

# Chemically Self-Consistent Modeling of the Globular Cluster NGC 2808 and its Effects on the Inferred Helium abundance of Multiple Stellar Populations.

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## ABSTRACT

Over its approximately 100 year history stellar modeling has become an essential tool for understanding certain astrophysical phenomena which are not directly observable. Modeling allows for empirical constraints — such as elemental abundances, luminosities, and effective temperatures — to strongly inform non-observables such as a star’s age, mass, and radius. Here we propose a thesis in five parts, related through their use of both modeling and the Dartmouth Stellar Evolution Program (DSEP) to conduct this modeling. In two of the parts of this thesis we will use DSEP, in conjunction with atmospheric boundary conditions generated by collaborators, to build chemically self-consistent models of multiple populations (MPs) in the globular clusters NGC 2808, 47 Tuc, and NGC 6752. We will infer helium abundances across MPs and compare these inferred abundances to those from models which do not consider as careful a handling of a star’s chemistry. PLACEHOLDER

## 1. INTRODUCTION

Globular clusters (GCs) are among the oldest observable objects in the universe (Peng et al. 2011). They are characterized by high densities with typical half-light radii of  $\leq 10$  pc (van den Bergh 2010), and typical masses ranging from  $10^4$ – $10^5$   $M_\odot$  (Brodie & Strader 2006) — though some GCs are significantly larger than these typical values **EXAMPLE**. GCs provide a unique way to probe stellar evolution (Baumgardt & Makino 2003), galaxy formation models (Boylan-Kolchin 2018; Kravtsov & Gnedin 2005), and dark matter halo structure (Hudson & Robison 2018). **BRING IN SOME MORE RECENT CITATIONS.**

Whereas, people have often tried to categorized objects as GCs through relations between half-light radius, density, and surface brightness profile, in fact many objects which are generally thought of as GCs don’t cleanly fit into these cuts **EXAMPLE + CITATION**. Consequently, Carretta et al. (2010) proposed a definition of GC based on observed chemical inhomogeneities in their stellar populations. The modern understanding of GCs then is not simply one of a dense cluster of stars which may have chemical inhomogeneities and multiple

populations; rather, it is one where those chemical inhomogeneities and multiple populations themselves are the defining element of a GC.

All Milky Way globular clusters older than 2 Gyr studied in detail show populations enriched in He, N, and Na while also being depleted in O and C (Piotto et al. 2015; Bastian & Lardo 2018). These light element abundance patterns also are not strongly correlated with variations in heavy element abundance, resulting in spectroscopically uniform Fe abundances between populations. Further, high-resolution spectral studies reveal anti-correlations between N-C abundances, Na-O abundances, and potentially Al-Mg (Snedden et al. 1992; Gratton et al. 2012). Typical stellar fusion reactions can deplete core oxygen; however, the observed abundances of Na, Al, and Mg cannot be explained by the likes of the CNO cycle (Prantzos et al. 2007).

Formation channels for these multiple populations remain a point of debate among astronomers. Most proposed formation channels consist of some older, more massive, population of stars polluting the pristine cluster media before a second population forms, now enriched in heavier elements which they themselves could not have generated (for a detailed review see Gratton et al. 2012). The four primary candidates for these polluters are asymptotic giant branch stars (AGBs, Ventura et al. 2001; D’Ercole et al. 2010), fast rotating massive stars (FRMSs, Decressin et al. 2007), super massive stars (SMSs, Denissenkov & Hartwick 2014), and

massive interacting binaries (MIBs, [de Mink et al. 2009](#); [Bastian & Lardo 2018](#)).

Hot hydrogen burning (proton capture), material transport to the surface, and material ejection into the intra-cluster media are features of each of these models and consequently they can all be made to *qualitatively* agree with the observed elemental abundances. However, none of the standard models can currently account for all specific abundances ([Gratton et al. 2012](#)). AGB and FRMS models are the most promising; however, both models have difficulty reproducing severe O depletion ([Ventura & D’Antona 2009](#); [Decressin et al. 2007](#)). Moreover, AGB and FRMS models require significant mass loss ( $\sim 90\%$ ) between cluster formation and the current epoch — implying that a significant fraction of halo stars formed in GCs ([Renzini 2008](#); [D’Ercole et al. 2008](#); [Bastian & Lardo 2015](#)).

In addition to the light-element anti-correlations observed it is also known that younger populations are significantly enhanced in Helium ([Piotto et al. 2007, 2015](#); [Latour et al. 2019](#)). Depending on the cluster, Helium mass fractions as high as  $Y = 0.4$  have been inferred (e.g. [Milone et al. 2015](#)). However, due to the relatively high and tight temperature range of partial ionization for He it cannot be observed in globular clusters; consequently, the evidence for enhanced He in GCs originates from comparison of theoretical stellar isochrones to the observed color-magnitude-diagrams of globular clusters. Therefore, a careful handling of chemistry is essential when modeling with the aim of discriminating between MPs; yet, only a very limited number of GCs have yet been studied with chemically self-consistent (structure and atmosphere) isochrones (e.g. [Dotter et al. 2015](#), NGC 6752). Here we present new, chemically self-consistent modeling of the two extreme populations of NGC 2808 identified by [Milone et al. \(2015\)](#), A and E.

## 2. MODELING

One key element of NGC 2808 modeling is the incorporation of new atmospheric models, generated from the MARCS grid of model atmospheres ([Plez 2008](#)), which match interior elemental abundances. MARCS provides one-dimensional, hydrostatic, plane-parallel and spherical LTE atmospheric models ([Gustafsson et al. 2008](#)). Members of our collaboration have generated atmospheric models for populations A and E. Integration of these new model atmospheres into DSEP is ongoing.

For similar reasons as discussed in §?? we conduct this research with OPLIB high-temperature opacity tables as opposed to OPAL tables. We will also generate low temperature opacity tables using the MARCS. Moreover, we confirm that the atmosphere and structure

meet in an optically thick region of the star by shifting the atmospheric fitting point from an optical depth of  $\tau = 2/3$  (used by DSEP currently for PHOENIX model atmospheres) to some higher  $\tau$ . We will experiment to identify the best optical depth to fit at.

These population have been studied in depth by Feiden and their chemical compositions were determined in [Milone et al. \(2015\)](#) (see Table 2 in that paper). While we cannot yet evolve DSEP models with these new boundary conditions, we can make a first pass investigation of the affect of OPLIB opacities (Figure ??). Note how the models generated using OPLIB opacity tables have a systematically lower luminosity. This discrepancy is consistent with the overall lower opacities of the OPLIB tables.

The isochrones generally used to infer the degree of helium enhancements assume that convection operates in the same manner in metal-poor stars as it does in the Sun. However, observations from *Kepler* of metal-poor red giants ([Bonaca et al. 2012](#); [Tayar et al. 2017](#)), in concert with interferometric radius determination of the metal-poor sub-giant HD 140283 ([Creevey et al. 2015](#)), have shown that the efficiency of convection changes with iron content. As the final portion of our work to more carefully handle a star’s chemistry, we will modify DSEP to capture this variation in convective efficiency.

## 3. FIDANKA

When fitting isochrones to the data we have four main criteria for any method

- The method must be robust enough to work along the entire main sequence, turn off, and much of the subgiant and red giant branches.
- Any method should consider photometric uncertainty in the fitting process.
- The method should be model independent, weighting any n number of populations equally.
- The method should be automated and require minimal intervention from the user.

While there are many packages which can measure fiducial lines very well [CITATIONS], we do not believe that any of these perfectly match our use case. Therefore, we elect to develop our own software suite, **Fidanka**. **Fidanka** is a python package designed to automate much of the process of measuring fiducial lines in CMDs, adhering to the four criteria we lay out above. Primary features of **Fidanka** may be separated into two categories: stellar population synthesis and isochrone optimization/fitting (distance modulus, B-V color excess, and binary mass fraction)

### 3.1. Fiducial Line Measurement

**Fidanka** takes an iterative approach to measuring fiducial lines, the first step of which is to make a “guess” as to the fiducial line. This guess will be used to verticalize the CMD so that further algorithms can work in 1-D magnitude bins without worrying about weighting issues caused by varying projections of the evolutionary sequence onto the magnitude axis. This initial guess is calculated by splitting the CMD into magnitude bins, with uniform numbers of stars per bin (so that bins are cover a small magnitude range over densely populated regions of the CMD while covering a much larger magnitude range in sparsely populated regions of the CMD, such as the RGB). A unimodal gaussian distribution is then fit to the color distribution of each bin, and the resulting mean color is used as the initial fiducial line guess. This rough fiducial line will approximately trace the area of highest density. We subtract the color of this fiducial line from that of each star to verticalize the CMD.

If **Fidanka** were to simply apply the same algorithm to the verticalized CMD then the resulting fiducial line would simply be a re-extraction of the initial fiducial line. To avoid this, we take a more robust, number density based approach, which considers the distribution of stars in both color and magnitude space simultaneously. For each star in the CMD we first use an **introselect** partitioning algorithm to select the 50th nearest stars. To account for the case where the star is at an extreme edge of the CMD, those 50 stars include the star itself (such that we really select 49 stars + 1). We use **qhull**<sup>1</sup>(Barber et al. 1996; ?) to calculate the convex hull of those 50 points. The number density at each star then is defined as 50/(area of convex hull). Because we use a fixed number of points per star, and a partitioning algorithm as opposed to a sorting algorithm, this method scales like  $\mathcal{O}(n)$ , where  $n$  is the number of stars in the CMD. It also intrinsically weights the density of each star equally as the counting statistics of per convex are uniform. We are left with a CMD where each star has a defined number density [FIGURE].

We can adapt this density map method to consider photometric uncertainties by adopting a simple monte carlo approach. For each star in the CMD we draw a random magnitude shift from a gaussian distribution with a standard deviation equal to the photometric uncertainty of the star in each filter. We then shift each star by this random amount and calculate the density map as before. We repeat this process  $m$  times, and then take

the median density at each point in the CMD [FIGURE]. This method will result in noisy density peaks with characteristic width less than that of the photometric noise smoothing out; while wider peaks will remain.

**Fidanka** can now exploit this density map to fit a better fiducial line to the data, as the density map is far more robust to outliers. There are multiple algorithms we implement to fit the fiducial line to the color density profile in each magnitude bin; they are explained in more detail in the **Fidanka** documentation. However, of most relevance here is the  $A^*$  path finding heuristic over peaks. Peaks are extracted from the color-density profile in at density bin [FIGURE]. The  $A^*$  heuristic is then used to find an optimal path (though not necessarily the optimal path) through the peaks [FIGURE]. The resulting path is then used as the fiducial line [FIGURE]. The heuristic considers the slope of the path from one bin to the next and simultaneously the change in density from one bin to the next. This allows the path to be robust to both steep slopes and low density regions. Due to the heuristic the fiducial line path is not necessarily the vertical line defined by the initial fiducial line guess and will instead be a more optimized/better guess.

This method of fiducial line extraction is very effective at tracing the median ridge line of the overall CMD; however, it struggles to discriminate between multiple populations. The density variations from one population to the next are often too subtle. Moreover, when sampling the density. Moreover, the spacing between main sequence populations may be of a similar order to the photometric uncertainties, and therefore the individual populations may smear into one and other. For these reasons, **Fidanka** does not attempt to extract multiple unique fiducial lines for each population; instead, it measures the width of the overall sequence. Width measurement again makes use of the color-density profile, selecting defining the width as the difference in color between the 5th and 95th percentile of the density [FIGURE].

### 3.2. Stellar Population Synthesis

In addition to measuring fiducial lines, **Fidanka** also includes a stellar population synthesis module. This module is used to generate synthetic CMDs from a given set of isochrones. This is of primary importance for binary population modelling. The module is also used to generate synthetic CMDs for the purpose of testing the fiducial line extraction algorithms against priors.

**Fidanka** uses MIST formatted isochrones [CITATION] as input along with distance modulus, B-V color excess, binary mass fraction, and bolometric corrections.

<sup>1</sup> <https://www.qhull.com>

An arbitrarily large number of isochrones may be used to define an arbitrary number of populations. Synthetic stars are samples from each isochroner based on a definable probability (for example it is believed that  $\sim 90\%$  of stars in globular clusters are younger population [CITATION]). Based on the metallicity,  $\mu$ , and  $E(B-V)$  of each isochrone, bolometric corrections are taken from bolometric correction tables. Where bolometric correction tables do not include exact metallicities or extinctions a linear interpolation is preformed between the two bounding values. [FIGURE] shows an example of a synthetic CMD generated from a set of 2

NGC 2808 isochrones as well as a comparison between those isochrones and the measured fiducial line of the synthetic population.

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## REFERENCES

- Barber, C. B., Dobkin, D. P., & Huhdanpaa, H. 1996, ACM Transactions on Mathematical Software (TOMS), 22, 469
- Bastian, N., & Lardo, C. 2015, MNRAS, 453, 357, doi: 10.1093/mnras/stv1661
- Bastian, N., & Lardo, C. 2018, Annual Review of Astronomy and Astrophysics, 56, 83
- Baumgardt, H., & Makino, J. 2003, MNRAS, 340, 227, doi: 10.1046/j.1365-8711.2003.06286.x
- Bonaca, A., Tanner, J. D., Basu, S., et al. 2012, The Astrophysical Journal Letters, 755, L12, doi: 10.1088/2041-8205/755/1/L12
- Boylan-Kolchin, M. 2018, MNRAS, 442, 1423, doi: 10.1093/mnras/sty1490
- Brodie, J. P., & Strader, J. 2006, Annu. Rev. Astron. Astrophys., 44, 193
- Carretta, E., Bragaglia, A., Gratton, R. G., et al. 2010, Astronomy & Astrophysics, 516, A55
- Creevey, O., Thévenin, F., Berio, P., et al. 2015, Astronomy & Astrophysics, 575, A26
- de Mink, S. E., Pols, O. R., Langer, N., & Izzard, R. G. 2009, A&A, 507, L1, doi: 10.1051/0004-6361/200913205
- Decressin, T., Meynet, G., Charbonnel, C., Prantzos, N., & Ekström, S. 2007, A&A, 464, 1029, doi: 10.1051/0004-6361:20066013
- Denissenkov, P. A., & Hartwick, F. D. A. 2014, MNRAS, 437, L21, doi: 10.1093/mnras/slt133
- D’Ercole, A., D’Antona, F., Ventura, P., Vesperini, E., & McMillan, S. L. W. 2010, MNRAS, 407, 854, doi: 10.1111/j.1365-2966.2010.16996.x
- D’Ercole, A., Vesperini, E., D’Antona, F., McMillan, S. L. W., & Recchi, S. 2008, MNRAS, 391, 825, doi: 10.1111/j.1365-2966.2008.13915.x
- Dotter, A., Ferguson, J. W., Conroy, C., et al. 2015, MNRAS, 446, 1641, doi: 10.1093/mnras/stu2170
- Gratton, R. G., Carretta, E., & Bragaglia, A. 2012, Astronomy and Astrophysics Reviews, 20, 50, doi: 10.1007/s00159-012-0050-3
- Gustafsson, B., Edvardsson, B., Eriksson, K., et al. 2008, A&A, 486, 951, doi: 10.1051/0004-6361:200809724
- Hudson, M. J., & Robison, B. 2018, Monthly Notices of the Royal Astronomical Society, 477, 3869, doi: 10.1093/mnras/sty844
- Kravtsov, A. V., & Gnedin, O. Y. 2005, The Astrophysical Journal, 623, 650
- Latour, M., Husser, T. O., Giesers, B., et al. 2019, A&A, 631, A14, doi: 10.1051/0004-6361/201936242
- Milone, A. P., Marino, A. F., Piotto, G., et al. 2015, ApJ, 808, 51, doi: 10.1088/0004-637X/808/1/51
- Peng, E. W., Ferguson, H. C., Goudfrooij, P., et al. 2011, The Astrophysical Journal, 730, 23
- Piotto, G., Bedin, L. R., Anderson, J., et al. 2007, The Astrophysical Journal Letters, 661, L53, doi: 10.1086/518503
- Piotto, G., Milone, A. P., Bedin, L. R., et al. 2015, AJ, 149, 91, doi: 10.1088/0004-6256/149/3/91
- Plez, B. 2008, Physica Scripta Volume T, 133, 014003, doi: 10.1088/0031-8949/2008/T133/014003
- Prantzos, N., Charbonnel, C., & Iliadis, C. 2007, A&A, 470, 179, doi: 10.1051/0004-6361:20077205
- Renzini, A. 2008, Monthly Notices of the Royal Astronomical Society, 391, 354, doi: 10.1111/j.1365-2966.2008.13892.x
- Snedden, C., Kraft, R. P., Prosser, C. F., & Langer, G. 1992, The Astronomical Journal, 104, 2121
- Tayar, J., Somers, G., Pinsonneault, M. H., et al. 2017, The Astrophysical Journal, 840, 17
- van den Bergh, S. 2010, The Astronomical Journal, 140, 1043, doi: 10.1088/0004-6256/140/4/1043
- Ventura, P., & D’Antona, F. 2009, A&A, 499, 835, doi: 10.1051/0004-6361/200811139

<sup>360</sup> Ventura, P., D’Antona, F., Mazzitelli, I., & Gratton, R.  
<sup>361</sup> 2001, ApJL, 550, L65, doi: [10.1086/319496](https://doi.org/10.1086/319496)