OGLE-III MICROLENSING EVENTS AND THE STRUCTURE OF THE GALACTIC BULGE

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ABSTRACT

We present and study the largest and most comprehensive catalog of microlensing events ever constructed. The sample of standard microlensing events comprises 3718 unique events from 2001–2009 with 1409 events that had not been detected before in real-time by the Early Warning System of the Optical Gravitational Lensing Experiment. The search pipeline uses machine learning algorithms to help find rare phenomena among 150 million objects and to derive the detection efficiency. Applications of the catalog can be numerous, from analyzing individual events to large statistical studies of the Galactic mass, kinematics distributions, and planetary abundances. We derive maps of the mean Einstein ring crossing time of events spanning 31 deg^2 toward the Galactic center and compare the observed distributions with the most recent models. We find good agreement within the observed region and we see the signature of the tilt of the bar in the microlensing data. However, the asymmetry of the mean timescales seems to rise more steeply than predicted, indicating either a somewhat different orientation of the bar or a larger bar width. The map of events with sources in the Galactic bulge shows a dependence of the mean timescale on the Galactic latitude, signaling an increasing contribution from disk lenses closer to the plane relative to the height of the disk. Our data present a perfect set for comparing and enhancing new models of the central parts of the Milky Way and creating a three-dimensional picture of the Galaxy.

Key words: catalogs – Galaxy: bulge – Galaxy: structure – gravitational lensing: micro

Supporting material: machine-readable tables

1. INTRODUCTION

Galactic gravitational microlensing is an astrophysical phenomenon that originates from the fact that in the curved spacetime around each sufficiently massive body (e.g., stars), light travels along bent (hence converging) paths. The foundations of the theory lie in the general theory of relativity of Einstein (Einstein 1936), and its practical uses within the scale of our own Galaxy were developed by Paczyński (Paczyński 1991) and Griest (Griest et al. 1991). This unique astrophysical tool has numerous and very interesting applications because, unlike other astrophysical phenomena, microlensing is sensitive to the mass of the object passing in front of a background star. This means that, in principle, the lens can be completely dark and still cause a microlensing event as long as it aligns with a background star and the relative motion between the source, lens, and observer is large enough for the event to last within a human timescale. During such an event, the background star appears brighter, typically by a factor of a few, occasionally reaching hundreds and very rarely thousands in the case of a perfect alignment when the images form an Einstein ring.

The fact that microlensing is sensitive to the mass of lensing objects turns this phenomenon into a powerful probe of the mass distribution of the Galaxy, allowing us to study the structure of the Milky Way. Kiraga & Paczyński (1994) defined the microlensing optical depth as a measure of the lensing probability toward the Galactic center and showed it as a convenient indicator of the total mass of the lensing populations along the line of sight. The first measurements of the optical depth obtained from the Optical Gravitational Lensing Experiment (OGLE) data (Udalski et al. 1994) and MACHO (Alcock et al. 1997) were significantly higher than expected based on theoretical models of the Galaxy (e.g., Dwek et al. 1995; Han & Gould 1995; Binney et al. 2000; Freudenreich 1998; Evans & Belokurov 2002). This discrepancy was partially explained by Paczyński et al. (1994), who introduced a bar to the models: an elongated solidly revolving structure placed at about a 20 deg angle toward the Sun. In subsequent years, measurements of the optical depth were limited to events in which the sources were red clump (RC) giants from the Galactic bulge (e.g., Afonso et al. 2003; Popowski et al. 2005). This trick moved the observed values significantly closer to the theoretical predictions, mainly because it mostly probed a single population of sources from the bulge and reduced the problem of blending (crowding) of stars. Blending is a demanding issue to deal with in extremely crowded sky regions such as the Galactic center. As shown in Smith et al. (2007), blending cannot be completely neglected in optical depth determinations, even in the case of the lensing of the brightest RC stars.

Nevertheless, despite the fact that there were many hundreds of events being detected in real-time every year by the OGLE (Udalski 2003) and MOA (Yock 1998) collaborations, the number of microlensing events used for the studies of the inner parts of the Galaxy were typically much smaller. For instance, the optical depth measured by the EROS group relied on 16 (Afonso et al. 2003) and 120 events (Hamadache et al. 2006), and MACHO used 99 events (Alcock et al. 2000) and 42 RC events (Popowski et al. 2005). Only 9 events were used to compute the first ever optical depth value from the...
OGLE-I data (Udalski et al. 1994), and then 32 events were used from the OGLE-II project (Sumi et al. 2006). The largest samples of standard single-lens events used so far for optical depth determinations have been 610 events from the OGLE-III years 2001–2004 (Wyrzykowski 2005) and 474 events found in MOA-II in 2006–2007 (Sumi et al. 2013). Moreover, Calchi Novati et al. (2008) constrained the initial mass function (IMF) based on just 42 events from MACHO and obtained a slope for main-sequence stars of $\alpha_{\text{MS}} = 1.7$ and $\alpha_{\text{ED}} = 1.6$ for Brown Dwarfs populations in the Bulge, in agreement with most theoretical predictions. However, a detailed mass spectrum can be obtained when using significantly larger samples of microlensing events. Increasing the number of good quality and robust standard microlensing events is essential for more detailed comparisons of observations to predictions over a range of Galactic coordinates (Mao 2012).

The Einstein ring crossing time, i.e., the timescale of an event, is the only parameter from the standard microlensing model that has a physical meaning. Still, its value is composed of multiple parameters:

$$t_E = \frac{\sqrt{\kappa M \pi}}{\mu_{\text{rel}}},$$

(1)

where $\kappa = 4G/c^2 \approx 8,144 \text{mas}/M_{\odot}$, $M$ is the mass of the lens, $\pi_{\text{rel}} = 1/D_d - 1/D_s$, $D_d$ and $D_s$ are the distances to the deflector (lens) and the source, respectively, and $\mu_{\text{rel}}$ is the relative proper motion between the source and the lens. Due to that degeneracy, the timescales can only be studied statistically in large numbers, as all parameters involved in the $t_E$ creation follow some distributions, which can be modeled for different populations within the Milky Way. As seen in Equation (1), the strongest influence on the $t_E$ value comes from $\mu_{\text{rel}}$, and therefore the distributions and dispersions of the proper motions of different Galactic populations will play a crucial role in interpreting the observed timescales. Measured distributions of the timescales of microlensing events have been used in the past as one way of verifying different scenarios for the composition and kinematics of the inner parts of the Galaxy, e.g., Evans & Belokurov (2002), Bissantz & Gerhard (2002), Wood & Mao (2005), Calchi Novati et al. (2008), Kerins et al. (2009), Sumi et al. (2013).

In this paper, we analyze the final and complete photometric data set gathered during the OGLE-III project in 2001–2009. We search for high-quality standard microlensing events using the optimized search criteria, supported by the machine learning method (Random Forest classifier), and use them to investigate the structure of the inner parts of the Milky Way.

The paper is organized as follows. First, we describe the OGLE-III data. In Section 3, we describe in detail the procedure of the search for events, divided into several sub-steps. Then, we report on the results of the search and present the catalog, compare it to the Early Warning System (EWS), and discuss the detection efficiency of events. This is followed by the discussion of the results, in which we describe the properties of the events as a whole, derive the distributions of the timescales of events over the sky, and compare it to the Galaxy models. We summarize and conclude the paper in Section 6.

2. DATA

The data used in this work were photometry of 150 million objects toward more than 31 deg$^2$ of the Galactic bulge observed in almost 74,000 frames, i.e., about 11,000 billion data points. We selected 91 fields out of all 177 ever observed by the Optical Gravitational Lensing Experiment (OGLE) Udalski et al. (2008) in its third phase from 2001 July until 2009 May, which had at least 250 observations. During the OGLE-III phase, the Warsaw Telescope, located at the Las Campanas Observatory, Chile, operated by the Carnegie Institution of Washington (now the Carnegie Institution for Science), was equipped with a mosaic CCD camera with eight 2k $\times$ 4k pixel detectors covering a total of 0.34 deg$^2$. The typical exposure time in the fields toward the Galactic bulge was 120s, allowing us to reach down to nearly 21 mag in the Johnson-Cousin $I$ band, that is, the filter in which a vast majority of the observations were carried out.

Figure 1 shows the positions of the OGLE-III fields toward the Galactic bulge. Each field was observed on average once per three nights. However, starting from the 2005 season, the observing strategy changed slightly so that the most dense fields at about $b \sim -2$ deg were observed with a higher cadence than the rest, typically two/three times per night. The number of observations collected in the $I$ band over eight years per field varied from 251 for BLG344 to 2540 for one of the central fields, BLG102.

There were typically between 1 and 35 $V$-band data points available for the fields investigated here. Those data were only used to obtain the averaged color of the baseline of the objects. The calibrated color was taken from the OGLE-III Bulge photometric maps (Szymański et al. 2011).

During operation of OGLE-III, the data collected each night were reduced on-the-fly with the state-of-the-art difference imaging technique (DIA, Wozniak 2000) and preliminary photometry was produced within a couple of hours. This was the basis for the EWS (Udalski 2003), which was designed to look for new microlensing events in real-time. As a result of seven years of operation (2002–2009), the OGLE-III EWS reported about 4000 candidates for microlensing events.

Toward the end of the OGLE-III phase, the entire observational material was re-reduced again with DIA using a new and better set of images for the composite reference images (Udalski et al. 2008), yielding significantly higher-quality output photometry. Figure 2 compares the quality of the photometry of a microlensing event OGLE-2005-BLG-069 reported by the EWS, obtained in the original and new reductions. The improvement in quality is primarily due to the somewhat better resolution of the new reference images.

Throughout this paper, we use the re-reduced data obtained after the end of OGLE-III. We searched for microlensing events in this final and complete data set of the observations of the Galactic bulge. For the final sample of microlensing events, we additionally produced new photometry which took into account the exact position of each event on the DIA image (better than a fraction of a pixel), which in many cases yielded higher quality light curves.

3. SEARCH PROCEDURE

The extraction of rare light curves, like microlensing events, from vast databases is not an easy task. In the past, the data comprised a relatively small number of objects, making it feasible to visually inspect a small group of a few thousand light curves after applying some basic selection criteria. Today, and in case of the OGLE-III data, it is necessary to seek help from automated methods of microlensing events selection. Moreover, a fully automatized search pipeline allows us to obtain the detection efficiency of events depending on their parameters. Machine learning algorithms were already successfully used in time-domain astronomy, e.g., Belokurov et al. (2003), Wyrzykowski...
et al. (2003), Debosscher et al. (2007), Richards et al. (2011), Pawlak et al. (2013), for the automatization of discovery and classification in large data sets.

In our previous searches for microlensing events in the OGLE data in the LMC and SMC fields (Wyżykowski et al. 2009, 2011a, 2011b), as well as in our preliminary search in the OGLE-III Bulge data (Wyżykowski 2005), we relied on a number of cuts applied to a small number of computed features, primarily microlensing model parameters. In those searches, the most powerful discriminator was typically the goodness of fit of the model, however, it worked fine only for those events with well-observed light curves, with corrected photometric error-bars, and with well-understood noise. Therefore, such a cut could remove plausible standard microlensing events, the photometry of which could have been affected by some observational or instrumental problems, which are generally very common in crowded areas such as the Galactic bulge, e.g., blending with variable stars. As shown in Wyżykowski et al. (2006), events with variability in their baseline can be useful to constrain at least some of the physical parameters of typically severely degenerated microlensing models.

Here, we developed and applied a new method for selecting microlensing events among all of the stars in the database. The database consisted of nearly a quarter of a billion objects, and therefore it required a more optimized and revised approach. In order to deal with such a vast data set, we relied on machine learning (ML) techniques, in particular, on the Random Forest (RF) classifier (Breiman 2001), which finds its own most successful multi-dimensional selection criteria. Like most ML methods, RF requires that all objects be described in a homogeneous way with various properties or features. An advantage of the RF is that it conveniently selects which features are most meaningful and carry the most information needed to correctly perform the classification. Therefore, the risk that too many features will blur the classification outcome is minimized, which allows for the preparation of a large number of various features for each object.

### 3.1. Preparatory Steps

Each individual light curve in the database was first pre-processed. This included outlier removal: single data points outlying by more than 3σ from the total mean of the entire light curve with the a point before and after lying within 1σ. Then, the photometric error bars were corrected following the method described in Wyżykowski et al. (2009) and Skowron (2009), which returned a correction coefficients as a function of the...
observed magnitude, derived from non-variable stars, taking into account all of the observational factors, e.g., seeing and airmass. Once the error bars were corrected, we were able to filter out all of the non-variable light curves because our main goal was to find singular brightening episodes in each light curve. As a variability indicator for a light curve, we used the ratio of the standard deviation to the mean error, \( \sigma_{\text{rel}} > 1.05 \). There were 105 million objects left from the original 150 million. Please note that not all of these were genuinely variable; the list also included many artifacts, e.g., differential refraction effects or seeing-dependent variability caused by nearby bright and saturated stars.

In the next step, we looked for objects exhibiting a positive flux increase over some period of time with respect to the rest of the light curve. For each light curve, we applied a running window search for peaks, following the concept used in Sumi et al. (2006) and Wyrzykowski et al. (2009). In this method, a window size of half of the time-span of the light curve was run over an entire light curve, and for each data point \( i \) a value of sigma was computed:

\[
\sigma_i = \frac{I_{\text{med},w} - I_i}{\sqrt{\Delta I_i^2 + \sigma_w^2}}.
\]

where \( I_i \) is the magnitude of the point \( i \) and \( \Delta I_i \) is its error bar, while \( I_{\text{med},w} \) and \( \sigma_w \) are the median and the rms in the outer window, respectively.

Before computation, we masked out all observations taken with airmass >2 (in most cases they were outlying due to differential refraction effects) and averaged data points taken within the same night. The OGLE-III sampling was typically differential refraction effects) and averaged data points taken within the same night. The OGLE-III sampling was typically one observation per two to three nights, however, there were occasionally many observations taken within a single night when the telescope switched to follow-up mode to cover more densely some interesting microlensing anomalies.

From the computation of running windows for each variable light curve, we obtained the following set of parameters (features):

1. \( N_{\text{peaks}} \), number of detected separate peaks, each defined as a series of points with \( \sigma_i > 2.0 \);
2. \( \text{maxsigma} \), maximum value of \( \sigma_i \) for the most pronounced peak (the highest \( \sigma_i \));
3. \( N_{\text{seq}} \), number of sequential data points in the most pronounced peak, all being above a threshold of \( \sigma_{\text{thresh}} = 2.0 \);
4. \( \text{peaksum} \), sum of \( \sigma_i \), within the most pronounced peak, i.e., the sum of \( N_{\text{seq}} \) sigmas;
5. \( \text{peaksum7} \), sum of \( \sigma_i \), of the maximum and three adjacent points from each side of the maximum (seven points);
6. \( \sigma_{\text{relB}} \), variability indicator for the outside window (window B) for the most pronounced peak; and
7. \( \sigma_{\text{relL}} \), variability indicator for the entire light curve.

At this stage, we narrowed the sample to only those objects which had at least four subsequent points in a detected peak, and we were left with about 8.5 million objects. Light curves of these were then fitted\(^6\) with the standard Paczyński (1996) microlensing model, (i.e., a point-source–point-lens microlensing event), which is described as

\[
I = I_0 - 2.5 \log \left[ \frac{f_S}{A} + (1 - f_S) \right] + 5 \log \left[ \frac{u}{u + 1} \right].
\]

where \( A = \frac{u^2 + 2}{u \sqrt{u^2 + 4}} \) and \( u = \sqrt{u^2 + \frac{(t - t_0)^2}{\tau_E^2}} \).

The fitted parameters are as follows: \( t_0 \)—the time of the maximum of the peak; \( \tau_E \)—the Einstein radius crossing time (the event’s timescale); \( u_0 \)—the event’s impact parameter; \( \tau_E \)—the baseline magnitude in the I band; and \( f_S \)—the blending fraction (ratio of lensed source flux to total blends’ flux in the I band). The fits were performed in two ways, namely, with the blending parameter fixed \( f_S = 1 \), i.e., with no blending, and with \( f_S \) being free. For clarity, parameters of the non-blended (four parameters) model are given the subscript \( u \). Because the standard microlensing model is symmetrical for the parameter \( u_0 \), we only used its positive value in further analysis.

Based on the visual inspection of a selection of variable objects from test fields BLG100.1 and BLG206.1, we derived “common-sense cuts” to the set of variable objects. A cut on \( N_{\text{seq}} \geq 4 \) was imposed to remove a vast majority of short duration artifacts, however, it also removed poorly sampled short timescale events, typically with timescales shorter than three days. A dedicated search for very short duration events will be presented elsewhere. We excluded events for which the minimization procedure returned no solution within the limited number of procedure calls, or returned unphysical values of \( t_E \) and \( f_S \) due to strong degeneracy between those two parameters. We further investigate the possible degeneracies by employing full MCMC modeling (see Section 4). In most cases, the lack of a solution for the Paczyński model indicated that the brightening was not caused by microlensing, but was some sort of eruptive variable star. For the remaining events with converged models, we required reasonable microlensing fit parameters, i.e., \( |u_0| \leq 2, 2150 < t_0 - 2450000 < 5000, 1 \text{days} < |t_{\text{E,4}}| < 400 \text{days}, 1 \text{days} < |t_E| < 400 \text{days}, \) and \( f_S < 1.4 \). Limits on the time of the maximum ensured that we only dealt with microlensing-like episodes of brightening, where the peak time \( t_0 \) remained within the available data span. The cut at 400 days in timescale is induced by the fact that we used the running-window method to find brightening episodes over light curves in which the window size was equal to half of the total span of the data. Events with a timescale of 400 days may, in practice, span more than 1600 days, depending on \( u_0 \), and therefore our detection efficiency for those will be smaller. Also, there is a large number of false events with alleged timescales above 400 days, which turn out to be low-amplitude, slowly varying variable stars. The blending parameter, \( f_S \), limited at 1.4, allowed for some amount of so-called “negative” blending (Smith et al. 2007). The border value was computed as the maximum value expected for crowded bulge data assuming background fluctuations due to unresolved stars at about 21 mag.

This pre-filtering narrowed our sample to 194,000 objects.

3.2. Ghost Events Filtering

It is very common in crowded stellar fields for the variability of one star to affect the photometry of nearby objects, often referred to as “ghosts” or “children.” The radius of influence depends on the seeing conditions as well as on the amplitude of the variability; therefore, some strongly amplified microlensing events can cause an effect wherein many nearby stars undergo a very similar brightening episode. Figure 3 shows an example of

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\(^6\) Fitting was performed using CERN’s MINUIT package, http://wwwasdoc.web.cern.ch/wwwasdoc/minuit/minmain.html.
such an effect in the OGLE-III data for the case of a microlensing event with an amplitude of many magnitudes.

Production of “ghost” events can significantly disturb the statistics and quality of detected microlensing events. Therefore, it is essential to recognize which star is actually linked to the main event, given the much better quality of the light curve.

For all of the light curves remaining after the steps described above, we derived a set of features used later for Random Forest classification. First, seven features were listed above and came from the running-window analysis of a light curve. Next, a set of features came from the microlensing fits to each light curve:

8. $t_{E_{bl}}$, timescale of the event fitted with blending fixed to 1, describing the overall longevity of the event;
9. $\log \mu_{04}$, logarithm of the impact parameter, sensitive to the actual height of the event;
10. $\chi^2_{p4}$, goodness of fit of the four-parameter model (no blending);
11. $\chi^2_{p4}/\text{dof}$, reduced goodness of fit of the four-parameter model;
12. $t_{E}$, timescale of the event with free blending;
13. $\log \mu_{04}$, logarithm of the impact parameter in the five-parameter model;
14. $\log \mu_{05}$, logarithm of the blending parameter;
15. $\chi^2_{p5}$, goodness of fit of the five-parameter model; and
16. $\chi^2_{p5}/\text{dof}$, reduced goodness of fit of the five-parameter model.

For each light curve, we also fitted a constant line to the out-of-event data, defined as data outside of the $\mu_{04} \pm 5t_{E_{bl}}$ region.
Such a fit returned a mean magnitude, rms scatter (sigma), and its goodness of fit. To the set of features, we added the following:

17. $\sigma_{\text{out}}$;
18. $\chi^2_{\text{out}}$; and
19. $\chi^2_{\text{out}}/\text{dof}$.

The following features were then derived, using combinations of microlensing model parameters. They reflected any dramatic changes between the four- and five-parameter models, which often signaled a non-microlensing origin for the event.

20. $\Delta I_0 = \log ([I_{04}-I_0])$;
21. $\Delta u_0 = \log ([u_{04}-u_0])$;
22. $I_{t,0} = \log ([I_{t,04}-I_{t,0}])$; and
23. $\Delta \chi^2 = \chi^2_{u4} - \chi^2_{\text{base}}$.

Microlensing modeling, which gave the above-mentioned parameters for each event, was performed over the entire light curve. In addition to that, we also determined the $\chi^2$ of the five-parameter microlensing model solely for the peak and baseline data. Such features carried information concerning details on how well the microlensing model recovers data, and were sensitive to small anomalies which a global model was much less sensitive to. Here, the peak was defined as $t_0 \pm 3\sigma_0$ and contained $N_{\text{peak}}$ data points. The rest of the data (baseline) contained $N_{\text{base}}$ data points.

24. $\chi^2_{\text{peak}}/N_{\text{peak}}$;
25. $\chi^2_{\text{base}}/N_{\text{base}}$, and
26. $\chi^2_{\text{peak}}/N_{\text{base}}/\chi^2_{\text{base}}$, ratio of both $\chi^2$ values.

The final feature to include was the $V-I$ color of the blended source, obtained from the OGLE-III photometric maps (Szymański et al. 2011):

27. $V-I$, color of the blended source.

This set of features was derived for all of the light curves that passed the basic filters described above.

### 3.4. Random Forest Classifier

For the classification of events described with 27 features derived above, we decided to use the Random Forest classifier from its Java implementation in the Weka package (version 3.6.5)\(^7\) developed at the University of Waikato in New Zealand. For training the classifier, we manually selected candidate microlensing events from the pre-filtered sample of objects from the fields with various sampling properties: BLG100 (about 2400 observations), BLG180 (about 1400 observations), and BLG206 (about 1300 observations). During the visual classification, we divided the events into three classes: *ULENS* for standard microlensing events, *EXOTIC* for non-standard microlensing events (e.g., binary lens events, events with parallax effect), and *OTHER* for all the remaining light curves. Among the latter were various types of outbursting variables, like Dwarf Novae or Be-type stars, but also numerous artifact events or other types of long-term variable stars (e.g., Skowron et al. 2009). The visual selection of the events for the training set was performed independently by a few authors (L.W., A.E.R., and M.P.) in order to cross-validate the results. The training set was also supplemented by 30 manually selected standard events reported by EWS.

Our final training set had the following composition: *ULENS*: 977, *EXOTIC*: 53, *OTHER*: 2135. The number of exotic examples was significantly smaller than the remaining classes, however, in this study, we did not intend to pick the exotic events with very high effectiveness. The main reason for adding that middle class was to differentiate those types of events (typically with high signal to noise and large values of $\chi^2$) from standard events and other types of variables and artifacts. The RF classifier was set up to use 15 random features in each of the 15 decision trees, the results of which were then aggregated and the winner chosen from the dominant class. The 10-fold cross-validation test of the RF classifier resulted in 96.7% correctly classified instances (over all classes), however, the false-positive rate at this stage was relatively high, 27.7%.

As our primary goal was to provide a sample of standard microlensing events with the lowest contamination, we added a second stage of classification to our search pipeline. This stage was designed to analyze only those events that were marked as *ULENS* during the first stage of the classification. The training set was comprised of only two classes, *GOOD* (706 instances) and *BAD* (271 instances), and was composed after visual inspection of the test runs of the stage 1 classifier on a fraction of the input list. For the verification, we used field BLG104, in which we manually identified 60 genuine events after removal of the ghost events. Running both stages of the RF classifier on the entire data of field BLG104 returned 56 events, with the remaining 4 event being of the lowest quality. This shows a very high efficiency of the Random Forest classifier with simultaneous high purity for the output. The overall false-positive rate, i.e., the expected contamination for the two-stage classifier, has dropped significantly to only 6.7%.

Figure 4 shows the normalized importance score for each of the features used in the RF classifier. The features are sorted from the most useful during the first stage of classification at the top to the least useful at the bottom, i.e., according to their importance in the decision making by the trees within the Random Forest. The most powerful is the peaksum7 feature, which describes how strong the event in the light curve is. Not surprisingly, the second most useful feature is $\chi^2/\text{dof}$, that is, the goodness of fit of the microlensing model. Also shown in this figure are the scores of the same features during the second stage. Because the classification here is more detailed than at stage 1, slightly different features play an important role in the classification. For example, the most important feature at stage 2 is the goodness of fit at the peak as well as its ratio to $\chi^2_{\text{base}}$. It shows that the hierarchical division of the classification was justified as the two steps functioned on different grounds.

### 4. CATALOG

The classification procedure employing the Random Forest classifier returned exactly 3700 events. We then cross-matched the catalog with itself, checking within a 3 arcsec radius and requiring $t_0$ to be within 10 days, and found 95 events as duplicates due to overlapping OGLE-III fields. We did not find any pair of events located within 3 arcsec which occurred at significantly different moments of time, which could have been caused by the same lensing object or a wide binary lens (e.g., Skowron et al. 2009). From each pair of duplicate events, we selected the event with a better quality light curve, i.e., the one with higher maxsigma, but the information on the multiplicity is stored in the table of events. Therefore, the catalog contains 3560 unique standard microlensing events, dubbed the “class A” sample. The density of events distributed over the sky in

\(^7\) http://www.cs.waikato.ac.nz/ml/weka/
Table 1: OGLE-III Standard Events of Class A

| ID             | R.A. J2000 (h:m:s) | Decl. J2000 (deg:m:s) | Field   | Starno | EWS id      | Duplicate |
|----------------|---------------------|-----------------------|---------|--------|-------------|-----------|
| OGLEIII-ULENS-|                     |                       |         |        |             |           |
| 0001           | 17:51:44.00         | −30:17:20.7           | BLG100.1| 27898  | 2007-BLG-258|           |
| 0002           | 17:52:21.54         | −30:16:19.0           | BLG100.1| 47983  |             |           |
| 0003           | 17:51:01.18         | −30:15:28.9           | BLG100.1| 55988  | 2007-BLG-459|           |
| 0004           | 17:51:11.06         | −30:14:20.6           | BLG100.1| 57414  |             |           |
| 0005           | 17:51:43.85         | −30:14:43.3           | BLG100.1| 89325  |             |           |
| 0006           | 17:52:13.46         | −30:13:22.9           | BLG100.1| 101269 | 2005-BLG-404|           |
| 0007           | 17:52:08.57         | −30:13:56.3           | BLG100.1| 102672 |             |           |
| 0008           | 17:52:19.37         | −30:13:13.9           | BLG100.1| 106173 | 2005-BLG-294|           |
| 0009           | 17:51:16.18         | −30:12:31.9           | BLG100.1| 119596 |             |           |
| 0010           | 17:51:16.71         | −30:11:10.7           | BLG100.1| 124027 |             |           |

(This table is available in its entirety in machine-readable form.)

Each event from the catalog was fit with the microlensing model using the Markov Chain Monte Carlo (MCMC) method. The priors on all of the model parameters were assumed to be uniform around the initial values, taken from the standard $\chi^2$ modeling with the MINUIT code. Therefore, for each event, we obtained the posteriori distributions for each parameter and the median and 1σ asymmetric errors (84.1345 and 15.8655 percentiles). Example results of the MCMC fitting to an event, along with the distributions and relations for $t_E$, $f_s$, and $n_0$, are shown in Figure 6. Such figures are available for all 3560 class A events in the supplementary material, allowing the reader to consider the degenerations of the model parameters in each of the events. The distributions of all of the fitted microlensing parameters for the class A sample are shown in Figure 7. Table 2 shows all of the standard Paczyński microlensing model parameters and their errors found in the MCMC models of the original data for events from class A.

The full machine-readable catalog, the light curves of all events, and their MCMC models are available as supplementary material and from the OGLE internet archive: http://ogle.astrouw.edu.pl.

The published light curves were reprocessed, taking into account the exact position of the event on the DIA image. This assures the best-possible photometric accuracy. The photometric

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The published content is a table listing the OGLE-III Standard Events of Class A, followed by a description of the microlensing fitting process and results. The table provides coordinates, field identification, and EWS id for each event, with a note on duplicate entries. The text explains the use of the Random Forest for feature selection, the application of the MCMC method, and the availability of the full catalog. The process is supported by diagrams and figures illustrating the distribution of events and the fitting results. The supplemental material and internet archive provide additional resources for the dataset.

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8 We used the Python module pymc from https://pypi.python.org/pypi/pymc/.
Figure 6. MCMC fitting results (density plots) for example events from the OGLE-III Bulge microlensing events catalog. The top panels in each figure show relations between the distributions of blending parameter ($f_S$), timescale ($t_E$), and impact parameter ($u_0$). Colors denote $\sigma$ contours: black, red, and green for 1, 2, and 3$\sigma$. A magenta-yellow circle shows where the median of each distribution is located. The lower left panel in each of the plots is the distribution of the timescales with the solid and two dashed lines marking the 50, 15, and 85 percentiles. The lower right panel shows the light curve of the event with the median model and its residuals (below the light curve with the offset) shown in magenta and the 1$\sigma$ models and their residuals. The full catalog and the MCMC models for all events are available as supporting material and on the OGLE web site.

data were not averaged nightly, however, some cleaning was applied, similar to the procedures described above, i.e., bad observations were masked out and the single outlying points were removed. The error bars were also corrected.

4.1. Class B Events

Apart from the fully automatized search procedure for finding microlensing events, we also applied a separate search for standard events for which the full blended fit was not converging, i.e., when the minimization procedure was not finding any solutions or was returning unphysical values for parameters, and events rejected during other stages of constructing of class A. From a sample of light curves rejected at the prefiltering stage, we selected those for which the $\chi^2_{\nu}/dof$ for the non-blended model was smaller than 2.5 if the baseline was fainter than 16 mag, and $\chi^2_{\nu}/dof < 5$ for $I_{\nu,4} < 16$. To ensure that only high-quality events passed through that filter, we also required that the peak be covered with at least 10 data points and selected only those events with significant amplification, i.e., with $u_{\nu,4} < 1$ in the non-blended model.

There were about 300 candidates that were then visually inspected, and an additional sample of 158 “class B” standard events was selected. Four additional events passed the criteria but were duplicates due to overlapping OGLE-III fields.
...variability on top of the microlensing bump, likely caused by events was in many cases some small, often gradual, long-term main reason for non-converging microlensing models for those events was in many cases some small, often gradual, long-term variability on top of the microlensing bump, likely caused by the intrinsic variability of the source or high proper motion of either the source or nearby stars. We provide the list of those candidate events in Table 3 and their light curves are also made available for further study. The events from class B are labeled using following the scheme: OGLEIII-ULENS-9nnnn, where the individual number encoded in nnnn is preceded by the number 9 in order to distinguish from class A events.

Because the microlensing models of class B events were not full and did not include blending, the derived timescales were not reliable in a vast majority of the cases. Moreover, those events would not be detected by the automated pipeline, and hence the detection efficiency did not include them and they were not used in the statistical studies below. However, because class B events are most likely the genuine standard microlensing events, they might be a useful reference for future searches of events in their vicinity.

4.2. Comparison with the EWS

Comparison with OGLE’s EWS\(^9\) (Udalski 2003) was tricky, as we relied on reference images used for the real-time analysis and production of the final photometry which had slightly better quality and depth. Thus, many stars were resolved in the new data, or the blending has changed. Nevertheless, we compared the catalog with the events from all years of the EWS (2002–2009).

Within the 91 fields analyzed here, EWS has detected 3796 events, among which were 162 duplicates due to overlapping fields, and therefore there were 3634 unique events reported. Using a 3 arcsec matching radius and the time of maximum, we identified 2309 events in our catalog that had previously been found. Therefore, 1409 (1333 class A + 76 class B) events are newly discovered standard microlensing events.

The main reason for the significant majority of EWS events not recovered in our analysis was the lack of convergence in the microlensing model with free blending. The converged modeling was among the preliminary pre-filtering requirements, i.e., we requested that both blending parameter and timescale be within sensible ranges. EWS was making events exhibiting some problems with data modeling with free blending by forcing \(f_s\) to be constant at one. In many cases, the models did not converge because the events were not due to single-lens-single-source, or exhibited additional effects like parallax or binary lens caustics.

The remaining EWS events that were rejected after pre-filtering at the later stage (RF classification) were inspected

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9 http://ogle.astrouw.edu.pl/ogle3/ews/NNNN/ews.html, where \(N = (2002, 2003, 2004, 2005, 2006, 2007, 2008, 2009)\).
OGLE-III data. Following the method of Wyrzykowski et al. (2006), we were able to derive the detection efficiency for finding the standard microlensing events in the automated, and therefore we were able to derive the detection efficiency for the bulk of the events is at the level of 30%–40% higher than for all sources, however, the overall shape of the efficiency curve is preserved. The efficiencies for the three regions of the OGLE-III fields observed with different sampling: dense, medium, and sparse. The detection efficiency for the bulk of the events is at the level of 30%–40% and drops below 10% for events with timescales shorter than five days. At the long end, the efficiency starts dropping from about 200 days to 400 days, which was the truncation in the simulations. The search procedure was not optimized for events with $t_E > 400$ days and was susceptible to numerous low-amplitude contaminants. A dedicated search for very long events will be presented separately. Because the three detection efficiency curves are similar, for further analysis we use the mean for all of the fields.

We also derived the detection efficiency for a subsample of events, requiring a source magnitude of 19 mag criterion for simulated events. As expected, the efficiency is about 20% higher than for all sources, however, the overall shape of the efficiency curve is preserved. The efficiencies for the three different sampling (or stellar density) regions are similar to within few percent, and therefore in further analysis we use the mean curve.

| ID   | OGLEIII-ULENS- | R.A.-J2000 (h:m:s) | Decl.-J2000 (deg:m:s) | Field | Starno | EWS id |
|------|----------------|-------------------|---------------------|-------|--------|--------|
| 90001| 17:52:12.90    | -30:13:38.5       | BLG100.1            | 101182| 2005-BLG-359 |
| 90002| 17:51:19.10    | -30:02:47.0       | BLG100.2            | 132033|
| 90003| 17:50:32.77    | -29:52:13.7       | BLG100.6            | 137109| 2007-BLG-194 |
| 90004| 17:50:06.77    | -30:08:46.5       | BLG100.7            | 9419  |
| 90005| 17:53:52.53    | -29:59:55.0       | BLG101.1            | 238410| 2007-BLG-090 |
| 90006| 17:52:43.65    | -29:39:20.2       | BLG101.5            | 20164 |
| 90007| 17:52:45.56    | -29:49:46.9       | BLG101.6            | 22645 |
| 90008| 17:53:29.42    | -29:56:57.0       | BLG101.7            | 59322 |
| 90009| 17:53:24.17    | -29:56:32.7       | BLG101.7            | 124729|
| 90010| 17:55:55.53    | -29:21:14.5       | BLG102.5            | 46864 | 2008-BLG-552 |

(This table is available in its entirety in machine-readable form.)
5. DISCUSSION

The large number of standard microlensing events allows us to derive various statistical properties of the events toward the Galactic bulge. For each event, we derived the microlensing model parameters using the MCMC modeling and each event in the class A sample is accompanied by the plot with relations between the main parameters, \( f_S \), \( u_0 \), and \( t_E \), allowing for detailed investigation of degeneracies in the models and the statistical properties of the events.

5.1. Properties of the Events

Figure 9 shows the distributions of the maximum amplifications for 2812 events selected from the entire sample to have well-constrained impact parameters, i.e., \( \Delta u_0 / u_0 < 1 \). The drop between 1 and 2 is caused by the lower detection efficiency for events that were not magnified significantly above the noise. There are 32 events with amplification greater than 100 and 6 with amplification greater than 300. The cumulative histogram in Figure 9 shows that half of the events had \( A > 3 \). Also shown (red dotted line) is the distribution of the observed amplification, \( A_{\text{obs}} = (A - 1) f_S + 1 \), i.e., the actual observed rise in brightness given the blending. There were eight and one events that increased in brightness by 100 and 300 times, respectively, typically with \( f_S \sim 1 \). Half of the events had observed magnifications greater than 2.0. The maximum amplification for simulated events presented a very similar distribution, indicating self-consistency between data and simulations.

Figure 10 shows how the MCMC errors (approximated here as symmetric) of microlensing parameters are spread. The events with poorly constrained amplification form a separate group on most of the panels, however, it can be seen that their timescales are still well recovered with relative errors for \( t_E \) below 1. Only about 2% of events have relative error in \( t_E \) greater than 100% and about 17% have errors larger than 50%. This allows us to select a subsample of events with well-constrained Einstein radius crossing times, events that can then be used for statistical studies, computing the optical depth, or constraining the shape of the IMF.

We note that a larger relative error on \( f_S \) and \( u_0 \) does not necessarily lead to a bad derivation of \( t_E \); however, it is clear that the majority of poorly constrained timescales are related to \( f_S < 0.5 \), i.e., where the blending is severe. Strong blending causes the light curve to show only the tip of the actual event when the observed amplification becomes sufficiently high to overcome the noise of the baseline.
We also find that a vast majority of poorly constrained timescales are related to the sparse sampling and not to the timescale itself. The bottom panels of Figure 10 show the dependence of the error on \( t_E \) as a function of the average number of data points taken per 1 day unit of the timescale of the event. It can be seen that all events with more than \( 1.5 \times t_E \) points collected had their timescales derived with small relative error. This property can be useful when designing future microlensing experiments, however, we emphasize that this is only valid for timescales longer than about \( t_E > 5 \) days, as there were not enough events below that range in our sample. The determination of the blending parameter is somewhat less sensitive to the average number of points taken during the event, however, it depends strongly on the coverage of the wings of the event, as previously shown in Woźniak & Paczynski (1997).

Figure 11 shows the blending parameter distribution in relation to \( u_0, I_0, \) and \( t_E \). We clearly see the observational bias that highly blended events (\( f_S \ll 1 \)) can only be detected if they are highly magnified, i.e., with very small \( u_0 \). Then, the observed (blended) baseline magnitude roughly follows the results of the blending simulations from Smith et al. (2007). Agreement with simulations indicates that the blending parameter obtained in our microlensing models follows the expected distribution, which, in turn, means that we derive the timescale of events correctly. The relation shows that for bright events, blending tends to be around one, however, it can also take much smaller values. As already pointed by Smith et al. (2007), events with a bright baseline cannot be assumed to suffer less blending than fainter events. For fainter events, below 18 mag, the blending parameter can be of any value. Events with relative errors on timescale larger than 100% tend to have smaller \( f_S \), indicating that the blending uncertainty is mainly responsible for larger errors in \( t_E \).

There is a signature visible on the \( t_E-f_S \) plot that a fraction of long events tends to have small \( f_S \). This could be an artifact of modeling and can lead to a bias in derived distributions of \( t_E \) toward longer timescales. However, as we show later, we found a way to avoid such biases. The same plot also shows that there is hardly any event with \( f_S \) shorter than 15 days at very small \( f_S \), which, in turn, is expected, as severely blended short timescale events have small \( A_{obs} \), and hence small detection efficiency.

### 5.2. Timescale Distribution

One of the main applications for a large ensemble of microlensing events is studying the structure of the inner parts of the Galaxy. This is usually done with the microlensing events rate (\( \Gamma \)) and the optical depth (\( \tau \), e.g., Evans & Belokurov 2002; Mao 2012). Both of these quantities rely on the timescale, however, they also require knowledge of the number of monitored stars. As noted in, e.g., Sumi et al. (2006) and Wyrzykowski et al. (2009), obtaining that value unambiguously is not straightforward for the dense stellar fields. Microlensing can occur for stars that are very faint and blended with brighter foreground stars. Therefore, in order to know the exact number of monitored stars, it is necessary to understand the blending in the observed fields, typically by comparing the observed luminosity function (LF) to those from images of much higher resolution (e.g., from the HST) in which the individual stars are resolved. In Wyrzykowski et al. (2011a) and Wyrzykowski et al. (2011b), such analysis was performed for the OGLE-III data of LMC and SMC, assuming no major variations in the LF between fields. However, repeating it for the Bulge data is much more complicated. OGLE-III covered a wide area of the sky toward the Galactic center where the extinction and the mix of stellar populations vary significantly from field to field. A detailed analysis of the number of stars and the blending distribution over a range of OGLE-III fields will be performed in the near future; here, however, we can still use the observed timescales, corrected for the detection efficiency, to investigate the effects of the structure of the Galaxy on the distribution of \( t_E \).

#### 5.2.1. Comparison to Besançon Model

The most recent model of the Galaxy and its microlensing yield in the Bulge (Kerins et al. 2009) derived the mean timescale for events that occurred on sources with resolved magnitudes brighter than \( I_S < 19 \) mag. From sample A of our catalog, we selected 1205 events for which the source magnitude (computed using \( I_0 \) and \( f_S \)) was brighter than 19 mag and the relative error on \( f_S \) was less than 100%. We binned the events into \( 1 \times 1 \text{deg}^2 \) bins, requiring at least five events in a bin—most bins actually contained about 30 events, with a maximum of about 100 in the densest area. Table 4 contains the values of mean timescale and the number of events in each bin.

Within each bin, we created a distribution of \( t_E \) in log-space, convolved it with the detection efficiency for bright sources, and computed the arithmetic mean. Additionally, in order to minimize the effects of single long- or short-timescale events affecting the computation of the mean \( t_E \), we also fitted the distribution in each bin with a log-normal model, and then computed the mean for that model. Figure 12 shows maps of the mean timescale obtained in those two ways. The maps are also overlaid with the expectations for the Besançon model from Kerins et al. (2009).
Figure 12. Efficiency-corrected mean $t_E$ map for 1205 events with source(resolved) magnitudes brighter than 19 mag and relative error for the timescale better than 100%. Dashed contours show the expected mean timescale (at 20, 25, and 30 days) as computed in Kerins et al. (2009). Within each bin (size 1 $\times$ 1 deg), the mean timescale was computed from the actual values of $t_E$ (upper map) and from the log-normal fit to the distribution (lower map). Both maps were smoothed with a Gaussian with FWHM = 1.75 deg.

Table 4

Table: Mean Timescale Bins for OGLE-III Events

| $l_{central}$ (deg) | $b_{central}$ (deg) | $\langle t_E \rangle_{uncorr}$ (days) | $\langle t_E \rangle_{corr}$ (days) | $\langle t_E \rangle_{Gauss}$ (days) | $N_{events}$ |
|---------------------|---------------------|-------------------------------------|-----------------------------------|---------------------------------|-------------|
| 5.5                 | −3.5                | 34.4                                | 32.8                              | 31.9                            | 9           |
| 5.5                 | 2.5                 | 46.8                                | 37.5                              | 30.9                            | 10          |
| 4.5                 | −3.5                | 47.1                                | 42.5                              | 23.4                            | 17          |
| 4.5                 | −2.5                | 42.8                                | 32.2                              | 29.4                            | 18          |
| 3.5                 | −4.5                | 29.1                                | 24.1                              | 19.7                            | 18          |
| 3.5                 | −3.5                | 33.5                                | 24.0                              | 19.7                            | 39          |
| 3.5                 | −2.5                | 34.9                                | 27.2                              | 18.6                            | 33          |
| 3.5                 | −1.5                | 30.8                                | 15.6                              | 24.5                            | 11          |
| 2.5                 | −4.5                | 28.5                                | 22.4                              | 23.1                            | 19          |
| 2.5                 | −3.5                | 26.7                                | 20.3                              | 17.5                            | 40          |

(This table is available in its entirety in machine-readable form.)

Computation of the mean timescale based on the log-normal model clearly is less prone to outliers in the $t_E$ distribution, as can be seen in the bins at high galactic longitudes where there were very few events in each bin. The averages computed from a log-normal fit are somewhat smaller in most of the bins, also proving that the regular mean is affected by long events.

As can be seen in Figure 12, OGLE-III events are located almost solely between two isolines of the Kerins et al. (2009) model, between 20 and 25 days. However, in the central parts, at $l \sim 0$, our values tend to be significantly below 20 days on both maps. The mean timescale then increases with increasing $|l|$, but with clear asymmetry and larger values on the negative galactic longitudes. This is most likely a signature of the bar geometry, which is also present as asymmetry on the synthetic map of Kerins et al. (2009).

The effect of asymmetry is also visible if the events are binned into three broad regions: for positive, central, and negative galactic longitudes, within the same galactic latitude band.
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Figure 13. Distribution of the timescales of events for three regions between $-2$ and $-4$ galactic latitudes: positive galactic longitudes (dashed red), central (dotted black), and negative (solid blue). Only events with $I_5 < 19$ mag and relative errors of $t_E < 100\%$ are used for the histograms. Also shown are the best-fit log-normal models with the vertical lines showing their mean values. The highest mean is measured as 24.2 days for the negative bins (solid blue).

The distributions for those regions are shown in Figure 13 along with the best-fit log-normal models. The standard mean $t_E$ (computed from the actual distribution) for the positive and central regions is $23.2 \pm 0.7$ days and $20.3 \pm 0.4$ days, respectively. For the negative longitudes bin, the mean timescale is $27.9 \pm 1.2$ days, which clearly stands out with respect to the other bins. The log-normal model mean $t_E$ values for the positive and central bins are 22.0 and 20.5 days, respectively. For the negative bins, it is 24.2 days, which is somewhat smaller than the standard mean, however, still clearly higher than the mean timescale in the positive and central parts of the map. Moreover, the mean timescales for the negative galactic longitudes are higher than expected for the Galactic model of Kerins et al. (2009).

OGLE-III fields do not cover the regions beyond $|l| > 5$ where the increase in the mean $t_E$ should be even more pronounced, however, the fact that the mean timescale increases somewhat quicker with galactic longitude may indicate that the bar is tilted somewhat more toward the line of sight. Another reason for such a rise could be that the boxy bar is wider than assumed in the Besançon model, producing more bar-bar events at lower $l$ than in the center. A future comprehensive analysis of the OGLE-IV survey data, which is monitoring the region up to $|l| = 10$ since 2010, will provide even more clues to verify the shape of the galactic bar.

When comparing the mean timescale structure to the theoretical predictions from Evans & Belokurov (2002) for the Freudenreich's bar model (their Figure 5), it resembles the model without bar streaming included. On the other hand, the values of the timescales here are 50% to 75% larger than predicted in Evans & Belokurov (2002), but still significantly lower than those expected for bar streaming.

5.2.2. All Events Sample

Figure 14 shows maps of the mean timescales computed in a standard way and from the log-normal-fit for all class A events with relative error in $t_E$ better than 100%, with no restriction regarding their source or baseline magnitude.

There were 3019 such events and the maps were binned with small bins of $0.4 \times 0.25$ deg, a similar size as shown on the map of mean timescales obtained from MOA-II data (Sumi et al. 2013). The main difference between standard and log-normal-
fit mean timescales is clearly visible again on the edges of the observed region where there were very few events (even just two per bin) to compute the \((t_E)\), and the arithmetic average was very sensitive to long events. There is some broad structure visible again on both maps, with the mean timescale values being lower on the positive galactic longitudes and higher on the negative longitudes, however, the finer elements of the map are of very low statistical significance due to the low number of events in each bin. The all-events sample is a mixture of events from various combinations of populations: bar-bar, disk-bar, and disk-disk. Therefore, the observed distributions are generally more blurred, as different pairs cause different duration events, with bar-disk being typically the shortest while bar-bar and disk-disk are typically the longest.

The overall log-normal fit mean timescale still stays within the predicted 25 days in the central parts, but for large \(|l|\) reaches close to 30 days. This map could be compared to Figure 4 of Evans & Belokurov (2002) for Freudenreich’s model (Freudenreich 1998), which shows the mean timescale for sources and lenses from either disk or the bar; however, due to different resolutions, it is difficult to conclude on the comparison. Nevertheless, the values on our map tend to agree with the expectations for the model with the contribution of the spiral structure for the Freudenreich’s model.

We can also compare our map of standard mean timescales for all class A events to the results of MOA-II (Sumi et al. 2013, their Figure 3, upper-most panel), which were based on 474 events. First, we see that our longest mean timescale is about 35 days, the value which actually appears only at the edges of our observing region and should be ignored as induced by very low number statistics in those areas (those regions completely disappear when using log-normal model mean timescales, see bottom map in Figure 14). Therefore, our longest value to compare with the MOA-II map is actually closer to 25 days, whereas the map in Sumi et al. (2013) shows areas with \((t_E)\) as high as 40 days. Moreover, on our map, we do not see any regions of high \((t_E)\) values, especially at \(l \approx +3\), as claimed by MOA-II and previous results (Alcock et al. 1997; Popowski et al. 2005), indicating that it was likely a statistical fluctuation driven by the small number of events available for those studies. The only part where the maps from OGLE-III and MOA-II agree is in the decrease of the mean \(t_E\) at \(l \approx +1\), \(b \approx −2\), which is even more clearly visible on the log-normal fit mean \(t_E\) map for OGLE-III. However, as mentioned above, the All Sample maps present a blurred view on the mean timescales due to the mixing populations and distances of the sources and lenses.

5.2.3. Bulge-source Events Sample

In order to minimize the impact on population mixing, we restricted our events to those with RC stars from the bulge as the most likely sources. Figure 15 shows the color–magnitude diagram of the sources of all events, marking the region of RC sources. The \(I\)-band magnitude was computed using \(I_0\) and \(fs\). However, since we did not have enough observations in the \(V\) band, the color of the source is assumed to be similar to the color of the baseline (i.e., source and blends). This approximation is close to reality because RC giants are typically much brighter than other (bluer) stars in the direction of the Bulge, and hence the color of the red giant dominates the baseline. Note that the opposite assumption, that the non-RC sources are bluer in the baseline, would not be true for the same reason.

Selecting RC sources allowed us to construct another map of mean timescales, shown in Figure 16. The values of \((t_E)\) are clearly much smaller than in the previous maps, most likely because most of events in this case have sources in the bar and the lenses are from the disk. Such combinations of lenses and sources typically have higher relative proper motion, and hence tend to produce shorter \(t_E\) (e.g., Di Stefano 2012. However, Figure 16 has two clearly distinct regions with different values of mean timescale, with the split occurring at about \(b \sim −3\) deg. The events closer to the Galactic center tend to have shorter \(t_E\) (well below 20 days), whereas those at higher Galactic latitudes have \(t_E\) above 20 days. The duality, or a gradient of \((t_E)\) with galactic latitudes, can be explained by the fact that at low \(b\) the dominating lensing configuration contains both a source and a lens from the Galactic bar, and hence causes shorter events due to a larger velocity dispersion. On the other hand, at larger \(b\), the bar density decreases and the relative fraction between the bar-bar and bar-disk events changes in favor of bar-disk events, which tend to be longer.

Our values of \((t_E)\) for the RC sample do not match either of the two scenarios presented in Figure 5 of Evans & Belokurov (2002), showing mean timescales for bar sources in Freudenreich’s model including and excluding the contribution.
of bar streaming. This might mean that there is very little stream-
ing in the bar, however, our sample of RC events is small and is
distributed over a small area of the sky, which might be influ-
encing our conclusions. More microlensing data is needed for
larger galactic longitudes to verify this issue.

5.2.4. Mass Function

Finally, in Figure 17, we show the distributions of efficiency-
corrected timescales of events in three subgroups: All, RC, and
within the two degrees around Baade’s Window (BW, l \sim 1, b \sim -2). Thick dashed lines show the expected power-law
slopes for the short and long tails of the distribution of the
timescales, valid for a range of mass functions from Mao &
Paczynski (1996). The slope of the distribution for the long end
agrees with the prediction, at least for the RC sources. For the
BW and All events, the long event tail seems to have a more
shallow slope, which could be caused by either the flatter mass
function of the disk, or the small relative velocity dispersion
for disk-disk events, as the BW and All samples contain more
disk-disk events, which typically have longer \( t_E \). This could also
just be the modeling bias mentioned earlier (see Section 5.1).
For the short timescales, the slope in the data is more flat, which
could be a sign of some additional population of either light
or fast lenses (Sumi et al. 2011). Log-normal model fit average
values for \( t_E \) were computed as 27.2, 25.5, and 24.9 days for the
All, RC, and BW samples, respectively.

5.2.5. Very Long and Very Short Events

We note that our sample contains a significant number of
long and short events: there are 9 events with \( t_E \) longer than
300 days, 205 (7%) events longer than 100 days, and 722
(24%) longer than 50 days. Because our search pipeline was
designed to select purely standard events, those events with
strong parallax signal were excluded; however, there still remain
a couple of events exhibiting some weak systematic deviation
from the standard microlensing model, likely due to the parallax
effect. The difference in \( t_E \) with and without the parallax model
included in those cases was within the reported error-bars for
\( t_E \), however. Therefore, those events can be safely included in
our sample of standard events. The entire OGLE-III data will
be searched separately for long events with strong parallax.

For short events, we see that 561 (19%) events have \( t_E < 10 \) days, 118 (4%) have \( t_E < 5 \) days, and there are
even 6 events with timescales between 1 and 2 days. Given
a relatively sparse sampling of the OGLE-III survey and low
detection efficiency for very short events, this might repre-
sent a high abundance of low-mass lensing objects like brown
dwarfs or unbound or wide-orbit planets, or just a surplus of
very fast lenses. A systematic optimized search for very short
OGLE-III and OGLE-IV events will be conducted in the near
future, along with a study of the potential instrumental or nu-
merical systematics causing the timescales to be shorter than
in reality.

6. SUMMARY

We have prepared and presented the largest homogenous
catalog of 3718 good quality standard microlensing events
toward the Galactic bulge using eight years of the OGLE-III
survey (2001–2009). 1409 of the events are new and were not
previously reported by the OGLE EWS. The full catalog is
available for the astronomical community, with all the light
curves, probability distributions plots for the microlensing
parameters, and values of all parameters with their uncertainties
in a machine-readable form.

Applications of such a catalog are numerous, from studying
the individual events to large sample analyses. Because of their
number and distribution over a wide range of galactic longitudes
and latitudes, it was possible to measure the mean \( t_E \) per region
of the sky robustly enough to provide a direct comparison to
the expectations. Our data are in good agreement with recent
models of the inner parts of the Milky Way, except that the
asymmetry in the mean timescale due to the bar angle seems
to be somewhat more pronounced. This might be evidence of
a slightly different geometry or shape of the Galactic bar and
may call for new models of the very center of our Galaxy.
In the near future, the catalog will be the basis for the optical
depth and microlensing rate computation for the OGLE-III data,
which will further allow for the verification of the models of the
Milky Way.

The OGLE-IV survey, during its first three years of operation,
has already detected about 5000 events, as reported by the EWS.
An analysis similar to the one presented here on the archival
OGLE-IV data will supplement the catalog of events from the
OGLE-III and form a colossal sample of standard microlensing
events spread over a wide range of galactic coordinates, allowing
for very detailed studies of the inner parts of the Galaxy.
OGLE-IV is hoped to continue functioning for many years,
and hence there is room for synergy with the ESA’s corner
stone astrometric mission Gaia. This will create a first-ever
opportunity to combine astrometry and photometry and derive
masses and distances to individual lenses in microlensing events
(Belokurov & Evans 2002; Wyrzykowski & Hodgkin 2012),
providing us with a completely new perspective for studies of
the Galactic structure.

We thank Marzena Śniegowska and Mateusz Zieliński for
their contributions during their summer project. We also ac-
knowledge Drs. Nicholas Rattenbury, Eamonn Kerins, and
Shude Mao for their useful comments and help. We thank the
anonymous referee for comments and corrections which im-
poved the paper.
Ł.W. and A.E.R. acknowledge support from the Polish Ministry of Science under “Iuventus Plus” program, grant No. 9003/IP3/2012/71. The OGLE project has received funding from the European Research Council under the European Community’s Seventh Framework Programme (FP7/2007-2013)/ERC grant agreement No. 246678 to A.U.

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