Title: Post-SM4 ACS/WFC L-flats and Photometric Errors from Observations of Stellar Fields

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Abstract

We present the first comprehensive post-SM4 study of the low-frequency correction to the ACS/WFC flat-field (L-flat). Using a large sample of constant brightness sources from archival image data, we map out variations in their brightness from multiple dithers over the WFC CCD area, and fit a low-order flat-field model that minimizes those variations. We find strong similarity between our resulting model and the current database L-flat, with $\lesssim 1\%$ differences everywhere, indicating that the L-flat has remained quite stable over time. However, even after correcting for the flat-field, we find that the photometric scatter of dithered point sources is larger than expected from current error models, ranging between $0.5\%$ to $3\%$ depending on instrumental magnitude and exposure time. This suggests that one or more of the terms in the current error model, which includes contributions from the various reference files (e.g. flats, darks, biases) and CTE losses, are underestimated. The team is now considering revising the error arrays and expanding the scope of the photometric error analysis.
1 Introduction

It has been known since shortly after the installation of ACS that WFC images exhibit significant (± ~ 10% effect) low-frequency flat-field (FF) structure (Mack et al., 2002; van der Marel, 2003) that is not captured by the laboratory flats which correct for the high-frequency, pixel-to-pixel FF structure (P-flats). There are two main approaches that have been previously used to determine this low-frequency correction to the FF (the ‘L-flat’) using on-orbit data. In one approach, deep images of relatively empty sky are fully reduced, and after carefully removing sources, any deviations from flatness can be attributed to remaining flat-fielding errors (Mack et al., 2018). In the other method, variations in the measured brightness of (assumed) constant brightness sources are mapped out over the detector area by using several dithers/roll angles. These variations are assumed to be attributed to remaining flat-fielding errors, and a model L-flat can be generated that corrects for this effect. Once obtained, the L-flat and the P-flat can be properly normalized and multiplied together to create what is called the ‘LP-flat’. The current database P-, L-, and LP-flats for F606W are shown in Figure 1.

The WFC L-flats were studied in-depth during the first few years of the instrument lifetime, and then again subsequent to the reduction of WFC operating temperature (Gilliland et al., 2006). The FF reference files have remained unchanged since 2006, and periodic monitors of internal tungsten lamp flats suggest that changes have been minor, though this has not been comprehensively quantified. Given the paramount importance of accurate flat-field corrections for science, in this work we aim to leverage the wealth of relevant post-SM4 data in order to recalculate the L-flats ‘from scratch’, and to investigate any residual FF structure and photometric errors after correcting for the L-flat. Much of this ISR is inspired by, and...
serves as an update to ACS ISR 2003-10 (van der Marel, 2003, hereafter VDM03), which we strongly encourage those interested in this work to read. All images used in this work are taken in the ACS/WFC F606W filter, meaning that our results and conclusions apply only to that filter.

2 Determining the L-flats from Brightness Variations of Dithered Observations of Stars

The description of this problem and corresponding solution is based on the detailed description found in VDM03 Section 2. We therefore limit our discussion to the most salient bits and the necessary context, and we parrot VDM03 in several places in the following text. Note however that there are several (rather inconsequential) differences between our approach and theirs: We employ an optimization routine rather than directly performing matrix operations, we do not have formal errors on each flux measurement, and we use flux units rather than magnitudes.

2.1 ProblemDescription

Consider a star \(i\), with a constant, but unknown, intrinsic flux. Here and henceforth, all fluxes are assumed to be calibrated to some arbitrary photometric system. The star is observed and imaged \(N_i\) times. Between observations, the telescope pointing is dithered or rotated, so that in each observation the (centroid of the) star falls on a different position \((x_{ij}, y_{ij})\) of the two-dimensional detector, where \(j = 1, \ldots, N_i\). For each pointing, point-source photometry is performed on the fully reduced (including flat-fielded) data. Dividing by the exposure time of the respective images, this yields measured fluxes in units of electrons per second \(F_{ij}\). In general, the exposure times of the various images are different. If a stellar field is observed, then these measurements are available for many different stars, \(i = 1, \ldots, S\).

If the data were properly corrected for flat-fielding and other calibration-related errors (i.e. assuming the only remaining source of error in the flux measurements is Poisson error), then for a given star \(i\), the distribution of flux values \(F_{ij}\) will be approximately Gaussian (assuming a sufficiently large number of observations \(N_i\) with a non-zero scatter that scales with the mean flux \(\langle F_i \rangle\). If the data were not properly corrected for FF errors (but all other things being equal), then the distribution of flux values \(F_{ij}\) will have a scatter that is always greater than the scatter in the absence of FF errors. It is easy to verify this claim for any non-trivial flat-field either analytically or using simple simulations. This fact provides the operating principle for our methodology for modeling the structure of the FF. In particular, we can frame this problem as an optimization problem for which the optimal solution is a correction image that, when applied to the science frames (multiplicatively), minimizes the scatter in photometry measurements.

We define the two-dimensional function that encapsulates this correction as \(R(x, y)\). If it is assumed that the FF that was applied in the data reduction is incorrect only in terms of its low-frequency content, then it makes sense to expand the function \(R(x, y)\) into a linear
sum of $K$ two-dimensional basis functions $R_k(x, y)$:

$$R(x, y) = \sum_{k=1}^{K} a_k R_k(x, y), \quad (k = 1, \ldots, K). \quad (1)$$

The basis functions are assumed to be known, and can be chosen to be polynomials or any other convenient functional form. The function $R(x, y)$ will henceforth be referred to as the $L$-flat. The $L$-flat, as defined here, does not describe a property of the actual FF. Rather, it measures the residual structure with respect to the pipeline flat field that was used to calibrate the data.

### 2.2 Solution

In order to determine the optimal model $L$-flat, we construct an optimization problem that minimizes an objective function $Q$ by iteratively updating the coefficients $a_k$ of the model $L$-flat $R(x, y)$ until convergence is reached. The relevant quantities in the machinery are defined as follows:

For a given star $i$, define the $L$-flat-corrected average flux as

$$\langle F_i \rangle = \frac{1}{N_i} \sum_{j=1}^{N_i} F_{ij} R(x_{ij}, y_{ij}). \quad (2)$$

For a given flux measurement $j$ of star $i$, the fractional difference about the average is

$$z_{ij} = \frac{F_{ij} R(x_{ij}, y_{ij}) - \langle F_i \rangle}{\langle F_i \rangle}. \quad (3)$$

Then, for star $i$, the RMS scatter is defined as

$$\sigma_i = \left( \frac{1}{N_i} \sum_{j=1}^{N_i} z_{ij}^2 \right)^{1/2}. \quad (4)$$

Finally, the objective function, taking into account all the stars, is defined as

$$Q = \sum_{i=1}^{S} \sigma_i. \quad (5)$$

The iteration of the parameters and objective function can be handled by a traditional minimization routine (e.g. implemented in `scipy.optimize.minimize`), a Markov

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1 In Equation (3), rather than weighting the deviations by the mean flux, we could in principle choose to weight by the error in the flux, in which case the mean of $z_{ij}^2$ for a given star $i$ resembles the familiar $\chi^2$ for a Gaussian likelihood. However, as previously mentioned, we do not have independent error estimates for each photometric measurement. Therefore, we would have to use a derived quantity such as the exposure time normalized Poisson error. We have verified that, as expected, both weighting options yield nearly identical results both qualitatively in terms of the structure and quantitatively ($\lesssim 0.1\%$ differences), using both artificial (Section 3) and real (Section 4) data.
Chain Monte Carlo (MCMC) sampler, or possibly other methods. We have verified that `scipy.optimize.minimize` and MCMC yield nearly identical results using both artificial (Section 3) and real (Section 4) data.

The data can only determine the L-flat up to an arbitrary additive constant, which can be taken to be the 0th order term (i.e. the constant) in the expansion of the L-flat (Equation (1)). The choice of this constant, which amounts to the normalization of the FF model, is up to the user, but with any given choice, the zeropoint of the photometric magnitude system becomes fixed. Without loss of generality, we impose that this term be equal to unity.

In order to facilitate the most meaningful comparison between our results and those of VDM03, we choose our basis functions of $R(x, y)$ to be 2D Legendre polynomials (implemented in `astropy.modeling.polynomial.Legendre2D`) with highest order of 4. The advantages and disadvantages of this choice of basis functions are described in their Section 2.4. We find that the choice of 4th-order Legendre polynomials captures the low frequency content of the residual FF structure sufficiently well. We have also verified that other orthonormal basis functions (e.g. 2D Chebyshev polynomial) produce nearly identical results. Also, since the WFC detector is comprised of two separate CCD chips, separate basis functions are used for each chip (i.e. the basis functions are set equal to zero outside the chip to which they apply). Stars that appear on both chips help to constrain the relative offset between the models for each chip. We also transform our coordinates using equation 28 of VDM03, remapping the pixel coordinates from the range $(0, 4096)$ to the range $(-1, 1)$.

3 L-flat Modeling Using Artificial Data

In order to test the efficacy of our method, we tested it using mock data/simulations. When generating the mock data, no attempt is made to mimic the actual properties of ACS, the astrophysical properties of a realistic stellar field in detail, or the photometry methods used to obtain the real photometric catalogs. The mock data are generated to loosely resemble the real photometric catalogs we use. In particular, the mock catalog has the same number of stars, and observations per star, as the real catalog and the flux values for each star are drawn from a Poisson distribution with mean corresponding to the mean flux of the star in the real data. The positions for the various pointings of each star are drawn from uniform distributions in the range $(0, 4096)$. (Assigning positions this way does not preserve the relative positions of stars in a stellar field between different dithers, as would be the case in real data, but this is irrelevant for simply testing the solution method.)

We inject an ‘input’ L-flat error, for which we use a 4th order 2D Legendre polynomial series with coefficients randomly drawn from a normal distribution with mean 0 and standard deviation $10^{-2}$ (except for the constant term). For any given randomization of the coefficients using these values, the resulting L-flat exhibits peak-to-peak variations in the range of $\sim \pm 3\%$ to $\pm 10\%$, which is consistent with the variations observed in the real data. The input L-flat is then applied to the mock photometry in the expected way, by dividing each flux ‘measurement’ by the value of the L-flat function at the coordinates of the ‘observation’.

With the mock catalogs in hand, we run them through the machinery described in Section 2 and an output model L-flat is obtained which can be compared to the input L-flat. The
Figure 2: Results from testing our L-flat modeling methodology on simulated data. The left panel shows the ‘input’ model, which is used to apply errors to the photometry. The middle panel shows the optimal solution output from our machinery. Note that the scale limits are the same for these two panels. The right panel shows the fractional difference between the two. The errors are $<0.1\%$ everywhere, demonstrating the efficacy of the method.

results of this exercise for a random realization of the input L-flat can be seen in Figure 2. As expected, the output and input are nearly identical, with variations $<0.1\%$ everywhere, which places a floor on the residuals we could hope to achieve using real data.

4 Real Data

4.1 Observations and Reduction

In applying this analysis to the actual ACS/WFC L-flat, we use observations of the globular cluster 47 Tuc, which has been used as a target for numerous calibration programs and studies over the ACS lifetime. We use a total of 214 images (listed in Appendix) observed through the F606W filter to generate the photometric catalogs. All the observations were taken post-SM4 (between 2009 and 2015), originate from several different observing programs, and span a range of exposure times (between $\sim30\,s$–$1500\,s$). Numerous different dithers and roll angles are represented, and the total footprint spans roughly two WFC chip lengths in diameter.

Since our aim is to derive an L-flat from scratch (rather than a ‘delta-L-flat’), we first downloaded and re-reduced all the raw images using CALACS, changing the flat file header keyword to point to a file containing only the P-flat component, downloaded from CRDS. The flc files we refer to henceforth are the ones output from this custom reduction.
4.2 Photometry and Source Catalog Generation

Construction of the photometric catalogs from the f1c frames was performed using a series of specialized codes. Details of the methods, including information on PSF libraries, PSF fitting, astrometric measurements, photometric measurements, and more, are described in [Anderson et al. (2006)], [Bellini et al. (2014)], [Bellini et al. (2017)], and [Bellini et al. (2018)]. Here, we briefly overview the steps:

First, source-finding and PSF-fitting is performed on the f1c single exposures using empirically derived PSFs, which results in positions and fluxes for each accepted source in each image. An isolation criterion is applied such that sources with close neighbors (< 9 pixels) are not selected. Next, geometric transformations between the single-exposure frames are calculated using well-measured sources (instrumental magnitude $-12 \lesssim m = -2.5 \log_{10} (\text{flux [e$^-$]}) \lesssim -10$ and PSF-fit error < 5%), and a master reference frame is generated. Lastly, matched source catalogs as well as a final photometric catalog are generated which, for each observation of each source, contains: a unique identifier for the source, position in detector coordinates, position in coordinates of the master frame, flux measurement from the single exposure, flux measurement zero-pointed to the master frame, and several diagnostic parameters related to the source-finding and PSF-fitting. The final photometric measurements are sky-subtracted, aperture-corrected, and corrected for pixel area/geometric distortion. The sources in the final catalog span a range of instrumental magnitudes between $\sim -9$ to $-14$. Since the central pixel of a typical ACS/WFC PSF contains $\sim 20\%$ of the total starlight [Bellini et al. (2018)], this range corresponds to a range in peak pixel values of $\sim 4,000$ to 80,000 electrons, the bright end of which is close to the pixel full-well depth.

The resulting catalog contains over 1.3 million total observations of over 30,000 unique sources. We then make several culls to this catalog. First, we cut on a diagnostic parameter that measures the quality of the PSF-fitting. We then remove all observations within a few pixels of a few well-known WFC CCD hot/bad columns. Finally, we remove all sources for which there are fewer than 10 observations. After these cleaning steps, we are left with a catalog of over 1.2 million total observations of over 19,000 unique sources, with between 10 and 165 observations per source. This catalog is then run through the machinery described in Section 2 and an output model L-flat is obtained.

4.3 Results

The left panel of Figure 3 shows a map of the average relative flux error binned over the detector area. This map gives us a visual sense of the FF structure that we are trying to capture. We generate this map with the help of `scipy.stats.binned_statistic_2d`, using the following procedure: First, all the observations are binned up spatially by their detector coordinates. The number of bins is the same in both the $x$ and $y$ directions, and is determined by finding the minimum number of bins $b$ such that at least $N_h$ observations fall into every bin $h$, where $N_h$ can be specified by the user. In order to have reasonable statistics in every bin, we choose $N_h = 5$, which results in $b = 188$ (or $\sim 22 \times 22$ pixel bins). Any given bin contains as few as 5 and as many as 85 observations, with a median of 34 observations per bin. Then, for each star falling in a given bin, we compute the fractional difference between that star’s flux measured in that bin and that star’s average flux over the
Figure 3: Left panel: Map of the FF structure estimated from over 1 million individual photometric measurements. Middle panel: Optimal model L-flat. Right panel: Residual FF structure after correcting for L-flat. This figure is described in detail in the text.

The peak-to-peak variations in the resulting map are $\gtrsim \pm 5\%$ as expected. As a check on whether the binned averages are robust, we also constructed maps (not shown) of the coverage (the number of sources in each bin), the binned average instrumental magnitude, and the RMS scatter of the distribution of values in every bin. Afforded by the excellent sampling of our dataset, these checks confirm no biases or gaps in the spatial coverage or magnitude distribution, and small ($\sim \pm 1\%$) scatter across the board. Note that the map in this panel is not actually used in constructing the L-flat model, but rather serves as a visual guide of the FF. The reason for binning the data as we have done for this map is simply that the density of scatter points for all the data is too high and obscures the structure we intend to visualize. In constructing the actual model L-flat, however, we do indeed use every datum individually.

The middle panel of Figure 3 shows the optimal L-flat model derived from the full dataset. The model L-flat has a noticeable discontinuity at the chip gap. Since this discontinuity is much more subtle in the simulation analysis (Figure 2), we infer that this effect is genuine and that the real FF structure is slightly discontinuous about the chip gap. This can also be seen by close visual inspection of the map in the left panel – there appears to be some structures which are not continuous across the chip gap. We have tested a version of the L-flat which is forced to be continuous at the boundary, but we find that it does not improve the quality of the correction (nor should we necessarily expect it to).

The right panel of Figure 3 is generated in exactly the same way as the left panel, except...
that the photometry catalog is first corrected using the optimal L-flat model. That is, each flux is multiplied by the value of the L-flat model function at the coordinates of the flux measurement. (Note that this is not exactly the same as re-reducing the data with the new L-flat model included in the pipeline and then re-generating the photometric catalog.) Then, the plotted map, which we call the ‘residual average fractional error’, is generated from that catalog. The overall RMS scatter of this map is $\sim 0.45\%$, compared with $\sim 2\%$ for the uncorrected map in the left panel, indicating a considerable improvement in the overall flatness. However, it can be seen that there is significant high-frequency residual structure, with $\gtrsim \pm 1\%$ peak-to-peak excursions. If there is inherent high-order structure in the FF, then this result is to be expected since our low-order polynomial model is not able to capture high-frequency structure. Some of this structure is associated with discrete features, such as the dust ring seen directly below the center of the map. While perhaps not immediately obvious, much of the rest of this structure is actually closely related to the structure of the P-flat (Figure 1). The high-frequency residuals suggests that either the structure and/or amplitude of the pixel-to-pixel FF has changed over time, or that it was never fully captured by the P-flats, or that there are other high-frequency position-dependent errors not currently corrected for in the standard reduction pipeline. A related question was studied by Gilliland & Bohlin (2007), who arrived at broadly similar conclusions for different filters, although those authors emphasize an excess of low-sensitivity structure, whereas we do not observe this excess using our approach.

In order to quantify the random errors in the L-flat model fit to the data, we use two separate methods. In the first, we use Equation 19 of VDM03 to generate a map of the formal errors. In the second, we randomly split the photometry catalog into 15 separate catalogs of roughly equal size (all observations of a given star populate one and only one sub-catalog), and re-run the optimization routine on each catalog separately, resulting in 15 different L-flat models. We then make a map of the RMS between all the individual models. Both of these methods yield random errors $\ll 1\%$ almost everywhere, with the exception of the corners and edges, where the uncertainties climb to a maximum of $\sim 0.6\%$. This only measures the random errors in the model – it does not address the quality of the correction, which is dominated by systematic errors. As a check on how stars with large photometric RMS affect the L-flat model solution, we ran the optimization routine on a subset of the initial photometric catalog in which all stars with relative photometric RMS $> 1.5\%$ (after correcting for the L-flat) were removed. We find that the differences between the resulting model and the fiducial model are very small.

A comparison between our result and the results presented in Mack et al. (2002) and VDM03 is shown in Figure 4. Note that those authors opted to smooth the discontinuity at the chip gap, whereas we did not, leading to the largest differences between the two models in that region. However, aside from that, the two models are qualitatively similar in terms of overall structure. The differences are $\lesssim 1\%$ everywhere, and a mean difference of $< 0.2\%$ over the whole image. The largest changes are near the edges of the detector and chip gap (which is also a set of edges). Despite that the models were generated using completely different data from epochs separated by roughly a decade, this suggests that the L-flat structure has been quite stable over time, and that there may not be an urgent need to deliver new FFs to the database.
Figure 4: A comparison between the F606W L-flat model presented in Mack et al. (2002) and van der Marel (2003) (left panel), and our newly derived model (middle panel). The fractional difference between the two is shown in the right panel, and is \( \lesssim 1\% \) everywhere.

5 Discussion and Future Work

5.1 Photometric Errors

With our new L-flat model in hand, we generated a new LP-flat file for testing. We then re-ran CALACS with the new LP-flat on all the images used in this study, and generated a photometric catalog from the resulting flc frames in exactly the same way as in Section 4. This catalog can then be used to study the photometric errors of fully reduced data in detail. We first separate the initial catalog into three sub-catalogs based on exposure time in order to more meaningfully cross-compare inhomogeneous datasets. The images are already naturally grouped into three different bins of exposure times: there are 42 ‘short’ (\( \sim 40\) s) exposures, 58 ‘medium’ (\( \sim 400\) s) exposures, and 114 ‘long’ (\( \sim 1400\) s) exposures.

In Figure 5 we show the relative photometric RMS scatter binned as a function of instrumental magnitude. The curves for the short, medium, and long exposures are indicated as such in the legend, with the solid line representing the binned mean (that is, the mean RMS across all stars in the bin), and the surrounding shaded bands representing the 1\(\sigma\) scatter. Relative errors of 0.5\%, 1\%, and 3\% are plotted as grey dashed lines and are annotated as such. The relative error expected from Poisson noise is shown as the magenta dot-dashed line, a constant error term of 0.45\% is shown as the cyan dot-dashed line, and the quadrature sum of the two is shown as the solid black curve. The value of the constant error term is the RMS of the FF residual error map (Figure 3), which becomes the dominant source of error for bright instrumental magnitudes. The median of the observed errors is \( \sim 1.5\% \). We can glean a few noteworthy results from this plot and analysis:

1) In general, the observed errors are larger than expected from the current ERR arrays of the image files, which, by construction, yield errors that closely trace the Poisson term.
Observed relative photometric scatter as a function of instrumental magnitude, after applying our new LP-flat. The three colored lines and surrounding shaded bands correspond to the three different exposure time bins, as described in the text. The dot-dashed lines represent the expected contributions from Poisson errors and residual FF errors, and the black curve is their quadrature sum. The observed photometric scatter systematically lies above the naively expected errors, suggesting additional terms in the error budget. Actual observations may be limited by the plotted signal-to-noise floors.

with secondary contributions from FF errors and other terms. We find that the contribution from one or more error terms in these formulae are underestimated and that, in order to be faithful to the observed errors, the error model may need to be increased.

2) Even accounting for the errors in the FF, the observed errors are systematically higher than the black curve, reaching as much as $\sim 3$ times the expected error. Additionally, the observed errors for the longer exposures are systematically higher than those for short exposures (except for the very brightest instrumental magnitudes in the short exposures, where CTE losses are likely increasing the error significantly). This suggests that there are additional terms in the error budget, at least one of which depends on exposure time, that are not currently accounted for in the error arrays nor the exposure time calculator. The precise sources of these errors and their relative contributions are not entirely clear at the moment, but the overall floor could be related to CTE errors, and the term(s) that depends on exposure time could be related to any combination of elevated background levels, contamination from bright halos and/or bleed trails of nearby bright stars, and cosmic ray contamination. Photometric errors may also arise from some combination of residual PSF variations and astrometric errors, but we expect these errors to be very small compared to the dominant sources of error at any given instrumental magnitude [Hoffmann & Anderson 2017].

Taken altogether, these results may have important ramifications for observers. For example, observers wanting to measure small photometric variations with ACS/WFC could be limited by these errors. In the best case scenarios (short exposure times, intrinsically bright sources), the maximum signal-to-noise is $\sim (4.5 \cdot 10^{-3})^{-1} \approx 220$, with a minimum of $\sim (3 \cdot 10^{-2})^{-1} \approx 33$ in the worst cases. Note however that these results only conclusively apply to widely dithered observations and for a relatively crowded field – it is possible that
a better photometric RMS can be achieved through repeated observations with minimal
dithering (in which case we might expect the FF error term to effectively drop out) and/or
for more isolated sources. We plan to explore this in future work.

Figure 6: Similar to Figure 5 but with observed relative photometric errors as a function of F606W
apparent magnitude, after applying our new LP-flat. The three colored lines and surrounding shaded bands
correspond to the three different exposure time bins, as described in the text.

In Figure 6, we show the same quantity on the vertical axis as in Figure 5, but here
plotted as a function of F606W apparent magnitude, which was transformed from the in-
strumental magnitudes using the appropriate STmag zeropoints (https://acszeropoints.
stsci.edu/). Over the ranges of apparent magnitude covered mutually by at least two
of the exposure time bins, this plot demonstrates the effects of varying exposure time on
the photometric scatter. In the range where there is both short and medium exposure
data (19.25 ≲ m ≲ 21.5), it can be seen that, for a given apparent magnitude, going to
medium length exposures decreases the photometric scatter over the short exposures, as is
expected from simple signal-to-noise considerations for sky-dominated observations. On the
other hand, over almost the entire range covered by both medium and long exposure data
(20.5 ≲ m ≲ 24), we see that there appears to be no noticeable improvement in the pho-
tometric scatter in going from medium to long exposures. (The exception to this seems to
be at the two ends of the range of overlap where the statistics may be less trustworthy due
to sparsely populated bins.) This result is noteworthy because it implies that, in terms of
improving photometric errors, there is seemingly strongly diminishing advantage to taking
exposures longer than a certain threshold.

5.2 Higher Order Corrections to the Flat-Field

It is natural to wonder whether better photometric errors can be achieved by correcting
for the residual high-frequency structure in the FF (Figure 3 right panel). It may be possible
to account for this in a few different ways. One way would be to simply use the binned map
in Figure 3 by interpolating and resizing the map to the proper shape of the science images
and then applying it as a multiplicative correction to the LP-flat. Another way would be to
attempt to model the residual structure in much the same way as the low-frequency structure, but using a very high order polynomial series. Both methods have potential issues, but may be worth exploring for the sake of further improving the science value of ACS/WFC data. A preliminary exploration of this suggests there may indeed be room for marginal improvement, but we leave a comprehensive analysis to future work.

6 Closing Remarks

The result of this work has been a new LP-flat for the F606W which the ACS team is now contemplating delivering to the CALACS reference file database, perhaps after extending this analysis to other filters and/or implementing higher order corrections. Additionally, the team is now contemplating updating the WFC images’ error arrays (and other relevant tools/information e.g. the ETC) in light of the results of Section 5. Regardless, we recommend that users take these results into consideration when considering their science goals and/or planning WFC observations.

Acknowledgements

This research made use of: NumPy (Van Der Walt et al., 2011), matplotlib (Hunter, 2007), Astropy (Price-Whelan et al., 2018), and Scikit-learn (McKinney, 2010).

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Hunter, J. D. 2007, Computing In Science & Engineering, 9, 90
Appendix

List of ACS/WFC datasets used in this work:
ja9702spq, ja9702srq, ja9702sxq, ja9702szq, ja9702t5q, ja9702t7q, ja9bw2a4q, ja9bw2a5q,
ja9bw2a7q, ja9bw2a9q, ja9bw2abq, ja9bw2adq, ja9bw2ykq, ja9bw2ylq, ja9bw2zdq, ja9bw2zfq,
ja9bw2zhq, ja9bw2zjq, ja9bw2zq, ja9bw2zsq, ja9bw2uq, ja9bw2uwq, jb6v01dq, jb6v01dkq,
jb6v01eq, jb6v01eq, jb6v01eq, jb6v01eq, jb6v01eq, jb6v01eq, jb6v01eq, jb6v01eq, jb6v01eq, jb6v01eq,
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jb6v01eq, jb6v01eq, jb6v01eq, jb6v01eq, jb6v01eq, jb6v01eq, jb6v01eq, jb6v01eq, jb6v01eq,
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