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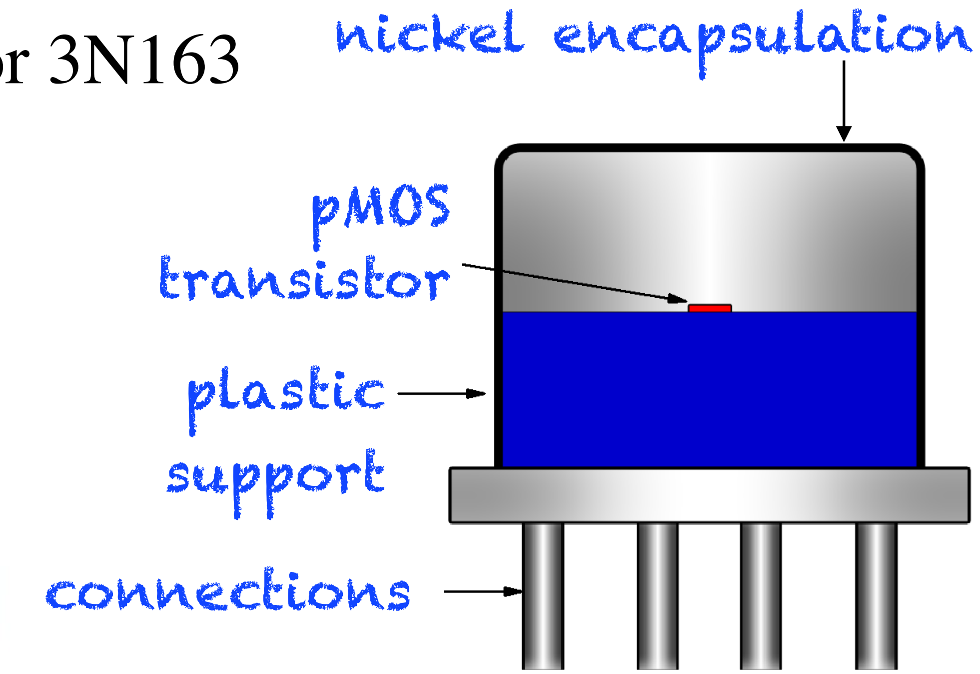

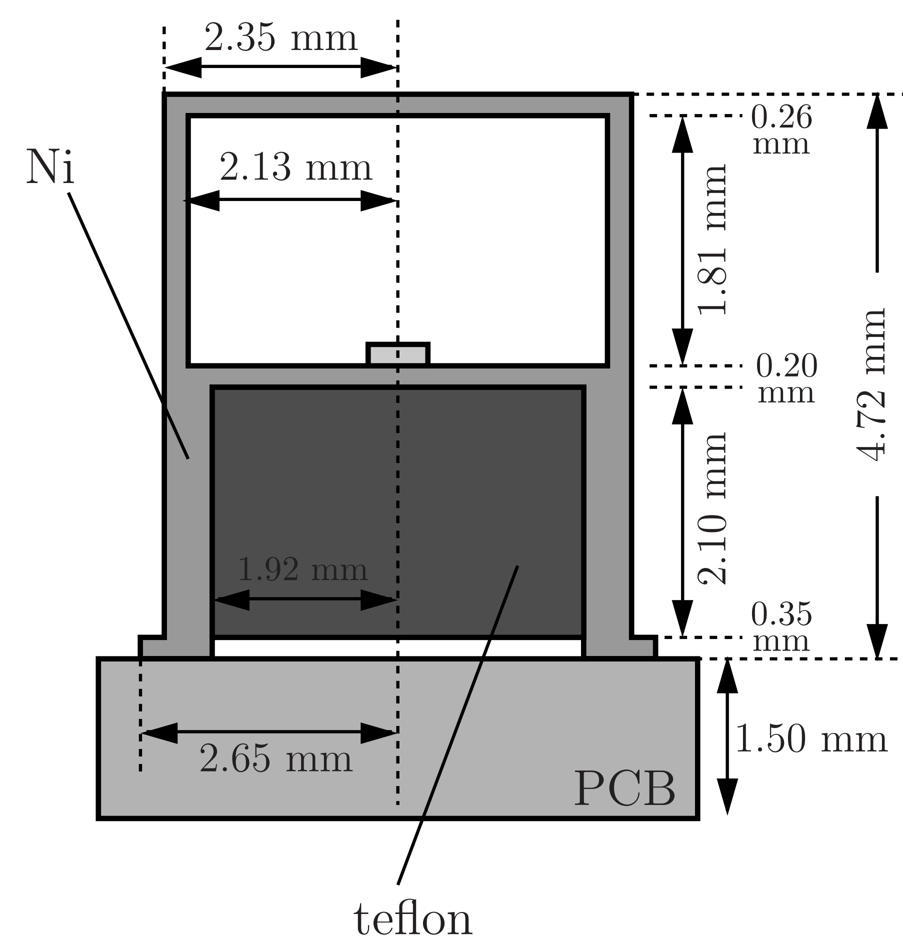

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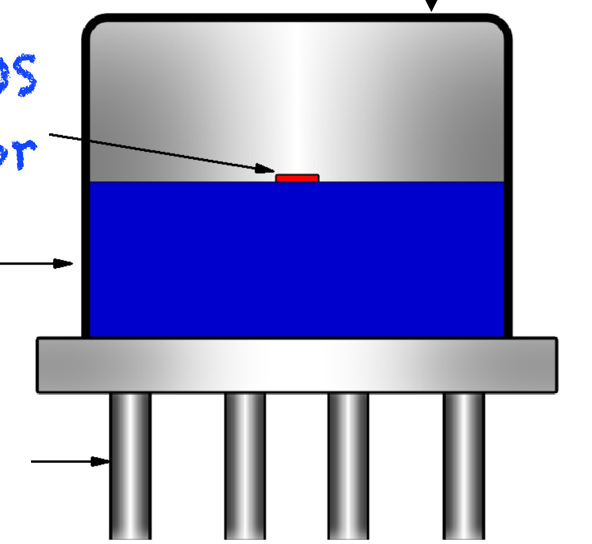

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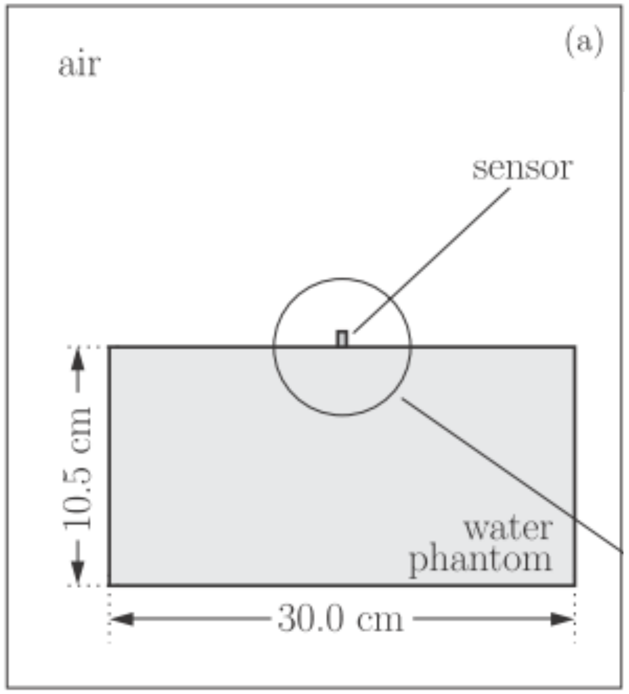

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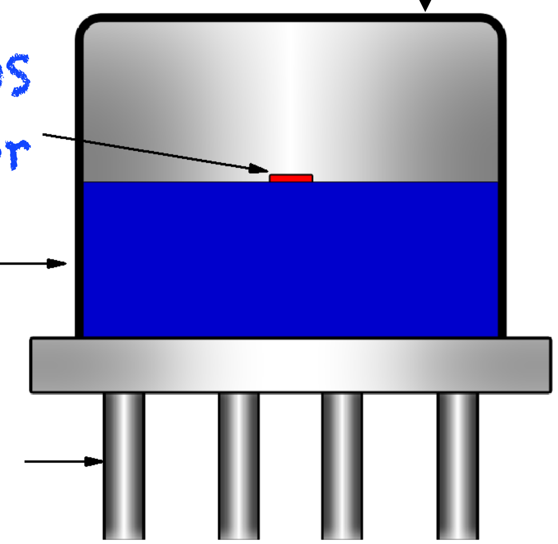

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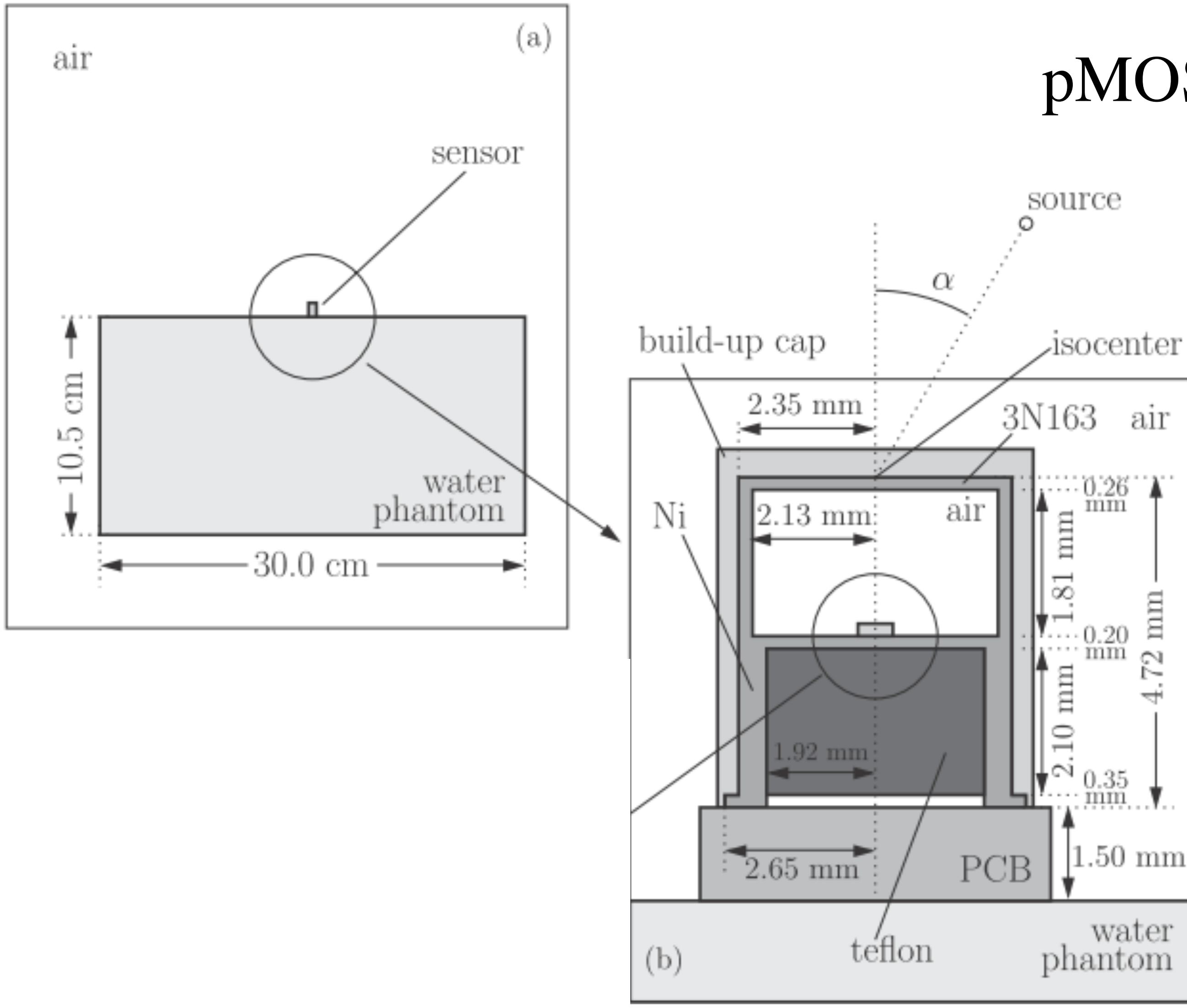

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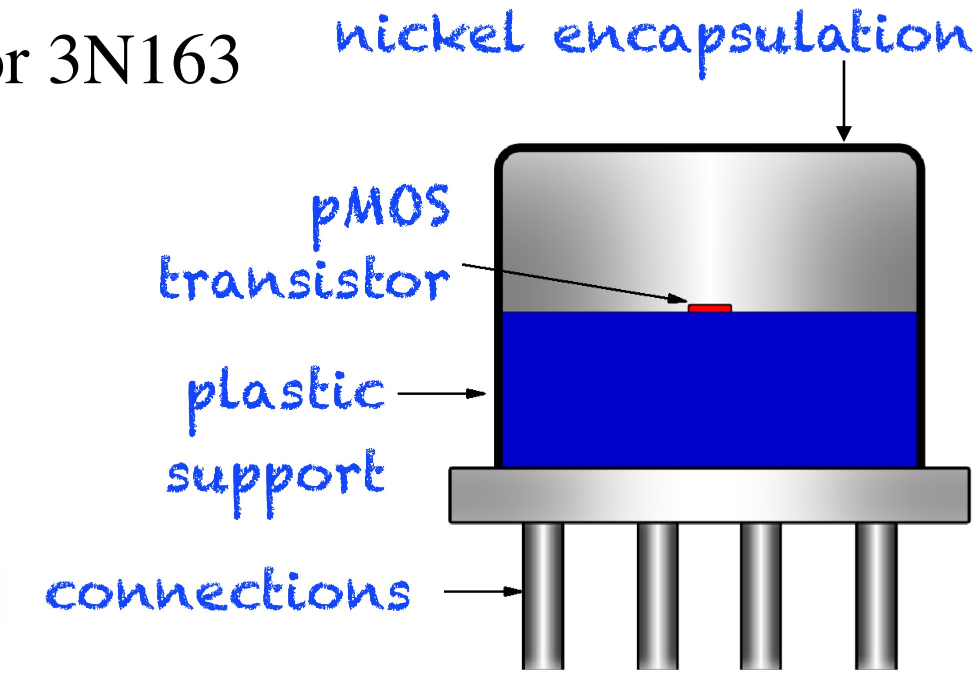

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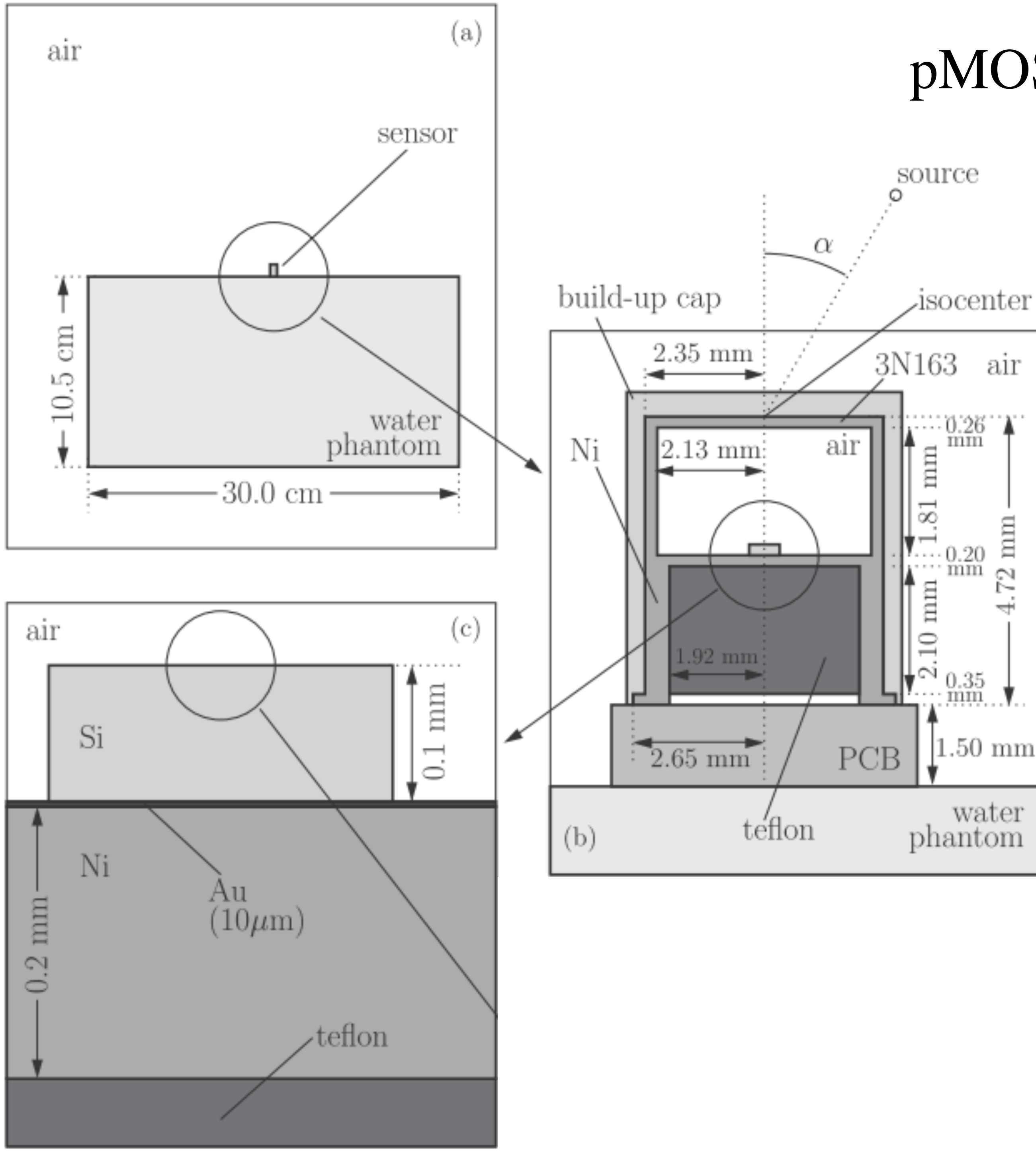

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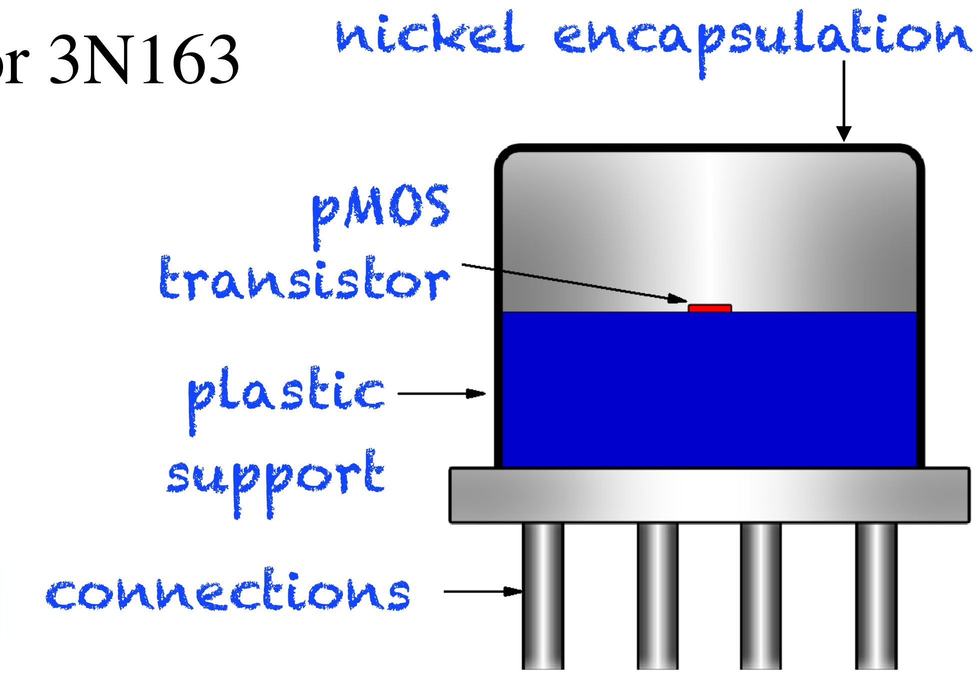

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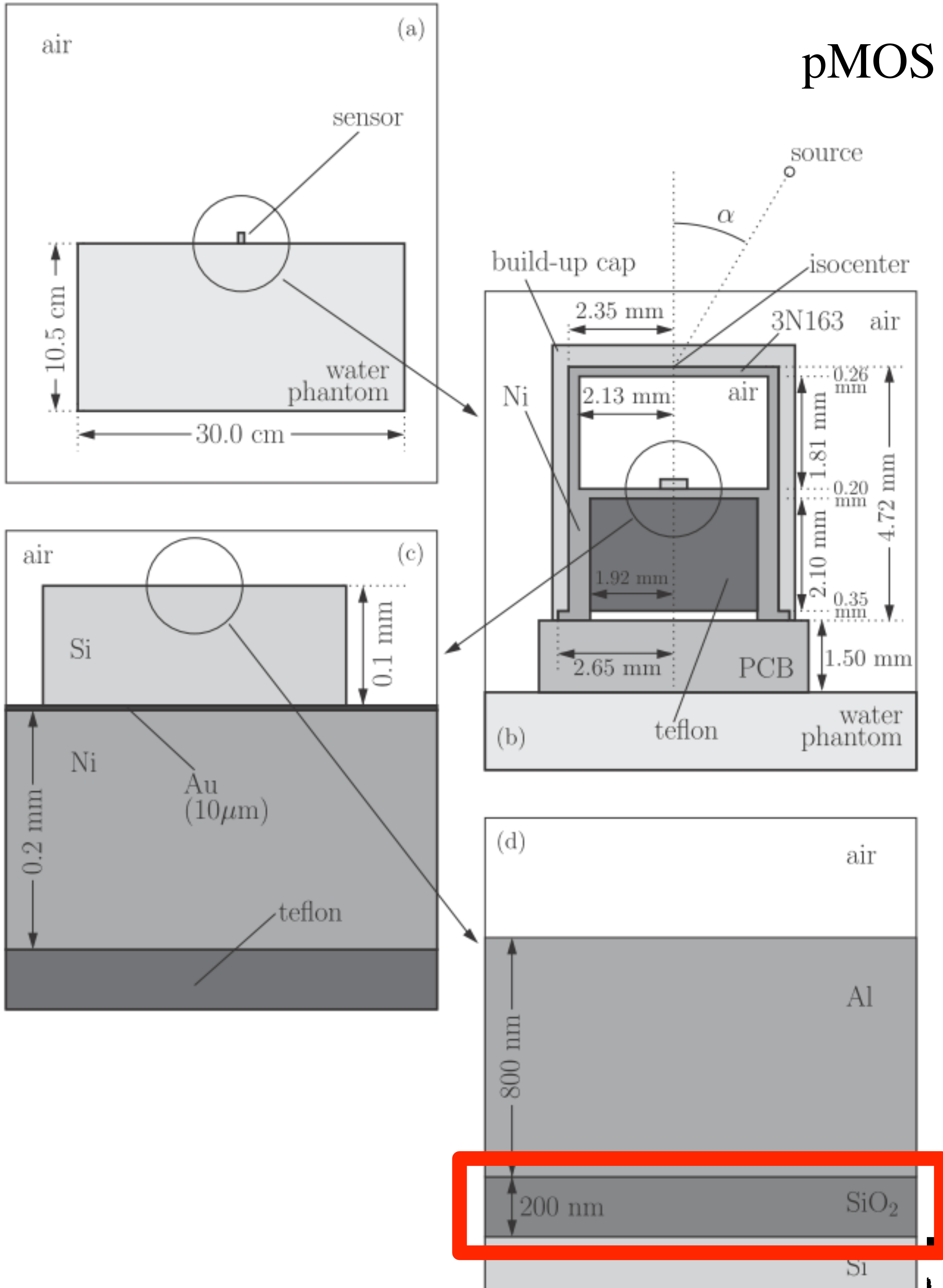

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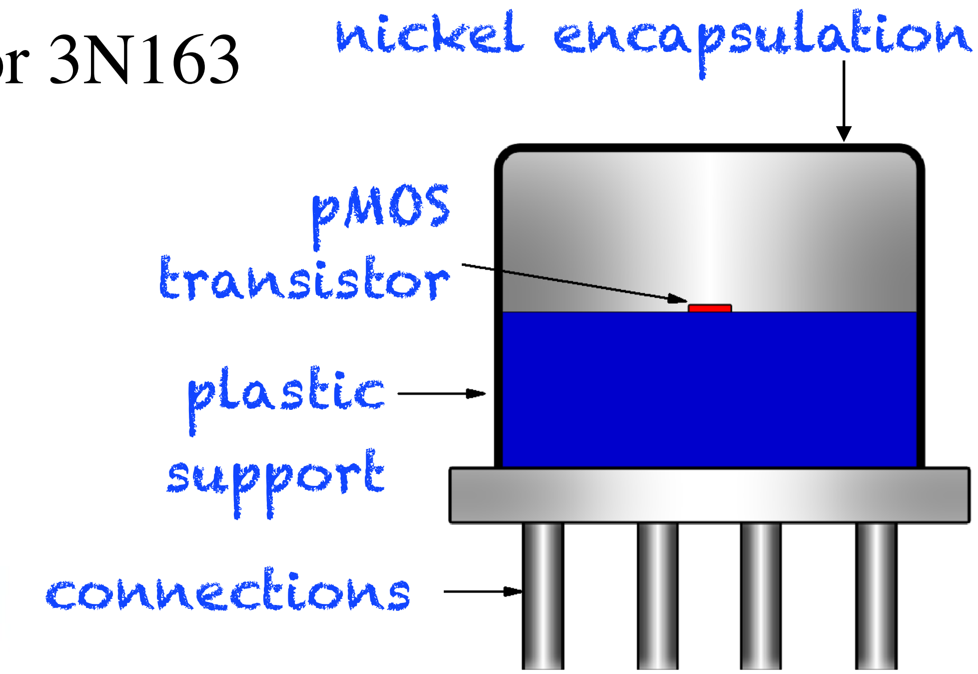

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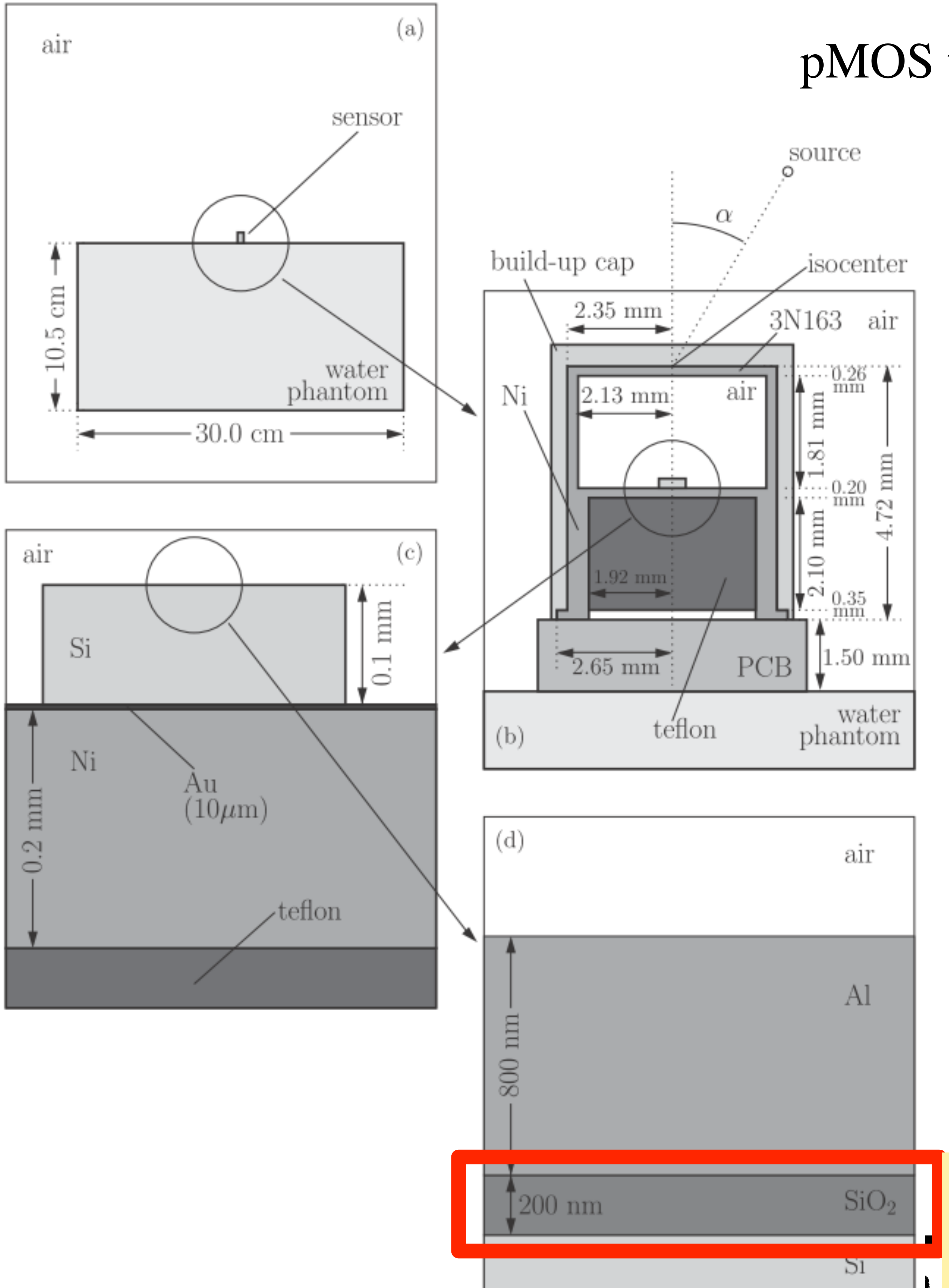

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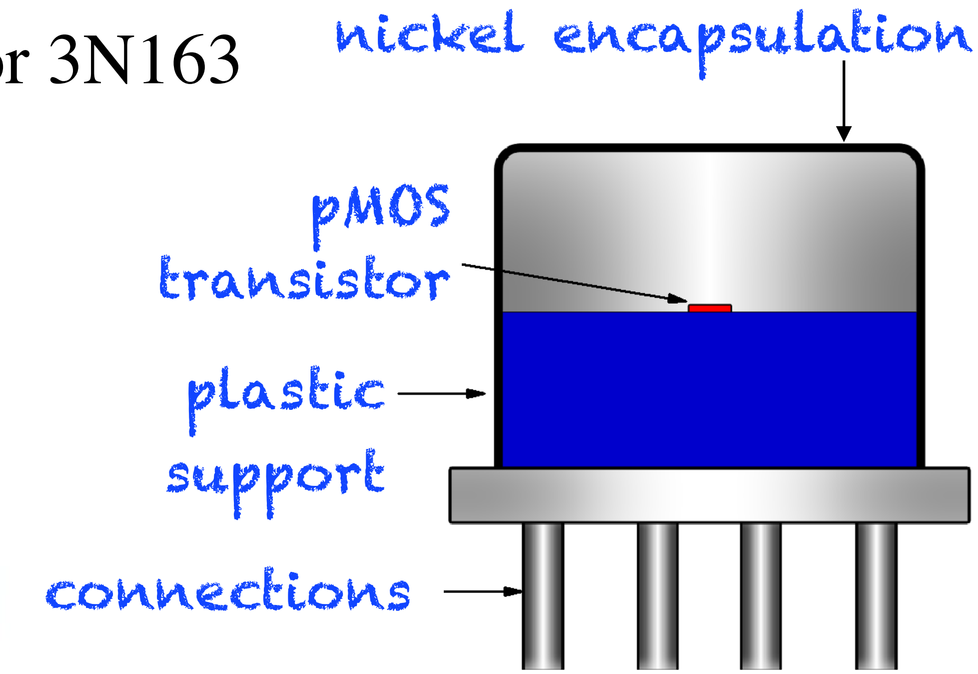

-MOSFET response:
energy deposited in the SiO_2 die

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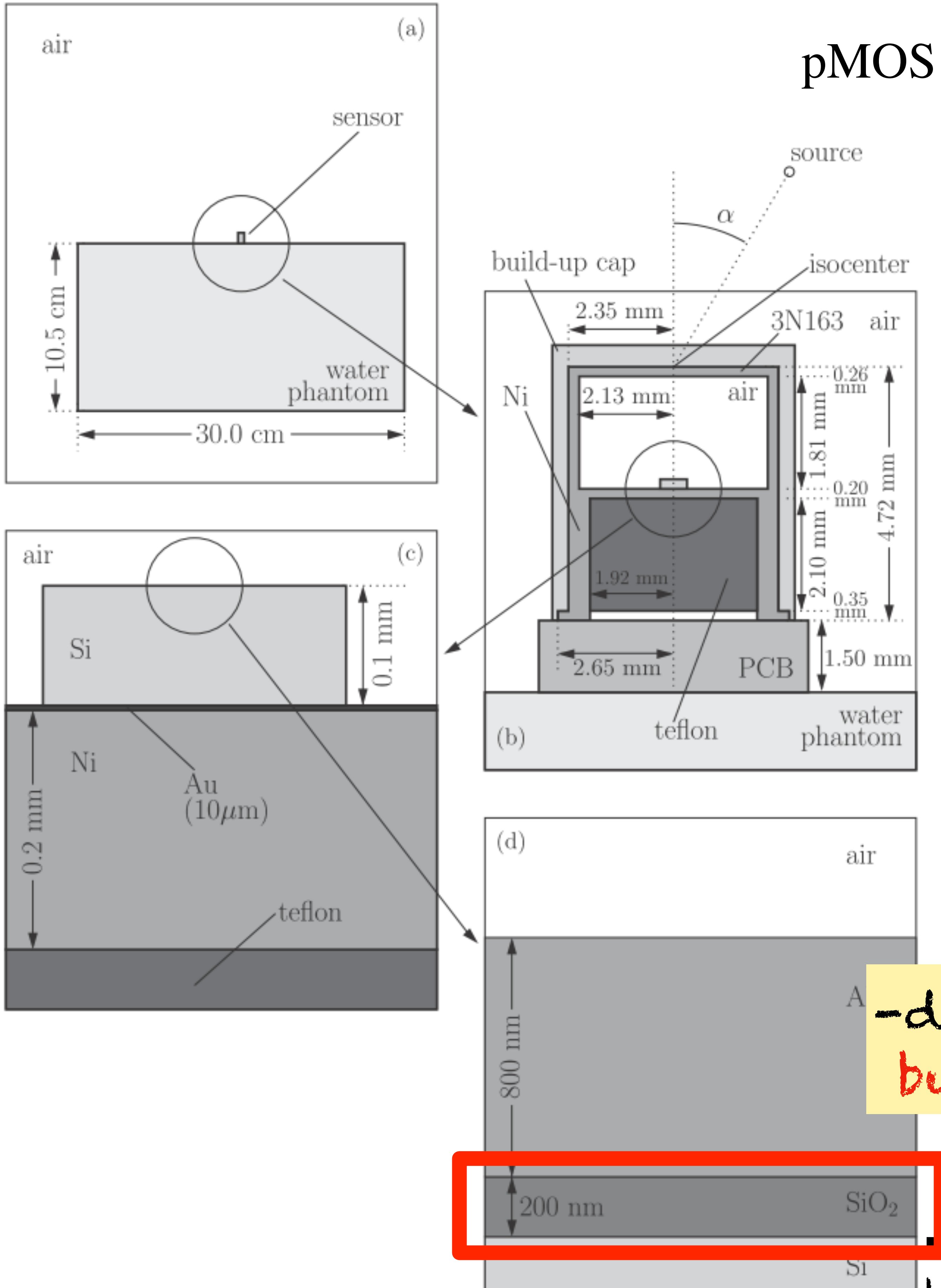

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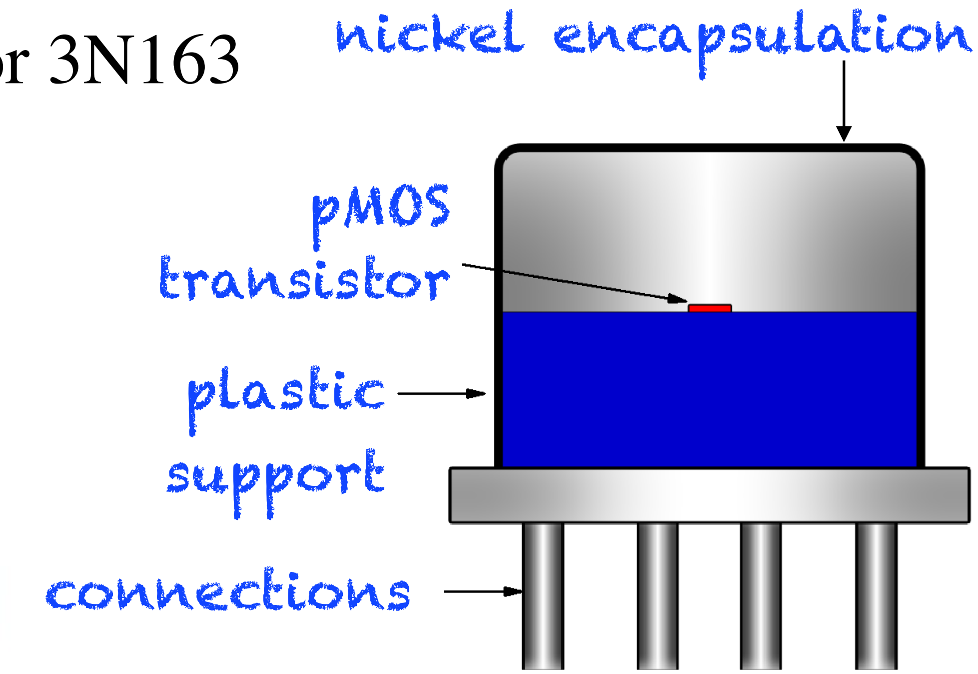

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but very low statistic

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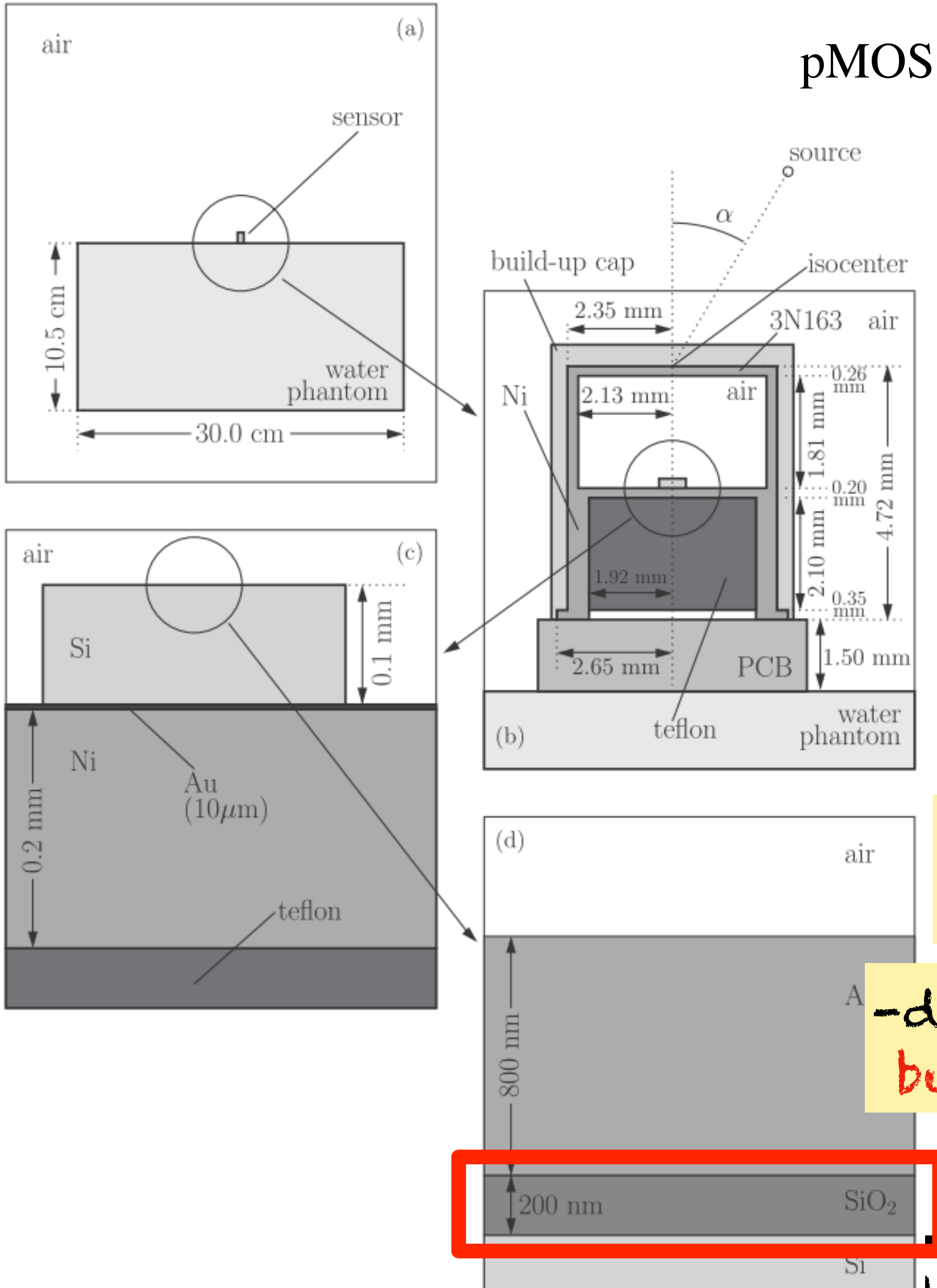

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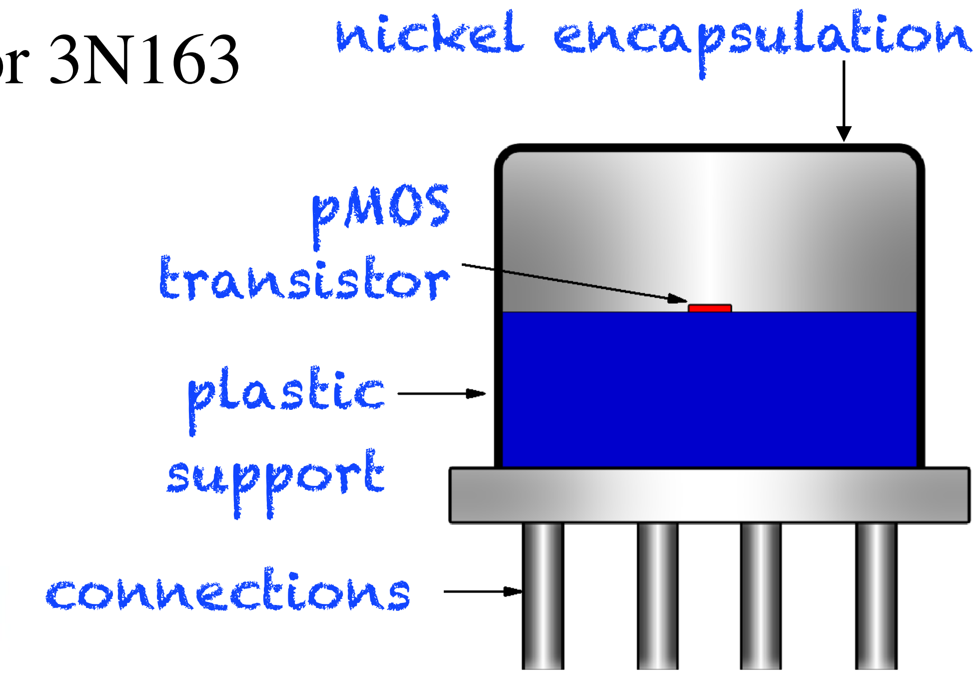

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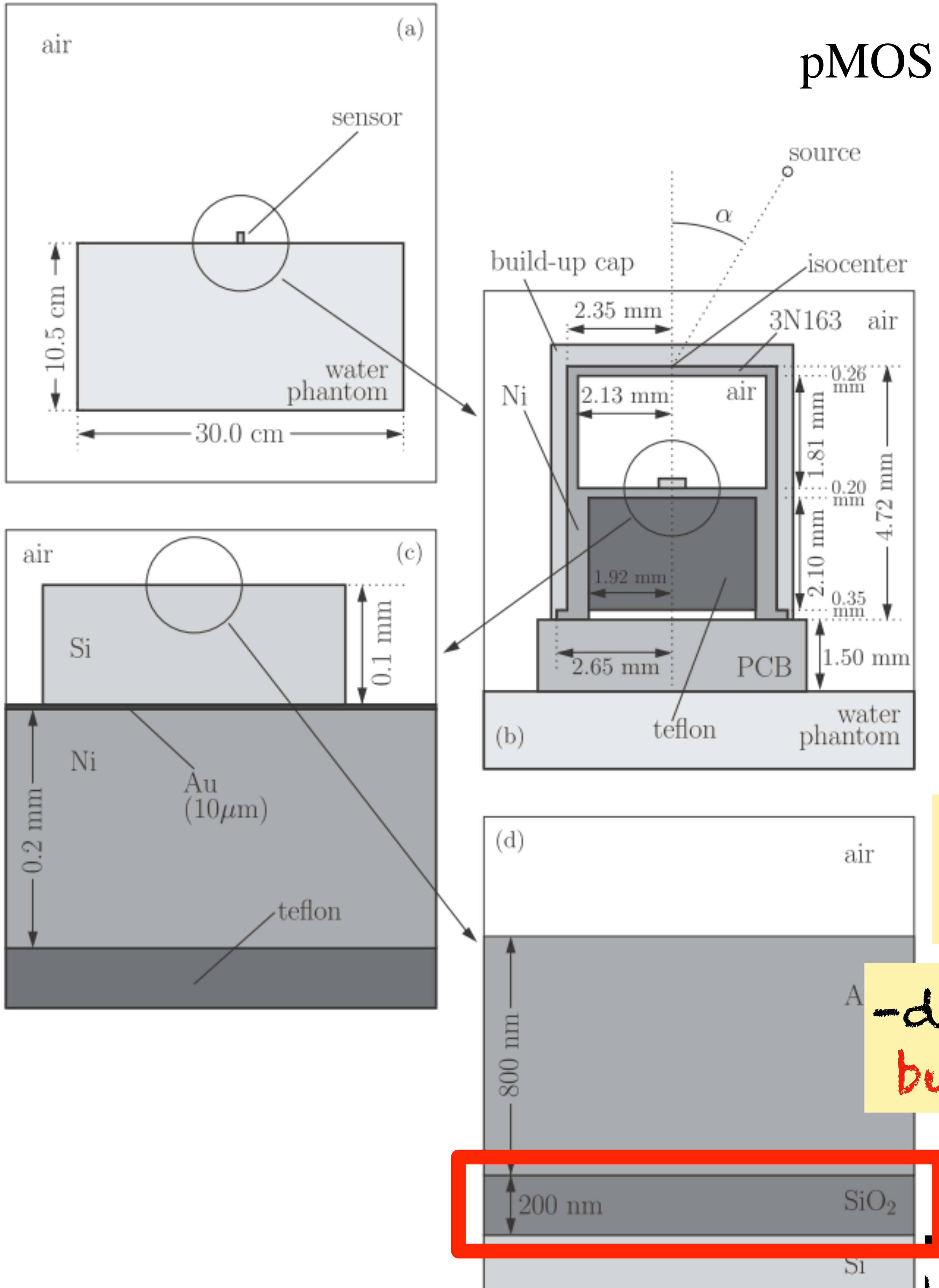

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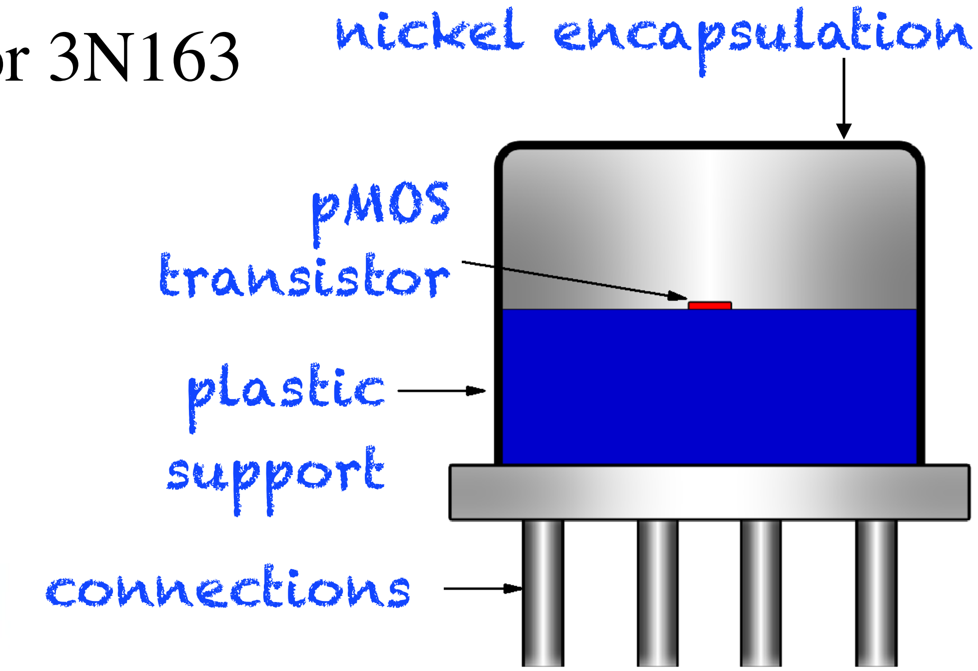

-or use
variance reduction techniques

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Variance reduction techniques in Monte Carlo simulations: ants at work!

Salvador García-Pareja
Hospital Regional Universitario, Málaga, Spain
Antonio M. Lallena
Universidad de Granada, Spain

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UNIVERSIDAD DE GRANADA

Outline

- Introduction
- Ant colony algorithm
- Results
- Conclusions

Introduction

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- interaction forcing
- directional bremsstrahlung splitting
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how to do it?

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- splitting

- Russian roulette

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with weight w_0, moving towards a RoI,
is transformed in $\mathcal{S} > 1$ particles,
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VRT effectiveness depends on:

- $\mathcal{S}$ and $\mathcal{K}$ values
- strategy used for splitting and killing

ant colony algorithm: Implementation

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-ants look for food following random walks
-if food is found, ants come back to the nest depositing pheromone
-ants tend to follow paths with the largest level of pheromone
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nest → particle source

paths → particle trajectories

food → RoI

ants → particles (photons)

pheromone → importance

-a particle source and a RoI are defined
-the whole geometry is divided into virtual cells
-each cell is characterized by an importance value

-importance in a cell tells about the probability that a particle passing through it reaches the ROI

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$$P_i = \frac{\mathcal{W}_i^{\mathrm{C}}}{\mathcal{W}_i^{\mathrm{P}}}$$

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$$k = \begin{cases} \left[5\frac{P(i)}{P(0)} - 5\right], & \text{if } P(i) \le P(0)\,, \\ \left[7\frac{P(i) - P(0)}{1 - P(0)}\right], & \text{if } P(i) > P(0)\,. \end{cases}$$

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- if w·I=1: do nothing

Results

MOSFET used as a in-vivo dosimeter

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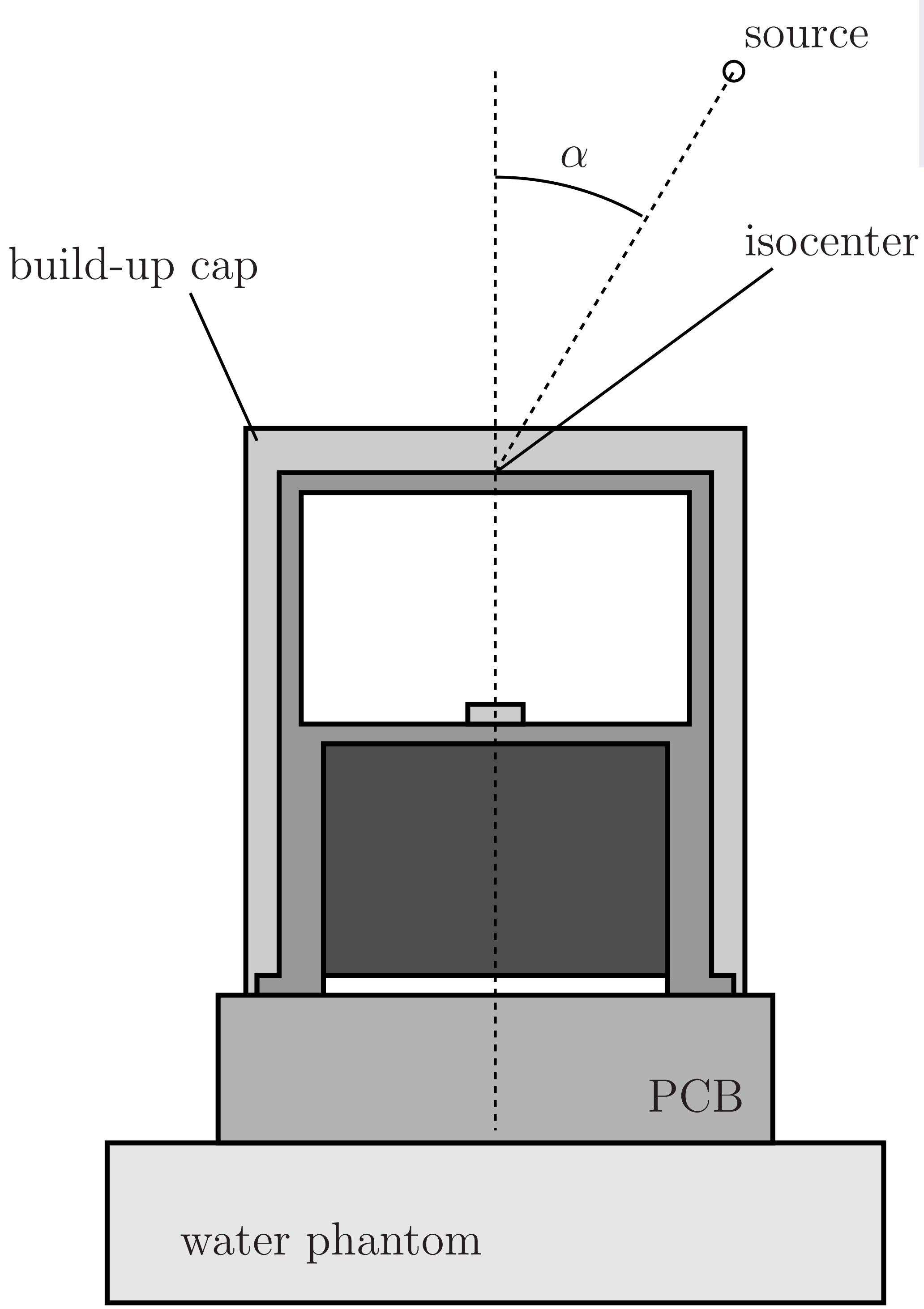
-address the possible angular dependence of the MOSFET response to irradiation



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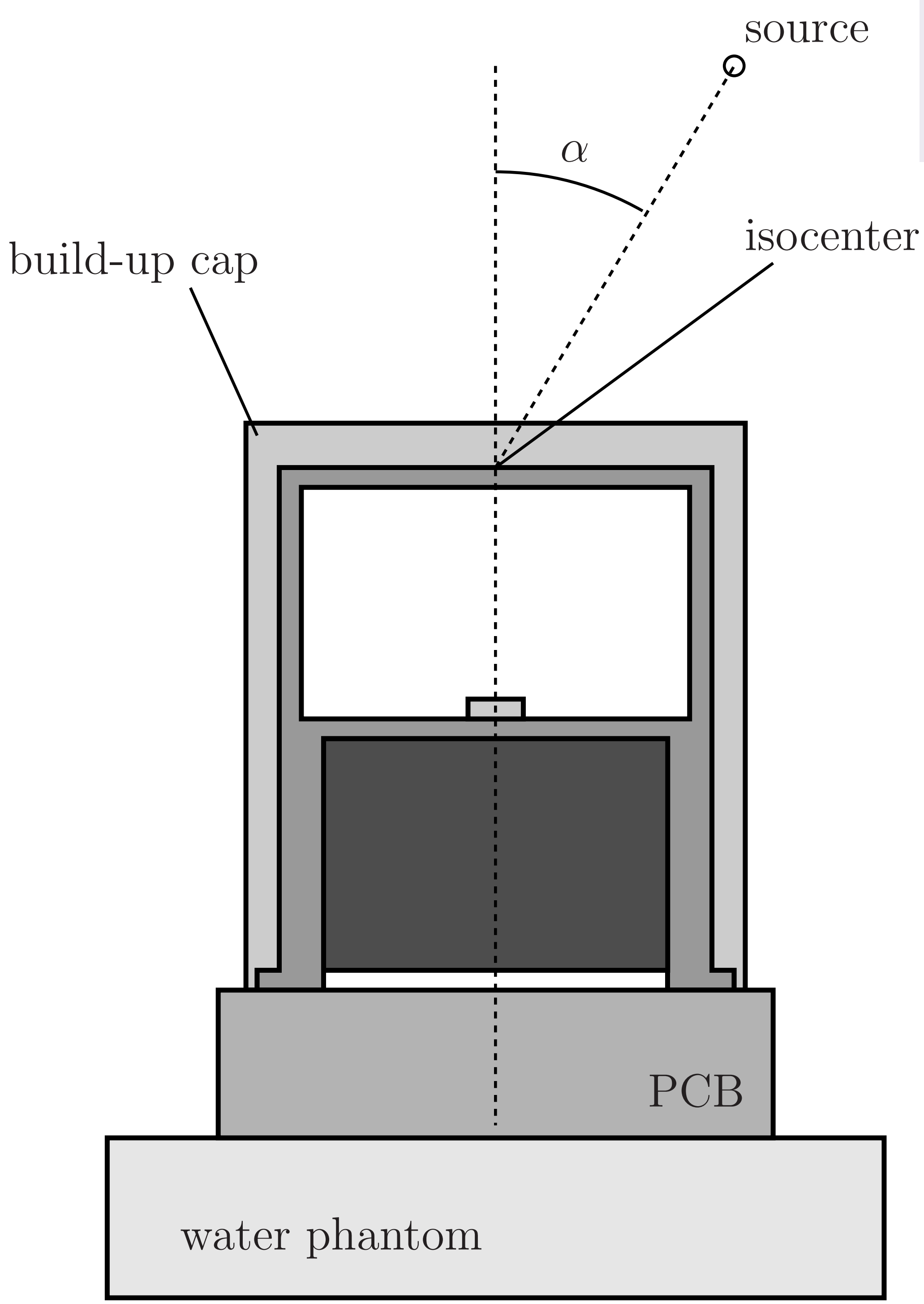

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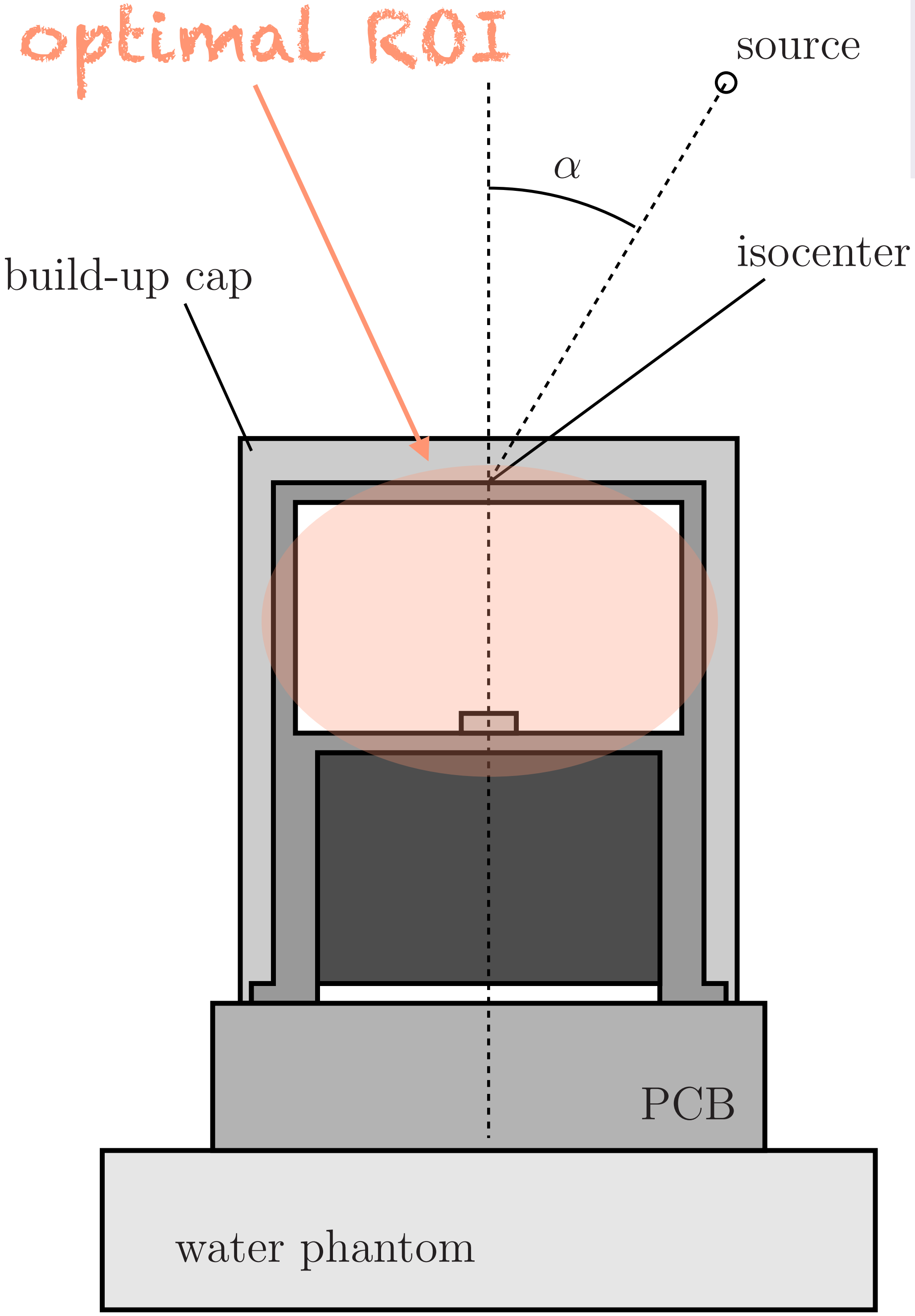

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- optimal RoI:
  - whole Si die + SiO_2 + air
  - a gain factor ~70 to fill the importance map and "human" CPU times to reach reasonable uncertainties

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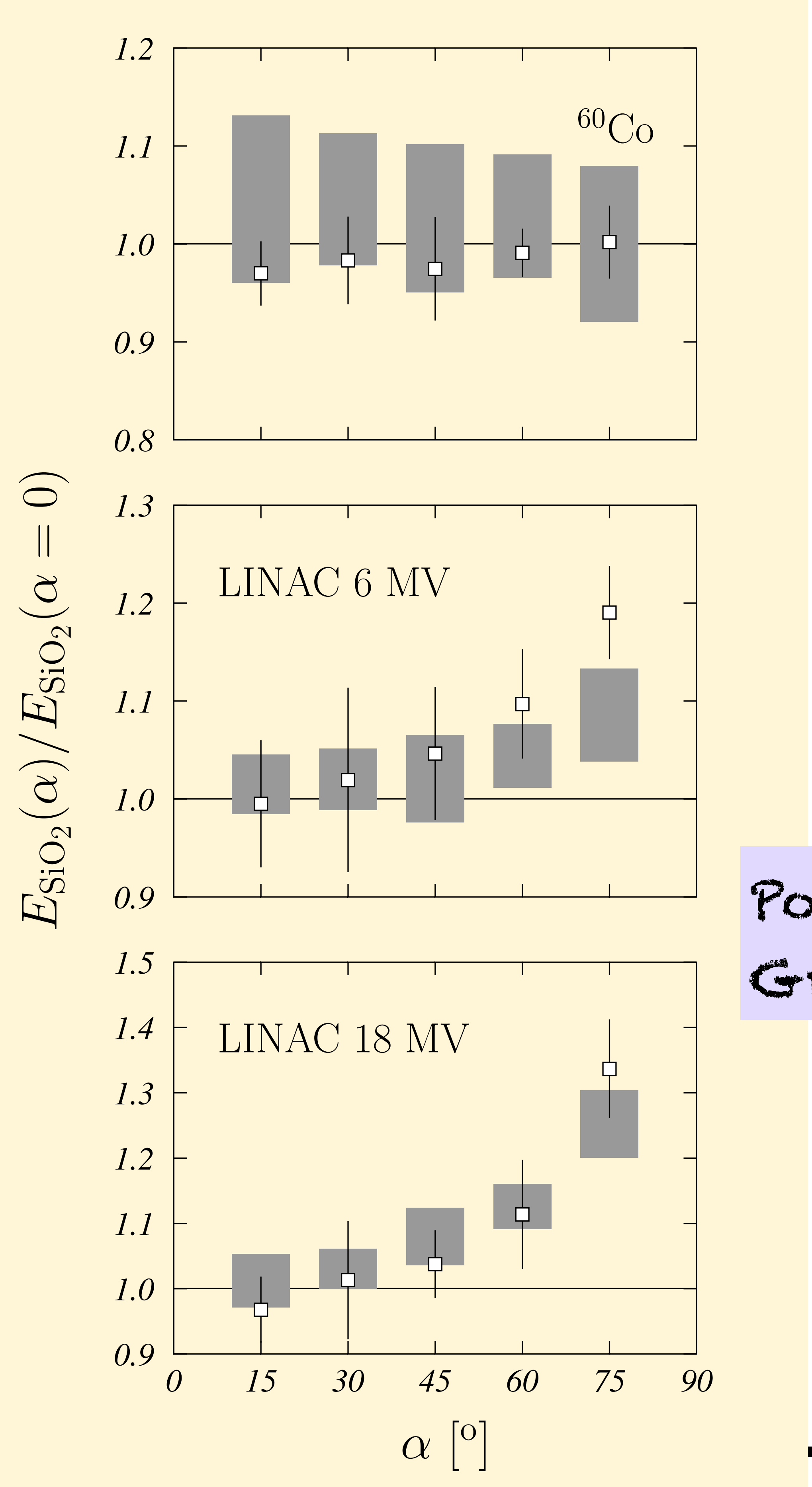
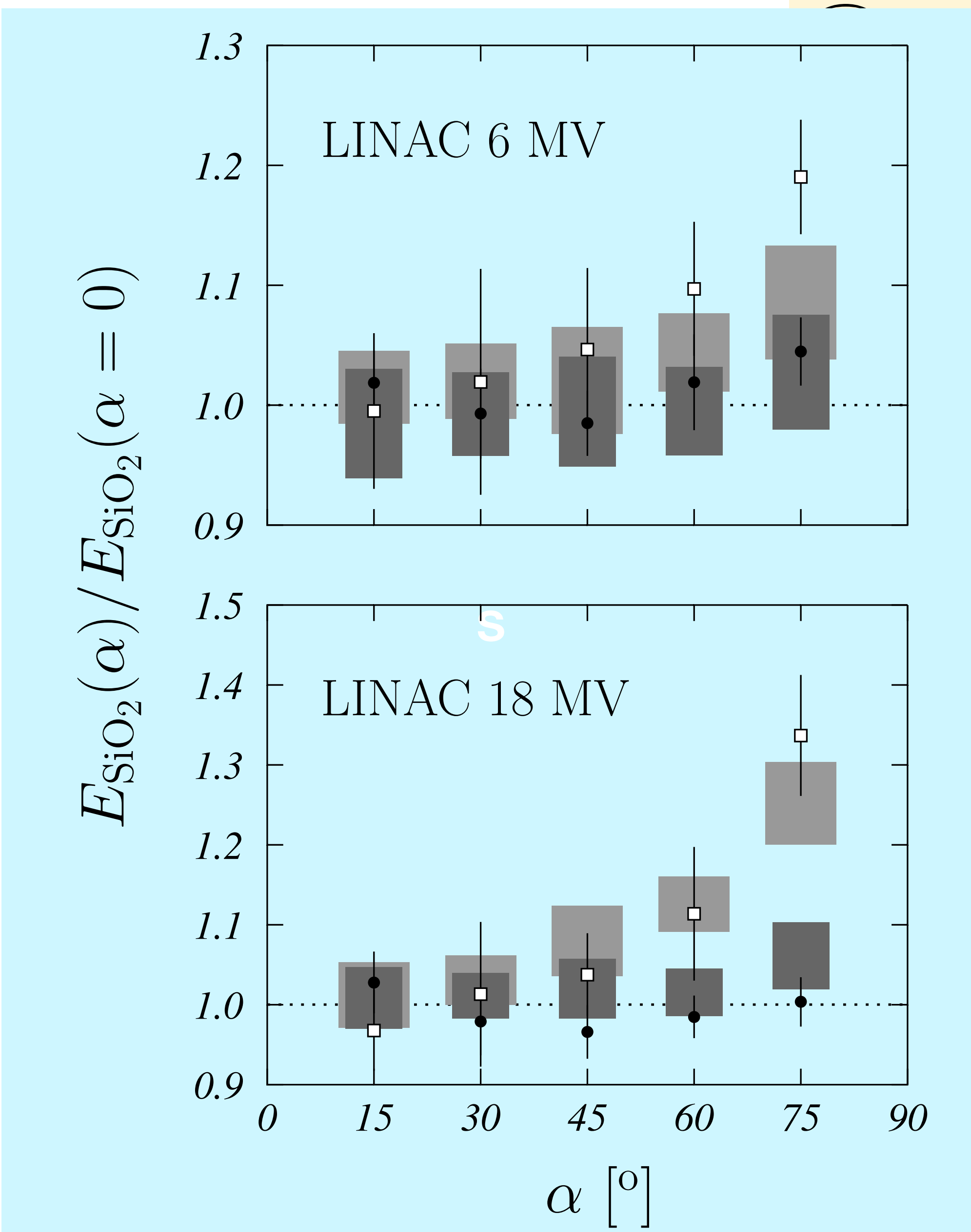
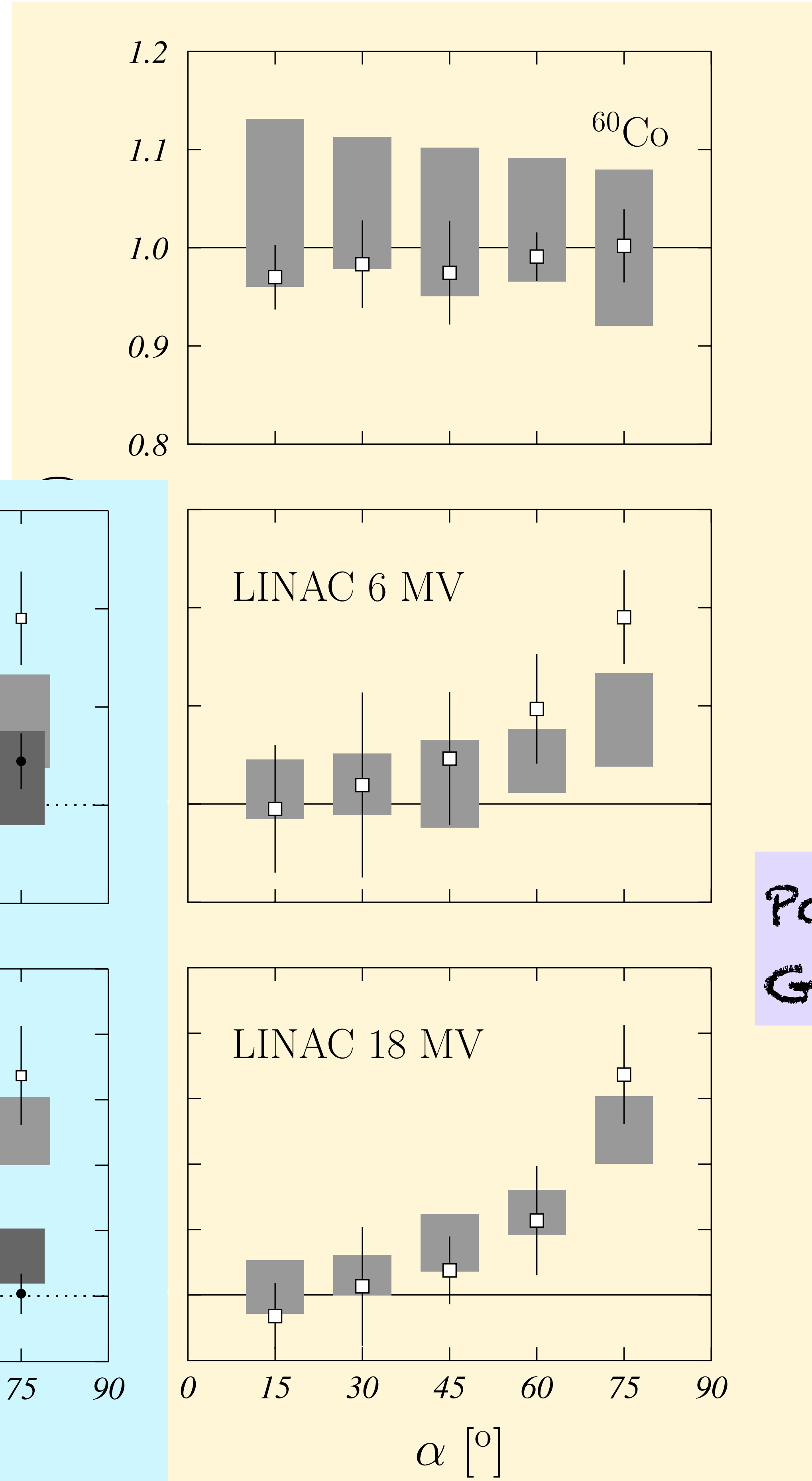


Points: experiment
Gray bands: Monte Carlo

Results





Points: experiment

Gray bands: Monte Carlo

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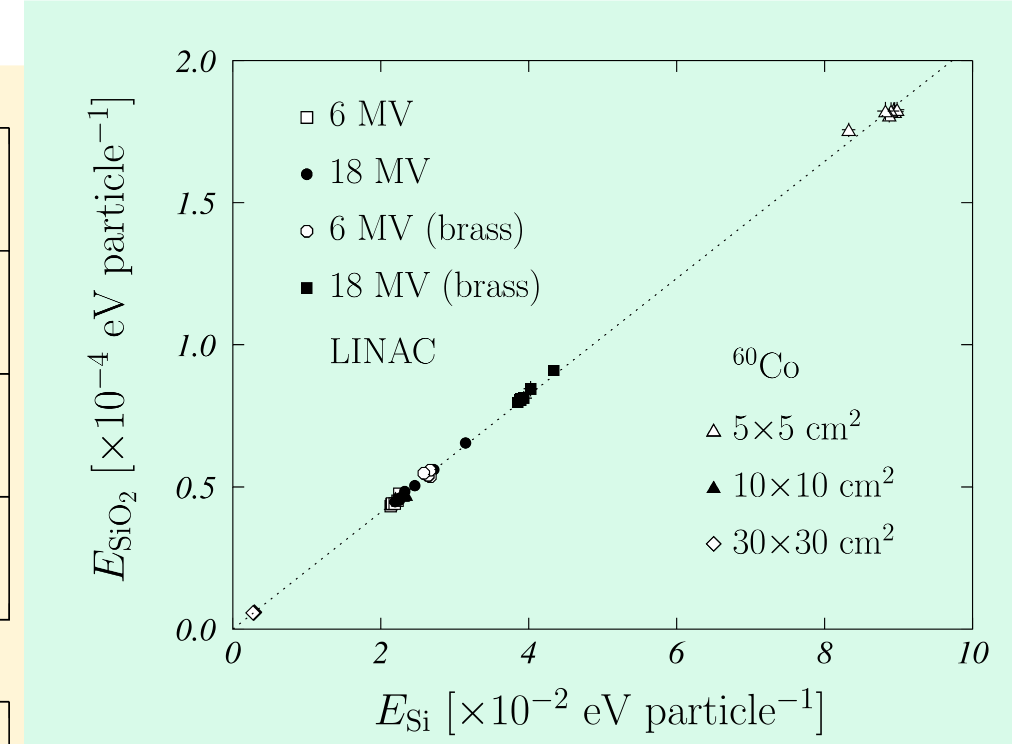

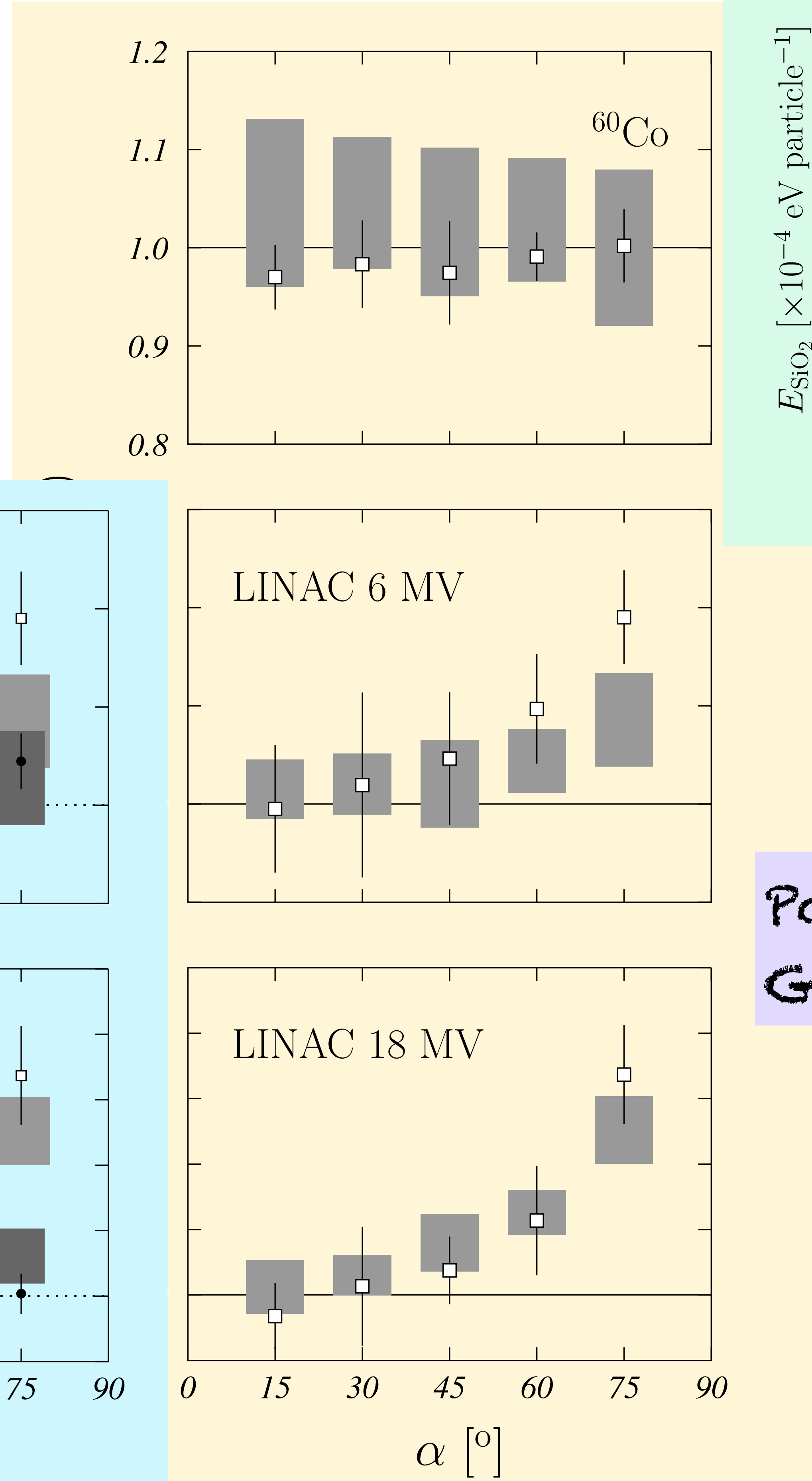

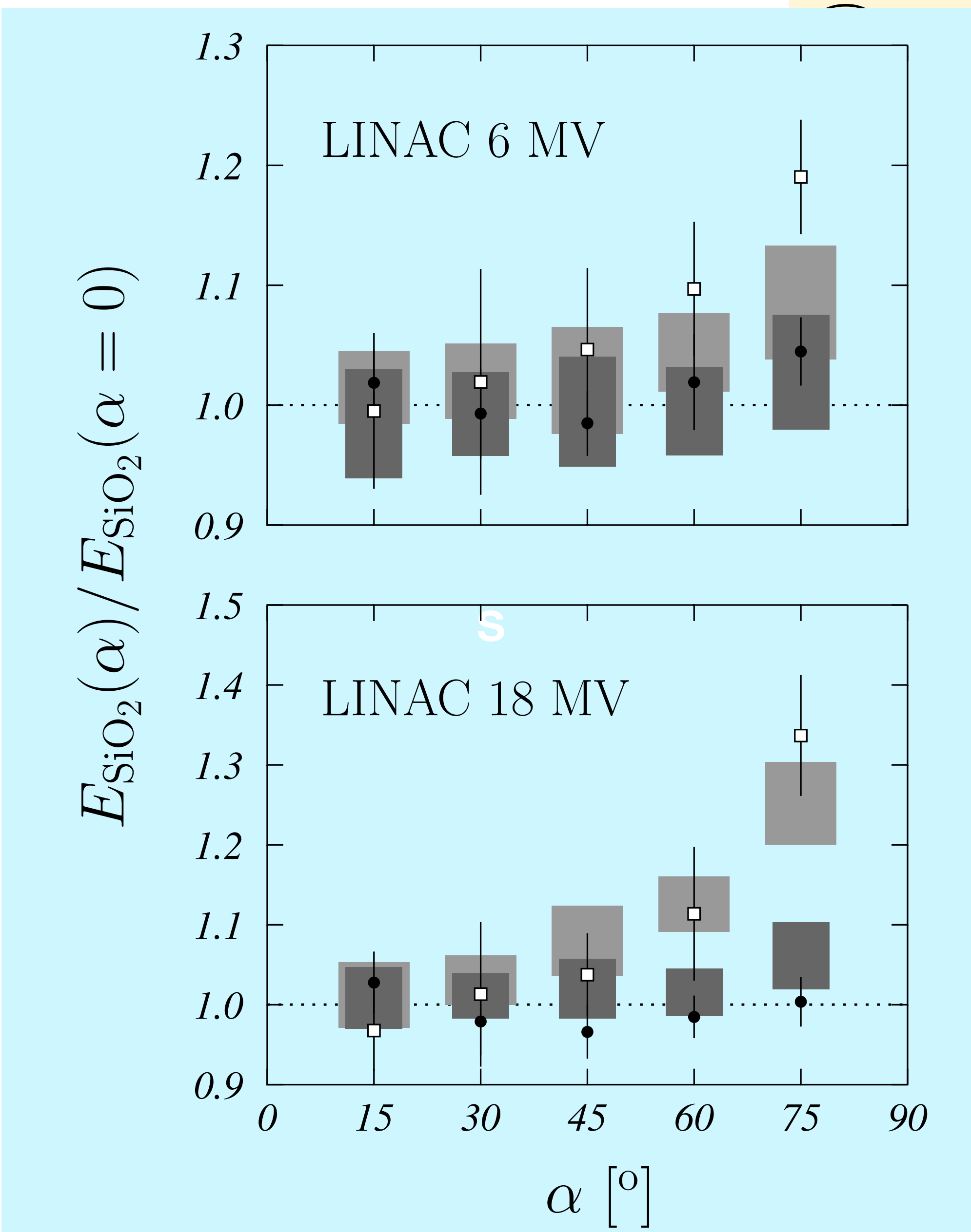

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- Applications in other problems:
  - clinical linacs
  - radiosurgery photon beams (very small fields)
  - specific absorbed fractions (nuclear medicine)
  - correction factors of small ionization chambers

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A. Palma, M.Á. Carvajal Univ. Granada (Spain)
D. Guirado Hosp. Univ. Granada (Spain)
F. Erazo SOLCA Cuenca (Ecuador)
M. Vilches IMOMA Oviedo (Spain)
P. Galán Hosp. Univ. Málaga (Spain)

Variance reduction techniques in Monte Carlo simulations: ants at work!

S. García-Pareja, A. M. Lallena

Thanks !!

Some applications

Photon beams for radio surgery

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-very narrow beams used for treatment of small lesions nearby healthy tissues that have to be preserved
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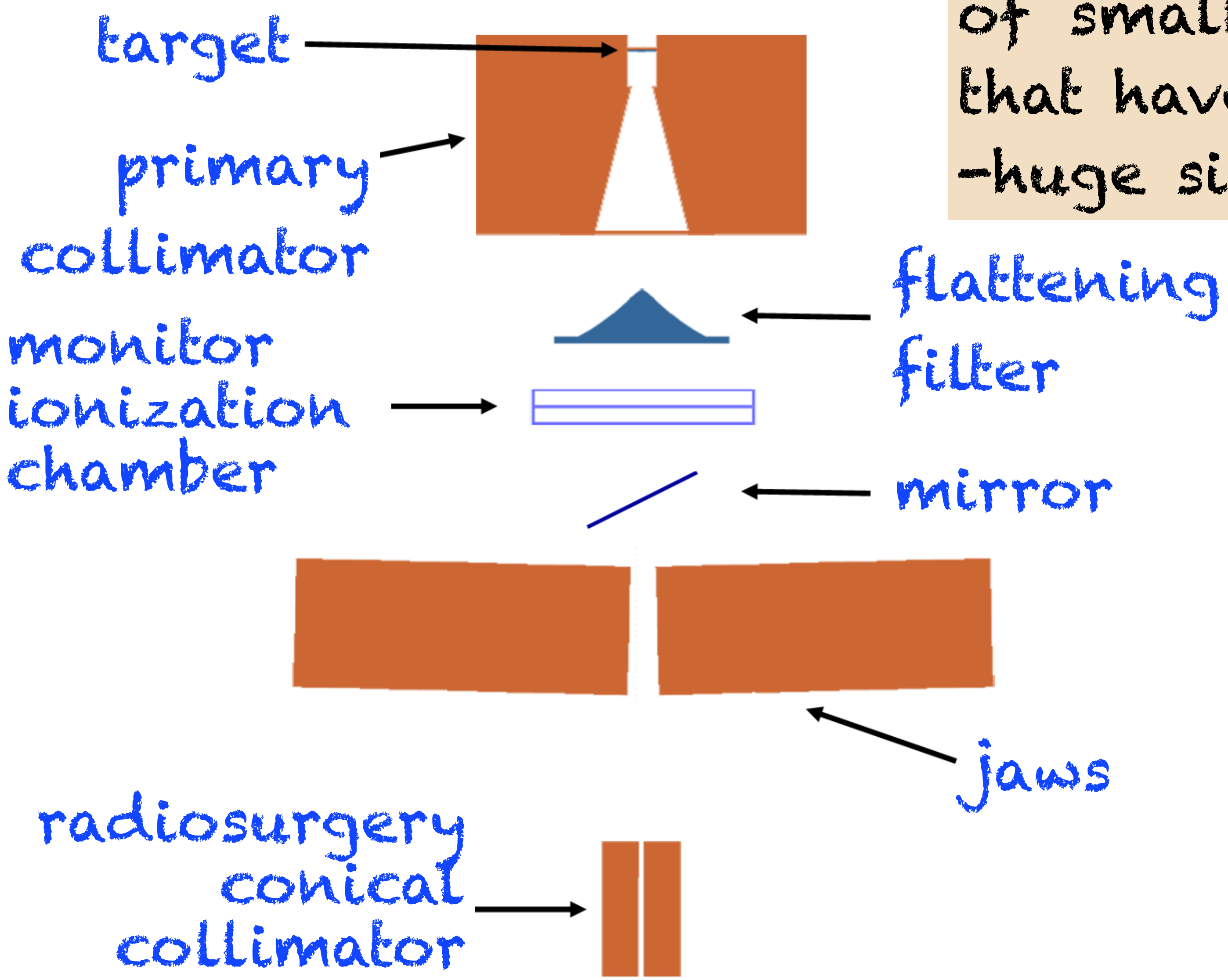

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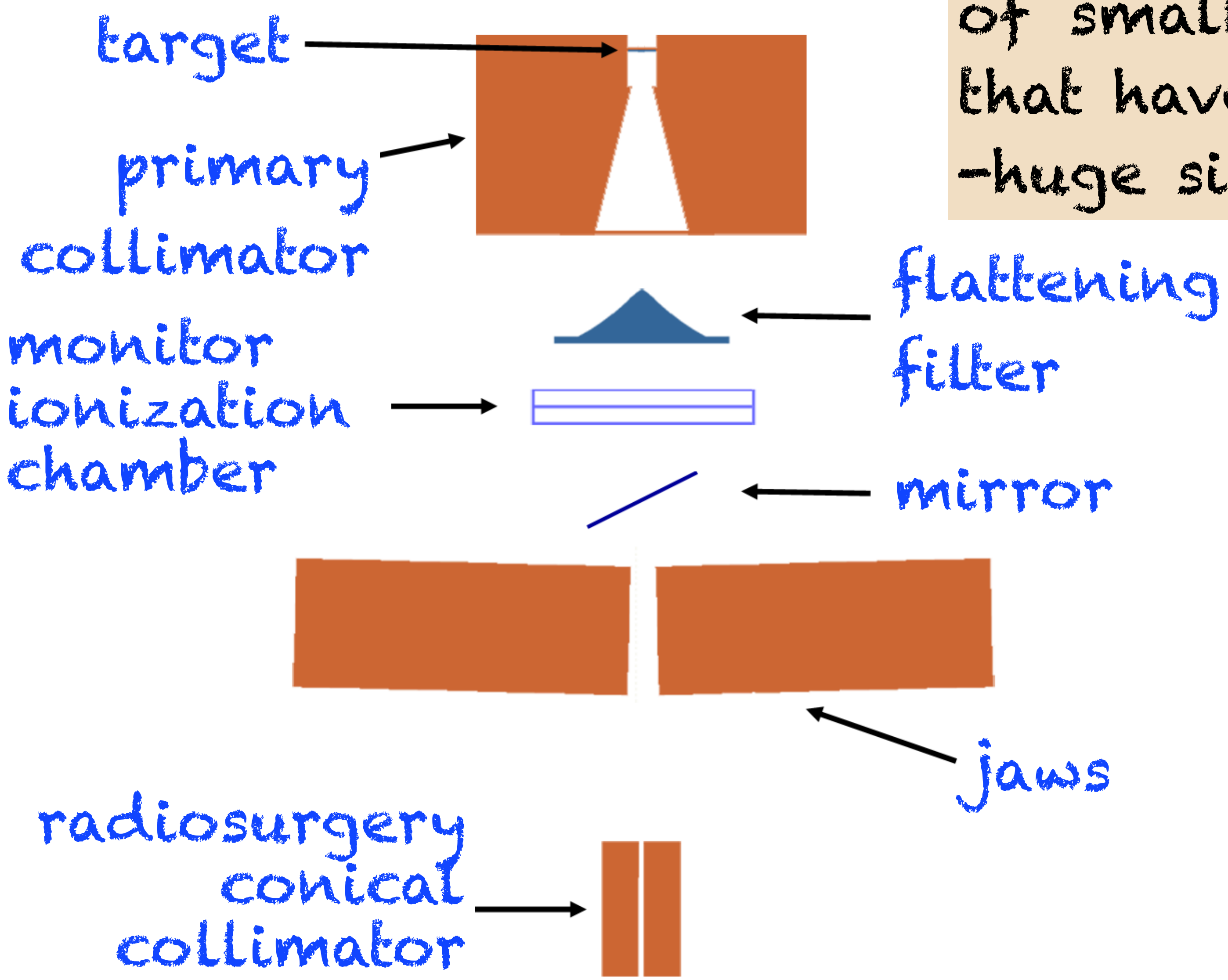

-VRT applied to both electrons and photons

$I_1 = I(x, y, z, E, M)$ for electrons.

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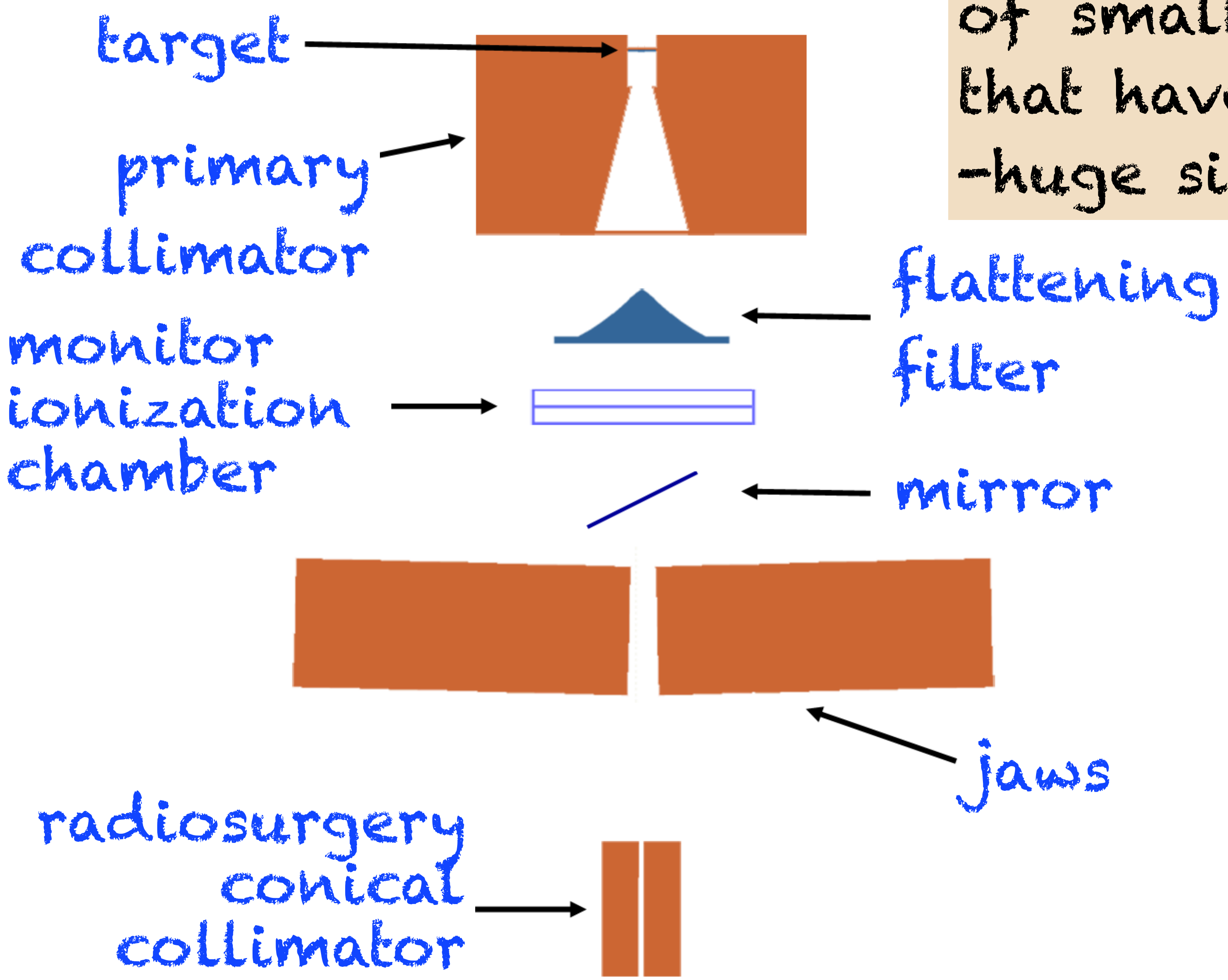

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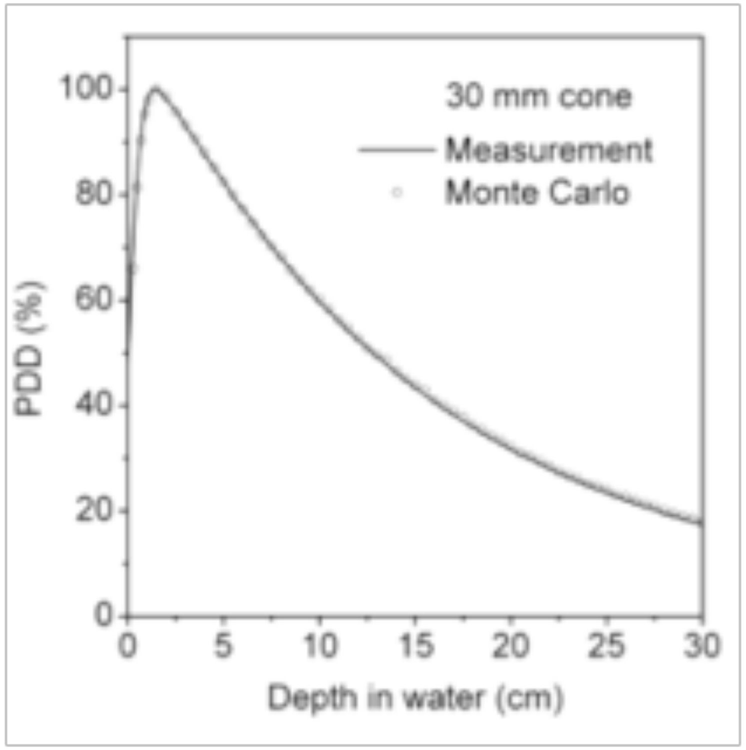

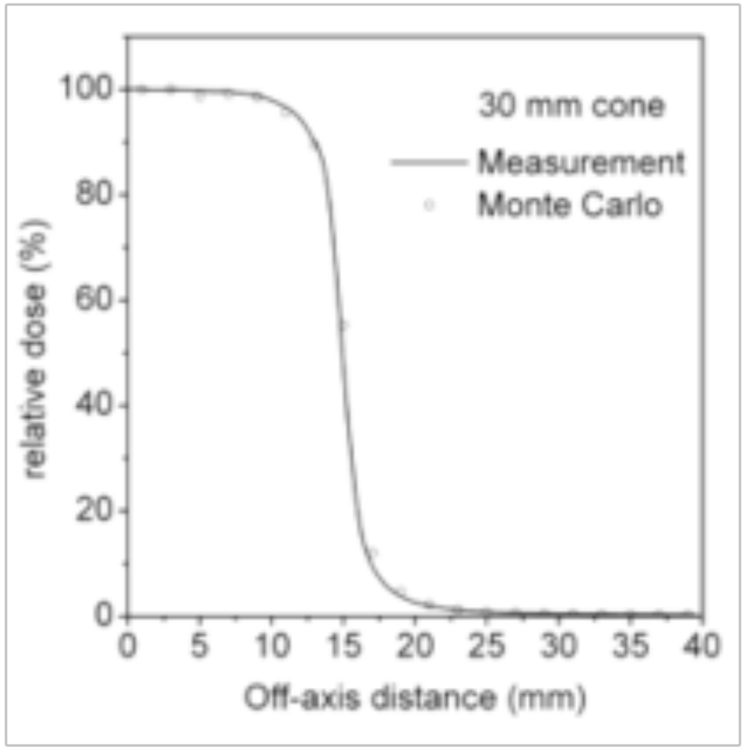

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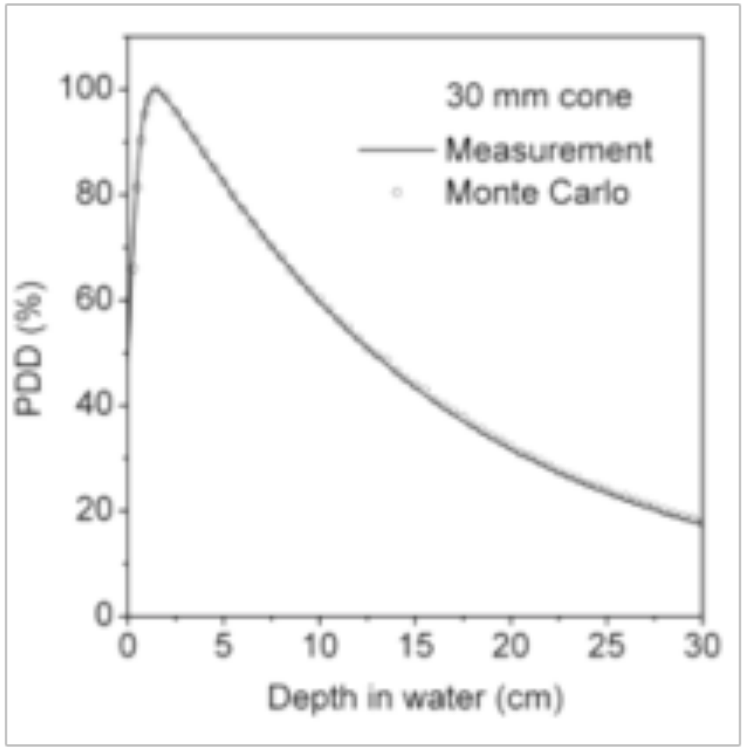

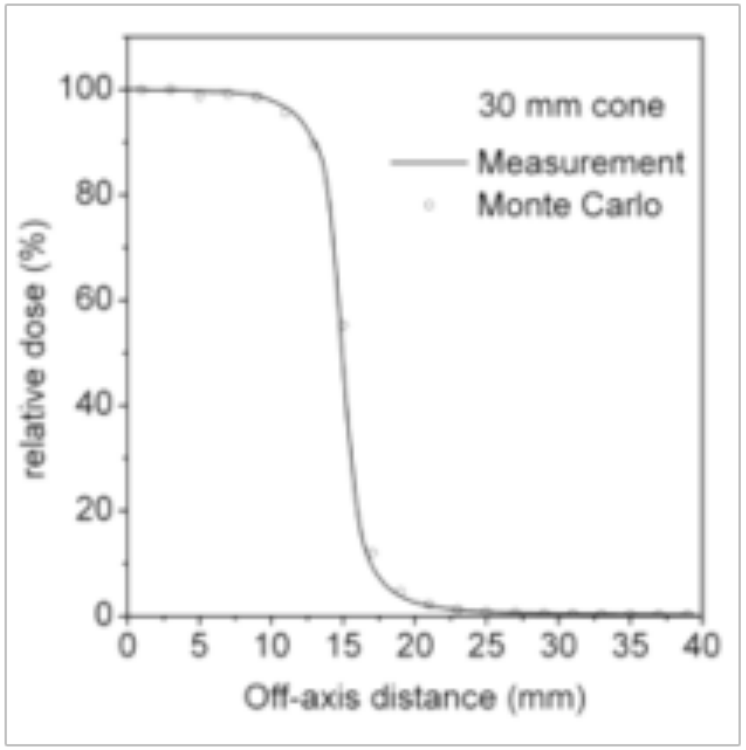

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9 h (10 mm) to 0.9 h (30 mm)

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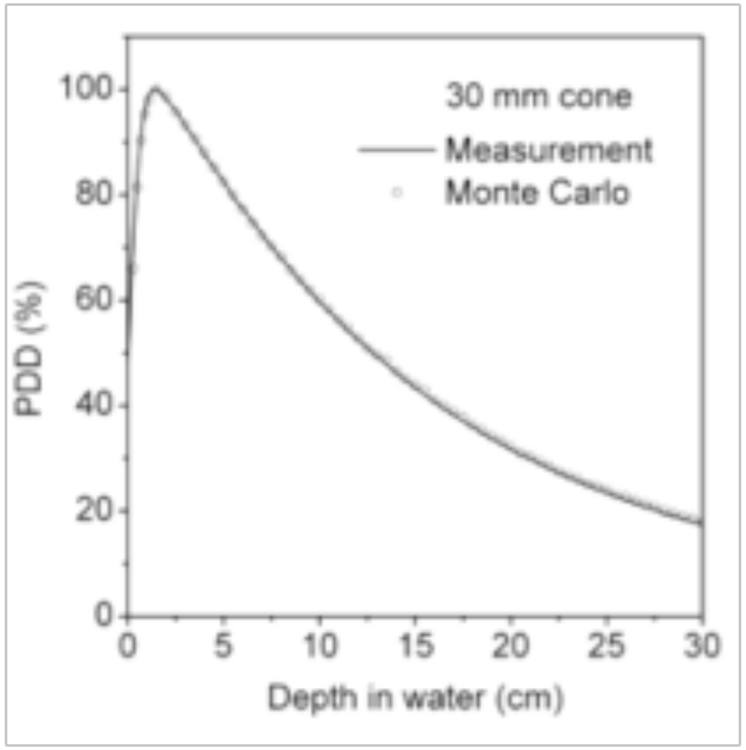

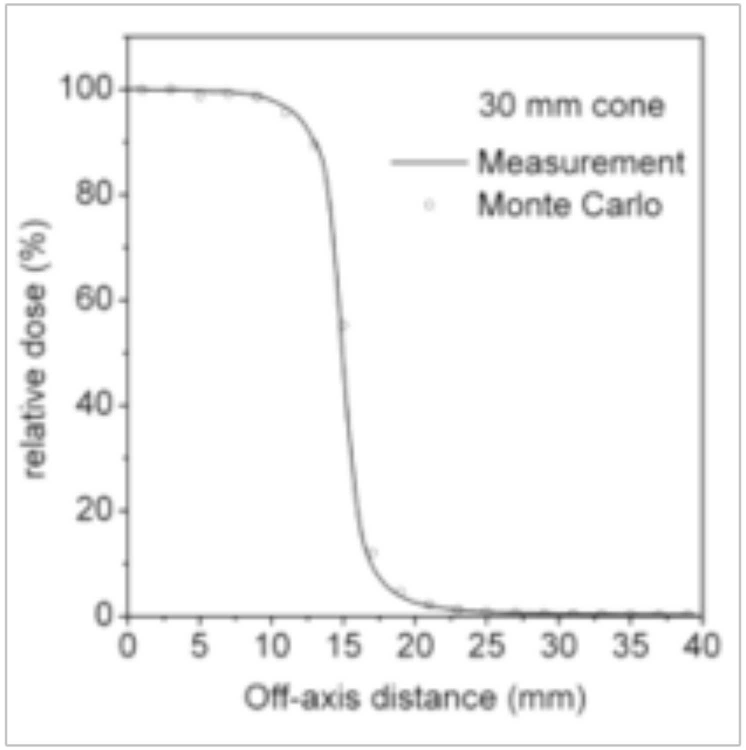

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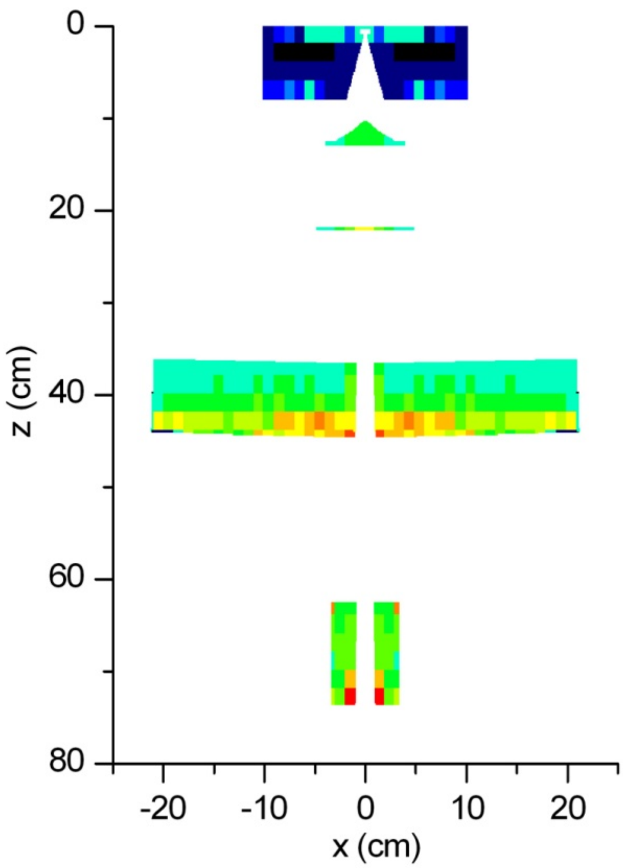
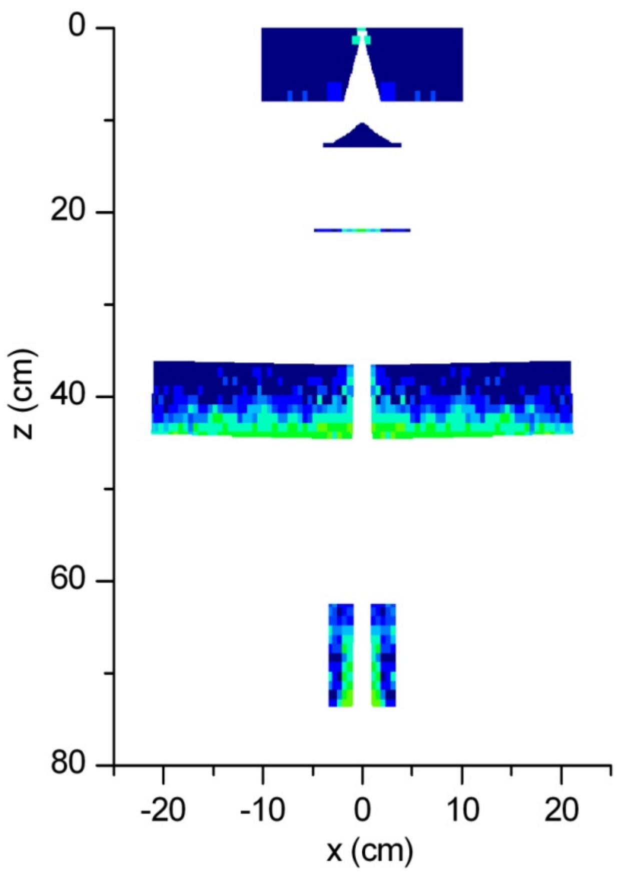


high energy electrons



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-inform about organ/tissue irradiation due to diagnostic or therapy of other organ

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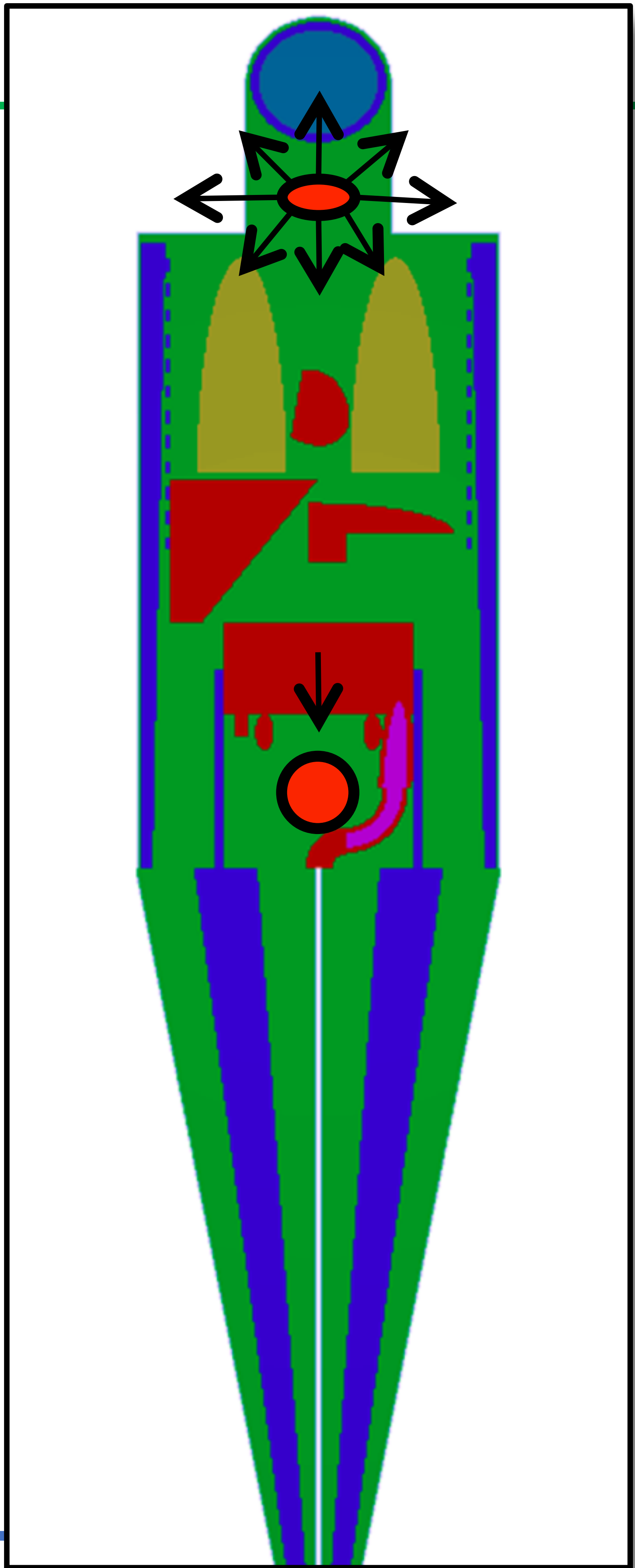

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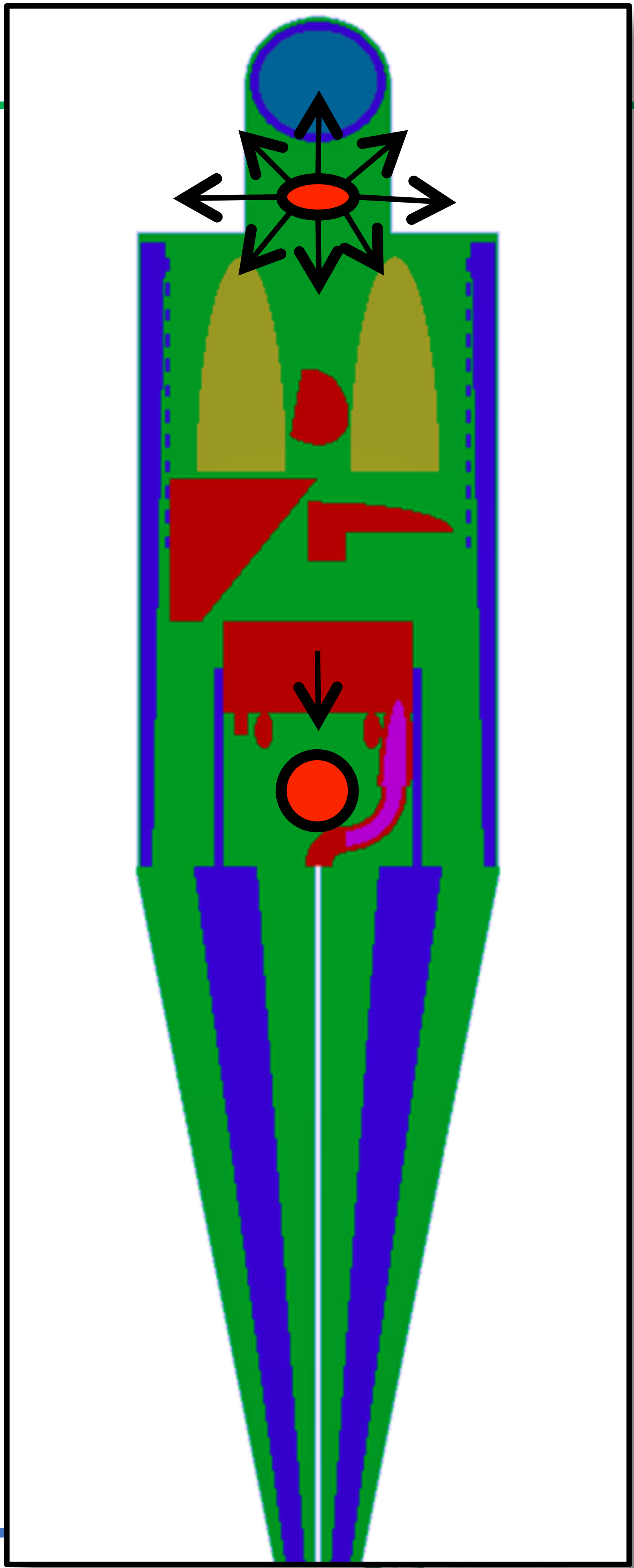

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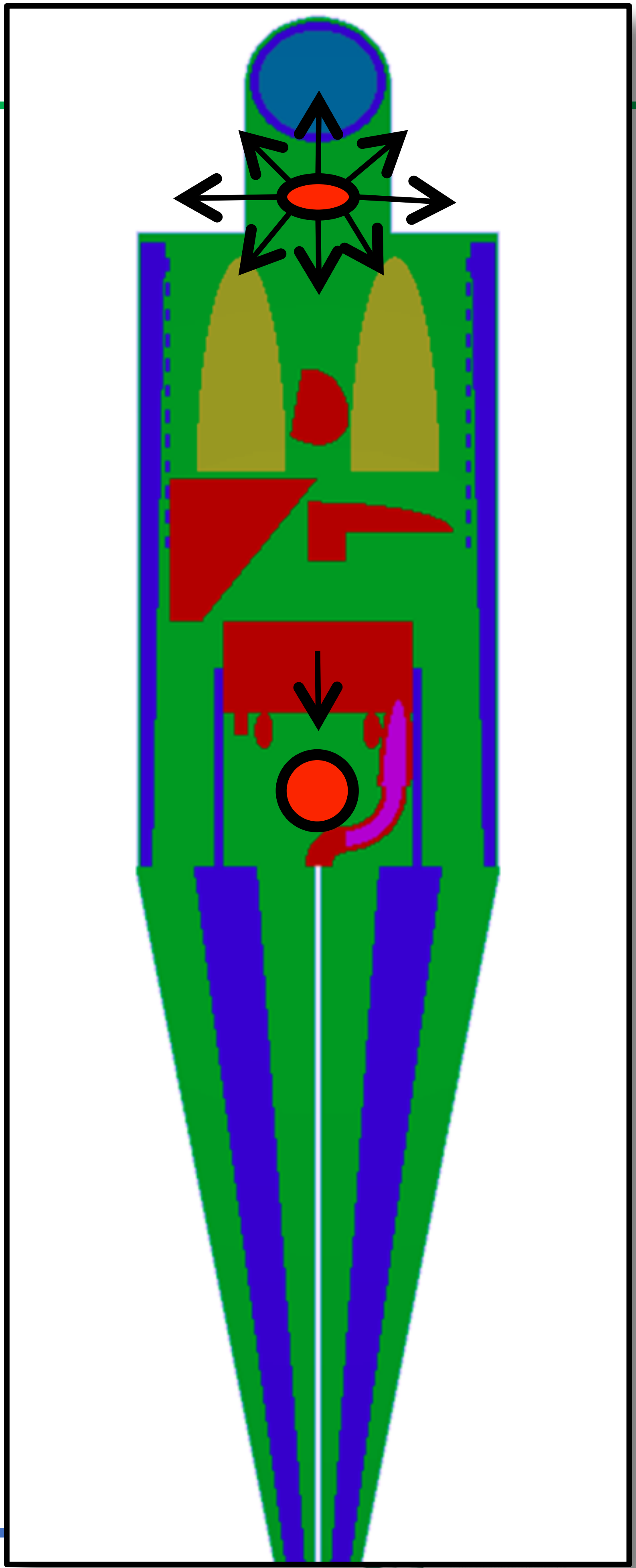

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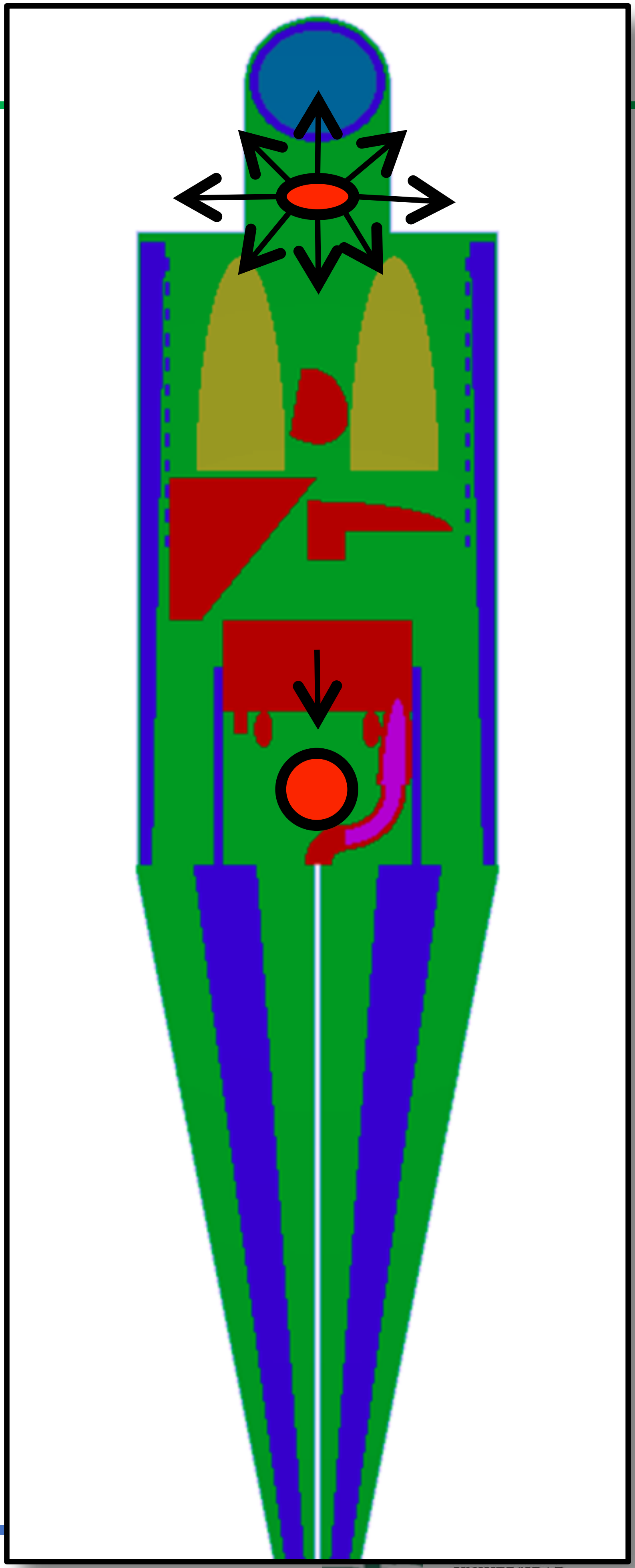

Correction factors of micro-chambers

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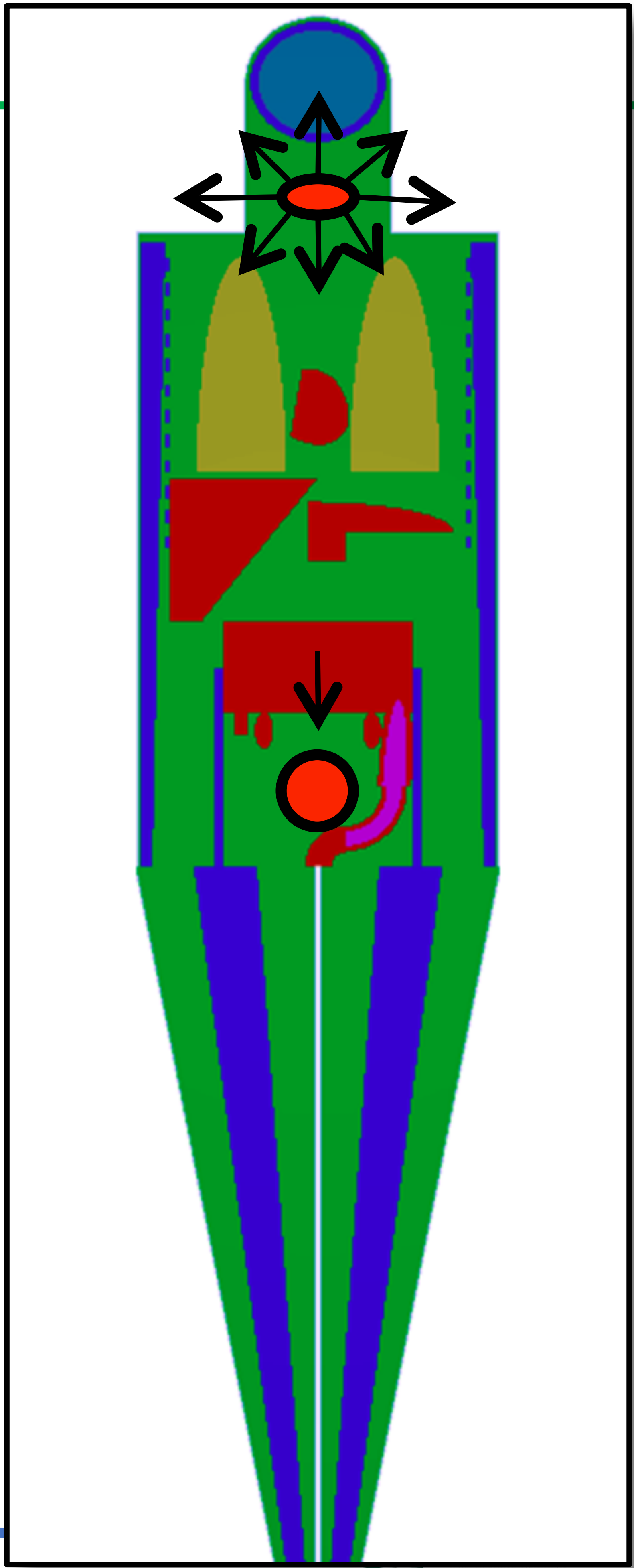

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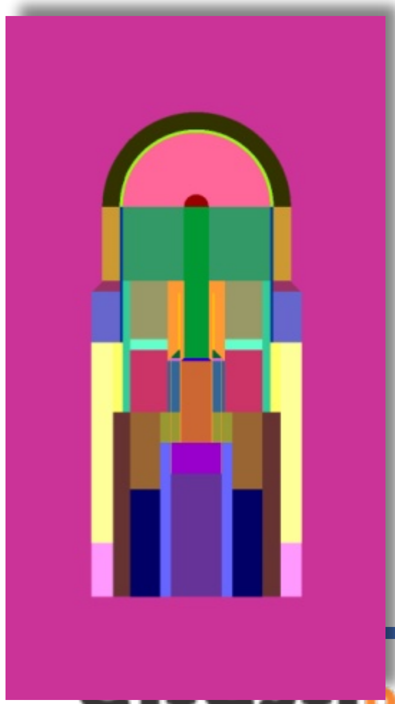

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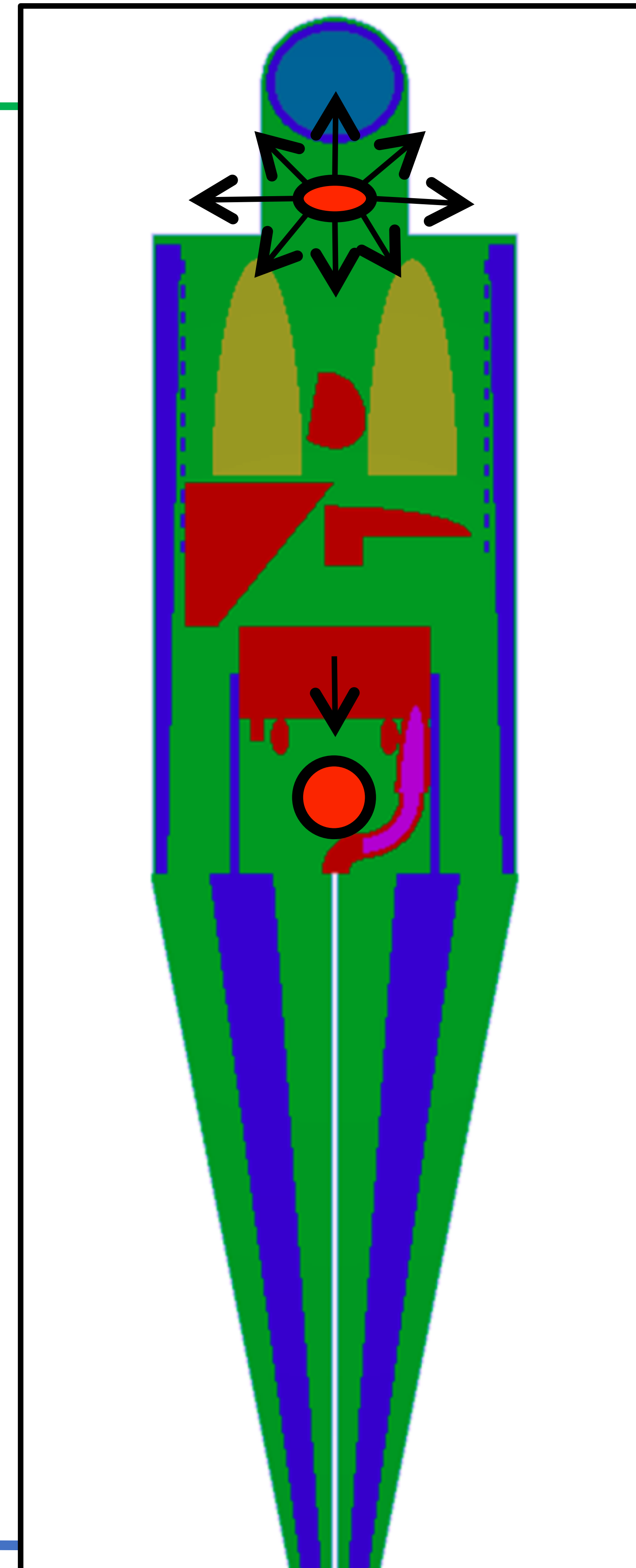

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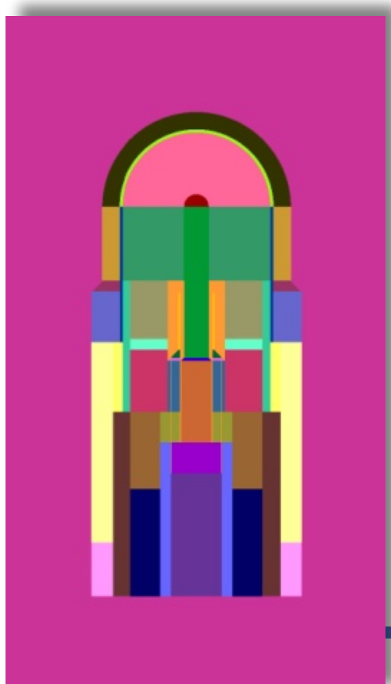

-efficiency increases by a factor 100!!

Conclusions

- An optimization algorithm based on 'ant colony behavior' has been developed
- It allows the efficient implementation of variance reduction techniques
- It uses the information scored on importance maps
- Minimum intervention by the user is required … but details are relevant