

## **Anonymous Referee #2**

*This paper uses high-frequency spatial and temporal glider data to quantify variability at the coastal San Pedro Ocean Time-series (SPOT) site in the San Pedro Channel (SPC) and provide insight into the underlying oceanographic dynamics for the site.*

*The glider data (a total of 1606 profiles) collected from March through July of 2013 and 2014 are used. This is a very rich data set and a detailed analysis is well justified for a publication. However, the manuscript in its current form is very difficult to read and follow. PCA is used to differentiate different profile types. It is confusing how the 54 end-member profiles are selected to define each of four dominant profile types, and then the remaining 1552 profiles are then projected onto the PC1 and PC2 coordinates. Maybe a more detailed description of the methodology is needed in the supplemental information.*

To address the overall concerns raised by the Reviewer, we have edited the text to clarify the methods, added additional analyses, and included a comparison between the glider data and ship-based SPOT measurements. To address the specific concern regarding the selection of the end-member profiles, we have added in an expanded methodology to clarify the way in which the main modes of variability (end-members) were identified and how the PCA analysis was conducted (*see Extended Methods attached at the end of this response*).

*Time series are mentioned as the motivation of this paper, although the SPOT data are not used in the analysis. Both weekly and monthly time scales are mentioned in the text, what is the time interval for the SPOT measurements? It is not true "most time-series are sampled ... approximately once per month. Many time series use mooring platforms collecting data every few minutes.*

We have clarified the text to highlight our goal of using high-resolution data-sets to provide context for time-series with low sampling frequency. We have also added a comparison between the glider profiles and both ship-based SPOT data from 2000-2011 and data from a set of cruises (UpRISEE) which occurred during the time of the glider deployments (2013-2014).

*p2, end of the 1st paragraph, "...at an individual site relative to a larger region may provide a path for leveraging numerous local time series sites in order to gain an understanding of larger scale oceanographic dynamics." What is the spatial scale for this "larger" region/scale? Maybe the SPOT time series can be used to quantify this spatial scale.*

We see this analysis as a proof of concept study of using high resolution glider data to determine whether coarse-resolution (monthly) sampling at a single point location is sufficient for capturing the variability within a larger (very dynamic) region. Here we use the SPOT time-series site as the point location and the San Pedro Channel as the larger region. However, based on previous work, we believe that the San Pedro Channel is in general representative of the larger Southern California Bight (e.g., Cullen and Eppley, 1981; Collins et al., 2011; Chow et al., 2013). The spatial scale for the 'larger' region will, however, be entirely site dependent and so we do not feel that our study is able to make a generalization on the larger spatial scale which can be

represented by time-series sites. However, we do feel that our framework could be applied to other sites in order to answer this question.

*p2, 2nd paragraph, "cloud contamination" is not mentioned as the primary reason to have limited coverage.*

We have edited the text to include cloud contamination as a primary limitation of satellite measurements.

*"coastal and offshore processes", define "coastal" and "offshore"*

*It seems arbitrary to have the four dominant water column profile types: early upwelling, surface phytoplankton bloom, subsurface chlorophyll maximum, and offshore influence. Again define "offshore" here. Should the wind forcing be used?*

We have edited the text to clarify our terminology and choice of end-member water column profile types. In addition, we have included an extended methods section providing additional detail on our methodology (*see Extended Methods attached at the end of this response*).

*p5, satellite data are mentioned, but should be used more to study the surface and subsurface linkage*

A large body of literature has commented on the relationship between satellite observable chlorophyll (within the first optical depth) and total integrated water column chlorophyll, as well as the need for increased *in situ* sampling to improve satellite chlorophyll and primary production algorithms due to mismatches and inconsistencies in modeling of the *in situ* chlorophyll profiles (e.g., Morel and Berthon, 1989; Stramska and Stramski, 2005; Sathyendranath et al., 1989; Montes-Hugo et al., 2009; Jacox et al., 2015; Seegers et al., 2015). Locally, while satellite surface chlorophyll estimates have been shown to aligned closely with *in situ* glider observations of nearshore surface blooms in the San Pedro Channel, subsurface chlorophyll layers farther offshore were undetected by satellite retrievals (Seegers et al., 2015). Here, we used our framework to identify which oceanographic states for the SPOT site may be most susceptible to satellite misinterpretation. We specifically avoided interpretation of the mismatch between the glider and satellite chlorophyll estimates for a number of reasons. Primarily, we do not find this mismatch surprising given the differences in temporal and spatial scales of these two measurements. Specifically, the glider data were collected at ~0.5km resolution continuously over 24 hours through the deployment while the satellite measurements represent a single pass every 1 to 2 days in the afternoon and averaged over 1 km (Esaias et al., 1998). Furthermore, inaccuracies in the CDOM corrections and atmospheric corrections could also contribute to the observed mismatch (Esaias et al., 1998; Hoge et al., 1999; Wang et al., 2009). We do not feel that our dataset or analysis is the correct one to evaluate the robustness of the MODIS product for the San Pedro Channel.

We believe the important take-away from this part of our analysis is that the inherent bias in satellite data of only quantifying chlorophyll over the first optical depth is not a significant issue

for samples with high PC2 values and low overall biomass. However, it becomes an increasingly important issue for samples with high biomass and low PC2 values, which have a large percentage of integrated chlorophyll beneath the first optical depth. Specifically, the sub-surface chlorophyll profiles for these samples deviate significantly from the traditional relationship between chlorophyll within OD1 and total integrated chlorophyll. The structured PCA framework provides a metric for assessing the water mass types that may be most problematic for the satellite algorithms. Specifically, our analysis suggests that the satellite vs integrated chlorophyll mismatch may be particularly problematic for some cool, high chlorophyll water mass types (nominally coastal blooms). This suggests that increased *in situ* sampling may be needed when these water mass types are present in order to accurately constrain estimates of biomass distributions and primary production. We have edited the text and Figure 7 to clarify our incorporation of satellite data into our analyses.

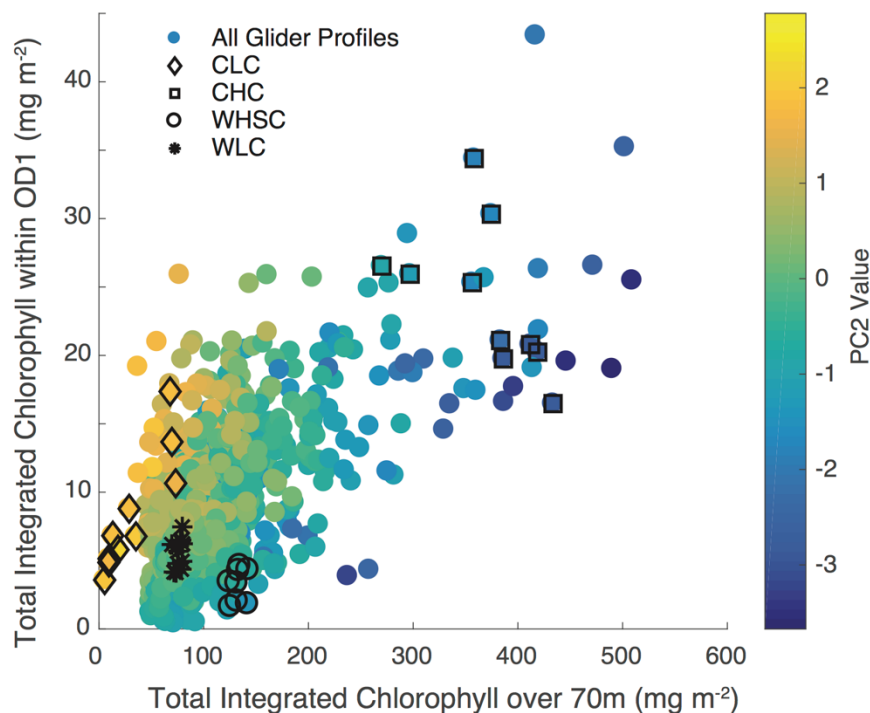


Figure 7: Integrated chlorophyll within the first optical depth (OD1) versus total integrated chlorophyll over 70 m for all 2013 and 2014 glider profiles. Each profile is colored by its PC2 value. The location of the four end-member profile types are also shown.

*p12, 5. Conclusion, end of the 1st paragraph, "...insensitive to coastal anthropogenic change...well positioned to identify a regional response to climate change." how do you derive such a conclusion?*

In the big picture, the SPOT time-series site is a coastal site. However, our analysis indicates that SPOT is more reflective of the offshore stratified environment rather than the near-

coastal upwelling environment where coastal discharge (outfalls and storm water) are a more significant factor. As such, we conclude that SPOT is more likely to be influenced by regional responses to climatic shifts than to local events (e.g. increased discharge into the port of Los Angeles). We have edited the text to clarify this point.

*Table 1, define "SPOT specific profiles", "SPOT samples", what is CI? C2*

We have expanded Table 1 to include an analysis of the ship-based SPOT measurements (see attached revised Table 1) and edited the caption to clarify the contents of the table.

*Figure 1, I understand the color represents bathymetry, why don't you state this in the caption?*

We have edited the caption.

*Figure 2, what is the arrows mean below the figure, PC1, PC2? what does the "n=" mean?*

The PC1 and PC2 arrows indicate the separation of the end-member profiles on the PCA axes. For example, subsurface chl max was associated with high PC1 values while early upwelling was associated with low PC1 values. N refers to the number of glider profiles used to define these end-member profiles. We have edited the caption and text to clarify this.

*Figure 3, is "box plot" a more standard term than "whisker plot", see [https://en.wikipedia.org/wiki/Box\\_plot](https://en.wikipedia.org/wiki/Box_plot); define "bin"*

We have edited the caption.

*Supplemental Figure S2, define "ideal profiles"*

We have included an Extended Methods sections describing how the end-member profiles were defined. We have replaced 'ideal profiles' with 'end-member' profiles throughout the text.

Table 1: Distribution of profile types as estimated by the structured PCA. The number of profiles that fall within with each end-member group (95% confidence interval) is given (N, %) for: all glider profiles (all glider), glider profiles from the SPOT bin (SPOT glider), all ship-based SPOT profiles (SPOT cruise), ship-based SPOT profiles from the months that the gliders were in the water (SPOT cruise March-July), all UpRISEE ship-based profiles (UpRISEE cruise), and UpRISEE profiles from the months that the gliders were in the water (UpRISEE cruise March-July).

	All Glider Samples (March-July)		SPOT Glider Samples (March-July)		SPOT Cruise Samples (All Months)		SPOT Cruise Samples (March-July)		UpRISEE Cruise Samples (All Months)		UpRISEE Cruise Samples (March-July)	
	N	%	N	%	N	%	N	%	N	%	N	%
Total Sample Size	1606	--	54	--	64	--	30	--	21	--	14	--
Cold High-Chlorophyll	19	1.2%	1	1.8%	0	0.0%	0	0.0%	0	0.0%	0	0.0%
Warm Sub-surface High Chlorophyll	398	24.8%	14	25.9%	10	15.6%	2	6.6%	4	19.0%	3	21.4%
Warm Low-Chlorophyll	194	12.1%	5	9.3%	8	12.5%	4	13.3%	4	19.0%	3	21.4%
Cold Low-Chlorophyll	25	1.6%	0	0.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%
Not Within 95% C.I.	970	60.4%	34	63.0%	46	71.8%	24	80.0%	13	61.9%	8	57.1%

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and satellite remote sensing in southern California, *Limnology and Oceanography*, 60, 754-764, 10.1002/lno.10082, 2015.

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## Expanded Methods:

***Glider Data:*** After all glider data had been gridded onto the cross-channel glider transect and partial glider profiles had been removed, secondary profile metrics were calculated for each profile. For each profile, we estimated the euphotic depth following the regionally validated method described in Jacox et al. (2015), which utilizes in-situ chlorophyll profiles and satellite daily PAR data. For this study, we used 9 kilometer satellite surface PAR data from MODIS Aqua for all light profile calculations. Euphotic depths during the 2013 and 2014 glider deployments were in good agreement with those collected from *in situ* PAR measurements during the concurrent Upwelling Regime In-Situ Ecosystem Efficiency study (UpRISEE) cruises at the SPOT site (Haskell et al., 2016).

Temperature profiles were used to calculate the mixed layer depth (MLD), mixed layer temperature (MLTemp), and the depth of the 12.5°C isotherm (z12p5). Chlorophyll a fluorescence profiles were used to calculate the depth of the chlorophyll maximum (zMaxChl), the maximum value of chlorophyll a along the profile (maxCHL), the integrated chlorophyll a within the top 70 meters (ChlInt70), and the ratio of integrated chlorophyll a within the top 20 meters versus the top 70 meters (ChlInt70Per20). Twenty meters was used to approximate the average mixed layer depth and surface thickness. Seventy meters was chosen as the maximum depth of chlorophyll integration as it included the full euphotic depth for 99% of the glider profiles from 2013 and 2014. In addition, we estimated from the ship-based SPOT time-series data (2003 - 2011) that on average PAR at 70m was 2.6% of the surface value, with a maximum of 4.5%. Ideally integrated chlorophyll would always be calculated for the entire euphotic zone, however here we were constrained to the upper 70 m due to the dive depth of the gliders.

***Principal Component Analysis (PCA):*** All glider profiles from 2013 and 2014 were combined into a single PCA after normalization and standardization of the 7 profile characteristics described above (*Figure R3*). The PCA loadings (eigenvectors) are also plotted showing the loading (weighting) of each of the original variables onto the PCA axes.

The results of this PCA showed that most profiles were clustered together, with a small subset of cold, high chlorophyll (nominally surface bloom) profiles driving much of the separation on both PC1 and PC2 (*Figure R3*). Analysis of this un-structured PCA suggested that there were meaningful distinctions within the large cluster of profiles. Specifically, two end-members within this cluster were apparent: 1) a cool, deep MLD, low chlorophyll water column profile type and 2) a warm, shallow MLD, low surface chlorophyll water column profile type. Based on the un-structured PCA, we defined three ‘end-member’ water column profile types:

- (1) *cool, high chlorophyll (CHC)*
- (2) *cool, low chlorophyll (CLC)*
- (3) *warm, subsurface high chlorophyll (WSHC)*



These three water column profile types align with our understanding of oceanographic states of the region. Specifically, periodic upwelling along the coast brings cool, high nutrient, low chlorophyll waters to the surface. The early stages of this upwelling, before the initiation of a bloom, resulted in the CLC end-member. The cool, high chlorophyll (CHC) end-member typified a coastal surface phytoplankton bloom that classically follows coastal upwelling. Finally, warm profiles with subsurface high chlorophyll (WSHC) are classic profiles for relatively oligotrophic waters with stronger subsurface chlorophyll maxima.

In addition to the three end-members identified in the un-structured PCA, we identified a fourth, unique, end-member water profile type based on our examination of the glider dataset and our understanding of the oceanography of the San Pedro Channel. This fourth type represented the oligotrophic end-member and was termed:

(4) *warm, low chlorophyll (WLC)*

This end-member typified relatively oligotrophic, warm, offshore waters with low chlorophyll throughout the upper water column that were being brought into the San Pedro Channel most likely as a result of the Southern California Eddy. All four of these end-member water column profile types were common within the glider curtain plots from the 2013 and 2014 glider deployments.

To identify these end-member profile types in an unbiased manner, we developed numerical criteria in order to quantitatively isolate the end-member profiles (Supplemental Table S1). For end-member types 1-3, we started with the profiles identified in the un-structured PCA and refined the criteria in order to isolate the most ‘pure’ examples of these water mass profile types. Using our criteria, we identified 54 ‘end-member profiles’: 10 for type 1 (CHC), 12 for type 2 (CLC), 15 for type 3 (WSHC), and 17 for type 4 (WLC). For another region, where different end-member water profile types are present, separate numerical criteria would need to be developed in order to select representative end-member profiles for that dataset.

In order to differentiate profile characteristics more efficiently and to better represent the observed variability within the glider profile types, we conducted a second PCA which used only the 54 ‘end-member’ profiles to define the PCA axes (hereafter referred to as the structured PCA). The remaining glider profiles were then projected onto these end-member defined PCA axes using the function `proj` within R software. Confidence intervals of 95% were calculated for each of the end-member groups based on PC1 and PC2 values for end-member profiles using the iso-contour of the Gaussian distribution after [www.visiondummy.com/2014/04/draw-error-ellipse-representing-covariance-matrix/](http://www.visiondummy.com/2014/04/draw-error-ellipse-representing-covariance-matrix/) and the function `ggbiplot` within R software. In brief, the magnitude of ellipse axes were determined by the variance within each end-member group, defined as the eigenvalues from the covariance matrix. The direction of the major axis was calculated from the eigenvector of the covariance matrix that corresponded to the largest eigenvalue.

The glider profiles were analyzed within the structured PCA space with specific focus on temporal and spatial changes, as well as how the profiles taken at the SPOT site related to and varied with profiles from the rest of the San Pedro Channel cross-section. The structured PCA resulted in clear separation of the 4 end-member profile types and allowed for better overall separation of the glider profiles. Specifically, the percent of explained variance for PC1 increased from 40.5% to 49.8%, and the percent of explained variance for PC2 increased from 21.5% to 32.7%. More importantly, the structured PCA allowed for more meaningful separation of the glider profiles into oceanographically relevant states allowing us to better understand and quantify the overall variance within the glider profile data. For example, movement along the first principal coordinate axis described changes in temperature-based characteristics while movement along the second principal coordinate axis described changes in chlorophyll-based characteristics. In addition, because the total variance associated with the PC1 and PC2 axes was similar, the distances in principal coordinate space could be used to define similarity between profiles.

***Comparison with time-series measurements:*** To interpret the San Pedro Ocean Time-series data (monthly sampling) within the context of the variability identified in the high resolution glider dataset, we incorporated these ship-based measurements into our analysis (Table 1). Specifically, profile characteristics (*described above*) were calculated for 64 ship-based SPOT profiles from 2000-2011. 30 of these profiles fell between March and July, the time-period during which the gliders were in the water. In addition, 21 profiles were calculated from the UpRISEE ship-based cruises that occurred every two weeks during 2013 and 2014 (Haskell et al., 2016), with 14 profiles occurring between March and July. Though there was good coherence between temperature measurements across all three datasets, the chlorophyll fluorescence measurements from the 2000-2011 SPOT site cruises were considerably lower than the fluorescence measurements from both in-situ gliders and ship-based cruises from 2013 to 2014. We assumed this to be inter-instrument variation in fluorescence to chlorophyll ratio, rather than changes in in-situ chlorophyll concentration itself. To allow for projection onto the glider-derived structured PCA axes, the chlorophyll fluorescence data from 2000-2011 SPOT cruises were scaled so that the March through July mean chlorophyll fluorescence value was equal to the March through July mean chlorophyll fluorescence value from the 2013 to 2014 UpRISEE cruises.

The profile characteristics (MLD, MLTemp, z12p5, zMaxChl, maxCHL, chlInt70, and chlInt70Per20) for the 85 ship-based profiles were used to project these samples onto the end-member based PCA axes. Corresponding PC1 and PC2 values for all ship-based SPOT site profiles were then compared with glider profiles to assess interannual profile variability at the SPOT site (*Figure 4*).

**References:**

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Jacox, M. G., Edwards, C. A., Kahru, M., Rudnick, D. L., and Kudela, R. M.: The potential for improving remote primary productivity estimates through subsurface chlorophyll and irradiance measurement, *Deep-Sea Research Part II-Topical Studies in Oceanography*, 112, 107-116, 10.1016/j.dsr2.2013.12.008, 2015.

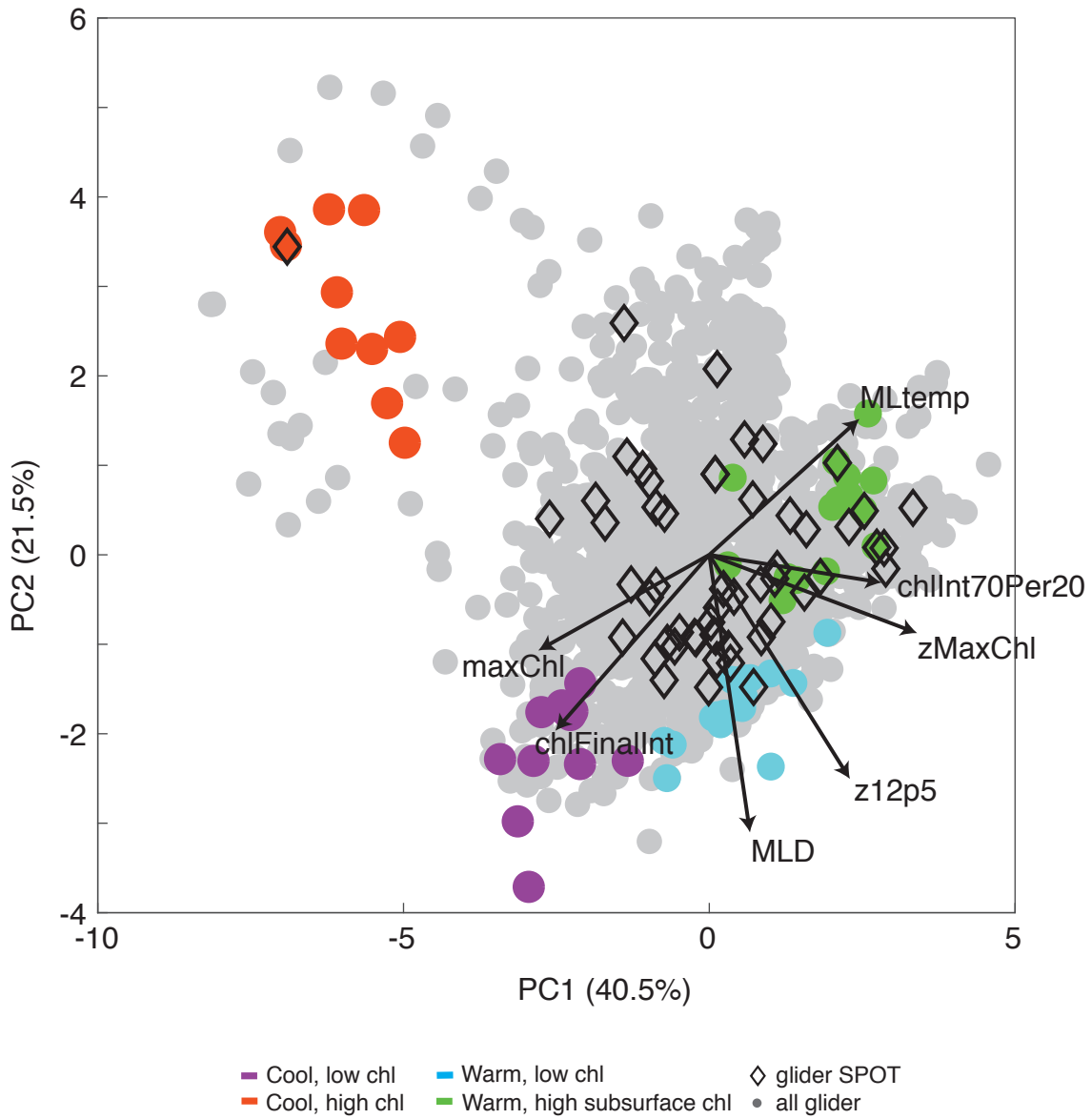


Figure R3: Un-structured Principal Component Analysis of glider profiles. The four end-member water column profile types and the SPOT glider profiles are highlighted. The black arrows denote the the loadings of each variable used in the PCA.

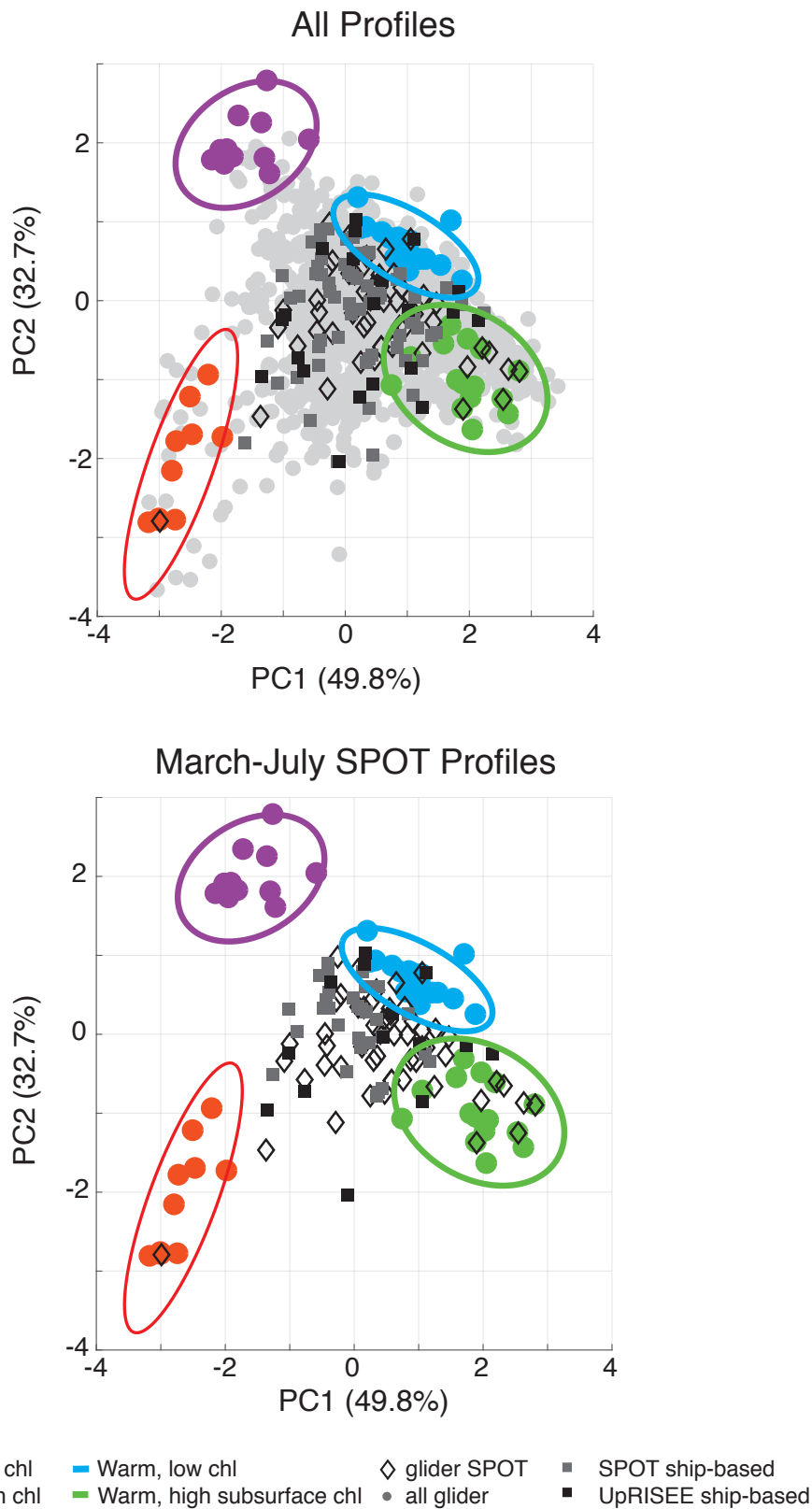


Figure 4: Structured Principal Component Analysis of glider and ship-based profiles. The four end-member water column profile types (Supplemental Figure S2) were used to create principal component axes. Physical variability was associated with PC1 (49.8% of total variance) and biological variability was associated with PC2 (32.7% of total variance). Panel A shows all data projected onto these axes including: all glider profiles collected in 2013 and 2014 (grey dots), glider profiles from the SPOT location (black diamonds), SPOT ship-based profiles (grey squares), and UpRISEE ship-based profiles (black squares).