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Introduction

- Diffusion is the incoherent motion of spins caused by thermal fluctuations in a fluid. Diffusion MRI is one measurement that can be obtained due to the destabilization of nuclear spins during an MRI process.
- It is a non-invasive imaging technique that is sensitive to the overall amount of diffusion happening in a scan voxel.
- Since diffusing particles interact with the surrounding tissue, diffusion MRI provides an insight into the microscopic structure of tissue

Findings

- Here we find that the differences in diffusivity between compartments leads to non-trivial equilibrium concentrations of spins, and thus contributions to the signal from regions with higher concentrations are larger than would be expected from the volume fraction alone leading to misrepresentation.
- We also find that it is necessary to allow the dynamics to equilibrate before the generation of synthetic diffusion signals from a simulation to avoid further bias due to transient dynamics.

Methods

- We use Monte-Carlo simulation [3], [4], [5] to generate synthetic diffusivity signal.
- The step length is defined by the diffusivity for the region and if a spin ends its step in a different region, the new step length is added.
- To avoid bias, we pick initial points uniformly distributed in the first region, and a step direction.
- We model tissue as an environment consisting of a closed box with a completely permeable membrane.
- The time to reach equilibrium is observed for each case indicated by the population reaching a plateau.

Model Parameters

1st diffusion coefficient D_1 is kept $2.3 \times 10^{-9} \text{ m}^2 \text{ s}^{-1}$
2nd diffusion coefficient D_2 = of $2.3 \times 10^{-9} \text{ m}^2 \text{ s}^{-1}$, $4.6 \times 10^{-10} \text{ m}^2 \text{ s}^{-1}$, $4.6 \times 10^{-11} \text{ m}^2 \text{ s}^{-1}$ and $2.3 \times 10^{-11} \text{ m}^2 \text{ s}^{-1}$
step length 5 % and 10 % of the entire box width
Timesteps = 20,000, 21,000, 25,000
Spin Population = 1,000

Results

Figures 1 and 2 show that larger disparity in diffusivities leads to decreased homogeneity between regions. The variability of free motion between regions will affect the speed it takes to fill the available space and this will lead to volumetric bias during signal contribution

Discussion

For two regions of tissue with different diffusivities and free exchange at equilibrium, (i.e. when the two regional populations reach a stable state with a balanced exchange of spins between compartments), the lower diffusivity region will contain a higher concentration of spins as a direct consequence of the diffusion dynamics. We also observe a transient period at the start of the simulation dynamics where there is a net flow of spins from one compartment to another which will bias model fitting and introduce a time dependence.

Significance & Further Work

- This work shows that lower diffusivity region will contribute with more weight to the signal than the higher diffusivity region, even though they are the same size.
- For modeling approaches which attempt to infer microstructural details from the diffusion signal providing insight to MRI output, the disparity will lead to a volumetric bias as signal fraction is no longer the same as volume fraction.

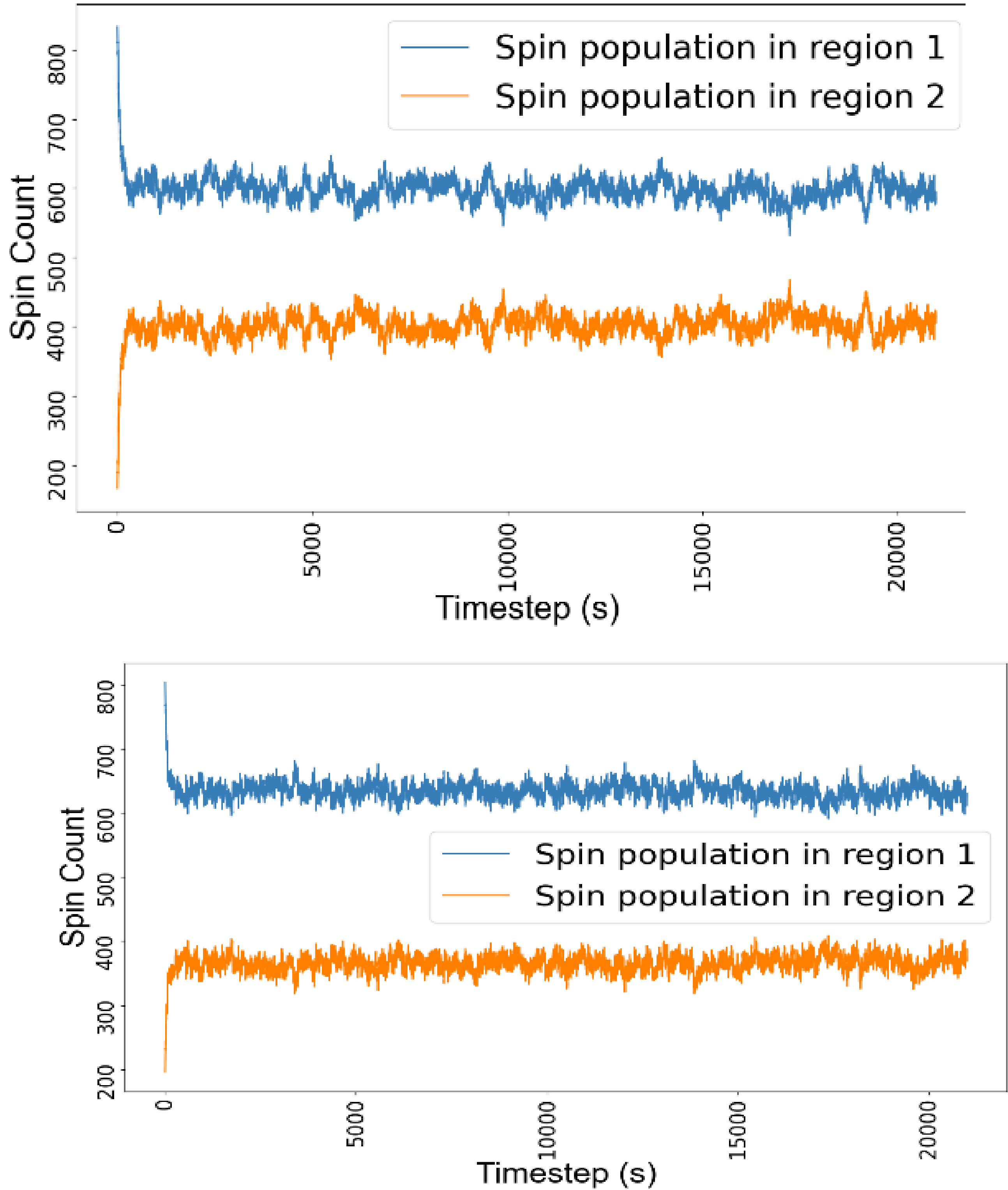


Figure 1: The growth and reduction of spin populations of the two rectangular regions over time; $D_2 = \frac{D_1}{5}$, bottom; $D_2 = \frac{D_1}{10}$

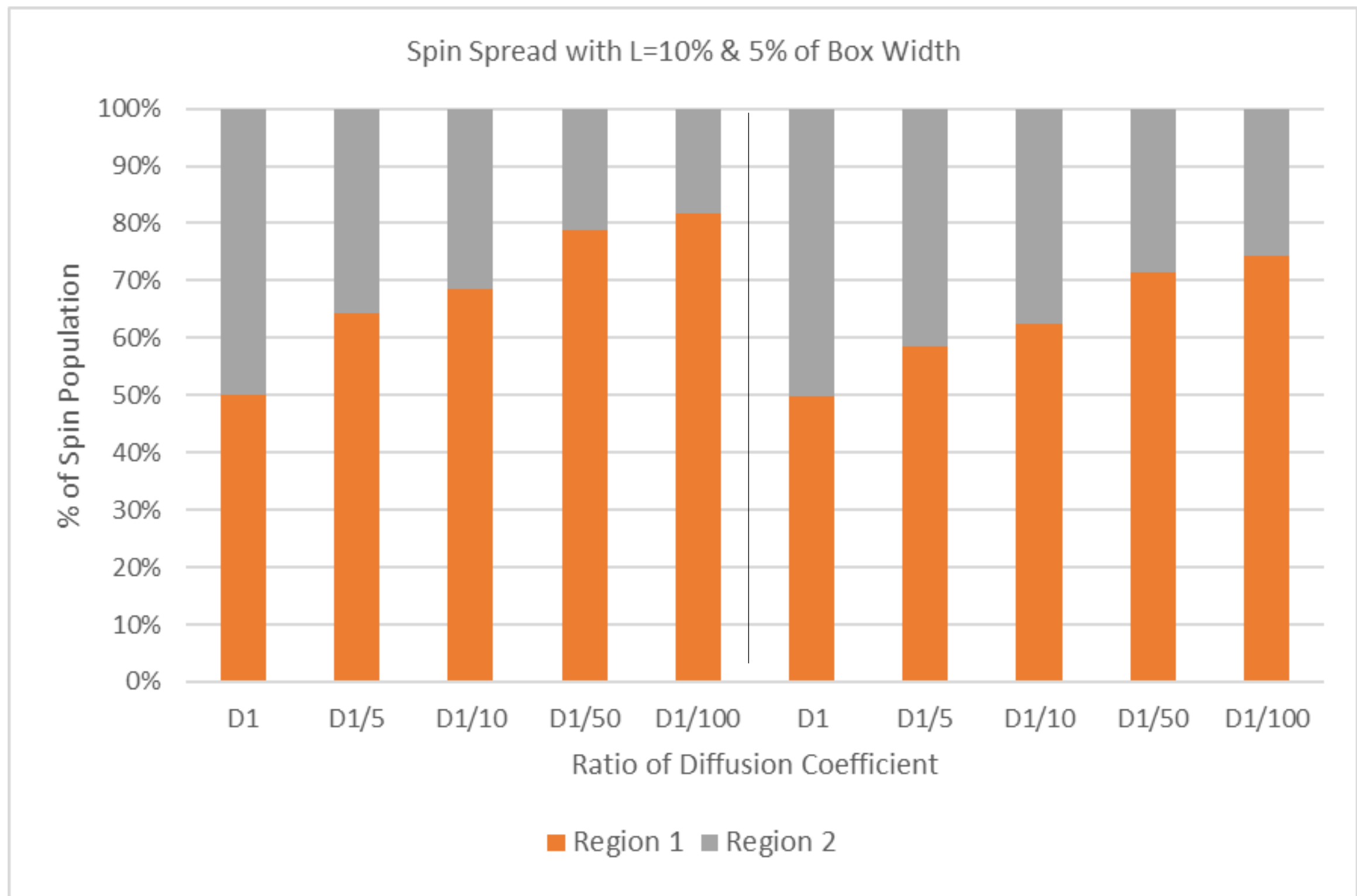


Figure 2: Distribution of nuclear spins over two rectangular regions as they diffuse with varying diffusion coefficients and box sizes.

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