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ABSTRACT

The use of baited remote underwater video to remotely observe fish and generate indices of relative abundance has steadily gained acceptance as a fisheries management tool particularly as survey time series have matured. Because 'capture' for this gear is visually derived, fish can possibly be counted multiple times and therefore different methods of estimating site abundances have been developed. We compared the performance of two video abundance estimation techniques, MaxN and MeanCount, by generating relative indices of abundance using a delta lognormal model. We demonstrated high correspondence between standardized indices produced through the years analyzed independent of the species evaluated, indicating there was little change in the information content between indices. Despite the agreement between the indices, estimates for proportion positive and coefficient of variation (CV) showed a general reduction in precision when using the MeanCount method for all species analyzed. Systematic underestimation of proportion positives and high CV values generated using MeanCount is problematic for the use of that abundance estimation method. Individual-based modeling results confirmed that MeanCount is linearly related to true abundance, while MaxN showed a power relationship. However, the MaxN estimate became linear as the area observed was increased in the model from 25% to 100%, which suggests that syncing cameras and generating counts over the entire observed area would eliminate the asymptotic relationship and simplify the use of MaxN estimators. Better understanding of catchability for optical type gears would enhance understanding of the relationship between the generated index and true population abundance, and supply assessment scientist with a clearer understanding of how to incorporate these types of survey data into assessments.

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1. Introduction

Video cameras have long been employed to sample reef fish where other capture gears such as traps, trawls, or hooked gears are limited by depth, selectivity, seafloor rugosity or fish behavior (Cappo et al., 2006). Video cameras are unlike many other survey gears in that data are a continuous stream and fish can potentially be observed (i.e. 'captured') many times during a single deployment and therefore can be recounted which artificially inflates abundance estimates. To avoid this, several abundance estimation methods have been developed for stationary-video surveys such as 'time at first occurrence', MaxCount, MaxN (also referred to as MinCount), and, most recently, MeanCount (Ellis and DeMartini, 1995; Priede and Merrett, 1996; Willis and Babcock, 2000; Watson et al., 2005; Merritt et al., 2011; Bacheler et al., 2013; Schobernd et al., 2014). In the southeast United States the use of fisheries-independent video-survey data in stock assessments has increased recently, particularly as survey time series have matured. For instance, three separate survey groups presented indices based on video-survey data at the most recent Gulf of Mexico (GOM) red snapper (*Lutjanus campechanus*) benchmark assessment (SEDAR, 2013), whereas the previous benchmark assessment included only

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one (SEDAR, 2004). Due to the increased use of video survey data for fisheries assessments, it is important to evaluate the properties of various methods used to estimate abundances from video.

The MaxN method is the most commonly used estimation method among various methods outlined above. MaxN is defined as the maximum number of individuals, of a particular species, that occurred in a single frame of a video read (Ellis and DeMartini, 1995). Therefore, MaxN represents a conservative estimate of the minimum number of individuals known to have been present in a sampling area over the course of filming. MaxN was developed out of the concern that summing counts over the course of a video (i.e. MaxCount) had an unknown probability of counting individuals more than once, and therefore, would artificially inflate abundance estimates (Cappo et al., 2006). Furthermore, if fish lengths were obtained from video in the same manner, the resultant length-frequency distributions would be similarly biased. Unless individuals can be effectively tracked over time and space, it becomes impossible to ensure multiple-counting is avoided.

The use of video-survey indices, like with any survey, requires investigation into the relationship between the calculated index and true population size. Usually, the biomass series created by a model is assumed to be linearly related to an index (Maunder and Starr, 2003). However, many fishery-dependent indices have shown nonlinear relationships (Bannerot and Austin, 1983; Harley et al., 2001; Hilborn and Walters, 1992; Erisman et al., 2014). These non-linear relationships between indices and population size can result in hyperstability where catch per unit effort (CPUE) trends remain constant, while population size is actually changing (Hilborn and Walters, 1992). For instance, in cases where fish spatially aggregate, CPUE can remain level while the population is actually declining, thereby masking true population trends (Colin et al., 2003; Erisman et al., 2011, 2014). Alternatively, a situation in which the gear cannot physically catch more individuals (i.e. gear saturation) would result in a level CPUE, despite increasing population sizes. For these reasons it is believed that the assumption of a constant catchability coefficient (q) is rarely met (Pope and Garrod, 1975).

A recent simulation experiment demonstrated that MaxN is nonlinearly related to true site abundance, and that at high levels of abundance it underestimates population size (Schobernd et al., 2014). Due to these concerns, the MeanCount estimation method was developed in conjunction with the video portion of the Southeast Fisheries-Independent Survey (SEFIS; Bacheler et al., 2013; Schobernd et al., 2014). MeanCount is estimated by taking counts over a series of individual video frames (either systematically or randomly selected), and then calculating the mean of those counts. Unlike MaxN that showed a power relationship with population size, the MeanCount method linearly tracked true abundance (Schobernd et al., 2014). The key reason that MeanCount was selected as the abundance metric for SEFIS lies in the linear relationship between the index and population size, and the assumption that stock assessment models require this relationship. While Schobernd et al. (2014) established that MaxN was nonlinearly related to population size, there was no explanation offered regarding the underlying mathematical properties. If there is a mathematical way to linearize MaxN, or to otherwise accommodate a nonlinear relationship, then that theoretical relationship needs investigation. Furthermore, methods could perhaps be identified that would alleviate the issue of nonlinearity if the specific relationship is driven by some other mechanism, such as gear efficiency.

The purpose of this investigation was to evaluate the performance of relative abundance indices created using the MaxN and MeanCount methods generated from the same data set. The National Marine Fisheries Service (NMFS) – Mississippi Laboratories (MS-Labs) Southeast Area Monitoring and Assessment Program (SEAMAP) reef fish video survey has a historical dataset that allowed calculation of both MaxN and MeanCount, and therefore was useful in this regard. This analysis was intended to reveal the potential tradeoffs between the various abundance metrics when calculating indices from video survey data. We also constructed and tested a spatially explicit individual-based model (IBM) to confirm the results of previous modeling efforts (Conn, 2011; Schobernd et al., 2014), and used the model to explore the underlying mechanisms driving the differing relationships between the two abundance metrics and true population size.

2. Methods

2.1. Sampling design

Mississippi Laboratories, which is part of the National Marine Fisheries Service – Southeast Fisheries Science Center (NMFS-SEFSC), has conducted an annual reef fish video survey of hard bottom habitats of the northern GOM since 1992 (Fig. 1). The survey uses a stratified-random sampling design in which samples are allocated to the proportion of reef contained in a strata and has sampled ~300 sites per year from ~1771 km^2 of known reef tract (i.e. mapped areas) – 1244 km^2 in the eastern GOM and 527 km^2 in the western GOM. The primary survey gear during the time span evaluated in this paper (1993–2007) was a baited array containing four orthogonally placed MiniDV cameras. At each sampling site the camera array was deployed for 40 min.

2.2. MaxN and mean count estimation

One video tape out of four possible from each station was randomly selected for viewing. Twenty minutes of the videos were viewed, starting from the time the view cleared of suspended sediment after impacting the seafloor. Viewers identified and enumerated all species that have federal management plans in place (FMP species) to the lowest taxonomic level during the 20 min viewable segment. Historically, videos were read for 60 min but an analysis of the impact of reducing read time to 20 min resulted in 68% conservation of taxa and only increased error by 5% for 32 taxa analyzed (Gledhill, 2001). Therefore read times were reduced to 20 min in 2001 to decrease video read times and produce usable data in a reasonable time frame for assessments. From 1993 to 2007, the time when each fish entered and left the field of view was recorded and this procedure was referred to as time in–time out (TITO). The extremely slow TITO method of reading videos created a five year backlog of work and was abandoned after 2007 in favor of estimating MaxN directly during the video read, vastly speeding up the process. From the TITO data we calculated a MaxN and a MeanCount for eight species, including scamp (*Myteroperca phenax*), red grouper (*Epinephelus morio*), gag (*M. microlepis*), vermilion snapper (*Rhomboplites aurorubens*), red snapper, gray snapper (*L. griseus*), almaco jack (*Seriola rivoliana*), and greater amberjack (*S. dumerilii*). These FMP species represent significant fisheries in the GOM and three behavioral types of fishes that may influence the relationship between relative (e.g. MaxN or MeanCount) and true abundance at a site. Snappers tend to loosely aggregate or school over reef and are generally active fish; groupers tend to hide within the reef and are more sedentary, and jacks tend to form small, active schools and are considered transient members of the reef assemblage.

Some videos were excluded from development and analysis of indices because various limitations either in design, implementation, or performance of gear caused issues with estimating counts. Data were dropped from analyses when videos were unable to be viewed due to any one of the following: (1) obstructions, (2) low

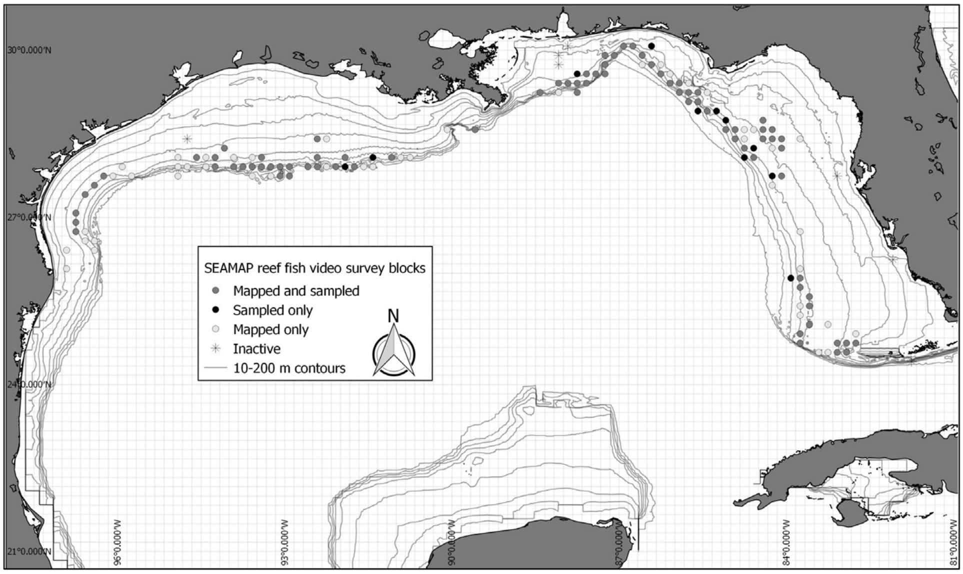

Fig. 1. Southeast Area Mapping and Assessment Program (SEAMAP) reef fish video survey sample blocks located in the Gulf of Mexico.

light level, (3) backlighting, (4) high turbidity, (5) out of focus, and (6) camera failure.

From the TITO data, we estimated the MaxN and MeanCount for each species at a given station. The MaxN method (Ellis and DeMartini, 1995) evaluated every single frame of the video and integrated that information into a single count following the procedures that have historically been used in MS-Labs survey under a different name, MinCount (Gledhill et al., 2005). MeanCount was estimated by systematically subsampling the same TITO data at three snapshot intervals (15, 30, or 60 s) (Conn, 2011; Schobernd et al., 2014). Those three intervals resulted in three sample sizes (81, 41, and 21) for the associated MeanCount at a station. Each subsample can therefore be thought of as a snapshot of the video at that moment. Therefore, MeanCount evaluated the information as a series of snapshots, but did not integrate that information over every possible frame of the video (i.e. frames between intervals are not evaluated).

2.3. *Calculation of relative abundance indices*

Delta-lognormal models (Lo et al., 1992) were used to estimate relative abundance indices for the eight species. This is the standard method that has been used by several video survey groups in the southeast, including two NMFS-SEFSC laboratories (MS-Labs and Panama City) and the Florida Wildlife Research Institute (FWRI), to calculate relative abundance indices. The main advantage of using the delta-lognormal method is allowance for the probability of zero catch (Ortiz et al., 2000). The index computed by this method is the product of yearly abundance estimates from two generalized linear models: a binomial (logistic) model that describes the proportion of positive abundance values (i.e. presence/absence) and a lognormal model that describes variability in only the non-zero abundance data (Lo et al., 1992). The delta-lognormal index of relative abundance (I_y) as described by Lo et al. (1992) was estimated as:

$$I_y = c_y p_y \tag{1}$$

where c_y is the estimate of mean CPUE for positive catches for year y, and p_y is the estimate of mean probability of occurrence during year y. Both c_y and p_y were estimated using generalized linear models. Data used to estimate abundance for positive catches (c) and probability of occurrence (p) were assumed to have a lognormal distribution and a binomial distribution, respectively, and modeled using the following equations:

$$\ln(c) = X\beta + \varepsilon \tag{2}$$

and

$$p = \frac{e^{X\beta+\varepsilon}}{1 + e^{X\beta+\varepsilon}} \tag{3}$$

where c is a vector of the positive catch data, p is a vector of the presence/absence data, X is the design matrix for main effects, β is the parameter vector for main effects, and ε is a vector of errors. Lognormal model errors are normally distributed with expectation zero and variance σ^2 whereas probability of occurrence is binomially distributed. Therefore, c_y and p_y were estimated as least-squares means for each year along with their corresponding standard errors, SE(c_y) and SE(p_y), respectively. From these estimates, I_y was calculated, as in Eq. (1), and its variance calculated as:

$$C(I_y) \approx \sim V(c_y)p_y^2 + c_y^2 V(p_y) + 2c_y p_y Cov(c, p) \tag{4}$$

where

$$Cov(c, p) \approx \rho_{c,p} \left\lfloor SE(c_y) SE(p_y) \right\rfloor \tag{5}$$

and $\rho_{\mathrm{c,p}}$ denotes correlation of c and p among years. In all cases, the only variable included in the submodels was year (2001–2007). Proportion positives (i.e. number of positive stations/number of total stations), index estimates and coefficient of variation (CV) were calculated in SAS (version 9.4).

2.4. *Individual-based model*

An IBM was constructed that simulated the movement of fish on a two-dimensional spatial grid with a camera placed in the center of the grid. The spatial grid consisted of 2500 cells, each measuring 1 m side^{-1}, making the domain 50 m^2. Spatial cells were denoted as either outside or inside the focal distance of the camera array (5 m). Individuals initially moved toward the set of cells within the focal distance of the camera which was defined by a 5 m radius around the center of the central cell (i.e. the camera location). This behavior simulates initial investigation of the camera following deployment. Each individual was tracked in x–y continuous space as their distance in meters from the lower left corner of the grid.

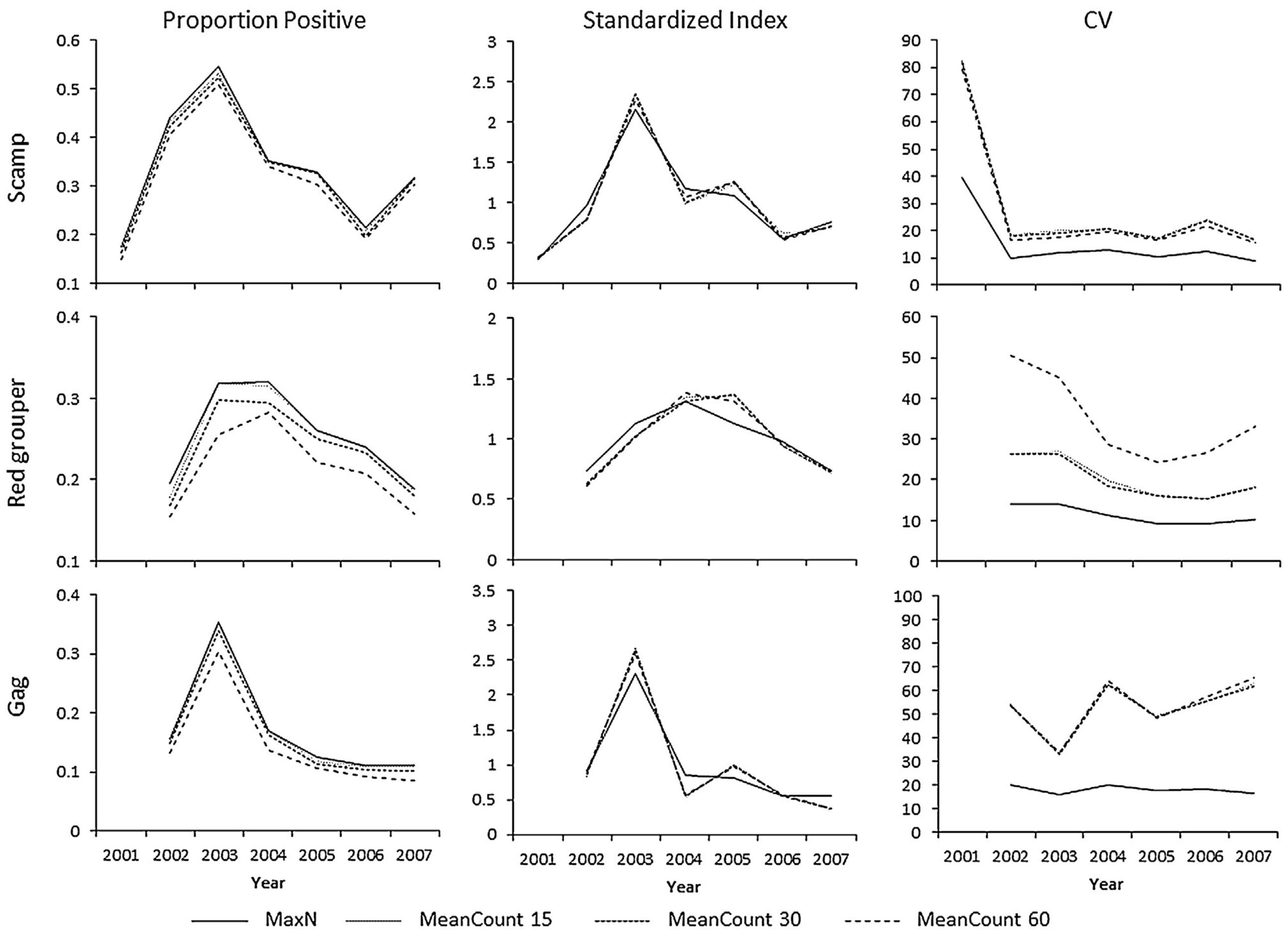

Fig. 2. Proportion positive, standardized index, and coefficient of variation (CV) for three grouper species calculated using MaxN and three MeanCount levels taken at 15-, 30-, and 60-s intervals.

For each minute of a 60 min simulation, the *x* and *y* positions of each individual were incremented, and their cell location updated using procedures similar to fitness-based movement (Campbell et al., 2011). After reaching the camera cells, movement was determined by randomly selecting a cell within a nine-cell neighborhood to move toward, while at the same time allowing the position of the fish to remain constant if the current cell position was chosen. While moving toward either a camera cell or a randomly selected cell, we introduced randomness into both the trajectory and speed of the individual. First we calculated a trajectory in radians (θ), randomly adjusted the trajectory ±0.5 radians, and adjusted the angle for any negative signs that were lost with the absolute values. The *x*-axis and *y*-axis positions were then updated for the individual based on θ, and we estimated movement in meters per second using red snapper as a model fish. Distance also included a random component, which added ±0.3 m to the average movement distance. If the individual's calculated movement resulted in an off-grid position, then the individual was moved away from the border the exact distance but in the opposite direction. Therefore, after reaching the camera cells, the fish randomly dispersed back over the grid throughout the remaining time steps which simulated fish losing interest in the novel item in the environment over time. In total the movement rules created an initial pulse of fish movement toward the camera cells followed by slow dispersal back over the grid.

With each time step of the model, we calculated the number of fish within the focal distance of the camera and summed those counts over the desired cells. Those values then were used to calculate MaxN and MeanCount as outlined previously. We ran four iterations of the model, in which the focal area included 25%, 50%, 75%, or 100% of the available cells surrounding the camera. This 25% area model run simulated the MS-Labs camera array setup which deployed four orthogonally placed cameras but only read a single camera at a station. Therefore, the percentage of the viewable area simulated in the subsequent iterations of the model roughly approximated increasing from a single camera read to reading all four cameras from a deployment. Eight simulations were run for eight levels of abundance (2, 5, 10, 25, 50, 100, 200, and 300). Model code was written in an editing program and then compiled using GFortran software (version 4.7). Model output was then evaluated and plotted in R (version 3.1.0).

3. Results

The delta-lognormal method index estimation output showed that MeanCount underestimated the nominal proportion positive values in comparison to MaxN for all species. Increasing the MeanCount interval resulted in increasing underestimation of proportion positive. Species that tend to move very little, such as groupers, were less prone to this underestimation (Fig. 2), while more mobile species magnified this issue (Figs. 3 and 4). Underestimation of proportion positive was particularly evident for the highly mobile schooling species such as vermilion snapper, greater amberjack, and almaco jack.

Relative abundance trends were highly similar, regardless of the metric used. Standardized index values and trends were similar

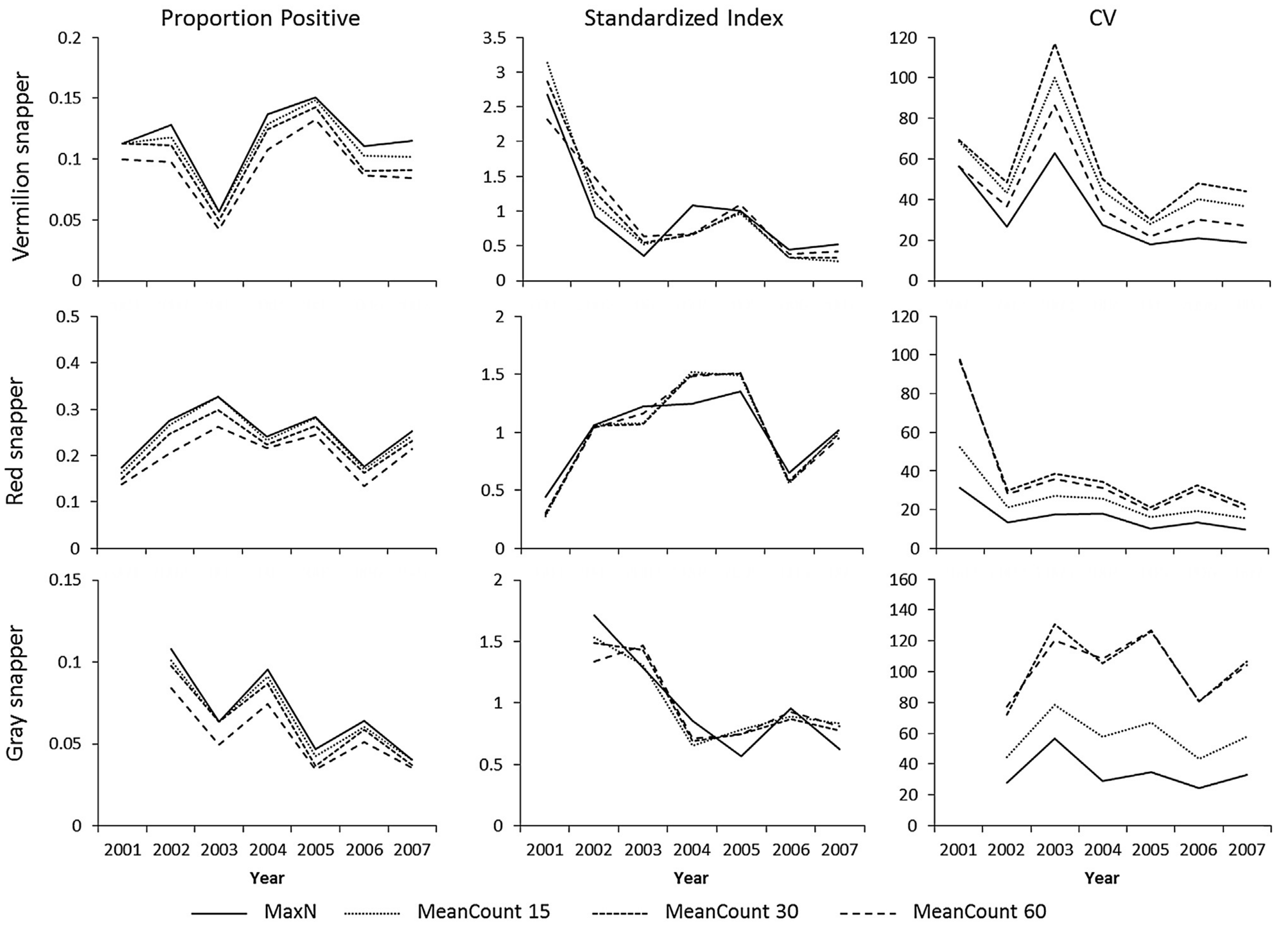

Fig. 3. Proportion positive, standardized index, and coefficient of variation (CV) for three snapper species calculated using MaxN and three MeanCount levels taken at 15-, 30-, and 60-s intervals.

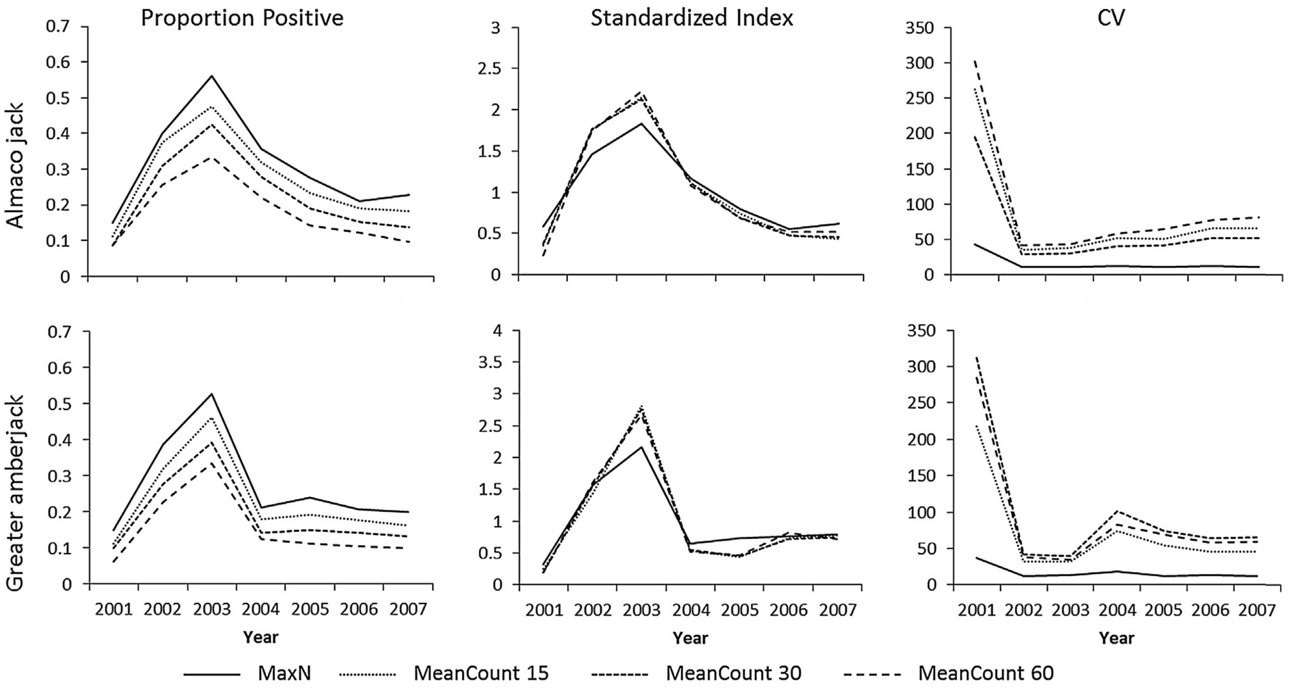

Fig. 4. Proportion positive, standardized index, and coefficient of variation (CV) for two jack species calculated using MaxN and three levels of MeanCount taken at 15-, 30-, and 60-s intervals.

Table 1
Average nominal MaxN count of the positive catch for eight federally managed species from the Gulf of Mexico observed during the Southeast Area Monitoring and Assessment (SEAMAP) reef fish survey pooled over 2001–2007.

Species	Average nominal MaxN	Standard error	Positive Stations	Total stations
Scamp	3.67	0.09	1870	2412
Red grouper	1.29	0.02	1190	2332
Gag	1.6	0.04	584	2332
Vermilion snapper	15.9	0.73	1004	2412
Red snapper	3.37	0.10	1444	2412
Gray snapper	4.37	0.29	499	2332
Almaco jack	2.53	0.12	1341	2412
Greater amberjack	3.28	0.15	1288	2412

between MaxN and MeanCount regardless of the species being evaluated (Figs. 2–4). The MeanCount estimator would predict nearly exact values and trends regardless of snapshot interval used while the MaxN was only slightly different. The frequency distributions of the video counts are likely Poisson or negative-binomial (Hall, 2000; Guenther et al., 2014), should not be considered normally distributed, and should minimally be log-transformed before being used to calculate a relative abundance index. Due to the use and acceptance of the delta-lognormal models in previous assessments conducted by the SEFSC we chose to only use and present those models here. However future indices may utilize other error distributions. The positive count data (i.e. exclusion of zeros) had average nominal MaxN values <5 for most species except vermilion snapper (Table 1). Furthermore, all of the count frequencies were left-skewed, indicating that in general on any given drop the camera is likely going to view few individuals.

Although index values and trends were similar between MaxN and MeanCount, the associated CVs of MeanCount were highly inflated compared to those of the MaxN (Figs. 2–4, Table 2). Increasing the interval of the MeanCount snapshot did not show consistent trends in CV performance across species like the proportion positive did. However, in general, the 30- and 60-s intervals produced the highest values. The highest CVs were usually associated with the 2001 survey, coinciding with the lowest sample size in the years evaluated and not an unexpected result. During 2001, only half of the survey was completed due to vessel issues. However, even in the years with stable sample sizes (2002+) MeanCount was not as precise as MaxN as measured by CV.

Results from a spatially explicit IBM that simulated a single camera read (25% efficiency) indicated that MeanCount has a positive, linear relationship, to simulated abundance. MaxN also showed a significant linear response at the 25% efficiency level (Fig. 5). However, a power relationship with increasing simulation abundance showed better fit to the data (linear fit $r^2 = 0.93$, power fit $r^2 = 0.99$). The asymptotic property of MaxN abated as the percent efficiency increased from 25% to 100%, simulating increasing from one to four camera reads. The 75% and 100% efficiency model runs showed positive, linear responses to true abundance.

Table 2
Percent inflation of coefficient of variation estimates for Mean15, Mean30, and Mean60 index runs relative to MaxN indices by species.

Species	Mean15	Mean30	Mean60
Vermilion snapper	56.3	76.0	26.9
Scamp	88.0	85.4	76.4
Almaco jack	410.8	295.5	497.9
Greater amberjack	320.1	485.5	425.7
Red snapper	56.5	143.2	131.4
Red porgy	66.7	72.5	72.0
Red grouper	80.2	76.4	204.9
Gray triggerfish	190.2	187.0	103.1
Gray snapper	69.2	202.2	200.5
Gag	193.0	189.1	195.7

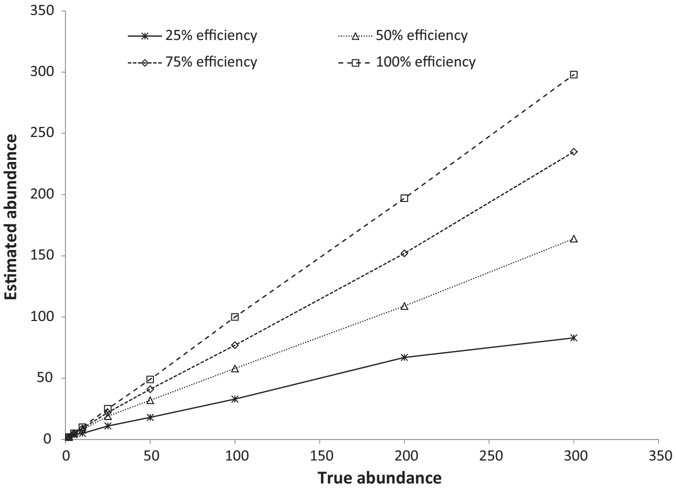

Fig. 5. Theoretical functional responses between population size and MaxN (power relationship) at four levels of camera efficiency (25%, 50%, 75%, and 100%) corresponding to increasing the number of cameras read from one camera pointed in a single direction to four cameras mounted orthogonally (i.e. increasing the area filmed and counted by the camera).

4. Discussion

Based on our results, MeanCount routinely underestimated proportion positive values relative to MaxN, and the magnitude of underestimation increased as the interval between observed snapshots increased. This result indicates that MeanCount systematically underestimates the presence of a species at any given sampling site, and overall in a given survey year. A major concern with using MeanCount abundance estimation is that the binomial portion of the delta-lognormal model underestimates proportion positives and inflates the occurrence of zero observations. This characteristic of MeanCount was not surprising given that the method excludes large sections of video and the likelihood of observing an individual on a video is reduced as the interval increases. This particular result was very strong in schooling species, such as the jacks and vermilion snapper, but was also apparent in less transient species like red snapper, gag and red grouper. Read intervals of 15 s appeared to be more robust than 30 or 60 s. However, even for the lowest interval, proportion positive was still underestimated for the jacks by ~10%. Standardized index values are calculated as the product of the mean CPUE for positive catches and the estimate of mean probability of occurrence during a given year, so underestimation of the proportion positive would ultimately result in a biased index value. The magnitude of error in the positive catch information would depend on whether the count missed an individual or an entire school of fish (i.e. information content would be unknown in these situations).

In addition to concerns with underestimating the proportion positive, MeanCount generated indices were less precise (i.e. high CVs) than did corresponding MaxN indices, a result that corroborates another study on the topic (Bacheler and Shertzer, 2015). The degree of CV inflation was species dependent, and was also impacted by the interval at which the MeanCount read was calculated (e.g. 15, 30, or 60 s), with a general reduction in precision as the number of frames read decreased. Unlike the proportion positives estimates, CV values did not systematically degrade in precision, but generally the 30- and 60-s read intervals were the least precise. We believe this inconsistency is related to the information content that is lost when proportion positives are underestimated. Exclusion of counts that normally would have contributed to the standardized index reduces sample size, and if proportion positives are already low, the result is increased variability and generally unstable estimates. Indices with high CV estimates indicate poor precision, which results in less confidence about the index, and are of reduced utility in an assessment model, particularly if higher precision indices are available. This is important because the Stock Synthesis models (Methot and Wetzel, 2013) currently used in SEFSC stock assessments use index CV as a measure of precision and assessment personnel can optionally exclude or down-weight indices with high CV values. Furthermore, any artificial tightening of CVs may result in risking introduction of spurious information into the assessment model. The way to reduce high CVs is to increase the number of samples in a survey, and given present resources (i.e. money, crew, vessel time, and video read time) this is not possible for the SEAMAP reef fish video survey conducted in the Gulf of Mexico. Further, current models used for index development treat MeanCount as a single value rather than an average of subsamples with an associated measure of variation. It is unclear whether this is entirely appropriate, and we recommend the exploration of more complex analytical models that incorporate both within-site (i.e. subsampled video) and between-site variability in a two-stage design.

The count data obtained by stationary video cameras, where individuals may be repeatedly observed, cannot be treated the same as catch data obtained by either passive (e.g. longlines, traps) or active capture gears (e.g. trawls) where individuals can only be captured once. Abundances derived from video observations should be conservative and insure that individuals are not counted more than once (Lyle et al., 2007). The MeanCount and MaxN methods both prevent over counting. However, the former inflates the number of zero observations. As demonstrated, the underestimation of proportion positives could have an impact on the estimation of population abundance which is dependent on both local size abundance and the range of geographic distribution. For many species, geographic range expands and contracts in conjunction with population growth and collapse, respectively (Lluch-Belda et al., 1989, 1992; Swain and Wade, 1993; Swain and Sinclair, 1994; Swain and Morin, 1996; Gledhill and Lyczkowski-Shultz, 2000; Rodríguez-Sánchez et al., 2002). Concomitantly, there may be little change in abundance at the center of the population distribution. If an increase in population size is only reflected in an increase in the number of individuals at sites already occupied, then these changes would likely not be detectible via MaxN once population size reaches a level where the relationship between MaxN and population size is not linear. However, if an increase in population size results in expansion into secondary habitats, perhaps at lower abundances, then the MeanCount, with its tendency to underestimate proportion positive, might result in poor estimation of population expansions and contractions. There is an obvious need to investigate this aspect of population dynamics from field observations to be certain about the tradeoffs, especially because it is likely that managed reef fish species exhibit both of these functional responses to changes in population size. Regardless, if the proportion positive sub-model is incorrectly estimated, the positive catch sub-model is clearly affected.

Usually the biomass series created by a model is assumed to be linearly related to an index (Maunder and Starr, 2003), as has been theoretically demonstrated with the MeanCount (Conn, 2011) and confirmed by the spatially explicit IBM output presented here. An index is calculated as the product of catchability and biomass ($I_y = qB_y$). An alternative to modeling the relationship between biomass and the index as a linear function would be to model it as a power function. The stock synthesis model, which is the current model used in GOM assessments, has a built-in method to incorporate power functions for the index-biomass-catchability relationship, therefore deviations from linearity can be dealt with as long as the functional relationship and associated coefficients can be established (Methot and Wetzel, 2013). If the linear relationship between MeanCount and absolute abundance established in Conn (2011) is true, then the deviation from that established linear relationship shown for MaxN type indices can be used to model that non-linear functional response. While estimating this aforementioned relationship is not a trivial process, Stock Synthesis can incorporate nonlinear relationships between indices and biomass, if that can be accomplished then precision of the index might be a more critical issue when estimating relative abundance indices.

The non-linear aspect of the MaxN relative abundance metric largely resulted from the spatial distribution of fish around the camera. At low abundances (2–10) the likelihood that all of the individuals in the spatial area end up in front of a single camera at some point during a video read increases. Alternatively, at high abundances the spatial distributions about the camera are maintained such that it becomes increasingly rare for all individuals to be located in front of a single camera simultaneously, which results in the asymptotic property of the MaxN estimate. As we increased the total amount of observed area around the camera from 25% to 100% the relationship between MaxN and true abundance became linear, indicating that the likelihood of observing all the fish in a defined area improved as we became more efficient. This result suggests that nonlinearity of the MaxN estimate could also be dealt with by reading all four cameras at each site simultaneously, assuming that all cameras were time synced. This was tested using a jack-like behavioral response to the camera and needs to be evaluated under field conditions as well. Currently, several companies are producing cameras with either 360° or complete spherical fields of view which could be used to generate counts and also allow for tracking individuals explicitly through time and space. Minimally, 360° or spherical views would allow for field investigations of the properties demonstrated in the IBM modeling. This solution would potentially increase workload by 4× thus an analytical solution to the issue might be more appropriate than increasing the area observed on camera.

Both theoretical models investigating the relationship between video count data and population abundance made the simplifying assumption that movement is either a completely, or in part, random process with little regard for behavior. Despite this simplifying assumption, it is likely that probability of detection changes through time, is species specific, is influenced by behavior, and is also dependent upon abundance/density at a site. In the SEAMAP reef fish video survey, carangids (*Seriola* spp.), which frequently occur in large schools, are commonly observed to investigate the camera when it is first dropped, but only remain around it for short periods of time. So, the likelihood of getting the same count for a carangid early and later in a video read is not equivalent. For groupers and similar sedentary species, their behavioral traits require that the temporal autocorrelation among the subsampled video must be accounted for because the counts cannot be relied upon to be independent samples of the local population and it is therefore highly likely that the same individuals are being observed many times over. The properties of both the MaxN and MeanCount need to be evaluated in the context of species specific behavior, and community dynamics and ecology. Our investigation demonstrated that proportion positive is underestimated for commonly observed species, and the implications of this underestimation would be amplified for rare species, subsequently resulting in underestimation of diversity metrics.

Given the properties of both methods, we contend that the MaxN (MinCount) is preferable over MeanCount for several reasons. Although MaxN indices vary nonlinearly with true site abundances, the average observed abundances for most species are well below the point where nonlinearity becomes a concern, and even then, it may be possible to account for nonlinearity using modern stock assessment methods. The additional work required to account for potential non-linear relationships is justified because of the significantly increased precision offered by MaxN indices. Within the Gulf of Mexico three cooperative groups that provide survey data to SEDAR recently combined data sets to maximize spatial coverage and this cooperative work was possible because all three groups are conducting surveys in identical fashion, including using the MaxN (MeanCount) method (Campbell et al., 2014; DeVries et al., 2014; Guenther et al., 2014). Precision of the data is of much higher concern, in particular the considerable underestimation of proportion positives and high CV values generated using the MeanCount methods. Given that the process to get video data from the survey into a data set is an intensive, time consuming effort, adopting a read strategy that would result in similar index trends but with less precision, and therefore less confidence in trends, is not preferred. Perhaps in future years as automated recognition of fish species and video reads becomes a reality, some of these issues could be resolved and multiple types of counts and resultant indices produced. Further work on the spatial IBM will help determine the functional relationship between MaxN and abundance, and future model runs should include species specific behavioral aspects.

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