

The GalSim lensing engine

ABSTRACT

This document describes the GalSim “lensing engine” for drawing shears randomly according to a user-specified shear power spectrum. It includes a brief description of the theory behind shear power spectra, the connection between the usual continuous description of the theory versus our representation in terms of the discrete Fourier transform, and a validation of the outputs for several test cases.

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1. Introduction

The lensing engine (in `galsim/lensing.py`) is the part of GalSim that is supposed to draw shears randomly according to a user-specified power spectrum. In this document, we begin with a brief description of the theory behind shear power spectra (§2), and then clarify the following issues:

1. How does the discrete representation that we use (on a grid) relate to the standard formulation of the theory, which uses continuous representations? (§3)
2. Are our outputs consistent with expectations?
 - How does it compare with another standard piece of software that generates shears using a different formalism? (§4)
 - Is the normalization (expressed as a variance) correct? (§5)
 - Does the variance behave appropriately when the grid size and spacing is changed? (§5)
 - Does the full $P(k)$ of the shears that were generated agree with our expectations? Does the result behave appropriately when the grid size and spacing is changed? (§6)
 - Is the behavior appropriate when inputting only E mode power, only B mode power, and both E and B mode power? (§6)
3. We should consider the impact of our current choice to force $P(k=0) = 0$, which effectively says there is no cosmic variance. (§7)

2. Theory

2.1. Continuous representation

The lensing engine requires a shear power spectrum, $P(k)$, and assumes we are in the flat-sky limit. Many standard references regarding lensing power spectra work in terms of the spherical harmonics ℓ , with the power spectrum denoted C_ℓ . In the flat-sky limit we can simply swap ℓ with k and C_ℓ with $P(k)$. It is standard practice to plot a dimensionless quantity Δ^2 defined as

$$\Delta^2 = \frac{\ell(\ell+1)C_\ell}{2\pi} \equiv \frac{k^2 P(k)}{2\pi}. \quad (1)$$

If we identify pairs of galaxies separated by an angle θ on the sky, and compute their shears in a coordinate system defined along the vector connecting them (γ_+) and at 45 degrees with respect

to it (γ_{\times}), then we can estimate correlation functions of the γ_{+} and γ_{\times} values, which we will call ξ_{++} and $\xi_{\times\times}$. Then the standard cosmological correlation functions ξ_{\pm} are defined as

$$\xi_{\pm}(\theta) = \xi_{++}(\theta) \pm \xi_{\times\times}(\theta) \quad (2)$$

$$= \frac{1}{2\pi} \int_0^{\infty} k \, dk P(k) J_{0/4}(k\theta) \quad (3)$$

where $J_{0/4}$ denotes the 0th and 4th Bessel function of the first kind, as is appropriate for ξ_{+} and ξ_{-} , respectively. Since correlation functions are dimensionless, we immediately see that $P(k)$ has dimensions of angle^2 .

The variance of the shear values for all of our galaxies is the zero-lag value of ξ_{+} ,

$$\text{Var}(\gamma) = \xi_{+}(\theta = 0) = \langle g_1^2 + g_2^2 \rangle. \quad (4)$$

Combining Eqs. 3 and 4, we can write the shear variance in terms of the power spectrum

$$\text{Var}(\gamma) = \frac{1}{2\pi} \int_0^{\infty} k \, dk P(k), \quad (5)$$

which essentially says the shear variance is the power integrated over the allowed area in k space.

2.2. Representation on grids

We will have to modify the above formalism to account for the fact that all of our calculations use a discrete representation on a finite grid. This grid is defined by

$$L = \text{length of grid along one dimension (angular units)} \quad (6)$$

$$d = \text{spacing between grid points (angular units)} \quad (7)$$

$$N = \text{number of grid points along one dimension} = L/d. \quad (8)$$

Given this grid, the k_{\min} along one dimension is $2\pi/L$, so we can think of this quantity as the grid spacing in Fourier space, i.e., $k_{\min} = \Delta k$. This value of k_{\min} corresponds to a Fourier mode that exactly fits inside of our square grid (in one dimension). The k range, again in one dimension, is from $k_1 = -\pi/d$ to π/d , i.e., $|k_1| < k_{\max} = \pi/d$. This corresponds to a mode that is sampled exactly twice (the minimum possible) given our choice of grid spacing. For the two-dimensional grid, the maximum value of $|k|$ is then $\sqrt{2}\pi/d$.

For a given grid point in Fourier space, it is somewhat a matter of taste as to whether it is considered to start at that k and extend to $k + \Delta k$, or whether it goes from $k - \Delta k/2$ to $k + \Delta k/2$. For the examples we will consider, the difference between these two options is typically of order 1%. In practice, the choice of convention just shifts the limits of integration in the equations below by at most Δk .

In the context of power spectra for gridded quantities, instead of using Eq. 5 it is more useful to think in terms of the 2D integral in Cartesian coordinates

$$\text{Var}(\gamma) = \frac{1}{(2\pi)^2} \int_{-\infty}^{\infty} dk_1 dk_2 P(k_1, k_2). \quad (9)$$

Note that this equation assumes that our grid is infinite and $P(k)$ is defined for all k . With a limited k range, and with the power spectrum forced to $P(0) = 0$ (see §7 for more discussion of this), we can rewrite Eq. 9 as

$$\text{Var}(\gamma) = \frac{4}{(2\pi)^2} \left[\int_0^{k_{\max}} \int_0^{k_{\max}} dk_1 dk_2 P(k) - \int_0^{k_{\min}} \int_0^{k_{\min}} dk_1 dk_2 P(k) \right]. \quad (10)$$

Here the factor of 4 compensates for the quadrants that are not represented explicitly (i.e., negative k_1 and/or k_2 values).

Another interesting point about gridded quantities is that it is not clear that we can enforce/check behavior of $\text{Var}(\gamma_1)$ or $\text{Var}(\gamma_2)$, particularly if there is a lot of shear power at small k . Probably we should only expect normal behavior for $\text{Var}(\gamma)$, but it's still worth verifying this explicitly in Sec. 5.

In the limit that our power spectrum drops to zero at k_{\max} , and that there is not too much power in the range $0 < k < k_{\min}$ relative to that in $k_{\min} < k < k_{\max}$, Eqs. 5, 9, and 10 should all give the same answer.

The above equations just include $P(k)$, but in principle there can be two such functions, P_E and P_B . These should simply be summed in Eqs. 5, 9, and 10.

3. Representing continuous fields using the Discrete Fourier Transform

This section includes is the formalism describing what the GalSim lensing engine is actually doing when representing shear fields as discrete fields defined on a finite grid, as opposed to the continuous representation in §2.

3.1. Conventions

The definition of the correlation function in equation (3) employs the *angular frequency, non-unitary*¹ definition of the (1D) Fourier transform:

$$\tilde{f}(k) = \int_{-\infty}^{\infty} f(x) e^{-ikx} dx \equiv \mathcal{F}\{f(x)\}; \quad (11)$$

$$f(x) = \frac{1}{2\pi} \int_{-\infty}^{\infty} \tilde{f}(k) e^{ikx} dk \equiv \mathcal{F}^{-1}\{\tilde{f}(k)\}, \quad (12)$$

with the usual simple generalizations to two or more dimensions.

The standard results in Discrete Fourier Transform (DFT) and its halfway-house the Discrete Time Fourier Transform (DTFT) are all derived under the unitary (i.e. without asymmetric prefactors of $1/2\pi$) convention in the online literature, adding to the complexity of interpretation. In the next section, we present some of the standard results of Fourier theory using the angular frequency, non-unitary convention above, since we will require them in Section 3.3.

3.2. Fourier transform properties

It can be readily shown that if we define $g(xL) \equiv f(x)$, the following well-known identity holds under our Fourier transform convention:

$$\mathcal{F}\{g(xL)\} = \frac{1}{L} \tilde{g}\left(\frac{k}{L}\right). \quad (13)$$

If we further define $s(h+x) \equiv g(x)$ then it is straightforward to show that

$$\mathcal{F}\{s(h+x)\} = e^{ikh} \tilde{s}(k). \quad (14)$$

Here we begin to get divergent results between conventions: there is an additional factor of 2π in the exponent when this property of FTs is expressed using the normal frequency convention.

The most important result for approximating continuous functions using DFTs is the Poisson summation formula, which under our conventions may be stated as

$$\sum_{n=-\infty}^{\infty} f(n) = \sum_{q=-\infty}^{\infty} \tilde{f}(2\pi q) \quad (15)$$

for integers n and q . This result can be derived by writing the expression for the inverse Fourier transform of $\tilde{f}(2\pi q)$ and considering the Fourier series expansion of the periodic Dirac comb function

$$\text{III}_L(x) = \sum_{n=-\infty}^{\infty} \delta(x - nL). \quad (16)$$

¹According to the paradigm described in http://en.wikipedia.org/wiki/Fourier_transform#Other_conventions

It should be noted that in the normal frequency, unitary transform convention form of the Poisson summation formula the 2π within $\tilde{f}(2\pi q)$ is absent. Using equation (13) we then find

$$\sum_{n=-\infty}^{\infty} f(nL) = \frac{1}{L} \sum_{q=-\infty}^{\infty} \tilde{f}\left(\frac{2\pi q}{L}\right), \quad (17)$$

which can be modified further using equation (14) to give the most useful expression of the Poisson summation formula:

$$\sum_{n=-\infty}^{\infty} f(nL + x) = \frac{1}{L} \sum_{q=-\infty}^{\infty} \tilde{f}\left(\frac{2\pi q}{L}\right) e^{i2\pi x q/L}. \quad (18)$$

If we define $\Delta k \equiv k_{\min} = 2\pi/L$ we can also write this as

$$\sum_{n=-\infty}^{\infty} f\left(\frac{2\pi n}{\Delta k} + x\right) = \left(\frac{\Delta k}{2\pi}\right) \sum_{q=-\infty}^{\infty} \tilde{f}(q\Delta k) e^{ix\Delta k q}. \quad (19)$$

These results give us most of what we need to understand DFTs with the non-unitary Fourier transform convention commonly adopted for weak lensing power spectra in the flat sky approximation.

3.3. The Fourier transform of discrete samples of the power spectra

In what follows we are going to derive results only for the ξ_+ correlation function of equation (3). This will not impact the understanding of how $P(k)$ is approximated using DFTs, but allows us to replace ξ_{\pm} and $J_{0/4}(k\theta)$ in equation (3) with the simpler ξ_+ and J_0 , respectively. We will just be aware subsequently that real ellipticity fields have two components, to be treated as described by equation (3).

The inverse Fourier transform of $P(k)$ to give $\xi_+(\theta)$ may be written in Cartesian coordinates as

$$\xi_+(\theta_1, \theta_2) = \frac{1}{(2\pi)^2} \iint_{-\infty}^{\infty} P(k_1, k_2) e^{i(k_1\theta_1 + k_2\theta_2)} dk_1 dk_2. \quad (20)$$

The relation between this and equation (3) makes use of Bessel's first integral:

$$J_n(z) = \frac{i^{-n}}{\pi} \int_0^{\pi} e^{iz \cos \theta} \cos(n\theta) d\theta. \quad (21)$$

What happens if we only have finite samples of $P(k_1, k_2)$? To answer that, let us define the following function:

$$P_{\Delta k}[q, p] \equiv (\Delta k)^2 P(q\Delta k, p\Delta k). \quad (22)$$

As here, we will use square brackets to denote functions with discrete, integer input variables. We will also use indices n, m in real space summations and q, p in Fourier space (i, j are awkward due to the common notations for $\sqrt{-1}$). Let us also define the 2D Dirac comb function in Fourier space

$$\mathbb{I}_{\Delta k}^2(k_1, k_2) = \sum_{q=-\infty}^{\infty} \delta(k_1 - q\Delta k) \sum_{p=-\infty}^{\infty} \delta(k_2 - p\Delta k). \quad (23)$$

It can then be shown that

$$\begin{aligned}
& \mathcal{F}^{-1} \left\{ \sum_{q,p=-\infty}^{\infty} \delta(k_1 - q\Delta k) \delta(k_2 - p\Delta k) P_{\Delta k}[q,p] \right\} \\
&= \mathcal{F}^{-1} \{ P(k_1, k_2) \cdot (\Delta k)^2 \text{III}_{\Delta k}^2(k_1, k_2) \} \\
&= \mathcal{F}^{-1} \{ P(k_1, k_2) \} * \mathcal{F}^{-1} \{ (\Delta k)^2 \text{III}_{\Delta k}^2(k_1, k_2) \} \\
&= \xi_+(\theta_1, \theta_2) * \left\{ \sum_{n=-\infty}^{\infty} \delta\left(\theta_1 - \frac{2\pi n}{\Delta k}\right) \sum_{m=-\infty}^{\infty} \delta\left(\theta_2 - \frac{2\pi m}{\Delta k}\right) \right\} \\
&= \sum_{n,m=-\infty}^{\infty} \xi_+\left(\theta_1 - \frac{2\pi n}{\Delta k}, \theta_2 - \frac{2\pi m}{\Delta k}\right) \tag{24}
\end{aligned}$$

Here we have again made use of the Fourier series expression for the Dirac comb function, and employed the convolution theorem (convolution denoted with $*$). We note that the final expression (24) is still continuous, but describes an infinite, periodic summation (of period $L = 2\pi/\Delta k$) of copies of the correlation function ξ_+ . For sufficiently small Δk , these copies may be well-enough spaced in the real domain to learn much about $\xi_+(\theta_1, \theta_2)$ in the non-overlapping regions.

We therefore define this function as

$$\xi_{\frac{2\pi}{\Delta k}}(\theta_1, \theta_2) \equiv \sum_{n=-\infty}^{\infty} \xi_+\left(\theta_1 - \frac{2\pi n}{\Delta k}, \theta_2 - \frac{2\pi m}{\Delta k}\right). \tag{25}$$

Using the expression of the Poisson summation formula in equation (19), we can also write the result

$$\xi_{\frac{2\pi}{\Delta k}}(\theta_1, \theta_2) = \sum_{q,p=-\infty}^{\infty} \left(\frac{\Delta k}{2\pi}\right)^2 P(q\Delta k, p\Delta k) e^{i\Delta k(\theta_1 q + \theta_2 p)} = \frac{1}{(2\pi)^2} \sum_{q,p=-\infty}^{\infty} P_{\Delta k}[q,p] e^{i\Delta k(\theta_1 q + \theta_2 p)} \tag{26}$$

(which, like the Poisson summation formula, can also be shown using equation 24 and substituting the Fourier series expression for $\text{III}_{\Delta k}^2$). This is the expression for the inverse of what is known as the Discrete Time Fourier Transform (DTFT), although this result is normally derived using unitary conventions for the transform pair. Note that the terms $P_{\Delta k}[q,p]$ are dimensionless, being composed of $(\Delta k)^2 = (2\pi/L)^2$ multiplied by the samples $P(q\Delta k, p\Delta k)$ of the power $P(k_1, k_2)$ (with dimensions of angle^2).

One intuitive way of looking at the approximation of equation (20) for the case of discretely sampled $P(k_1, k_2)$ is that the terms in the discrete sum should be considered as *impulses* of area $(\Delta k)^2$ and height $P(q\Delta k, p\Delta k)$.

3.4. The Fourier transform of discrete, finite samples of the power spectra

The expression in equation (26) is periodic with period $2\pi/\Delta k = L$. All of the information it contains about $\xi_+(\theta_1, \theta_2)$ is therefore also contained in one period of the function only. For

approximating this information discretely, as desired in numerical analysis, we can imagine taking N equally spaced samples of the function in equation (26) along a single period L in each dimension (leading to N^2 samples total since we are working in 2D). These samples are therefore separated by $\Delta\theta = 2\pi/\Delta k N = d$ in real space, and we define the sampled function itself as

$$\xi_{\Delta\theta}[n, m] \equiv \xi_{\frac{2\pi}{\Delta k}}(n\Delta\theta, m\Delta\theta) = \frac{1}{(2\pi)^2} \sum_{q, p=-\infty}^{\infty} P_{\Delta k}[q, p] e^{i2\pi(qn+pm)/N}, \quad (27)$$

for the integer indices $n, m = 0, 1, \dots, N-1$, by substitution into equation (26). Using the periodicity of the exponential term in the expression above, this may be written as

$$\xi_{\Delta\theta}[n, m] = \frac{1}{(2\pi)^2} \sum_{q, p=0}^{N-1} P_N[q, p] e^{i2\pi(qn+pm)/N} \quad (28)$$

where we have defined

$$P_N[q, p] \equiv \sum_{i, j=-\infty}^{\infty} P_{\Delta k}[q - iN, p - jN]. \quad (29)$$

Needless to say, in order to be able to calculate the values of $P_N[q, p]$ in practice we must also truncate the $P_{\Delta k}$ sequence to be finite in length. A *very* common choice is to use the same number N of samples in both real and Fourier space: this is also efficient, as it allows the direct use of the Fast Fourier Transform algorithm. We will say a little more about this below.

Choosing to use only N samples from $P_{\Delta k}$ then gives us a somewhat more familiar expression for the inverse Discrete Fourier Transform (DFT), written here for the non-unitary Fourier transform convention:

$$\xi_{\Delta\theta}[n, m] = \frac{1}{(2\pi)^2} \sum_{q, p=0}^{N-1} P_{\Delta k}[q, p] e^{i2\pi(qn+pm)/N}. \quad (30)$$

The overwhelmingly more common definition of the inverse DFT, and that adopted by NumPy, instead reads as:

$$f[n, m] = \text{numpy.fft.ifft2}(\tilde{f}[p, q]) \equiv \frac{1}{N^2} \sum_{q, p=0}^{N-1} \tilde{f}[q, p] e^{i2\pi(qn+pm)/N}, \quad (\text{NumPy convention}) \quad (31)$$

where the factor of $1/N^2$ is a convention commonly found in DFT implementations, and ensures that the DFT followed by the inverse DFT yields the original, input array.

We must use the convention of equation (31) for performing the calculation within the code, and so this means that we must attempt to account for the factors of 2π , N and Δk ourselves. Let us begin with the user specifying the key dimensions of the problem L and $d = \Delta\theta$ at the outset, as assumed in Section 2, sensibly chosen (of course) so that $N = L/\Delta\theta$ is an integer. These choices also set $\Delta k = 2\pi/L$. Beginning with equation (30), we may re-express the convenient $P_{\Delta k}[q, p]$ as

samples of the dimensional $P(k_1, k_2)$ once again:

$$\xi_{\Delta\theta}[n, m] = \frac{1}{(2\pi)^2} \sum_{q,p=0}^{N-1} P_{\Delta k}[q, p] e^{i2\pi(qn+pm)/N} \quad (32)$$

$$= \frac{1}{(2\pi)^2} \times \frac{(2\pi)^2}{L^2} \sum_{q,p=0}^{N-1} P(q\Delta k, p\Delta k) e^{i2\pi(qn+pm)/N} \quad (33)$$

$$= \frac{1}{L^2} \sum_{q,p=0}^{N-1} P(q\Delta k, p\Delta k) e^{i2\pi(qn+pm)/N} \quad (34)$$

$$= \text{numpy.fft.ifft2} [P(q\Delta k, q\Delta k)/(\Delta\theta)^2] . \quad (35)$$

This equation explains why we require a division of the amplitudes by $d = \Delta\theta$ in the lensing engine. Dimensional analysis tells us that we require a division by something with dimensions of angle, but this equation is justification for exactly what angle is used.

Finally, we said we would say little more about the implications of the choice to use N as the number of samples in *both* real and Fourier space, the final step in arriving at equation (30). This choice ensures the close interrelation of N , L and the grid spacings $\Delta\theta$, Δk . The use of discrete, periodic sampling to represent continuous, non-periodic functions is only an approximation, and one that depends heavily on good choices of these interrelated sampling parameters.

The two effects that must be minimized for a good approximation are of course aliasing and unwanted ‘overlapping’ of functions in either real or Fourier space due to the sampled, periodic representation inherent in the DFT. Adequately sampling our functions, and zero-padding them where possible to artificially extend L , are the primary strategies for making the DFT and its inverse a good approximation to the Fourier transforms of equations (11) and (12).

4. Comparison software

We will compare the outputs from GalSim against those from a completely independent piece of software, Chris Hirata’s spherical harmonic transform code which is described in multiple papers (for example, Hirata et al. 2004). This does not use the flat-sky approach, but that should not make too much difference even for our $L = 10$ deg. It is something to bear in mind if we start looking for agreement at a few % level on the largest θ or smallest k . That software wants $C_\ell(\ell)$ as its inputs.

5. Tests of variances

We begin with tests of the shear variances from GalSim and the SHT code. The theoretical description for the variances was outlined in §2.

5.1. General considerations

As discussed in §2, most of our tests of the variance will focus on the sum of the components, rather than the variance of individual components. Also, for our grid to properly represent the theoretical power spectrum (and for the equations in §2 to be valid), we need to be well-sampled in k space, so we should not use functions that do unreasonable things like $P(k) \propto k^{-2}$.

Since we will want to check that the results behave properly when the grid changes, we will do all tests in this section with three different grids:

1. A standard GREAT10 grid, which has $L = 10$ degrees and $N = 100$, so $d = 0.1$ degree = 360 arcsec.
2. A grid with $L = 5$ degrees and $N = 50$, thus preserving d and k_{\max} , while increasing k_{\min} (the Fourier-space grid spacing) by a factor of 2.
3. A grid with $L = 10$ degrees and $N = 50$, thus doubling d and halving k_{\max} , while preserving the Fourier-space grid spacing (k_{\min}) compared to the original case.

5.2. Variance for Gaussian $P(k)$

Our first test case is a Gaussian $P(k)$, i.e., $P(k) = P_0 e^{-\sigma^2 k^2/2}$. Here both P_0 and σ^2 both have dimensions of angle². By Eq. 10, this means that we expect

$$\text{Var}(\gamma) = \frac{4P_0}{(2\pi)^2} \left[\left(\int_0^{k_{\max}} e^{-\sigma^2 k^2/2} dk \right)^2 - \left(\int_0^{k_{\min}} e^{-\sigma^2 k^2/2} dk \right)^2 \right] \quad (36)$$

$$= \frac{P_0}{2\pi\sigma^2} \left[\left(\text{Erf}(k_{\max}\sigma/\sqrt{2}) \right)^2 - \left(\text{Erf}(k_{\min}\sigma/\sqrt{2}) \right)^2 \right]. \quad (37)$$

For each of the grids, we define the Gaussian σ such that there is essentially no power left at our k_{\max} : $\sigma k_{\max} = 2.5$, or $\sigma = 286.5$ arcsec for the first two grids and $\sigma = 573$ arcsec for the last grid. Given how large σk_{\max} is, in all cases, $\text{Erf}(k_{\max}\sigma/\sqrt{2}) = 0.988$. The resulting values of σk_{\min} for the three grids are 0.05, 0.1, and 0.05, or $\text{Erf}(k_{\min}\sigma/\sqrt{2}) = 0.04, 0.08, \text{ and } 0.04$ (since these are squared in the above expression, they don't end up mattering much). With $P_0 = 1$ arcsec², the predicted variances for the three grids are 1.89×10^{-6} , 1.88×10^{-6} , and 4.72×10^{-7} .

The code to do this once is:

```
import galsim
import numpy as np
test_ps = galsim.PowerSpectrum(lambda k : np.exp(-0.5*((286.5*k)**2)))
g1, g2 = test_ps.buildGriddedShears(grid_spacing=360., ngrid=100)
```

```
print np.var(g1), np.var(g2), np.var(g1)+np.var(g2)
g1, g2 = test_ps.buildGriddedShears(grid_spacing=360., ngrid=50)
print np.var(g1), np.var(g2), np.var(g1)+np.var(g2)
test_ps = galsim.PowerSpectrum(lambda k : np.exp(-0.5*((573.0*k)**2)))
g1, g2 = test_ps.buildGriddedShears(grid_spacing=720., ngrid=50)
print np.var(g1), np.var(g2), np.var(g1)+np.var(g2)
```

We actually do this 1000 times to beat down the noise in the resulting variances.

The results are 1.87×10^{-6} , 1.85×10^{-6} , and 4.63×10^{-7} in the last case. So we have the approximately correct amplitude and scaling with the grid spacing and grid size, and the results are 1%, 1.5%, and 2% smaller than the predictions.

We also check what happens if we make all the grids larger by a factor of 4 (in N , i.e., decrease k_{\min} by a factor of 4 while maintaining k_{\max}). In this case, the variances increase by 1-2%, whereas the predictions based on Eq. 37 only increase by 0.1%. Thus, the results with grids that are a factor of two larger are completely in accordance with the predictions, and the percent-level deviations for the original grids can be explained by finite-gridding effects.

The variance is fairly evenly divided between components, but the variance in γ_2 tends to be larger than the variance of γ_1 by 3–4%. This is likely because the $P(k)$ emphasizes large scales, where the grid genuinely looks different along the diagonals as it does along the coordinate axes. It’s a feature of using grids to represent shears drawn randomly from a power spectrum with finite P_E but with $P_B = 0$, not a bug. If we set $P_B = P_E$ (unlike in the above example where $P_B = 0$) then this difference between the variances of γ_1 and γ_2 vanishes.

5.3. Variance for flat $P(k)$

A flat $P(k)$ has a worrisome amount of power at large k , so we use a modified version of it: We use $P(k) = P_0$ for $k \leq k_{\lim}$, where $k_{\lim} < k_{\max}$ for all the grids; and we set $P(k > k_{\lim}) = 0$. Using Eq. 10, we expect

$$\text{Var}(\gamma) = \frac{4P_0}{(2\pi)^2} \left[\frac{1}{4} \int_0^{k_{\lim}} 2\pi k \, dk - k_{\min}^2 \right] \quad (38)$$

$$= \frac{P_0}{\pi^2} \left(\frac{\pi}{4} k_{\lim}^2 - k_{\min}^2 \right). \quad (39)$$

For the set of grids from the previous test, k_{\min} is 0.000175, 0.00035, and 0.000175 arcsec $^{-1}$. We will set $k_{\lim} = 10k_{\min}$, so we can write

$$\text{Var}(\gamma) = \frac{(25\pi - 1)P_0 k_{\min}^2}{\pi^2}. \quad (40)$$

With $P_0 = 1$, we expect shear variances that are 2.4×10^{-7} , 9.6×10^{-7} , and 2.4×10^{-7} .

The code is

```
import galsim
import numpy as np
def pfunc1(k):
    parr = np.zeros_like(k)
    parr[k<=0.00175] = 1.
    return parr
def pfunc2(k):
    parr = np.zeros_like(k)
    parr[k<=0.0035] = 1.
    return parr
test_ps1 = galsim.PowerSpectrum(pfunc1)
test_ps2 = galsim.PowerSpectrum(pfunc2)
g1, g2 = test_ps1.buildGriddedShears(grid_spacing=360., ngrid=100)
print np.var(g1), np.var(g2), np.var(g1)+np.var(g2)
g1, g2 = test_ps2.buildGriddedShears(grid_spacing=360., ngrid=50)
print np.var(g1), np.var(g2), np.var(g1)+np.var(g2)
g1, g2 = test_ps1.buildGriddedShears(grid_spacing=720., ngrid=50)
print np.var(g1), np.var(g2), np.var(g1)+np.var(g2)
```

Since the variances are noisy, we averaged the results over 10000 realizations², and found 2.36×10^{-7} , 9.45×10^{-7} , and 2.36×10^{-7} . These are all $\sim 2\%$ below my naive calculation. Since the overall behavior is correct when we change the grid size and spacing, it seems possible that this small discrepancy comes from some finite-gridding effect.

If we redo the above test but double the values of ‘ngrid’, thus halving the step size of the grid in Fourier space, then the variances increase slightly³ to 2.4×10^{-7} , 9.6×10^{-7} , and 2.4×10^{-7} , so they are now completely consistent with the predictions from before. In principle the predictions also have to change, since now we have $k_{\text{lim}} = 40k_{\text{min}}$ and the k_{min} decreases by a factor of 4, but the predictions only increased by 1% whereas the results increased by 2%. This result supports the claim that finite-gridding effects might be responsible for the slightly low variances, rather than anything more problematic (i.e., a true bug). Finite gridding effects can be accounted for by including them in the predictions before comparing with results.

²This takes about 1 minute to run on a single CPU.

³This change is statistically significant given the number of realizations.

6. Test of full $P(k)$

We use a WMAP7 LCDM prediction for the cosmic shear signal for a sample with $z_{\text{med}} \sim 0.55$ as an input to both the SHT code and ours. Given the range of ℓ for which it is defined, $2 < \ell < 2000$, we cannot use our standard grid, which has $k_{\text{max}} = \sqrt{2} \times 1800 = 2546 \text{ radians}^{-1}$. So, for this test we use a grid with $L = 10$ degrees (as before), but $N = 50$ (i.e., d gets doubled), which means a two-dimensional $k_{\text{max}} = 1273 \text{ radians}^{-1}$.

Using the SHT code (§4), we made gridded shears for $P_E = P(k)$ and $P_B = 0$; $P_B = P(k)$ and $P_E = 0$; and $P_E = P_B = P(k)$ (5 realizations of each). For GalSim, since it is much faster, we averaged over several hundred realizations. It is crucial to inform GalSim that the inputs have units of radians.

The python script `test_pk.py` in `devel/external/test_gridshear/` does the following:

1. Generates shears according to this PS using GalSim.
2. Runs the GREAT10 power spectrum code on both (must flip sign of one shear component before doing so), and averages it over several noise realizations.

The python script `test_pk_sht.py` in that directory does the following:

1. Manipulate outputs of the SHT code to be consistent with expectations (including one sign flip for `e1`).
2. Runs the GREAT10 power spectrum code on it.

Finally, `plot_pk_test.py` in that directory plots the original and simulated $P(k)$ based on these files. The results for the three cases (input P_E , input P_B , and input $P_E = P_B$) are in Figures 1, 2, 3.

We can conclude several things from these figures:

- The SHT code gives roughly a consistent shear power spectrum compared to our inputs (modulo possible slight differences in scaling that may not be worth investigating until our own PS estimation code is ready), though there are signs of E vs. B leakage in the case where one or the other is zero.
- GalSim: we don't see E vs. B leakage at any significant level. The amplitudes and scaling of our output power spectra with ℓ are approximately correct.
- The amplitude for the GalSim power spectra is slightly below that for the SHT code. It is worth investigating whether this is some finite-gridding effect on our part.

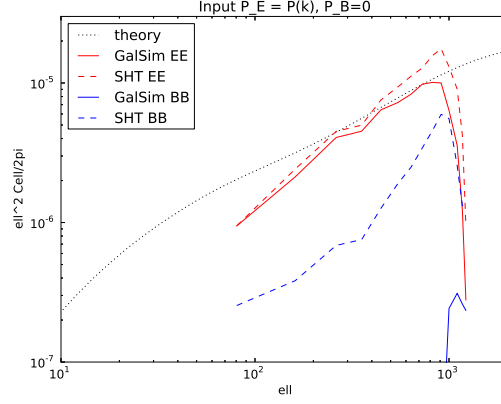


Fig. 1.— Output shear power spectra (plotted as the dimensionless Δ^2) for the grids described in Sec. 6, where the input P_E is a realistic cosmological one (shown as the ‘theory’ line on the plot) and the input $P_B = 0$. The results for GalSim and the comparison SHT code are both plotted.

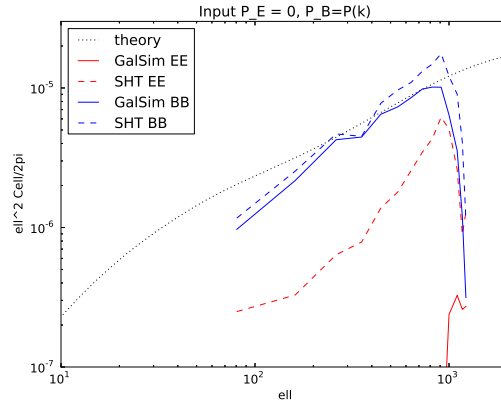


Fig. 2.— Output shear power spectra (plotted as the dimensionless Δ^2) for the grids described in Sec. 6, where the input P_B is a theoretical one and the input $P_E = 0$. The results for GalSim and the comparison SHT code are both plotted.

- While the big-picture results seem good, there are some finer details that require investigation, in particular the fact that both codes seem to give steeper $P(k)$ than the theory. Given how these tests were done, it could have to do with the k -space binning in the power spectrum estimator, the sizes of the bins, etc. rather than some issue with GalSim. This is particularly true given that the SHT code was well-validated and exhibits nearly the same slope as the GalSim outputs.

To address the last point, the simplest possible test is simply to change the ℓ binning in the PS estimation code. This will let us check whether we are encountering some finite-binning effects in the PS estimation. The original calculations had 20 ℓ bins; the new one uses 50 within the same ℓ range. To beat down the noise, we used 400 realizations of the shears from GalSim, instead of 20 as before. The result is shown in Fig. 4. It is clear that the results are, as compared to Fig. 1, closer to the theory. In particular, the amplitude *and* slope are both close to theory for $\ell > 100$. Note that the jitter in that curve does not go away if we use more realizations. This could have to do with the exact locations of the annular ℓ bins in the PS estimation code, as compared to the finite set of ℓ modes that are probed by our grid.

Since the log plot makes it hard to see how large differences between theory and the GalSim results are, Fig. 5 shows the ratio between the GalSim outputs and the theory. For $\ell < 100$, the GalSim results are too low by $\sim 20\%$. For $\ell > 100$, the GalSim outputs seems to give power spectra that are 5% too low, which is suspiciously similar to the results of the variance tests. This finding suggests that users *must* account for the effects of finite ℓ -binning on the theoretical power spectrum when generating the shears, unless they can choose sufficiently fine ℓ bins to minimize this problem. In support of this claim that finite gridding is responsible, we found that with a grid that is doubled in size (and hence a Fourier-space grid that is twice as finely spaced), the ratio of observed to expected power spectrum is closer to 1 (but still 3% too low).

In detail, finite-gridding effects can arise because our gridded approach amounts to estimating the power at specific k_1 and k_2 values (or rather in k_1 and k_2 bins of width Δk). When the PS estimator gets the power using the DFT approach, it’s essentially calculating these as $P(k = \sqrt{k_1^2 + k_2^2})$ which are, again, defined at a set of specific values. However, we then tell the PS estimator “tell me the power in some set of bins in $\log k$ ”, the edges of which are not aligned in any particular way with respect to our actual k values at which we have estimated the power using the DFT approach. The PS estimator gets the power in each of our logarithmic bins via summation over the $P(k)$ for all k values that happen to fall into that logarithmic bin. This means there is some interplay between the grid geometry (determining the k values for which we’ll have $P(k)$) and the choice of log bins, which could result in jitter depending on how the two relate.

We have confirmed that the results are fairly robust to the grid spacing, for example by making the grid a factor of two more finely spaced (and extending the WMAP7 $P(k)$ as a constant above $\ell = 2000$ so that we can do this) and confirming that the results agree with Fig. 1.

A final comment about noise: shape noise and the effect of pixel noise in galaxy shape mea-

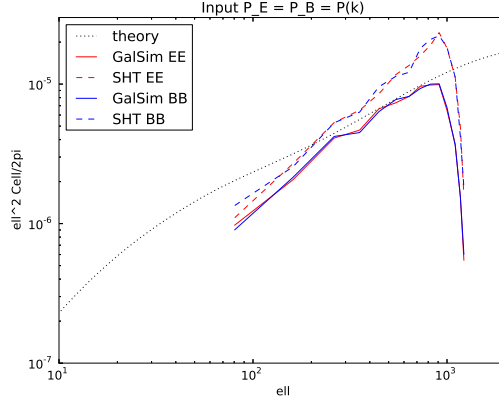


Fig. 3.— Output shear power spectra (plotted as the dimensionless Δ^2) for the grids described in Sec. 6, where the input $P_E = P_B$ is shown as the ‘theory’ line. The results for GalSim and the comparison SHT code are both plotted.

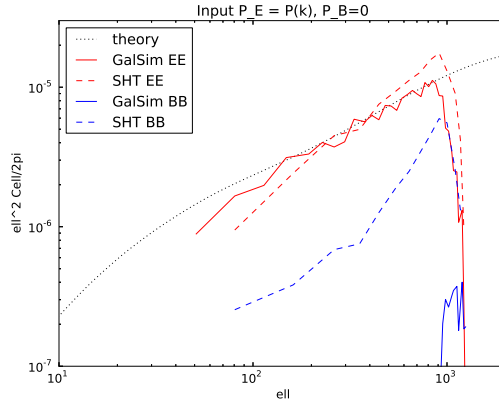


Fig. 4.— Output shear power spectra (plotted as the dimensionless Δ^2) for the grids described in Sec. 6, where the input P_E is a realistic cosmological one (shown as the ‘theory’ line on the plot) and the input $P_B = 0$. The results for GalSim and the comparison SHT code are both plotted, but for GalSim we used 50 ℓ bins in the PS estimation, rather than 20 as in Fig. 1.

measurements add a term to the power, however here we are doing tests of just the cosmological shear without either of the above effect, so that is why it is not included in the above formalism. A realistic test of power spectra from simulated images would have to include these effects.

The deficit in power at low ℓ is likely the same phenomenon seen in the CMB: the assumption of Gaussian distributions for C_ℓ stops being true because there aren't enough samples for the central limit theorem to apply. As a result, using the RMS $a_{\ell m}$ as the inputs to the shear generation code (which is what we are effectively doing) starts to be wrong. The simplest solution to this problem is to use simulations to predict the magnitude of the effect, and then compare results with that prediction.

7. Shear power on larger scales than our grid

It is not clear that we should really be enforcing $P(k = 0) = 0$, i.e., no power below our k_{\min} . This is a valid condition for the full-sky power spectrum, but will not in general be valid for a small patch of the sky, due to cosmic variance. In order to include this sampling variance, it would be preferable to assign $P(k = 0)$ to be some kind of integral over $P(k < k_{\min})$ (perhaps an average power in that k range; details to be worked out later), *if* the power function is defined for those value of k . However, this limitation is only a problem if we are checking quantities like the shear correlation function or its value at $\theta = 0$, i.e., the shear variance. If we are testing the ability to recover a power spectrum $P(k)$ defined at the values of k that are accessible to our grid, the $P(0) = 0$ condition that we have imposed should be irrelevant.

Nonetheless, we may wish to modify the lensing engine to check whether the power function is defined for $0 < k \leq k_{\min}$, and assign some appropriately-weighted integral over that range as $P(k = 0)$.

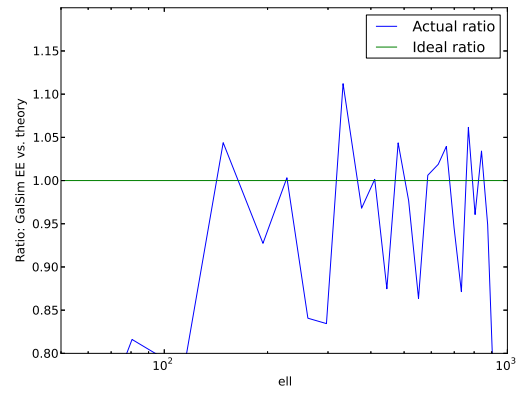


Fig. 5.— Ratio of GalSim EE PS vs. theory from Fig. 4.