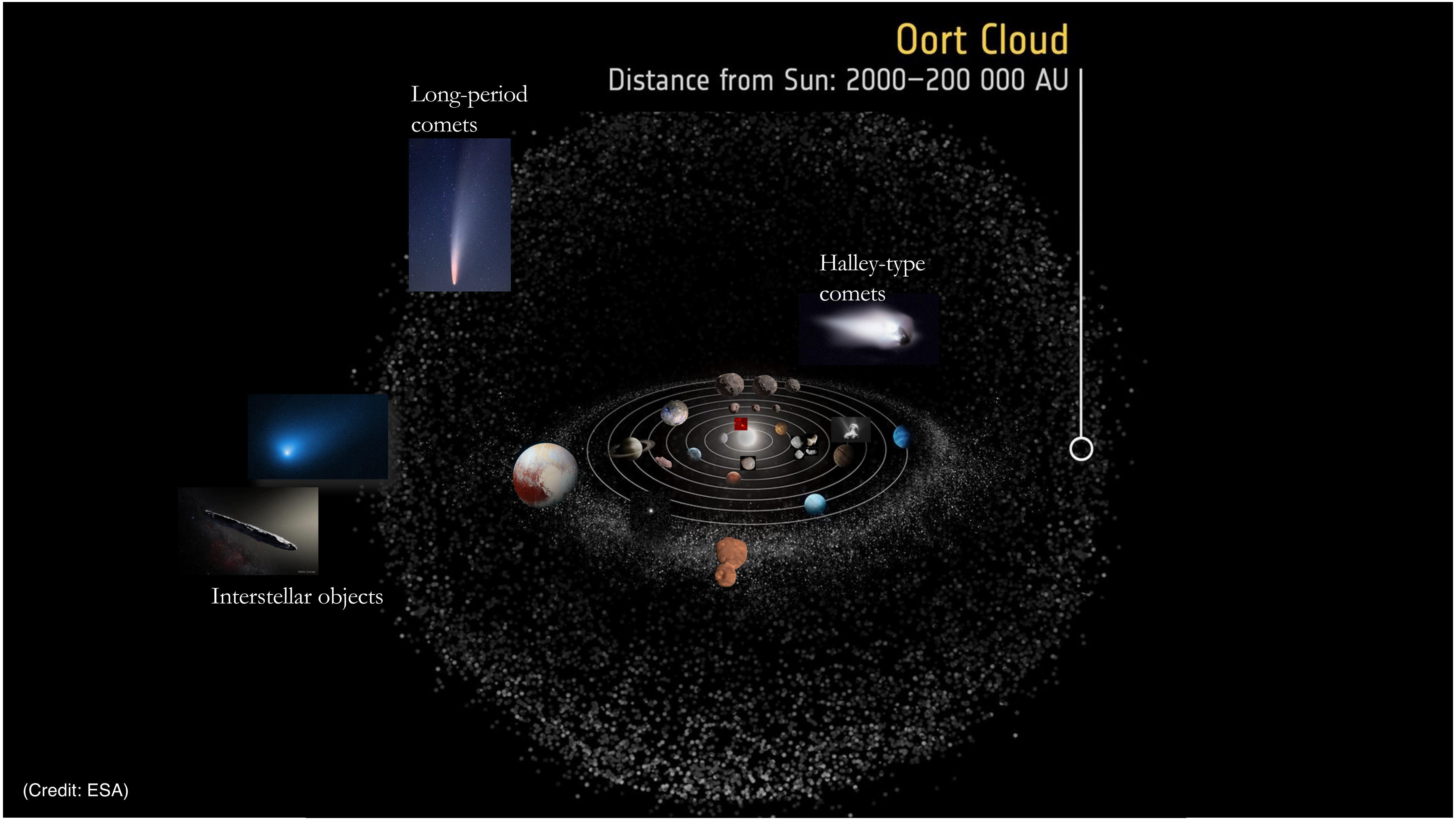

951 Gaspra
18.2 × 10.5 × 8.9 km
Galileo, 1991
162173 Ryugu
1.0 × 0.9 km
Hayabusa2, 2018
101955 Bennu
0.5 km
OSIRIS-REx, 2018
25143 Itokawa
0.5 × 0.3 × 0.2 km
Hayabusa, 2005
Dactyl
[(243) Ida I]
1.6 × 1.2 km
Galileo, 1993
243 Ida - 58.8 × 25.4 × 18.6 km
Galileo, 1993
9969 Braille
2.1 × 1 × 1 km
Deep Space 1, 1999
2867 Steins
5.9 × 4.0 km
Rosetta, 2008
4179 Toutatis
4.6 × 2.3 × 1.9 km
Chang'e-2, 2012
5535 Annefrank
6.6 × 5.0 × 3.4 km
Stardust, 2002
486958 Arrokoth
34 km long
components 19.5 & 14.2 km wide
New Horizons, 2019
433 Eros - 33 × 13 km
NEAR, 2000
253 Mathilde - 66 × 48 × 44 km
NEAR, 1997
21 Lutetia - 132 × 101 × 76 km
Rosetta, 2010
1P/Halley - 16 × 8 × 8 km
Vega 2, 1986
19P/Borrelly
8 × 4 km
Deep Space 1, 2001
9P/Tempel 1
7.6 × 4.9 km
Deep Impact, 2005
81P/Wild 2
5.5 × 4.0 × 3.3 km
Stardust, 2004
103P/Hartley 2
2.2 × 0.5 km
Deep Impact/EPOXI, 2010
67P/Churyumov-Gerasimenko
4.1 × 3.2 × 2.5 km
Rosetta, 2014
THE PLANETARY SOCIETY
Montage by Emily Lakdawalla of The Planetary Society.
Data for Ida, Dactyl, Braille, Annefrank, Gaspra, Borrelly, Wild 2: NASA/JPL. Data for MU69: NASA / JHUAPL / SwRI. Data for Steins, Lutetia, Churyumov-Gerasimenko: ESA / OSIRIS team. Eros, Mathilde: NASA / JHUAPL. Itokawa, Ryugu: ISAS / JAXA. Halley: Russian Academy of Sciences . Tempel 1, Hartley 2: NASA / JPL / UMD. Toutatis: China National Space Agency.
Processing: Eros, Gaspra, Hartley 2, Ida, Lutetia, Mathilde, Steins: Daniel Machacek. Itokawa, Tempel 1: Gordan Ugarkovic. Halley, Borrelly, Braille, Annefrank: Ted Stryk. MU69: Thomas Appere. Revised 2019-04-03



Main Asteroid Belt
Distance from Sun: 2.1–3.3 AU
1 Ceres
Near-Sun Objects
Jupiter Family Comets
Near-Earth Objects
Main Belt Objects
Irregularly-shaped moons
(Credit: ESA)


Kuiper Belt
Distance from Sun: 30–50 AU
Trojans
Pluto
Centaurs
Kuiper
Belt
Objects

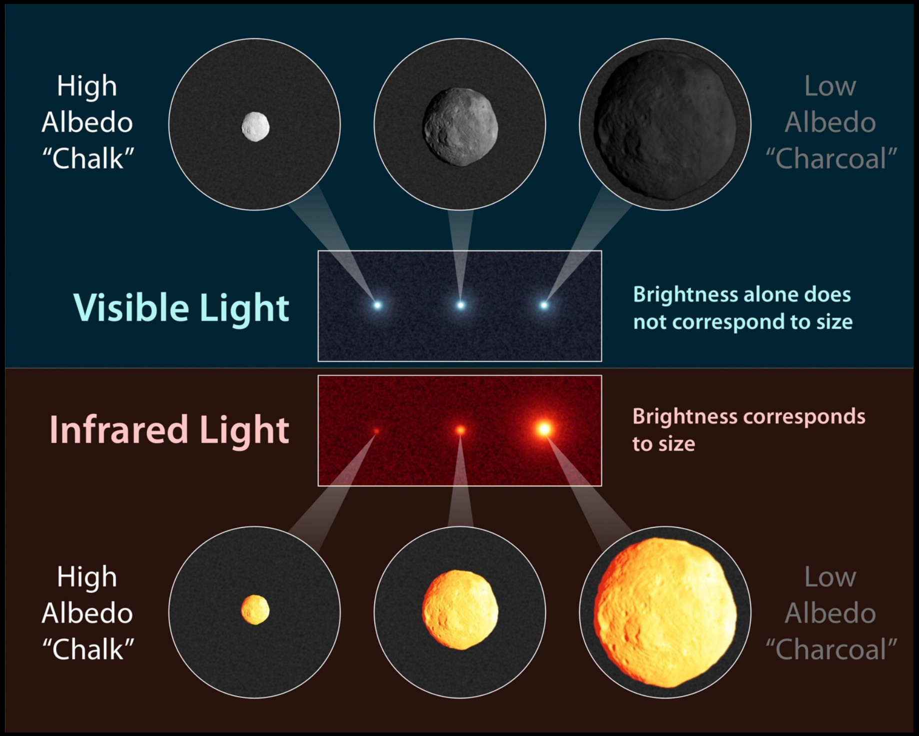
(Credit: ESA)


Oort Cloud
Distance from Sun: 2000–200 000 AU
Long-period comets
Halley-type comets
Interstellar objects
(Credit: ESA)

We need thermophysical modelling for the
Inversion of physical properties

- Size and shape
- Density and porosity
- Thermal inertia
- Surface roughness

...



(credit: the planetary society)

We need thermophysical modelling for the
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- Density and porosity
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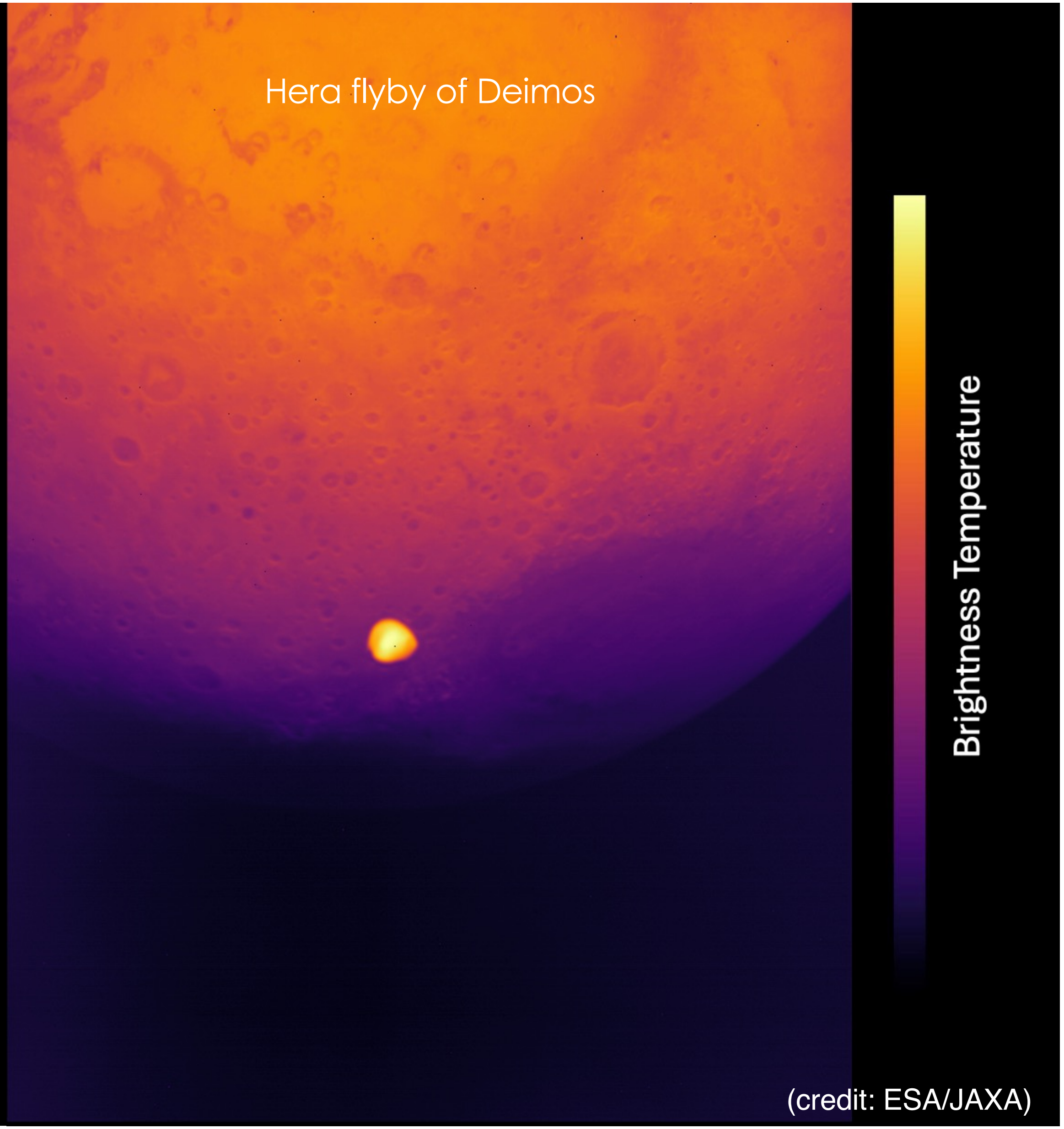
- Surface roughness

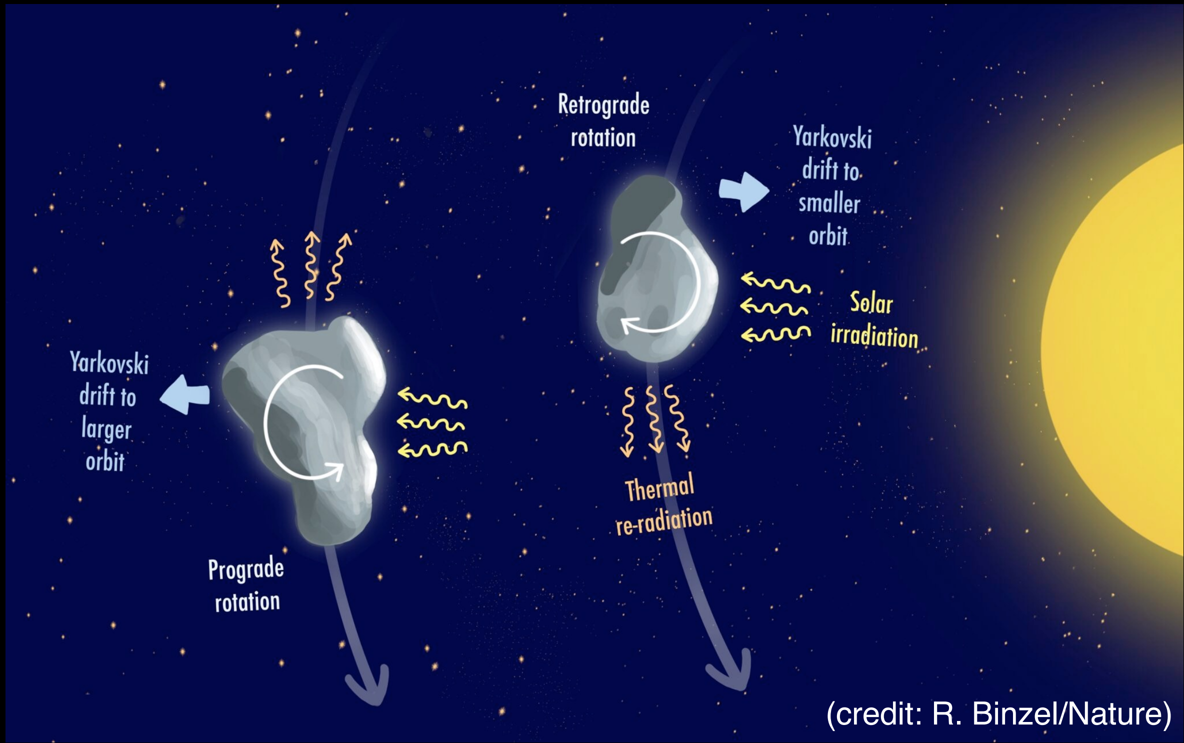
...



We need thermophysical modelling for the
Reconstruction and/or prediction of dynamical evolution

Non-gravitational effects

- Yarkovsky
- YORP
- Sublimation recoil
- ...



(credit: R. Binzel/Nature)

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Reconstruction and/or prediction of dynamical evolution

Non-gravitational effects

- Yarkovsky
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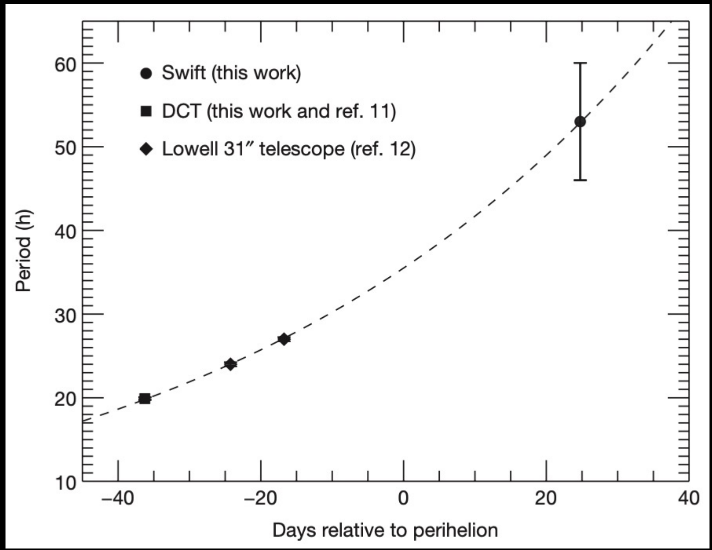
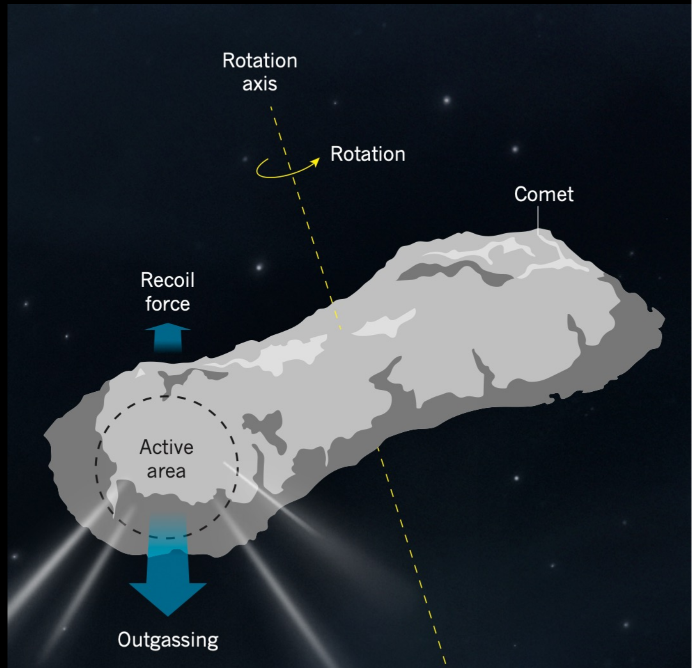


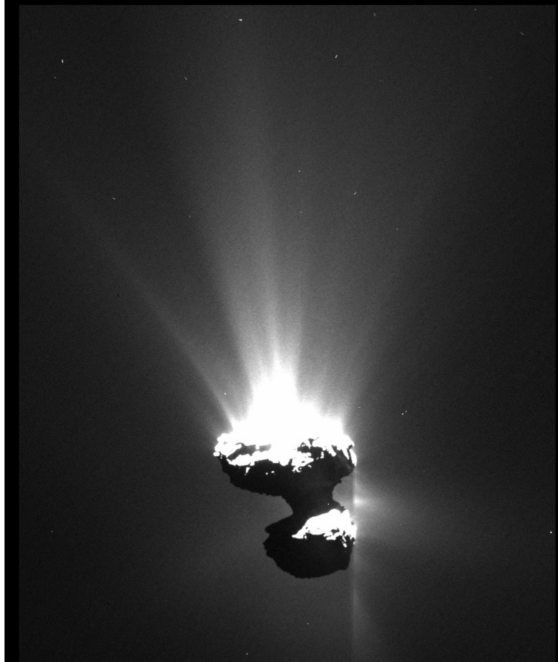
(Bodewits et al, 2018)



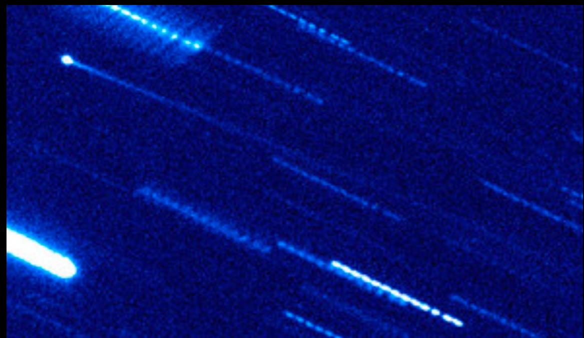
(Agarwal, 2018)

We need thermophysical modelling for
Deciphering activity

Comets

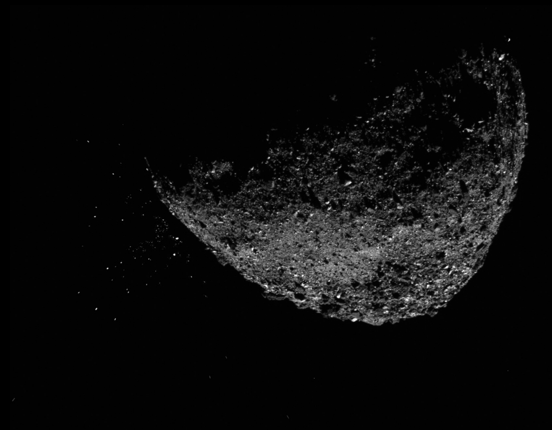


Active Main-belt objects



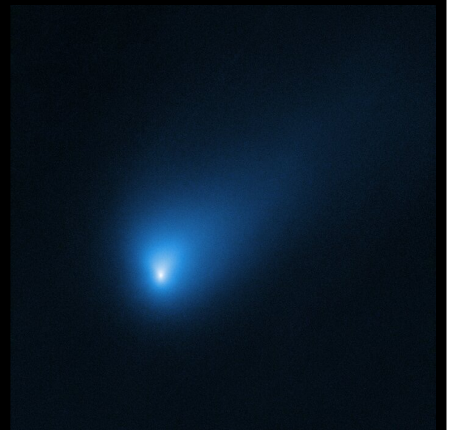
(Hsieh et al. 2004)

Active Near-Earth objects



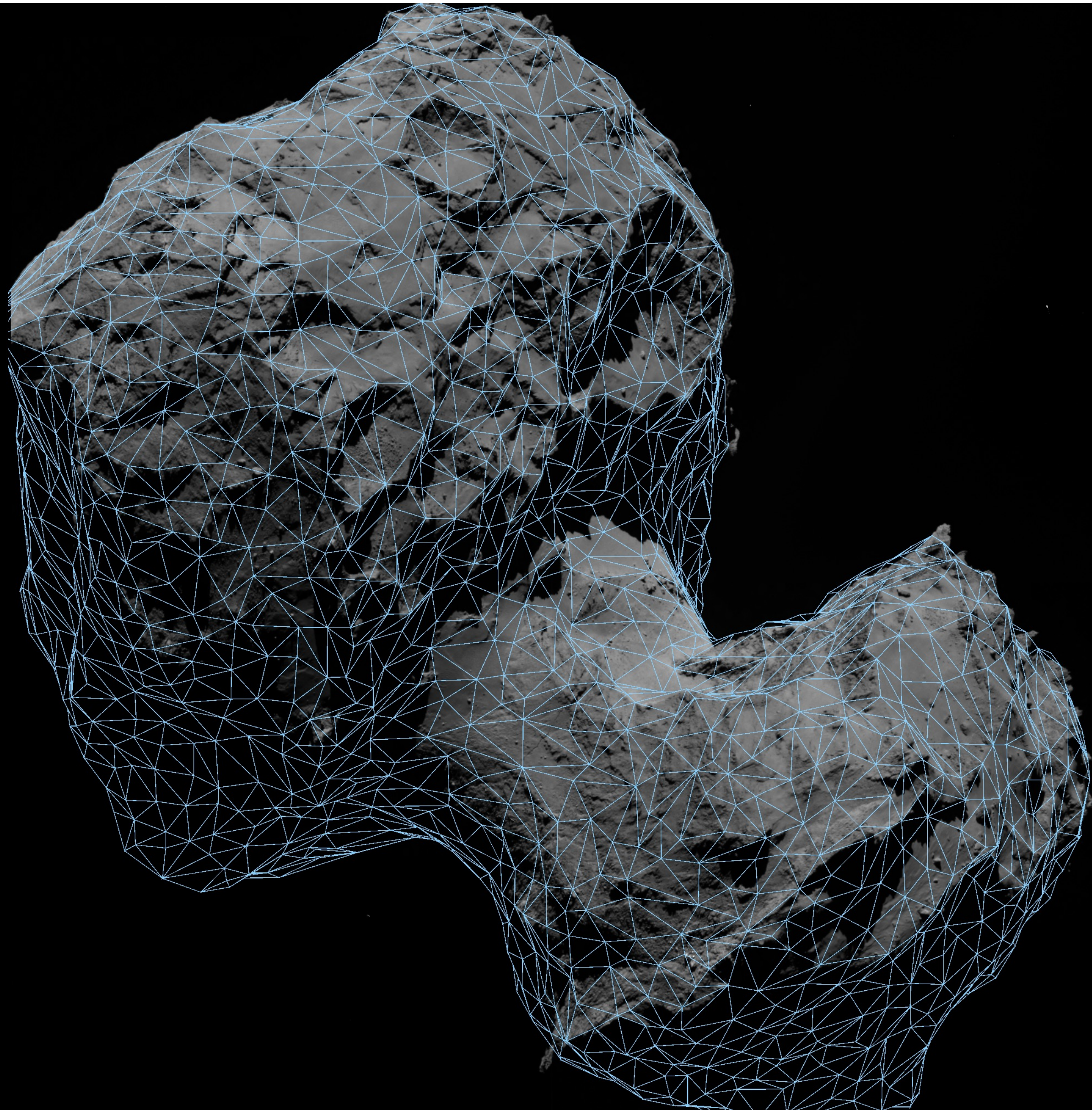
(Lauretta et al. 2019)

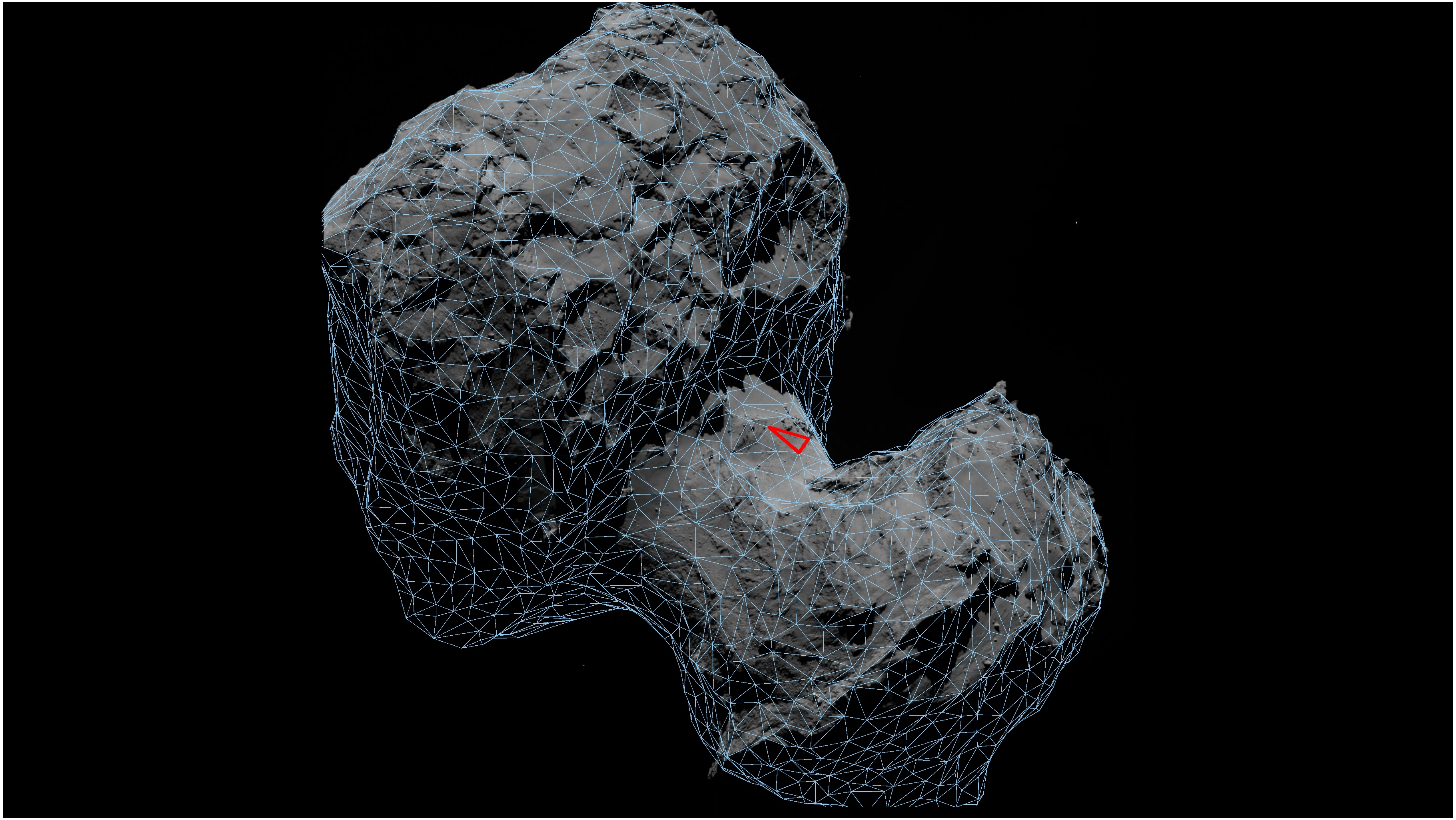
Interstellar comets

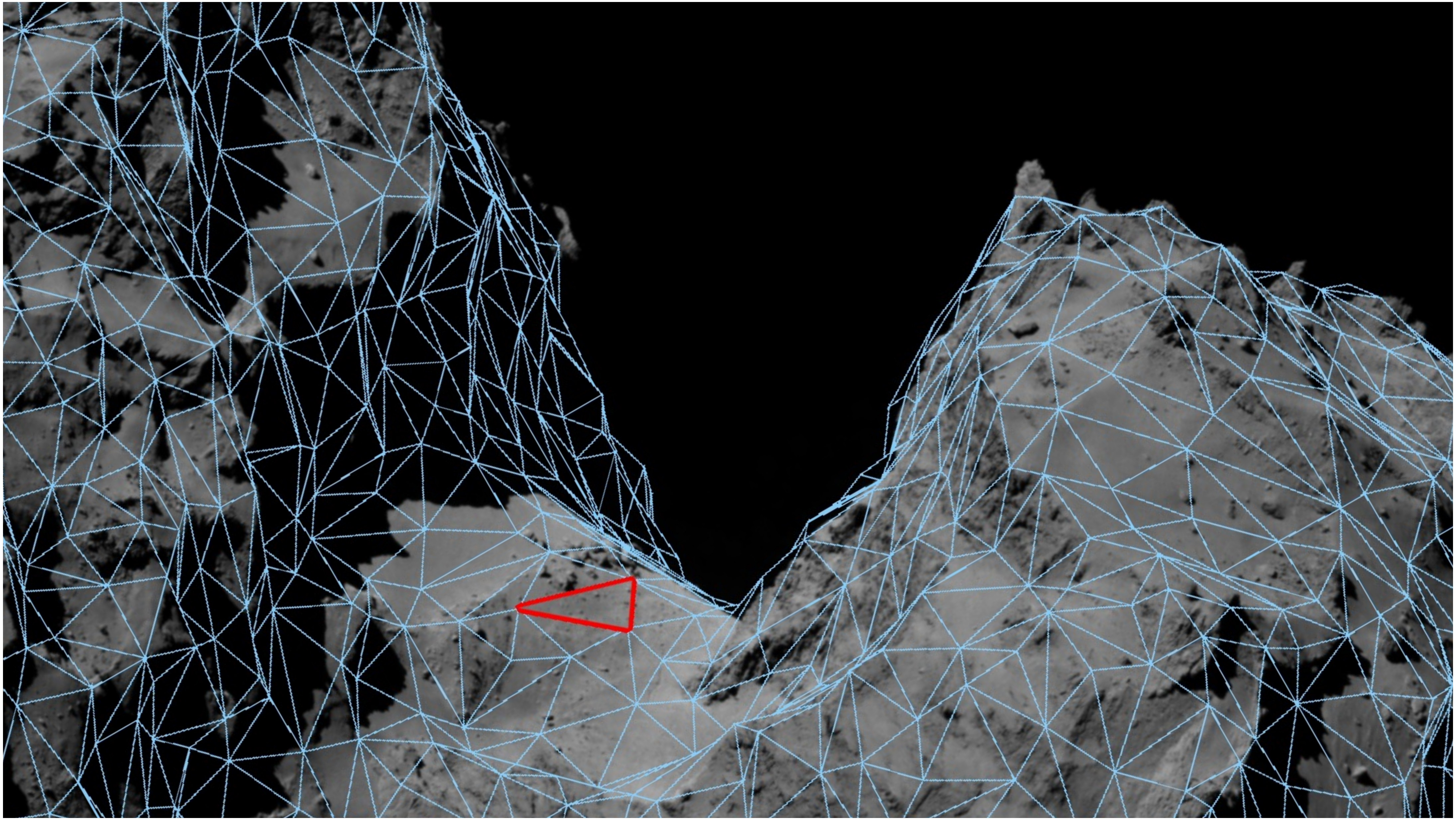


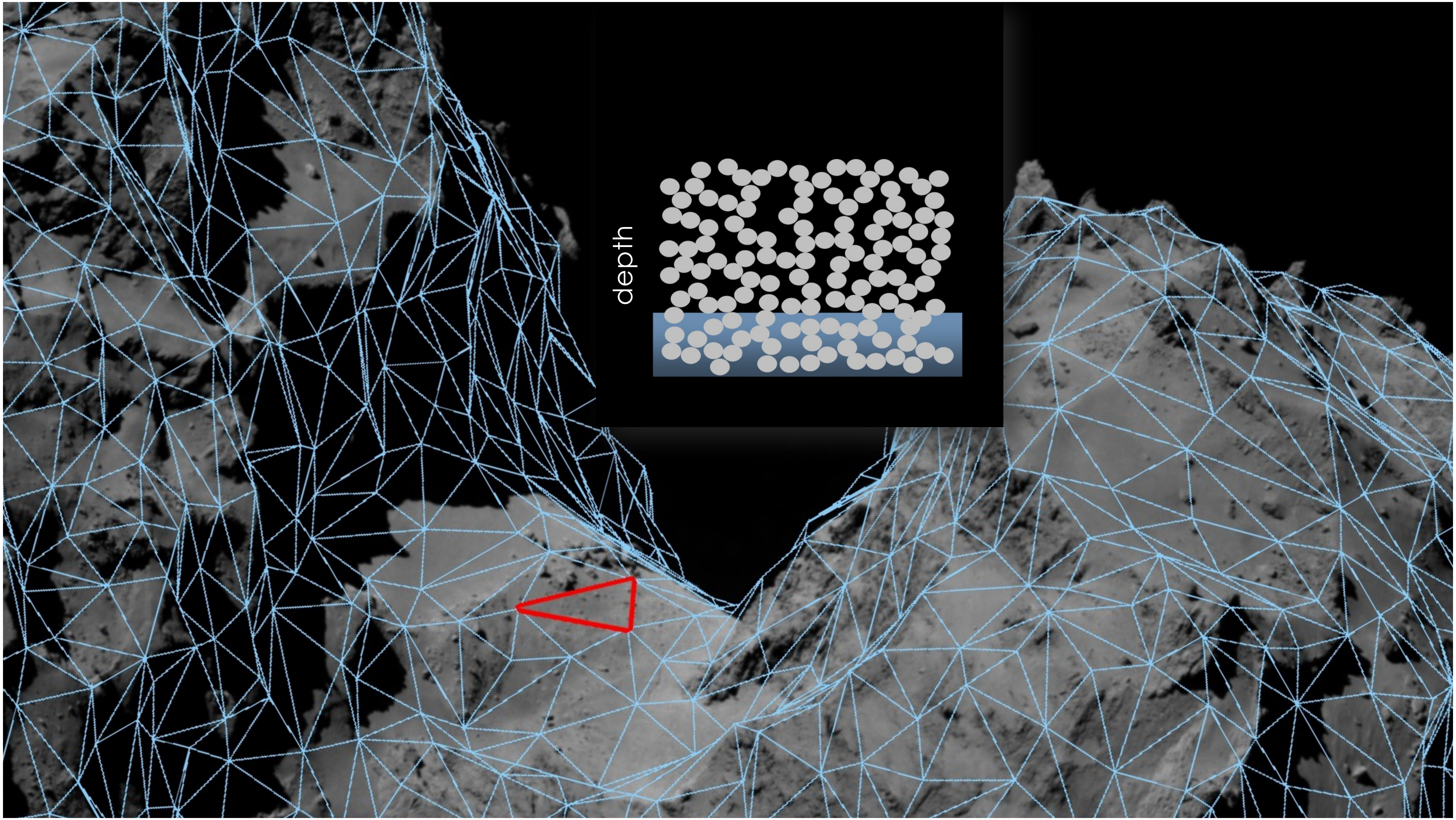
(NASA, ESA, D. Jewitt (UCLA))

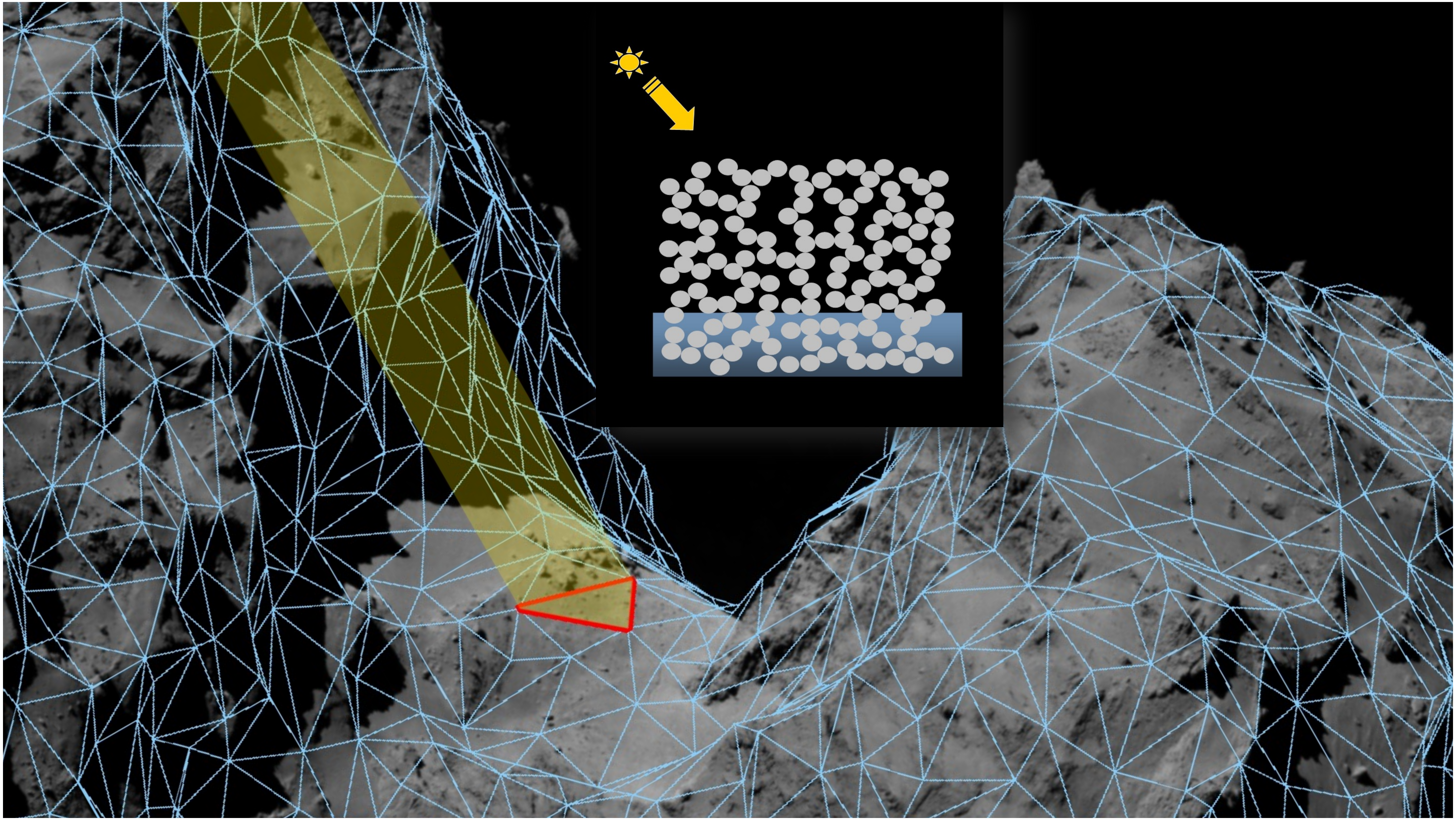
Conventional
1D
Thermophysical
Model
(for an icy body)

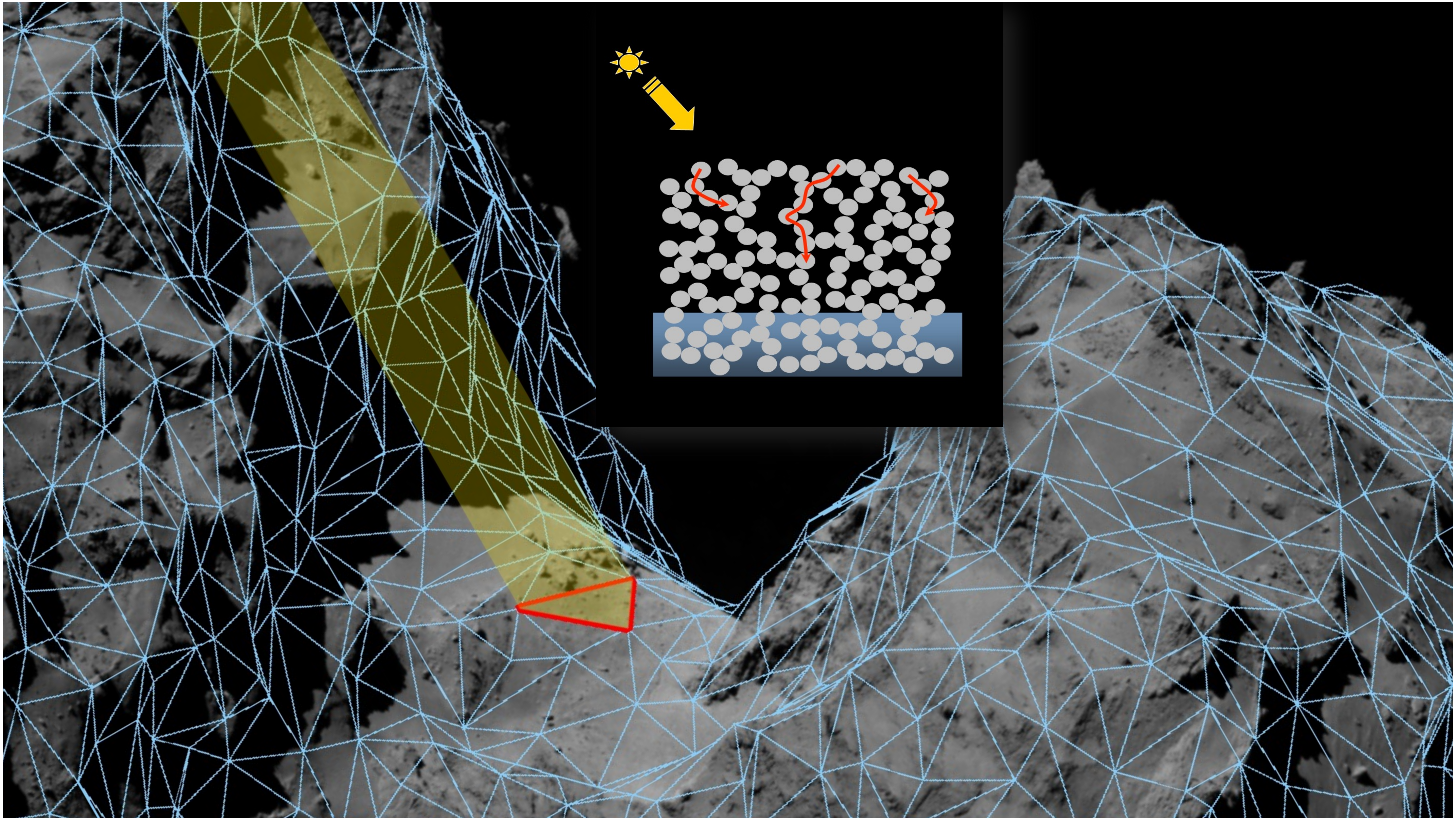


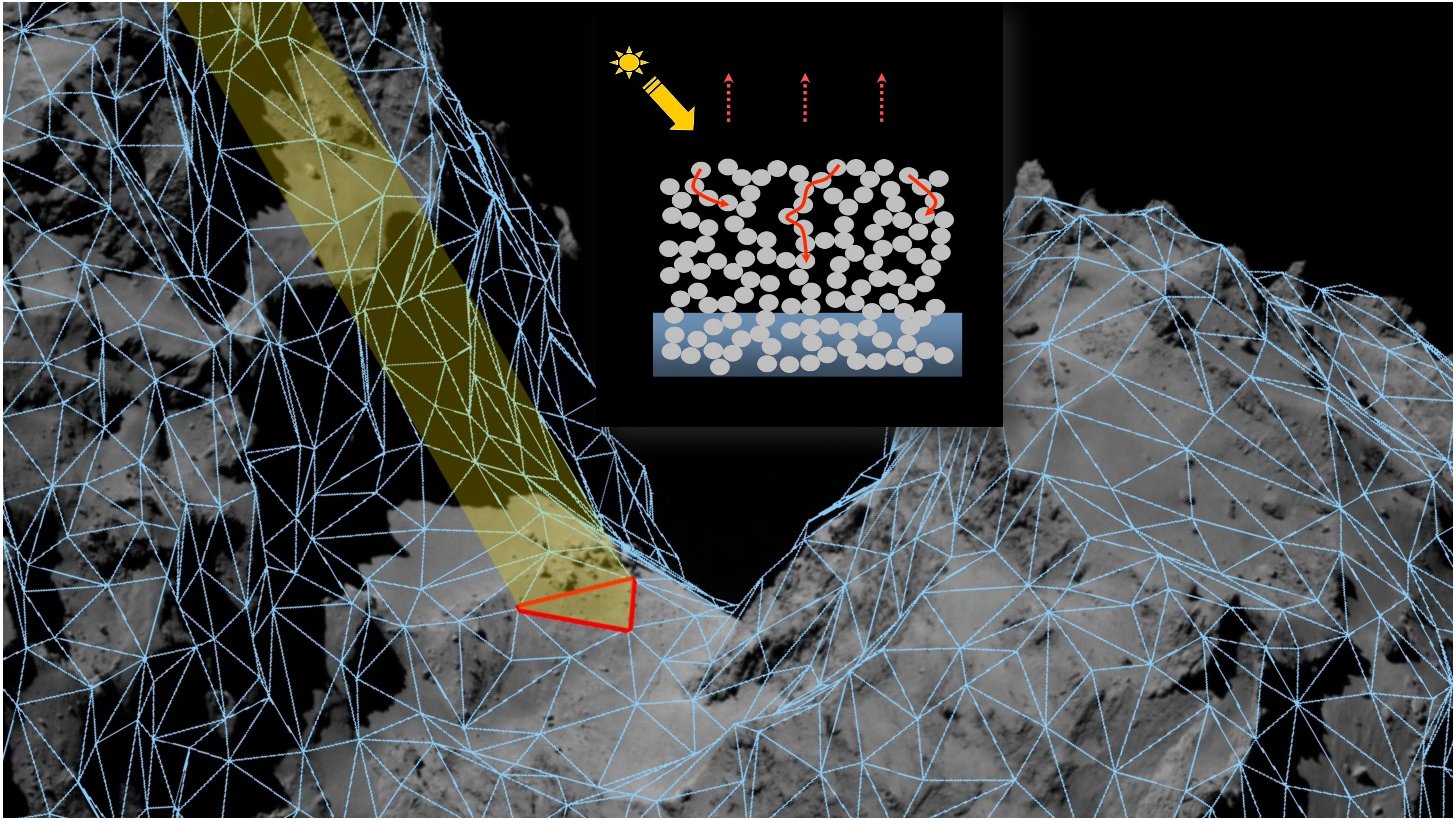


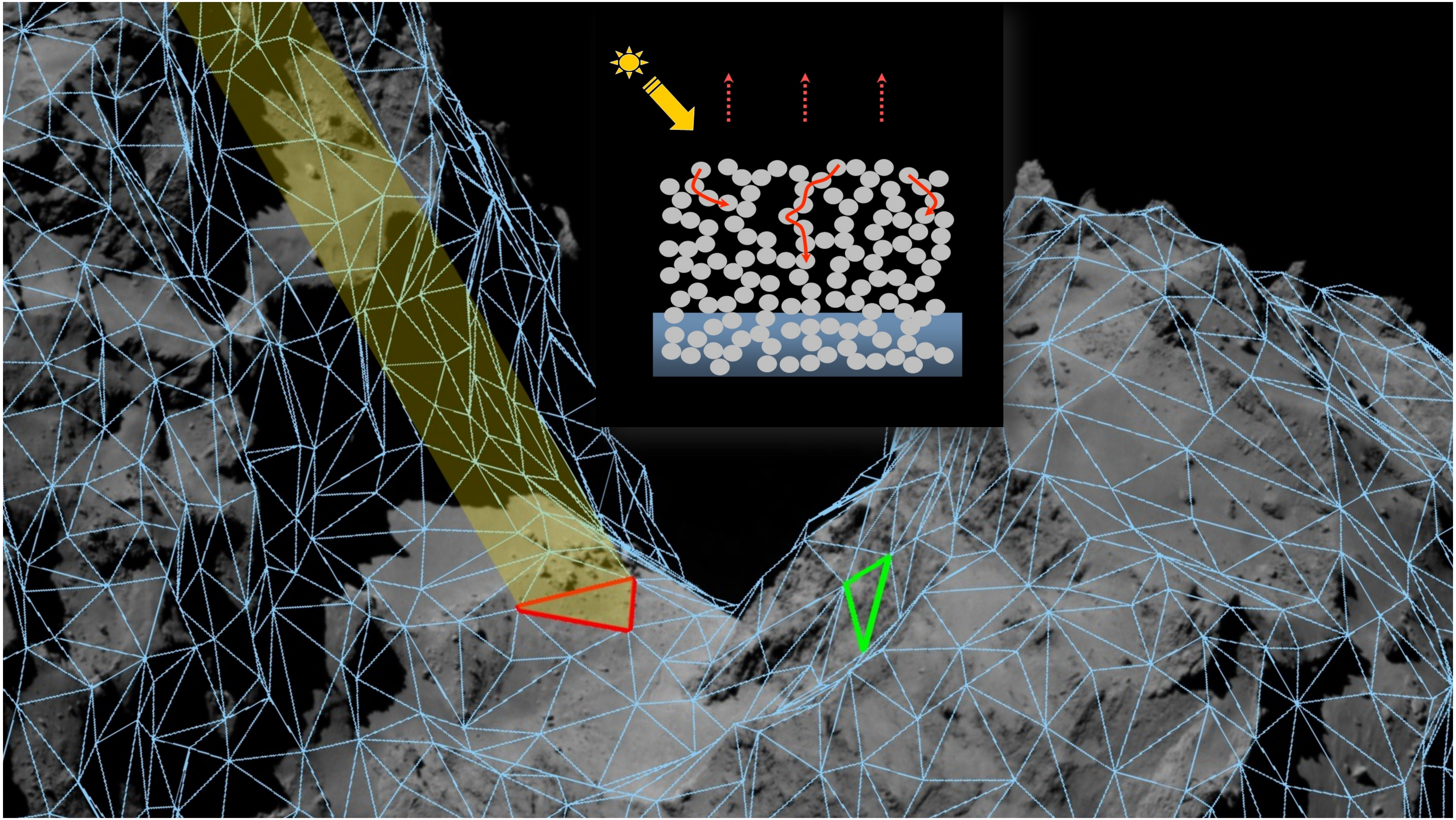


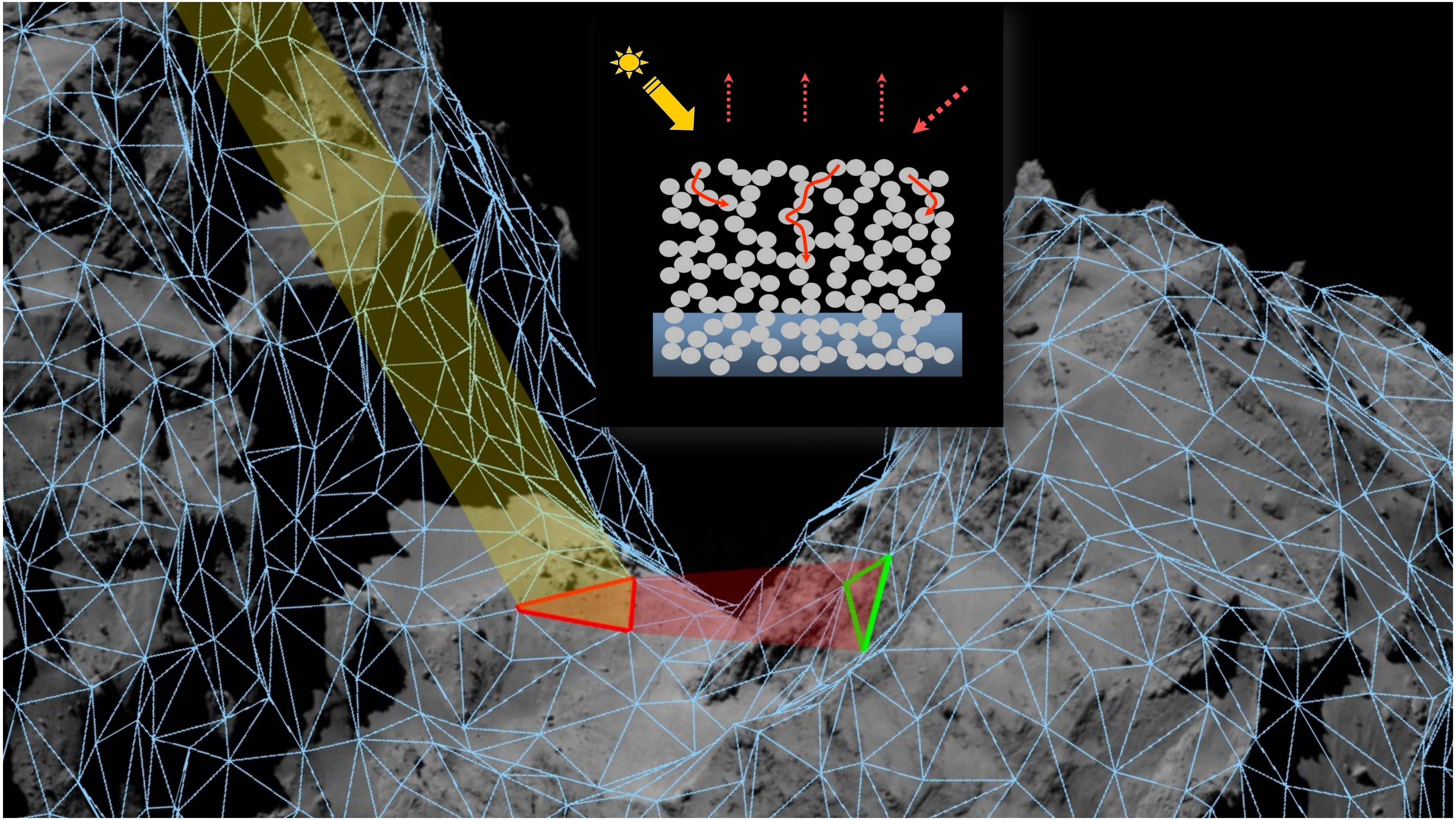

depth

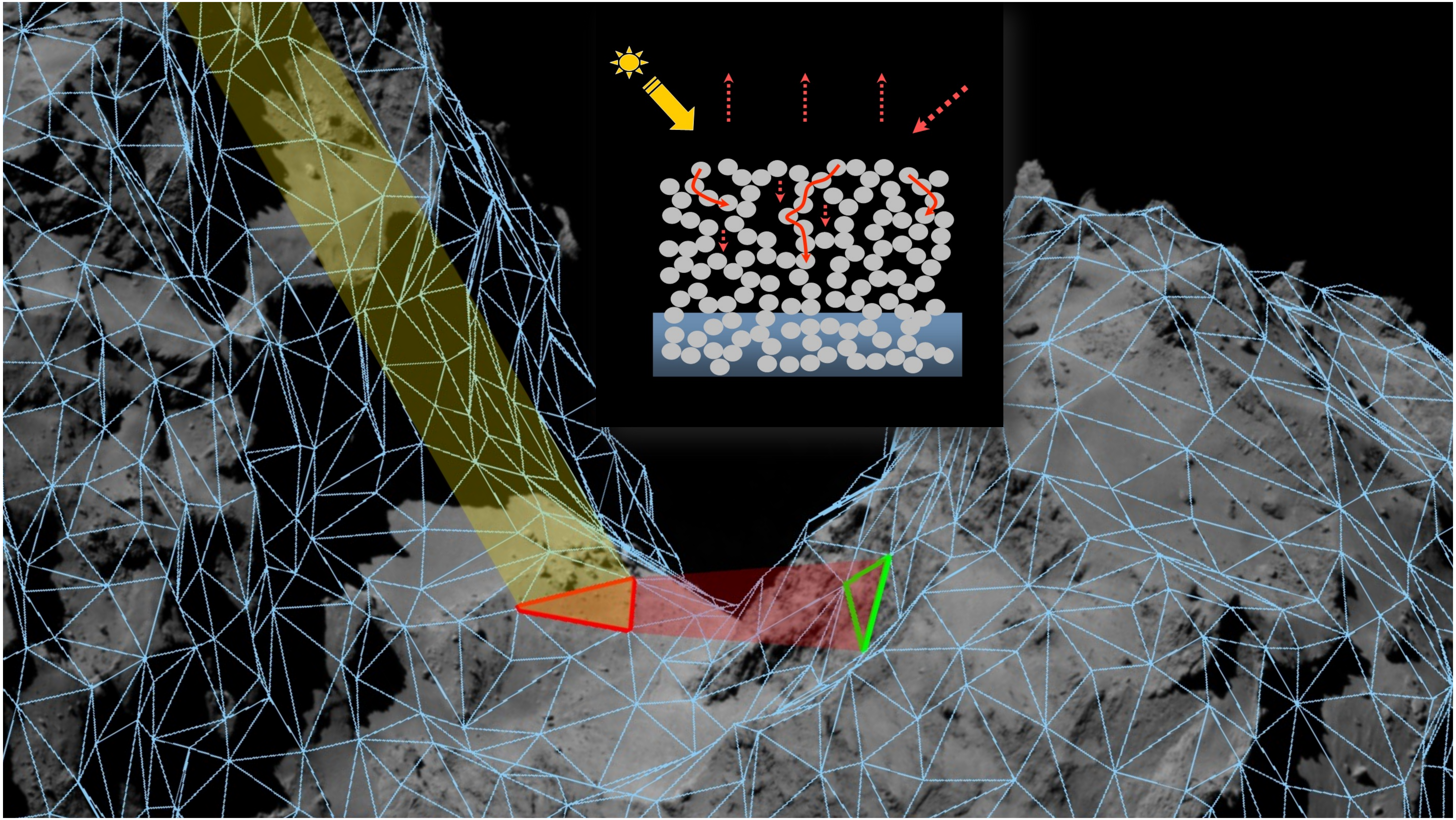


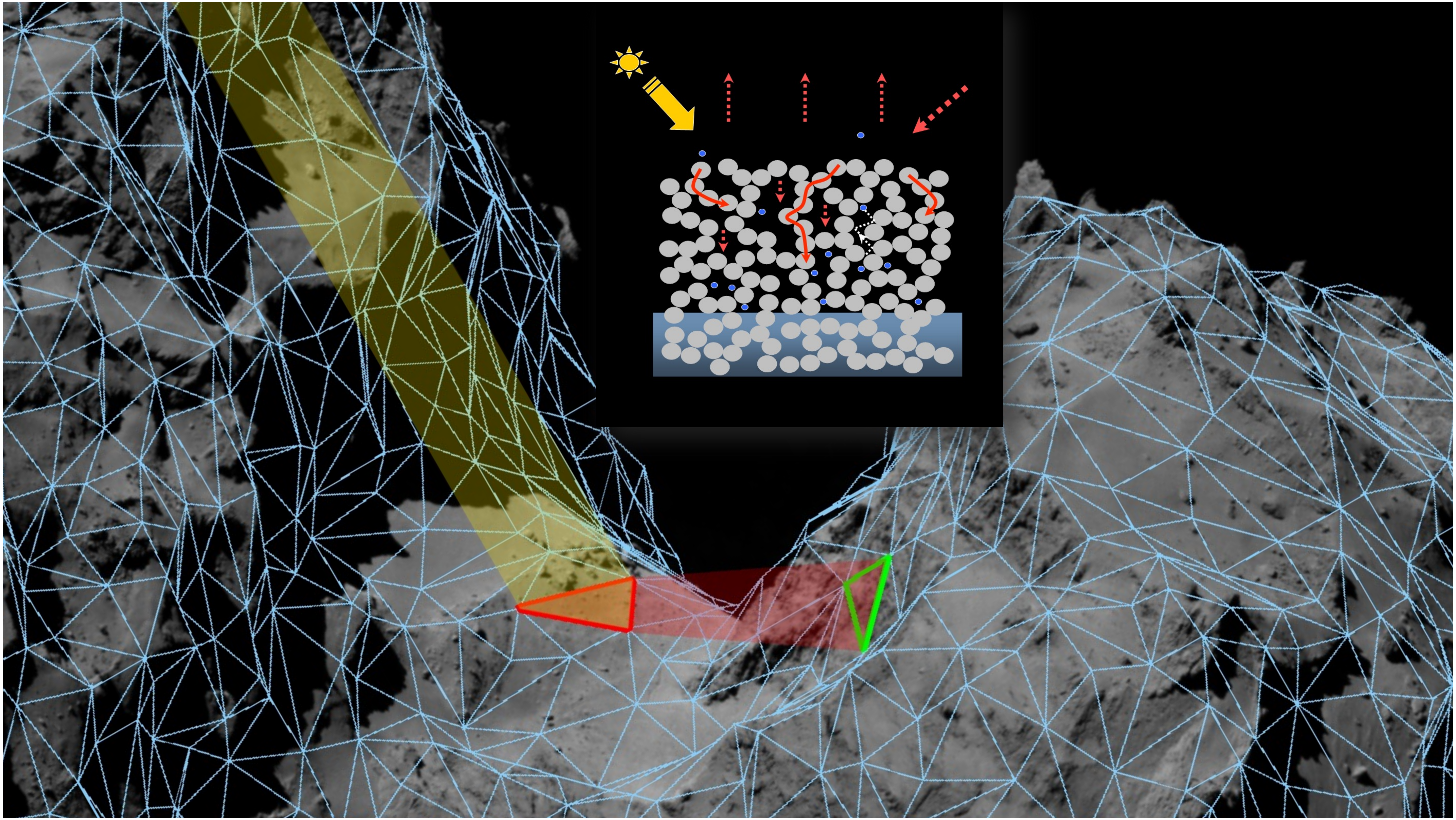








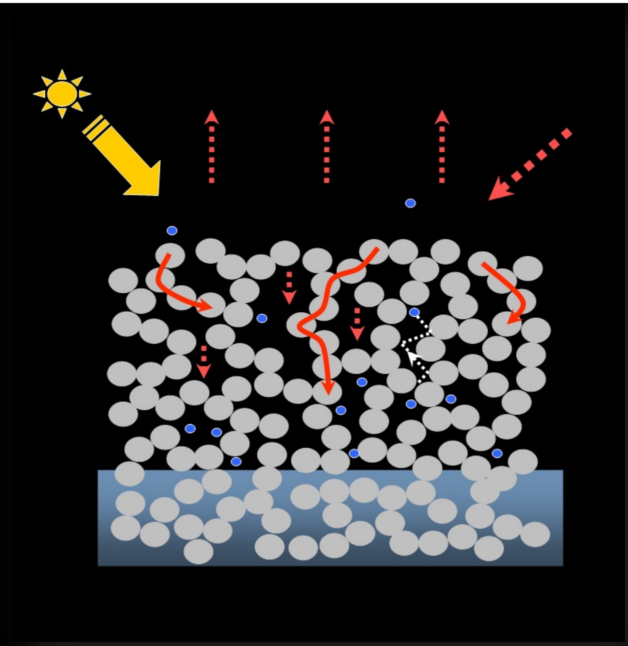




Numerical treatment

Asteroid:
Lagerros (1996a, b, 1997, 1998), Capek & Vokrouhlicky (2005), Rozitis & Green (2011) ,...

Comet:
Mendis+(1977), Fanale+(1984), Kömle+(1992), Prialnik+(1991), Kührt+(1994), Davidsson+(2002), Capria+(2003), Gundlach+(2012), Keller+(2015), Hu+(2017, 2021),...



- solar radiation
- shape, porosity, layering, ice fraction, etc.
- conductivity, albedo, etc.
- ...

$$\rho C \frac{\partial}{\partial t}T = \kappa \frac{\partial^2}{\partial x^2}T, \qquad \rho_m C_m = (1-f)\rho_d C_d + f\rho_i C_i, \quad \kappa_m = h((1-f)\kappa_d + f\kappa_i)$$

$$\epsilon\sigma T^4_{x=0} - \kappa_d \frac{\partial}{\partial x}T_{x=0} = (1-A_B)s\psi F_{\odot},$$

$$-\kappa_d \frac{\partial}{\partial x}T_{x=X^-} = -\kappa_m \frac{\partial}{\partial x}T_{x=X^+} + lZ_{(X)},$$

$$-\kappa_d \frac{\partial}{\partial x}T_{x=X^-} = -\kappa_m \frac{\partial}{\partial x}T_{x=X^+} + lZ_{(X)}, \quad Z_{(X)} = \Psi f Z^{\mathrm{H-K}}(T_{(X)}),$$

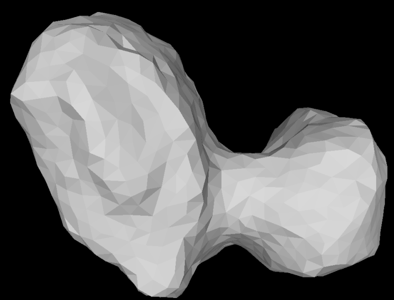
$$\frac{\partial}{\partial x}T_{x\to\infty} = 0.$$

- Temperature

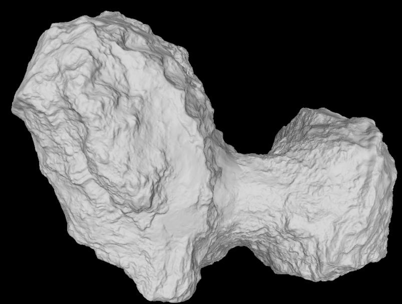
Limitations

- High-resolution modelling
- Long-term modelling
- Large parameter space

→ High computation cost



3 000 facets



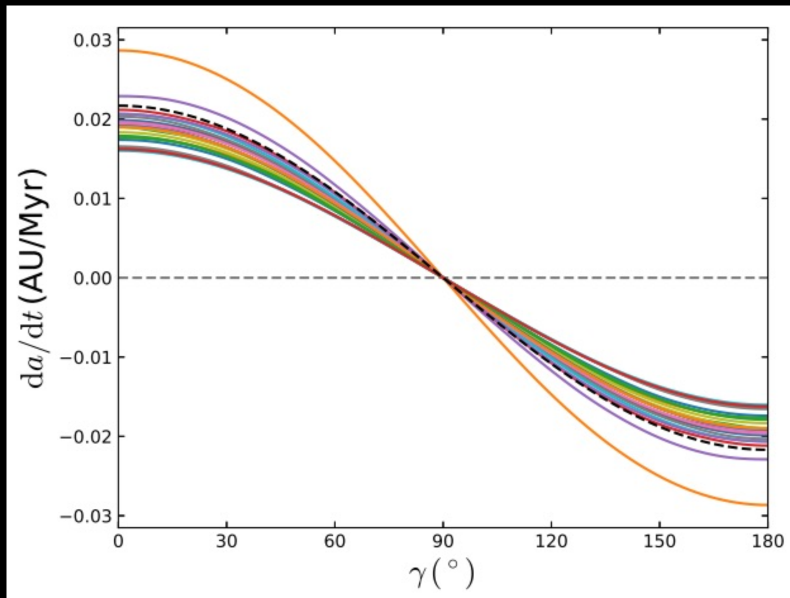
2 000 000 facets

(Jorda et al. 2016)

Limitations

- High-resolution modelling
- Long-term modelling
- Large parameter space

➡ High computation cost



(Xu et al. 2022)

Differences in modeled Yarkovsky effect by assuming different shapes

Deep Learning - based thermophysical modelling

- High-resolution modelling
- Long-term modelling
- Large parameter space

→ Moderate computation cost

- solar radiation
- shape, porosity, layering, ice fraction, etc.
- conductivity, albedo, etc.
- ...

→ Deep Operator Neural Network →

- Temperature

Deep Operator Neural Network (DeepONet) (Lu et al., 2019, 2021)

ARTICLES
https://doi.org/10.1038/s42256-021-00302-5
nature machine intelligence

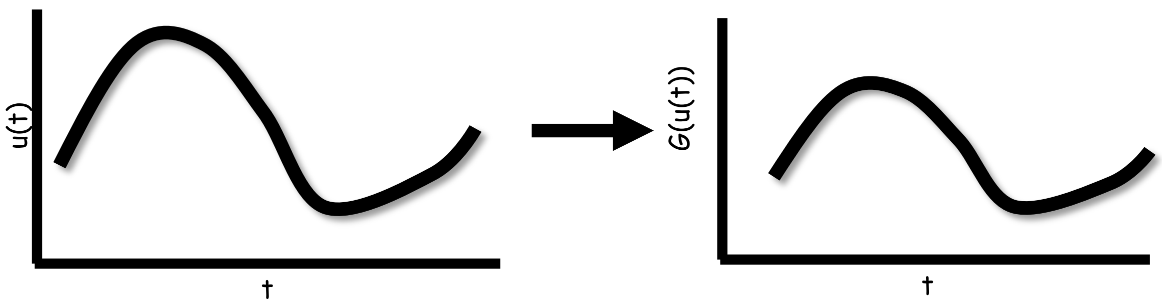
Check for updates

Learning nonlinear operators via DeepONet based on the universal approximation theorem of operators

Lu Lu[1], Pengzhan Jin[2,3], Guofei Pang[2], Zhongqiang Zhang[4] and George Em Karniadakis[2]

Universal Operator Approximation Theorem (Chen&Chen, 1995)

A neural network can accurately approximate any nonlinear operator for mapping from one space of functions to another space of functions.



$u(t)$ $\qquad$ $G(u(t))$

Deep Operator Neural Network (DeepONet) (Lu et al., 2019, 2021)


ARTICLES
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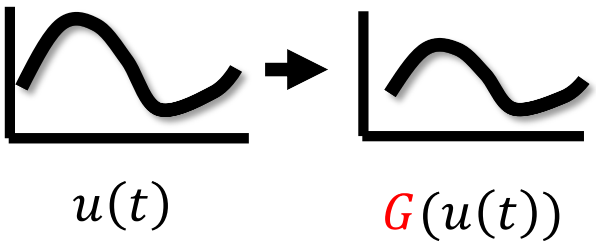
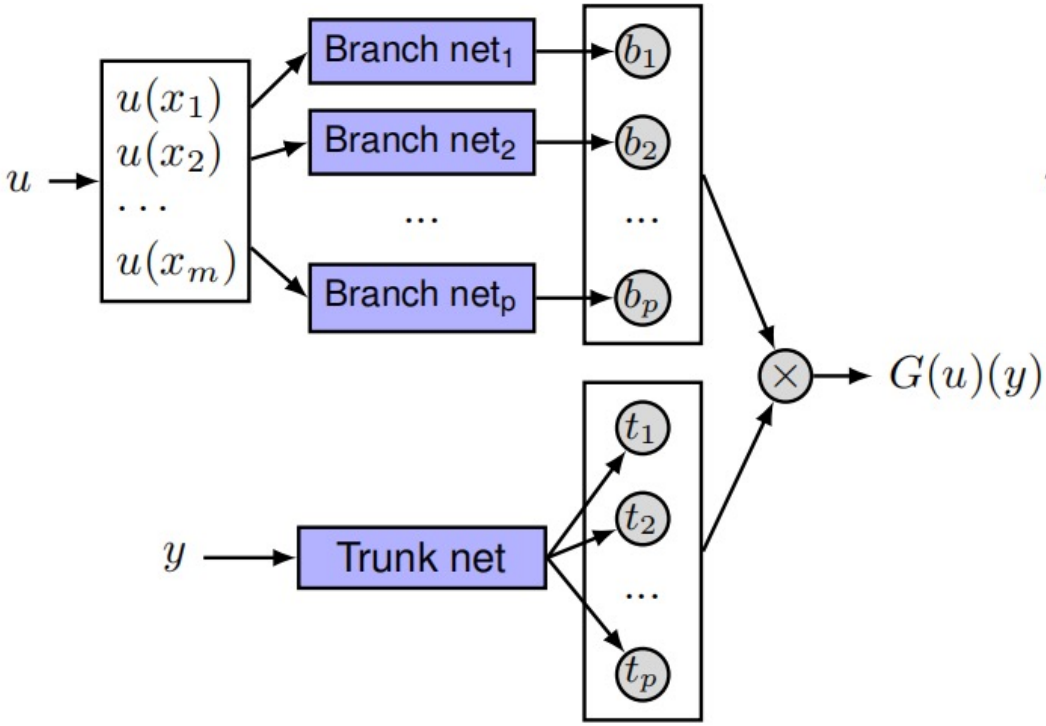
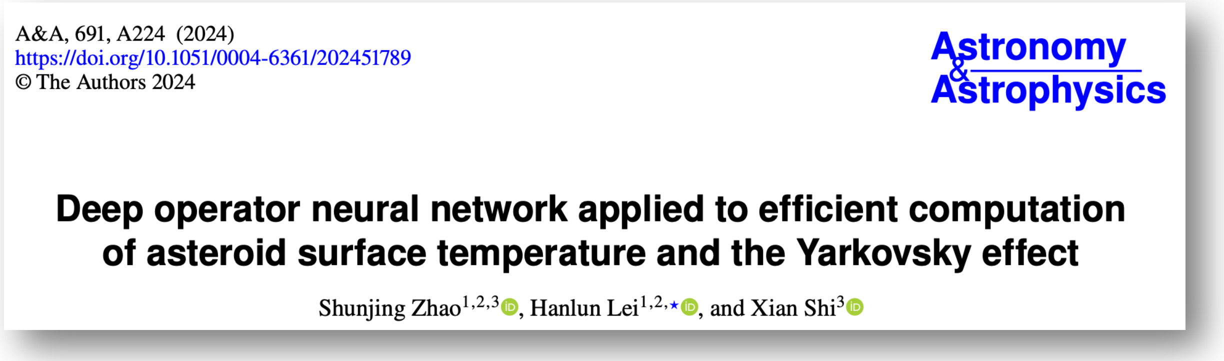




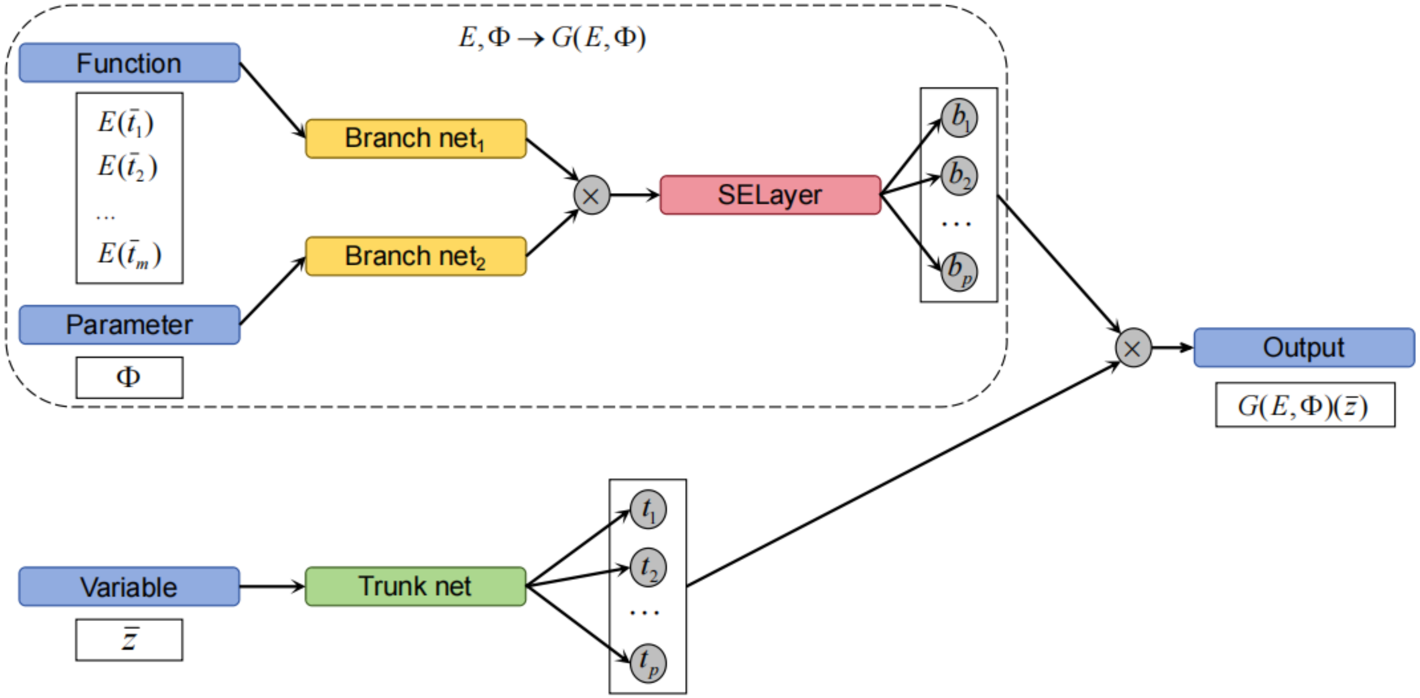
DeepONet for asteroid thermophysical modelling (Zhao et al. 2024)


A&A, 691, A224 (2024)
https://doi.org/10.1051/0004-6361/202451789

Astronomy & Astrophysics

Deep operator neural network applied to efficient computation of asteroid surface temperature and the Yarkovsky effect

Shunjing Zhao[1,2,3], Hanlun Lei[1,2,⋆], and Xian Shi[3]



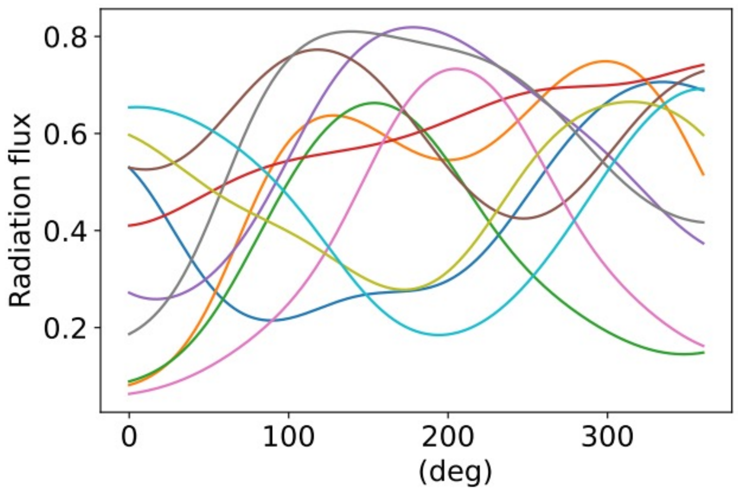
Training of the network

Batch size	600
Epochs	30,000
Initialization	normal distribution
Loss function	MSE
Method	Adam ($\beta_1 = 0.8, \beta_2 = 0.99$)
Initial learning rate	0.001

Formation of training dataset
- Input
  - Random insolation curves
  - Random physical parameters

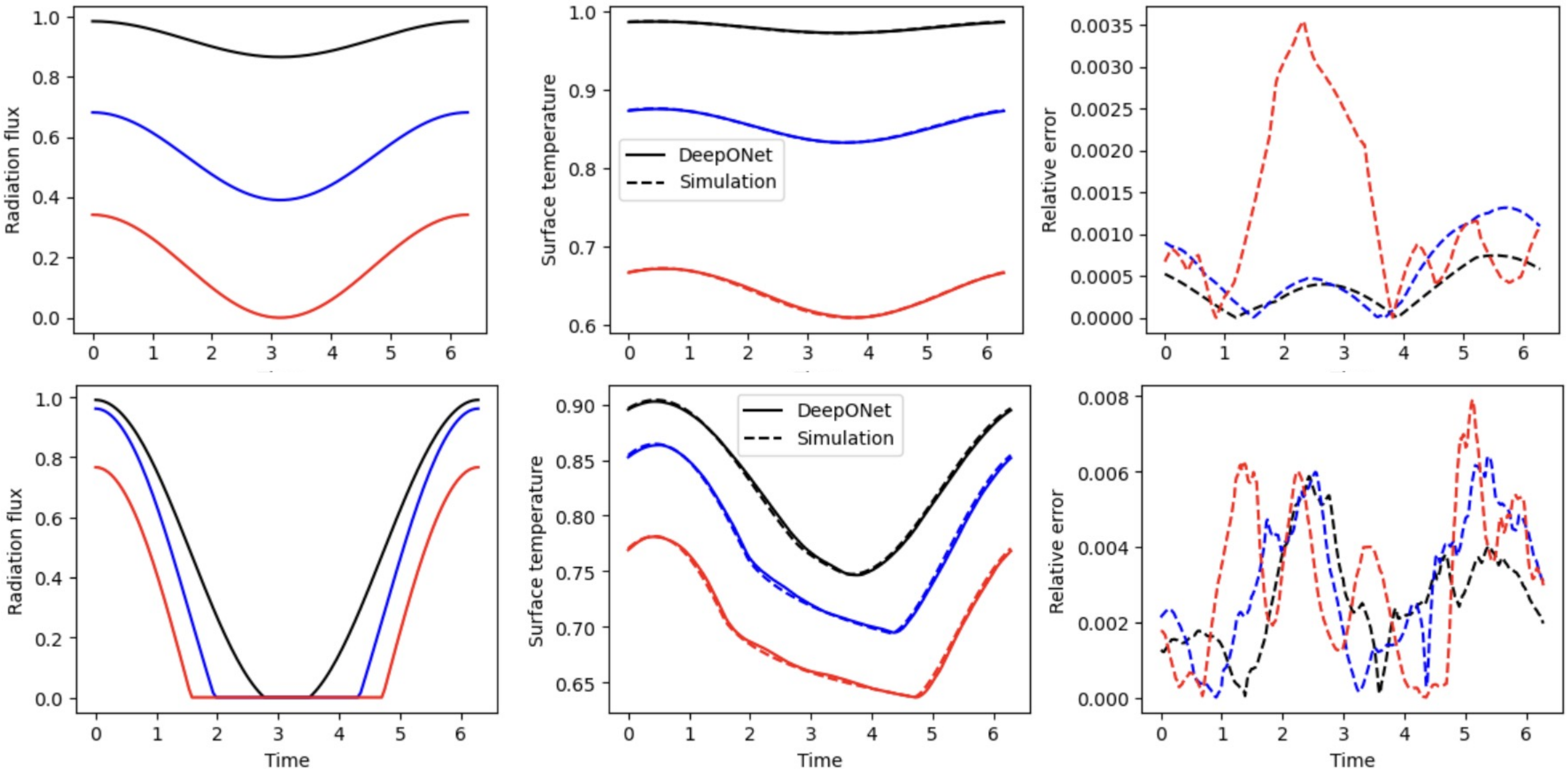
Ensure generalisation

- Output
  - Surface temperature derived by numerical simulations

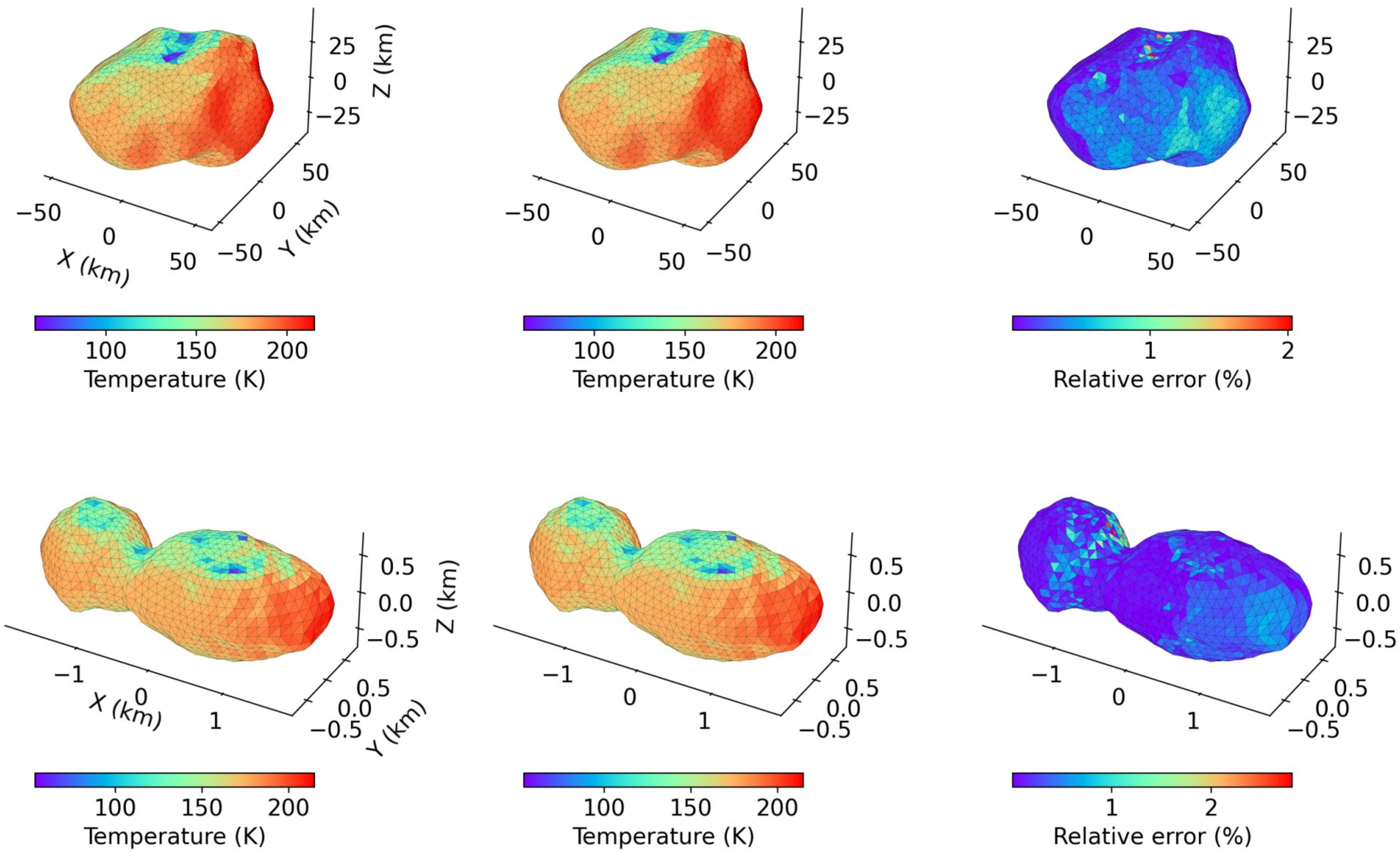


Insolation curves: Gaussian Random Field (GRF)

Performance assessment

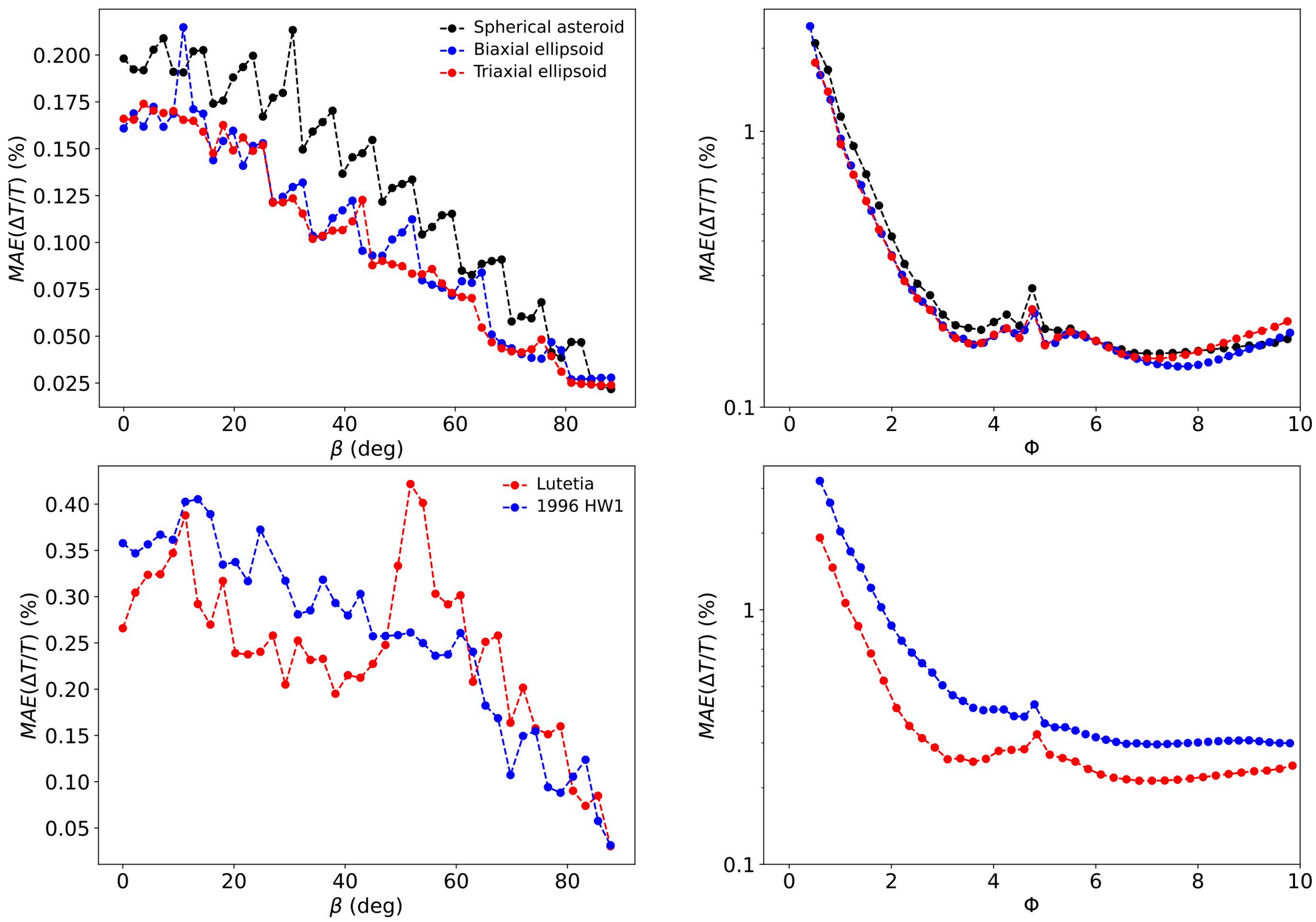


Performance assessment



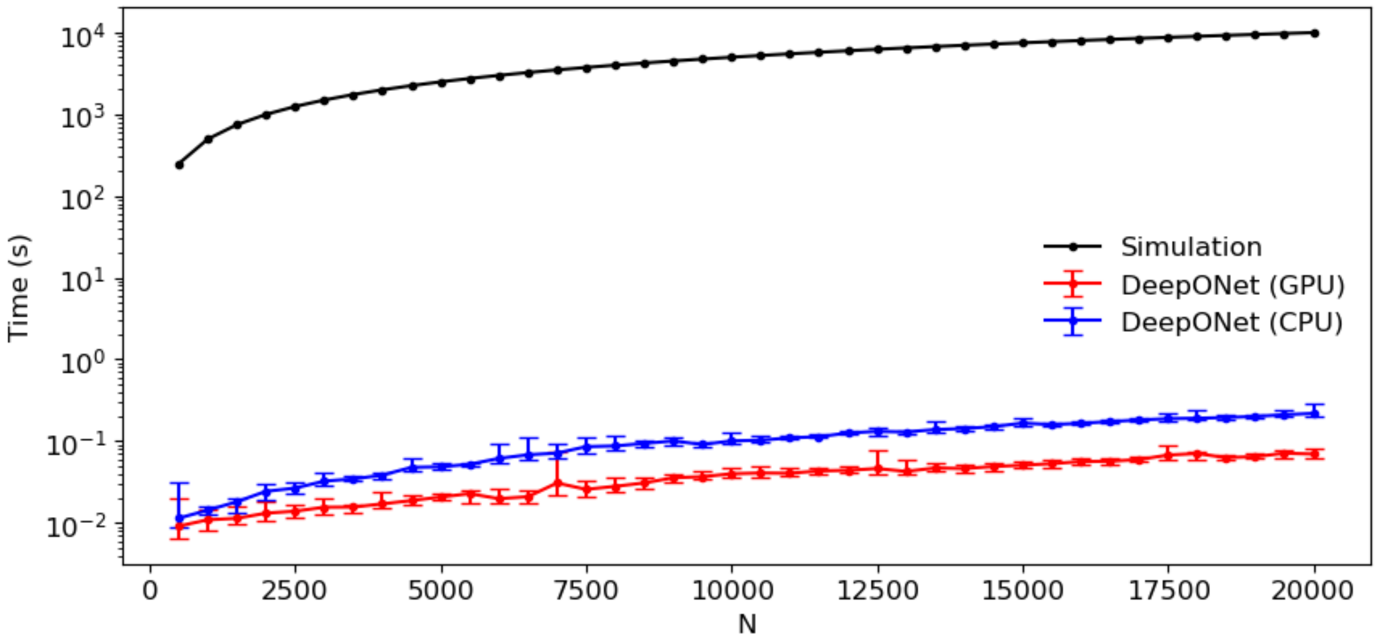
(a) DeepONet (b) Simulation (c) Error

Performance assessment



(Zhao et al. 2024)

Computation cost

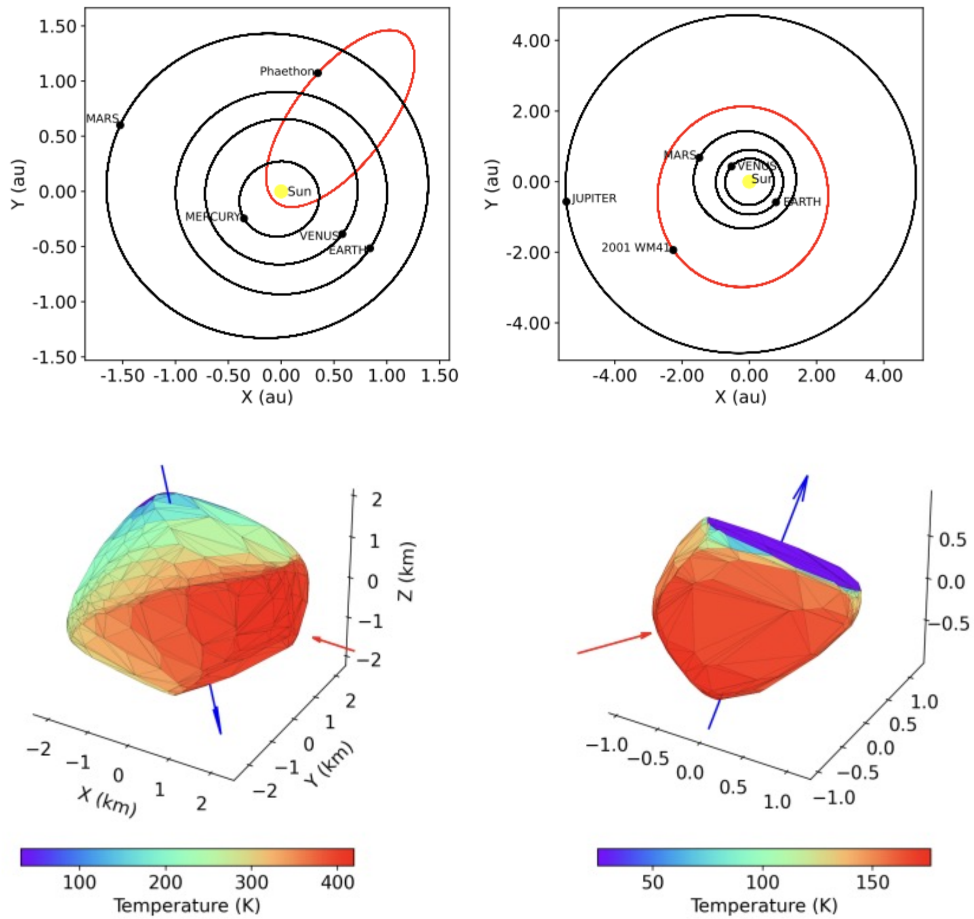


(Zhao et al. 2024)

Applications
High-fidelity Yarkovsky effect

Integrated high-fidelity Yarkovsky accelerations in orbit propagation

Property	Phaethon	2001 WM41
Bond albedo A_B	0.122	0.332
Emissivity ϵ	0.9	0.9
Thermal inertia Γ (J m^{-2}s$^{-1/2}$K^{-1})	300	300
Density ρ (kg/m^3)	1500	1500
Diameter d (km)	5.1	2.5
Direction of Spin axis (λ, β)	(318°, −47°)	(72°, 61°)
Rotation period P (h)	3.6	7.7



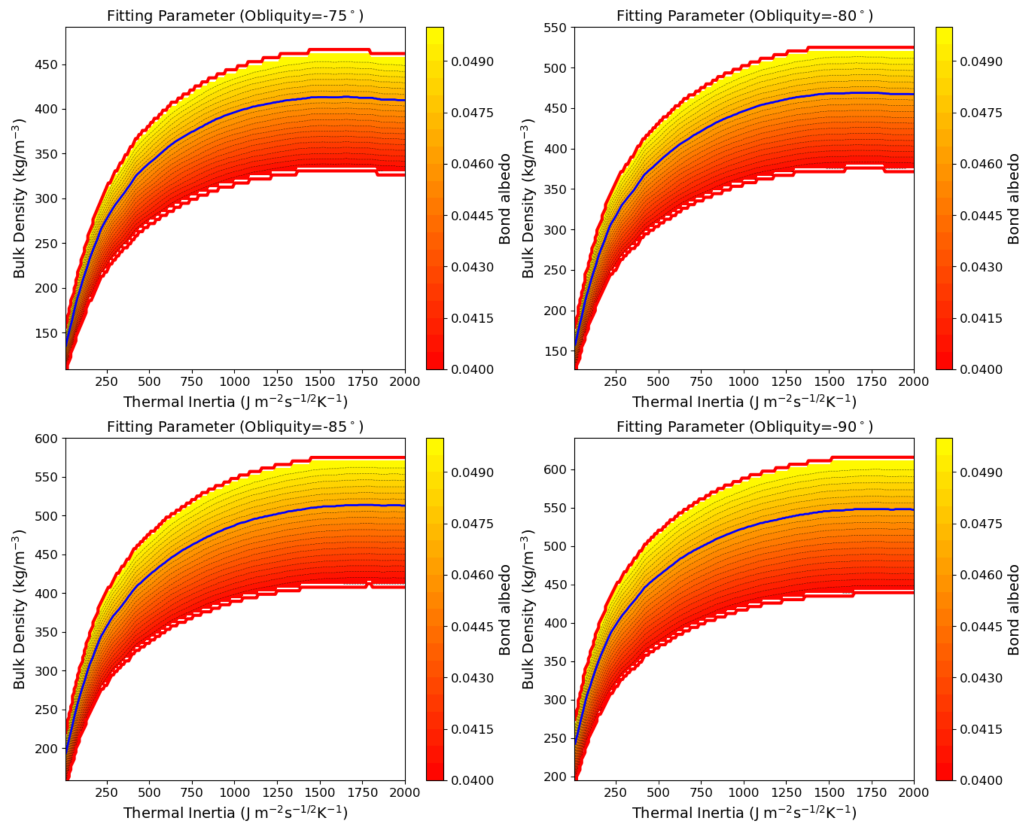
(Zhao et al. 2024)

Applications

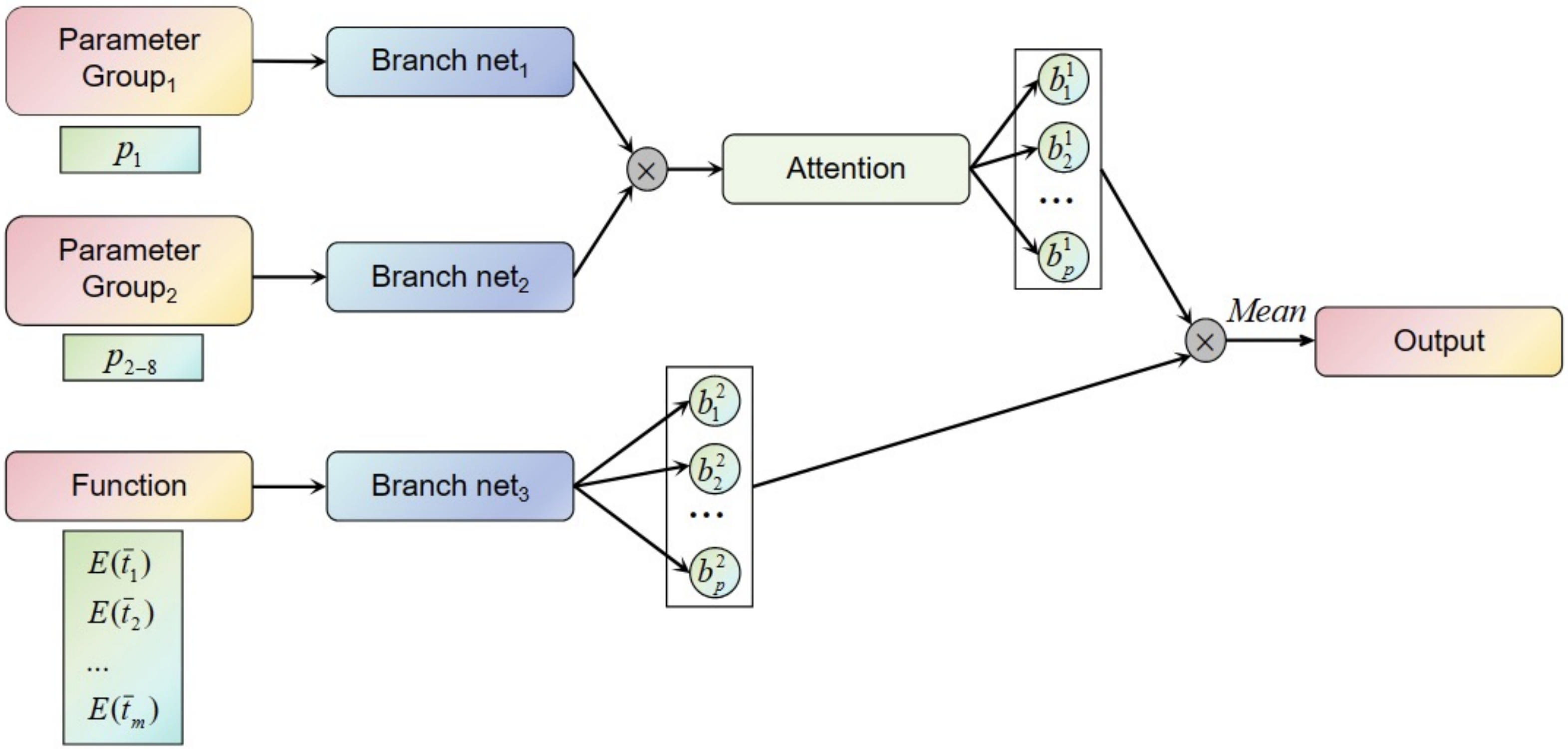
Physical properties inferred by Yarkovsky effect (Hui et al. to be submitted)

- Previous works: Dziadura+ (2023, 2024)

- Using the trained network to generate lookup tables of Yarkovsky effect over a large parameter space

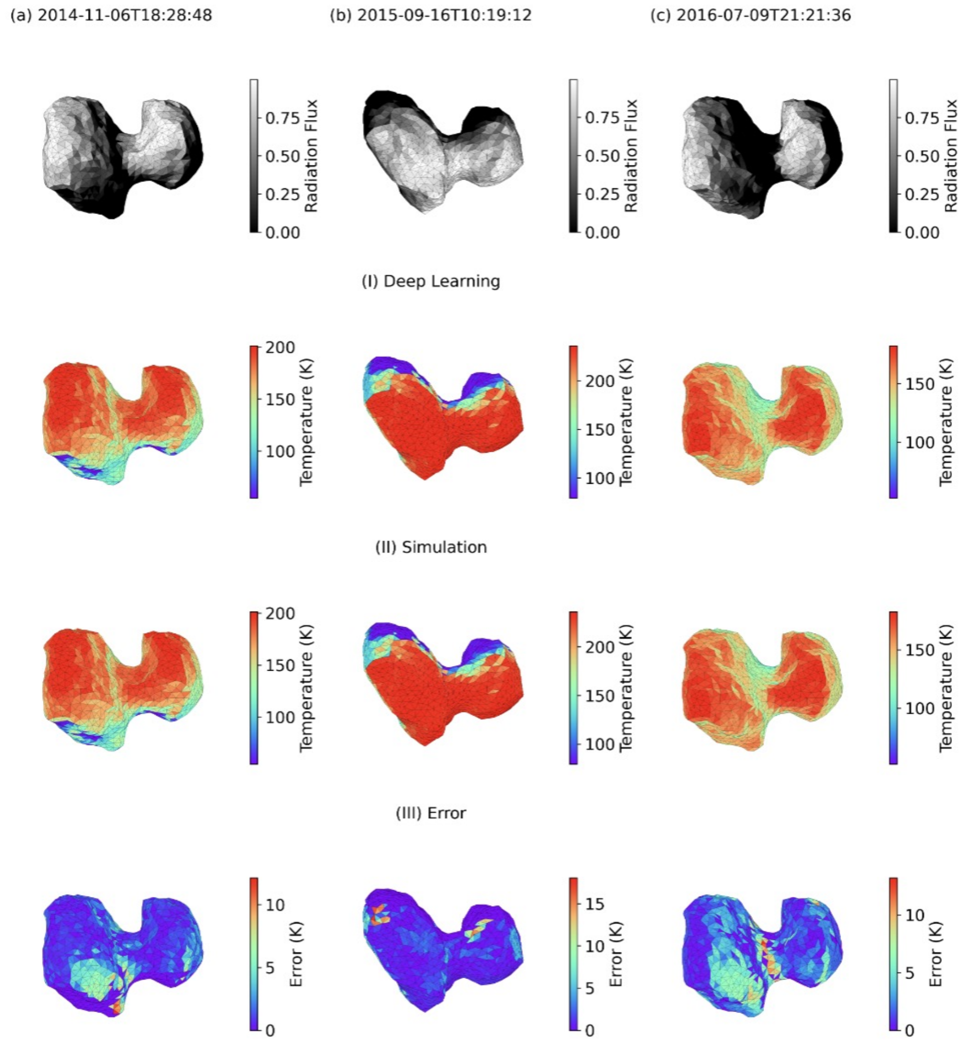


ThermoONet – Deep Learning-based network for comet thermophysical modelling (Zhao et al. in press)

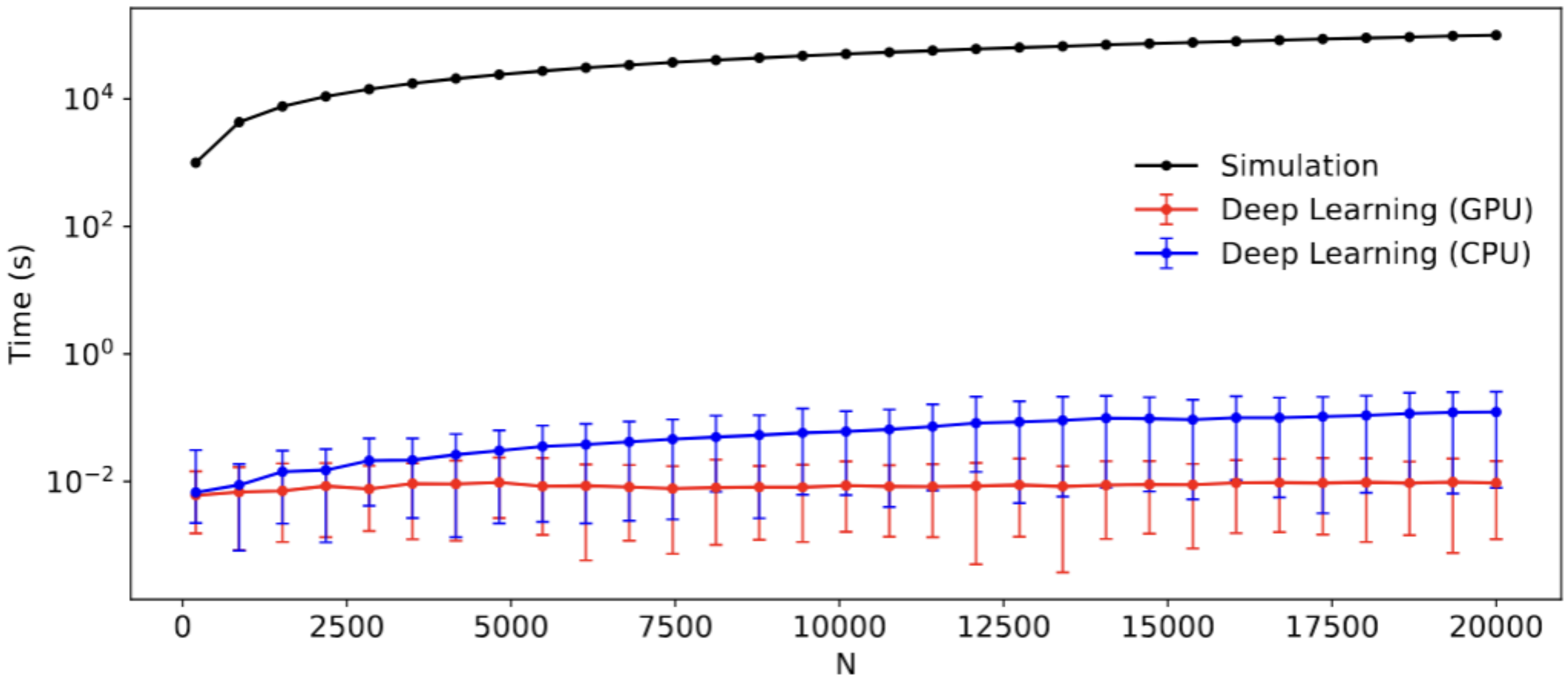


ThermoONet – performance assessment

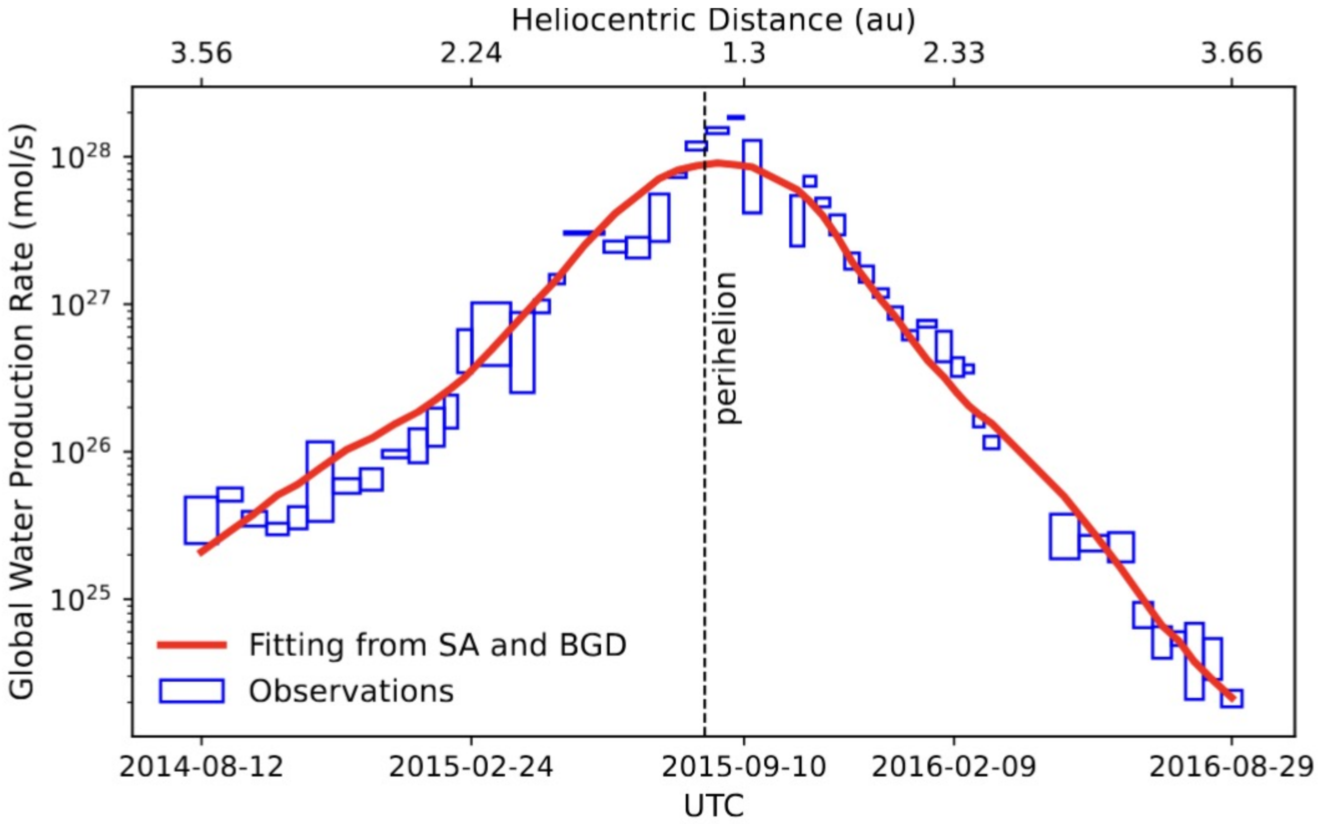
- Average error: 2%



ThermoONet – computation cost



Applications
ThermoONet for fitting cometary water production rate curve



Best-fit parameters:

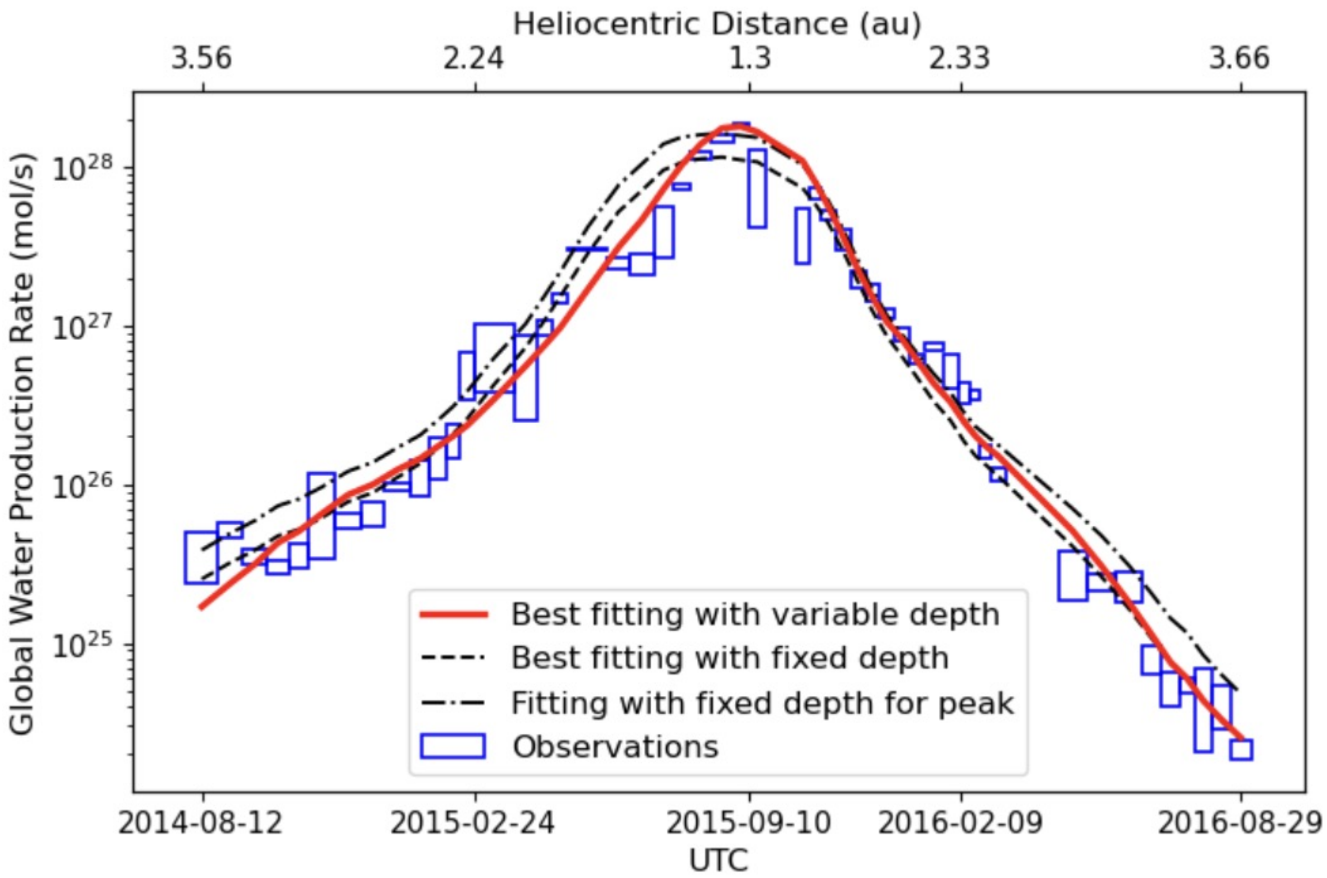
Dust mantle thickness
X = 3.61mm

Ice fraction:
F = 0.644%

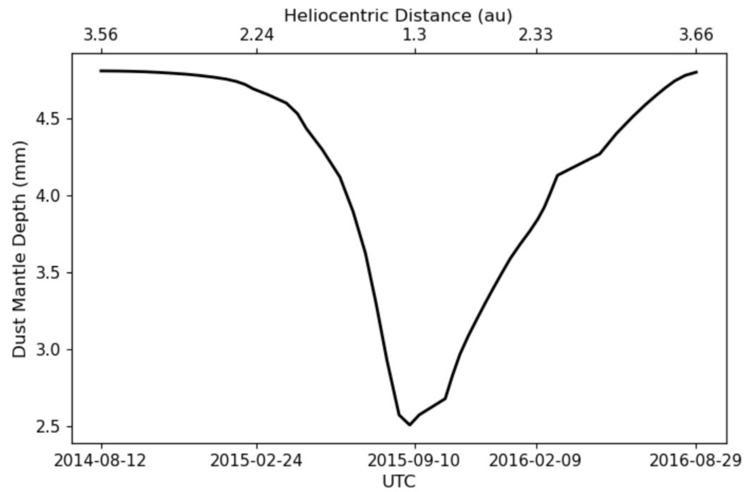
Data from Läuter et al. (2020)

Applications

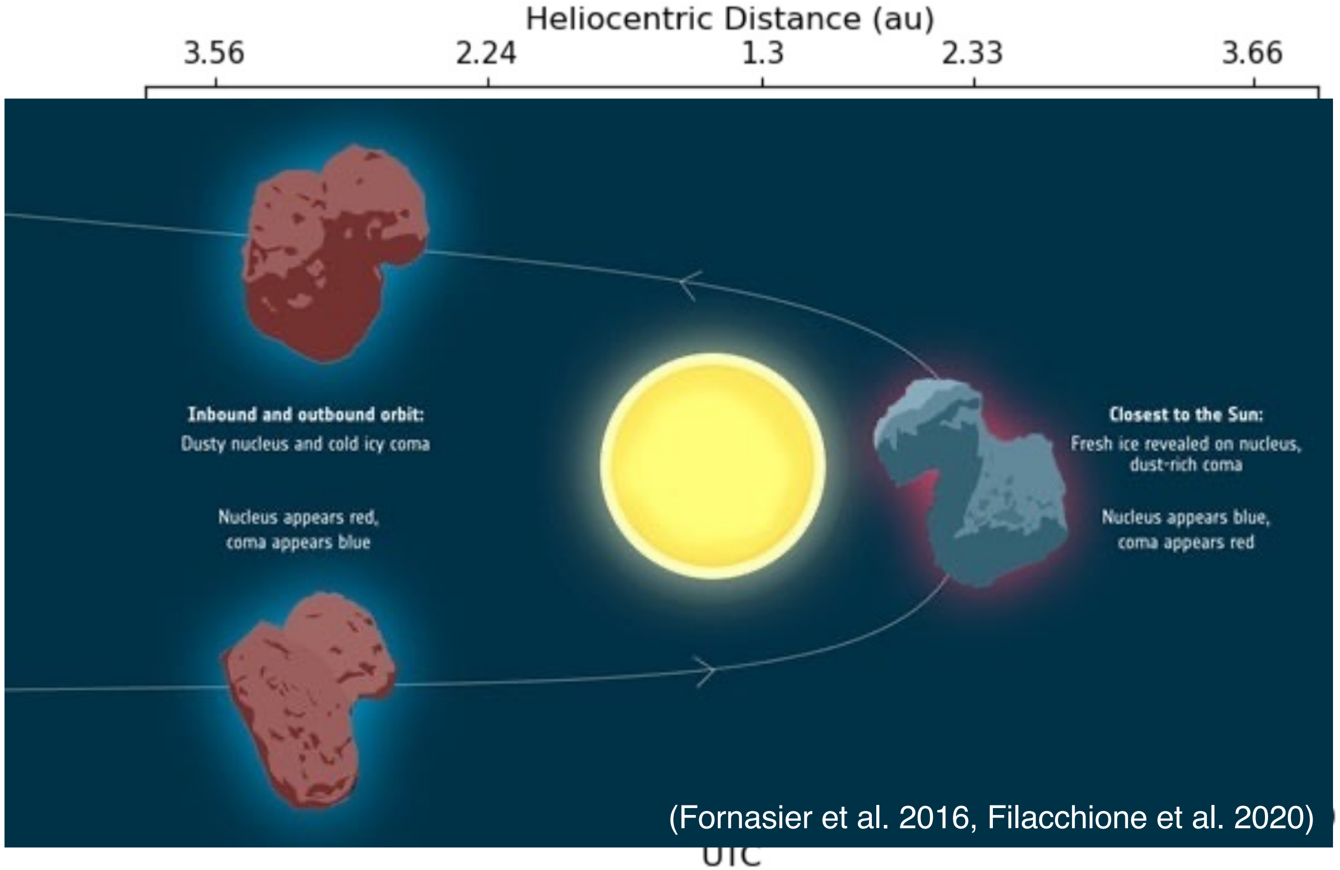
ThermoONet for analyzing the variation of comet's dust mantle



With a varying depth of dust mantle

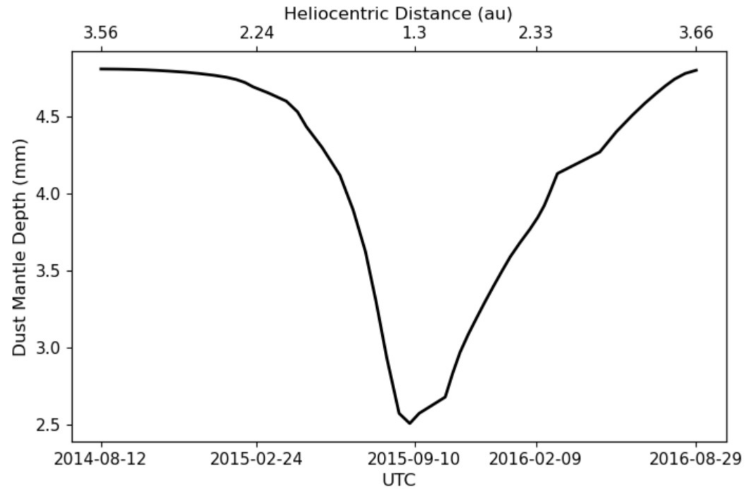


Applications
ThermoONet for analyzing the variation of comet's dust mantle

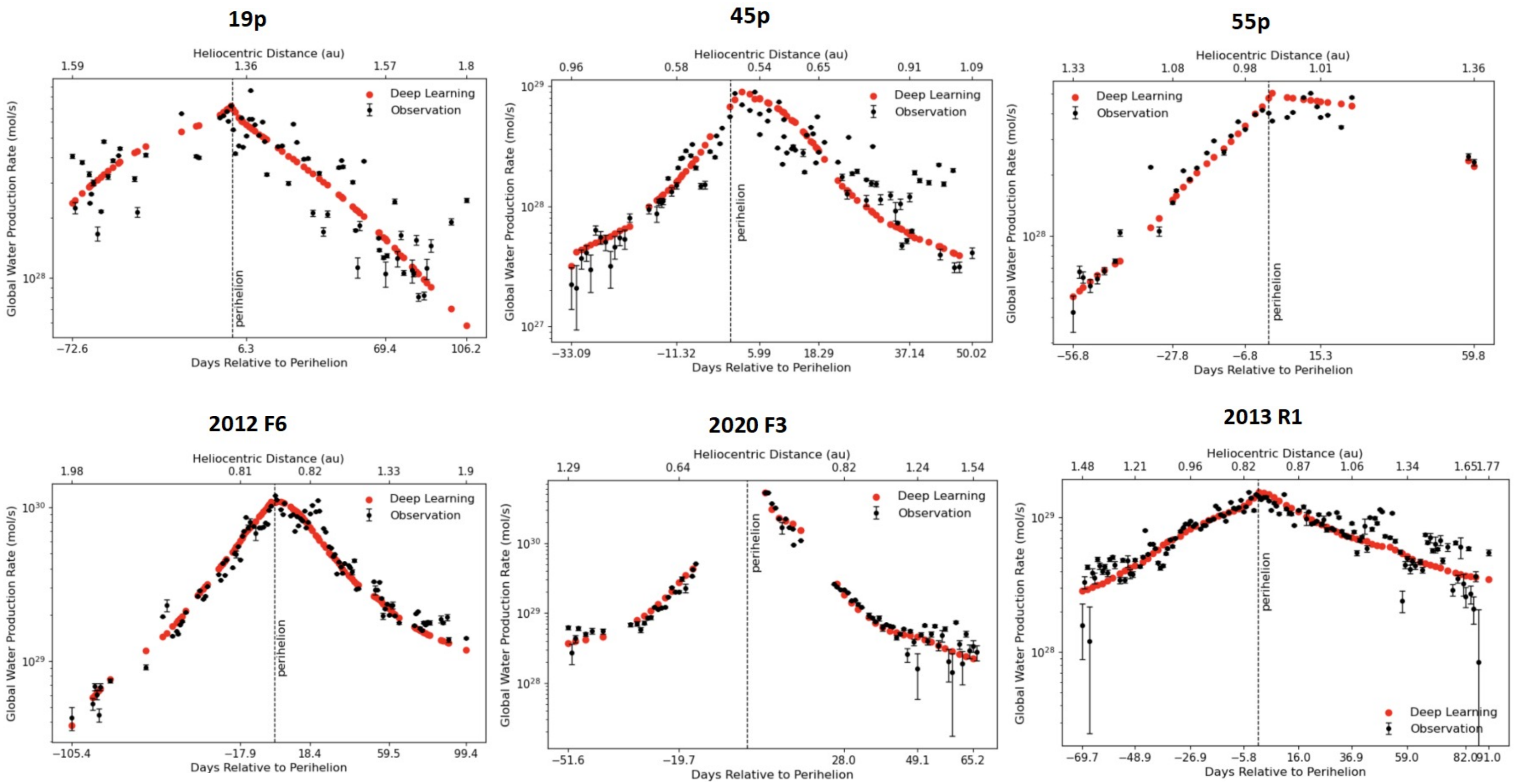


(Fornasier et al. 2016, Filacchione et al. 2020)

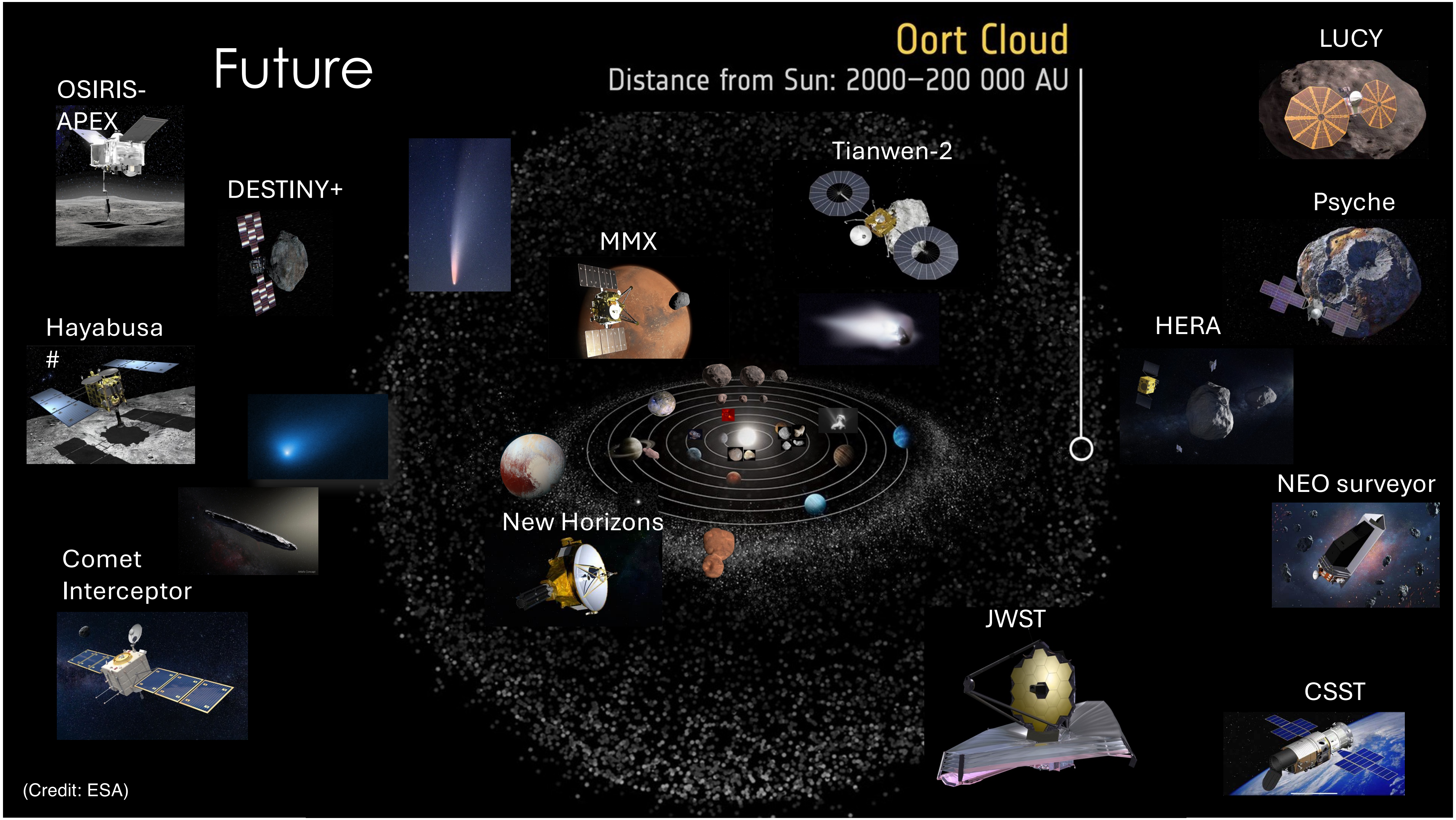
With a varying depth of dust mantle



Applications
ThermoONet for retrieving properties of comets by fitting their water production rate curves



Data from Combi et al. (2019)



Future
Oort Cloud
Distance from Sun: 2000–200 000 AU
OSIRIS-APEX
DESTINY+
Hayabusa #
Comet Interceptor
MMX
Tianwen-2
New Horizons
LUCY
Psyche
HERA
NEO surveyor
JWST
CSST
(Credit: ESA)

Next steps

- Network training with larger training dataset
- Integration of trained networks in the analyses of observation data, e.g. Gaia, NEOWISE, etc.
- Improved networks trained with more sophisticated models and real measurements.

Thank you for your attention!

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