# Preliminary Study of Photometric Redshifts Based on the Wide Field Survey Telescope Postprint

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## Abstract

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## Full Text

## Preamble

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Preliminary Study of Photometric Redshifts Based on the Wide Field Survey Telescope

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## Abstract

The Wide Field Survey Telescope (WFST) is a dedicated time-domain multi-band (u, g, r, i, and z) photometric survey facility currently under construction. In this paper, we present a preliminary study assessing the quality of photometric redshifts based on WFST by utilizing mock observations derived from the galaxy catalog in the COSMOS/UltraVISTA field. We apply the template fitting technique to estimate photometric redshifts using the ZEBRA photometric-redshift code and adopt a modified set of adaptive templates. We evaluate the bias (median relative offset between output photometric redshifts and input redshifts), normalized median absolute deviation ($\sigma$NMAD), and outlier fraction (f_{outlier}) of photometric redshifts in two typical WFST observational cases: single 30 s exposure observations (hereafter shallow mode) and co-added 50 minute exposure observations (hereafter deep mode). We find bias \$ \$0.006, $\sigma$NMAD \$ \$0.03, and f_{outlier} \$ \$5% in the shallow mode, and bias  0.005, $\sigma$NMAD  0.06, and f_{outlier}  17%–27% in the deep mode, respectively, under various lunar phases.

Combining the WFST mock observational data with that from the upcoming CSST and Euclid surveys, we demonstrate that the z_{phot} results can be significantly improved, achieving f_{outlier}  1% and $\sigma$NMAD  0.02.

Key words: galaxies: distances and redshifts – galaxies: high-redshift – galaxies: photometry

## 1. Introduction

The development of modern astronomy has given rise to an increasing demand for powerful multi-band photometric sky surveys. Such surveys—for example, the Sloan Digital Sky Survey (SDSS; e.g., Brescia et al. 2014; Albareti et al. 2017; Zhao et al. 2021), Dark Energy Survey (DES; e.g., Drinkwater et al. 2010; DES-Collaboration et al. 2016; Ivezić et al. 2019), and Hyper Suprime-Cam Subaru Strategic Program Survey (HSC-SSP; e.g., Aihara et al. 2018; Hikage et al. 2019)—have demonstrated their strong impacts on modern astronomy through well-designed equipment, reasonable observational strategies, and fruitful scientific results in stellar physics, galaxy physics, and cosmology.

The Wide Field Survey Telescope (WFST) is a dedicated time-domain multi-band (u, g, r, i, and z) photometric survey facility under joint construction by the University of Science and Technology of China and Purple Mountain Observatory, which is expected to begin commissioning observations around 2023 August. WFST features a 2.5 m primary mirror, an active optical system, and a 0.73 Gigapixel mosaic CCD camera on the main focus plane. Moreover, WFST is located near the summit of Saishiteng Mountain in the Lenghu area, a world-class observational site (Deng et al. 2021), thereby achieving high-quality imaging over a field of view of 6.5 $\deg^2$. The main science goals of WFST surveys include time-domain sciences such as supernovae, tidal disruption events, multi-messenger events, and active galactic nuclei (AGNs); asteroids and the solar system; the Milky Way and its satellite dwarf galaxies; and galaxy formation and cosmology (Wang et al. 2023).

Robust determination of cosmological redshifts is one of the most crucial factors in fulfilling these WFST science goals. However, high-precision galaxy redshift measurements require spectroscopic observations for each source (i.e., obtaining spectroscopic redshifts, z_{spec}), which is not only expensive but also time-consuming. Alternatively, redshifts can be measured using photometric surveys (i.e., obtaining photometric redshifts, z_{phot}), which is much more efficient than spectroscopic observations. Although this method is not as precise as z_{spec} measurements, it has demonstrated its accuracy through extensive use in determining z_{phot} for huge numbers of survey targets simultaneously (e.g., Benjamin et al. 2010; Brescia et al. 2014; Cavuoti et al. 2017; Sánchez & Bernstein 2019). The application of z_{phot} has enabled a wide range of exciting extragalactic sciences as mentioned above.

To date, a series of methods have been developed to estimate z_{phot}, which can generally be divided into two main categories. One is based on template fitting, where observed photometry is compared to a given set of pre-assumed galaxy templates to determine the best-fit redshift corresponding to the maximum likelihood (e.g., Benítez 2000; Feldmann et al. 2006; Brammer et al. 2008; Luo et al. 2010; Rafferty et al. 2011; Yang et al. 2014; Cao et al. 2018). The other is the training-set method, which constructs a neural network (e.g., Collister & Lahav 2004; Blake et al. 2007; Sánchez et al. 2014; Pasquet et al. 2019) and performs machine learning to obtain z_{phot}, focusing on finding empirical relations between redshift and galaxy properties (e.g., magnitudes and colors). This method usually requires a large sample of secure z_{spec}, which are mostly available in the lower-redshift universe. However, since the magnitude limits of all WFST bands are deeper than most current z_{spec} surveys, it is difficult to find a sample of well-measured z_{spec} that is representative of the full survey sample. Therefore, in this paper we choose to measure z_{phot} of mock WFST observations based on the template fitting technique.

The main goal of this paper is to preliminarily assess the z_{phot} quality of the WFST photometry system. We utilize the COSMOS/UltraVISTA multi-wavelength galaxy photometry catalog (Muzzin et al. 2013) to produce mock

WFST data. This survey has deeper magnitude limits than WFST observations, making it suitable for selecting a subsample of galaxies whose magnitudes meet the WFST detection limits. Using this subsample, we generate the mock flux of each WFST filter passband based on WFST instrumental parameters with good data quality and then estimate the corresponding observational error. We choose to use the ZEBRA code (Feldmann et al. 2006) for z_{phot} estimation. The main advantage of this code is that it can generate a new set of templates adaptive to the observations to minimize the mismatch between observed spectral energy distributions (SEDs) and galaxy templates that are either from theoretical synthesis models or observed certain types of galaxy SEDs in the local universe, thereby improving z_{phot} quality.

This paper is organized as follows. In Section 2, we introduce the WFST photometry system, COSMOS/UltraVISTA galaxy catalog, and generation of mock WFST data. In Section 3, we describe the process of z_{phot} computation. In Section 4, we present z_{phot} results and make comparisons with other works. In Section 5, we summarize our results. All magnitudes quoted are AB magnitudes.

## 2.1. Overview of the WFST Photometry System

WFST has six filters: u, g, r, i, z (see Figure 1 [Figure 1: see original paper]), and w, with the white-light w band specifically designed for detecting asteroids in the solar system and thus excluded from z_{phot} computation in this paper. There are two planned key programs for the 6 yr WFST survey: the wide-field survey (WFS) program and the deep high-cadence u-band survey (DHS) program.

The WFS program aims to survey approximately 8000 deg$^2$ of sky area in the u, g, r, and i bands in the northern hemisphere, with about 90 visits in each band over 6 yr, given a single exposure of 30 s for each visit. The DHS program plans to routinely monitor approximately 720 deg$^2$ of sky area in the highly sensitive u band surrounding the equator every year, with a much higher observing cadence (down to hours) and supplemented by a multi-band ancillary survey. The z-band imaging is excluded from the WFS program due to its relatively low efficiency and limited contribution to time-domain sciences; moreover, high-quality z-band imaging data will be achieved by other northern-hemisphere surveys such as Wide Imaging with Subaru HSC of the Euclid Sky (WISHES). However, WFST will allocate some time (about 1300 hr over 6 yr) for additional observational specific purposes or particular interests, such as capturing time-critical targets and mapping the Galactic plane, which require intensive scanning of certain sky areas using z-band imaging.

In this paper, we compute z_{phot} in two typical WFST observational cases: single 30 s exposure observations (hereafter shallow mode) and co-added 50 minute exposure observations (hereafter deep mode). The deep mode can be realized by integrating all the observational time in each band mainly with the

WFS program, thus achieving deeper detection limits than any existing single-telescope surveys with comparable survey areas in the northern hemisphere (Lei et al. 2023; Wang et al. 2023).

The average night sky background brightness at the WFST site (Saishiteng Mountain, Lenghu Town, Qinghai Province) is approximately V = 22.3 mag arcsec$^{-2}$ when the moon is below the horizon. Under new moon conditions, the best sky level can reach 22.3 mag arcsec$^{-2}$ in the extreme case when the bright part of the Galactic Disk is far away from the local zenith (Deng et al. 2021). Under this circumstance and with no moon, the 5$\sigma$ limiting magnitudes can reach depths of ugriz = [22.31, 23.42, 22.95, 22.43, 21.50] in the shallow mode and ugriz = [24.86, 25.95, 25.48, 24.96, 24.03] in the deep mode, respectively (Wang et al. 2023). The modeling results of the 5$\sigma$ limiting magnitudes and sky backgrounds in different lunar phases are listed in Table 1 (Lei et al. 2023).

## 2.2. The COSMOS/UltraVISTA Galaxy Catalog

In this paper, we adopt the multiwavelength galaxy photometry catalog in the COSMOS/UltraVISTA field (Muzzin et al. 2013) to produce mock WFST data, given that it has deep optical coverage, broadband photometry, and high-quality z_{phot} and corresponding best-fit galaxy SEDs.

This catalog covers a sky area of 1.62 deg$^2$ with point-spread function (PSF) matched photometry in 30 bands, with the wavelength range extending from 0.15 to 24  m. This includes two ultraviolet bands (FUV and NUV) from the GALEX satellite (Martin et al. 2005), seven broadband (u*, g+, r+, i+, z+, Bj, Vj) and 12 medium-band (IA427–IA827) optical data from the Subaru and Canada–France–Hawaii Telescope (Capak et al. 2007; Taniguchi et al. 2007), four near-infrared imaging bands (Y, J, H, Ks) from the UltraVISTA survey (McCracken et al. 2012), and the 3.6, 4.5, 5.8, 8.0, and 24  m channels from Spitzer's IRAC and MIPS cameras (Sanders et al. 2007). The 5$\sigma$ depths of the COSMOS/UltraVISTA survey in all bands are tabulated in Table 2 , with typical depths in optical bands being deeper than those of WFST (see Table 1).

Photometric redshifts of galaxies in the COSMOS/UltraVISTA catalog are computed based on the template-fitting technique with the EAZY photometric-redshift code (Brammer et al. 2008). The default seven EAZY templates are comprised of six templates derived from the PEGASE models (Fioc & Rocca-Volmerange 1999) and a red galaxy template from the models of Maraston (2005). To improve the quality of the fitting, Muzzin et al. (2013) added two additional galaxy templates: one is a one-gigayear-old single-burst galaxy template generated from the Bruzual & Charlot (2003) model to improve template fitting for galaxies at z > 1 with post-starburst-like features; and the other is a slightly dust-reddened young galaxy template to improve fitting of UV-bright Lyman break galaxies (LBGs) with heavy dust extinction at 1.5 < z < 3.5. EAZY fits the observed multiwavelength photometry of galaxies using linear combinations of the above nine initial templates (as shown in Figure 2 [Figure 2: see original paper]) based on the  2 minimization algorithm. Muzzin et al. (2013) provided in their COSMOS/UltraVISTA catalog the best template combination coefficients for each galaxy, enabling us to generate its best-fit SED. We show some examples of best-fit galaxy SEDs and their respective redshifts from the COSMOS/UltraVISTA catalog in Figure 3 [Figure 3: see original paper]. Photometric redshifts derived by Muzzin et al. (2013) are of high quality, being consistent with z_{spec} from the zCOSMOS survey: up to z  1.5, their z_{phot} are accurate to Δz/(1 + z) = 0.013, with an outlier fraction of only 1.6%; up to z  3, their z_{phot} show good agreement with z_{phot} from the NEWFIRM Medium Band Survey.

## 2.3. Generation of Mock WFST Data

First, the mock flux in each band for each galaxy in the given catalog can be calculated by convolving the galaxy redshifted SED with the filter transmission curve, which can be expressed as:

$$F_{\text{mock}} = \frac{\int S_\lambda(1+z)R(\lambda)\,d\lambda}{\int R(\lambda)\,d\lambda}$$

where $S_\lambda$ is the best-fit observed SED of the COSMOS/UltraVISTA galaxy, and $R(\lambda)$ is the transmission curve of one of the five WFST filters. The mock flux $F_{\text{mock}}$ is then calibrated to the mock observational flux according to the i-band apparent magnitude (Subaru i+ flux, $F_{i+}$) given in the COSMOS/UltraVISTA galaxy catalog. This conversion is performed by $F_{\text{obs}} = F_{\text{mock}} \times (F_{i+}/F_{\text{mock},i+})$, where $F_{\text{obs}}$ is the mock observational flux, and $F_{\text{mock},i+}$ is the mock flux of a galaxy SED in each of the five WFST bands.

Dust extinction is taken into account when generating mock flux data. The SED flux density after dust reddening from the interstellar medium (Calzetti et al. 1994; Galametz et al. 2017) can be expressed as:

$$S_{\text{extinct}}(\lambda_{\text{rest}}) = S_{\text{intrinsic}}(\lambda_{\text{rest}}) \times 10^{-0.4E(B-V)k(\lambda)}$$

where $E(B-V) = A_V/R_V$ is the color excess and $k(\lambda)$ is the Calzetti et al. (2000) dust extinction curve. We adopt this extinction curve with $R_V$ for this attenuation law set as 4.05. For each galaxy, the value of attenuation $A_V$ is given by the COSMOS/UltraVISTA catalog, which is derived through the SED fitting technique. We directly use it to generate the mock extinction-corrected fluxes.

We also consider intergalactic medium (IGM) absorption for high-redshift galaxies. At wavelengths shorter than the Ly$\alpha$ line, the emission can be absorbed by neutral hydrogen clouds in the IGM along our line of sight to the high-redshift galaxy. We account for this extinction by making use of the Madau (1995)

IGM attenuation law. This is carried out by applying the average flux decrement $\langle D_A \rangle$ between Ly$\alpha$ and Ly$\beta$, and $\langle D_B \rangle$ between Ly$\beta$ and the Lyman limit, such that the IGM absorption-corrected flux can be written as:

$$S_{\text{absorption}} = S_{\text{initial}} \times 10^{-0.4\langle D_A \rangle} \times 10^{-0.4\langle D_B \rangle}$$

where $S_{\text{initial}}$ is the initial flux density in the rest frame, adopted as the interstellar dust extinction-corrected galaxy flux $S_{\text{extinct}}(\lambda_{\text{rest}})$ obtained from Equation (2). After these correction procedures, the galaxy SED flux density $S_{\text{absorption}}$, with dust extinction and IGM absorption corrected, is substituted into Equation (1) to generate mock flux data for all five WFST bands.

Next, we estimate flux errors with respect to mock WFST fluxes. For a ground-based telescope, the signal-to-noise ratio (S/N) can be evaluated via the following equation (Lei et al. 2023):

$$\frac{S}{N} = \frac{S\tau A}{\sqrt{S\tau A + n_{\text{pix}}(\text{Sky} + D\tau + R^2)}}$$

where $S$ is the source signal with a constant spectral flux, $\tau$ is the exposure time, $A$ is the effective area of the WFST primary mirror ( $4.12 \times 10^4$ cm$^2$), $D$ is the dark current of the CCD ($D = 0.005$ e$^-$ pixel$^{-1}$ s$^{-1}$ at $-100$ °C), $R$ is the readout noise of the CCD ($R = 8$ e$^-$ rms), and $n_{\text{pix}}$ is the total pixel number in the PSF region. The factor of 2 applied here is because we assume that the calculation is performed on sky-subtracted images. We adopt an optimal PSF aperture of 1.18 times the full width at half maximum (0.111 arcsec) for a non-adaptive optics case according to the Integration Time Calculator of Gemini. Sky in Equation (4) is the sky background signal that actually lands on the detector in units of e$^-$ s$^{-1}$ pixel$^{-1}$, which is given by:

$$\text{Sky} = f_\lambda T_{\text{opt}} Q_{\text{CCD}} \frac{\lambda}{hc} \Delta\lambda$$

where $f_\lambda$ is the surface brightness of the sky background, $T_{\text{opt}}$ is the throughput of the optics (including the primary mirror, analog-to-digital converters, and the five corrector lenses), and $Q_{\text{CCD}}$ is the quantum efficiency of the CCD.

The photometric error can be evaluated through the approximate magnitude error relation (Pozzetti et al. 1998; Bolzonella et al. 2000):

$$\sigma_m \approx \frac{2.5}{\ln 10} \frac{1}{S/N}$$

We also add a systematic error $\sigma_{\text{sys}} = 0.02$ mag (Cao et al. 2018), and the total magnitude error is then given by $\sigma_{m,\text{tot}} = \sqrt{\sigma_m^2 + \sigma_{\text{sys}}^2}$. Thus we can obtain the flux error $\sigma_F$ of each band from $\sigma_m$ via error propagation. Finally, a random error drawn from a Gaussian probability distribution function (with $\sigma = \sigma_F$) is added to the mock flux in each band as the final mock photometry.

After computing and correcting these mock fluxes, the mock observational targets for the WFST shallow mode and deep mode are generated. In this paper, we adopt $3\sigma$ detections to include sources into various samples as in Muzzin et al. (2013); that is, galaxies with fluxes that meet the $3\sigma$ depth thresholds of the five WFST bands (see Table 1) are selected as the mock observational samples for subsequent z_{phot} calculation (see Section 4).

## 3. Computation of Photometric Redshifts

In this paper, we compute z_{phot} of galaxies using the mock WFST data and the ZEBRA photometric-redshift code (Feldmann et al. 2006) with default parameters unless stated otherwise. The main advantage of ZEBRA is that it can generate a new set of templates adaptive to observed galaxy SEDs to minimize the mismatch between observed SEDs and available templates. This is performed by creating a training set of galaxies to optimize the shape of spectral templates that can better match predicted galaxy colors with observed ones. We adopt the same set of nine initial galaxy templates (see Figure 2) as in Muzzin et al. (2013) for z_{phot} calculation using ZEBRA. Since we have removed all point sources that are likely bright stars or AGNs in the COSMOS/UltraVISTA catalog, we do not include any AGN templates during our template fitting.

First, we run ZEBRA in photometry-check mode to identify and correct systematic errors in the photometry based on the maximum-likelihood algorithm. ZEBRA derives a simple photometric offset in each band that minimizes the residuals between the mock observed fluxes and those of the best-fit templates, with redshifts set as the input ones (i.e., z_{spec} or high-quality z_{phot} from Muzzin et al. 2013, if z_{spec} are not available). These corrections are then applied to the mock WFST photometry data, and ZEBRA iterates this procedure five times to ensure that the median offset in each band converges.

Second, we run ZEBRA in non-template-improvement mode based on this photometric systematic offset-corrected mock catalog, using the nine initial galaxy templates shown in Figure 2. ZEBRA iteratively performs five logarithmic interpolations in magnitude space between any adjacent pair of the nine templates, generating $5 \times 8 = 40$ templates added to the nine initial templates, resulting in a total of 49 templates.

Third, we run ZEBRA in template-improvement mode, where ZEBRA transforms the discrete template space into a linearly continuous space, using a Karhunen–Loéve expansion to iteratively correct the eigenbases of a lower dimensional subspace through a $^{2}$ minimization scheme. As a result, adaptive spectral templates are generated to better match the galaxy SEDs of the training set than the set of 49 templates.

For each galaxy sample considered, we randomly divide all its galaxies into two equal halves: one half serves as the training set to generate a new set of adaptive templates, and z_{phot} computation is performed on the other half as the validation set based on these new adaptive templates plus the above 49 templates as a blind test of z_{phot} quality. We compare multiwavelength photometry and input redshifts of both the training and validation sets in Figures 4 and 5, respectively. We find that they have almost identical photometric and redshift properties, such that templates generated based on the randomly selected training set of galaxies can be adaptive to the full galaxy sample, and z_{phot} computation on the validation set as a blind test can be representative of the result for the full sample.

In the template-improvement mode, ZEBRA iterates twice: over the redshift range 0–3 as one single bin and in smaller redshift bins of 0.5 to train the 49 templates based on a chosen training set. Narrowing down the redshift bin (e.g., Δz = 0.2) only increases the total number of adaptive templates generated but has little effect on the final z_{phot} results. Therefore, we use a total of 49 × 6 + 49 = 343 final templates and run ZEBRA to compute z_{phot} for each selected galaxy sample.

## 4. Results and Discussion

In this section, we present z_{phot} results with mock WFST data in the shallow and deep modes given various lunar phases (see Sections 4.1 and 4.2, respectively), compare our WFST z_{phot} results with those from recent works (see Section 4.3), and assess the improvement of z_{phot} quality with the addition of other data (see Section 4.4).

### 4.1. z_{phot} Results in the Shallow Mode

The z_{phot} results with mock WFST data in the shallow mode are shown in Figure 6 [Figure 6: see original paper], with left and right panels for the non-template-improvement and template-improvement modes under various lunar phases, respectively. To evaluate z_{phot} quality, we adopt three commonly used quantities: (1) normalized median absolute deviation (e.g., Brammer et al. 2008), i.e., *σ{NMAD} = 1.48 × median(|Δz - median(Δz)|/(1 + z*{input})), where Δz = z_{output} - z_{input}, with z_{output} and z_{input} being the output z_{phot} and input redshifts from the COSMOS/UltraVISTA catalog (Muzzin et al. 2013), respectively; (2) outlier fraction f_{outlier}, defined as the fraction of sources with |Δz|/(1 + z_{input}) > 0.15; and (3) bias, i.e., median of Δz/(1 + z_{input}) with outliers removed.

According to Figure 6, under various lunar phases we achieve bias = -0.001–0.006, *σ{NMAD} = 0.015–0.031, and f*{outlier} = 3.23%–5.19% in the non-template-improvement mode, and bias = 0.000–0.006, *σ{NMAD} = 0.011–0.029, and f*{outlier} = 3.72%–5.27% in the template-improvement mode, respectively. The template-improvement mode delivers smaller biases and $\sigma_{NMAD}$ than the non-template-improvement mode, which is expected. However, the former mode provides comparable or even slightly larger $f_{outlier}$ than the latter mode, due to misidentification of Lyman break as Balmer break or vice versa caused by the relatively limited photometry (i.e., only ugriz bands), although the significantly enlarged template set can cover the full parameter space of observed galaxy SEDs.

As shown in Figure 7 [Figure 7: see original paper], $z_{phot}$ quality shows some variation with lunar phases: $z_{phot}$ quality improves as the lunar phase increases, with the best $z_{phot}$ result achieved under the lunar phase of 180° (full moon). Two factors can influence $z_{phot}$ quality of the selected sample under different lunar phases. One is the lunar phase itself: under brighter lunar phases, the sky light background contributed by the moon becomes larger, resulting in larger uncertainties on photometry and eventually worse $z_{phot}$ quality. The other is the sample selection effect: under brighter lunar phases, only brighter sources can be well observed, which usually have higher-S/N photometry that leads to higher-quality $z_{phot}$.

To make a more sensible evaluation of the lunar phase influence and consider these two factors separately, we restrict the sample to galaxies observable under full moon and measure $z_{phot}$ under different lunar phases, with results shown as red dashed lines in Figure 7. It is clear that the lunar phase has a very limited influence on $z_{phot}$ results of a fixed sample. Therefore, the variation in $z_{phot}$ quality under different lunar phases in the shallow mode is primarily driven by the sample-selection effect.

### 4.2. $z_{phot}$ Results in the Deep Mode

The $z_{phot}$ results with mock WFST data in the deep mode under various lunar phases, with ZEBRA run in the template-improvement mode, are shown in Figure 8 [Figure 8: see original paper]. Apparently, the inclusion of faint galaxies significantly reduces $z_{phot}$ quality: $\sigma_{NMAD}$ grows from 0.041 to 0.064 with the dimming of lunar phases; $f_{outlier}$ increases to 26.6% when there is no moon; bias 0.005, being almost constant and comparable to the situations of faint lunar phases in the shallow mode.

In the deep mode, $z_{phot}$ quality shows a stronger variation with lunar phases than in the shallow mode, as shown in Figure 9 [Figure 9: see original paper]. However, this does not mean that dimming of moonlight will cause $z_{phot}$ quality to decrease for a fixed galaxy sample. When we consider the fixed sample of galaxies observable under full moon, we find that dimming of sky background caused by moonlight slightly reduces photometric uncertainties and thus improves $z_{phot}$ quality, e.g., $f_{outlier}$ decreasing from 17.1% (full moon) to 14% (no moon) (see the red dashed lines in Figure 9). Thus, the downgrade of $z_{phot}$ quality under fainter lunar phases in the deep mode is a direct result of the sample-selection effect, same as in the shallow mode. The dimmer moonlight in the deep mode enables the detection of fainter populations of galaxies, which often exhibit poorer photometry qualities, leading to a continuous decrease in the accuracy and reliability of z_{phot} estimation. Therefore, we conclude that lunar phase only has negligible or very slight effects on z_{phot} quality for a given sample of galaxies; however, it can have a strong influence on sample selection, resulting in "apparent" variation of z_{phot} quality across different samples.

### 4.3. Comparison with Other z_{phot} Results

We compare our WFST z_{phot} results with relevant works; for simplicity, we fix the lunar phase in the WFST mock to 90° (half moon) here. Figure 10 [Figure 10: see original paper] shows Δz/(1 + z_{input}) as a function of r-band magnitude in the shallow mode and deep mode (see black contours), respectively. Overall, bright sources in the shallow mode have much better z_{phot} than faint sources in the deep mode, with the scatter of Δz/(1 + z_{input}) of the latter being  2–3 times larger than that of the former. The red curves in Figure 10 show the average cumulative rms deviation between z_{phot} and z_{spec} as a function of r-band magnitude in the SDSS survey early data release (using ugriz-band photometry; Csabai et al. 2003), where z_{phot} were derived with a hybrid technique (empirical and template fitting methods) to calibrate galaxy SED templates, utilizing a training set of galaxies with secure z_{spec}. We find that at m_r < 22, our Δz/(1 + z_{input}) scatter is generally comparable to or smaller than that of Csabai et al. (2003). This is partly because their training set of galaxies is restricted to the bright population, making it difficult to constrain z_{phot} scatter toward the faint end. Recently, Yang & Shen (2023) estimated z_{phot} of galaxies and quasars in the Southern Hemisphere DES wide survey based on a Bayesian analysis algorithm in multi-color space, using grizY-band photometry. We show the standard deviation of Δz/(1 + z_{input}) of their galaxies in blue bars in Figure 10, which is comparable to our result in the shallow mode.

Figure 11 [Figure 11: see original paper] shows Δz/(1 + z_{input}) as a function of z_{input} in the shallow mode and deep mode, respectively, in comparison with several other works. In general, our Δz/(1 + z_{input}) shows a smooth distribution in each smaller redshift bin; the biases and scatters of our z_{phot} are smaller than many quoted results from other works up to z  3. This may be because the training sets we use to improve the galaxy SED templates are randomly selected, thereby having good coverage of various galaxy properties and being representative of the full galaxy sample (see Figures 4 and 5). However, in real observations, z_{spec} of the training sets would be mostly limited to bright sources and low redshifts, making it difficult to well cover the full properties of the selected galaxy sample. In addition, observed galaxy SEDs can be very different from the galaxy templates adopted here; therefore, a nonnegligible effect on actual biases and scatters of our z_{phot} in real observations would be expected.

Figure 12 [Figure 12: see original paper] shows *σ{NMAD} and f*{outlier} as a function of $z_{input}$ in the shallow mode and deep mode, respectively, in comparison with the aforementioned works. Again, our $z_{phot}$ results are overall in line with those in the literature. At $z < 1.5$, our $z_{phot}$ quality is comparable to those of most other works, but not better than those based on machine deep learning, e.g., using random forest algorithms or convolutional neural networks. At $z \geq 1.5$, both our $z_{phot}$ results and the quoted results deteriorate; our $f_{outlier}$ is larger than results based on 5-band HSC photometry that includes the near-infrared Y band conducive to $z_{phot}$ improvement at high redshifts. In contrast, our $\sigma_{NMAD}$ remains largely constant and acceptably small both in the shallow mode and deep mode, and within the full redshift range of 0–3 explored here.

It is clear that at low redshifts ($z < 1.5$), machine deep learning procedures can effectively improve $z_{phot}$ results compared to traditional template-fitting techniques, which is usually done by applying a large training sample with secure $z_{spec}$ and high-quality observed SEDs. At higher redshifts ($z \geq 1.5$), however, such a training sample would become very incomplete, making it difficult to cover the full parameter space of all observed sources; thus, uncertainties of $z_{phot}$ measurement at high redshifts are unlikely to be precisely constrained simply based on machine learning. At $z \geq 1.5$, the traditional template-fitting technique still shows advantages in some respects, e.g., as shown in Figure 12, our $\sigma${NMAD} *outperforms that of machine-learning results, because ZEBRA can extend the known templates in multi-parameter space and improve the fitting result by creating new templates and optimizing their shapes to be adaptive to galaxy multiwavelength photometry. However, the ZEBRA template-improvement procedure does not seem to effectively reduce* $f${outlier} at $z \geq 1.5$, mainly due to misidentification of spectral breaks or other spectral features in galaxy SEDs because of the limited ugriz-band photometry. In contrast, the most recent machine learning methods based on the Direct Empirical Photometric (DEmP) or Nearest Neighbor (NNPz) method seem to have the potential to reduce $f_{outlier}$ to a large extent. Therefore, in the future we can combine machine learning methods with adaptive template fitting procedures to further improve WFST $z_{phot}$ quality.

### 4.4. Improvement of $z_{phot}$ Quality with the Addition of Other Data

We further investigate the improvement of WFST $z_{phot}$ quality by including mock data from the China Space Station Telescope (CSST, to be launched around 2024; Zhan 2011) and Euclid space telescope (launched in 2023 July; Laureijs et al. 2012), both of which can provide additional high-quality ultraviolet and/or near-infrared data over large sky areas that are critically supplementary to WFST data.

We consider the CSST NUV- and y-band mock data, whose photometric errors are measured via S/N (Ubeda 2011):

$$\frac{S}{N} = \frac{C_s t}{\sqrt{C_s t + N_{\mathrm{pix}}(B_{\mathrm{det}} t + N_{\mathrm{read}} R_n^2)}}$$

where $t$ is the exposure time and $N_{\mathrm{pix}}$ is the number of detector pixels covered by a source. $N_{\mathrm{pix}}$ is 16 by default, corresponding to the case of a point source in the image; changing the $N_{\mathrm{pix}}$ value does not significantly alter the final result. $N_{\mathrm{read}}$ is the number of detector readouts, $B_{\mathrm{det}}$ is the detector dark current, and $R_n$ is the read noise. Default parameter settings of $t = 300$ s, $N_{\mathrm{read}} = 2$, $B_{\mathrm{det}} = 0.02$ e$^-$ s$^{-1}$ pixel$^{-1}$, and $R_n = 5$ e$^-$ pixel$^{-1}$ are adopted. $C_s$ is the count rate from the source in units of e$^-$ s$^{-1}$. $B_{\mathrm{sky}}$ in Equation (6) is the sky background in e$^-$ s$^{-1}$ pixel$^{-1}$. For more details about the CSST mock flux and error estimation, we refer readers to Section 2.3 in Cao et al. (2018).

We consider the Euclid YE-, JE-, and HE-band mock data. Since we do not have specific details of Euclid (such as those of CSST shown in Equation (6)), we adopt photometric errors in the similar Y, J, and H bands of the VISTA survey for approximation; i.e., photometric errors of mock Euclid data are directly taken from the Muzzin et al. (2013) catalog, which are scaled proportionally to mock YE-, JE-, and HE-band fluxes. Given that there is a slight bias between the ground-based VISTA telescope and Euclid, we apply a constant conversion factor to convert the VISTA errors to the Euclid mock errors, defined as the ratio of flux error between the CSST y band and VISTA Y band for each source at the given magnitude. We then compute mock fluxes and flux errors in the CSST NUV, y and Euclid YE, JE, and HE bands, which are subsequently combined with WFST mock data for z_{phot} improvement.

Figure 13 [Figure 13: see original paper] shows the z_{phot} results in the deep mode with the addition of 5-band mock data from CSST and Euclid. It is clear that z_{phot} quality is significantly improved (see Figure 8), because the 10-band mock photometry that well covers the wavelength range from ultraviolet to near infrared is vital for both ZEBRA photometry-check mode and template-improvement mode. In the non-template-improvement mode, f_{outlier} and *σ{NMAD} are effectively reduced to 5% and 0.03, respectively; the lunar phase has little influence on z*{phot} results, mainly due to the fact that mock CSST and Euclid data are almost unaffected by the lunar phase. In the template-improvement mode, f_{outlier} and σ_{NMAD} are further reduced to 1% and 0.02, respectively; meanwhile, the bias is also better calibrated, being 0.0.

Fulfillment of many scientific goals is heavily dependent on z_{phot} accuracy. For example, z_{phot} for future photometric weak lensing surveys need to achieve at least *σ{NMAD} < 0.05 (e.g., Zhan 2006; LSST-Collaboration et al. 2009), with many studies setting σ*{NMAD} 0.02 as a goal, which is crucial to depict the redshift-dependent growth of dark matter fluctuations, analyze weak lensing cosmic shears, and investigate the redshift-dependent weak lensing signal behind clusters of galaxies under the constraints of the dark energy equation of state framework (Brimioulle et al. 2008). As shown above, such requirements on z_{phot} accuracy can be met when the mock WFST, CSST, and Euclid data are combined.

## 5. Summary

In this paper, we conduct a preliminary study assessing z_{phot} quality based on mock WFST ugriz-band photometry in the shallow mode and deep mode. We adopt the multiwavelength photometric catalog in the COSMOS/UltraVISTA field to generate mock WFST data, as it has deeper limiting magnitudes than WFST observations. During this process, mock fluxes are computed through convolution of galaxy SEDs with the five WFST filter transmission curves, with interstellar dust extinction and IGM absorption taken into account, and mock flux errors are evaluated through consideration of instrumental parameters, sky background, and systematic errors.

We calculate z_{phot} using the ZEBRA code, which can generate new adaptive templates that better describe observed galaxy SEDs. We find bias $ $0.006, *σ{NMAD} $ $0.03, and f*{outlier} $ $5% in the shallow mode, and bias  0.005, *σ{NMAD}  0.06, and f*{outlier}  17%–27% in the deep mode, respectively, under various lunar phases. A lunar phase has limited influence on z_{phot} results, and the decrease of z_{phot} quality with dimming of the lunar phase is primarily caused by sample-selection effect—that is, the involvement of increasingly more faint sources that have larger photometric uncertainties.

We compare our WFST z_{phot} results with those from relevant works, finding general agreement between various results. Given that adaptive template fitting and machine learning methods have their respective merits, it would be sensible to use all these methods jointly to further improve WFST z_{phot} quality in the future.

Finally, we compute z_{phot} by combining the mock WFST data with ultraviolet and near-infrared data from CSST and Euclid. As expected, we find significant improvements in z_{phot} quality with f_{outlier}  1% and *σ{NMAD}  0.02, thanks to the full wavelength coverage from ultraviolet to near infrared. Such high-quality z*{phot} can help fulfill many scientific goals that heavily rely on z_{phot} accuracy.

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*Note: Figure translations are in progress. See original paper for figures.*