

# **Simulation and Fitting of FRAP Data in Python**

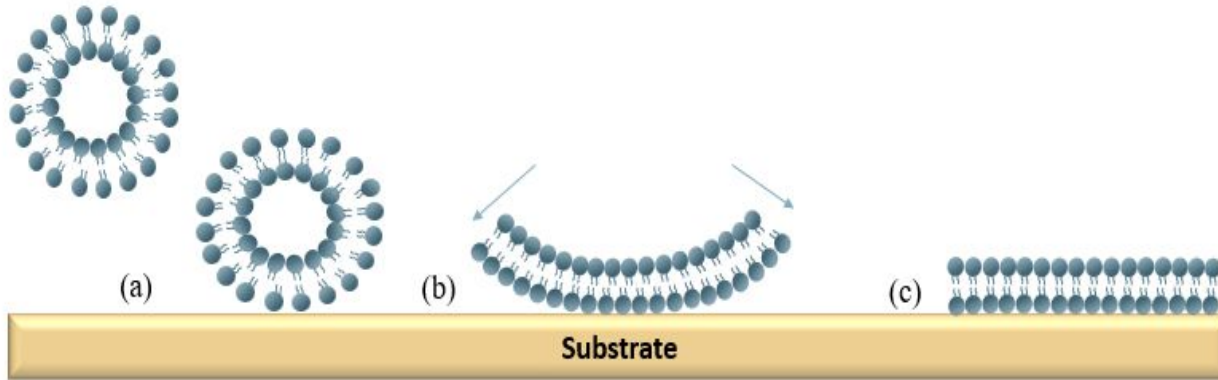
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# What are Supported Lipid Bilayers?

- Supported lipid bilayers (SLBs) - a mimic of the cell membrane formed on a substrate such as glass
- Spontaneously forms a nice, homogenous surface

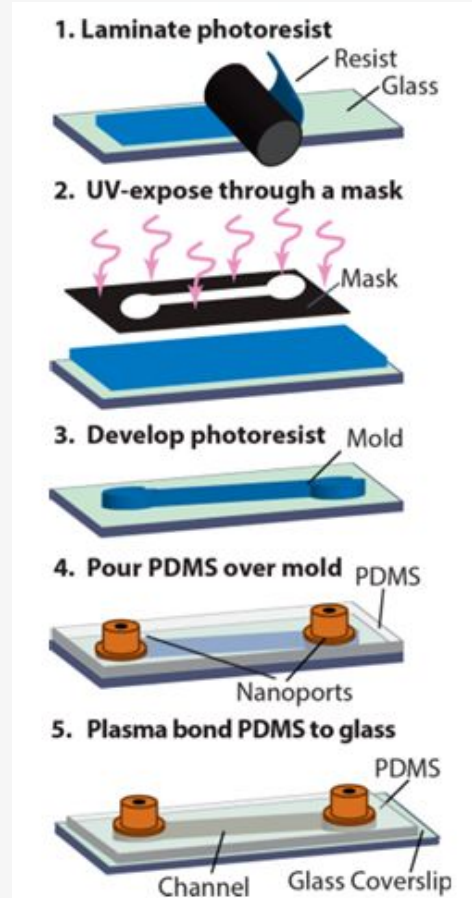
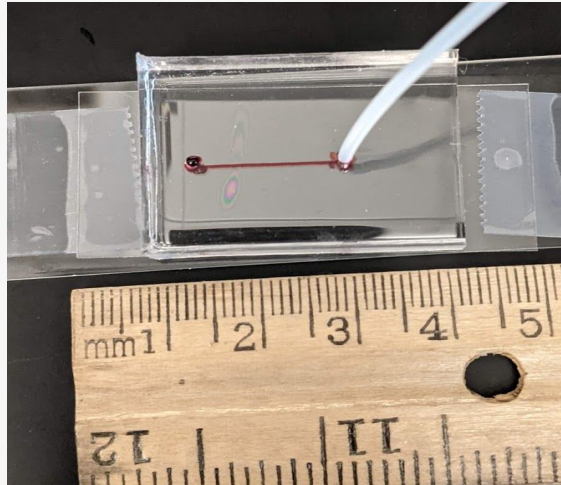
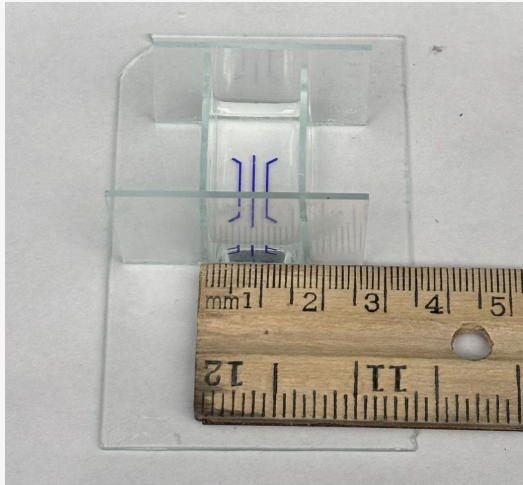


Significance:

- biosensor
- diagnostics
- surface coating

# Microfluidics

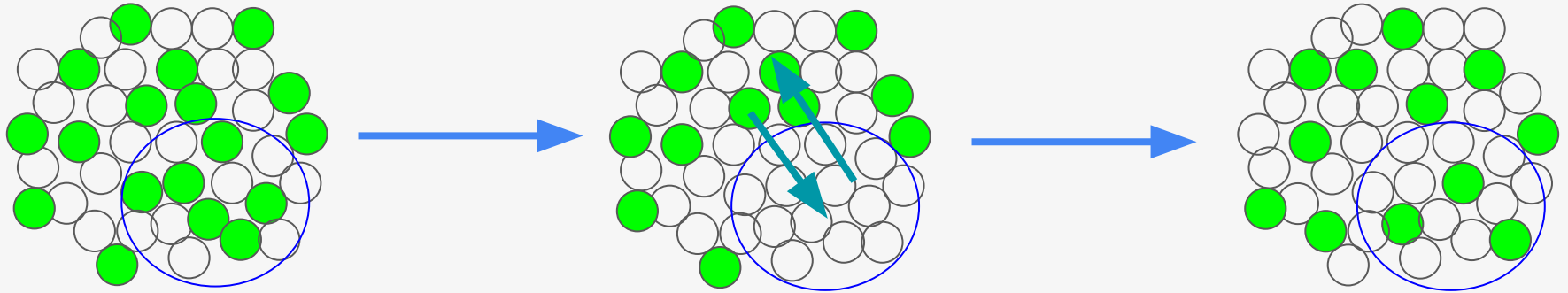
- polydimethylsiloxane (PDMS)-based
- Simultaneous imaging of different bilayers
- Controlled environment to conduct experiments



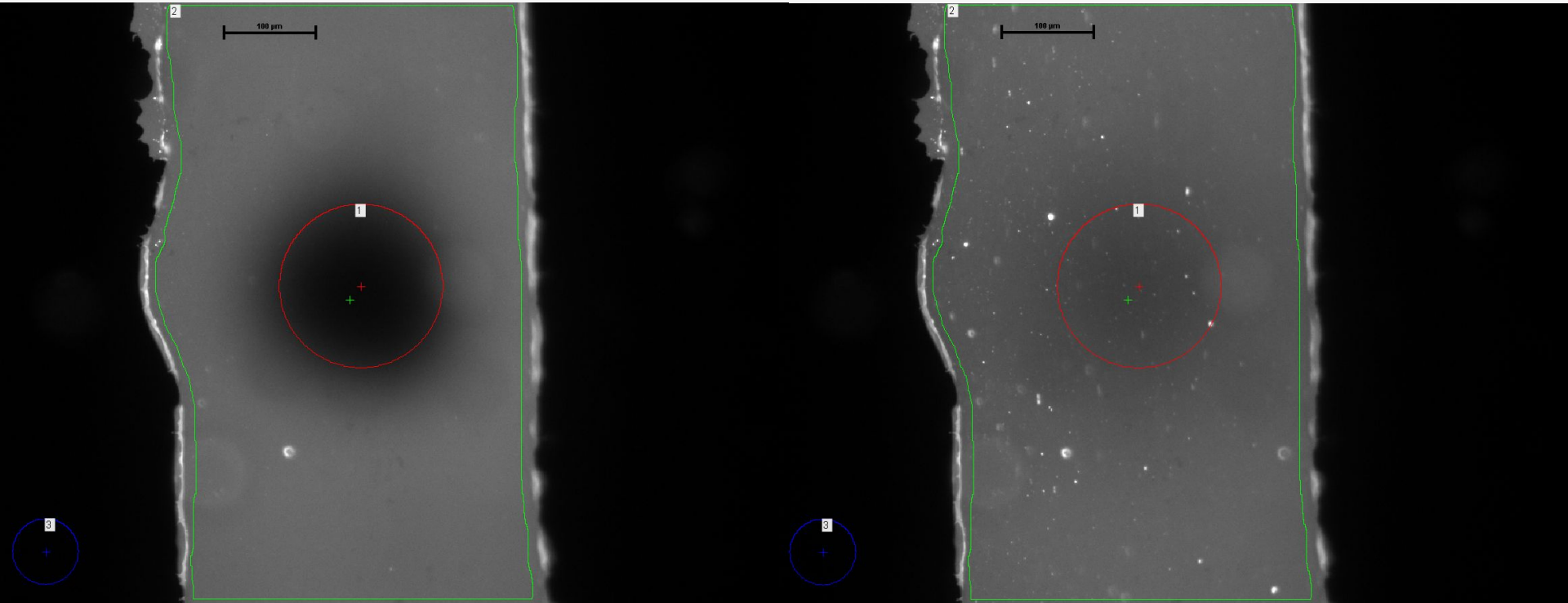
# FRAP analysis

## Fluorescence Recovery After Photobleaching (FRAP)

- Part of a lipid bilayer is shot with a fine laser
- This destroys the fluorescence of the bilayer at that location
- If bilayer is fluid, then the fluorescence will recover at that position

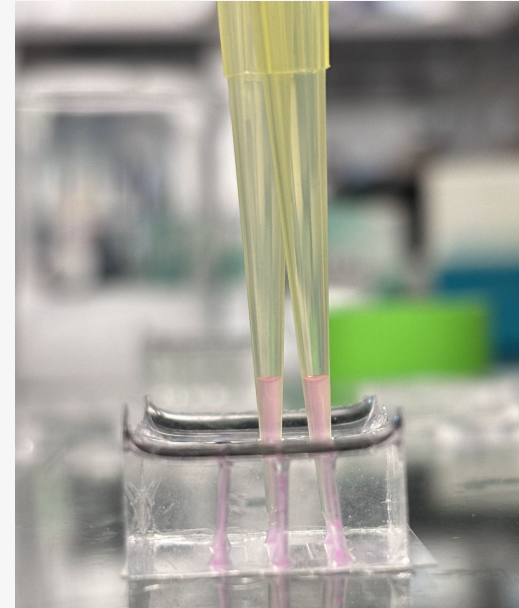


# Typical FRAP - before & after



# Research Question

- Many experiments desire the knowledge of the fluidity of their SLB in the system they are in.
- Therefore, we want to be able to control and measure the fluidity of SLBs in microfluidic devices.
- We currently use the EasyFRAP software to determine the fluidity with poor accuracy
- Can we use a simulation method with Python to more accurately analyze FRAP data to obtain diffusion coefficients?



# Goals

- Create code for a simulation of our experimental data to obtain diffusion coefficients
- Use our approach for multiple FRAP experiments
- Create an easy-to-use framework for future students

# Diffusion Differential Equation

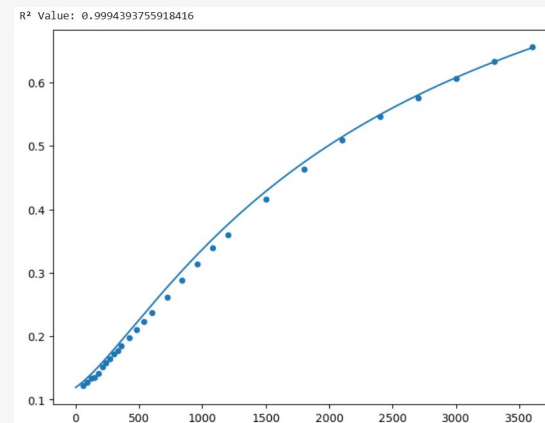
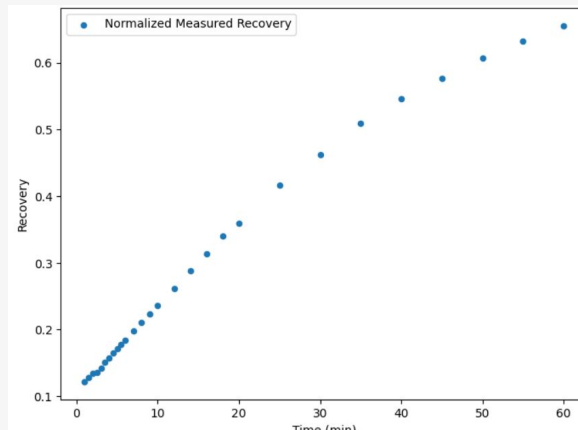
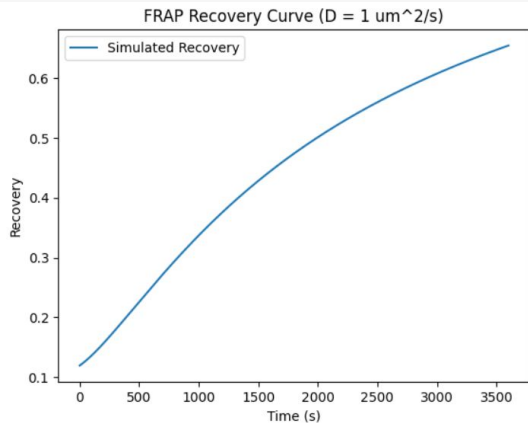
- We are looking to find the diffusion coefficient  $D$  which obeys the diffusion equation:  $\partial C(r, t) / \partial t = D \nabla^2 C(r, t)$ 
  - $D$  represents the speed at which the lipid bilayer moves
- We can use Laplace's equation with the finite difference method to simulate diffusion over time

$$\nabla^2 f(i, j) = f(i + 1, j) + f(i - 1, j) + f(i, j + 1) + f(i, j - 1) - 4f(i, j)$$



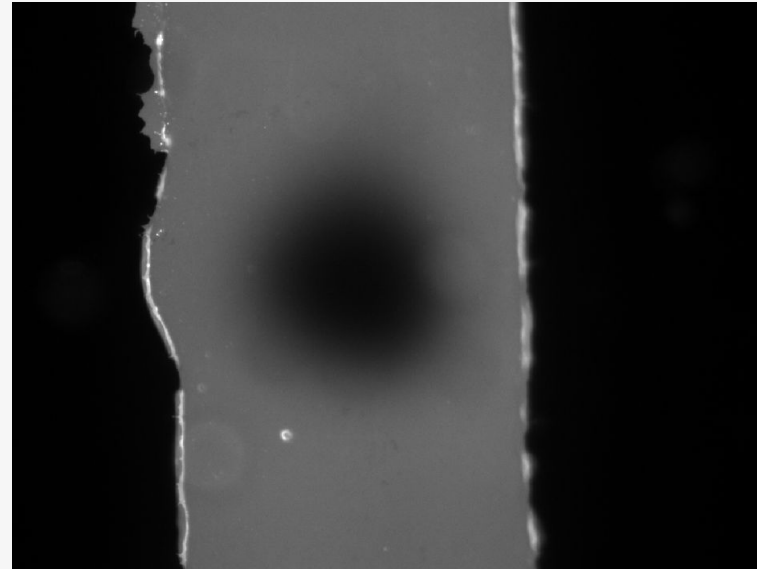
# Methodology

- 1) Run a simulation on an initial condition for an experiment
- 2) Track intensity data for our experiment through time
- 3) Compare the two to get the correct D value



# Step 1: Simulate

- We need to be able to set up an initial condition for a situation like this one:
  - Shape of the channel (fluorescent region)
  - Shape of the outside of the channel
  - Shape of the gaussian spot

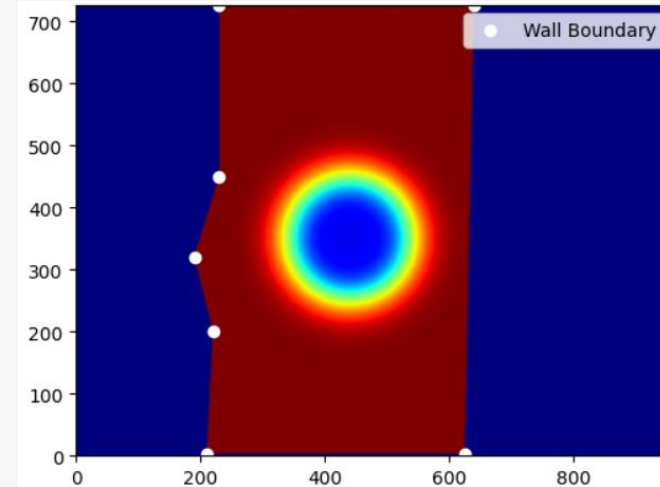
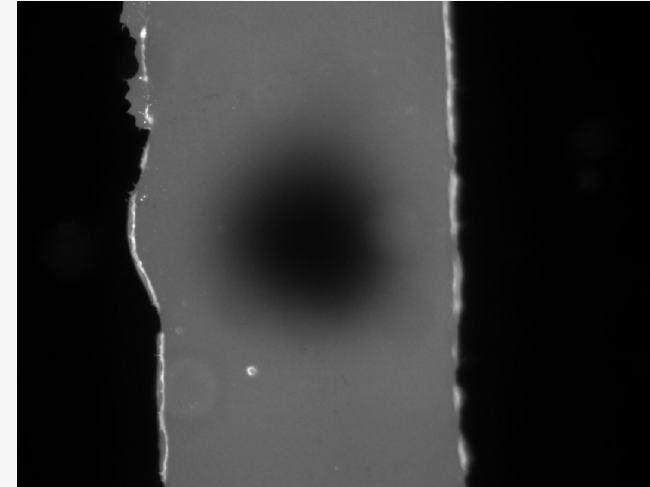


# Step 1: Simulation

- Manually plugged in points to make an approximate boundary around our channel
- Inside the boundary: concentration = one
- Outside the boundary: concentration = zero
- Used a nested exponential function to model our laser spot

$$C(r) = C_c + (1 - C_c) \cdot e^{-Pe^{-r^2}}$$

$C_c$  = Initial center brightness     $P$  = laser power



# Step 1: Simulation

- Now that the initial conditions are realistic, we are ready to simulate.
- Use the finite difference method with Laplace's equation to get the new concentration for a given time step.

```
# Calculate the Laplacian (second derivative) using finite differences
d2C_dx = (C[j+1, i] - 2*C[j, i] + C[j-1, i]) / dx**2
d2C_dy = (C[j, i+1] - 2*C[j, i] + C[j, i-1]) / dy**2
# Update concentration based on the diffusion equation
new_C[j, i] = C[j, i] + D * dt * (d2C_dx + d2C_dy)
```

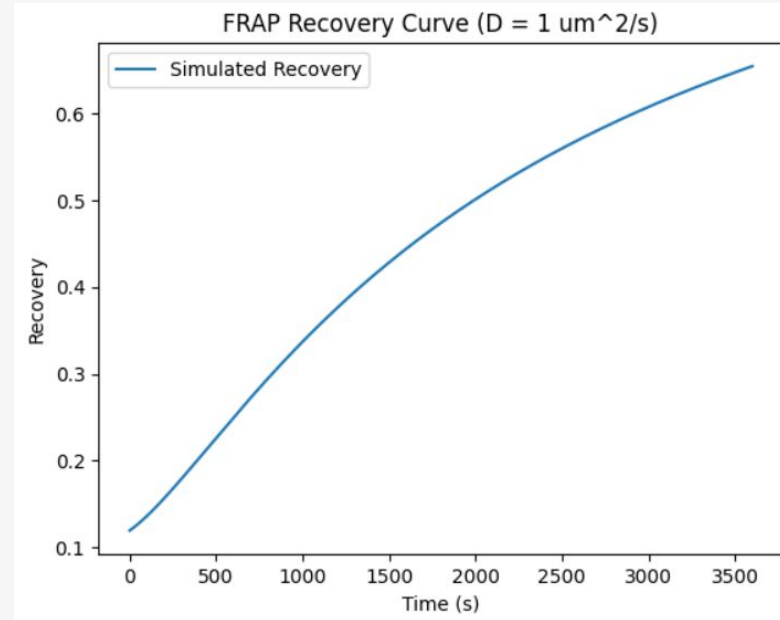
# Step 1: Simulation

- Run throughout time to get a FRAP recovery curve for a given  $D$  value
- The recovery is measured by tracking the intensity of the bleached spot over time

```
for t in range(time_steps):
    C = diffuse(C, D, dx, dt)

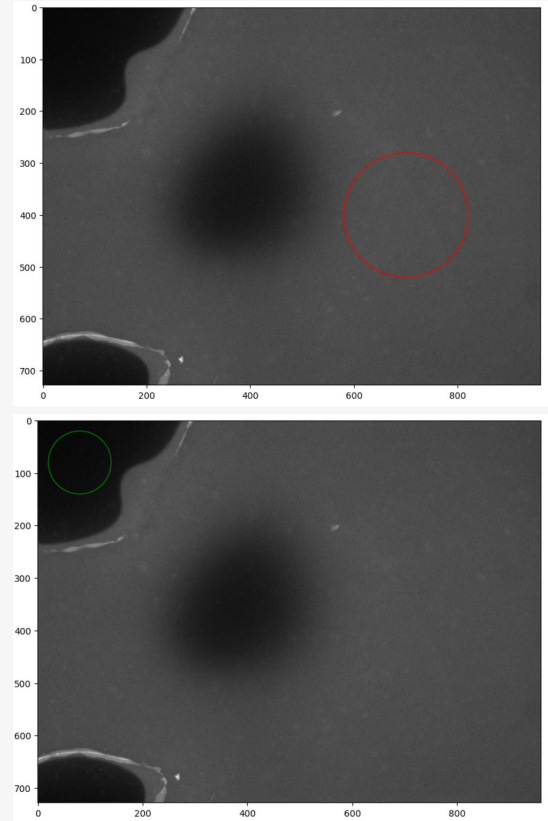
    # Calculate the recovery by averaging the concentration in the bleached region
    # We take the average concentration in a circular region around the center
    recovery = 0
    for i in range(grid_size_x):
        for j in range(grid_size_y):
            if (i - center_x)**2 + (j - center_y)**2 <= sigma**2:
                recovery += C[j, i]

    # Average over the pixels in the bleached region
    recovery /= np.pi * sigma**2
    intensity_curve.append(recovery)
```



# Step 2: Experimental Data

- 28 images per FRAP experiment
- Track intensity of a circular ROI through time
- First we grab a section of unbleached bilayer and a section of background to aid with later normalization



# Step 2: Experimental data

- Make a circular mask around the bleached spot
- Obtain the average intensity for the pixels in this region
- Do this for each of the 28 images



```
# Create a mask for the circular region
y, x = np.ogrid[:size[0], :size[1]] # Create coordinate grids for the image
mask = (x - center[0])**2 + (y - center[1])**2 <= radius**2 # Circular mask

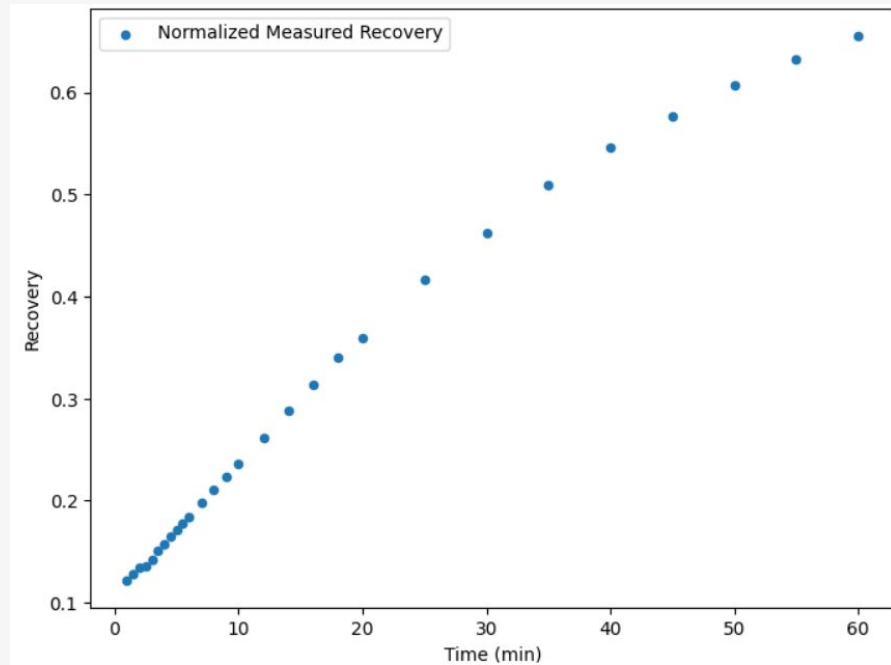
# Set all entries outside the circle to 0
image_outside_circle = np.copy(image)
image_outside_circle[~mask] = 0

# Calculate the average value of the pixels inside the circle
pixels_inside_circle = image[mask] # Get the pixel values inside the circle
average_value_inside_circle = np.mean(pixels_inside_circle)

# Append the average value to the list
average_values.append(average_value_inside_circle)
time.append(i)
```

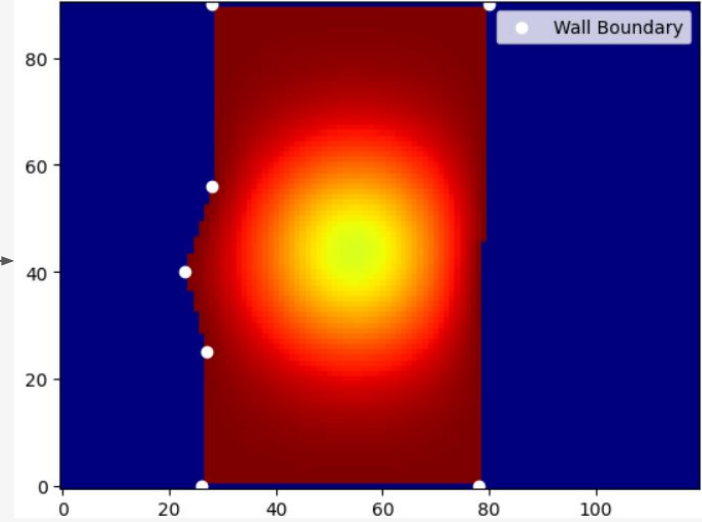
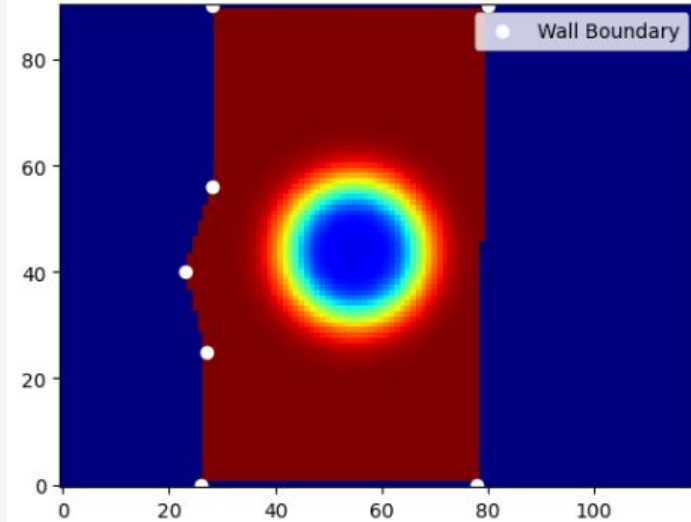
# Step 2: Experimental Data

- These intensities give us an unnormalized FRAP recovery curve
- The y-axis is currently based directly on the original image pixel values
- We want the y-axis to range from 0 to 1 so compare it to the simulation.
- Normalizing the data yields us a curve like this

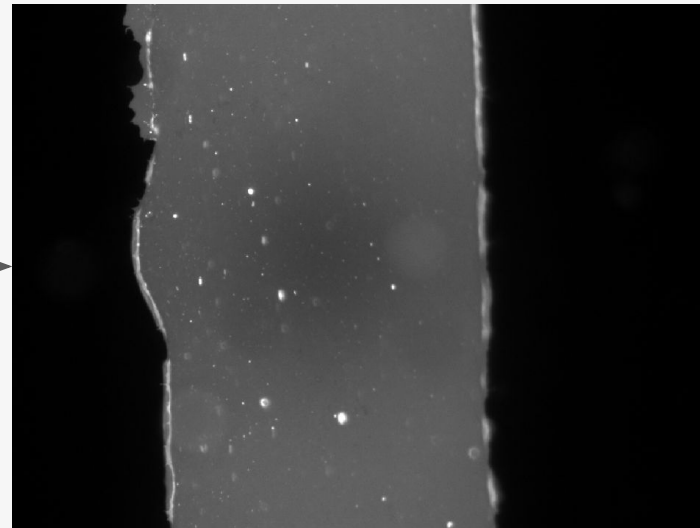
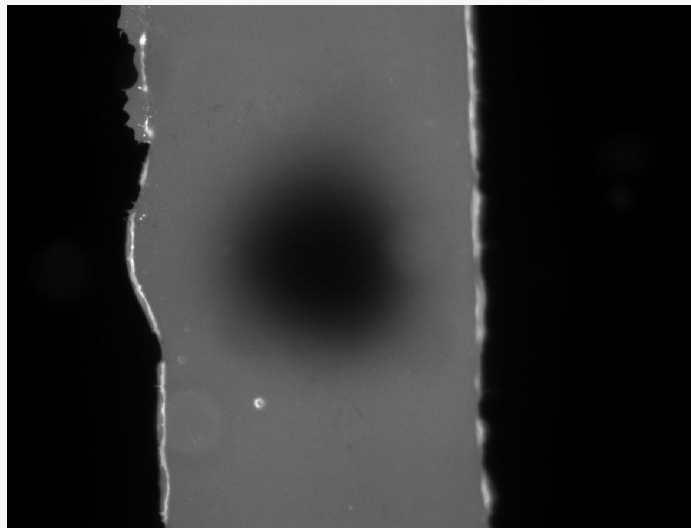




# Simulation

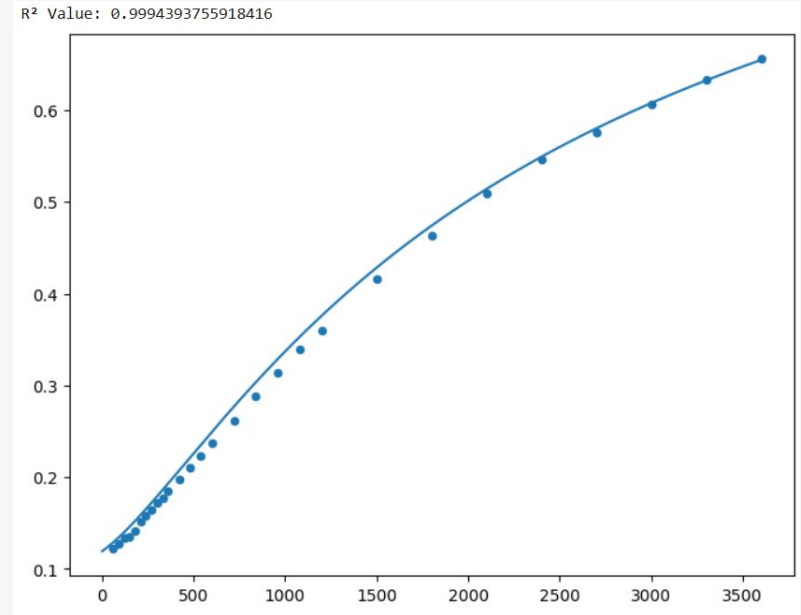


# Experiment



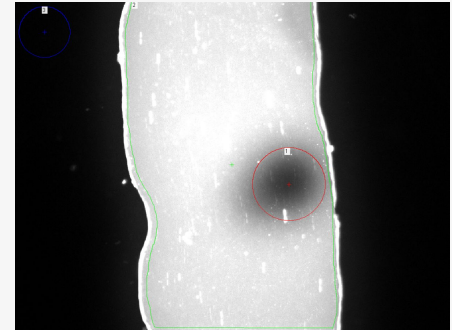
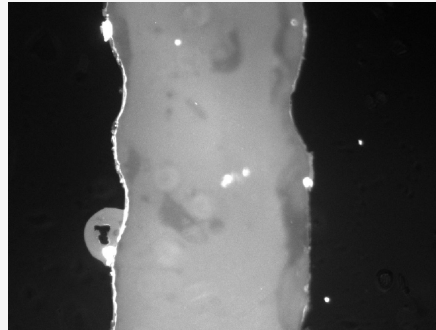
# Step 3: Compare

- After plugging in and testing some D values, we find one that overlaps well
- In this case we find that  $D = 1 \mu\text{m}^2/\text{s}$
- 3 other FRAP experiments yield similar values of 0.95, 1.1, and  $1.3 \mu\text{m}^2/\text{s}$  based on our “eyeball method”



# Discussion

- The literature values of the diffusion coefficient for the lipids we use (DOPC and POPC) are also in the neighborhood of  $D = 1 \mu\text{m}^2/\text{s}$ , giving us confidence in our method.
- There are other experimental factors to consider in our analysis
  - Surface cleanliness
  - Loose vesicles
  - Spot size
  - Bleach time
  - Temperature



# Next Steps

We have many steps to take to improve this analysis

1. Run our simulation on the rest of the available data
2. Automatic boundary and spot drawing
3. A more robust fitting method
4. Streamlining our code

6-10 through 6-26 FRAPs (all 1 hr, full scaled normalized and single fitted)					
filename	T-half	Mobile Fraction	R square	Bleaching Depth	Gap Ratio
10_53a.xlsx	13.2	0.74	0.98	0.56	0.89
10_53b.xlsx	23.76	1	1	0.6	0.92
11_52a.xlsx	29.05	1	0.97	0.48	0.84
11_52b.xlsx	10.91	0.63	0.99	0.22	1.29
12_52a.xlsx	35.61	0.98	1	0.71	0.75
12_52b.xlsx	50.16	1	0.97	0.6	0.87
12_53b.xlsx	18.07	0.84	1	0.5	0.81
13_55a.xlsx	59	0.98	1	0.87	0.78
13_55b.xlsx	30.39	0.9	1	0.64	0.69
6-17 FRAP 53a.xlsx	14.26	0.74	0.96	0.87	0.71
6-17 FRAP 56a.xlsx	29.71	0.81	1	0.75	0.81
6-17 FRAP 56b.xlsx	35.9	0.73	1	0.87	0.82
6-18 FRAP 53a.xlsx	26.28	0.96	1	0.77	0.7
6-18 FRAP 53b.xlsx	19.06	0.85	0.99	0.75	0.73
6-18 FRAP 57a.xlsx	31.38	0.94	1	0.74	0.78
6-20 FRAP 56a.xlsx	33.85	0.81	1	0.89	0.75
6-20 FRAP 56b.xlsx	35.61	0.85	1	0.92	0.58
6-20 FRAP 57a.xlsx	29.72	0.93	1	0.8	0.79
6-21 FRAP 57b.xlsx	18.2	0.89	0.99	0.72	0.78
6-24 FRAP 56a.xlsx	34.88	0.82	1	0.89	0.73
6-25 FRAP 56b.xlsx	36.09	0.67	1	0.8	0.73
6-25 FRAP 56a.xlsx	27.48	0.95	1	0.88	0.71
6-26 FRAP 56b.xlsx	19.61	0.74	0.98	0.83	0.76
7-1 FRAP 55a.xlsx	23.15	0.84	1	0.82	0.72
7-1 FRAP 55b.xlsx	30.35	0.85	1	0.88	0.63
7-3 FRAP 55a.xlsx	26.93	0.86	1	0.82	0.75
7-3 FRAP 55b.xlsx	31.36	1	1	0.92	0.67
7-3 FRAP 58b.xlsx	352.92	0.55	0.99	0.94	0.62
7-9 FRAP 58b.xlsx	25.62	0.21	0.92	0.96	0.67
7-10 FRAP 58b.xlsx	30.4	0.13	0.99	0.8	0.76
Mean:	39.43033	0.806667		0.76	0.768
Standard Deviation:	60.04993	0.208613		0.1647778	0.125104095

# Conclusion

- FRAP analysis is a powerful method for determining lipid bilayer properties.
- Being able to perform this analysis in microfluidic channels can help users control bilayer fluidity.
- We have shown that our code is able to provide accurate values for the diffusion coefficient



# References

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