

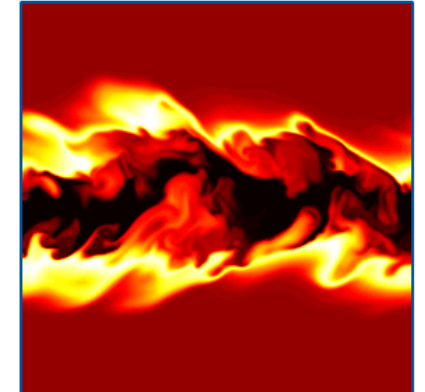
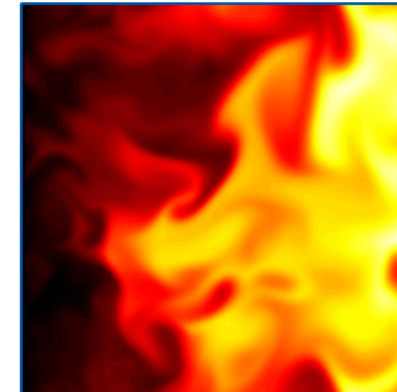
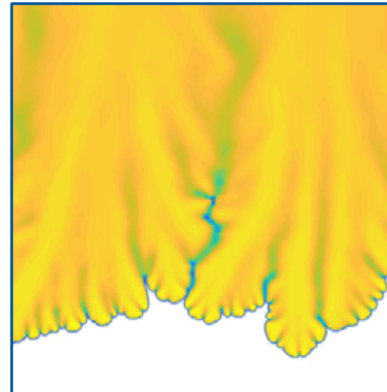
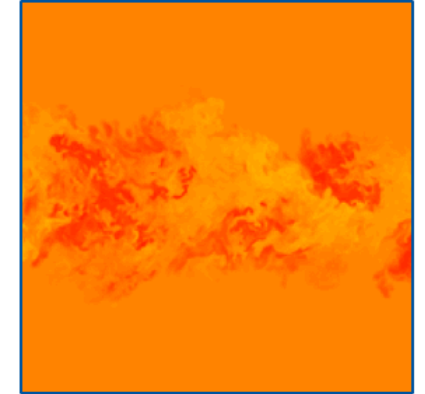
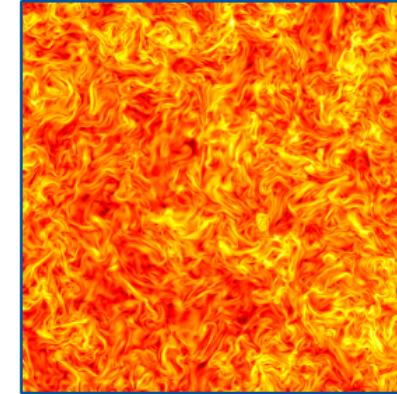
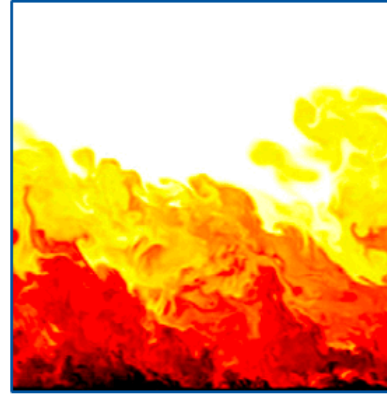
# aPriori: a Python package to process Direct Numerical Simulations

PhD Candidate: Lorenzo Piu<sup>1,2</sup>

Supervisors: Prof. Alessandro Parente<sup>1</sup>, Prof. Heinz Pitsch<sup>2</sup>

# Direct Numerical Simulations (DNS) can provide highly detailed physical insights

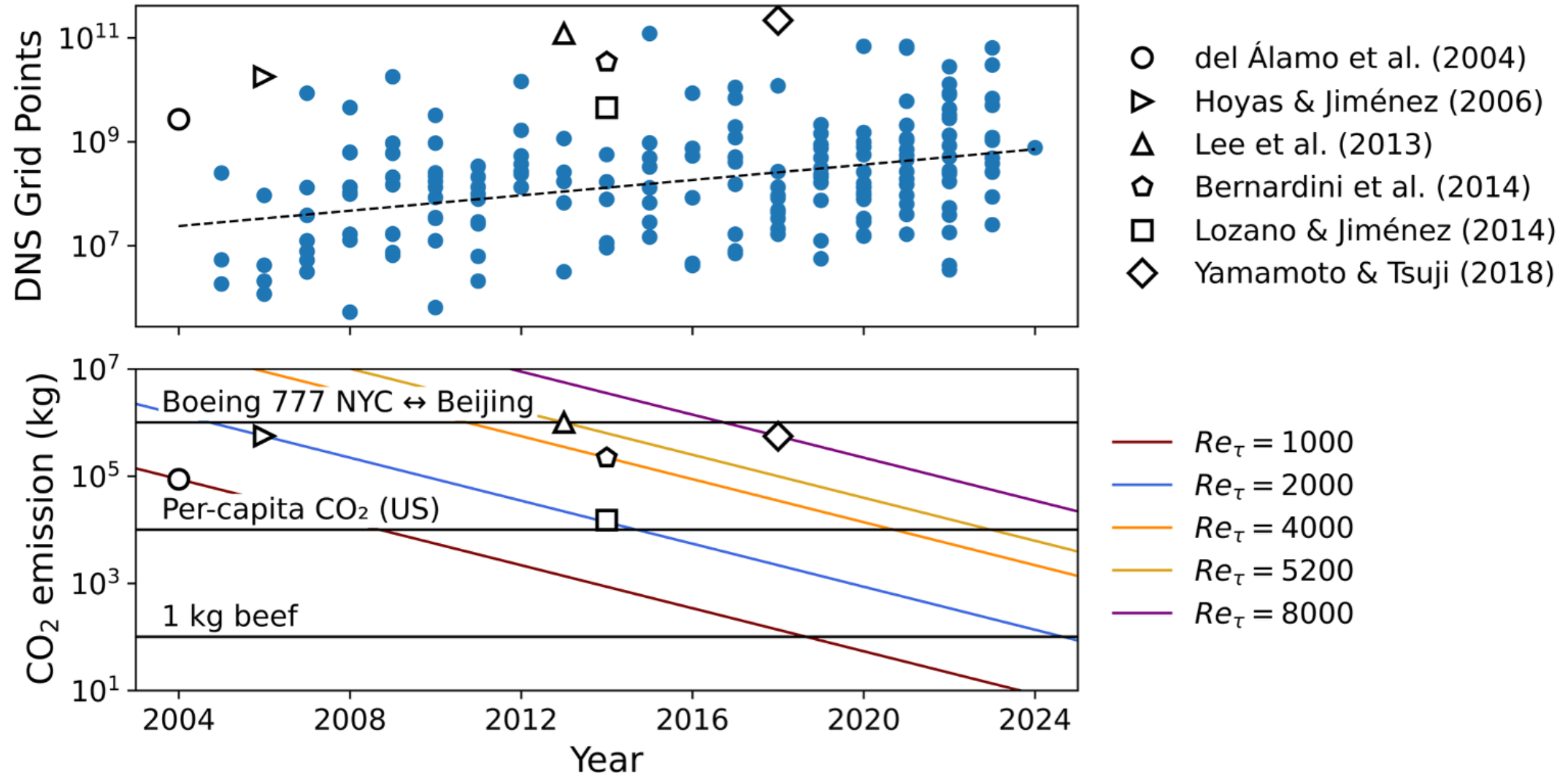
- Boundary layer structure [1]
- Homogeneous isotropic turbulence [2]
- Thermo-diffusive instabilities in premixed laminar hydrogen flames [3]
- Soot emissions in methane diffusion flames [4]
- Non-conventional combustion regimes (MILD combustion) [5,6]



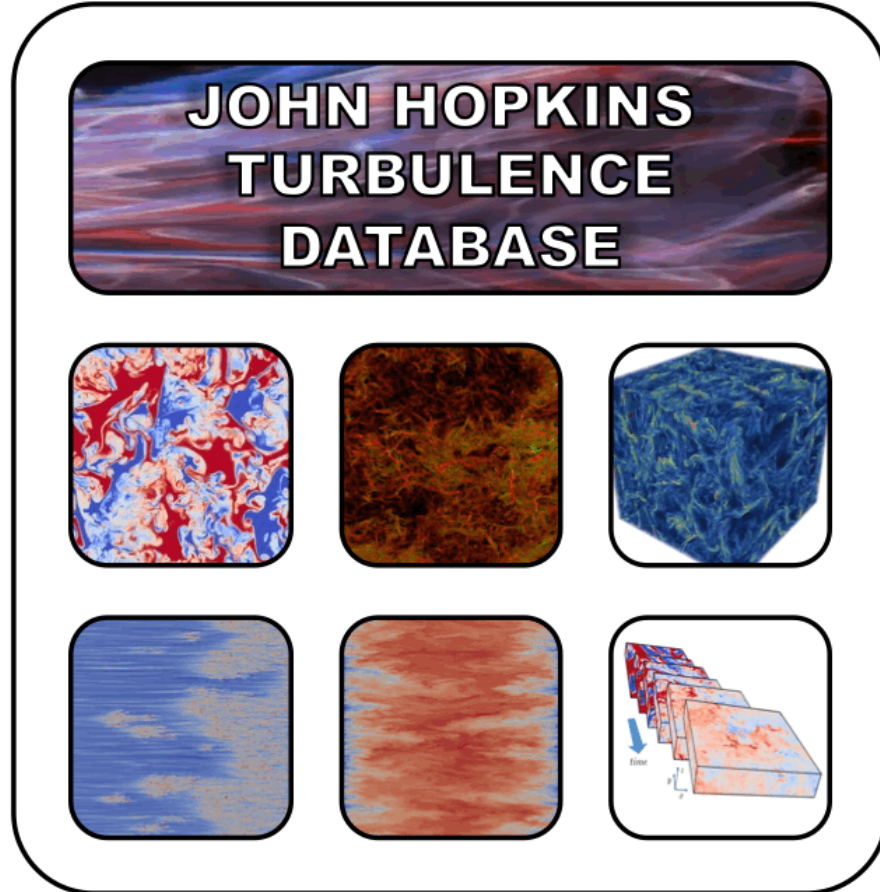
[1] Watanabe, T., Zhang, X., & Nagata, K. (2019). *Computers & Fluids*.  
[2] Gauding, M., Thiesset, F., et al. (2022). *Journal of Fluid Mechanics*  
[3] Berger, L., Kleinheinz, K., Attili, A., Pitsch, H., (2019) . *Proceedings C. I.*

[4] Attili, A., Bisetti, F., Mueller, M. E., & Pitsch, H. (2014). *Combustion and Flame*  
[5] Frascino, L., Scialabba, G., Chu, H., & Pitsch, H. (2025). Zenodo.  
[6] Doan, N.A. K., Swaminathan, N., & Minamoto, Y. (2018). *Combustion and Flame*

# DNS have a non-negligible impact on CO2 emissions



# Databases reduce the carbon footprint by avoiding redundant computations



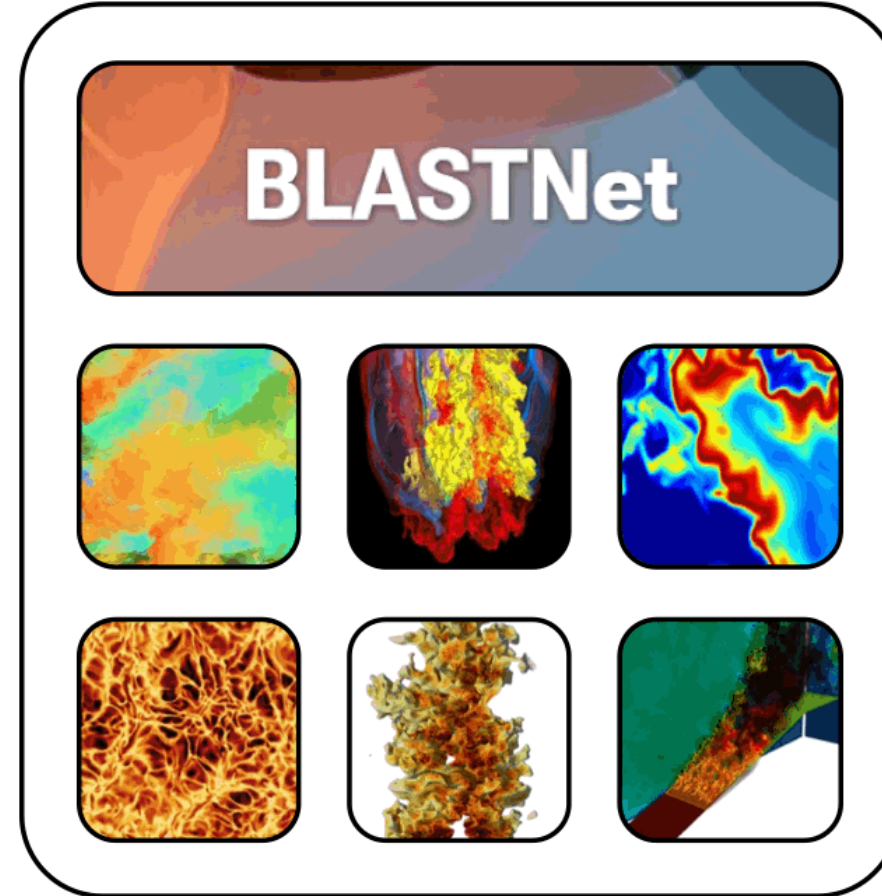
**~ 3.3 million metric tons of carbon emissions saved [1]**

- Focus on **non-reactive** cases,
- Large files, lots of timesteps available for **statistics**

# Databases reduce the carbon footprint by avoiding redundant computations



- Focus on **non-reactive** cases,
- Large files, lots of timesteps available for **statistics**

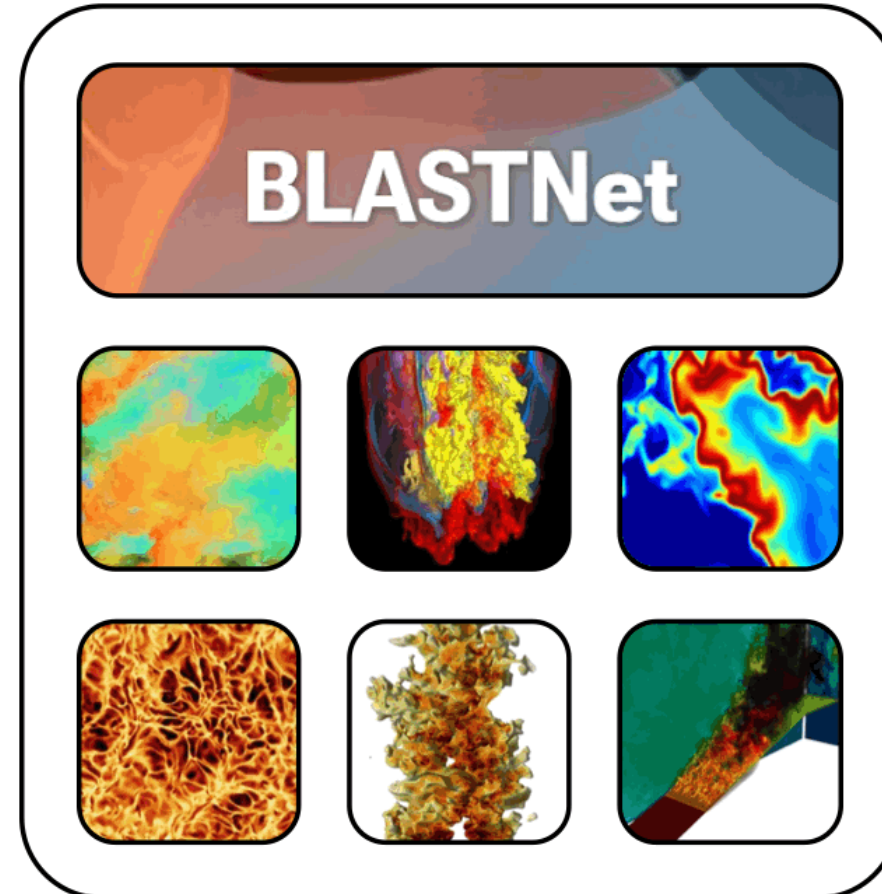


- Focus on datasets **diversity**
- Applications in **machine learning** for **reactive flows**

# Shared DNS data still require notable post-processing



- **Ready to use**, labeled data
- Easy to handle, **accessible** dataset

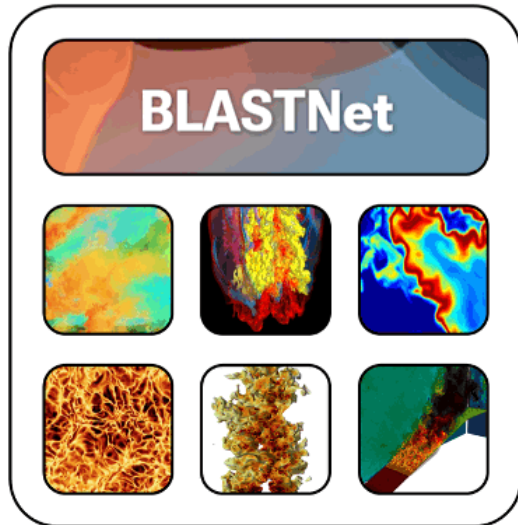


- Data to be **processed** (e.g. sub-filter closures)
- Large dimensions (up-to **100s GB**)

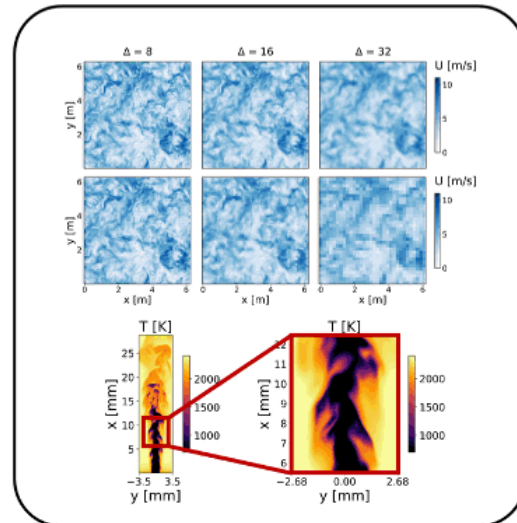
# aPriori is an open-source python library to enhance DNS data accessibility



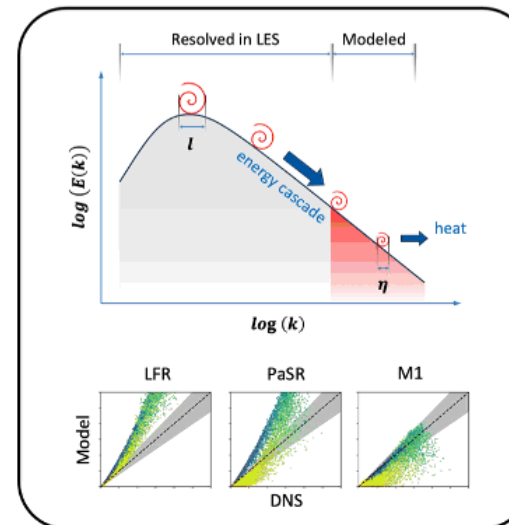
1. Handling large datasets from open-source repositories



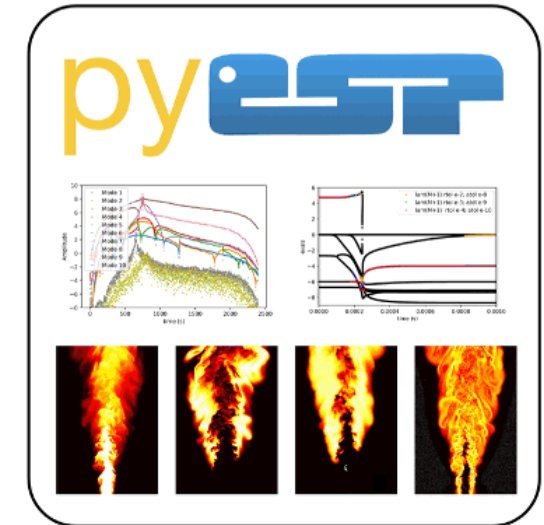
2. Filtering, downsampling, and sub-domain extraction



3. Sub-filter quantities and model assessment

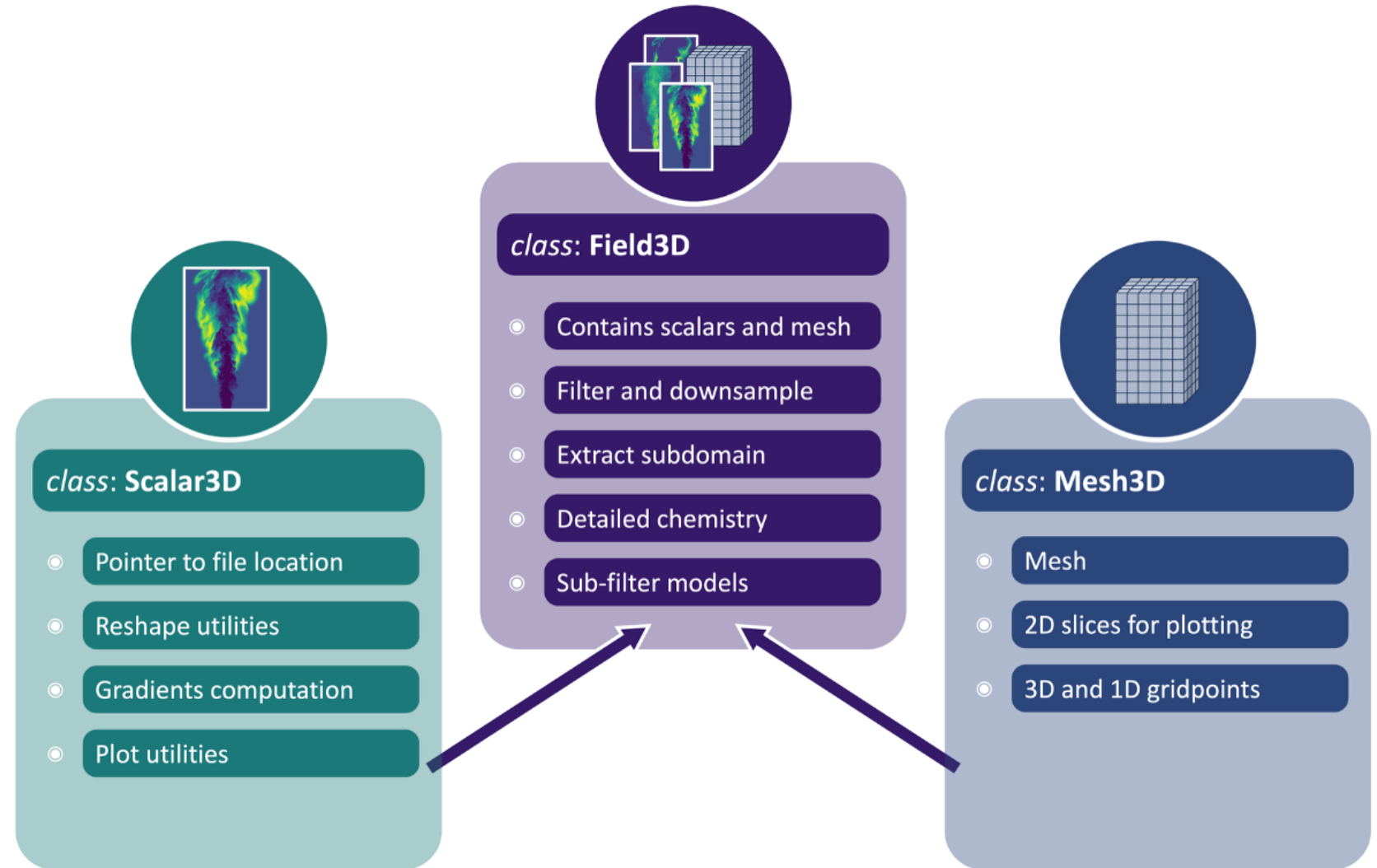


4. CSP and complex chemical analyses for reactive flows



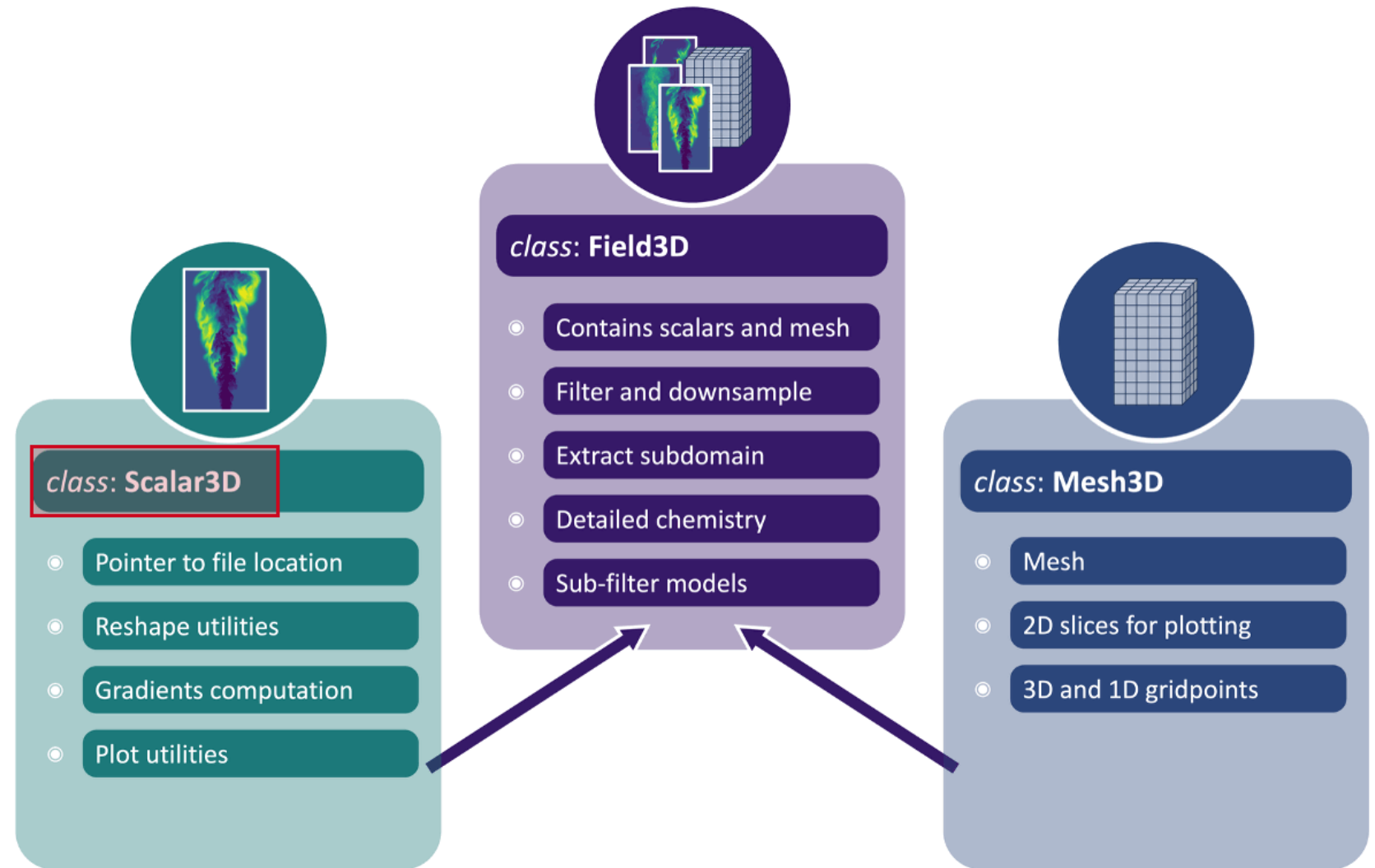
# The software architecture is modular and object-oriented

```
chem_thermo_tran
├── li_h2.yaml
data
├── P_Pa_id000.dat
├── RHO_kgm-3_id000.dat
├── T_K_id000.dat
├── UX_ms-1_id000.dat
├── UY_ms-1_id000.dat
├── UZ_ms-1_id000.dat
├── YH2O2_id000.dat
├── YH2O_id000.dat
├── YH2_id000.dat
├── YHO2_id000.dat
├── YH_id000.dat
├── YN2_id000.dat
├── YO2_id000.dat
├── YOH_id000.dat
├── YO_id000.dat
grid
├── X.m.dat
├── Y.m.dat
├── Z.m.dat
info.json
```



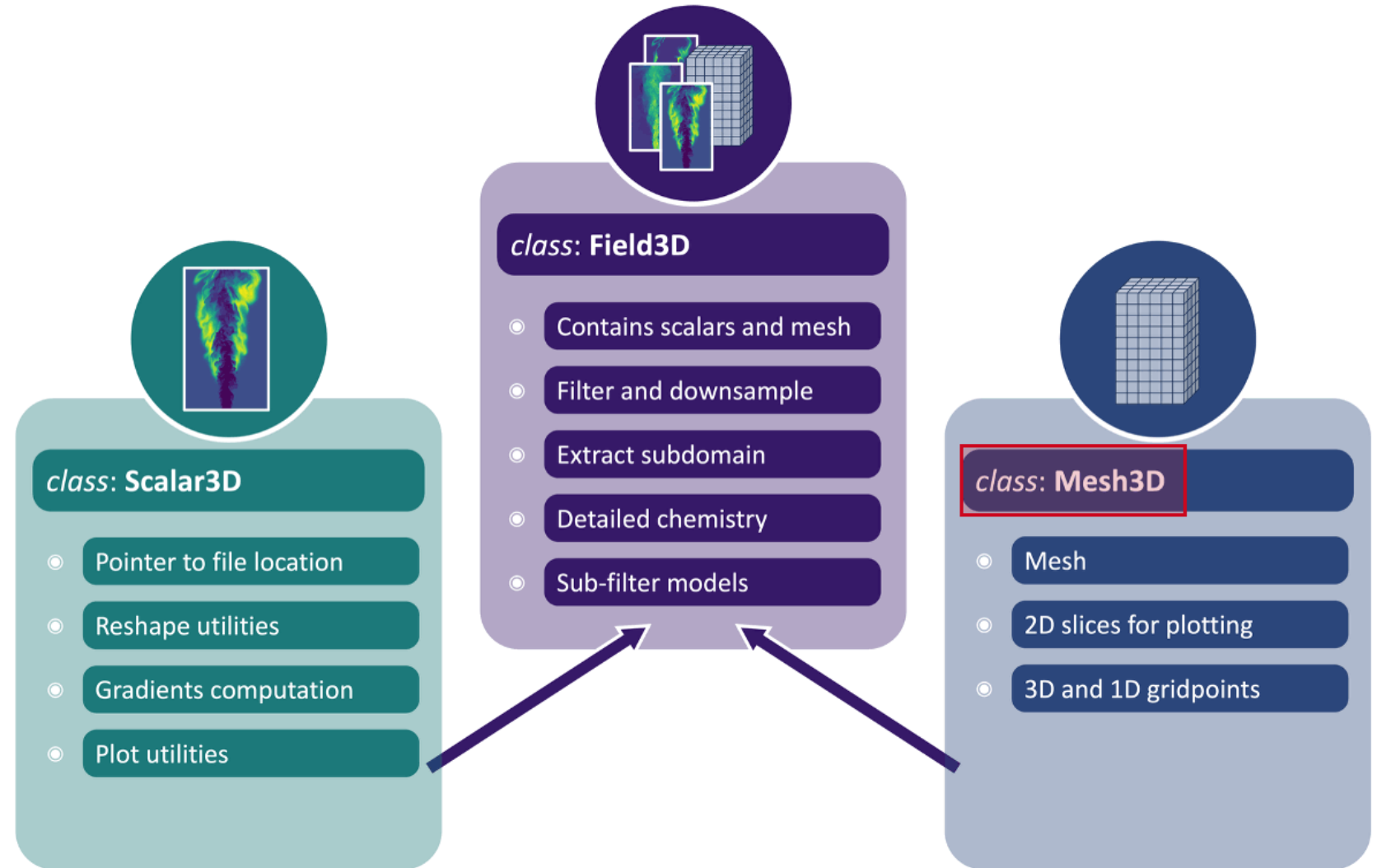
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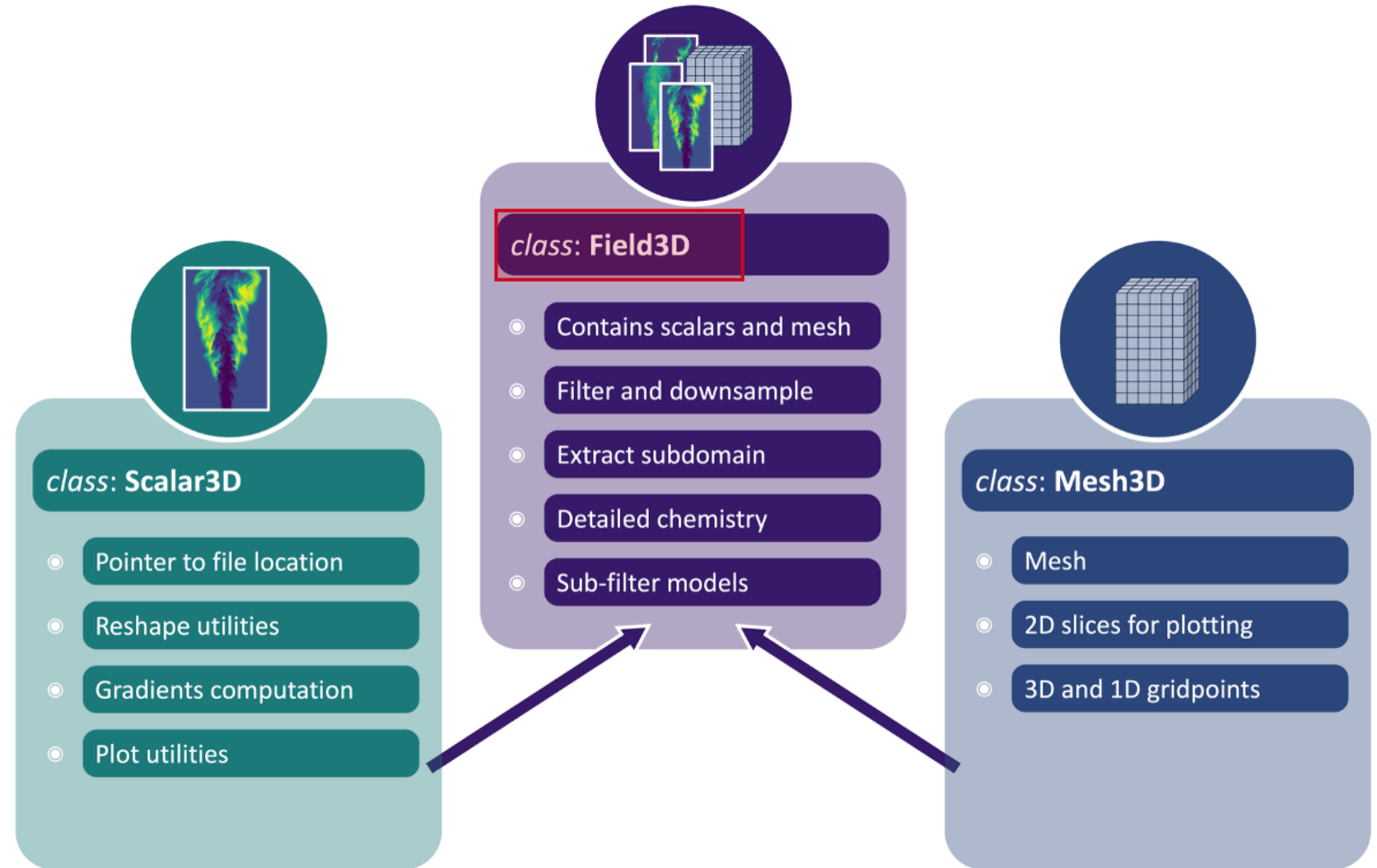
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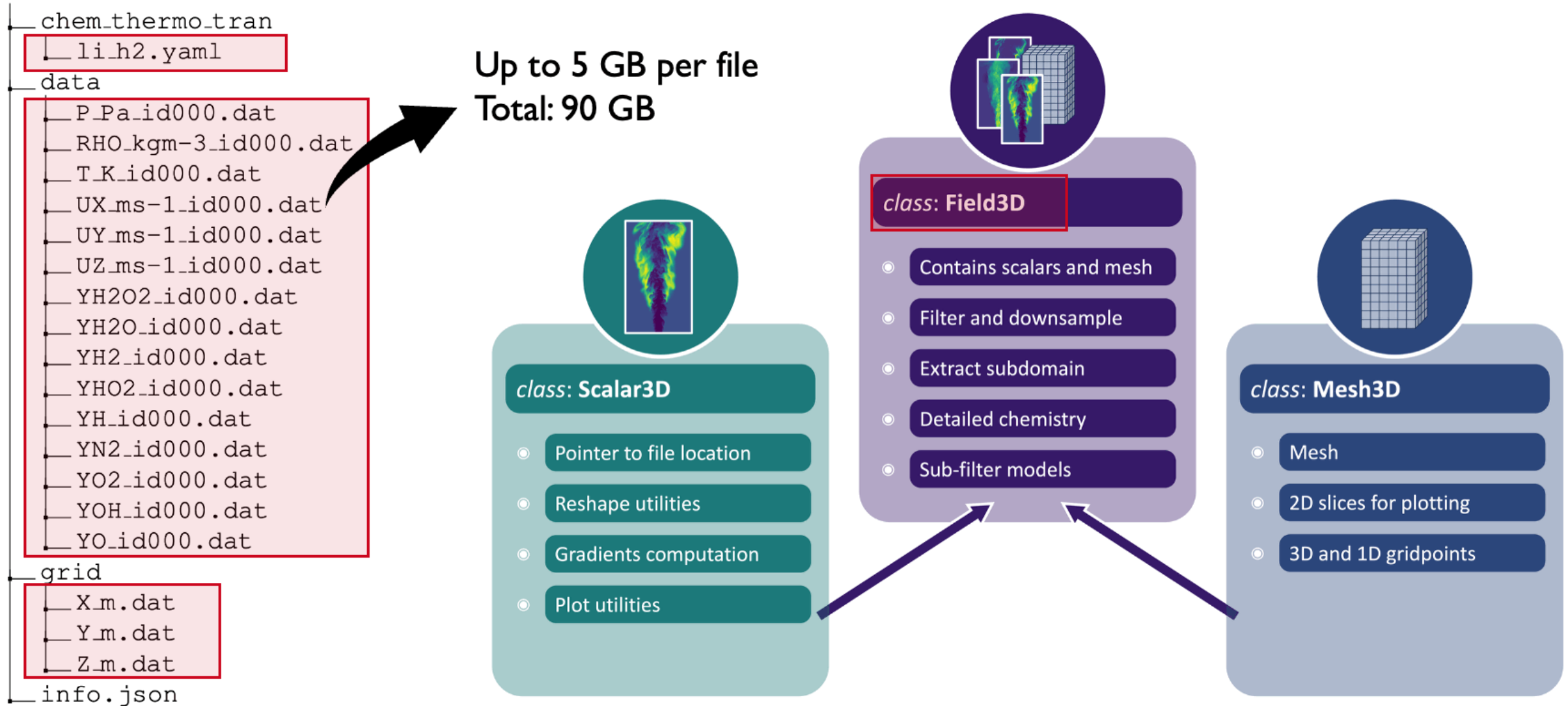


# The software architecture is modular and object-oriented

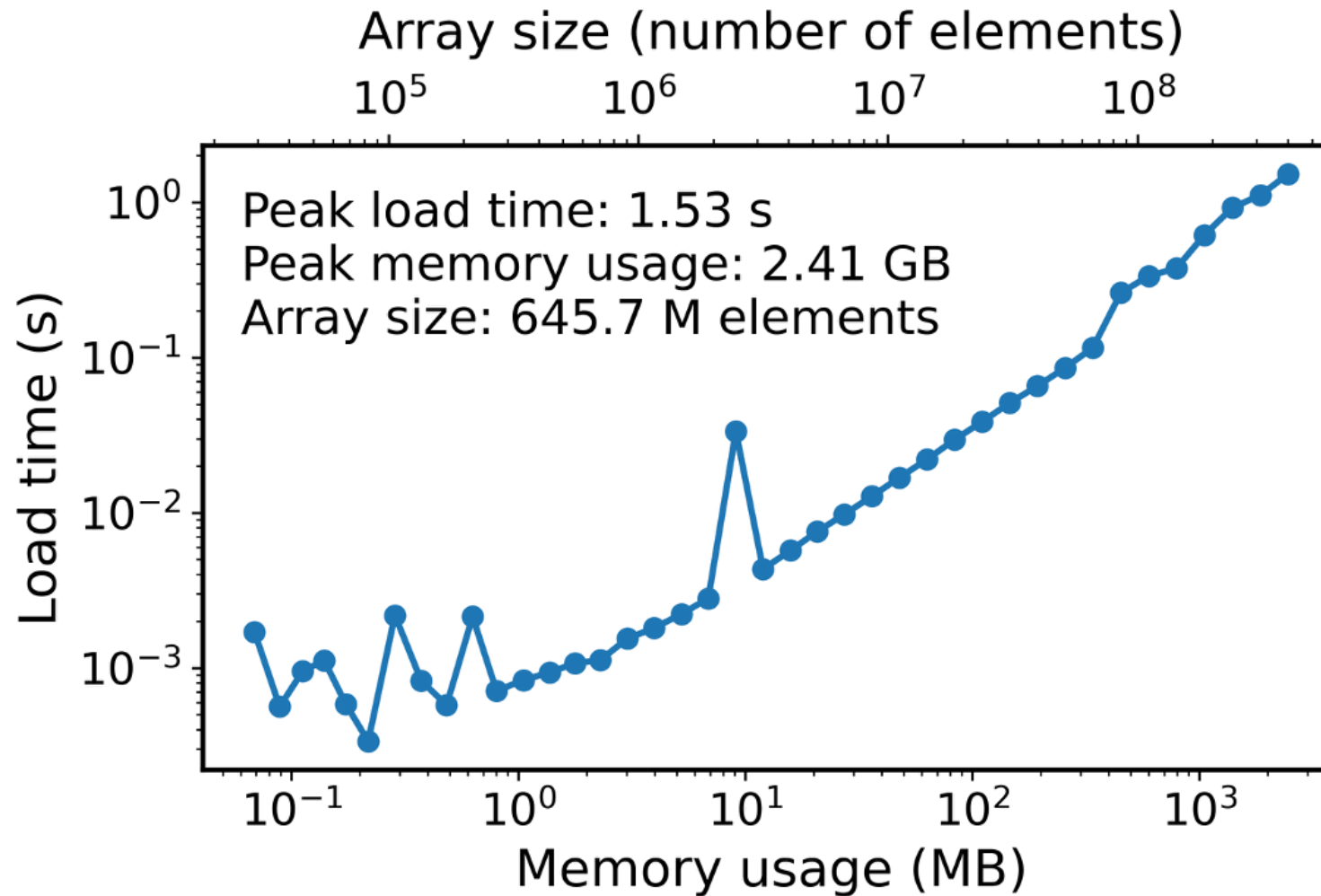
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└── info.json
```



# The software architecture is modular and object-oriented



# The load time for typical datasets sizes is in the order of seconds



# Smagorinsky model assessment example

```
DNS_field = ap.Field3D('DNS_data')
```

```
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│   ├── P_Pa_id000.dat
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│   └── Y_id000.dat
```

# Smagorinsky model assessment example

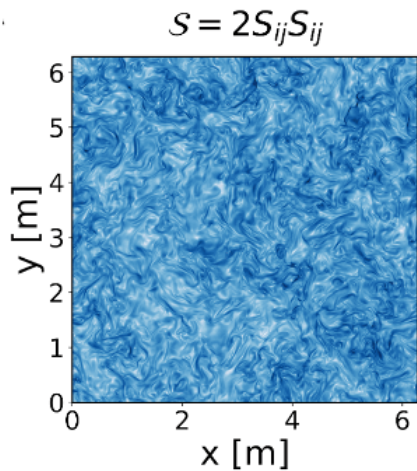
```
DNS_field = ap.Field3D('DNS_data')  
  
DNS_field.compute_strain_rate()
```

```
DNS_data  
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│   ├── Y_id000.dat  
│   └── S_DNS_s-1_id000.dat
```

# Smagorinsky model assessment example

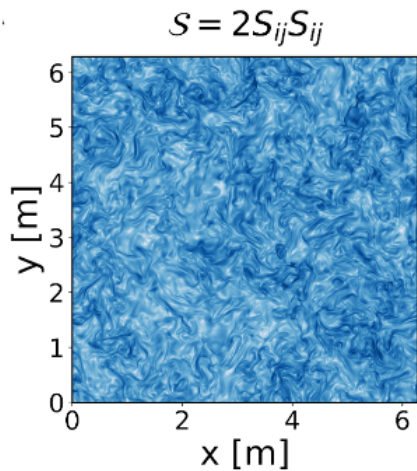
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```



# Smagorinsky model assessment example

```
DNS_field = ap.Field3D('DNS_data')  
  
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f_name = DNS_field.filter(filter_size, 'Gauss')
```

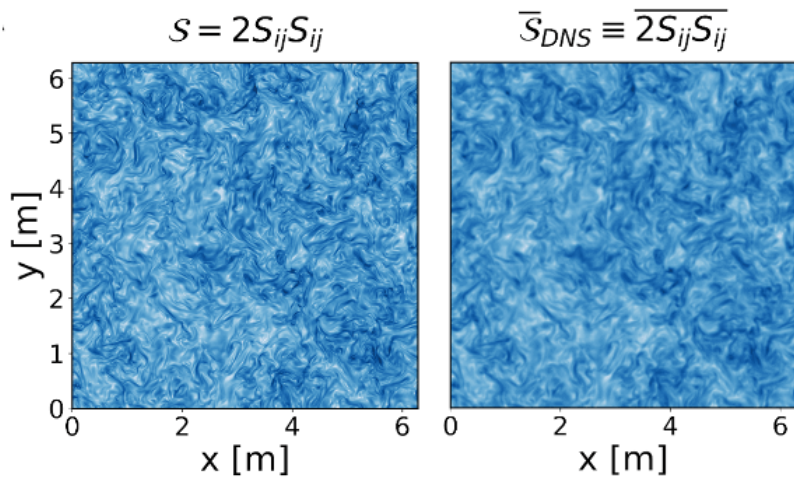


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│   ├── UZ_ms-1_id000.dat  
│   ├── Y_id000.dat  
│   └── S_DNS_s-1_id000.dat
```

```
Filter8Gauss  
├── data  
│   ├── P_Pa_id000.dat  
│   ├── UX_ms-1_id000.dat  
│   ├── UY_ms-1_id000.dat  
│   ├── UZ_ms-1_id000.dat  
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│   └── S_DNS_s-1_id000.dat
```

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DNS_field.compute_strain_rate()  
  
f_name = DNS_field.filter(filter_size, 'Gauss')  
  
filtered_field = ap.Field3D(f_name, reactive=False)
```

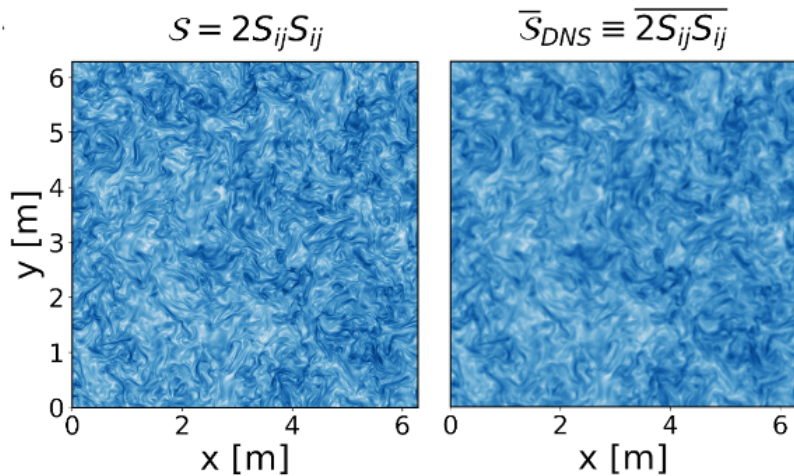


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DNS_data  
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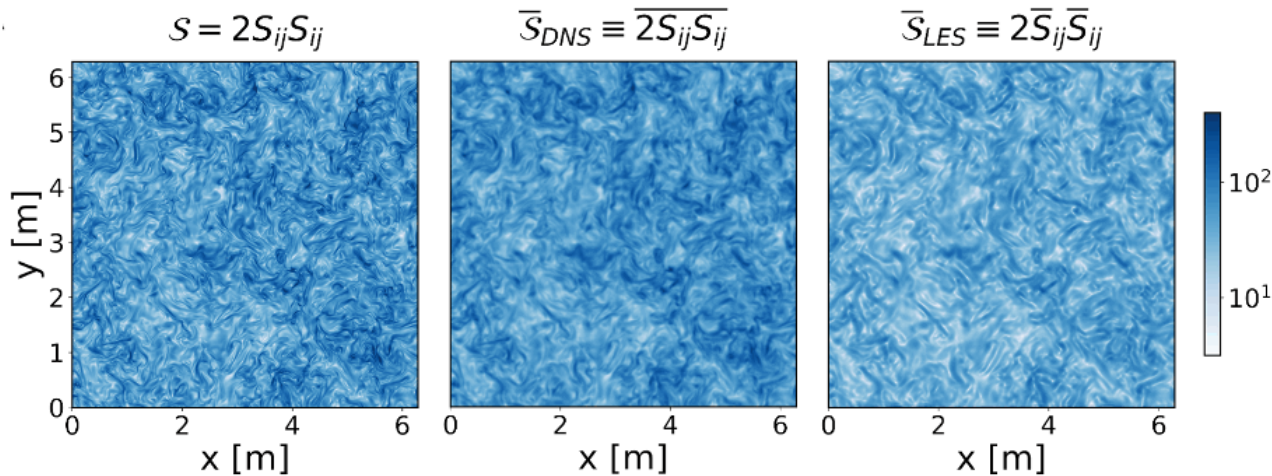


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│   ├── Y_id000.dat  
│   ├── S_DNS_s-1_id000.dat  
│   └── S_LES_s-1_id000.dat
```

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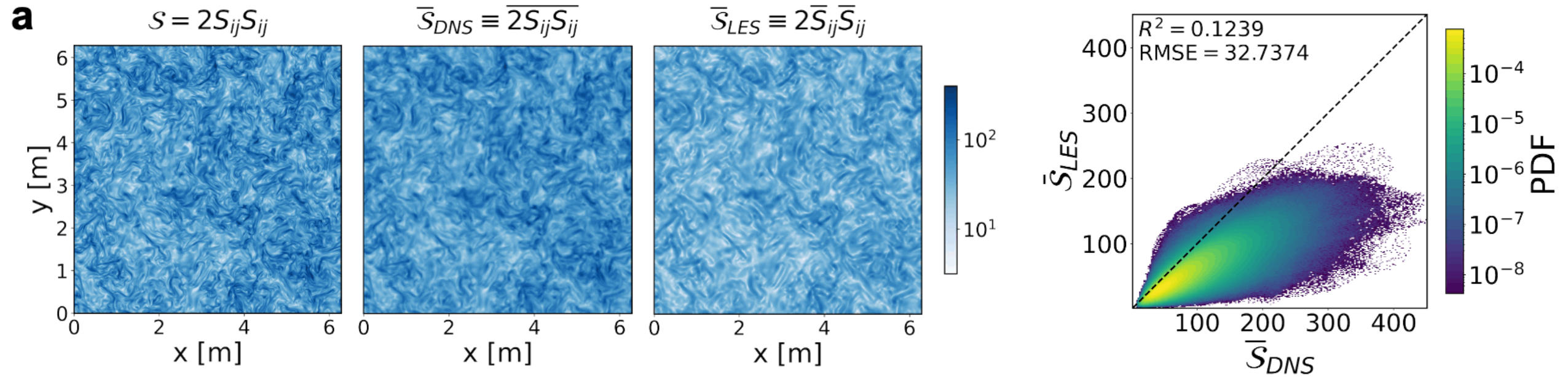
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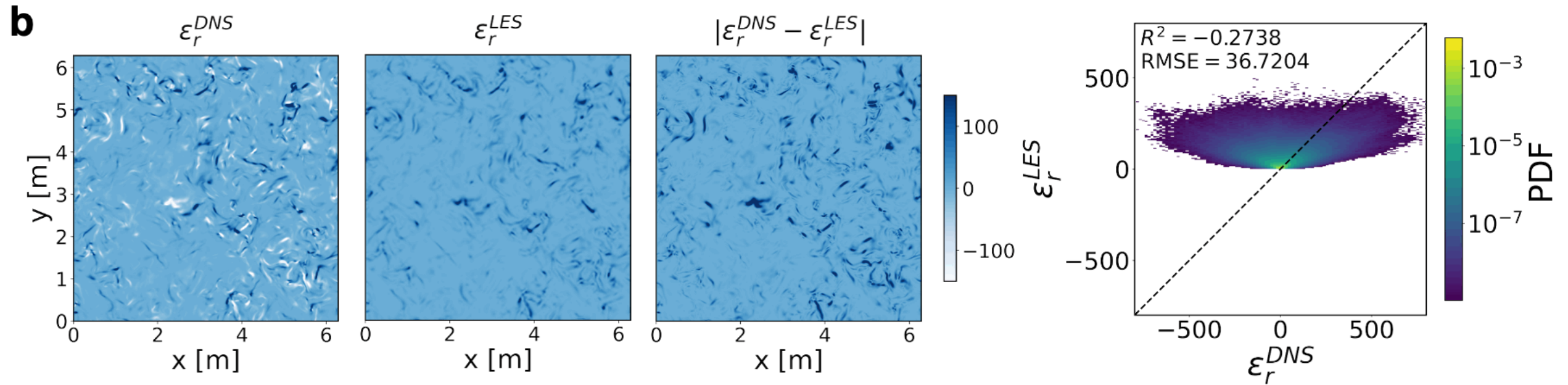
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```

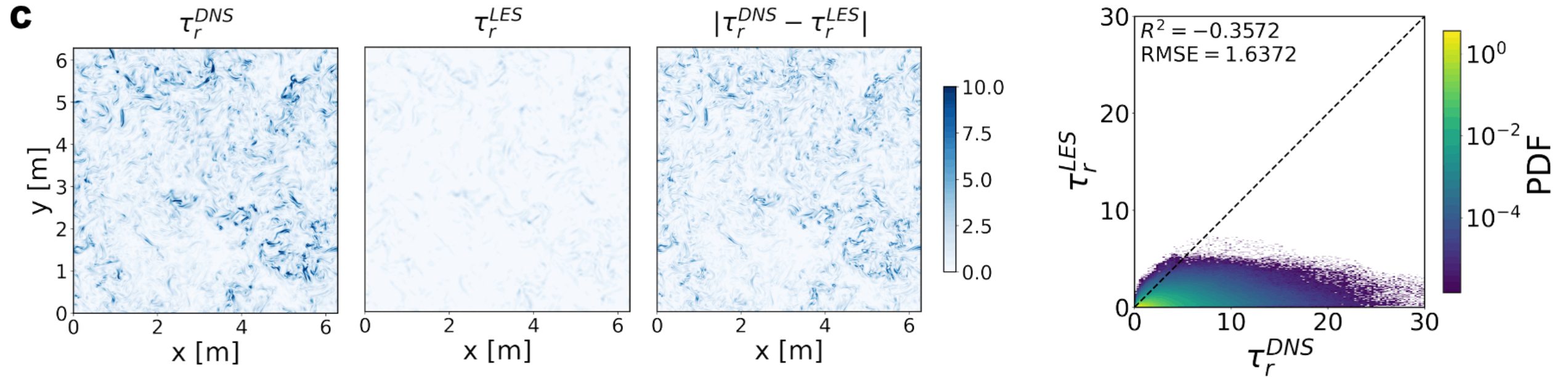
# Smagorinsky model assessment example



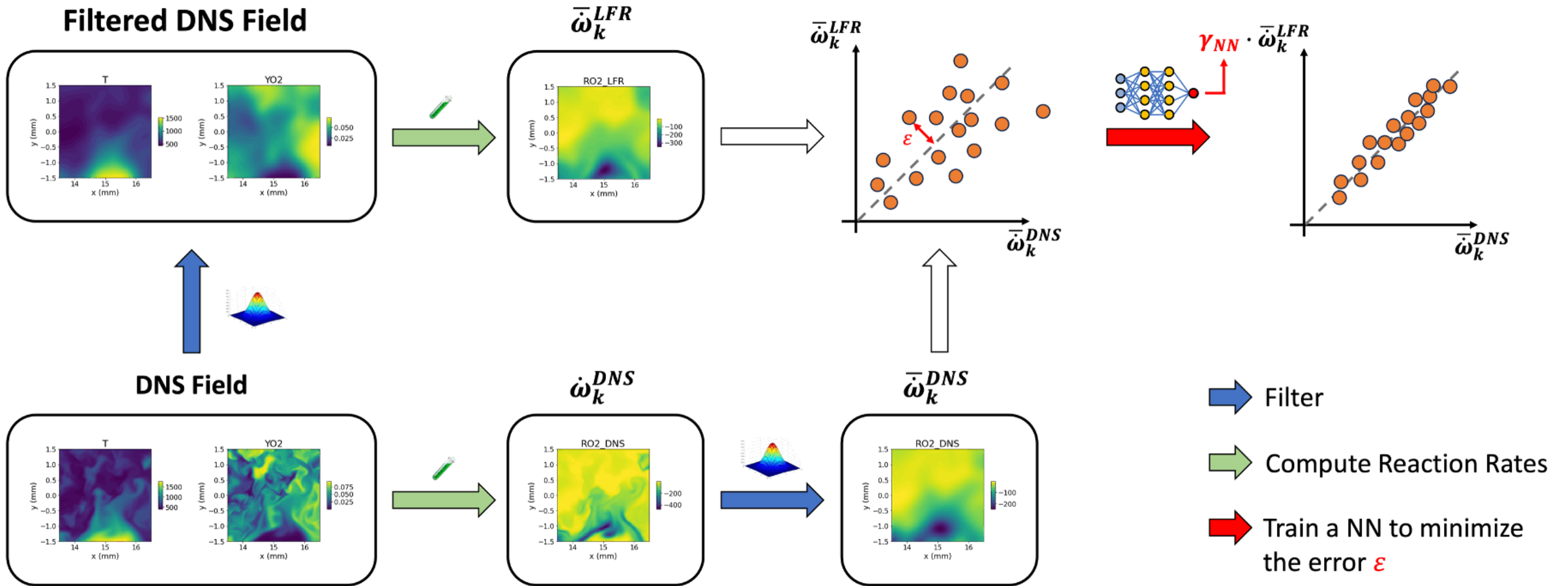
# Smagorinsky model assessment example



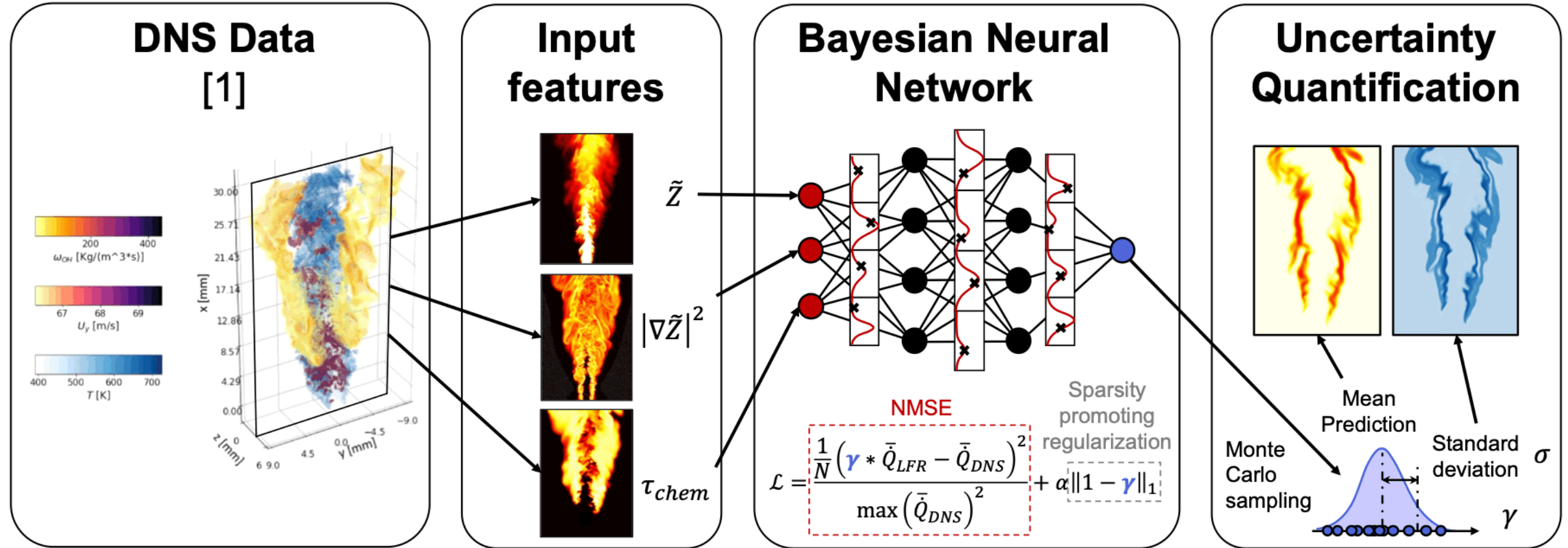
# Smagorinsky model assessment example



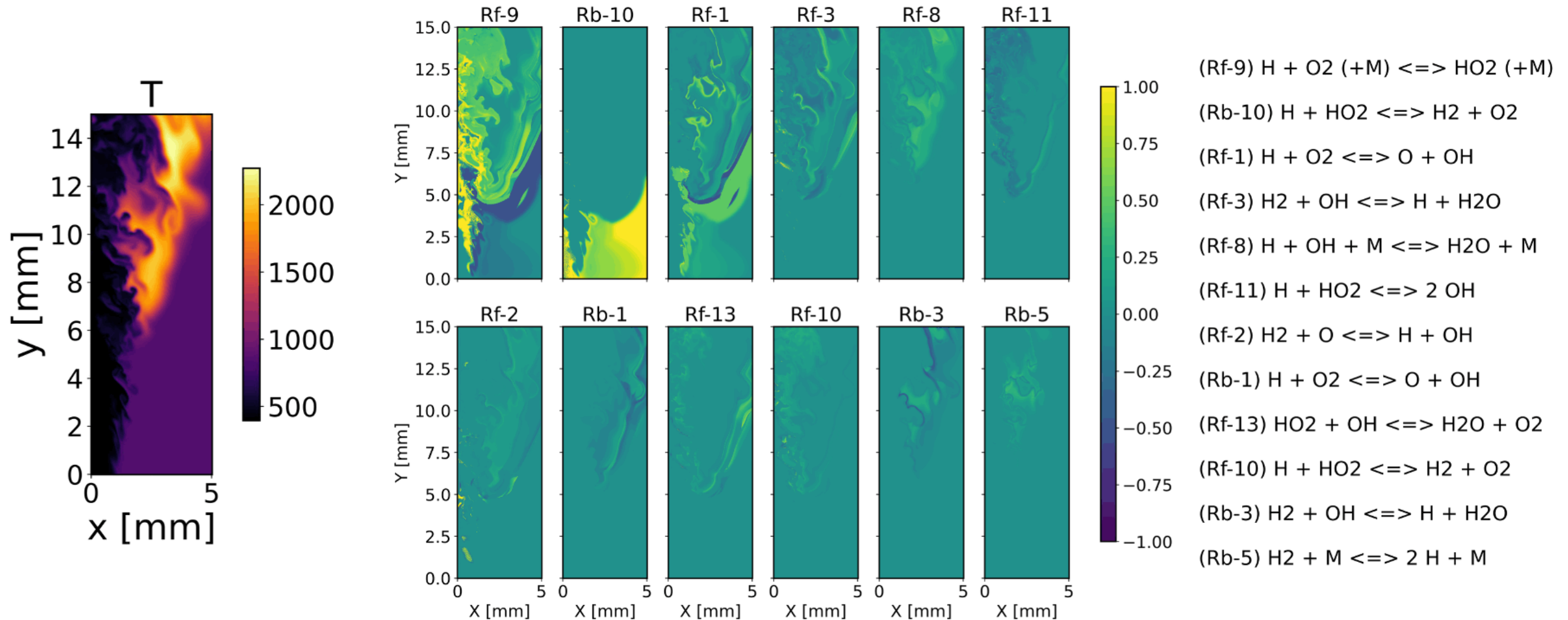
# Turbulent combustion modeling with machine learning



# The library was used to process reactive DNS in previous research work



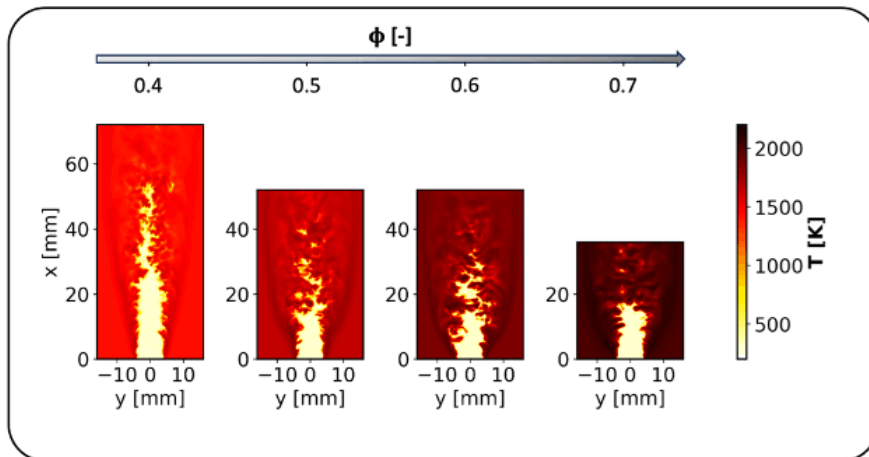
# Coupling with pyCSP allows complex chemical analyses



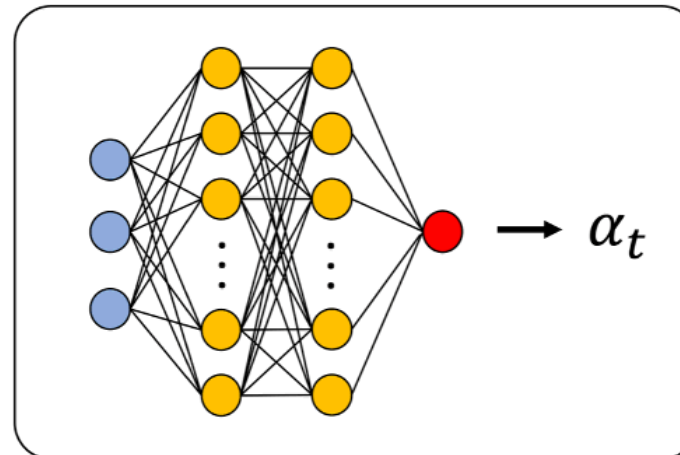
# aPriori was largely employed to develop the CYPHER ML challenge (Friday)

## Codabench

### 1. Training data processing



### 2. Online model training



### 3. Closure model evaluation

$$\frac{\partial}{\partial t} (\bar{\rho} \tilde{C}) + \nabla \cdot (\bar{\rho} \tilde{u} \tilde{C}) = \nabla \cdot [\bar{\rho} (\alpha_c + \alpha_t) \nabla \tilde{C}] + \bar{\rho} \dot{\omega}_c$$

# The library aims at solving four main issues

---

1. Create a tool for BlastNet users to **streamline post-processing** and *a priori* sub-filter models validation
2. Enlarge big **data accessibility** leveraging pointers
3. Creating a Python **interface** which bridges the gap between CFD solvers (C++, Fortran) and modern statistics and machine learning libraries (Python-based). This allows connectivity with other libraries (Matplotlib, PyCSP...)
4. Perform **complex chemical computations** such as CSP or reactor-based models for sub-filter closures, thanks to the data-chunking implementation

## Further improvements

---

- Enhance **gradient computation**
  - Implement more accurate and flexible gradient computation schemes
- Expand **visualization** capabilities
  - Add 3D visualization utilities
- Increase **modularity**
  - Support more abstract data types (e.g., vectors and tensors)
- Emphasize **open-source evolution**
  - aPriori is designed to evolve with community needs
  - Invites contributions and encourages a user-driven roadmap

Thank you for your attention



Documentation website

