



Rotational Light-curve Recovery and Predictions of the LSST Yield of Hildas

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Abstract

The Hilda population occupies the stable 3:2 mean-motion resonance of Jupiter and provides a window into solar system evolution, including collisional processes. The National Science Foundation and Department of Energy Vera C. Rubin Observatory will conduct the 10 yr Legacy Survey of Space and Time (LSST). We present a simulation of Rubin’s discovery of Hildas with the *SORCHA* survey simulator and the recovery of their light curves. We constructed a synthetic Hilda population model that includes distributions of orbital properties, sizes, collisional families, and colors. We applied three distinct populations of sinusoidal light curves to this same orbit–size–color model: (1) a Gaussian kernel density estimate fit to rotational periods and amplitudes from the Lightcurve Database (LCDB), (2) a superfast rotator population, and (3) a superslow rotator population. Over the 10 yr simulated survey, we predict LSST will discover $\sim 33,400$ Hildas, a fivefold increase over the known population. Using a multiband Lomb–Scargle Periodogram via *Astropy* we confidently recover $\sim 45.96\%$ of Hildas in our LCDB-based population, higher than typical in observational searches. This suggests our light-curve population model may differ from the intrinsic population. We find strong biases in light-curve amplitude, with recovery efficiency dropping sharply below 0.1 magnitudes, while biases from rotational period are comparatively weak aside from cadence-related features such as LSST’s ~ 36 minute revisit cadence. Our recovery efficiency is likely overestimated due to our assumption of constant sinusoidal light curves, which correspond to optimal pole orientations. These results are the first test of light-curve recovery from simulated LSST observations.

Unified Astronomy Thesaurus concepts: [Hilda group \(741\)](#); [Small Solar System bodies \(1469\)](#)

1. Introduction

The Hildas are a dynamically stable population of small bodies in the 3:2 mean-motion resonance of Jupiter, with semimajor axes near ~ 4 au. Their resonance prevents close encounters with Jupiter and preserves a characteristic triangular configuration in the frame corotating with Jupiter (K. A. Farrell et al. 2025). Because of their long-term stability, Hildas preserve clues about planetary migration and solar system evolution (D. Vokrouhlický et al. 2025) such as the timescales over which the outer planets reached their current orbits (F. A. Franklin et al. 2004; A. Morbidelli et al. 2015) and the epoch when this migration occurred, whether during giant planet instability or earlier in the primordial solar system (F. A. Franklin et al. 2004; H. F. Levison et al. 2009; F. Roig & D. Nesvorný 2015; D. Vokrouhlický et al. 2016; D. Nesvorný 2018; S. Pirani et al. 2019). Their absolute magnitude (and thus inferred size) distributions have been characterized by D. Vokrouhlický et al. (2025; Figure 1), who found that the background population and collisional families exhibit distinct magnitude-distribution slopes. The optical colors of Hildas closely resemble those of the Jupiter Trojans (I. Wong & M. E. Brown 2017), supporting a common origin with the Trojans and with outer solar system populations, making the Hildas the nearest large reservoir of trans-Neptunian material in the solar system. Roughly 60% of currently known

Hildas are associated with collisional families (M. Brož & D. Vokrouhlický 2008; D. Vokrouhlický et al. 2025), and this fraction may vary with object size due to differences in collisional size distributions. Figure 2 shows our simulated Hilda population in the space of proper orbital elements, following the approach of Figure 6 in D. Vokrouhlický et al. (2025), and highlights the clusters corresponding to the major collisional families. These collisional families (from largest to smallest) are Hilda family, Schubart family, and Potomac family. Studying these families can provide insight into collisional physics in the outer main belt, the evolution of fragment orbits due to nongravitational effects like the YORP effect, and the long-term stability of asteroid populations.

As of 2025 October 15, the Minor Planet Center (MPC) lists 6622 known Hildas (Minor Planet Center 2026), mostly discovered incidentally by major asteroid surveys rather than dedicated Hilda searches. The Vera C. Rubin Observatory’s Legacy Survey of Space and Time (LSST) represents the next major leap in solar system science. Its 10 yr duration, six-filter optical/NIR coverage, image depth, and broad sky coverage will enable unprecedented characterization of the Hilda population, including their rotational properties. One of LSST’s primary scientific goals is to obtain an “inventory of the solar system” (LSST Science Collaboration et al. 2009) by discovering and characterizing as many small bodies as possible. Using a comprehensive simulation of LSST’s solar system capabilities, J. A. Kurlander et al. (2025) found that LSST will discover several times more objects than are currently known in each orbital class and will meet the Rubin Observatory Metrics Analysis Framework (R. L. Jones et al. 2014) metric



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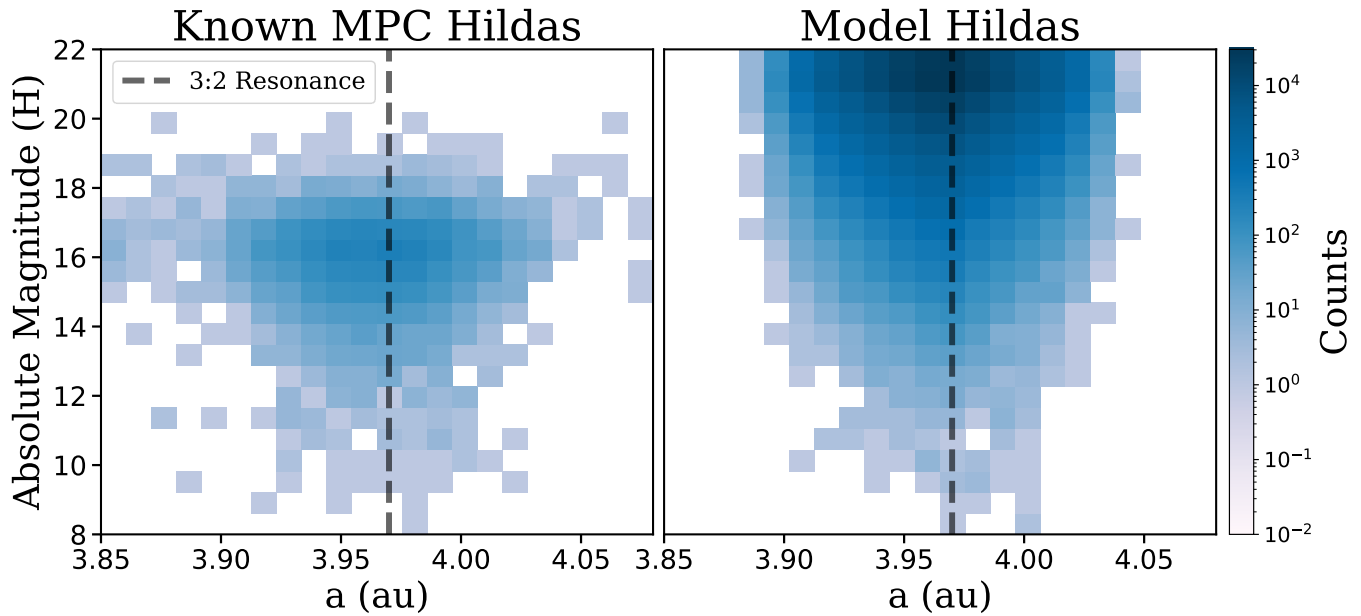


Figure 1. Comparison of the known Hilda population from the MPC (left) and our synthetic Hilda population (right) in semimajor axis (a) and absolute magnitude (H). The vertical line at $a = 3.971$ au marks the location of the 3:2 mean-motion resonance with Jupiter, which defines the Hilda population. Our input sample reproduces the observed distribution in both a and H while extending to fainter magnitudes beyond the MPC limit.

for high-quality light curves on 3%–8% of the non-near-Earth object bodies it observes. Given their comparable dynamical states, one might expect similar behavior between the Hilda and Trojan populations, but this expectation remains untested as no equivalent LSST yield analysis has been conducted for the Hildas.

We use `SORCHA` (M. J. Holman et al. 2025; S. R. Merritt et al. 2025), a solar system survey simulator that models LSST’s detection and discovery of asteroids and creates a simulated source catalog. We then perform our own rotational analyses on these simulated detections to assess LSST’s ability to measure rotational properties. Simulating the survey enables us to examine how cadence, depth, and other observational factors influence which objects are detected and how well their light curves are sampled. These detections and effects then determine which rotation periods and amplitudes can be reliably recovered, making it essential to quantify their impact when interpreting the observed light-curve distributions and inferring the intrinsic properties of small solar system bodies.

Rotational light curves are the primary means of determining asteroid spin rates, shapes, and surface features, but they are challenging to obtain. Of the 6622 Hildas currently listed by the MPC, only 195 have measured light-curve amplitudes and rotational periods in the LightCurve Database (LCDB; B. D. Warner et al. 2009, as of 2025 June 26), and only about one third of these objects have the full spin state reconstructed (e.g., J. Ďurech & J. Hanuš 2023). This small fraction may reflect observational limitations or intrinsically low variability in the Hilda population if most are axially symmetric. The currently available empirical Hilda population light-curve data are strongly shaped by observational biases and do not represent the intrinsic distributions of rotational period or amplitude. Larger amplitudes are typically easier to find, while successfully finding a rotational period of an object with roughly zero amplitude might be impossible. Recorded light curves are therefore biased toward larger amplitudes.

To explore the limits of LSST’s rotational sensitivity, we consider two extreme rotational populations: superfast rotators

(SFRs) and superslow rotators (SSRs). SFRs are small solar system bodies that rotate faster than the critical period a rubble-pile asteroid could survive without internal cohesion. Measuring these rapid rotation rates provides insight into internal strength, cohesion, and composition. In contrast, SSRs rotate on such long timescales that their light-curve variations unfold over many nights. These objects may record long-term rotational evolution driven by processes such as the YORP effect (e.g., D. Vokrouhlický et al. 2015) or follow from the split of tidally evolved binary systems (e.g., D. Nesvorný et al. 2020). Among the 111 Hildas observed by the Kepler Space Telescope’s K2 mission, about 18% exhibited rotational periods greater than 100 hr, indicating SSRs may be more common among Hildas than in other asteroid populations (G. M. Szabó et al. 2020). In comparison, the Transiting Exoplanet Survey Satellite in its DR1 has observations of 26 Hildas with 17 reliably determined rotation periods, among which there are only 2 greater than 100 hr ($\sim 12\%$; D. E. Vavilov & B. Carry 2025). Although lower, this fraction is broadly consistent with the K2 result given the smaller sample size. Rubin’s wide field and 10 yr cadence are well suited for characterizing these slow rotators, offering more complete coverage than narrow state-of-the-art surveys such as the DECam Ecliptic Exploration Project (R. Strauss et al. 2024).

While real small-body light curves often contain higher-order structure from irregular shapes, surface variations, or binarity, this complexity is difficult to model in detail. We therefore adopt a simple sinusoidal model that does not include these higher-order features. Although the observed Hilda population shows a high binary fraction (G. M. Szabó et al. 2020), this approximation provides a simple framework in which we can evaluate recovery efficiency purely as a function of light-curve amplitude and rotational period. Using this simplified model, which does not take into account pole orientation, we simulate Rubin’s detection of Hildas to evaluate its ability to recover rotational periods. A key limitation of our light-curve model is the absence of

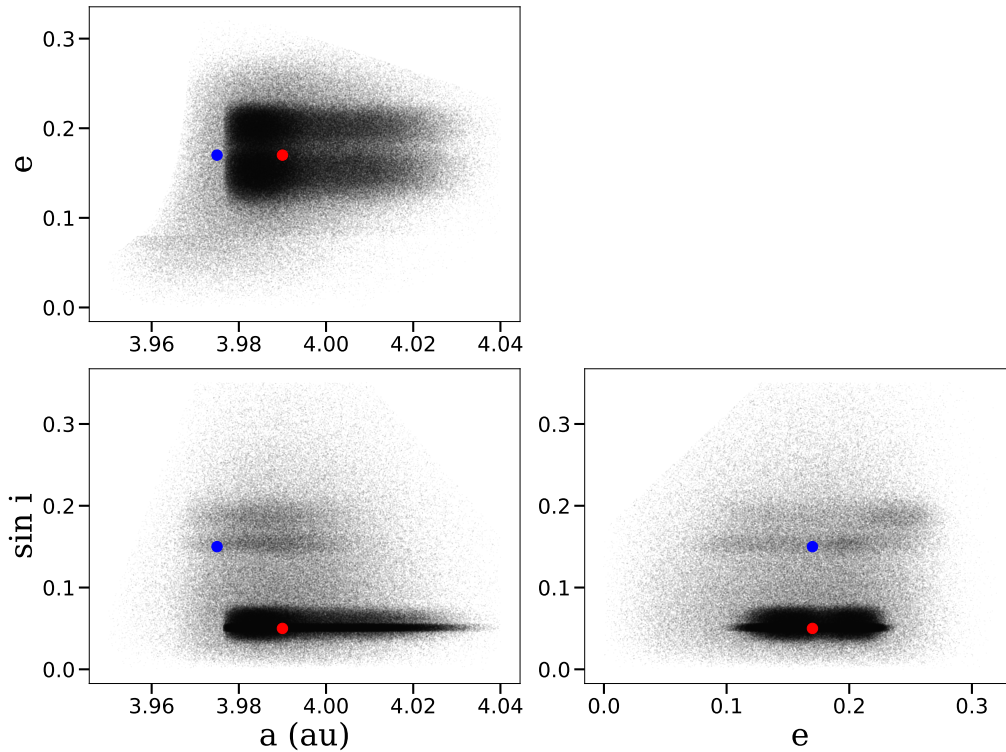


Figure 2. Distribution of our 485,807 simulated Hildas projected onto 2D planes of their proper orbital parameters. (i) (a, e) top left; (ii) $(a, \sin(i))$ bottom left; and (iii) $(e, \sin(i))$ bottom right. Each dark point represents an object from our simulated Hilda population. Approximate locations of the two largest collisional families associated with (153) Hilda (blue marker) and (1911) Schubart (red marker) are indicated for reference (D. Vokrouhlický et al. 2025).

rotation-pole orientations. The observed Hilda population shows some concentration of pole obliquities near 0° and 180° (J. Ďurech & J. Hanuš 2023), but a substantial number occupy intermediate obliquities, which affect the recoverability of their light curves. Similarly, real objects have diverse phase slopes, introducing additional brightness variations not captured in our constant-phase model. While the effect of pole obliquity on light-curve recovery is uncharacterized, these assumptions mean the current period recovery rate is likely an upper limit.

In Section 2 we describe our methods, including the model Hilda population and the *Sorcha* simulation of LSST. Section 3 presents our results, including expected discovery yields and light-curve recovery. Section 4 provides the conclusions, literature discussion, and future work.

2. Methods and Inputs

2.1. Orbital, Size, and Color Distributions

We construct a synthetic Hilda population of orbits, sizes, and colors. We sample 485,807 independent and bias-corrected orbits and magnitudes from D. Vokrouhlický et al. (2025), reproducing both the background population and the three major collisional families. We assigned two $g-r$ colors (0.51 and 0.64) for the red and less-red subpopulations. The remaining color indices ($u-r$, $i-r$, $z-r$, $y-r$) were sampled from the magnitude-dependent Trojan distributions of J. A. Kurlander et al. (2025), assuming the Hildas share the same bimodality as the Jupiter Trojans (I. Wong & M. E. Brown 2017). We set a constant-phase slope of $G = 0.15$ (see review of the $H-G$ photometric system in E. Bowell et al. 1989; K. Muinonen et al. 2010), though in reality this parameter likely varies with composition, surface texture, and

wavelength. A more complete treatment of phase-angle effects could improve the accuracy of the simulated photometry, especially for objects observed over a large range of phase angles.

2.2. Rotational Inputs

Building on previous *Sorcha* simulation work, we include rotational behavior for our simulated objects. We assign each synthetic Hilda a sinusoidal light curve to simulate rotational variability, allowing us to test how Rubin’s cadence and depth affect the recovery of rotation periods across a range of amplitudes. To probe how Rubin’s cadence and depth affect the recovery of rotational periods as a function of both period and amplitude, we model three light-curve populations: a realistic baseline population (Figure 3), SFRs with periods shorter than 3 hr (C.-K. Chang et al. 2022) and SSRs with periods longer than 100 hr (G. M. Szabó et al. 2020)

Our baseline population is constructed from the 223 Hildas in the LCDB with at least one measured light-curve property (rotational period or amplitude), which are used to build the kernel density estimate (KDE) distributions. Although subject to observational bias, it remains the most comprehensive source of Hilda light-curve data. The distributions of rotational periods and light-curve amplitudes were modeled using a Gaussian KDE of the LCDB Hilda observational data. Each KDE generates a smooth, continuous function, from which we can sample arbitrarily many periods and amplitudes. Separate KDEs were generated for periods and amplitudes for each collisional family: Hilda, Schubart, and the background population. A total of 120 of these LCDB Hildas are within the Hilda resonance but are not confirmed members of any collisional family. The Potomac family had no Hildas with

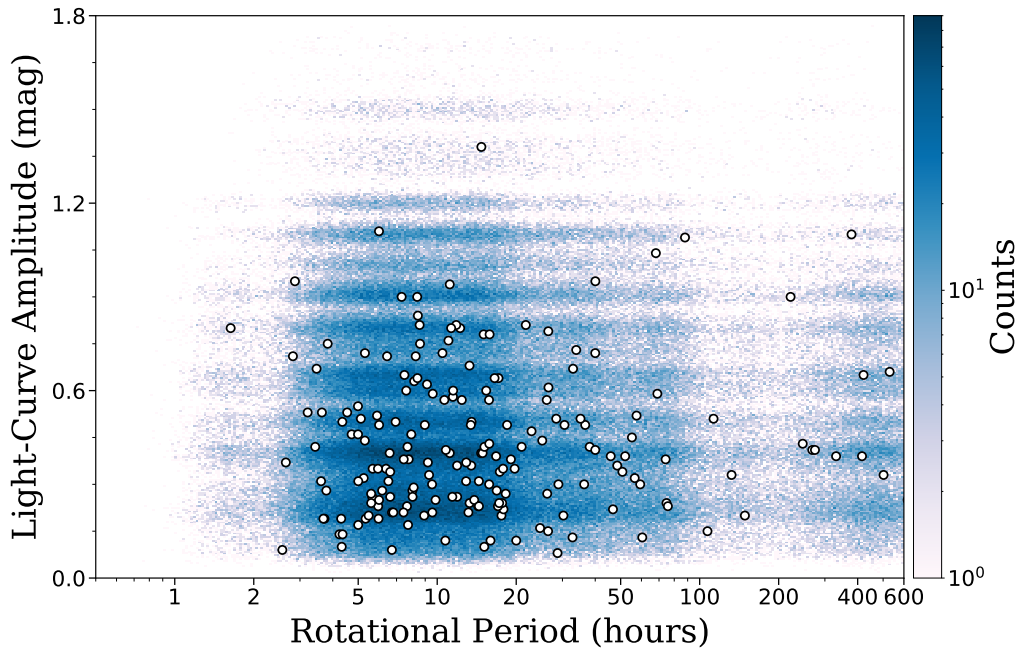


Figure 3. Comparison of simulated and observed Hilda light-curve distributions. This shows a 2D histogram of rotational period versus light-curve amplitude for the combined simulated population, created by sampling from KDEs constructed using LCDB Hildas with measured rotational periods and/or light-curve amplitudes (223 objects total). White points indicate the subset of LCDB Hildas with both measured rotational periods and amplitudes (195 objects). Our KDE-based sample is consistent with the rotational properties of observed Hildas.

measured light curves in the LCDB, so we assign their rotational properties from the Hilda collisional family that shares similar orbital parameters. We adjusted the bandwidth for each KDE (See Table 1) to obtain the widest distribution that did not spread the bulk of periods above 20 hr, below which roughly 70% of the observed Hilda periods lie. This choice results in some gaps and discretization at longer periods. Using these KDEs, we identically and independently draw periods and amplitudes according to each collisional family, creating a population representative of the LCDB population, though not necessarily representative of the intrinsic population.

To complement our KDE-based LCDB population, we also construct extreme input period and amplitude distributions to focus on the most exciting objects while probing potential systematic biases and blind spots in Rubin’s cadence. These distributions are not intended to represent the physical Hilda population but rather to test the full range of periods and amplitudes that may be underrepresented or absent in the LCDB. We defined our SFR boundary following C.-K. Chang et al. (2022), from the critical 3 hr limit for objects with bulk density of $\sim 1.5 \text{ g cm}^{-3}$, though main-belt observations include extreme cases with periods as short as 0.21 hr (R. Strauss et al. 2024) and now faster by S. Greenstreet et al. (2026). We set the SSR lower bound to 100 hr following G. M. Szabó et al. (2020) and its upper bound to 1400 hr—roughly twice the largest period among the 1465 LCDB Hildas. For each population, we drew rotational periods uniformly: from 0 to 3 hr for SFRs and from 100 to 1400 hr for SSRs. We sampled amplitudes uniformly between 0 and 2.5 mag, approximately twice the largest observed Hilda amplitude in the LCDB, to account for possible highly elongated shapes. Together, these extreme populations enable us to explore detectability limits and identify potential systematic biases arising from Rubin’s

Table 1
Input Parameters of Simulated Hilda Populations

Parameter	Input Value / Parameter
Range of semimajor axis (a)	3.8858–4.0396 (au)
Range of eccentricity (e)	0.0012–0.3905
Range of inclination (i)	0.015–21.69 (deg)
Phase slope parameter (G)	0.15
Range of Absolute magnitude (H_v)	7.53–21.75 (mean = 20.63)
Color ($g - r$)	0.51 (483,215 objects), 0.64 (2,592 objects)
Color index ($u - r$)	1.4353
Color index ($i - r$)	−0.22
Color index ($z - r$)	−0.39
Color index ($y - r$)	−1.1804
Phase function model	<i>HG</i>
Light-curve model	Sinusoidal
Period KDE bandwidth (Hilda / Schubart / Background)	0.0045 / 0.008 / 0.01
Amplitude KDE bandwidth (Hilda / Schubart / Background)	0.07 / 0.05 / 0.08

Note. Orbital elements and absolute magnitudes are derived from D. Vokrouhlický et al. (2025) and colors from I. Wong & M. E. Brown (2017).

cadence, complementing our more realistic LCDB-based rotational population.

2.3. *Sorcha* Simulations

We simulate LSST observations of Hildas using *Sorcha*, a solar system survey simulator designed for large-scale wide-field surveys like LSST. Given a survey’s cadence, field coverage, and a model solar system population, *Sorcha* accurately integrates orbits (M. J. Holman et al. 2025) and rotational light curves for each object and evaluates their detectability in each exposure. Detections brighter than the

~ 16.0 mag saturation limit are excluded as they are not reliably measured.

We adopt the latest Rubin-published (v4.2) baseline LSST cadence (P. Yoachim et al. 2023; F. Delgado et al. 2014; P. Yoachim & L. Jones 2025, as of 2025 July 17), which provides a realistic model of the telescope’s observing pattern. This 10 yr simulated survey begins 2026 January 1 and emphasizes the wide–fast–deep strategy, supplemented by deep-drilling fields and the Northern Ecliptic Spur to maximize solar system discovery. Observing conditions such as filter, sky brightness, and limiting magnitude are also included so that the simulated detections accurately reflect LSST’s observing capabilities. For each detection of each object in each image, *Sorcha* provides the photometric measurements we use to construct light curves for our recovery tests. We adopted *Sorcha*’s default parameters and ran all simulations on the UW Epyc cluster, requiring roughly 100 core hours in total.

2.4. Period Recovery

To test whether we could recover rotational periods from simulated LSST observations, we applied a multiband Lomb–Scargle periodogram via *Astropy* (A. M. Price-Whelan et al. 2022) to the simulated light curves. The Lomb–Scargle periodogram produces a power spectrum across a range of frequencies. The multiband implementation adds a color offset parameter for each optical filter (R. Strauss et al. 2024; J. T. VanderPlas & Ž. Ivezić 2015), allowing data from each filter to contribute to the determination of a single period.

We limited the frequency search window to the bounds of each input population. For our SFRs, we limited our search window to 0.2–3 hr. Periods approaching 0 hr require increasingly dense frequency sampling and substantially increase computational runtime, and a lower limit of 0.2 hr allows for the recovery of the 0.21 hr period main-belt asteroid (R. Strauss et al. 2024). For SSRs our search window spans 24–1400 hr to match the input population and to allow objects to be fit to the common 24 hr alias. These frequency windows are intentionally restricted and do not represent the full physical range of rotational periods but make period recovery computationally feasible. We set the Lomb–Scargle samples-per-peak parameter, which controls the frequency resolution, to 50 for each period search (J. T. VanderPlas 2018).

For each simulated light curve, the periodogram identified the period associated with the highest-power peak. To assess the reliability of each period fit, we introduce a “reduced inverse power” confidence metric. For each object we identify the highest periodogram power P_{\max} across all frequencies and compute

$$R = \frac{1}{P_{\max} (N_{\text{obs}} - N_{\text{Parameters}})}, \quad (1)$$

where P_{\max} is the maximum periodogram power, N_{obs} is the number of observations, and $N_{\text{Parameters}}$ represents the number of parameters in our model. Here, $N_{\text{Parameters}} = 9$, accounting for the sinusoidal terms, period, and the multiband offset parameters. We then compare our best period fit with the input period for each object and define an accurate fit as being within 1% of the true input period (including half and double harmonics). We define our confidence threshold at the value of R below which 99% of periods are accurately recovered; this

yields $R = 0.00994$. This represents the strictest cutoff among the three simulated populations, and we apply it for all populations for consistency. The distribution of R values for correct and incorrect periods is shown in Figure 4. Lower R values correspond to higher confidence, with most accurate period recoveries concentrated at low R and incorrect periods increasingly likely at higher R .

3. Simulated LSST Yield For Hildas

3.1. Discovery Yield and Completeness

Our simulated LSST survey discovers 33,367 Hildas in the baseline population. This represents a factor-of-five increase over the 6622 currently known Hildas (NASA/JPL Solar System Dynamics 2025; Figure 5). The simulated survey has very high discovery completeness for bright Hildas. Completeness is 100% for Hildas with H_r between 9.03 and 17.67 and remains above 90% for H_r up to 18.0. The faintest object detected has an H_r of 22.0 with the faintest Hilda in the MPC database of 19.7 magnitudes. Completeness drops at the bright end due to the $m_r \approx 16.0$ due to saturation and at the faint end due to the surveys limiting depth. The average number of observations of discovered Hildas in the baseline population is 173.6. In all, 74 objects were detected at least 1000 times each, with the most-detected object having 3762 detections. For comparison, K2 observations of Hildas ranged from 218 to 1596 detections per object with 10 of 102 Hildas listed having greater than 1000 detections (G. M. Szabó et al. 2020). LSST is expected to reveal tens of thousands of faint members of the Hilda population that were previously undetectable by past surveys.

3.2. Light-curve Recovery

We are highly confident in our recovered periods for 15,300 of 33,290 (45.96%) Hildas in our LCDB simulation population (Figure 6). Period recovery efficiency is largely determined by light-curve amplitude. For light-curve amplitudes greater than 0.2 mag, recovery generally exceeds 45%. Among the uniform input populations, we achieved roughly 9% high-confidence recovery for amplitudes from 0 to 0.05 magnitudes. For the SSR population, we see a peak of 45% confidence around 0.5 magnitudes before a steady decline in recovery rate to roughly 35% at 2.5 mag. This decline largely reflects the limited number of detections for very faint, long-period objects. Many of these bodies remain detectable for only a portion of the survey window, so their light curves are sparsely sampled, reducing the likelihood of successful period recovery. We also note that only 21 periods (searched from 24 to 1400 hr) were folded to the 24 hr alias, and none were flagged as highly confident recoveries.

For the SFR population, period recovery is generally higher compared to the other two populations, most likely due to its larger fraction of high-amplitude light curves compared to the LCDB population. Recovery rates are typically around 65% but have higher variance than the other populations. We see a characteristic dip in recovery efficiency near LSST’s typical revisit cadence of ~ 36 minutes and its harmonic at 18 minutes. On either side of this cadence-related dip, the recovery rate exceeds 60%, while within the dip the rate falls to $\sim 45\%$ (Figure 6).

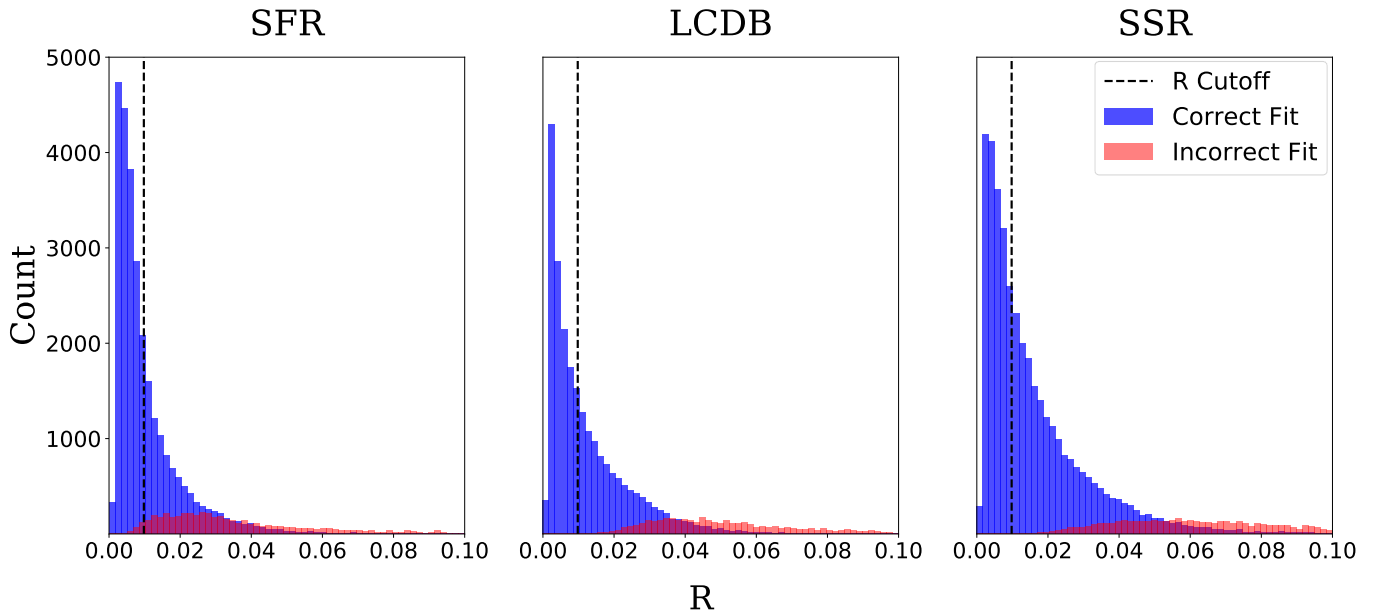


Figure 4. Distributions of the reduced inverse power metric R (Equation (1)) for the SFR, LCDB, and SSR simulated light-curve populations, separated into the correctly and incorrectly recovered rotational periods. The vertical dashed line shows the confidence threshold $R = 0.00994$, defined as the value below which at least 99% of SFR periods are accurately recovered (including half/double-period harmonics). Correct fits (blue) concentrate strongly at low R , while incorrect fits (red) populate a broader tail toward larger R , demonstrating that smaller R values correspond with more reliable period recoveries.

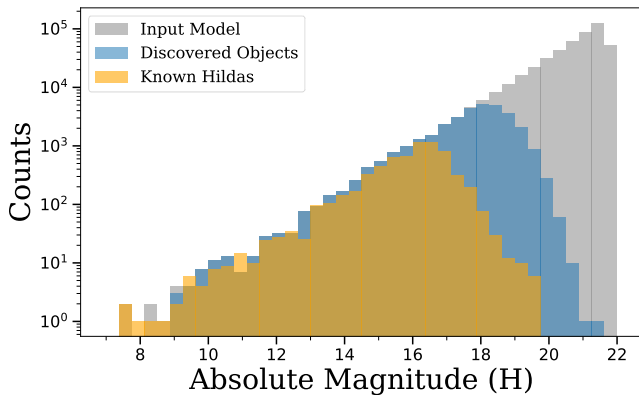


Figure 5. Comparison of absolute magnitude (H) distributions for the known, input, and discovered Hilda populations. The orange histogram shows the currently known Hildas from the MPC. The blue distribution represents the Hildas discovered in our simulated survey with the gray being the full input population. The synthetic discoveries extend ~ 1.5 – 2 magnitudes fainter than the known population, demonstrating LSST’s ability to probe substantially deeper and expand the observed Hilda population beyond current detection limits.

For the SSR population, recovery fraction decreases with rotational period. For periods from 100 to 200 hr, the recovery confidence is approximately 45% and remains around 40% until approximately 700 hr. Beyond 700 hr, recovery confidence steadily declines to roughly 35% at extremely long periods, near 1300 hr. In Figure 6, compared to the LCDB and SFR populations, the SSR population shows slightly higher recovery fractions at intermediate amplitudes (0.3–1.0 mag) and shorter periods (< 700 hr) but lower discovery rate, likely because objects with high amplitudes (2.0–2.5) and long periods (> 700 hr) spend more time near maximum brightness, increasing the chance of being detected in three tracklets in a row (Figure 7). However, many of these objects are very dim and sparsely observed, so their light curves remain poorly sampled, which

reduces the likelihood of accurate period recovery compared to brighter, constantly detected objects. Only 21 periods (0.04%) in the SSR population are affected by the 24 hr nightly alias. Among these, over 70% correspond to input periods exceeding 1000 hr, and the average number of detections was below 20, suggesting that extremely slow rotators that are observed less frequently are particularly susceptible to being folded to this daily timescale. None of these folded objects meet our confidence threshold, so we safely label all of these aliased periods as unreliable.

Variations in surface properties and light-curve amplitudes among Hildas can strongly influence our ability to measure rotational periods. We assume a constant-phase slope ($G = 0.15$) and uniform surface properties only crudely represent the diverse surfaces of these objects. Most importantly, a large majority of our simulated objects have light-curve amplitude that can be measured: 97.9% of our input Hildas having amplitudes greater than 0.1 mag, while the intrinsic population could possibly have amplitudes far lower than this. The MPC lists 6622 known Hildas currently, and the LCDB lists light-curve parameters for 195 of them, suggesting that many Hildas may have low amplitudes, making accurate period recovery significantly more difficult.

4. Discussion

4.1. Summary

1. Using the *Sorcha* survey simulator, we predict LSST will increase the known Hilda population roughly fivefold and discover all bright Hildas with H_r between 9.03 and 17.67.
2. We recover 45.96% of periods in our LCDB-based population.
3. For amplitudes > 0.2 mag, period recovery generally exceeds 45%; for amplitudes 0–0.05 mag, high-confidence recovery is below 10%.

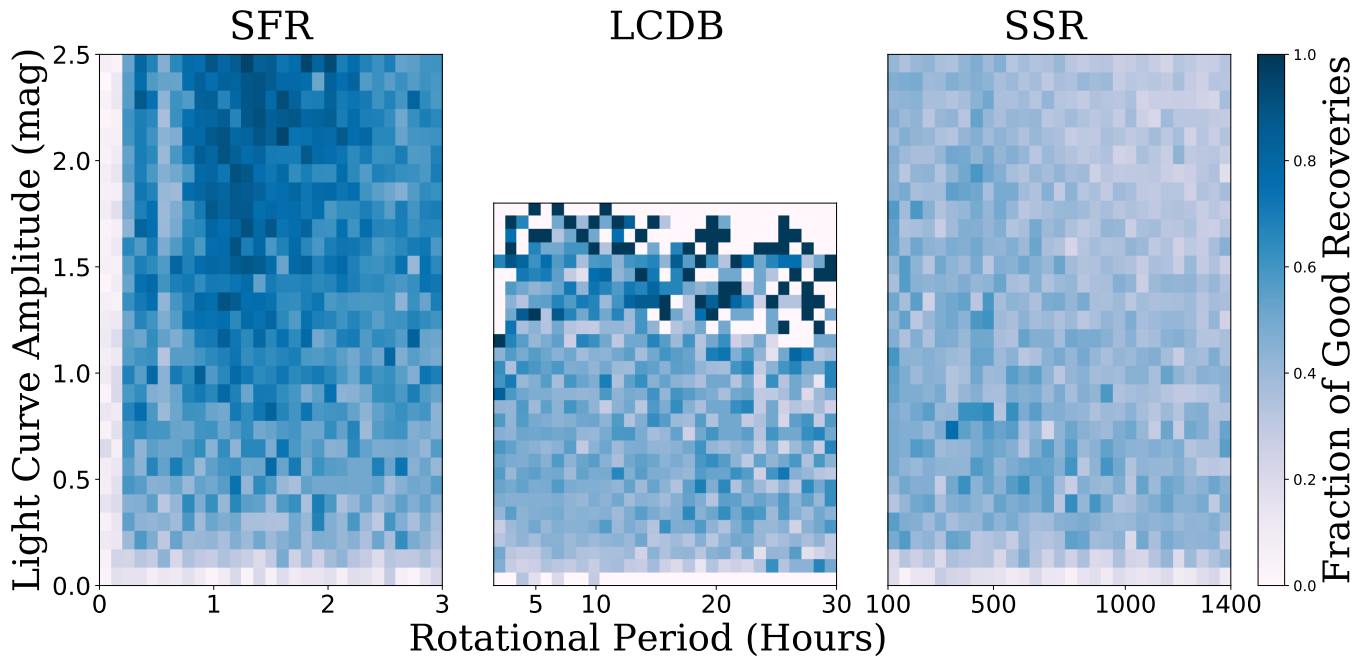


Figure 6. Fraction of light curves meeting the 99% confidence threshold as a function of light-curve amplitude and rotational period. Each bin shows the fraction of objects whose Lomb–Scargle periodogram structure indicates high confidence in the recovered period. Recovery confidence decreases significantly at lower amplitudes, where weaker variability reduces the reliability of period identification.

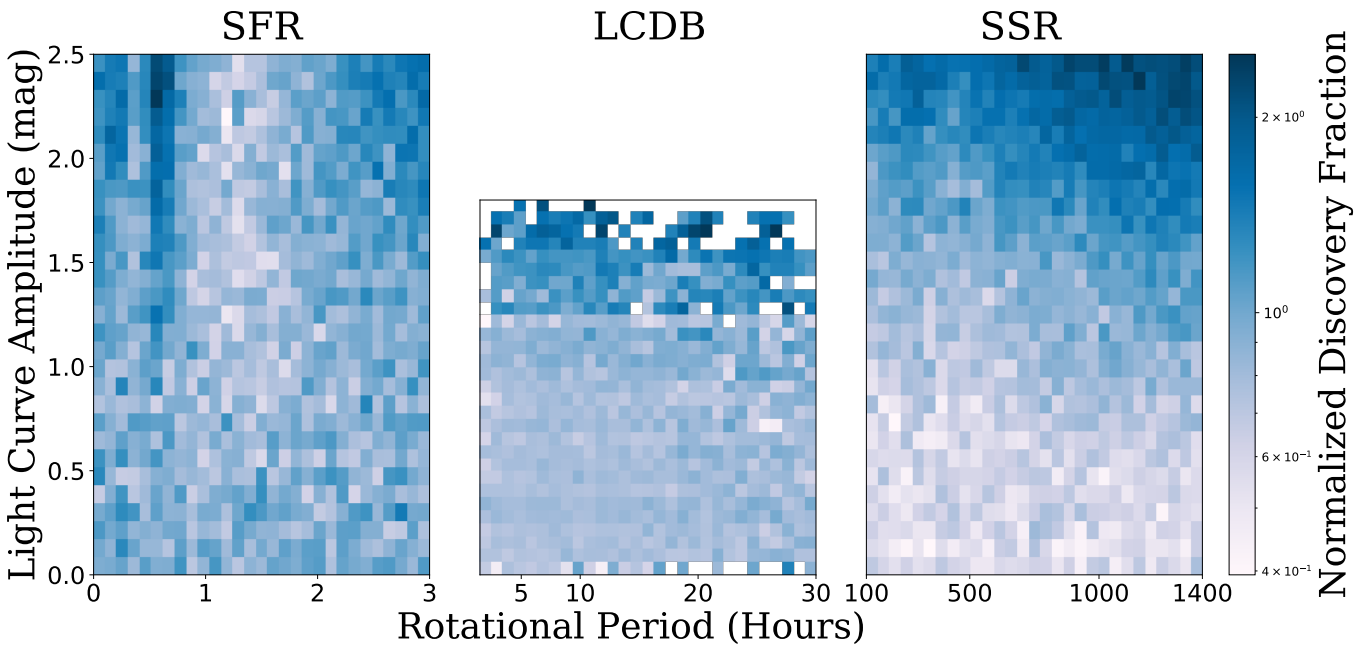


Figure 7. Discovery fraction of our simulated Hildas for the SFR, LCDB, and SSR populations. Each panel displays the per-bin fraction of objects that were detected in our simulated survey, normalized by the overall discovery fraction so that an average bin has a value of 1.0.

- Nearly all (97.9%) of our simulated Hildas have measurable light-curve amplitudes >0.1 mag, while the true population may have lower typical amplitudes.

4.2. Literature Discussion and Future Work

The repeated measurements provided by LSST will enable the construction of a bias-corrected catalog of rotational properties for the Hilda population. Hundreds of detections per object allow survey simulations to account for observational

biases in period and amplitude, and comparisons between debiased rotational states of collisional families can inform collisional physics, YORP-driven spin evolution, and population formation. Our results provide a benchmark for LSST and are expected to scale to other populations with similar brightness distributions and cadence (e.g., the main belt).

S. Greenstreet et al. (2026) analyzed Rubin Observatory First Look (RFL) data and performed light-curve period and amplitude fitting using a method similar to ours. Their search was limited to a narrow 14 deg^2 field over 12 days, but the

dozens of consecutive repeat measurements in their cadence make light-curve recovery far more efficient than the LSST 10 yr baseline simulation. In order to constrain the intrinsic spin-state distribution of main-belt asteroids we would need to model the selection function of the RFL survey using a survey simulation just like this one. After validating *Sorcha*'s default model of Rubin with real Rubin data, simulating asteroid populations against the RFL cadence using a more sophisticated ellipsoidal light-curve model with pole obliquities, we would search the simulated population for light curve periods and amplitudes, creating a light-curve recovery selection function. Using that selection function, we could test which light-curve population models are consistent with the RFL data and constrain the intrinsic spin-state distribution of main-belt asteroids.

Additional parameters will be incorporated in future simulations to better simulate real objects, such as variable pole orientations modeled in *Sorcha* simulations and expanding the selection function model to amplitude, period, and obliquity. These may allow LSST observations to constrain intrinsic pole obliquity distributions and inform collisional and YORP-driven spin evolution (J. Ďurech & J. Hanuš 2023). The multiband photometry provided by LSST also opens opportunities to explore color-dependent effects on light-curve recovery, and in this study we assigned two colors classes. Future work could incorporate more complex parameters to investigate formation and evolution of small solar system bodies.






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