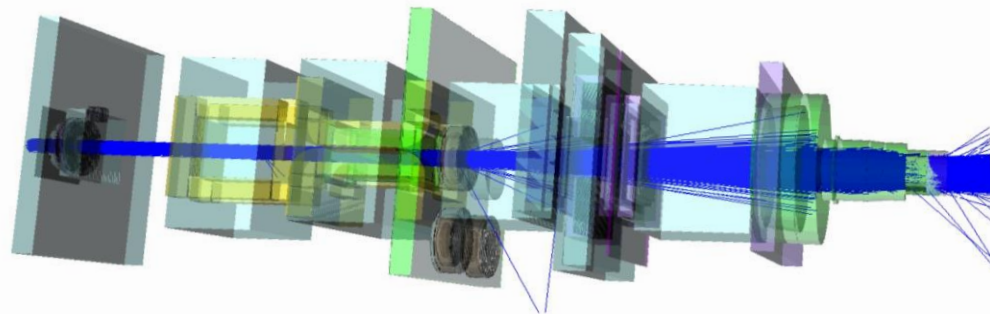


Monte Carlo simulations for research as well as clinical support in proton therapy



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HARVARD
MEDICAL SCHOOL

Harald Paganetti PhD

Professor of Radiation Oncology, Harvard Medical School
Director of Physics Research, Massachusetts General Hospital, Department of Radiation Oncology

Monte Carlo tools

Versatile

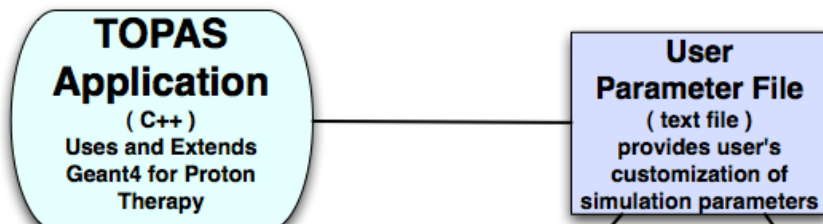
Limited functionality

Tasks

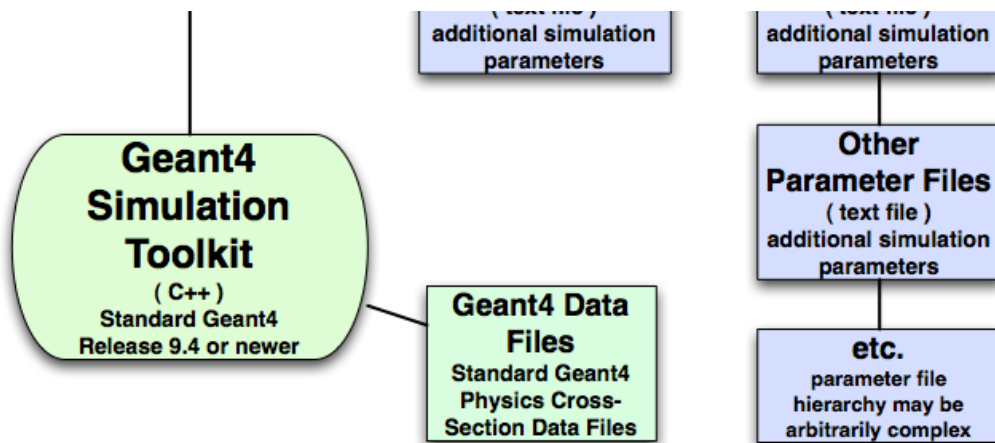




Tool for Particle Simulation

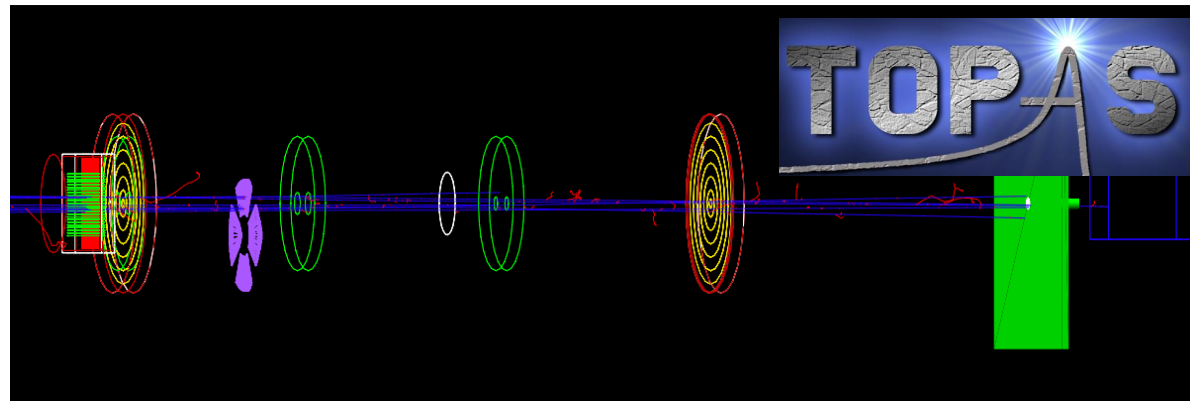
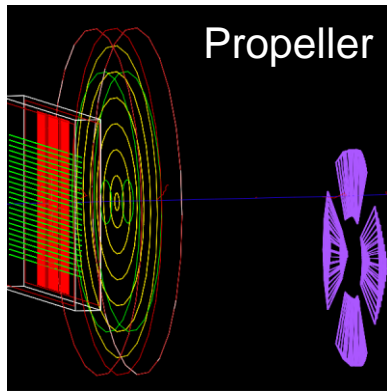


~150 users at ~50 institutions

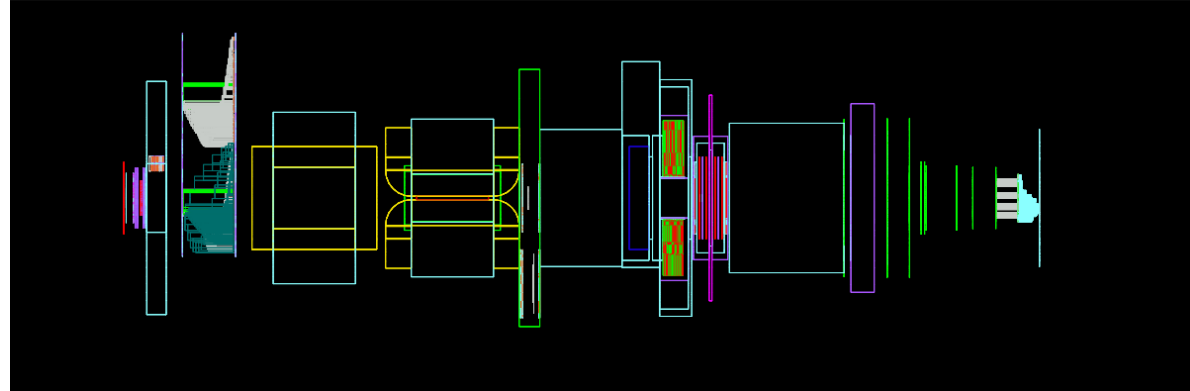
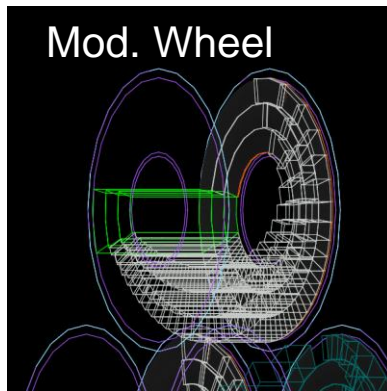


Perl J; Shin J; Schuemann S; Faddegon BA and Paganetti H: TOPAS - An innovative proton Monte Carlo platform for research and clinical applications. Medical Physics 2012 39: 6818-6837

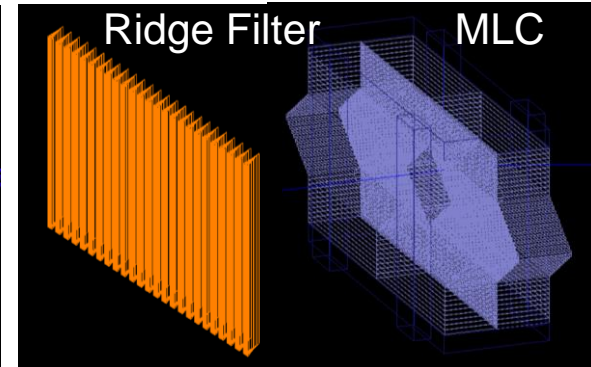
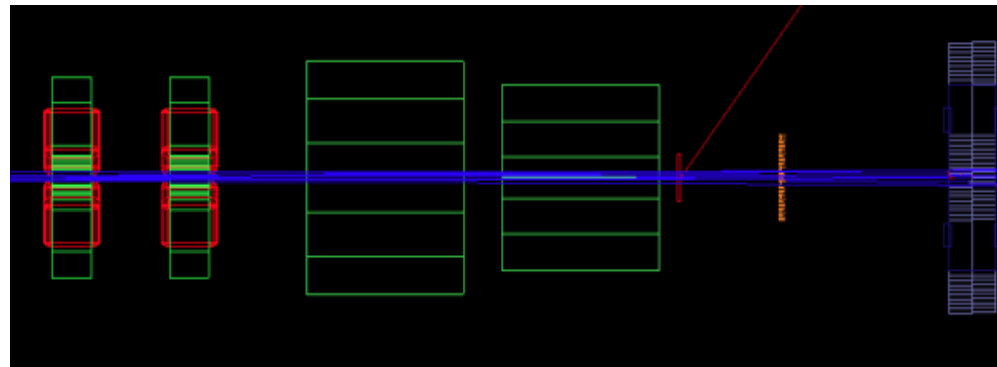
UC Davis
eye
treatment
delivery
system



MGH gantry
treatment
delivery
system

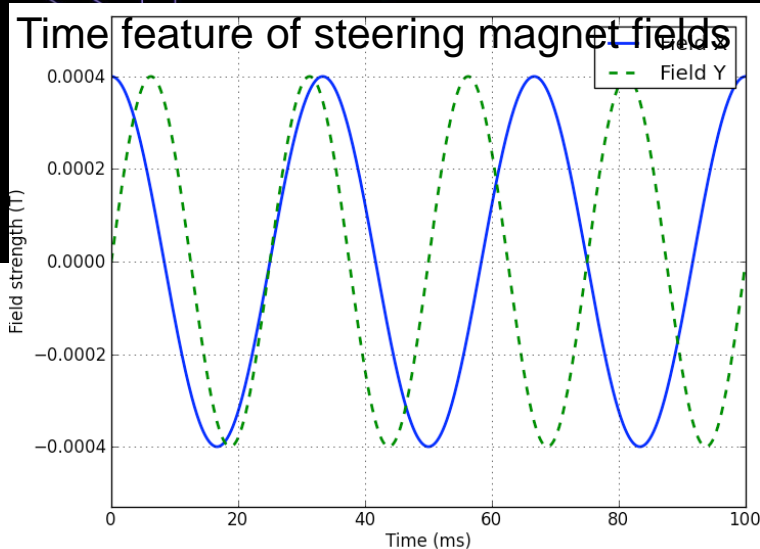
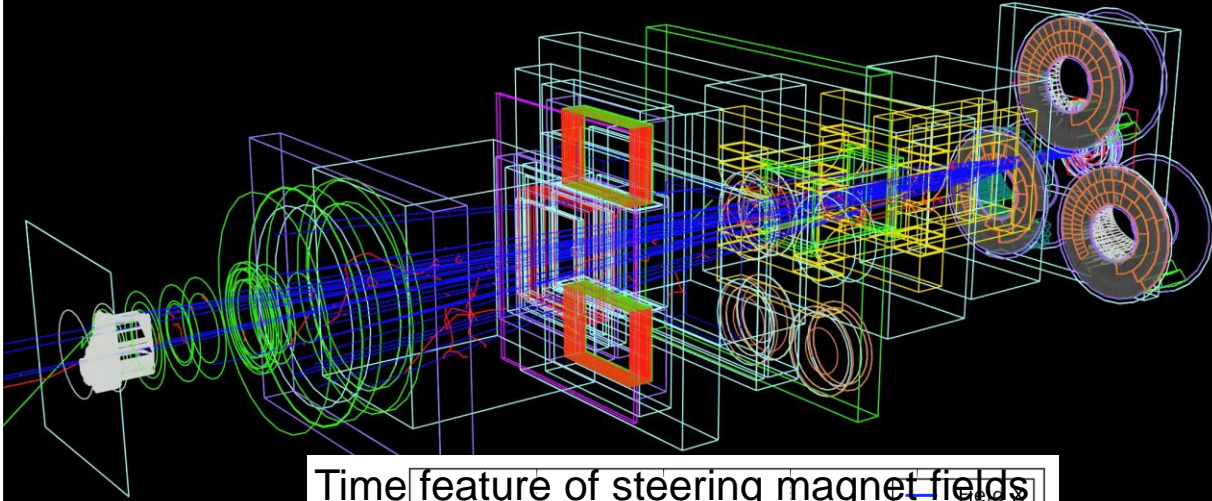


Samsung
Medical
Center



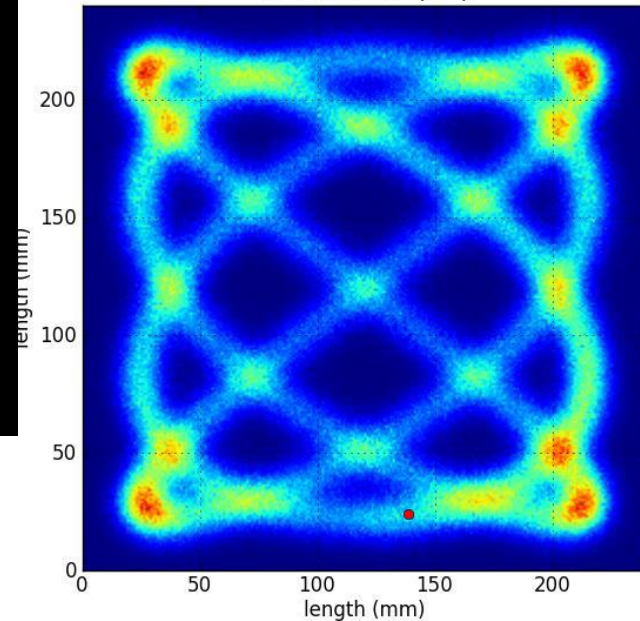
Perl J; Shin J; Schuemann S; Faddegon BA and Paganetti H: TOPAS - An innovative proton Monte Carlo platform for research and clinical applications. Medical Physics 2012 39: 6818-6837

TOPAS



Points of every 0.5 ms

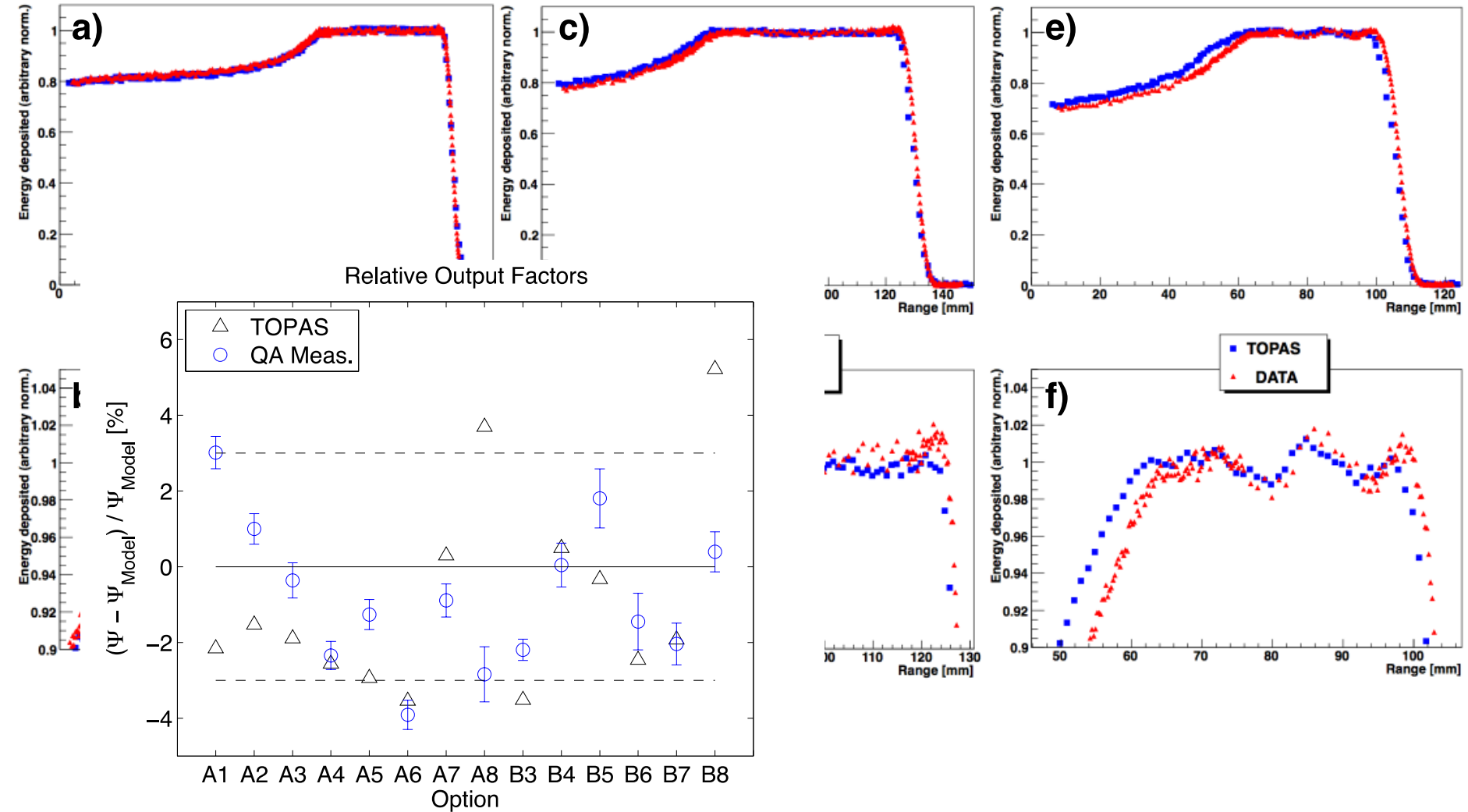
Time 0.0 0.5 (ms)



Shin J; Perl J; Schuemann S; Paganetti H and Faddegon BA: A modular method to handle multiple time-dependent quantities in Monte Carlo simulations. *Physics in Medicine and Biology* 2012 57: 3295-3308



Validation



Testa M; Schümann J; Lu H-M; Shin J; Faddegon B; Perl J and Paganetti H: Experimental validation of the TOPAS Monte Carlo system for proton therapy simulations. Medical Physics 2013 40: 121719

Monte Carlo tools

Versatile

Limited functionality





- Proton transport physics

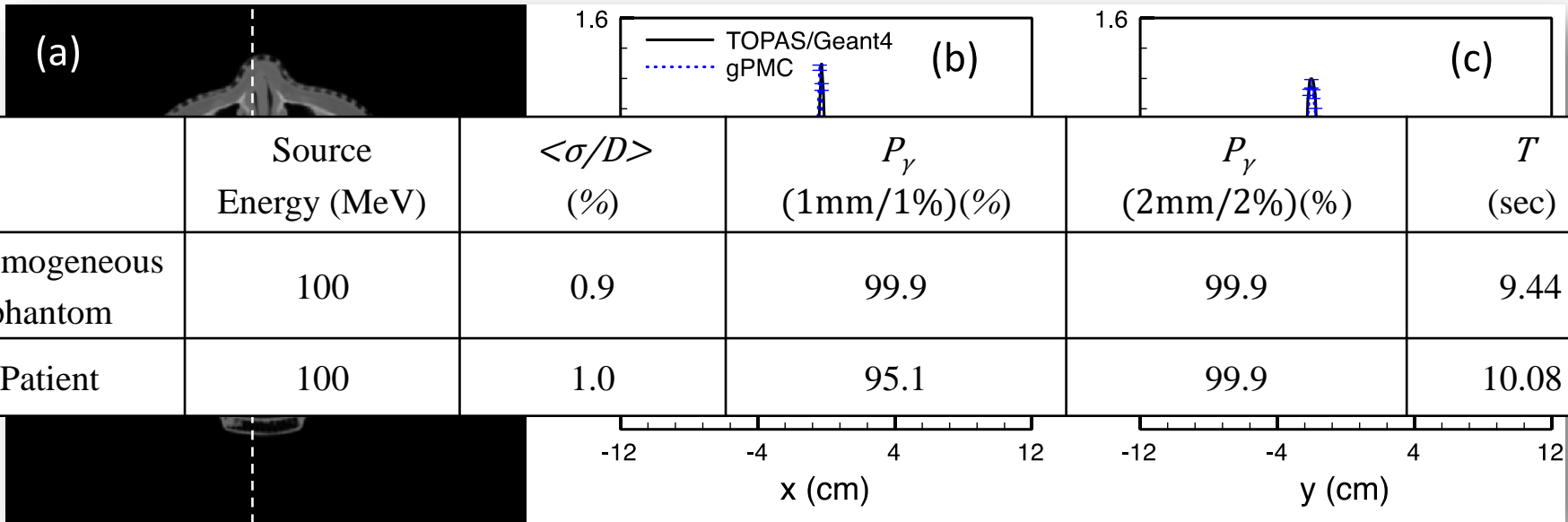
- Physics models

Kawrakow, *Med Phys*, **27**, 485(2000), Fippel *et. al.*, *Med Phys*, **31**, 2263 (2004), Penelope manual (2009), Geant4 physics manual (2011)

- Multiple scattering and energy straggling

- Nuclear interaction is handled by an empirical strategy

Fippel *et. al.*, *Med Phys*, **31**, 2263(2004)



Jia X; Schuemann J; Paganetti H and Jiang SB: GPU-based fast Monte Carlo dose calculation for proton therapy. *Physics in Medicine and Biology* 2012 57: 7783-7798



Monte Carlo tools

Versatile

Limited
functionality



Research

Tasks



Monte Carlo for Research

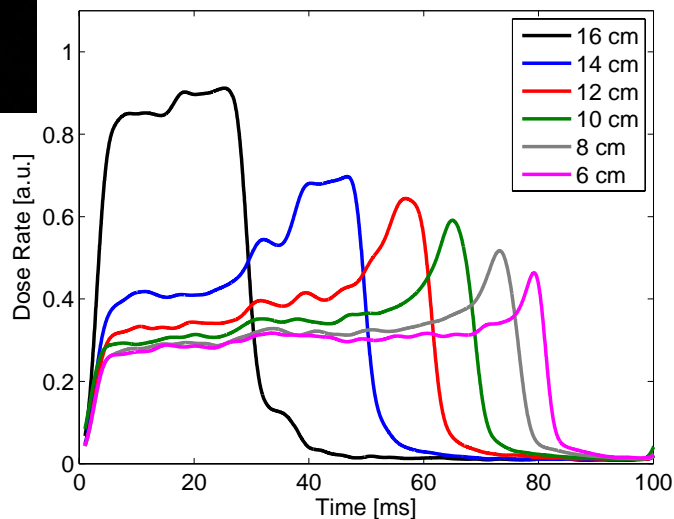
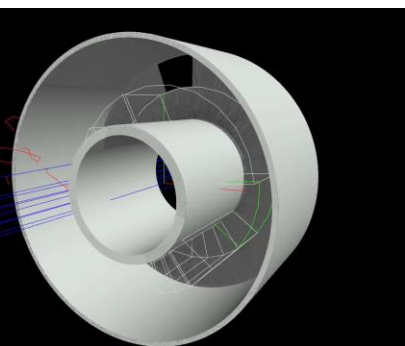
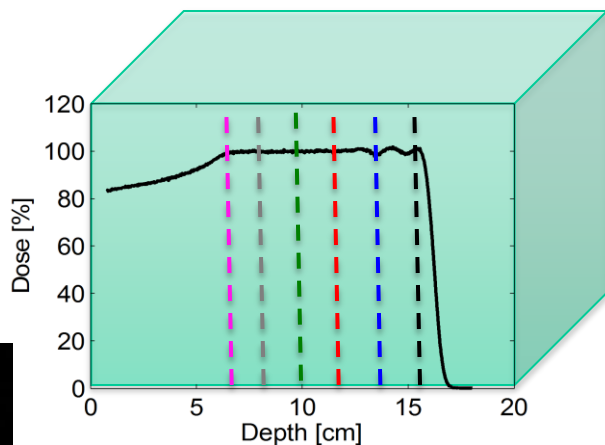
Example:

New concepts using prompt gamma range verification

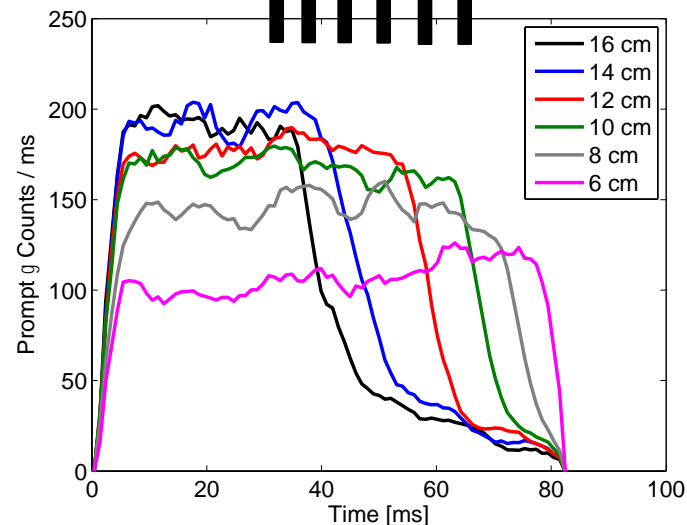
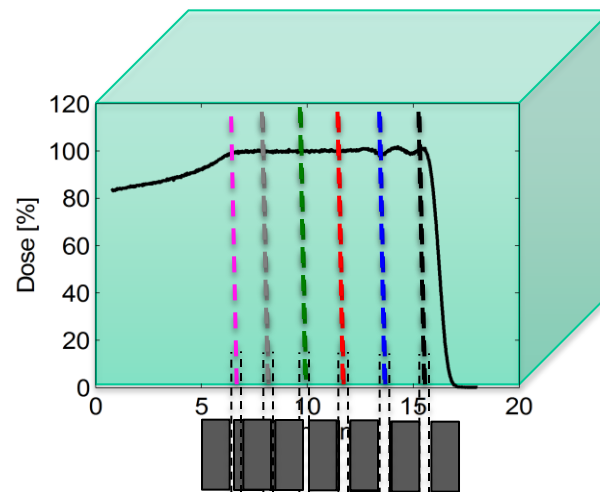


Correlation of Prompt Gamma Rate Functions with position along an SOBP

Dose Rate Functions: IC Measurements

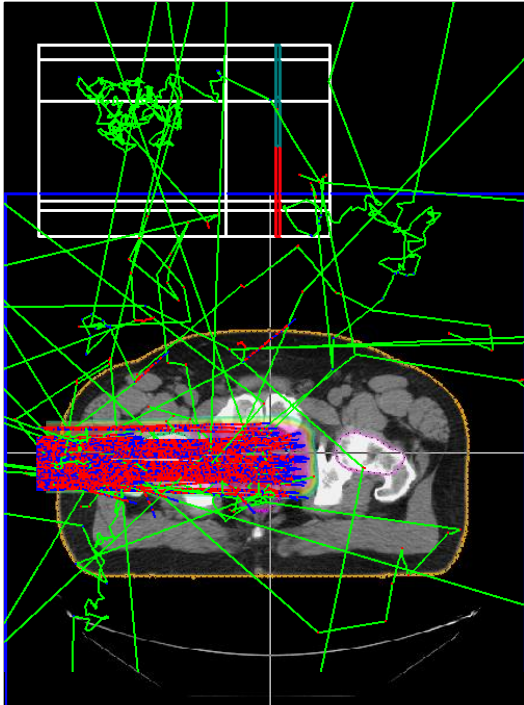


Prompt Gamma Rate Functions: TOPAS

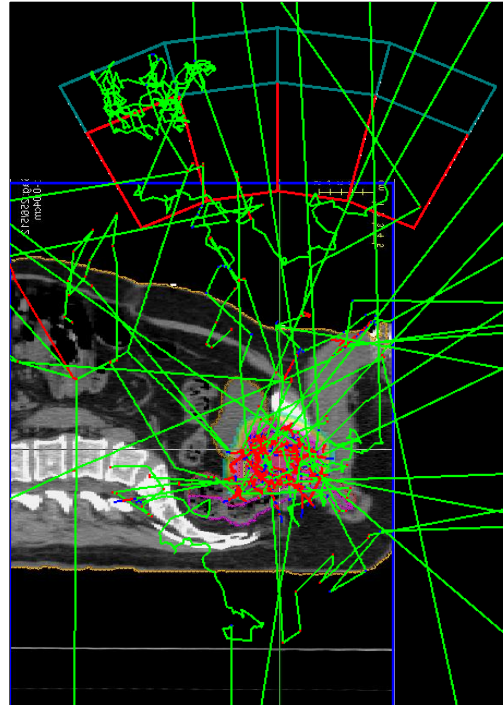


Testa; Min; Verburg; Schümann; Lu; Paganetti: Range verification in proton therapy based on the characteristic prompt-gamma time-patterns of passively modulated beams. Submitted

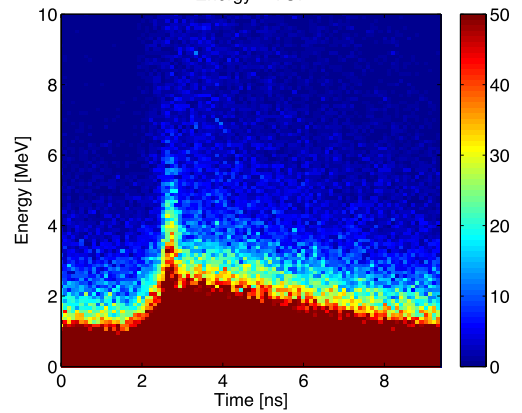
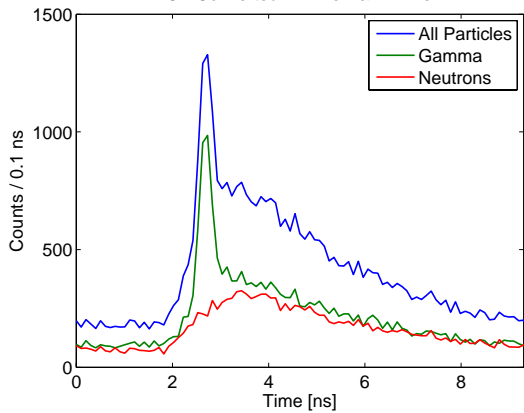
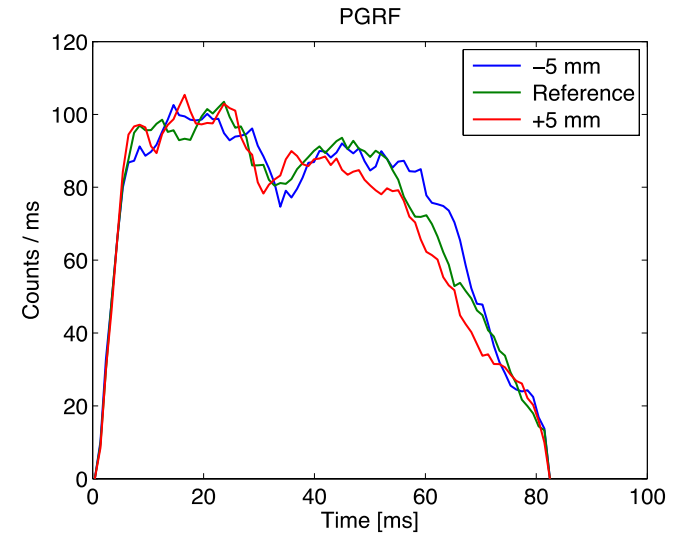
Application to a Prostate Patient



TOF Converted E>2MeV & E<7MeV



Energy - TOF



SOBP

Range: 25.7 cm
 Mod. Width: 8.5 cm
 Dose: ~ 2.5 cGy

Testa; Min; Verburg; Schümann; Lu; Paganetti: Range verification in proton therapy based on the characteristic prompt-gamma time-patterns of passively modulated beams. Submitted

Example:

New concepts using prompt gamma range verification

- Prompt Gamma Ray Functions can be determined by MC-simulations.
- 2mm range verification is achievable in a water phantom for a dose of 2.5cGy.
- For a typical prostate tumor treatment a 4mm resolution in range is achievable for a dose of 15cGy.
- Energy and TOF-selection simplifies the detection design and is effective in discriminating the prompt-gamma signal from the background.

Testa; Min; Verburg; Schümann; Lu; Paganetti: Range verification in proton therapy based on the characteristic prompt-gamma time-patterns of passively modulated beams. Submitted



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Monte Carlo tools

Versatile

Limited
functionality



Research

Clinical
Research

Tasks



Monte Carlo for Clinical Research

Example 1: Understanding the interplay effect when treating lung cancer with pencil beam scanning



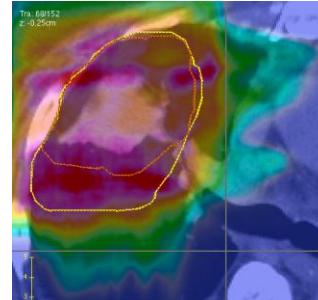
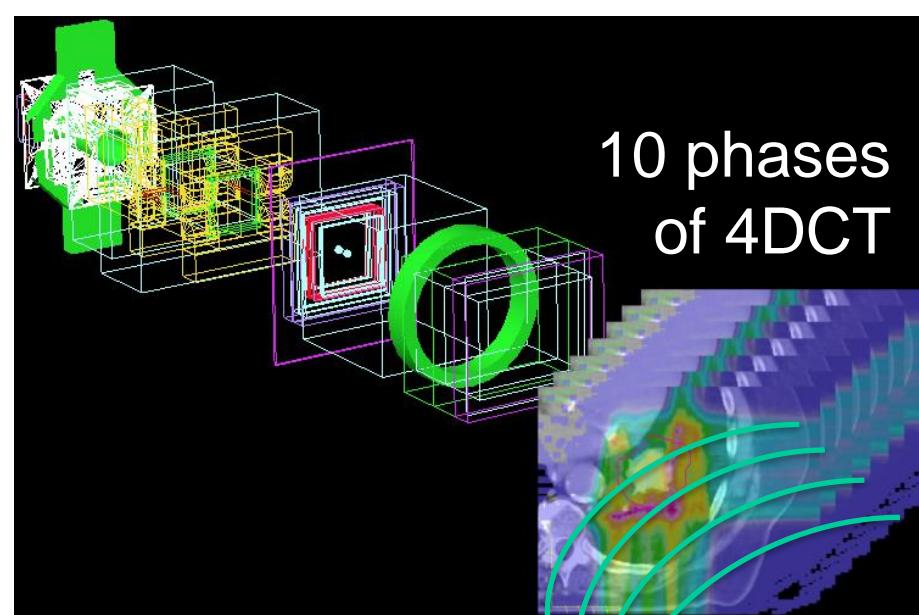
Treatment planning
(ASTROID)

MCAUTO-4D

MC simulation
on 10 4DCT phases

plastimatch

Dose distribution on
reference phase (4D)



transform the
resulting 10 dose
distributions back to a
reference phase (T₅₀)

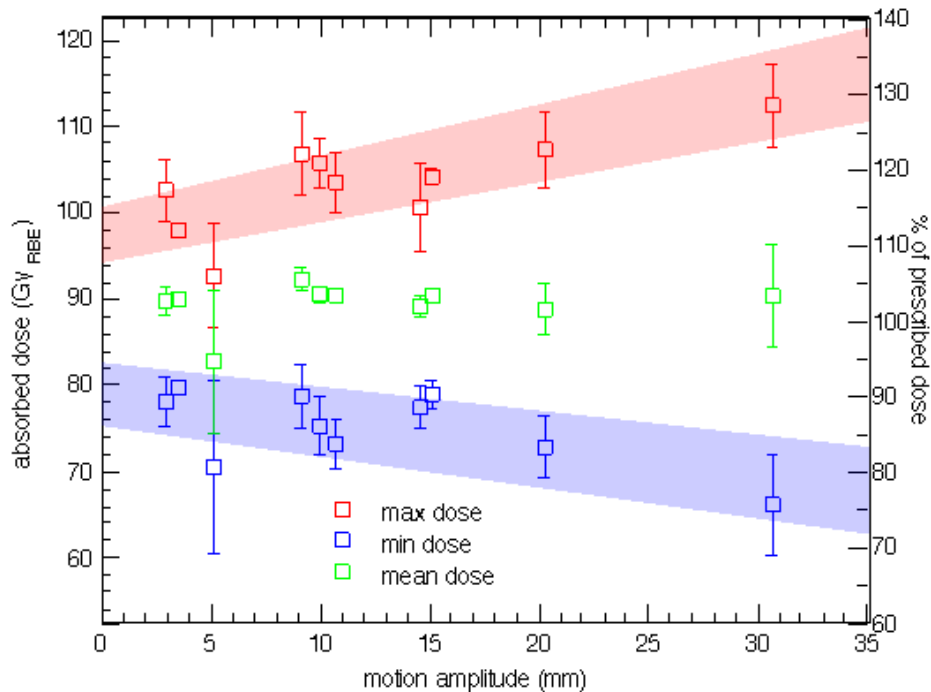


Grassberger; Dowdell; Shackelford; Sharp; Choi; Willers; Paganetti: Motion interplay as a function of patient parameters and spot size in spot scanning proton therapy for lung cancer. International Journal of Radiation Oncology, Biology, Physics 2013 86: 380-386

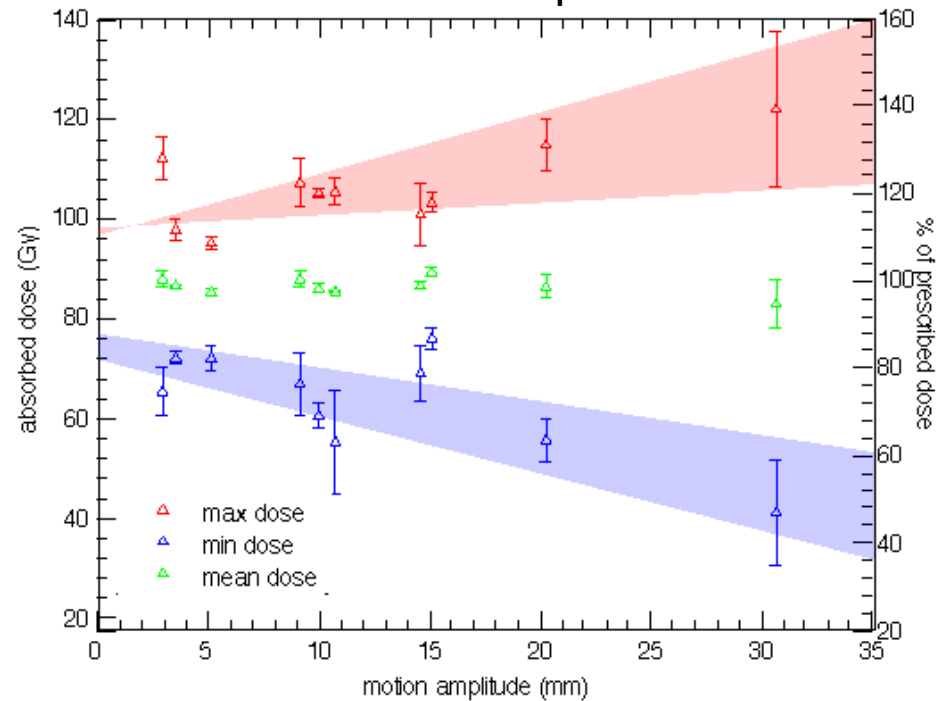
Results for single fraction delivery

attention: different scale

BigSpots



SmallSpots

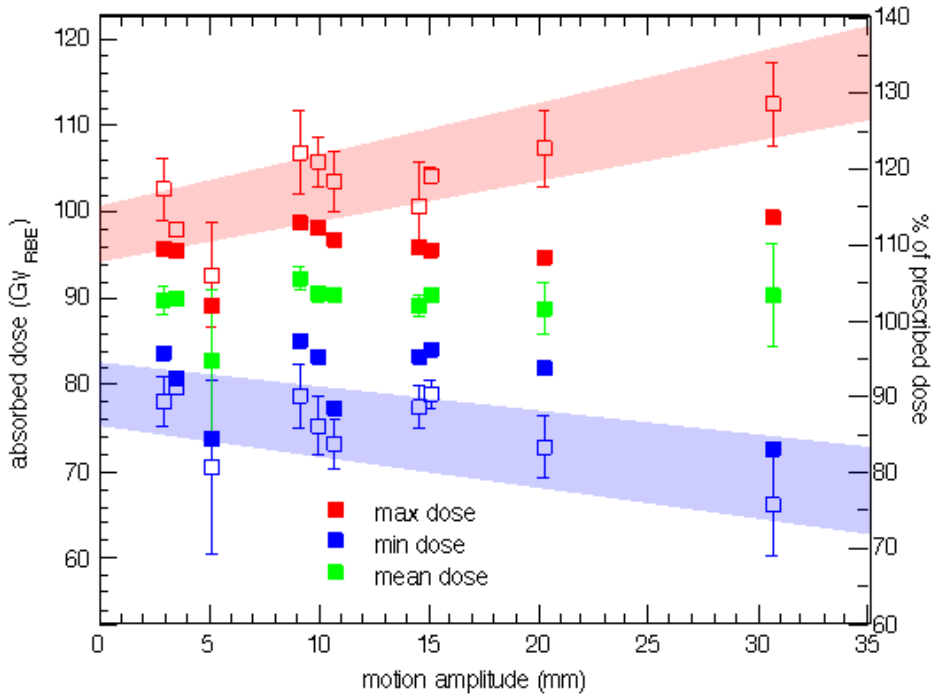


Grassberger; Dowdell; Shackelford; Sharp; Choi; Willers; Paganetti: Motion interplay as a function of patient parameters and spot size in spot scanning proton therapy for lung cancer. International Journal of Radiation Oncology, Biology, Physics 2013 86: 380-386

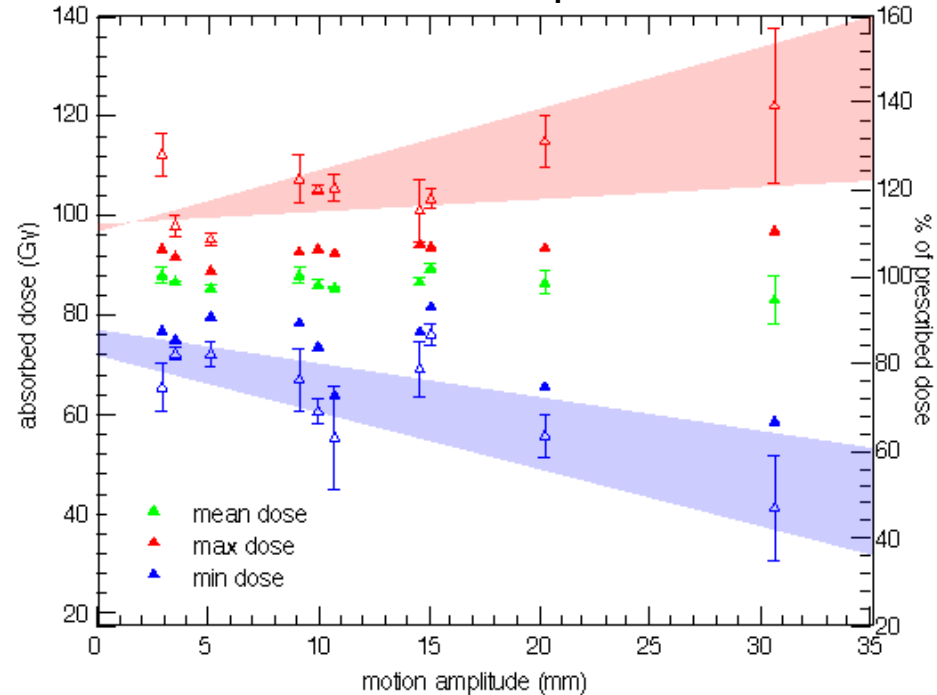
Results for 35 fraction delivery

attention: different scale

BigSpots



SmallSpots



Grassberger; Dowdell; Shackelford; Sharp; Choi; Willers; Paganetti: Motion interplay as a function of patient parameters and spot size in spot scanning proton therapy for lung cancer. International Journal of Radiation Oncology, Biology, Physics 2013 86: 380-386

Example 1: Understanding the interplay effect when treating lung cancer with pencil beam scanning

- Local control is preserved using a large spot size and conventional fractionation, but not for SBRT
- Small spots appear to be generally more sensitive to interplay effects
- Up to 10% loss in 12-month local control even for 30 fractions using small spots
- Tumors with high amplitudes relative to their size show more significant interplay
- There is significant patient variability depending on tumor location and size

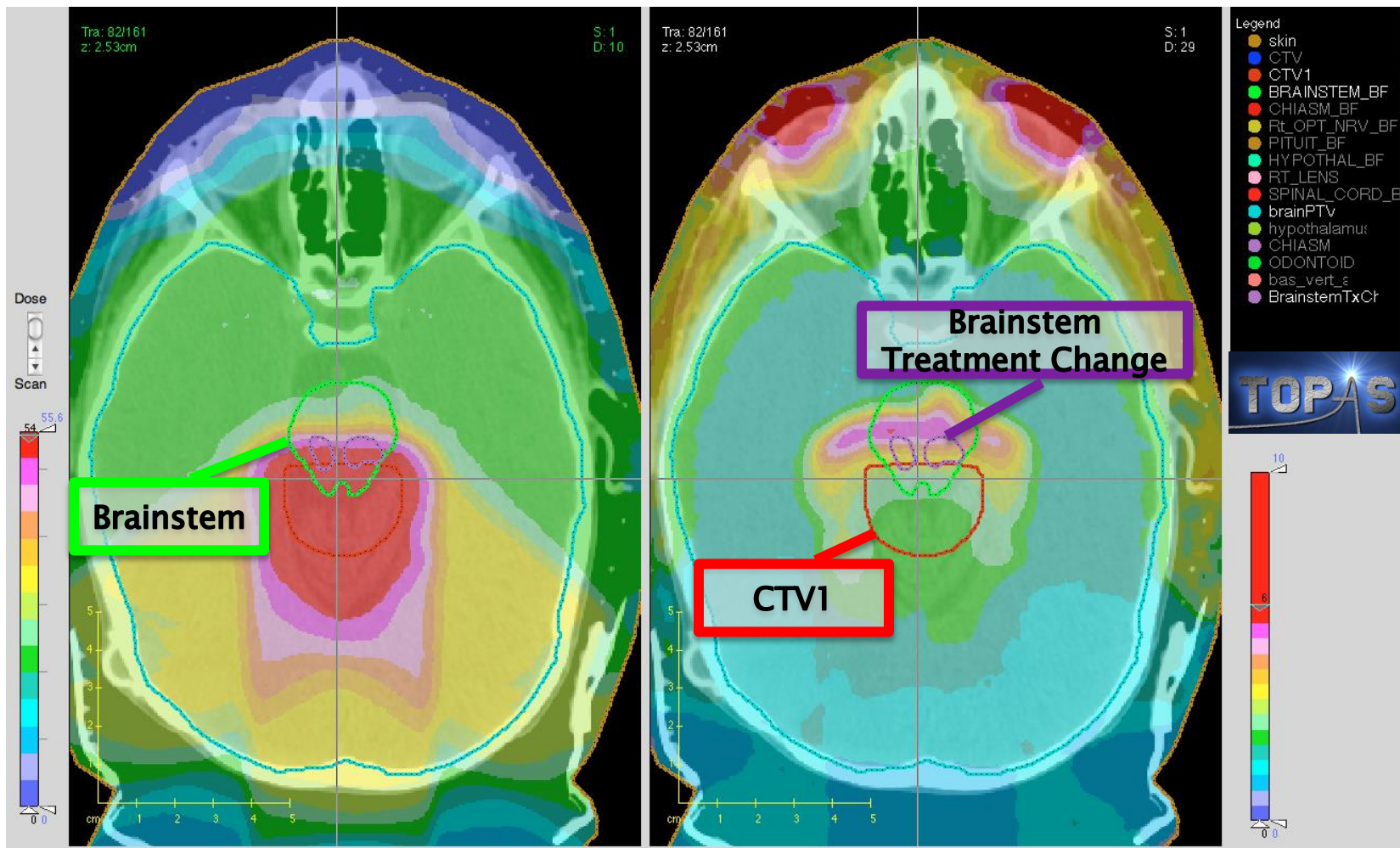
Grassberger; Dowdell; Shackelford; Sharp; Choi; Willers; Paganetti: Motion interplay as a function of patient parameters and spot size in spot scanning proton therapy for lung cancer. International Journal of Radiation Oncology, Biology, Physics 2013 86: 380-386



Monte Carlo for Clinical Research

Example 2: The use of LET information in proton therapy treatment planning



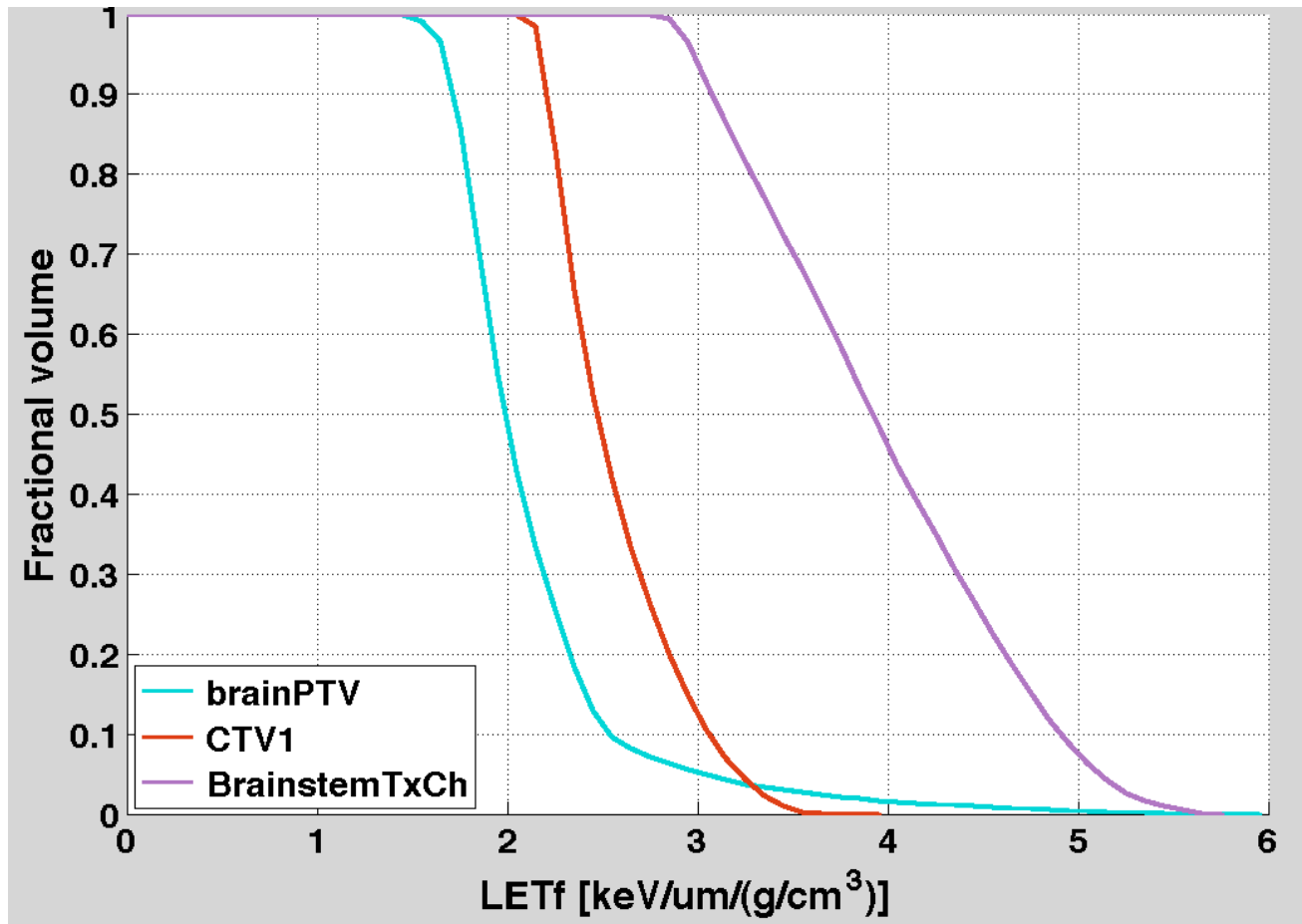


DOSE

LET

Sethi; Giantsoudi; Raiford; Rappalino; Caruso; Yock; Tarbell; Paganetti; MacDonald: Patterns of failure following proton therapy in medulloblastoma; LET distributions and RBE associations for relapses. International Journal of Radiation Oncology, Biology, Physics 2014 88: 655-663



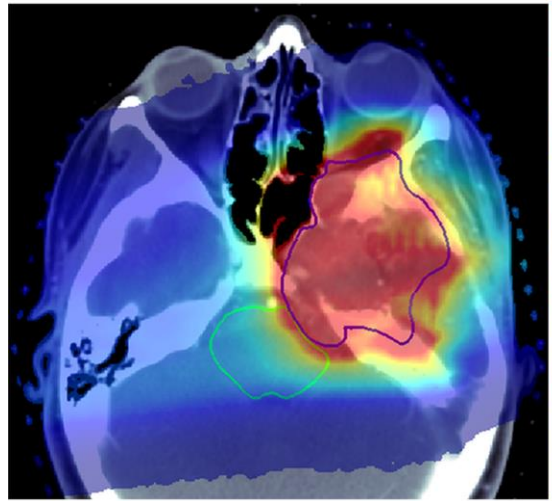


Sethi; Giantsoudi; Raiford; Rappalino; Caruso; Yock; Tarbell; Paganetti; MacDonald: Patterns of failure following proton therapy in medulloblastoma; LET distributions and RBE associations for relapses. International Journal of Radiation Oncology, Biology, Physics 2014 88: 655-663

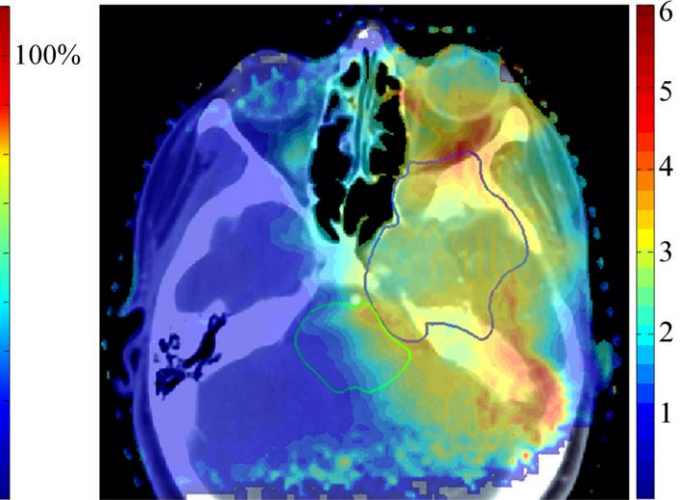


Intensity-modulated proton therapy (IMPT)

PLAN 1

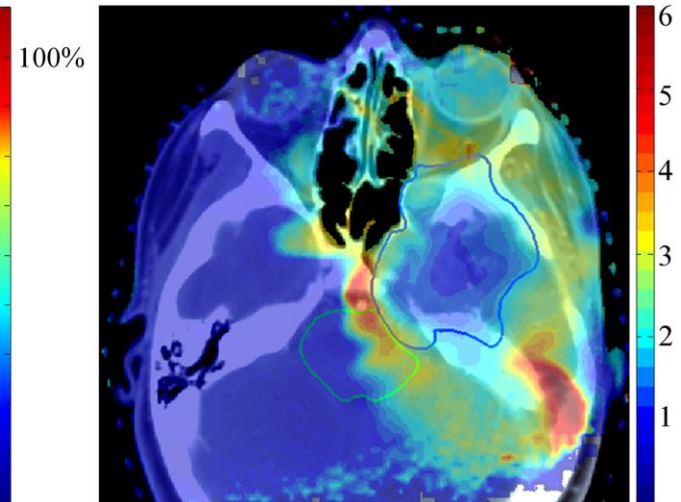
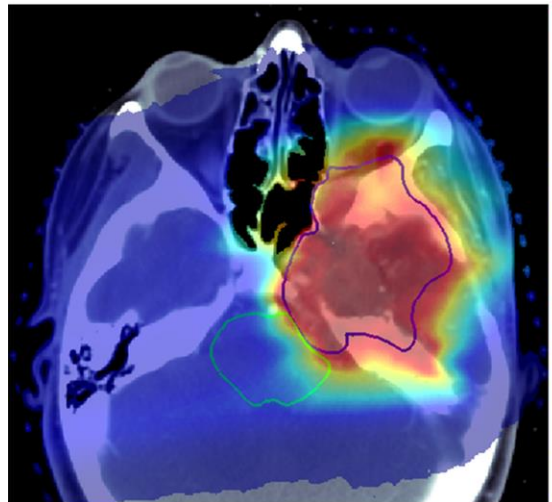


Dose



LET_d

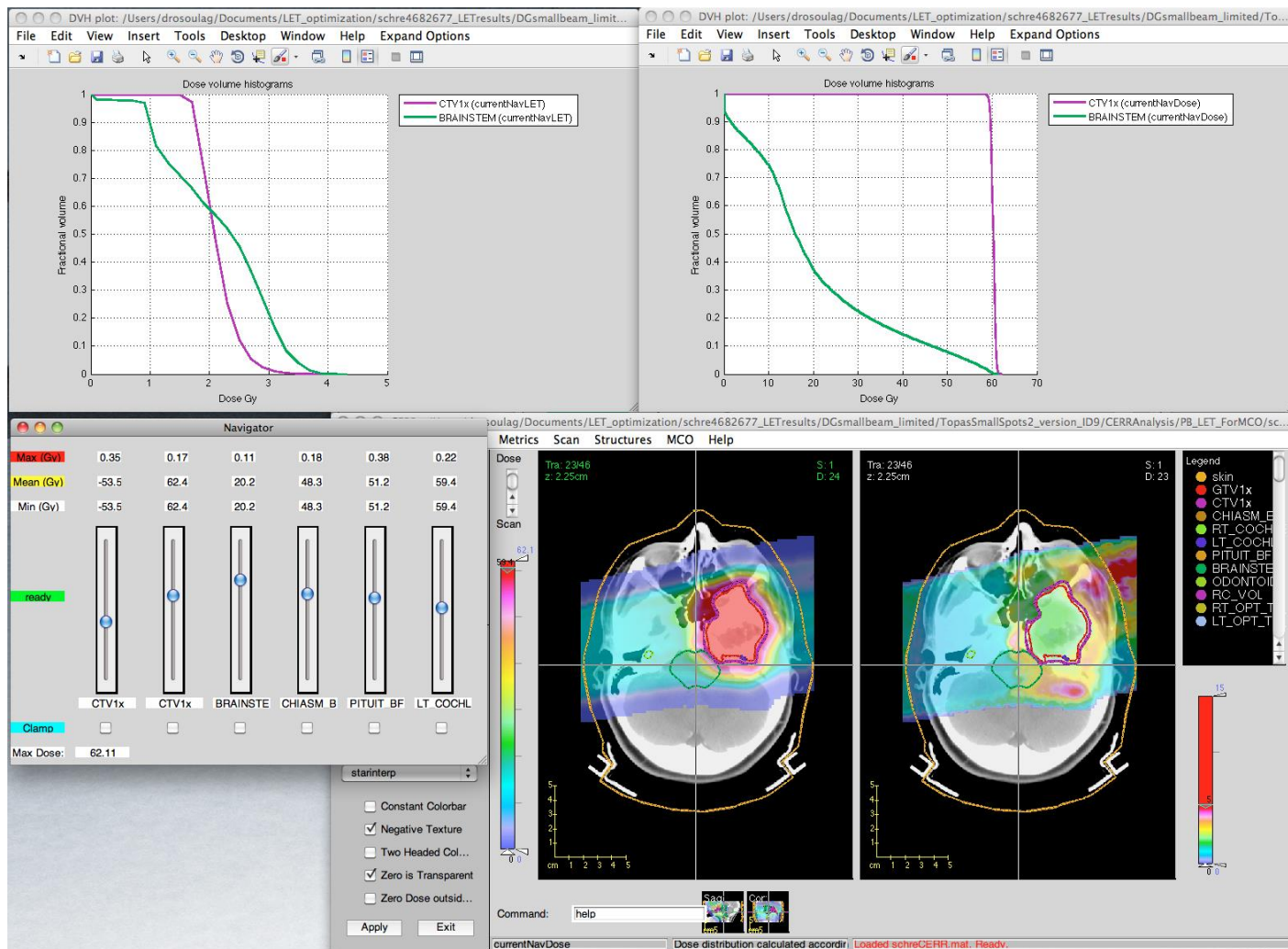
PLAN 2



Grassberger C; Trofimov A; Lomax A and Paganetti H: Variations in linear energy transfer within clinical proton therapy fields and the potential for biological treatment planning. International Journal of Radiation Oncology, Biology, Physics 2011 80: 1559-1566

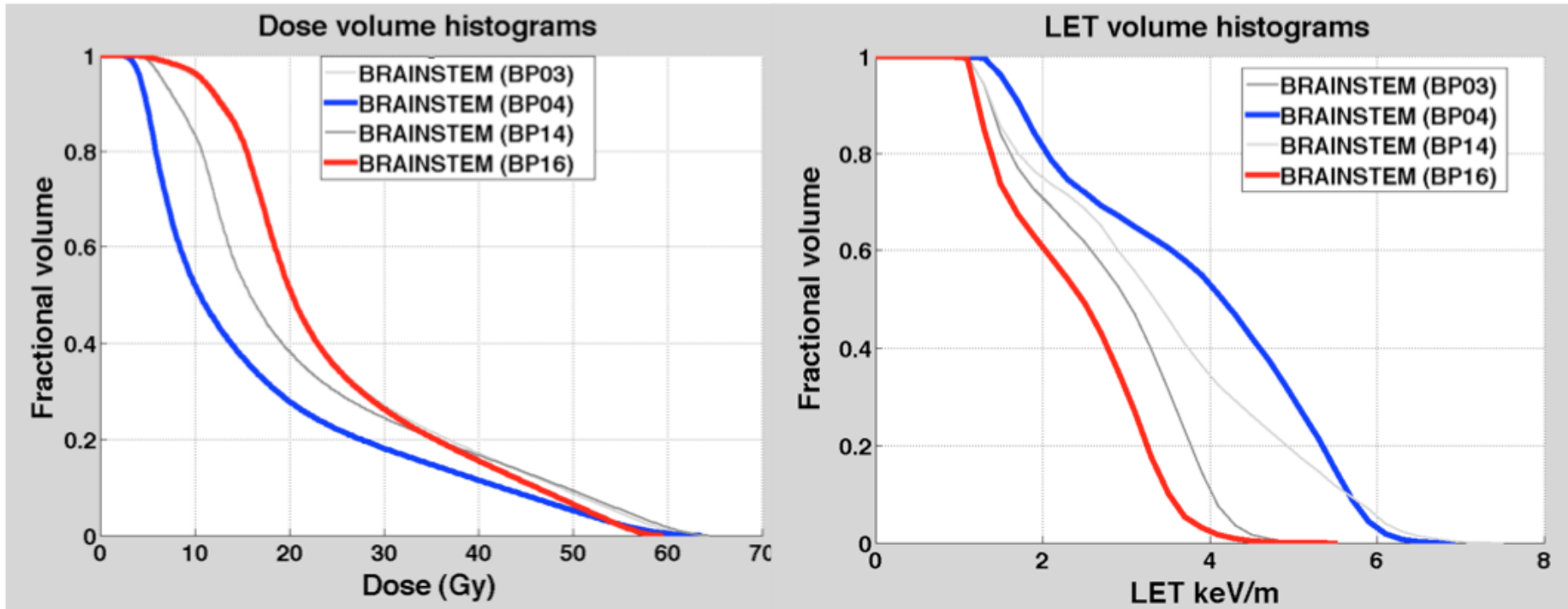
Biological dose optimization based on LET

LET-guided multi-criteria optimization (MCO)



Giantsoudi; Grassberger; Craft; Niemierko; Trofimov; Paganetti: Linear energy transfer (LET)-Guided Optimization in intensity modulated proton therapy (IMPT): feasibility study and clinical potential. Int J Radiat Oncol Biol Phys 2013 87: 216-222

LET-guided MCO



Giantsoudi; Grassberger; Craft; Niemierko; Trofimov; Paganetti: Linear energy transfer (LET)-Guided Optimization in intensity modulated proton therapy (IMPT): feasibility study and clinical potential. Int J Radiat Oncol Biol Phys 2013 87: 216-222



Example 2: The use of LET information in proton therapy treatment planning

- For doses and LET values relevant in proton therapy, one can assume a close to linear relationship between LET and RBE for a given α/β . LET information can potentially be used to understand unexpected side effects
- LET information can be used as additional parameter in treatment optimization

Giantsoudi; Grassberger; Craft; Niemierko; Trofimov; Paganetti: Linear energy transfer (LET)-Guided Optimization in intensity modulated proton therapy (IMPT): feasibility study and clinical potential. Int J Radiat Oncol Biol Phys 2013 87: 216-222



Monte Carlo tools

Versatile

Limited functionality

Research

Clinical
Research

Clinical

Tasks



Uncertainties in predicting the beam range in patients

Source of range uncertainty in the patient	Range uncertainty	
Independent of dose calculation:		
Measurement uncertainty in water for commissioning	± 0.3 mm	
Compensator design	± 0.2 mm	
Beam reproducibility	± 0.2 mm	
Patient setup	± 0.7 mm	
Dose calculation:		
Biology (always positive)	+ 0.8 %	
CT imaging and calibration	± 0.5 %	
CT conversion to tissue (excluding I-values)	± 0.5 %	
CT grid size	± 0.3 %	
Mean excitation energies (I-values) in tissue	± 1.5 %	
Range degradation; complex inhomogeneities	- 0.7 %	
Range degradation; local lateral inhomogeneities *	± 2.5 %	
Total (excluding *)	2.7% + 1.2 mm	Typical
Total	4.6% + 1.2 mm	Worst case

H. Paganetti: Range uncertainties in proton beam therapy and the impact of Monte Carlo simulations. Phys. Med. Biol. 57: R99-R117 (2012)

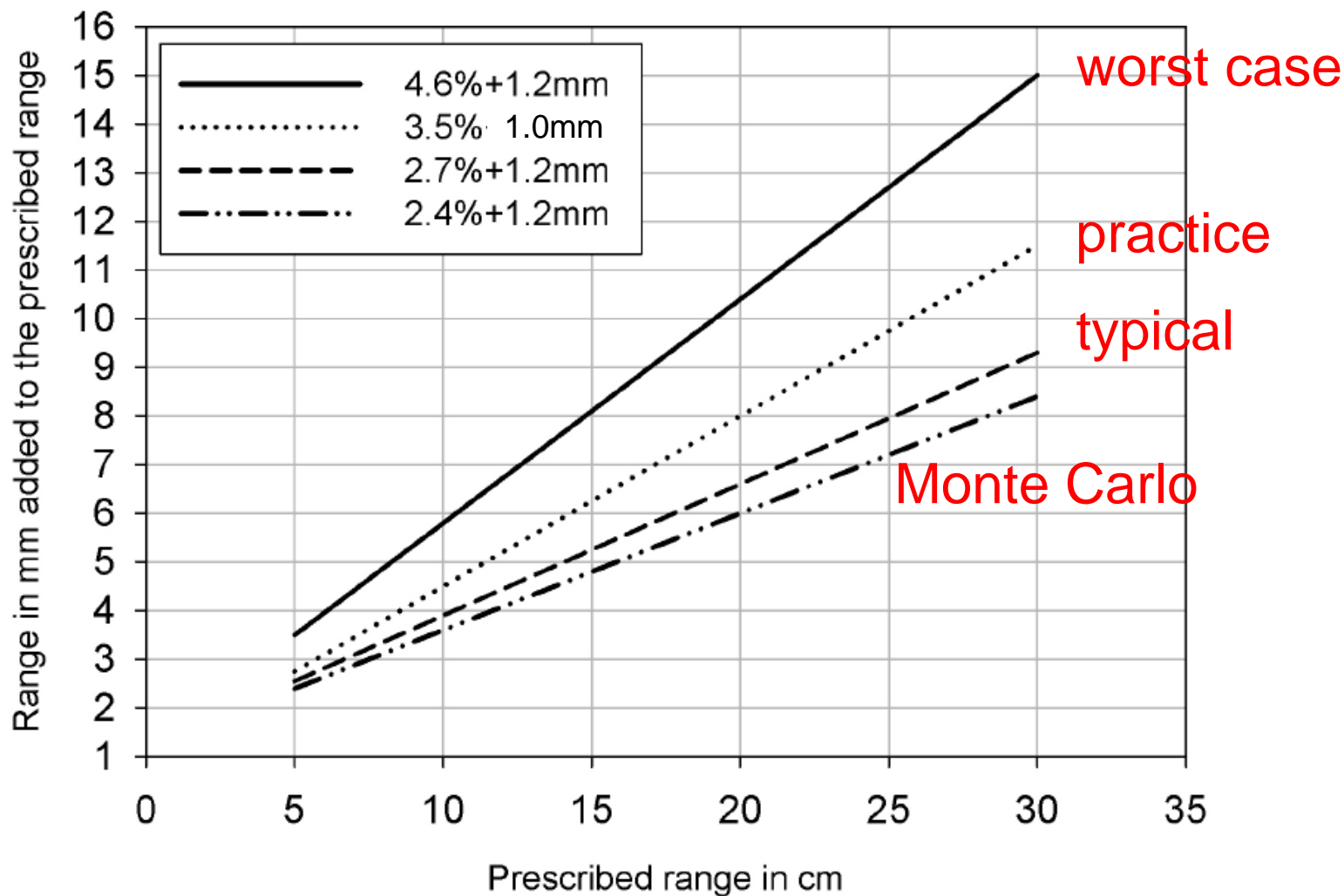


Uncertainties in predicting the beam range in patients

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Beam reproducibility	± 0.2 mm	
Patient setup	± 0.7 mm	
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Biology (always positive)	+ 0.8 %	
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CT conversion to tissue (excluding I-values)	± 0.5 %	± 0.2 %
CT grid size	± 0.3 %	
Mean excitation energies (I-values) in tissue	± 1.5 %	
Range degradation; complex inhomogeneities	- 0.7 %	± 0.1 %
Range degradation; local lateral inhomogeneities *	± 2.5 %	± 0.1 %
Total (excluding *)	2.7% + 1.2 mm	2.4 % + 1.2 mm
Total	4.6% + 1.2 mm	

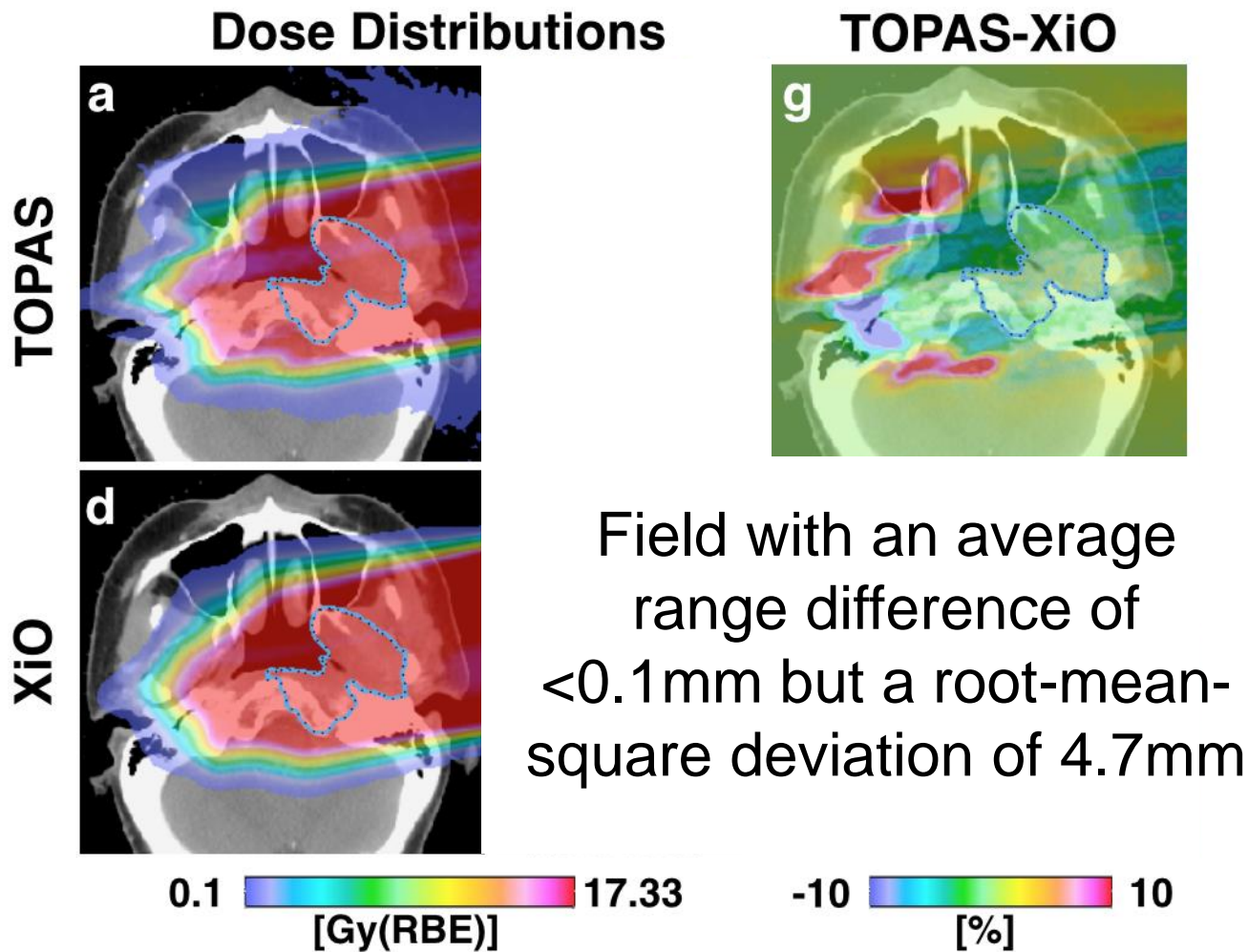
H. Paganetti: Range uncertainties in proton beam therapy and the impact of Monte Carlo simulations. Phys. Med. Biol. 57: R99-R117 (2012)

Uncertainties in predicting the beam range in patients



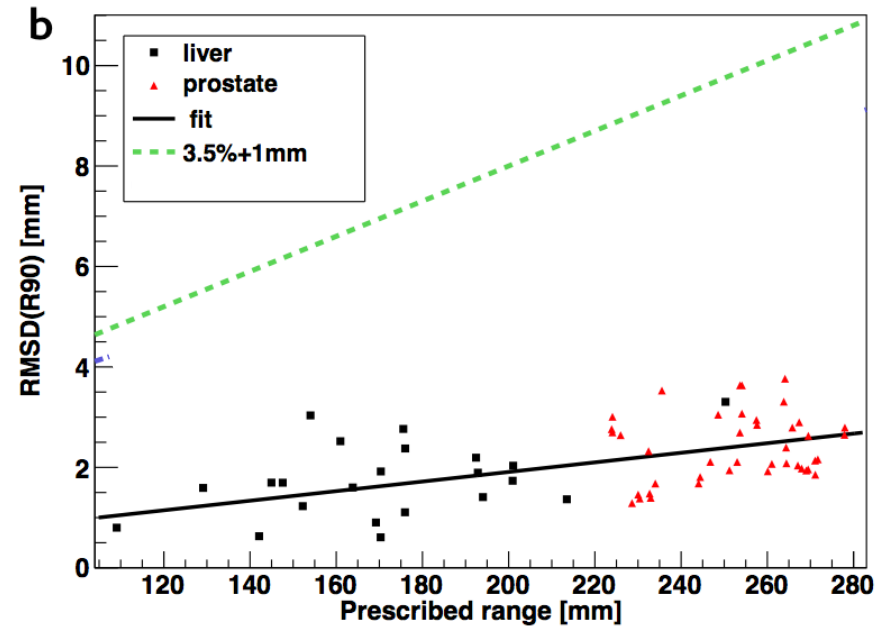
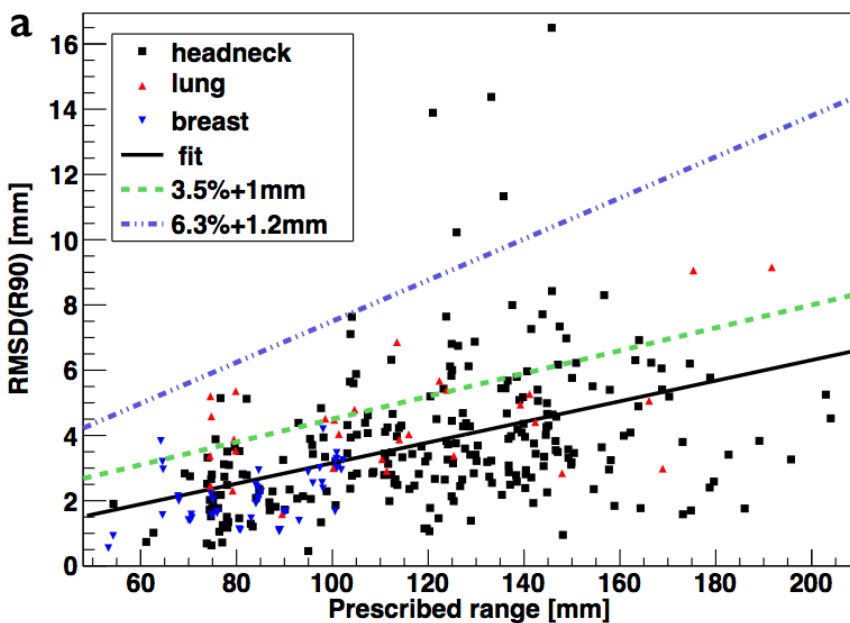
H. Paganetti: Range uncertainties in proton beam therapy and the impact of Monte Carlo simulations. Phys. Med. Biol. 57: R99-R117 (2012)

Range differences between analytical and Monte Carlo based dose calculation analyzed by comparing distal dose surfaces in patients



Schuemann, Dowdell, Min, Paganetti: Site-specific range uncertainties caused by dose calculation algorithms for proton therapy: Phys. Med. Biol. submitted

Estimation of range uncertainties by performing MC dose calculation on 508 fields



includes uncertainties from sources other than dose calculation

Schuemann, Dowdell, Min, Paganetti: Site-specific range uncertainties caused by dose calculation algorithms for proton therapy: Phys. Med. Biol. submitted

Monte Carlo for Clinical Use

- Monte Carlo in routine dose calculation has the potential to reduce treatment margins
- Monte Carlo can be used to revise current margins and better understand uncertainties due to dose calculation





MGH Radiation Oncology Physics Research team

Funding by the NCI

- P01 CA021239-31
“Proton Therapy Research”
- R01 CA111590-05
“Four-dimensional Monte Carlo dose calculation”
- R01 CA140735-05
“TOPAS. Fast and easy to use Monte Carlo system for proton therapy”
- Federal Share on C06 CA059267
“Accurate Monte Carlo Dose Calculation for Proton Therapy Patients”
- MGH ECOR
“Biologically Optimized Treatment Planning for Proton Beam Therapy”

