

# Convergence Analysis of MAP based Blur Kernel Estimation Supplementary

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• Some results are shown in Figure 4	

# MATLAB Source Code for Figure 6

```
% To make Fig. 6 in the paper
function psf = deblur_single_level(blurred, k_size)
lambda_l = 0.0006;
alpha = 0.1;
lambda_k = 0.001;
num_iters = 20;

% initial PSF
psf = zeros(k_size);
psf((k_size(1)+1)/2,(k_size(2)+1)/2) = 1;

% prepare gradient maps of blurred
blurred = edgetaper(blurred,fspecial('gaussian',60,10));
bx = imfilter(blurred, [0 -1 1], 'corr', 'circular');
by = imfilter(blurred, [0;-1;1], 'corr', 'circular');
blurred_g = cat(3, bx, by);

% alternating estimation
for iter=1:num_iters
    latent_g = deconv_sps(blurred_g,psf,lambda_l,alpha);

    [energy data prior_l prior_k] = energy_func(...
        latent_g, blurred_g, psf, ...
        lambda_l, alpha, lambda_k);
    fprintf('%d\t%f\t%f\t%f\n', ...
        iter, energy, data, prior_l, prior_k);

    psf = estimate_psf(blurred_g, latent_g, psf_size, lambda_k);
end
end
```

```
function [energy data prior_l prior_k] ...
    = energy_func(latent, blurred, psf, lambda_l, alpha, lambda_k)
tau = 0.01;

K = psf2otf(psf, size(blurred));
b = real(ifft2(fft2(latent).*K));
diff = b - blurred;
data = sum(diff(:).^2);

w = max(abs(latent),tau).^(alpha-2);
prior_l = sum(w(:).*latent(:).^2);
prior_k = sum(psf(:).^2);

energy = data + lambda_l*prior_l + lambda_k*prior_k;
end
```

# MATLAB Source Code for Figure 6

```
function latent = deconv_sps(blurred, psf, lambda_l, alpha, num_iters)
tau = 0.01;
if ~exist('num_iters', 'var')
    num_iters = 15;
end
% initial latent image
B = fft2(blurred);
K = psf2otf(psf, size(blurred));
L = conj(K).*B./(conj(K).*K+lambda_l);
latent = real(ifft2(L));
% iterative update using IRLS
for iter=1:num_iters
    w = max(abs(latent),tau).^(alpha-2);
    latent = deconv_L2(blurred,latent,psf,lambda_l,w,5);
end
end

function latent = deconv_L2(blurred, latent, psf, ...
    lambda_l, weight, n_iters)
img_size = size(blurred);
psf_f = psf2otf(psf, img_size);
b = real(ifft2(fft2(blurred).*conj(psf_f)));
% run conjugate gradient
p.lambda_l = lambda_l;
p.psf_f = psf_f;
p.weight = weight;
latent = conjgrad(latent, b, n_iters, 1e-4, @Ax, p);
end

function y = Ax(x, p)
y = real(ifft2(conj(p.psf_f).* p.psf_f.*fft2(x)));
y = y + p.lambda_l*p.weight.*x;
end
```

```
function x=conjgrad(x, b, n_iters, tol, Ax_func, func_param)
r = b - Ax_func(x,func_param);
p = r;
rsold = sum(r(:).^2);

for iter=1:n_iters
    Ap = Ax_func(p,func_param);
    alpha = rsold/sum(p(:).*Ap(:));
    x=x+alpha*p;
    r=r-alpha*Ap;
    rsnew=sum(r(:).^2);
    if sqrt(rsnew)<tol
        break;
    end
    p=r+rsnew/rsold*p;
    rsold=rsnew;
end
end
```

# MATLAB Source Code for Figure 6

```
function psf = estimate_psf(blurred, latent, psf_size, lambda_k)
B = fft2(blurred);
L = fft2(latent);
Bx = B(:,:,1);
By = B(:,:,2);
Lx = L(:,:,1);
Ly = L(:,:,2);
Lap = psf2otf([0 -1 0;-1 4 -1; 0 -1 0], ...
    [size(blurred,1), size(blurred,2)]);
K = (conj(Lx).*Bx + conj(Ly).*By) ...
    ./ (conj(Lx).*Lx + conj(Ly).*Ly + lambda_k.*Lap);
psf = real(otf2psf(K, psf_size));
psf(psf < max(psf(:))*0.05) = 0;
psf = psf / sum(psf(:));
end
```

```
% To find the globally optimal latent image
% for the no-blur case
function l = find_optimal_no_blur(blurred, lambda_l, alpha)
LUT = make_LUT(lambda_l, alpha);
bx = blurred(:,:,1);
by = blurred(:,:,2);
lx = interp1(LUT(1,:), LUT(2,:), bx(:, ), 'linear', 'extrap');
lx = reshape(lx, size(bx));
ly = interp1(LUT(1,:), LUT(2,:), by(:, ), 'linear', 'extrap');
ly = reshape(ly, size(by));
l = cat(3, lx, ly);
end

function LUT = make_LUT(lambda_l, alpha)
% for every b find the optimal l
% which minimizes |b-l|^2 + lambda_l |l|^\alpha
v = -1:0.1/256:1;
[b l] = meshgrid(v,v);
tau = 0.01;
w = max(abs(l),tau).^(alpha-2);
prior_l = w.*l.^2;
energies = (b-l).^2 + lambda_l * prior_l;
[min_energies min_indices] = min(energies);
LUT = [v; l(min_indices)];
end
```

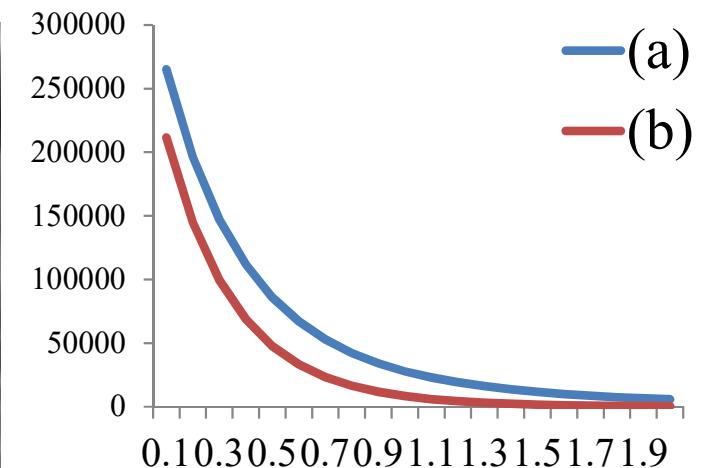
# Figure 1



(a) Sharp image and  
a blur kernel



(b) Blurred image and  
a delta kernel



(c) Sparsity prior values  
of (a) and (b)

# Figure 2



(a)  $\hat{l}_{gt}^{\text{IRLS}}$

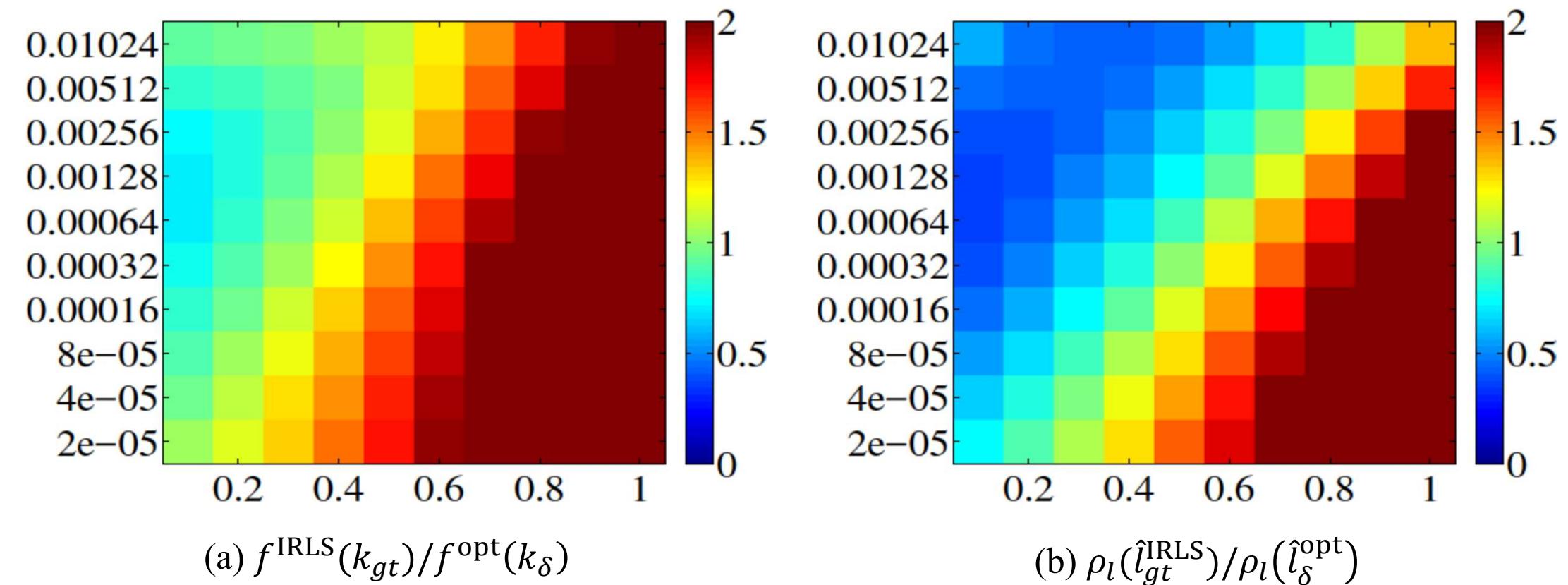


(b)  $\hat{l}_\delta^{\text{IRLS}}$

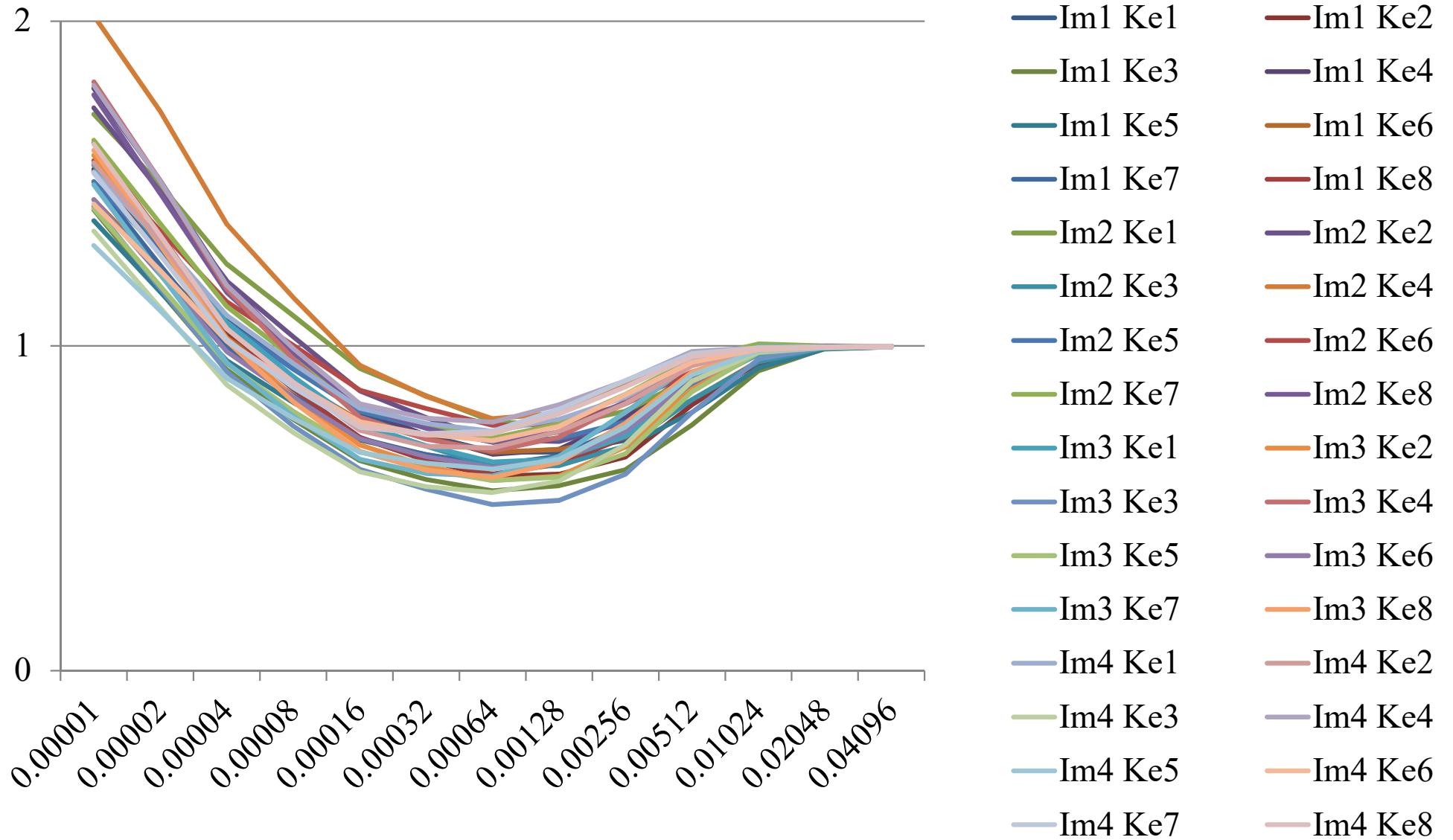


(c)  $\hat{l}_\delta^{\text{opt}}$

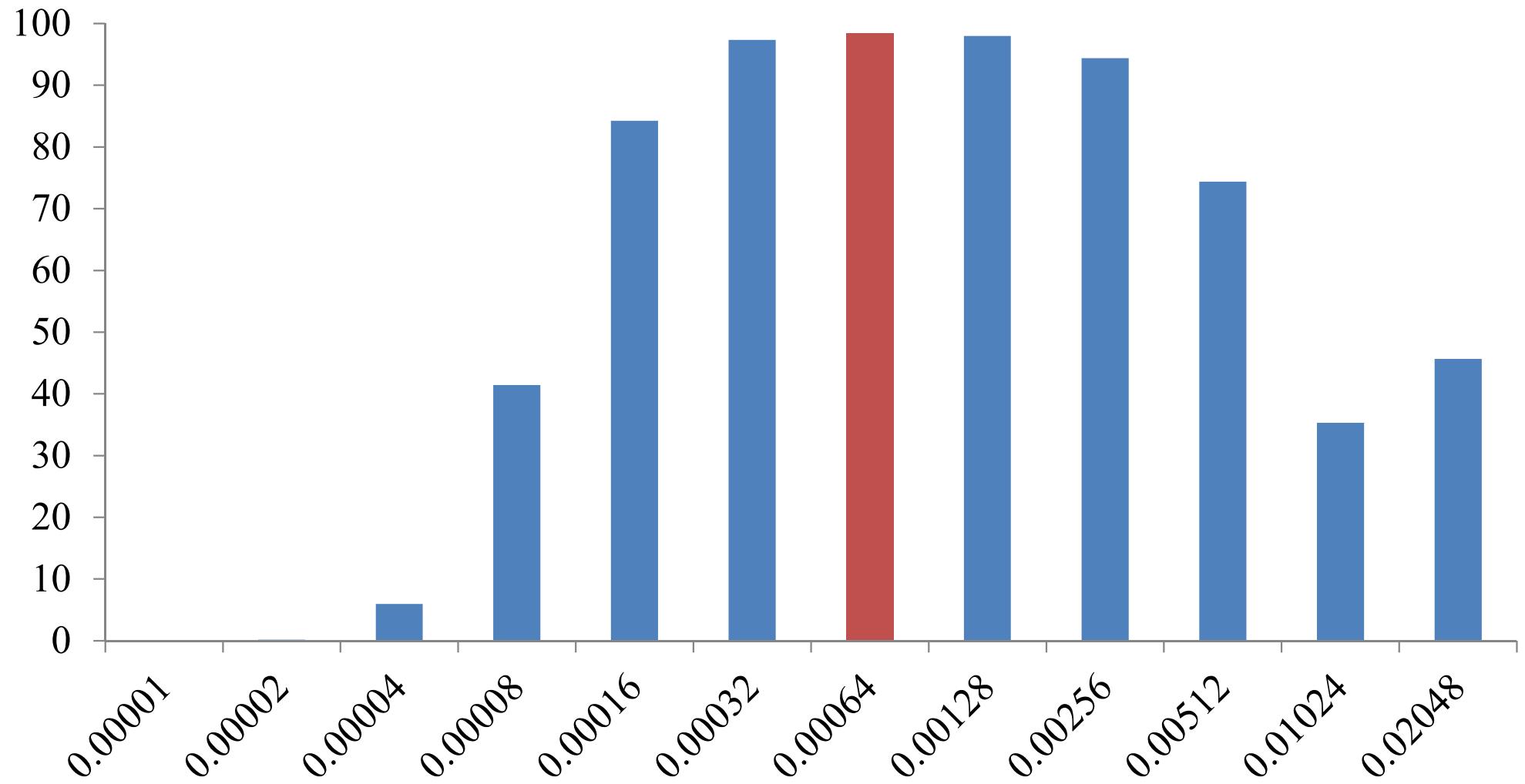
# Figure 3



# Figure 4



# Figure 5



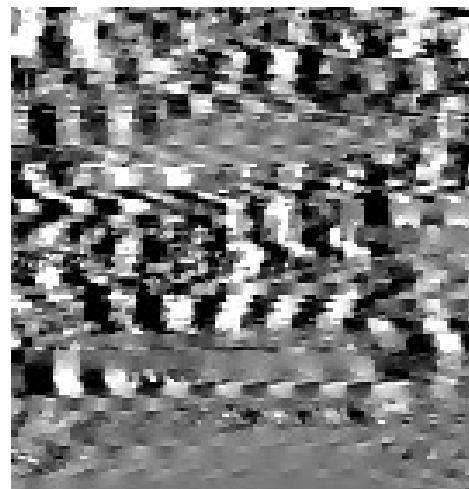
# Figure 6



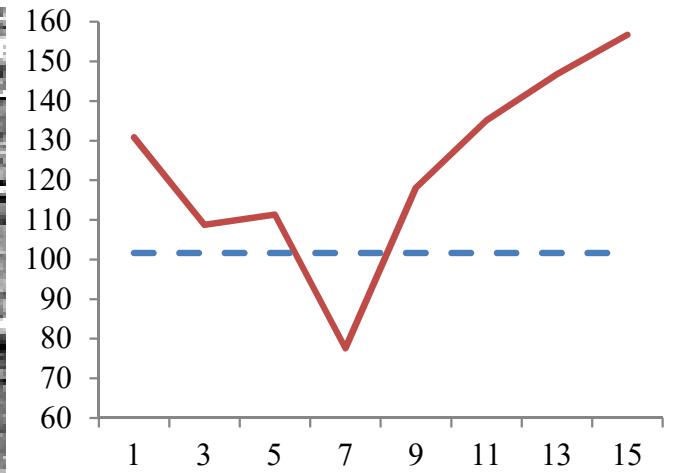
(a) Latent image from  
the blur kernel of  
length 1



(b) Latent image from  
the blur kernel of  
length 7

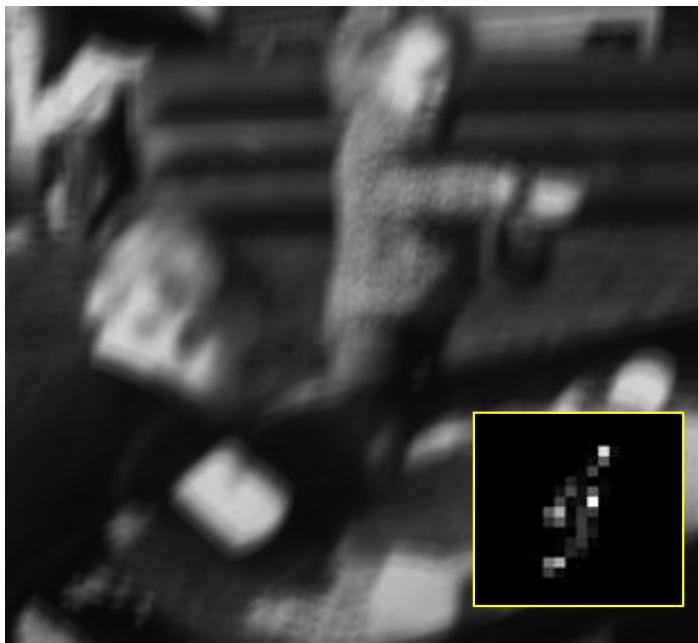


(c) Latent image from  
the blur kernel of  
length 15

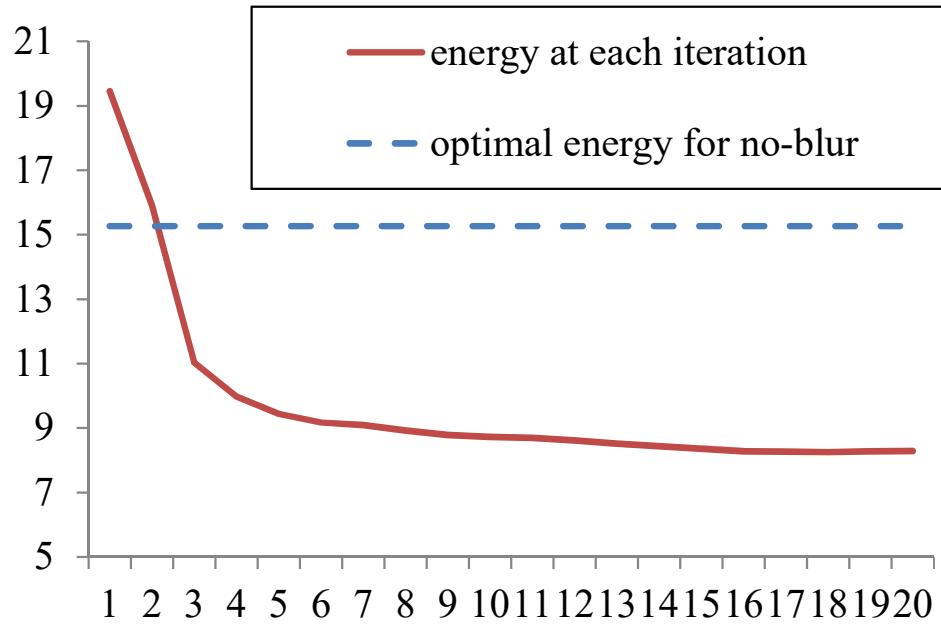


(d)

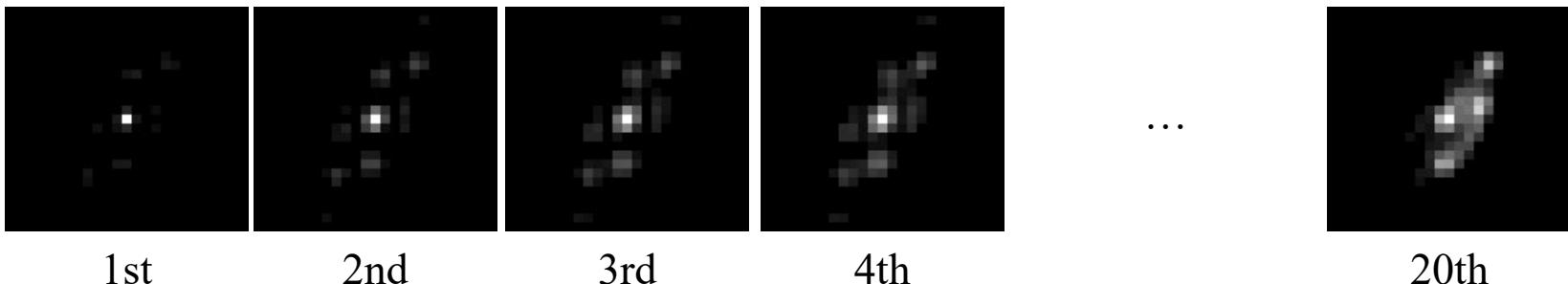
# Figure 7



(a) Blurred image &  
its ground truth blur kernel

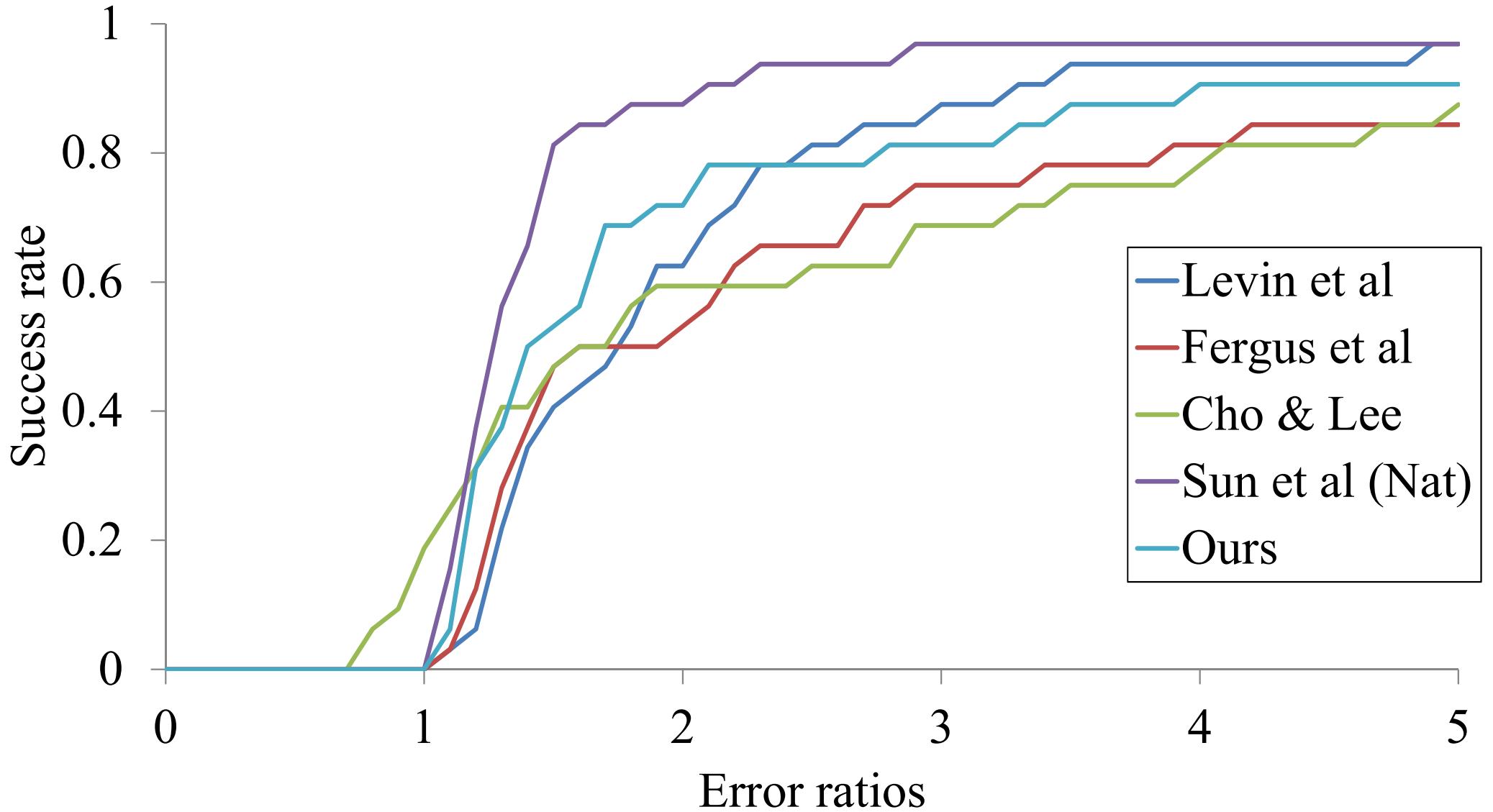


(b) Energy values along iterations

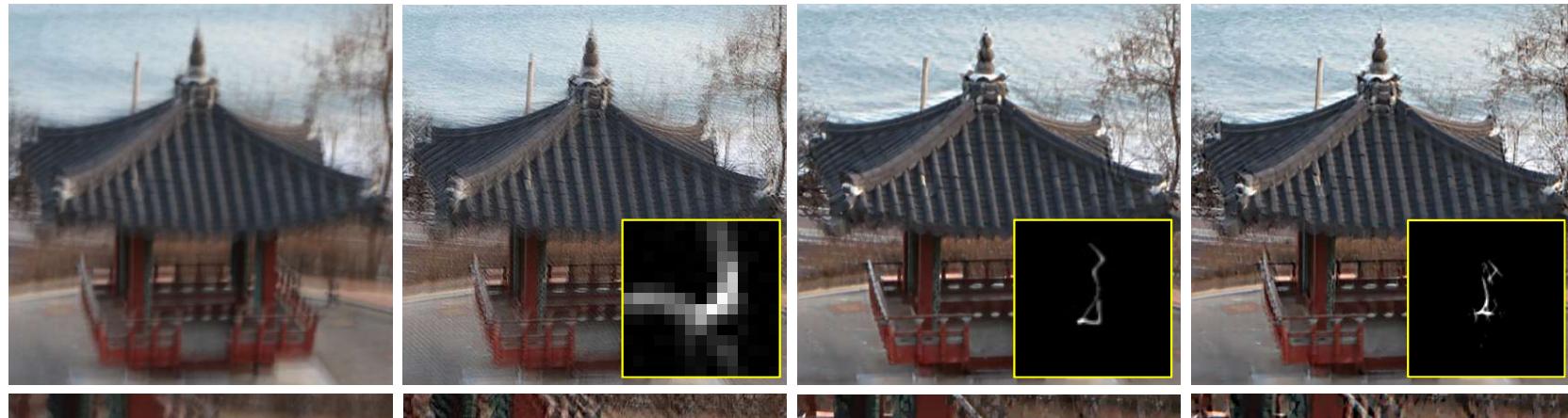


(c) Blur kernels at different iterations

# Figure 8



# Figure 9

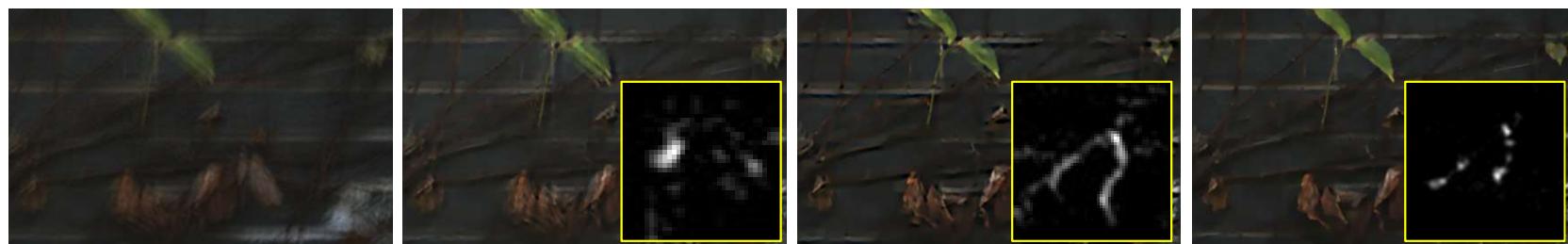


(a) Blurred image

(b) 15x15 kernel  
Energy: 124.2

(c) 75x75 kernel  
Energy: 121.0

(d) 115x115 kernel  
Energy: 130.2



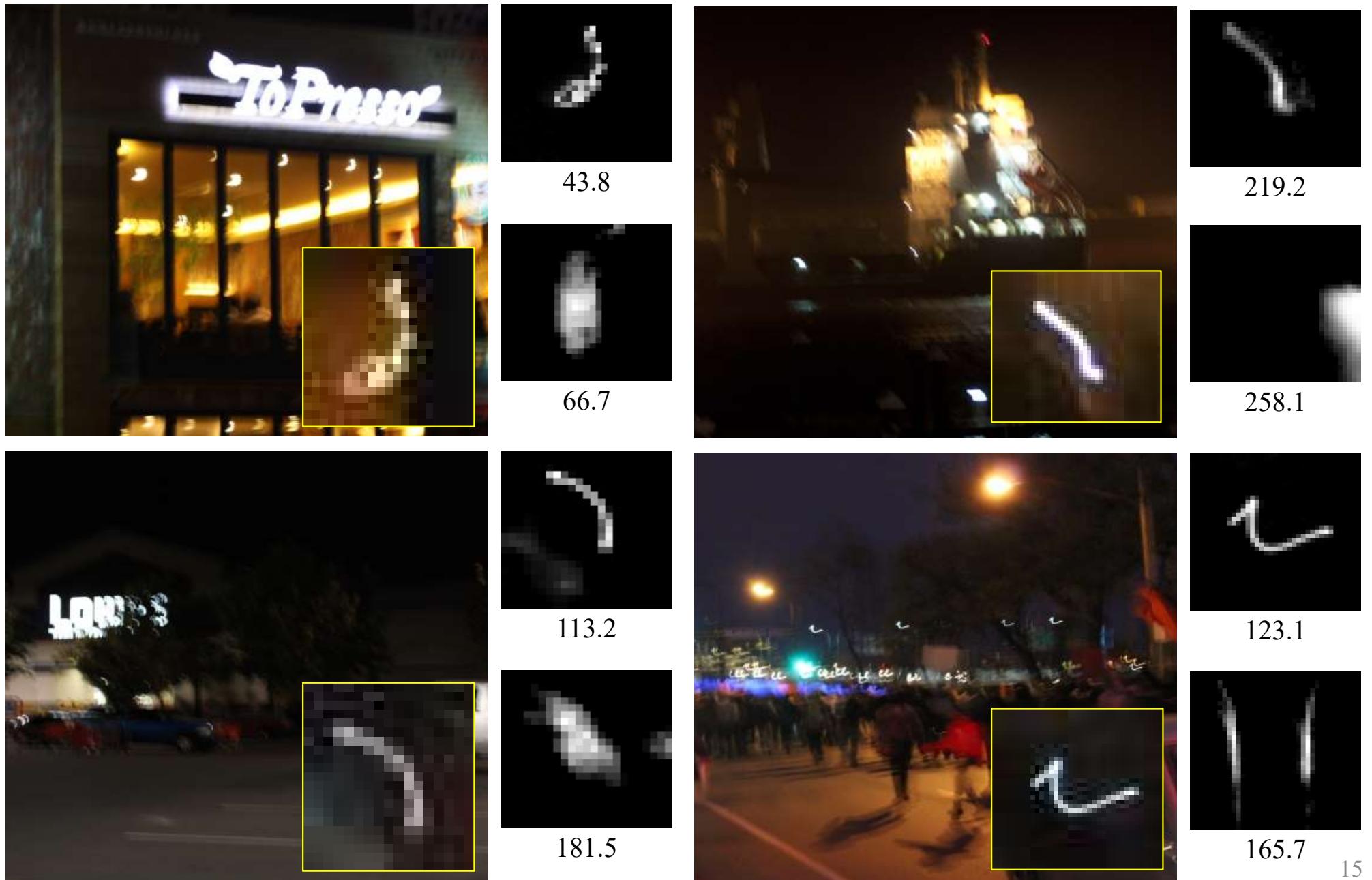
(e) Blurred image

(f) 35x35 kernel  
Energy: 19.4

(g) 55x55 kernel  
Energy: 20.2

(h) 75x75 kernel  
Energy: 18.9

# Figure 10



# Figure 11



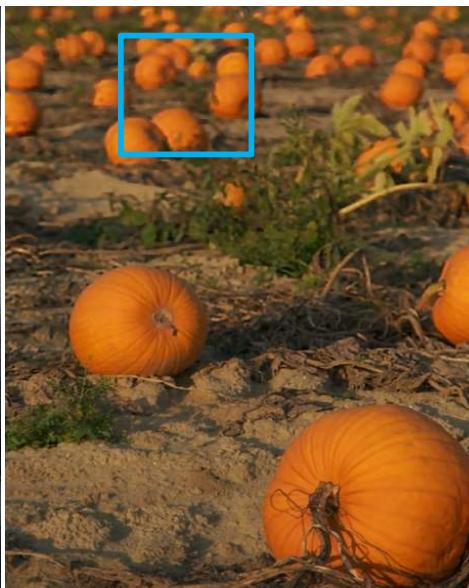
(a) Input image



(b) Sparse defocus map



(c) Dense defocus map

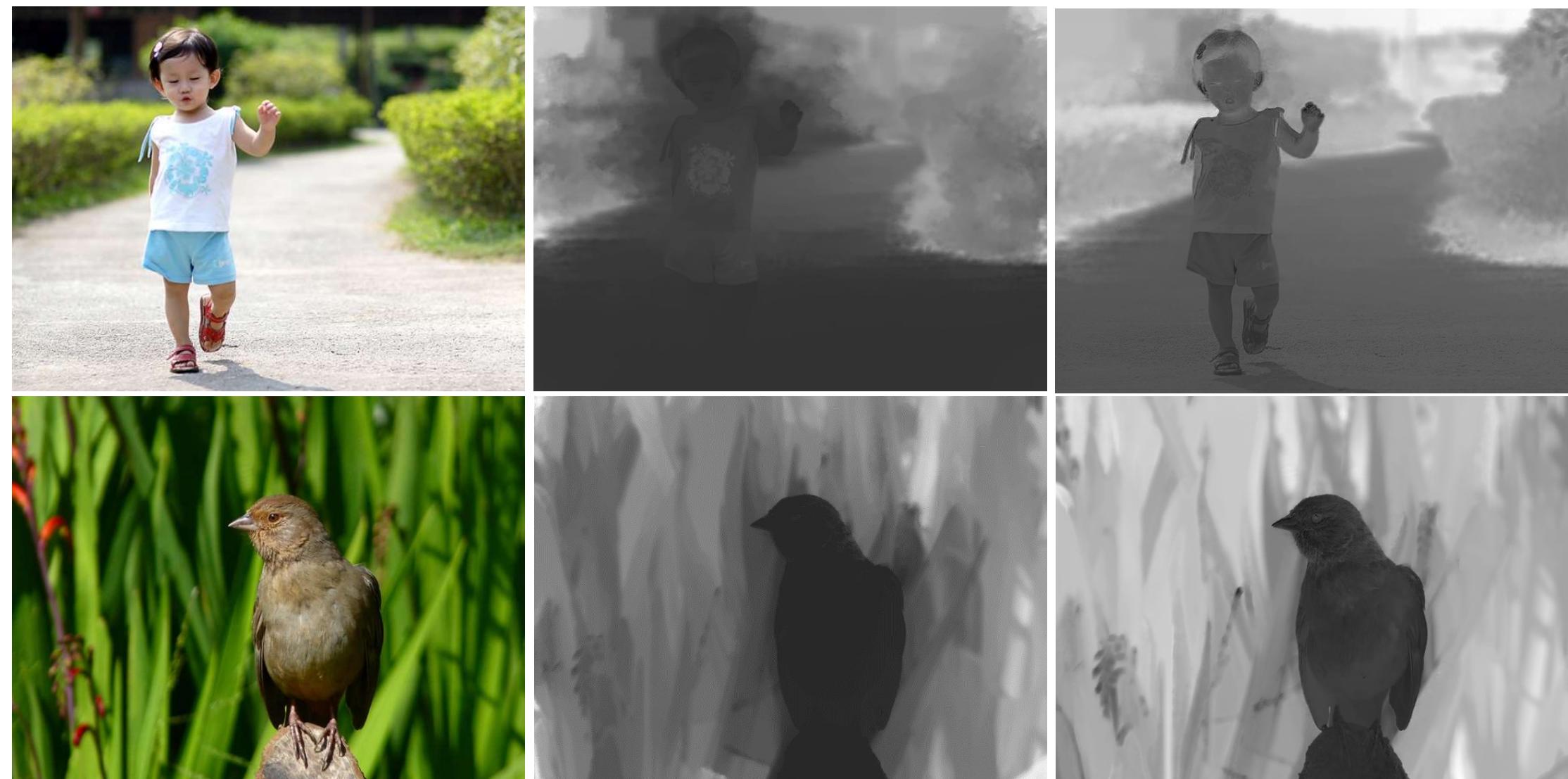


(d) All-focus image



(e) Magnified views  
of (a) & (d)

# Figure 12



(a) Input images

(b) Our defocus maps

(c) Zhuo and Sim [25]

# Figure 8 Our Results



Error ratio: 1.18

Error ratio: 1.11

Error ratio: 1.26

Error ratio: 1.31



Error ratio: 1.22

Error ratio: 1.66

Error ratio: 1.53

Error ratio: 1.35

# Figure 8 Our Results



Error ratio: 1.16

Error ratio: 1.03

Error ratio: 1.14

Error ratio: 1.11



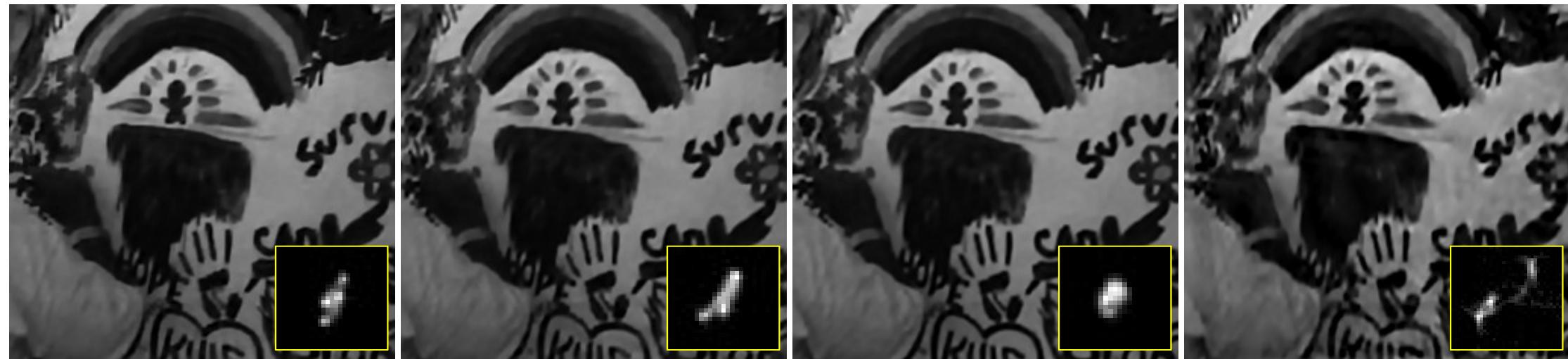
Error ratio: 1.14

Error ratio: 2.06

Error ratio: 1.48

Error ratio: 29.19

# Figure 8 Our Results

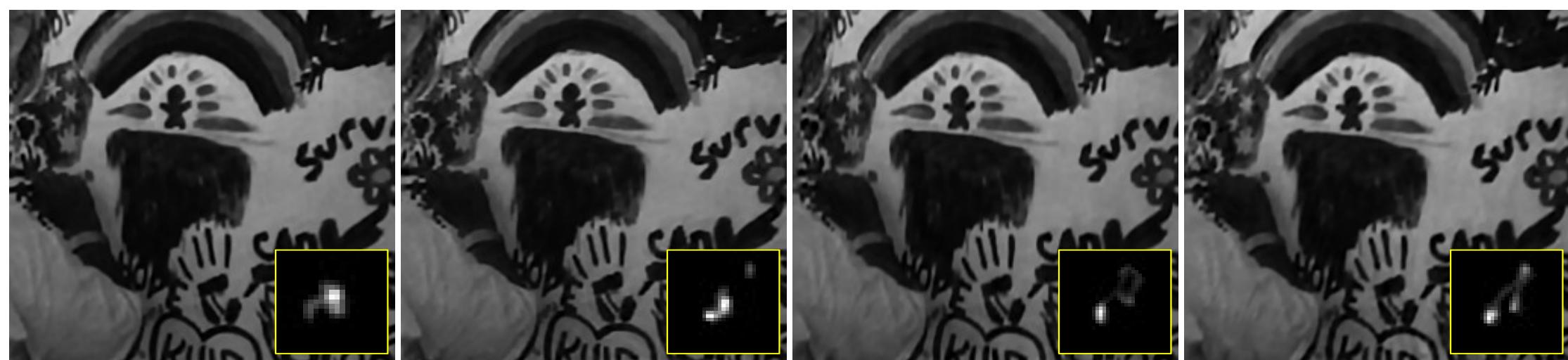


Error ratio: 1.08

Error ratio: 1.15

Error ratio: 1.19

Error ratio: 3.47



Error ratio: 1.34

Error ratio: 2.79

Error ratio: 1.60

Error ratio: 1.34

# Figure 8 Our Results



Error ratio: 1.61

Error ratio: 2.02

Error ratio: 1.88

Error ratio: 3.99



Error ratio: 1.62

Error ratio: 3.26

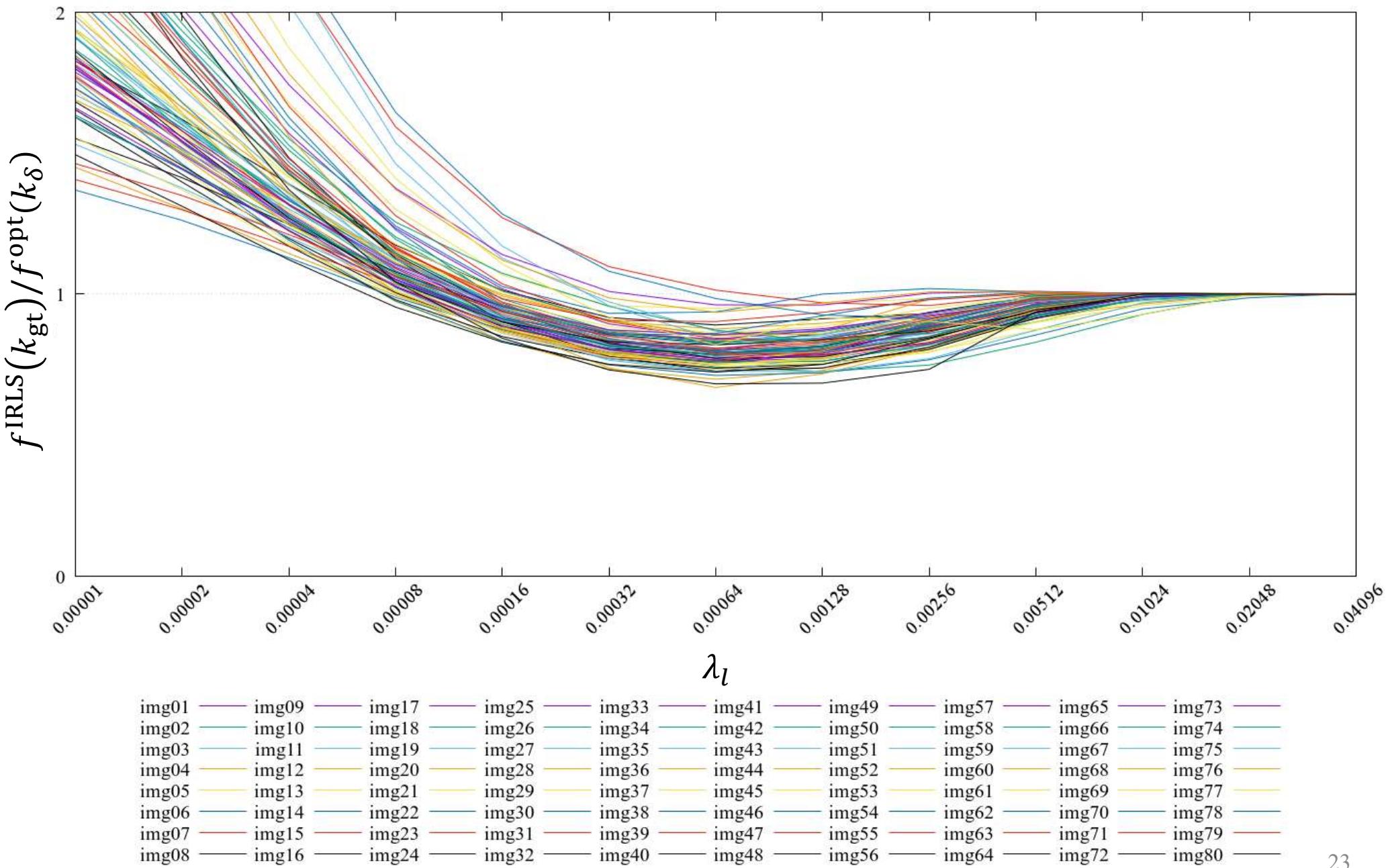
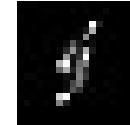
Error ratio: 9.84

Error ratio: 5.55

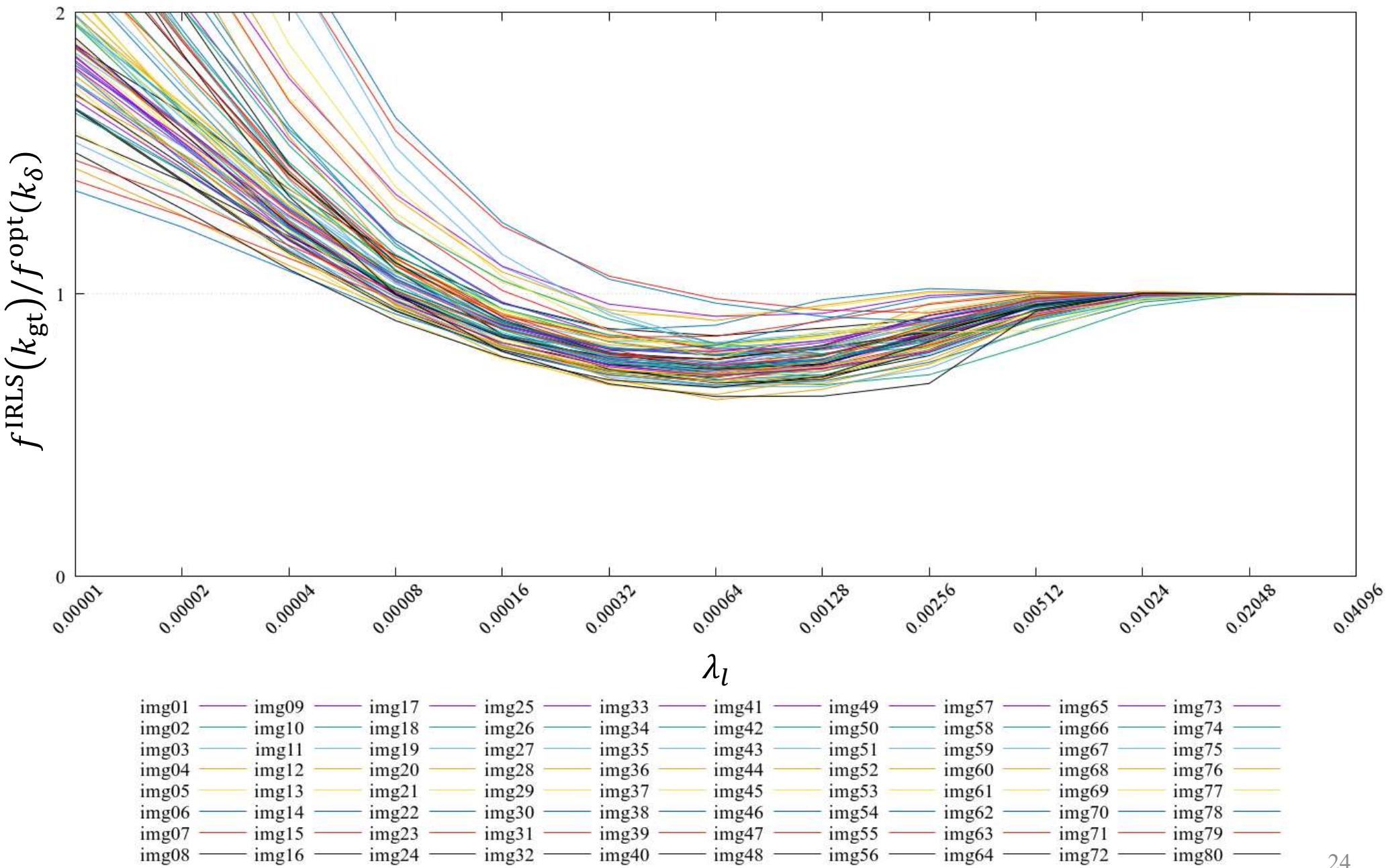
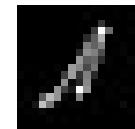
# Experimental Results using Sun et al.'s dataset [19]

- Plots in the following pages show  $f^{\text{IRLS}}(k_{gt})/f^{\text{opt}}(k_\delta)$  with respect to different  $\lambda_l$ 's
  - For each kernel, and then for each image.
  - A couple of them are shown in Fig. 4 in the paper.
- $f^{\text{IRLS}}(k_{gt})/f^{\text{opt}}(k_\delta) < 1$  means that the ground truth blur kernel is preferred to the delta kernel by the energy function.
- Sun et al.'s dataset consists of 640 synthetically blurred images generated from
  - 80 sharp images ranging from natural to man-made scenes, and
  - 8 blur kernels.

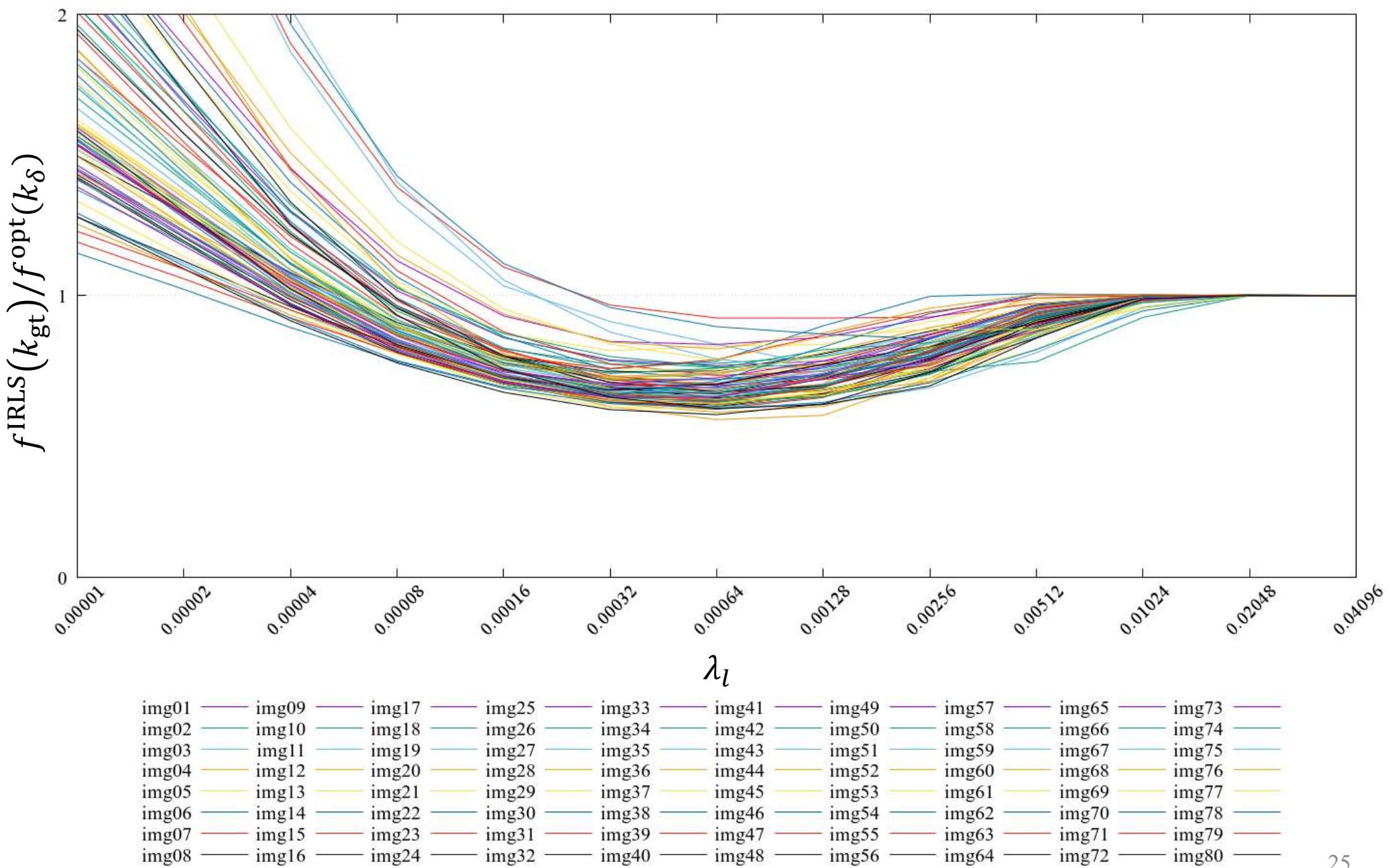
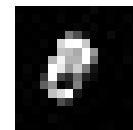
# Sun et al.'s dataset - Kernel 1



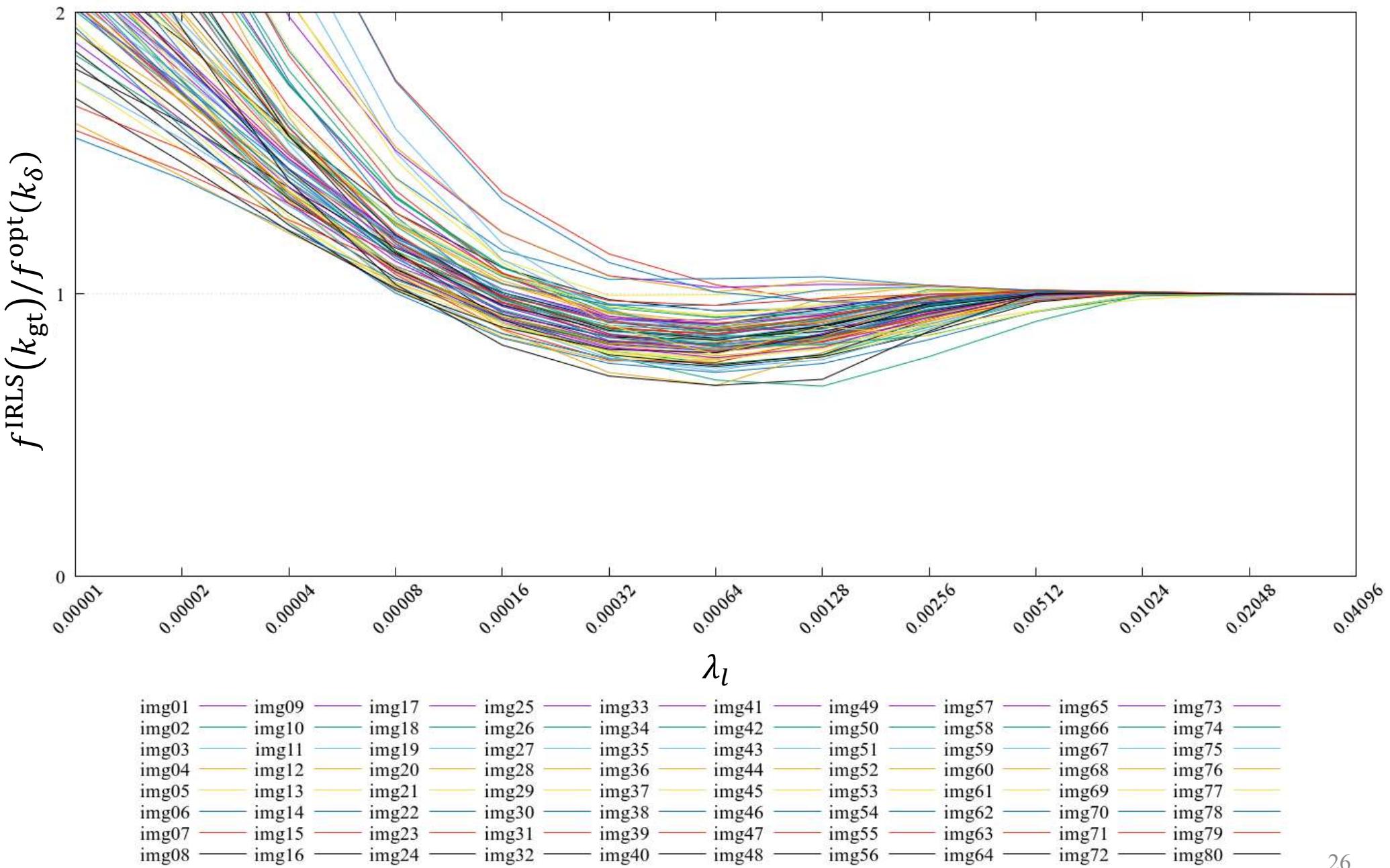
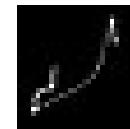
# Sun et al.'s dataset - Kernel 2



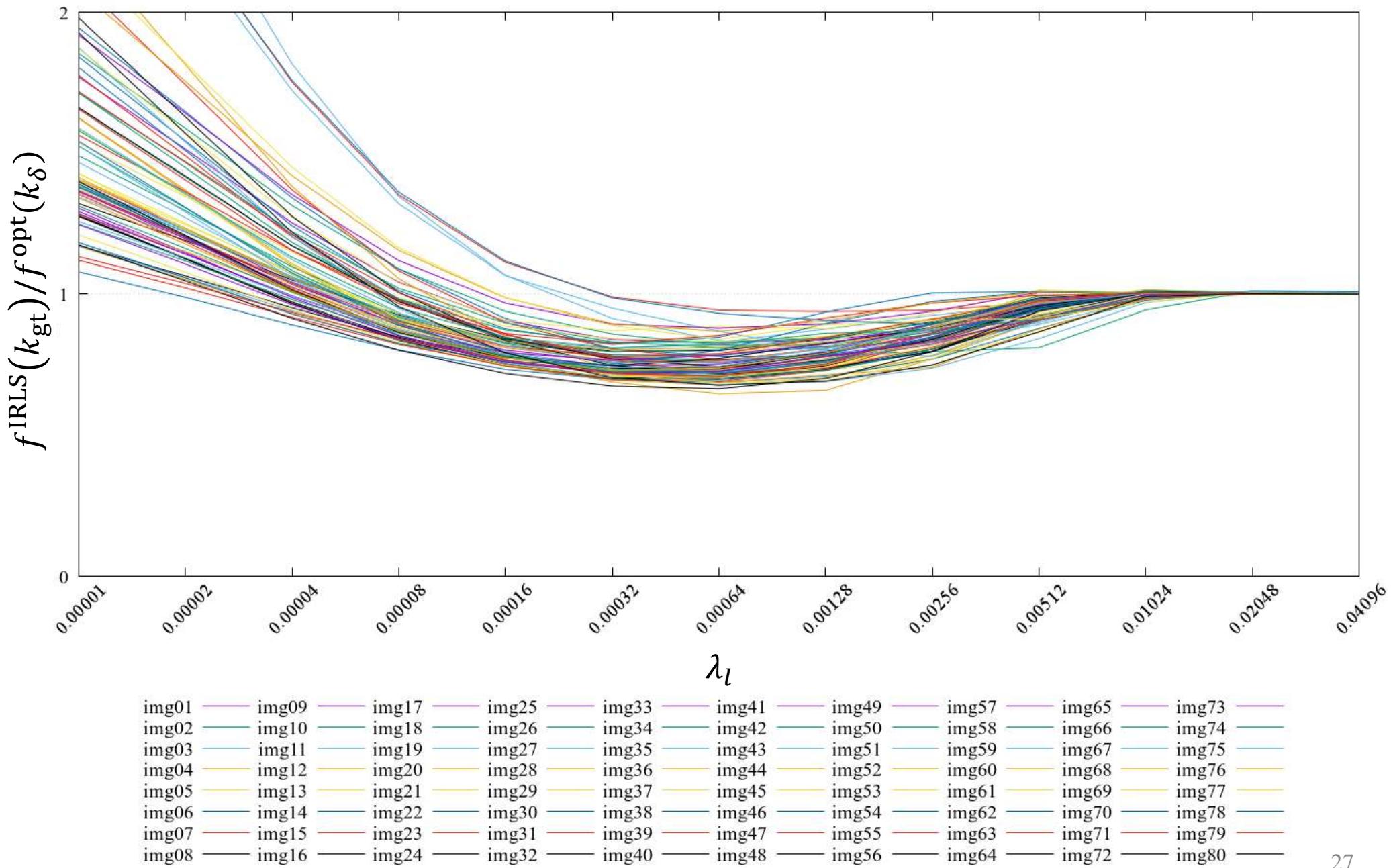
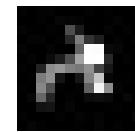
# Sun et al.'s dataset - Kernel 3



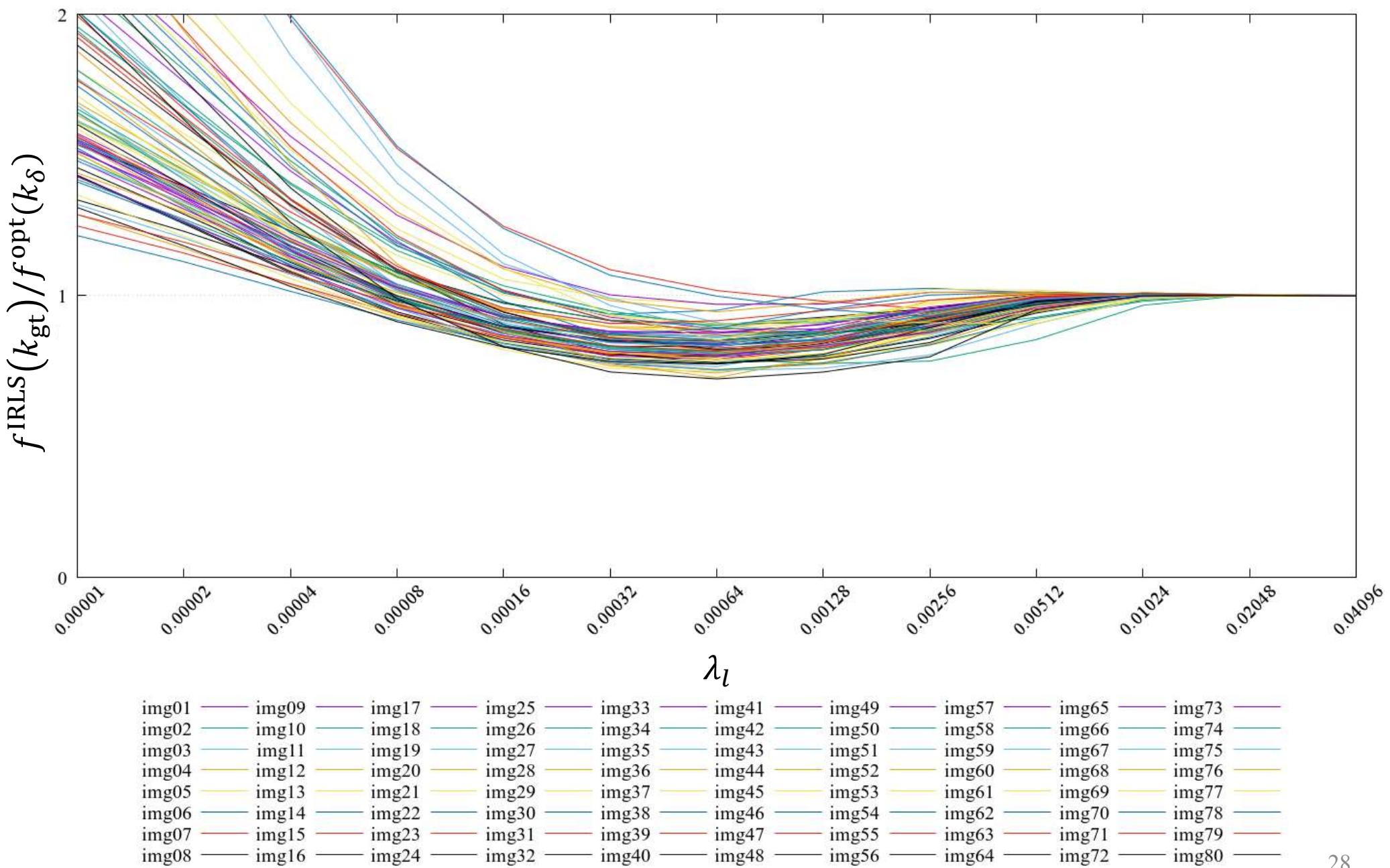
# Sun et al.'s dataset - Kernel 4



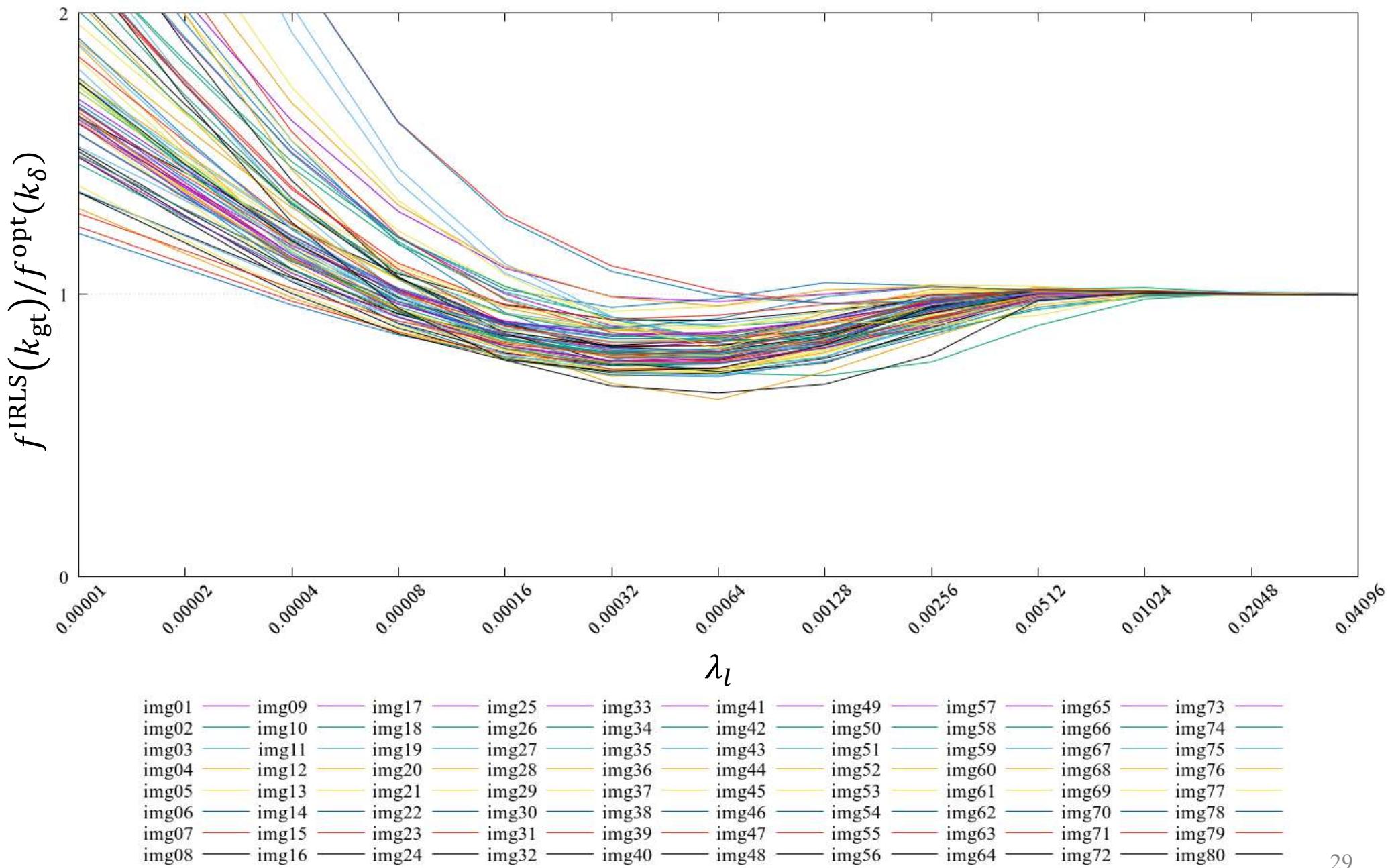
# Sun et al.'s dataset - Kernel 5



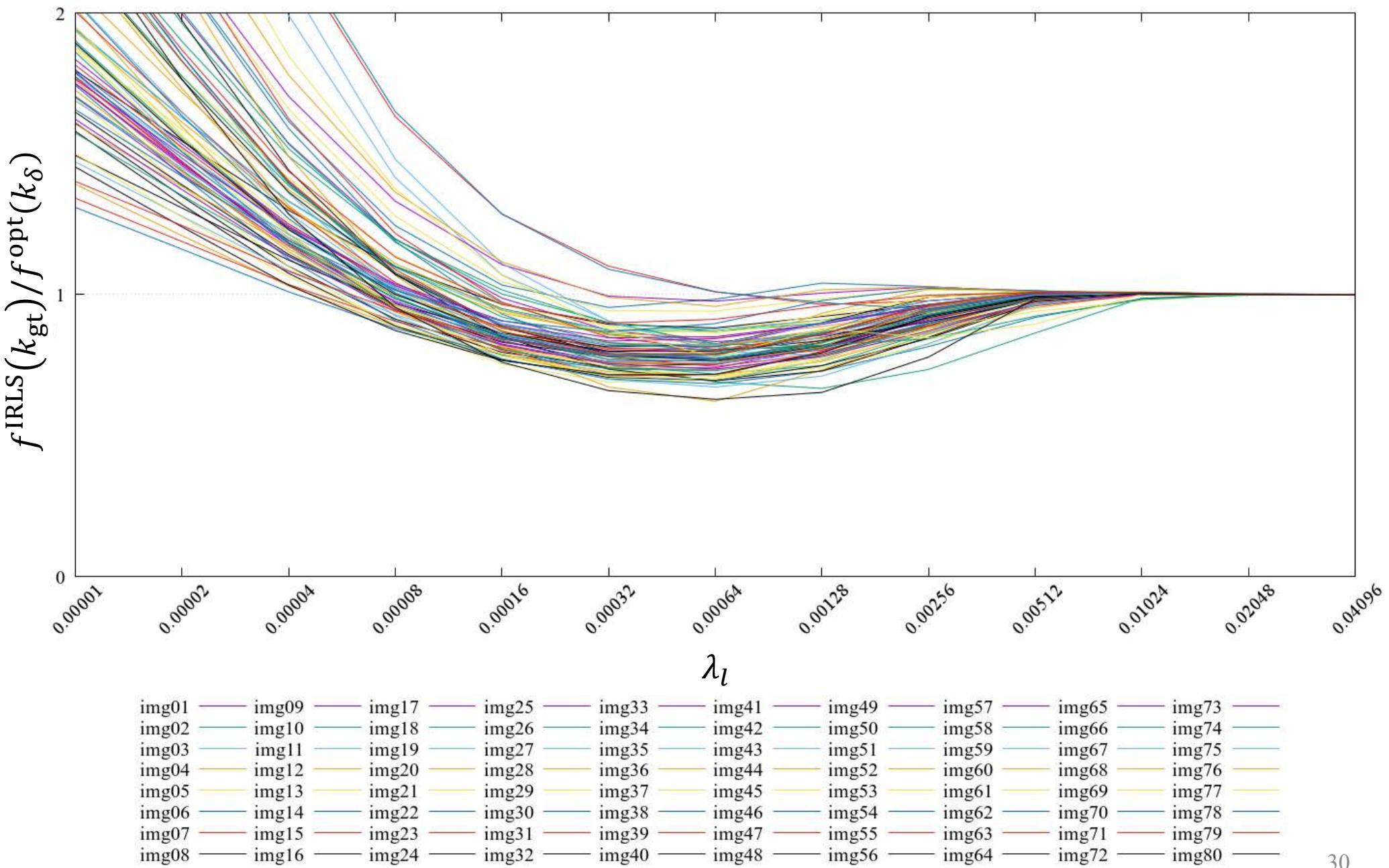
# Sun et al.'s dataset - Kernel 6



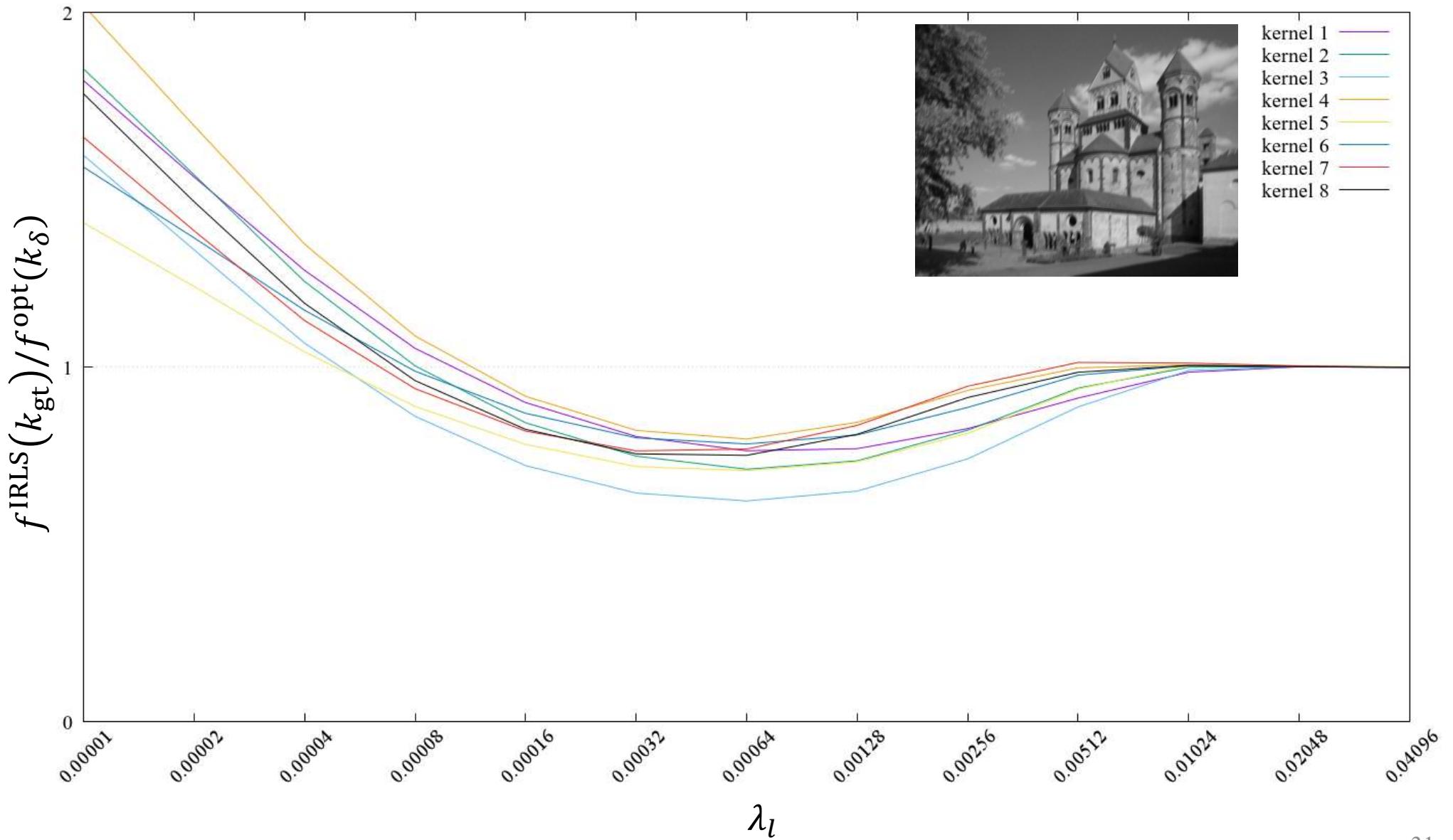
# Sun et al.'s dataset - Kernel 7



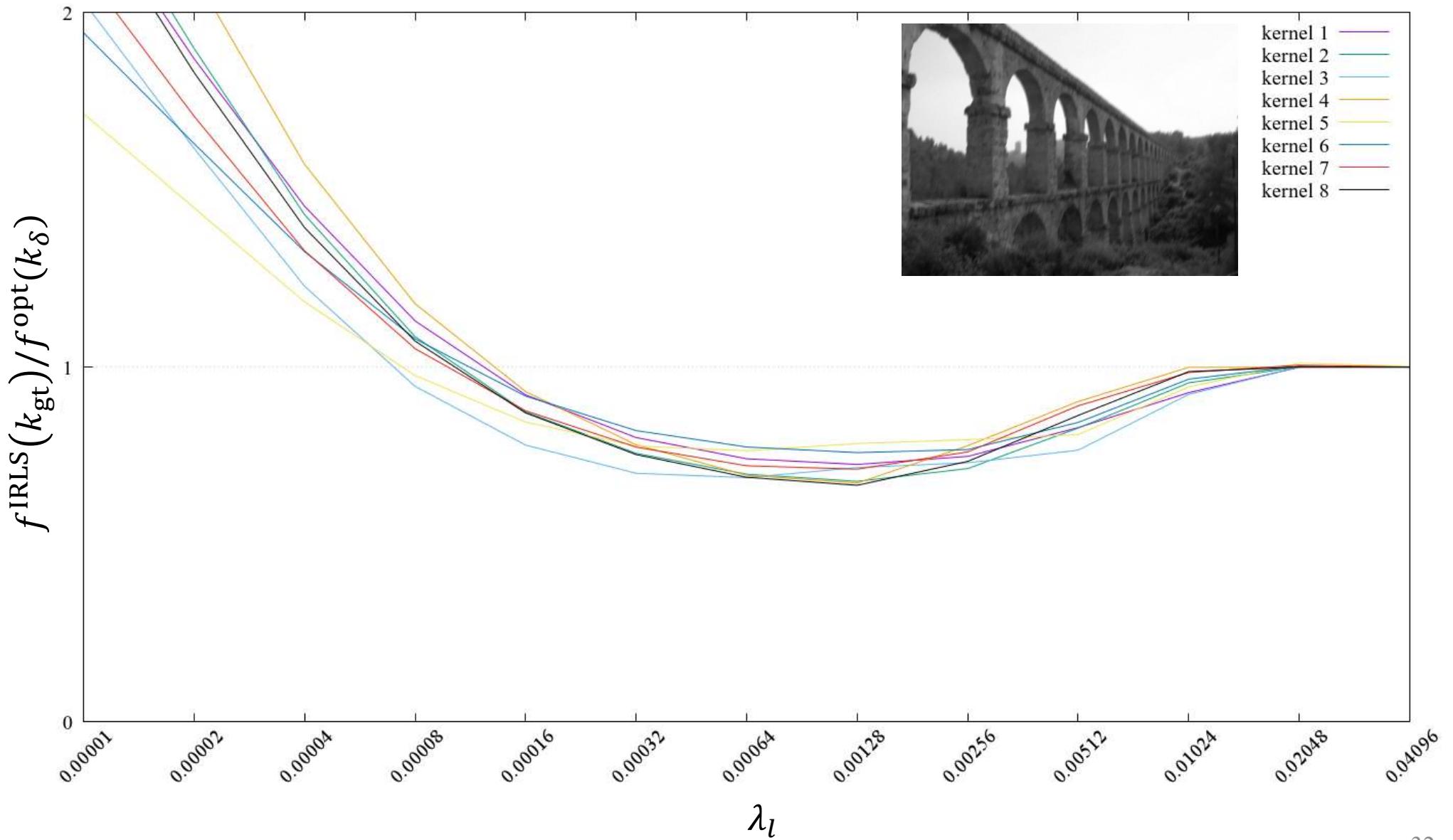
# Sun et al.'s dataset - Kernel 8



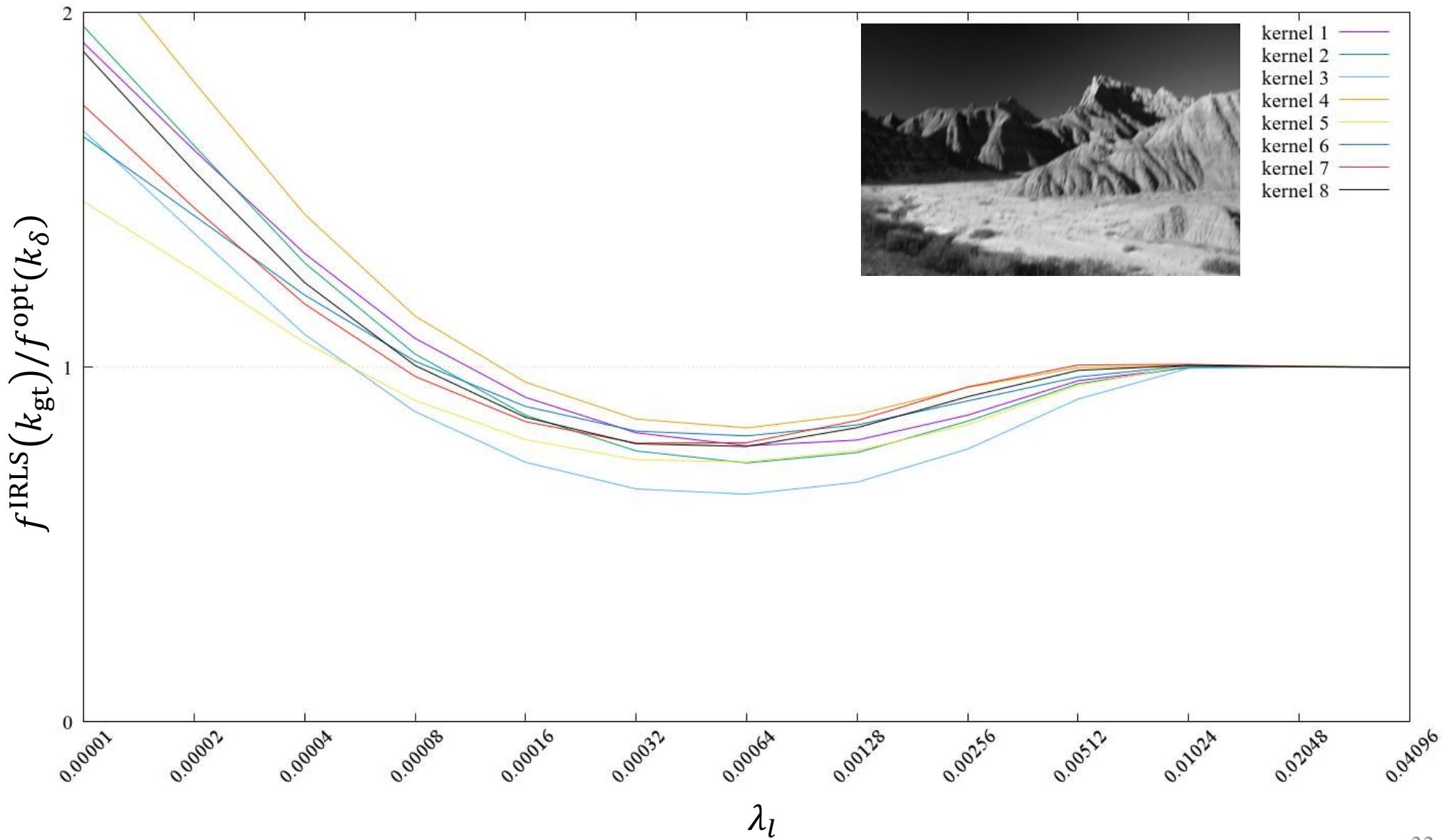
# Sun et al.'s dataset - Image 01



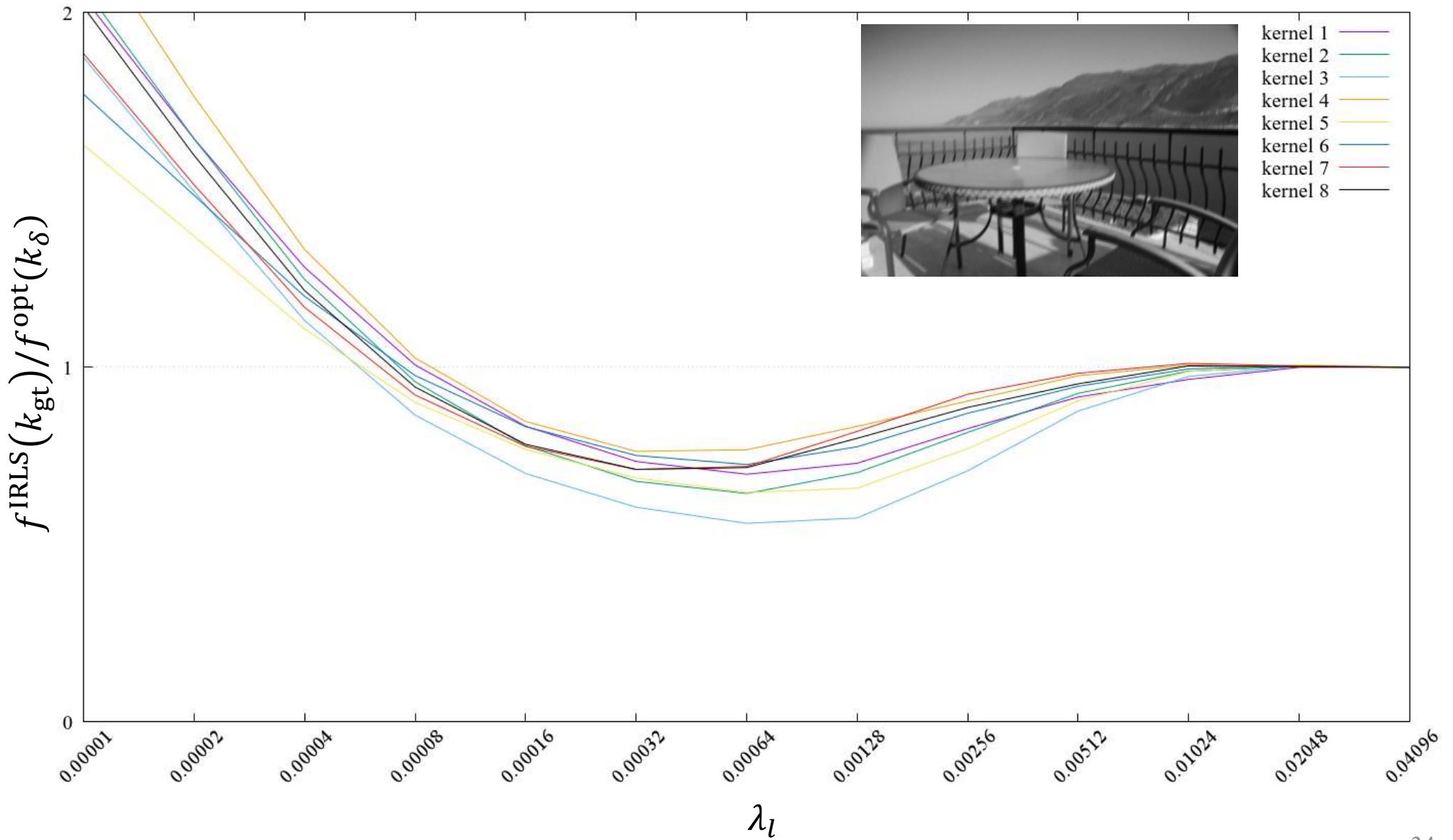
# Sun et al.'s dataset - Image 02



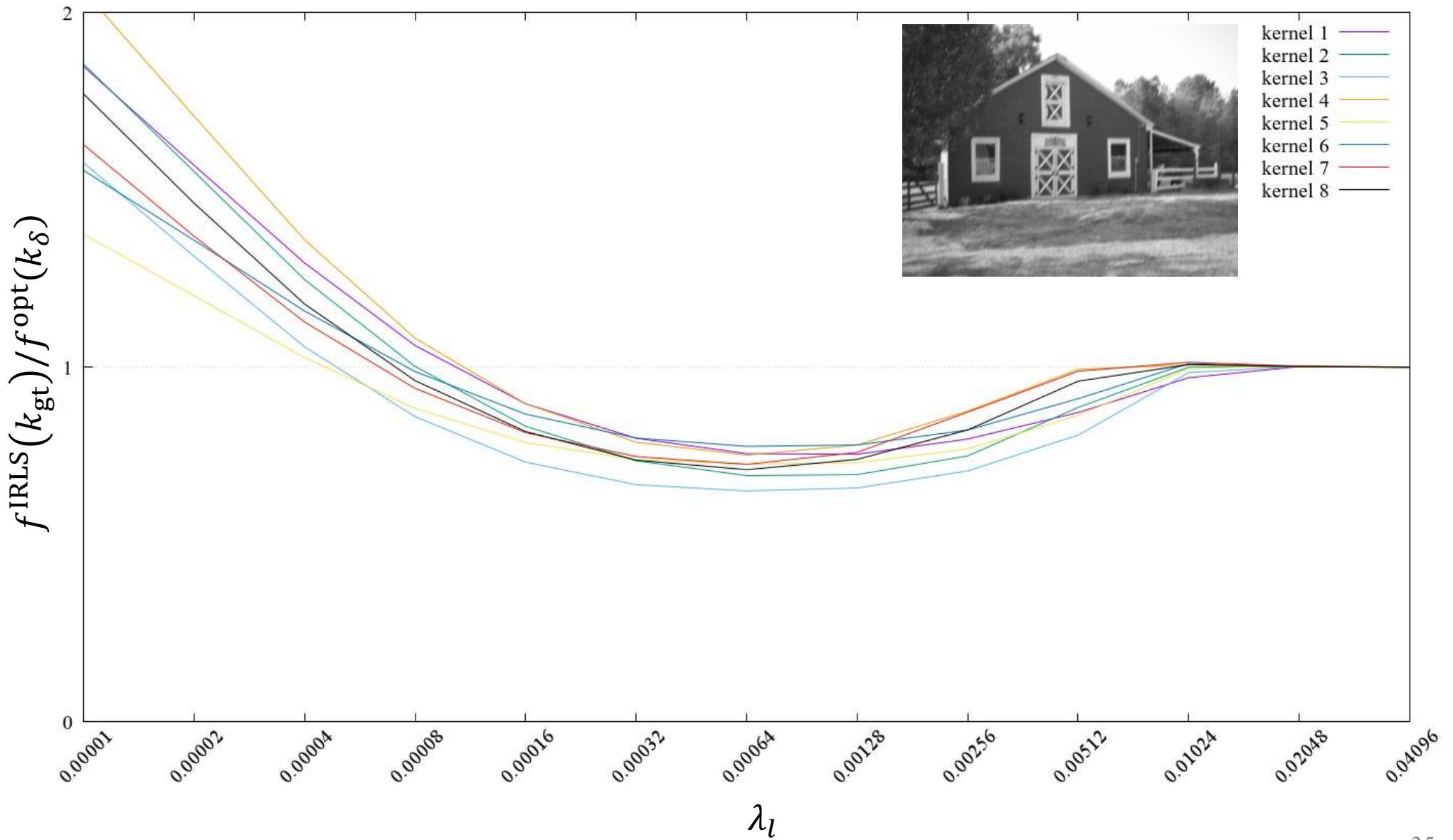
# Sun et al.'s dataset - Image 03



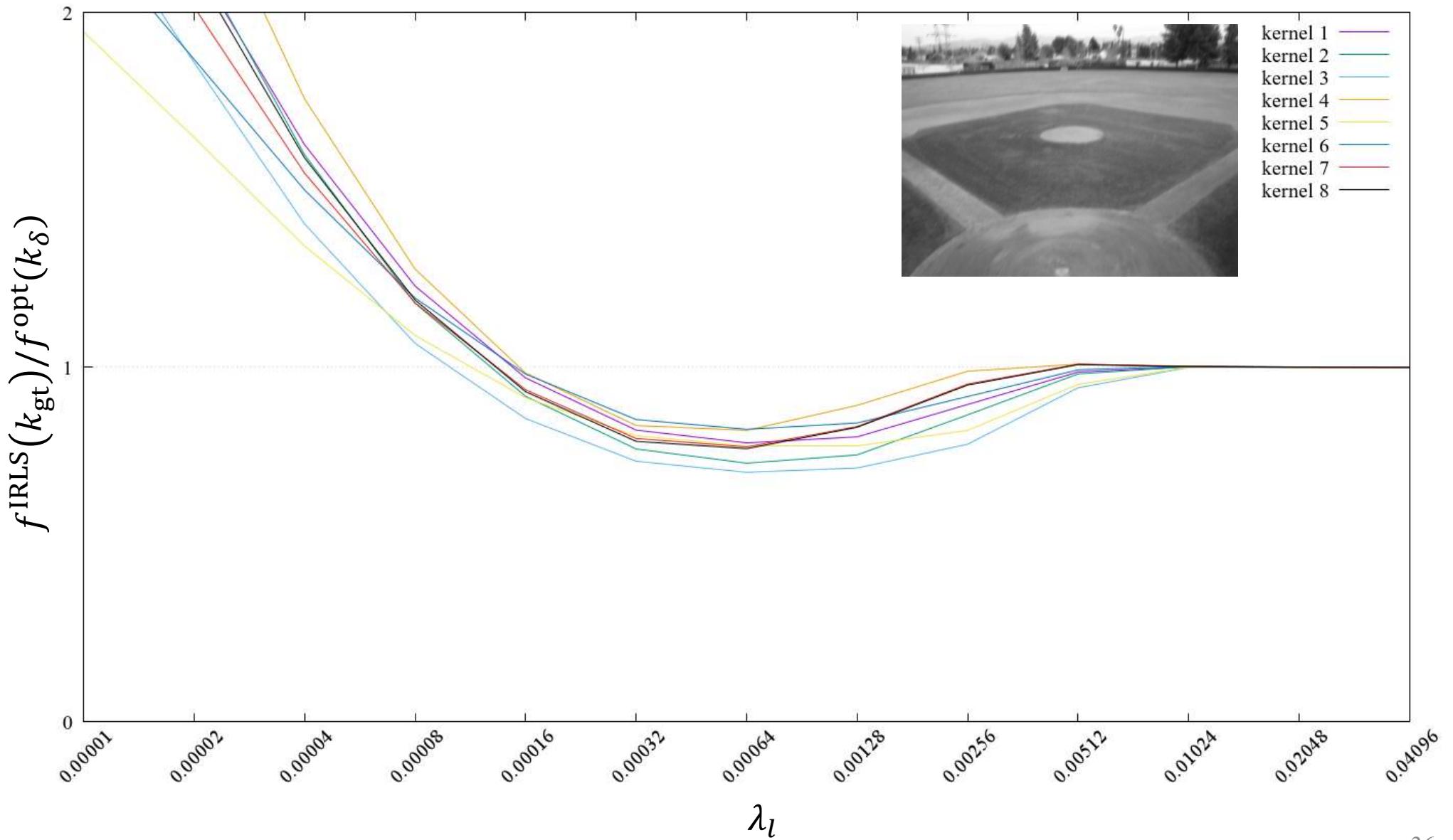
# Sun et al.'s dataset - Image 04



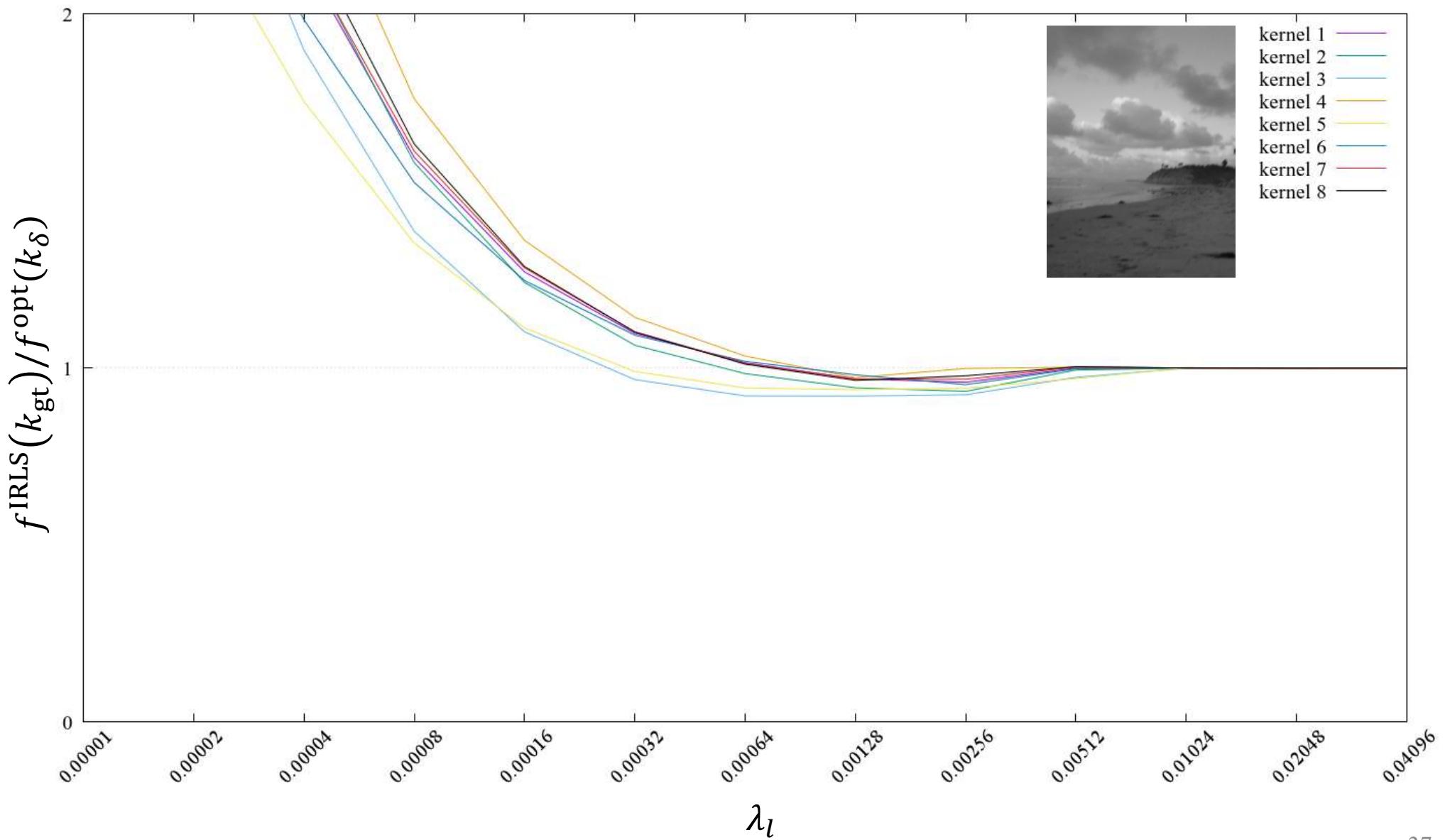
# Sun et al.'s dataset - Image 05



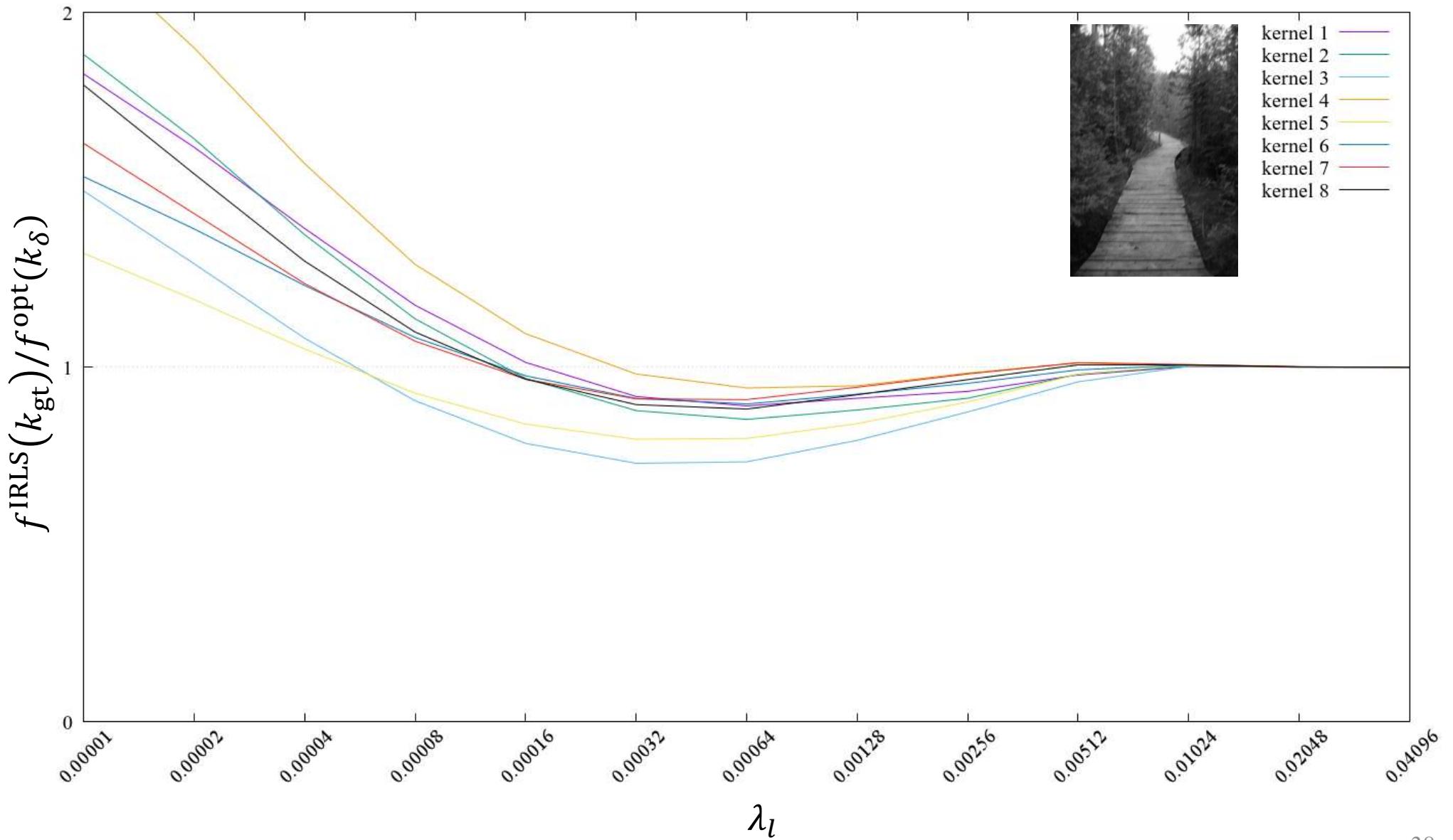
# Sun et al.'s dataset - Image 06



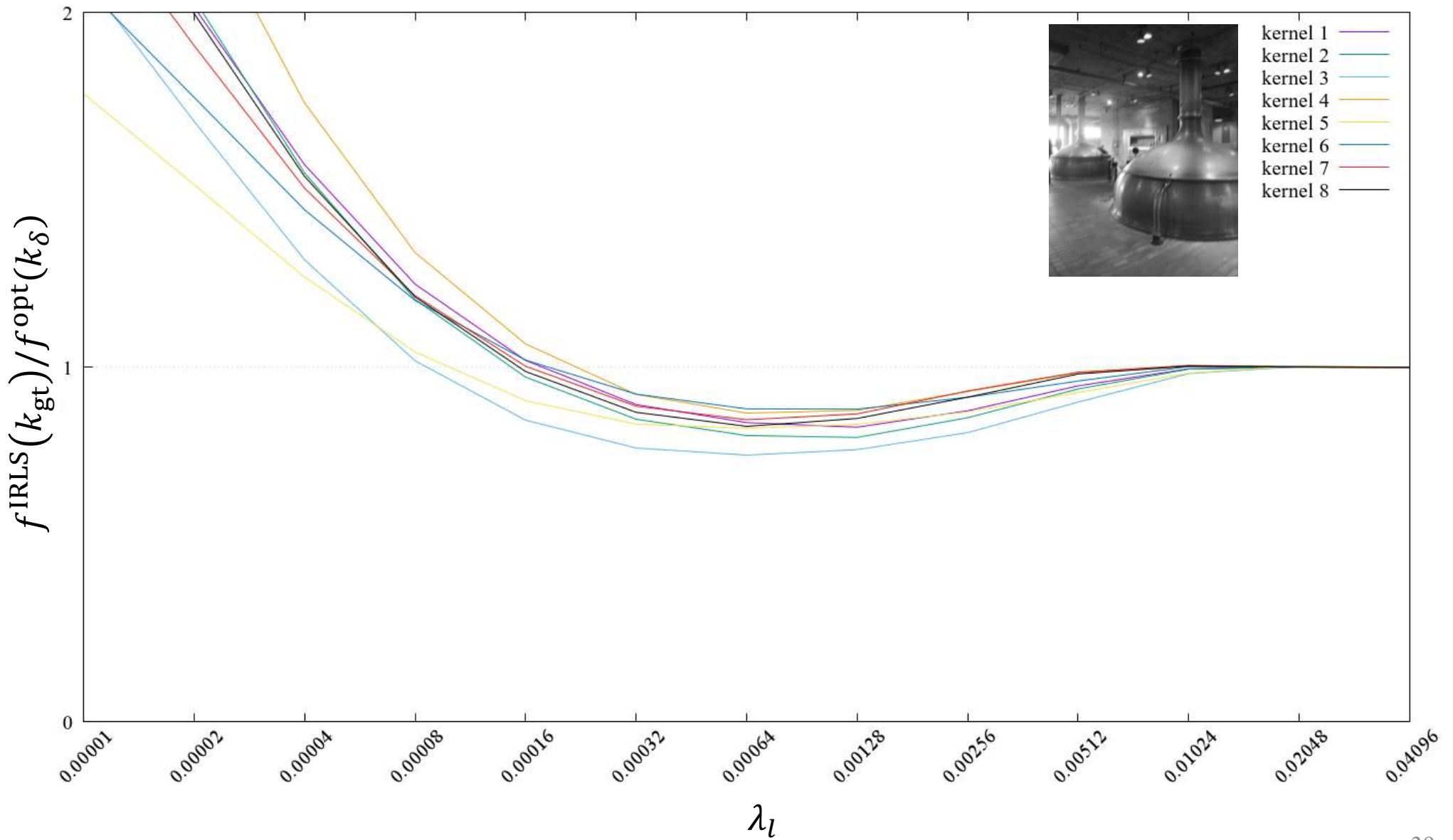
# Sun et al.'s dataset - Image 07



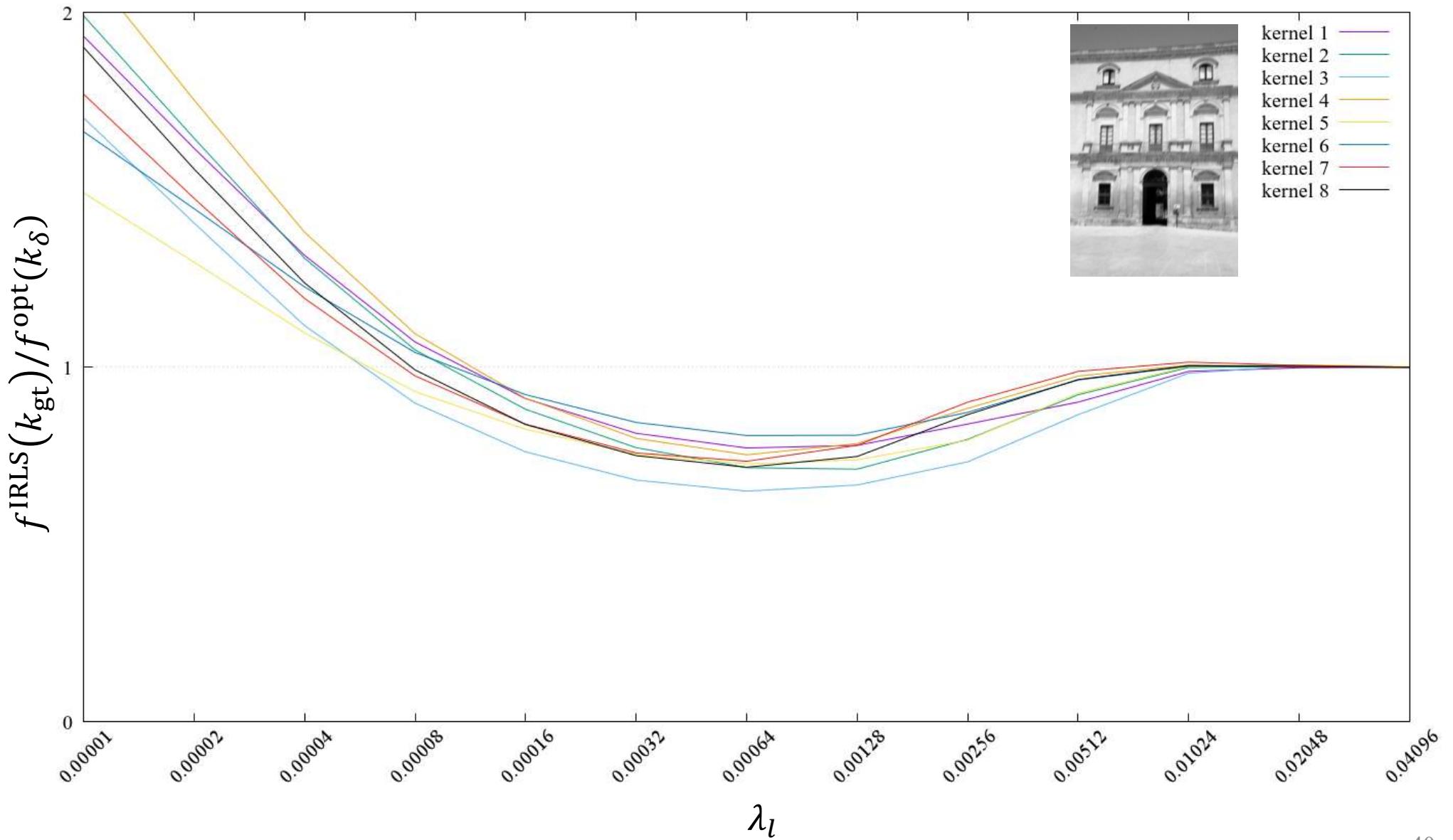
# Sun et al.'s dataset - Image 08



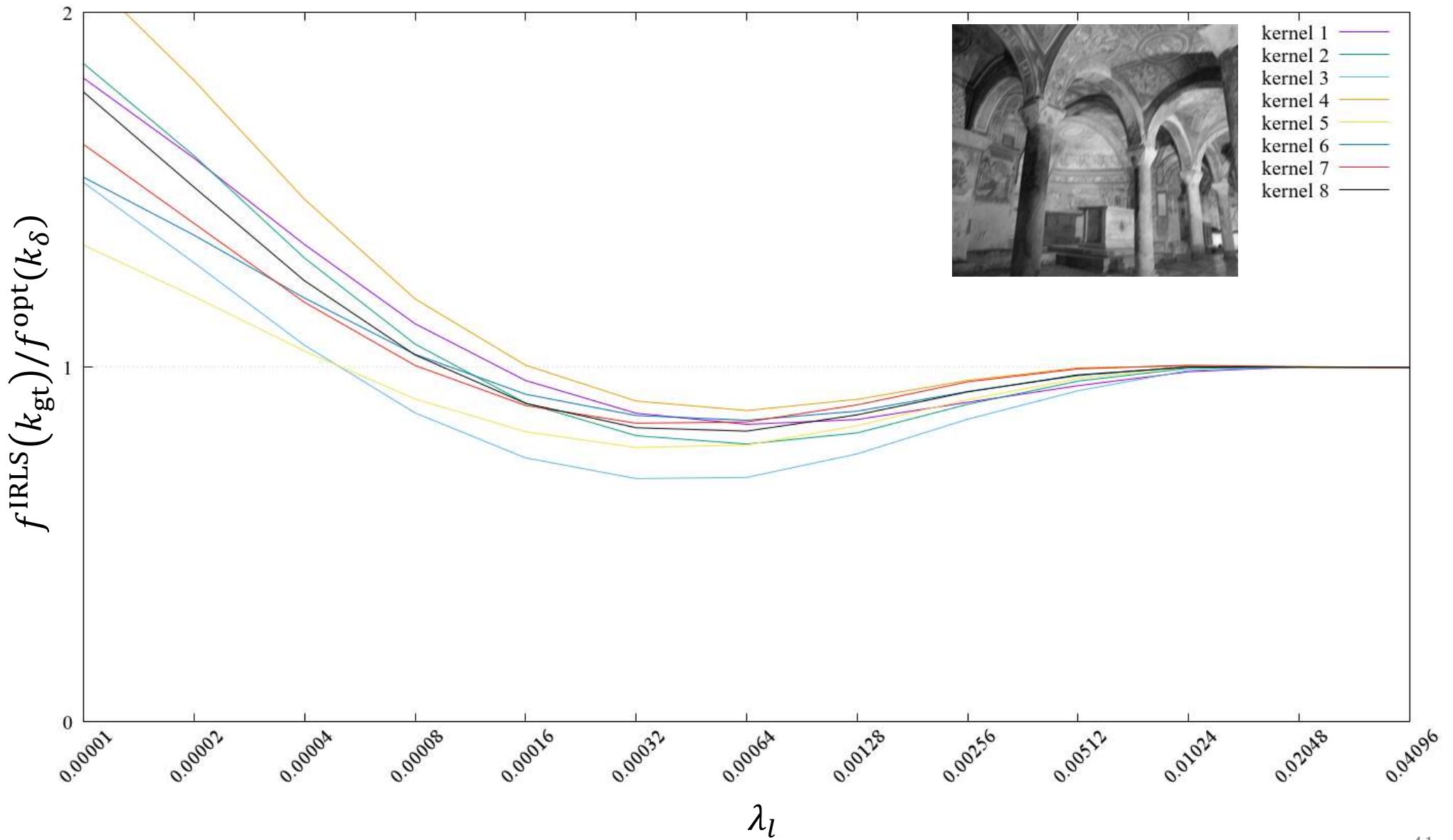
# Sun et al.'s dataset - Image 09



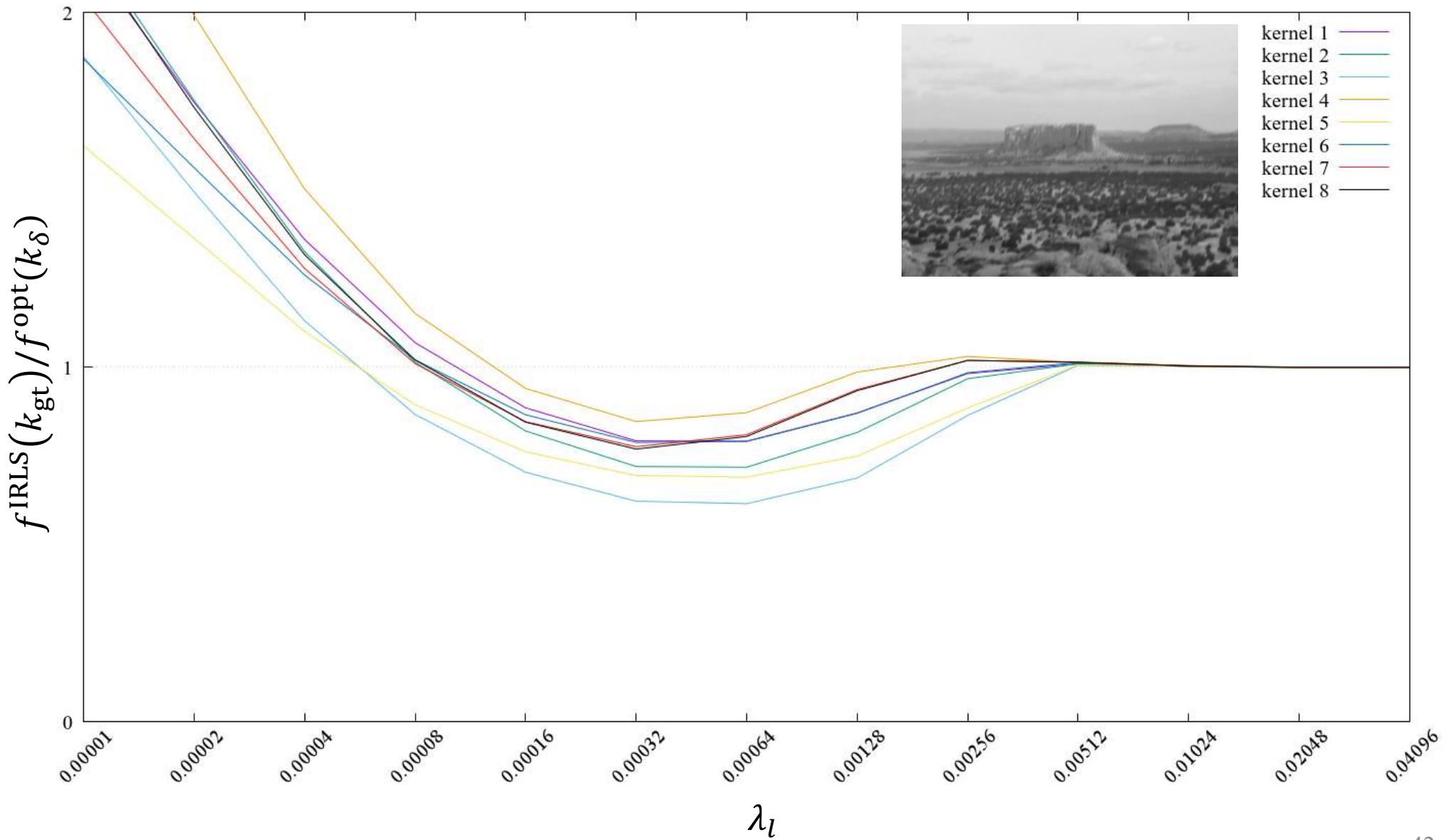
# Sun et al.'s dataset - Image 10



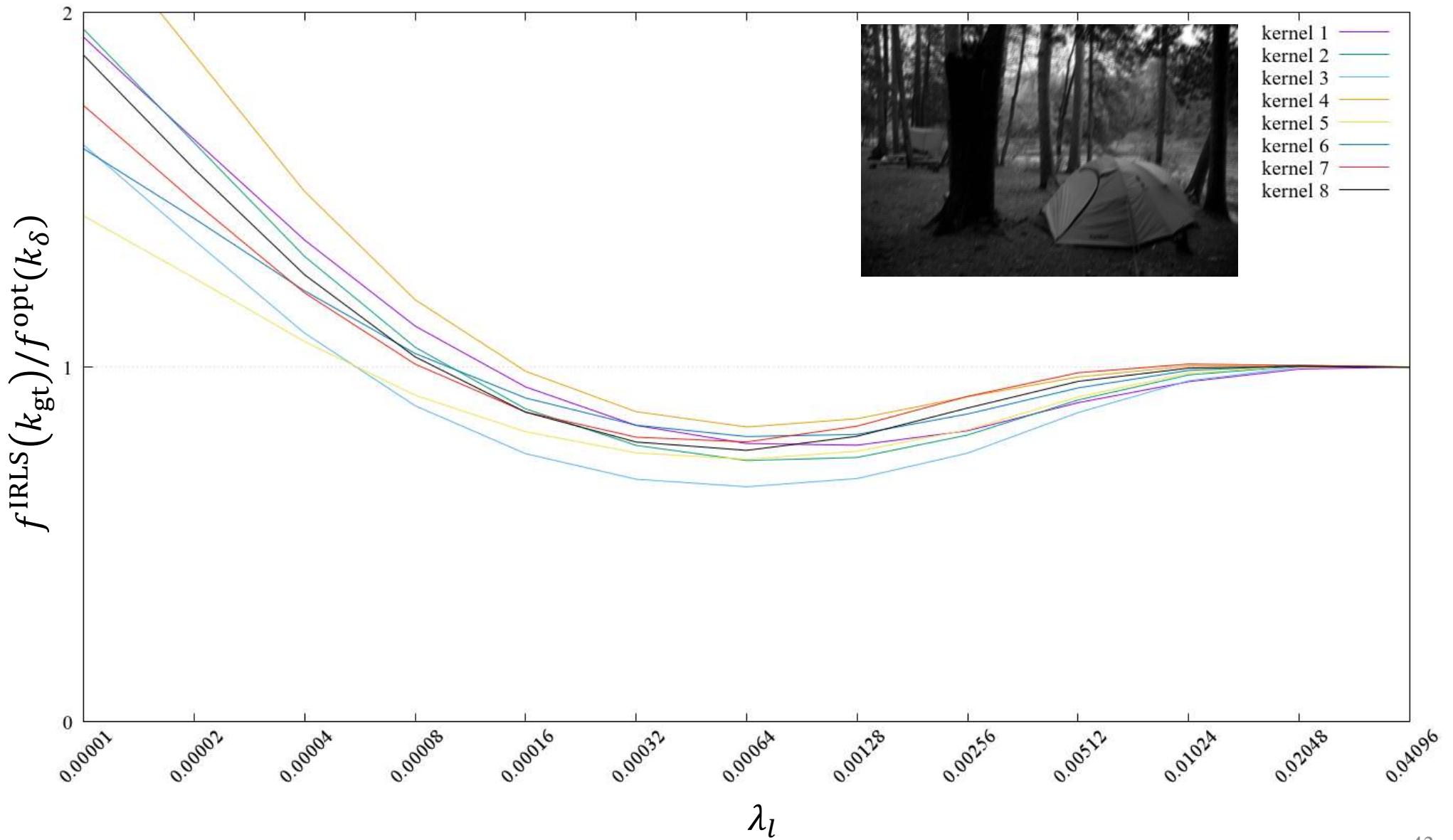
# Sun et al.'s dataset - Image 11



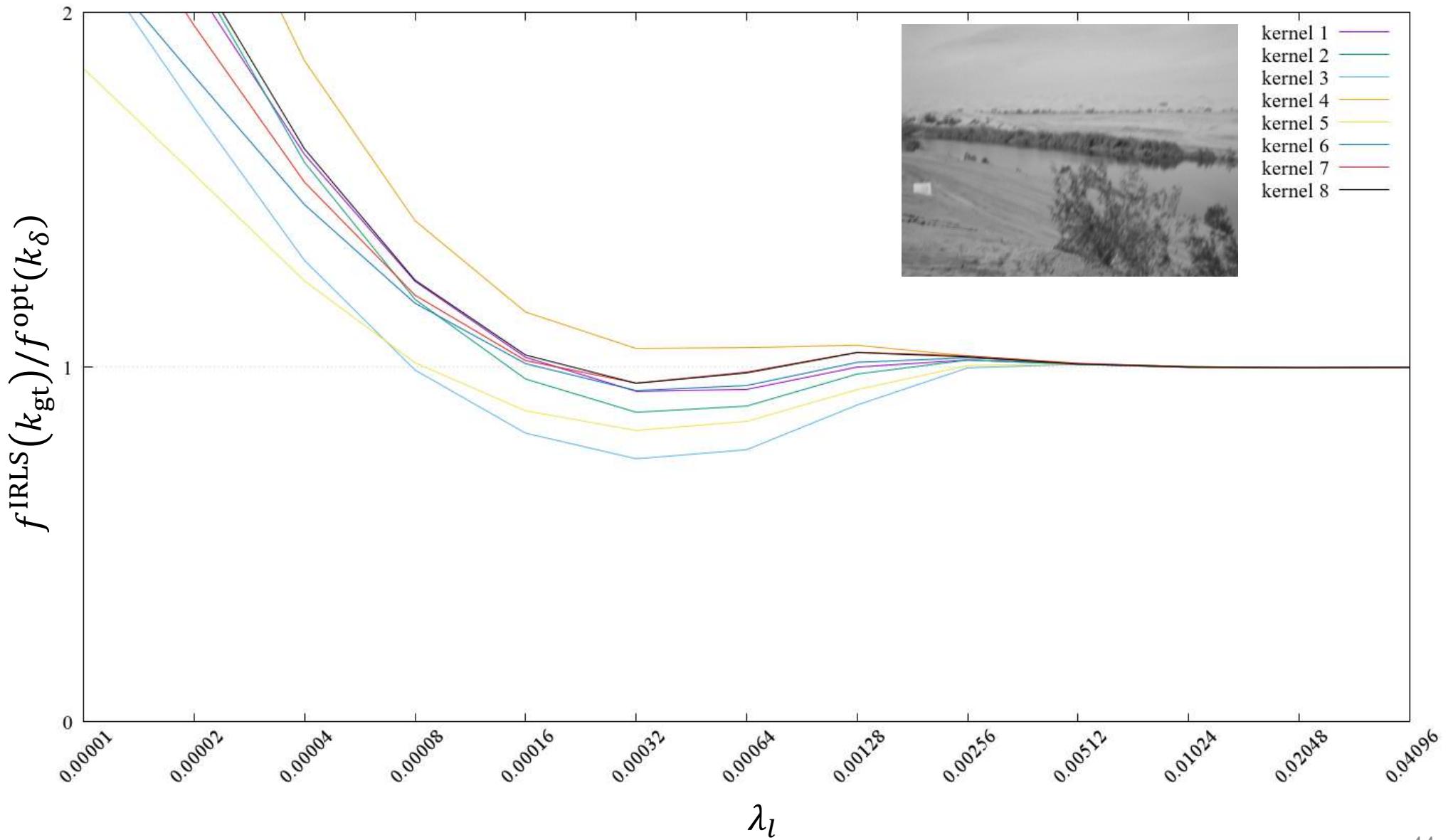
# Sun et al.'s dataset - Image 12



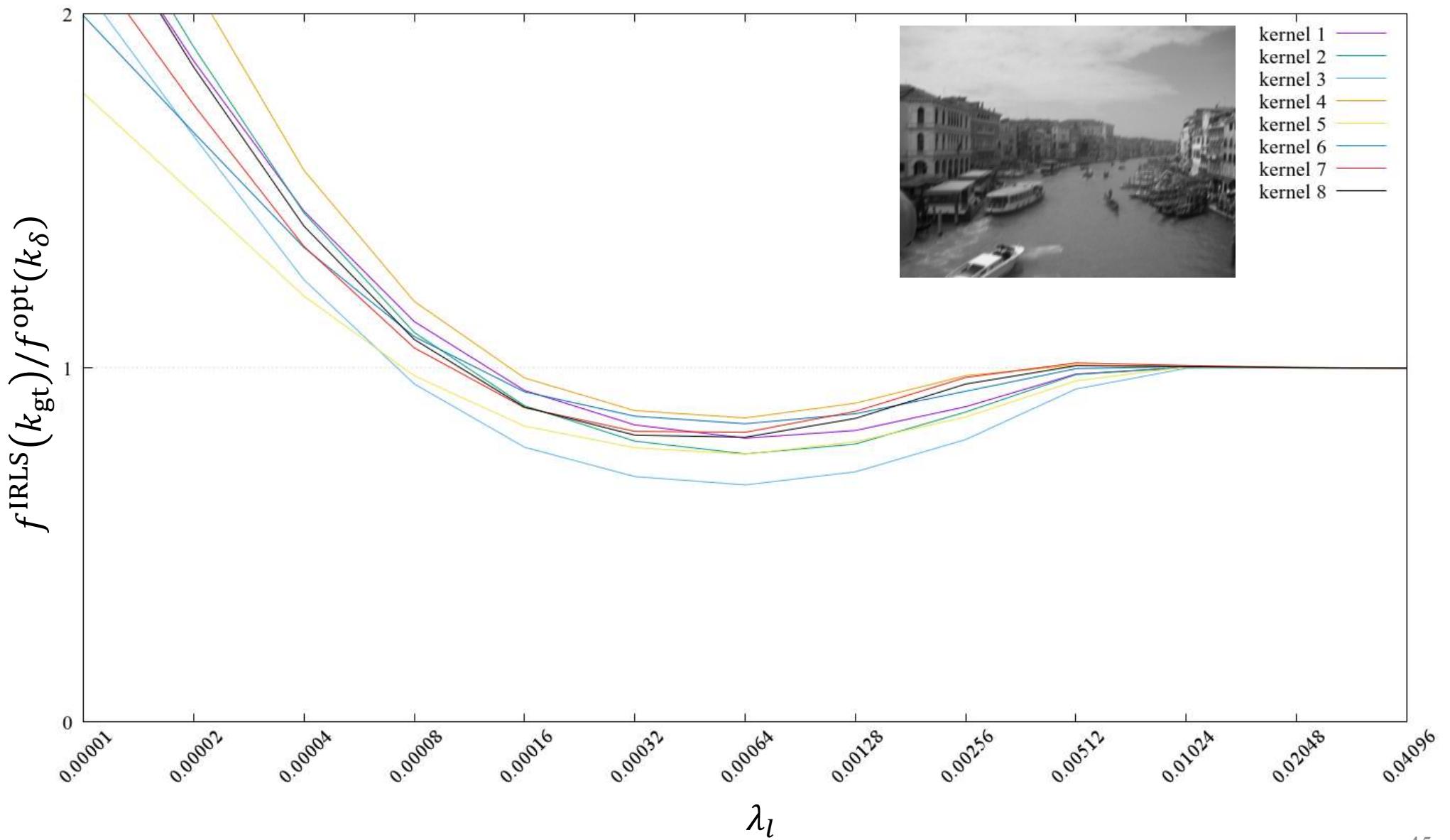
# Sun et al.'s dataset - Image 13



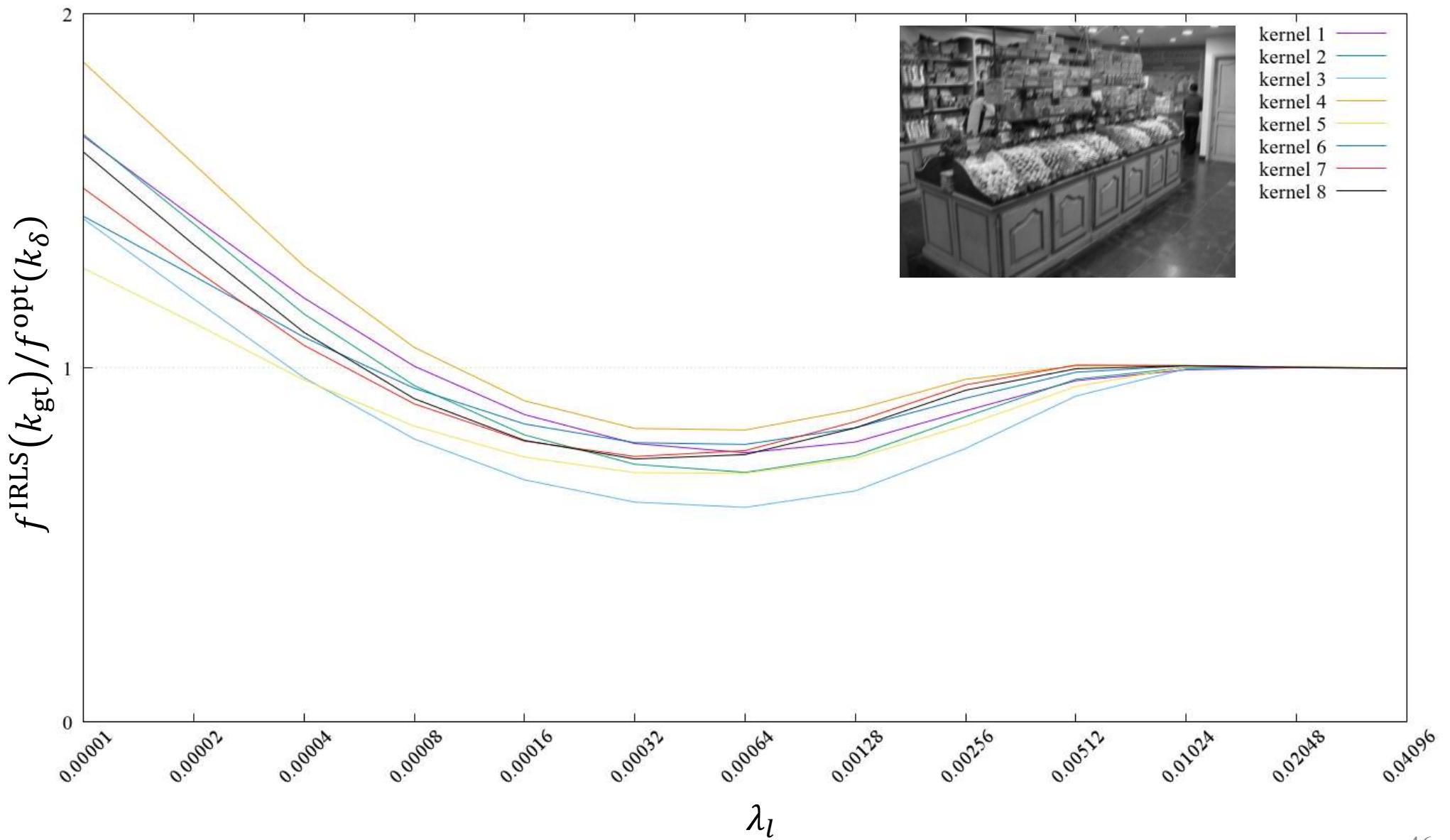
# Sun et al.'s dataset - Image 14



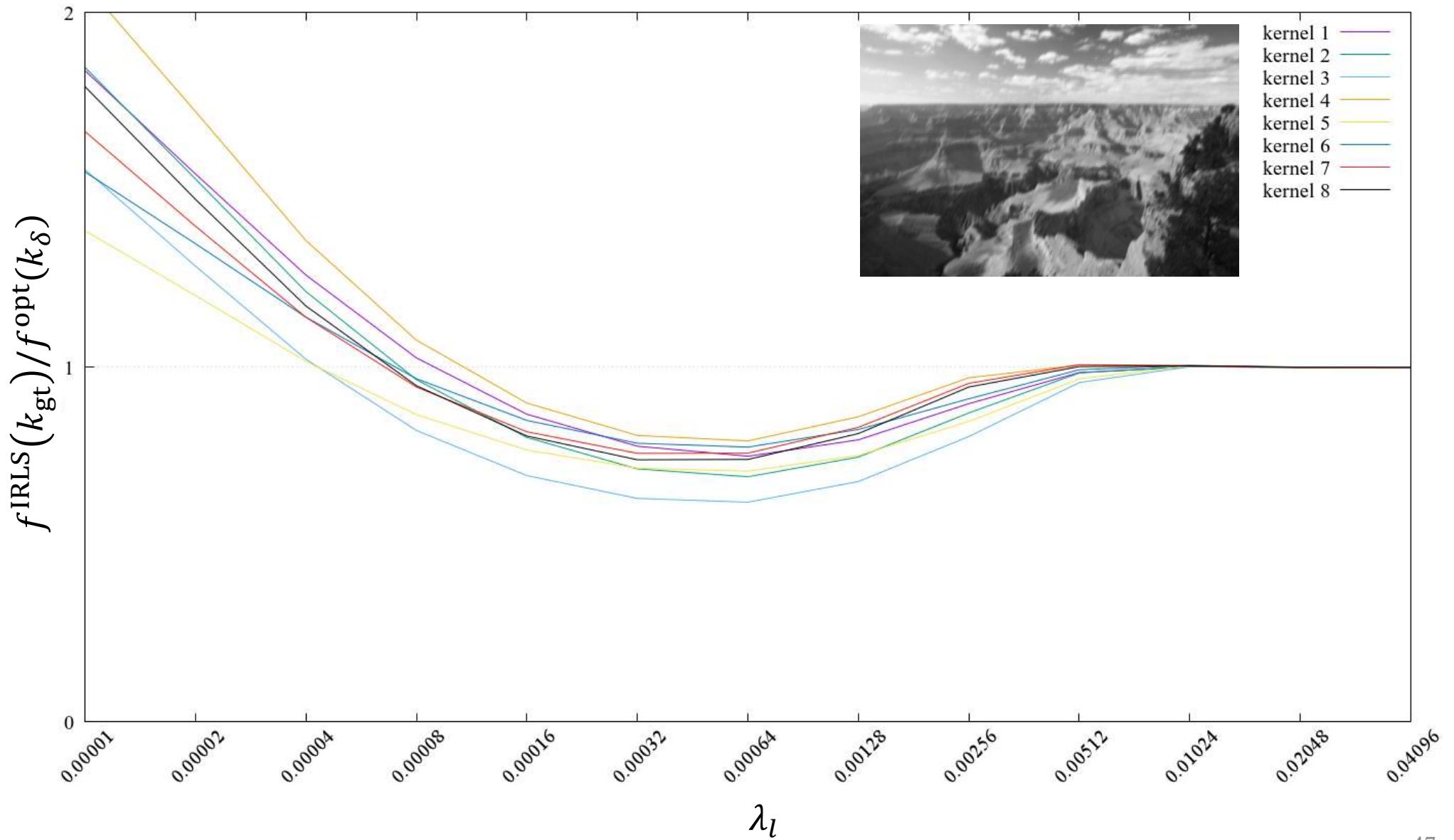
# Sun et al.'s dataset - Image 15



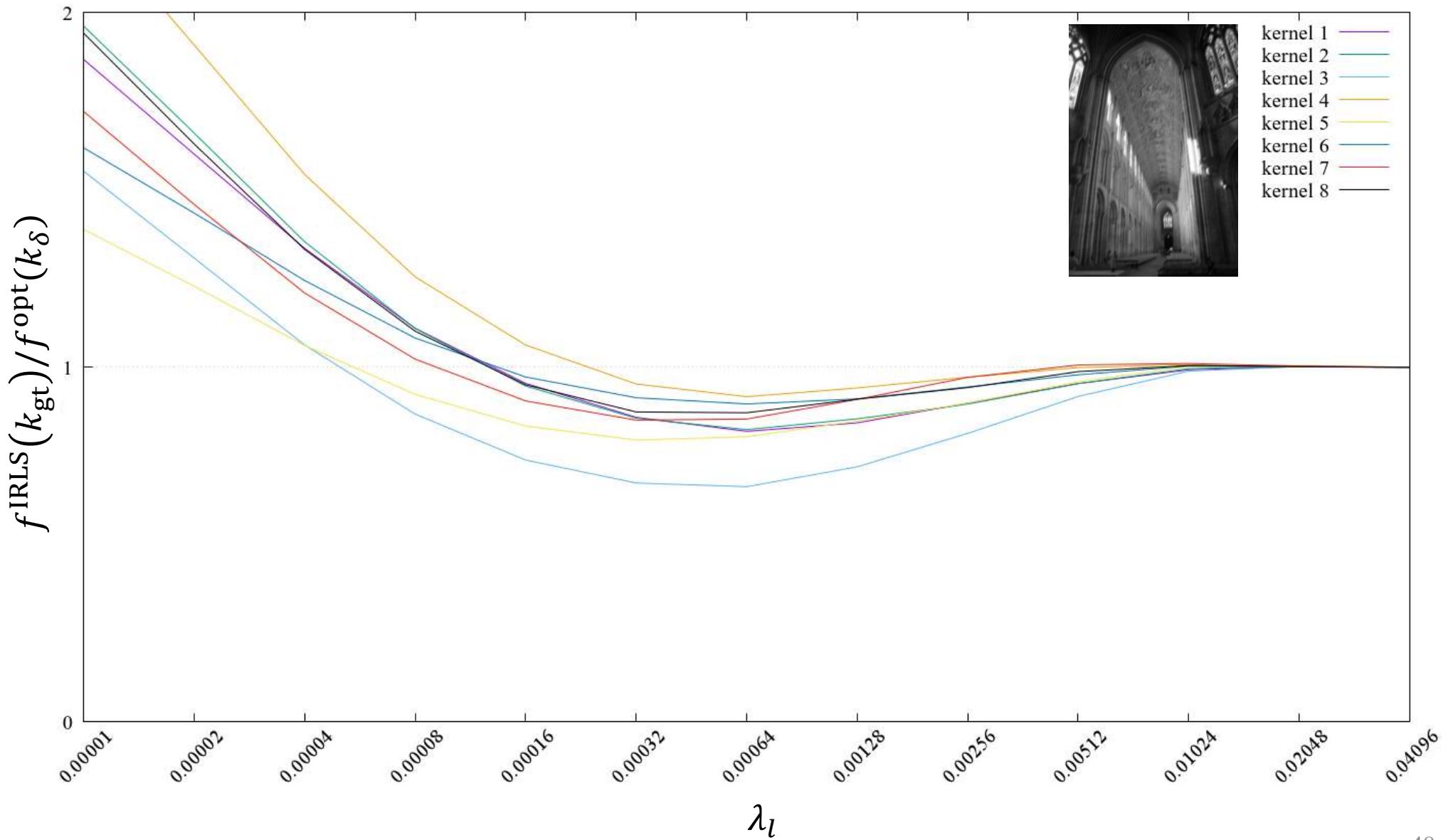
# Sun et al.'s dataset - Image 16



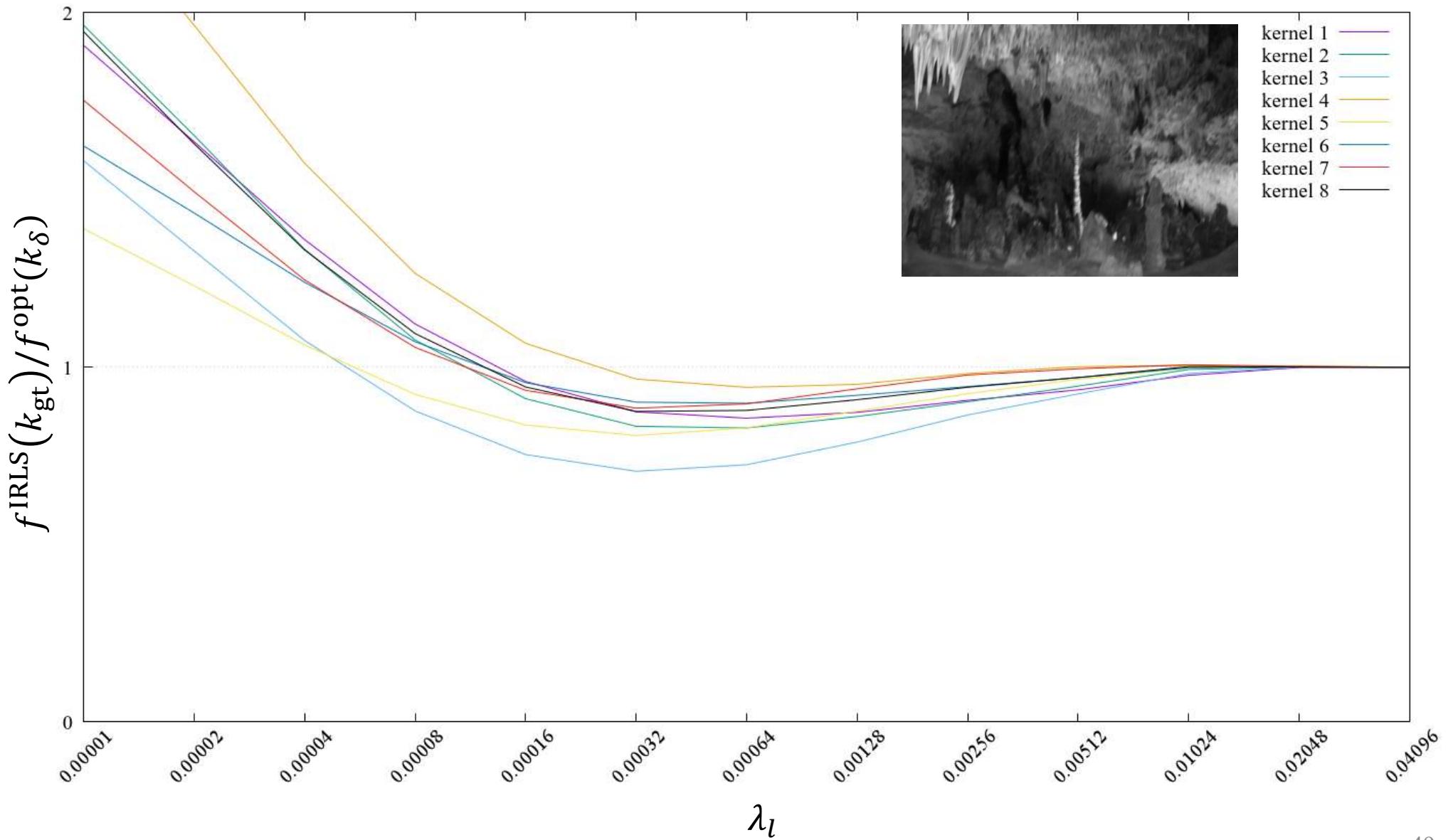
# Sun et al.'s dataset - Image 17



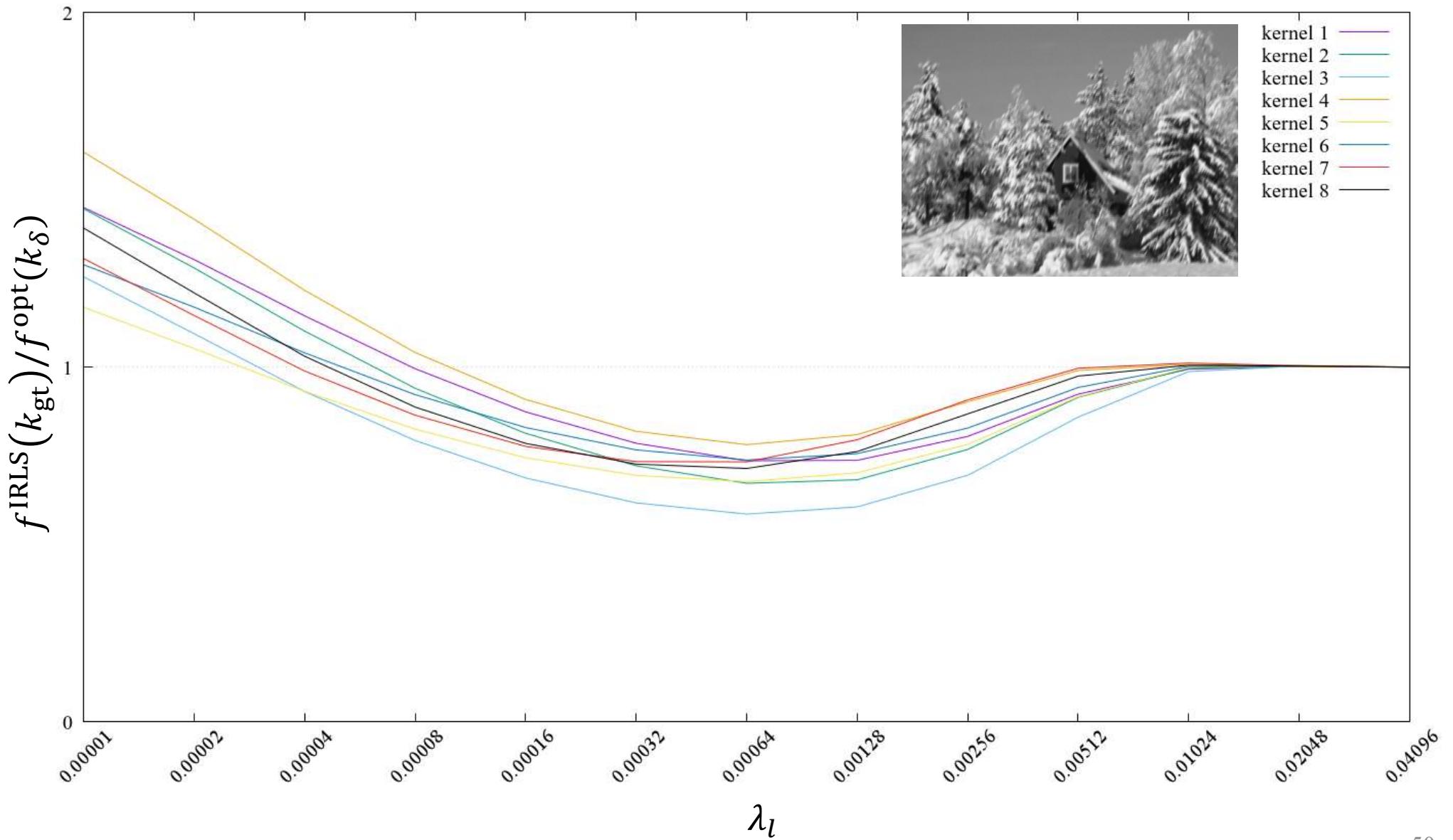
# Sun et al.'s dataset - Image 18



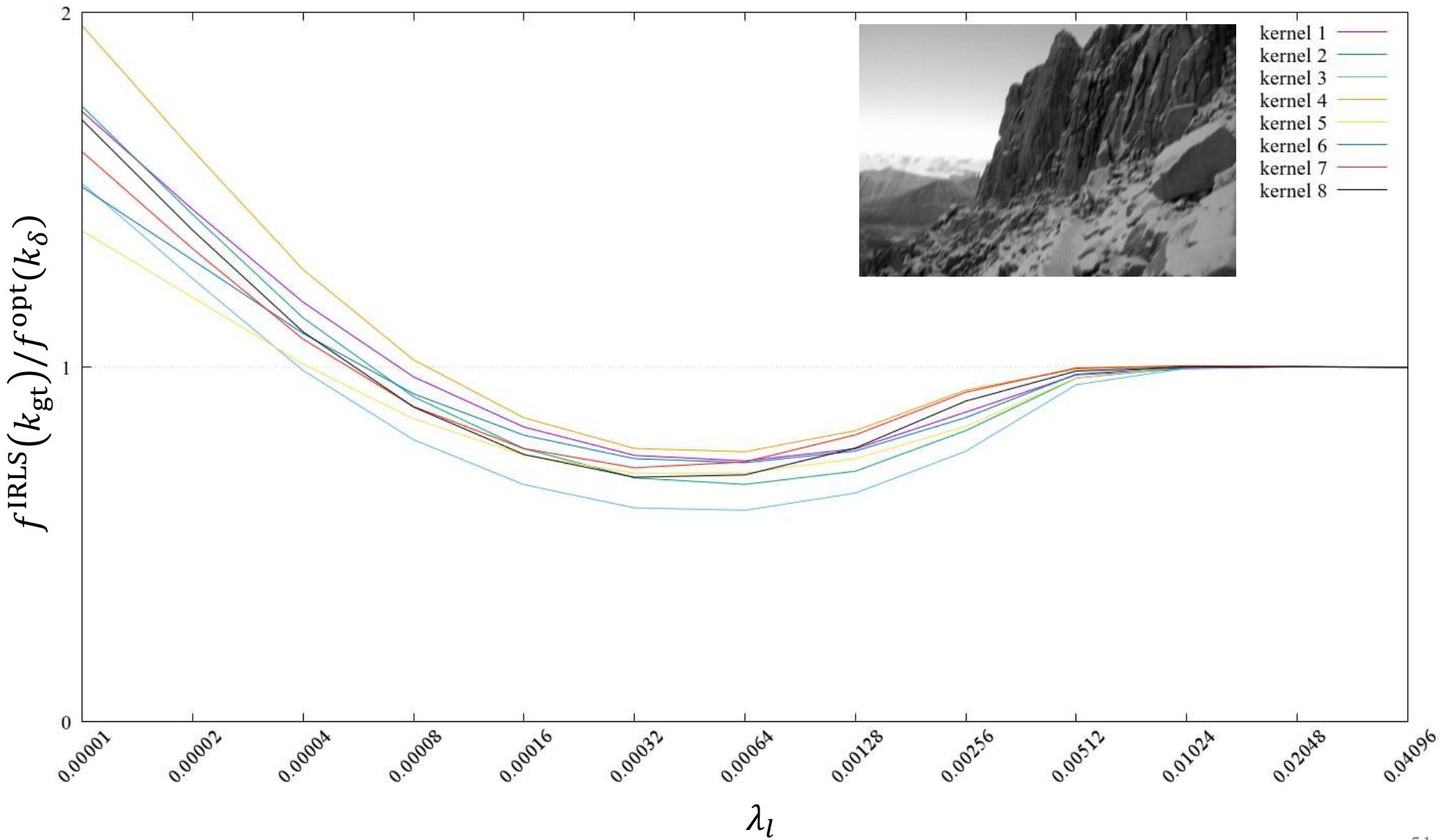
# Sun et al.'s dataset - Image 19



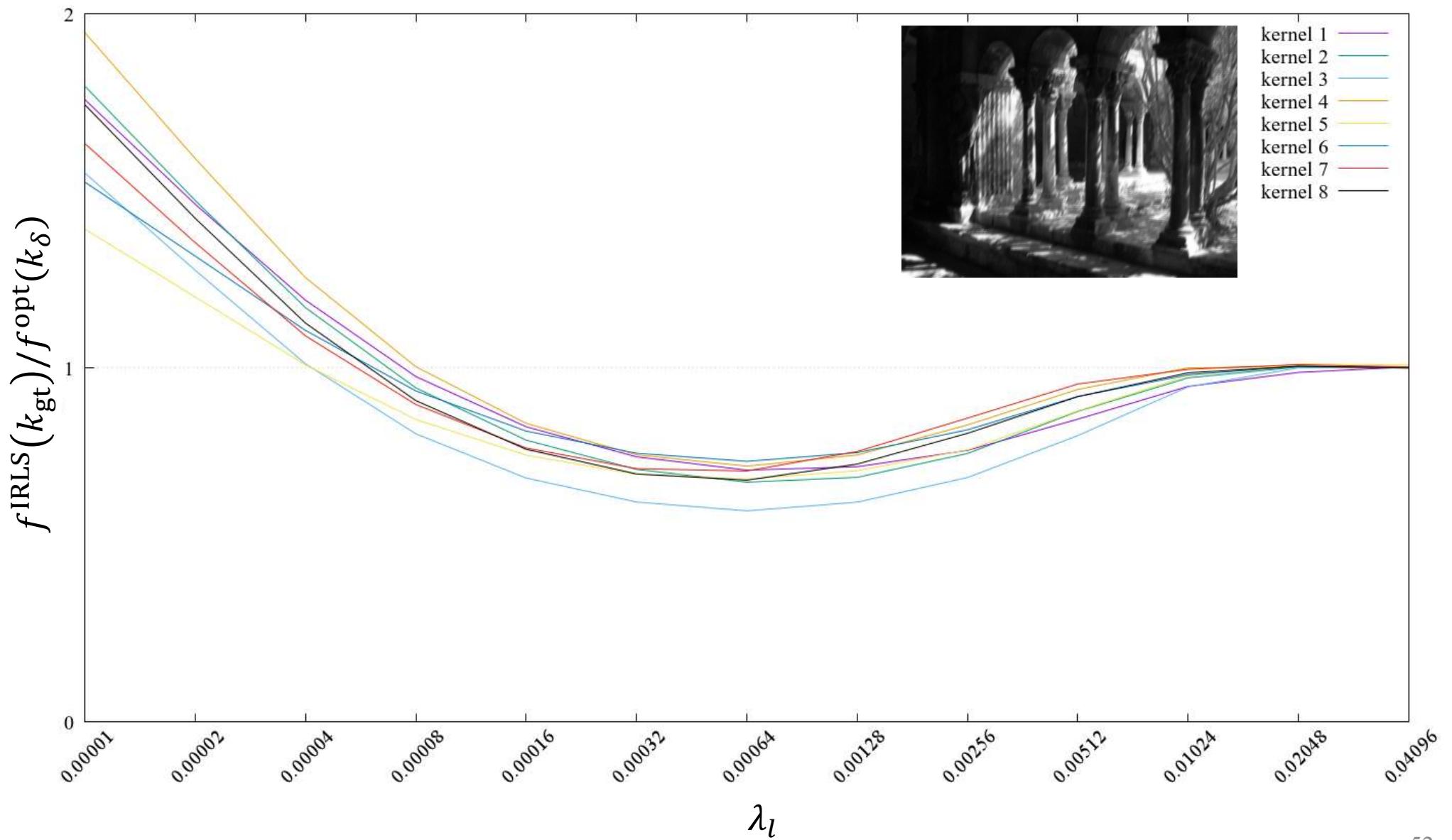
# Sun et al.'s dataset - Image 20



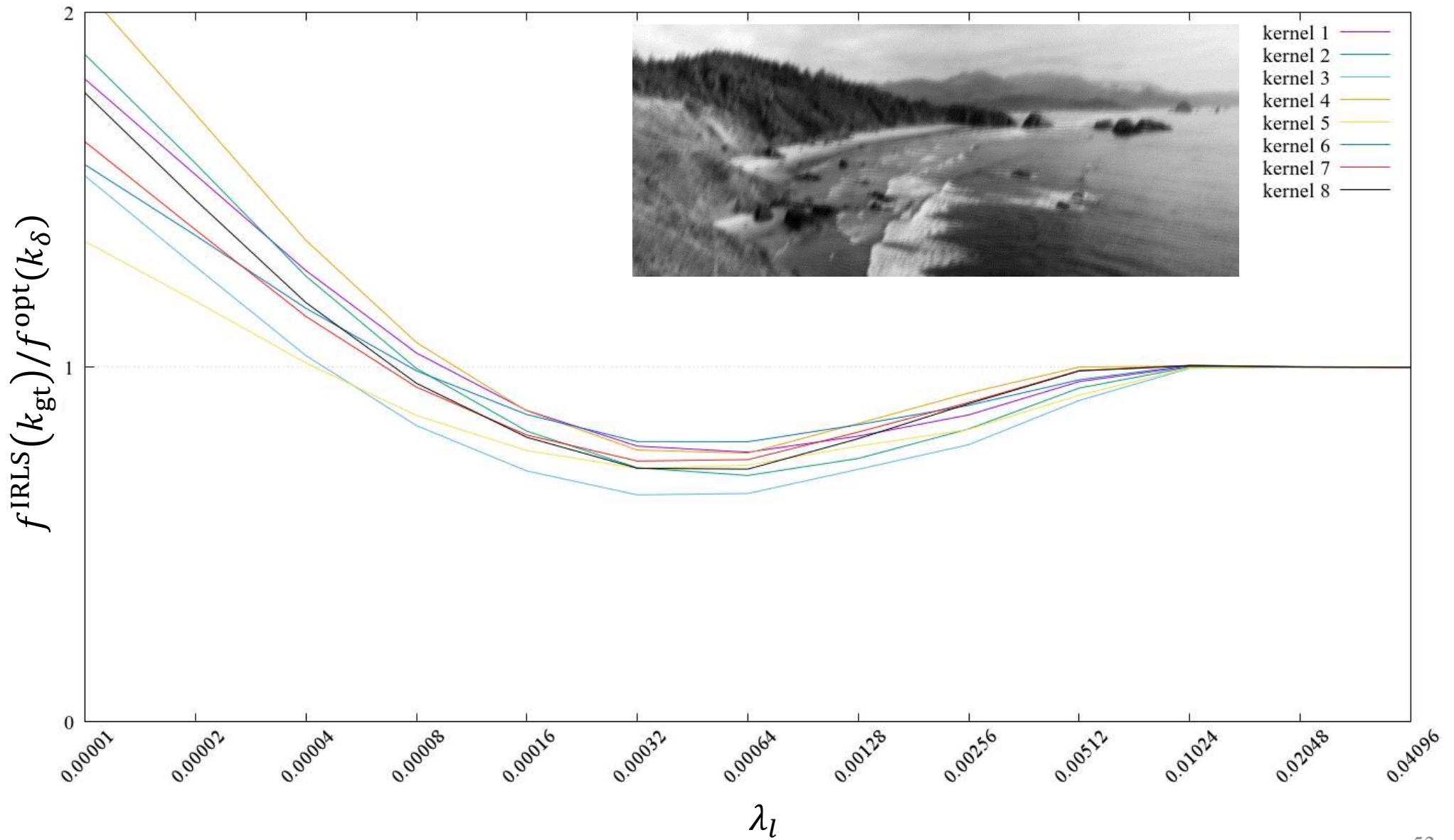
# Sun et al.'s dataset - Image 21



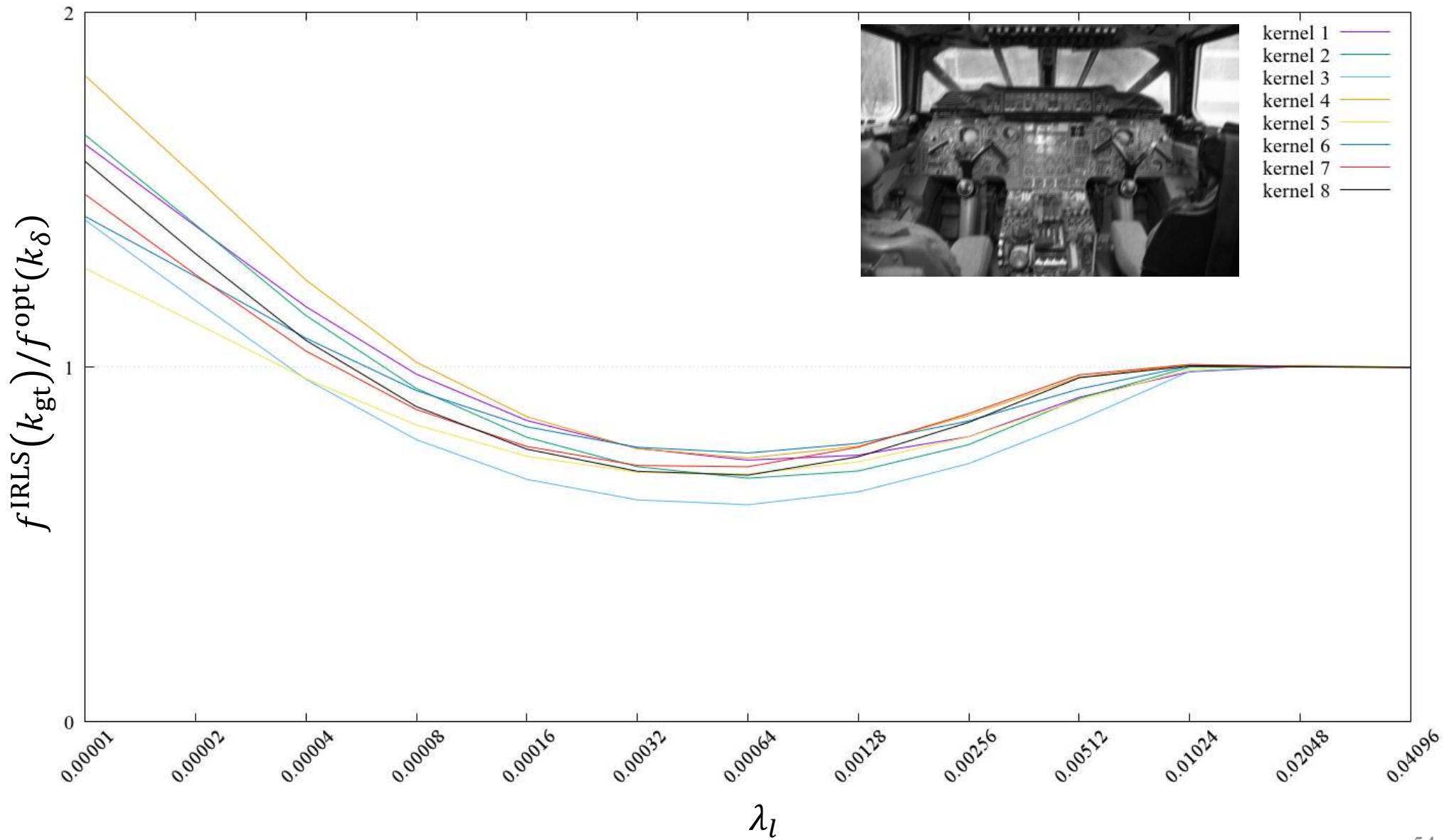
# Sun et al.'s dataset - Image 22



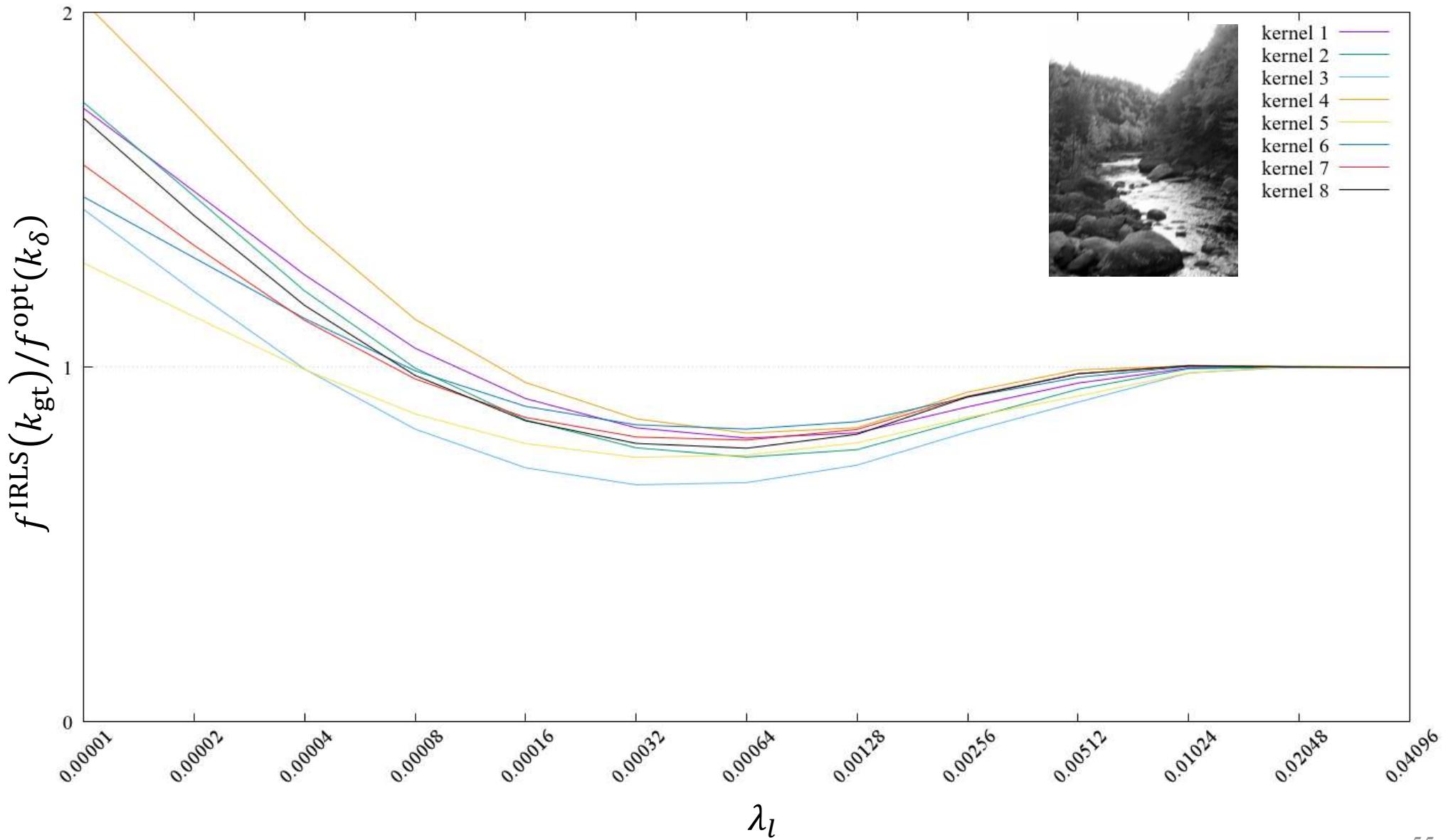
# Sun et al.'s dataset - Image 23



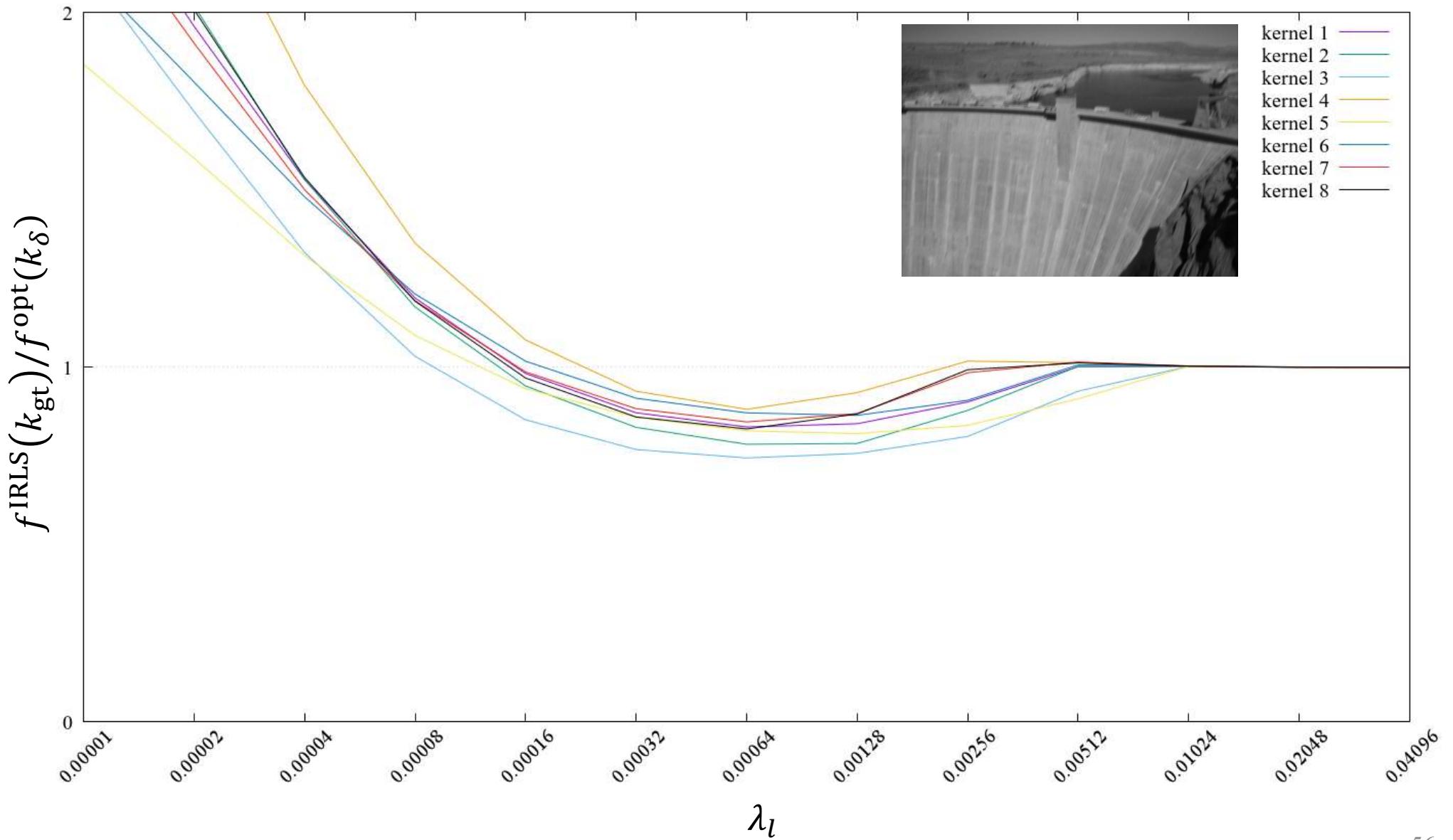
# Sun et al.'s dataset - Image 24



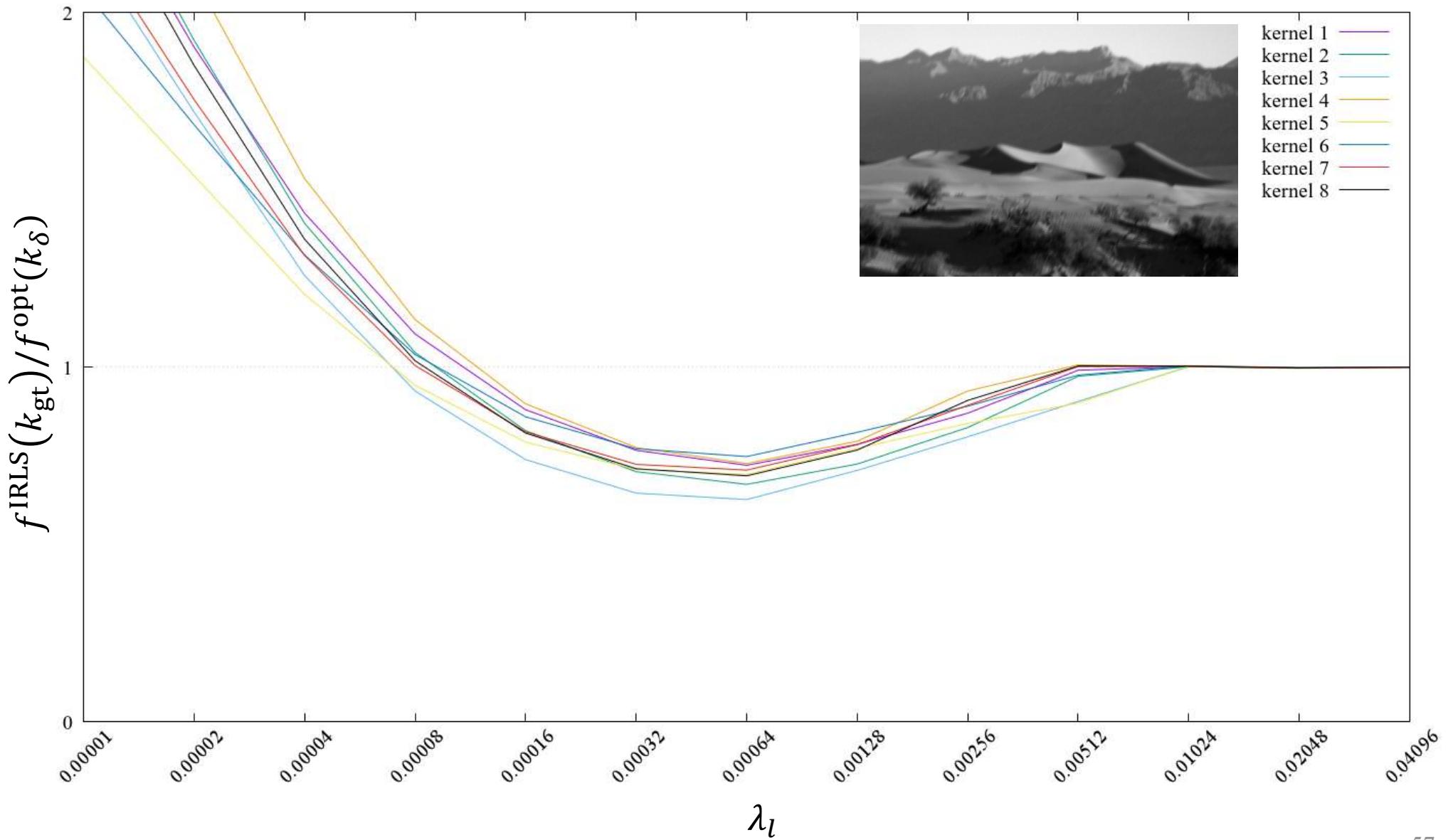
# Sun et al.'s dataset - Image 25



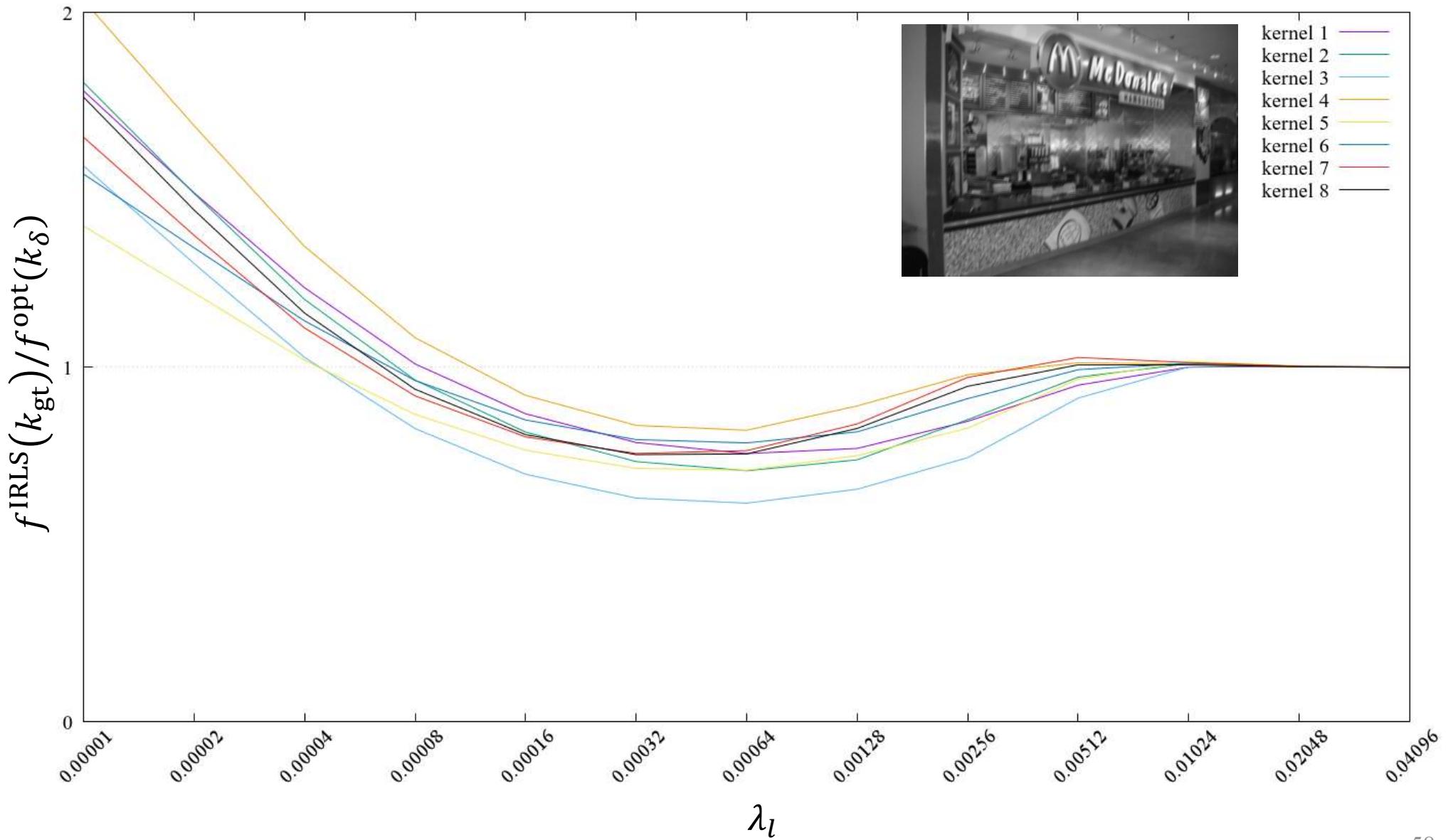
# Sun et al.'s dataset - Image 26



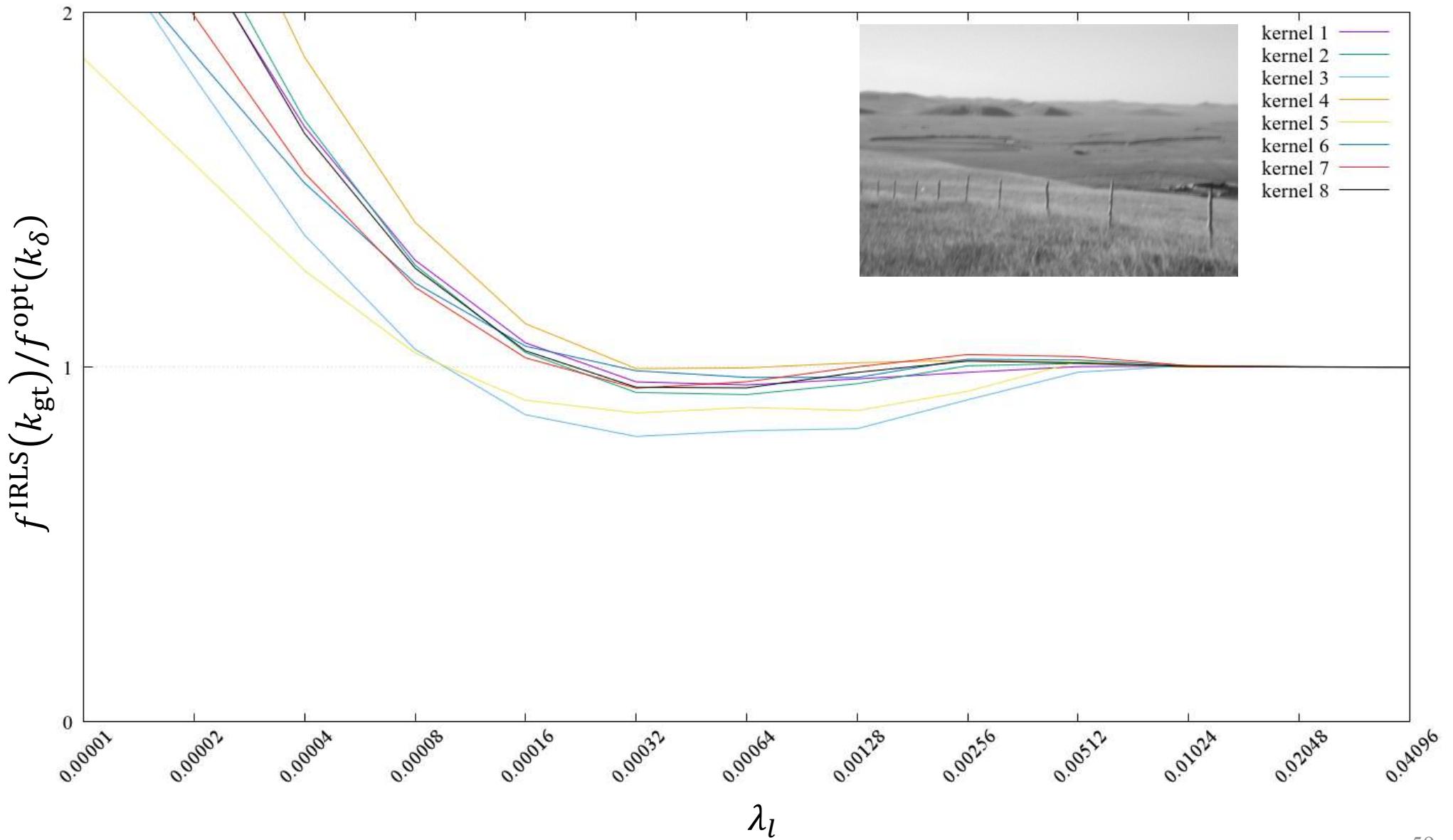
# Sun et al.'s dataset - Image 27



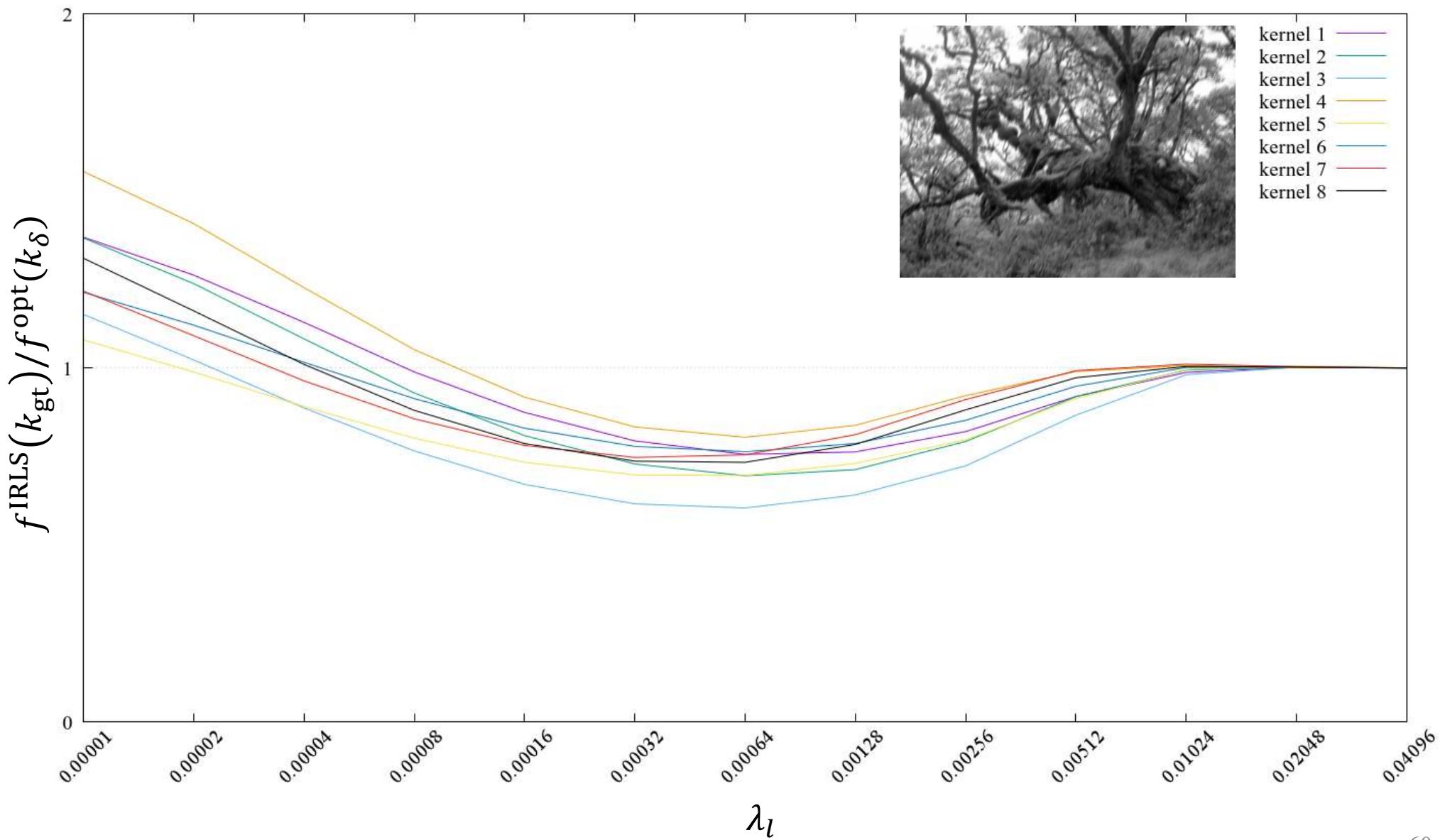
# Sun et al.'s dataset - Image 28



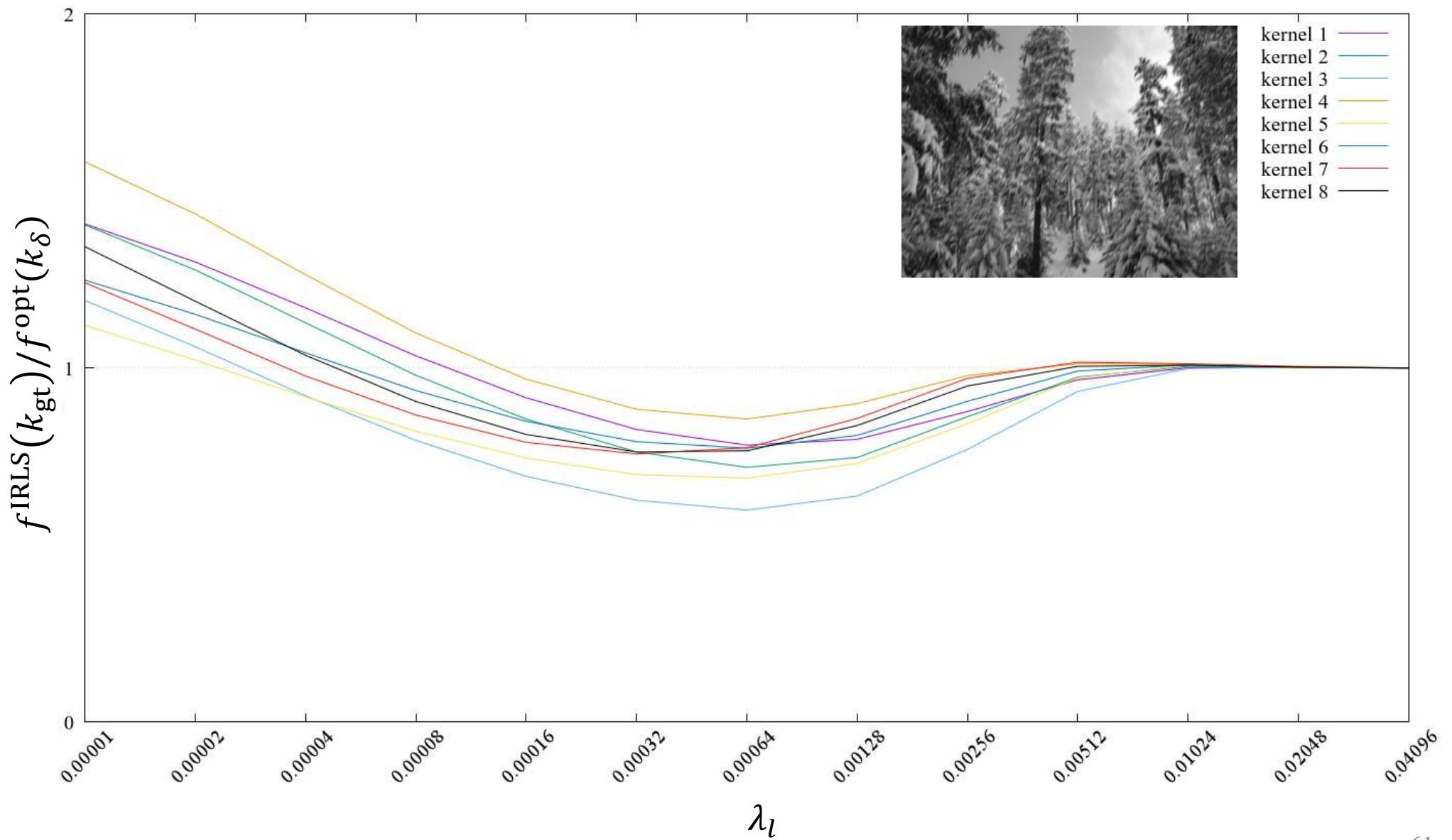
# Sun et al.'s dataset - Image 29



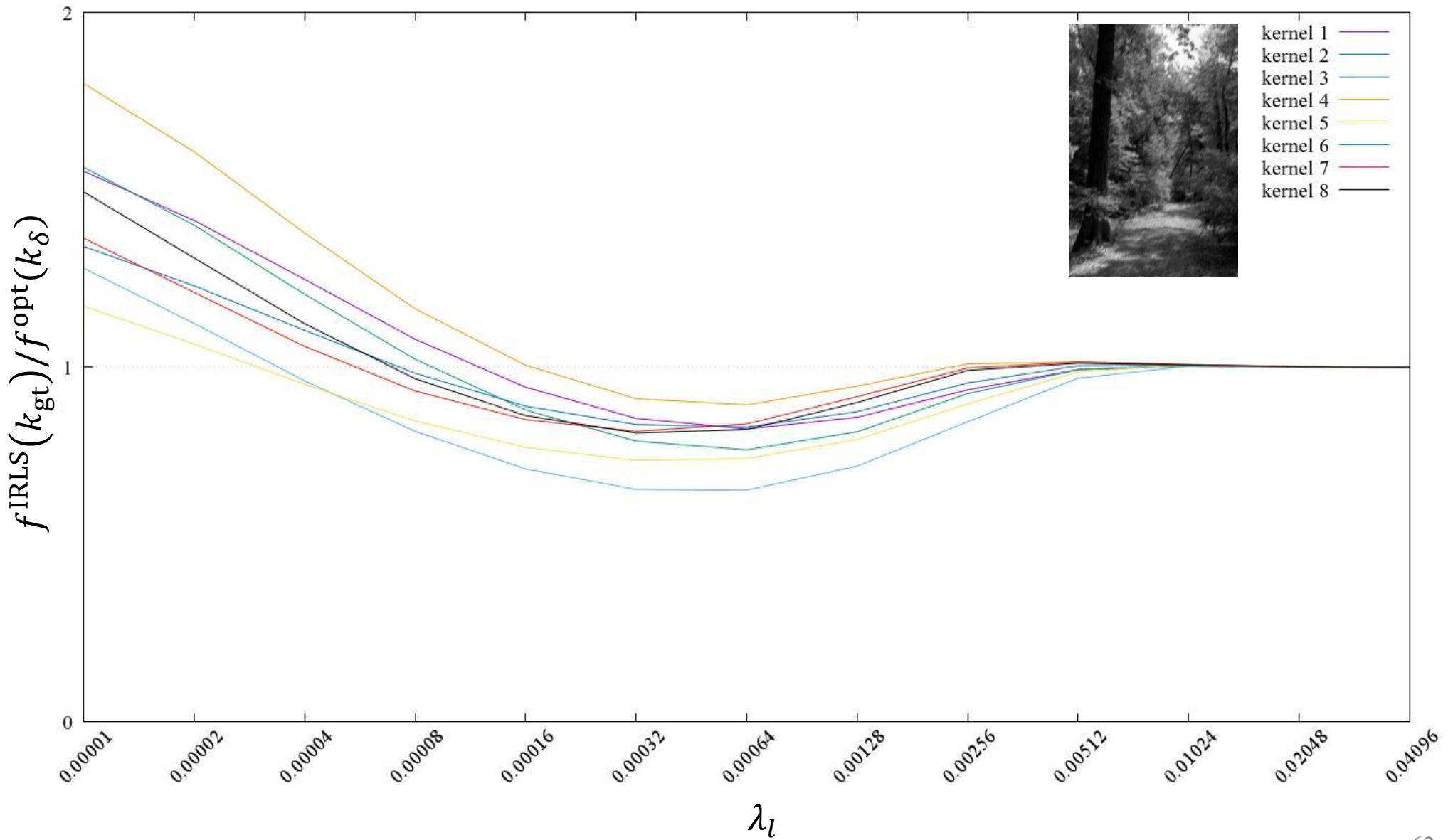
# Sun et al.'s dataset - Image 30



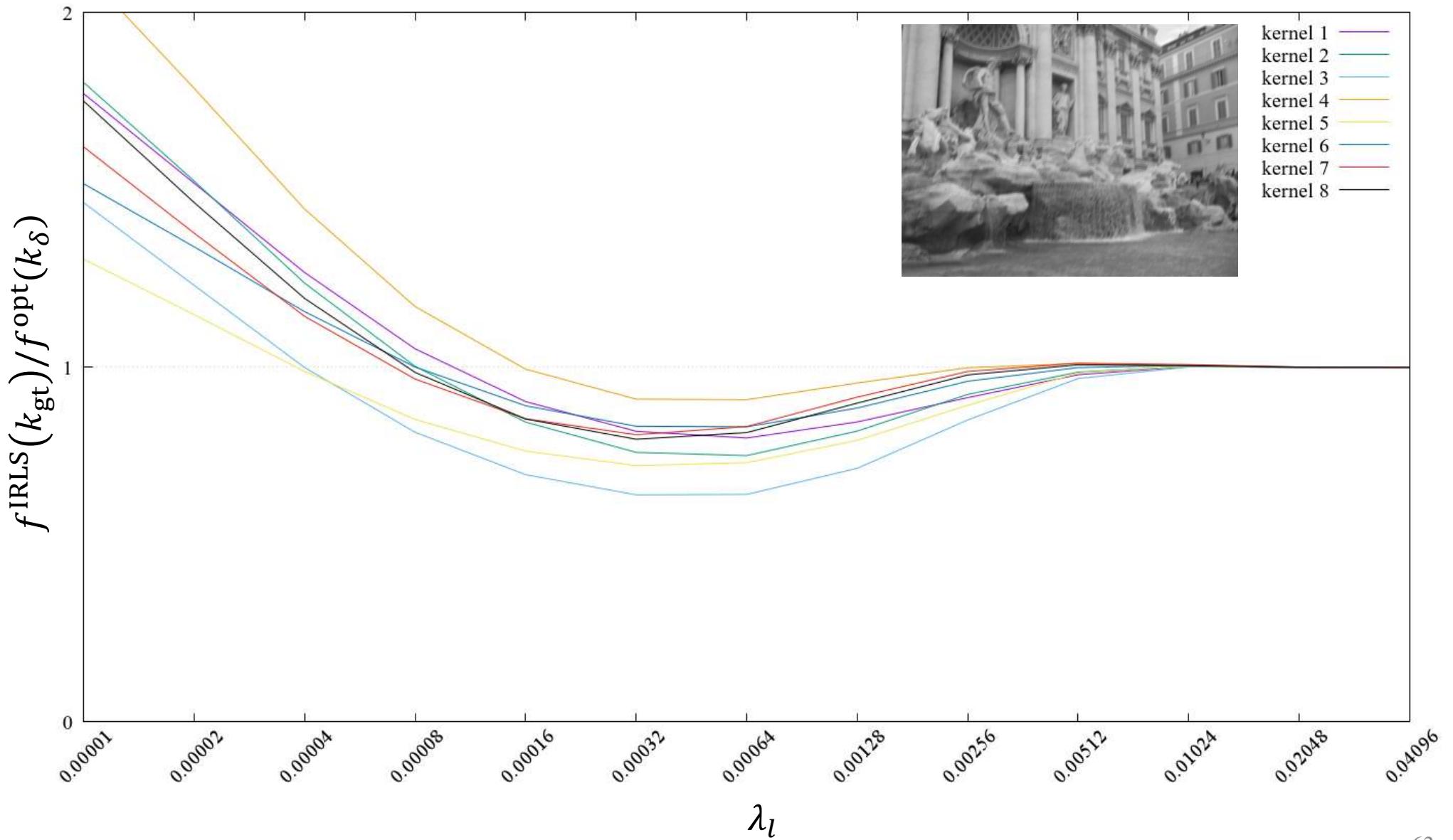
# Sun et al.'s dataset - Image 31



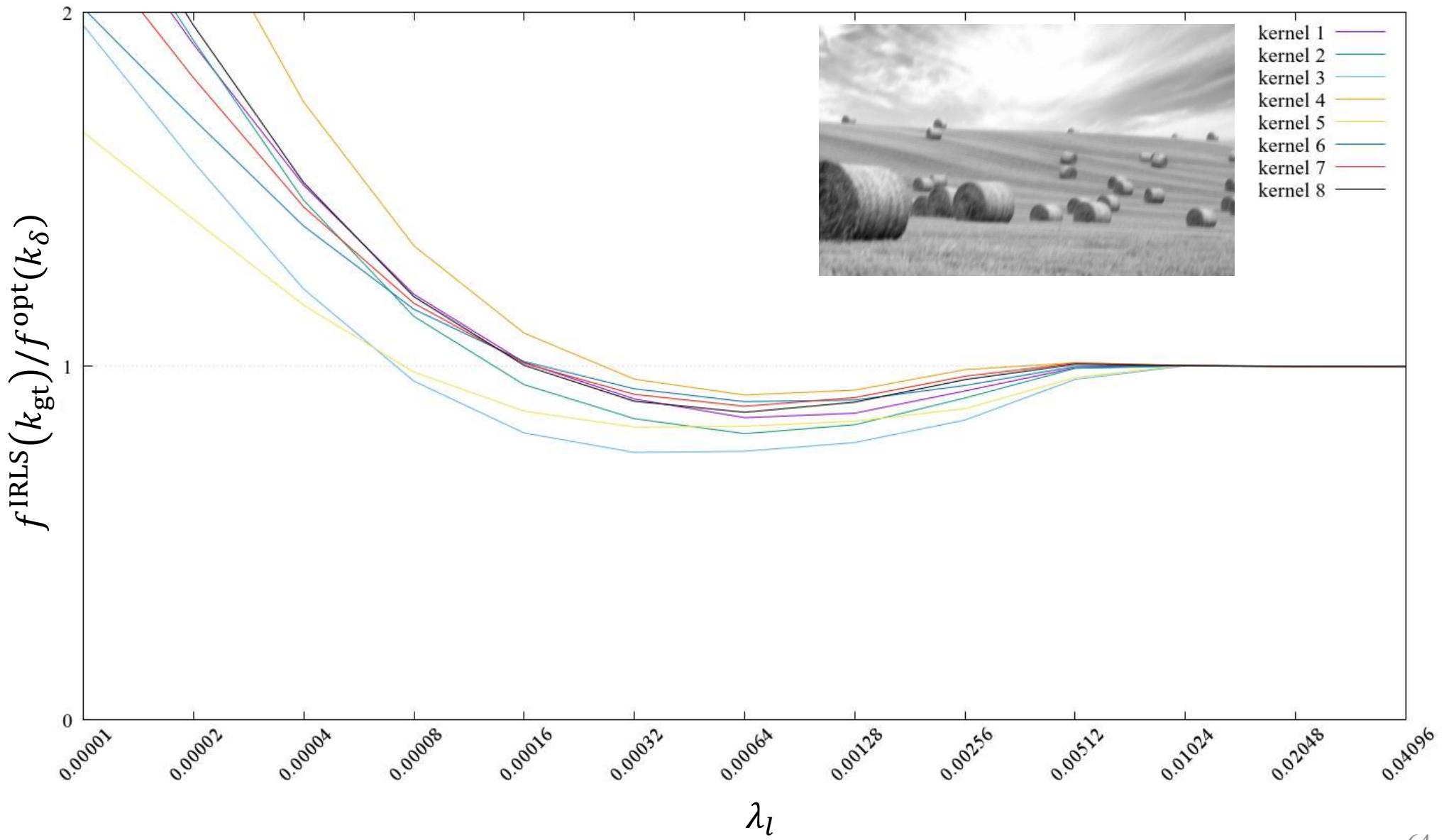
# Sun et al.'s dataset - Image 32



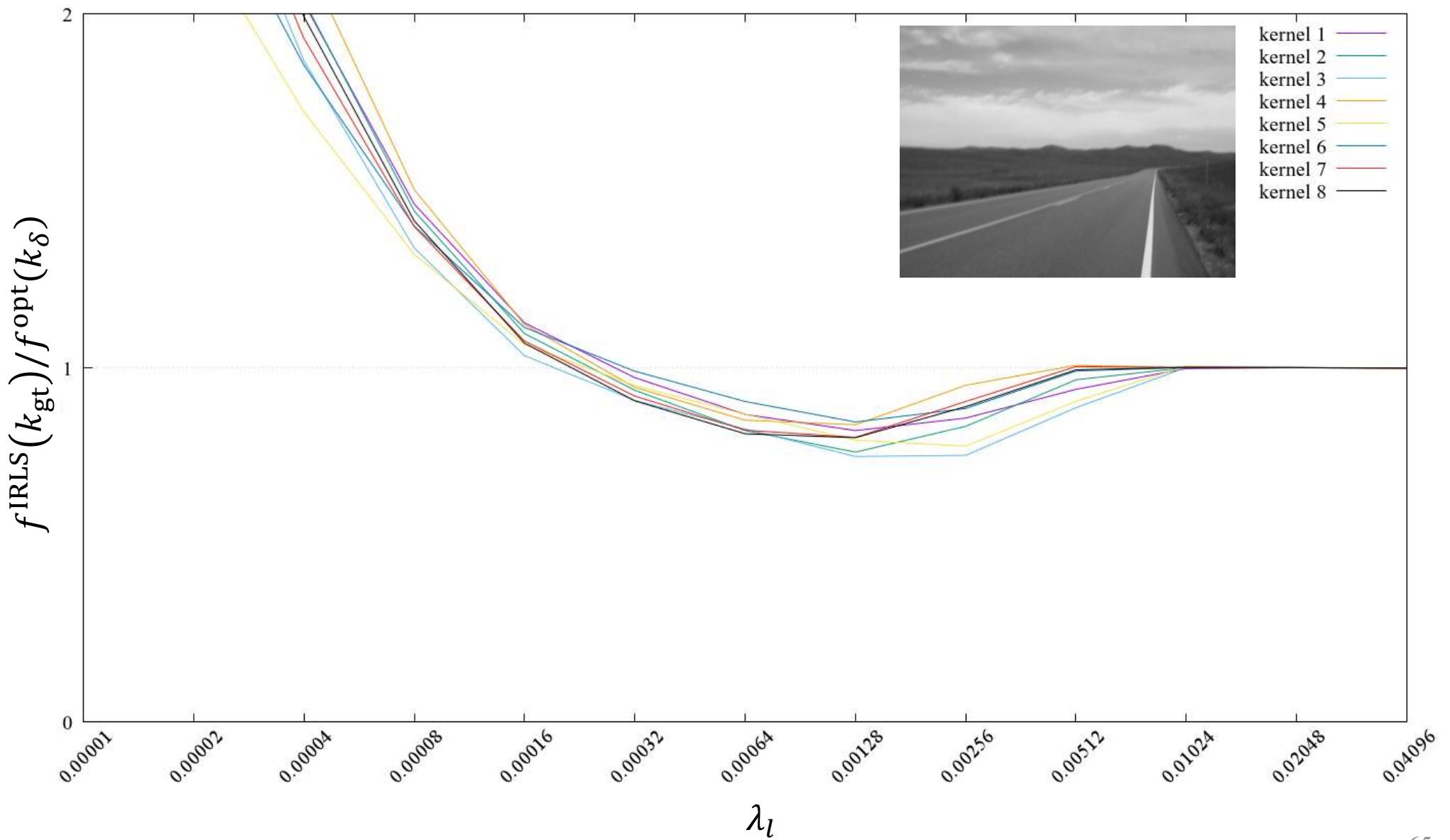
# Sun et al.'s dataset - Image 33



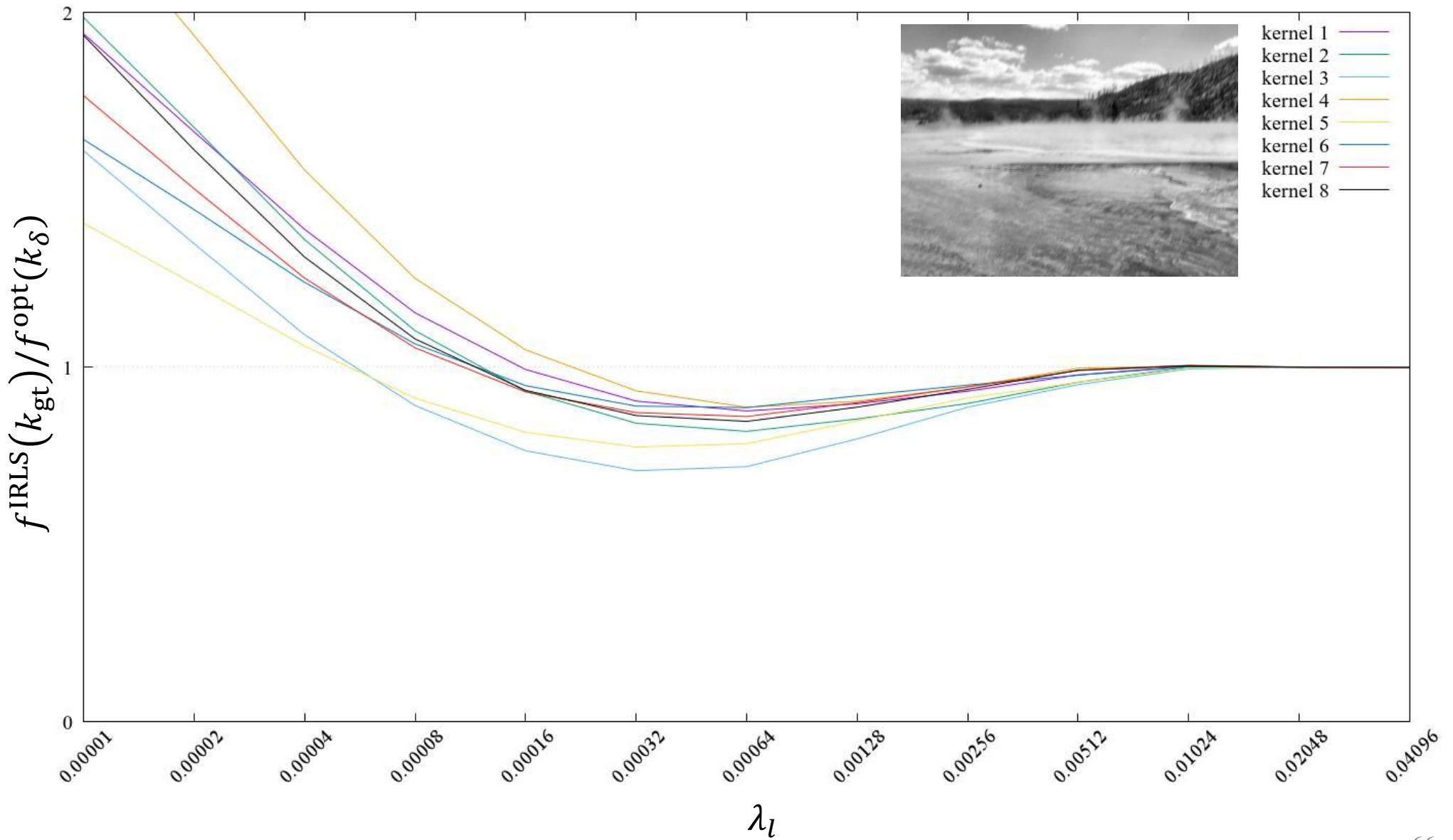
# Sun et al.'s dataset - Image 34



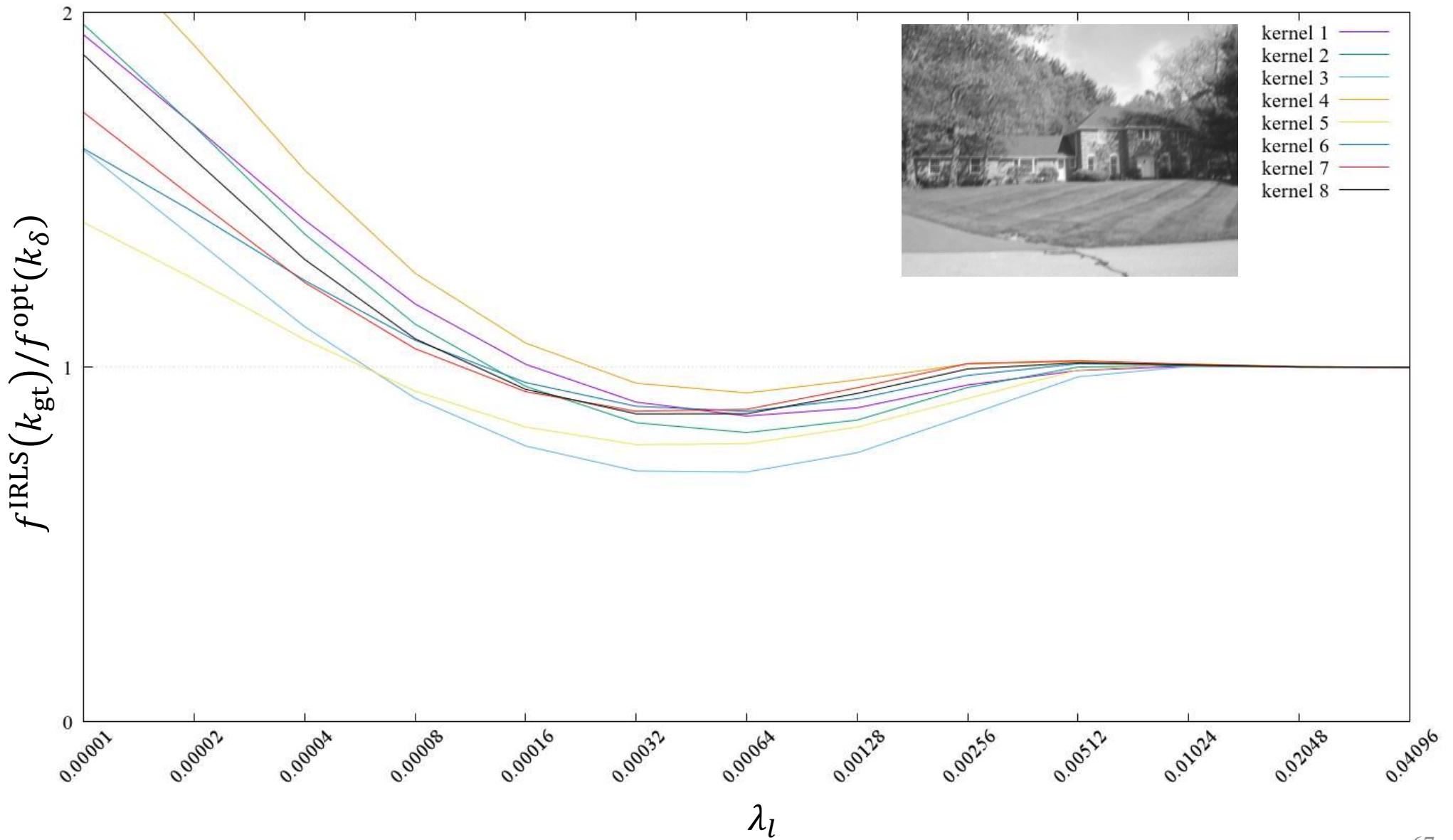
# Sun et al.'s dataset - Image 35



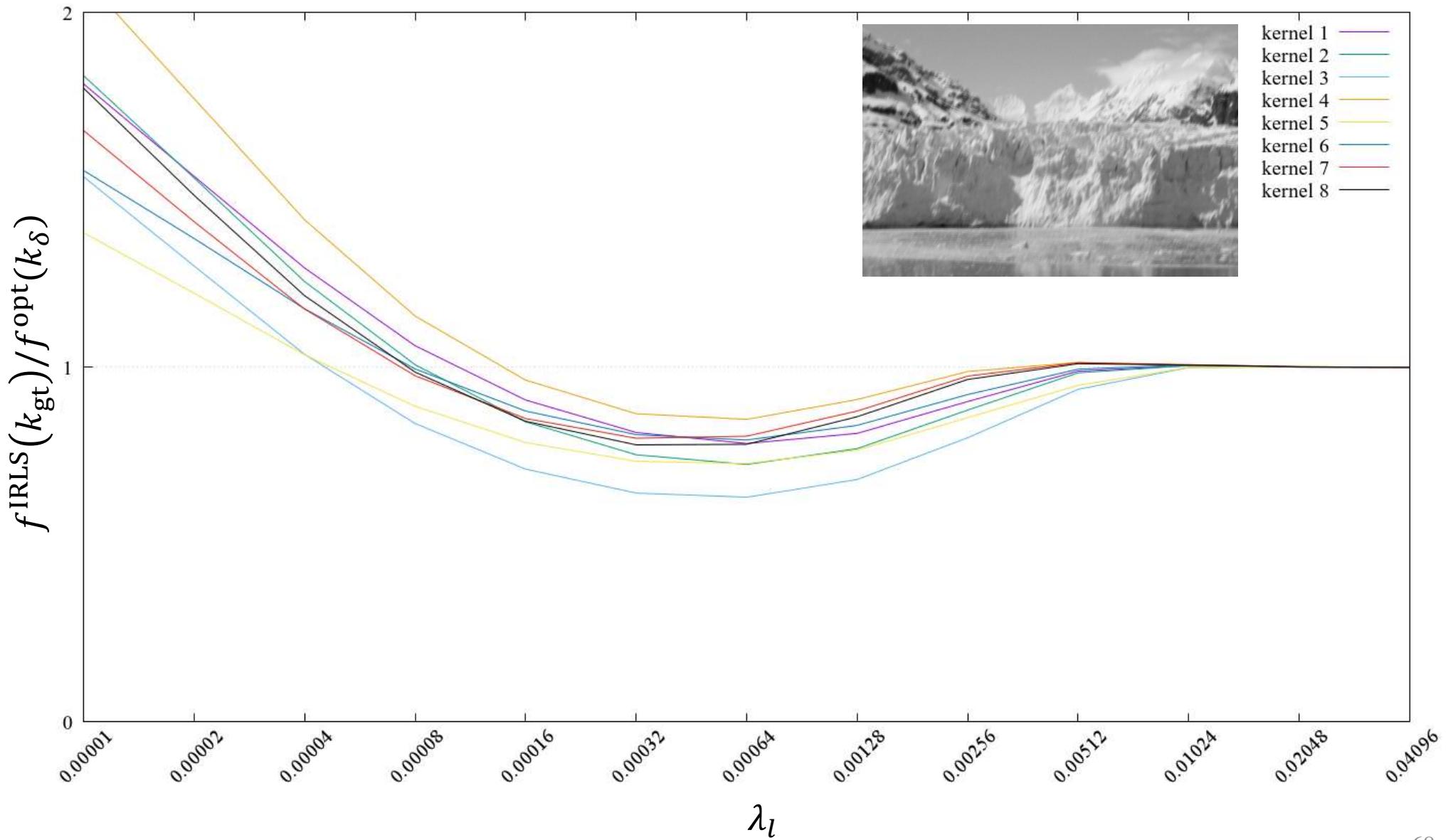
# Sun et al.'s dataset - Image 36



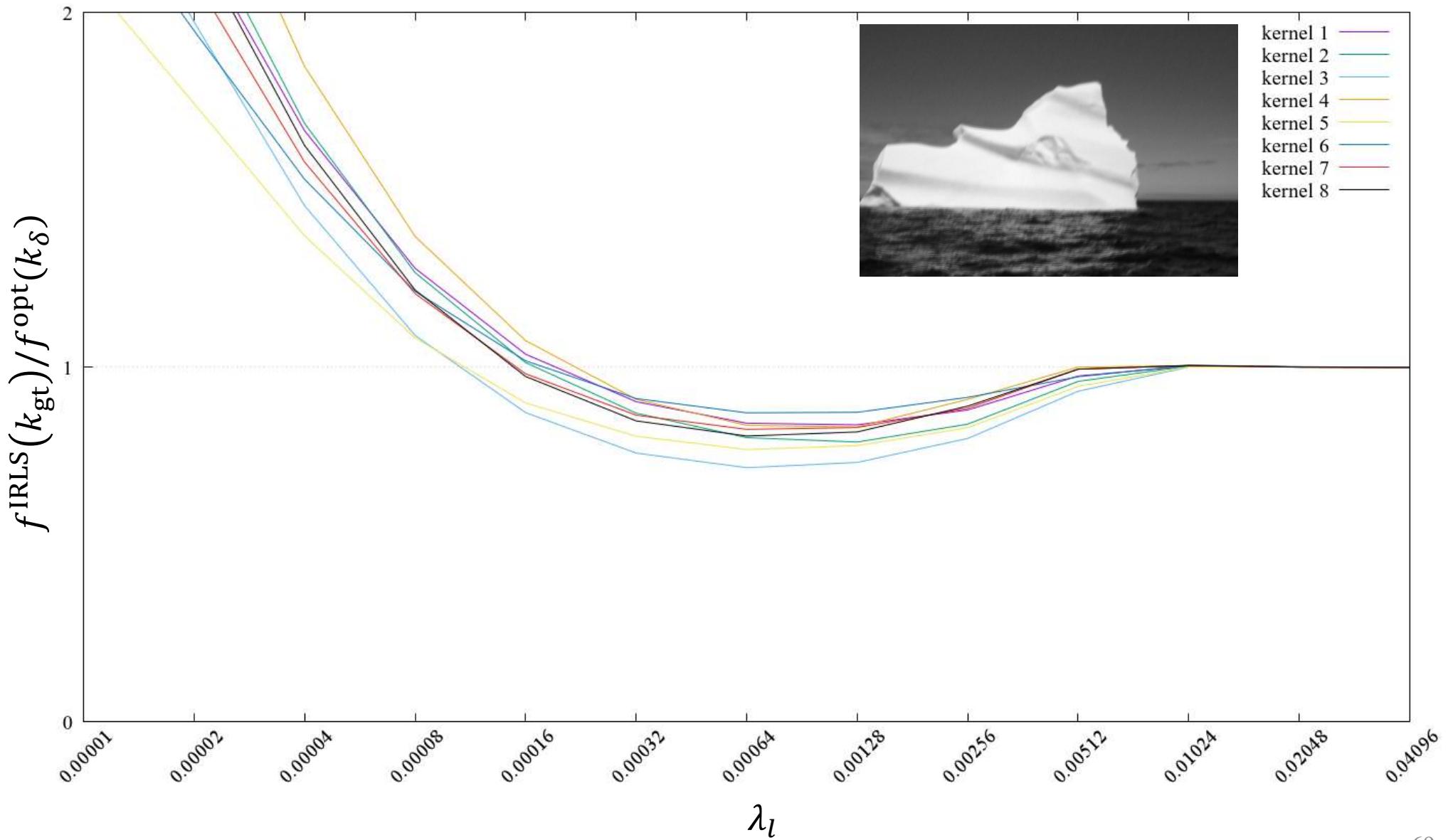
# Sun et al.'s dataset - Image 37



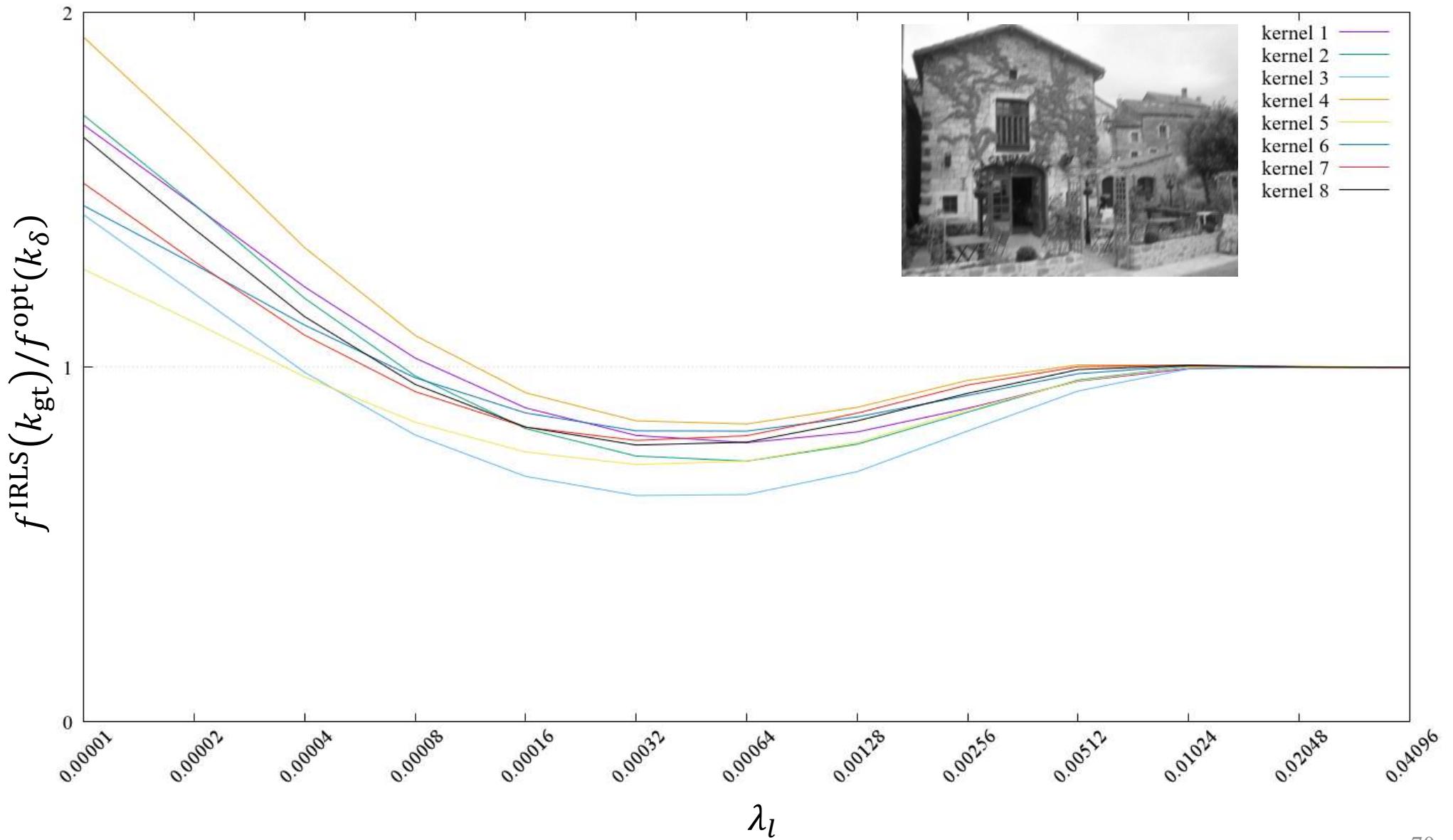
# Sun et al.'s dataset - Image 38



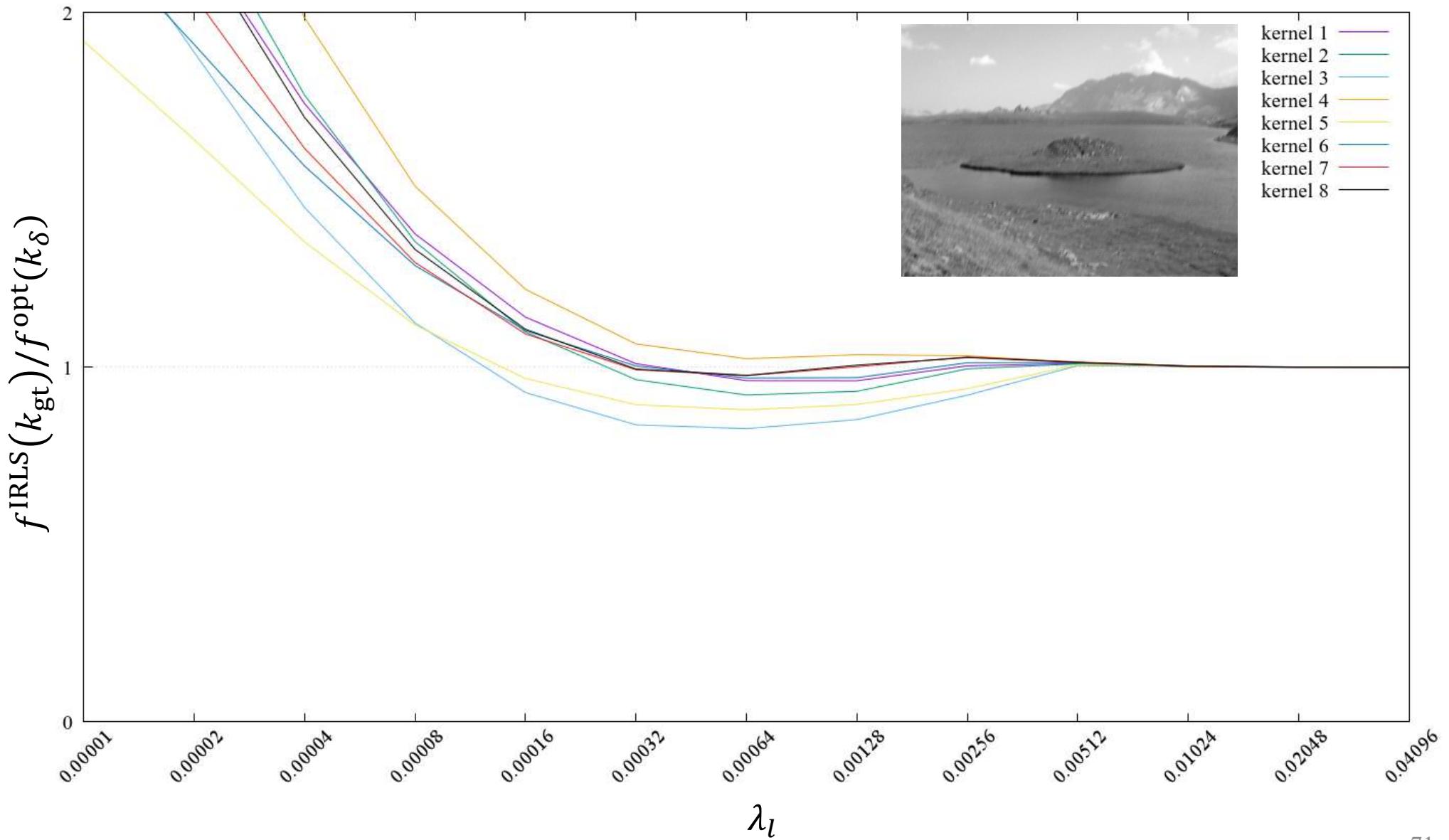
# Sun et al.'s dataset - Image 39



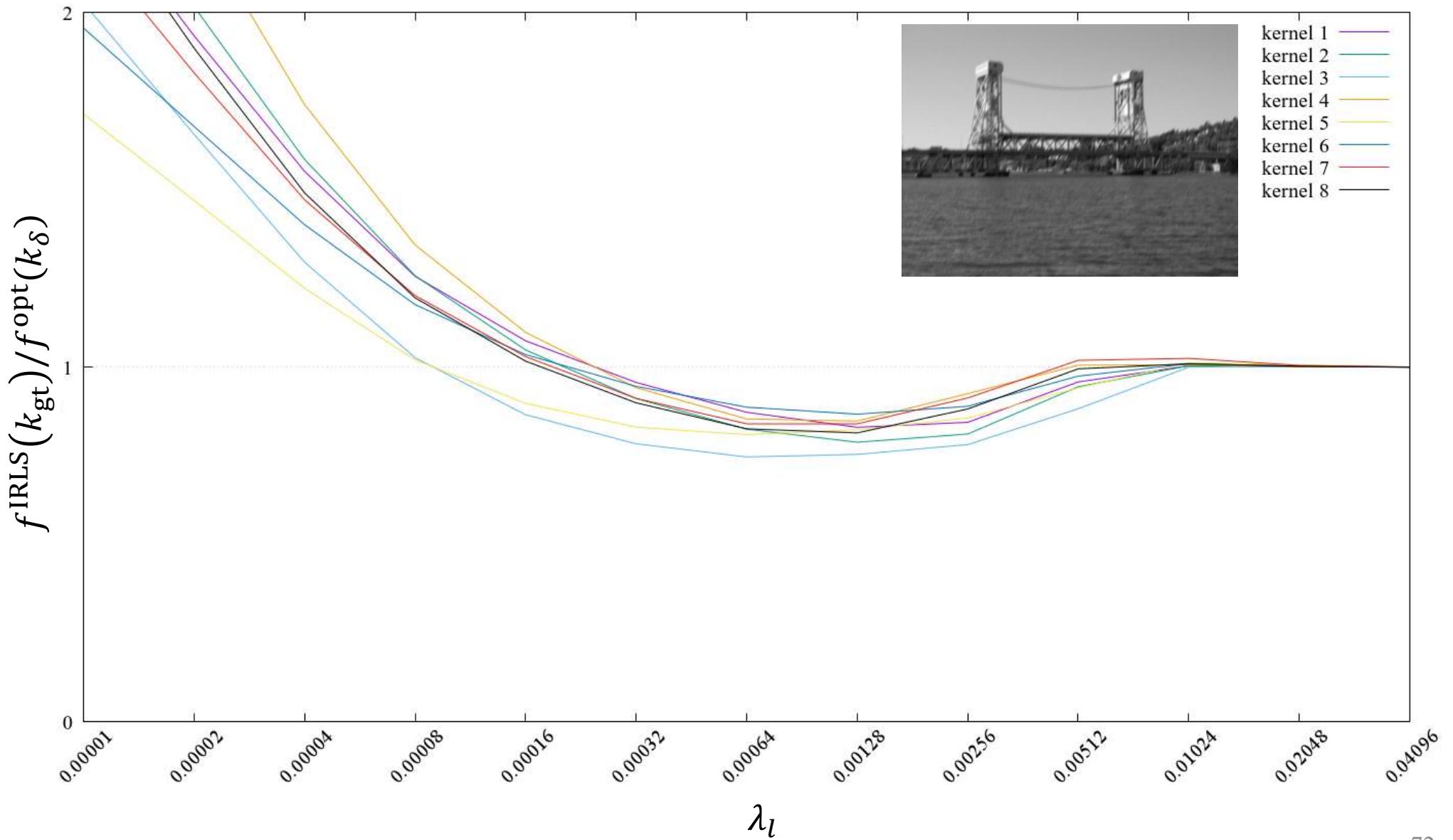
# Sun et al.'s dataset - Image 40



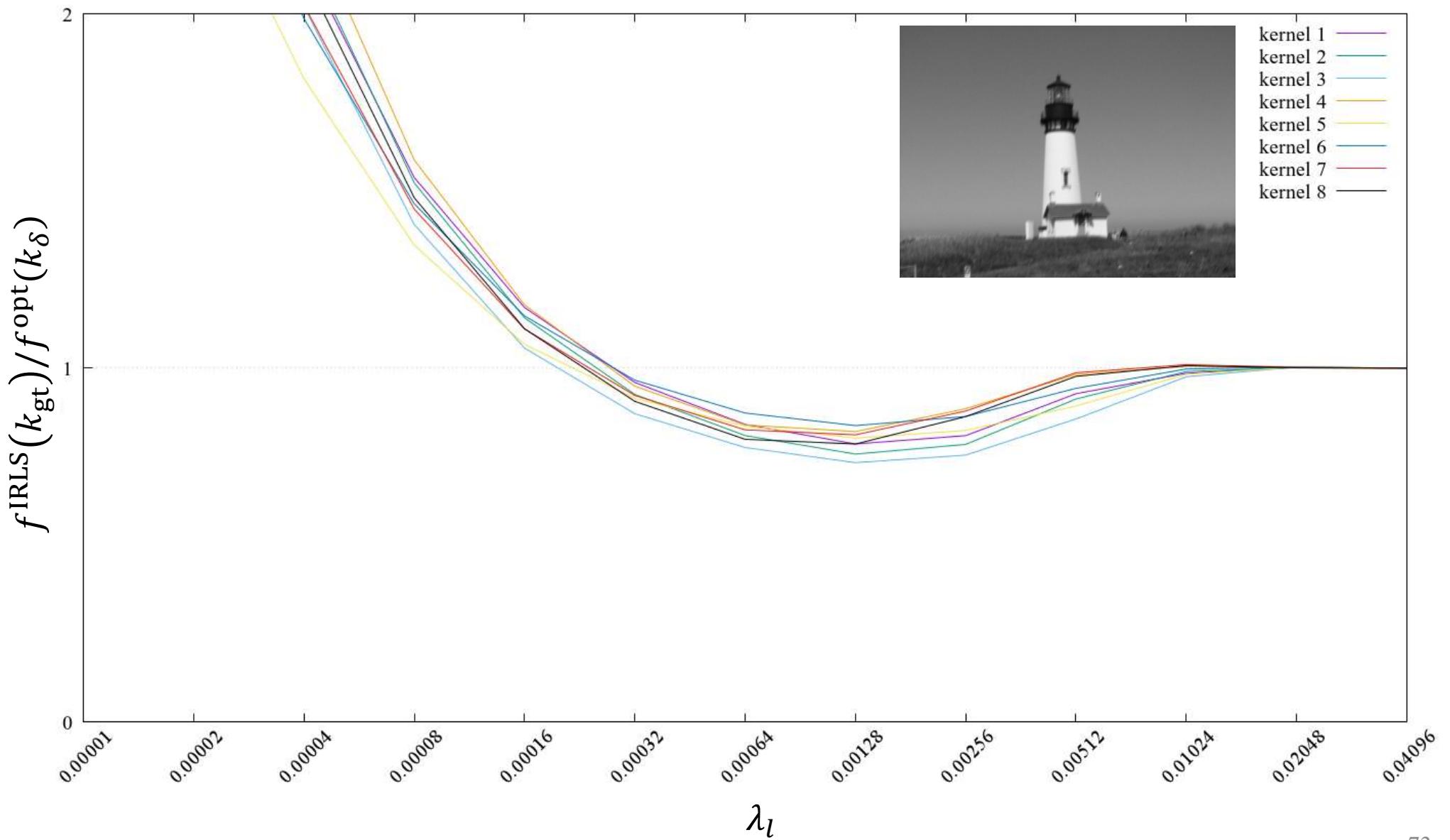
# Sun et al.'s dataset - Image 41



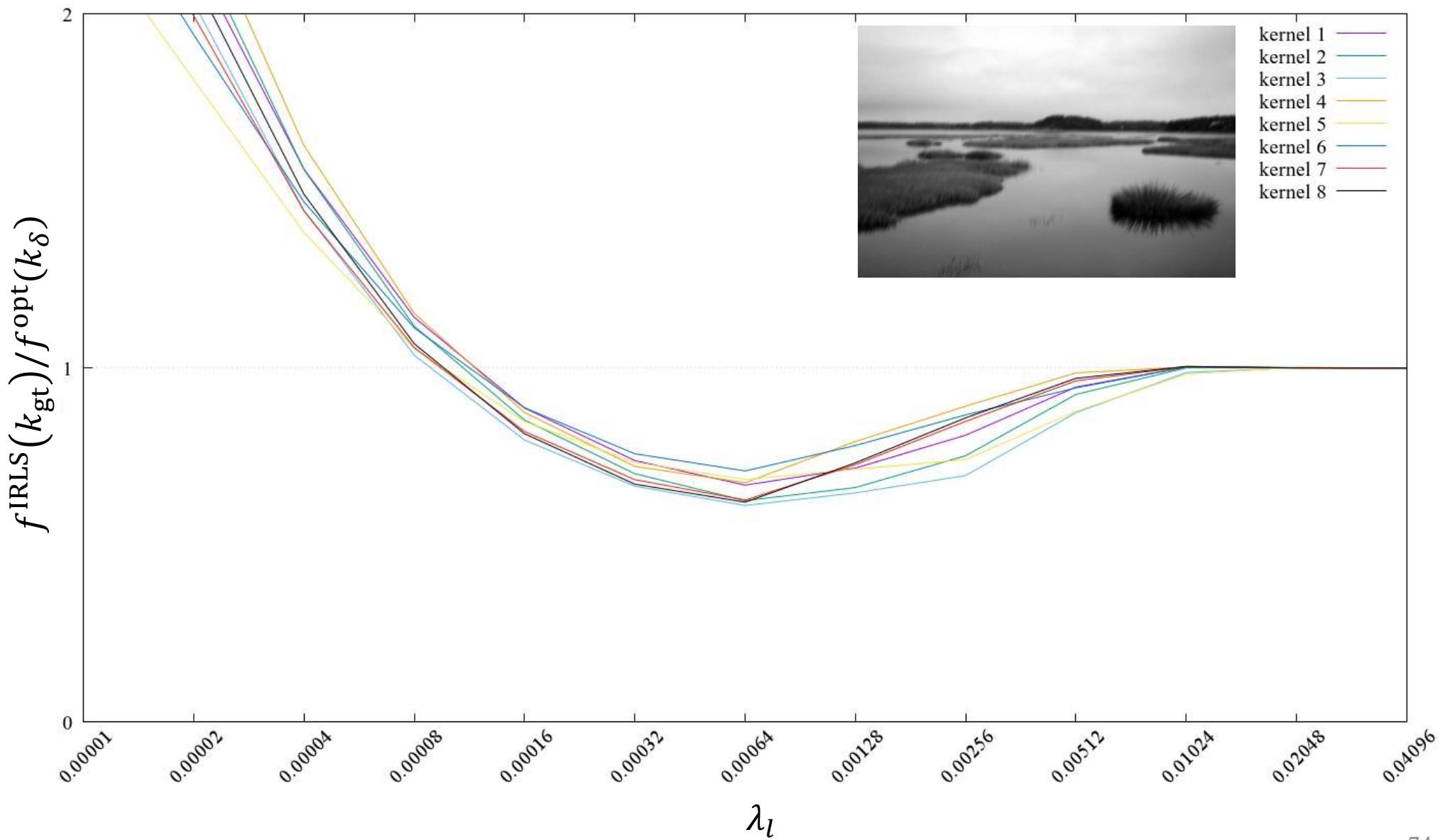
# Sun et al.'s dataset - Image 42



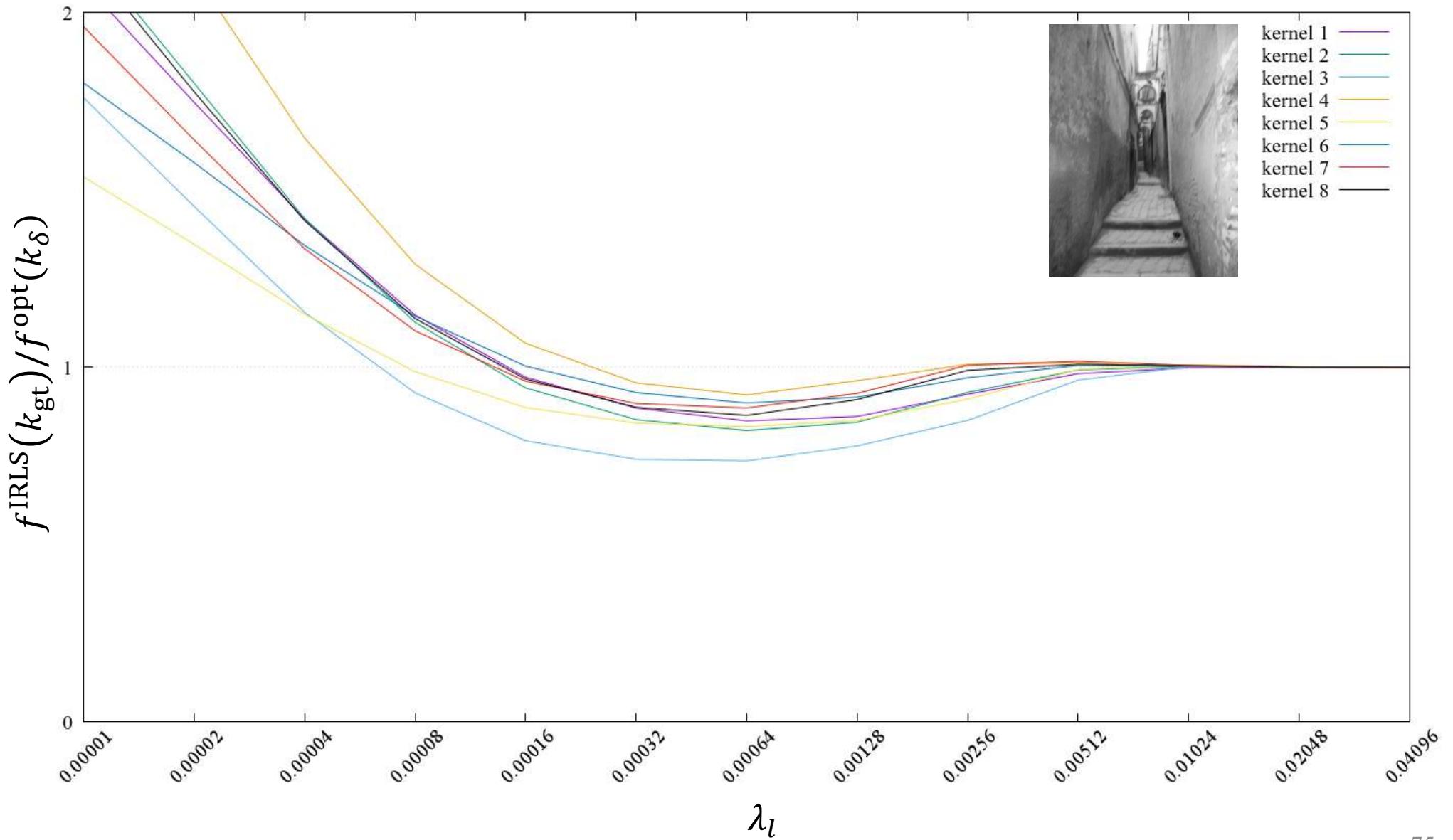
# Sun et al.'s dataset - Image 43



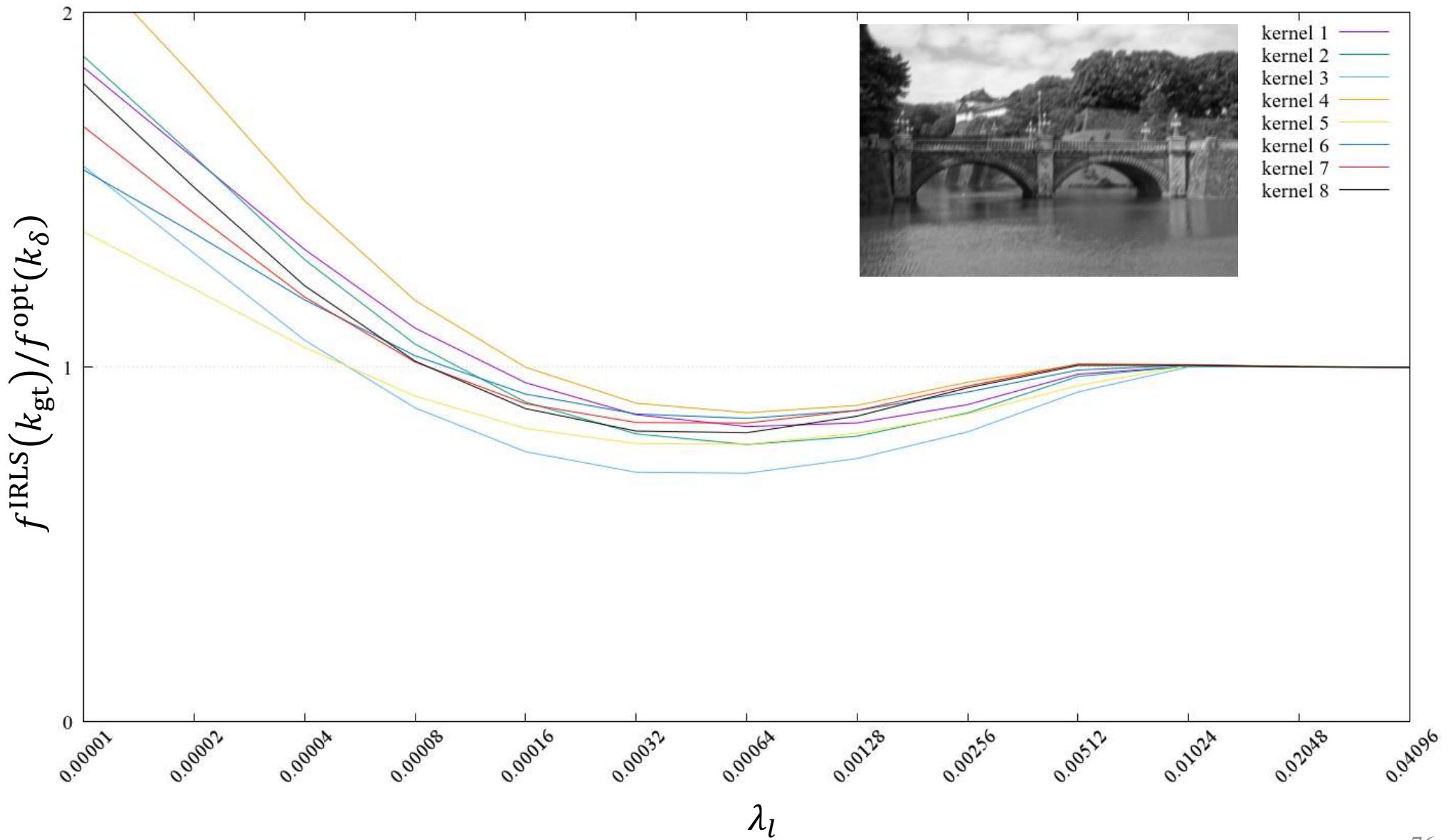
# Sun et al.'s dataset - Image 44



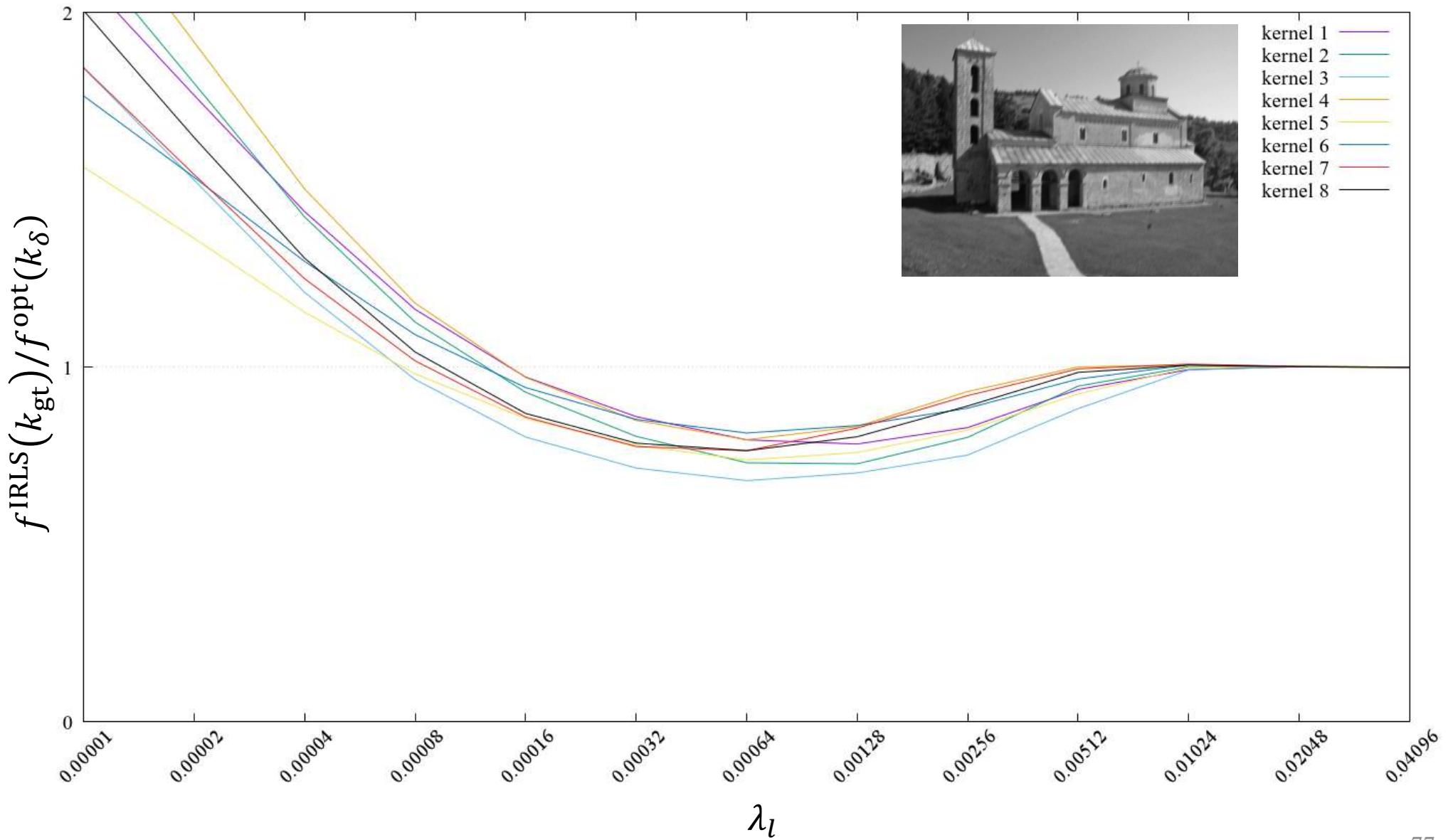
# Sun et al.'s dataset - Image 45



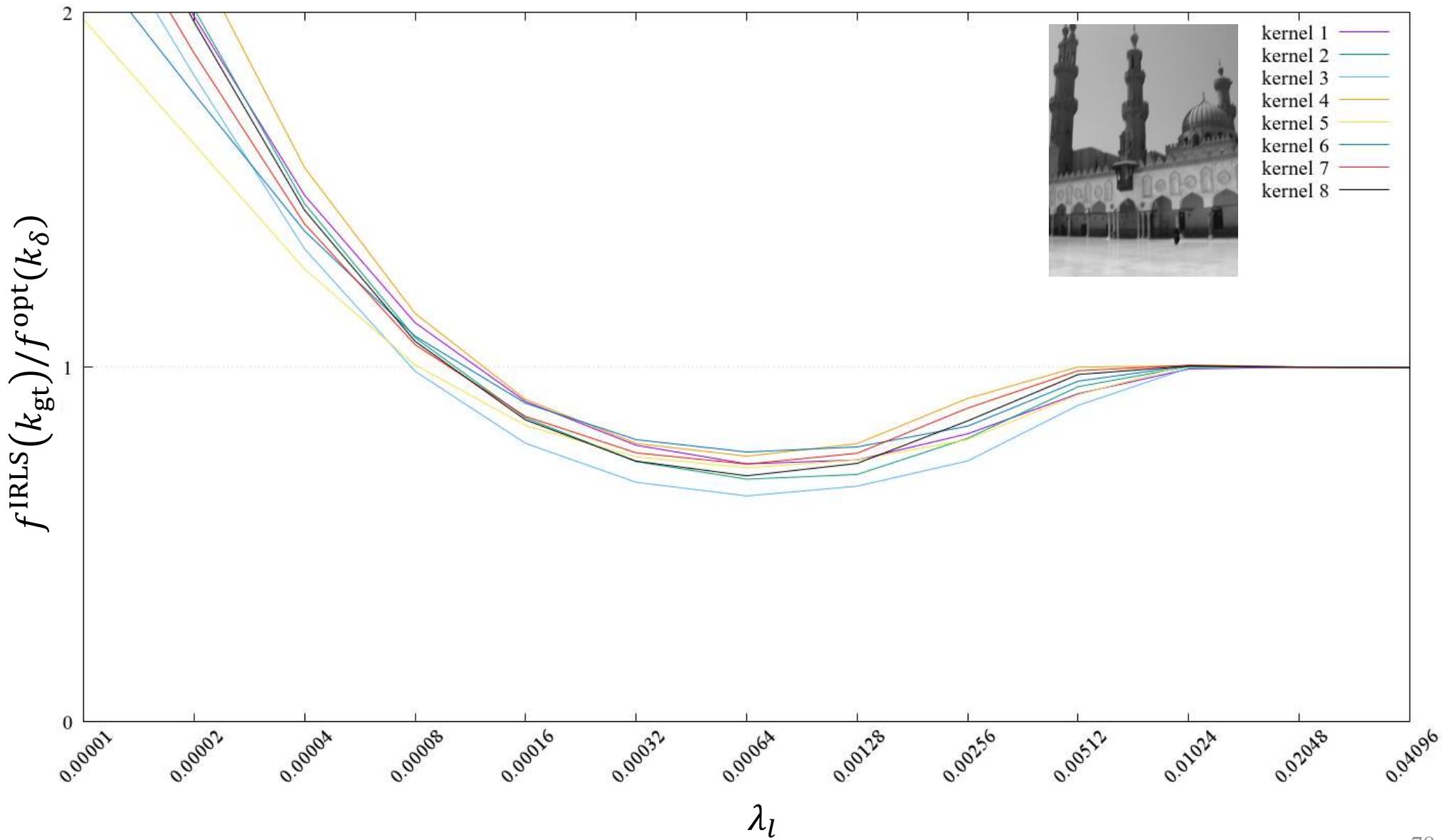
# Sun et al.'s dataset - Image 46



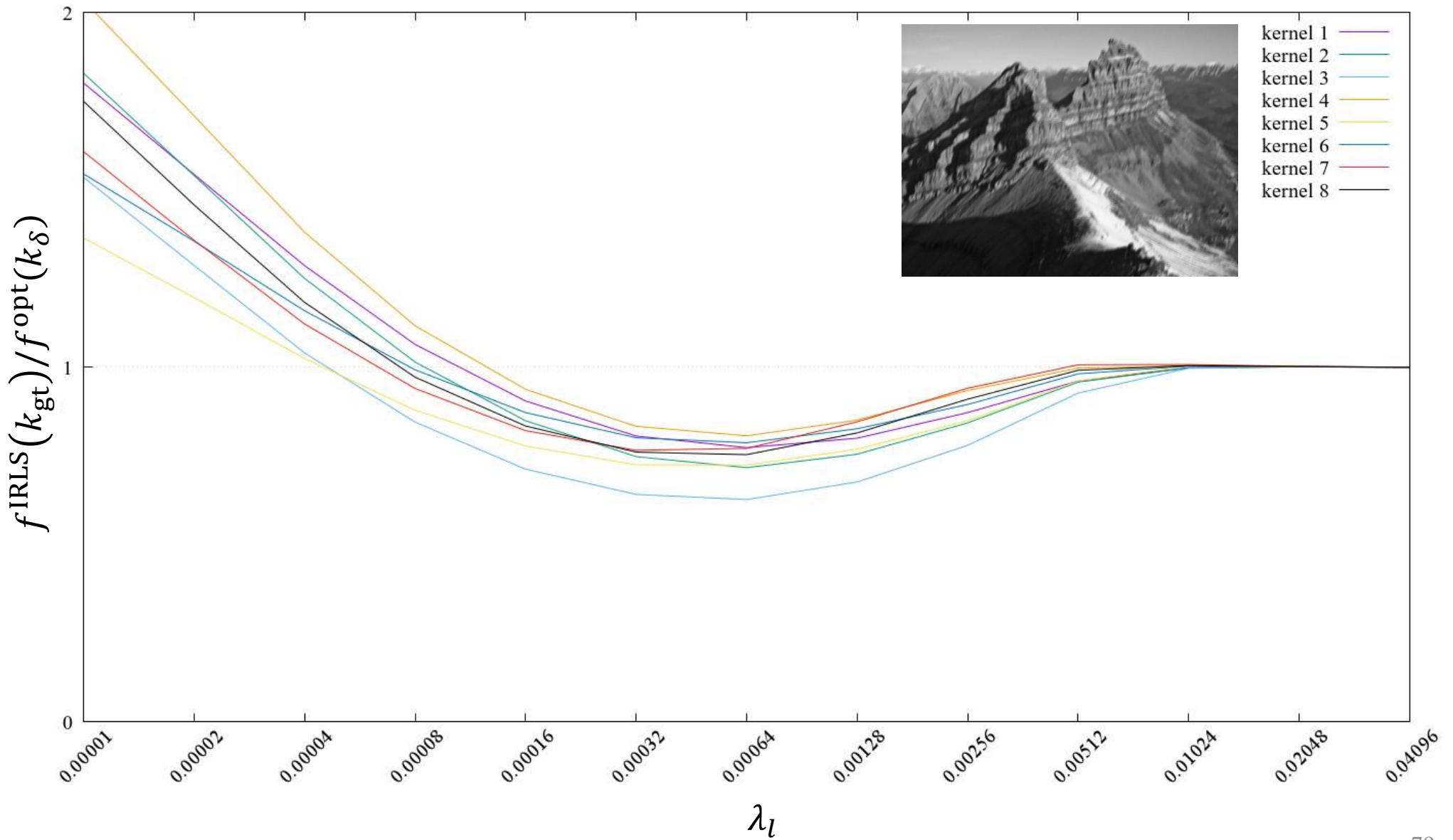
# Sun et al.'s dataset - Image 47



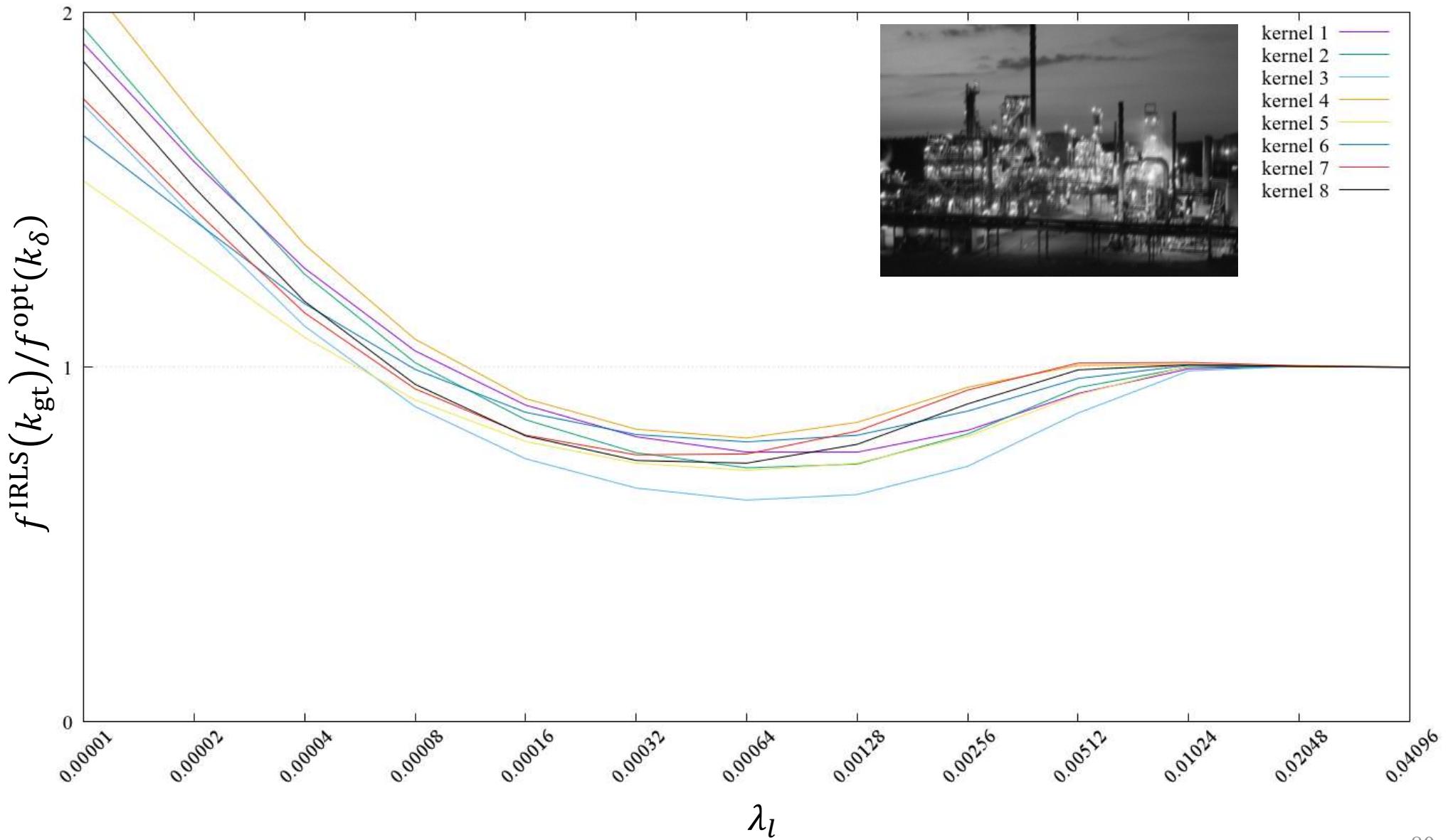
# Sun et al.'s dataset - Image 48



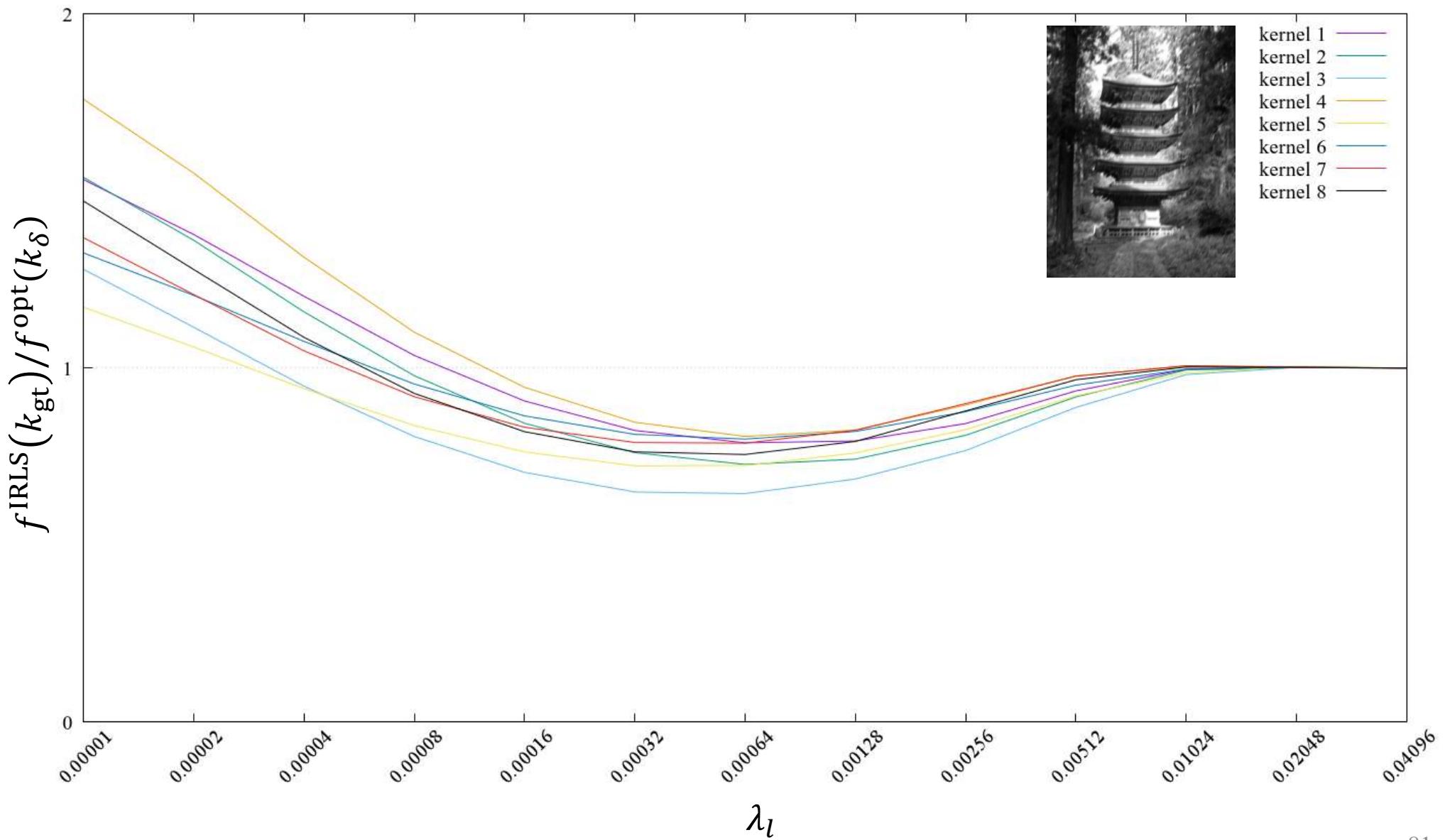
# Sun et al.'s dataset - Image 49



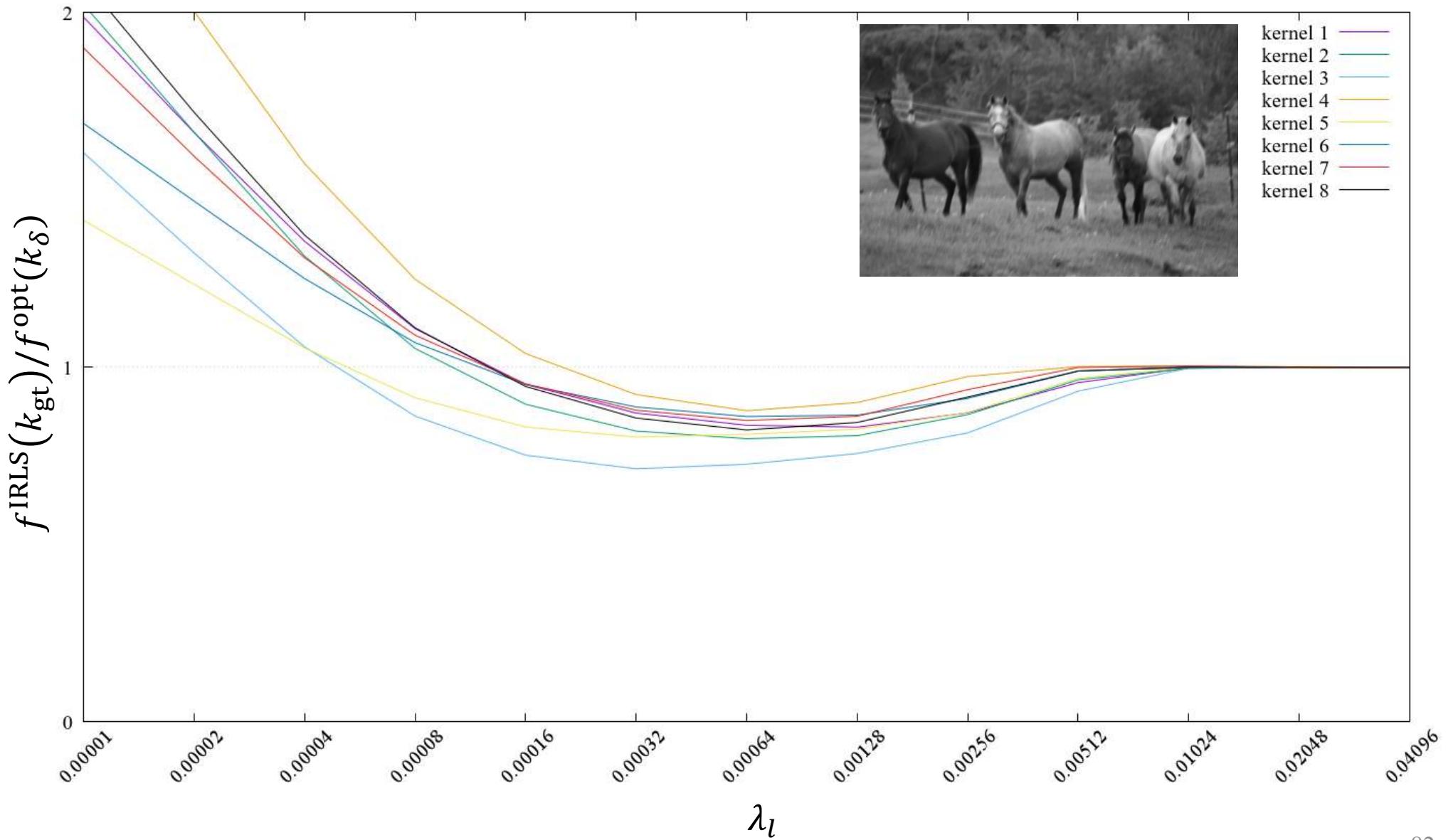
# Sun et al.'s dataset - Image 50



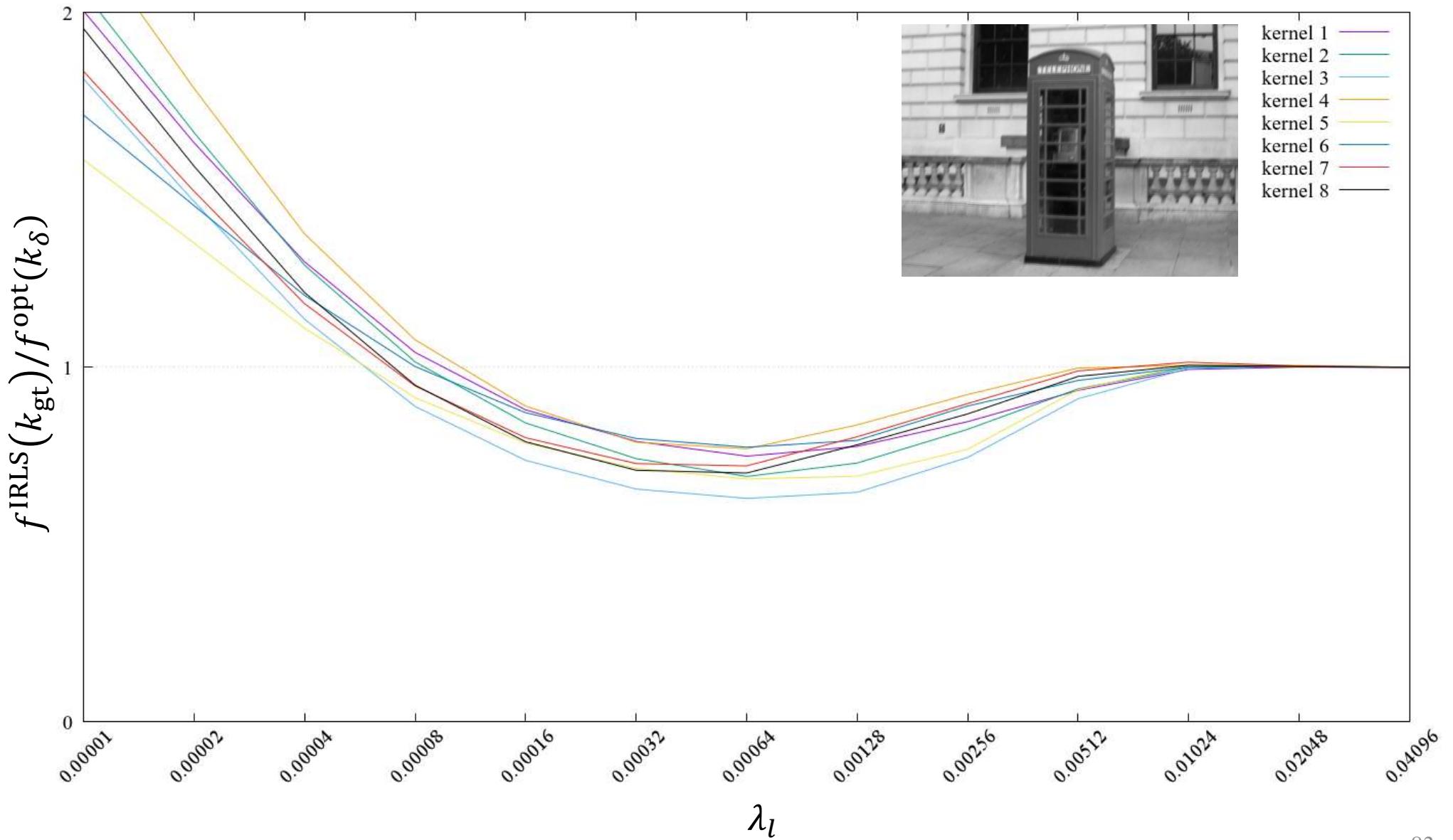
# Sun et al.'s dataset - Image 51



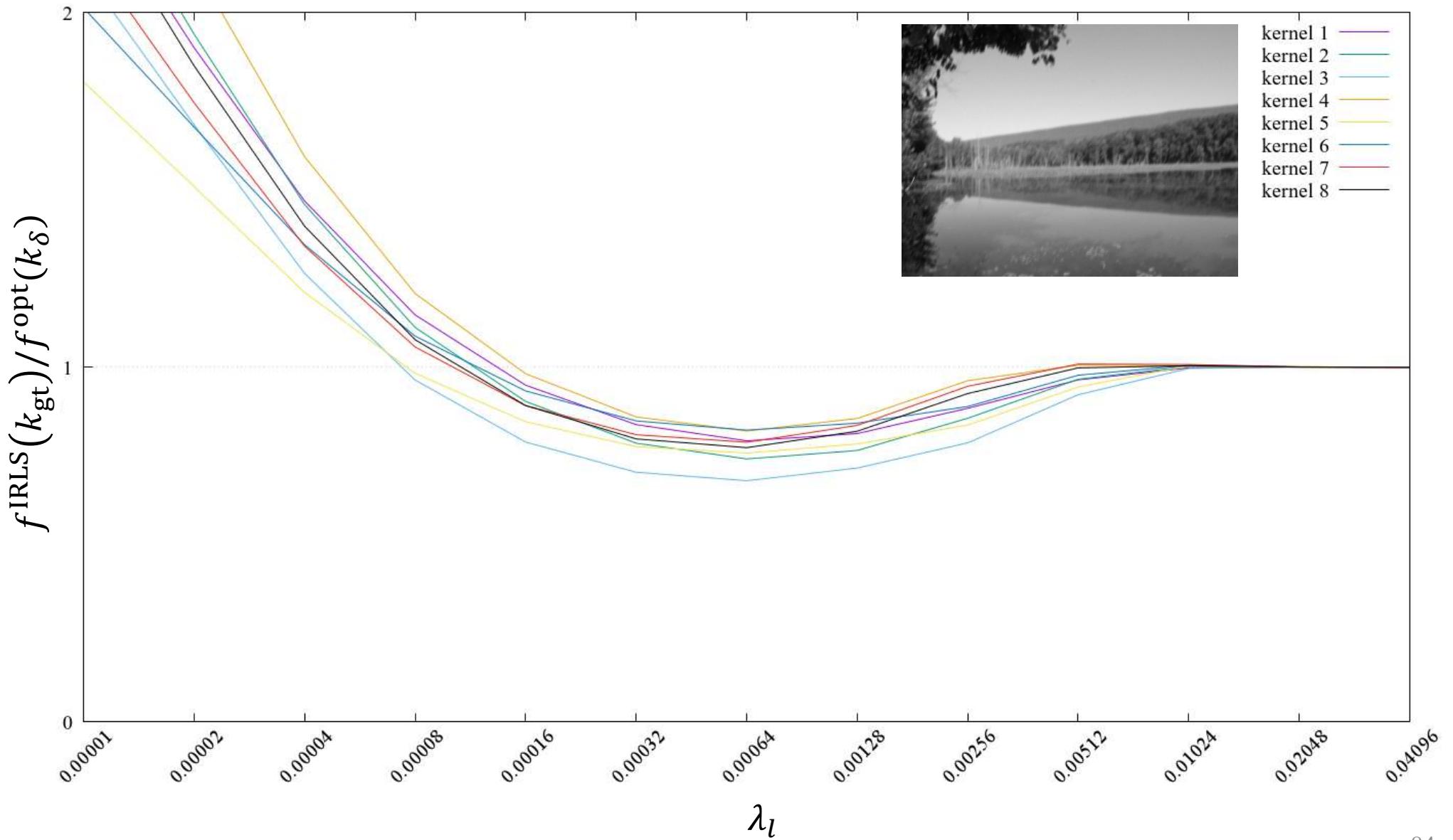
# Sun et al.'s dataset - Image 52



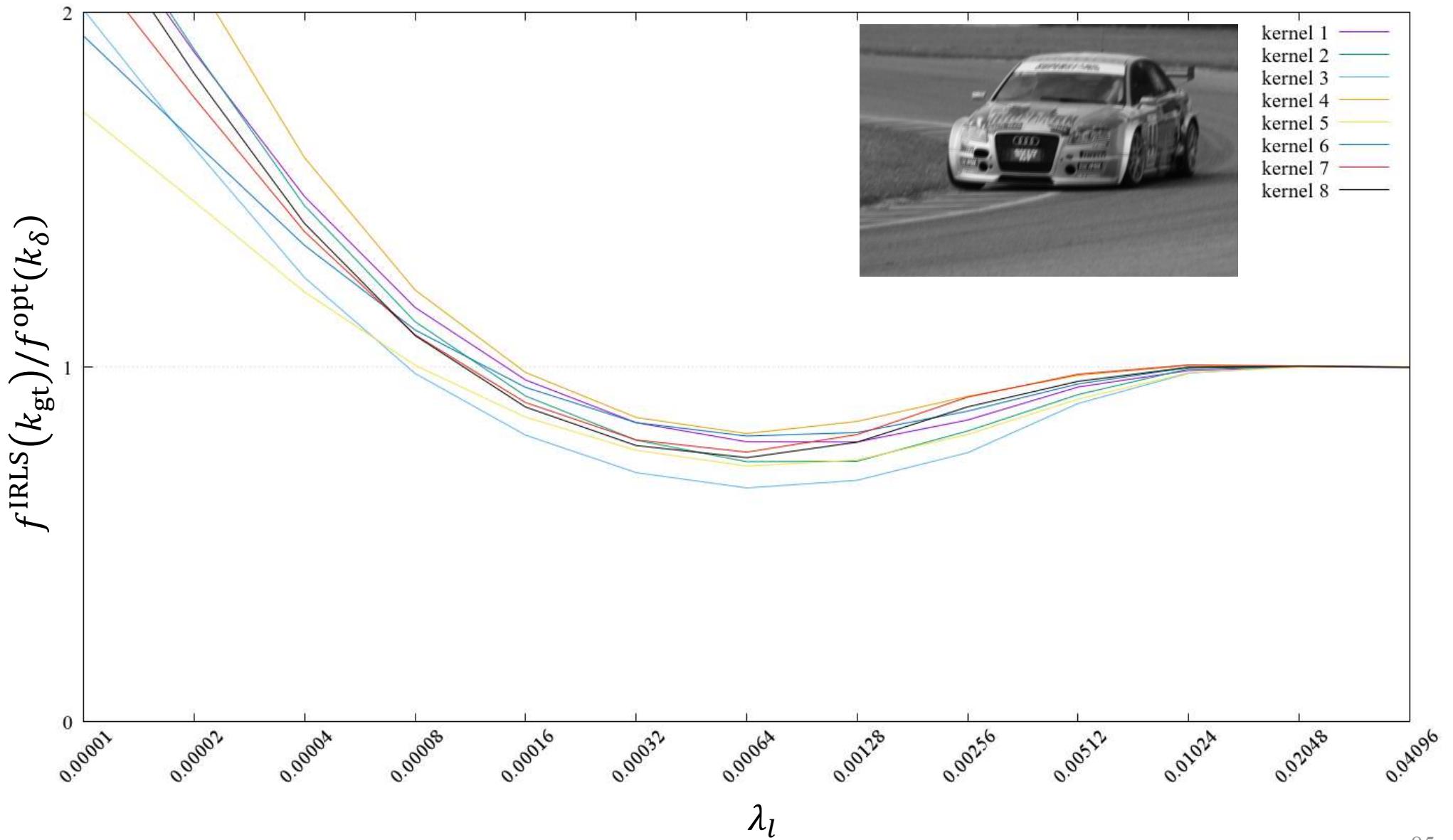
# Sun et al.'s dataset - Image 53



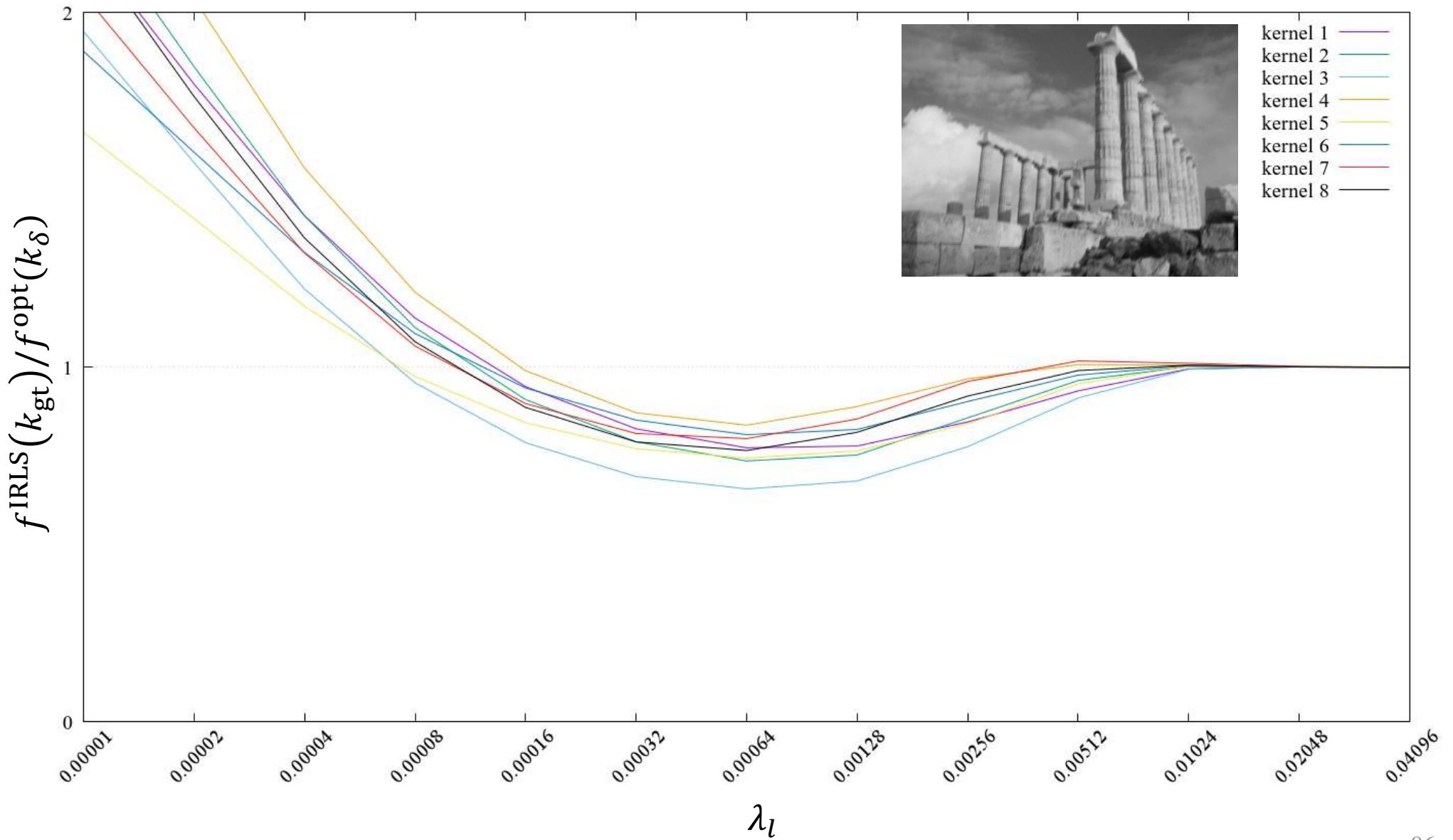
# Sun et al.'s dataset - Image 54



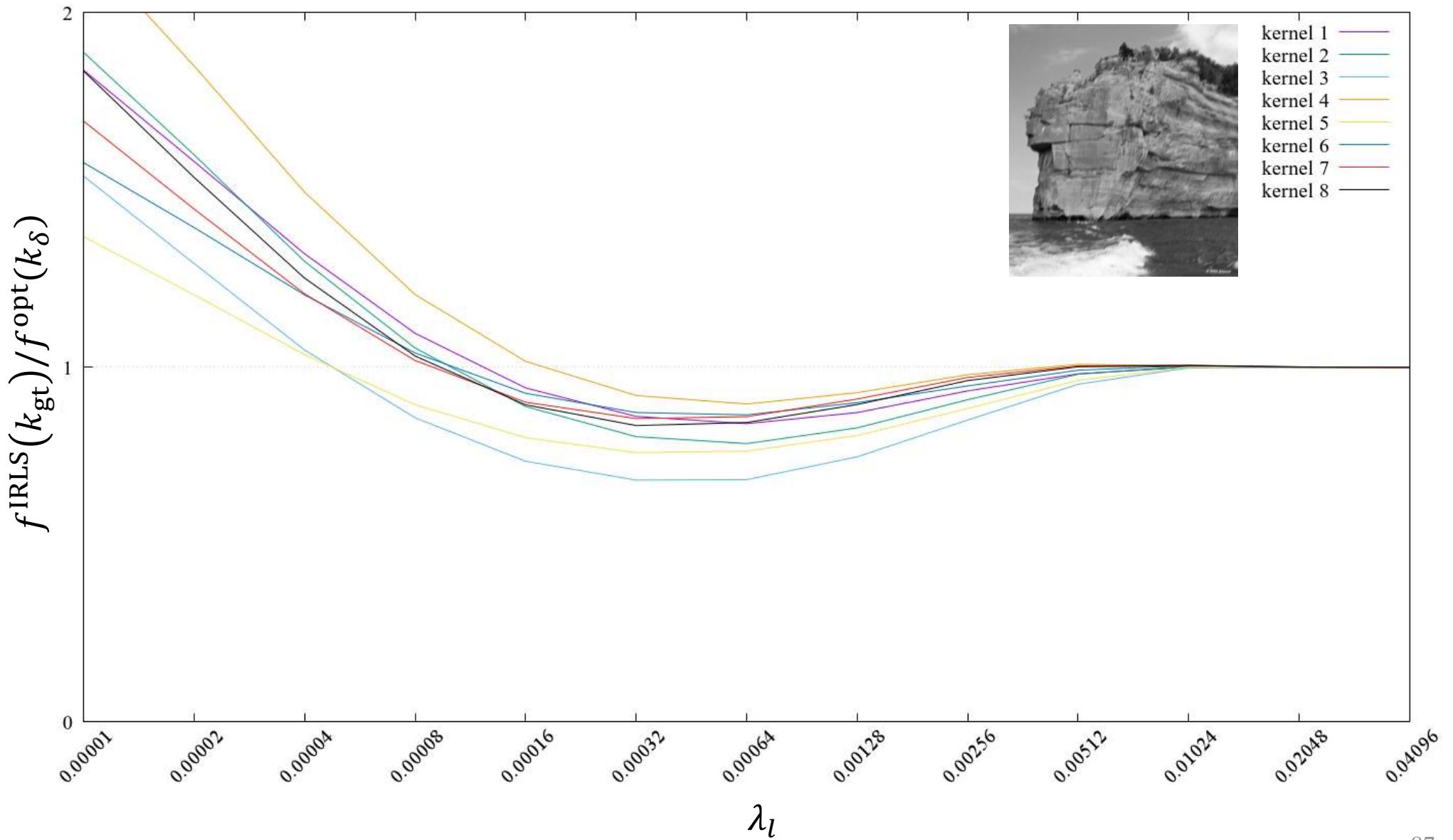
# Sun et al.'s dataset - Image 55



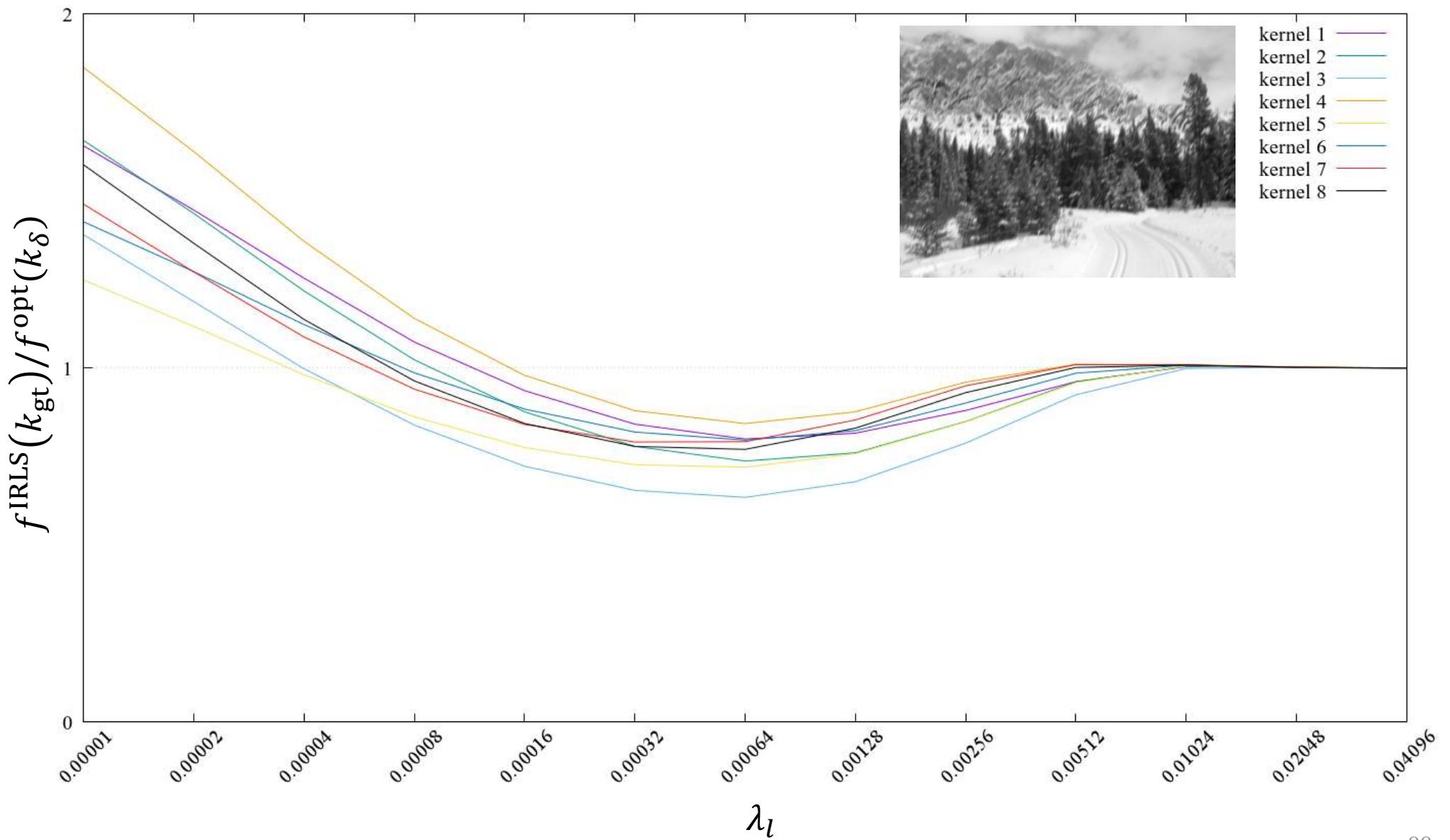
# Sun et al.'s dataset - Image 56



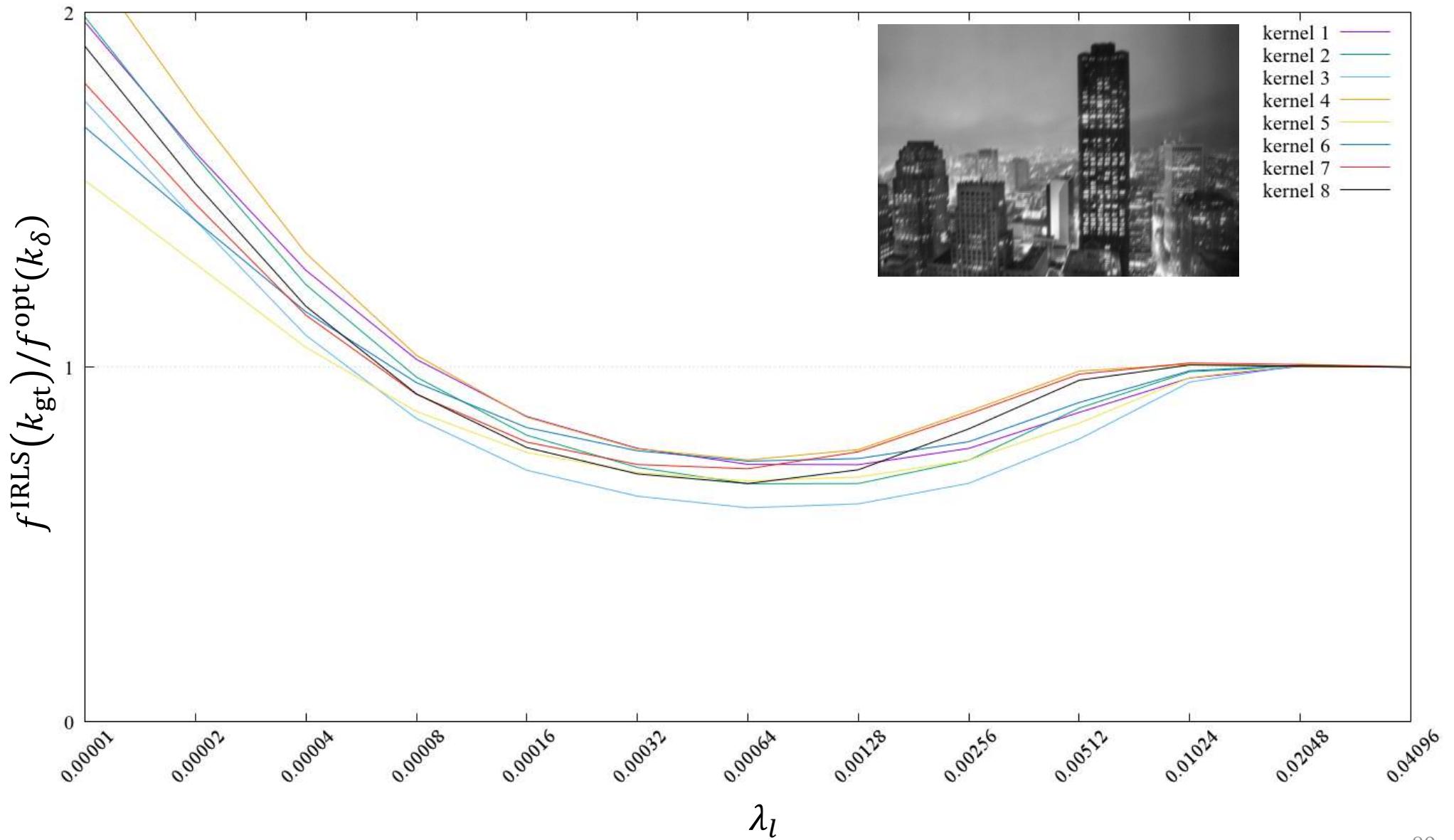
# Sun et al.'s dataset - Image 57



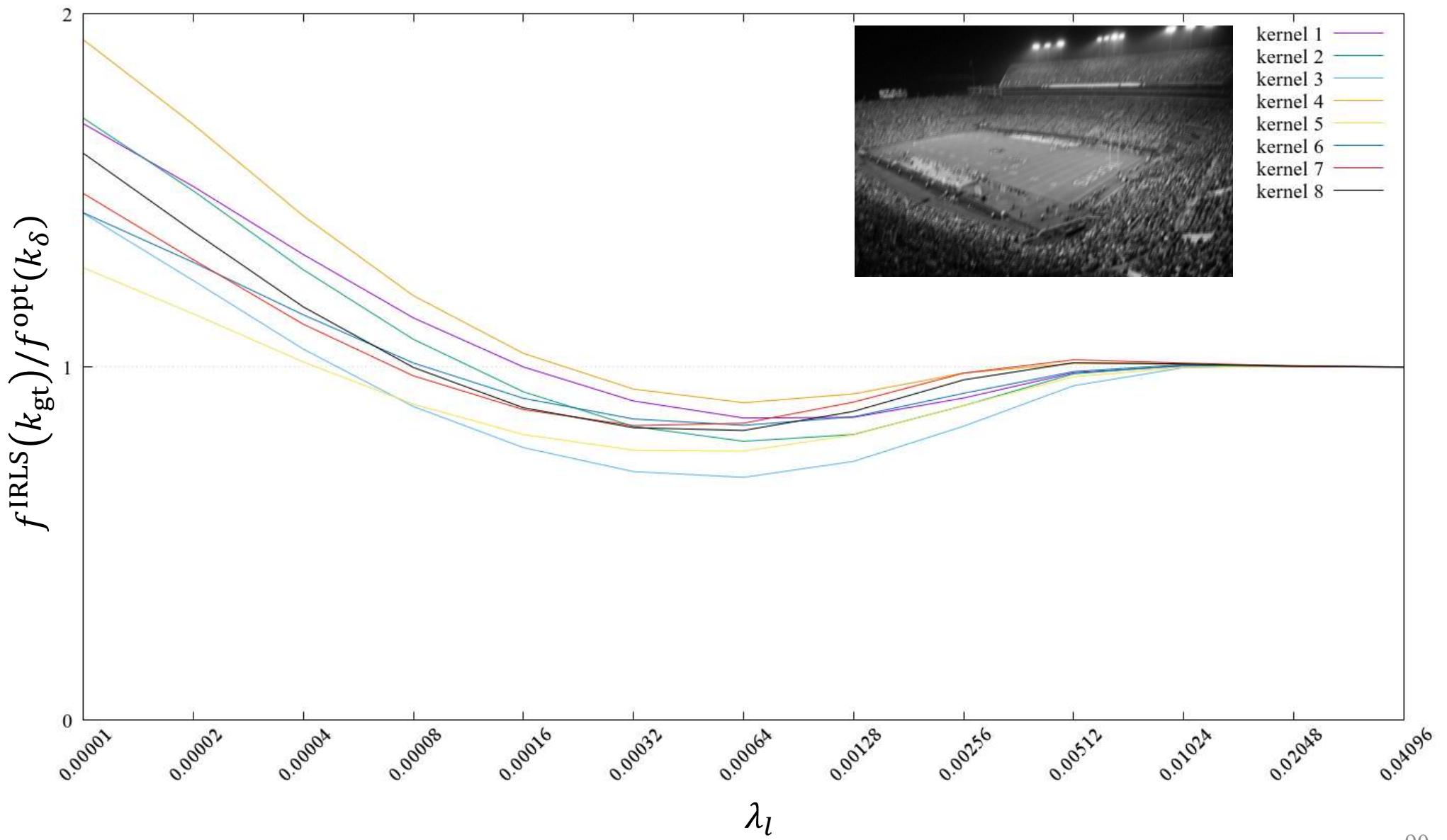
# Sun et al.'s dataset - Image 58



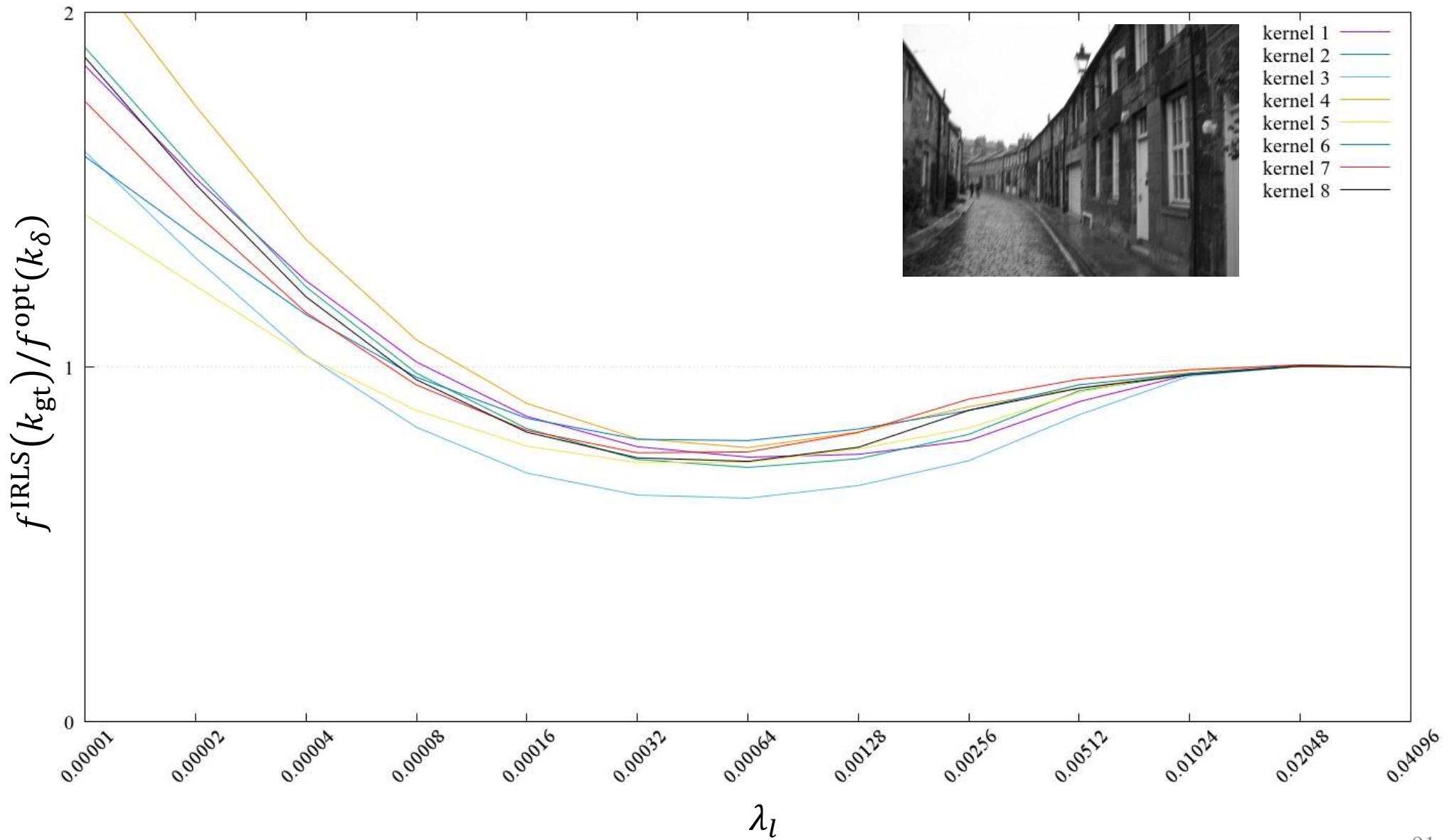
# Sun et al.'s dataset - Image 59



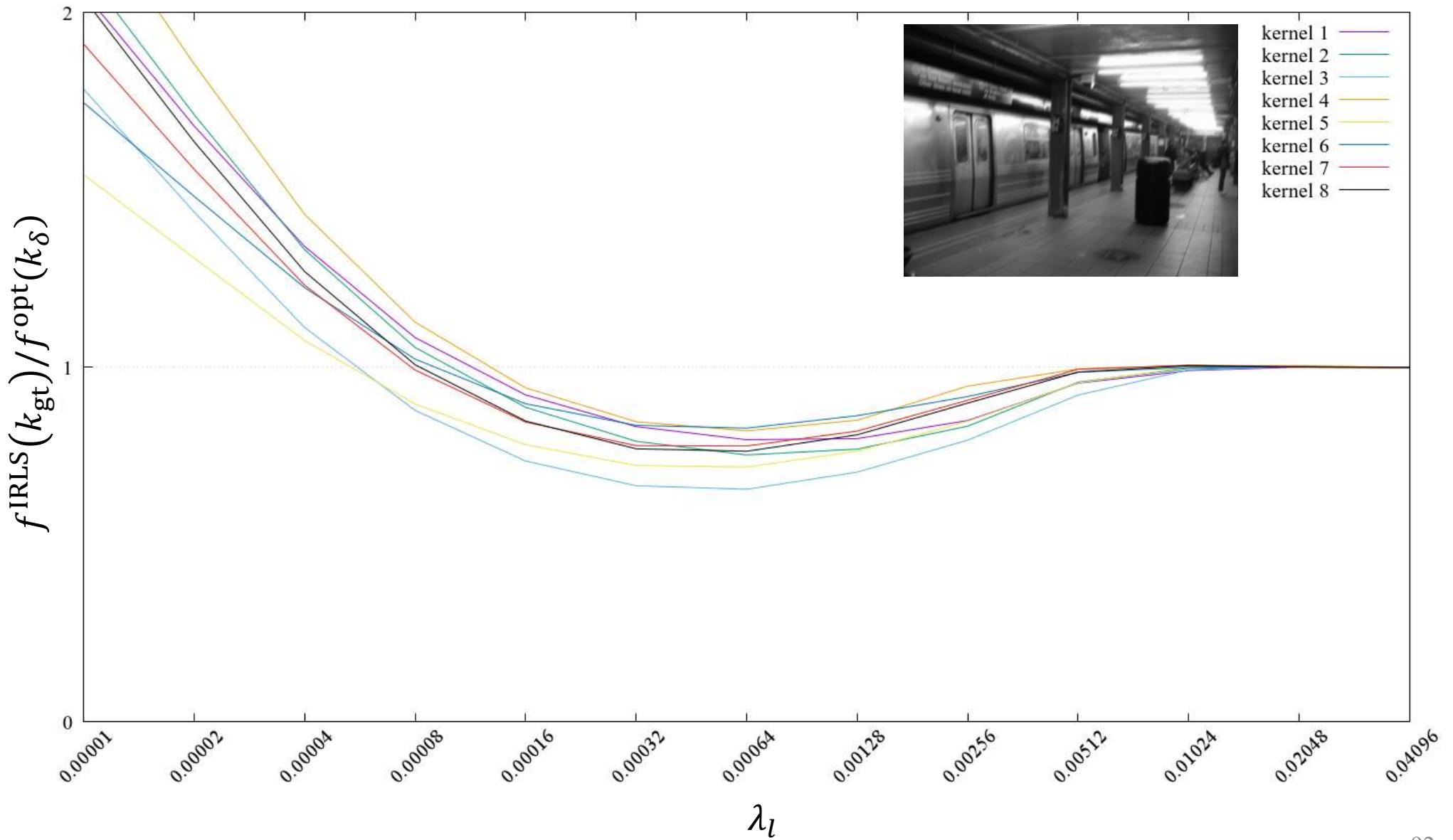
# Sun et al.'s dataset - Image 60



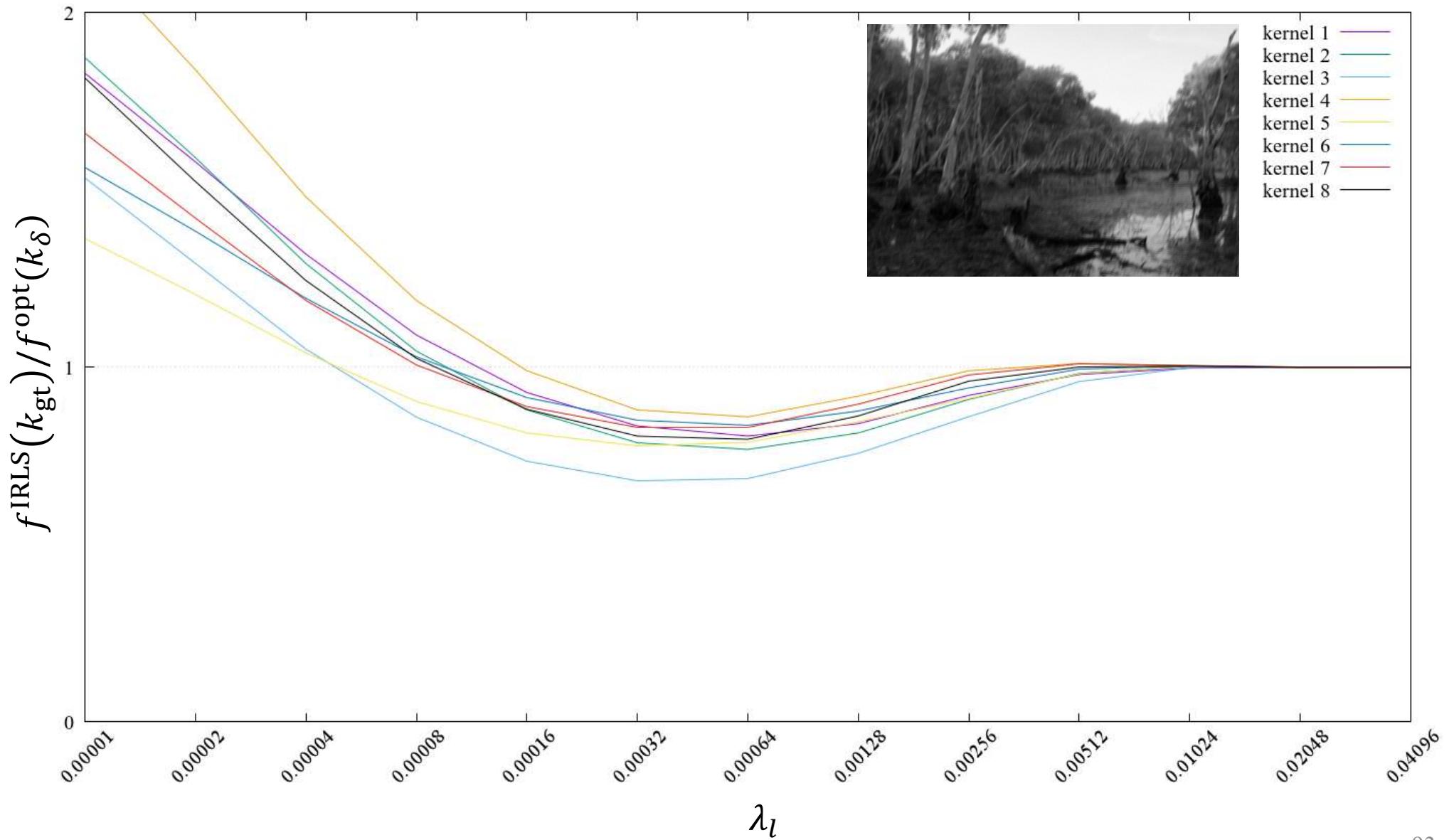
# Sun et al.'s dataset - Image 61



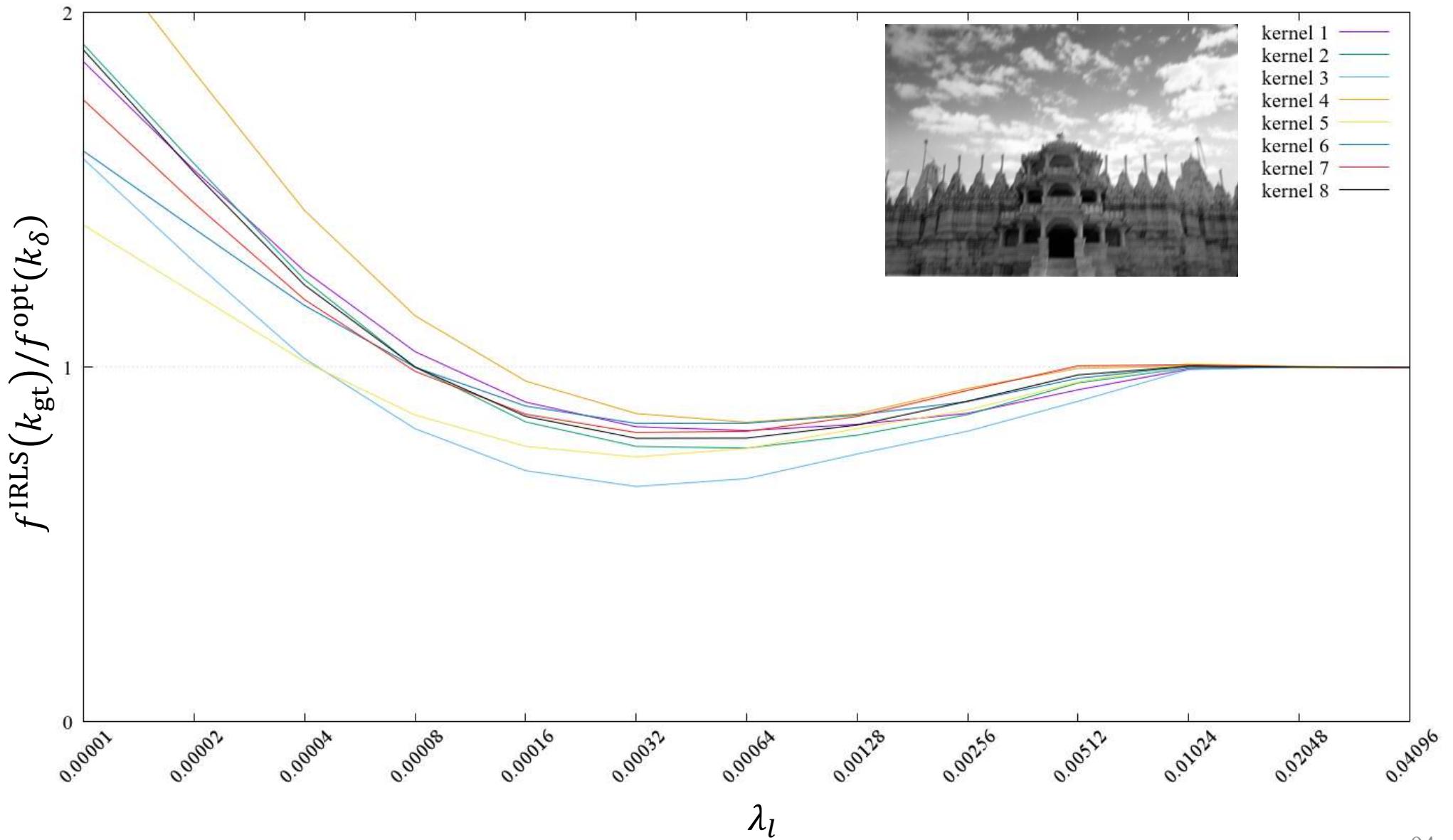
# Sun et al.'s dataset - Image 62



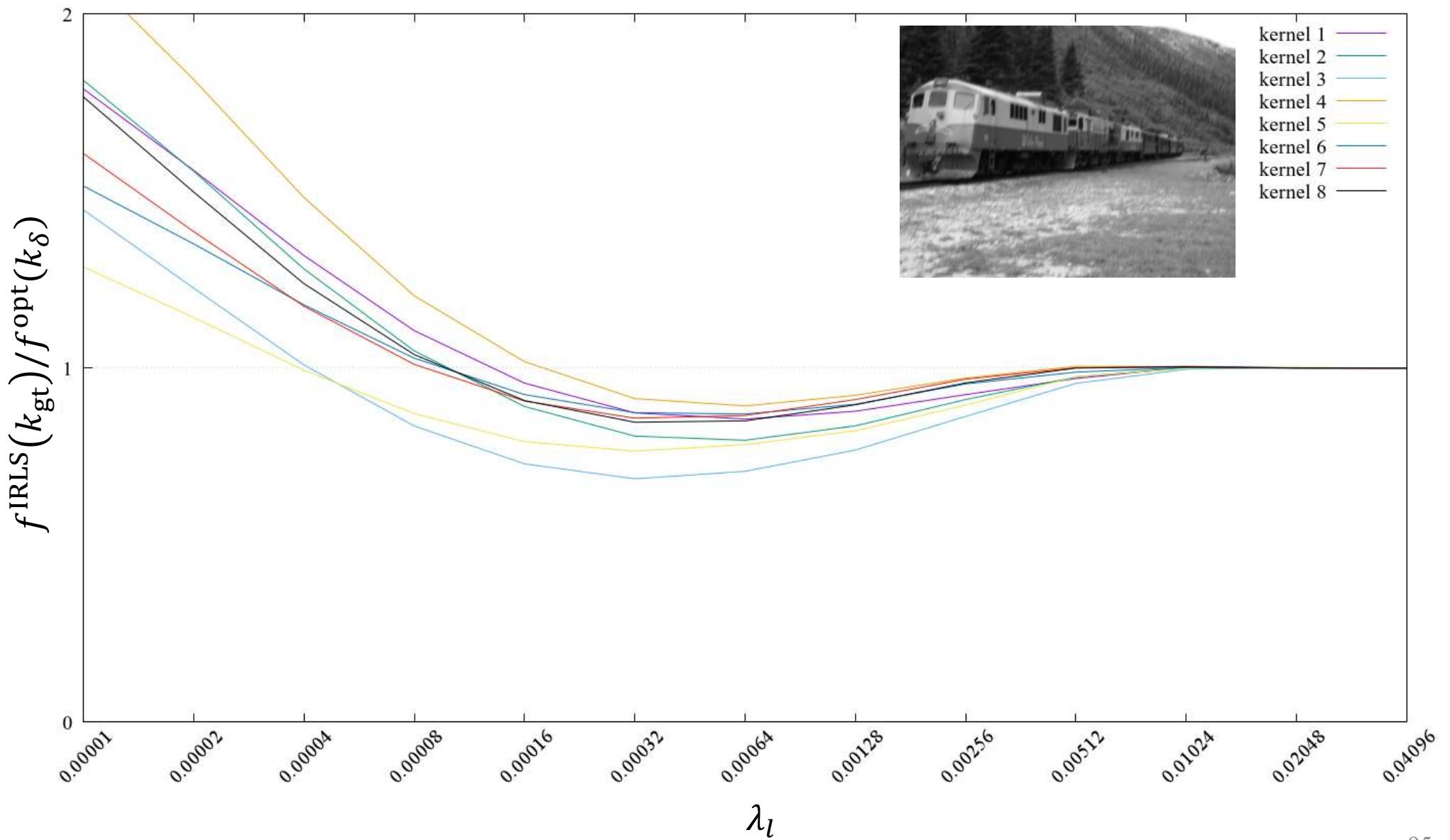
# Sun et al.'s dataset - Image 63



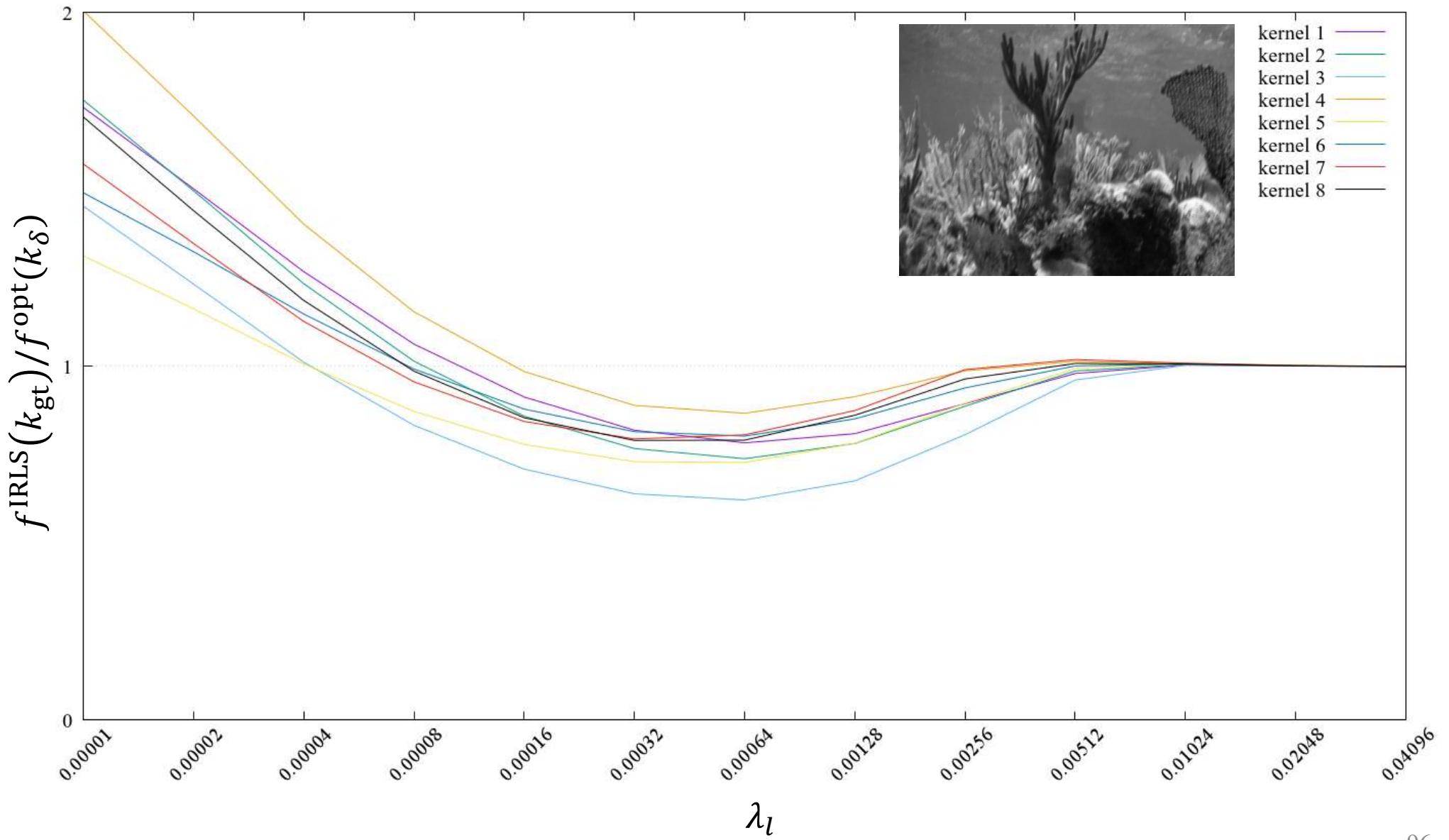
# Sun et al.'s dataset - Image 64



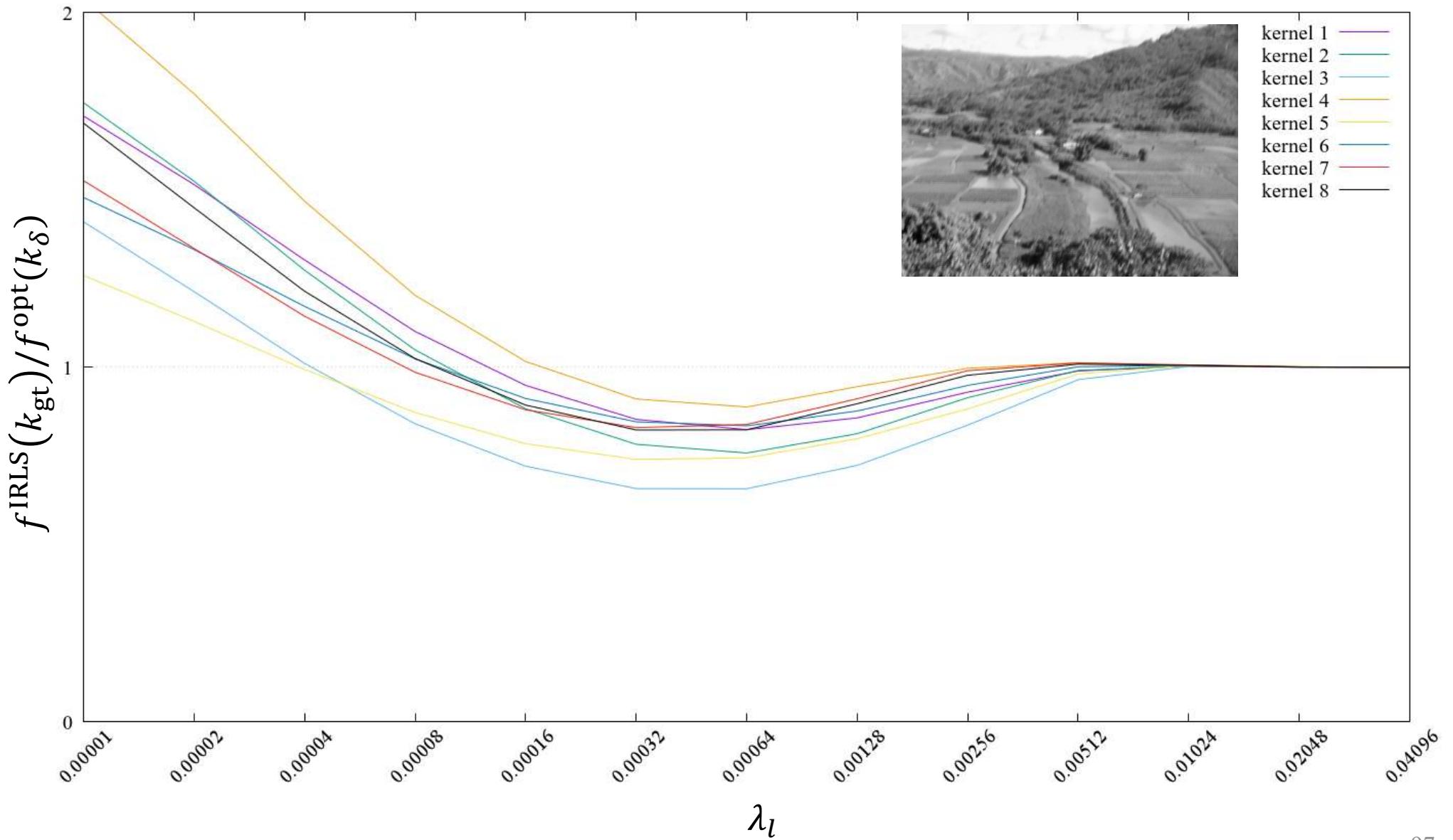
# Sun et al.'s dataset - Image 65



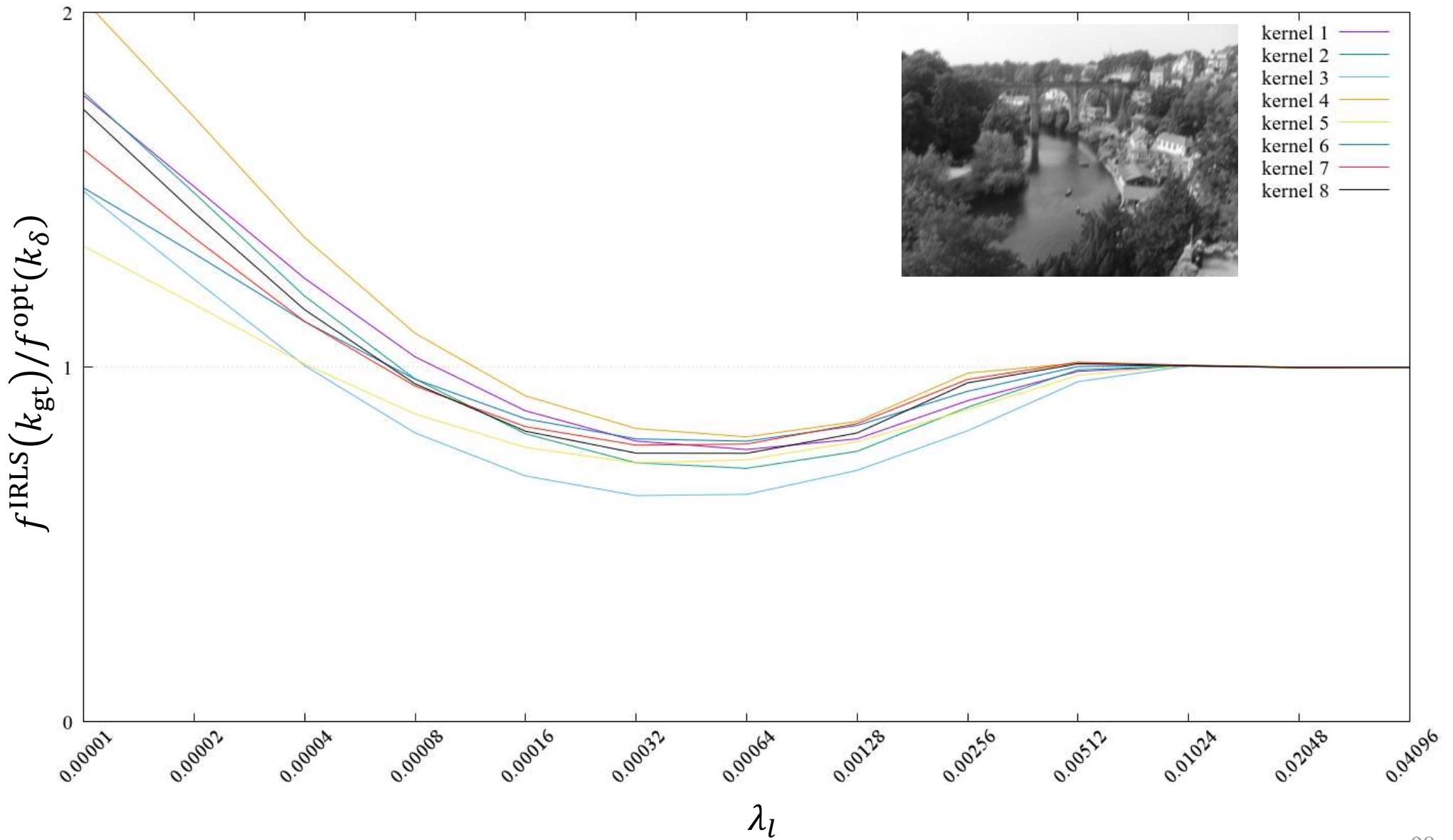
# Sun et al.'s dataset - Image 66



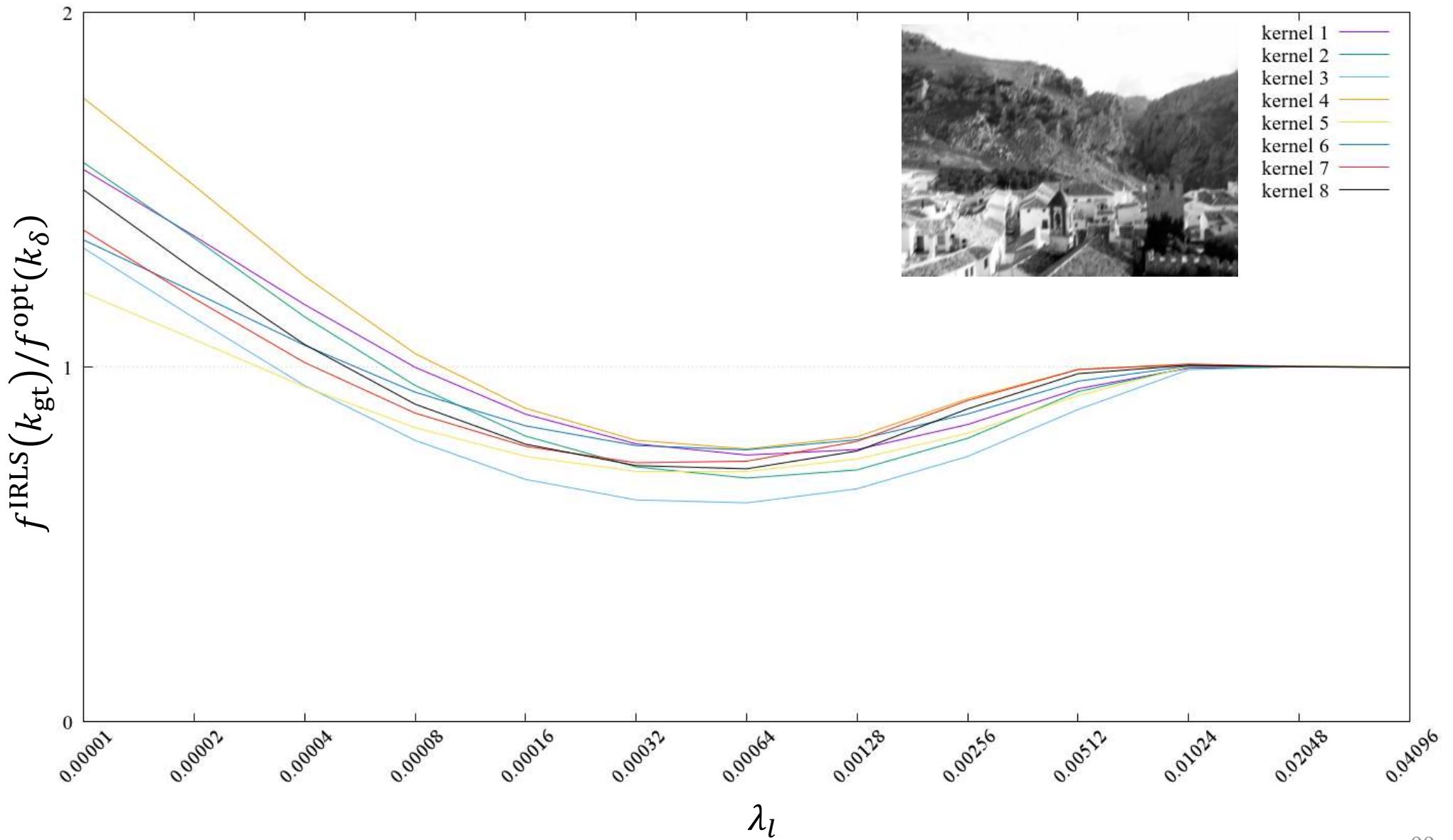
# Sun et al.'s dataset - Image 67



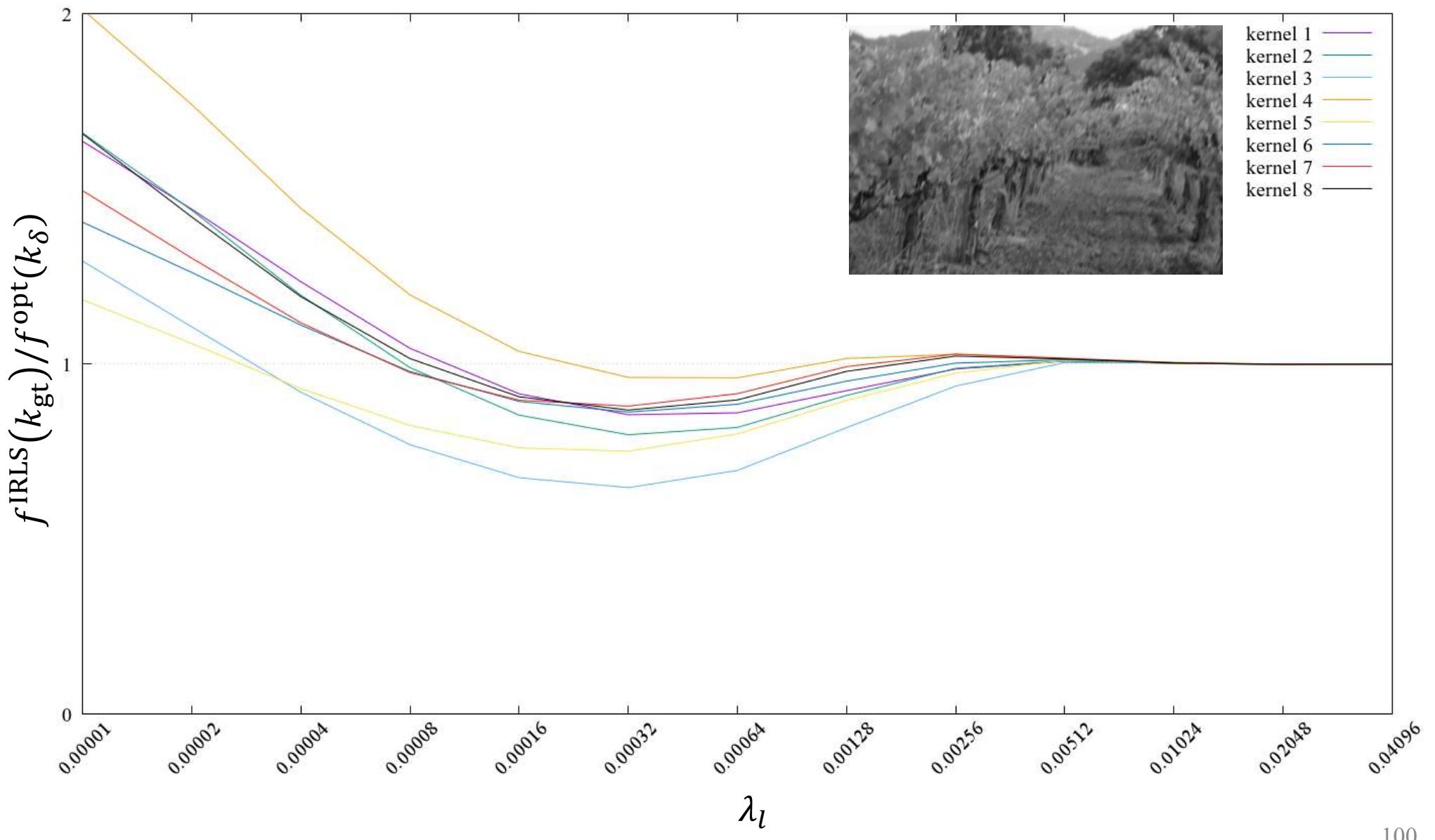
# Sun et al.'s dataset - Image 68



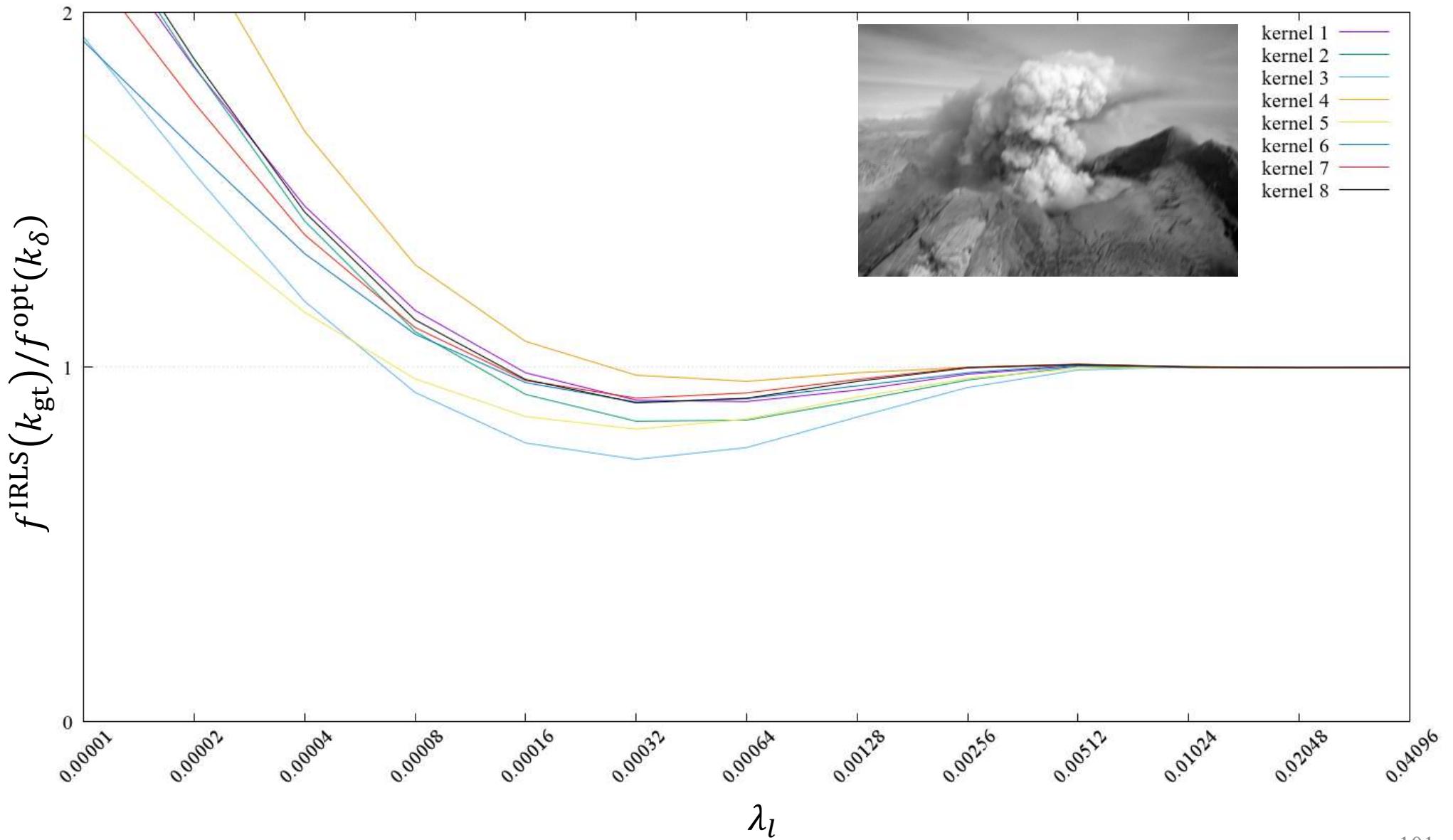
# Sun et al.'s dataset - Image 69



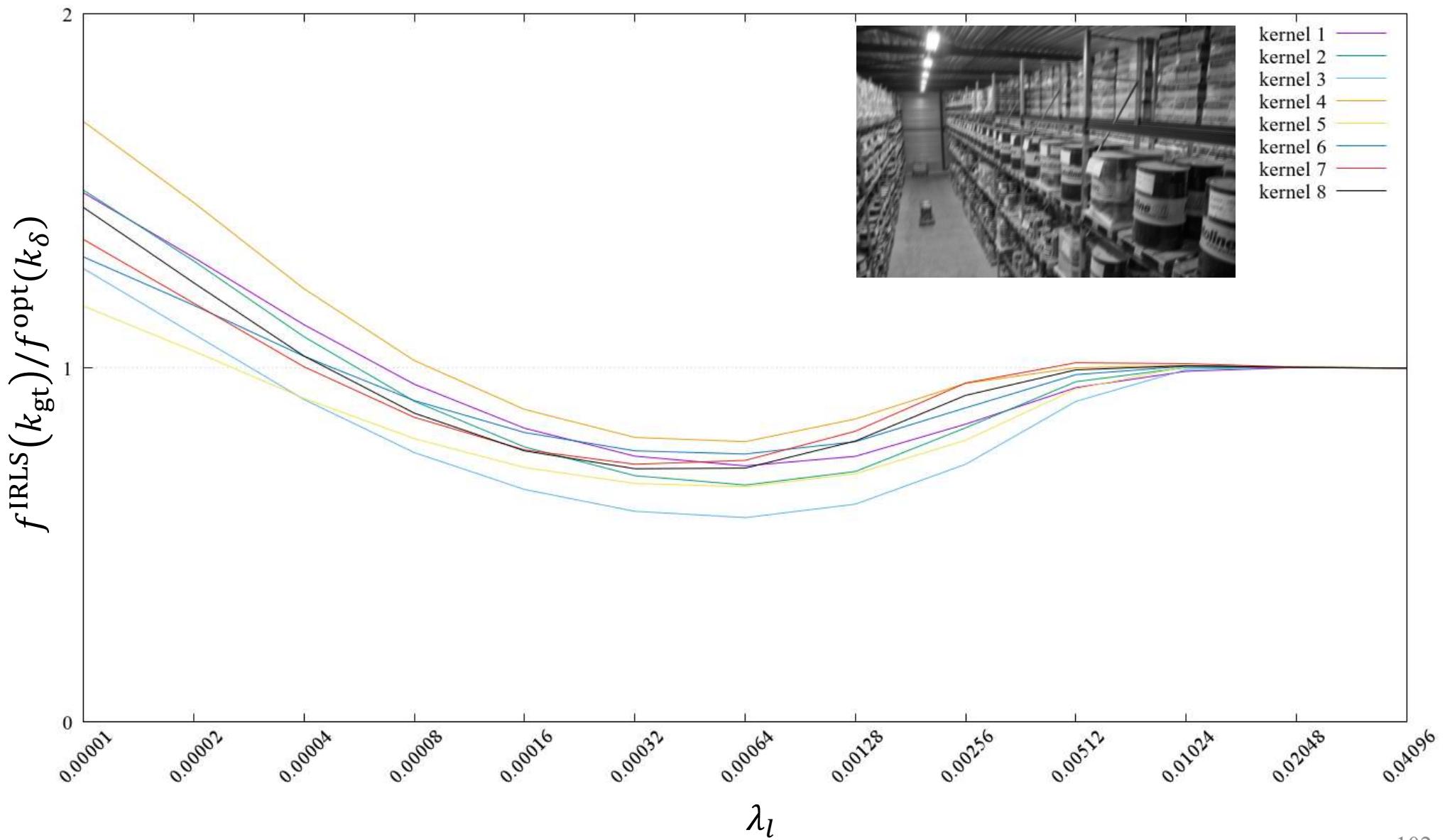
# Sun et al.'s dataset - Image 70



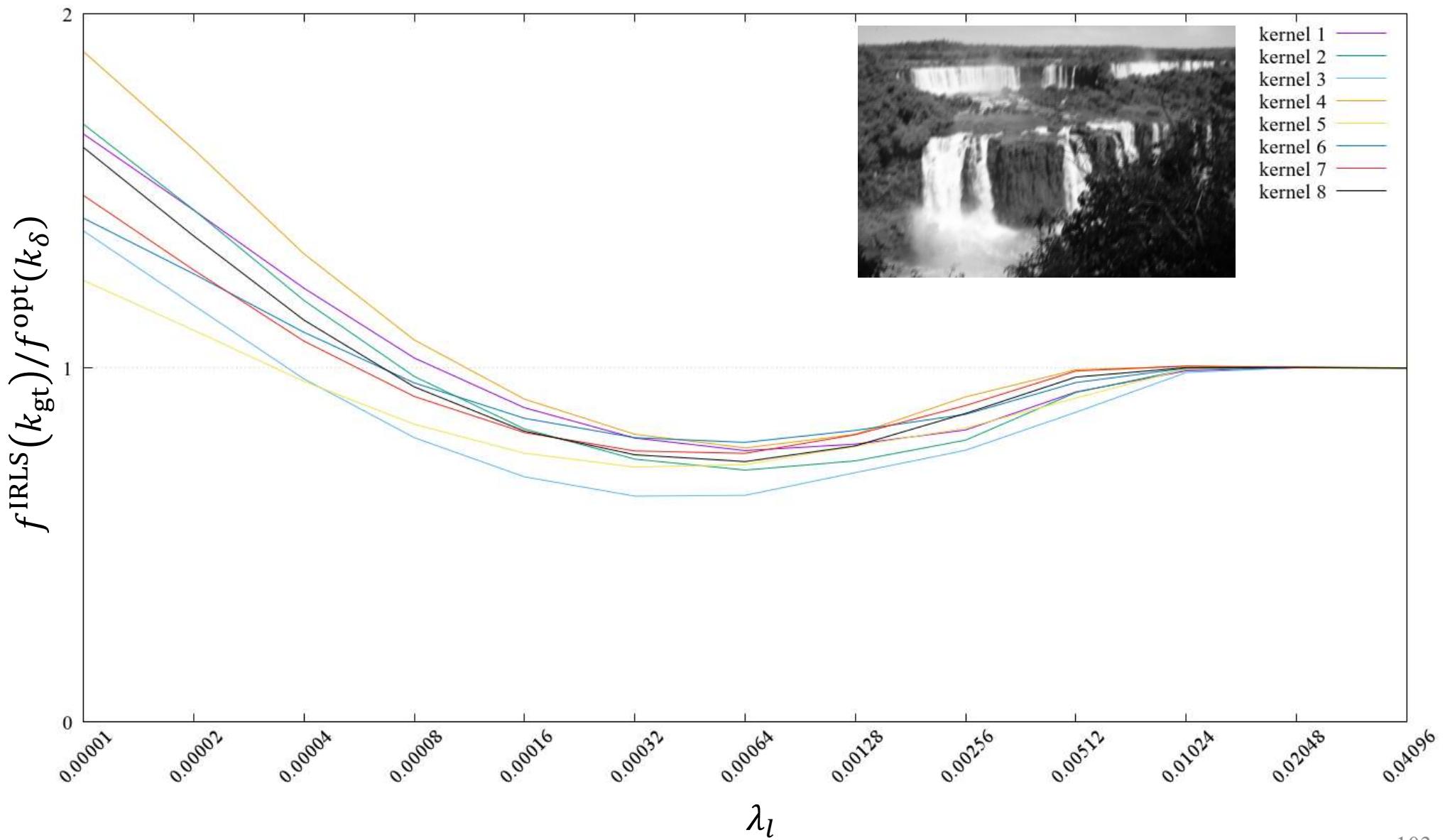
# Sun et al.'s dataset - Image 71



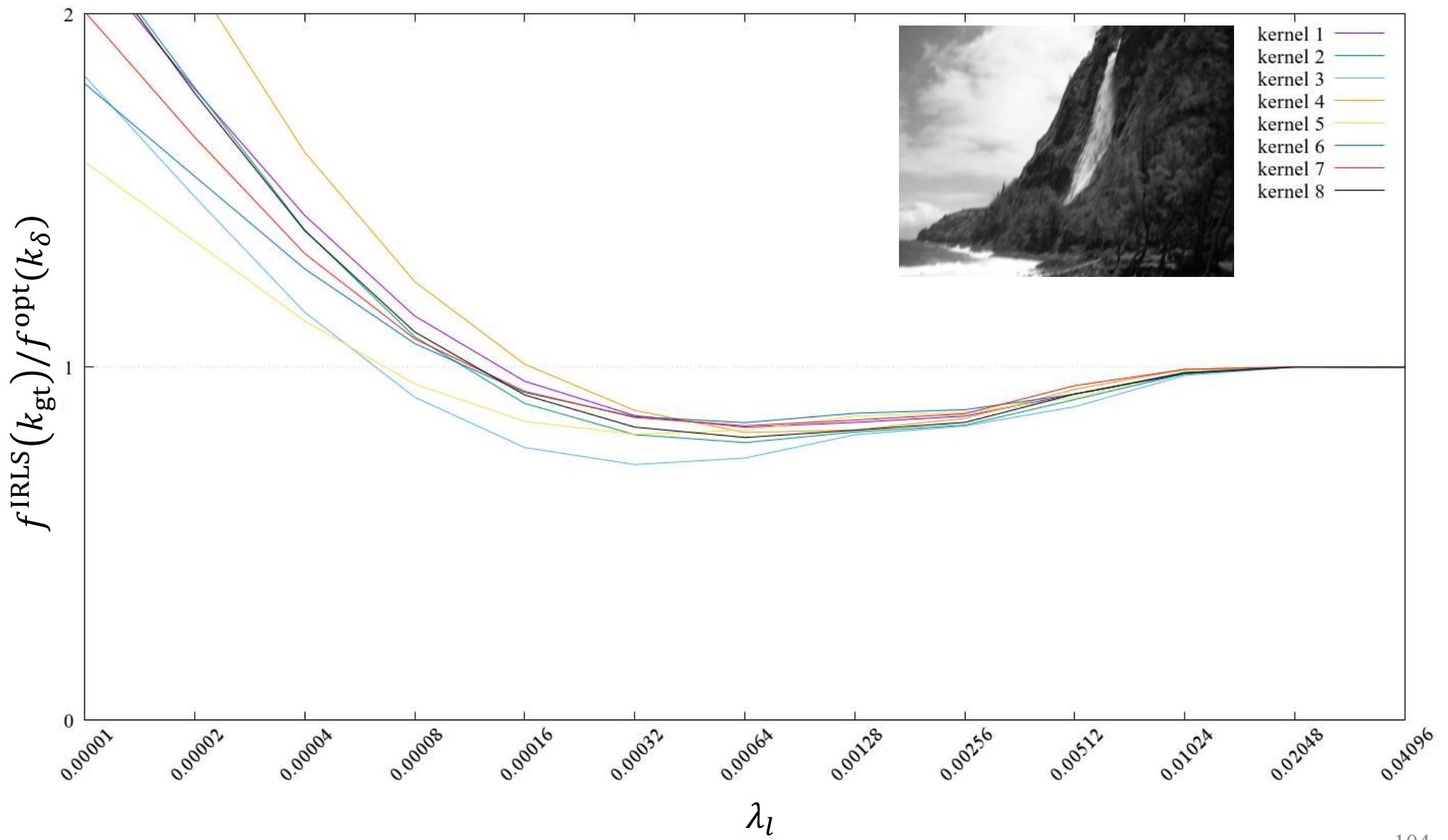
# Sun et al.'s dataset - Image 72



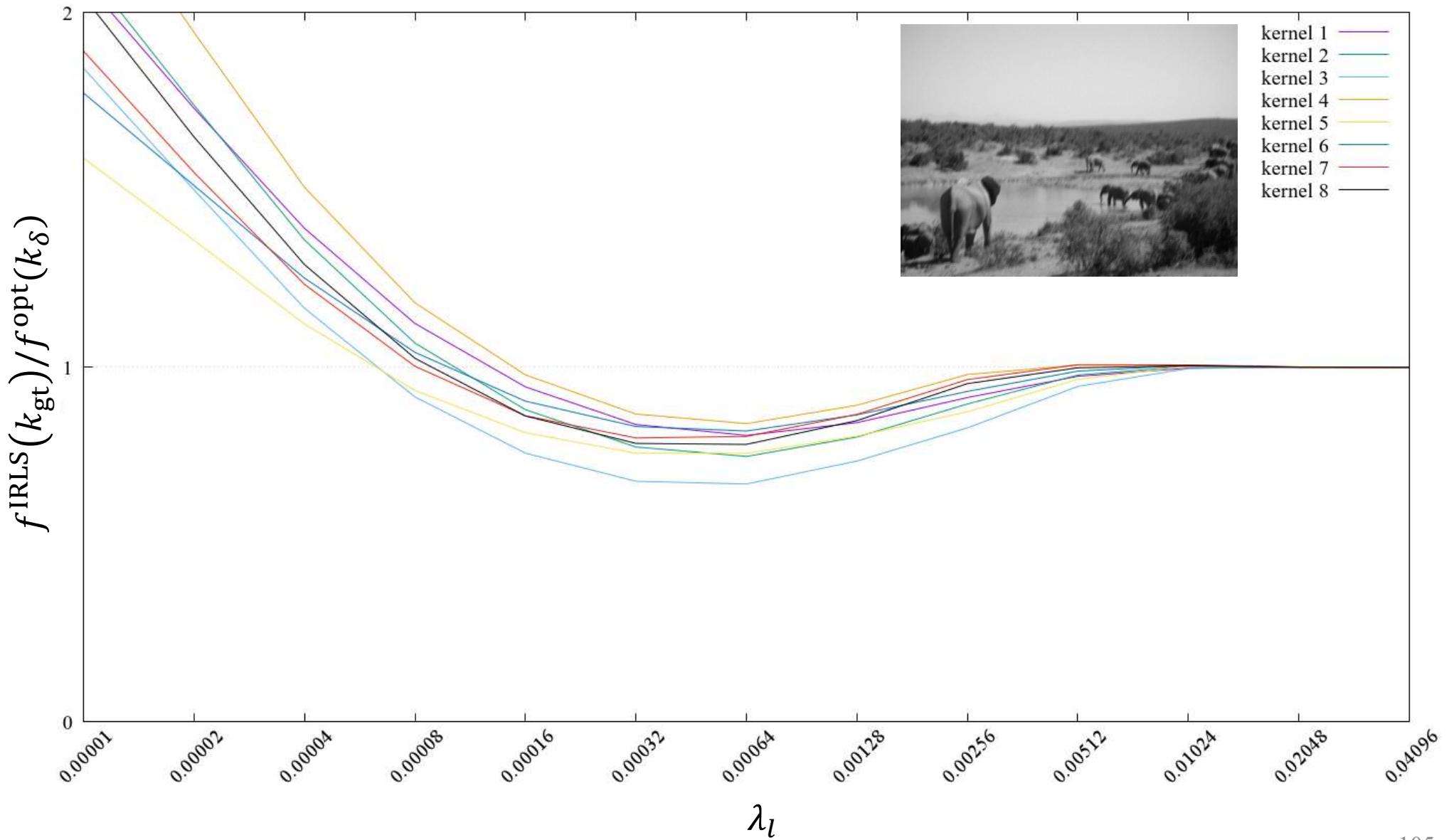
# Sun et al.'s dataset - Image 73



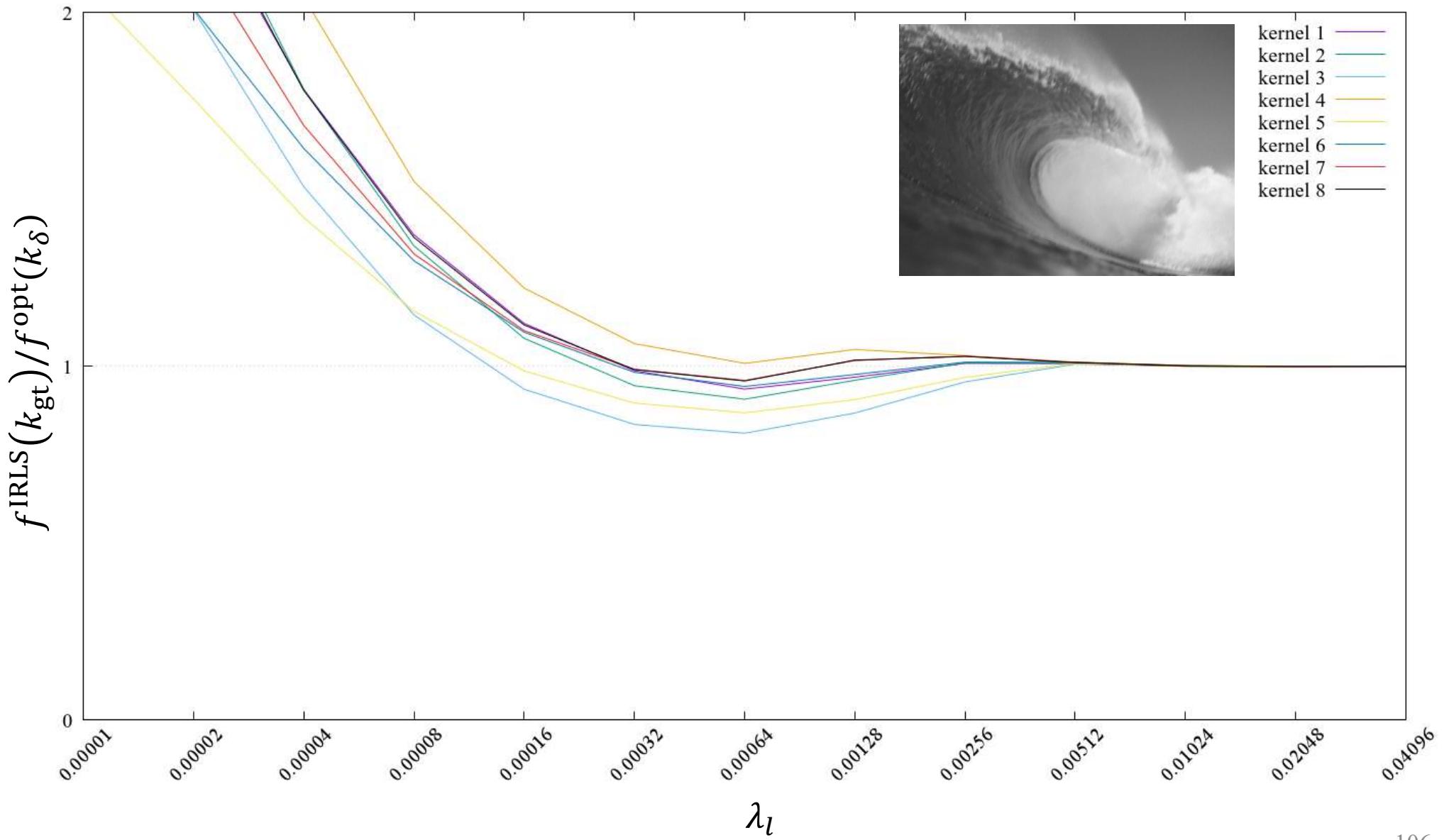
# Sun et al.'s dataset - Image 74



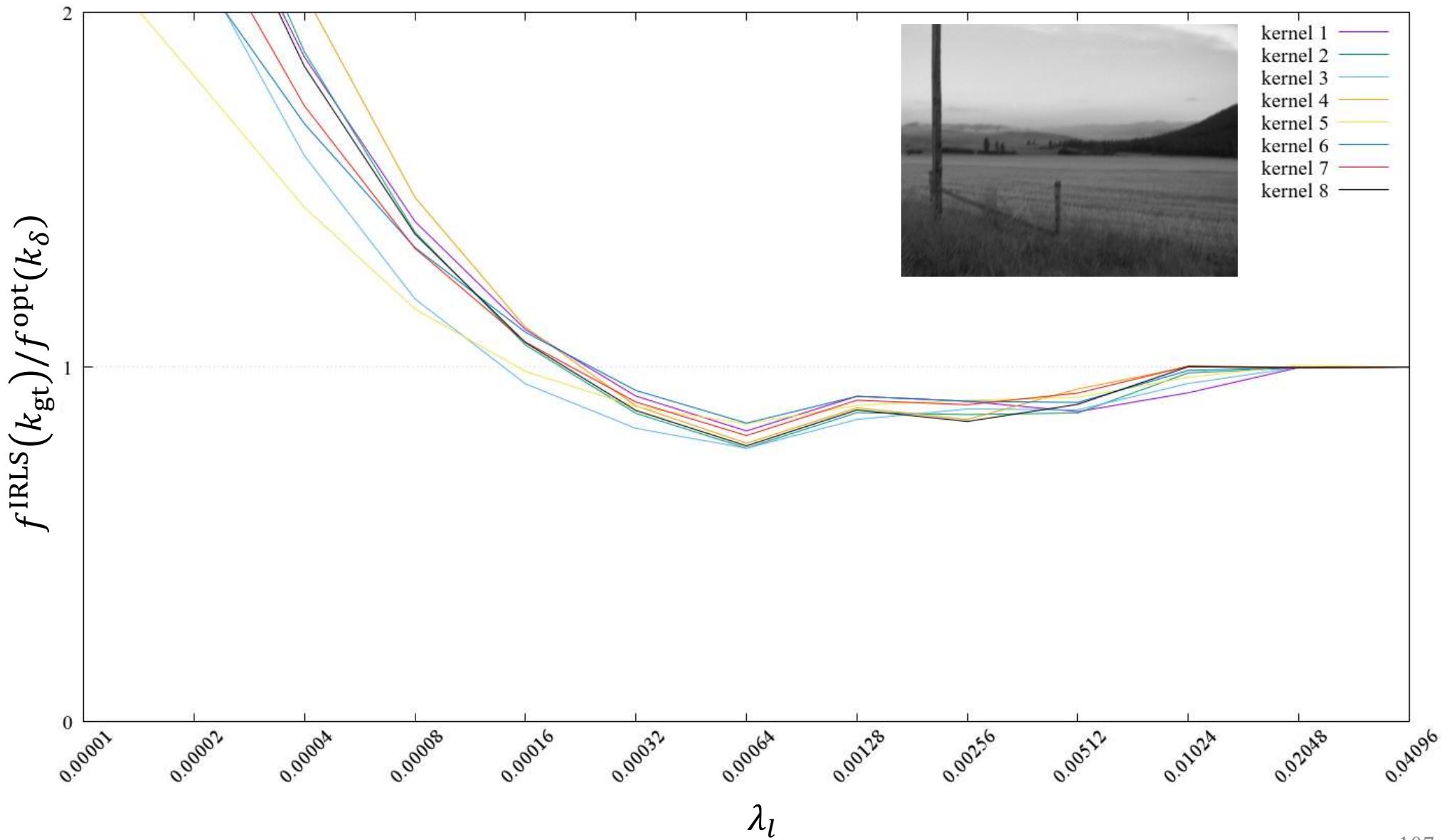
# Sun et al.'s dataset - Image 75



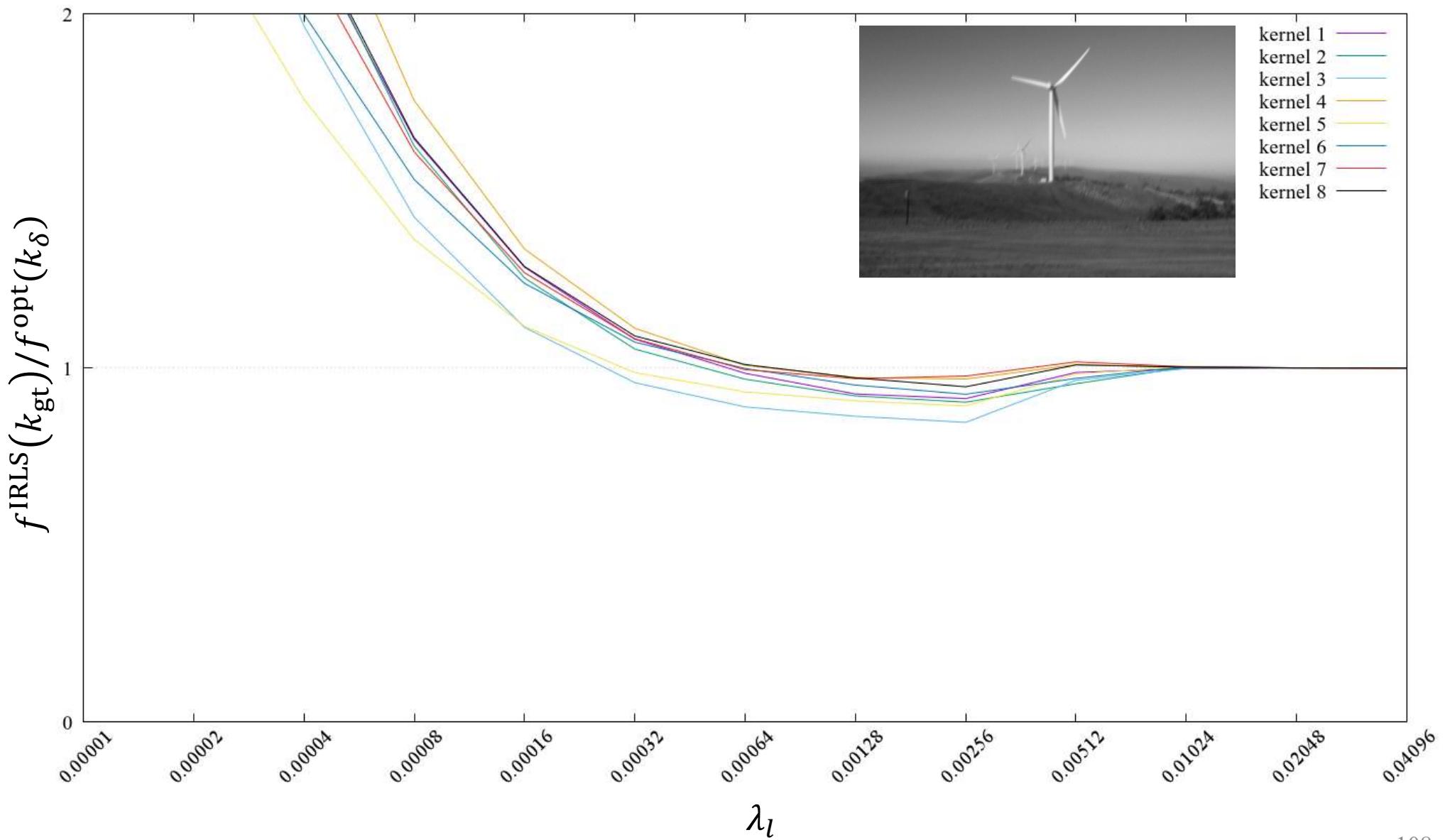
# Sun et al.'s dataset - Image 76



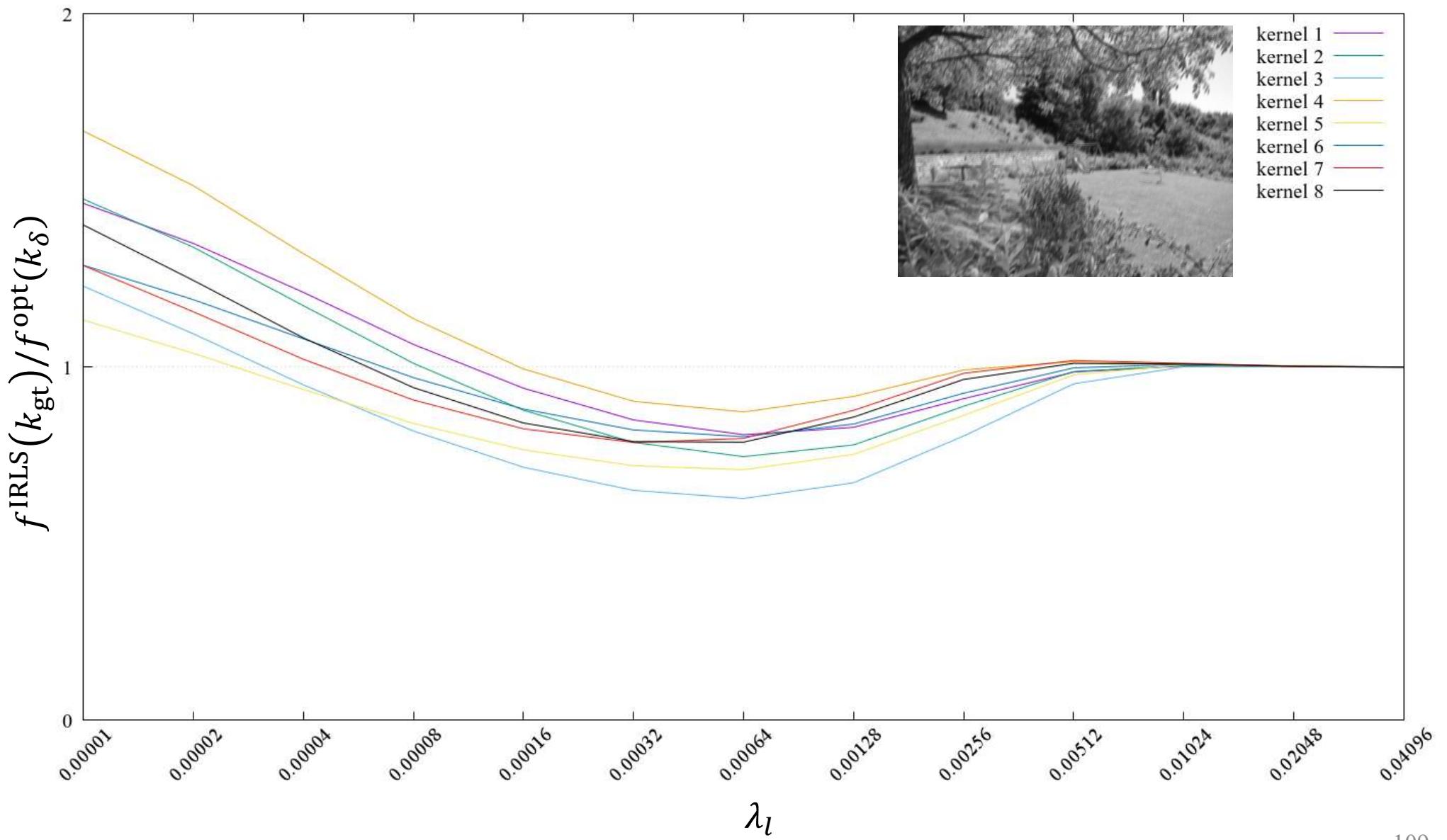
# Sun et al.'s dataset - Image 77



# Sun et al.'s dataset - Image 78



# Sun et al.'s dataset - Image 79



# Sun et al.'s dataset - Image 80

