The ASAS-SN Catalog of Variable Stars V: Variables in the Southern Hemisphere

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ABSTRACT

The All-Sky Automated Survey for Supernovae (ASAS-SN) provides long baseline (~4 yrs) light curves for sources brighter than $V \lesssim 17$ mag across the whole sky. As part of our effort to characterize the variability of all the stellar sources visible in ASAS-SN, we have produced \~30.1 million V-band light curves for sources in the southern hemisphere using the APASS DR9 catalog as our input source list. We have systematically searched these sources for variability using a pipeline based on random forest classifiers. We have identified \~220,000 variables, including \~88,300 new discoveries. In particular, we have discovered \~48,000 red pulsating variables, \~23,000 eclipsing binaries, \~2,200 \textsc{δ}-Scuti variables and \~10,200 rotational variables. The light curves and characteristics of the variables are all available through the ASAS-SN variable stars database (https://asas-sn.osu.edu/variables). The pre-computed ASAS-SN V-band light curves for all the \~30.1 million sources are available through the ASAS-SN photometry database (https://asas-sn.osu.edu/photometry). This effort will be extended to provide ASAS-SN light curves for sources in the northern hemisphere and for $V \lesssim 17$ mag sources across the whole sky that are not included in APASS DR9.

Key words: stars:variables – stars:variables:Delta Scuti – stars:binaries:eclipsing – catalogues –surveys

1 INTRODUCTION

Recent large scale sky surveys such as the All-Sky Automated Survey (ASAS; Pojmanski 2002), the Optical Gravitational Lensing Experiment (OGLE; Udalski 2003), the Northern Sky Variability Survey (NSVS; Woźniak et al. 2004), MACHO (Alcock et al. 1997), EROS (Derue et al. 2002), the Catalina Real-Time Transient Survey (CRTS; Drake et al. 2014), the Asteroid Terrestrial-impact Last Alert System (ATLAS; Tonry et al. 2018a; Heinze et al. 2018), and Gaia (Gaia Collaboration et al. 2018a; Holl et al. 2018; Gaia Collaboration et al. 2018b) have revolutionized the study of stellar variability. These surveys have collectively discovered $\gtrsim 10^6$ variable stars across the whole sky.

Variable stars are excellent astrophysical probes and
have been used in numerous astronomical contexts. Pulsating variables such as Cepheids and RR Lyrae stars are commonly used as distance indicators as they follow distinct period-luminosity relationship (e.g., Leavitt 1908; Matsunaga et al. 2006; Beaton et al. 2018, and references therein). Eclipsing binary stars are excellent probes of stellar systems and with sufficient radial velocity followup, allow for the derivation of fundamental stellar parameters, including masses and radii of the stars in these systems (Torres et al. 2010). Variable stars are also useful for the study of stellar populations and Galactic structure (Matsunaga 2018; Feast, & Whitelock 2014).

The All-Sky Automated Survey for SuperNovae (ASAS-SN, Shappee et al. 2014; Kochanek et al. 2017) monitored the visible sky to a depth of V ≲ 17 mag with a cadence of 2–3 days using two units in Chile and Hawaii each with 4 telescopes. Starting in 2017, ASAS-SN expanded to 5 units with 20 telescopes. All the current ASAS-SN units are equipped with g-band filters and are currently monitoring the sky to a depth of g ≲ 18.5 mag with a cadence of ~1 day. The ASAS-SN telescopes are hosted by the Las Cumbres Observatory (LCO; Brown et al. 2013) in Hawaii, Chile, Texas and South Africa. ASAS-SN primarily focuses on the detection of bright supernovae (e.g., Holoien et al. 2017, 2018a), tidal disruption events (e.g., Holoien et al. 2014, 2016, 2018b) and other transients (e.g., Tucker et al. 2018; Rodríguez et al. 2018), but its excellent baseline allows for the characterization of stellar variability across the whole sky. ASAS-SN team members have also studied the relative specific Type Ia supernovae rates (Brown et al. 2018) and the largest amplitude M-dwarf flares seen in ASAS-SN (Schmidt et al. 2018).

In Paper I (Jayasinghe et al. 2018a), we reported ~66,000 new variables that were flagged during the search for supernovae, most of which are located in regions close to the Galactic plane or Celestial poles which were not well-sampled by previous surveys. In Paper II (Jayasinghe et al. 2019a), we uniformly analyzed ~412,000 known variables from the International Variable Stars Index (VSX,Watson et al. 2006), and developed a robust variability classifier utilizing the ASAS-SN V-band light curves and data from external catalogues. As data from The Transiting Exoplanet Survey Satellite (TESS; Ricker et al. 2015) became available, we have explored the synergy between the two surveys. ASAS-SN provides long baseline (≳4 yr) light curves sampled at a cadence of ~1–3 days, that complement the high cadence TESS light curves. In Paper III (Jayasinghe et al. 2019b), we characterized the variability of ~1.3 million sources within 18 deg of the Southern Ecliptic Pole towards the TESS continuous viewing zone and identified ~11,700 variables, including ~7,000 new discoveries. We also identified the most extreme heartbeat star system thus known, and characterized the system using both ASAS-SN and TESS light curves (Jayasinghe et al. 2018d). We have also explored the synergy between ASAS-SN and APOGEE (Holtzman et al. 2015) with the discovery of the first likely non-interacting binary composed of a black hole with a field red giant (Thompson et al. 2018) and we identified 1924 APOGEE stars as periodic variables in Paper IV (Pawlak et al. 2019). We have also identified rare variables, including 2 very long period detached eclipsing binaries (Jayasinghe et al. 2018b,c) and 19 R Coronae Borealis stars (Shields et al. 2018).

Here, we extracted the ASAS-SN light curves of ~30.1 million sources from the AAVSO Photometric All-Sky Survey (APASS; Henden et al. 2015) DR9 catalog with V < 17 mag in the southern hemisphere (δ < 0 deg). In this work, we systematically search this sample for variable sources. In Section 2, we discuss the ASAS-SN observations and data reduction procedures. Section 3 discusses the variability search and classification procedures. In Section 4, we discuss our results and present a summary of our work in Section 5. All the light curves of these sources are made available to the public through our online database.

2 OBSERVATIONS AND DATA REDUCTION

We started with the APASS DR9 catalog as our input source catalog. We selected all the APASS sources with V < 17 mag in the southern hemisphere (δ < 0 deg), excluding the ~1.3M sources towards the Southern Ecliptic Pole which were analyzed in Paper III. This resulted in a list of ~30.1M sources. Figure 1 illustrates the spatial distribution of these sources. ASAS-SN V-band observations were made by the “Brutus” (Haleakala, Hawaii) and “Cassius” (CTIO, Chile) quadruple telescopes between 2013 and 2018. Each ASAS-SN field has ~200-600 epochs of observation to a depth of V ≲ 17 mag. Each camera has a field of view of 4.5 deg², the pixel scale is 8″0 and the FWHM is ~2 pixels. ASAS-SN nominally saturates at ~10–11 mag, but light curves of saturated sources are sometimes quite good due to corrections made for bleed trails (see Kochanek et al. 2017). The light curves for these sources were extracted as described in Jayasinghe et al. (2018a) using image subtraction (Alard & Lupton 1998; Alard 2000) and aperture photometry on the subtracted images with a 2 pixel radius aperture. The APASS catalog was also used for calibration. The zero point offsets between the different cameras were corrected as described in Jayasinghe et al. (2018a). The photometric errors were recalculated as described in Jayasinghe et al. (2019b).

While we decided to use the APASS DR9 catalog as our input source list due to its all-sky coverage, this catalog has several shortcomings (Henden et al. 2015; Marrese et al. 2019). While the APASS DR9 sky coverage is nearly complete, there are regions towards the Galactic plane that are missing (see Figure 1). In addition, the DR9 catalog includes a number of duplicate entries, which appear to be caused by the merging process, where poor astrometry in a given field may cause two centroids to be included for a single source. centroiding in crowded fields is also poor and blends cause both photometric and astrometric errors. The APASS DR9 catalog does not provide unique identifiers, thus we used the VizieR (Oellkers et al. 2018) rencd field as unique identifiers. To address the issue of incomplete sky coverage we will use the ATLAS All-Sky Stellar Reference Catalog (Tonry et al. 2018b) in the next paper to produce light curves for the missing sources in APASS DR9.

3 VARIABILITY ANALYSIS

Here we describe the procedure we used to identify and characterize variables in the source list. We describe how we cross-matched the APASS sources to external catalogues in Section 3.1. In Section 3.2, we describe the procedure we
took to identify candidate variable sources. In Section §3.3, we discuss the application of the V2 random forest classifier model from Jayasinghe et al. (2019a) to classify these variables. In Section §3.4, we discuss the corrections done to mitigate the effects of blending on the candidate variables and in Section §3.5, we discuss the quality checks that we used to improve the final variables catalog.

3.1 Cross-matches to external catalogs

We crossmatch the APASS sources with Gaia DR2 (Gaia Collaboration et al. 2018a) using a matching radius of 5′′. The sources were also cross-matched to the Gaia DR2 probabilistic distance estimates from Bailer-Jones et al. (2018). Even though we used a liberal matching radius, ∼84% (∼94%) of the sources have a cross-match in Gaia DR2 within 2′′ (3′′). We also crossmatch the sources with 2MASS (Skrutskie et al. 2006) and AllWISE (Cutri et al. 2013; Wright et al. 2010) using a matching radius of 10′′. We used TOPCAT (Taylor 2005) to cross-match the APASS sources with the Gaia DR2, 2MASS and AllWISE catalogs.

Sources in the Small Magellanic Cloud (SMC) are also included in our input source list. We used Gaia DR2 (Gaia Collaboration et al. 2018c) to identify ∼1,600 sources from our source list that are SMC members. For sources in the SMC, we use a distance of $d = 62.1$ kpc (Graczyk et al. 2014) in our variability classifier. The LMC was covered in Paper III.

3.2 Random Forest Variable Identification

In Paper III we used several methods, including linear cuts on periodogram statistics, light curve features and external photometry to identify variable sources. Here, we take a different approach by training and apply a random forest classifier to distinguish candidate variables from constant sources. We built a variability classifier based on a random forest model using scikit-learn (Pedregosa et al. 2012; Breiman 2001). The set of variable sources used to train this classifier consisted of ∼302,000 variables from Papers II and III with definite classifications. Variables with uncertain classifications, including ‘VAR’ and ‘ROT’, were not included in this list as they reduced the accuracy of the final random forest classification model. The set of constant sources in the training list consisted of ∼600,000 sources randomly selected from the list of constant sources in Paper III.

The goal was to provide classifications into two broad groups: CONST (constant stars) and VAR (potential variables). The potential variables will be analyzed in further detail so it is more important not to lose real variables than to accidentally include non-variables. These broad classes were selected to reduce the complexity of the classifier, and to provide an accurate initial separation prior to reclassifying the variable sources with the random forest variable type classifier from Paper II. To generate periodicity statistics, we used the astropy implementation of the Generalized Lomb-Scargle (GLS, Zechmeister & Kürster 2009; Scargle 1982) periodogram to search for periodicity over the range 0.05 ≤ $P$ ≤ 1000 days in all ∼30.1M light curves. We utilize the best GLS period, false alarm probability (FAP) and the power of the best GLS period as features. The complete list of 20 features and their importances to the random forest classifier is summarized in Table 1. Feature importances are calculated as Gini importances using the mean decrease impurity algorithm (Pedregosa et al. 2012).

We set the number of decision trees in the forest as n_estimators=1000, pruned the trees at a max-
The training sample was split for training ($\text{class_weight='balanced_subsample'}$) and set the number of samples at $\text{min_samples_split}=10$. To further reduce over-fitting, weights were assigned to each class by initialising $\text{class_weight}='balanced_subsample'$. These parameters were optimized using cross-validation to maximize the overall $F_1$ score of the classifier. For any given source, the RF classifier assigns classification probabilities $\text{Prob(\text{Const})}$ and $\text{Prob(Var)} = 1 - \text{Prob(\text{Const})}$. The output classification of the RF classifier is the class with the highest probability. The training sample was split for training (80%) and testing (20%) in order to evaluate the performance of the RF classifier. We illustrate the ability of the RF model to classify new objects with the confusion matrix shown in Figure 2. The greatest confusion (2%) arises from input variable sources that are subsequently classified as constant stars. The performance of the classifier is summarized in Table 2. The overall $F_1$ score for the classifier is 98.5%.

We applied the trained random forest classifier to the entire sample of $\sim 30.1$M sources and identified 3,553,235 candidate variables. The distinction between the constant sources and the candidate variables is illustrated in Figure 3 through the distributions of the four features with the largest importance: LS$_{\text{Pow}}$, T$(\phi|P)$, J$-K_s$ and log(LS$_{\text{FAP}}$). We find that candidate variable sources are strongly periodic, as is illustrated by high values of LS$_{\text{Pow}}$ and smaller values of log(LS$_{\text{FAP}}$) and T$(\phi|P)$. In addition, the distribution of the 2MASS color J$-K_s$ differs significantly between constant and variable sources. Variable sources are skewed towards redder NIR colors with J$-K_s > 1$ mag while constant sources largely peak around J$-K_s \sim 0.5$ mag. Cooler, evolved stars are more likely to be variable, so this is not unexpected.

### 3.3 Variability Classification

Once candidate variables are identified, we aimed at classifying these sources into the various standard classes of variable stars. We use the variability classifier implemented in Jayasinghe et al. (2019a), which consists of a random forest classifier plus several refinement steps. Given the large number of candidates, we changed our variability classification strategy as follows.

- Initially, we classified all the candidate variables using just the GLS periods derived in §3.2.
- Following this, we derive periods for a limited set of sources (see below) using the astrobase implementation (Bhatti et al. 2018) of the Box Least Squares (BLS, Kovács et al. 2002) periodogram to improve the completeness for eclipsing binaries whose periodicity cannot be easily identified with GLS.

We also run the variability classifier twice, once using the best period (GLS or BLS) and once using twice the best period. The final classification is the one which yields the greatest classification probability. This step greatly improves the separation of EW type eclipsing binaries from RRC variables, and also improves upon the efficiency of the automated period doubling algorithm that was used for eclipsing binaries in Paper II.

To identify possible eclipsing binaries, we selected $\sim 576,000$ candidate variables with $\text{APL} > 2$ (Table 1) from our original list. Periods were searched over the range $0.05 \leq P \leq 1000$ days and the BLS periodogram was initialized with 200 phase bins and a minimum (maximum) transit duration of 0.1 (0.3) in phase. BLS periods were only selected if the BLS power was $< 0.3$.

### 3.4 Blending Corrections

The large pixel scale of the ASAS-SN images ($8\arcsec0$) and the FWHM ($\sim 16\arcsec0$) results in blending towards crowded regions. The APASS catalog was constructed with images that have a significantly smaller pixel scale ($2\arcsec6$), so multiple APASS sources can fall into a single ASAS-SN pixel. We do not correct for the contaminating light in the photometry of the blended sources, but we identify and correct blended variable groups in our catalog.

Since we extracted light curves for the positions of APASS sources, we can have two or more APASS sources inside a single ASAS-SN resolution element. This is further exacerbated towards low Galactic latitudes by crowding. If we select the sources with another APASS neighbor within $30\arcsec0$, we find that $\sim 1.1$M of the $\sim 3.6$M candidate variables had a neighbor within $30\arcsec0$. We compute the flux variability amplitudes for these sources using a random forest regression model (Jayasinghe et al. 2019a). The majority of the variable “groups” consisted of two sources, with a few groups consisting of up to three or more sources. For each variable group, we consider the source with the largest flux variability as the ‘true’ variable, and remove the other overlapping sources from the final list. Following this treatment, our list of candidate variables consisted of $\sim 3$M sources.
Table 1. Variability features and their importances for variable star identification

| Feature   | Description                                                                 | Importance | Reference                      |
|-----------|-----------------------------------------------------------------------------|------------|--------------------------------|
| LS_Per    | Best Lomb-Scargle period                                                   | 1%         | -                              |
| LS_Pow    | Power corresponding to the best Lomb-Scargle period                         | 24%        | -                              |
| log(LS_FAP)| Base 10 logarithm of the False Alarm Probability corresponding to the best Lomb-Scargle period | 11%        | Jayasinghe et al. (2019a)     |
| T(t)      | Lafler-Kinman String Length statistic of the light curve sorted by time    | 4%         | Jayasinghe et al. (2019a)     |
| T(φ|P)     | Lafler-Kinman String Length statistic of the light curve sorted by phase   | 18%        | Jayasinghe et al. (2019a)     |
| δ         | Normalized difference between T(t) and T(φ|P)                            | 5%         | Jayasinghe et al. (2019a)     |
| Skew      | Skewness of the magnitude distribution                                      | 2%         | -                              |
| Kurt      | Kurtosis of the magnitude distribution                                      | 2%         | -                              |
| Median    | Median of the magnitude distribution                                       | 1%         | -                              |
| σ         | Standard deviation of the light curve                                       | 2%         | -                              |
| IQR       | Difference between the 75th and 25th percentiles in magnitude               | 2%         | -                              |
| rms       | Root-mean-square statistic of the light curve                              | 7%         | -                              |
| A         | Amplitude of the light curve                                                | 7%         | -                              |
| A_HL      | Ratio of magnitudes brighter or fainter than the average                   | 2%         | Kim & Bailer-Jones (2016)      |
| T_m       | M-test statistic                                                           | 3%         | Kinemuchi et al. (2006)        |
| MAD       | Median absolute deviation of the light curve                               | 2%         | -                              |
| 1/η        | Inverse of the η (Von Neumann index) value for the light curve              | 3%         | Von Neumann et al. (1941)      |
| m_slope   | Slope of a linear fit to the light curve                                   | 1%         | -                              |
| J − K_s   | 2MASS J − K_s color                                                        | 12%        | Skrutskie et al. (2006)        |
| H − K_s   | 2MASS H − K_s color                                                        | 9%         | Skrutskie et al. (2006)        |

Figure 3. Distribution of the sources classified as CONST and VAR in the LS_Pow, T(φ|P), J − K_s and log(LS_FAP) features. Sources with log(LS_FAP)<−10 are not shown for clarity.
At this stage, visual review of a random set of light curves suggested that quality checks must be implemented to distinguish true variability signals from variability due to bad photometry, and other survey specific issues (e.g., shutter failures, etc.). In Paper III, given the significantly shorter list of candidate variables, this was accomplished through simple visual review of the light curves. In this work, given the shear number of sources, visual review is not a feasible option. Thus, we choose to implement various criteria in lieu of visual review, to distinguish the true variables from the ‘noise’.

We first restrict the list to sources with $V_{\text{mean}} > 10$ mag, $A > 0.05$ mag and $T(\phi) < 0.9$. We implemented the cut in the ASAS-SN V-band magnitude to minimize noise due to saturation artifacts. We also calculate the ratio between the amplitude estimated by random forest regression ($A$) to the IQR (Table 1) of the light curve, $a = A/IQR$, \hfill (1)

and the reddening-free Wesenheit magnitudes (Madore 1982; Lebzelter et al. 2018)

\[ W_{RP} = M_{GKP} - 1.3(G_{RP} - G_{RP}), \hfill (2) \]

and

\[ W_{IK} = M_{K_0} - 0.686(J - K_0), \hfill (3) \]

for each source. The Wesenheit magnitudes are used in the pipeline from paper II to refine variable type classifications. The quantity $a$ can be used to identify light curves with significant outliers as we expect $a \approx 2$ for most sources.

The criteria used in lieu of visual review are summarized in Table 3. We note that these criteria are applied in addition to the refinement criteria in Paper II. These are not replacements but additional quality checks intended to improve the purity of our catalog. In addition to the criteria summarized in Table 3, we further scrutinize sources with periods that are close to aliases of a sidereal day (e.g., $P \approx 1$ d, $P \approx 2$ d, $P \approx 30$ d, etc.). This is accomplished by tightening the criteria on $T(\phi)$, log($LS_{\text{FAP}}$), $LS_{\text{Pow}}$ and $\delta$. This process slightly reduces the completeness of our catalog at these periods, but greatly reduces the number of false positives. In addition, we removed QSO contaminants in this list by cross-matching our list of variables to the Liao et al. (2019) catalog of known QSOs using a matching radius of 5″. We identified 336 cross-matches, out of which 325 were classified as YSOs in our pipeline. At this point we had ≈247,200 sources nominally classified as variable stars.

We inspected 5000 randomly selected sources classified as non-variable and the same number classified as variable. This was partly just a sanity check but also driven by the concern that the large size of our initial list (~10% of the sources) suggested that our false positive rates had to be higher than suggested by Table 2. Among the non-variable sources, we identified only 3 (~ 0.06%) that might be low level variables, which suggests that we are missing few variables that can be detected in this data. For the variable stars, we found significant contamination in the following variable classes: GCAS (~50%), L (~25%), VAR (~45%) and YSO (~13%). The implied false positive rate for the variable sources was ~5.9% at this point.

Light curves that are contaminated by systematics tend to be classified as irregular or generic variables as they are inherently aperiodic in nature. Thus, we decided to review all ~32,800 sources that were classified as L, VAR, GCAS, or YSO to improve the purity of our catalog. Initial results suggested that L variables with $T(\phi) > 0.65$ were dominated by noise, so we rejected ~14,300 such sources without further visual review. We visually reviewed the remaining ~18,500 sources, and rejected ~12,600 sources (~68%) and only retained ~5,900 of these sources in the final catalog. When we carried out a new inspection of 5000 randomly selected variables, the false positive rates were now EA (~1.4%), L (~0.6%), SR (~2.6%), and VAR (~0.9%). This implies an overall false positive rate for the final catalog of variable sources of ~1.3%.

After these criteria are applied, we end up with a list of ~220,000 variables. This means that our initial candidate list had a false positive rate of ~93%. The larger than expected false positive rate is partly due to a biased training set in the source classifier. The training set of constant sources was derived from a region of the sky away from the Galactic plane. The increased crowding and blending towards the Galactic plane will systematically affect constant stars at low latitudes and introduce spurious variability signals into their light curves. Our classifier will identify these constant sources as candidate variables. In addition to this, sources in the vicinity of bright, saturated stars in our data are likely to have spurious variability signals in their image subtraction light curves due to the corrections made for bleed trails (see Kochanek et al. 2017). This effect is again exacerbated towards the Galactic plane.

### 4 Results

The complete catalog of ~220,000 variables and their light curves are available at the ASAS-SN Variable Stars Database (https://asas-sn.osu.edu/variables) along with the V-band light curves for each source. Most of the known variables identified in this work were already added to the Variable Stars Database in Paper II. We have overhauled the web interface for the ASAS-SN Variable Stars Database to include interactive light curve plotting and photometry from Gaia DR2, APASS DR9, 2MASS and ALLWISE. Table 4 lists the number of sources of each variability type in the catalog.

We matched our list of variables to the VSX (Watson et al. 2006) catalog, with a matching radius of 16″ to identify previously discovered variables. The variables discovered by the All-Sky Automated Survey (ASAS; Pojmanski 2002) and the Catalina Real-Time Transient Survey (CRTS; Drake et al. 2014) are included in the VSX database. We also match our variables to the catalogs of variable stars discovered by ASAS-SN (Jayasinghe et al. 2018a), the catalogs of vari-

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**Table 2.** Performance of the ASAS-SN random forest source classifier

| Class   | Precision | Recall | $F_1$ score | Sources |
|---------|-----------|--------|-------------|---------|
| CONST   | 99%       | 99%    | 99%         | 600,000 |
| VAR     | 98%       | 98%    | 98%         | 302,021 |

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Table 3. Summary of the variability refinement criteria for each variable class.

| Class                              | Summarized refinement Criteria                                      |
|------------------------------------|--------------------------------------------------------------------|
| $\delta$ Scuti (HADS, DSCT)        | $\text{Skew} < 0.15, \log(\text{LS\_Pow}) < 0.25, \log(\text{LS\_FAP}) < -7, A < 0.5 \text{ mag}, T(\phi|P) < 0.5, -1 < W_{JK} < 3 \text{ mag}$ |
| RR Lyrae (RRAB, RRC, RRD)          | $\text{RRAB and } \log(\text{LS\_FAP}) < -10, \text{LS\_Pow} > 0.2, A > 0.08 \text{ mag}, T(\phi|P) < 0.6, \text{Skew} < 0.15, \alpha < -0.25$  $\text{RRC/RRD and } \log(\text{LS\_FAP}) < -10, \text{LS\_Pow} > 0.2, A > 0.08 \text{ mag}, T(\phi|P) < 0.6, \text{Skew} < 0, \alpha < -0.25$ |
| Cepheids (DCEP, DCEPS, CWA, CWB, RVA) | $\text{Skew} < 1, \log(\text{LS\_FAP}) < -10, \text{LS\_Pow} > 0.3, A < 2 \text{ mag}, T(\phi|P) < 0.6, \delta < -0.25$ |
| Rotational Variables (ROT)         | Period $> 0.6 \text{ d and } \log(\text{LS\_FAP}) < -5, \text{LS\_Pow} > 0.2, A > 0.08 \text{ mag}, T(\phi|P) < 0.6, \delta < 0$ Period $> 0.6 \text{ d and } W_{JK} > 2.5 \text{ mag}, \text{Prob} > 0.9$ |
| Eclipsing Binaries (EA, EB, EW)    | $\text{EA (GLS) and } \alpha < 100, T(\phi|P) < 0.6, A > 0.08 \text{ mag}$ $\text{EB (GLS) and } \log(\text{LS\_FAP}) < -7, \text{LS\_Pow} > 0.2, A > 0.08 \text{ mag}, T(\phi|P) < 0.6$ $\text{EW (GLS) and } \log(\text{LS\_FAP}) < -7, \text{LS\_Pow} > 0.2, A > 0.08 \text{ mag}, T(\phi|P) < 0.6, \text{Skew} > 0$ $\text{EA (BLS) and } \alpha < 100, T(\phi|P) < 0.45, \text{Prob} > 0.8$ |
| Semiregular and Irregular Variables (SR, L) | $\alpha < 5, V_{\text{mean}} > 11 \text{ mag}, A > 0.08 \text{ mag}$ Period $> 100 \text{ d and } \log(\text{LS\_FAP}) < -3, J - K_s > 1.1, A > 0.1 \text{ mag}, T(t) < 0.7$ 10 $\leq$ Period $\leq 100 \text{ d and } \log(\text{LS\_FAP}) < -8, A > 0.08 \text{ mag}$ |
| Mira Variables (M, M$^*$)          | $\log(\text{LS\_FAP}) < -3, \text{LS\_Pow} > 0.5, T(\phi|P) < 0.5$ |
| Young Stellar Objects (YSO)        | Period $< 100 \text{ d and } \alpha < 5, \log(\text{LS\_FAP}) < -10, \text{LS\_Pow} > 0.25, T(\phi|P) < 0.6$ |
| Outbursting Be stars (GCAS, GCAS:) | $\alpha < 5, V_{\text{mean}} > 11 \text{ mag}, J - K_s < 1.1, 0.25 < A < 1 \text{ mag}, T(t) < 0.5$ |
| Generic Variables (VAR)            | $\alpha < 5, 0.1 < A < 2 \text{ mag}, W_{JK} > -4 \text{ mag}, V_{\text{mean}} > 11 \text{ mag}, T(\phi|P) < 0.5 \text{ OR } T(t) < 0.5$ |

It is evident that previous surveys, including our discoveries from paper I, successfully discovered sources that vary with large amplitudes or are strongly periodic. Most (~54%) of our new discoveries are red, pulsating variables. We also discover a large number of binaries and rotational variables, amounting to ~26% and ~12% of the newly discovered variable sources, respectively. It is also noteworthy that we discover many more $\delta$ Scuti sources than previously known. These variables are particularly interesting as they pulsate at high frequencies (P $< 0.3$ d) and are located towards the lower end of the instability strip (Breger 1979). $\delta$ Scuti variables are also known to follow a period-luminosity relationship (Lopez de Coca et al. 1990).

The Wesenheit $W_{RP}$ vs. $G_{BP} - G_{RP}$ color-magnitude diagram for all the variables with excellent variable type classification probabilities (Prob $> 0.9$) is shown in Figure 4. Generic and uncertain variable types are not shown. We have sorted the variables into groups to highlight the different classes of variable sources. A similar Wesenheit $W_{RP}$ vs. $G_{BP} - G_{RP}$ color-magnitude diagram for all the newly discovered variables, separated by probability, is shown in Figure 5. The sharp cutoffs seen in the sample of semi-regular variables with Prob $< 0.9$ are inherited from the variable type refinements from paper II. Most variables with Prob $< 0.9$ are located in similar areas of the CMD as the variables with Prob $> 0.9$. However, we note two interesting clusters of these low-probability variables at $(G_{BP} - G_{RP}, W_{RP})$ ~
(2.5,−4.5) and (0.75,1.8) corresponding to semi-regular and rotational variables respectively.

The Wesenheit $W_{RP}$ vs. $G_{RP} − G_{RP}$ color-magnitude diagram for all the variables with $\text{Prob} > 0.9$ and the points colored according to the period is shown in Figure 6. This essentially highlights the large dynamic range in period probed by the ASAS-SN light curves. Owing to the ASAS-SN survey cadence and our long time baseline, we are able to probe both short period variability ($P < 0.1$ d) and long period variability ($P > 1000$ d). The ASAS-SN survey continues to monitor the sky in the g-band, which lends itself well to the analysis of long term trends and unusual variability. As a testament to this, Jayasinghe et al. (2019c) noted a sudden dimming episode (flux reduction of ∼70% in the g-band) in an APASS source (ASASSN-V J213939.3−702817.4) that was non-variable for ∼1800 d. This source was classified as a constant source in this work.

The combined Wesenheit $W_{JK}$ period-luminosity relationship (PLR) diagram for the periodic variables with $\text{Prob} > 0.9$ is shown in Figure 7. The PLR sequences for the Cepheids are well defined (Soszynski et al. 2005). Sharp PLR sequences can also be seen for Delta Scuti variables and contact binaries. The Mira variables also form a distinct PLR sequence beyond $P > 100$ d. The slight deficits of variables at the aliases of a sidereal day (e.g., $P ≈ 1$ d, $P ≈ 2$ d, $P ≈ 30$ d, etc.) are due to the quality checks implemented in §3.5.

The period-amplitude plot for the periodic variables with $\text{Prob} > 0.9$ is shown in Figure 8. The high prior completeness of the Mira, RR Lyrae and Cepheid variables is evident. We do not discover many of these variables in this work. The large majority (∼98.7%) of the new discoveries are of different variable types with smaller variability amplitudes and/or weak periodicity.

We also examine the period-color relationship of the variables in the $W_1 − W_2$ color space in Figure 9. Most variables have $W_1 − W_2 ∼ 0$, but the NIR infrared-excess increases with increasing period for the long period variables. This is even more dramatic for the Mira variables that are on the asymptotic giant branch (AGB). Dust formation is commonly traced through infrared excesses. Our findings agree with McDonald et al. (2018), for example, that strong mass loss and increased dust formation first occurs for pulsation periods of $P ≥ 60$ d for Galactic stars.

As an external check of our classifications, we used data from our cross-match to Gaia DR2 to produce Figure 10. We define a “variability” color $\beta$,

$$\beta = \frac{\text{phot}_\text{rp}_\text{mean}_\text{flux}_\text{error}}{\text{phot}_\text{rp}_\text{mean}_\text{flux}}$$

which is a measure of the difference in variability between the bluer and redder Gaia bands and compare it to the inverse of the quantity $\text{phot}_\text{rp}_\text{mean}_\text{flux}_\text{over} \text{error}$ which is a measure of the mean signal to noise ratio. The different groups of variables fall in distinct regions, with red pulsating variables having smaller values of $\beta$ compared to bluer variables. Comparing the known variables and the new discoveries, we find that the new discoveries mostly fall in the same regions as the known variables. This provides an independent confirmation of the purity of the newly discovered variables and validates our quality assurance methodology in §3.5.

Examples of the newly identified periodic variables are shown in Figure 11 and examples of the newly discovered irregular variables are shown in Figure 12. The light curves for the red giant pulsators, including the irregular variables, are complex, and often multi-periodic, which requires further Fourier analysis. In order to better understand these pulsating red giants, Percy, & Fenaux (2019) recommended a more detailed analysis, combining visual inspection of the light curves and a more advanced period analysis, in lieu of the automated classification used by ASAS-SN.

We illustrate the sky distribution of the newly discovered variables in Figure 13. Most of these discoveries are
clustered towards the Galactic disk, as is expected. We note the scarcity of high amplitude Mira variables, RR Lyrae and Cepheid variables and the abundance of lower amplitude semi-regular/irregular variables among the newly discovered variables. Variables with large amplitudes and strong periodicity are relatively easily discovered and characterized by wide field photometric surveys, so the existing completeness of these variable types is very high. The gaps in coverage will be rectified in the next paper in this series. We also show the sky distribution of the known variables identified in this work in Figure 14. Here, we note the abundance of Mira variables, eclipsing binaries and Cepheid variables that have been discovered by previous surveys.

5 CONCLUSIONS

We systematically searched for variable sources with $V < 17$ mag in the southern hemisphere ($\delta < 0$ deg), excluding the $\sim$1.3M sources near the Southern Ecliptic Pole which were analyzed in Paper III. Through our search, we identified $\sim$220,000 variable sources, of which $\sim$88,300 are new discoveries. In particular, we have discovered $\sim$48,000 red pulsating variables, $\sim$23,000 eclipsing binaries, $\sim$2,200 $\delta$-Scuti variables and $\sim$10,200 rotational variables.

The V-band light curves of all the $\sim$30.1M sources studied in this work are available online at the ASAS-SN Photometry Database (https://asas-sn.osu.edu/photometry). To highlight the possible, blended sources, a flag is assigned to each source if the distance to the nearest APASS neighbor is $<16''$. The new variable sources have also been added to the ASAS-SN variable stars database (https://asas-sn.osu.edu/variables). Most of these sources will also fall into the TESS footprint, thus short baseline TESS light curves that possess better photometric precision can also be obtained to complement the long baseline ASAS-SN light curves.

This work greatly improves the completeness of bright variables in the Southern hemisphere and provides long baseline V-band light curves. As part of our ongoing effort to systematically analyze all the $\sim$50 million $V < 17$ mag APASS sources for variability, we will next update this database with the light curves for the sources across the northern hemisphere and include the light curves for sources missing from the APASS DR9 catalog.

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Figure 5. The Wesenheit $W_{RP}$ vs. $G_{BP} - G_{RP}$ color-magnitude diagram for the newly discovered variables with $\text{Prob} < 0.9$ (left), and $\text{Prob} > 0.9$ (right).

This research has made use of the VizieR catalogue access tool, CDS, Strasbourg, France. This research made ualso of Astropy, a community-developed core Python package for Astronomy (Astropy Collaboration, 2013).

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Figure 6. The Wesenheit $W_{RP}$ vs. $G_{BP} - G_{RP}$ color-magnitude diagram for the periodic variables with Prob > 0.9, that have already been discovered (left), and the new discoveries (right). The points are colored by the period.

Figure 7. The Wesenheit $W_{JK}$ PLR diagram for the periodic variables with Prob > 0.9, that have already been discovered (left), and the new discoveries (right).
Figure 8. Period-amplitude plot for the periodic variables with $\text{Prob} > 0.9$, that have already been discovered (left), and the new discoveries (right). Reference amplitudes of 1 and 2 mag are shown in red and blue respectively.

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Figure 9. The period vs. $W_1 - W_2$ color diagram for the variables with Prob > 0.9, that have already been discovered (left), and the new discoveries (right).

Figure 10. The Gaia DR2 BP/RP variability ratio $\beta$ against $1/\text{phot}_\text{rp\_mean\_flux\_over\_error}$
Figure 11. Phased light curves for examples of the newly discovered periodic variables. The light curves are scaled by their minimum and maximum V-band magnitudes. Different colored points correspond to data from the different ASAS-SN cameras. The different variability types are defined in Table 4.
Figure 12. Light curves for examples of the newly discovered irregular variables. The format is the same as for Fig. 11.
Figure 13. Spatial distribution of the ~88,300 newly discovered variables in Equatorial coordinates. Sources in the gap centered at the Southern Ecliptic Pole ($\alpha = 90$ deg, $\delta = -66.55$ deg) were analyzed in Jayasinghe et al. (2019b). The other gaps are in the APASS catalog.
Figure 14. Spatial distribution of the ~131,900 known variables in Equatorial coordinates. Sources in the gap centered at the Southern Ecliptic Pole ($\alpha = 90$ deg, $\delta = -66.55$ deg) were analyzed in Jayasinghe et al. (2019b). The other gaps are in the APASS catalog.