

ABSTRACT

Purpose: Prostate SBRT demands high geometric precision due to large fractional doses and steep dose gradients. Conventional PTV margins are typically derived from population-level estimates and may not reflect individual patient-specific motion^{1,2}. This work introduces a Bayesian hierarchical framework to simulate intrafraction motion and evaluate its dosimetric consequences.

Methods: A cohort of 205 patients treated with five-fraction prostate SBRT from 2020 to 2024 were retrospectively analyzed. Mid-treatment shifts were extracted from CBCT records and used to represent unintentional motion during treatment. These data trained a multivariate Student-T model with partial pooling, capturing population-level trends while retaining individual variability. Posterior predictive sampling generated synthetic shifts, which were applied to patient dose grids using rigid transformations. Population-based cumulative dose distributions were recalculated and evaluated using standard DVH metrics.

Results: Simulated shifts reproduced the central tendency, spread, and directional correlations of recorded patient data. Failure rates under clinical margins closely matched those in patient records, and correlation structures between axes were preserved. Population-level analysis showed very close agreement in DVH deviations across prostate, bladder, and rectum when simulated for 5 fraction deliveries.

Conclusion: This modeling framework offers a flexible approach to reconstructing patient-specific motion, even with limited empirical data. By leveraging partial pooling, it balances individual detail with population-informed inference. Its ability to replicate real-world distributions, failure rates, and dose perturbations underscores its validity as a simulation engine. Importantly, this approach enables probabilistic “what-if” testing without requiring additional imaging or patient intervention—offering a principled method for stress-testing clinical practices. In doing so, it advances clinical conversation around personalization in radiation therapy and highlights the role of statistical modeling in improving treatment, safety, and precision.

INTRODUCTION

Rectal sparing is a central challenge in prostate SBRT due to steep dose gradients and close anatomic proximity between target and rectum.³ The framework presented here introduces a probabilistic, population informed approach to margin evaluation using routinely acquired image guidance data. By placing individual patients within a learned population motion distribution, this approach enables patient-informed assessment and adaptation of planning margin strategies over the course of treatment, supporting evaluation of rectum sparing posterior margins without additional imaging or patient intervention.

METHODS AND MATERIALS

Patient Shift Modeling:

Observed intrafraction shift patterns and cross-axis correlations are summarized in Fig. 1. Intrafraction shifts were derived from mid-treatment CBCT for 205 patients treated with five-fraction prostate SBRT (2020–2024). A hierarchical Bayesian multivariate Student-t model⁴ was fit to the 3D shift vectors to capture correlated motion and interpatient variability. Posterior predictive sampling generated synthetic shifts for population-based dose perturbation.

Dose Perturbation and Population DVH Generation

Sampled shifts were applied as rigid transformations of the 3D dose grid, and DVH metrics were recomputed for targets and organs at risk. Dose perturbations were also computed using the recorded CBCT shifts directly for comparison with model-based simulations.

Planning Approach: Rectum-Sparing Posterior Margin Concept

Given the observed directional correlations in patient motion (Fig. 1), a rectum-sparing planning strategy was evaluated by reducing the posterior margin through rectal cropping of the PTV. Plans were optimized to meet NRG-GU005 target coverage requirements, with rectal dose minimized to ALARA while maintaining protocol consistent coverage. Plan robustness was evaluated under both statistically sampled correlated shifts and recorded CBCT shifts.



Figure 1. Scatter plots of mid-treatment CBCT-derived intrafraction shift vectors for the full cohort (205 patients), shown by axis pairings. Overlaid contours/fit illustrate the multivariate Student-t model capturing both spread and cross-axis correlation in the observed shifts.

RESULTS

Population DVH perturbations for rectum, bladder, and prostate under correlated motion are shown in **Fig. 2**, comparing nominal plans, statistically sampled shifts, and recorded CBCT-based shifts. Across all structures, model-based perturbations closely tracked those obtained using recorded shifts, demonstrating that the framework reproduced the clinically observed dosimetric variability associated with intrafraction motion. The simulated motion distributions preserved both the magnitude and directional correlation structure of observed patient shifts, supporting their use for population-level robustness evaluation.

The geometric effect of correlated motion on target coverage is illustrated in **Fig. 3** for the case corresponding to the largest sampled shift magnitude. Despite the large displacement, target coverage remained stable due to correlated motion components preserving alignment relative to high-gradient dose regions. This example highlights how directional correlations can reduce the occurrence of true worst-case geometric scenarios that would otherwise be predicted under independent motion assumptions.

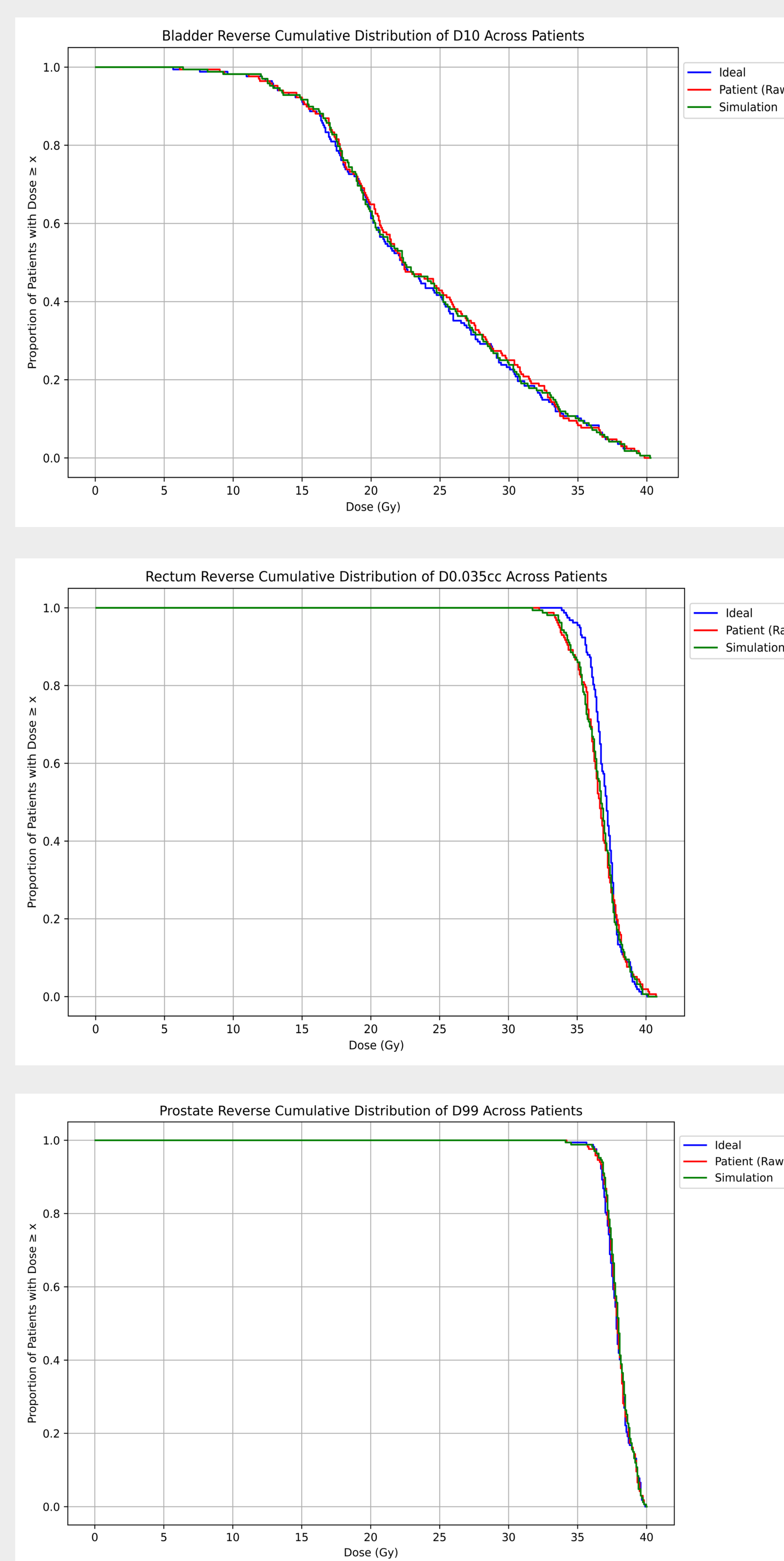


Figure 2: Population distributions of representative DVH endpoints for (a) bladder (b) rectum, and (c) prostate/target volumes. Curves/points compare the nominal planned dose to doses recalculated after rigid dose perturbations using (i) posterior-predictive sampled correlated shifts from the hierarchical model and (ii) recorded CBCT shifts (raw perturbation). Agreement between model-based and raw-shift distributions supports the validity of the statistical motion model for population-level dosimetric evaluation.

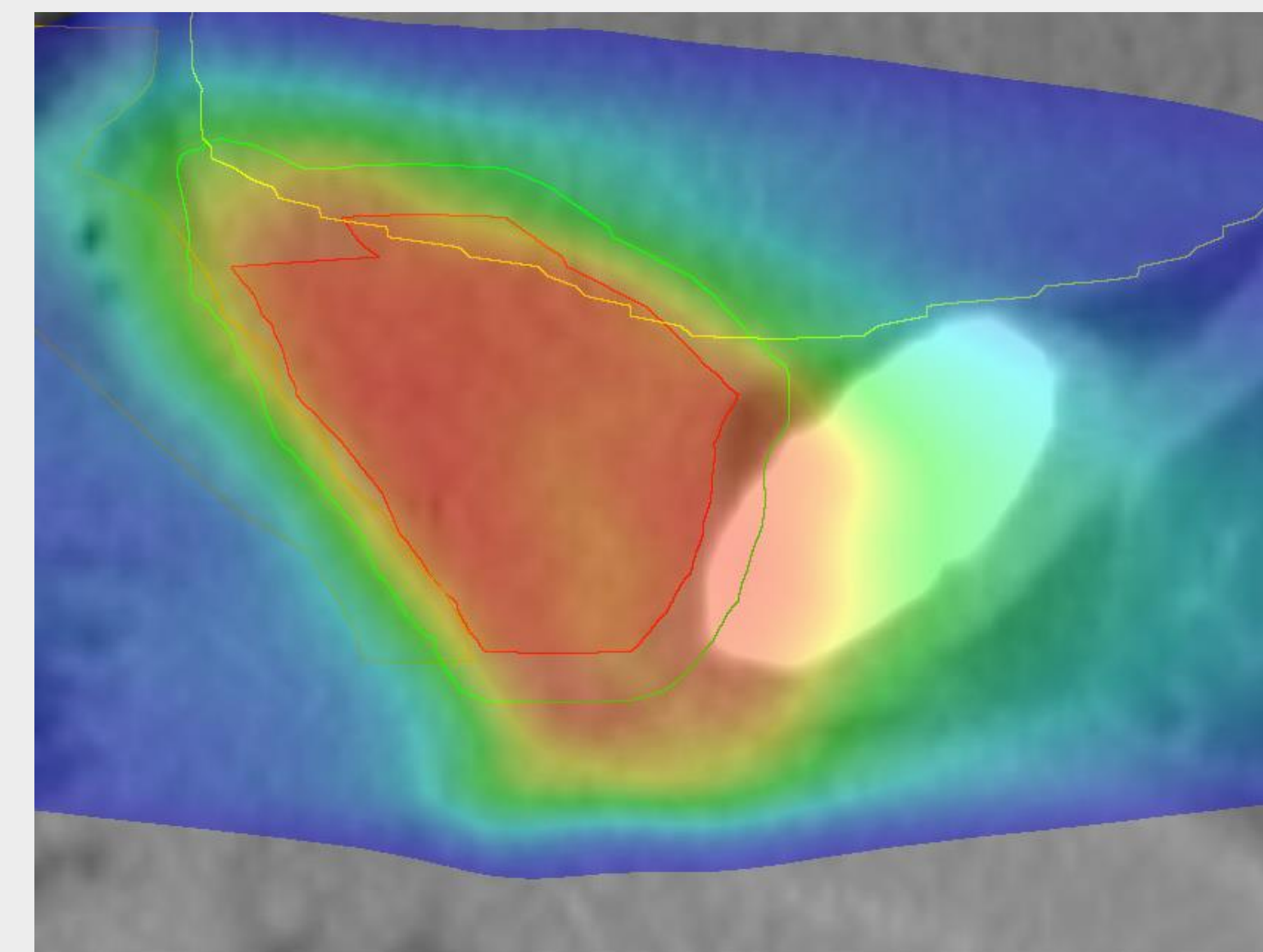


Figure 3: Dose display for the patient corresponding to the largest sampled shift magnitude. Illustrating why correlation structure materially affects inferred robustness.

DISCUSSION

The close agreement between simulated and recorded motion demonstrates that the proposed hierarchical Bayesian framework provides a realistic representation of intrafraction prostate motion for evaluating treatment robustness. Beyond reproducing observed motion, the framework enables probabilistic assessment of planning strategies using routinely acquired image guidance. As patient-specific motion data accumulate during treatment, individual observations can be interpreted within the learned population distribution to evaluate whether standard planning margins remain appropriate or whether alternative margin strategies, such as rectum-sparing approaches, can be adopted while maintaining target coverage. This provides a pathway toward personalized, data-driven margin adaptation without requiring additional imaging or changes to the clinical workflow.

CONCLUSIONS

This work establishes a probabilistic framework for evaluating treatment margin robustness under realistic intrafraction motion. By combining routinely acquired image guidance with population-informed statistical modeling, the framework enables patient-specific assessment of planning margins based on an individual's observed motion characteristics. This creates the potential for adaptive strategies in which margins may be reduced for consistently stable patients or expanded for patients demonstrating greater motion, improving the balance between target coverage and normal tissue sparing.

REFERENCES

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