

Personalized Dosimetry in the Age of AI: A Multi-Physics Framework Integrating Machine Learning and Monte Carlo for Radioactive Aerosol Exposure Assessment

Council on Ionizing Radiation Measurements & Standards

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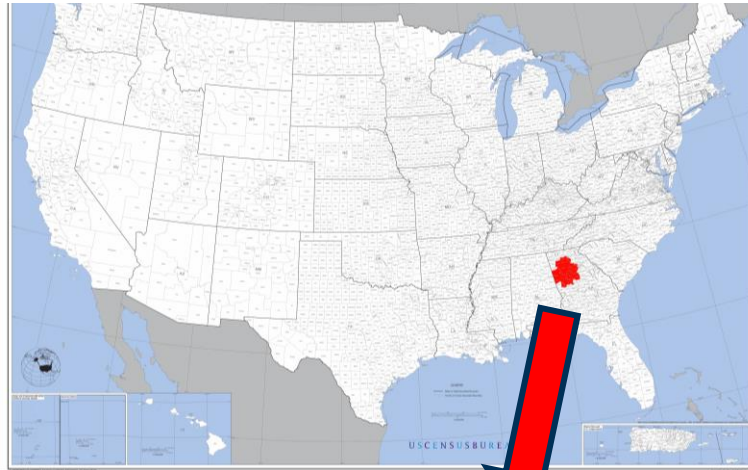
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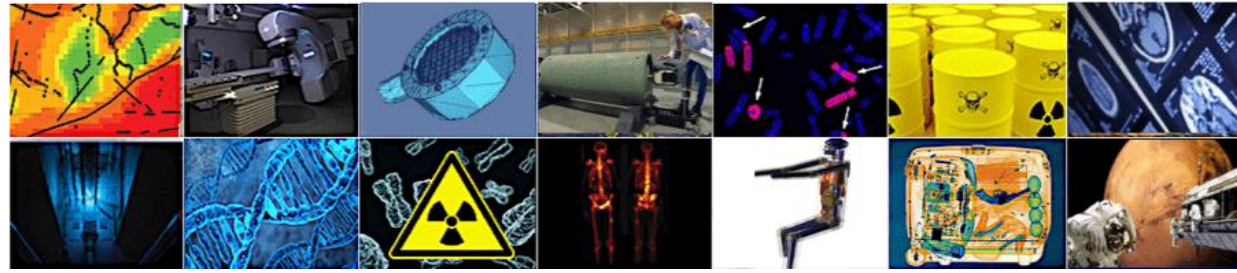
April 29, 2024



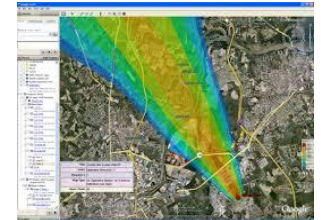
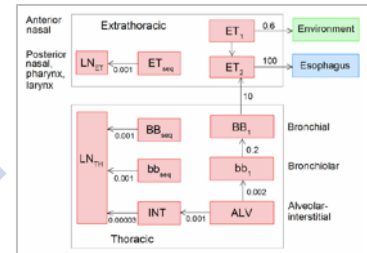
RED² Laboratory – Overview and Collaborations



- **Spring 2024 Research Group**
- 10 Ph.D. students in NRE and MP
- 3 M.S. students
- 6 Undergraduate students
- 1 Post-doctoral Fellow
- 1 Research Engineer
- 1 Visiting Professor



Mission: The Radiological Engineering, Detection, and Dosimetry (RED²) Laboratory, led by Dr. Shaheen Dewji, conducts innovative, interdisciplinary research focusing on harnessing **both computational capabilities** in Monte Carlo radiation transport modeling and **experimental measurements** for applications in **radiation detection**, **radiation protection and shielding**, **dosimetry**, **health physics**, and **nuclear materials accounting**.



Computational Dosimetry and Shielding

Development of dose coefficients and shielding design using Monte Carlo radiation transport codes

Age/sex-specific anthropomorphic computational phantoms

Radionuclide biokinetic models for emergency response and nuclear medicine

Radiation Detection

Employment of validation and verification of gamma-ray spectroscopic detector responses

Contaminated environmental media for environmental assessment and decommissioning

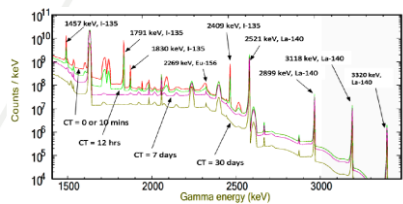
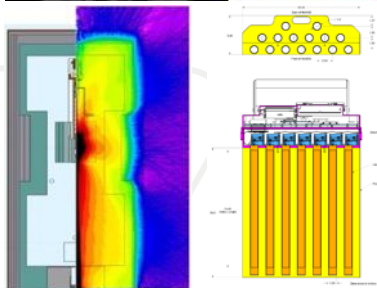
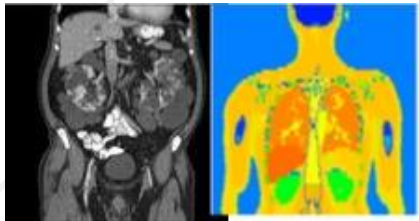
Field triage of uptake during nuclear, radiological, and fission product release events

Nuclear Nonproliferation and 3S (Safety, Security & Safeguards)

Nuclear materials control, accounting, and safeguards of SNM

Gamma-ray spectroscopic analysis for safeguards by design of advanced non-LWR reactors

Neutron multiplicity counting for field search/detection and criticality safety



RED² Laboratory – Research Collaborations

Thrust Area 1: Computational Dosimetry

- Evaluation of Exposure Pathway, Internalized Uptakes, and Dosimetry for Military Personnel from Radiological and Toxic Metal Sources
- Uncertainty Analysis of Dose Coefficients for Nuclear Incident Response
- Low Dose Exposure Evaluation on Human Population Health
- Enhancement of Biokinetics using Physiologically-Based Models for Internalized Radionuclides

Thrust Area 2: Radiation Detection

- Evaluation of Exposure Pathway, Internalized Uptakes, and Dosimetry for Military Personnel from Radiological and Toxic Metal Sources
- A Hybrid Radiation Transport Detector Response Function Methodology for Modeling Contaminated Sites
- Neutron dosimetry and Assay with a Portable Neutron Multiplicity Detector

Thrust Area 3: Radiation Shielding

- Shielding Design And Optimization Of Novel MV Photon Preclinical FLASH Radiotherapy System
- Activation Studies in Petawatt Laser Facilities

Thrust Area 4: Nuclear Safety, Security & Nonproliferation Policy, and Nuclear Knowledge Management

- Risk-informed Consequence-Driven Physical Protection System Optimization for Microreactor Sites
- Nuclear Material Accountancy During Disposal and Reprocessing of Molten Salt Reactor Fuel Salts

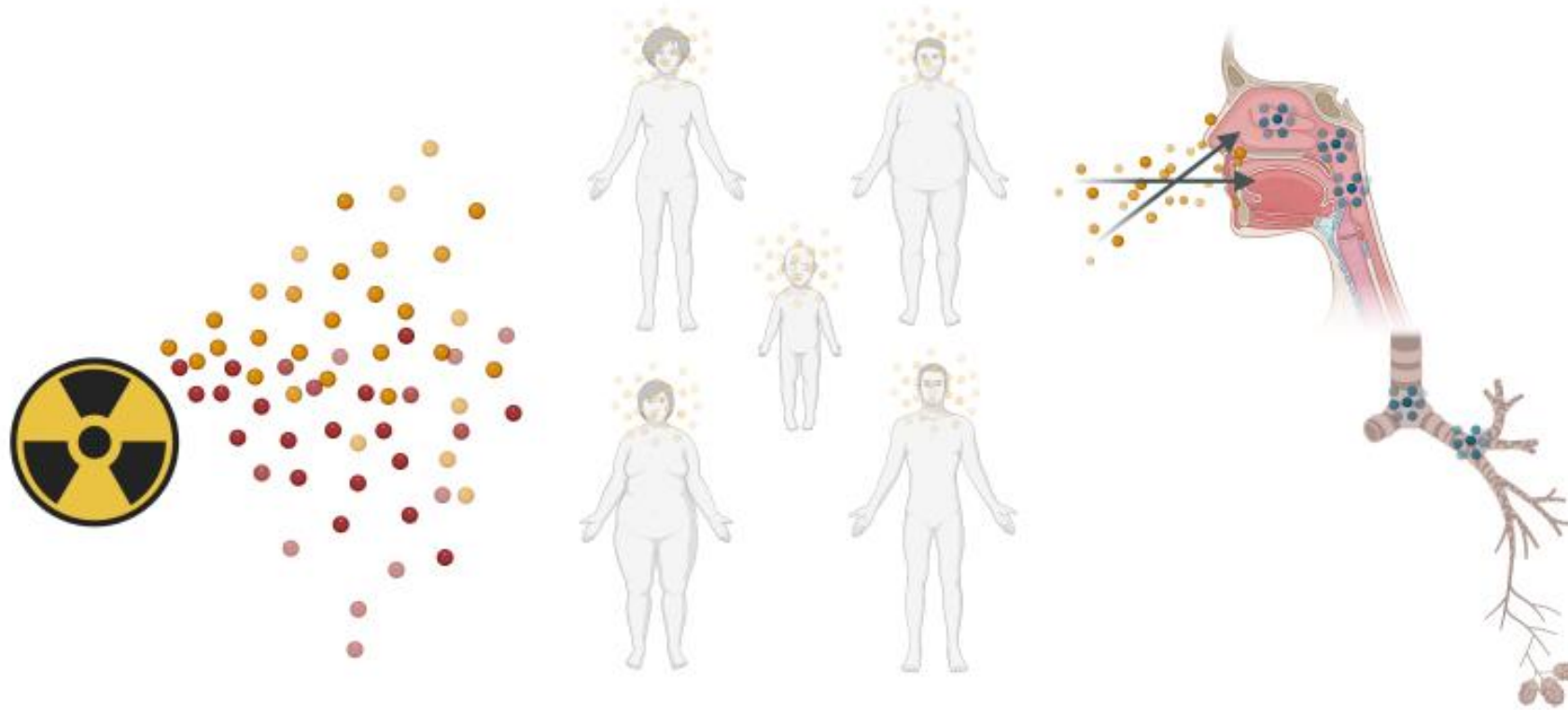
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Alliance for Radiological Exposures and Mitigation Science



Introduction: Pathways for Internal Exposure



1. Radiological event

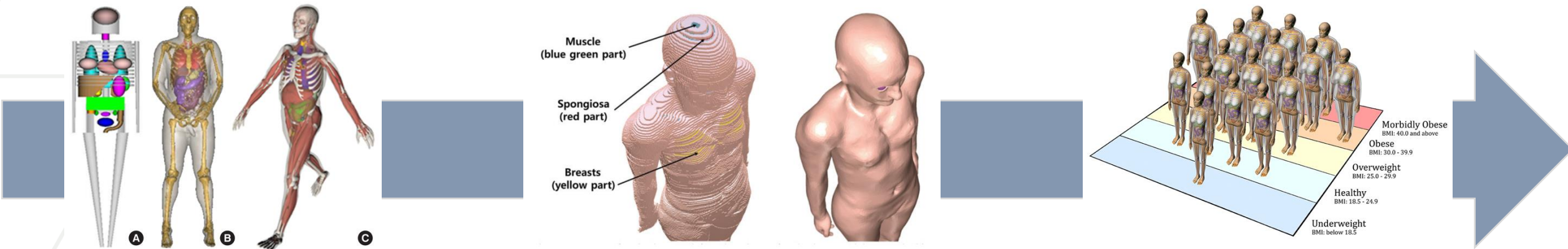
2. Aerosolized radioactive particles released from the scenario.

3. Wide range of population exposed to the radiological cloud

4. Particles entering to the HRT. CFPD analysis needed for accurate deposition profiles.

Introduction: Evolutions in Radiation Dosimetry

- Breakthroughs driven by medicine in radiation sciences
 - “Digital twins”
 - “Personalized medicine”
- Computational capabilities have afforded vast improvements in radiation modeling
 - Anatomical models (anthropomorphic phantoms)

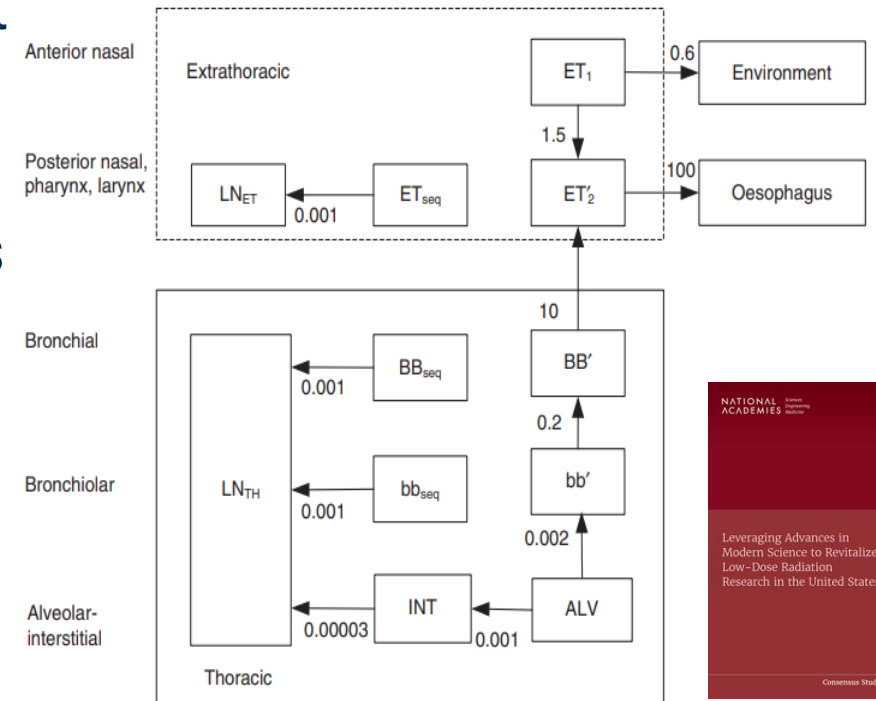
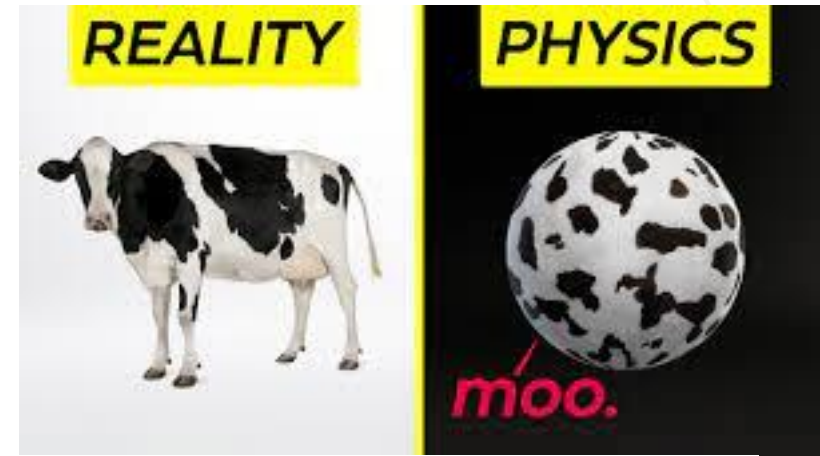


Introduction: Evolutions in Radiation Dosimetry

- Computational capabilities have afforded vast improvements in [radiation/biological] modeling

- **Greatest** source of variability in dose assessment from internal emitters
- Physiologically-based models of radiation behavior can also employ advanced technologies

- Age
- Sex
- Non-reference
 - Height
 - Weight
 - Pregnancy

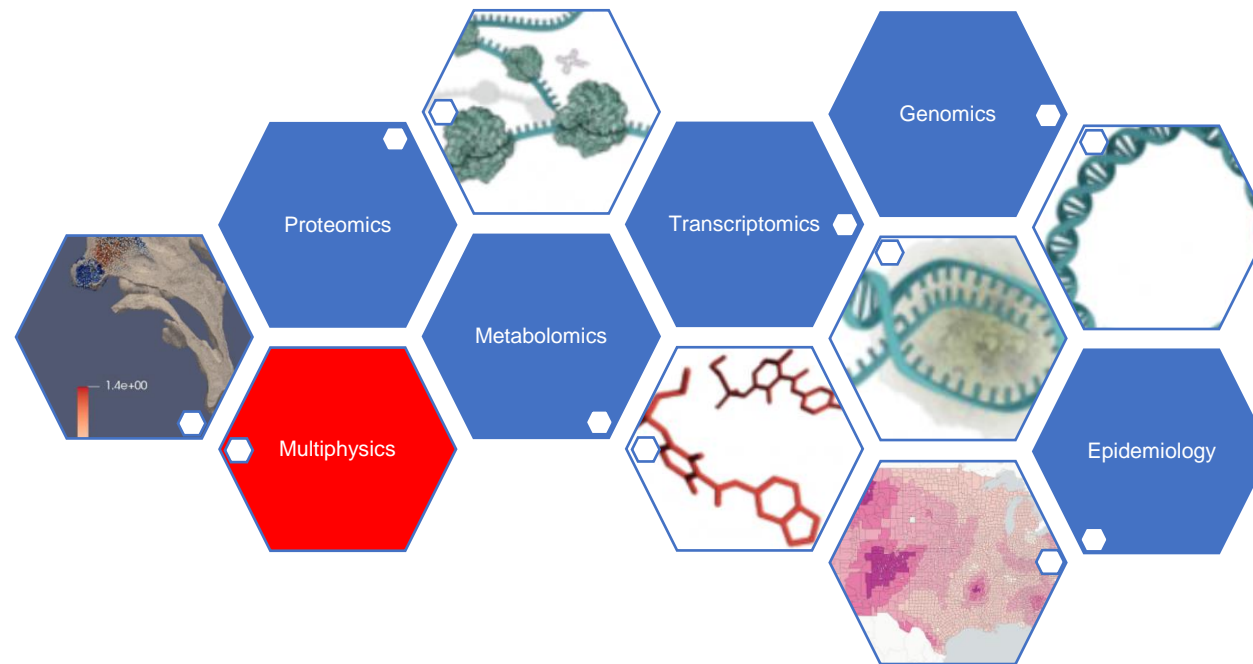


$$\dot{y} = f(t, y), \quad t_0 \leq t \leq t_{final}$$

$$y(t_0) = y_0,$$

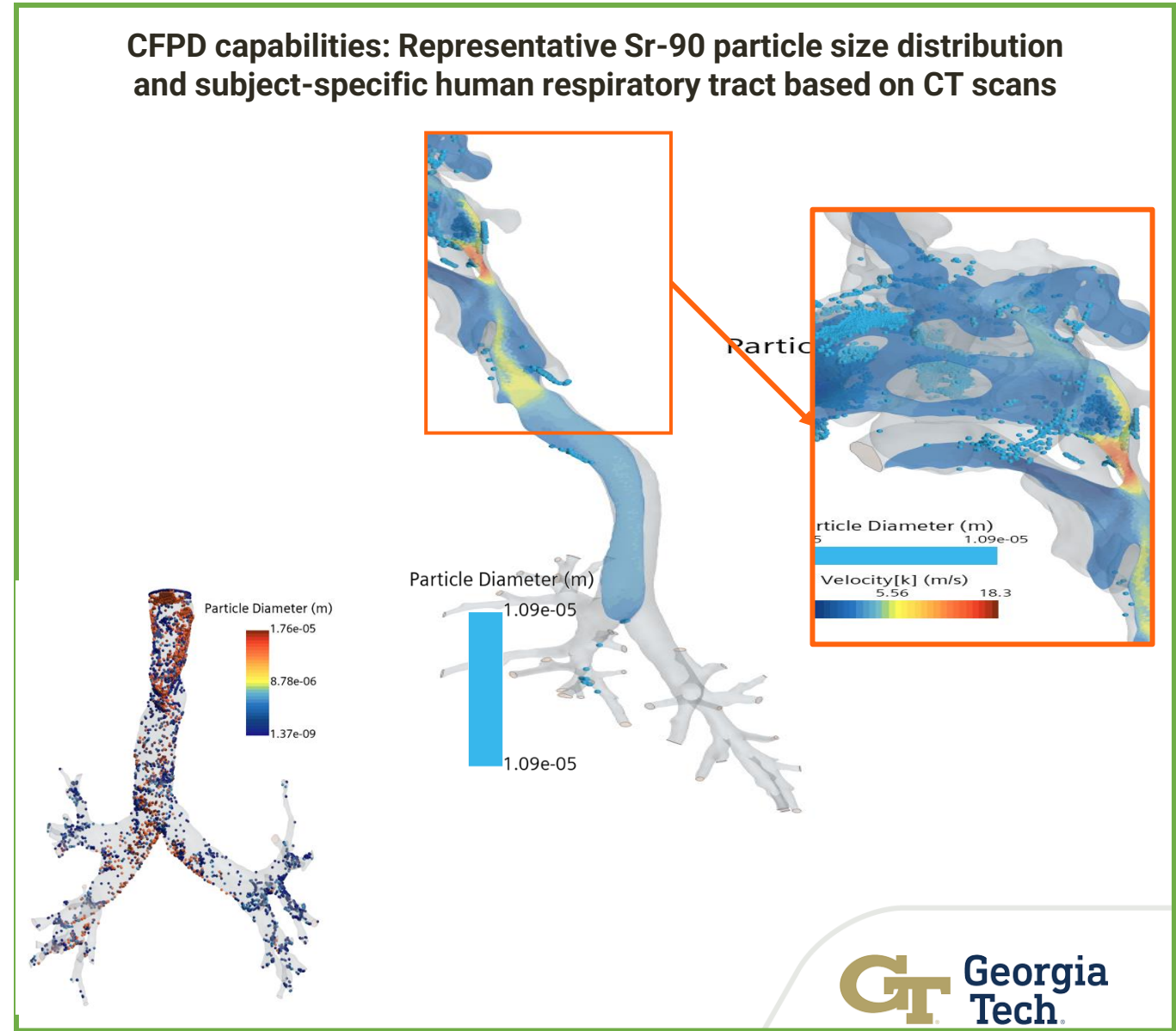
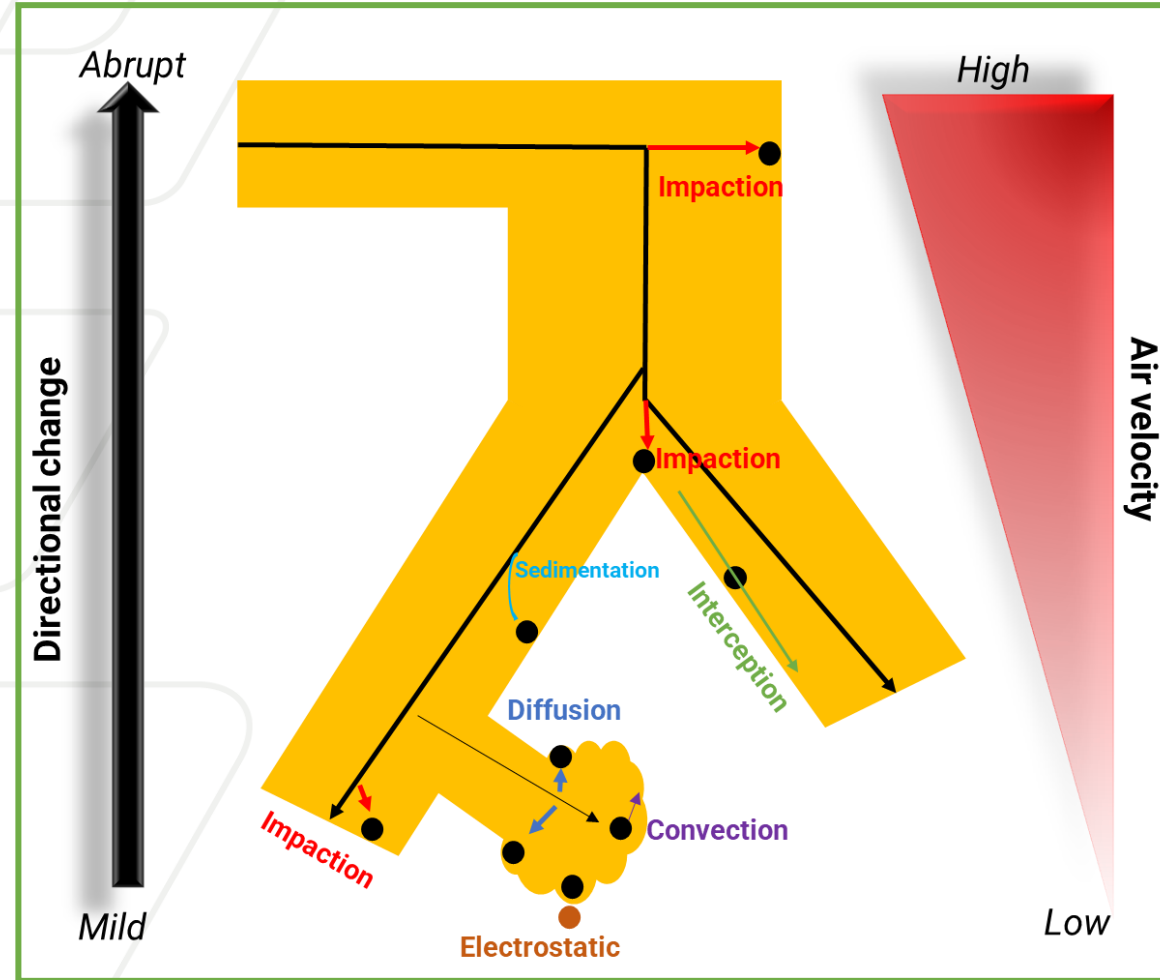
Overview: ~~Evolutions~~ **Revolutions** in Radiation Dosimetry

- Large and complex datasets available
- Mechanistic behavior of internalized radiation in the body can be conducted using multi-scale models



Multiphysics Modeling of Physiological Behavior

STRONTIUM-90 ICRP VS COMPUTATIONAL FLUID AND PARTICLE DYNAMICS DEPOSITION MODELING



Multiphysics Modeling of Physiological Behavior: Computational Fluid Particle Dynamics Modeling of Deposition

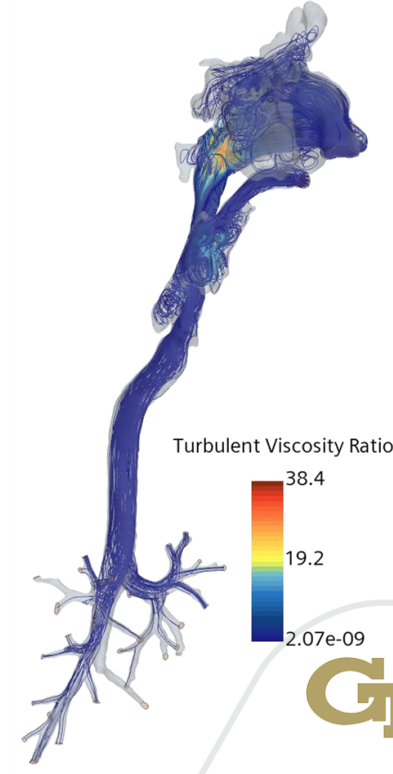
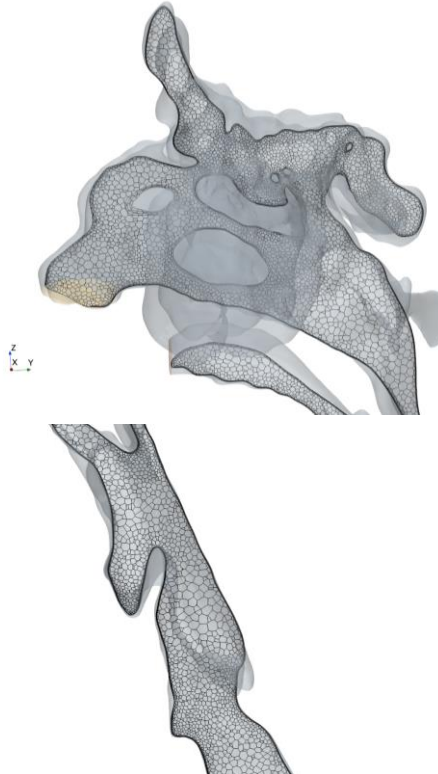
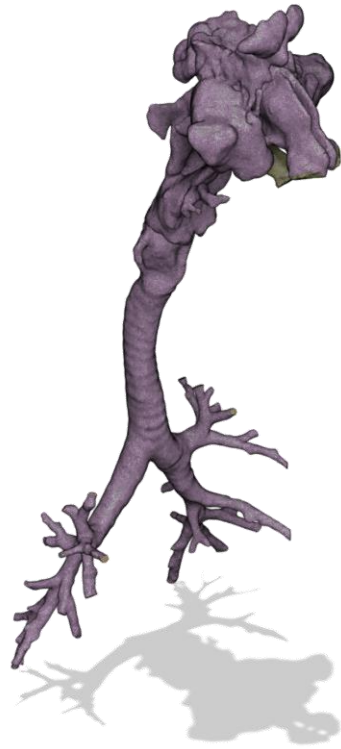
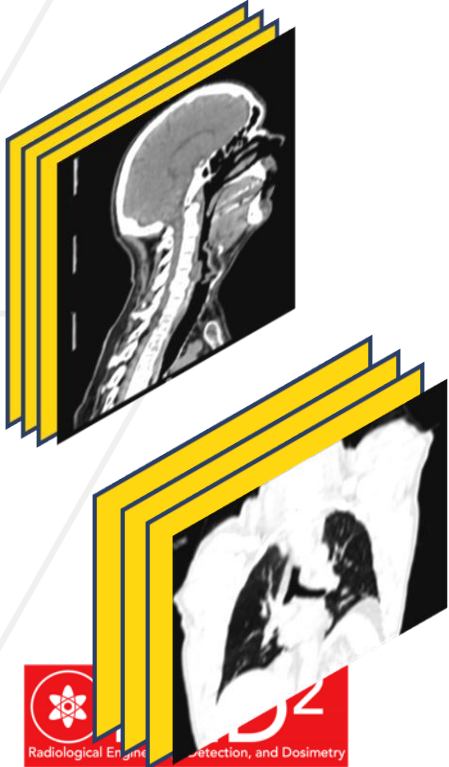
Chest
+
Neck-Head
CT Scans

3D Reconstruction
→ Developed
automatized, open-
source Python
algorithms

Automated setup of
CFPD simulation.
→ Pre-computed
converged grid
parameters (GCI)

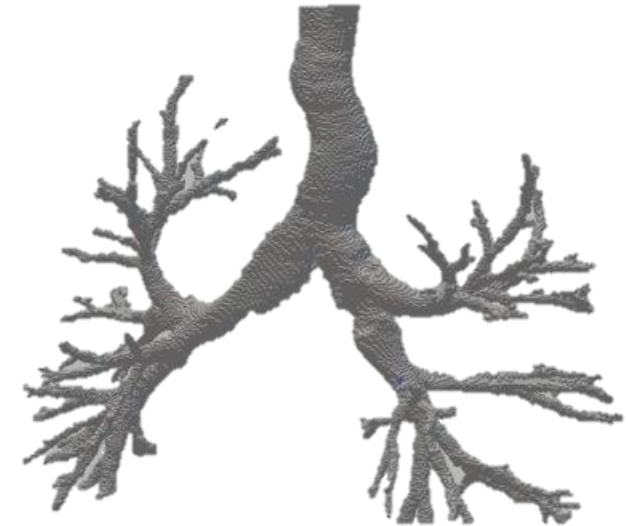
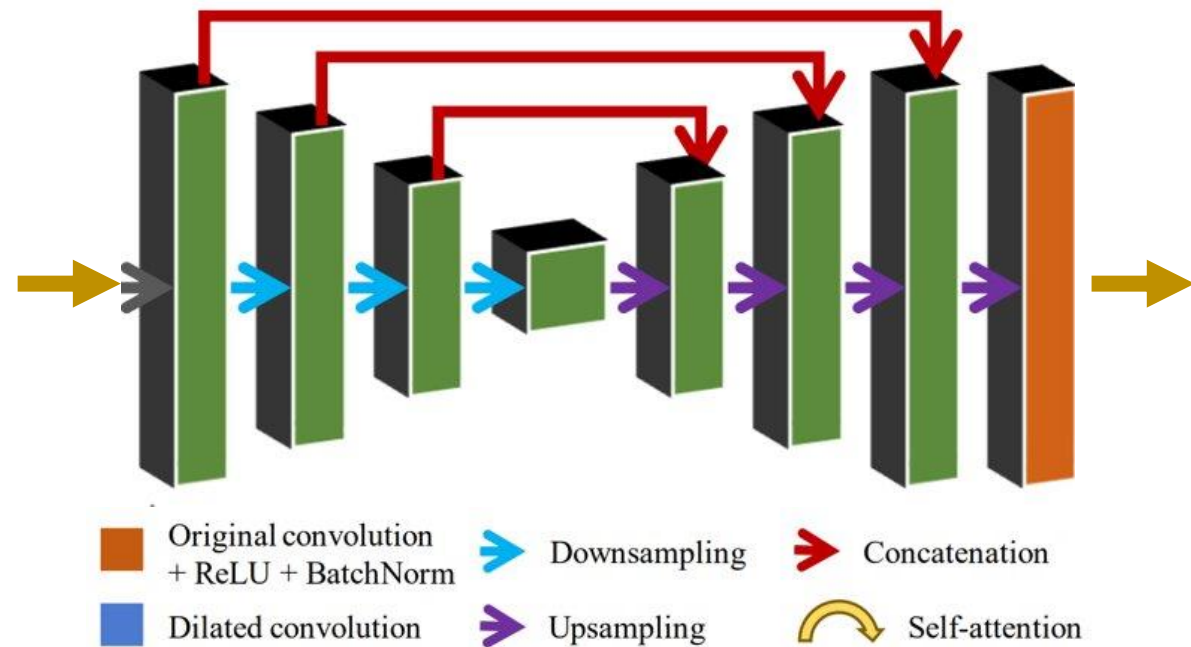
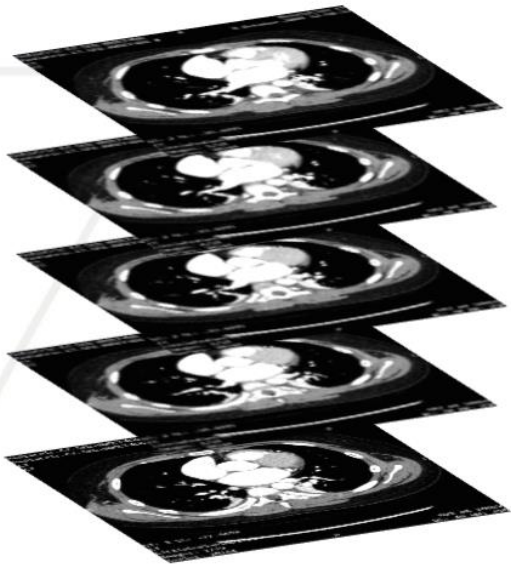
CFPD simulation
→ Pre-validated
models

Data analysis



Multiphysics Modeling of Physiological Behavior: AI → CFPD

CT Segmentation - Convolutional Neural Network (CNN)

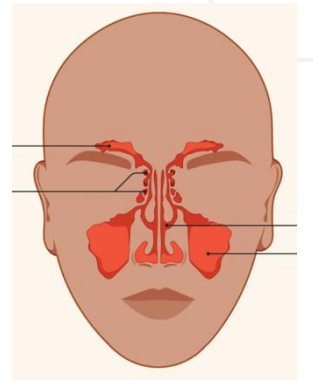


Multiphysics Modeling of Physiological Behavior: AI → CFPD

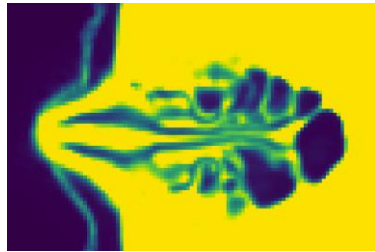
Morphological Techniques: CT Segmentation Upper HRT

Nasal cavity, automatic segmentation algorithm:

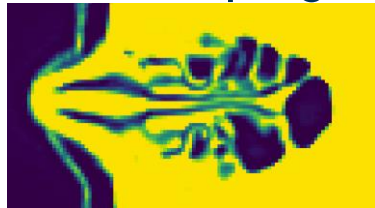
- Complex geometry
- Very challenging to capture all the sinus (in fact most of the manual segmentations by physicians does not consider some cavities)



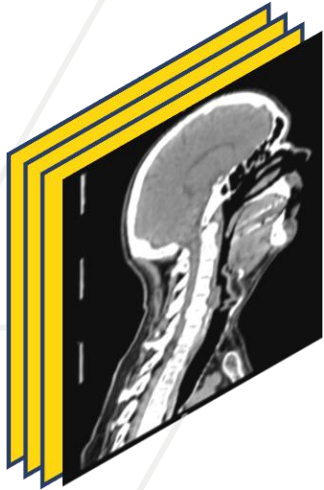
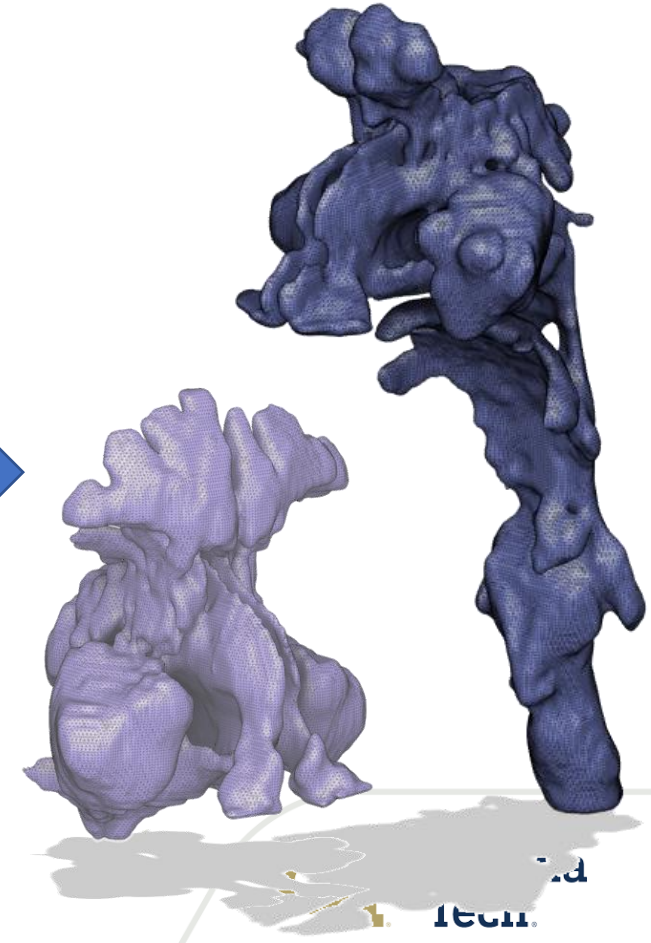
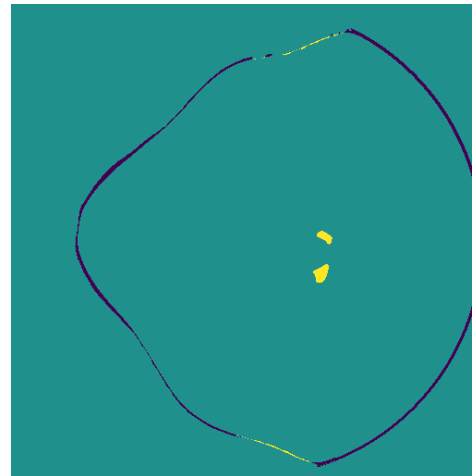
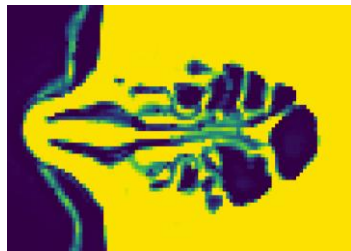
Smooth+threshold



Unsharpening



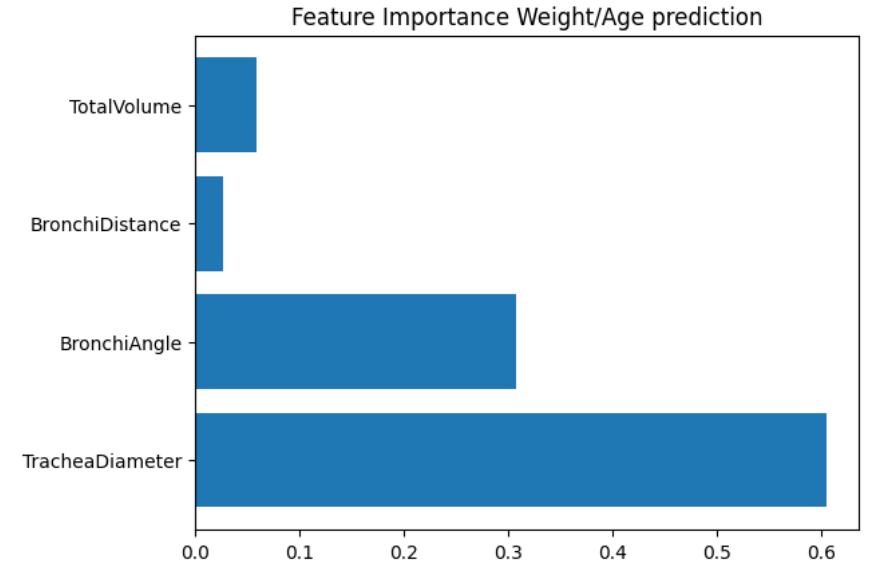
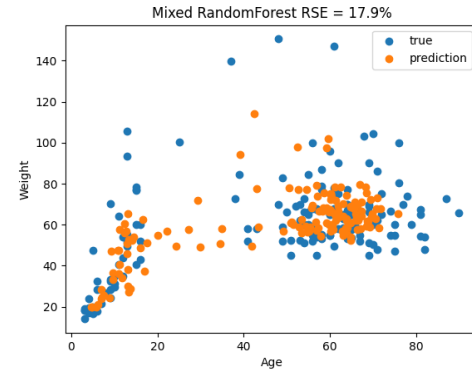
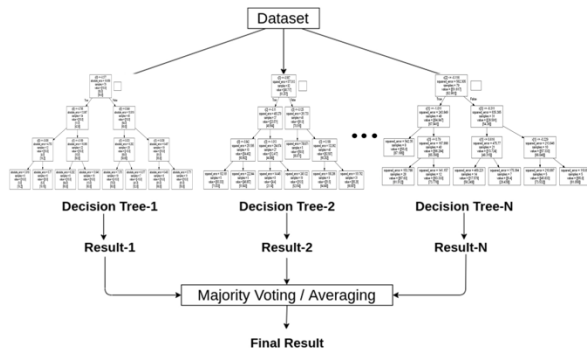
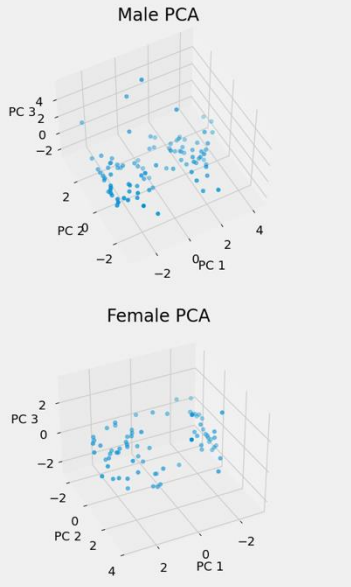
Binary operations



Multiphysics Modeling of Physiological Behavior: AI →CFPD

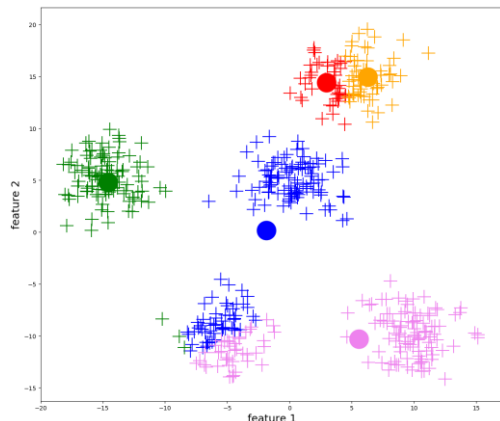
Supervised Learning: Random Forest Regressor

Trained on metrics of the respiratory tract → Extract the importance of features

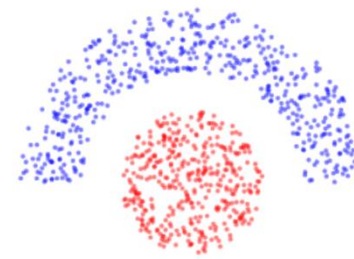


Unsupervised Learning: Kernel k-means Clustering

This algorithm makes K clusters by joining data points that are closest to each other.



(a) K-means



(b) kernel K-means

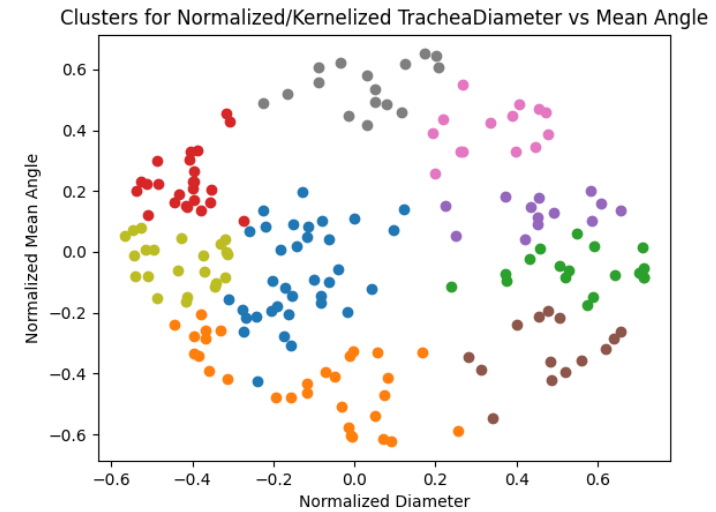
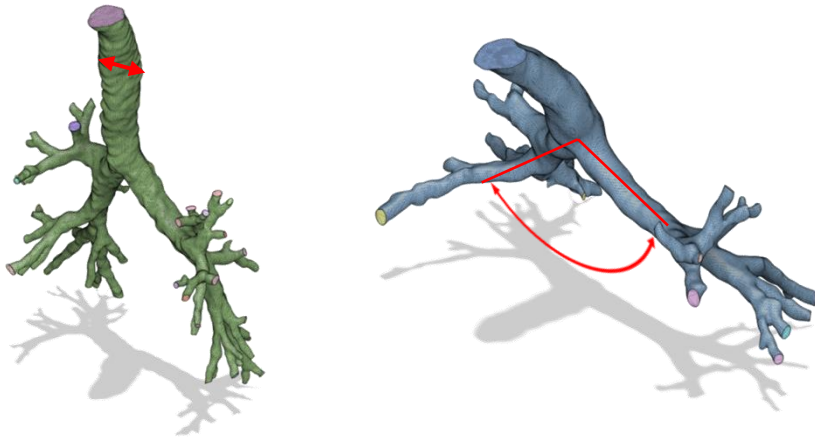
k=5

Before clustering, using a function or “kernel” on the data, allows us to “linearize” non-linear patterns in data.

Multiphysics Modeling of Physiological Behavior: AI \rightarrow CFPD

Unsupervised Learning: Kernel k-means Clustering

- Our work show that for members of the public, the metrics best that describes each airway are **Trachea Diameter** and **Bronchi Angle**

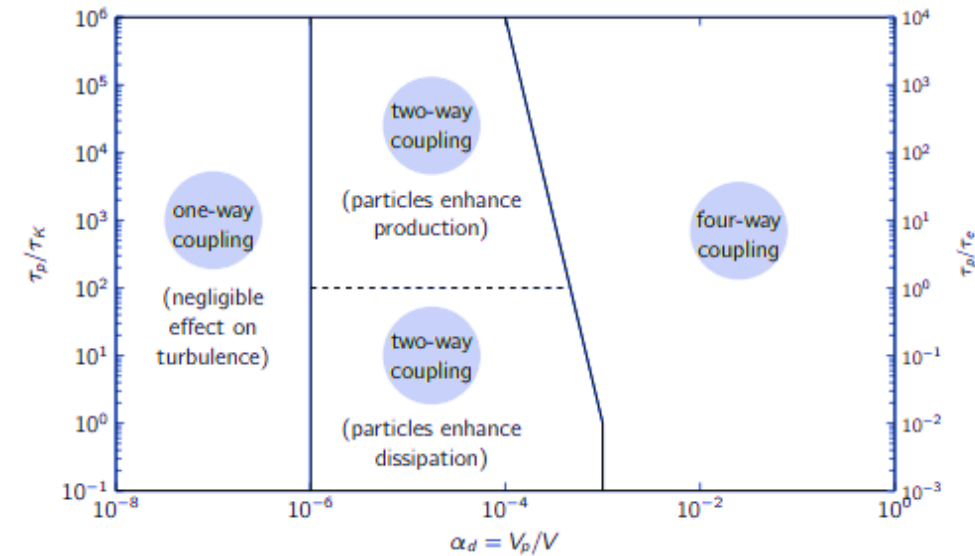


Multiphysics Modeling of Physiological Behavior: AI →CFPD

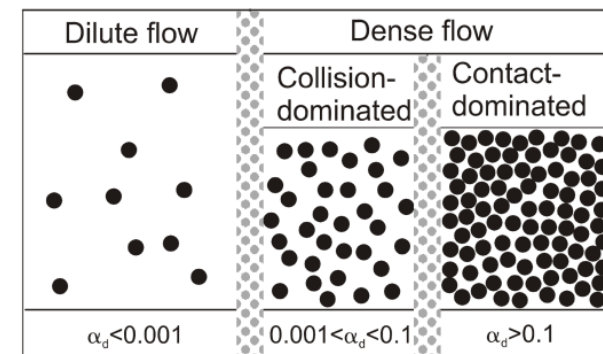
Lagrangian Particle Tracking

Laminar (Nose) → Turbulent (Trachea) → Relaminarize

- Solutions to **Navier Stokes**
 - k-omega Shear Stress Transport (SST) Langtry Menter
- Numerical technique for simulated tracking of particle paths.
- **Coupling:**
 - **2-way coupling** considering the interaction between the continuous and particulate phase only by momentum exchange terms.
 - **4-way coupling** considering particle-particle collision; momentum exchanged between the fluid and particles; and turbulence energy exchange between the gas and particles

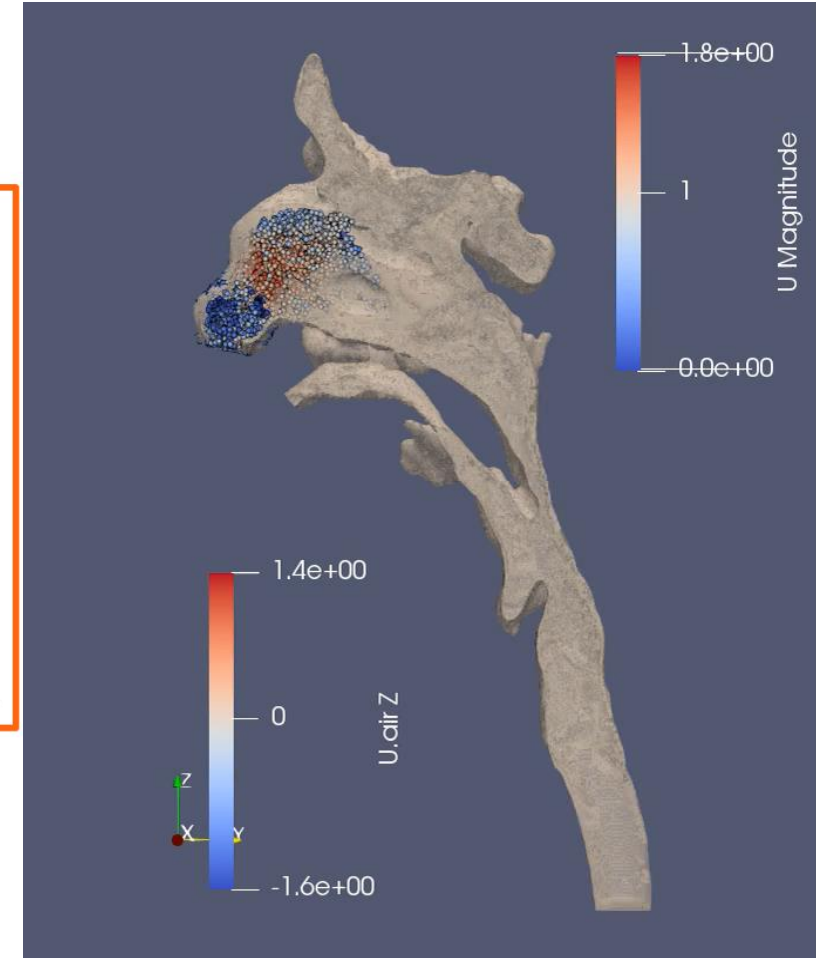
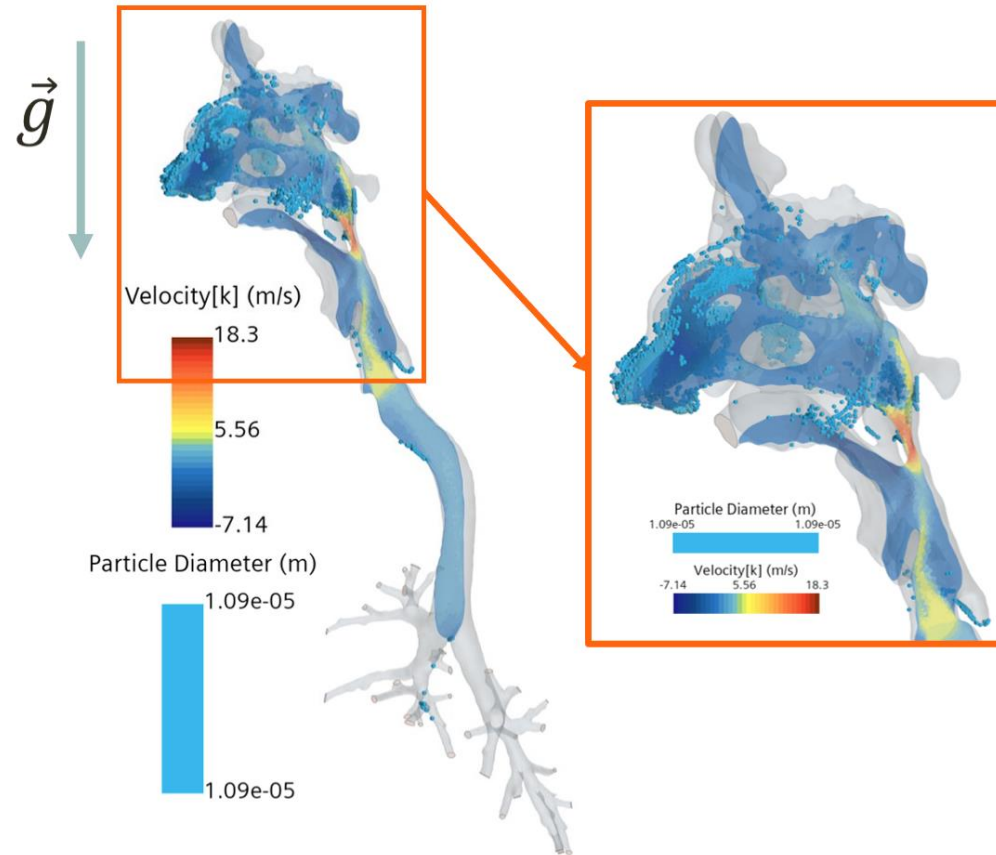
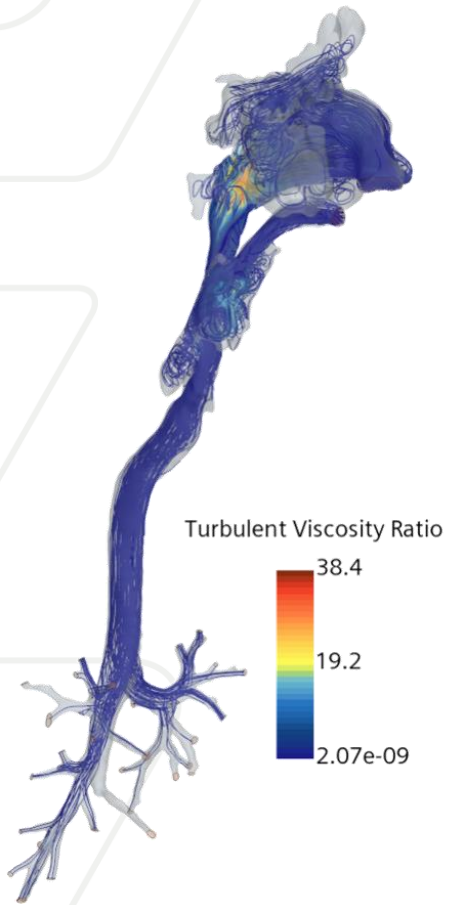


Stokes number vs void coefficient



Multiphysics Modeling of Physiological Behavior: AI \rightarrow CFPD

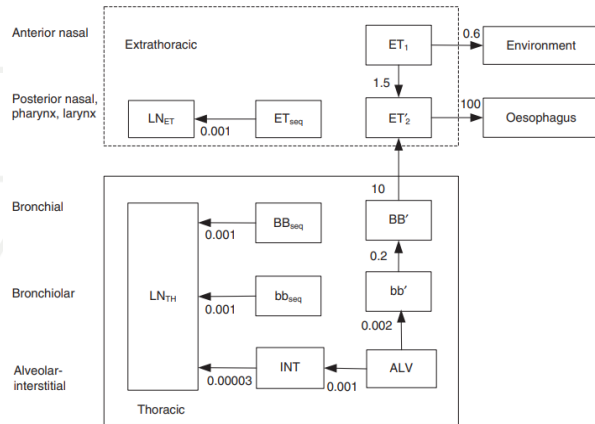
Application - Fluid and Particle Dynamics in Respiratory Tract



Multiphysics Modeling of Physiological Behavior: AI → CFPD

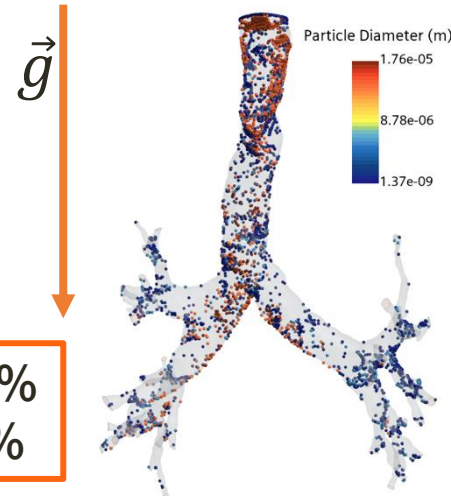
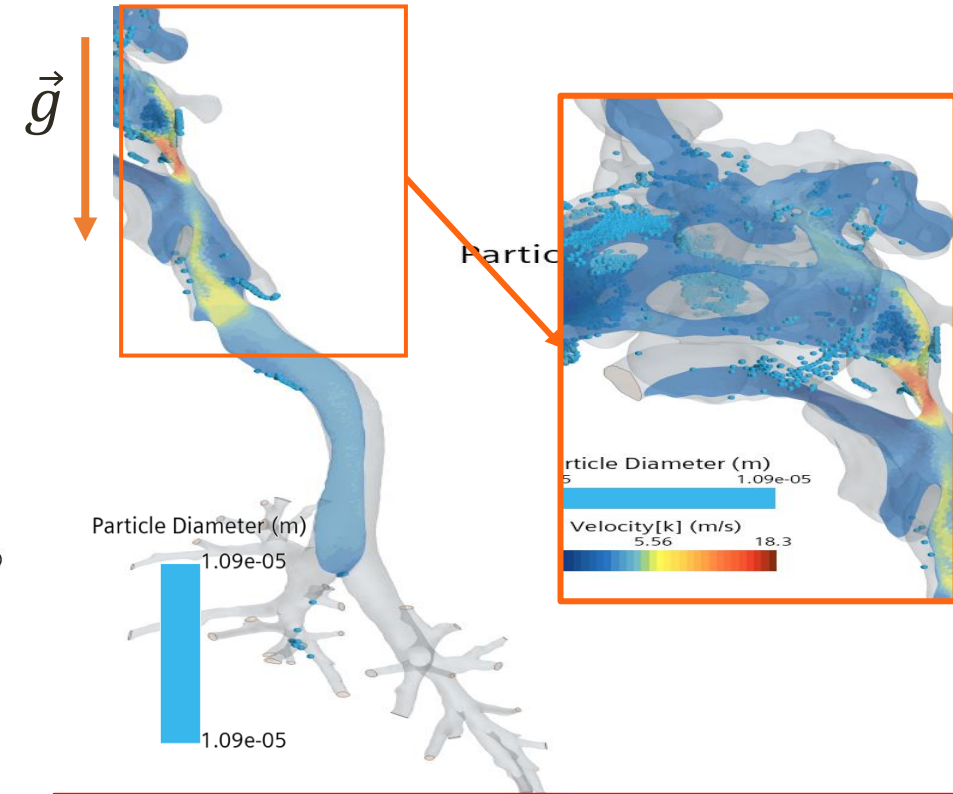
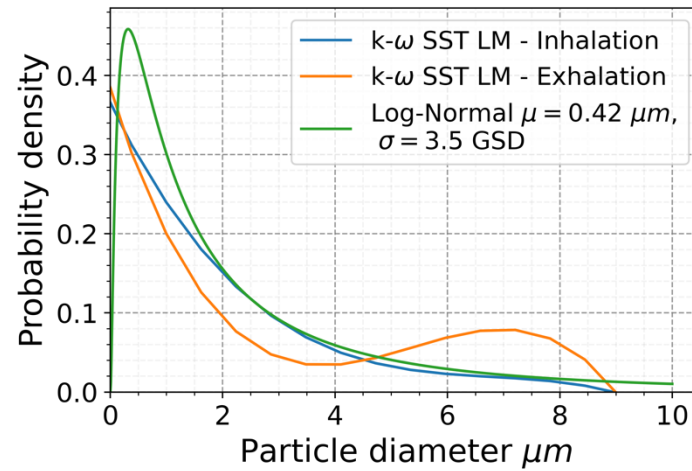
STRONTIUM-90 ICRP VS COMPUTATIONAL FLUID AND PARTICLE DYNAMICS MODELING

HRTM for Sr-90 from ICRP 66/130



ICRP 1st order linear equation model of the HRTM + clearance to other organs

CFPD capabilities: Representative Sr-90 particle size distribution and subject-specific human respiratory tract based on CT scans

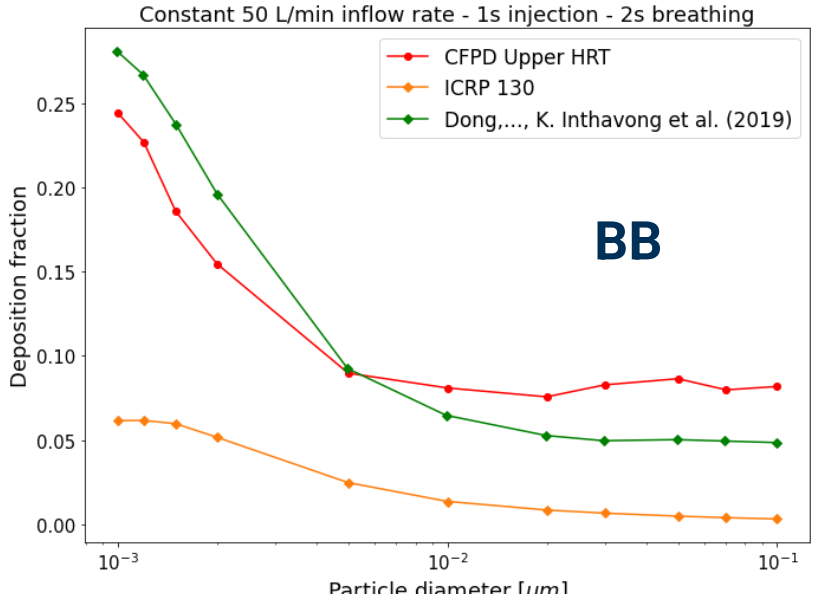
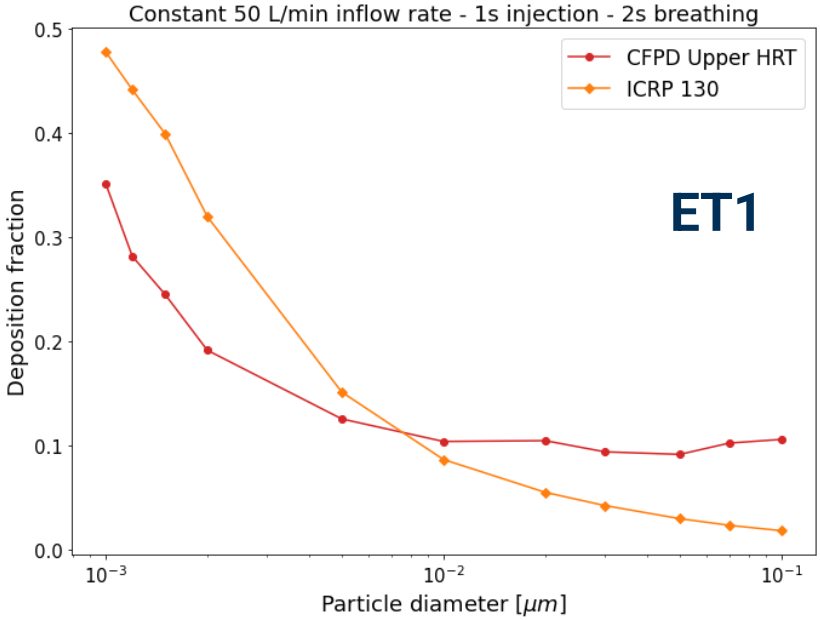
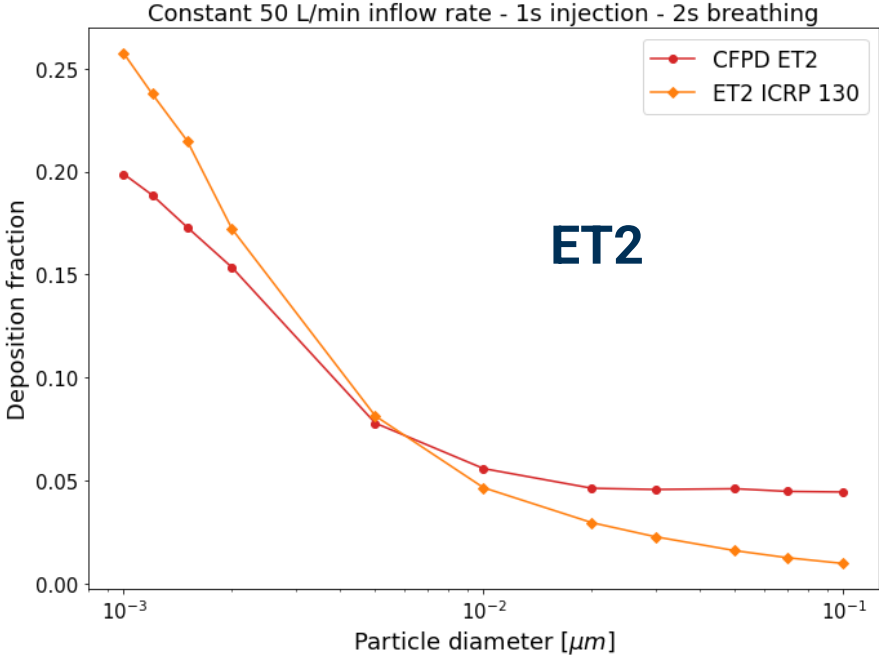
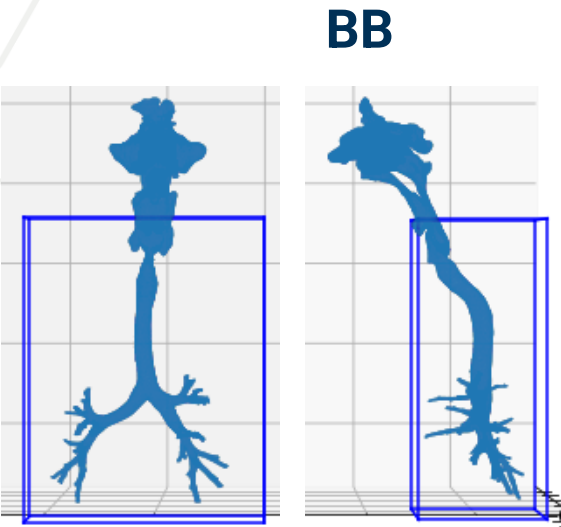
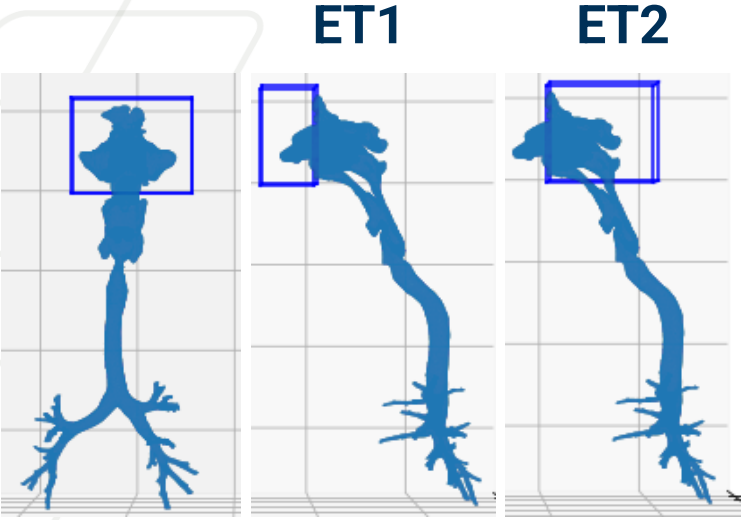


mDF=81.5%
nDF=40.9%

These inputs can then serve as a **source distribution** for a Monte-Carlo transport code. → Accurate **spatial dose distribution**

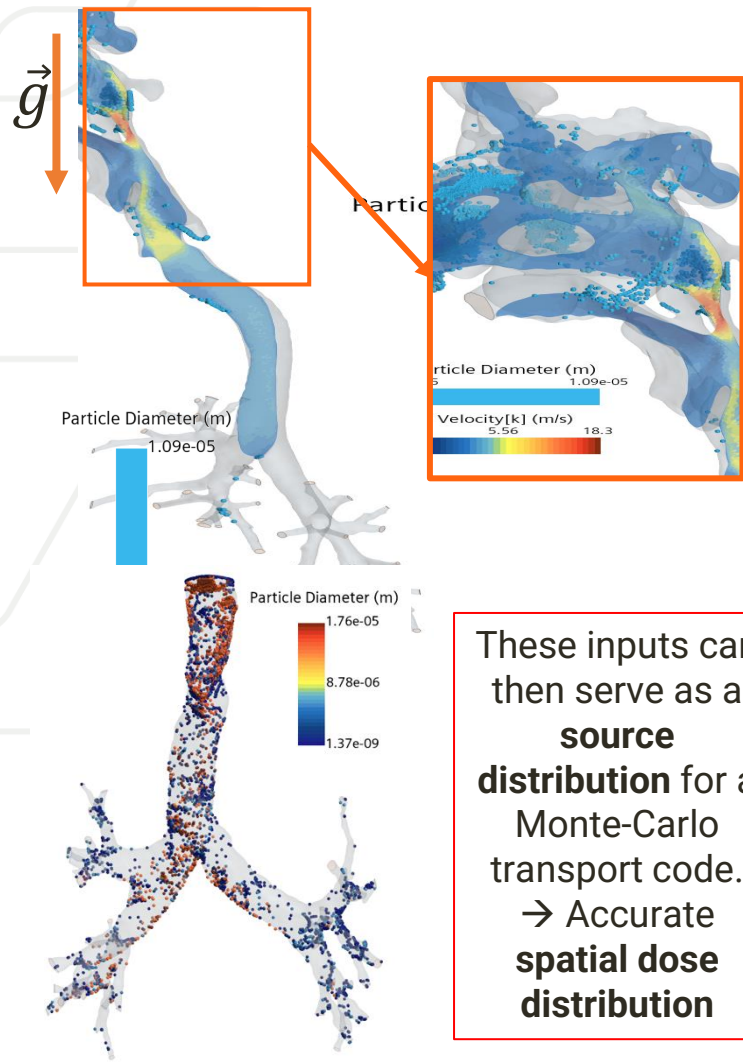
Multiphysics Modeling of Physiological Behavior: AI →CFPD

Results: Deposition Fractions vs ICRP 130

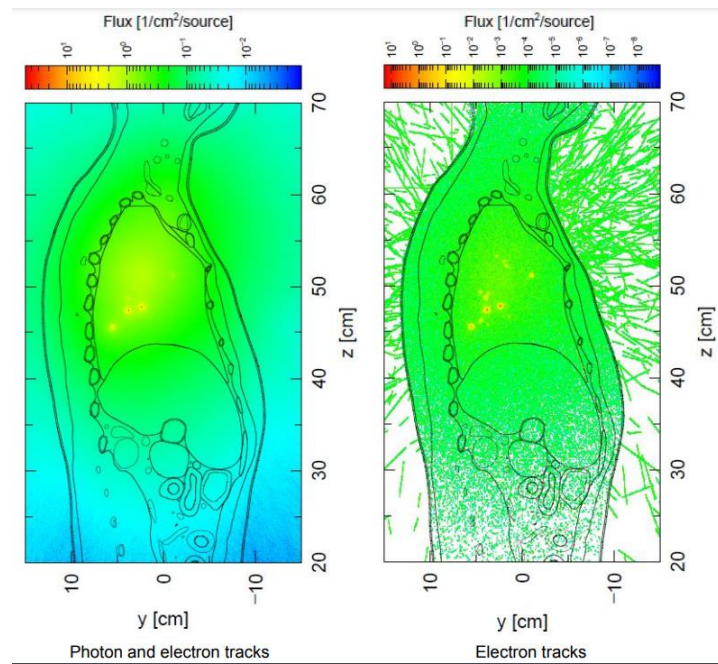
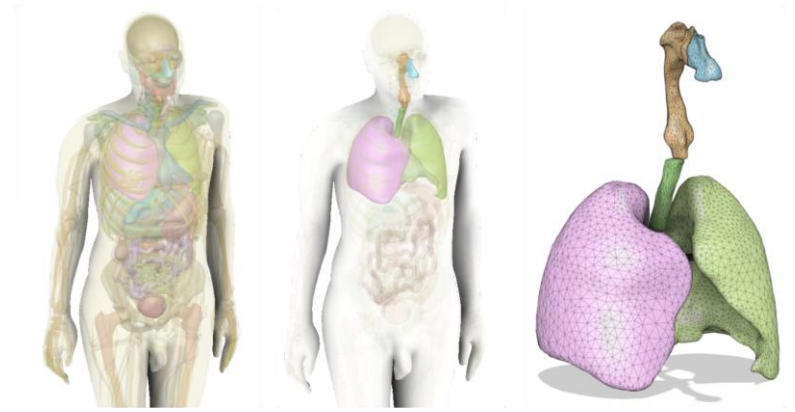
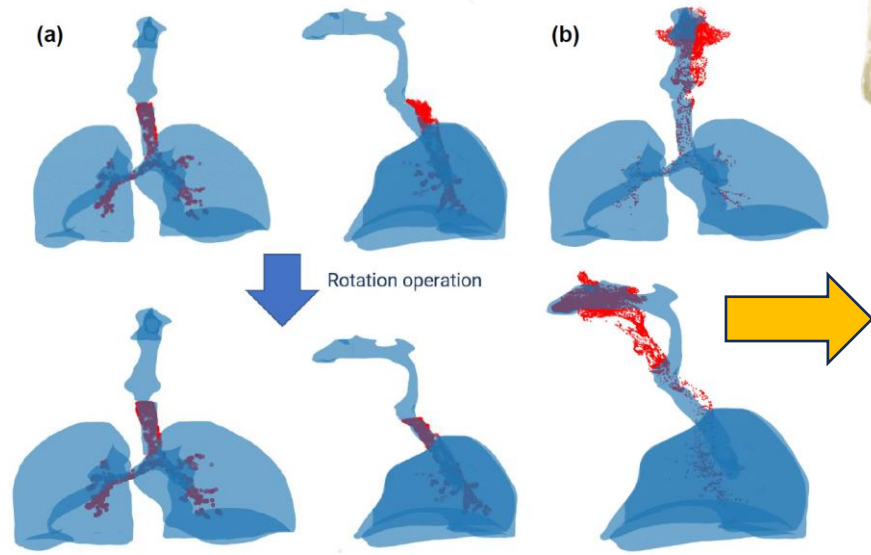


Multiphysics Modeling of Physiological Behavior: CFPD → Monte Carlo

STRONTIUM-90 ICRP VS CFPD AND PHITS MONTE-CARLO SOFTWARE



These inputs can then serve as a **source distribution** for a Monte-Carlo transport code. → Accurate **spatial dose distribution**

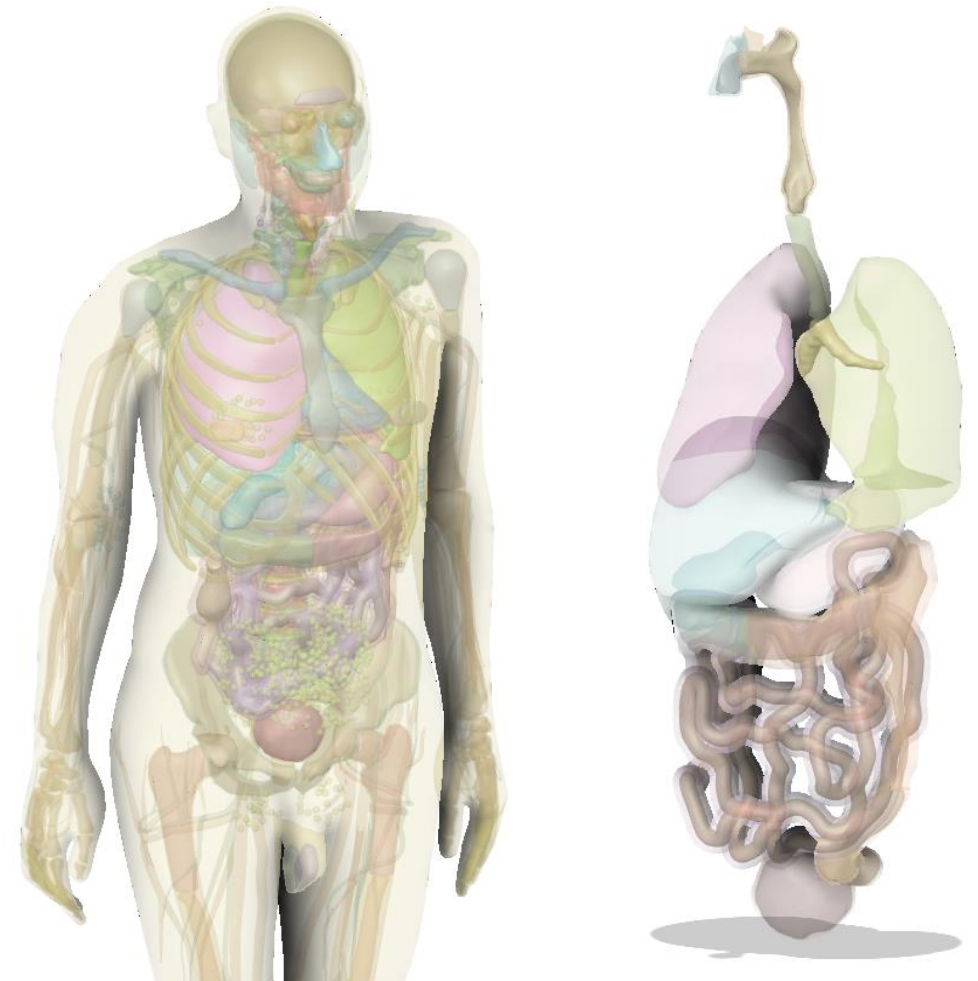


Multiphysics Modeling of Physiological Behavior: CFPD → Monte Carlo

STRONTIUM-90 ICRP VS CFPD AND PHITS MONTE-CARLO SOFTWARE

Organ	Volume [cm^3]	Dose [$pGy/source$]	Relative error [%]
Right Lung	1342.1	0.609	0.072
Left Lung	1123.8	1.069	0.062
Liver	1800.9	0.0074	1.10
Stomach	151.5	0.32	1.05
Bladder	39.7	2.57×10^{-3}	11.40
Small Intestine	672.9	0.0049	1.62
Ascending Colon	93.5	0.0025	6.12
Descending Colon	93.5	0.0075	4.41
Sigmoid Colon	41.6	5.59×10^{-3}	14.0
Transverse Colon	124.7	0.11	3.06

Table: Dose per unit source to the most important organs surrounding the lungs in the human body, using a I-131 as the isotope for the point sources.

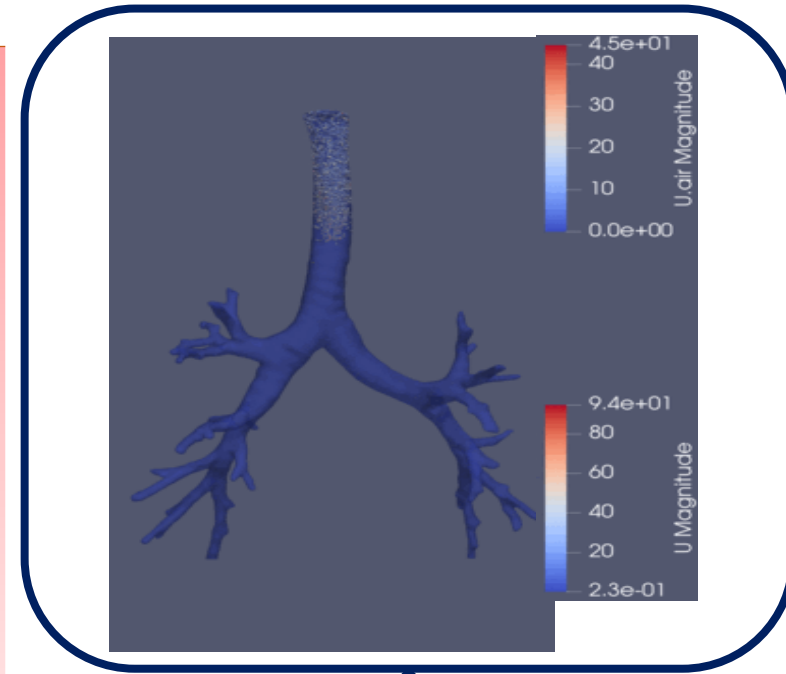
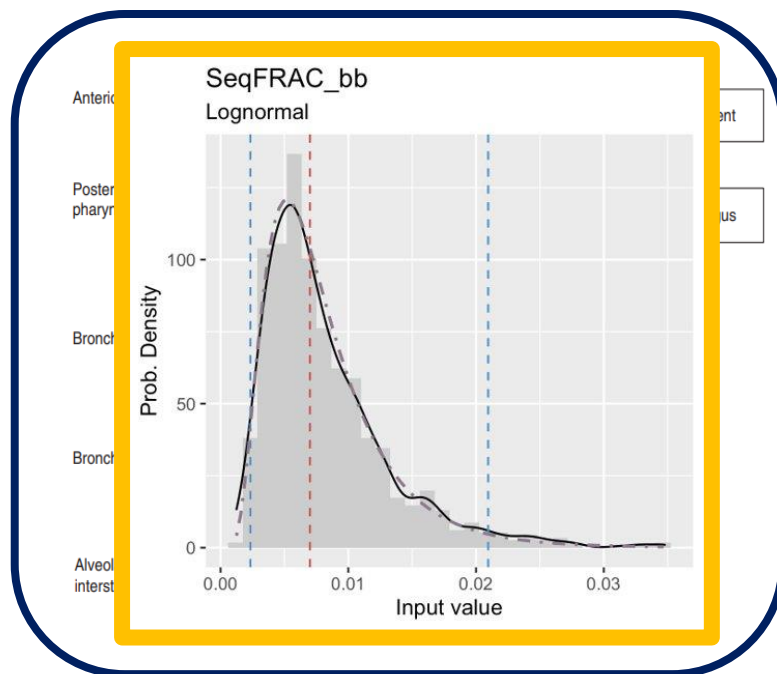
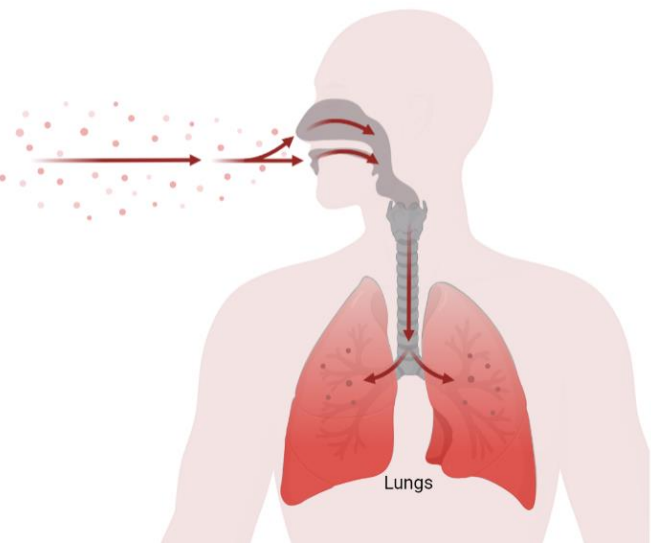


Multiphysics Modeling of Physiological Behavior: CFPD → Monte Carlo

Next Steps for Population-Specific Integration

Integration and Summary

Inhalation



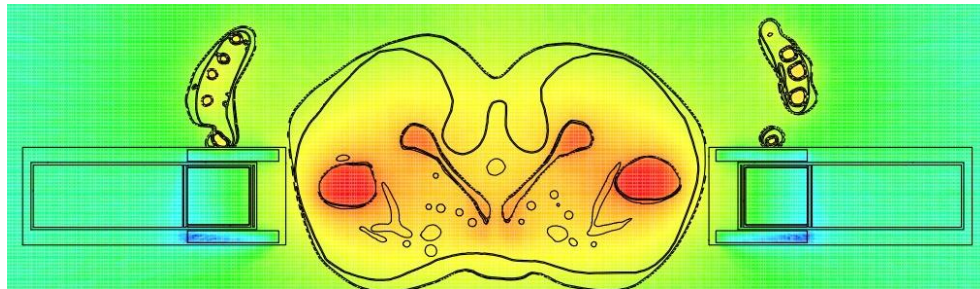
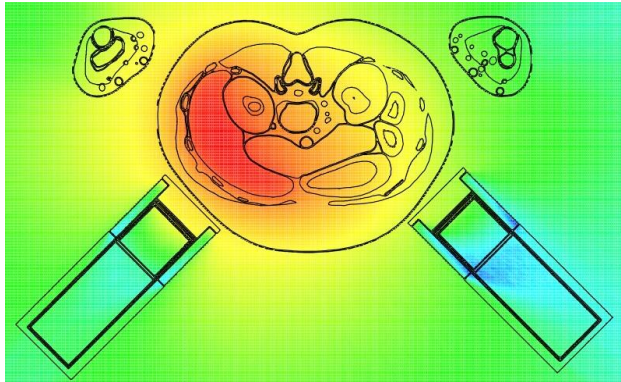
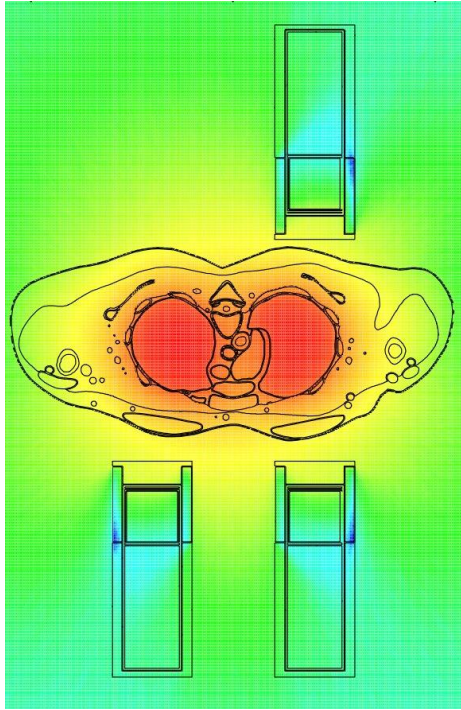
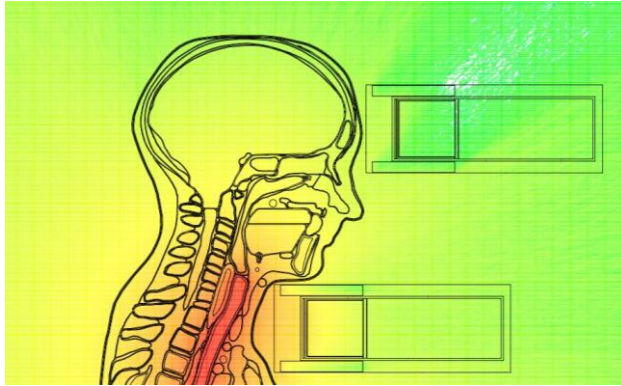
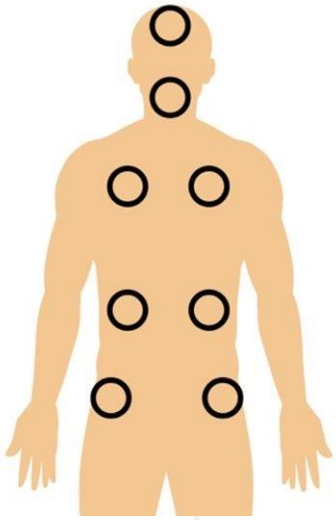
Biokinetic model: Account for particle deposition, retention, and clearance

Surrogate model: Physiologically-enhanced CFPD Model

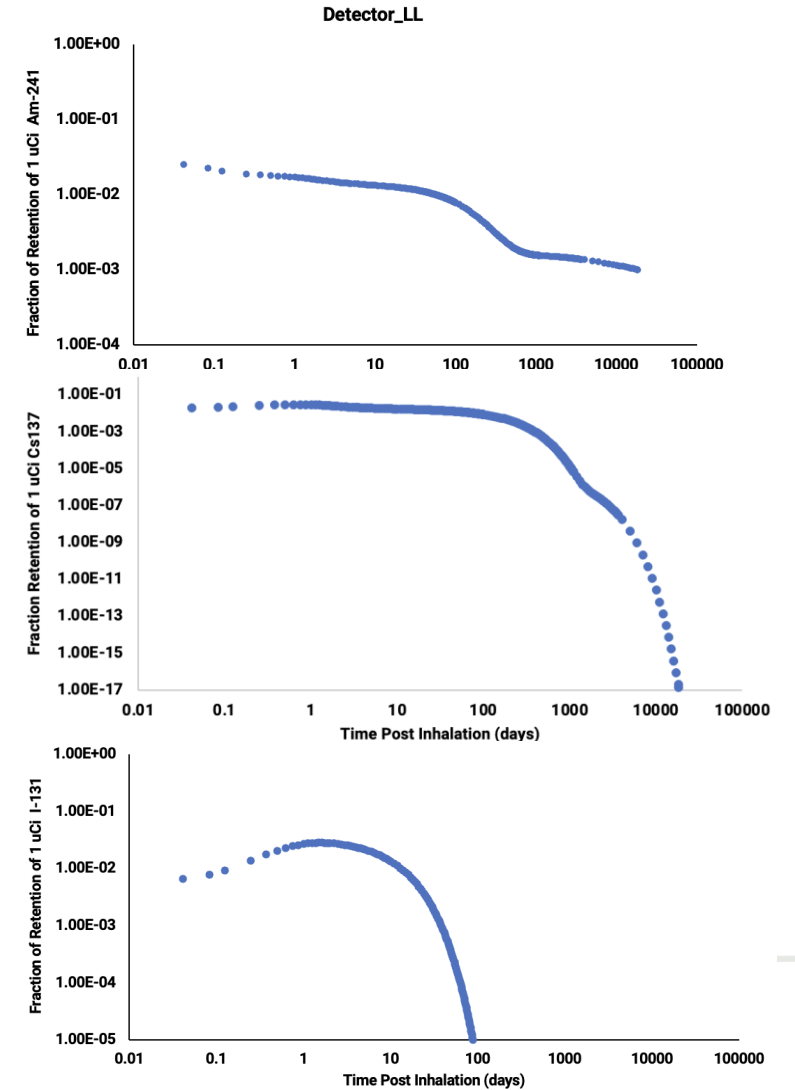
Physiologically-enhanced biokinetic model

Multiphysics Modeling of Physiological Behavior: Monte Carlo → Biokinetics

PHITS SIMULATION OF RETENTION IN SOURCE ORGANS AND DETECTOR RESPONSES



Top to Bottom: Am-241, Cs-137, I-131



Takeaways

The use of machine-learning technologies has dramatically enhanced research capabilities. Standardization of techniques has also broadened these capabilities.

By utilizing big datasets previously unattainable, researchers can now acquire deeper insights.

One example of a good study case is the human respiratory tract, due to the abundance of publicly available data and studies.

These techniques can improve mechanistic behavior of radiation in the body, complemented by radiation epidemiology, making these studies more representative. Additionally, the complexity of testing, improving, and reiterating designs, methods, and models has been significantly reduced.

RED² Laboratory Team at GT

GT Graduate Research Students

- Dmitri Margot
- Heechan Lee
- Emmanuel Mate-Kole
- Ignacio Bartol
- Vanessa Wei
- David Gonzalez
- Patrick Connolly
- Sherry Adadi
- Jesse Bruner
- Sergio Ruiz
- Jarred Jordan

Key Personnel

- Mauricio Tano, Ph.D. (TAMU/INL)
- Martin Graffigna (GT, Research Engineer)
- Lotem Buchbinder Shadur, Ph.D. (GT, Postdoctoral Fellow)

GT Undergraduate Research Students

- Lianna Arnold
- Alejandro Martinez
- Grant Espy



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Feinberg School of Medicine | Radiation Oncology | Woloschak Lab Grant

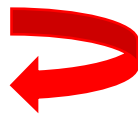
Alliance for Radiological Exposures and Mitigation Science

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- Department of Defense - Peer Reviewed Medical Research Program (DOD PRMRP) under award number W81XWH-21-1-0984



Questions!



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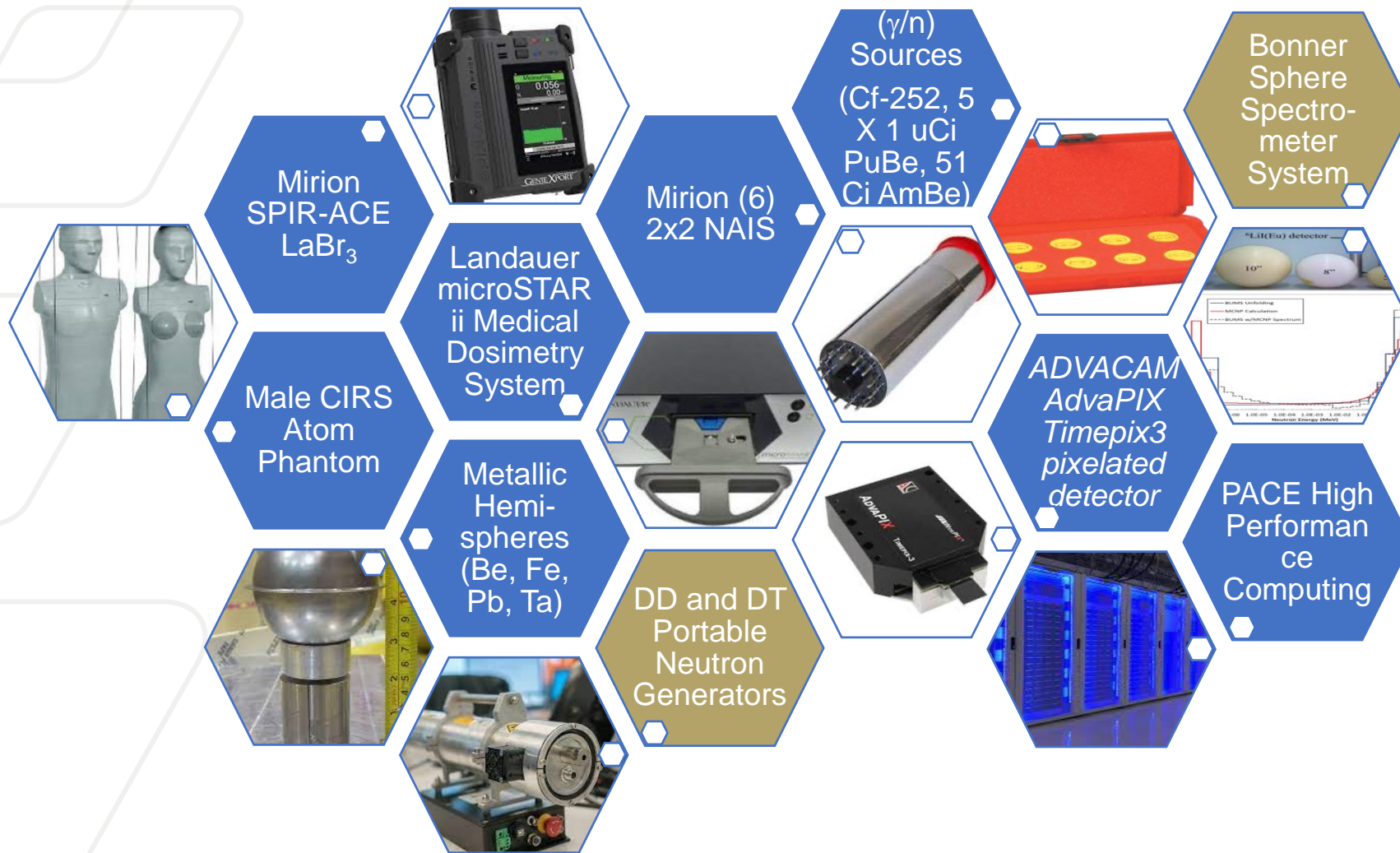
Contact Info (.vcf)



RED²
Laboratory
Website



RED² Laboratory



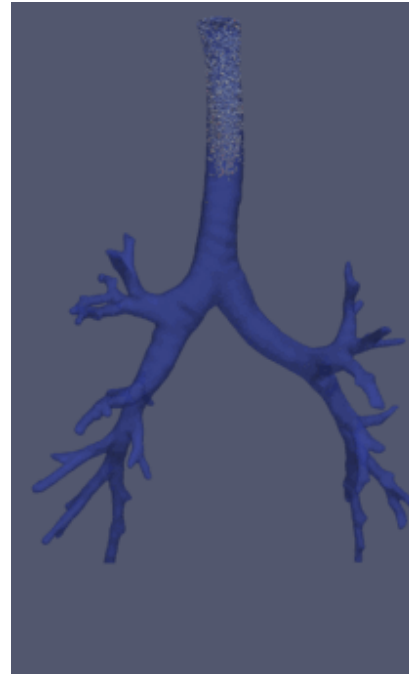
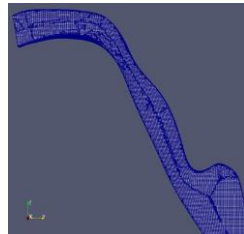
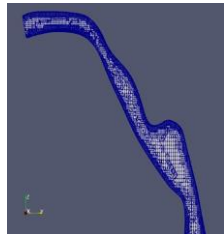
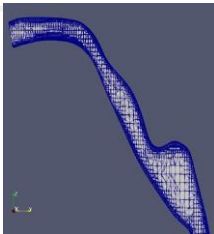
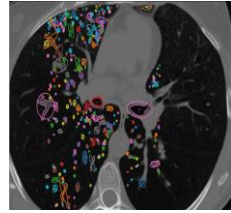
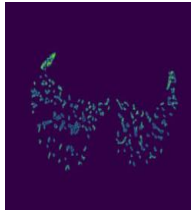
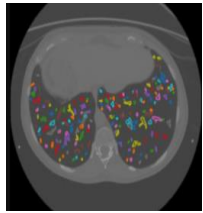
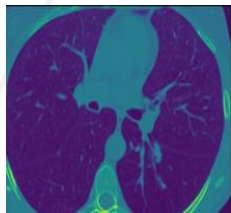
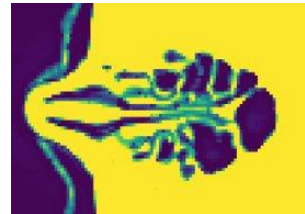
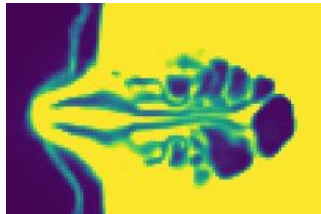
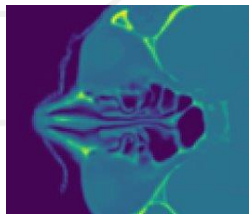
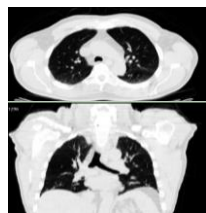
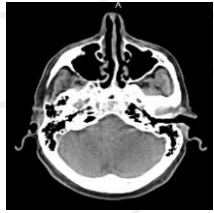
Supplementary Slides

Results: Deposition Fractions

Table: Comparison of deposition values (**relative difference (RD)** and **absolute difference (AD)**) for **polydisperse particle distribution (5 μm AMAD)** for **light exertion level (breathing rate = 1.5 $\text{m}^3 \text{h}^{-1}$)** by an **adult male**

Region	In-house Dep_Module	ICRP 130	RD%	AD%
ET1	0.491	0.492	-0.345	-0.170
ET2	0.264	0.265	-0.377	-0.100
BB	0.018	0.018	-1.110	-0.020
bb	0.009	0.009	-2.537	-0.023
AI	0.049	0.045	10.250	0.460
Total	0.831	0.829	0.178	0.147

Topic 1: Aim 2 - Computational Fluid Particle Dynamics modeling of Deposition



Automated 3D CT-based algorithm of **real patients** (**EXACT '09** and **TCIA databases**) used to reconstruct realistic HRT geometry representative of population.

- Inclusion of the **nasal cavity** and the **paranasal sinuses** (omitted in prior non-radiation studies).
- Significantly impact **overall biodistribution** of radionuclides body.

Reduced-order discrete element model (DEM) of the CFPD modeling the **complex physics in the airways** (*laminar to turbulent to irregular laminar*)

- Integrated into a Bayesian analysis of aerosol dynamics for improving HRT transfer coefficients (**Aim 1, 3**).

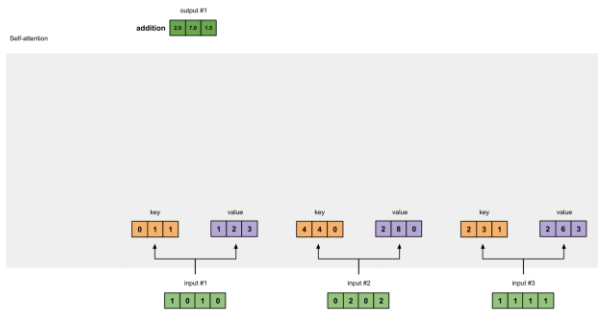
Sensitivity analysis will be conducted **compared to ICRP's 15 generation HRTM** deterministic phantom model

- Revised S-values, harnessing **morphometric/physiological data** and **particulate distribution** (morphology, deposition velocity)
- **Benchmarked with animal tomogram data** of deposition from aluminosilicate particles.

AI Convolutional Neural Network: Basic Operations

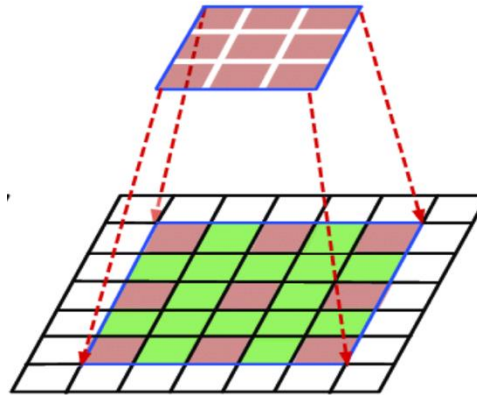
Self-attention

Provides a way to focus on different sections of data at a time

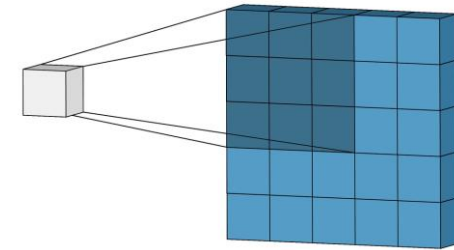


Dilated Convolution

$3 \times 3, d = 2$

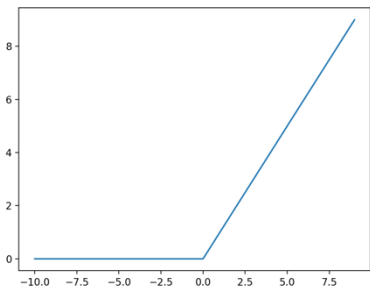


Regular Convolution



ReLU Activation Function

(positive if convolved pixel above a certain threshold)



Batch Normalization

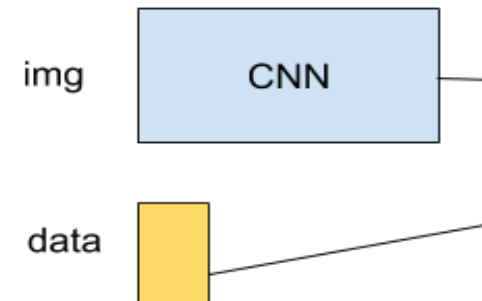
$$\mu_{batch} = \sum_{i=1}^m x_i \quad \text{batch mean}$$

$$\sigma_{batch} = \sqrt{\sum_{i=1}^m (x_i - \mu_{batch})^2} \quad \text{batch variance}$$

$$x_{input} = \frac{x_i - \mu_{batch}}{\sqrt{\sigma_{batch}^2 + \epsilon}}$$

$$y_i = \gamma \cdot x_{input} + \beta$$

Concatenation

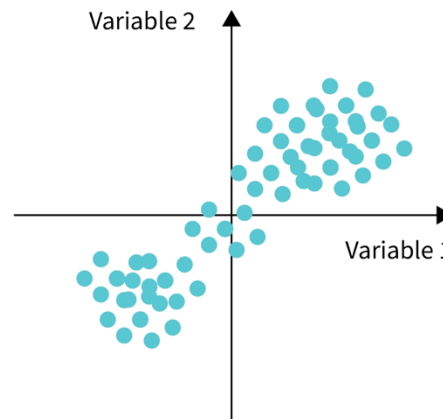
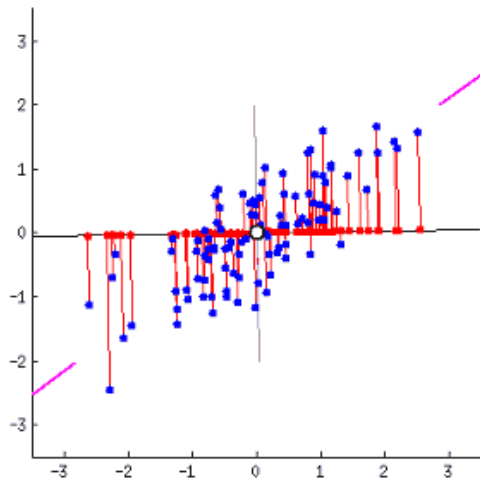


AI → CFPD → Advanced Mathematics

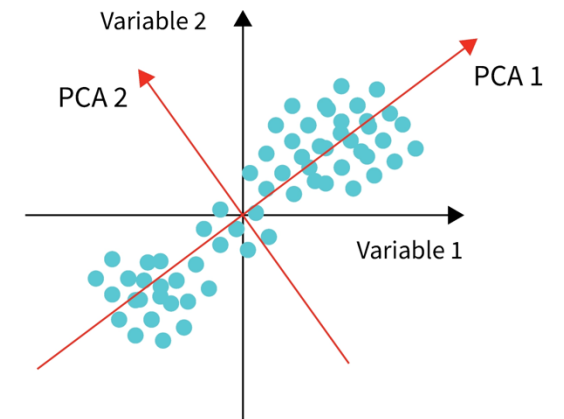
Singular Value Decomposition: Principal Component Analysis

Extracts the dimension or “Component” in the data with more linear variance.

Essentially, it looks for the direction in which the data is most spread



PCA

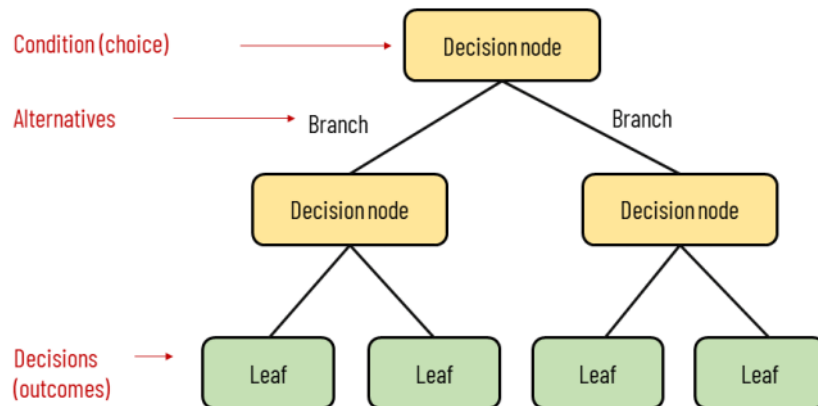


AI → CFPD → Advanced Mathematics → AI

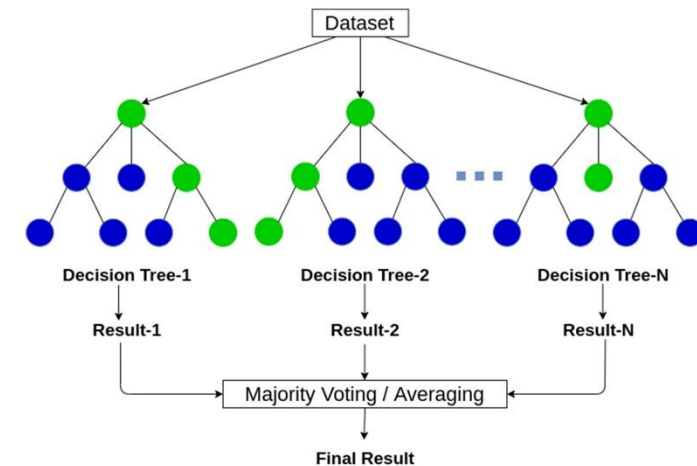
Supervised Learning: Random Forest Regressor

- Used to evaluate the most essential features in the dataset.
- The most used variable by the decision trees to divide the branches is the feature that best describes the dataset

Elements of a decision tree



Random Forest

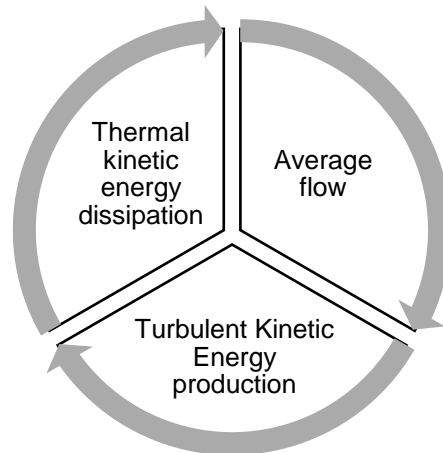
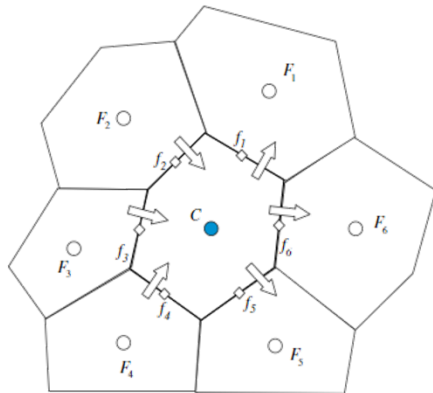


AI → CFPD

Finite Volume method - Reynold Average Navier-Stokes (RANS)

Finite Volume Method

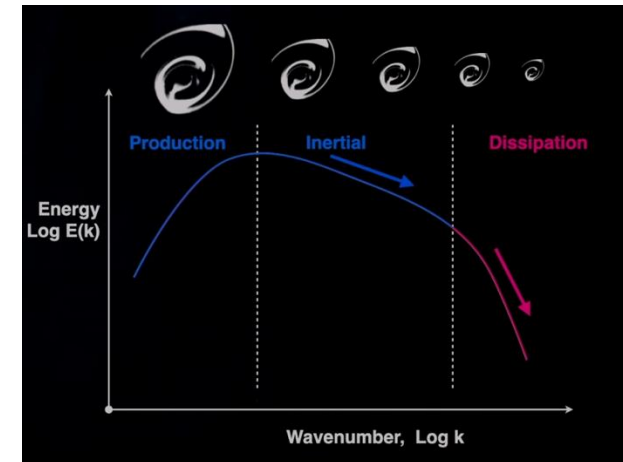
- Used to model fluid dynamics numerically.
- Preserve quantities such as energy and mass – Physically meaningful
- The exact method for average values – fewer approximations committed



Turbulence Modeling:

Closure Equation: RANS – $k-\omega$

- No analytical theory to predict turbulence – persists at all scales (macro/meso/micro).
- Model averages flow and treats fluctuations separately.



Expanding Capabilities

- **Generative Adversarial Networks** (GAN's) can model bone remodeling processes in orthopedics or dental applications. These models could **predict bone growth** or resorption patterns and assist in treatment planning for fractures, joint replacements, or dental implants.
- **Convolutional Neural Networks** (CNN's) can analyze **endoscopic images** or other GI-related data to **detect abnormalities**, such as polyps, ulcers, or lesions. These models could help in early diagnosis and treatment planning for conditions like colorectal cancer or inflammatory bowel disease.
- **Convolutional Neural Networks** (CNN's) could analyze medical images like MRIs or CT scans to detect and quantify **abnormalities in blood vessels**. This can aid in diagnosing conditions like aneurysms, vascular stenosis, or arteriovenous malformations.

