MEASURING GALAXY ENVIRONMENTS WITH DEEP REDSHIFT SURVEYS

Michael C. Cooper, Jeffrey A. Newman, Darren S. Madgwick, Brian F. Gerke, Renbin Yan, and Marc Davis

ABSTRACT

We study the applicability of several galaxy environment measures (nth-nearest neighbor distance, counts in an aperture, and Voronoi volume) within deep redshift surveys. Mock galaxy catalogs are employed to mimic representative photometric and spectroscopic surveys at high redshift (z ~ 1). We investigate the effects of survey edges, redshift precision, redshift-space distortions, and target selection on each environment measure. We find that even optimistic photometric redshift errors (σ_z = 0.02) smear out the line-of-sight galaxy distribution irretrievably on small scales; this significantly limits the application of photometric redshift surveys to environment studies. Edges and holes in a survey field dramatically affect the estimation of environment, with the impact of edge effects depending on the adopted environment measure. These edge effects considerably limit the usefulness of smaller survey fields (e.g., the GOODS fields) for studies of galaxy environment. In even the poorest groups and clusters, redshift-space distortions limit the effectiveness of each environment statistic; measuring density in projection (e.g., using counts in a cylindrical aperture or a projected nth-nearest neighbor distance measure) significantly improves the accuracy of measures in such overdense environments. For the DEEP2 Galaxy Redshift Survey, we conclude that among the environment estimators tested the projected nth-nearest neighbor distance measure provides the most accurate estimate of local galaxy density over a continuous and broad range of scales.

Subject headings: galaxies: high-redshift — galaxies: statistics — large-scale structure of universe — methods: data analysis — methods: statistical — surveys

1. INTRODUCTION

The observed properties of galaxies have long been known to depend on the environment in which they are located. For instance, red, non–star-forming galaxies (e.g., local ellipticals and lenticulars) are systematically overrepresented in highly overdense environments such as clusters (e.g., Davis & Geller 1976; Dressler 1980; Postman & Geller 1984; Balogh et al. 1998). Recent studies have shown that the observed correlations between galaxy properties and environment are not limited to the cores of rich clusters, but extend to less dense domains, including the outer regions of clusters, galaxy groups, and the field (e.g., Balogh et al. 1999, 2004; Carlberg et al. 2001; Blanton et al. 2005; Croton et al. 2005).

There are a variety of physical processes that can readily explain these observational trends, including the action of dynamical friction, tidal stripping, or gas pressure in dense environments. These mechanisms, in combination with the hierarchical model of galaxy formation (Kauffmann et al. 1993; Somerville & Primack 1999; Cole et al. 2000), in which galaxies form in less dense environments and are then accreted into larger groups and clusters, are generally consistent with the current observations. From the empirical evidence, however, it remains uncertain in what environment(s), by what mechanisms, and on what timescales galaxies evolve from a field-like population to a cluster-like population. Still, the strong correlation of local galaxy density with galaxy properties over a broad range of environment does indicate that it plays an important role in galaxy formation and evolution.

To study galaxy properties spanning a broad and continuous range of local environment requires a thorough census of the three-dimensional galaxy distribution over a large volume. Such data sets are only collected via large, systematic redshift surveys. For the nearby galaxy population, wide-field spectroscopic and photometric surveys (e.g., 2dFGRS [Colless et al. 2001] and SDSS [York et al. 2000]) have provided excellent data sets for studying galaxy environments ranging from voids to rich clusters. Recent results from these large surveys have shown that galaxy environments correlate strongly with the colors, luminosities, and morphologies of local galaxies (e.g., Balogh et al. 2004; Hogg et al. 2003, 2004; Blanton et al. 2005).

With the advent of new high-redshift surveys (e.g., the VLT-VIMOS Deep Survey [VVDS; Le Fèvre et al. 2003, 2005] and the DEEP2 Galaxy Redshift Survey [DEEP2; Davis et al. 2003; S. M. Faber et al. 2005, in preparation]), studies of galaxy environment will be able to extend beyond the local universe. Such deep, high-redshift surveys will provide a representative snapshot of the galaxy population and corresponding local densities when the universe was half its present age, thereby permitting an investigation into the influence of environment on galaxy evolution and formation. That is, extending environment studies to higher redshift will enable a determination of whether the correlations among galaxy properties observed in the local universe are the result of physical processes acting over the entire lifetime of the galaxy or whether the correlations were established during the early formation of the galaxy.

While redshift surveys have grown in scale and studies of galaxy environment have increased in prevalence, few published tests have detailed the degree to which environment measures are affected by survey limitations. For instance, the confined sky coverage of surveys introduces geometric distortions (or edge effects) that bias local density measures near boundaries or holes in the
survey field. Environment statistics can also be impacted by the redshift precision and target selection requirements of a given survey. Mock galaxy catalogs provide an excellent means for testing the biases introduced to a given density measure by effects such as these.

In this paper, we test the applicability of several popular density estimators within deep redshift surveys utilizing the mock galaxy catalogs of Yan et al. (2004). In particular, we investigate the effects of redshift precision, survey field edges, redshift-space distortions, and target selection. We also devote specific attention to the DEEP2 survey, with the goal of identifying the optimal density measure for use within the survey. Within this study, we do not consider global measures of environment trends (such as correlation functions), but instead focus on measures that can estimate environmental properties of individual objects. The outline of the paper is as follows. In the next section, we present the mock galaxy catalogs used to test environment measures at high redshift. Subsequently (§ 3), we describe the environment measures to be tested. In § 4 we examine the significance of redshift precision in determining local galaxy densities. In § 5 we conduct a detailed analysis of edge effects with respect to each environment parameter. In §§ 6 and 7 we then address the influence of redshift-space distortions and target selection on the various environment estimators. In § 8 the roles of completeness and the survey selection function are discussed. Finally, in §§ 9 and 10 we conclude with a summary of the applicability of each environment measure at high redshift and a discussion of the suitability of current deep surveys to measuring local galaxy densities.

2. SIMULATING DEEP REDSHIFT SURVEYS

Beginning with the Center for Astrophysics Redshift Survey (Davis et al. 1982), large redshift surveys have played a major role in studying galaxy properties, measuring cosmological parameters, and studying the large-scale structure of the universe. With improvements to astronomical instruments, local redshift surveys have ballooned in size, and surveys at high redshift (z ∼ 1) have become possible. At present, high-z surveys take two forms: (1) obtaining precise (σ_z ≤ 0.001) redshifts using spectroscopic observations of galaxies (e.g., DEEP2 and VVDS), and (2) using deep photometry in many passbands to make less precise (σ_z ≥ 0.05) photometric redshift estimates (e.g., COMBO-17; Wolf et al. 2003). Each of these has its advantages and disadvantages.

Even utilizing highly multiplexed multiobject spectrographs (e.g., DEIMOS; Faber et al. 2003) on large-aperture telescopes, a deep spectroscopic redshift survey requires a vast amount of telescope time and is invariably limited in the number of galaxies for which it can measure redshifts. Slit or fiber collisions constrain the number of objects able to be targeted during a given exposure, while the forest of OH sky lines in the optical and infrared plus instrument defects and limited signal-to-noise ratios cause redshifts to be missed for some percentage of targeted objects. Spectroscopic surveys benefit from a higher level of redshift precision that permits studies of kinematics within galaxies and galaxy groups, while also measuring spectral properties such as emission-line equivalent widths. On the other hand, using an imager with a large field of view and observing in many passbands, less precise photometric redshifts can be obtained for nearly all galaxies above a given magnitude limit in the targeted field. For this reason, photometric surveys are often able to build larger samples and are ideal for measuring the galaxy luminosity function or galaxy-galaxy lensing, for which a high level of velocity accuracy is not necessary.

In this paper, we employ the simulated galaxy catalogs of Yan et al. (2004) to model both photometric and spectroscopic surveys at z ∼ 1. The simulations and all work in this paper employ a ΛCDM cosmology with Ω_M = 0.3, Ω_Λ = 0.7, h = 1, and σ_8 = 0.9. The mock catalogs are derived from N-body simulations by populating dark halos with galaxies according to a halo occupation distribution (HOD) function (Peacock & Smith 2000; Seljak 2000), which describes the probability distribution of the number of galaxies in a halo as a function of the host halo mass. The luminosities of galaxies are then assigned according to the conditional luminosity function (CLF) introduced by Yang et al. (2003), which describes the luminosity function in halos of mass M. Models for the HOD and the CLF are constrained from the 2dFGRS luminosity function (Madgwick et al. 2002) and two-point correlation function (Madgwick et al. 2003). By assuming that the manner in which dark matter halos are populated with galaxies does not evolve from z ∼ 1 to z ∼ 0 (Yan et al. 2003), the mock catalogs are built using simulation outputs at corresponding redshifts. The simulated galaxy catalogs show excellent agreement with the lower z (0.7 < z < 0.9) DEEP2 correlation function (Coil et al. 2004) and the COMBO-17 luminosity function (Wolf et al. 2003); they therefore should provide a realistic data set for studying measures of the environment of galaxies at z ∼ 1. For further details regarding the construction of the mock catalogs, refer to Yan et al. (2003).

From the volume-limited mock catalogs, we are able to mimic a typical photometric redshift survey by selecting all galaxies above a given magnitude limit and applying to each galaxy redshift a random offset drawn from a Gaussian distribution with standard deviation σ_z. We utilize the DEEP2 survey as a model high-redshift spectroscopic survey. The volume-limited mock catalogs are selected according to the DEEP2 magnitude limit of R_AB ≤ 24.1 and passed through the DEEP2 target-selection and slit-mask–making code, which is able to place approximately 60% of available targets on slit masks for spectroscopy (Davis et al. 2005). Finally, 30% of objects are randomly rejected to reflect a conservative redshift success rate of ∼70%. The 12 mock catalogs cover fields of 120′ × 30′ in area with a total of ∼120 DEEP2 slit masks tiling the 1 square degree. To simulate larger survey fields, we tiled multiple mock catalogs without overlap or discontinuity. Such large-field mocks were essential for studying edge effects (§ 5) and for building large sample sizes.

In each mock catalog, we have a complete tally of the total galaxy distribution down to a luminosity of 0.1L*, along with subsets of objects that pass the DEEP2 target-selection criteria, were placed on a slit mask for observation, and yielded a successful redshift. Such a census enables detailed study of the survey selection function and the manner in which slit-mask making and target selection affect environment statistics. Throughout this paper, we utilize several subsets drawn from the mock catalogs as described in Table 1. Note that for each mock galaxy, the simulations provide accurate positions in both real space and redshift space.

| Sample Description |
|---------------------|
| Volume limited....... |
| Full mock galaxy catalog; L > 0.1L* |
| Magnitude limited..... |
| R_AB ≤ 24.1 |
| DEEP2 selected....... |
| R_AB ≤ 24.1; passed DEEP2 target-selection and slit-mask–making criteria; random ∼70% redshift success rate; high-redshift precision (σ_z = 0.0001) |

Note.—We present a list of commonly used subsamples drawn from the mock galaxy catalogs of Yan et al. (2004).
3. ENVIRONMENT MEASURES

The environment of a galaxy is typically defined in terms of the density of galaxies located in its immediate vicinity. However, a variety of density measures are often employed in estimating environment. For example, many previous analyses have focused on the identification of predefined groups or clusters of galaxies, which can be contrasted to those galaxies not inhabiting these overdense regions, that is, the field population (e.g., Kuntschner et al. 2002; van den Bergh 2002; Lewis et al. 2002; Christlein 2000). Another approach is to instead derive a continuous measure of the galaxy density distribution, such as by measuring the distance to the nth-nearest neighbor (e.g., Gómez et al. 2003; Mateus & Sodrê 2004) or by directly smoothing the observed galaxy distribution on a fixed scale (e.g., Hogg et al. 2003; Beuing et al. 2002; Kauffmann et al. 2004). The underlying theme in each of these methods is that one requires a measure of the local number density of galaxies at the position of each galaxy in the sample.

In our analysis, we focus on density estimators that do not rely on identifying galaxy groups or clusters in any way. Lumping galaxies into predefined classifications provides a poorly sampled range of galaxy environments, especially when compared to continuous measures of environment. At high redshift, where dense regions are commonly undersampled and clusters and groups are less numerous, a more continuous definition of environment is all the more desirable. Still, identifying galaxies in groups at high z is possible and has been tested in a separate paper (Gerke et al. 2005). In this analysis, we compare three popular density estimates: nth-nearest neighbor distance, counts in an aperture, and the Voronoi volume. This set of measures is in no way presumed to be complete. Other promising methods for measuring local galaxy density, including using a Gaussian kernel to smooth the galaxy distribution over a given scale (e.g., Hogg et al. 2003; Balogh et al. 2004), are not discussed in this work.

3.1. nth-Nearest Neighbor Distance, \(D_n\) and \(D_{p,n}\)

As first employed by Dressler (1980), the local galaxy density can be estimated using the distance to the nth-nearest spectroscopically observed neighbor of a given galaxy. Often, redshift information is simply employed to exclude foreground and background sources—by restricting neighbors to a given velocity interval—and the nearest-neighbor distance is measured in projection. Commonly, the projected nth-nearest neighbor distance, \(D_{p,n}\), is expressed as a surface density, \(n = n/(\pi D_n^2)\). Measuring nearest-neighbor distances in projection is particularly useful when studying the density of galaxies in groups and clusters (e.g., Dressler 1980; Lewis et al. 2002), where the appropriate velocity interval by which to exclude background and foreground galaxies may be selected according to the velocity dispersion of the group or cluster. In this manner, one may confidently exclude galaxies not associated with the group or cluster; furthermore, as shown in § 6, measuring in projection minimizes the impact of redshift-space distortions.

For less dense environments or poorly sampled groups, there may be few neighbors within the selected velocity interval, causing \(D_{p,n}\) to reflect the distance to other structures rather than the local density. In environments where working in projection is problematic, an alternative is to compute the nth-nearest neighbor distance in three dimensions by searching in spherical apertures for the nth-nearest spectroscopically observed neighbor. Similar to its projected counterpart, the three-dimensional nth-nearest neighbor distance, \(D_n\), is often expressed as a number density, \(n = (3n)/(4\pi D_n^3)\). Throughout this paper, all nth-nearest neighbor distances are quoted in units of comoving \(h^{-1}\) Mpc, and the symbols \(D_n\) and \(D_{p,n}\) are employed to denote the three-dimensional and projected nth-nearest neighbor distances, respectively.

To study the effectiveness of the three-dimensional and projected nth-nearest neighbor distance measures at tracing the local density of galaxies in different environments, we compute both \(D_n\) and \(D_{p,n}\) for a DEEP2-selected sample consisting of 12,636 galaxies as drawn from a 120’ × 60’ mock catalog. In Figure 1 we compare the values of \(D_n\) and \(D_{p,n}\) for each galaxy in the sample as measured using the redshift-space galaxy positions to the measured value of \(D_n\) as computed using the real-space positions for each galaxy, which should reflect the true local environment. We find that at high densities, where redshift-space distortions are greater, the projected nth-nearest neighbor distance is superior at tracing the real-space density of galaxies but still suffers greatly from peculiar velocities. On scales corresponding to intermediate- and low-density environments, the three-dimensional measure of \(D_n\) is a slightly more accurate estimate of the true galaxy density.
distribution. For a DEEP2-selected mock catalog, \( \sim 15\% \) of the observed sample resides in the regime \( \log_{10}(D) < 0.5 \) where the three-dimensional \( n \)-th-nearest neighbor distance saturates and loses sensitivity.

In addition to a lack of sensitivity on given scales, the behavior of the projected and the three-dimensional \( n \)-th-nearest neighbor distances depends on the choice of \( n \). A measure of the \( n \)-th-nearest neighbor distance effectively smooths the galaxy distribution in a nonlinear fashion according to the adopted value of \( n \). If \( n \) is chosen to be much larger than the richness of typical groups in the sample, then the \( n \)-th-nearest neighbor distances for galaxies in these groups will be pushed to erroneously high values, as they will reflect the distance to the next-nearest structure. In this work, we study both the projected and the three-dimensional methods for computing the \( n \)-th-nearest neighbor distance employing a variety of values for \( n \). We limit most discussion to values of \( n = 2, 3, \) and 5, which correspond to the sizes of small groups detected in the DEEP2 survey (Gerke et al. 2005) and to the typical sizes of groups in the mock catalogs (see Fig. 2). For these values of \( n \), the sensitivity of the \( n \)-th-nearest neighbor measure is rather independent of \( n \). In underdense environments, the dependence on \( n \) is very weak, while in dense environments the strong clustering of groups (Padilla et al. 2004; Coil et al. 2005) arranges to curb \( D_n \) for \( n \approx n_{\text{group}} \). Also, in galaxy groups redshift-space distortions are a much greater source of error in \( D_n \) than small variations in the choice of \( n \).

For the projected \( n \)-th-nearest neighbor distance measure, we test the sensitivity of \( D_{n,n} \) using line-of-sight velocity intervals ranging from \( \pm 750 \) to \( \pm 2000 \) km s\(^{-1} \). As shown in Table 2, using a larger velocity interval by which to exclude foreground and background sources increases the accuracy of \( D_{n,n} \) in dense environments but also sacrifices sensitivity at low densities. We find that for a DEEP2-selected sample, a velocity interval of \( \pm 1000 \) to \( \pm 1500 \) km s\(^{-1} \) is best suited for a broad range of environments. Compared to photometric redshift errors (in the best data sets, \( \sigma_z \sim 6000 \) km s\(^{-1} \)), the sizes of the tested line-of-sight velocity windows are small. However, larger velocity intervals sacrifice sensitivity on small scales and provide poorer measures of the local density about each galaxy; a window large enough not to be dominated by photometric redshift errors is also large compared to the typical length scales of large-scale structure (e.g., the correlation length and typical void sizes), and thus provides a poor measure of environment.

### 3.2. Counts in an Aperture, \( C \)

Another method for estimating the local galaxy density is to count galaxies within a fixed metric aperture. For example, Hogg et al. (2003) count spectroscopically observed galaxies in the SDSS within spheres of radii \( 8 \) \( h^{-1} \) comoving Mpc centered on each spectroscopically observed galaxy. In high-redshift surveys where the survey field may cover \( \sim 1 \) deg\(^2\) or less, such a large spherical aperture will be dramatically affected by the survey edges (see § 5). For instance, within a \( 30'' \) sphere field (i.e., \( 20 \) \( h^{-1} \) comoving Mpc on a side at \( z \sim 1 \)), 81\% of spherical apertures with a radius of \( 1 \) \( h^{-1} \) comoving Mpc will fit within the surveyed field, while for apertures of radii 3 and 5 \( h^{-1} \) comoving Mpc, only 49\% and 25\% of the field, respectively, will be unaffected by edges. Furthermore, local studies indicate that larger apertures do not provide any advantage or additional information worth this high price. Both observational and theoretical studies suggest that galaxy properties are more closely related to dark matter halo mass and small-scale environment than the large-scale environment of the galaxy (e.g., Lemoine & Kauffmann 1999; Blanton et al. 2004).

While choosing smaller spherical apertures would reduce the amount of survey volume affected by edges, apertures smaller than approximately \( \pm 1000 \) km s\(^{-1} \) along the line of sight will not be sensitive to galaxy groups or clusters. The counts in an aperture measure effectively smooth the data on some adopted scale, thereby losing sensitivity on smaller and larger scales. In our analysis, we employ a series of cylindrical apertures measuring \( 1--2 \) \( h^{-1} \) comoving Mpc transverse (radius) and \( \pm 500 \) to \( \pm 2000 \) km s\(^{-1} \) along the line of sight. The dimensions of our cylindrical apertures are chosen to match the typical sizes of halos in the simulations (Yan et al. 2004).
The Voronoi volume is a geometric measure that has been seen use from engineering and biology to astronomy (Ramella et al. 2001; Marinoni et al. 2002). Unlike counts in an aperture, the Voronoi volume does not smooth the galaxy distribution in any way. It provides a continuous, adaptive measure of galaxy density on all scales by measuring a unique volume about each spectroscopically observed galaxy.

As illustrated in Figure 3, the Voronoi partition of space is the three-dimensional analog of the two-dimensional Dirichlet tessellation, in which a plane containing a set of data points is divided into a set of polygons, each containing one of the points. A Voronoi polyhedron is the unique three-dimensional convex region of space surrounding a data point (the seed), such that within the polyhedron every point is closer to the seed than to any other data point. The faces of the Voronoi polyhedron are defined by the perpendicular bisecting planes of the vectors connecting the seed to its neighbors, where a seed’s neighbors are those points connected to it by the Delaunay complex, the set of tetrahedra whose vertices are at the data points and whose unique, circumscribing spheres contain no other data points. The Voronoi partition and Delaunay complex are thus geometrical duals of one another.

Computing the Voronoi partition for a galaxy redshift survey provides a natural way to measure the local density of galaxies, since the volume of a galaxy’s Voronoi polyhedron will vary inversely with the distance to its closest neighbors. For this reason, the Voronoi volume associated with each galaxy serves as a natural parameterization of that galaxy’s environment. Galaxies in dense regions will have small Voronoi volumes, while isolated galaxies will have larger volumes. Our methods for computing the Voronoi partition are identical to those of Marinoni et al. (2002), and we refer the reader to that work for computational details and for further discussion of the usefulness and historical context of the Voronoi partition and Delaunay complex. In this paper, we will employ the symbol $V$ to denote the Voronoi volume of a given galaxy, and all Voronoi volumes are measured in units of co-moving $(h^{-1}\text{Mpc})^3$.

4. REDSHIFT PRECISION AND TARGET SELECTION RATE: PHOTOMETRIC VERSUS SPECTROSCOPIC SURVEYS

As discussed in §2, photometric and spectroscopic redshift surveys differ in the precision with which they are able to measure galaxy redshifts. To test the significance of redshift precision in measuring local galaxy environment, we have produced a variety of mock surveys with differing characteristics. First, we simulate two photometric redshift surveys that mimic the varying precisions of the COMBO-17 photometric redshift survey quoted in the literature. Our first simulated photometric redshift survey adopts a magnitude limit of $R_{\text{AB}} \leq 24.1$ and redshift uncertainty of $\sigma_z \approx 0.02$, which reaches equally deep and is more precise than the COMBO-17 specifications of $R_{\text{Vega}} \leq 24, \sigma_z \approx 0.03$, as given by Wolf et al. (2003). In addition, we simulate a photometric redshift survey with the same magnitude limit of $R_{\text{AB}} \leq 24.1$ and a redshift precision of $\sigma_z \approx 0.05$, as specified for COMBO-17 by Taylor et al. (2004). Both magnitude-limited samples are drawn from the same volume-limited mock catalog and include 22,961 galaxies covering a $120' \times 30'$ field. Note that our assumed redshift uncertainties are lower limits to the redshift precision for the COMBO-17 survey. As discussed by Bell et al. (2004), the photometric redshift precision for COMBO-17 depends strongly on the galaxy type and redshift; galaxies such as starbursts that lack a strong 4000 Å break yield redshifts with much greater uncertainties ($\sigma_z \sim 0.1$), while at higher redshifts K-correction uncertainties introduce systematic redshift errors.

Running the same volume-limited galaxy catalog through the DEEP2 target-selection and slit-mask–making software and assuming a conservative redshift success rate (see §2), we also produce a mock spectroscopic sample with redshift precision of $\sigma_z \sim 0.0001$, mimicking the DEEP2 redshift survey. This DEEP2-selected spectroscopic sample includes 9302 galaxies covering the same 1 deg$^2$ field (sampling ~50% of galaxies to the magnitude limit). To simulate the VVDS “deep survey” in the CDF-S (Le Fèvre et al. 2005), we randomly select 25% of objects to the same $R_{\text{AB}} \leq 24.1$ magnitude limit. This “VVDS-selected” sample is an optimistic simulation of VVDS, assuming a 100% redshift success rate (Vanzella et al. 2005) and ignoring differences in the bandpass used. Lastly, as a comparison sample we select the full magnitude-limited mock catalog (22,961 galaxies at $R_{\text{AB}} \leq 24.1$), assigning redshifts according to the real-space positions of the galaxies as defined in the mock simulations. Each environment estimator (nth-nearest neighbor distance, Voronoi volume, and counts in an aperture) is then computed on the photometric, spectroscopic, and real-space galaxy samples.

For this comparison, we restrict our analysis to the redshift range $0.7 < z < 1.4$ and to only those galaxies at transverse distances of greater than 4 $h^{-1}$ comoving Mpc from the nearest edge in the survey volume. These restrictions make edge effects in both the redshift and transverse directions negligible but do not introduce any selection biases (see §5). Note that the mock catalogs are not subject to interior edges; that is, the simulations cover a contiguous 1 deg$^2$ of sky with no holes.

We find that the precision of even the best photometric redshifts is not sufficient to measure local galaxy environments. Figure 4 shows the comparison between Voronoi volumes, $V$, as measured using the real-space galaxy positions compared to
those calculated using the observed redshifts for two representative surveys. Even assuming redshift errors as small as \( \sigma_z \approx 0.02 \), the environment measured in a photometric redshift survey is insensitive for all but the very lowest density environments; the Spearman ranked correlation coefficient between the real-space and photometric measures of Voronoi volumes is \( \rho = 0.4 \). For the spectroscopic survey, redshift-space distortions introduce some scatter at high densities, but the overall distribution of environments is well measured. In all, the Voronoi volumes measured from the observed spectroscopic redshift distribution trace the real-space Voronoi volumes with much greater precision, yielding a correlation coefficient of \( \rho = 0.73 \). Very similar results are observed for the \( D_n, D_{p,n} \), and \( C \) environment estimators.

In Table 3 we expand our analysis to a better sampled range of redshift uncertainties. Even if the precision of photometric redshifts is greatly improved—by a factor of 2 or 4—we find that low-resolution spectroscopic surveys with galaxy sampling comparable to DEEP2 provide a significantly better trace of the three-dimensional galaxy environment. It is only at very high redshift precisions (\( \sigma_z \leq 0.005 \)) and when measuring densities in projection that photometric redshift surveys are able to rival their spectroscopic counterparts as probes of galaxy environment.

Among the spectroscopic redshift surveys simulated, the greater sampling and improved redshift precision of the DEEP2 survey prove significantly superior to the VVDS in tracing the real-space density of galaxies. On the other hand, at precisions better than the 30 km s\(^{-1}\) uncertainty in DEEP2 redshifts, redshift-space distortions dominate the ability to measure local densities and thereby limit any advantage of improved redshift measurements (see Table 3). Note that the galaxy samples in Table 3 transition from a magnitude-limited (\( R_{AB} \leq 24.1 \)) sample at low redshift precision to mimic photometric or grism spectroscopic redshift

---

**TABLE 3**

| Sample               | \( \sigma_z \) | \( \rho \) | \( \rho_{0.5} \) | \( \rho_{0.01} \) |
|----------------------|-----------------|------------|----------------|-----------------|
| \( R_{AB} \leq 24.1 \) | 0.05            | 0.307      | 0.310          | 0.389           |
| 0.02\(^1\)          | 0.400\(^1\)    | 0.396\(^1\) | 0.473\(^1\)   |                 |
| 0.01                | 0.494          | 0.478      | 0.575          |                 |
| 0.05                | 0.596          | 0.579      | 0.688          |                 |
| 0.0025              | 0.675          | 0.677      | 0.803          |                 |
| 0.005               | 0.749          | 0.751      | 0.802          |                 |
| 0.0001\(^1\)       | 0.726\(^1\)    | 0.749\(^1\) | 0.802\(^1\)   |                 |
| 0                   | 0.726          | 0.751      | 0.801          |                 |

**Notes.**—For a range of redshift precisions \( \sigma_z \), we compute the fifth-nearest neighbor distance \( D_n \), Voronoi volume \( V \), and projected fifth-nearest neighbor distance \( D_{p,n} \) for the galaxies in a 120' \times 30' mock catalog. As described in the main text, three samples are selected from the same mock catalog according to (1) the DEEP2 target-selection and slit-mask–making procedure (DEEP2 selected), (2) a magnitude limit of \( R_{AB} \leq 24.1 \), and (3) a 25% random sampling to the same magnitude limit of \( R_{AB} \leq 24.1 \) (VVDS selected). Restricting to the redshift range \( 0.7 < z < 1.4 \) and more than 4 h\(^{-1}\) comoving Mpc removed from a field edge, the magnitude-limited sample contains 9310 galaxies while the DEEP2-selected and VVDS-selected samples include 4538 and 2375 of those galaxies, respectively. For each sample and redshift precision, we (rank) correlate estimates of \( V, D_n, \) and \( D_{p,n} \) with similar measures computed on a magnitude-limited sample using the real-space galaxy positions. Note that \( \sigma_z = 0.0001 \) corresponds to the redshift precision of the DEEP2 survey and that surveys reflecting the COMBO-17, VVDS, and DEEP2 attributes have been denoted with daggers in the table.

---

**FIG. 4.—** *Left:* Comparison of Voronoi volumes measured for the 4539 galaxies in a 120' \times 30' simulated DEEP2 spectroscopic redshift survey sample (\( \sigma_z \sim 0.0001 \)) that are more than 4 h\(^{-1}\) comoving Mpc away from the nearest survey edge and within the redshift range \( 0.7 < z < 1.4 \). Plotted is the logarithm of the Voronoi volumes as measured in the simulated DEEP2-selected sample vs. the logarithm of the Voronoi volumes as measured on the full magnitude-limited, real-space catalog. *Right:* Comparison of Voronoi volumes measured for the 9310 galaxies in a high-precision (\( \sigma_z \sim 0.02 \)) simulated photometric redshift survey sample that were more than 4 h\(^{-1}\) comoving Mpc away from the nearest survey edge and within the redshift range \( 0.7 < z < 1.4 \). Plotted is the logarithm of the Voronoi volumes as measured in the simulated photometric survey sample vs. the logarithm of the Voronoi volumes as measured on the full magnitude-limited, real-space catalog. In each plot, the Spearman ranked correlation coefficient \( \rho \) is given in the upper left corner. The dashed lines follow a correlation of 1. While both samples are influenced by redshift-space distortions (see \S 6) and the spectroscopic sample (*left*) suffers from poorer sampling, the inferior redshift precision of the photometric survey causes the line-of-sight galaxy distribution to smear out irretrievably on all but the largest scales.
surveys to a sample selected using the DEEP2 target-selection and slit-mask–making procedures or a VVDS-like selection to simulate higher resolution spectroscopic surveys, which have superior redshift precision but lower sampling rates.

5. EDGE EFFECTS

When measuring galaxy densities within any survey, one must always be careful of edge effects introduced by the limited area of sky covered in the survey. Even using the largest optical telescopes and an instrument with a generous field of view, a deep redshift survey is limited in its ability to cover large regions. Furthermore, to minimize the effects of cosmic variance on the data set, a high-redshift survey is likely to spread the sky coverage over several fields. This limits the amount of contiguous sky coverage and increases the proportion of the survey area that is near an edge. In addition to the edges created by the chosen geometry of the survey field(s), edges and holes can be created in the data set by effects such as bright stars in a field or problematic regions in photometric detection that prohibit any galaxies from being targeted there. To start, we will restrict our discussion to survey edges in the plane of the sky, but later discussion will address edges in the line-of-sight direction.

The general effect of edges on each density estimator is to push the measurement toward lower density. To quantify the degree to which each environment measure is affected by edges, we compute each measure on a large DEEP2-selected spectroscopic mock galaxy catalog covering a wide field, 120' × 90'. From the center of this larger simulation we extract a smaller rectangular survey field covering 40' × 30' and rerun each environment measure on this data set. For every galaxy in the smaller survey field, we then have measurements of environment unaffected by edges (when measured on the larger sample) and measurements in which survey edges play a greater role (when measured on the smaller field). Trimming to the redshift range 0.7 < z < 1.4, the smaller sample consists of 2803 galaxies. In the following subsections, we discuss how each environment measure is affected by the edges of the survey region on the plane of the sky. Note that we also ran tests incorporating holes and irregular survey edges with very little change in the relative results for the tested environment measures.

For each galaxy in the studied sample, we express the difference in a given environment measure due to survey edges as a fraction of the width of the distribution for that measure. Specifically, we define the percent change in environment measure $X$ for galaxy $q$ by

$$\Delta_n(X) = \frac{\log_{10}(X_{2q}) - \log_{10}(X_{1q})}{\sigma_1} \times 100\%,$$

where $X_{2q}$ is the measure of $X$ for galaxy $q$ computed on the smaller mock, $X_{1q}$ is similarly computed on the wide-field mock, and $\sigma_1$ is a measure of the Gaussian width of the logarithmic distribution of environment measure $X$ as calculated in the larger simulation. Quantifying the change in each environment measure in this fashion enables the role of edge effects to be compared between different environment estimators in a uniform manner.

5.1. Survey Edges and nth-Nearest Neighbor Distance

The nth-nearest neighbor distance environment measure—in both projection and three dimensions—is affected by edges in a predictable manner. Any galaxy with an edge located closer than the measured nth-nearest neighbor distance must be affected by the survey edges. However, to remove all such galaxies based on this criterion ($D_n > D_{\text{edge}}$ or $D_{p,n} > D_{\text{edge}}$) biases the sample toward overdense environments by excluding less-dense regions over a greater volume than more-dense regions. To avoid such biasing of the sample, a simple cut in edge distance can be made, excluding all galaxies within some distance of the nearest edge. This cut introduces no environment-dependent bias but does allow some contamination to the sample at underdense environments, depending on the severity of the cut. In our simulations, we find that removing all galaxies within 2 h⁻¹ comoving Mpc of a survey edge creates a catalog with minimal contamination [roughly 5% of the sample has $\Delta_n(D_1) > 10\%$] and still retains 65% of the data set. Relaxing the constraint to $D_{\text{edge}} > 1 h^{-1}$ comoving Mpc, the level of contamination in the sample doubles to ~10% with $\Delta_n(D_1) > 10\%$ while the percentage of the sample retained increases to ~85%.

As illustrated in Figure 5, we find that edge effects show a clear dependence on $n$; the level of contamination due to survey edges in the plane of the sky increases by roughly a factor of 2 for $D_2$ relative to $D_3$. Also, for a fixed value of $n$, the projected nth-nearest neighbor distance is slightly more robust to edge effects in the regime where sample size is maximized ($D < 2 h^{-1}$ Mpc in Fig. 5).

5.2. Survey Edges and Counts in an Aperture

For an aperture of fixed comoving size, the edge effects on the counts in an aperture density measurement are easily understood and cleaned from the sample. Only galaxies located within $r_\alpha$ of an edge are affected, where $2r_\alpha$ is the transverse diameter of the chosen aperture. Thus, by removing any galaxies within $r_\alpha$ of an

\[ D_{\alpha} > 2 h^{-1} \text{ Mpc}. \]
edge, the sample is entirely devoid of edge-affected galaxies. Such a trimming of the data set does not introduce a selection effect; that is, there is no bias toward environments of a given sort.

In our simulated spectroscopic data set of 2803 galaxies, ~15% of the sample are positioned within $r_e$, a survey edge using a cylindrical aperture of $r_e = 1 h^{-1}$ comoving Mpc. However, only for a scant ~3% of the sample did we find $\Delta C \neq 0$ when comparing measurements of $C$ made on the smaller simulation to those made on the wide-field sample. One possible means for salvaging some edge-affected galaxies would be to scale the measured counts in each aperture by the amount of the aperture contained within the survey area. Due to the low rate at which $C$ is perturbed by survey edges, however, such a correction actually causes an overestimate of $C$ for the majority of galaxies near the edge ($D_{\text{edge}} < r_e$) of the survey field.

5.3. Survey Edges and Voronoi Volumes

Due to the geometrical complexity of the Voronoi tessellation, understanding the effects of edges on the calculated Voronoi volumes is less straightforward than for the previously discussed density measures. For galaxies very close to exterior edges in the survey field, Voronoi volumes can be unbounded, and such galaxies should consequently be discarded from the sample. On a more subtle level, edge effects, including interior edges, will also cause volumes to be increased in size while the volumes still remain bounded. Some of these edge-affected volumes can be detected as having Voronoi vertices outside of the survey field. However, many other edge-affected Voronoi volumes are not detectable in such a manner.

As illustrated in Figure 6, even excluding galaxies located near a survey edge (e.g., within $2 h^{-1}$ comoving Mpc), the distribution of Voronoi volumes is still greatly affected by edges with a bias toward large volumes being pushed to even larger values (see Fig. 6). It is possible to minimize this effect by retaining only galaxies with $V$ below some limit. In our simulations, by truncating at $\log_{10}(V) = 3.1$, the amount of contamination due to edge effects can be reduced to approximately 20% of the sample with $\Delta_e(V) > 10%$. While making such cuts according to distance to the nearest edge ($D_{\text{edge}} > 2 h^{-1}$ comoving Mpc) and Voronoi volume ($\log_{10}(V) < 3.1$) effectively reduces the number of edge-affected galaxies in the sample, it also restricts the dynamic range of the Voronoi measure and considerably reduces the size of the sample. For our simulated spectroscopic sample of 2803 galaxies, the Voronoi volume density measure was the most dramatically affected by edges with $\geq 45%$ of the sample being corrupted, that is, having $\Delta_e(V) > 10%$.

5.4. Effects of Finite Redshift Range

As a secondary effect, the finite redshift range probed by any survey imposes edges in the line-of-sight direction. The role of these edges is more easily handled by restraining all scientific analysis to a limited, well-sampled range of redshifts. In the DEEP2 survey, the ability to measure redshifts at $z > 1.4$ or $z < 0.7$ decreases significantly as the [O II] emission-line doublet leaves the observed optical window. In a DEEP2-selected mock catalog, we find that by restricting our sample to those galaxies at $0.7 < z < 1.4$, less than 1% of the sample has a fifth-nearest neighbor distance, $D_5$, greater than the distance to the $z = 0.7$ or $z = 1.4$ edge. Similar contamination rates are found for the other environment estimators.

A second concern for spectroscopic redshift surveys is the possibility of missing redshifts over specific wavelength intervals, especially in the far-optical and near-infrared, where OH sky lines can dominate the spectrum. At $z \sim 1$, where optical surveys often rely on a singular spectral feature (e.g., the [O II] doublet at $\lambda_{\text{rest}} \sim 3727 \AA$) for redshift measurements, a hole in wavelength coverage translates directly into a hole in the survey’s redshift sampling. For the DEEP2 survey, the high-resolution ($R \sim 5000$) of the DEIMOS data minimizes this effect, as the sky lines are then narrower than the components and spacing of the [O II] doublet. In truth, the DEEP2 redshift distribution exhibits no significant cross-correlation with a sky spectrum mapped to redshift according to either the central wavelength of the [O II] doublet or the wavelengths of either subcomponent (J. A. Newman et al. 2005, in preparation). However, for lower resolution surveys such as the VVDS, windows of redshift insensitivity may be a concern that must be addressed in measuring galaxy densities.

6. REDSHIFT-SPACE DISTORTIONS

While spectroscopic redshift surveys are able to measure galaxy redshifts with great precision, redshift measurements by
nature are measurements of velocity and not distance. Accordingly, converting differences in redshift to relative line-of-sight distances is subject to the peculiar velocities of the galaxies. Such peculiar motions are greatest in dense regions such as groups or clusters where the velocity dispersion of the group causes the intermember spacing to be larger in redshift space than in real space. Due to this environmental dependency of redshift-space distortions, it is essential to understand the manner in which they affect a given galaxy density measure.

Within a mock DEEP2-selected spectroscopic galaxy catalog covering 120° × 90°, we compute each environment measure using both the real-space positions of the galaxies and the observed redshift-derived positions. Restraining our analysis to galaxies at edge distances greater than 4 h⁻¹ comoving Mpc and within the redshift range 0.7 < z < 1.4, we quantify the effect of redshift-space distortions on each environment estimator by calculating the change in each measure as computed on the real-space mock relative to the corresponding measure derived from the observed spectroscopic mock. As in § 5, we express the difference in a given environment measure as a fraction of the width of the real-space distribution for that environment measure. For example, the percent change in environment measure X for galaxy q is given by

$$\Delta_q(X) = \frac{\log_{10}(X_{q,g}) - \log_{10}(X_{q,a})}{\sigma_g} \times 100\%,$$  (2)

where $X_{q,g}$ is the measure of X for galaxy q computed from the redshift-derived position and $X_{q,a}$ is similarly computed from the real-space position. The width $\sigma_g$ is determined via a Gaussian fit to the logarithmic distribution of environment measure X for all galaxies in the real-space simulation. Here $\sigma_g$ can be measured on the real-space distribution of $\log_{10}(X')$ or the redshift-space distribution with negligible difference for the DEEP2-selected sample.

As illustrated in Figure 7, the Voronoi volume and the three-dimensional third- or fifth-nearest neighbor distances are similarly affected by redshift-space distortions. For each measure, the effects of redshift-space distortions are nonnegligible and, as shown in Figure 8, are greatest in overdense environments. In comparison to the V and three-dimensional $D_q$ measures, the counts in an aperture density estimator, C, and projected nth-nearest neighbor measure, $D_{p,n}$, are less affected by the “finger of God” due to their effective smoothing in the redshift direction; by definition, the projected estimators, C and $D_{p,n}$, satisfy sensitivity in the redshift direction, which reduces their susceptibility to redshift-space distortions. For nearly 80% of the sample, C is unaffected ($\Delta C = 0$) by peculiar motions when using a cylindrical aperture with a length of ±1000 km s⁻¹ and diameter of 1 h⁻¹ comoving Mpc. The sensitivity of C to redshift-space distortions is somewhat dependent on the choice of the aperture size in the line-of-sight direction such that a smaller aperture is more adversely affected. For more than 90% of galaxies in our sample, we find $|\Delta C| \leq 1$, again using an aperture with length of ±1000 km s⁻¹. Similar results are found for the projected nth-nearest neighbor distance measure; more than 80% of the sample meets the criterion $\Delta_q(D_{p,n}) \leq 5\%$ for $n = 3$ and 5 and using a velocity interval of ±1000 km s⁻¹ to exclude foreground and background sources.

7. TARGET SELECTION AND OBSERVATION

There are inevitable trade-offs between the number density of sources targeted for observation and the area of sky covered in a redshift survey. Clustering of high-redshift galaxies and fiber or slit collisions on multiobject spectrographs conspire to limit the fraction of target objects that a survey can observe at one time. Furthermore, not every object targeted will successfully yield a redshift, generally due to finite signal-to-noise ratios and instrumental effects.

The DEEP2 redshift survey will target ~50,000 galaxies covering 3.5 deg² of sky over 80 nights on the Keck II telescope (Davis et al. 2005; S. M. Faber et al. 2005, in preparation). This impressive survey, however, will only target approximately 60% of available high-redshift (0.7 < z < 1.4) galaxies in its four fields and successfully measure redshifts for about 75% of targeted galaxies.
studying large-scale structure and galaxy properties at high redshift. Thus, the survey design attempts to maximize the number of redshifts obtained, to sample the galaxy distribution over a broad range of length scales, and to minimize the effects of cosmic variance. Due to slit collisions on DEIMOS slit masks, the DEEP2 survey systematically undersamples regions of sky with a high surface density of galaxies (see Fig. 9). It is critical for a study of galaxy environments to understand how this bias may affect the environment measured used.

While the detailed effects of target selection and redshift incompleteness are clearly specific to each survey, the goal of this section is to understand how a given environment measure is affected by the limited sampling common to all deep redshift surveys. In this work, we adopt the DEEP2 survey as a representative high-redshift spectroscopic survey. As discussed in §2, the DEEP2 survey targets all galaxies at $R_{AB} \leq 24.1$ according to a probabilistic algorithm that preferentially selects high-$z$ galaxies. Applying the DEEP2 target-selection and slit-mask–making algorithms to a magnitude-limited ($R_{AB} \leq 24.1$) mock catalog covering $40' \times 30'$, the simulated survey targets and successfully measures redshifts for 2839 of the 5866 galaxies in the field and with $0.7 < z < 1.4$ (assuming a redshift success rate of $\sim 70\%$). To study the combined effects of target selection, slit-mask making, and redshift success, we compute each environment measure on the DEEP2-selected sample and on the full magnitude-limited sample.

As illustrated in Figure 10, the counts in an aperture measure, $C$, shows no indication of an environment-dependent bias in the DEEP2 target selection. If DEEP2 severely undersamples dense environments, then we would expect to see a saturation in the observed value of $C$ at high densities relative to the estimation of $C$ computed on the magnitude-limited sample. Instead, we find a linear relation extending to dense environments that follows the $\sim50\%$ overall completeness of the DEEP2-selected mock catalog.

Due to the fixed comoving aperture size of the counts in an aperture environment measure, the measure probes the same physical scale independent of how the targeted galaxies are selected. The $n$th-nearest neighbor distance measure, on the other hand, can sample systematically different effective scales depending on the galaxy sampling. As illustrated in Figure 11, within the observed spectroscopic sample, the fifth-nearest neighbor distance is roughly tracing the tenth-nearest neighbor distance in the magnitude-limited mock; this is sensible, as the DEEP2-selected mock samples $\sim50\%$ of galaxies and what was the tenth-nearest neighbor in the magnitude-limited sample will typically be the fifth in the DEEP2-selected sample. Similarly, the second- and third-nearest neighbor distances are effectively tracing the fourth- and sixth-nearest neighbor distances, respectively, in the magnitude-limited mock (see Fig. 11). While target selection and slit-mask making affect the scale on which the $n$th-nearest neighbor distance samples the galaxy distribution, they do so in a manner that does not depend on environment. Thus, while DEEP2 undersamples dense regions of sky, the survey does not undersample dense environments (see Fig. 12).

The limited galaxy sampling of the DEEP2 survey causes the calculated Voronoi volumes to be systematically larger than if computed on the full magnitude-limited sample. We find that the level to which a given Voronoi volume is affected by the DEEP2 sample selection does not depend on $V$ or redshift; the limited sampling of the DEEP2 survey simply introduces a random scatter toward larger volumes. Similar to $D_3$ and $C$, we see no evidence for an environment-dependent bias due to the DEEP2 target-selection procedures.

8. CORRECTING FOR THE SURVEY SELECTION FUNCTION

For any magnitude-limited survey, the fraction of total galaxies in a volume-limited sample within the magnitude limits varies (commonly decreasing) as a function of redshift. This variable sampling of the galaxy distribution as a function of redshift causes measurements of galaxy densities to depend strongly on $z$. For instance, if a survey undersamples at high redshift, then estimates of $D_3$ and $C$ at high $z$ will be artificially inflated relative to estimates at low $z$; similarly, $C$ will be underestimated at higher redshift. Often, magnitude-limited redshift surveys are trimmed to a volume-limited subsample to avoid these issues. At high redshift, however, this can dramatically reduce the sample size; for example, selecting a volume-limited subsample within a DEEP2-selected mock catalog excludes as many as $40\%$ of the observed galaxies. Furthermore, over regimes where luminosity evolution is significant ($\Delta_z \gtrsim 0.1$), even defining a volume-limited sample can be problematic.

To utilize the entire survey sample, or for surveys that do not follow a simple magnitude-limited target selection, the variations in the galaxy sampling rate with redshift may be quantified in terms of a survey selection function $s(z)$, with which density...
estimates (number of galaxies per comoving volume or number of galaxies per projected comoving area) may be corrected as follows:

$$X_0(\alpha, \delta, z) = \frac{X_f(\alpha, \delta, z)}{w(\alpha, \delta)},$$

where $X_f$ is the density estimate computed from the observed redshift distribution, $w$ is a two-dimensional survey completeness map that accounts for variation in redshift completeness from field to field within the survey, and $X_0$ is the corrected density estimate.

There are several ways to determine the selection function of a survey. The most common approach is to first estimate the galaxy luminosity function (LF) for all of the galaxies in the redshift survey, and then use it to predict the redshift distribution of the sample (e.g., Madgwick et al. 2003). However, unless evolution is correctly incorporated, the LF will not alone be able to correctly predict the redshift dependence of the observed number density of galaxies in a deep survey. Furthermore, working at high redshift, it becomes increasingly difficult to constrain the galaxy LF since observations are limited to the brightest sources, thereby making estimations of the characteristic luminosity, $M_\star(z)$, and faint-end slope, $\alpha(z)$, less secure (e.g., Willmer et al. 2005; Wolf et al. 2003; Bell et al. 2004). For this reason, the selection function for a survey is often estimated by smoothing the observed number density of galaxies, $n(z)$, as a function of redshift and then normalizing according to an assumed dependence of the comoving number density of galaxies on $z$ (e.g., Coil et al. 2004). This has the disadvantage that density inhomogeneities in the survey will somewhat affect the derived redshift distribution, even with large smoothing kernels, due to the strength of cosmic variance; also, kernels large enough to minimize this will distort real features in $n(z)$, especially where there are large gradients. On the other hand, any evolution in the observed number density of galaxies with $z$ will be automatically incorporated into the estimation of $s(z)$.

Yet another approach to estimating $s(z)$ is to compute an analytical fit to the observed data from which the selection function is then derived (e.g., M. C. Cooper et al. 2005 and S. M. Faber et al. 2005, both in preparation). Similar to a selection function estimated from smoothing the observed $n(z)$ distribution, an analytical fit to the data—the “fitting” method for estimating $s(z)$—is subject to cosmic variance, but to a much smaller degree than the “smoothing” method, as small-scale variations in $n(z)$ that do not match the model are not allowed.

In this work, we estimate the survey selection function for the mock DEEP2 survey according to four different prescriptions: (1) estimating $s(z)$ by smoothing the observed $n(z)$ distribution in a DEEP2-selected mock catalog ($120' \times 30'$) assuming no evolution in the comoving number density of galaxies with redshift, using a similar algorithm as Coil et al. (2004) (“smoothing” method), (2) fitting for the selection function assuming a functional form for the redshift dependence of the successfully observed $dn/dz$ and again assuming no evolution in the comoving number density of galaxies (“fitting” method), (3) determining the true selection function by computing the number density of available targets over many DEEP2 mock pointings relative to the volume-limited number density of galaxies in the mocks, and (4) deriving $s(z)$ from the conditional LF assumed in constructing the mock catalogs. This last approach is identical to the commonly used method of estimating the selection function using the measured LF and predicting the redshift distribution of the underlying galaxy population. Methods 1 and 2 are analogous to
methods one might use to derive $s(z)$ solely from the observational data in a deep redshift survey and are subject to cosmic variance and uncertainties in the assumed normalization and redshift dependence of the comoving number density of galaxies. Methods 3 and 4 are effectively identical and test that the mock catalogs are working as advertised.

In Figure 13 we present the mock selection functions derived using each of the methods described above. In general, the agreement between the different approaches for determining $s(z)$ is quite good. At the highest redshifts ($z > 1.0$), the different estimations of the selection function differ due to differences in the assumed comoving number density of galaxies. Methods 3 and 4 are effectively identical and test that the mock catalogs are working as advertised.

In Figure 13 we present the mock selection functions derived using each of the methods described above. In general, the agreement between the different approaches for determining $s(z)$ is quite good. At the highest redshifts ($z > 1.0$), the different estimations of the selection function differ due to differences in the assumed comoving number density of galaxies. Methods 3 and 4 are effectively identical and test that the mock catalogs are working as advertised.

The footprint of large-scale structure on a selection function derived from smoothing the observed DEEP2-selected mock $n(z)$ distribution is reduced if a large smoothing kernel is used; here we apply two successive smoothing windows of width $\Delta z = 0.15$. If the smoothing kernel is too small, the presence or absence of

![Graphs showing correlation between log(D_n) and log(D_o) for three different methods with correlation coefficients r = 0.875, r = 0.894, and r = 0.914 respectively.](image1)

![Graph showing distribution of available targets vs. observed targets for DEEP2.](image2)
structures such as filaments or walls (i.e., cosmic variance) will cause us to overestimate or underestimate the fraction of galaxies sampled at a given redshift. Accordingly, over- or underdensities of galaxies will be inappropriately reduced in amplitude when corrected by the survey selection function; e.g., the presence of a filament will push the measured $s(z)$ up at its redshift, reducing the corrected density measured, $X_0$, artificially. Any smoothing large enough to erase the effects of cosmic variance in a survey covering a few square degrees will, unfortunately, cause flattening in the shape of $s(z)$, especially near the limits of the redshift range probed. Due to the drawbacks of smoothing, fitting for the selection function as detailed above is often a superior method for estimating $s(z)$ from the observed data, but it does require assumptions about the form of $dN/dz$, which smoothing does not.

To study the effectiveness of correcting the measured galaxy densities by the factor of $1/s(z)$ (see eq. [3]), we have computed the projected seventh-nearest neighbor surface density, $\Sigma_7$, within a volume-limited mock catalog covering $120' \times 30'$ of sky. We then compare this to the projected third-nearest neighbor surface density, $\Sigma_3$, for those galaxies successfully observed in the DEEP2-selected sample. We then correct these “observed” $\Sigma_3$ values using each of the $s(z)$ shown in Figure 13, and also attempt an empirical correction. This correction is given by dividing each observed density value by the median $\Sigma_3$ for galaxies at that redshift where the median is computed in a bin of $\Delta z = 0.04$.

Correcting the measured densities in this manner converts the $\Sigma_3$ values into measures of overdensity relative to the median density and is similar to the methods employed by Hogg et al. (2003) and Blanton et al. (2005).

Figure 14 illustrates the effectiveness of each selection function at reproducing the redshift dependence of the galaxy density distribution as measured in the volume-limited sample. Within

| $s(z)$ | $\rho$ |
|--------|--------|
| Observed | 0.180 | 0.576 |
| Smoothing | 0.094 | 0.608 |
| Fitting | 0.083 | 0.603 |
| Mock CLF | 0.096 | 0.608 |
| z-dependence | 0.049 | 0.606 |

Notes.—For each determination of the selection function, we compute the Spearman ranked correlation coefficient $\rho$ between the corrected third-nearest neighbor surface density $\Sigma_3/s(z)$ measured in a DEEP2-selected mock catalog and the seventh-nearest neighbor surface density measured in a volume-limited sample. We also present the rms fluctuations for each relation plotted in Fig. 14 over the redshift range $z > 0.8$. Each of the selection functions improves the correlation $\rho$ between the measured environment within the DEEP2-selected sample and the “true” environment measured in the volume-limited sample; the empirical correction (z-dependence) has the smallest residual scatter with redshift (partially by construction).
redshift bins of $\Delta z = 0.02$, we compute the difference in median density between the corrected $\Sigma_5$ values and the median density $\Sigma_7$ of objects in the volume-limited sample. While each of the methods for estimating the survey selection function is an improvement over the uncorrected density distribution, an empirical correction (as described in the previous paragraph) that removes all $z$-dependence in the observed density distribution is at least as effective as correcting using a selection function (see Table 4).

9. DISCUSSION

Every environment measure that we have considered has its advantages and disadvantages. The counts in an aperture measure, $C$, lacks sensitivity in low-density environments, and while not lacking in dynamic range, it provides a noncontinuous (or quantized) measure of environment, a particular disadvantage if the typical value of $C$ is small. It is best suited for working in dense environments where $C$ is more robust to redshift-space distortions than other measures and for analyses in which one wishes to classify a sample into coarse density bins or classes. The counts in an aperture statistic is unique among the environment estimators tested in that it measures the galaxy density on a clearly defined, fixed length scale. In contrast, the projected and three-dimensional $n$th-nearest neighbor distance measures probe the radius enclosing some total number of galaxies and are not direct density measures. The $C$ parameter also provides a great advantage via its robustness to survey edge effects.

Similar to the counts in an aperture statistic, the projected $n$th-nearest neighbor distance measure is well suited for measuring density in groups and clusters. However, unlike $C$, the projected $D_{p,n}$ parameter provides a continuous estimate of galaxy density extending to underdense environments, where it still provides a reasonably accurate measure. While slightly more robust to edges than its three-dimensional counterpart, $D_n$, the projected $n$th-nearest neighbor distance is more prone to survey edge contamination than the counts in an aperture statistic. Figure 15 shows the correlation between $D_{p,3}$ and $C$ as computed in a $40' \times 30'$ simulated DEEP2 pointing. The saturation of $C$ in less-dense regions is striking and proves to be a significant drawback for a density estimator that is otherwise extremely robust to survey edges and redshift-space distortions.

The three-dimensional $n$th-nearest neighbor distance and Voronoi volume statistics are the best suited for measuring underdense environments. In groups and clusters, however, these density estimators are significantly affected by redshift-space distortions, causing each measure to become saturated. As illustrated in Figure 16, far removed from survey edges, the Voronoi volume and $D_5$ measures agree very well over all environments observed in the DEEP2-selected mock catalogs. However, for the simulated DEEP2 survey data, the $n$th-nearest neighbor distance is much more robust to edge effects and is less expensive to calculate.

For studies of environment at high redshift, including analysis in the DEEP2 survey, we conclude that among the environment measures tested the projected $n$th-nearest neighbor distance provides the most accurate estimate of local galaxy density over the broadest range of scales. For work in dense environments, $D_{p,n}$ offers great robustness to redshift-space distortions and maintains a reasonably high level of accuracy in underdense environments. While $D_{p,n}$ can be affected by survey edges, contamination
from geometric distortions is easily understood and effectively minimized without dramatically reducing the galaxy sample.

10. CONCLUSIONS

We have studied the applicability of several galaxy-density estimators within deep redshift surveys at \( z \sim 1 \) utilizing the mock galaxy catalogs of Yan et al. (2004). We conclude as follows:

1. Photometric redshifts derived from multiband photometry (\( \sigma_z \approx 0.02 \)) are not suitable for measuring galaxy densities. Current photometric redshift surveys such as COMBO-17 do not have the redshift precision needed to study environment at high redshift. While more costly to obtain, spectroscopic redshifts are requisite to accurately probe the local galaxy environment in a large survey.

2. With the exception of the counts in an aperture estimator, \( C \), survey field edges are a major source of contamination for each environment measure tested. To reduce these edge effects without biasing the sample, all galaxies within some comoving distance \( \sim 1-2 \ h^{-1} \) comoving Mpc for DEEP2) of a transverse survey edge should be rejected. At \( z \sim 1 \), excluding all galaxies within \( 1 \ h^{-1} \) comoving Mpc of an edge removes roughly 0.05% along each dimension of the survey field. For smaller high-redshift surveys, such as CFRS (Lilly et al. 1995) or CNOC2 (Yee et al. 2000), edge effects introduce contamination to a considerable portion of the survey data set, thereby limiting the statistical power of the samples. Likewise, for a survey of the GOODS-North field (Giavalisco et al. 2004), edge effects would bias density measurements over \( \sim 75\% \) of the field. Testing each environment measure on a simulated DEEP2-selected mock sample \( (40' \times 30') \), the Voronoi volume is most severely affected by edges, with more than 2 times as much contamination from edge effects than \( D_n \) or \( D_{n,0} \). The counts in an aperture measure displays the best behavior near edges of a survey field, with a nearly negligible portion of the sample contaminated in our simulations.

3. Redshift-space distortions are a significant and fundamental roadblock to measuring accurate galaxy densities in overdense environments. The \( n \)th-nearest neighbor distance measured in three dimensions and the Voronoi volume are most greatly affected, while estimators such as projected \( n \)th-nearest neighbor distance and counts in an aperture, which smooth the galaxy distribution along the line of sight, are less affected by the “finger of God.” Still, it should be noted that less than 15% of a simulated \( R_{AB} \leq 24.1 \) galaxy sample occupies environments at which the \( V \) and \( D_n \) statistics saturate due to redshift-space distortions.

4. The target selection algorithm employed by a survey could lead to environment-dependent biases in the observed galaxy sample. The DEEP2 survey, which slightly undersamples dense regions of sky, is equally sensitive at high and low densities. That is, we find that the DEEP2 survey equally samples all environments at \( z \sim 1 \) (see Fig. 12). Also, we find that while the DEEP2 survey samples only \( \sim 50\% \) of galaxies at \( z \sim 1 \), this uniform incompleteness simply introduces a random scatter in the measured environments and does not introduce an environment-dependence bias.

5. In examining the evolution of galaxy environments as a function of redshift, the estimation of the survey selection function plays a critical role. Uncertainties in the comoving number density of galaxies at high \( z \) make comparisons over large redshift intervals \( (\Delta z \sim 0.5) \) problematic. Apart from such ambiguities, simple empirical corrections for densities as a function of redshift are highly effective.

6. For the DEEP2 Galaxy Redshift Survey, the projected \( n \)th-nearest neighbor distance provides the most accurate estimate of local galaxy density over a continuous and broad range of scales. The \( D_{n,0} \) statistic is reasonably robust to redshift-space distortions and still effective at tracing galaxy environments in underdense regions.

7. Among current data sets at high redshift, we find that the DEEP2 Galaxy Redshift Survey provides the best opportunity for measuring accurate galaxy environments over a broad and continuous range of scales. The high sampling rate and excellent redshift-precision of DEEP2 enable environments to be measured in even the most overdense regions and yield improved accuracy over other deep surveys. Furthermore, DEEP2’s high-precision redshifts and large survey area (3.5 deg\(^2\)) minimize the effects of edges in both the transverse and line-of-sight directions.

We wish to thank Chris Marinoni for providing his Voronoi-Delaunay method group-finding code. This work was supported in part by NSF grant AST 00-71048. J. A. N. and D. S. M. acknowledge support by NASA through Hubble Fellowship grants HST-HF-01165.01-A and HST-HF-01163.01-A, respectively, awarded by the Space Telescope Science Institute, which is operated by AURA, Inc., under NASA contract NAS5-26555. B. F. G. acknowledges support from an NSF fellowship. M. C. C. thanks Mike Blanton for useful discussions about this work. M. C. C. also thanks Josh Simon and Alison Coil for careful reading of this manuscript and many insightful suggestions that have improved this work. Lastly, the authors are humbly indebted to Steve Dawson for his invaluable assistance with various technical aspects of this effort.

REFERENCES

Balogh, M. L., et al. 2004, MNRAS, 348, 1355
Bell, E. F., et al. 2004, ApJ, 608, 752
Beuing, J., Bender, R., Mendes de Oliveira, C., Thomas, D., & Maraston, C. 2002, A&A, 395, 431
Balogh, M. L., Morris, S. L., Yee, H. K. C., Carlberg, R. G., & Ellingson, E. 1998, ApJ, 504, L75
Balogh, M. L., Morris, S. L., Carlberg, R. G., & Ellingson, E. 1999, ApJ, 527, 54
Balogh, M. L., Schade, D., Morris, S. L., Yee, H. K. C., Carlberg, R. G., & Ellingson, E. 2005, ApJ, 527, 54
Figs. 16.—Correlation between Voronoi volume \( V \) and three-dimensional fifth-nearest neighbor distance \( D_5 \) measured on a DEEP2-selected mock field (120’ \times 30’). Here we restrict the plot to those galaxies far removed from any survey edges \((D_{edge} > 5 \ h^{-1} \text{comoving Mpc})\). Note that the \( D_5 \) values have been cubed to facilitate comparison to the Voronoi volumes. The Spearman ranked correlation coefficient, \( p = 0.85 \), quantifies the strong agreement between the different density estimators.
