

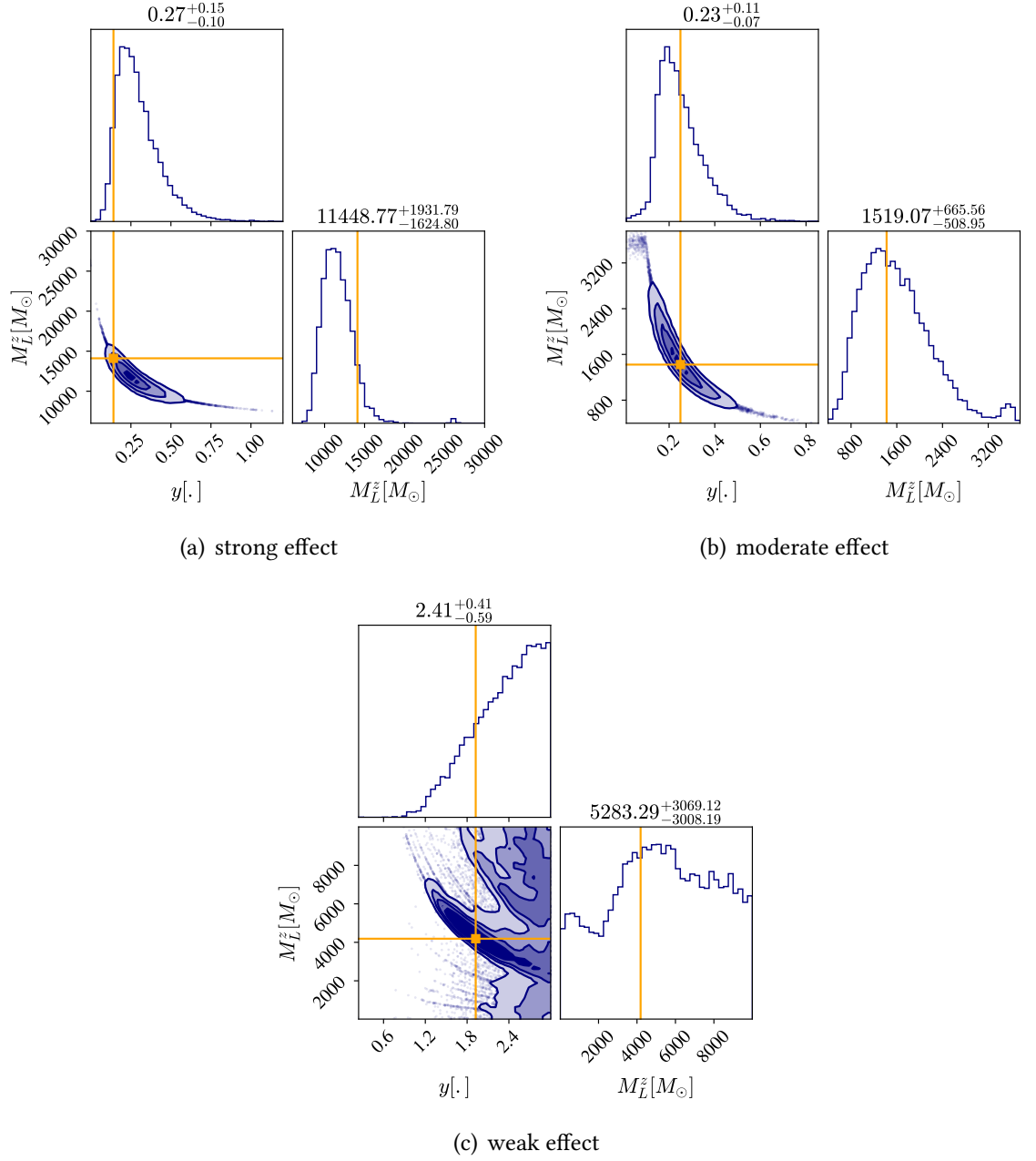


Figure 5.1: Corner plots showing the posterior distributions of M_L^z and y for the (a) strong, (b) moderate, and (c) weak microlensing cases.

However, a Bayes factor alone is not sufficient to claim a microlensing detection. High values of $\mathcal{B}_U^{\text{ML}}$ may also arise from statistical fluctuations in the noise or from non-lensing effects. As discussed in Section 1.3.2, to assess the statistical significance, one needs to construct a background distribution using a large number of unlensed injections, each analysed under both the microlensing and unlensed hypotheses. The resulting distribution of $\mathcal{B}_U^{\text{ML}}$ under the unlensed background allows us to quantify the significance of the observed Bayes factor. The false-positive probability (FPP) of the observed Bayes factor, $\mathcal{B}_{\text{obs}}$, is defined as:

$$\text{FPP} = \frac{\text{number of background events with } \mathcal{B}_U^{\text{ML}} > \mathcal{B}_{\text{obs}}}{\text{total number of background events}}. \quad (5.2)$$

If the FPP is sufficiently small, a microlensing detection may be claimed.

However, when multiple independent events are analysed, the probability of obtaining a large Bayes factor from noise or statistical fluctuations increases. This is commonly referred to as the *look-elsewhere effect*, for which the FPP must be corrected by accounting for the associated *trial factor* [308, 309]. Therefore, the significance inferred from a single event must be adjusted to account for the total number of independent events included in the search. In this context, each analysed GW event constitutes an independent trial. The relevant quantity is then the global FPP, defined as the probability of obtaining at least one event with $\mathcal{B}_U^{\text{ML}} > \mathcal{B}_{\text{obs}}$ among all analysed events. Assuming statistical independence, the global FPP (equivalently, the global p -value) is given by:

$$\text{FPP}_{\text{global}} = 1 - (1 - \text{FPP})^{N_{\text{event}}}, \quad (5.3)$$

where N_{event} denotes the total number of independent events.

5.1.2 Geometrical-optics Regime

Similar to microlensing, phenomenologically lensed signals are characterised by a single distorted waveform arising from the coherent superposition of multiple lensed images [166]. In this framework, each image is described within the geometric-optics approximation, providing a lens-model-agnostic description. The lensed signal is thus modelled as a coherent sum of K image components rather than as discretely resolvable events, where each component shares the same intrinsic waveform as the unlensed signal.

As noted in Section 2.4, the amplification factor $F(f)$ for phenomenological lensing is basically the same as Eq. (2.74). However, since the main parameters to be estimated are the relative magnification μ_{rel} , the time delay Δt , and the total number of images K , it is more convenient to rewrite the lensed waveform as:

$$\tilde{h}_{\text{Phenom}}(f) = F(f) \tilde{h}_U(f) \sqrt{\mu_1} \left[1 + \sum_{j=2}^K \sqrt{\mu_{\text{rel},j}} \exp(2\pi i f \Delta t_j - i\pi n_j) \right] \tilde{h}_U(f), \quad (5.4)$$

where μ_1 denotes the magnification factor of the first-arriving signal, while $\mu_{\text{rel},j}$ and Δt_j represent the magnification and time delay of the j^{th} image relative to the first, respectively.

Following the hypothesis-testing and background-construction framework established for the microlensing analysis in Section 5.1.1, the phenomenological analysis yields a Bayes factor ($\mathcal{B}_U^{\text{Phenom}}$), along with posterior distributions for the lensing observables. These results are subsequently evaluated using the global FPP defined in Eq. (5.3).

In the phenomenological lensing regime, the time delays between superposed images range from milliseconds to $\mathcal{O}(0.1)$ s [166]. Given the sensitive frequency band of current ground-based detectors, these delays correspond to lens masses in the range $M_L \sim 10^2$ – $10^6 M_\odot$. In this mass range, unlike microlensing, which is typically well-motivated by point-mass models, phenomenological lensing can arise from a variety of lens candidates, including IMBHs and dark-matter subhalos embedded within a larger galactic lens [166]. Consequently, for a robust astrophysical interpretation, the parameters inferred from this agnostic framework should be compared with the results of lens-model-dependent analyses based on representative physical models that produce such phenomenological signatures.

Shifting focus to the strong lensing regime, a single strongly lensed signal can show a lensing signature if it corresponds to a Type II image [157, 305, 306, 307]. For Type II images ($n_i = 0.5$), the phase factor in the amplification factor (Eq. (2.74)) becomes $\exp(-i\pi/2) = -i$, which corresponds to a constant $\pi/2$ phase shift across all frequencies. In the time domain, this operation is equivalent to a Hilbert transform of the waveform, introducing a frequency-dependent time delay for different frequency components.

For a signal dominated by the quadrupole mode ($\ell = |m| = 2$), this constant phase shift is completely degenerate with a shift in the coalescence phase (ϕ_c) of an unlensed signal, rendering it indistinguishable. However, this degeneracy can be broken if the signal contains non-negligible HOMs (e.g., $\ell = 3, m = 3$). Because the phase shift applies globally to all modes, while the physical phase evolution of each mode scales with its m -index ($\Phi_{\ell m} \approx m\Phi_{\text{orb}}$), the relative phase between different harmonics is altered. The lensed waveform for a Type II image is given by [157]:

$$h_{\text{TypeII}}(t) \propto \sum_{\ell, m} \mathcal{A}_{\ell m} e^{-i(\Phi_{\ell m}(t) + \pi/2)}, \quad (5.5)$$

where $\mathcal{A}_{\ell m}$ is the amplitude of each mode. In an unlensed signal, a shift in the orbital phase Φ_{orb} by $\Delta\Phi$, a constant shift in the orbital phase at coalescence, would result in a phase shift of $m\Delta\Phi$ for each mode. Since the Type II transformation introduces a shift of $\pi/2$ for all m , no single value of $\Delta\Phi$ can mimic this effect across multiple harmonics (e.g., a $\pi/2$ shift looks like an orbital shift of $\pi/4$ for $m = 2$, but $\pi/6$ for $m = 3$). This inconsistency allows for the unambiguous identification of a Type II image.

Following the methodologies described above, the search for Type II images aims to calculate Bayes factors for observed GW events and compare them against a background distribution. Given that strong lensing can produce three distinct image types (Type I, II, and III), the analysis involves calculating the Bayes factors between Type II and Type I images ($\mathcal{B}_I^{II}$), as well as between Type II and Type III images ($\mathcal{B}_{III}^{II}$) [238]. If both Bayes factors are sufficiently high, corresponding to a low FPP, the evidence for lensing becomes compelling.

5.2 Multiple Repeated Lensed Signals

As discussed previously, searches for lensing signatures within a single distorted signal rely on identifying distinctive waveform modulations that are not expected in unlensed signals, such as interference-induced amplitude and phase variations, as well as the characteristic phase shifts associated with specific image types. In contrast, the search strategy for multiple lensed signals from the same source (i.e., strongly lensed GW (SLGW) events) is qualitatively different.

Because gravitational lensing in the geometric-optics limit is achromatic and does not alter the morphology of the GW waveform, intrinsic source parameters, such as the component masses (m_1, m_2), spin magnitudes (χ_1, χ_2), and source redshift (z_s), are invariant across all lensed images. In addition, the sky locations of different images are expected to be nearly identical, since the current GW detector network does not have sufficient angular resolution to distinguish them [20]. In contrast, the extrinsic parameters, such as the luminosity distance (d_L), arrival time (t_c), and coalescence phase (ϕ_c), can differ between images [155, 156, 157]. Consequently, strong lensing searches rely on the expectation that multiple lensed images share the same intrinsic source properties, with the differences in observable extrinsic parameters being consistent with physically plausible lensing scenarios.

We discuss how to utilise the consistency in the intrinsic parameters to identify candidate pairs or multiplets of SLGW signals originating from a common source and lensed by a macrolens³. Furthermore, we extend our discussion to more complex scenarios in which both strong lensing and microlensing occur simultaneously. In these cases, the lens's complex mass distribution can produce both multiple discrete signals and subtle waveform distortions in individual images.

5.2.1 Joint Parameter Estimation

To quantitatively assess whether a pair of GW events originates from strong lensing of a common source, we analyse the events under two competing hypotheses: the strong-lensing hypothesis, $\mathcal{H}_{\text{SL}}$, in which the event pair shares a common source, and the unlensed hypothesis, $\mathcal{H}_{\text{U}}$, in which the two events are unrelated unlensed signals. We then compute the corresponding Bayes factor, $\mathcal{B}_{\text{U}}^{\text{SL}}$. This procedure is referred to as *joint parameter estimation* (JPE), where "joint" indicates that the two events are analysed in a correlated manner, either by conditioning one event on the parameters of the other or by estimating parameters for both events simultaneously [300, 301, 302].

3. A macrolens refers to a large-scale gravitational lens, such as a galaxy or galaxy cluster, that produces multiple, discretely resolvable signals and is well described by the geometric optics limit, in contrast to microlensing, which can induce wave-optics effects and interference patterns.

Let d_1 and d_2 denote the data streams containing the two GW signals. The Bayes factor is defined as [300, 301, 302]:

$$\begin{aligned} \mathcal{B}_U^{\text{SL}} &\equiv \frac{\mathcal{Z}(d_1, d_2 \mid \mathcal{H}_{\text{SL}})}{\mathcal{Z}(d_1, d_2 \mid \mathcal{H}_U)} \\ &= \frac{\alpha^2}{\beta} \frac{\int d\boldsymbol{\theta} d\boldsymbol{\lambda} p(d_1, d_2 \mid \boldsymbol{\theta}, \boldsymbol{\lambda}, \mathcal{H}_{\text{SL}}) \pi(\boldsymbol{\theta}, \boldsymbol{\lambda} \mid \mathcal{H}_{\text{SL}})}{\prod_{i=1}^2 \int d\boldsymbol{\theta}_i p(d_i \mid \boldsymbol{\theta}_i, \mathcal{H}_U) \pi(\boldsymbol{\theta}_i \mid \mathcal{H}_U)}, \end{aligned} \quad (5.6)$$

where $\boldsymbol{\theta}$ denotes the set of source parameters shared by the two lensed images, while $\boldsymbol{\lambda}$ represents lensing-related parameters and image-dependent extrinsic parameters. Here, $p(d_1, d_2 \mid \boldsymbol{\theta}, \boldsymbol{\lambda}, \mathcal{H}_{\text{SL}})$ is the joint likelihood for the two signals under $\mathcal{H}_{\text{SL}}$, and $\pi(\boldsymbol{\theta}, \boldsymbol{\lambda} \mid \mathcal{H}_{\text{SL}})$ denotes the corresponding prior distribution for the parameters. In contrast, under $\mathcal{H}_U$, each event is described by an independent parameter set, $\boldsymbol{\theta}_i$. Since the two events are assumed to be independent under $\mathcal{H}_U$, the joint likelihood factorises into the product of the individual-event likelihoods. Note that α and β are normalisation constants associated with the strong-lensing and unlensed hypotheses, respectively, which account for selection effects arising from detector sensitivity and detection thresholds [302].

A high value of $\mathcal{B}_U^{\text{SL}}$ suggests that the event pair is more likely to originate from a strongly lensed common source. However, like the case of a single distorted signal discussed in Section 5.1, the Bayes factor alone is not sufficient to claim a decisive detection. The BBH population spans a broad and nearly continuous region of the physically allowed mass-spin parameter space, and therefore, unrelated events can coincidentally exhibit similar source parameters, resulting in false alarms. To quantify this possibility, it is necessary to construct the background distribution of $\mathcal{B}_U^{\text{SL}}$ expected from pairs of independent unlensed events and compute FPP or global FPP in Eqs. (5.2) and (5.3).

Up to this point, we have only considered pairs of GW events. However, as discussed in Section 2.2, a single GW source can produce more than two strongly lensed images. In such cases, the formalism of $\mathcal{B}_U^{\text{SL}}$ in Eq. (5.6) remains unchanged in principle, but the analysis becomes increasingly complicated because additional image-dependent parameters must be considered. Nevertheless, it is not always necessary to analyse all lensed images simultaneously for an initial search. More specifically, even if a quadruply lensed GW signal is observed, performing JPE on only a randomly selected image pair can still enable the identification of a strong-lensing candidate, since the two signals originate from the same underlying source. A more complete joint analysis incorporating all images would then be required as a follow-up study to fully characterise the lens system and improve constraints on the lensing configuration (e.g., [300, 310, 311]).

In practice, performing a full JPE for a pair of GW events is substantially more computationally expensive than standard parameter estimation for a single unlensed signal. This issue becomes increasingly important as the number of detected CBC events grows. For example, the GWTC-4 catalogue already contains more than 200 CBC events [20], and future observing runs are expected to detect significantly more signals. Since the number of possible event pairs scales as $N(N - 1)/2$, the total number of candidate pairs increases rapidly with the catalogue size. Consequently, performing full JPEs for all possible pairs would require prohibitive computational resources and analysis time.

To address this challenge, recent strong-lensing searches [238] employed several low-latency ranking and filtering pipelines to identify promising candidate pairs before performing full JPEs. This hierarchical strategy restricts the computationally intensive follow-up analyses to only those event pairs flagged as potentially lensed, enabling a substantially more efficient use of computational resources.

5.2.2 Strong Lensing with Substructures

Astrophysical compact objects that produce microlensing signatures in the wave-optics regime are typically embedded within larger gravitational structures such as galaxies or galactic halos. Consequently, a GW propagating near such a system can experience both galaxy-scale strong lensing and additional perturbations from smaller embedded structures. In this scenario, the macrolens first generates multiple strongly lensed images (so-called *macroimages*), after which each image can undergo further lensing distortions due to a microlensing field composed of compact objects or substructures along its individual propagation path [312, 313, 314, 315, 316, 317, 318, 319, 320].

Figure 5.2 illustrates an example of such a complex lensing configuration, in which a BBH is lensed by microlenses embedded within a macrolens. Since the microlensing fields need not be identical across macroimages, reflecting different shear effects near each image as well as the non-uniform stellar distribution within the lens galaxy, each image may experience distinct waveform modulations. As a result, different macroimages do not necessarily share identical waveform morphologies, even though they originate from the same underlying source parameters. This situation poses a challenge for strong-lensing searches based on Eq. (5.6), because the corresponding JPE framework is lens-model-independent and primarily relies on the consistency of the inferred source parameters between the two events. Such approaches may not fully capture the signatures of complex lensing configurations. In particular, microlensing-induced waveform distortions can bias the inferred source parameters and potentially reduce the apparent consistency between strongly lensed images, thereby causing genuine lensed pairs to be missed [320, 321, 322].

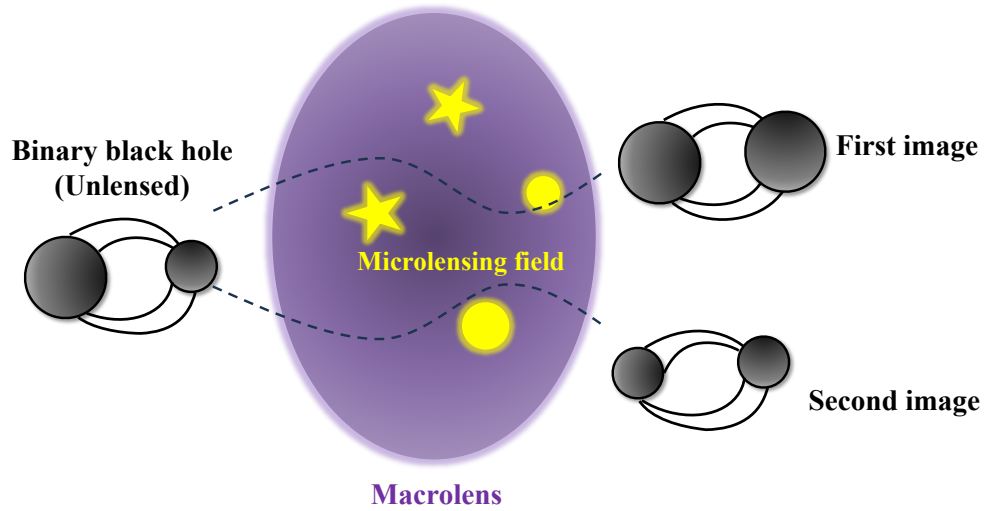


Figure 5.2: A complex lensing system in which a BBH signal is strongly lensed into multiple macroimages by a galaxy-scale macrolens, with additional microlensing effects arising from stellar fields or compact objects embedded within the macrolens.

A similar limitation also arises in searches for single distorted lensed signals. As discussed in Section 5.1.1, microlensing searches typically assume the isolated PM lens model. In realistic astrophysical environments, however, multiple compact lenses may contribute to the amplification factors. In addition, the macrolens itself can introduce external shear and convergence, further modifying the lensing effects [314, 318, 319].

As a simple example, the amplification factor in Eq. (2.71) for a system consisting of a macrolens and a PM microlens can be described by introducing an additional convergence (κ) and shear (γ), given by:

$$\begin{aligned}
 F(w, \mathbf{y}) &= \frac{w}{2\pi i} \int d^2x \left[\exp \left\{ iw \left(\frac{1}{2} |\mathbf{x} - \mathbf{y}|^2 - \psi(\mathbf{x}) \right) \right\} \right] \\
 &= \frac{w}{2\pi i} \int d^2x \left[\exp \left\{ iw \left(\frac{1}{2} |\mathbf{x} - \mathbf{y}|^2 - \ln \mathbf{x} + \frac{\kappa}{2} (|\mathbf{x}|^2) + \psi_\gamma(\mathbf{x}) \right) \right\} \right], \quad (5.7)
 \end{aligned}$$

where $\psi_\gamma(\mathbf{x})$ is defined in Eq. (2.56).

Figure 5.3 compares three frequency-dependent amplification factors: those of an isolated PM microlens (see Eq. (2.73)), and an embedded-lens configuration in which an SIE macrolens contains the same PM microlens evaluated at two different macroimage positions, corresponding to Type I and Type II images (for the image type, see Section 2.1.3). The two embedded cases correspond to the amplification factors given by Eq. (5.7) for the same PM microlens evaluated at different macroimage locations within the macrolens po-

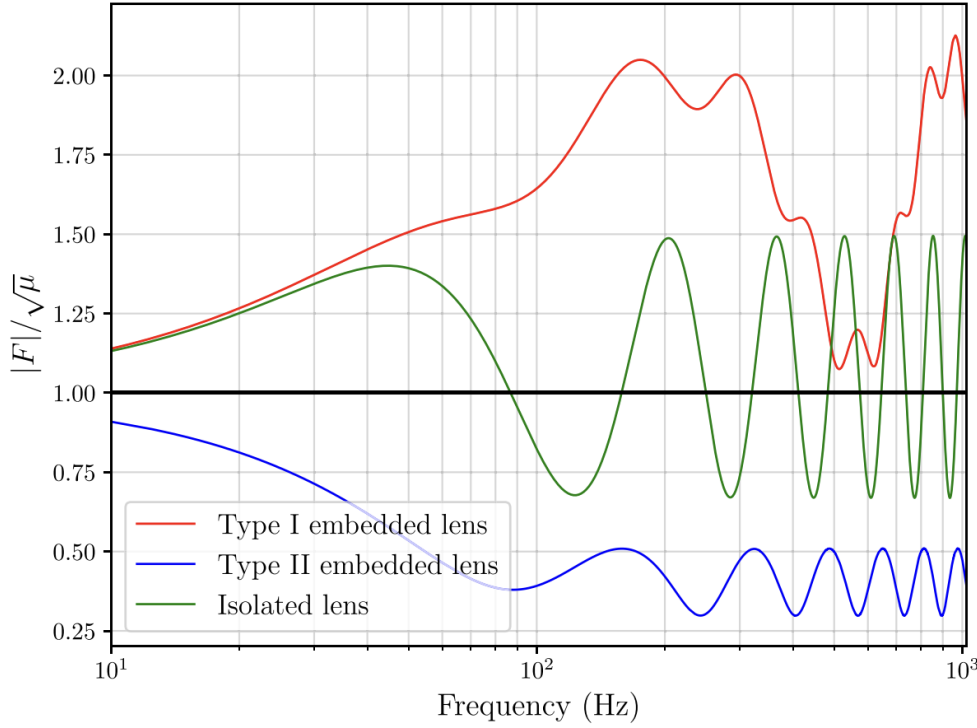


Figure 5.3: An example of amplification factors for an isolated PM lens and for the same PM perturber embedded in Type I and Type II macroimages produced by a common macrolens galaxy. Figure is from [318].

tential. This locational difference corresponds to the distinct local lensing environments, which can be effectively interpreted as different external shear conditions induced by the macrolens potential at each image position. Therefore, the two embedded amplification factors can differ substantially, and both deviate significantly from the isolated PM case.

Moreover, the example still represents an idealised configuration involving a single PM microlens. Realistic lens environments are expected to contain multiple compact objects or substructures, which produce even more complex interference patterns [315, 319, 323]. Consequently, the isolated PM approximation may fail to reproduce the true amplification factors, introducing non-negligible systematic mismatches between the assumed lens model and the actual lens. Such lens-model systematics can reduce the resulting Bayes factors and may weaken or even hinder the detection of microlensing signatures.

One of the most promising approaches for searching for such complexly lensed GW signals is to explicitly incorporate the effects of all relevant substructures into the lensed waveform model by parameterising the lensing perturbations and jointly inferring the lens parameters together with the CBC source parameters, analogous to the method introduced in Section 5.1. However, such analyses rapidly become computationally prohibitive. Bayesian inference for GW signals typically requires millions of likelihood evaluations, and the com-

putational cost can increase dramatically with the complexity of the lens model. In addition, the integration in Eq. (5.7) itself is computationally expensive due to the highly oscillatory nature of the integrand. A more efficient approach for the rapid identification of both strongly lensed and microlensed signals will be discussed in Chapter 7.

Chapter 6

Search for Microlensing Signatures in O4a BBHs

Disclaimer

The following chapter is based on the paper *GWTC-4.0: Searches for Gravitational-Wave Lensing Signatures* [238], carried out by the LVK Lensing Group. The author contributed to this work both as a data analyst conducting microlensing searches for observed BBH events and as a member of the paper writing team, contributing to manuscript preparation and figure generation. This work has been submitted to the *Astrophysical Journal* for publication.

As discussed in Section 5.1, lensing signatures can be identified within a single distorted GW signal. However, from the first two observing runs (O1–O2) [324] through the third (O3) [325, 326], the LVK Collaboration reported no decisive evidence for lensing in GW observations.

We have extended these searches to BBH events observed during the first part of the fourth LVK observing run (O4a), with a specific focus on microlensing signatures, as detailed in Section 5.1.1. The author has contributed to microlensing searches since the first half of O3, continuing through analyses of the full O3 dataset through participation in data analysis and interpretation. Building on these earlier efforts, the analysis of O4a data adopts more advanced and dedicated frameworks: `LensingFlow`, an automated workflow manager designed for large-scale lensing analyses [327], and `Gravelamps`, a pipeline specialised in performing full wave-optics hypothesis testing employing a grid-based approach to calculate amplification factors [298]. These tools enable more systematic and computationally efficient exploration of microlensing effects.

In this chapter, we present the results of the O4a microlensing search and examine the event GW231123_135430 (hereafter GW231123) in more detail. To date, this special event exhibits the highest Bayes factor in favour of the microlensing hypothesis over the unlensed hypothesis among all analysed candidates. While the high Bayes factor does not yet provide definitive evidence for lensing, it makes the event a strong candidate. This motivates a more detailed investigation to distinguish possible lensing effects from intrinsic source properties or instrumental artifacts.

6.1 Analysis Setup

We analyse 84 BBH events observed during the O4a to assess the presence of microlensing signatures. As described in Section 5.1.1, we examine the properties of these events under the microlensing hypothesis and evaluate their Bayesian evidence. The analysis employs the isolated PM lens model, and for the waveform we adopt IMRPHENOMXPHM-SPINTAYLOR [288, 289] (XPHM-ST) waveform model, one of the fiducial models used in the GWTC-4.0 analysis [20].

To estimate the two PM lens parameters, we define priors based on the expected physical characteristics of potential lenses. For the redshifted lens mass (M_L^z), we employ a uniform prior between $1 M_\odot$ and $10^4 M_\odot$. This range spans the masses of stars and stellar remnants ($\sim 1 M_\odot$) up to IMBHs ($\sim 10^4 M_\odot$). Beyond this upper limit, the time delay between the two microimages typically becomes large enough that they are resolved as separate signals, rather than appearing as a single distorted waveform. Meanwhile, the prior for the dimensionless impact parameter (y) is set as $p(y) \propto y$ with $y \in [0.1, 3]$, maintaining consistency with previous microlensing searches [324, 325, 326]. A value of $y < 0.1$ is statistically rare because of the small cross-section, whereas for $y > 3.0$, the microlensing effect becomes negligible for current ground-based detectors.

It is important to note that a normalisation error was identified in the likelihood evaluation using Bilby, which serves as the foundational framework for both the unlensed analyses in this chapter and the Gravelamps pipeline (see Section 5.10 of Abac et al. [328] for more details). To address the likelihood issue, we employ a reweighting scheme applied directly to the nested sampling chains for all Gravelamps and complementary unlensed analyses. Unlike reweighting only the final posterior samples, reweighting the full nested sampling chains also consistently updates the Bayesian evidence. In practice, this is done by recalculating the weights of the nested sampling points using the corrected likelihood values, leading to a more robust estimate of the evidence.

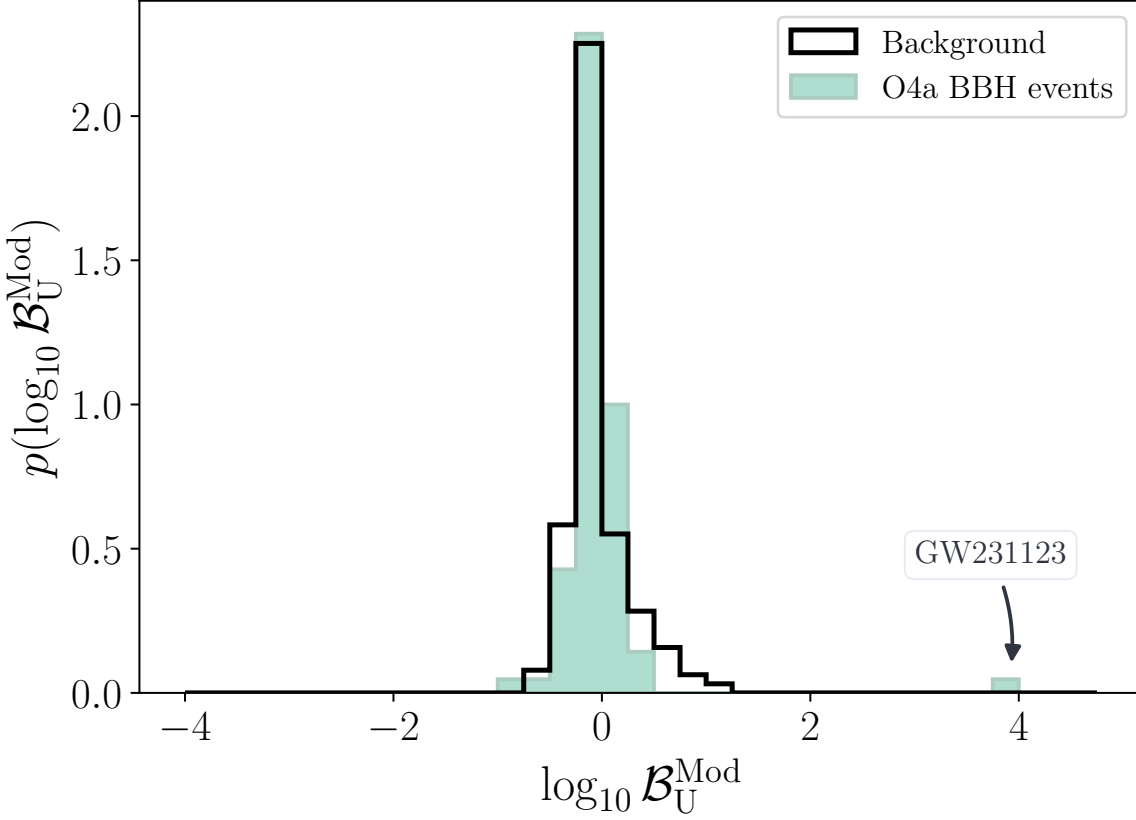


Figure 6.1: Histogram of $\log_{10} \mathcal{B}_U^{\text{Mod}}$ for O4a BBH events and background injections. GW231123 is clearly separated from the background distribution.

6.2 Point-Mass Microlensing Search

From the parameter estimation setup described above, we calculate the evidence for each event under the PM microlensing hypothesis ($\mathcal{B}^{\text{ML}}$) and the unlensed hypothesis ($\mathcal{B}^{\text{U}}$). The resulting Bayes factors, $\mathcal{B}_U^{\text{ML}}$, serve as our main statistic for the hypothesis test, as detailed in Section 5.1.1.

Figure 6.1 displays the distribution of $\mathcal{B}_U^{\text{ML}}$ for the 84 O4a candidates (green histogram). To robustly evaluate these values, we generated a background injection set comprising 254 detectable mock unlensed GW signals ($\rho_{\text{net}} > 8$) (see Appendix B of [238] for more details). The distribution of $\mathcal{B}_U^{\text{ML}}$ for the background is also shown in Figure 6.1 (black histogram). While most O4a events have low Bayes factors consistent with the background, GW231123 clearly stands out as an outlier, with $\log_{10} \mathcal{B}_U^{\text{ML}} \simeq 3.8$, the most substantial value identified in our lensing searches to date [329].

To quantify the statistical significance of this result, we estimate the FPP defined in Eq. (5.2). In this context, the FPP represents the likelihood that an unlensed signal—due to noise fluctuations or intrinsic parameter degeneracies—could yield a Bayes factor as high as that of GW231123. Since the observed value lies outside the range of the background distribution, we cannot directly calculate the FPP from it. In particular, none of the $N_{\text{bg}} = 254$

background samples produced a value larger than the observed Bayes factor. Rather than assigning $\text{FPP} = 0$, we place a conservative upper bound using the rule of succession [330], which accounts for the finite number of background samples:

$$\text{FPP}_{\text{upper}} = \frac{N(\mathcal{B}_{\text{U}}^{\text{ML}} > \mathcal{B}_{\text{obs}}) + 1}{N_{\text{bg}} + 1} = \frac{0 + 1}{254 + 1} \approx 0.0039, \quad (6.1)$$

where N_{bg} is the total number of the background events. An FPP of 0.39 % indicates that such a high Bayes factor is rare under the background distribution, making the signal stand out relative to typical events.

However, when accounting for the trial factor across the 84 independent events we analysed, the global FPP is significantly higher. Using Eq. (5.3), we obtain an upper bound for the global FPP of $\text{FPP}_{\text{global}} < 28\%$. The $\text{FPP}_{\text{global}}$ value is not sufficiently low to claim a definitive microlensing detection, which would typically require $\text{FPP}_{\text{global}} \ll 1\%$. This relatively high value is primarily due to the limited background size. With only 254 injections for an analysis of 84 events, the background is insufficient to resolve the far tail of the distribution. For example, to achieve a 3σ significance ($\text{FPP}_{\text{global}} \approx 0.0027$) for such a high Bayes factor, a background set of $\mathcal{O}(10^4)$ injections would be required to sample rare noise and degeneracy configurations.

Furthermore, the current background may not adequately represent events with properties similar to GW231123, which is characterised by a high total mass and evidence of non-negligible effective precessing spin [329]. In particular, such events are relatively rare in the background, and their absence can bias the FPP estimate. We consider two main effects:

1. **Precessing spin-lensing degeneracy:** The modulations induced by precession can mimic the interference patterns of lensing due to small mass objects [331]. If a background does not contain enough precessing BBHs, the risk of a false positive increases.
2. **Signal duration and non-Gaussianity:** Due to its high mass, GW231123 is a short-duration signal (~ 0.1 s), making it more susceptible to non-Gaussian instrumental noise, such as glitches. While our background is constructed to mitigate such non-Gaussian features, it may not fully capture their impact, which can be misinterpreted as either high spin [332] or a lensing signature.

Consequently, while the high Bayes factor of GW231123 is compelling, the current background limitations and potential degeneracies imply that more thorough follow-up is needed before we can claim microlensing.

6.3 GW231123: The Most Lensing-Favoured Event

6.3.1 Inferred Lens Properties

In Section 6.2, we found that GW231123 exhibits the highest Bayes factor ($\log_{10} \mathcal{B}_U^{\text{ML}}$) recorded to date in GW lensing searches. To assess the robustness of this result against waveform modelling uncertainties, we repeat the analysis using alternative waveform models IMRPHENOMXO4A (XO4A) [333] and NRSUR7DQ4 (NRSUR) [334]. These models incorporate different physical prescriptions and modelling systematics relative to the baseline XPHM-ST model. The recovered $\log_{10} \mathcal{B}_U^{\text{ML}}$ values for each waveform are shown in Table 6.1. Notably, the Bayes factors exhibit a strong dependence on the choice of waveform model. As all other aspects of the analysis, such as the data segment, prior assumptions, and noise treatment, are held fixed, the observed differences across waveform models indicate that the high Bayes factor obtained with XPHM-ST is likely driven by its specific modelling characteristics, rather than by external factors such as non-Gaussian noise transients.

	Waveform model		
	XPHM-ST	NRSUR	XO4A
$\log_{10} \mathcal{B}_U^{\text{ML}}$	3.8	1.5	0.1
$M_L^z [M_\odot]$	911^{+504}_{-292}	803^{+489}_{-299}	687^{+13208}_{-356}
y	$0.61^{+0.27}_{-0.21}$	$0.69^{+0.37}_{-0.26}$	$2.13^{+0.79}_{-1.54}$

Table 6.1: Bayes factors and inferred point-mass lensing parameters for GW231123 across different waveform models.

We observe a clear hierarchical decrease in $\mathcal{B}_U^{\text{ML}}$ in the order of XPHM-ST, NRSUR, and XO4A. This trend indicates an inverse relationship between $\mathcal{B}_U^{\text{ML}}$ and the quality of the fit (i.e., the Bayesian evidence) under the unlensed hypothesis. Specifically, among the three waveforms, XPHM-ST yields the lowest Bayesian evidence for the data, followed by NRSUR, with XO4A providing the strongest evidence (see Appendix B in [329] for details). This suggests that waveform models that provide a relatively poorer fit to the data under the unlensed hypothesis may show a stronger preference for the additional flexibility introduced by the PM microlensing model. Consequently, the relatively high Bayes factor obtained with XPHM-ST may, at least in part, reflect the interplay between waveform modelling systematics and the added degrees of freedom in the microlensing model, rather than arising solely from a distinct microlensing signature.

For each microlensing analysis performed with a given waveform model, the inferred values of the two point-mass parameters (M_L^z, y), including their medians and 90 % C.I, are summarised in Table 6.1. The corresponding posterior distributions are shown in Figure 6.2. For the XPHM-ST and NRSUR models, the posteriors are well constrained and exhibit clear peaks. In contrast, the XO4A results show broader posterior distributions, with support

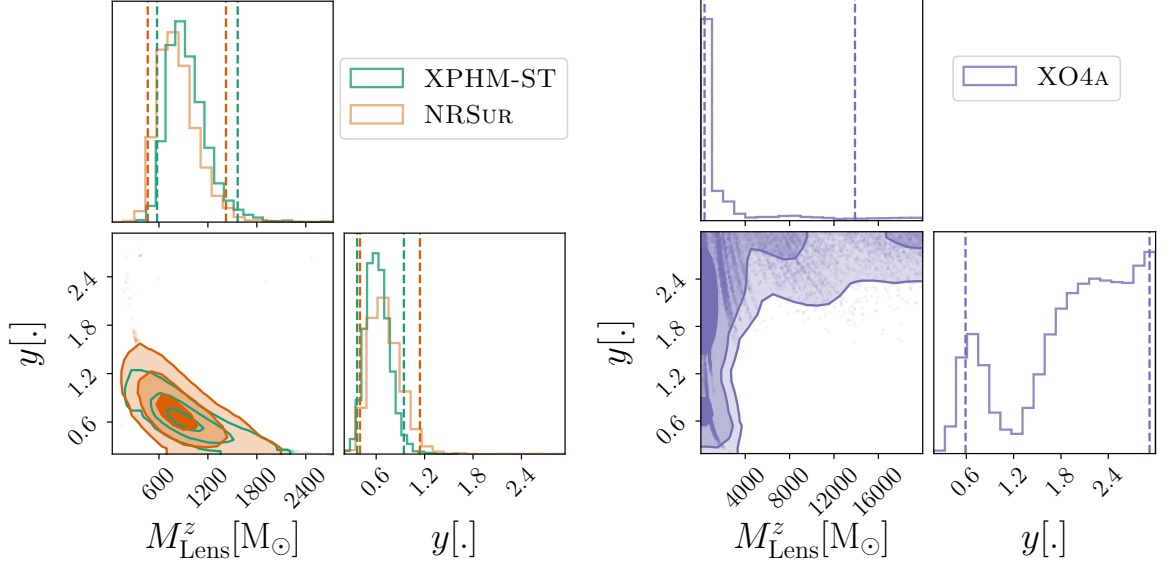


Figure 6.2: Posterior distributions of the redshifted lens mass and dimensionless impact parameter inferred from point-mass lensing analyses using the XPHM-ST (green), NRSUR (orange), and XO4A (purple) waveform models.

extending over a wider region of parameter space, although some overlap with the peaks identified by XPHM-ST and NRSUR is still apparent. This behaviour is consistent with the lower Bayes factor obtained for XO4A and indicates comparatively weaker support for the microlensing hypothesis.

The recovered redshifted lens mass ($M_L^z \sim 10^2\text{--}10^4 M_\odot$) and source redshift ($z_s \sim 0.2 - 0.7$) point to several plausible lens candidates. While an IMBH is a natural interpretation in this mass range, the lens could also correspond to a dense DM subhalo or a PBH, both of which are predicted to exist within galactic halos under various cosmological models. Although our analysis adopts an isolated PM model, a compact lens is more likely to be embedded within a complex environment rather than in isolation, as discussed in Section 5.2.2. Possible environments include the centers of globular clusters, where IMBHs may form, or galactic disks, where the lens could be embedded within a larger macrolensing field. The relatively high Bayes factor obtained for the isolated PM model may arise because the observed signal is primarily sensitive to the local gravitational potential within the Einstein radius of the compact object. In this local approximation, the influence of the surrounding stellar population or the host galaxy potential becomes subdominant to the effect of the primary deflector on the GW wavefront.

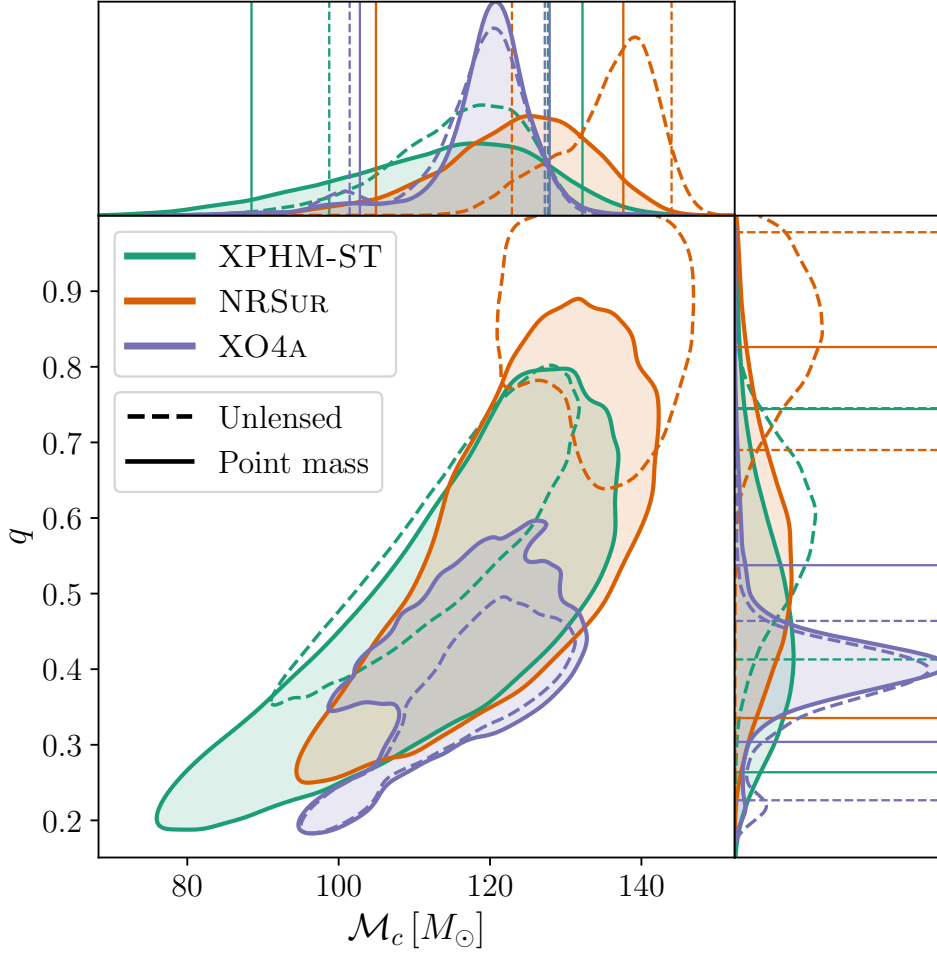


Figure 6.3: Comparison of the detector-frame chirp mass posteriors and mass-ratio under the PM microlensing (solid line) and unlensed (dashed line) hypotheses using XPHM-ST, NRSUR, and XO4A waveform models.

6.3.2 Inferred Source Properties

In addition to the inferred lens properties, we compare the inferred source properties under the microlensing hypothesis to those obtained under the unlensed case.

Figure 6.3 presents the joint posterior distributions for the detector-frame chirp mass ($\mathcal{M}_c$) and mass ratio (q), with 90 % credible regions, along with the corresponding 1D marginal distributions for each waveform model, including their 90 % C.I.. Under the unlensed hypothesis, the inferred parameters exhibit noticeable discrepancies across the three waveform models. In particular, the NRSUR model favours higher chirp masses and mass ratios than the IMRPhenom family. This behaviour likely reflects increased modelling uncertainty in the high-mass regime, where the signal contains relatively few in-spiral cycles and the inference becomes more sensitive to waveform systematics.

In contrast, under the microlensing hypothesis, the posterior distributions for the two parameters become broader across all models, mainly attributed to the increased degrees of freedom in the microlensing model. At the same time, the level of disagreement between waveform models is reduced. Notably, the NRSUR posterior shifts toward lower masses and mass ratios, bringing it into closer agreement with the IMRPhenom-based results. This trend is also evident in the 2D credible regions, which show increased overlap compared to the unlensed case. Overall, while the broader posteriors indicate increased parameter degeneracy, the improved cross-model consistency suggests that the microlensing framework may partially mitigate waveform-dependent discrepancies present in the unlensed analysis.

We further investigate the impact of the microlensing hypothesis on the inferred source-frame masses ($m_{1,s}$ and $m_{2,s}$) and spin magnitudes (χ_1 and χ_2), focusing on the NRSUR model, which provides the most physically rigorous representation by minimising the averaged mismatch with NR waveforms [329].

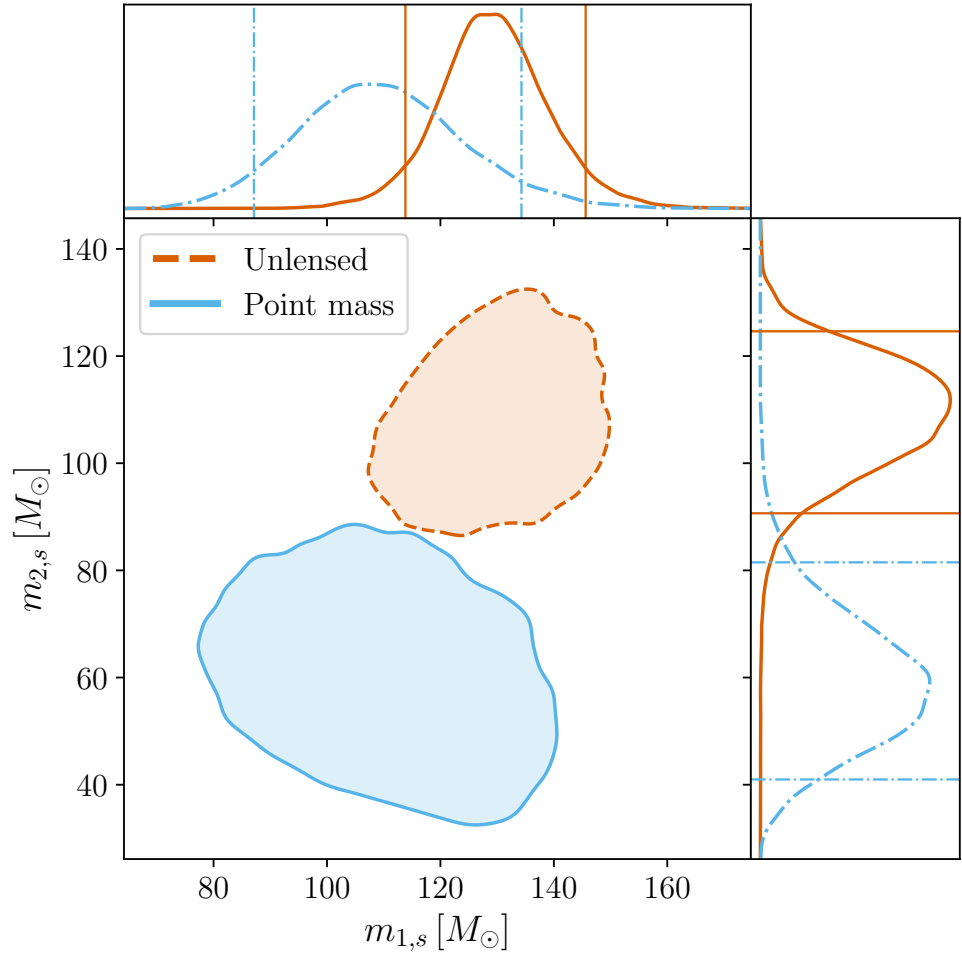


Figure 6.4: Comparison of the posterior distributions of the source-frame component masses for GW231123 inferred with the NRSUR model under the unlensed (orange) and point-mass microlensing (sky blue) hypotheses.

A key feature of PM lensing is that it produces magnification only ($\mu \geq 1$). Under this interpretation, the observed GW signal corresponds to a magnified version of a more distant source. As a result, the inferred luminosity distance (d_L) increases, implying a higher source redshift (z_s). Since the source-frame masses scale as $m_s = m/(1 + z_s)$, this leads to systematically lower intrinsic mass estimates. Figure 6.4 shows the posterior distributions of $m_{1,s}$ and $m_{2,s}$, under the microlensing and unlensed hypotheses. While the reduction in $m_{1,s}$ is relatively modest, $m_{2,s}$ decreases more significantly. Quantitatively, the median and 90 % C.I. shift from $129^{+16.4}_{-15.4} M_\odot$ and $106^{+15.2}_{-18.8} M_\odot$ in the unlensed case to $109^{+25.2}_{-21.9} M_\odot$ and $59^{+22.6}_{-18.0} M_\odot$ under the lensing hypothesis. This difference is consistent with the behaviour seen in Figure 6.3, where the NRSUR analysis under the microlensing hypothesis favours smaller mass ratios. Consequently, whereas the unlensed interpretation places the event in an ambiguous outlier regime, the lensed scenario shifts it toward values more consistent with the known BBH population.

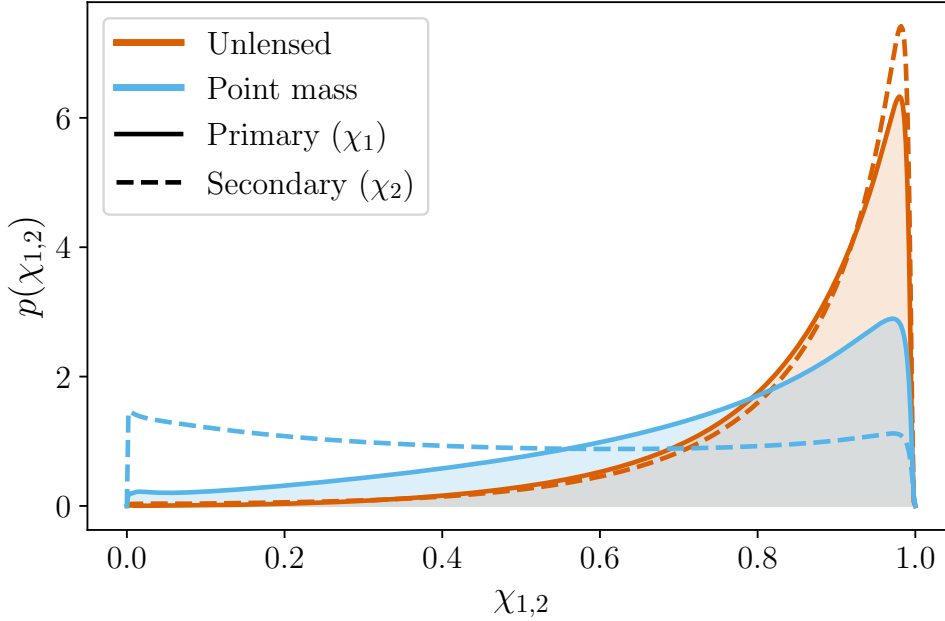


Figure 6.5: Comparison of the posterior distributions of the dimensionless spin magnitudes for GW231123 inferred with the NRSUR model under the unlensed (orange) and point-mass microlensing (sky blue) hypotheses.

Furthermore, the inferred χ_1 and χ_2 shift toward more moderate values under the microlensing hypothesis across all waveform models, with χ_2 in particular exhibiting a broader and less peaked distribution. Figure 6.5 shows the corresponding posteriors for the NRSUR cases. This behaviour can be understood in terms of a morphological degeneracy between spin-induced modulations and lensing-induced distortions. As discussed in [331], spin precession can introduce waveform modulations that resemble the interference-like features produced by a compact lens, particularly when the spin magnitudes are large. Within the microlensing framework, such features can instead be accommodated by lensing

Parameter	$\mathcal{M}_c$		χ_1		χ_2	
	KS	JSD	KS	JSD	KS	JSD
Unlensed	0.647	0.294	0.150	0.044	0.051	0.002
Lensed	0.342	0.089	0.097	0.009	0.026	4×10^{-4}

Table 6.2: KS statistics and JS divergence (in nats) computed between the chirp mass and spin magnitude posteriors inferred from individual-detector analyses under the unlensed and lensed hypotheses, using the NRSUR waveform model

parameters, thereby reducing the preference for extremely high spin values. Similar to the trends observed in the mass parameters, this shift toward more moderate spin values improves the agreement across waveform models, leading to a more consistent interpretation of the signal.

6.3.3 Single-Detector Analysis and Consistency Checks

If a GW signal is genuinely affected by lensing, the associated distortions are expected to appear consistently across all detectors in the network. To test this, we perform independent microlensing analyses using data from the aLIGO Hanford (LHO) and aLIGO Livingston (LLO) detectors. As noted in the case of GW200208_130117 [335], a lensing-like feature present in only a single detector is more plausibly explained by local instrumental noise or a transient glitch that mimics the lensing morphology. In contrast, a consistent signature observed across independent detectors is less likely to have a terrestrial origin.

Using the NRSUR model, we obtain $\log_{10} \mathcal{B}_U^{\text{ML}} = 0.62$ for LHO and 2.64 for LLO, both of which independently favour the microlensing hypothesis. The higher Bayes factor obtained for LLO can be attributed to its higher SNR relative to LHO, which enables a more precise resolution of the interference patterns. Part of the discrepancy between the two detectors may also arise from differences in data treatment: the LHO data were deglitched, whereas the LLO analysis used the original data [336]. Residual noise artifacts or variations in data conditioning can, therefore, introduce modest shifts in the inferred evidence.

To quantify the consistency of the intrinsic parameters, specifically the chirp mass, mass ratio, and spin magnitudes, inferred from each single-detector analysis, we compute the Kolmogorov–Smirnov (KS) statistic and the Jensen–Shannon (JS) divergence. These measures are applied to the posteriors obtained under both the unlensed and microlensing hypotheses. As shown in Table 6.2, both the KS and JS values are lower in the microlensing case than in the unlensed case, which indicates that the parameter estimates inferred from the two detectors are more consistent under the microlensing hypothesis, suggesting that it provides a more coherent description of the signal across the detector network.

To further assess whether the apparent preference for the lensing hypothesis reflects a genuine feature of the data or arises from modelling degeneracies, we compare the inferred waveforms with a model-independent reconstruction obtained from an unmodelled search pipeline [337]. This reconstruction is performed using cWB [44], which employs a wavelet basis to reconstruct coherent signal power across detectors, providing a data-driven baseline that does not rely on specific waveform assumptions.

Given the high $\mathcal{B}_U^{\text{ML}}$ values, which motivate the lensing interpretation, several scenarios can explain the observed agreement:

- **Consistent lensing signature:** The reconstructed waveform exhibits features consistent with the lensed templates, supporting the interpretation that the data contain lensing-induced distortions.
- **Degeneracy-driven agreement:** The reconstructed waveform does not exhibit clear lensing-specific features, whereas the lensed templates achieve a better fit by exploiting degeneracies (e.g., between spin-induced modulations and lensing effects), suggesting that the apparent support for lensing may be driven by model flexibility.
- **Ambiguous or noise-dominated structure:** The reconstructed waveform does not clearly favour either scenario, suggesting that the apparent agreement may be influenced by noise fluctuations or limited information content in the signal.

Figure 6.6 shows a time-domain comparison between the reconstructed waveform (h_{rec}) and the waveforms generated using the parameters inferred under the unlensed and microlensing hypotheses with the NRSUR model (h_{model}). The shaded regions correspond to the 90 % C.I. of the waveforms obtained from parameter-estimation analyses. Visual inspection alone does not clearly indicate which waveform better matches the cWB reconstruction. We therefore quantify the agreement by computing the mismatch (MM), which measures the dissimilarity between two signals [76, 338]:

$$\text{MM} = 1 - \max_{t_0, \phi_0} \frac{\langle h_{\text{rec}} | h_{\text{model}} \rangle}{\sqrt{\langle h_{\text{rec}} | h_{\text{rec}} \rangle \langle h_{\text{model}} | h_{\text{model}} \rangle}}, \quad (6.2)$$

where $\langle \cdot | \cdot \rangle$ denotes the noise-weighted inner product defined in Eq. (1.41). The maximisation is performed over relative time and phase shifts (t_0, ϕ_0) to account for trivial offsets in the coalescence time and phase, ensuring that the comparison reflects only intrinsic waveform differences rather than arbitrary alignments.

The term MM in Eq. (6.2) is computed using a restricted data segment spanning -0.15 s to $+0.1$ s around the trigger time (as illustrated in Figure 6.6), rather than the full 8 s data stream. Outside this interval, the signal is subdominant, and the data are effectively noise-dominated, so those regions do not contribute meaningfully to the comparison. Figure 6.7 shows the distributions of MM values between the cWB reconstruction and waveform realisations drawn from the unlensed and microlensed posteriors, restricted to samples within the 90 % C.I., for each LIGO detector. The mismatch between the cWB reconstruction and

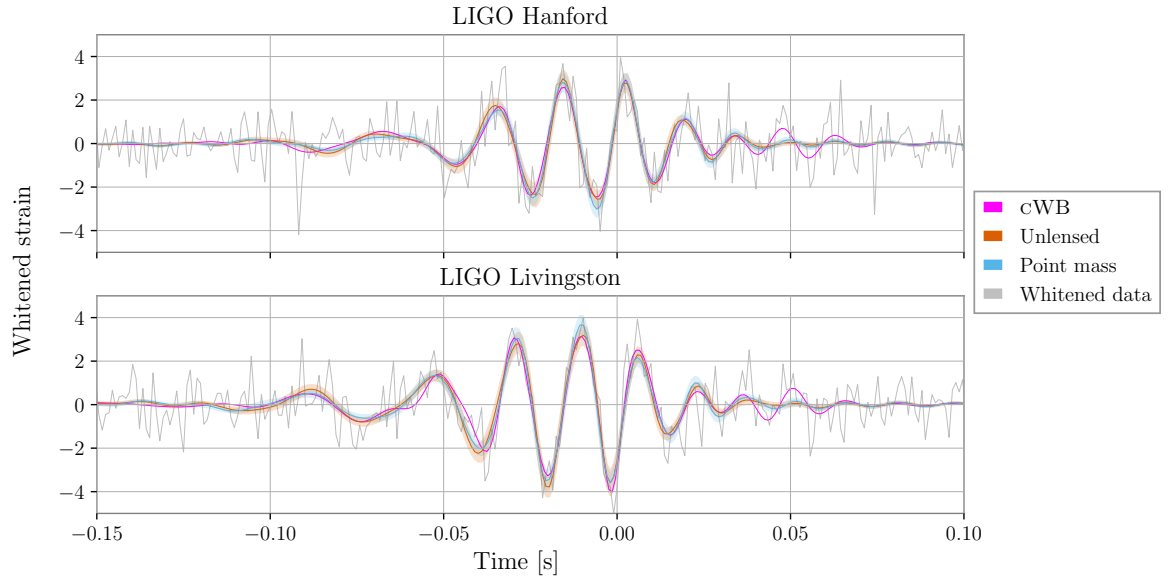


Figure 6.6: Comparison between the cWB reconstruction (magenta) and the 90 % credible waveforms inferred under the lensed (sky blue) and unlensed hypotheses (orange). The time represents the time relative to 2023 November 23 at 13:54:30.619 UTC.

the mean waveform is 0.029 (0.033) for the unlensed case and 0.022 (0.025) for the microlensed case in LHO (LLO), respectively, indicating that the microlensed reconstruction provides a closer match to the model-agnostic baseline. This trend is also reflected in the full mismatch distributions: for the unlensed model, the median and 90 % C.I. are $0.040^{+0.012}_{-0.009}$ and $0.045^{+0.012}_{-0.015}$ for LHO and LLO, while for the microlensed model they are $0.029^{+0.008}_{-0.006}$ and $0.033^{+0.010}_{-0.007}$. The difference between the mismatch distributions for the microlensed (sky-blue) and unlensed (orange) cases is further quantified using the KS statistic, yielding values of 0.75 for LHO and 0.68 for LLO. These results indicate that, although the two distributions partially overlap, they remain statistically distinguishable.

While the results consistently favour the microlensing hypothesis, it remains unclear whether this preference reflects genuine lensing-induced features or arises from degeneracies in the waveform modelling, particularly given the short duration of the signal, which limits the ability to distinguish between lensing effects and modelling degeneracies.

6.4 Conclusion

We reanalysed 84 BBH candidates detected during the first half of the LVK fourth observing run under the PM microlensing hypothesis, focusing on frequency-dependent lensing distortions. Among these, 83 events yield Bayes factors ($\mathcal{B}_U^{\text{ML}}$) that are either negligible or fully consistent with the expected unlensed background distribution. GW231123 stands out as the sole outlier, exhibiting a Bayes factor that exceeds the background and represents the highest value reported in GW lensing searches to date.

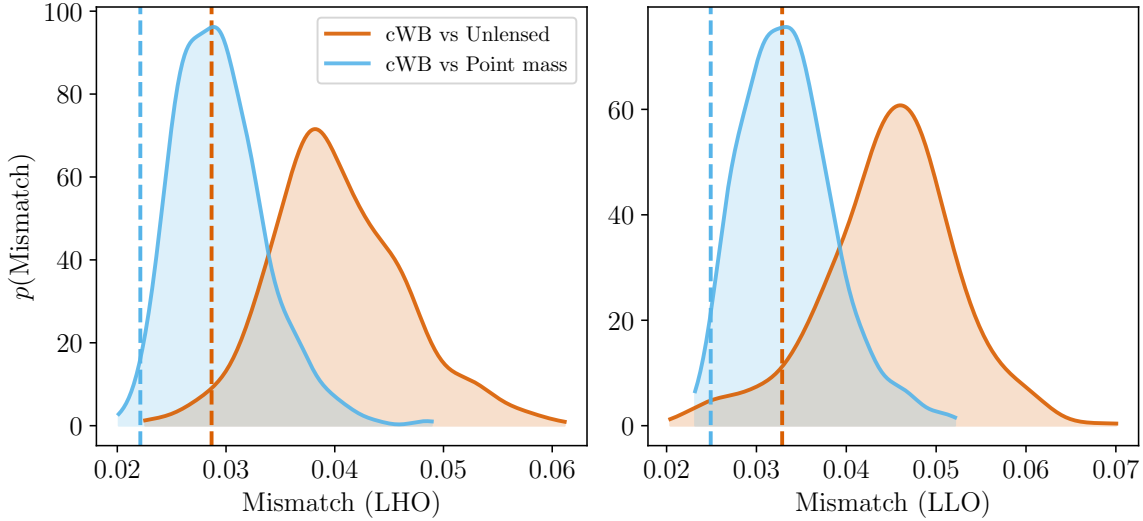


Figure 6.7: Distribution of the mismatch between the cWB reconstruction and the recovered lensed (sky blue) and unlensed (orange) waveforms for GW231123 within the 90 % C.I.. The vertical dashed lines indicate the mismatch values between the cWB reconstruction and the mean unlensed and mean lensed waveforms, respectively.

Due to the limited size of the current background injection set, we obtain an upper bound of 28 % for the global FAP, indicating that statistical fluctuations cannot yet be excluded with high confidence. Furthermore, we must consider the possibility that missing physics in current unlensed waveform models may artificially enhance the Bayes factor. Specifically, if the unlensed templates (e.g., XPHM-ST) fail to perfectly capture complex physical features present in the data, such as advanced spin precession or subtle NR corrections, the Bayesian evidence may compensate for these modelling residuals by favouring the additional degrees of freedom provided by the lensing parameters. In this case, the preference for lensing may reflect modelling degeneracies rather than a genuine lensing signal. Despite a more detailed investigation of the inferred lens properties, source parameters under the microlensing hypothesis, and consistency across individual detectors, we find that the evidence remains inconclusive. Although GW231123 represents the most compelling candidate identified so far, a robust lensing claim requires a larger background sample and improved control over waveform systematics.

Finally, it is worth considering an alternative and plausible astrophysical interpretation accessible to the current detector network: the overlapping-signals scenario [339]. In this picture, two or more independent GW signals from unrelated sources coincidentally arrive at the detectors within a very short time window. Such a superposition can produce a distorted waveform that mimics the interference patterns expected from micro-images separated by millisecond time delays. Under this scenario, [340] demonstrated that the Bayes factor favouring a multi-signal model over a single unlensed signal can also be significantly large, comparable to the value obtained for GW231123. Distinguishing between microlensing and

overlapping signals remains challenging, as both can produce similar phenomenological signatures. Disentangling these possibilities, whether the signal arises from a single lensed source or from multiple coincident sources, will be essential for a definitive interpretation and constitutes an important direction for future work.

Chapter 7

Residual Test to Search for Microlensing Signatures in Strongly Lensed Gravitational-Wave Signals

Disclaimer

The following chapter is based on the paper *Residual Test to Search for Microlensing Signatures in Strongly Lensed Gravitational Wave Signals* [104]. The author is the first author of this paper and contributed to the development of methodology, data analysis, interpretation of the results, scientific discussion, manuscript preparation, and generation of all figures. This paper was published in the *Astrophysical Journal*.

Roughly, $\mathcal{O}(1)$ SLGW signals per year are expected for the LVK detectors at their design sensitivities, while third-generation (3G) detectors are anticipated to observe approximately $\mathcal{O}(10)$ such events per year [158, 159, 341]. To date, however, dedicated searches conducted by the LVK Collaboration across all BBH events from the O1 through O4a observing runs have yielded no conclusive evidence for either strong-lensing or microlensing signatures [238, 324, 325, 326, 335]. Current search schemes employ different methodologies depending on the lensing regime. Strong-lensing searches are typically agnostic to the lens model and rely on the geometrical-optics approximation [299, 300, 301, 302, 303, 304, 342, 343, 344, 345, 346, 347, 348], whereas the microlensing pipeline assumes a specific physical configuration, such as a single, isolated microlens [298].

In a more realistic scenario, as noted in Section 5.2.2, a GW signal strongly lensed by a galaxy or galaxy cluster is likely to experience further perturbation from stellar fields or DM substructures embedded within the lens. These effects can imprint complex signatures on individual SLGW signals. Consequently, the BBH parameters inferred from individual images can exhibit apparent discrepancies. Neglecting such microlensing effects in strong-lensing searches may lead to missed detections. Incorporating these additional complexities into current search pipelines, however, would substantially increase the computational cost. In the context of the rapidly growing number of detected events, such an approach is likely to become computationally prohibitive [349, 350, 351].

To circumvent this limitation, we propose a residual-based approach rather than performing full parameter estimation with template families that explicitly model both microlensing and strong-lensing effects. Specifically, if a standard strong-lensing analysis—which assumes that multiple images from the same source share an identical waveform morphology—is applied to strongly lensed signals that also exhibit microlensing, the resulting best-fit waveform will fail to fully capture the observed data. We then exploit the resulting residuals as a diagnostic to identify these additional lensing-induced distortions. This strategy is conceptually analogous to testing GR, which aims to identify deviations from GR-predicted templates within the observed signals [352, 353, 354, 355].

7.1 Methodology

7.1.1 Amplification Factors for Microlensing Fields within a Macrolens

The total lensing effect on a GW signal induced by a microlensing field embedded within a macrolens can be computed using Eq. (2.71), with an appropriate Fermat potential $T(\mathbf{x}, \mathbf{y})$ that describes the full lens configuration. In particular, the Fermat potential must incorporate both the macrolens contribution¹ and the microlensing effects, the former of which can be parametrised by the convergence (κ) and shear (γ) [103]. Under this setup, the Fermat potential for N point masses in the vicinity of a macroimage located at $\mathbf{x} = (x_1, x_2)$ is given by [319, 356, 357]:

$$T(\mathbf{x}, \mathbf{x}^m, \mathbf{y}_{\text{macro}} = 0) = \frac{k}{2} \left((1 - \kappa + \gamma)x_1^2 + (1 - \kappa - \gamma)x_2^2 \right) - \left[\frac{k}{2} \sum_m^N \ln(\mathbf{x}^m - \mathbf{x})^2 + k\phi_-(\mathbf{x}) \right], \quad (7.1)$$

where $\mathbf{x}^m$ denotes the position of the m^{th} microlens, and $k = 4Gm_{\text{L}}^z/c^3$, with m_{L} representing the average microlens mass. The term ϕ_- corresponds to a negative mass sheet introduced to compensate for the contribution of the microlenses, such that the total convergence remains unchanged. In Eq. (7.1), the macrolensing contribution is obtained through a local expansion of the lensing potential, where the expansion center can be chosen arbitrarily. For convenience, we set the macroimage position as the expansion center, i.e., $\mathbf{y}_{\text{macro}} = 0$.

Substituting Eq. (7.1) into Eq. (2.71), the amplification factor as a function of the dimensionless frequency w can be written as [323]:

$$F(w) = \frac{w}{2\pi i} \int d^2\mathbf{x} [\exp\{i w T(\mathbf{x}, \mathbf{x}^m, \mathbf{y}_{\text{macro}} = 0)\}], \quad (7.2)$$

1. We assume an SIE profile (see Section 2.2.4) for the macrolens in this work.

7.1.2 Mock Data Generation and Joint Parameter Estimation

For mock lensed GW signals, we first simulate 100 BBH systems using PYCBC [358]. Source parameters are drawn via a Monte Carlo procedure based on a merger-rate density that traces the star formation rate (SFR) following [295], assuming a characteristic time delay of 50 Myr between star formation and the BBH merger (see Appendix B of [359] for details). We adopt a POWERLAW + PEAK mass distribution with hyperparameters and parameter ranges as defined in [360] to sample the component masses (m_1, m_2) . The inclination angle is drawn from $p(\iota) \propto \sin \iota$, while the remaining parameters—component spins $(\vec{a}_1, \vec{a}_2)$, polarisation angle ψ , right ascension α , declination δ , coalescence time t_c , and coalescence phase ϕ_c —are sampled from uniform distributions over their respective physically allowed ranges. The waveforms are then modelled with IMRPHENOMPV2 [278].

For each BBH, we construct two pairs of lensed signals under two distinct lensing hypotheses:

- $\mathcal{H}_{\text{SL}}$: the BBH is strongly lensed by a single macrolens, producing two macroimages.
- $\mathcal{H}_{\text{MLSL}}$: the BBH is strongly lensed by the same macrolens as in $\mathcal{H}_{\text{SL}}$, and each macroimage is further microlensed by stellar fields embedded within the macrolens.

Under $\mathcal{H}_{\text{SL}}$, we generate 100 pairs of SLGWs using the previously made 100 BBH systems. For each BBH system, we assign strong-lensing parameters following the SIE model, including the axis ratio (q), velocity dispersion (σ_v), and impact parameter (y). The σ_v values are sampled from SDSS galaxy distributions [361], while the q values are drawn from a Rayleigh distribution with the scaling parameter corrected following [341]. The y values are sampled from a uniform distribution. Given these SIE lens parameters, the corresponding κ and γ are computed using Eqs. (??) and (2.21). For lensing systems that produce quadruple images, we select the first two arriving images to ensure that each system yields exactly two detectable GW signals.

Next, under $\mathcal{H}_{\text{MLSL}}$, to generate signals that exhibit both strong-lensing and microlensing effects, we simulate microlensing fields by assuming a stellar mass distribution that follows the late Salpeter initial mass function (IMF) [362] and a Sérsic radial profile [363]. For consistency with [319, 364], we configure the IMF to include remnant objects, assuming their mass density constitutes 10 % of the total stellar mass density. Stellar microlens masses are sampled in the range $0.1\text{--}1.5 M_\odot$, while compact remnant masses span $0.1\text{--}28 M_\odot$. For each lensing system, the number of microlenses (N) is determined by the microlensing convergence (κ_*) as inferred from a Sérsic profile and the microlens masses. Table 7.1 summarises the main parameter distributions and ranges used to generate the lensed waveforms.

Finally, we construct a mock signal set consisting of 100 pairs of SLGW signals ($h_{\text{SL},1}^{\text{inj}}, h_{\text{SL},2}^{\text{inj}}$) and 100 pairs of signals that are both strongly lensed and microlensed ($h_{\text{MLSL},1}^{\text{inj}}, h_{\text{MLSL},2}^{\text{inj}}$) to serve as injections. Note that the lensing effect in $\mathcal{H}_{\text{SL}}$ is described by $F_{\text{geo}}(w)$ in Eq. (2.74), whereas for $\mathcal{H}_{\text{MLSL}}$, the amplification is governed by the frequency-dependent factor $F(w)$

in Eq. (7.2). We inject all lensed signals into simulated stationary Gaussian noise n for the aLIGO-Hanford, aLIGO-Livingston, and AdV detectors, using the O4 design sensitivity PSDs [365]². To assess future prospects, we also employ the anticipated O5 sensitivity curves [365]³. We consider only those signals with a network SNR exceeding the threshold of $\rho_{\text{net}} = 12$, following [319].

Parameter	Distribution or Model	Range
m_1	Power Law + peak	$[5, 85]M_\odot$
m_2	Uniform	$[5, m_1]M_\odot$
m_L (stellar)	Salpeter IMF	$[0.1, 1.5]M_\odot$
m_L (remnant)	Spera et al. (2015) [362]	$[0.1, 28]M_\odot$
κ_*	Sérsic profile	-
$N(\kappa_*, m_L)$	-	$[10^3, 10^6]$
κ, γ	SIE (q, σ_v, y)	-

Table 7.1: The assumptions for component masses, macrolens, and microlens parameters adopted to simulate lensed GW signals.

To conduct JPEs for the 200 pairs of lensed GW signals, we employ the `GoLum` pipeline [300, 303]. The joint likelihood function in this pipeline assumes that the two input signals originate from the same source and are purely strongly lensed, thereby neglecting any potential microlensing effects.

First, from the JPEs performed on the 100 pairs of SLGW signals, we obtain the maximum-likelihood waveforms for the first lensed signals ($h_{\text{SL},1}^{\text{maxL}}$). As a complementary step, we also extract the maximum-likelihood values of the lensing observables, including relative magnification factors (μ_{rel}), differences between arrival times (Δt), and differences between Morse factors ($\Delta\phi_n$). One can then determine the maximum-likelihood waveforms of the second lensed signals ($h_{\text{SL},2}^{\text{maxL}}$) by transforming the luminosity distances, coalescence times, and Morse factors according to:

$$\begin{aligned}
 d_L^{\text{maxL}}|_{\text{SL},2} &= d_L^{\text{maxL}}|_{\text{SL},1} \times \sqrt{\mu_{\text{rel}}^{\text{maxL}}}, \\
 t_c^{\text{maxL}}|_{\text{SL},2} &= t_c^{\text{maxL}}|_{\text{SL},1} + \Delta t^{\text{maxL}}, \\
 \phi_n^{\text{maxL}}|_{\text{SL},2} &= \phi_n^{\text{maxL}}|_{\text{SL},1} + \Delta\phi_n^{\text{maxL}}.
 \end{aligned} \tag{7.3}$$

2. The PSD data were obtained from the LIGO Document Control Center (DCC) under document LIGO-T2000012, available at <https://dcc.ligo.org/LIGO-T2000012/public>.

3. The projected O5 PSDs for each detector are sourced from the `PyCBC.PSD` package [366].

As discussed in Section 4.3.2, waveform morphology can be significantly altered in the presence of non-negligible eccentricity, precessing spins, or HOMs. Nevertheless, Eq. (7.3) remains valid even for lensed waveforms exhibiting such phase modulations, provided that the JPE utilises waveform templates incorporating these features [157, 306, 367]. We underline that a JPE analyses two lensed signals simultaneously, enabling accurate inference of lensing observables, such as the Morse factors and their difference [367]. Consequently, $h_{\text{SL},2}^{\text{maxL}}$ can be obtained from $h_{\text{SL},1}^{\text{maxL}}$ in the frequency domain.

Similarly, we obtain the maximum-likelihood waveforms for the pairs of microlensed signals $(h_{\text{MLSL},1}^{\text{maxL}}, h_{\text{MLSL},2}^{\text{maxL}})$. The morphologies of $h_{\text{MLSL}}^{\text{maxL}}$ differ from those of $h_{\text{MLSL}}^{\text{inj}}$, as the templates used in the pipeline account only for strong lensing. This mismatch is expected to manifest as non-negligible residuals.

7.1.3 Residual Test

Since the adopted pipeline does not account for microlensing, the discrepancies between $h_{\text{MLSL}}^{\text{maxL}}$ and $h_{\text{MLSL}}^{\text{inj}}$ are expected to be significantly larger than those between $h_{\text{SL}}^{\text{maxL}}$ and $h_{\text{SL}}^{\text{inj}}$. To statistically quantify these differences between the maximum-likelihood waveforms retrieved under the two hypotheses, we investigate the residuals ($r \equiv d - h$), which represent the strain remaining after subtracting the signal model (h) from the observed data (d). If the true GW signal embedded in the data perfectly matches the model, the residual will be consistent with pure detector noise⁴.

We assume that the data in the i^{th} detector, containing a lensed GW signal, can be expressed as:

$$d^i = h_{\text{SL}}^i + dh^i + n^i, \quad (7.4)$$

where h_{SL}^i is the purely strongly lensed signal excluding microlensing effects, dh^i represents the frequency-dependent distortion induced by microlensing, and n^i is the detector noise.

Under $\mathcal{H}_{\text{SL}}$, the lensing effects are governed by F_{geo} and the waveform morphology remains unchanged, meaning the dh terms vanish. Consequently, the residual in the i^{th} detector is given by:

$$\begin{aligned} r^i | \mathcal{H}_{\text{SL}} &\equiv d^i - h^{i,\text{maxL}} \\ &= h_{\text{SL}}^i + n^i - h^{i,\text{maxL}} \\ &= \delta h_{\text{SL}}^i + n^i, \end{aligned} \quad (7.5)$$

4. Non-Gaussian features, such as glitches, can occasionally overlap with a signal. In such cases, the residuals would not align with the stationary detector noise characterised at other times.

where δh_{SL}^i denotes the difference between the true lensed signal and the maximum-likelihood waveform recovered under $\mathcal{H}_{\text{SL}}$. Since $h^{i,\text{maxL}}$ is obtained by fitting the noisy data, rather than the noiseless signal, δh_{SL}^i does not generally vanish. In the idealised limit where the maximum-likelihood waveform exactly reproduces the observed data, $h^{i,\text{maxL}} \rightarrow h_{\text{SL}}^i + n^i$, and hence $\delta h_{\text{SL}}^i \rightarrow -n^i$, giving $r^i \rightarrow 0$. In practice, for a correctly specified hypothesis and a waveform model, the residual should instead be statistically consistent with the instrumental noise.

Conversely, dh is non-zero under $\mathcal{H}_{\text{MLSL}}$. In this case, the residual is given by:

$$\begin{aligned} r^i | \mathcal{H}_{\text{MLSL}} &\equiv d^i - h^{i,\text{maxL}} \\ &= h_{\text{SL}}^i + dh^i + n^i - h^{i,\text{maxL}} \\ &= \delta h_{\text{MLSL}}^i + n^i, \end{aligned} \tag{7.6}$$

where δh_{MLSL}^i denotes the difference between the true microlensed signal, $h_{\text{SL}}^i + dh^i$, and the maximum-likelihood waveform inferred under $\mathcal{H}_{\text{SL}}$. Since the analysis pipeline uses templates that do not account for microlensing, this difference generally contains a contribution from the microlensing effect in addition to any waveform mismatch. As with δh_{SL}^i , δh_{MLSL}^i does not necessarily remain non-zero, since the maximum-likelihood waveform is obtained by fitting the noisy data. However, if the microlensing contribution cannot be adequately absorbed by the $\mathcal{H}_{\text{SL}}$ waveform model, it can leave a coherent structure in the residual that is inconsistent with the expected instrumental-noise distribution. A schematic representation of the expected residuals under each hypothesis is shown in Figure 7.1, illustrating that the residual under $\mathcal{H}_{\text{MLSL}}$ is more pronounced than that under $\mathcal{H}_{\text{SL}}$.

To evaluate the extent to which residuals deviate from pure detector noise (denoted by $\mathcal{H}_{\text{N}}$) under a given signal hypothesis $\mathcal{H}_{\text{X}}$, where X is either SL or MLSL, we analyse the cross-correlation between residuals from different detectors. We introduce a statistic, Λ , to represent this quantity. In [368], the cross-correlation of residuals—defined as the deviation between observed microlensed strain and the best-fit unlensed templates—was utilised to search for microlensing signatures in otherwise unlensed GW observations. Following the methodology in [347], these cross-correlations are computed by introducing a time shift τ to one residual relative to another. This approach assesses the coherence of the residual power across the detector network. We adapt this technique by calculating the inner product of the residuals from each detector to obtain Λ , which quantifies the alignment between the two signals.

For strain data from the i^{th} and j^{th} detectors with corresponding residuals r^i and r^j , Λ is defined as:

$$\Lambda_{\mathcal{H}_{\text{X}}} = \exp \left[\frac{1}{2} \langle r^i(t)_{\mathcal{H}_{\text{X}}}, r^j(t + \tau)_{\mathcal{H}_{\text{X}}} \rangle \right], \tag{7.7}$$

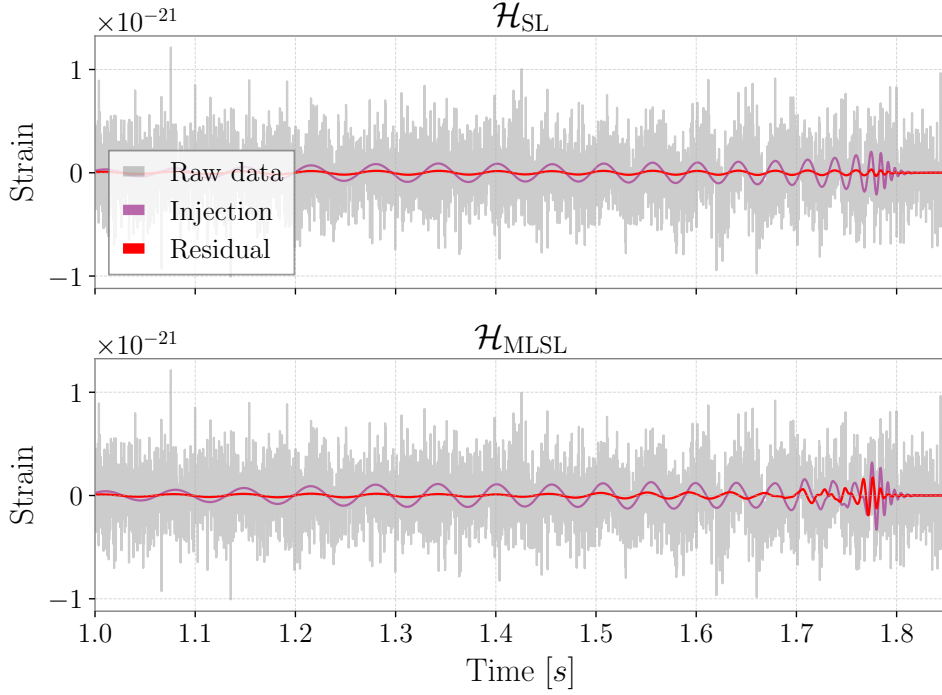


Figure 7.1: Time domain strains of raw data (grey solid lines), injected waveforms (purple solid lines), and residuals (red solid lines) for a representative BBH event in the LIGO-Hanford detector, assuming $\mathcal{H}_{\text{SL}}$ and $\mathcal{H}_{\text{MLSL}}$ in the top and bottom panel, respectively. We assume the same BBH and macrolens parameters for the two injected waveforms.

where τ is the relative time delay between the i^{th} and j^{th} detectors, and the inner product $\langle \cdot, \cdot \rangle$ is defined as in Eq. (1.41). When calculating Λ , we do not use a time window spanning the entire signal duration. Instead, we adopt a targeted time window of the form:

$$t \in [t_c - \alpha t_s + \Delta t, t_c + \Delta t], \quad (7.8)$$

where t_c is the coalescence time, t_s is the signal duration inferred from the JPE, and α is a scaling constant used to tune the window size. The term Δt ensures sufficient coverage of the ringdown phase; we set $\Delta t = 0.2$ s. In the subsequent analysis, we use $\alpha = 0.25$, as this value yields optimal performance for our residual-based diagnostic. A detailed discussion on the efficiency of the time window will be presented in Section 7.2.3.

Recall that the residual r is decomposed into a model-mismatch component δh and a detector noise component n . When evaluating Eq. (7.7), δh contributes directly to the inner product because it remains coherent across detector segments when aligned with the correct time shift τ . In contrast, the noise components n are uncorrelated between detectors due to their stochastic nature, and thus, their cross-contributions tend to average to zero. Consequently, a higher value of δh results in a higher value of Λ .

The distributions of Λ obtained under each hypothesis can be differentiated if their corresponding residuals are sufficiently distinct. In this study, the $\Lambda_{\mathcal{H}_{\text{SL}}}$ distribution effectively serves as a background distribution, allowing us to determine which hypothesis is favoured for a given event by evaluating where its computed Λ value falls relative to this background. We consider an event to favour $\mathcal{H}_{\text{MLSL}}$ if its $\Lambda_{\mathcal{H}_{\text{MLSL}}}$ value exceeds the upper bound of the 2σ C.I.⁵ of the $\Lambda_{\mathcal{H}_{\text{SL}}}$ distribution.

It is important to note that, while the AdV detector is included in the initial parameter estimation, it is excluded from the calculation of Λ in Eq. (7.7). This is because AdV's noise level is generally higher than that of the LIGO detectors. Although a larger detector network typically improves the total network SNR, the inclusion of a high-noise detector can degrade the residual test performance by broadening the Λ distribution, thereby reducing sensitivity to microlensing signatures.

7.2 Results

7.2.1 Analysis using Realistic Population-based Events

From the JPEs conducted on the two independent sets of 100 pairs, simulated under the scenarios of pure strong lensing and superimposed microlensing (see Sec. 7.1.2), we obtain the maximum-likelihood waveforms (i.e., 200 $h_{\text{SL}}^{\text{maxL}}$ and 200 $h_{\text{MLSL}}^{\text{maxL}}$). Using Eqs. (7.5)-(7.7), we compute the values of $\Lambda_{\mathcal{H}_{\text{SL}}}$ from the 200 r_{SL} and $\Lambda_{\mathcal{H}_{\text{MLSL}}}$ from the 200 r_{MLSL} . Note that the instrumental noise realisations n^i used for both r_{SL}^i and r_{MLSL}^i are identical. Additionally, we generate a set of 200 pure Gaussian noise segments (N) for each detector, based on the same PSDs used for the data generation, to compute the corresponding $\Lambda_{\mathcal{H}_{\text{N}}}$ values.

Since the detector noise is assumed to be stationary and Gaussian, and the JPE framework accurately recovers h_{SL} , the $\Lambda_{\mathcal{H}_{\text{SL}}}$ distribution is expected to closely follow the $\Lambda_{\mathcal{H}_{\text{N}}}$ distribution, which typically behaves as a normal distribution with a mean of 1 and unit variance. In contrast, the distribution of $\Lambda_{\mathcal{H}_{\text{MLSL}}}$ is expected to deviate from $\Lambda_{\mathcal{H}_{\text{N}}}$, indicating that the microlensing-induced terms δh_{MLSL} in Eq. (7.6) contribute more significantly to the residual than δh_{SL} .

Figure 7.2 shows the Λ distributions for the residuals and Gaussian noises, along with their corresponding Gaussian kernel density estimates (KDEs). As previously noted, an event is identified as a candidate that is both strongly lensed and microlensed if its Λ value exceeds the upper bound of the 95 % (2σ) C.I. of the $\Lambda_{\mathcal{H}_{\text{SL}}}$ distribution. For O4 sensitivity, 11 % of the 200 microlensed events favour $\mathcal{H}_{\text{MLSL}}$. A primary factor contributing to this relatively low percentage is that most events in our realistic population exhibit small mismatch

5. All one-dimensional credible intervals computed in this work are central, meaning they contain equal probability mass above and below the bounds.

values ($\text{MM} \leq 0.03$) relative to h_{SL} (see Eq. (6.2))⁶. In this chapter, the MM is defined as follows:

$$\begin{aligned} \text{MM} &\equiv 1 - \mathcal{M}(h_{\text{MLSL}}, h_{\text{SL}}) \\ &= 1 - \max_{\phi_0, t_0} \frac{\langle h_{\text{MLSL}}, h_{\text{SL}} \rangle}{\sqrt{\langle h_{\text{MLSL}}, h_{\text{MLSL}} \rangle \langle h_{\text{SL}}, h_{\text{SL}} \rangle}}. \end{aligned} \quad (7.9)$$

Such events are intrinsically difficult to distinguish, even when using specialised microlensing pipelines like GRAVELAMPS [298]. In Section 7.2.2, we will discuss how the detection efficiency improves for high-mismatch events, which are expected to be more readily detectable.

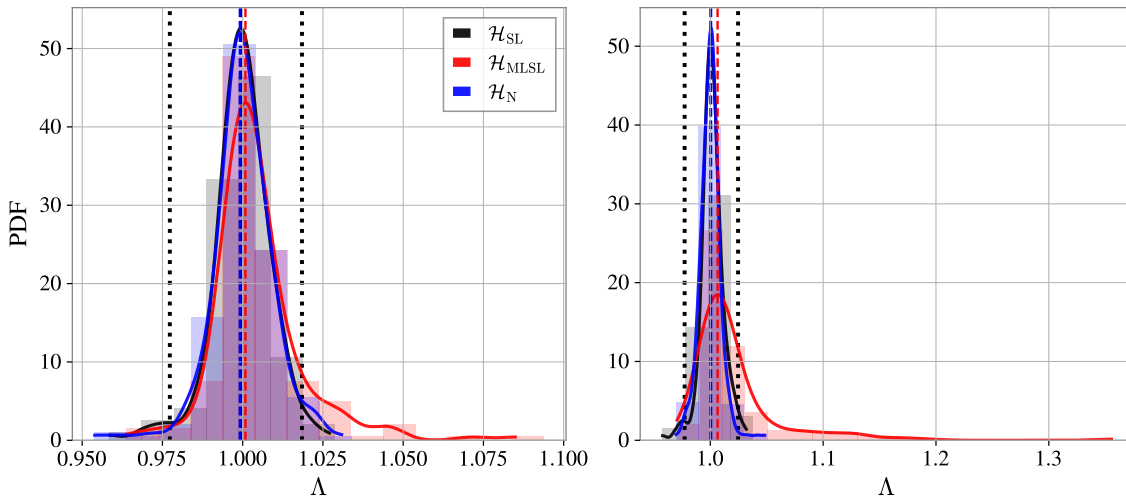


Figure 7.2: *Left panel:* The Λ distributions and their corresponding Gaussian KDEs for each of 200 N (blue), r_{SL} (black), and r_{MLSL} (red) samples obtained using the O4 sensitivity. r_{SL} and r_{MLSL} have the same underlying noise strain. *Right panel:* The results obtained by employing the O5 sensitivity.

In addition to the O4 analysis, we repeat our study using the projected LIGO O5 sensitivity to quantify the improvement in our residual-based test. We anticipate enhanced performance if: (1) the δh_{SL} term in Eq. (7.5) is minimised through more precise parameter estimation, and (2) the reduced noise floor maximises the relative contribution of dh to the Λ statistic in Eq. (7.6). As expected, for the same population of strongly lensed and microlensed events, the percentage of signals favouring $\mathcal{H}_{\text{MLSL}}$ increases to 21.5 % at O5 sensitivity.

6. MM values are computed by averaging the two MM values obtained using h_{SL} and h_{MLSL} detected in the aLIGO-Hanford and aLIGO-Livingston detectors.

To verify that more significantly microlensed events yield larger Λ values, we calculate the difference $\Delta\Lambda \equiv \Lambda_{\mathcal{H}_{\text{MLSL}}} - \Lambda_{\mathcal{H}_{\text{SL}}}$ for individual BBH events. This allows us to investigate the correlation between $\Delta\Lambda$ and both the MM and the maximum strain of δh_{MLSL} —the latter representing the residual amplitude remaining after subtracting the best-fit strongly lensed template. A positive $\Delta\Lambda$ value indicates that r_{MLSL} is more significant than r_{SL} .

As shown in Figure 7.3, microlensed events with larger δh are concentrated in the high $\Delta\Lambda$ region, consistent with the definition of Λ in Eq. (7.7). Similarly, events with relatively high MM values tend to exhibit higher $\Delta\Lambda$, although the correlation between $\Delta\Lambda$ and δh is stronger than that between $\Delta\Lambda$ and MM. In the O4 case, most high-MM events are located within the 2σ C.I. of the $\Lambda_{\mathcal{H}_{\text{SL}}}$ distribution (black dotted lines), as the noise power is relatively high compared to the residual power. Consequently, the statistical fluctuations of $\Lambda_{\mathcal{H}_{\text{SL}}}$ tend to be broader than those of $\Delta\Lambda$. In contrast, the reduced noise levels in the O5 case result in most high-MM events above the 2σ threshold.

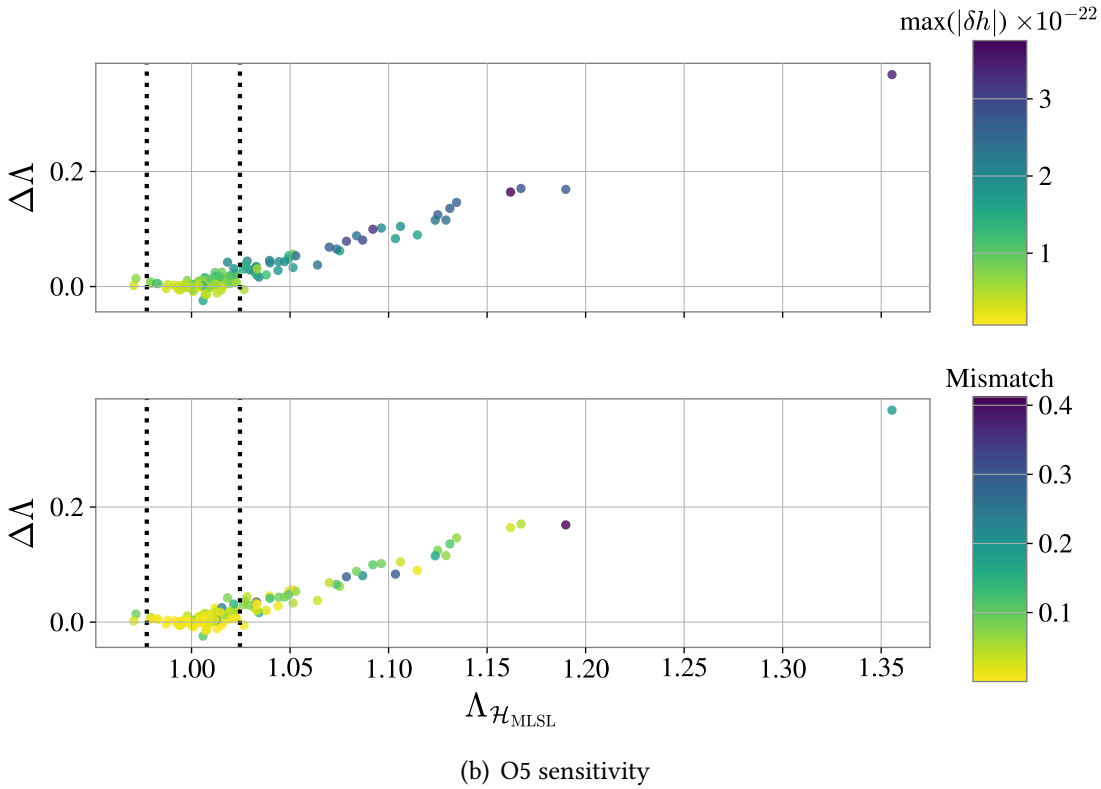
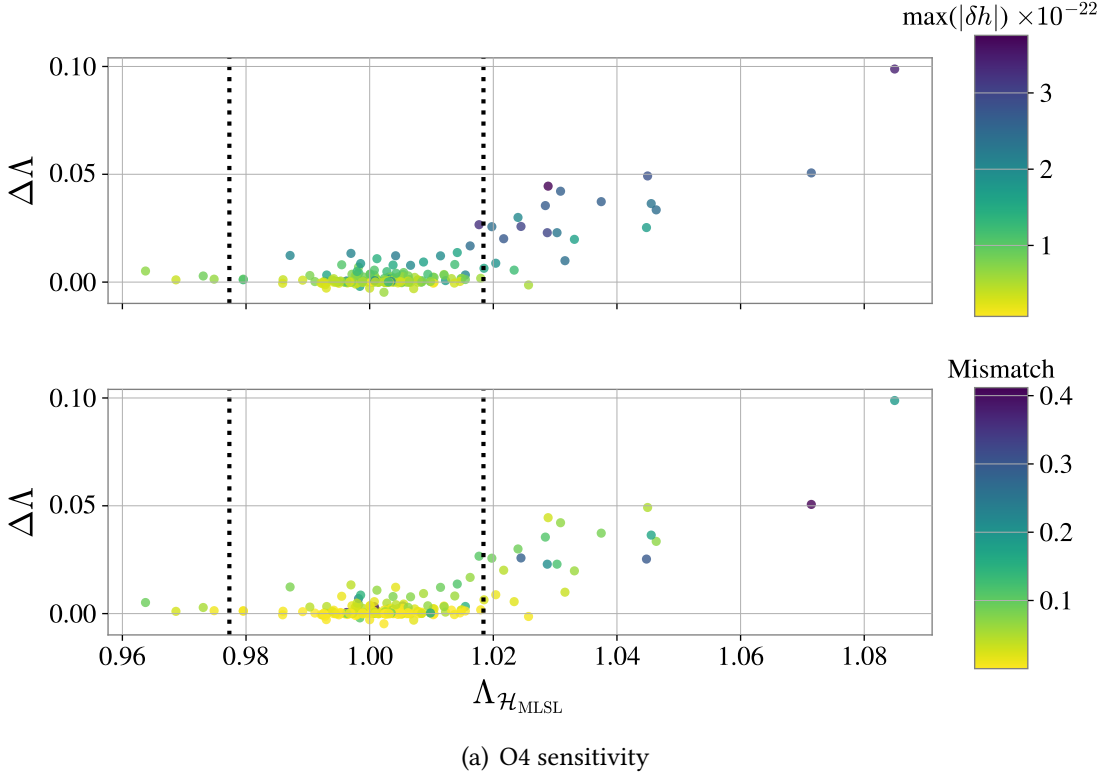


Figure 7.3: Scatter plots showing the correlation between $\Lambda_{\mathcal{H}_{\text{MLSL}}}$ and $\Delta\Lambda$ for (a) O4 and (b) O5 sensitivities, colour-coded based on $\max(|\delta h|)$ and mismatch, denoting the maximum strain of the pure residual and mismatch between h_{SL} and h_{MLSL} computed by averaging the values obtained from aLIGO-Hanford and aLIGO-Livingston, respectively.

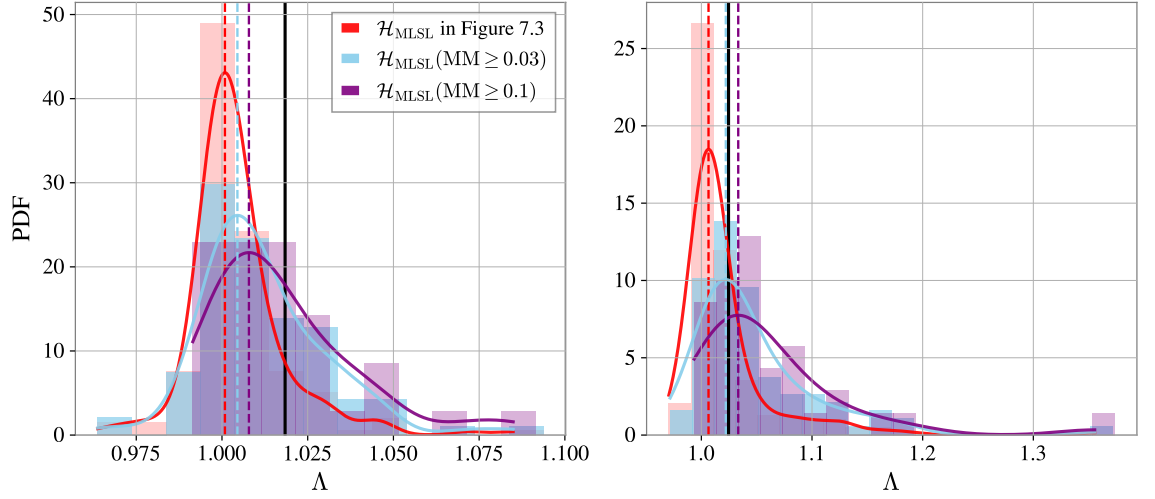


Figure 7.4: The same configuration as Figure 7.2, but now showing Λ distributions for realistic population-based microlensed events (red), events with $MM \geq 0.03$ (cyan), and events with $MM \geq 0.1$ (purple).

It is important to note that a high MM does not necessarily indicate a large δh . If a significantly distorted signal has a low SNR, the absolute value of δh remains low despite the high MM. Conversely, even for weakly distorted signals, if the time delay between microlensed images is very short, the resulting repeated merger part of the waveform may not be fully captured by the recovered best-fit waveform. This leads to a high δh and, consequently, a high $\Delta\Lambda$.

7.2.2 Analysis using High-mismatch Events

The majority of the simulated h_{MLSL} exhibit small MM values, which is consistent with expectations for a realistic microlensing population [315]. Therefore, we also focus on microlensed events with $MM \geq 0.03$ and $MM \geq 0.1$, which are more likely to be detectable with current pipelines, to better evaluate the effectiveness of our residual-based test. To obtain more robust results for the high-MM regime, we created an additional set of events with $MM \geq 0.3$ by artificially enhancing the microlensing effects. Specifically, we increased the macrolens magnification to $\mu = 100$ to produce significantly microlensed signals that do not follow the realistic population distribution.

Figure 7.4 compares the Λ distributions for events with $MM \geq 0.03$ and $MM \geq 0.1$ against the realistic population-based distributions shown in Figure 7.2. For events with higher MM values, there is a clear increase in the proportion of signals identified as microlensed (i.e., those with Λ values exceeding the upper bound of the 2σ C.I. of the $\Lambda_{\mathcal{H}_{\text{SL}}}$ distribution). This confirms that the residual test is a valid diagnostic for identifying microlensed events in the high-MM regime. A summary of the results is tabulated in Table 7.2.

O4 sensitivity

Condition	N_{total}	N_{ML}	R_{ML}
Realistic population	200	22	0.110
Events with $\text{MM} \geq 0.03$	94	26	0.277
Events with $\text{MM} \geq 0.1$	35	12	0.343

O5 sensitivity

Condition	N_{total}	N_{ML}	R_{ML}
Realistic population	200	43	0.215
Events with $\text{MM} \geq 0.03$	94	49	0.521
Events with $\text{MM} \geq 0.1$	35	23	0.657

Table 7.2: Summary of the results of residual test depicted in Figures 7.2 and 7.4. N_{total} , N_{ML} , and R_{ML} denote the total number of events satisfying the specified condition, the number of events discerned as a microlensed signal, and the ratio between the two numbers.

Furthermore, we constructed receiver operating characteristic (ROC) curves to assess the overall performance of our residual-based approach. As shown in Figure 7.5, all area under the curve (AUC) values exceed 0.5, indicating that the residual test effectively distinguishes between microlensed and purely strongly lensed GW signals. The AUC values improve with higher detector sensitivity and larger mismatch values, consistent with the trends presented in Table 7.2.

7.2.3 Effect of the Time Window on Λ

In Sections 7.2.1 and 7.2.2, Λ values were calculated using a specific time window of the form shown in Eq. (7.8), with $\alpha = 0.25$ and $\Delta t = 0.2$ s, effectively excluding the early inspiral portion of the time-domain waveform. For BBH sources, the GW strain is lower during the early inspiral stage and reaches its maximum during the late inspiral and merger phases. Consequently, the early parts of the signal are more susceptible to noise fluctuations compared to segments closer to the merger. Our approach mirrors those adopted in tests of GR [353, 354, 355], where narrower time windows are generally employed to minimise noise contributions that are unrelated to potential non-GR features. However, a narrow window must be chosen carefully for microlensing, as the time delays between microimages vary. A window that is too restrictive risks excluding data segments, particularly in the post-merger phase, that may contain significant microlensing signatures. To address this, we investigate various time windows covering different portions of the GW signal to evaluate the impact of noise fluctuations on the Λ distributions.

A representation of the $\Lambda_{\mathcal{H}_{\text{MLSL}}}$ distributions obtained using various time windows is shown in Figure 7.6. The coloured segments (red, cyan, and purple) of the curves represent events correctly identified as microlensed, while the gray segments correspond to events identified as unmicrolensed. As shown, smaller values of α result in a higher proportion of

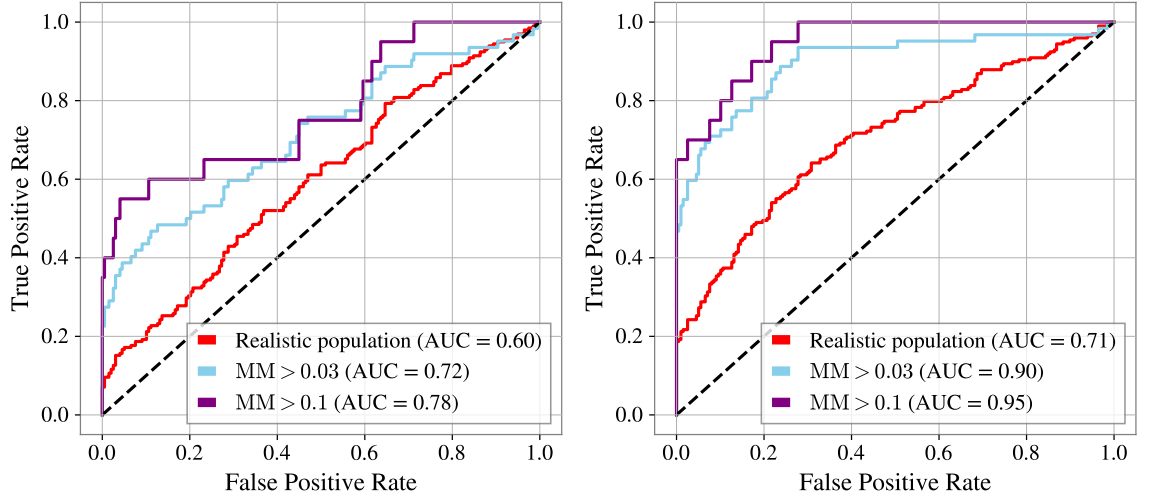


Figure 7.5: ROC curves for the residual test constructed by comparing each of the three event groups— $\Lambda_{\mathcal{H}_{\text{MLSL}}}$ values of events drawn from a realistic population (red), events with $\text{MM} \geq 0.03$ (cyan), and events with $\text{MM} \geq 0.1$ (purple)—against the background distribution given by the $\Lambda_{\mathcal{H}_{\text{SL}}}$ values shown in Figure 7.2 (*Left*: O4 sensitivity, *Right*: O5 sensitivity). The corresponding AUC values have also been estimated.

the $\Lambda_{\mathcal{H}_{\text{MLSL}}}$ distribution being identified as microlensed. This trend is expected because GW microlensing is most prominent when the time delays between images are shorter than the chirp time, and the resulting signatures are more distinctive in the high-frequency regime. Since the merger and ringdown phases predominantly consist of high-frequency components, using a targeted time window centered on the merger rather than the entire signal duration enhances the efficiency of the residual test. The detection ratios (R_{ML}) for each time window and mismatch condition are summarised in Table 7.3. Empirically, we find that a time window with $\alpha = 0.25$ yields the optimal efficiency for microlensing detectability.

7.3 Conclusion

Strongly lensed GW signals likely experience microlensing effects due to stellar fields embedded within the lens galaxy, which imprints complex patterns onto the GW waveforms. Current strong-lensing Bayesian inference pipelines are not designed to detect these distortions, as they typically assume repeated signals share an identical time-frequency evolution. However, incorporating both strong lensing and microlensing into a joint Bayesian analysis is computationally challenging due to the expanded parameter space and the complexity of calculating amplification factors for dense stellar fields.

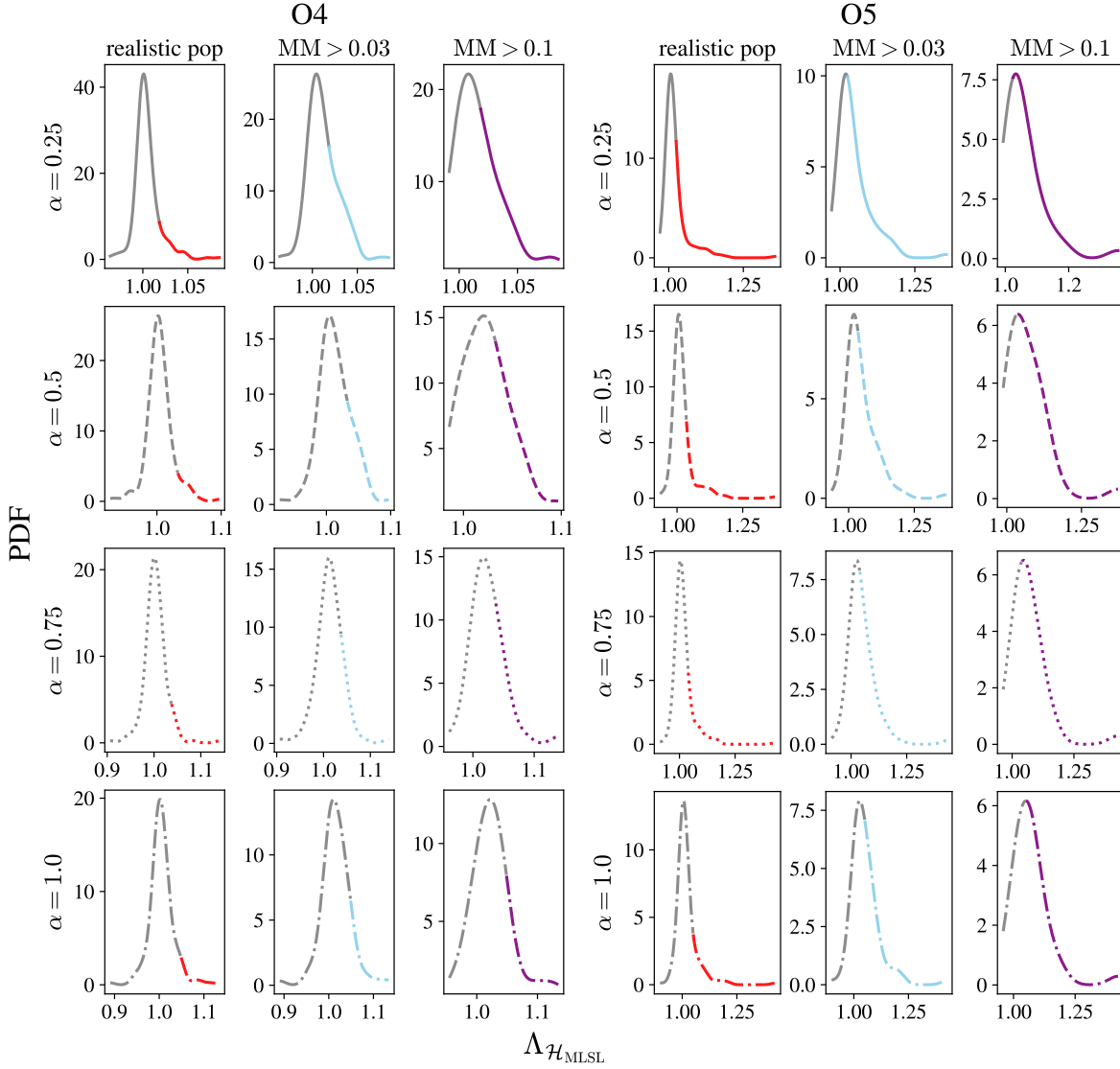


Figure 7.6: $\Lambda_{\mathcal{H}_{\text{MLSL}}}$ distributions obtained using various time windows determined by a constant α and mismatch conditions (*Left: O4 sensitivity, Right: O5 sensitivity*). Coloured segments in the distributions represent microlensed events with $\Lambda_{\mathcal{H}_{\text{MLSL}}}$ falling within the range identified as microlensed, whereas grey segments indicate microlensed events misclassified as unmicrolensed.

Our results highlight the potential of residual tests as a robust diagnostic for identifying microlensing signatures in SLGW signals. This approach can serve as a low-latency pre-analysis pipeline, enabling us to efficiently prioritise events for follow-up with more intensive, full-parameter-estimation microlensing pipelines. By focusing on the residuals—the difference between the recovered best-fit purely strongly lensed waveform and the observed data—we can uncover events with significant microlensing signatures that might otherwise remain overlooked in traditional analyses. The distribution of cross-correlation values for both strongly lensed and microlensed signals, compared with that for purely strongly lensed ones, suggests that microlensing effects can create statistically measurable deviations in residual tests.

O4 sensitivity				
Condition	R_{ML}	$R_{\text{ML}}^{\alpha=0.5}$	$R_{\text{ML}}^{\alpha=0.75}$	$R_{\text{ML}}^{\alpha=1.0}$
Realistic population	0.110	0.075	0.065	0.050
Events with $\text{MM} \geq 0.03$	0.277	0.213	0.170	0.106
Events with $\text{MM} \geq 0.1$	0.343	0.314	0.257	0.114

O5 sensitivity				
Condition	R_{ML}	$R_{\text{ML}}^{\alpha=0.5}$	$R_{\text{ML}}^{\alpha=0.75}$	$R_{\text{ML}}^{\alpha=1.0}$
Realistic population	0.215	0.160	0.155	0.140
Events with $\text{MM} \geq 0.03$	0.521	0.447	0.447	0.404
Events with $\text{MM} \geq 0.1$	0.657	0.657	0.629	0.571

Table 7.3: The same configuration as in Table 7.2, but showing the ratio of events identified as microlensed to the total number of events.

As discussed in earlier studies, however, certain waveform features such as spin precession and orbital eccentricity can mimic microlensing by introducing similar modulations [321, 331, 369], potentially leading to residuals being mistakenly attributed to microlensing. While we have neglected these effects in this study, as lensing of BBHs with extreme precession or eccentricity is expected to be rarer than the standard population [370, 371, 372], distinguishing between residuals arising from microlensing versus those from intrinsic source properties should be addressed in future work.

In our current cross-correlation framework, we utilised maximum-likelihood waveforms to obtain a single statistic per event. A more exhaustive approach would involve using the full posterior distribution of waveforms to generate a distribution of cross-correlation values for each event. One could then assess the degree of overlap between this distribution and the full cross-correlation distribution obtained from all events. Furthermore, while we used Gaussian noise realisations to establish a baseline, real detector noise often includes non-Gaussian features, such as glitches. Therefore, robust deglitching procedures must be applied before the residual test, although microlensing features may be inadvertently removed if the lens model is not incorporated into the cleaning.

It is also important to note that while we employed one of the state-of-the-art microlensing models and realistic parameter ranges as a baseline, the results could vary with different microlensing population models and macromodel magnifications. In general, higher macrolens magnification and higher density of microlenses lead to larger mismatches, thereby increasing the probability of detection. For further investigation into the role of the macromodel across various parameter spaces, we refer the reader to [312, 315, 323]. Beyond our baseline estimates for a realistic population, we also quantify our detection capability

using selected high-mismatch waveforms (Table 7.2), allowing our results to be interpreted within the context of these specific distortions. A comprehensive investigation of diverse microlensing fields in conjunction with complex galaxy lens models is reserved for future work.

When focusing specifically on high-mismatch events, which are typically detectable by existing microlensing pipelines, the residual test demonstrates improved performance at both O4 and O5 sensitivities. However, a caveat remains: excessively distorted microlensed signals may suffer substantial SNR loss during the initial matched-filtering process if the templates do not account for microlensing effects [322]. In such cases, a dedicated search pipeline incorporating microlensed templates may be required to avoid missing these events entirely.

When considering the entire dataset containing microlensed events in both low- and high-mismatch regimes, our results suggest that aLIGO O4 sensitivity may not be sufficient to reliably detect most realistic microlensing effects. However, the projected improvements for O5 are expected to significantly enhance our ability to discern these signatures. In the era of next-generation detectors, where the detection rate of lensed GW signals will be significantly higher, such low-latency methods will become increasingly important. We anticipate our approach to be even more efficient for next-generation detectors due to the longer signal durations, higher SNRs, and improved sensitivity in the high-frequency regime. A detailed quantitative study of the efficiency in these future scenarios will be conducted in future work.

Finally, the computational advantage of our method is substantial. A single JPE followed by the residual test for a pair of lensed events takes approximately half a day, as a single likelihood evaluation in our approach requires only a few milliseconds. In contrast, using a frequency-domain source model that explicitly incorporates both strong and microlensing effects in a standard search pipeline (e.g., within a nested sampling framework) results in likelihood evaluations taking approximately 10 seconds per waveform. This makes the full analysis roughly 10^4 times slower than our method. Consequently, the residual test presented in this chapter has the potential to serve as a high-speed, low-latency pre-analysis tool, alerting us to potential microlensing candidates before committing to more computationally intensive investigations.

PART III

COSMOLOGICAL AND POPULATION INFERENCE

Chapter 8

Lens Reconstruction for Delensing

Disclaimer

The following chapter is based on two papers: *Gravitational Lensing aided Luminosity Distance Estimation for Compact Binary Coalescences* [373], published in *Physical Review D*, and *Inferring Properties of Dark Galactic Halos using Strongly Lensed Gravitational Waves* [311], published in the *Astrophysical Journal*. In the former work, the author served as a co-first author and contributed to the development of the analysis framework, data analysis, manuscript preparation, and generation of all figures. In the latter work, the author was the first author and contributed to the development of the methodology, data analysis, interpretation of the results, scientific discussion, manuscript preparation, and generation of all figures.

In microlensing analysis, a lens model is typically assumed a priori, and the lens parameters are inferred simultaneously during parameter estimation. While some correlations exist, the source parameters are not completely degenerate with the lens parameters. In contrast, the analysis of detected SLGW signals, which often relies on model-independent comparisons of the relative magnification factors, time delays, and phase shifts between multiple images, faces a fundamental challenge: the inferred luminosity distance of each image is completely degenerate with the lensing magnification. Consequently, the measured distances do not represent the *true* luminosity distance to the source.

This degeneracy poses a critical issue for GW cosmography. As discussed in Section 3.2.2, lensing introduces a systematic bias in the inferred luminosity distance. Consequently, any cosmological inference based on this biased distance, such as measurements of the Hubble constant (H_0), will also be biased, even if the source redshift is precisely determined from EM counterparts. Therefore, in the study of SLGWs, it is imperative to perform a lens reconstruction to *delens* the signals and recover the true luminosity distance. By accurately modelling the mass distribution of the lens responsible for multiple imaging, the distance–magnification degeneracy can be broken or mitigated. This approach enables simultaneous constraints on lens properties and the recovery of unbiased luminosity distances required for precision cosmology.

In this chapter, we first present a proof-of-principle study of the delensing procedure using analytic lens models, including the PM and SIS models described in Section 2.2.1 and Section 2.2.2, respectively. In these simplified cases, lens reconstruction and the recovery of the true luminosity distance can be performed using closed-form analytical relations. We specifically examine how SLGW detection can improve the precision of luminosity distance measurements compared to unlensed signals, thereby strengthening constraints for GW cosmography. We then extend the analysis to more realistic scenarios. We explore numerical approaches to lens reconstruction under more general lens models in Sections 2.2.3–2.2.6, where the mapping between lens parameters and lensing observables is no longer one-to-one, precluding closed-form solutions.

8.1 Analytic Delensing with PM and SIS Models

For the PM and SIS models, within the geometric-optics approximation, the relevant lens parameters are the redshifted lens mass and the dimensionless impact parameter, $\theta_l = (M_l^z, y)$. The SIS model provides a simple and widely used description of galaxy-scale lenses in the strong-lensing regime, and is therefore well-motivated for studies of SLGWs. In contrast, the PM model is not generally representative of galactic-scale lenses, although it can serve as an effective approximation in simplified configurations where the mass distribution is highly centrally concentrated. Despite this, we adopt the PM model alongside the SIS model for its analytical simplicity and its utility as a baseline model, as both models admit closed-form relations between lensing observables and lens parameters.

In this section, we present an analytic delensing procedure and quantify the reduction in luminosity distance uncertainty by using mock BBHs lensed by the two lens models, constructed to resemble real BBHs selected from GWTC-3 [374].

8.1.1 Effective Luminosity Distance

As described in Eqs. (2.35) and (2.43), the PM lens produces two images for any non-zero y , whereas the SIS lens yields two images only for $y < 1$.

For both the PM and SIS models, the magnification of each image is uniquely determined by the impact parameter y . As a result, the effective luminosity distances defined in Eq. (2.75) can be directly expressed as a function of y . For the PM lens, this relation is given by:

$$d_{L,\pm}^{\text{PM}} = \frac{d_L}{\sqrt{\frac{1}{2} \pm \frac{y^2+2}{2y\sqrt{y^2+4}}}}, \quad (8.1)$$

Table 8.1: Injection parameters and SNR values of three BBHs similar to GW200208_222617, GW200216_220804, and GW200219_094415.

Event	m_1 [$M_\odot$]	m_2 [$M_\odot$]	χ_{eff}	d_L [Gpc]	SNR
GW200208_222617	51.0	12.3	0.45	4.1	7.94
GW200216_220804	51.0	30.0	0.10	3.8	10.35
GW200219_094415	37.5	27.9	−0.08	3.4	9.86

while for the SIS lens it takes the form:

$$d_{L,\pm}^{\text{SIS}} = \frac{d_L}{\sqrt{1 \pm \frac{1}{y}}}, \quad (8.2)$$

where the $+$ and $-$ signs denote the first-arriving (positive-parity) and second-arriving (negative-parity) images, respectively.

8.1.2 Parameter Estimation Framework

We simulate BBHs based on selected interesting candidates from the GWTC-3 catalogue [374], including GW200208_222617 (a low mass-ratio candidate; $q_m = m_2/m_1$), GW200216_220804 (an eccentric candidate), and GW200219_094415 (a high-spin candidate). These systems are chosen to span different regions of the binary parameter space, and to contrast with the equal-mass BBH case typically used as a baseline. In particular, such systems tend to exhibit more complex waveform morphology (see Section 4.3.2), which can make parameter estimation more challenging and may lead to larger uncertainties in inferred source properties, including the luminosity distance. We adopt the median values of the component masses (m_1, m_2), effective spin χ_{eff} and luminosity distance d_L , which are summarised in Table 8.1.

We generate both injection and template GW waveforms using the IMRPhenomXPHM model [288] to avoid systematic biases arising from waveform mismatches. For each simulated unlensed signal ($h_u(f)$), we perform parameter estimation using the *bilby* library [240] and the *dynesty* [263]. This setup is labeled as *normal PE* in Figure 8.1. We assume a detector network consisting of aLIGO-Hanford (H), aLIGO-Livingston (L), and AdV (V), referred to as the HLV network. To achieve optimal distance estimation under ideal sensitivity conditions and to assess the impact of detector noise and performance, we consider two configurations:

- **Case A:** Design PSD [365] with zero-noise realisations.
- **Case B:** O3a PSDs with Gaussian noise, where the O3a PSDs correspond to the first three months of the third observing run¹.

1. The corresponding PSD data for H, L, and V can be found at <https://dcc.ligo.org/LIGO-T2000012/public>

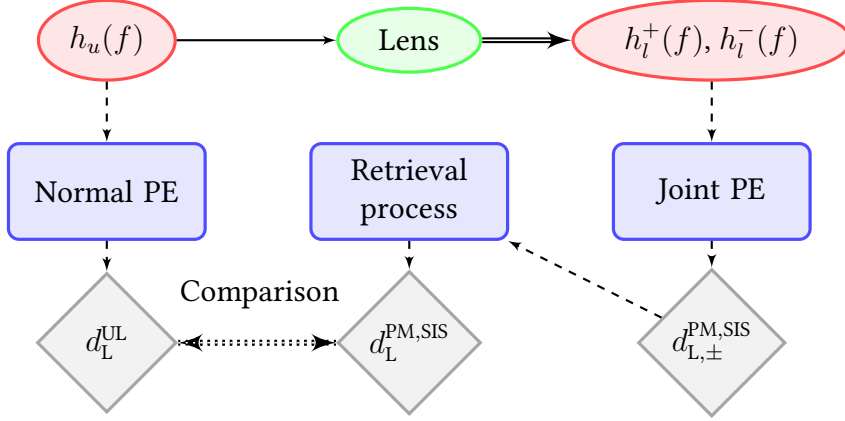


Figure 8.1: Flowchart of parameter estimation for an unlensed signal and its corresponding strongly lensed pair constructed from it. The posterior of d_L^{UL} is first inferred from the unlensed signal. The posteriors of $d_L^{\text{PM,SIS}}$ for the two lensed signals are then obtained via joint parameter estimation and retrieval. Finally, the inferred distance posteriors are compared to assess the precision of the posterior on the true luminosity distance.

For the luminosity distance prior, we assume a uniform distribution in Euclidean volume, corresponding to $p(d_L) \propto d_L^2$, i.e., a constant source density in Euclidean space (the low-redshift limit of a comoving volume prior), over the range $[0.1, 10]$ Gpc. For other source parameters, we adopt the default precessing BBH priors implemented in Bilby [240, 375].

Next, we simulate mock lensed signals by assuming that each unlensed signal is lensed by both a PM and an SIS lens, producing two lensed signals per model (i.e., three unlensed signals produce a total of six lensed signals).

As discussed earlier, we restrict the dimensionless impact parameter to the range $y \in [0.1, 1.0)$, ensuring the formation of at least two images. The lower bound is motivated by the expected occurrence rate of SLGWs [301, 324, 325, 326, 376]. As an optimistic scenario for strong lensing, we consider the regime of maximum amplification, which occurs at $y = 0.1$ for the lens models considered here; accordingly, we set $y = 0.1$ in our injections. We also adopt a lens mass of $M_{lz} = 10^{11.5} M_\odot$, corresponding to typical galactic-scale lenses. This choice yields time delays between the two lensed images ranging from weeks to months over the considered range of y , consistent with expectations for galaxy-scale strong lensing.

To construct lensed signal pairs, we use the same intrinsic source parameters as in the unlensed case, except for the luminosity distance, which is modified by lensing magnification. For example, the chirp mass is assumed to be identical for all images, i.e., $\mathcal{M}_{c,+} = \mathcal{M}_{c,-} = \mathcal{M}_c$. The sky locations of the lensed images are also taken to be identical, as current detector sensitivities do not enable us to resolve small angular separations between

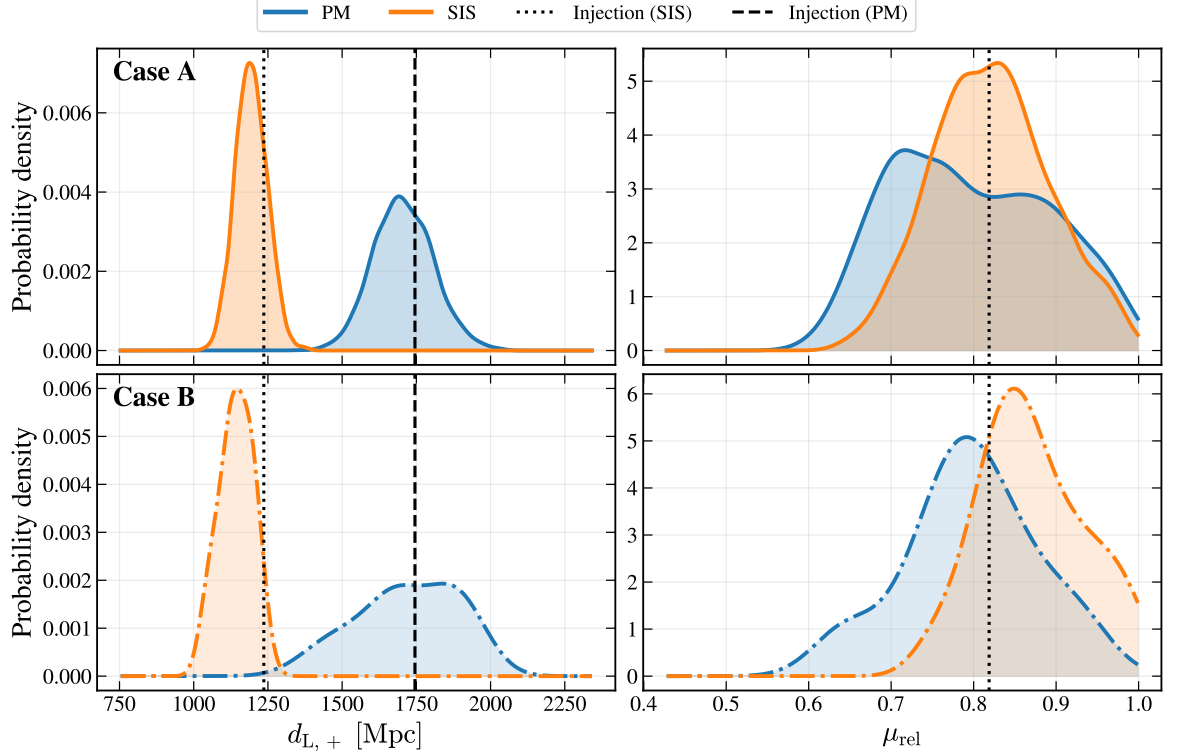


Figure 8.2: Posteriors of $d_{L,+}$ and μ_{rel} obtained from JPEs of a pair of signals from GW200208_222617 lensed by SIS (orange) and PM (blue) models. Black dotted and dashed lines indicate the injected values of $d_{L,+}$ for the SIS and PM cases, respectively. The injected values of μ_{rel} are nearly identical for the two lens models ($\mu_{\text{rel}}^{\text{PM}} \simeq \mu_{\text{rel}}^{\text{SIS}} \simeq 0.818$); therefore, only a single vertical line is shown for μ_{rel} .

images (e.g., [374]). We do not include time delays or phase shifts in the analysis, as they do not directly affect luminosity distance estimation. The prior assumptions for the lensed signals are taken to be the same as those used for the unlensed case, except that we adopt a uniform prior on the relative magnification, μ_{rel} [300].

For Cases A and B, we perform JPEs on the lensed signal pairs for each lens configuration using the method described in Section 5.2.1, implemented via the Golum pipeline [300, 303] (labeled as *joint PE* in Figure 8.1). While the full analysis infers both source parameters and lensing observables, we focus on the relative magnifications and the luminosity distances, which are the quantities of interest in this work.

8.1.3 Results

From the JPE of the lensed signal pairs, we obtain posteriors for the relative magnification factors and effective luminosity distances for both the PM and SIS models under Cases A and B. Figure 8.2 shows the resulting posteriors of μ_{rel} and $d_{L,\pm}^{\text{PM,SIS}}$ for each pair of lensed signals from the GW200208_222617-like event as a representative example. The top and bottom panels correspond to Cases A and B, respectively. The posteriors $p(\mu_{\text{rel}})$ are consistent with the injected values for both lens models and are nearly identical, as $y = 0.1$ yields $\mu_{\text{rel}} \simeq$

0.8 for both models. In contrast, the distance posteriors differ between the models. The distributions $p(d_{L,+})$ inferred under the SIS model are narrower than those obtained with the PM model within the 99 % C.I., indicating improved precision in parameter estimation. This difference arises from the higher μ_+ , and consequently higher SNR, in the SIS model ($\mu_+^{\text{SIS}} = 11$, $\text{SNR}_{\text{SIS}} \simeq 26.34$) compared to the PM model ($\mu_+^{\text{PM}} \simeq 5.5$, $\text{SNR}_{\text{PM}} \simeq 18.66$). In addition, the presence of noise in Case B leads to a noticeable reduction in the precision of the luminosity-distance measurement, particularly for the PM case. For the SIS case, however, the effect appears less significant due to its substantially higher SNR.

Following [300], we improve parameter constraints by reweighting the posterior samples of the individual lensed signals. The reweighted posterior is constructed by combining the posteriors of the lensing and apparent source parameters (see Eq. (15) of [300]). For both models, the first-arriving (+) image is more strongly magnified and is therefore used as the reference. In this procedure, the posterior $p(d_{L,+})$ is refined using information from $p(d_{L,-})$.

To recover the true luminosity distances, we convert the reweighted effective distances using μ_+ posteriors, which are obtained analytically from the reweighted μ_{rel} posteriors (denoted as *retrieval process* in Figure 8.1). Using Eqs. (2.36) and (2.44), we obtain the posterior of y , which is then mapped to μ_+ via Eqs. (2.35) and (2.43). To illustrate an optimal scenario in which only the uncertainty in $d_{L,+}$ is taken into account, we estimate the true luminosity distance using a fixed μ_+ corresponding to its maximum-likelihood value, without propagating the uncertainty in μ_+ . For Cases A and B, the retrieved luminosity distance distributions for the lensed pair from the GW200208_222617-like event are shown in Figure 8.3, together with the posterior of the true distance obtained from parameter estimation of the corresponding unlensed signal (d_L^{UL}) for comparison.

To quantify how much the recovered luminosity distances are improved in precision relative to the unlensed case, we compare the widths of the 99 % C.I. of the recovered distances posteriors, denoted by $\mathcal{W}_{99}$. We define the ratio $\mathcal{R}_{99} \equiv \mathcal{W}_{99}^{\text{UL}} / \mathcal{W}_{99}^{\text{X}}$, where X denotes one of the adopted O3b-like BBHs, labeled here using the shorthand event identifiers 208, 216, and 219. For convenience, we use abbreviated event labels obtained by dropping the first three and last six digits of the original event IDs in the superscripts of $\mathcal{W}_{99}$ and $\mathcal{R}_{99}$. Table 8.2 summarises the resulting $\mathcal{W}_{99}$ and $\mathcal{R}_{99}$ values for the three mock BBHs considered in this section.

The results are broadly consistent across all BBHs: the luminosity-distance posteriors inferred from lensed signals are more tightly constrained than those obtained from the corresponding unlensed signals. Differences in $\mathcal{W}_{99}$ and $\mathcal{R}_{99}$ values for the three BBHs are mainly due to the SNRs of the original unlensed events since identical lens parameters are adopted for each lens model. For example, the GW200208_222617-like event has the lowest

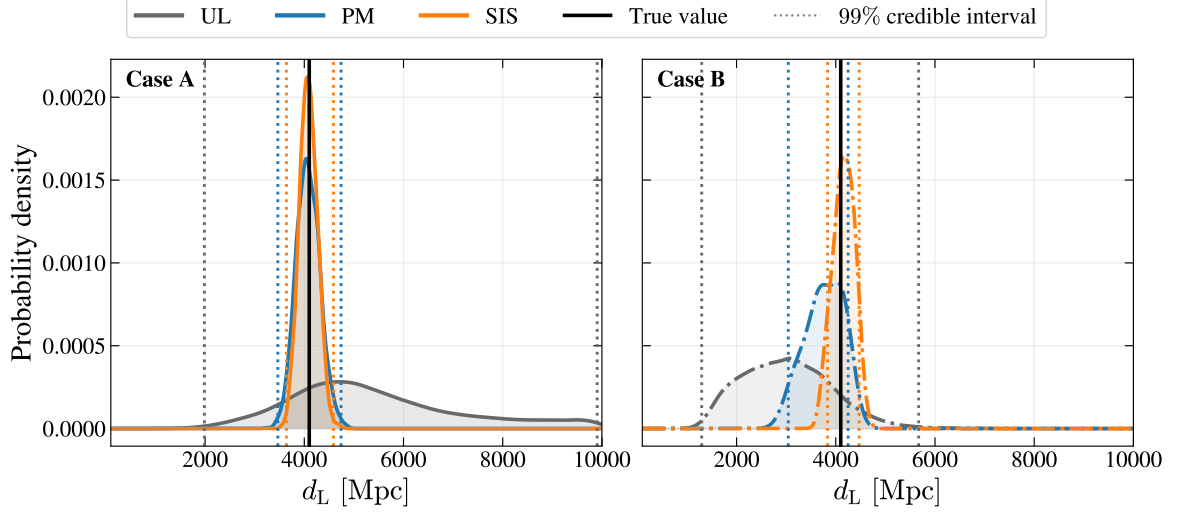


Figure 8.3: Posteriors of the recovered true luminosity distance (d_L) of the GW200208_222617-like event for the PM (blue) and SIS (orange) cases. For comparison, the distance posterior obtained from the corresponding unlensed signal, $p(d_L^{\text{UL}})$ (grey), is also shown. The left and right panels correspond to the results from Cases A and B, respectively. The black solid line indicates the true value. Coloured vertical dashed lines denote the lower and upper bounds of the 99 % C.I. for each posterior distribution in the corresponding colour.

unlensed network SNR among the three systems considered in Case A. Correspondingly, its unlensed distance posterior exhibits the broadest C.I., with $\mathcal{W}_{99} \simeq 8$ Gpc. As a result, the impact of strong lensing appears most pronounced for this event, yielding $\mathcal{R}_{99}^{208} \sim 8$, compared to $\mathcal{R}_{99} \sim 4$ for the other BBHs.

As expected, the presence of noise tends to reduce the improvement from strong lensing, since the SNR enhancement from magnification and from combining multiple repeated signals becomes less effective. Nevertheless, even in the presence of Gaussian noise, the recovered luminosity-distance precision remains improved by a factor of approximately two to seven relative to the unlensed case (see the Case B results in Table 8.2). Overall, these proof-of-principle results demonstrate the potential of strong lensing to improve luminosity-distance measurements by providing multiple magnified observations of the same GW source, leading to tighter distance constraints

8.2 Beyond Simple Lens Models: Numerical Reconstruction

As shown in the previous section, delensing based on successful lens reconstruction can significantly enhance the precision of luminosity distance estimates. However, for more realistic lens models, the lens parameters cannot be determined analytically from lensing observables. In this section, we present a numerical approach to infer lens parameters from

Case A: HLV design PSDs with zero-noise realisation

Signal	$\mathcal{W}_{99}^{208}$ [Mpc]	$\mathcal{R}_{99}^{208}$	$\mathcal{W}_{99}^{216}$ [Mpc]	$\mathcal{R}_{99}^{216}$	$\mathcal{W}_{99}^{219}$ [Mpc]	$\mathcal{R}_{99}^{219}$
Unlensed	7,918	1.00	4,806	1.00	4,167	1.00
Lensed (PM)	1,274	6.21	1,786	2.69	1,146	2.68
Lensed (SIS)	948	8.35	1282	3.75	1,147	3.63

Case B: HLV O3a PSDs with a Gaussian-noise realisation

Signal	$\mathcal{W}_{99}^{208}$ [Mpc]	$\mathcal{R}_{99}^{208}$	$\mathcal{W}_{99}^{216}$ [Mpc]	$\mathcal{R}_{99}^{216}$	$\mathcal{W}_{99}^{219}$ [Mpc]	$\mathcal{R}_{99}^{219}$
Unlensed	4,373	1.00	7,675	1.00	3,961	1.00
Lensed (PM)	1,206	3.63	1,882	4.08	2,133	1.86
Lensed (SIS)	637	6.86	1,693	4.53	1,437	2.76

Table 8.2: The $\mathcal{W}_{99}$ and $\mathcal{R}_{99}$ values that are obtained from GW200208_222617-, GW200216_220804-, and GW200219_094415-like BBHs. Results from Cases A and B are compared for each injection.

GW signals using the rejection sampling technique. This method can be applied to a wide range of lens models once the relevant lens parameters are defined. We also explore how the reconstruction can be further improved by incorporating multi-messenger information, such as the identification of the host galaxy of the GW source and the lens galaxy.

8.2.1 Analysis Setup

We simulate nine distinct GW lensing systems based on the lens models described in Section 2.2. The parameters are randomly chosen from a pool of θ_l that can generate the specified detectable multiple images. To maintain consistency, we use a single intrinsic unlensed signal from a GW150914-like event, generated with the IMRPHENOMXPHM waveform model [288]. For most lensing configurations, we assume a luminosity distance of $d_L = 3$ Gpc and a redshifted lens mass of $M_l^z = 10^{12} M_\odot$. However, for the NFW and PNFW models, the strong lensing cross-sections for sources at low redshifts are significantly smaller than the other models (see Figure 2 in [311]). To ensure a non-negligible lensing probability for the two models, we instead inject the signals at $d_L = 10$ Gpc with a higher redshifted lens mass of $M_l^z = 10^{13} M_\odot$.

The resulting lensing configurations span from double-image to quintuple-image systems, with the image multiplicity determined by model-dependent lens parameters. Simulated lensed GW signals are injected into Gaussian noise characterised by the projected LIGO-Virgo O4 PSD [365]. Consistent with the projected detectability of the detector network [365], we assume that lensed GW signals ($h_l(f)$) are detected with a network SNR $\rho_{\text{net}} > 8$ except for NFW and PNFW cases. An exception arises for Type III images in NFW and PNFW models, which are strongly demagnified by the lens geometry and often yield lower SNRs. For each system, the injected lens parameters (θ_l) are listed in Table 8.3. The

ID	Model	Injected θ_l	No. of images
1	PM	$y = 0.22$	Double
2	SIS	$y = 0.22$	Double
3	NFW	$(y, \kappa_s) = (0.004, 0.167)$	Triple
4	SIE	$(q, y) = (0.85, 0.22)$	Double
5	SIE	$(q, y) = (0.63, 0.22)$	Quadruple
6	SPEMD	$(q, y, \gamma) = (0.85, 0.22, 1.5)$	Double
7	SPEMD	$(q, y, \gamma) = (0.58, 0.17, 0.75)$	Quadruple
8	PNFW	$(q, y, \kappa_s) = (0.6, 0.011, 0.167)$	Triple
9	PNFW	$(q, y, \kappa_s) = (0.82, 0.008, 0.167)$	Quintuple

Table 8.3: Injected θ_l values used to simulate the nine GW lensing systems considered in this section.

recovered SNRs vary across systems: Systems 1, 2, and 4–7 yield $\rho_{\text{net}} \in [11, 16]$, while Systems 3, 8, and 9 fall within $\rho_{\text{net}} \in [4, 10]$. For highly demagnified images, we adopt an SNR threshold of $\rho_{\text{net}} = 4$, assuming such signals can be identified with dedicated sub-threshold search pipelines [325, 326, 377].

To conduct JPEs for each lensing system, we again use the Golum pipeline [300, 303]. As this pipeline is optimised to analyse two signals, the estimations are performed on pairs of the first lensed signal ($h_{l,1}$) and the j -th lensed signal ($h_{l,j}$), which means that we can get posteriors of $\mu_{\text{rel},1j}$ and Δt_{1j} , where $j = 1, 2, \dots, n$ if the system has n lensed GW signals. We assume uniform prior distributions for $\mu_{\text{rel},1j}$ and Δt_{1j} . For the source parameters, we adopt the prior distributions for precessing BBHs in [375]. Priors for the main parameters used in this work are shown in Table 8.4.

Parameter	Prior	Range
m_1, m_2	UNIFORM	$[5, 100] M_\odot$
d_L	UNIFORMCOMOVINGVOLUME	$[0.1, 5] \text{Gpc}$ OR $[0.1, 10] \text{Gpc}$
RA	UNIFORM	$[0, 2\pi]$
DEC	ISOTROPIC	-
μ_{rel}	UNIFORM	$[0.1, 10]$
Δt	UNIFORM	-

Table 8.4: Priors on the main source parameters, including component masses (m_1, m_2), luminosity distance (d_L), and sky location (RA, DEC), as well as lensing observables ($\mu_{\text{rel}}, \Delta t$) employed in this work. A broader prior on d_L ($[0.1, 10] \text{Gpc}$) is adopted for NFW and PNFW systems to account for injected effective distances, $d_L^{\text{eff}} > 5 \text{Gpc}$.

8.2.2 Lensing Observable Catalogue and Rejection sampling

A key challenge in lens reconstruction is that, for most lens models beyond simple cases such as PM and SIS, the mapping between the lensing observables and the lens parameters is not one-to-one. In addition, the observables are inferred as posterior distributions rather than precise point estimates, and their associated uncertainties further hinder accurate recovery of the underlying lens properties.

To address this, we employ a rejection sampling technique [254] to infer θ_l . This approach is particularly well-suited for our framework because, while the mapping from observables to parameters is not analytically invertible, forward modelling allows us to efficiently compute μ_{rel} and Δt for any given set of θ_l . By comparing these forward-modelled predictions with the likelihood implied by the inferred posteriors of the observables, we effectively sample the posterior distribution of θ_l .

For each aforementioned lens model, we select sets of lens parameters θ_l that produce multiple image solutions (i.e., at least two images). For each θ_l , we calculate the corresponding relative magnification factors ($\mu_{\text{rel},1j}$) and Fermat potential (ΔT_{1j}) using LENSTRO-NOMY [378]. Note that the physical time delay is given by $\Delta t = D_{\Delta t} \Delta T$, where $D_{\Delta t}$ does not affect the image configuration in the geometrical optics limit. The resulting parameter–observable combinations are stored as ordered triplets, ($\Theta = \{\theta_l, \mu_{\text{rel}}, \Delta T\}$) forming *lensing observable catalogues*.

We use the constructed catalogues for the detected lensed signals in each system listed in Table 8.3. For simplicity, we assume that the correct lens model is known for each system. Figure 8.4 illustrates an example using the posterior distribution $P(\mu_{\text{rel}})$ from lensing system ID 2 (see Table 8.3). In the rejection sampling procedure, candidate values of μ_{rel} , drawn from the catalogue triplets Θ , are first proposed according to a distribution $Q(\mu_{\text{rel}})$ (solid blue line). Each sample is then accepted with probability proportional to the ratio $P(\mu_{\text{rel}})/MQ(\mu_{\text{rel}})$, where M is chosen such that $P(\mu_{\text{rel}}) \leq MQ(\mu_{\text{rel}})$ (solid yellow line) over the domain, ensuring that the accepted samples populate the region under the target distribution $P(\mu_{\text{rel}})$ (solid black line). Green and magenta dots indicate the accepted and rejected Θ , respectively.

Finally, the accepted values of θ_l effectively represent the posterior probability distributions of the lens parameters. Furthermore, the associated time-delay samples, ΔT , can be converted into the corresponding redshifted lens mass samples, M_l^z , by applying the analytical relationship defined in Eq. (2.44).

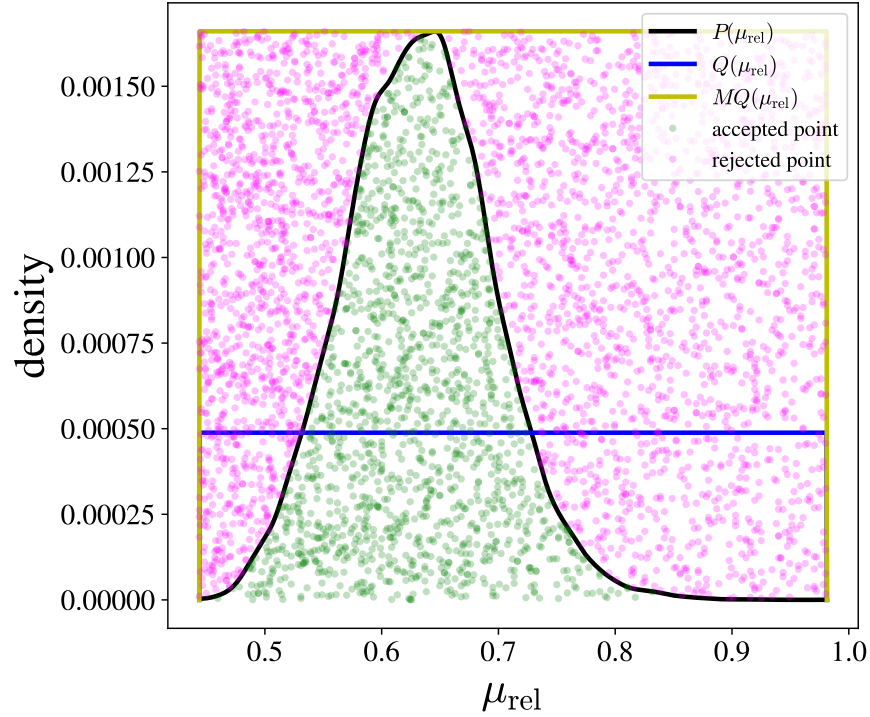


Figure 8.4: Illustration of rejection sampling.

In terms of computational performance, the rejection sampling technique is efficient. For a double-image system, the total computation time is typically less than one CPU hour. For more complex systems with triple to quintuple images, the required time increases to a few CPU hours. This is due to the sequential nature of the sampling process, where the rejection sampling for the j^{th} image pair (first and j^{th}) is conducted only after the posterior results for the preceding i^{th} pair (first and i^{th} , where $i < j$) have been obtained.

8.2.3 Axially Symmetric Lenses

To confirm the validity of the rejection sampling technique, we first compare the θ_l posteriors obtained via rejection sampling against the analytical posteriors derived through univariate transformations of the μ_{rel} posteriors using Eqs. (2.36) and (2.44) for the PM and SIS models, respectively. As shown in Fig. 8.5, the recovered posteriors for M_l^z and y for System 1 (PM Double) and System 2 (SIS Double) peak near the injected values. The results from the two methods are nearly identical: the analytical posteriors are represented by dashed gray and black lines, while the rejection sampling results are shown in solid colours. The solid black vertical lines indicate the true injected values, and the vertical dashed lines denote the 90 % C.I. for each parameter.

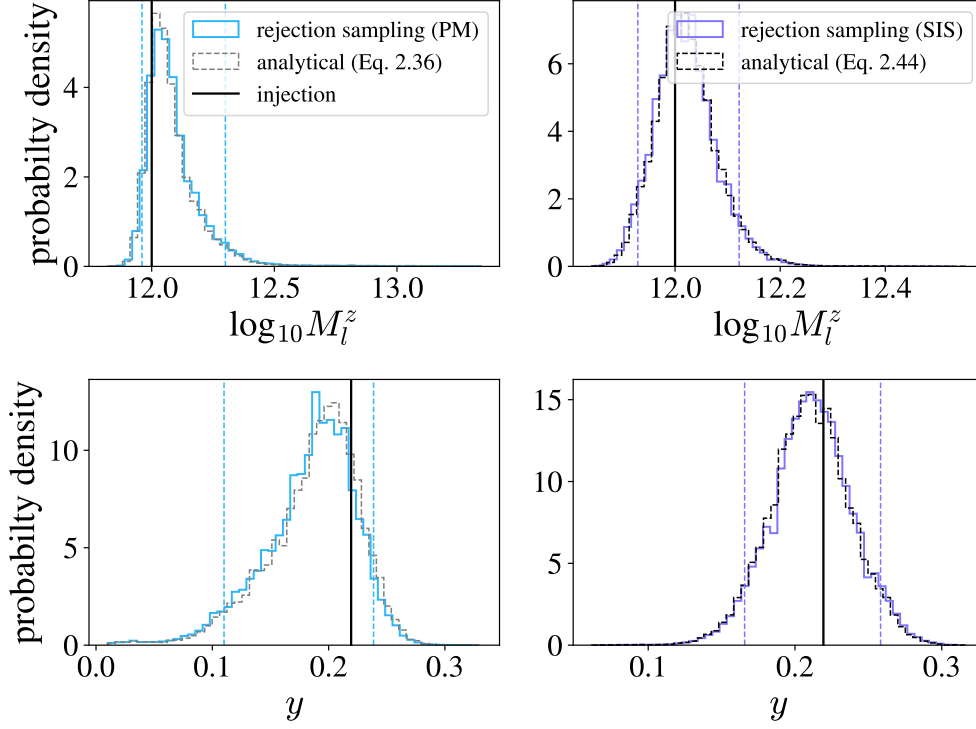


Figure 8.5: Posteriors of θ_l and redshifted lens mass M_l^z for System IDs 1 and 2. The coloured distributions are obtained using the rejection sampling technique, while the grey distributions are derived analytically from μ_{rel} posteriors using Eqs. (2.36) and (2.44).

The high degree of agreement between the analytical and numerical distributions successfully demonstrates the validity of the rejection sampling technique as a tool for mapping lensing observables back to lens parameters. However, it is important to note that while this validates the methodology, rejection sampling does not inherently bypass all physical degeneracies. The ability to successfully recover θ_l remains subject to intrinsic degeneracies among parameters that may exist within more complex lens models.

As introduced in Section 2.2.3, among the spherically symmetric lens models considered, the NFW model does not have an analytic expression for the lensing observables. Thus, we use the rejection sampling technique for System ID 3 (NFW triple). After identifying the estimated μ_{rel} posteriors with the detected triple images as a target distribution, we draw μ_{rel} samples from the lensing observable bank of the NFW to conduct rejection sampling.

Figure 8.6 shows the recovered posteriors for the lens parameters θ_l and the redshifted lens mass M_l^z for the NFW case. Although the injected values are successfully recovered within the 90 % C.I., the posteriors are poorly constrained. In particular, κ_s remains largely consistent with the prior, indicating that it is weakly constrained. This behaviour reflects the intrinsic nature of galaxy-scale lensing: for an NFW profile, the relatively low surface density implies that strong lensing, and hence the formation of multiple images, occurs only for very small values of y . Within this narrow range, many of the (y, κ_s) combinations

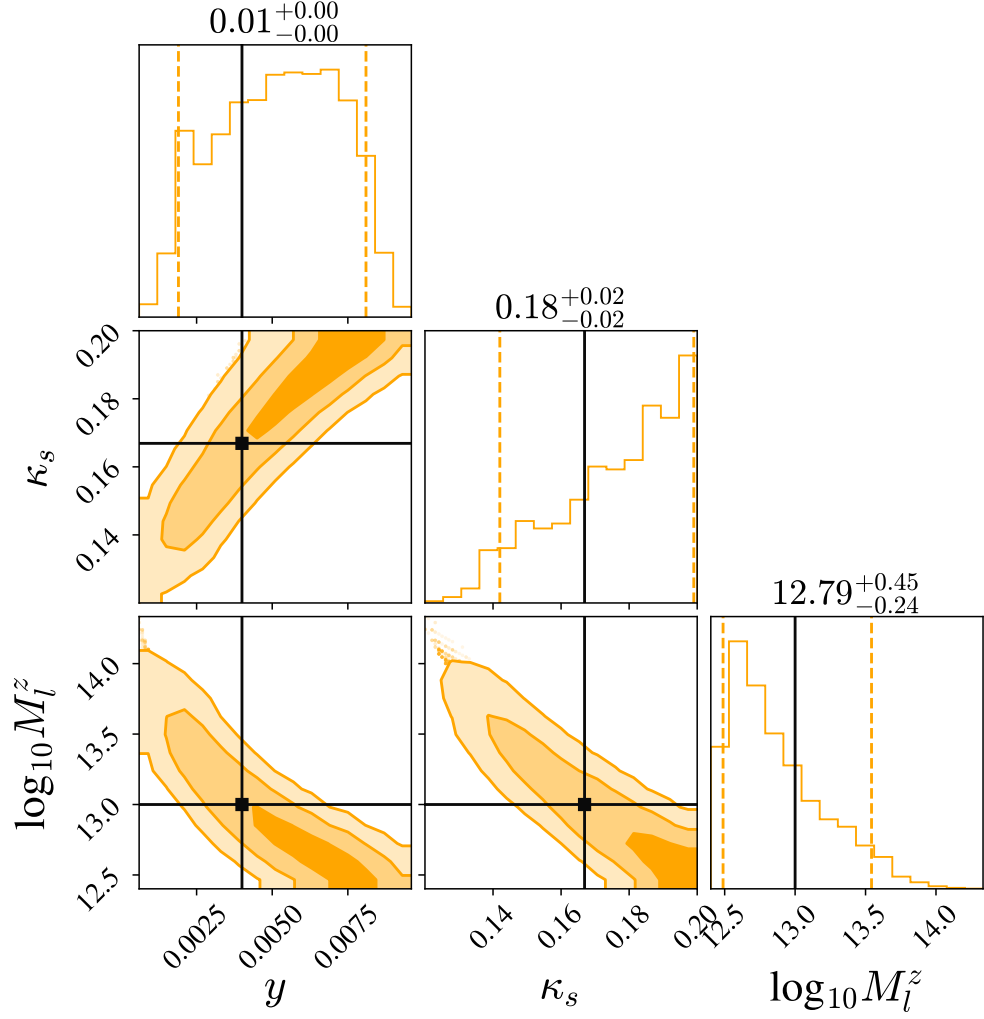


Figure 8.6: Corner plot showing the posteriors of the lens parameters $\theta_l = (y, \kappa_s)$ and redshifted lens mass M_l^z for System ID 3.

from the prior produce nearly identical μ_{rel} values, leading to a strong degeneracy between these parameters. Accordingly, the M_l^z does not peak at the true value. The precision of the obtained μ_{rel} posterior is currently insufficient to break this fundamental degeneracy, resulting in the broad, uninformative posteriors.

8.2.4 Non-Axially Symmetric Lenses

In more realistic astrophysical scenarios, strong lens candidates such as galaxies are not perfectly spherical but exhibit ellipticity. The introduction of ellipticity complicates the lens model and introduces stronger degeneracies between θ_l . Consequently, we expect the posteriors for θ_l and M_l^z in non-axially symmetric models to be more poorly constrained than those in the axially symmetric cases. In addition, the inclusion of extra parameters to describe the lens profile, such as the profile density slope γ , further increases the complexity of the parameter space and exacerbates these degeneracies.

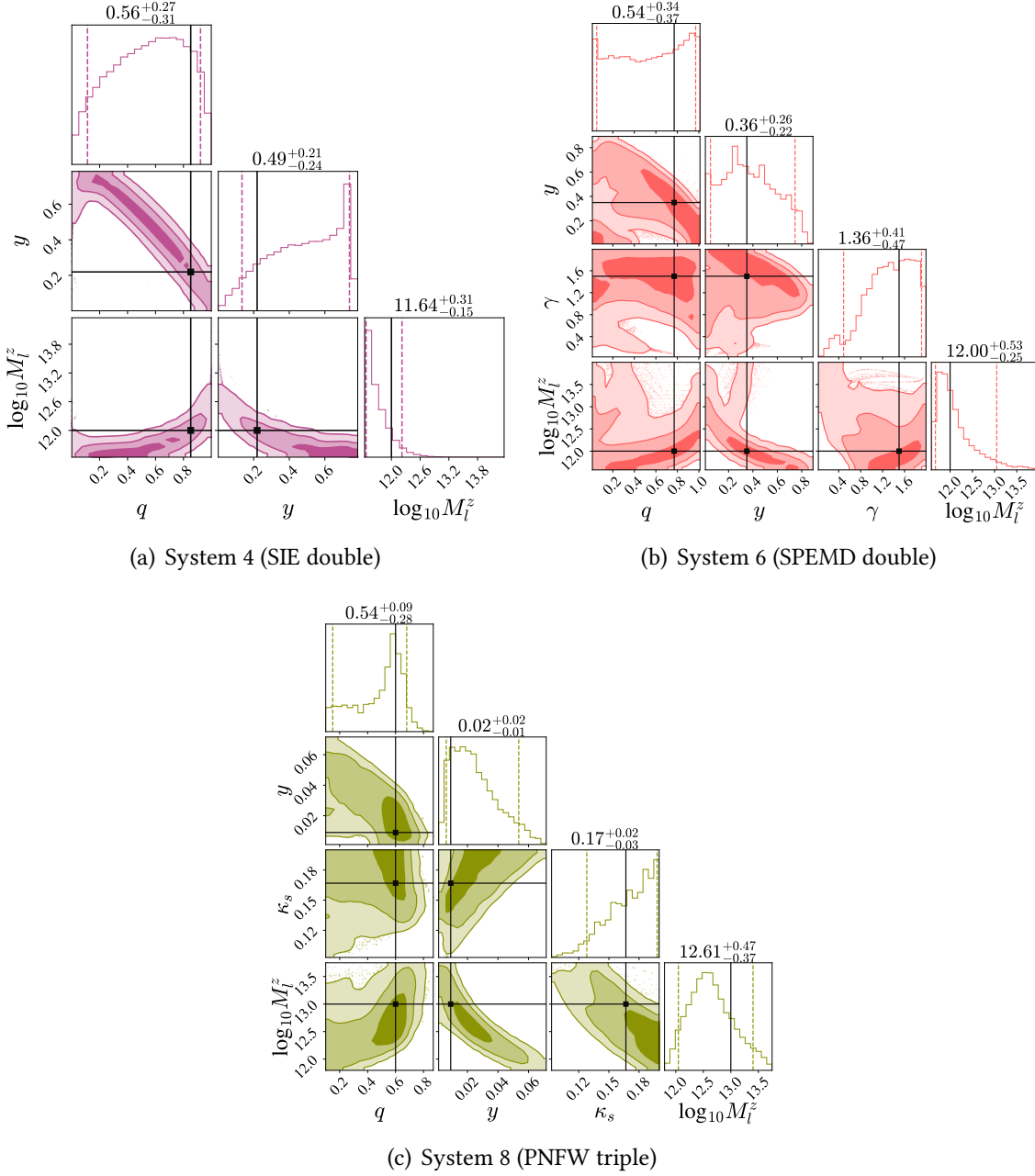


Figure 8.7: Corner plots showing the posteriors of θ_l and M_l^z for System IDs 4, 6, and 8.

Figure 8.7 shows the inferred posteriors for System IDs 4, 6, and 8, corresponding to double-image configurations (SIE and SPEMD) and a triple-image configuration (PNFW). While the true injected values lie within the 2σ credible regions of the joint 2D posteriors for all three models, the marginal 1D posteriors often do not peak at the true values and remain poorly constrained. Notably, the M_l^z posteriors are better constrained than the structural parameters. This is because M_l^z is primarily constrained by the time delays between images (Δt), which are typically better constrained than μ_{rel} with GW observations. These results indicate that the properties of an elliptical lens cannot be robustly recovered when the lensing configuration produces only double or triple images under our modelling assumptions.

However, the detection of more than two images provides additional independent constraints that help break degeneracies between lens parameters. By obtaining more lensing observables ($\mu_{\text{rel},j}$ and Δt_j), the parameter constraints become tighter, leading to better-constrained posteriors compared to double-image systems. Figure 8.8 shows the results for System IDs 5, 7, and 9, which produce quadruple or quintuple images. To account for the possibility that only a subset of images may be observed in practice, we consider two scenarios: (1) the detection of only a pair of GW images (gray) and (2) the detection of all available GW images (coloured).

Table 8.5 quantifies the improvement in lens parameter recovery when these additional constraints from more images are included. We define the ratio, $\mathcal{R}_{A/B}^{\theta_l}$, as the relative width of the 90 % C.I. between the *pair-only* case (A) and the *all-images* case (B). Except for the SIE case, the C.I. widths of θ_l narrow down by tens of percent when all images are included. This additional information improves the agreement between the inferred posteriors and the injected values, particularly for the SPEND case, where all posteriors converge well to the injected values. In contrast, the PNFW case continues to exhibit a significant degeneracy between y and κ_s , similar to the NFW results. Thus, for non-axially symmetric models, the posteriors of θ_l and M_l^z remain only weakly constrained by GW information alone. Despite these limitations, the posterior width of q consistently decreases across all models. This improved constraint on the lens structure is particularly valuable for multi-messenger astronomy, as it can aid in localising and identifying candidate lens galaxies associated with the GW host galaxy within the inferred sky area.

8.2.5 Non-Axially Symmetric Lenses with EM Observation

While GW information alone is often insufficient to recover lens parameters with high precision, incorporating EM observations offers a powerful means of breaking existing parameter degeneracies. By leveraging extra constraints from EM data, we can significantly refine the estimation of structural parameters and, consequently, obtain a more robust constraint on the redshifted lens mass M_l^z . For instance, if a lens galaxy is identified within the GW sky localisation region, its structural properties, such as the axis ratio and position angle, can be directly measured from high-resolution imaging. In addition, the image positions of the lensed host galaxy can provide further spatial constraints.

However, identifying the correct lens galaxy remains challenging, as the GW localisation uncertainty is still large enough to contain thousands of candidate galaxies. In this context, several studies [310, 379, 380] have proposed localising the host–lens system using wide-field surveys such as the Legacy Survey of Space and Time (LSST) [381]. This approach generally assumes the joint detection of lensed GW and EM signals from the same

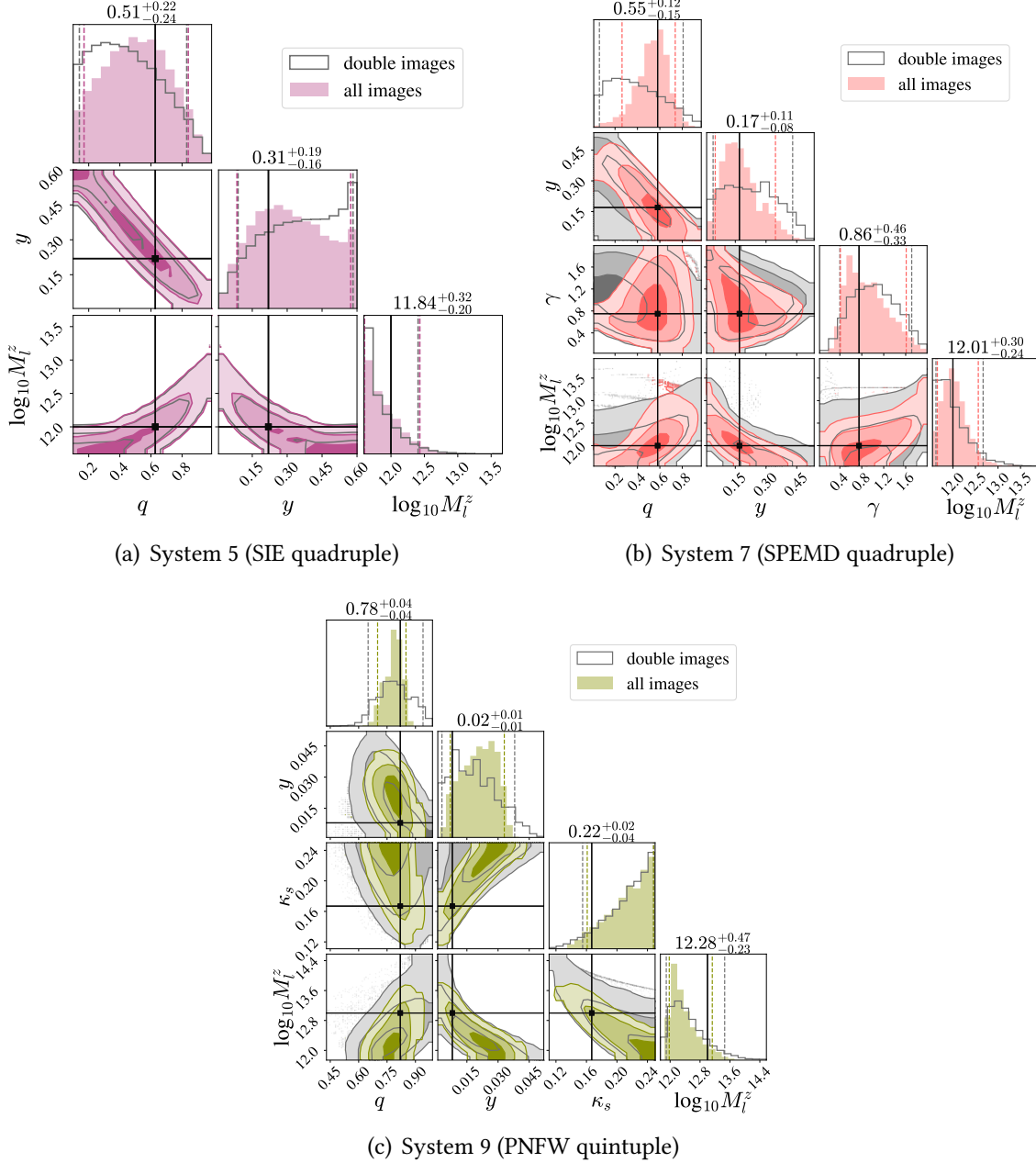


Figure 8.8: Same configurations as in Figure 8.7, but showing the posteriors of θ_l and M_l^z for System IDs 5, 7, and 9.

host galaxy². By combining lensing observables from both messengers, specifically through the joint application of Eqs. (2.76)–(2.79), the number of candidate systems within the GW localisation region can be significantly reduced, enabling identification of the most probable lens-source configuration.

² In general, the host galaxy of a GW source is also lensed by the intervening galactic halo.

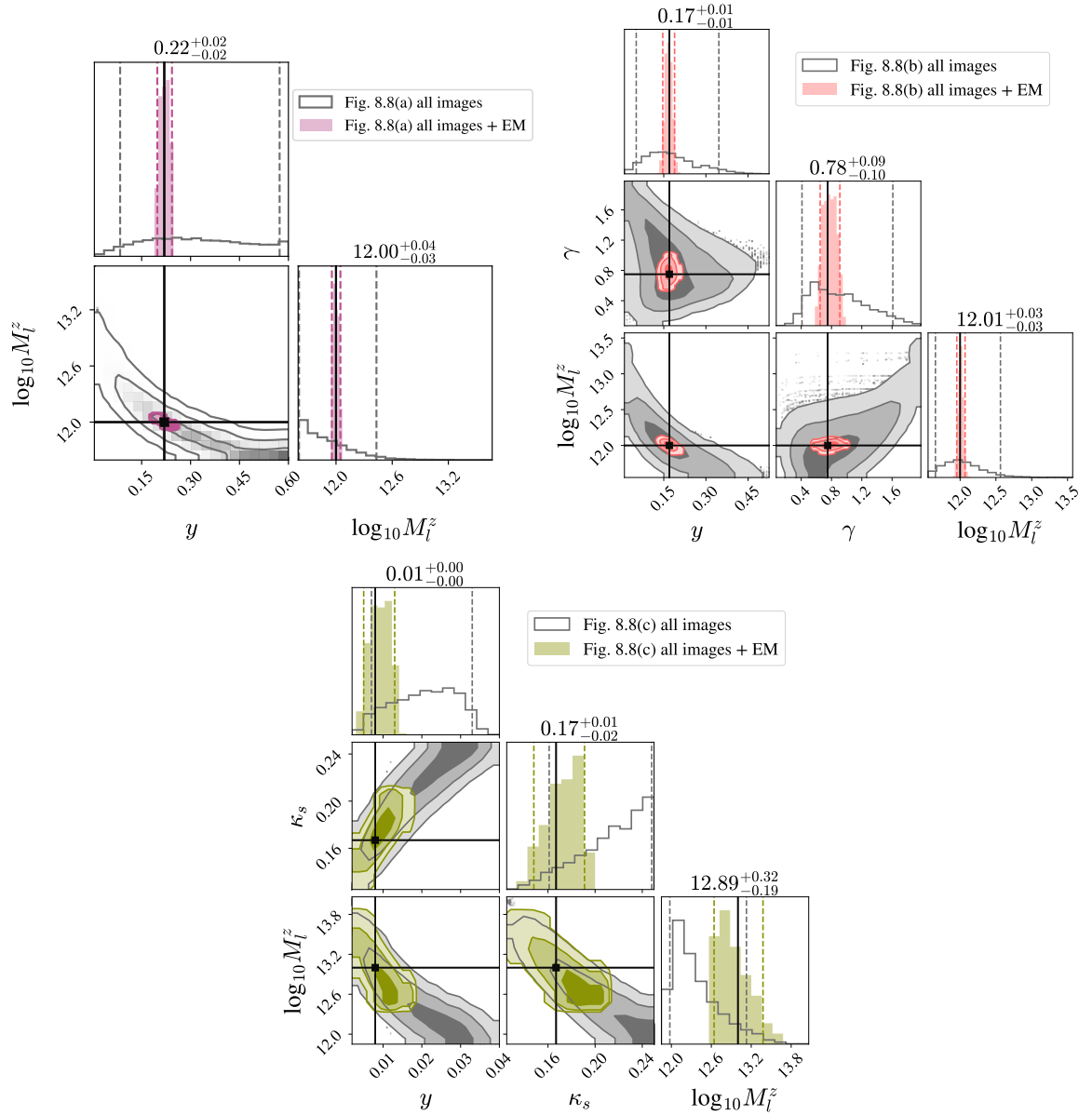


Figure 8.9: Same configurations as in Figure 8.8, but with the assumption that quadruple (quintuple) image systems are detected with the additional EM observations and thereby, axis ratios and image positions are confined with $\pm 5\%$ and $0.1''$ error ranges.

In particular, [310] argue that the detection of quadruple GW images can significantly reduce the sky localisation area with current LIGO–Virgo detectors. Furthermore, as shown in Figure 8.8, the axis ratio of a lens galaxy can be more precisely constrained when four or more GW images are identified, providing a critical starting point for identifying the lens galaxy in EM surveys.

To quantify the impact of multi-messenger constraints, we consider a scenario in which the lens galaxy has been successfully identified. Motivated by typical observational uncertainties, we assume that the axis ratio and EM image positions are constrained to within $\pm 5\%$ and 0.1 arcseconds, respectively. Figure 8.9 shows the recovered posteriors for θ_l and M_l^z for the non-axially symmetric lens systems under these assumptions. All θ_l posteriors

$P_{\text{dbl}}(\theta_l)$ vs $P_{\text{all}}(\theta_l)$ in Figure 8.8

Model	$\mathcal{R}_{\text{dbl/all}}^q$	$\mathcal{R}_{\text{dbl/all}}^y$	$\mathcal{R}_{\text{dbl/all}}^{\log_{10} M_l^z}$	$\mathcal{R}_{\text{dbl/all}}^\gamma$	$\mathcal{R}_{\text{dbl/all}}^{\kappa_s}$
SIE	1.03	1.01	0.97	-	-
SPEMD	1.55	1.33	1.22	1.11	-
PNFW	1.89	1.36	1.30	-	1.06

 $P_{\text{all}}(\theta_l)$ vs $P_{\text{all+EM}}(\theta_l)$ in Figure 8.9

Model	$\mathcal{R}_{\text{all/all+EM}}^y$	$\mathcal{R}_{\text{all/all+EM}}^{\log_{10} M_l^z}$	$\mathcal{R}_{\text{all/all+EM}}^\gamma$	$\mathcal{R}_{\text{all/all+EM}}^{\kappa_s}$
SIE	9.87	8.17	-	-
SPEMD	6.94	7.90	4.21	-
PNFW	3.07	1.51	-	1.85

Table 8.5: Quantitative evaluation of the improvement in lens parameter recovery from additional constraints, such as multiple GW images and indicative EM observations.

become significantly tighter and peak near the injected values. We quantify this improvement in Table 8.5 using the ratio $\mathcal{R}_{\text{all/all+EM}}^{\theta_l}$, defined as the relative width of the 90 % C.I of the *all-GW images* to the *all-GW + EM* scenarios. Most importantly, M_l^z is recovered with high precision. By combining the inferred M_l^z with the lens redshift z_l obtained from EM spectroscopy, the intrinsic lens mass M_l can be determined, completing the reconstruction of the lensing system.

8.3 Conclusion

In this chapter, we first demonstrate the delensing process through analytic lens reconstruction. Our proof-of-concept study shows that we can retrieve the true luminosity distance with significantly improved precision by detecting SLGWs from a single BBH. Even in the presence of simulated detector noise, an optimal strong-lensing configuration enhances the distance constraint by a factor of several relative to the unlensed case. Although the initial demonstration is restricted to simple PM and SIS models with double images, more complex lens models, such as those introduced in Section 8.2.4, can yield higher magnifications and increased image multiplicity, further improving the precision of luminosity distance estimates.

As the lens models become more complex, the reconstruction procedure becomes increasingly challenging. An inference framework based on rejection sampling is implemented to address this challenge, further demonstrating that the precision of lens reconstruction is significantly improved when joint GW and EM observations are available. In addition to the geometric information provided by EM imaging, spectroscopic measurements of both the lens galaxy and the lensed host galaxy enable precise redshift measurement, supplying an additional and critical constraint on the lensing configuration, such as the Einstein radius.

Successful lens reconstruction directly enables more precise and accurate luminosity distance estimates, providing critical input for studies of the formation and evolution of compact binary populations. Furthermore, these improved distance measurements offer a powerful avenue for constraining the Hubble constant through the Hubble–Lemaître law discussed in Section 3.1.3. By mitigating the intrinsic uncertainties in standard GW distance inference, SLGWs may play a key role in resolving the current Hubble tension in the coming decades.

However, real-world detection scenarios are expected to be significantly more challenging, and several key issues remain to be addressed. We highlight three primary directions for future investigation.

First, observational completeness. In practice, only a subset of the full image ensemble may be detected (e.g., two images from a quadruple-image SIE system), either because additional images have not yet arrived due to long time delays or because their SNRs fall below the detection threshold. A natural extension is to incorporate rejection sampling to compare different image-multiplicity scenarios and identify the statistically preferred configuration.

Second, model selection and hypothesis testing. Because the lens density profile is not known a priori, rejection sampling should be embedded within a JPE framework to enable rigorous hypothesis testing. Such an approach can not only identify the most probable lens model but also improve search pipelines by reducing FAR, as suggested by [382, 383].

Finally, complex lensing environments (macro–micro lensing). As discussed in Chapter 7, galactic substructures, such as star clusters and DM subhalos, can induce additional microlensing effects on top of the macrolensing signal. Neglecting these contributions may bias lens parameter estimates. Developing parameter estimation frameworks that incorporate the associated wave-optics effects remains an important goal for future work, particularly in the context of space-based interferometers, where higher SNR and improved sky localisation will help disentangle these complex degeneracies [384, 385, 386].

Chapter 9

The Impact of Strong Lensing on H_0 Measurements with Gravitational-Wave Dark Sirens

Disclaimer

The following chapter is based on the paper *The Impact of Strong Lensing on Hubble Constant Measurements with Gravitational-Wave Dark Sirens* [387]. The author was the first author and contributed to every stage of this work, including mathematical derivations, framework development, data generation and analysis, interpretation of the results, scientific discussion, figure production, and manuscript preparation. This paper was published in the *Astrophysical Journal Supplement Series*.

As discussed in Section 3.1.4, the precise value of H_0 remains under debate due to the Hubble tension, between early-Universe measurements inferred from the cosmic microwave background [175], which report $H_0 = 67.4 \pm 0.5 \text{ km s}^{-1} \text{ Mpc}^{-1}$, and late-Universe measurements based on the Cepheid-supernova distance ladder [181], which find $H_0 = 72.3 \pm 1.4 \text{ km s}^{-1} \text{ Mpc}^{-1}$. This discrepancy has motivated growing interest in independent approaches to measuring H_0 . In this context, as introduced in Section 3.2, GW standard sirens provide a promising alternative, particularly given the rapid expansion of GW astronomy over the past decade, with more than 200 CBCs detected by the LVK network [20].

In this chapter, we focus on the galaxy-catalogue-based dark siren method [219, 220], in which each GW event is statistically associated with multiple candidate host galaxies within its sky localisation volume. By weighting these galaxies according to their spatial probabilities and luminosities, one can construct a probabilistic redshift distribution for the GW source and subsequently perform hierarchical inference of H_0 . For the galaxy-catalogue-based method, improving constraints on H_0 primarily depends on two factors: accurate sky localisation to reduce the number of potential host galaxies, and precise measurements of the luminosity distance. In this context, we consider SLGW events, which, as demonstrated in Section 8.1, are expected to yield improved luminosity-distance precision.

In addition, SLGWs can provide more informative constraints than unlensed events for sky localisation [310, 388], both of which are essential for robust host-galaxy identification in the dark-siren framework. Furthermore, the additional lensing information encoded in these systems can provide complementary cosmological constraints on H_0 .

Although no unambiguous detection of SLGWs has yet been reported in the latest GWTC catalogue [238], the LVK detector network is expected to observe GW strong lensing at a rate of $\mathcal{O}(1) \text{ Gpc}^{-3}, \text{ yr}^{-1}$ at design sensitivity [158, 159, 160, 326, 341, 359, 389]. Such systems are expected to provide cosmological information analogous to that obtained from time-delay measurements of strongly lensed quasars [111, 390, 391]. As the number of detected SLGWs increases in future LVK observing runs [102, 326] and with next-generation observatories such as the Einstein Telescope [200, 392, 393], joint analyses incorporating both source and lens population models will become increasingly important. At the same time, unlensed dark sirens should not be excluded from analyses, as combining lensed and unlensed GW events within a unified hierarchical framework can substantially improve the precision and robustness of the inferred H_0 . In this regard, tools such as `gwcosmo` [219, 220, 394] provide a flexible Bayesian framework for incorporating population information and jointly inferring cosmological parameters from both lensed and unlensed GW events.

In this chapter, we investigate the impact of SLGWs on H_0 inference, highlighting how lensing information can strengthen cosmological constraints relative to conventional unlensed dark sirens. Two observational scenarios are considered. In the first scenario, multiple lensed signals originating from a single dark siren event are detected. Once the host galaxy is uniquely identified through lensing observables and cross-correlation with galaxy catalogues, the Hubble–Lemaître law (Eq. (3.33)) can be directly used to infer H_0 . In the second scenario, a population of lensed dark siren sources is detected, requiring a hierarchical framework that consistently combines all events. This framework incorporates comparisons with galaxy-galaxy lensing catalogues to construct more informative redshift maps and thereby improve the precision of the inferred H_0 . We additionally quantify potential systematic biases in H_0 inference arising from neglected or incorrectly modelled lensing effects. Throughout this chapter, we assume a fiducial flat Λ CDM cosmology with $\Omega_m = 0.25$, $\Omega_b = 0.044$, $\Omega_\Lambda = 0.7$, and $H_0 = 70 \text{ km}, \text{ s}^{-1}, \text{ Mpc}^{-1}$.

9.1 Mock Data

9.1.1 Galaxy catalogue

We adopt the MICE-Grand Challenge light-cone halo and galaxy catalogue (MICECATv2) [395, 396, 397, 398, 399] for our galaxy distribution, while separately investigating how catalogue incompleteness affects the inference of H_0 . The simulation volume covers approximately 5000 deg^2 of the sky over a redshift range of $0.07 < z < 1.42$. The catalogue provides abso-

lute and apparent magnitudes across multiple photometric bands, alongside both true and observer-frame redshifts. We specifically select the r -band for our analysis, as MICECATv2 is calibrated using the r -band Schechter function from [400], with galaxy evolution models applied at higher redshifts [401]. Although completeness estimates were originally derived using i -band data, we use the r -band data to ensure a direct and consistent application of the Schechter parameters for incompleteness corrections. Here, completeness is defined as the fraction of observable galaxies successfully included in the catalogue.

To maintain computational efficiency within `gwcsmo`, we utilise a randomly selected one-eighth subset of the full MICECATv2 catalogue, comprising approximately 6.2×10^7 galaxies¹. We select galaxies with r -band absolute magnitudes $M_r < -20$ and assume this subset is 100 % complete down to an r -band apparent magnitude $m_r < 24$ at $z = 1.42$ [401]. The absolute-magnitude cut is imposed to achieve an approximately uniform number density in comoving volume, thereby constructing a volume-limited sample. This selection prevents an overabundance of faint, low-redshift galaxies while avoiding a significant bias toward only the brightest sources. We exclude galaxy clusters to focus exclusively on galaxy-galaxy strong lensing. Hereafter, this complete catalogue is referred to as the *Unlensed Galaxy catalogue* (UGC0).

Within the landscape of galaxy surveys, certain catalogues focus exclusively on lensed systems; for example, the SLACS survey [402, 403] targets confirmed strong-lensing systems. Complementary efforts have produced dedicated catalogues of strong gravitational lenses, such as `lenscat` [404], which facilitate the identification of host galaxies associated with lensed transient events. In this context, we simulate a catalogue of lensed galaxies derived from UGC0. Compared to the unlensed case, a lensed galaxy catalogue contains significantly fewer potential host-galaxy candidates per unit sky area within a given GW localisation region. This sparsity effectively mitigates source-identification uncertainty in the statistical H_0 inference performed with `gwcsmo`. To simulate lensing systems, we assume that all galaxies in our mock catalogue follow SIE density profiles described in Section 2.2.4.

Since MICECATv2 does not directly provide the SIE lens parameters, we model their underlying distributions. We adopt the functional forms described in [359]; however, rather than fixing the galaxy number density at a specific redshift within the Schechter function, we compute it independently at each redshift using the MICECATv2 data and sample velocity dispersion σ_v accordingly. For the shape parameters, we assume a uniform distribution for the orientation angle ϕ_e and a Rayleigh distribution for the axis ratio q , extending the lower limit to $q_{\min} = 0.1$ to include highly elliptical galaxies.

1. The resulting number density is 0.00146 Mpc^{-3} (reduced from the original 0.0117 Mpc^{-3}), which more closely approximates the number densities of observational catalogues like GLADE+ [214] used in dark siren GW cosmology.

The number of strongly lensed galaxies, N_{Lgal} , in a given catalogue is determined by the optical depth, τ_{gal} , as follows:

$$\begin{aligned} N_{\text{Lgal}} &= N_{\text{gal}} \times \tau_{\text{gal}} \\ &= N_{\text{gal}} \times \sum_i^{N_{\text{gal}}} \int \tau(z_i) P(z_i) dz_i, \end{aligned} \quad (9.1)$$

where $\tau(z_i)$ is the optical depth for the i^{th} galaxy at redshift z_i , and $P(z_i)$ represents the probability that a galaxy from the catalogue resides at redshift z_i . Thus, τ_{gal} corresponds to the combined optical depth across the entire galaxy population in the given universe (see Eq. (2.31)).

Since we adopt an SIE lens model, only two or four images of a source galaxy can be produced. The resulting lensed galaxy catalogue contains $\sim 4.6 \times 10^4$ double-image systems and $\sim 1.0 \times 10^4$ quadruple-image systems. Hereafter, this complete lensed galaxy catalogue, comprising all double- and quadruple-image systems generated from the UGC0, is referred to as the *Lensed Galaxy catalogue* (LGC0). Figure 9.1 shows the redshift distribution of galaxies in the UGC0 alongside the distributions of double- and quadruple-image systems in the LGC0. As expected, the distribution of lensed galaxies peaks at higher redshifts, as galaxies at higher redshift have a higher probability of encountering a foreground lens.

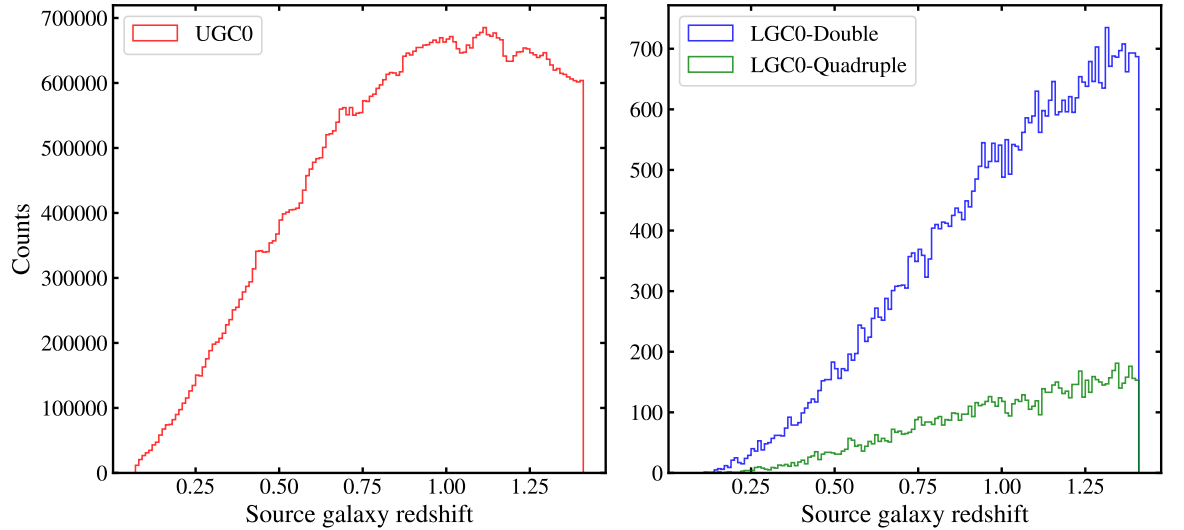


Figure 9.1: The redshift distributions of galaxies in the unlensed catalogue (UGC0; red), and of background galaxies in double-image (blue) and quadruple-image (green) systems in the lensed catalogue (LGC0).

In practice, observational galaxy catalogues are incomplete and do not capture every potential host galaxy of a GW source. This incompleteness must be accounted for when inferring H_0 using dark sirens and galaxy catalogues. To mimic these observational limitations, we impose an apparent magnitude cut of $m_{\text{th}} = 21.87$, removing galaxies fainter than this threshold from both the UGC0 and LGC0. The resulting incomplete catalogues are hereafter referred to as UGC1 and LGC1, respectively; their application in the H_0 measurement will be discussed in Section 9.3.

9.1.2 Dark Sirens

For our dark-siren simulations, we adopt the parametric models of BBH populations described in Section 4.4.2, along with the source parameter ranges and hyperparameters inferred from the GWTC-3 analysis [293]. We assume a fixed observation time of $T_{\text{obs}} = 2.26\text{yrs}$, corresponding to the duration of the O4 observing run. For the remaining BBH parameters, including spins, we assume uniform distributions.

Each simulated BBH is assigned to a host galaxy in the UGC0 catalogue following a physically motivated weighting scheme. A galaxy's probability of hosting a BBH depends on its SFR, stellar mass, metallicity, and the delay time between binary formation and merger [405, 406]. While explicitly incorporating all these factors can improve H_0 convergence by accurately reflecting the true host distribution, inaccurate or oversimplified prescriptions risk introducing systematic biases into the H_0 posterior [407, 408]. In this study, rather than modelling the full complexity of host-galaxy properties, we adopt a luminosity-based weighting scheme as a practical approximation, assigning higher hosting probabilities to more luminous galaxies. Unlensed GW signals are generated using the IMRPHENOMXPHM-SPINTAYLOR waveform model [288, 289] and injected into a detector network consisting of aLIGO–Livingston, aLIGO–Hanford, and AdV at their expected O4 sensitivities [365]. We consider only those signals detected in all three detectors with a network SNR above 8 ($\rho_{\text{net}} > 8$).

In addition to the unlensed GW signals, SLGW signals are generated by applying the lensing effects of galaxies in the LGC0 to the previously simulated unlensed signals using the amplification factors (see Eq. (2.74)). To determine the number of lensed GW signals (N_{lgw}), we follow a procedure analogous to that used in constructing the LGC0: the optical depth for BBHs is computed based on the galaxies in the UGC0, such that:

$$N_{\text{lgw}} = N_{\text{gw}} \times \tau_{\text{BBH}}. \quad (9.2)$$

Note that τ_{BBH} is the combined optical depth for the entire BBH population, computed using the complete unlensed catalogue, UGC0.

In practice, it is computationally prohibitive to calculate the dimensionless impact parameters (y) for every potential galaxy-galaxy pair while accounting for sky positions and angular diameter distances between the source, lens, and observer. Therefore, we randomly select N_{lgw} source-lens pairs from the LGC0, where each source galaxy is assumed to host a BBH that is strongly lensed by its associated foreground lens galaxy. Consequently, y values that ensure strong lensing are assigned, which are drawn from a uniform distribution over the range $y \in [0.01, 1.2]$. The upper bound of 1.2 corresponds to the maximum for which strong lensing can occur within the axis-ratio range adopted for our SIE model. Table 9.1 summarises the assumed distributions for the representative source and lens parameters.

Parameter	Distribution model	Range
m_1	Power Law + Peak	$[5, 112]M_{\odot}$
m_2	Truncated Power Law	$[5, m_1]M_{\odot}$
q	Rayleigh	$[0.1, 1.0]$
σ_v	Schechter	$[50, 500]\text{km/s}$
y	Uniform	$[0.01, 1.2]$

Table 9.1: Assumed probability distributions for component masses (m_1, m_2) of the source of dark sirens and the main lens parameters, including the axis-ratio (q) and the velocity dispersion (σ_v), and dimensionless impact parameter (y), employed in simulating strongly lensed GW signals.

Among the simulated SLGW signals, only those with $\rho_{\text{net}} > 8$, evaluated using the same detector configuration as in the unlensed case, are considered detected². In a realistic scenario, it is not immediately known whether a detected signal is lensed. Candidate lensed pairs (or higher-order multiplets) must first be identified by low-latency search pipelines. For instance, posterior-overlap tests identify events with mutually consistent intrinsic parameters—such as component masses and spins—and overlapping sky localisations, while accounting for differences in arrival times and strain amplitudes [299]. For high-ranking candidates, JPE is subsequently performed. During this step, as discussed in Section 5.2.1, the lensing evidence is computed by jointly analysing the data segments under the lensing hypothesis, thereby assessing whether the candidate multiplet is coherently described as multiple lensed signals of the same GW source. In this work, the true associations between lensed signals are known by construction, allowing us to perform the JPE directly on the correct signal sets. Only those systems for which the lensing hypothesis is statistically supported by the JPE analysis are retained for the subsequent cosmological inference.

2. In actual observations, thresholds for the astrophysical probability (p_{astro}) and FAR are applied to ensure signals are of astrophysical origin. For this study, we assume all signals satisfying the SNR threshold also meet these criteria.

9.2 H_0 Measurement with a Strongly Lensed Dark Siren

Assuming the detection of a lensed dark siren, significantly improved sky localisation can be achieved relative to the unlensed case [310, 388], along with more precise measurements of the luminosity distance (d_L) [373], as described in Chapters 3 and 8. Within this more tightly constrained sky area, candidate lens galaxies and host galaxies can be identified, enabling the use of the host redshift in combination with the improved luminosity distance to infer H_0 with higher precision. However, the detectability of the lensing system remains dependent on the lens mass, luminosity, and redshift.

9.2.1 Method

If a source-lens system can be uniquely specified, the redshift of the source galaxy (z_s) can be obtained via EM observations, either through photometric or spectroscopic methods. The obtained z_s can then be used to apply the Hubble-Lemaître law ($H_0 = v_r/d_p$), where

$$v_r(z) = \int_0^z \frac{c \, dz'}{\sqrt{\Omega_m(1+z')^3 + \Omega_\Lambda}} \quad (9.3)$$

is the recessional velocity of the source galaxy, and d_p is its proper distance from the observer. In a flat- Λ CDM universe, where the scale factor at $z = 0$ is set to $a_0 = 1$, the proper distance is equivalent to the comoving distance to the source galaxy ($d_C = d_L/(1+z_s)$). In this study, we ignore the peculiar velocity of the source galaxy. This assumption can introduce biases in H_0 measurement using bright sirens, such as binary-neutron stars, but it is reasonable for dark-siren analyses, where host galaxies are typically not located in the nearby Universe ($d_L < 200$ Mpc) [228, 229].

Since the redshift of a galaxy cannot be determined perfectly, we assign uncertainties such that the measured redshift follows a Gaussian distribution, where the standard deviation is σ_z . For the photometric and spectroscopic methods, we adopt $\sigma_z = 0.033(1+z_s)$ and $\sigma_z = 0.001(1+z_s)$, respectively [409]. Using these estimated redshift distributions, the recessional velocity of the source can be determined, and the measured luminosity distance can be converted into the corresponding comoving distance. Note that the measured luminosity distance from the j^{th} lensed signal is not the true distance to the source, but is rescaled by the lensing magnification factor, as described in Eq. (2.75). Recovering the true distance, therefore, requires delensing, which involves estimating the individual magnification factors μ_j from lens reconstruction.

From the lens-model-independent JPE for the lensed signals described in Section 5.2.1, one can obtain not only source parameters, but also lensing observables for each pair of signals. For a double-image system, this corresponds to a single triplet, $(\mu_{\text{rel},12}, \Delta t_{12}, \Delta \phi_{n,12})$. For a quadruple-image system, three such triplets are theoretically available, $(\mu_{\text{rel},1j}, \Delta t_{1j}, \Delta \phi_{n,1j})$

with $j = 2, 3, 4$, although fewer triplets may be obtained if some images are missing or undetectable. These lensing observables can then be converted into model-dependent lens parameters either analytically [410] or numerically using a rejection-sampling framework introduced in Section 8.2.

Once the lens parameters are constrained, one can further utilise shape parameters from EM observations, such as the axis ratio (q) and elliptical angle (ϕ_e) of the lens galaxies, as well as the inferred redshifted lens mass, to aid in uniquely identifying the source-lens system within the sky localisation. This approach relies on the assumption that both the lens galaxy and the lensed source images are included in the catalogue. Therefore, we use LGC0 for this case. When accounting for catalogue incompleteness by imposing m_{th} , both the lens galaxy and the lensed source galaxy images must be contained within LGC1.

With the lens parameters determined, we can reconstruct the lens galaxy under a given lens model to obtain individual magnification factors, which are used to delens the apparent luminosity distance and retrieve the true distance to the source. However, it is important to note that the rejection-sampling approach does not always yield accurate lens reconstructions, owing to degeneracies between lensing observables and the underlying lens properties, as well as from the limited availability of EM information due to survey magnitude limits. This issue will be addressed in Section 9.4.1.

9.2.2 Results

Among the simulated double- and quadruple-image systems, we present four representative detected cases. For each system type, we identify: (1) the system with the highest mean SNR (ρ_{mean}), defined as the average network SNR of its lensed signals, and (2) the system with the lowest ρ_{mean} .

For a given detector network and comparable ρ_{mean} , the sky localisation of a double-image system is more precise than that of an unlensed event. A quadruple-image system yields further improvement since more independent measurements of the same event are available. Figure 9.2 displays the skymap posteriors for the four representative systems. When cross-referencing these localisations with the complete lensed galaxy catalogue (LGC0), the inferred 90 % credible sky areas ($\Delta\Omega_{90\%}$) contain $\mathcal{O}(1)$ and $\mathcal{O}(2-3)$ galaxies with properties compatible with the GW observables for the double- and quadruple-image cases, respectively. The exact counts of identified galaxies for each system are summarised in Table 9.2.

To further constrain the potential lensing candidates, we utilise lensing observables, specifically the relative magnification factors and the time delays between images. Since these quantities can be directly obtained from the lensed galaxy catalogue, we can compare the EM-derived properties of a candidate source-lens system with the parameters inferred from the lensed GW signals.

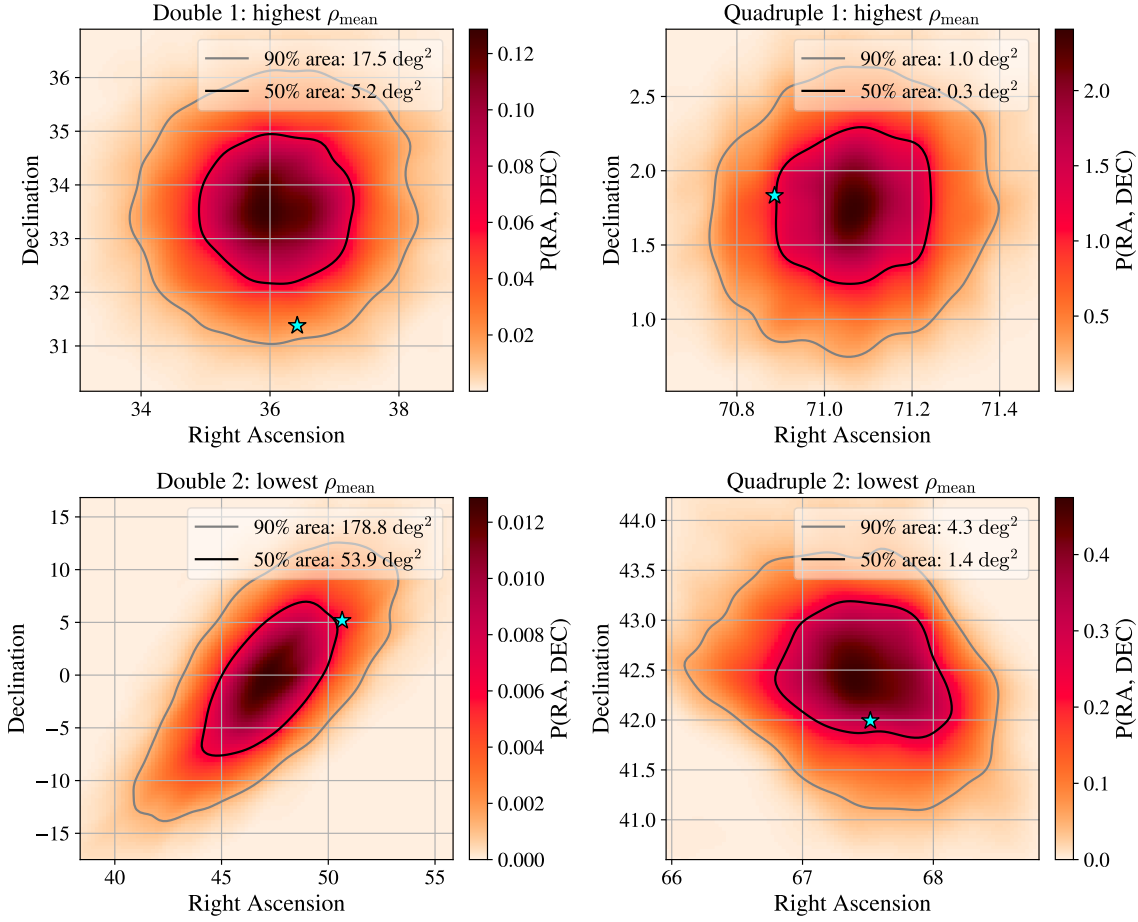


Figure 9.2: Sky localisation maps for the selected double- and quadruple-image systems. The star symbols mark the true sky positions of the corresponding GW lensing systems.

As shown in Figure 9.3, for the double-image systems in the LGC0, the number of candidates consistent with the inferred lensing observables is reduced to a few. For GW signals, the time delay is measured with high precision, providing a significantly more stringent constraint than the relative magnification factors, which are inferred from the less precise luminosity distances. In practice, uniquely identifying the source-lens pair in a double-image configuration, a prerequisite for measuring the source-galaxy redshift, remains challenging. Such identification is typically feasible only for high-SNR events that

Table 9.2: The mean SNR values (ρ_{mean}), 90 % credible sky area ($\Delta\Omega_{90\%}$), numbers of galaxies within these area ($N_{\text{G-G}}$), and reduced numbers of galaxies whose properties are consistent with those inferred from the lensed GW signals for each system ($N'_{\text{G-G}}$).

System	ρ_{mean}	$\Delta\Omega_{90\%}[\text{deg}^2]$	$N_{\text{G-G}}$	$N'_{\text{G-G}}$
DOUBLE 1	22	17.5	306	5
DOUBLE 2	8.1	178.8	1971	1
QUADRUPLE 1	30.0	0.97	1	1
QUADRUPLE 2	9.0	4.35	13	1

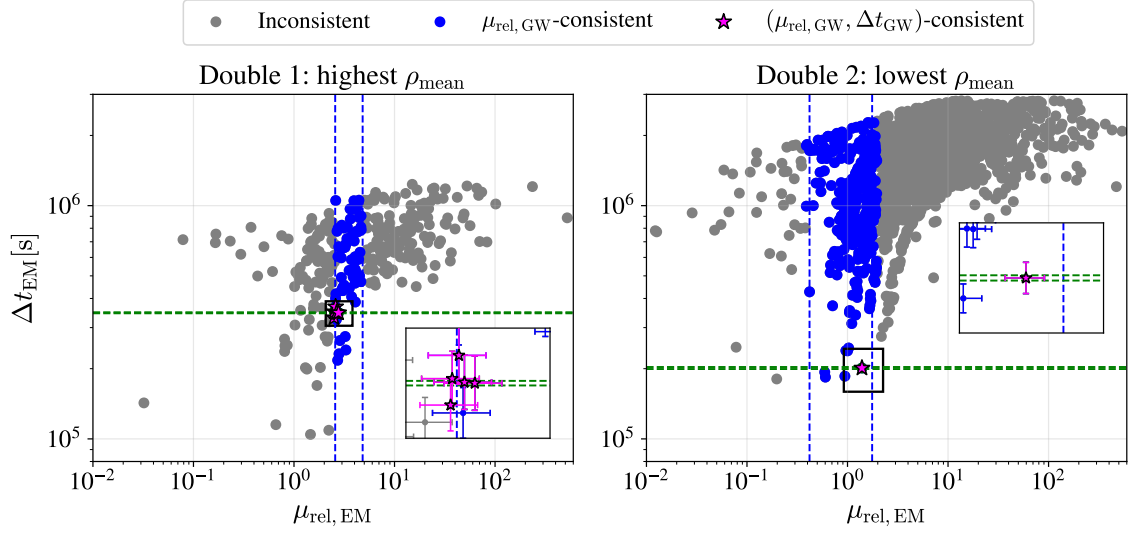


Figure 9.3: Distributions of the median relative magnification factors and time delays obtained from EM observations for the source–lens galaxy systems within the localised sky area of each double-image case. In the inner box, the error bars of $\mu_{\text{rel, EM}}$ and Δt_{EM} are shown.

yield exceptionally tight sky localisations (e.g., $\Delta\Omega_{90\%} \lesssim 20 \text{ deg}^2$) [310, 380]. In contrast, quadruple-image systems provide much tighter constraints. The additional images allow for the unique identification of the source-lens system among only a handful of candidates, as shown in Table 9.2.

Despite the inherent difficulties in double-image cases, we proceed under the assumption that the source-lens pair can be uniquely identified for each system. Once the lensing systems are correctly identified, as discussed in Section 8.2.5, we can further exploit the observed image positions of the lensed source galaxy and the shape parameters of the lens galaxy to more tightly constrain the remaining lens parameters, especially the impact parameter y . This enables a more accurate determination of the individual magnification factors³. Following [311], we assume that the shape parameters (q, ϕ_e) can be determined from EM observations with an uncertainty of $\pm 5\%$, and that image positions can be measured with a precision of $0.1''$.

The inferred individual magnification factors are presented in Figure 9.4. These distributions are utilised to retrieve the true luminosity distances from the previously obtained apparent distances following Eq. (2.75). Specifically, we perform a stochastic delensing procedure by drawing random samples from the posterior distribution of the magnification factor and multiplying them by samples drawn from the apparent-distance posterior. This yields a corresponding posterior realisation of the true luminosity distance. As expected,

3. In general, a galaxy, as an extended source, does not share the same source-plane position y as the point-like GW event embedded within it (i.e., $y_{\text{gal}} \neq y_{\text{gw}}$). Since the magnification factor is highly sensitive to y , it is essential to utilise y_{gw} rather than y_{gal} for cosmological inference.

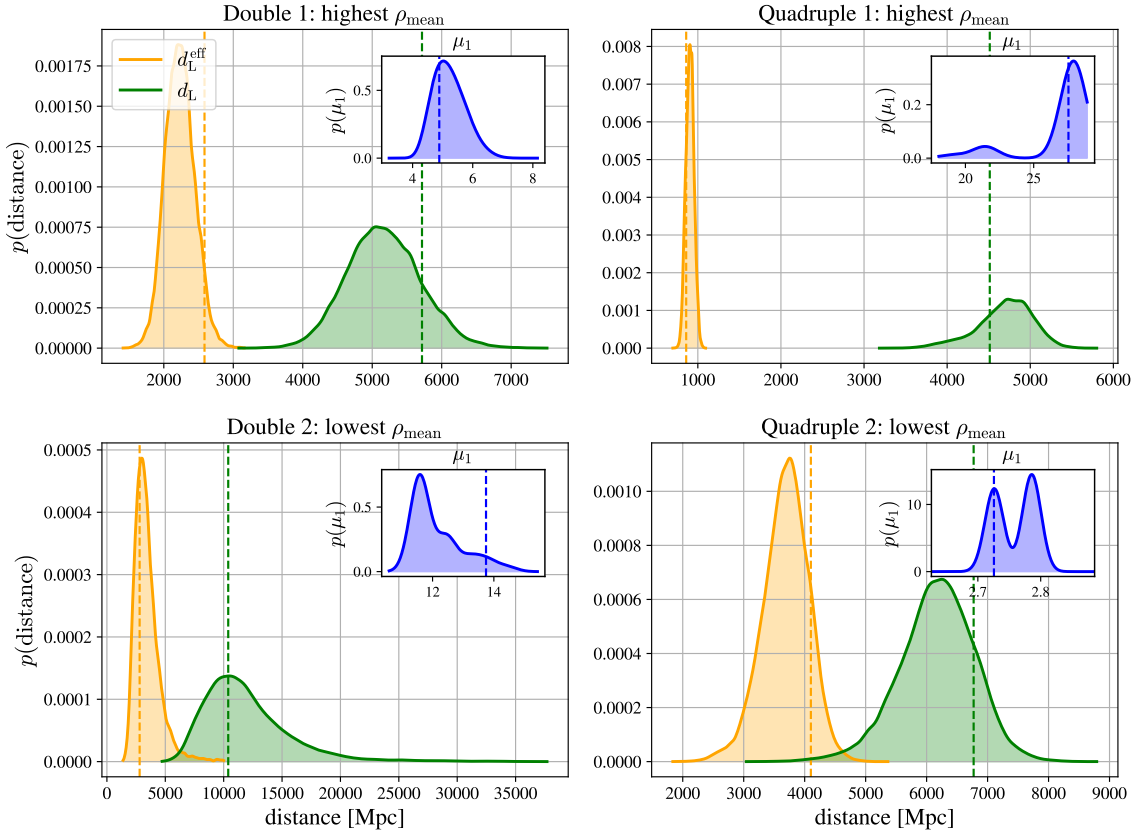


Figure 9.4: Posteriors of the apparent (orange) and retrieved true (green) luminosity distances for each case, along with the recovered magnification factor (blue), μ_1 , for the first-arriving lensed GW signal obtained via rejection sampling.

lens reconstruction, the inference of individual magnification factors, is less accurate for double-image systems, where only two observables (μ_{rel} and Δt) are available. In contrast, quadruple-image systems provide much higher accuracy due to the four additional constraints provided by the extra images.

Using the recovered true luminosity distances along with the photometric or spectroscopic redshifts of the identified host galaxies in the lensing systems, we compute the corresponding comoving distances and recessional velocities. The Hubble–Lemaître law is then applied to derive H_0 . Figure 9.5 shows the H_0 posteriors obtained for the four representative cases. The 90 % C.I. for the quadruple-image systems, when combined with spectroscopic redshifts, are significantly narrower than those in the other cases.

To quantify the degree of constraint on the H_0 posteriors, we define the relative uncertainty, δ_{H_0} , as:

$$\delta_{H_0} \equiv \frac{90\% \text{ C.I.}}{H_{0,\text{med}}}, \quad (9.4)$$

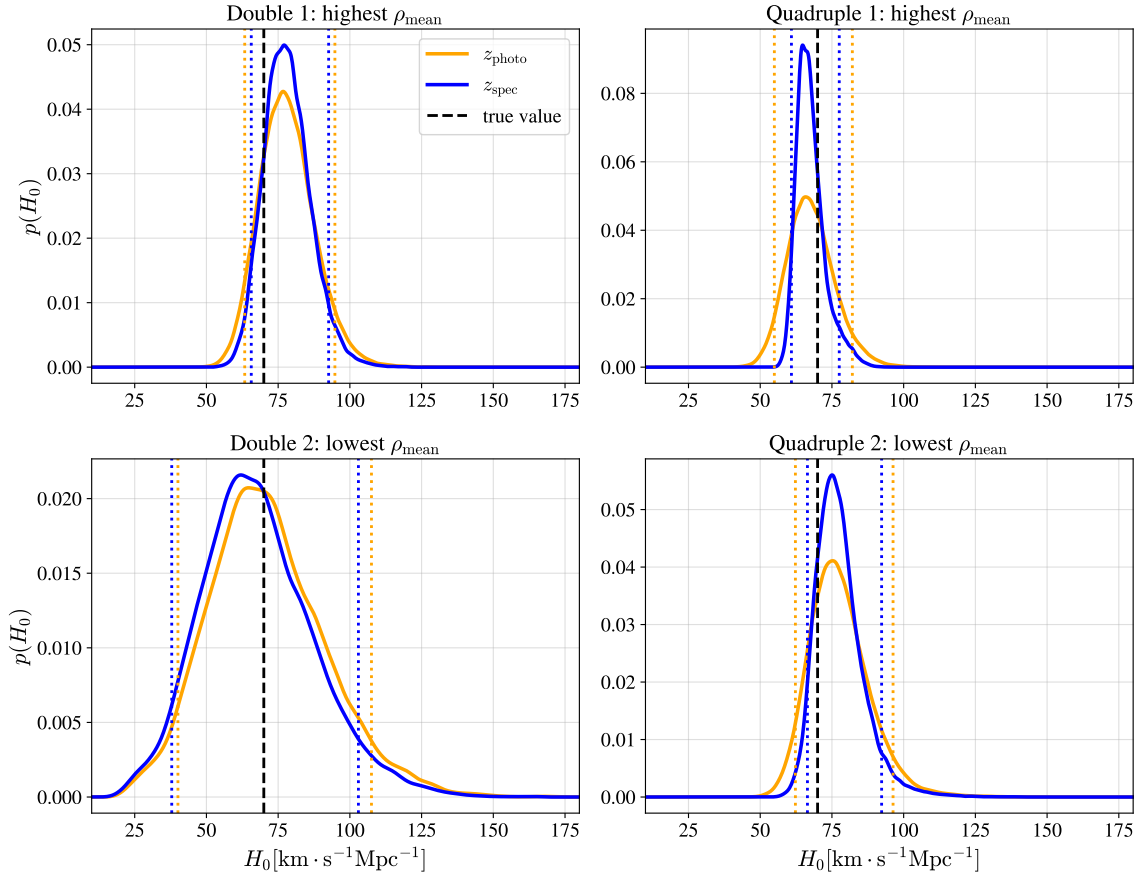


Figure 9.5: The posteriors of the Hubble constant for the four representative lensing systems.

where $H_{0,\text{med}}$ denotes the median of the posterior. Normalising the C.I. by the median, rather than the mean, which is inherently more sensitive to skewed or long-tailed distributions, provides a dimensionless measure of the fractional uncertainty, analogous to the coefficient of variation. A lower δ_{H_0} value thus indicates a more tightly constrained posterior.

For each representative system, the estimated H_0 with its 90 % C.I. and the corresponding δ_{H_0} are summarised in Table 9.3. Among systems with the same number of lensed images, a higher ρ_{mean} leads to tighter H_0 posteriors and, consequently, a lower δ_{H_0} , as expected, since higher-SNR events yield narrower posteriors for the inferred luminosity distance. Furthermore, at a comparable SNR, quadruple-image systems yield narrower posteriors than double-image systems, resulting in systematically lower δ_{H_0} values. This improvement arises because the four lensed signals provide more independent constraints, enhancing the precision of the delensed luminosity distance.

The low SNR of lensed GW signals contributes significantly to the large uncertainties, as the inferred apparent luminosity distances are often poorly constrained. However, for sources located at high redshift, the uncertainty can remain substantial regardless of the SNR. Such high- z detections generally fall into two representative cases: (1) light BBH events that become observable only through significant magnification, and (2) intrinsic-

Table 9.3: Relative uncertainties and the corresponding Hubble constant posteriors, along with their 90 % C.I., inferred using spectroscopic redshifts for the double- and quadruple-image lensing systems.

System	H_0 [$\text{km} \cdot \text{s}^{-1} \cdot \text{Mpc}^{-1}$]	δ_{H_0}
DOUBLE 1	$77.7^{+14.6}_{-11.8}$	0.34
DOUBLE 2	$67.4^{+48.4}_{-33.6}$	1.22
QUADRUPLE 1	$66.3^{+7.2}_{-5.7}$	0.19
QUADRUPLE 2	$76.5^{+16.3}_{-10.0}$	0.34

ally heavy BBH events that require only moderate magnification to exceed the detection threshold. In the first case, the apparent luminosity distances may be relatively well-constrained initially; however, after the delensing procedure is applied to recover the true distances, the variance increases in proportion to the magnification factor. In the second case, the apparent distances are inherently broad, as the luminosity distance-redshift relation flattens at high z , leading to increased uncertainty in the inferred distances. In both scenarios, the resulting H_0 posteriors are expected to be poorly constrained.

Figure 9.6 shows how δ_{H_0} varies across the $\rho_{\text{mean}}-z_s$ plane for all detected lensed signals. For both doubly and quadruply lensed systems, δ_{H_0} increases towards lower ρ_{mean} and higher z_s . At high redshifts, double-image systems generally exhibit uniformly higher δ_{H_0} values. In contrast, for quadruple-image systems, the uncertainty is dominated by low ρ_{mean} rather than high z_s . This indicates that detecting quadruple-image systems is particularly beneficial for constraining H_0 from distant sources, as the additional image constraints help mitigate the uncertainties inherent to high- z observations.

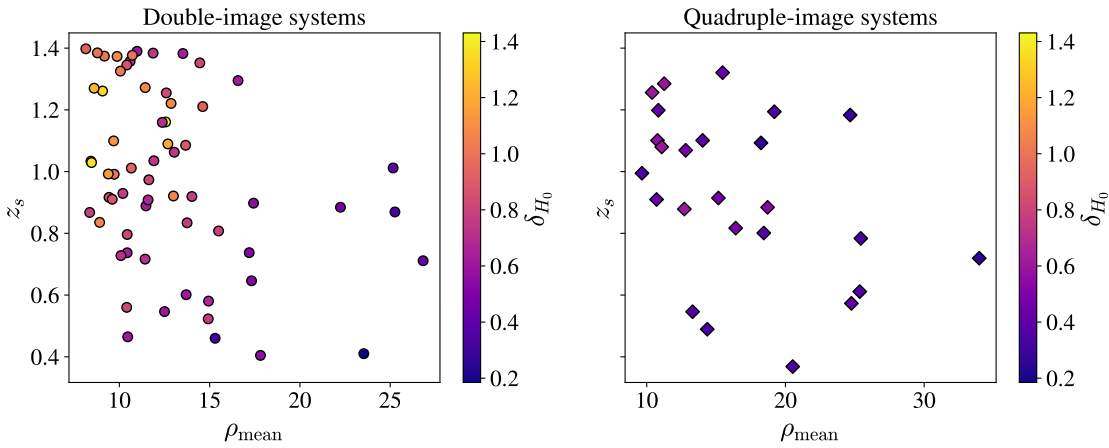


Figure 9.6: Scatter plots showing the distributions of ρ_{mean} and z_s for all detected doubly- (circle markers) and quadruply-lensed (diamond markers) GW systems in our sample pool, colour-coded by δ_{H_0} .

Beyond statistical uncertainties related to detector sensitivity, inaccurate delensing can introduce additional errors even when the apparent luminosity distance is well constrained, and the source lies in a relatively low- z universe. Such errors may arise during the rejection sampling process due to degeneracies between lensing observables and the underlying lens parameters. If the individual magnification factors obtained through delensing, which are used to recover the true luminosity distance, are not sufficiently constrained, the resulting distance posterior will broaden, losing the sharp peak required for an accurate measurement. Consequently, achieving a tightly constrained delensed luminosity distance is essential for inference of precise H_0 .

In this section, we assume a complete galaxy-galaxy lensing catalogue and the unique identification of each lensing system. Under these idealised conditions, delensing is expected to be highly accurate, allowing us to neglect the associated systematic uncertainties. In practice, however, observational limitations often lead to multiple candidate host galaxies within the GW sky-localisation region, or to missing hosts that are fainter than the catalogue's magnitude threshold. These factors introduce additional uncertainty into the H_0 inference for individual events. The complexity further increases when combining information from multiple dark sirens across different lensing systems. In the following section, we describe the framework for combining multiple lensed dark sirens while accounting for catalogue incompleteness, the redshift distributions of potential hosts, and the effects of imperfect delensing.

9.3 H_0 Measurement with Multiple Strongly Lensed Dark Sirens

When multiple strongly lensed dark sirens from different lensing systems are detected, the individual H_0 posteriors discussed in Section 9.2 cannot be combined through simple multiplication. Instead, a joint likelihood must be constructed and then multiplied by the H_0 prior distribution to obtain the overall posterior distribution. In this section, we adapt `gwcsmo` [219, 220, 394]⁴, a Bayesian inference pipeline specifically designed for cosmological studies and population analysis using GW events, to estimate the H_0 posterior for lensed GW observations.

4. The `gwcsmo` code is available at <https://git.ligo.org/lscsoft/gwcsmo>.

9.3.1 Method

Given the detection of $N_{\text{lens,det}}$ lensed GW systems, each consisting of multiple signals denoted collectively as $\{x_{\text{lgw}}\}$ with corresponding detection flags $\{D_{\text{lgw}}\}$, the posterior for H_0 is expressed as:

$$p(H_0 \mid \{x_{\text{lgw}}\}, \{D_{\text{lgw}}\}) \propto p(H_0) p(N_{\text{lens,det}} \mid H_0) \times \prod_{i=1}^{N_{\text{lens,det}}} \mathcal{L}(x_{\text{lgw},i} \mid D_{\text{lgw},i}, H_0), \quad (9.5)$$

where $p(H_0)$ is the prior on H_0 and $p(N_{\text{lens,det}} \mid H_0)$ is the probability of detecting $N_{\text{lens,det}}$ lensed systems for a given H_0 . In the unlensed case, the detection count term $p(N_{\text{det}} \mid H_0)$ is typically treated as independent of H_0 by adopting a rate prior of $p(R) \propto 1/R$ [219, 220, 290]. However, in the lensed case, the detection probability is a function of magnification, which is H_0 -dependent. Consequently, $p(N_{\text{lens,det}} \mid H_0)$ retains a dependence on H_0 through the magnification-dependent selection effects. The last term in Eq. (9.5) represents the joint likelihood of the $N_{\text{lens,det}}$ systems. The likelihood for a single lensed system is defined as:

$$\mathcal{L}(x_{\text{lgw}} \mid D_{\text{lgw}}, H_0) = \frac{p(x_{\text{lgw}} \mid H_0)}{p(D_{\text{lgw}} \mid H_0)}, \quad (9.6)$$

where

$$p(D_{\text{lgw}} \mid H_0) = \int p(D_{\text{lgw}} \mid x_{\text{lgw}}, H_0) \times p(x_{\text{lgw}} \mid H_0) dx_{\text{lgw}}. \quad (9.7)$$

The term $p(D_{\text{lgw}} \mid x_{\text{lgw}}, H_0)$ takes a value of unity if the data $\{x_{\text{lgw}}\}$ is successfully identified as a GW lensing system, and 0 otherwise. As discussed in Section 5.2, a system is classified as strongly lensed when multiple signals satisfy the detection criterion (in this work, $\rho_{\text{net}} > 8$), and exhibit mutually consistent intrinsic parameters and sky localisations, supported by a sufficiently high Bayes factor favouring the strong-lensing hypothesis. In practice, however, the finite duty cycle of GW detectors implies that one or more signals in a lensed multiplet may be missed if the detectors are offline at the time of arrival. In such cases, only a subset of the lensed signals, potentially just a single signal, may be observed. The signal would likely be misclassified as unlensed and analysed accordingly, thereby introducing a potential systematic bias in the inferred H_0 . We discuss this effect and its implications in Section 9.4.2.

The term $p(x_{\text{lgrw}} | H_0)$ represents the probability of obtaining the observed lensed GW data for a given value of H_0 . In practice, $p(x_{\text{lgrw}} | H_0)$ depends on the full set of parameters that determine the SNR of the GW event, which includes not only H_0 , but also the lens and source parameters (θ_l, θ_s) ⁵, the redshifts (z_s, z_l) , and the specific sky patches (Ω) that constitute the sky-localisation map. Hereafter, all dependencies on x_{lgrw} are written explicitly. Following this convention, Eq. (9.6) can be reformulated as:

$$\begin{aligned} \mathcal{L}(x_{\text{lgrw}} | D_{\text{lgrw}}, H_0) &= \left[\iiint \sum_j^{N_{\text{pix}}} p(D_{\text{lgrw}} | \Omega_j, \theta_s, \theta_l, z_s, z_l, H_0) p(\theta_s, \theta_l, z_s, z_l | \Omega_j, H_0) p(\Omega_j) d\theta_s d\theta_l dz_s dz_l \right]^{-1} \\ &\times \iiint \sum_j^{N_{\text{pix}}} p(x_{\text{lgrw}} | \Omega_j, \theta_s, \theta_l, z_s, z_l, H_0) p(\theta_s, \theta_l, z_s, z_l | \Omega_j, H_0) p(\Omega_j) d\theta_s d\theta_l dz_s dz_l, \end{aligned} \quad (9.8)$$

where the term $p(x_{\text{lgrw}} | \dots)$ is represented in a pixelated form by partitioning the sky-localisation map into discrete patches on a HEALPix grid [411, 412]⁶. In this scheme, each sky patch is assigned the subset of likelihood samples whose inferred sky locations fall within that specific region [394]. This pixelation approach is adopted to account for the sky-varying incompleteness characteristic of galaxy catalogues. Under this discretisation, the integral over the sky position is effectively replaced by a summation over the pixels.

The term $p(\theta_s, \theta_l, z_s, z_l | \Omega_j, H_0)$ represents the joint prior distribution of the source and lens parameters, along with their respective redshifts, for a given H_0 . In contrast to the analysis of individual dark-siren events described in Section 9.2, where a unique host is identified, the source and lens redshifts are inferred statistically by cross-matching the sky localisation of the detected lensed signals with a galaxy-galaxy lensing catalogue, such as the LGC0.

For a specific sky patch Ω_j , the redshift distributions of the source and lens galaxies are determined by selecting all catalogue galaxies located within that patch. These patch-specific distributions define the *line-of-sight (LoS) redshift prior*, which is independent of the intrinsic distributions of the GW source parameters. Consequently, the joint prior can be decomposed as:

$$p(\theta_s, \theta_l, z_s, z_l | \Omega_j, H_0) = p(\theta_s | H_0) p(z_s, z_l, \theta_l | \Omega_j, H_0). \quad (9.9)$$

5. θ_s denotes the intrinsic source parameters, excluding the source redshift z_s . Likewise, θ_l refers to the lens parameters other than the lens redshift z_l .

6. <http://healpix.sf.net>.

Because the intrinsic properties of the GW source—such as masses, spins, and orbital parameters—are independent of the sky location, the first term $p(\theta_s | H_0)$ carries no explicit dependence on Ω_j .

The denominator in Eq. (9.8) accounts for selection effects arising from the finite sensitivity of GW detectors, which introduces a bias toward louder signals in the detected GW population. Accurate modelling of these effects is required to avoid selection biases, such as Malmquist bias, and to obtain unbiased estimates of population-level parameters [292]. In the context of lensing, the selection effect is defined as the fraction of all GW sources whose lensed signals are detected with a network SNR exceeding the detection threshold, $\rho_{\text{thr}} = 8$. For doubly lensed systems, we require both signals to individually exceed ρ_{thr} . For quadruply lensed systems, at least two signals must exceed the threshold, as a minimum of two distinct detections is necessary to confidently identify a strongly lensed event.

In principle, one could perform a dedicated sub-threshold search to identify counterparts of a detected super-threshold signal that fall below the detection threshold due to insufficient magnification or demagnification [377, 413]. Furthermore, a lensed signal could potentially be identified from a single image by searching for waveform distortions in Type-II images, such as those induced by the phase shift of HOM [157, 367] as described in Section 5.1. However, these effects are neither directly relevant to the high-magnification regime nor contribute to the improvements in sky localisation. Consequently, we do not consider these scenarios in this work.

Regarding EM selection effects, although a complete catalogue was assumed in Section 9.2, realistic galaxy surveys may fail to include source-galaxy images or lens galaxies whose apparent magnitudes fall below the survey’s detection threshold. The resulting incompleteness introduces additional selection effects as a part of the redshift information required for the LoS redshift prior remains missing. To account for these effects, we construct the LoS redshift prior by marginalising over the absolute and apparent magnitudes of both the source and lens galaxies, following the methodology in [220]. Since the LoS prior is defined for galaxies that are potential hosts within the GW sky-localisation region, we introduce binary parameters s and l , denoting, respectively, whether a given source galaxy hosts a GW source and whether the detected signals are genuine counterparts corresponding to multiple lensed images of a single underlying GW source.

As described in Section 9.1.1, we impose an apparent-magnitude threshold $m_{\text{th}} = 21.87$ to construct incomplete catalogues from the UGC0 and LGC0. At this threshold, the resulting UGC1 contains approximately half of the galaxies in the UGC0 ($\sim 3.1 \times 10^7$ galaxies). Under the same cut, the LGC1 retains approximately 34 % of the galaxy–galaxy lensing systems from the LGC0. Using these four simulated catalogues, we compute the LoS redshift

priors on a HEALPIX grid. We adopt a resolution of $n_{\text{side}} = 128$ for the UGCs to ensure consistency with the framework in [220]. For the LGCs, we use $n_{\text{side}} = 64$ because the number of objects decreases significantly due to the small strong-lensing optical depth, making a coarser grid more appropriate for maintaining sufficient statistical coverage per pixel.

By substituting the joint likelihood of the lensed GW signals from Eq. (9.8) into Eq. (9.5), and incorporating the joint prior expressions from Eq. (9.9), the posterior for H_0 can be written explicitly as:

$$\begin{aligned}
 p(H_0 | \{x_{\text{lgw}}\}, \{D_{\text{lgw}}\}) &\propto p(H_0) p(N_{\text{lens,det}} | H_0) \\
 &\times \left[\iiint p(D_{\text{lgw}} | \theta_s, \theta_l, z_s, z_l, H_0) p(\theta_s | H_0) \sum_j^{N_{\text{pix}}} p(z_s, z_l, \theta_l | \Omega_j, H_0, s, l) d\theta_l d\theta_s dz_l dz_s \right]^{-N_{\text{lens,det}}} \\
 &\times \prod_i^{N_{\text{lens,det}}} \left[\iiint \sum_j^{N_{\text{pix}}} p(x_{\text{lgw},i} | \Omega_j, \theta_s, \theta_l, z_s, z_l, H_0) p(\theta_s | H_0) p(z_s, z_l, \theta_l | \Omega_j, H_0, s, l) d\theta_l d\theta_s dz_l dz_s \right].
 \end{aligned} \tag{9.10}$$

A comprehensive derivation of Eq. (9.10), along with a detailed explanation of the contribution of each constituent term, is provided in Appendix A.

9.3.2 Results

To estimate H_0 , we construct two separate analyses using (i) unlensed signals with UGCs and (ii) lensed signals with LGCs. In each case, we draw random sub-samples from the simulated population of detectable events to emulate a realistic observing run. The first sample pool comprises 250 unlensed signals, consistent with the number of events detected until the LVK fourth observing run. Under an optimistic scenario, the second pool consists of six doubly lensed and two quadruply lensed systems. Although this number of lensed events exceeds conservative expectations⁷, it is adopted to ensure sufficient statistics for reconstructing smooth posterior distributions while maintaining the expected ratio between double- and quadruple-image systems.

Figure 9.7 shows the H_0 posteriors for four analysis scenarios: unlensed and lensed GW signals combined with either complete or incomplete galaxy catalogues. Note that we employ spectroscopic redshift measurements from the galaxy catalogues. In all cases, the posteriors converge well to the true value; however, the 90 % C.I. is noticeably narrower for the lensed signals with complete catalogues. Specifically, among the lensed systems, doubly-lensed signals exhibit broader sky localisation (as shown in Figure 9.2), resulting in numerous potential host galaxies along the line of sight and complicating the identification of the true lensing system. Furthermore, the uncertainty in their luminosity dis-

7. In a realistic observing scenario, a fraction of lensed GW signals may be missed due to the finite detector duty cycle and the limited efficiency of search pipelines.

tance remains relatively large, yielding only modest constraints on H_0 . In contrast, while quadruply lensed signals are less frequent, they provide substantially improved sky localisation, which significantly reduces the number of candidate host galaxies and narrows the luminosity-distance uncertainty, resulting in considerably tighter constraints on H_0 .

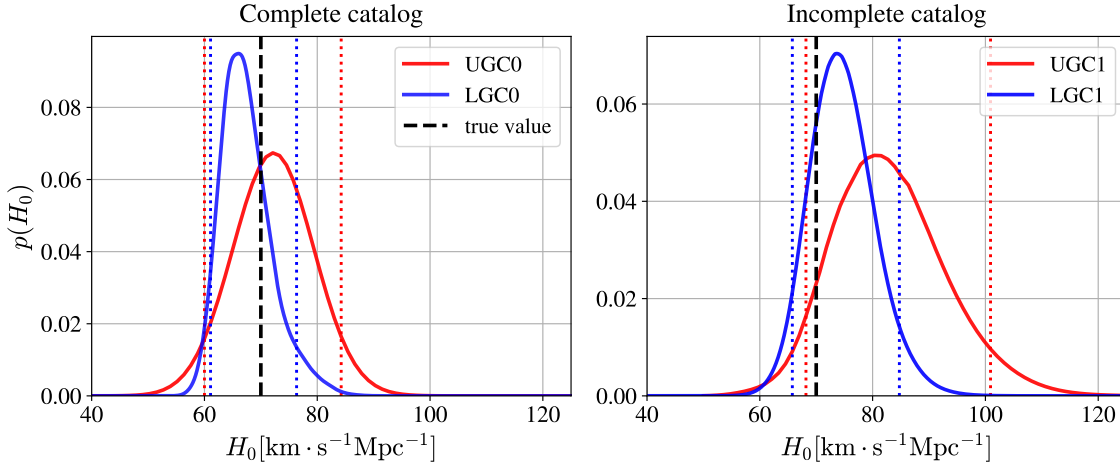


Figure 9.7: Posteriors of H_0 for the four analysis scenarios. The left panels use complete galaxy catalogues (UGC0 and LGC0), while the right panels incorporate catalogue incompleteness (UGC1 and LGC1).

In cases involving incomplete catalogues (UGC1 and LGC1), the H_0 posteriors are broader than those from the corresponding complete-catalogue cases, as the uncertainty in identifying the true host galaxy increases. In particular, in the LGC1 scenario, delensing accuracy is further reduced due to incomplete information on the lensing systems. This limitation directly increases uncertainty in the luminosity distance.

Overall, our results demonstrate that analysing even a small number of strongly lensed dark sirens with a dedicated galaxy–galaxy lensing catalogue can improve the precision of H_0 by approximately 50 % compared to a standard analysis using several hundred unlensed dark sirens. Detailed results are provided in Table 9.4. To achieve a few-percent fractional uncertainty ($\delta_{H_0} < 0.1$), comparable to the constraints provided by Type Ia supernova measurements, our framework indicates that a few tens of lensed GW systems would be required, assuming a complete catalogue. For instance, in a scenario using a randomly selected sample of 32 doubly lensed and 8 quadruply lensed events, we obtain a relative uncertainty of $\delta_{H_0} = 0.09$.

Table 9.4: Median values and 90 % C.I.s of recovered H_0 posteriors and their relative C.I. values (δ_{H_0}) for each catalogue case.

catalogue	Completeness	$H_0[\text{km} \cdot \text{s}^{-1} \cdot \text{Mpc}^{-1}]$	δ_{H_0}
UGC0	100	$72.12^{+12.12}_{-12.12}$	0.34
UGC1	50	$82.73^{+18.18}_{-14.55}$	0.40
LGC0	100	$66.85^{+9.49}_{-5.77}$	0.23
LGC1	34	$74.29^{+10.45}_{-8.53}$	0.26

9.4 Challenges in Measurement due to Lensing Bias

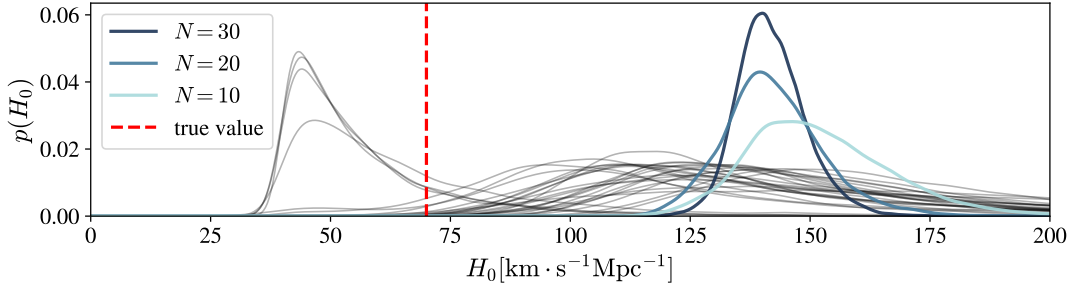
In this section, we investigate potential systematic biases in H_0 inference arising from two scenarios: (i) when lensing effects are either entirely ignored by adopting a conventional unlensed framework or not fully captured by a given lens model, and (ii) when a specific number of signals are misclassified, such that lensed events are identified as unlensed and vice versa.

9.4.1 Systematic Bias in Lens Reconstruction

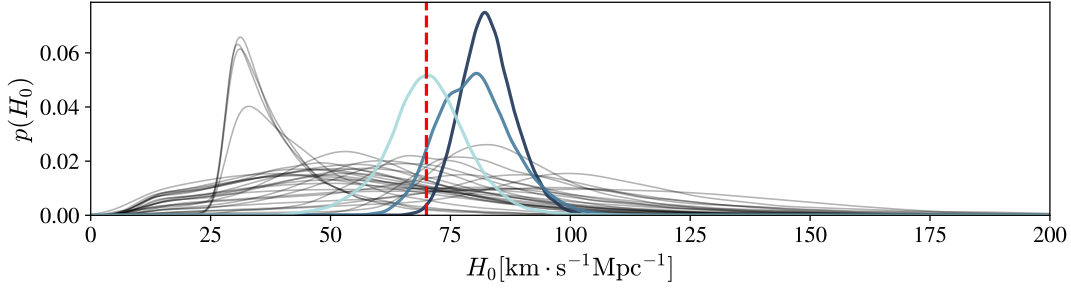
Accurate measurements of H_0 using lensed GW signals depend fundamentally on reliable lens reconstruction. If lensing effects are ignored or if the reconstructed lens model fails to fully capture the foreground galaxy's lensing potential, e.g., due to unresolved mass substructure, significant biases can be introduced into the inferred parameters. These biases primarily affect the recovered luminosity distance to the GW source and, by extension, the derived value of H_0 . Consequently, minimising these systematic biases is essential for robust cosmological inference.

To quantify the impact of incorrect lens reconstruction and imperfect delensing, we analyse multiple simulated GW signals sharing the same underlying lensing configuration. Specifically, we adopt the galaxy-galaxy lensing configuration of the DOUBLE 1 system shown in Table 9.2. We keep the lens parameters, source distance, and all other source parameters fixed, while varying only the BBH component masses and noise realisations, thereby generating different signals that probe the same lensing geometry. This controlled setup allows us to study the impact of lens-modelling errors while accounting for variations in the source waveform and detector noise.

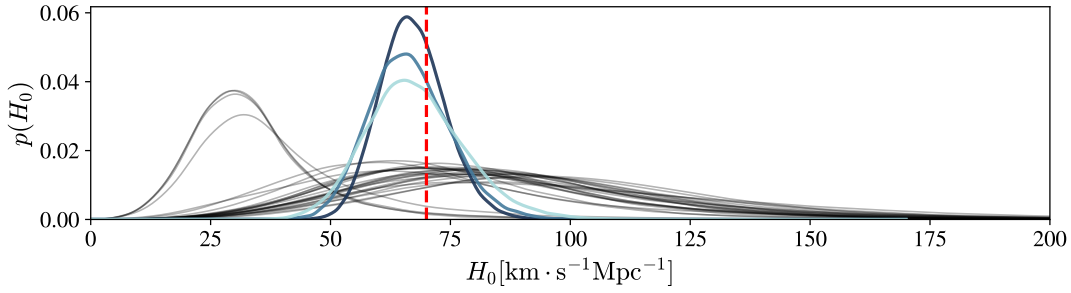
We simulate 30 such realisations and analyse them under three distinct modelling assumptions: (1) an unlensed configuration (no delensing applied); (2) an SIS profile, representing an incorrect lens model; and (3) an SIE profile, corresponding to the correct lens model. Figure 9.8 illustrates the H_0 posteriors inferred from individual lensed BBH events



(a) No delensing applied



(b) Delensing with SIS model



(c) Delensing with SIE model

Figure 9.8: H_0 posteriors obtained from multiple simulated GW signals sharing the same doubly lensed lensing configuration with a true SIE density profile. The BBH component masses and noise realisations are varied while keeping the lens parameters and the other source parameters fixed. The dashed red lines indicate the true value of H_0 . The top, middle, and bottom panels correspond to the cases of no delensing, SIS delensing, and delensing with the correct SIE model, respectively.

(gray curves), together with the progressively combined posteriors for each case (sky-blue for $N = 10$, blue for $N = 20$, and navy for $N = 30$). While systematic biases may be difficult to diagnose from the posterior of a single realisation, combining multiple events reveals clear trends.

In the no-delensing case (Figure 9.8a), the inferred H_0 is significantly biased for all numbers of combined realisations, as uncorrected magnification leads to a systematic underestimation of the luminosity distance. For the SIE case (Figure 9.8c), the posteriors converge consistently toward the true value, with the C.I. narrowing as more realisations are accu-

mulated. In contrast, for the SIS-delensing case (Figure 9.8b), the bias remains subtle when only $N = 10$ realisations are combined but becomes increasingly evident, as more realisations are accumulated. These results demonstrate that lens-reconstruction errors, while potentially masked by statistical noise in individual dark-siren measurements, can accumulate into significant systematic biases in joint analyses, particularly within the gwcosmo framework.

9.4.2 Selection Bias in Lensing Identification

In the lensed dark-siren case, selection effects are more intricate than in the unlensed case. For unlensed events, detectability is determined solely by whether a signal exceeds the threshold ρ_{thr} , and only the population of dark sirens needs to be considered. In contrast, selection effects for lensed events must account not only for the detectability of each lensed signal but also for the requirement that multiple signals are correctly associated with the same underlying GW source. This identification process is typically quantified by the FAR of the lensing hypothesis.

Consequently, misidentification can occur in two ways: first, independent unlensed signals may be falsely identified as lensed signals from a single source (false positives); and second, a genuine lensed signal—whose counterparts are missed, delayed beyond the observation window, or too faint to be detected—may be misclassified as unlensed (false negatives). Such misidentification leads to incorrect selection-bias corrections and failures in lens reconstruction, resulting in the biased recovery of the source luminosity distance. As the number of observed events increases, the lensing misidentification can introduce substantial systematic biases into the inferred H_0 , potentially dominating the statistical uncertainty. Figure 9.9 illustrates the bias in the H_0 posteriors arising from misidentification in the two scenarios described above. To isolate the effects of misidentification from uncertainties related to catalogue incompleteness, we use the complete UGC0 and LGC0 catalogues.

In the first scenario, we replace 4, 8, or 12 unlensed signals from the 250-event baseline with two, four, or six pairs of double-image signals ($N_{\text{pair}}^{\text{DBL}} = 2, 4, \text{ or } 6$). These pairs are intentionally misclassified as unlensed events to mimic pipeline identification failures. We then estimate H_0 using the UGC0 and the selection-effect corrections appropriate for unlensed signals. Figure 9.9a shows the H_0 posteriors for these three cases, together with the reference unlensed H_0 posterior from Figure 9.7. Because these lensed signals remain unlensed, their inferred luminosity distances are systematically underestimated, as the magnification factor is typically greater than unity ($\mu > 1$). This bias shifts the inferred H_0 to higher values, as shown in Figure 9.8a. However, the impact remains modest: for every additional two $N_{\text{pair}}^{\text{DBL}}$, the median H_0 increases by approximately one unit (from the red solid line to the blue dotted line), as the fraction of contaminated signals remains small compared to the overall population.

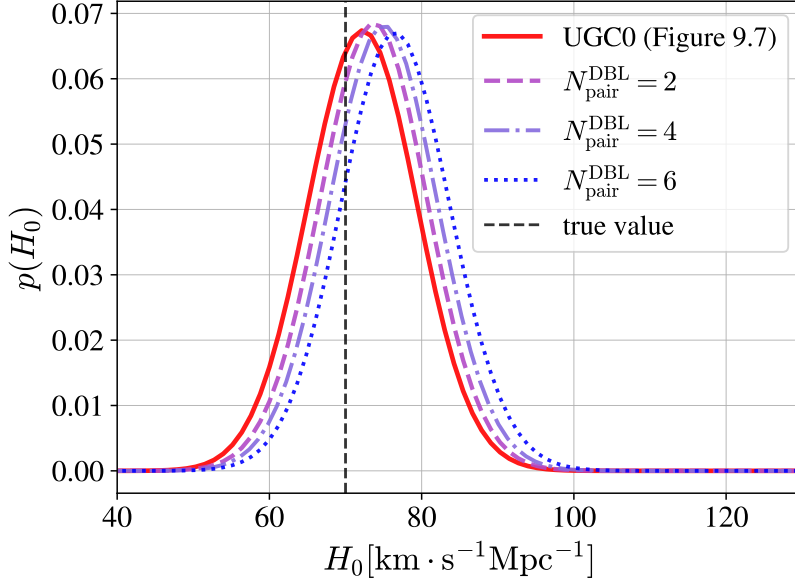
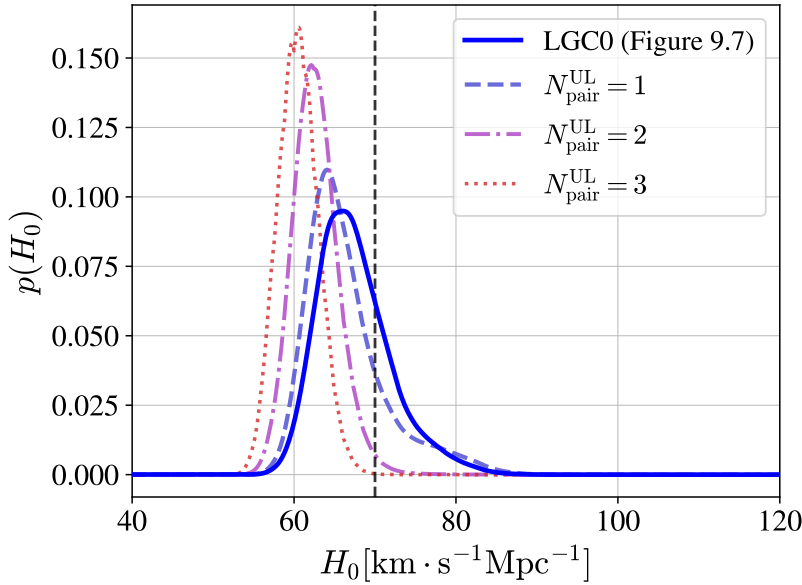
(a) H_0 inferred from an unlensed population containing hidden lensed signals(b) H_0 inferred from a lensed population containing hidden unlensed signals

Figure 9.9: Biased H_0 posteriors obtained when a subset of signals is misclassified in a population where the majority are correctly identified. The top and bottom panels show biases arising from classifying unlensed signals as lensed and lensed signals as unlensed, respectively. The dashed black lines denote the true value of H_0 , while the correctly inferred posterior from Figure 9.7 is shown for reference. As the number of misclassified events increases ($N_{\text{pair}}^{\text{DBL}}$ in the left panel and $N_{\text{pair}}^{\text{UL}}$ in the right panel), the inferred posteriors progressively shift away from the true value.

In the second scenario, we replace one, two, or three of the double-image systems out of the six doubles and two quads with an equivalent number of independent unlensed signals ($N_{\text{pair}}^{\text{UL}} = 1, 2, \text{ or } 3$) that are coincidentally and incorrectly identified as lensed pairs by the search pipeline. H_0 inference is then performed using the LGC0 and the selection-effect

corrections for lensed signals. Figure 9.9b shows the results for these three cases, with the reference lensed H_0 posterior from Figure 9.7 included for comparison. Since the unlensed signals are erroneously delensed, their inferred distances are systematically larger than their true values. Consequently, as the number of false positive unlensed pairs increases, the H_0 posterior shifts progressively toward lower values (from the blue solid line to the red dotted line). Compared to the first scenario, the fraction of misclassified signals within this smaller population is significantly higher, resulting in a more pronounced systematic bias in the H_0 inference.

9.5 Conclusion

We have demonstrated that strong lensing significantly enhances the cosmological utility of dark sirens. When paired with a dedicated galaxy-galaxy lensing catalogue, the improved sky localisation and tighter luminosity-distance constraints provided by lensing enable significantly more informative redshift inference than in the unlensed case. Our results show that even a single strongly lensed dark siren, particularly a quadruply lensed event, can yield competitive constraints on H_0 , approaching the precision of bright sirens. Furthermore, combining just a few lensed dark sirens can lead to a substantial improvement in the Hubble constant estimate, achieving constraints comparable to, or even tighter than, those obtained from several hundred unlensed events.

Robust cosmological inference from strongly lensed dark sirens fundamentally requires accurate lens reconstruction to recover the intrinsic luminosity distance to the GW source. While lens reconstruction is generally reliable with both EM and GW observations when the galactic mass distribution follows a simple profile, such as the SIE model adopted in this work, real galaxies exhibit structural complexities beyond this idealisation. Substructures and small-scale mass components embedded within galaxies can introduce additional lensing effects that may induce wave-optics signatures in GW signals. Such effects can modify the observed waveform morphology [312, 313, 314, 315, 316, 317, 318, 319]. Consequently, accurate reconstruction in these regimes requires incorporating wave-optics corrections associated with such small-scale structures.

Beyond these small-scale complexities, lens reconstruction for cosmological inference is subject to a more fundamental large-scale limitation: the mass-sheet degeneracy (MSD) [414]. The MSD arises because observed image positions and lensing observables remain invariant under a transformation that both rescales the projected mass density and introduces a uniform mass sheet. As a result, lensing data alone cannot uniquely determine the absolute mass normalisation or the time-delay distance, leading to a direct degeneracy with the inferred value of H_0 .

The MSD can be broken by multiple sources at different redshifts lensed by the same galaxy, although such configurations are exceptionally rare, or by introducing independent physical constraints. A powerful tool is stellar kinematics, specifically the measurement of the velocity dispersion of stars bound to the lens galaxy [415]. These measurements probe the lens's gravitational potential independently of the lensing geometry. By jointly modelling the lensing configuration and stellar kinematics, the mass normalisation inferred from lensing (e.g., the projected mass within the Einstein radius) can be directly compared with that inferred from the dynamics, thereby constraining the mass-sheet transformation parameter. Furthermore, in the wave-optics regime, distortions induced by substructure can provide additional constraints to help break the degeneracy [416].

As discussed, strongly lensed GW systems can provide tight constraints on H_0 , even when their sample size is significantly smaller than that of unlensed events. Increasing the number of lensed detections to several tens of systems further tightens the precision to the few-percent level. Next-generation ground-based detectors are expected to detect a large number of SLGWs, potentially $\mathcal{O}(100)$ events, assuming a relative lensed-to-unlensed detection rate of 10^{-3} , as the lensing optical depth increases with the detector horizon. These facilities may even detect demagnified lensed signals that currently lie below the detection threshold. With improved sky localisation and higher mean SNRs, the identification and characterisation of lensed GW sources will be significantly enhanced compared to current-generation detectors [417].

Furthermore, space-based detectors such as LISA [418] will achieve sub-degree-level localisation even for unlensed events [419]. Strongly lensed supermassive black hole mergers and extreme mass-ratio inspirals will thus provide exceptionally powerful probes for constraining H_0 [420]. However, galaxy catalogue incompleteness is expected to worsen as detector horizons extend to higher redshifts. The impact of this incompleteness will become increasingly significant, as cosmological inference will be progressively dominated by prior assumptions in regions where the catalogue is sparse.

In addition, since our work focuses exclusively on H_0 , we do not consider hyperparameters describing the population properties of BBHs and lens galaxies, nor additional cosmological parameters such as the matter density, Ω_m , or the dark energy equation-of-state, w_0 introduced in Section 3.2.1. Strong lensing, however, has the potential to provide complementary constraints on these parameters [417, 421]. A fully hierarchical Bayesian analysis that incorporates population-level parameters for both sources and lenses may yield a more reliable inference of H_0 alongside Ω_m and w_0 . In particular, realistic population models for lens galaxies, including the halo mass function, redshift distribution, and structural and luminosity distributions, should be incorporated to improve the framework.

In summary, we have developed distinct frameworks for inferring H_0 from single and multiple lensed dark sirens, respectively, incorporating lensed galaxy catalogues and accounting for lensing selection effects, including detection efficiency and catalogue incompleteness. We systematically quantify how the SNR of lensed GW signals, intrinsic source redshift, and delensing uncertainties affect the precision of recovered luminosity distances and the resulting H_0 posterior. Our analysis further demonstrates that even a small fraction of misclassified events can induce measurable systematic biases in H_0 . These results highlight the importance of accurate lens modelling, robust lens identification, and a consistent treatment of selection effects in future GW cosmology involving strong lensing.

Chapter 10

Gravitational-Wave Microlensing as a Probe of Compact Object Populations

Disclaimer

The following chapter is based on the paper *Gravitational-Wave Microlensing as a Probe of Compact Object Populations*. The author is the first author and contributed to all stages of this work, including data generation, development of the analysis framework, data analysis, interpretation, scientific discussion of the results, manuscript preparation, and generation of all figures. This paper is currently in preparation and will be submitted to the *Astrophysical Journal Letters*.

Unlike galaxy surveys or star-cluster searches in the local Universe, detecting small and faint compact objects at cosmological distances remains exceptionally challenging. This difficulty is particularly severe for non-luminous objects that emit no EM radiation, leaving significant uncertainties in the compact-object population. GW lensing provides a unique observational probe of such otherwise inaccessible compact objects. In particular, compact lenses can produce characteristic wave-optics signatures in GW signals, imprinting distinctive frequency-dependent diffraction patterns on the waveform, as introduced in Section 2.4.2. As discussed in Section 5.1.1, these signatures can additionally provide direct constraints on the redshifted lens mass, offering information that is difficult to obtain through traditional EM microlensing observations, which primarily probe magnification variability [422, 423].

Constraining the abundance and mass function of these compact objects would provide important insight into their formation channels and their contribution to the overall matter content of the Universe [424, 425]. Such measurements could further help determine whether the observed compact-object population can be explained solely by conventional stellar remnants or requires additional exotic components, such as IMBHs or PBHs [426, 427]. However, individual GW lensing events generally provide only limited information. In most cases, the waveform primarily constrains the redshifted lens mass, leaving a degeneracy between the intrinsic lens mass and lens redshift. As a result, robust population inference requires a statistical framework that combines information from many detections.

Hierarchical Bayesian inference introduced in Section 4.4 provides a natural approach to this problem. By jointly modelling the distribution of lens masses and redshifts across multiple events, one can infer the underlying population properties and constrain the hyperparameters governing the compact-object population. In particular, incorporating lens-redshift information can help alleviate the mass–redshift degeneracy and enable direct constraints on the intrinsic lens-mass distribution and its cosmological evolution.

As mentioned in Chapter 6, no compelling evidence for GW microlensing has yet been identified in current observations. Current analyses, therefore, primarily place constraints through the absence of microlensing detection [428]. Future GW observatories, however, are expected to substantially increase the number of detected GW events lensed by compact objects whose masses fall within the range that can produce observable wave-optics effects in their frequency band [429]. This motivates a quantitative investigation of how accurately the underlying compact-object population can be reconstructed from a large sample of microlensed GW events.

In this Chapter, we investigate the detectability of microlensed GW signals and assess how populations of compact lenses can be constrained using hierarchical inference from multiple microlensing detections. Throughout this chapter, we adopt the PLANCK15 cosmology [174] as our fiducial baseline model.

10.1 Methodology

10.1.1 Mock Microlensed GW Signals

To simulate microlensed GW signals, we consider only BBHs, whose detection horizon with current ground-based detectors extends to the largest distances among CBC sources. Source parameters are drawn from the population models described in Section 4.2.2 with hyperparameters inferred from GWTC-3 analysis [293] to generate a synthetic BBH population. GW signals are then generated using the XPHM-ST waveform model [288, 289].

We draw microlensing parameters based on a PM population described by two hyperparameters: n_0 , the comoving number density of microlenses, and α_{ML} , the slope of the lens-mass distribution. Following [427], which demonstrated that IMBH number densities are well constrained around $n_0 = 10^6 \text{ Mpc}^{-3}$, this fiducial value is adopted. We assume a power-law distribution for the intrinsic lens mass (M_l), motivated by stellar lenses following the initial mass function and compact objects observed by the LVK network [237, 430]:

$$p(M_l \mid \alpha_{\text{ML}}) \propto M_l^{-\alpha_{\text{ML}}}, \quad (10.1)$$

where we set a limited lens-mass range $M_l \in [1, 10^5] M_\odot$. Above this upper bound, lensing effects shift from the wave-optics regime into the geometrical-optics regime within the LVK frequency band. We adopt $\alpha_{\text{ML}} = [1, 2]$ for the M_l distribution to explore two representative population scenarios. The choice $\alpha_{\text{ML}} = 1$ corresponds to a log-uniform mass distribution, providing a relatively broad and agnostic baseline model. In contrast, $\alpha_{\text{ML}} = 2$ represents a steeper distribution in which low-mass lenses dominate the population more strongly. Comparing these two cases allows us to assess how constraints on the underlying lens population depend on the steepness of the mass function of that population.

Since only a fraction of GW signals are expected to undergo detectable microlensing, we first estimate the probability that a BBH signal generated at source redshift z_s is microlensed by a compact object located at $z_l < z_s$.

The probability that a GW signal generated at z_s encounters a microlens at $z_l < z_s$ is related to the optical depth, given by Eq. (2.28). For a given comoving number density n_0 , the optical depth can be written as:

$$\tau(z_s) = \int dM_l \int_0^{z_s} dz_l n_0 \pi y_{\text{max}}^2 R_E^2 \frac{dV_c}{dz_l}, \quad (10.2)$$

where V_c and R_E are the comoving volume and Einstein radius, respectively. The factor y_{max} is introduced because, in the wave-optics regime, diffraction effects allow detectable microlensing signatures to extend beyond R_E commonly associated with EM microlensing ($y_{\text{max}} = 1$). Consequently, the effective lensing cross-section expands to $\sigma = \pi y_{\text{max}}^2 R_E^2$ [147]. Using Eq. (2.31) together with the simulated BBH population and Eq. (10.2), we calculate the population-averaged optical depth and determine the expected number of microlensed GW events in our simulations. As will be discussed later (see Figure 10.1), we adopt $y_{\text{max}} = 2.75$ and $y_{\text{max}} = 2.07$ for the $\alpha_{\text{ML}} = 1$ the $\alpha_{\text{ML}} = 2$ populations, respectively.

Since GW microlensing measurements constrain the detector-frame lens mass, i.e., the redshifted lens mass M_l^z , it is convenient to express the microlensing probability directly in terms of M_l^z . Combining the optical depth with the assumed M_l distribution $p(M_l | \alpha_{\text{ML}})$, the probability that a BBH at redshift z_s is microlensed by a lens with detector-frame mass M_l^z is given by:

$$\begin{aligned} p(M_l^z | \alpha_{\text{ML}}, z_s) &= \tau(z_s) p(M_l | \alpha_{\text{ML}}) \\ &\propto \int_0^{z_s} dz_l (M_l^z)^{1-\alpha_{\text{ML}}} (1+z_l)^{\alpha_{\text{ML}}-2} \frac{D_l D_{ls}}{D_s} \frac{dV_c}{dz_l}. \end{aligned} \quad (10.3)$$

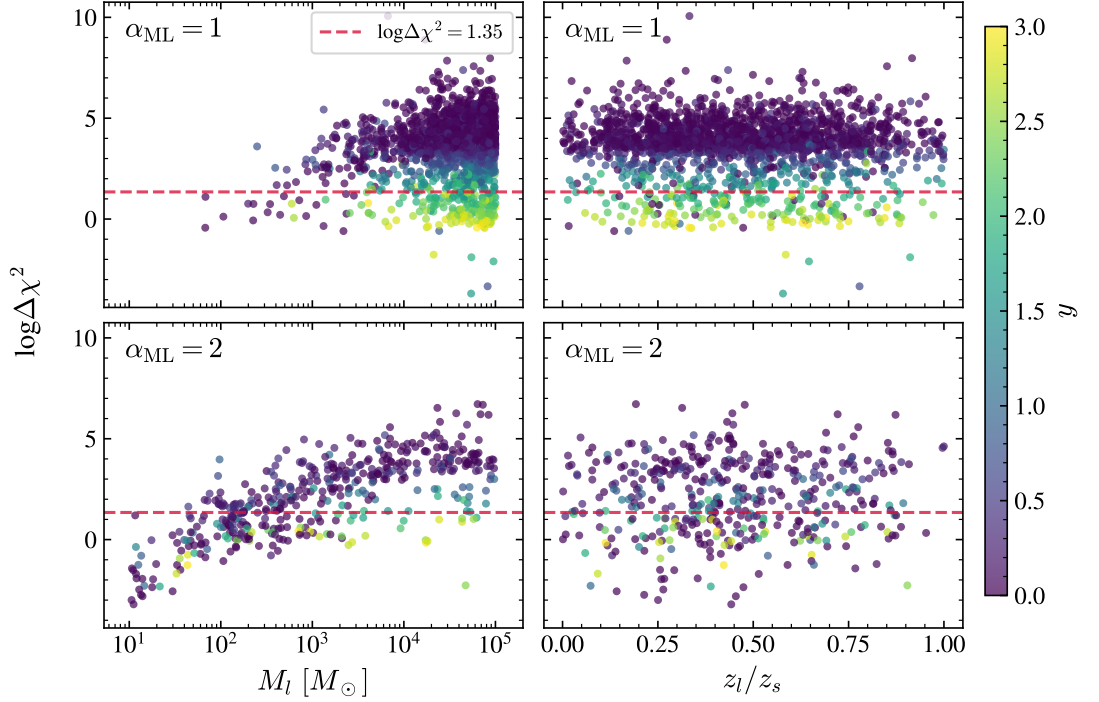


Figure 10.1: Distributions of $\log \Delta\chi^2$ between microlensed and corresponding unlensed waveforms for signals satisfying the network detection threshold $\rho_{\text{net}} > 8$, shown as a function of M_l and the redshift ratio z_l/z_s . The colour scale represents y . The red line indicates the adopted distinguishability criterion.

Using Eq. (10.3), we sample M_l^z within the range $[1, 10^5]M_\odot$. Next, y values are sampled from a geometric prior distribution, $p(y) \propto y$, within the range $[0.01, 3.0]$. This standard distribution naturally arises from the differential lensing area under the assumption of a spatially uniform source population in the source plane. Extremely small values of y are statistically disfavoured because they correspond to a small geometric lensing cross-section, whereas observable microlensing distortions become increasingly suppressed at large y .

Although the optical depth determines the expected number of microlensed GW events, only a subset of these events produces detectable wave-optics signatures in GW observations. The detectability of GW microlensing depends not only on the network SNR, ρ_{net} , but also on the waveform mismatch ϵ between microlensed and unlensed signals, which quantifies the degree of waveform distortion induced by wave-optics effects (see Eqs. (6.2) and (7.9)).

Following [431], we adopt a fiducial distinguishability criterion based on the statistic $\Delta\chi^2$, which is equivalent to Λ in Eq. (1.43) but is interpreted here as a measure of how distinguishable a microlensed waveform is from its unlensed counterpart. In the limit of small waveform mismatches, $\Delta\chi^2$ can be approximated as:

$$\Delta\chi^2 \simeq 2\rho_{\text{net}}^2 \epsilon_{\text{net}}, \quad (10.4)$$

where ϵ_{net} denotes the network-averaged mismatch computed from the individual detector signals. We assume the conventional GW detection threshold $\rho_{\text{net}} > 8$ together with a fiducial mismatch threshold $\epsilon_{\text{net}} > 0.03$, corresponding to the approximate level at which waveform distortions become distinguishable in GW observations. These values yield $\Delta\chi^2 = 3.84$ ($\log \Delta\chi^2 \simeq 1.35$).

Figure 10.1 shows the resulting $\Delta\chi^2$ values between simulated microlensed waveforms and their corresponding unlensed counterparts for signals satisfying the SNR detection threshold ($\rho_{\text{net}} > 8$), as a function of M_l and z_l/z_s for both $\alpha_{\text{ML}} = 1$ and $\alpha_{\text{ML}} = 2$ populations. In both cases, $\Delta\chi^2$ shows a decreasing trend with increasing y , reflecting the progressive suppression of wave-optics distortions at larger y . We estimate y_{max} used in Eq. (10.2) based on the adopted $\Delta\chi^2$ threshold.

In addition, a positive correlation between M_l and $\Delta\chi^2$ is evident, as expected from the stronger and more distinguishable waveform distortions produced by more massive lenses. Since the $\alpha_{\text{ML}} = 1$ population contains a larger fraction of high M_l lenses than the steeper $\alpha_{\text{ML}} = 2$ distribution, a correspondingly larger fraction of simulated events satisfy the final distinguishability criterion in the $\alpha_{\text{ML}} = 1$ case. The minimum lens mass capable of producing detectable microlensing signatures is approximately $\mathcal{O}(2)M_\odot$ for $\alpha_{\text{ML}} = 1$, whereas detectable signals in the $\alpha_{\text{ML}} = 2$ case can extend down to approximately $\mathcal{O}(1)M_\odot$. Moreover, no clear correlation is observed between $\Delta\chi^2$ and z_l/z_s . While the lensing probability is maximised for lenses located roughly midway between the source and observer due to geometric effects, the strength of observable wave-optics distortions depends more strongly on M_l^z and y .

It is important to note that some simulated microlensed signals may satisfy the distinguishability criterion while still failing the network SNR requirement ($\rho_{\text{net}} > 8$). Such events would not be initially detectable. We therefore retain only events satisfying both detectability criteria and classify them as detectable microlensed GW signals. From this detectable population, we randomly select 200 microlensed events and inject them into simulated aLIGO–Livingston, aLIGO–Hanford, and AdV detector data, assuming their projected O4a sensitivity and Gaussian-noise realisations [365].

10.1.2 Hierarchical Bayesian Inference of Hyperparameters

To estimate the parameters of microlensed waveforms, we adopt the Gravelamps [298]. As shown in Chapter 6, the pipeline yields posterior distributions for the PM lens parameters, M_l^z and y , together with the Bayesian evidence for the microlensing hypothesis, $\mathcal{B}_{\text{ML}}$. Performing parameter estimation for the same signal under the unlensed hypothesis additionally yields the corresponding evidence $\mathcal{B}_{\text{U}}$, allowing the Bayes factor between microlensing and unlensed hypotheses, $\mathcal{B}_{\text{U}}^{\text{ML}}$, to be evaluated. A microlensed signal is expected to favour the lensing hypothesis when $\mathcal{B}_{\text{U}}^{\text{ML}} > 1$. In realistic searches, microlensing detec-

tions would additionally require a robust FPP assessment based on a large population of unlensed background events, as discussed in Section 5.1. In this work, however, we adopt a pragmatic criterion and regard microlensed events with $\mathcal{B}_U^{\text{ML}} > 1$ and well-constrained posteriors for M_l^z and y as confidently identified microlensing events, yielding a total of 132 events.

From the identified microlensing events, the posterior distribution of the hyperparameters (λ) can be inferred through a hierarchical Bayesian framework that combines information from all detected events ($\mathbf{d}$) (see Eqs. (4.27) and (4.29)). The corresponding posterior is given by:

$$p(\lambda \mid \mathbf{d}) \propto p(\lambda) p(N_{\text{ML,det}} \mid \lambda) \times \frac{\prod_i^{N_{\text{ML,det}}} p(d_i \mid \boldsymbol{\theta}_{s,i}, M_{l,i}^z, y_i) p_{\text{pop}}(\boldsymbol{\theta}_{s,i}, M_{l,i}^z, y_i \mid \lambda)}{\beta(\lambda)^{N_{\text{ML,det}}}}, \quad (10.5)$$

where $N_{\text{ML,det}}$ is the number of detected microlensed events and $\beta(\lambda)$ indicates the detection efficiency for a given hyperparameter set, corresponding to a selection-bias correction [291, 292]. The hyperparameter set consists of both source-population and lens-population parameters, i.e. $\lambda = (\lambda_s, \lambda_l)$. Here λ_s describes the BBH population e.g., introduced in Eqs. (4.35)–(4.39), while $\lambda_l = (\alpha_{\text{ML}}, n_0)$ in this work.

The first term in Eq. (10.5) is the prior on the hyperparameters. In this work, we fix λ_s parameters to their injected values to focus exclusively on the inference of λ_l . We adopt broad priors for λ_l , namely $\alpha_{\text{ML}} \in \text{U}[-4, 12]$, consistent with the power-law index priors for the primary BH of a BBH commonly used in LVK population studies [237, 293], and $\log_{10} n_0 \in \text{U}[0, 10]$, following the range adopted in [427].

The second term, $p(N_{\text{ML,det}} \mid \lambda)$, describes the probability of detecting $N_{\text{ML,det}}$ microlensing events, which is modelled using a Poisson-distributed variable with an expected number given by Eq. (4.28):

$$\langle N_{\text{ML,det}} \rangle = N_{\text{UL}} \bar{\tau}(\lambda) \int p_{\text{pop}}(\boldsymbol{\theta}_s, M_l^z, y \mid \lambda) P_{\text{det}}(\boldsymbol{\theta}_s, M_l^z, y) d\boldsymbol{\theta}_s dM_l^z dy \quad (10.6)$$

where N_{UL} is the mean of the Poisson process for unlensed events (i.e., the expected total number of unlensed events, including both detected and undetected ones) and $\bar{\tau}(\lambda)$ is the population-averaged optical depth defined in Eq. (2.31), which depends on the given hyperparameters. P_{det} denotes the indicator that a microlensed signal with the given source and lens parameters satisfies the adopted detection and distinguishability criteria.

The third term in Eq. (10.5) represents the joint likelihood of all detected microlensed events, constructed as a product of individual event contributions, assuming that each event is statistically independent given λ . This assumption allows the joint likelihood to be factorised into a product of event-level terms. In the numerator, $p(d_i \mid \boldsymbol{\theta}_{s,i}, M_{l,i}^z, y_i)$ denotes the event-level likelihood of each set of observed microlensed GW data, evaluated using pos-

terior samples obtained from parameter estimation. The term $p_{\text{pop}}(\theta_s, M_l^z, y \mid \lambda)$ encodes the underlying astrophysical population model for both the source and lens parameters. In this work, the lens population is described by M_l^z distribution given in Eq. (10.3), together with the geometric prior on y .

In the denominator, $\beta(\lambda)$ represents the probability that a source drawn from the underlying population is successfully identified as a detectable microlensing event under the adopted detector sensitivity and distinguishability criteria. It can be interpreted as an overall detection efficiency that accounts for selection effects induced by both the SNR threshold and waveform distinguishability requirements. Based on Eq. (4.30), the detection efficiency for microlensed signals can be rewritten as:

$$\begin{aligned} \beta(\lambda) &\equiv \frac{\langle N_{\text{ML,det}}(\lambda) \rangle}{N_{\text{UL}} \bar{\tau}(\lambda)} \\ &= \int p_{\text{pop}}(\theta_s, M_l^z, y \mid \lambda) P_{\text{det}}(\theta_s, M_l^z, y) d\theta_s dM_l^z dy. \end{aligned} \quad (10.7)$$

As shown in Eq. (4.32), $\beta(\lambda)$ is estimated using numerous microlensed injections, as follows:

$$\beta(\lambda) \simeq \frac{1}{N_{\text{inj}}} \sum_i^{N_{\text{inj,det}}} \frac{p_{\text{pop}}(\theta_{s,i}, M_{l,i}^z, y_i \mid \lambda)}{\pi(\theta_{s,i}, M_{l,i}^z, y_i)}, \quad (10.8)$$

where N_{inj} and $N_{\text{inj,det}}$ denote the total number of injected and successfully detected microlensed signals, respectively, and π is the prior distribution used in the injection campaign.

10.2 Results

10.2.1 Inference of the Compact-Lens Distribution

From Eq. (10.5), we infer the joint posterior distribution for α_{ML} and n_0 . To evaluate the minimum sample size required to obtain meaningful constraints on these population parameters, we analysed three scenarios with varying numbers of detected microlensed events: $N_{\text{ML,det}} = 50, 100$, and the full sample of 132. As shown in Figure 10.2, the widths of posteriors for both hyperparameters become progressively narrower as the number of detections increases, while the posterior peaks converge toward their respective true values. Notably, n_0 is less well constrained than α_{ML} . This difference arises from its strong degeneracy with y , which more directly governs the microlensing probability and magnification than the lens mass M_l^z .

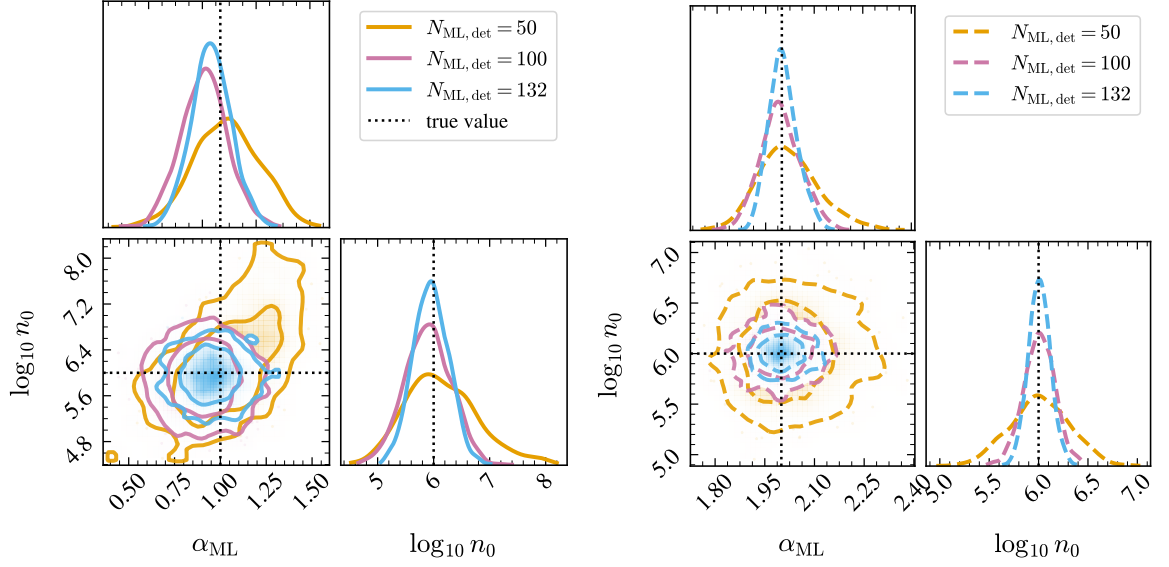


Figure 10.2: Corner plots showing the posteriors of α_{ML} and $\log_{10} n_0$ inferred from the $N_{\text{ML,det}} = 50, 100$, and 132 cases for the two fiducial scenarios $\alpha_{\text{ML}} = 1$ (left panel) and $\alpha_{\text{ML}} = 2$ (right panel). The black dotted lines denote the corresponding true values.

Furthermore, in the $\alpha_{\text{ML}} = 1$ scenario, the $N_{\text{ML,det}} = 50$ case exhibits a positive correlation between α_{ML} and n_0 . When the number of detected events is limited, uncertainties in α_{ML} can be partially compensated by shifts in n_0 . Physically, larger values of α_{ML} correspond to lens populations dominated by lower-mass compact objects, which generally produce weaker microlensing signatures. Consequently, a higher lens number density is required to maintain a comparable detection rate, giving rise to the observed $\alpha_{\text{ML}}-n_0$ degeneracy. In contrast, for larger catalogues ($N_{\text{ML,det}} = 100$ and 132), the shape of the lens-mass distribution becomes much more tightly constrained by the data itself. The inferred value of α_{ML} is then effectively determined, substantially reducing the allowed compensation through n_0 . As a result, the $\alpha_{\text{ML}}-n_0$ degeneracy is progressively broken, yielding nearly circular 2D posteriors.

In the $\alpha_{\text{ML}} = 2$ scenario, the intrinsic lens-mass distribution is strongly concentrated toward M_{min} . Even the $N_{\text{obs}} = 50$ case is therefore dominated by low-mass lenses, and the absence of high-mass lenses provides strong constraints on α_{ML} , thereby also constraining n_0 .

10.2.2 Constraining the Microlens Fraction in Dark Matter

According to [432], the comoving number density n_0 appearing in Eq. (10.2) can be written as

$$\begin{aligned} n_0 &= \frac{\rho_l}{\langle M_l \rangle} \\ &= \frac{\rho_c \Omega_l}{\langle M_l \rangle} \\ &= \frac{3H_0^2 \Omega_l}{8\pi G \langle M_l \rangle}, \end{aligned} \quad (10.9)$$

where ρ_l and ρ_c denote the compact-lens density and the critical density of the Universe, respectively, and $\Omega_l \equiv \rho_l/\rho_c$ is the corresponding density parameter of compact lenses. $\langle M_l \rangle$ denotes the expectation value of the intrinsic lens mass, analytically derived from the assumed mass distribution $p(M_l|\alpha_{\text{ML}})$ within the mass range $[M_{\text{min}}, M_{\text{max}}]$. For a given α_{ML} , the theoretical $\langle M_l \rangle$ is given by:

$$\langle M_l \rangle = \begin{cases} \left(\frac{1 - \alpha_{\text{ML}}}{2 - \alpha_{\text{ML}}} \right) \frac{M_{\text{max}}^{2-\alpha_{\text{ML}}} - M_{\text{min}}^{2-\alpha_{\text{ML}}}}{M_{\text{max}}^{1-\alpha_{\text{ML}}} - M_{\text{min}}^{1-\alpha_{\text{ML}}}}, & \alpha_{\text{ML}} \neq 1, 2, \\ \frac{M_{\text{max}} - M_{\text{min}}}{\ln(M_{\text{max}}/M_{\text{min}})}, & \alpha_{\text{ML}} = 1, \\ \left(\frac{M_{\text{min}} M_{\text{max}}}{M_{\text{max}} - M_{\text{min}}} \right) \ln \left(\frac{M_{\text{max}}}{M_{\text{min}}} \right), & \alpha_{\text{ML}} = 2. \end{cases} \quad (10.10)$$

If the compact lenses are interpreted as dark compact objects, such as PBHs, the lens density parameter can be expressed as $\Omega_l \equiv f_{\text{DM}} \Omega_{\text{DM}}$, where f_{DM} denotes the integrated fraction of total DM contained in compact lenses across the prescribed mass range. Consequently, constraints on n_0 and α_{ML} obtained from the hierarchical Bayesian analysis can be translated into constraints on f_{DM} assuming a fiducial DM density parameter $\Omega_{\text{DM}} \simeq 0.26$. Under these assumptions, the DM fraction associated with compact lenses can be written as:

$$f_{\text{DM}} = \frac{8\pi G n_0 \langle M_l \rangle}{3H_0^2 \Omega_{\text{DM}}}. \quad (10.11)$$

Figure 10.3 shows the posteriors of f_{DM} , calculated from the posterior samples of n_0 and α_{ML} for all detected microlensed signals. Here, f_{DM} denotes the fraction of DM in the compact objects within the mass range $[M_{\text{min}}, 10^5] M_{\odot}$, where M_{min} represents the minimum lens mass capable of producing detectable microlensing signatures for a given α_{ML} scenario (see Figure 10.1). Note that $f_{\text{DM}} = 1$ implies that all DM is comprised of compact objects within this mass range.

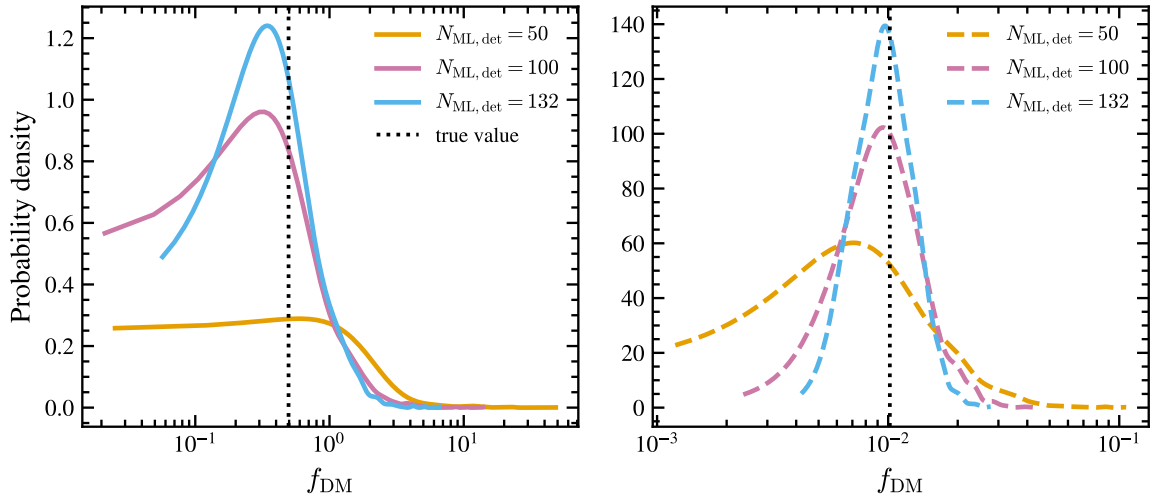


Figure 10.3: Posteriors of f_{DM} inferred for the $\alpha_{\text{ML}} = 1$ (left panel) and $\alpha_{\text{ML}} = 2$ (right panel) scenarios using catalogues with $N_{\text{ML,det}} = 50, 100$, and 132 detected microlensing events. The black dotted lines denote the corresponding true values.

In the $\alpha_{\text{ML}} = 1$ scenario, the average lens mass is relatively high, corresponding to a true DM fraction of $f_{\text{DM}} \simeq 0.5$. The posterior obtained from the $N_{\text{ML,det}} = 50$ catalogue remains relatively flat over a broad range of f_{DM} . As discussed in Figure 10.2, this behaviour arises from the degeneracy between α_{ML} and n_0 . Nevertheless, the lower bound on f_{DM} becomes progressively tighter as $N_{\text{ML,det}}$ increases.

By contrast, for the $\alpha_{\text{ML}} = 2$ scenario, the average lens mass is substantially lower, yielding a correspondingly lower true DM fraction of $f_{\text{DM}} \simeq 1.02 \times 10^{-2}$. The posterior distributions peak near the true value even for the $N_{\text{ML,det}} = 50$ catalogue, reflecting the reduced $\alpha_{\text{ML}}-n_0$ degeneracy discussed previously.

It is worth noting that while the physical boundary strictly requires $f_{\text{DM}} \leq 1$, our posterior samples for the $\alpha_{\text{ML}} = 1$ scenario extend into the unphysical regime ($f_{\text{DM}} > 1$). This issue arises because the analysis was performed using broad hyperparameter priors that do not explicitly impose the physical constraint on f_{DM} . In our simplified population model, the physically allowed region in the $(n_0, \alpha_{\text{ML}})$ parameter space can be estimated relatively straightforwardly. In more realistic compact-object population models, however, the mapping between hyperparameters and the implied value of f_{DM} is expected to become substantially more complex. For this reason, adopting broad priors at the hyperparameter level and subsequently excluding posterior samples with $f_{\text{DM}} > 1$ provides a more flexible and model-independent approach than imposing hard physical boundaries a priori.

We can also estimate the differential DM fraction as a function of lens mass, enabling us to quantify how much DM is contributed by lenses of different masses. The differential DM fraction per $\log_{10} M_l$ is given by

$$\frac{df_{\text{DM}}}{d\log_{10} M_l} = \frac{8\pi G n_0}{3H_0^2 \Omega_{\text{DM}}} M_l^{2-\alpha_{\text{ml}}} \ln(10). \quad (10.12)$$

Figure 10.4 illustrates the resulting differential spectra. In the $\alpha_{\text{ML}} = 1$ scenario, the spectrum is tightly constrained at the low-mass end but exhibits progressively broader C.I.s toward the high-mass regime. This behaviour directly reflects the error propagation in Eq. (10.12): since the mass dependence remains close to $\sim M_l^1$, even small statistical fluctuations in the inferred slope α_{ML} become exponentially amplified at large M_l . A qualitatively similar trend is also observed in the $\alpha_{\text{ML}} = 2$ scenario, although the differential spectrum remains substantially flatter. In this case, the mass dependence in Eq. (10.12) becomes negligible, thereby suppressing the propagation of errors toward larger M_l .

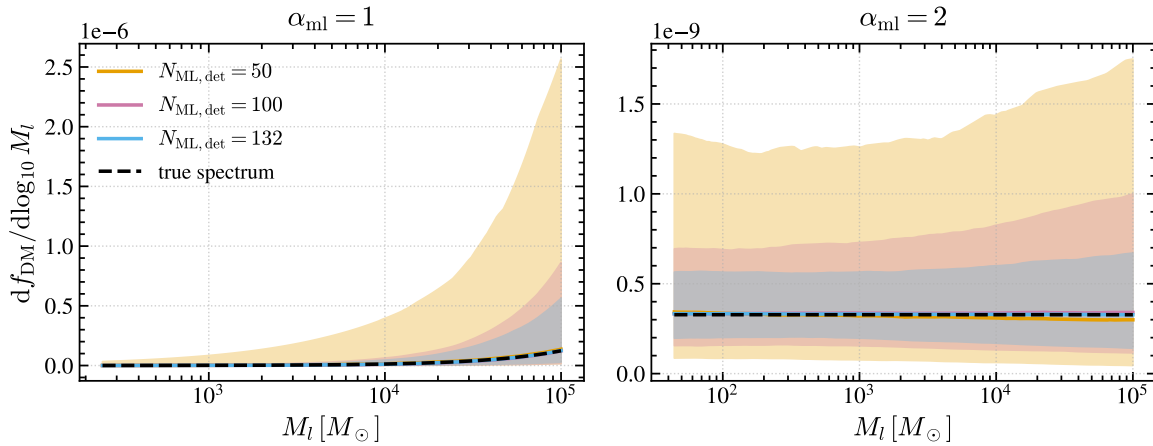


Figure 10.4: The differential fraction of DM, $\frac{df_{\text{DM}}}{d\log_{10} M_l}$, for the $\alpha_{\text{ML}} = 1$ (left panel) and $\alpha_{\text{ML}} = 2$ (right panel) scenarios using catalogues with $N_{\text{ML,det}} = 50, 100$, and 132 detected microlensing events. The black dashed lines denote the corresponding true spectra. The solid coloured lines denote the median recovered spectra.

10.3 Conclusion

In this chapter, we have investigated the feasibility of constraining compact-object populations through hierarchical Bayesian inference applied to a catalogue of confidently identified GW microlensing events, while consistently accounting for selection effects. Using simulated microlensed BBH signals drawn from two representative power-law lens-mass distributions, with $\alpha_{\text{ML}} = 1$ and $\alpha_{\text{ML}} = 2$, we demonstrated that the accumulation of microlensed detections can place meaningful constraints on both the mass-function slope α_{ML} and the comoving lens number density n_0 , while simultaneously breaking the degeneracy between these parameters.

We have further translated these constraints into the compact-DM fraction, f_{DM} , and its differential mass spectrum. The hierarchical framework allows the hyperparameter space to be explored without imposing explicit hard priors derived from the physical bounds on f_{DM} . Such priors become increasingly difficult to construct as the mapping between the population hyperparameters and the physically allowed DM fraction grows more complicated for realistic population models. Instead, the physical and unphysical regions can be identified directly at the level of the inferred f_{DM} posterior, making the framework more flexible and model-agnostic.

We found that steeper lens-mass distributions yield tighter constraints on the inferred f_{DM} for the same number of detections. This behaviour arises because the parameter degeneracy between α_{ML} and n_0 is more efficiently broken for steeper mass functions, while the smaller characteristic lens masses lead to weaker amplification of the statistical uncertainties in n_0 when propagating them into f_{DM} . In addition, steeper mass functions suppress the contribution from the high-mass regime, where statistical uncertainties are more strongly amplified in the inferred differential DM spectrum, thereby producing more stable constraints across the parameter space. Consequently, compact-object populations dominated by relatively low-mass lenses can, in principle, yield more robust constraints on the compact-DM fraction.

Although our framework provides a robust foundation for population inference, several simplifying assumptions adopted in this work motivate important directions for future refinement. First, we employed a simplified population configuration in which the source-population hyperparameters are fixed, thereby focusing exclusively on the lens population. Incorporating uncertainties in the source population would weaken the constraints on the population properties. However, such an extension would also enable a direct investigation of potential degeneracies between the source and lens populations, particularly in scenarios where both originate from dark compact objects. This possibility becomes especially relevant if a fraction of the BBH population detected by LVK is itself primordial in origin [433, 434], since the source and lens populations could then share common formation channels and population characteristics.

In addition, we adopted a simple power-law model for the intrinsic lens-mass distribution. If the compact lenses are interpreted as PBHs, more physically motivated mass functions should be considered¹. We also assumed a constant n_0 , despite the possibility that the compact-lens population evolves over cosmic time. A more realistic treatment could incorporate redshift evolution through a parameterisation such as $n_l(z) = n_0(1+z)^k$, analogous to Eq. (4.38), where k characterises the evolution of the lens abundance. Such models generally require additional hyperparameters and would introduce further correlations between the source and lens population properties.

1. For a recent overview of PBH mass-function models and population studies, we refer readers to [435].

Nevertheless, once the underlying hyperparameters are sufficiently constrained, it may become possible to infer the lens redshift distribution statistically. In particular, the recovered intrinsic lens-mass distribution may also help partially break the degeneracy between the detector-frame lens mass M_l^z and the lens redshift z_l through population-level marginalisation. Such a partial separation of z_l from M_l^z would allow the detected compact-lens population to be grouped into redshift bins, enabling the evolution of the compact-DM fraction, $f_{\text{DM}}(z_l)$, to be investigated as a function of cosmic time.

Constraining the redshift evolution of the compact-lens abundance may provide an important clue to their astrophysical origin. If the inferred compact-object density increases significantly following the peak of the cosmic star-formation history ($z \sim 2$) [295], such behaviour would strongly favour a conventional stellar-remnant origin. In contrast, if compact lenses continue to be detected at higher redshifts while the inferred f_{DM} remains approximately constant over cosmic time, this would be difficult to explain through stellar evolution alone. Instead, they would provide compelling evidence for an additional exotic compact-object population, such as PBHs formed in the early Universe before the onset of star formation.

From the perspective of detectability, the microlensing selection criteria should be refined using more realistic FPP estimates derived from dedicated background injections, rather than relying solely on Bayes factors, as discussed in Chapters 5 and 6. Our injection-and-recovery framework also relied exclusively on isolated point-mass lens templates. However, as discussed in Chapter 7, strongly lensed GW signals are expected to undergo additional microlensing perturbations from stellar fields embedded within a galaxy potential, producing waveform distortions substantially more complex than those generated by isolated point-mass lenses alone. Addressing these limitations will require both more robust statistical detection frameworks and the development of more sophisticated waveform models in future analyses.

PART IV

CONCLUSIONS

Chapter 11

Executive Summary and Future Prospects

General Relativity, formulated by Albert Einstein, stands as a monumental triumph of twentieth-century physics [9, 10], predicting two cornerstone astrophysical phenomena: gravitational waves [7, 8] and gravitational lensing [88, 89]. The intricate interplay between these two predictions offers a unique avenue for probing the distribution of matter across a wide range of scales, as well as the evolutionary history of the Universe. This thesis aims to translate these profound theoretical frameworks into observational methodologies. In particular, this work addresses two central questions: *“how gravitationally lensed GW signals can be reliably identified in detector data.”* (Part II) and *“how such signals can be used to extract meaningful astrophysical and cosmological information once detected.”* (Part III)

The direct detection of GWs has marked a paradigm shift in modern astrophysics and multi-messenger astronomy, opening an entirely new window onto the distant Universe [14, 16, 17]. Unlike EM observations, GWs enable direct access to the most extreme and highly dynamical gravitational environments, such as CBCs, many of which are inaccessible to conventional EM observations due either to the intrinsic absence of EM emission or to observational limitations at high redshift. **Chapter 1** established the theoretical and observational foundations of GW physics. The mathematical framework of GW generation was introduced together with the astrophysical properties of compact binaries and other potential GW sources [21, 24, 30]. We also reviewed the operating principles of ground-based interferometric detectors and the methodologies used to identify GW signals within noisy detector data [24, 61, 66, 72].

Gravitational lensing further extends the scientific reach of GW observations. Intervening matter distributions can act as cosmic telescopes that magnify distant sources, thereby providing a unique probe of the distribution of both baryonic and dark matter along the line of sight [103]. At the same time, lensing introduces characteristic signatures into GW signals, such as relative magnifications, time delays, and wave-optics interference patterns, which encode information about both the lensing structures and the underlying source population. Motivated by these possibilities, **Chapter 2** developed the theoretical framework

of gravitational lensing for GWs, beginning with general lensing theory and extending to lens models, lensing probabilities, and the physical distinctions between EM and GW lensing [103, 114, 131, 147]. Within this framework, the key observables of lensed astrophysical signals and their associated implications were systematically explored.

11.1 Toward Realistic Searches for GW Lensing

To extract physical source information from GW observations and identify possible lensing signatures, we first reviewed the Bayesian inference framework for GW parameter estimation in *Chapter 4* [248, 253]. Bayesian inference plays a central role in GW astronomy because the underlying source properties cannot be directly observed, but must be statistically inferred from noisy detector data through waveform modelling [236, 252]. In contrast to many EM observations, GW analyses rely on coherent matched-filtering and likelihood exploration, making Bayesian techniques indispensable for robust source characterisation and uncertainty quantification. Within this framework, we further examined the physics of CBC signals and the high-dimensional parameter space describing them. Since CBC signals are characterised by a large number of correlated parameters, efficient stochastic samplers become essential for accurately obtaining posterior distributions [236, 240, 243, 244, 245, 246, 247].

Building upon this theoretical and computational foundation, we addressed the first central question of this thesis. *Chapter 5* investigated practical searches for gravitational lensing signatures in GW observations using advanced Bayesian inference techniques and modern computational pipelines [238, 327]. In particular, we explored two complementary classes of lensing searches: (1) searches for single distorted signals and (2) searches for multiple lensed images originating from the same source. Through these analyses, we highlighted the conceptual and methodological differences between waveform-distortion-based searches and correlation-based multiple-image searches.

Despite these methodological advances, our isolated PM microlensing analysis of BBH events from recent observing runs, as presented in *Chapter 6*, has not yet yielded decisive and unambiguous evidence for GW microlensing. GW231123 [329], however, remains a particularly intriguing candidate. When interpreted under the microlensing hypothesis, this event exhibits the highest Bayes factors obtained to date ($\log_{10} \mathcal{B}_U^{\text{Mod}} \simeq 3.8$), improved agreement with model-agnostic reconstructed waveforms, and source parameters that are more consistent with the currently inferred astrophysical BBH population [238]. Despite these suggestive features, more rigorous validation, including extensive robustness tests against waveform systematics [331] and detector artifacts [332], together with broader population-level analyses across future GW catalogues, will be required before a confident microlensing detection can be established.

A major limitation of many existing lensing searches is that they rely on idealised lensing scenarios, such as isolated PM lenses or lens-model-independent multiple-image searches. Consequently, current search pipelines may not fully capture the complexity of realistic astrophysical lensing environments [314, 317, 318, 320, 321]. As discussed in *Chapter 7*, a more physically realistic scenario involves the simultaneous presence of strong lensing and microlensing. To address this complexity, we introduced a residual-based framework designed to identify hidden microlensing signatures embedded within strongly lensed GW signals. Rather than performing computationally expensive, fully model-dependent parameter estimation over complex lens configurations, this method exploits characteristic structures remaining in the waveform residuals through our statistics $\Lambda_{\mathcal{H}}$ (see Eq. (7.7)). This approach enables a low-latency search strategy while retaining sensitivity to subtle wave-optics features generated by realistic lensing systems.

Nevertheless, achieving robust and quantitatively reliable identification of such complexly lensed signals ultimately requires fully lens-model-dependent Bayesian inference employing realistic astrophysical lens models. Consequently, alongside the continued development of low-latency non-parameter-estimation-based search pipelines, future efforts should prioritise the efficient and accurate computation of the oscillatory amplification factor, $F(f)$, in the wave-optics regime (see Eq. (2.71)).

11.2 Strong- and Micro- Lensing: Inferences on H_0 and f_{DM}

The successful identification and interpretation of lensed GW signals provide a unique opportunity to connect GW astronomy directly with precision cosmology [202]. GWs themselves serve as standard sirens, providing a completely independent probe of cosmology. Since the GW waveform directly encodes the luminosity distance to the source without relying on the traditional cosmic distance ladder, GW observations offer a powerful and largely unbiased method for measuring the expansion history of the Universe, as discussed in *Chapter 3*. This cosmological potential is further amplified when these standard sirens undergo gravitational lensing. Lensing magnification increases the effective sensitivity of GW detectors to high- z sources. In addition, both magnification and the joint analysis of multiple lensed signals from a single event can improve source localisation and luminosity-distance (d_L) estimation. Ultimately, combining strong lensing with standard sirens offers a promising pathway to constrain H_0 and address the ongoing Hubble tension.

To fully exploit the potential of these lensed standard sirens, *Chapter 8* established the necessary methodologies for analysing individual strong lensing systems. While multiple lensed signals can yield exceptional precision in d_L and sky localisation as mentioned above, translating these measurements into astrophysical and cosmological insight requires reliable host-galaxy identification and accurate reconstruction of the lens mass distribution.

We demonstrated that combining EM observations of the host–lens system with precise GW measurements enables tight constraints on the lens-model parameters. Such accurate lens reconstruction is an essential prerequisite for the delensing process, which aims to recover the intrinsic luminosity distance required for unbiased H_0 inference.

Building upon these enhanced parameter constraints, *Chapter 9* explored the cosmological applications of lensed dark sirens by integrating galaxy catalogues with the hierarchical Bayesian framework introduced in *Chapter 4*. We first demonstrated how the improved sky localisation and luminosity-distance measurements discussed in the previous chapter enable robust H_0 inference even from a single strongly lensed dark siren via the Hubble–Lemaître law. In particular, we showed that a single quadruply lensed dark siren can provide an H_0 constraint comparable to that obtained from a bright siren event.

Next, extending the analysis from individual systems to population-level cosmological inference requires a statistical framework capable of self-consistently incorporating source populations, selection effects, and lensing probabilities. To address this, we developed a comprehensive hierarchical Bayesian framework for lensed dark siren populations. Our analysis demonstrated that a small number of lensed GW events can achieve an H_0 precision comparable to that from hundreds of unlensed signals, and that future populations of multiply lensed GW events can constrain H_0 at a level competitive with existing EM observations. Finally, we investigated potential systematic biases arising from missed or incorrect lensing classifications, highlighting the importance of robust lens-identification pipelines to prevent cosmological misinterpretations.

Shifting the focus from the expansion history of the Universe to compact-object populations, *Chapter 10* explored the astrophysical implications of GW microlensing. In particular, we investigated the information that could be extracted from a future catalogue of confidently identified microlensed GW events. By statistically combining multiple detections within a hierarchical Bayesian framework, while consistently accounting for microlensing selection effects, we demonstrated that the mass and spatial distributions of the compact lenses can be tightly constrained.

Furthermore, if we assume that the microlensing events originate from intrinsically dark compact objects, their inferred population properties provide a direct probe of the DM fraction, f_{DM} , composed of compact objects spanning the stellar- to IMBH-mass regime, in contrast to previous studies that have primarily constrained compact-object populations through the non-detection of microlensing signatures (e.g., [428]). Our framework illustrates how future GW microlensing observations can evolve beyond individual-event studies into a population-level probe of otherwise inaccessible compact-object populations, opening a new observational window onto both astrophysics and fundamental cosmology.

11.3 Challenges and Future Directions in GW Lensing

The current absence of definitive lensed GW detections should not be interpreted as evidence against the existence of such systems, but rather as a consequence of the intrinsic observational limitations of the present detector era. The primary limitation arises from the low intrinsic lensing probability for events detectable by existing second-generation detector networks. The optical depth for strong lensing increases rapidly with source redshift, approximately scaling as $\tau(z_s) \propto z_s^3$ at low redshift, where the Universe is approximately Euclidean. However, current GW detectors are primarily sensitive to BBH mergers at $z \lesssim 1\text{--}1.5$, where the expected strong-lensing probability remains only $\tau \sim 10^{-4}\text{--}10^{-3}$ [238]. Given that present GW catalogues contain only several hundred detected BBH mergers, the absence of an unambiguous lensed detection in current observing runs is therefore statistically unsurprising.

The optical depth for GW microlensing remains substantially more uncertain because the underlying population of compact lenses is not yet well constrained. Nevertheless, compact objects capable of producing microlensing are expected to be more abundant than galaxy-scale strong lenses, potentially implying a higher occurrence rate of microlensing signatures. Identifying such events in observational data, however, remains highly challenging. Microlensing signatures typically manifest as subtle frequency-dependent modulations, such as interference fringes or beating patterns, whose detectability is fundamentally limited by the distinguishability between lensed and unlensed waveforms in the presence of detector noise. Weak microlensing configurations, such as those involving low lens masses ($M_l \lesssim 100M_\odot$) or large impact parameters ($y > 1$), are expected to occur more frequently than configurations with high lens masses or small impact parameters. In such cases, the induced waveform distortions typically produce only very small mismatches ($\text{MM} \ll 1$) between the lensed and unlensed templates (see Eq. (6.2)). In the presence of realistic detector noise, these weak distortions can be easily obscured by statistical fluctuations, preventing Bayesian model selection from decisively favouring the microlensing hypothesis. Consequently, a substantial region of the physically relevant microlensing parameter space remains effectively inaccessible to current detector sensitivities.

These challenges, however, are not expected to remain fundamental limitations in the era of third-generation detectors. The Einstein Telescope [393] and Cosmic Explorer [436] will dramatically extend the observable volume of the Universe, substantially increasing the lensing optical depth and enabling the routine detection of high- z binary mergers. Simultaneously, the exceptionally high SNRs ($\rho_{\text{net}} > 100$) and long in-spiral durations accessible to next-generation detectors will allow subtle wave-optics modulations to be resolved with far greater precision.

Nevertheless, the transition toward precision GW lensing science will require advances beyond detector sensitivity alone. As discussed in *Chapter 6*, GW lensing signatures can exhibit significant phenomenological degeneracies with intrinsic complexities of CBC signals (e.g., [331, 340, 369]). If the frequency-dependent amplitude and phase modulations induced by lensing significantly overlap with waveform features produced by non-standard binary configurations, such as orbital eccentricity, spin precession, or overlapping GW signals, standard Bayesian inference may misidentify these effects as evidence for lensing, potentially leading to biased parameter estimation or false-positive lensing detections. Therefore, as detector sensitivities improve and statistical uncertainties decrease in the high-SNR regime, increasingly accurate waveform models incorporating both realistic source physics and lensing effects will become essential. In parallel, low-latency, computationally efficient inference pipelines capable of exploring realistic lens models will be critical for fully exploiting the scientific potential of future GW observations.

Ultimately, the coming decades are expected to transform GW lensing from a candidate-driven search into a precision observational framework for probing cosmology and compact structures across multiple astrophysical scales.

In the context of advanced cosmological inferences, next-generation detectors will provide substantially improved sky localisation and luminosity-distance measurements, facilitating host-galaxy identification and redshift determination for GW sources. In particular, a future catalogue of SLGW events will enable time-delay cosmography with unprecedented precision. Since GW arrival times can be measured to millisecond accuracy, the corresponding time-delay distances (see Eq. (2.25)) may provide sub-percent constraints on H_0 , potentially competitive with existing EM-only probes such as the CMB and Type Ia supernovae.

Beyond constraining the local expansion rate, these lensed GW observations can also address evolving cosmological phenomena. Recent DESI results [197] have shown increasing evidence for dynamical dark-energy models in which the equation-of-state parameter evolves with redshift, rather than remaining fixed at $\omega = -1$ as assumed in the standard Λ CDM framework [437, 438] (see Eqs. (3.18) and (3.21)). In this context, strongly lensed GW observations from next-generation detector networks may provide an important and highly complementary probe of the cosmic expansion history and the possible evolution of dark energy [417].

Complementing these large-scale cosmological inferences, future GW detectors with improved sensitivity will additionally become capable of identifying lower-mismatch microlensing signals, substantially increasing the number of detectable compact-lens candidates and strengthening population-level constraints. In particular, the detection of microlensing signatures from compact DM candidates at cosmological distances would place stringent constraints on the compact-DM fraction beyond the peak of the cosmic star-

formation history, where conventional stellar-remnant populations become increasingly difficult to produce. Such observations may also probe lower compact-object mass ranges that are less contaminated by ordinary stellar populations, thereby providing a cleaner window into possible primordial compact-object populations [424, 439].

Furthermore, access to lower GW frequencies in future detectors would extend the observable wave-optics regime toward more massive lenses, enabling interference signatures produced by intermediate-mass and heavier compact objects ($10^5 M_\odot < M_l^z \lesssim 10^8 M_\odot$) to be probed directly [386]. Such observations could open a new avenue for constraining the population properties of IMBHs and other massive compact objects across cosmic history.

Although the unambiguous detection of a lensed GW signal remains an outstanding milestone, the field is rapidly transitioning from a theoretical possibility to an imminent observational reality. As detector sensitivities continue to improve and the catalogue of GW events expands, the methodologies and investigations presented in this thesis serve as a useful foundation for the eventual identification and scientific exploitation of GW lensing. Looking further ahead, the emergence of multi-messenger lensing, in which GW and EM signals are jointly observed from the same lensed source, will establish a new paradigm for probing both cosmology and compact-object populations [102]. Ultimately, future GW lensing observations will transcend current methodological challenges, helping to address long-standing questions surrounding the nature of dark matter, the demographics of compact objects, and the evolution of the Universe itself.

APPENDIX

A Posteriors of the Hubble Constant

In this appendix, we provide a detailed description of each component in Eq. (9.10). The derivation presented here builds upon the formalism of Gray et al. [220]. Rewriting the expression, the posterior distribution of the Hubble constant, H_0 , for a set of lensed dark sirens, x_{lgw} , with corresponding detection indicators, D_{lgw} (where each element is either 0 or 1), and assuming $N_{\text{lens,det}}$ detected lensed systems, can be written as:

$$\begin{aligned}
 p(H_0 | \{x_{\text{lgw}}\}, \{D_{\text{lgw}}\}) &\propto p(H_0) p(N_{\text{lens,det}} | H_0) \\
 &\times \left[\iiint p(D_{\text{lgw}} | \theta_s, \theta_l, z_s, z_l, H_0) p(\theta_s | H_0) \sum_j^{N_{\text{pix}}} p(z_s, z_l, \theta_l | \Omega_j, H_0, s, l) d\theta_l d\theta_s dz_l dz_s \right]^{-N_{\text{lens,det}}} \\
 &\times \prod_i^{N_{\text{lens,det}}} \left[\iiint \sum_j^{N_{\text{pix}}} p(x_{\text{lgw},i} | \Omega_j, \theta_s, \theta_l, z_s, z_l, H_0) p(\theta_s | H_0) p(z_s, z_l, \theta_l | \Omega_j, H_0, s, l) d\theta_l d\theta_s dz_l dz_s \right], \tag{1}
 \end{aligned}$$

where θ_s , θ_l , z_s , and z_l denote the GW source parameters excluding the distance, the lens parameters of the source-lens galaxy system, the source redshift, and the lens galaxy redshift, respectively. $p(z_s, z_l, \theta_l | \Omega_j, H_0, s, l)$ is the LoS redshift distribution of source and lens galaxies obtained from the galaxy-galaxy lensing catalogue. The GW sky localisation is discretised into N_{pix} pixels, with Ω_j corresponding to the sky direction of the j^{th} pixel. $p(H_0)$ denotes the prior on the Hubble constant, which is a uniform distribution over the range of $[20, 140] \text{ km} \cdot \text{s}^{-1} \cdot \text{Mpc}^{-1}$. More detailed descriptions of the remaining terms are provided in the following subsections.

A.1 Selection Effect Associated with Lensed Gravitational Waves

Selection bias arises when the number of detectable signals differs from the total number of mergers due to limited detector sensitivity. The inferred H_0 becomes biased if selection effects are ignored. For example, low-redshift events are more easily detected, which would incorrectly suggest an overabundance of GW sources at low redshift. To correct for this, the likelihood of each GW event must be divided by its detection efficiency, that is, the probability that an event with given parameters would be observed.

Given the detection probability for a source with parameters $\vec{\theta} = (\theta_s, \theta_l, z_s, z_l)$, $p_{\text{det}}(\vec{\theta})$ and the underlying population distribution $p_{\text{pop}}(\vec{\theta})$ for a given set of hyperparameters Λ , such as Eqs. (4.35), (4.37), and (4.39), the expected number of detections of lensed GW events is given by:

$$\begin{aligned} \langle N_{\text{lens,det}}(\Lambda) \rangle &= N_{\text{lens}} \int p_{\text{det}}(\vec{\theta}) p_{\text{pop}}(\vec{\theta}|\Lambda) d\vec{\theta} \\ &= N_{\text{lens}} \iiint p(D_{\text{lgw}}|\theta_s, \theta_l, z_s, z_l, \Lambda) p(\theta_s, \theta_l, z_s, z_l|\Lambda) d\theta_s d\theta_l dz_l dz_s, \end{aligned} \quad (2)$$

where N_{lens} denotes the total number of lensed mergers [291]. The detection efficiency is the same as the ratio between the total and expected number of detection. To efficiently evaluate the detection efficiency of lensed GW events, we generated numerous injections from a fiducial distribution $\pi(\vec{\theta})$ (see [292] for more details). For a given set of detected lensed GW events, the detection efficiency, equivalent to the selection-effect term in Eq. (1), can be evaluated as follows:

$$\begin{aligned} \frac{\langle N_{\text{lens,det}}(\Lambda) \rangle}{N_{\text{lens}}} &= \iiint p(D_{\text{lgw}}|\theta_s, \theta_l, z_s, z_l, \Lambda) p(\theta_s, \theta_l, z_s, z_l|\Lambda) d\theta_s d\theta_l dz_l dz_s \\ &\simeq \frac{1}{N_{\text{inj}}} \sum_i^{N_{\text{inj,det}}} \frac{p_{\text{pop}}(\vec{\theta}_i|\Lambda)}{\pi(\vec{\theta}_i)} \\ &= \frac{1}{N_{\text{inj}}} \sum_i^{N_{\text{inj,det}}} \frac{p_{\text{pop}}(m_{1,i}, m_{2,i}, z_{s,i}|\Lambda)}{\pi(m_{1,i}, m_{2,i}, z_{s,i})} \frac{p_{\text{pop}}(\theta_{l,i}, z_{l,i}|z_{s,i}, \Lambda)}{\pi(\theta_{l,i}, z_{l,i})} \\ &= \frac{1}{N_{\text{inj}}} \sum_i^{N_{\text{inj,det}}} \frac{p_{\text{pop}}(m_{1,i}, m_{2,i}, z_{s,i}|\Lambda)}{\pi(m_{1,i}, m_{2,i}, z_{s,i})} \frac{p_{\text{pop}}(\vec{\mu}_i|\Lambda)}{\pi(\vec{\mu}_i)}, \end{aligned} \quad (3)$$

where $m_{1,i}$, $m_{2,i}$, and $\vec{\mu}_i$ indicate the component masses and individual magnification factors of the i^{th} lensed event, respectively.

Instead of sampling the θ_l and z_l directly, we first compute $\vec{\mu}$ from the lens parameters, creating multiple images under a specific lens model. The resulting magnification factors define a distribution from which we draw samples, as these factors directly affect the SNR of the lensed signals. We adopt the population models in Section 4.4.2 for the source-frame primary and secondary masses and redshift. All other source parameters are drawn from hyperparameter-independent distributions. For these latter parameters, the population prior p_{pop} reduces to the prior π and is thus omitted.

Since detectability is determined in the detector frame, we draw injections in the detector frame, which modifies Eq. (3) as follows,

$$\begin{aligned}
 \frac{\langle N_{\text{lens,det}}(\Lambda) \rangle}{N_{\text{lens}}} &\simeq \frac{1}{N_{\text{inj}}} \sum_i^{N_{\text{inj,det}}} \frac{p_{\text{pop}}(m_{1,i}, m_{2,i}, z_{s,i} | \Lambda)}{\pi(m_{1,i}, m_{2,i}, z_{s,i})} \frac{p_{\text{pop}}(\vec{\mu}_i | \Lambda)}{\pi(\vec{\mu}_i)} \\
 &= \frac{1}{N_{\text{inj}}} \sum_i^{N_{\text{inj,det}}} \frac{p_{\text{pop}}(m_{1,i}, m_{2,i}, z_{s,i}, \vec{\mu}_i | \Lambda)}{\pi(m_{1,i}^d, m_{2,i}^d, d_{L,i}^{\text{eff}})} \left| \frac{\partial(m_{1,i}, m_{2,i}, z_{s,i}, \vec{\mu}_i)}{\partial(m_{1,i}^d, m_{2,i}^d, d_{L,i}^{\text{eff}})} \right| \\
 &= \frac{1}{N_{\text{inj}}} \sum_i^{N_{\text{inj,det}}} \frac{p_{\text{pop}}(m_{1,i}, m_{2,i}, z_{s,i}, \vec{\mu}_i | \Lambda)}{\pi(m_{1,i}^d, m_{2,i}^d, d_{L,i}^{\text{eff}})} \prod_j \left| \frac{2\mu_{i,j}}{d_{L,i,j}^{\text{eff}}} \right| \frac{1}{(1+z_{s,i})^2} \left| \frac{\partial z_s}{\partial d_L} \right|_{z_s=z_{s,i}}, \tag{4}
 \end{aligned}$$

where m_1^d and m_2^d are detector-frame primary and secondary masses. Although injections are generated in the detector frame, the selection function is evaluated by reweighting them to the source-frame population model, including the full Jacobian associated with the transformation between $(m_1^d, m_2^d, d_{L,i}^{\text{eff}})$ and $(m_1, m_2, z_s, \vec{\mu})$.

To determine whether a signal is detected, the unlensed case is straightforward. A single event is considered detected if its network SNR exceeds the chosen threshold, $\rho_{\text{net}} = 8$. However, for lensed events, multiple signals from the same source must not only exceed the network SNR threshold, but also be confirmed to originate from the same source and truly lensed through a lensing hypothesis test. Strong lensing can be verified using pipelines equipped with joint parameter estimation, such as [300, 301, 302, 303] employed in projects of searching for GW lensing signatures [238, 324, 325]. In this study, we assume that all lensed signals pass the hypothesis test. Hence, the detection criterion reduces to verifying that lensed signals are detected above the SNR threshold and correctly identified as lensed. Accordingly, $N_{\text{lens,det}}$ in Eq. (3) denotes the number of GW lensing systems that satisfy both the detection threshold and the lensing hypothesis test.

For doubly lensed GW systems, if one of the signals falls below the detection threshold, the lensing nature of the system cannot be inferred from the single detected signal alone. In principle, one may nevertheless perform a dedicated sub-threshold search to identify a counterpart of a detected super-threshold GW signal that is insufficiently magnified or strongly demagnified to be detected above the threshold [377, 413]. Furthermore, a lensed GW signal could be identified even from a single image by searching for waveform distortions in Type-II images induced by higher-order GW modes [157, 367]¹.

For quadruply lensed systems, only two or three of the four images may be detected in realistic scenarios. We impose the analogous requirement to the doubly-lensed case that at least two signals must exceed the detection threshold for the system to be identified as strongly lensed. Since the lensing hypothesis test determines the number of detected lensed

1. However, such effects are not directly relevant to the high-magnification regime or to improvements in sky localisation, and therefore we do not consider this possibility in this study.

signals in each system, we consider three cases: two, three, or all four images detected, when accounting for selection effects. It is important to note that partially detecting only two or three of the four images can make it initially unclear whether the system originates from a quadruply lensed source. Accounting for selection effects under the assumption that such systems are doubly or triply lensed leads to a biased inference of the Hubble constant.

Once a specific lens model is adopted, however, the possible number of lensed signals becomes fixed, and the corresponding population distributions of lensing observables, such as relative magnification factors and time delays, are determined. Under the SIE model, for example, only two or four images can be produced. Thus, if three images are detected, the event can be unambiguously identified as a quadruply-lensed system, allowing the appropriate quadruple-image selection effects to be applied. When only two images are detected, however, both the doubly-lensed and quadruply-lensed interpretations remain possible, and selection effects from both cases must be considered.

The term $p_{\text{pop}}(\vec{\theta}|\Lambda)$ in Eq. (2) can be expressed in terms of the underlying population distribution function, $dN/d\vec{\theta}$ [291, 292]. We begin by defining the number of compact binary mergers per unit observer time and unit redshift, defined as:

$$\frac{d^2N}{dt dz} = \frac{\mathcal{R}(z)}{1+z} \frac{\partial V_c}{\partial z}, \quad (5)$$

where $\mathcal{R}(z)$ is the intrinsic merger rate per comoving volume, V_c , at source redshift z , and the $(1+z)^{-1}$ factor accounts for cosmological time dilation.

To obtain the subset of these merger events that undergo strong lensing, the optical depth introduced in Eq. (2.28) can be rewritten as:

$$\tau(z_s, H_0) = \int_0^{z_s} dz_l \frac{dV_c}{d\Omega dz_l} \int d\theta_l n_l(z_l, \theta_l) \hat{\sigma}_{\text{SL}}(z_s, z_l, \theta_l, H_0), \quad (6)$$

where $dV_c/(d\Omega dz_l)$ denotes the differential comoving volume per steradian at the lens redshift z_l , n_l is the comoving number density of lenses with properties θ_l , and $\hat{\sigma}_{\text{SL}}$ represents the strong lensing cross-section of an individual lens for a given z_s , z_l , θ_l , and H_0 .

From Eq. (5), $dN/d\vec{\theta}$ can then be related to the intrinsic merger rate, together with the corresponding optical depth in Eq. (6) as follows:

$$\begin{aligned} \langle N_{\text{lens, det}}(H_0) \rangle &= N_{\text{lens}} \iiint p(D_{\text{lgw}}|\theta_s, \theta_l, z_s, z_l, H_0) \frac{1}{N_{\text{lens}}} \left(\frac{d^4 N_{\text{lens}}}{d\theta_s d\theta_l dz_l dz_s} \right) d\theta_s d\theta_l dz_l dz_s \\ &= T_{\text{obs}} \iiint p(D_{\text{lgw}}|\theta_s, \theta_l, z_s, z_l, H_0) \tau(z_s, H_0) \frac{\mathcal{R}(z_s)}{1+z_s} \frac{\partial V_c}{\partial z_s} d\theta_s d\theta_l dz_l dz_s, \end{aligned} \quad (7)$$

where T_{obs} denotes the observation period. Eq. (7) encodes the distribution of θ_l and z_l , both of which depend on H_0 in contrast to the z_s and θ_s , which are independent of H_0 . Therefore, unlike in the unlensed case, the probability of detecting $N_{\text{lens,det}}$ lensed dark siren system for a given value of H_0 , $p(N_{\text{lens,det}} | H_0)$, cannot be neglected even when adopting a scale-invariant prior on the merger rate, $P(\mathcal{R}) \propto 1/\mathcal{R}$. For a given expected number of detections ($\langle N_{\text{lens,det}} \rangle$), $p(N_{\text{lens,det}} | H_0)$ in Eq. (1) can be expressed as a Poisson distribution as follows:

$$p(N_{\text{lens,det}} | H_0) = e^{-\langle N_{\text{lens,det}} \rangle} (\langle N_{\text{lens,det}} \rangle)^{N_{\text{lens,det}}} . \quad (8)$$

A.2 Line-of-sight Redshift Prior

The LoS redshift prior is constructed by using the measured redshift, luminosity, and apparent magnitude information of galaxies in a given catalogue to identify which galaxies lie within the GW sky localisation, to weight them by their probability of hosting a BBH merger (e.g., luminosity weighting) and being lensed, and to correct for the incompleteness of the galaxy catalogue. This framework enables the inference of the redshift distribution of the observed BBH events from GW observations.

For the purpose of identifying galaxies within a given GW localisation, a galaxy-galaxy lensing catalogue, in which both source and lens galaxy information is available for each system, can be more informative than a standard galaxy catalogue containing only unlensed galaxies. However, luminosity weighting and corrections for catalogue incompleteness require the intrinsic source-galaxy luminosity (i.e., the absolute magnitude) and the redshift. While galaxy-scale gravitational lensing is achromatic and leaves the observed redshift unchanged to within the precision of spectroscopic measurements, the absolute magnitude can be significantly altered by lensing magnification. Therefore, delensing is required to recover the intrinsic absolute magnitudes of source galaxies in order to obtain robust luminosity weights and incompleteness corrections. Accordingly, the LoS redshift prior must account for whether both the source and lens galaxies are included in the catalogue.

A.2.1 Complete catalogue

We first consider the complete catalogue case, in which there is no apparent magnitude limit, such that every lens galaxy and all lensed images of the source galaxy for each system are included in the catalogue. In this case, the LoS redshift prior in Eq. (1), $p(z_s, z_l, \theta_l | \Omega_j, H_0, s, l)$, is given by:

$$p(z_s, z_l, \theta_l | \Omega_j, H_0, s, l) = \iint p(z_s, z_l, \theta_l, M_s, m'_s, M_l, m_l | \Omega_j, H_0, s, l) dM_s dm'_s dM_l dm_l, \quad (9)$$

where M_s and M_l denote the intrinsic absolute magnitudes of source and lens galaxies, respectively. m_l and m'_s are the apparent magnitude of the lens galaxy and lensed source-galaxy images (see Eq. (2.59)), respectively. Note that M_s cannot be correctly obtained from m'_s using the standard distance modulus alone, as the magnification factor of the lensed image must be taken into account. Hereafter, we define $\vec{M} = (M_s, M_l)$ and $\vec{m} = (m'_s, m_l)$ to concisely represent the absolute and apparent magnitudes. The integrand in Eq. (9) can then be written as:

$$\begin{aligned}
& p(z_s, z_l, \theta_l, \vec{M}, \vec{m} \mid \Omega_j, H_0, s, l, \mathcal{M}_{\text{SIE}}) \\
&= \frac{1}{p(s, l \mid \Omega_j, H_0)} p(z_s, z_l, \theta_l, \vec{M}, \vec{m} \mid \Omega_j, H_0, \mathcal{M}_{\text{SIE}}) p(s, l \mid z_s, z_l, \theta_l, \vec{M}, \Omega_j, H_0, \mathcal{M}_{\text{SIE}}) \\
&= \frac{1}{p(s, l \mid \Omega_j, H_0)} \delta(M_s - M_s(z_s, z_l, \theta_l, m'_s, H_0, \mathcal{M}_{\text{SIE}})) \delta(M_l - M_l(z_l, m_l, H_0)) \\
&\times p(z_s, z_l, \theta_l, m'_s, m_l \mid \Omega_j, H_0) p(s, l \mid z_s, z_l, \theta_l, M_s, H_0),
\end{aligned} \tag{10}$$

where $\mathcal{M}_{\text{SIE}}$ indicates that SIE profiles are assumed to infer M_s from m'_s of their images.

Since all lensed images and the lens galaxy are observed in a complete catalogue, the intrinsic luminosity of the source galaxy can, in principle, be accurately recovered. We therefore assume that the intrinsic absolute magnitude of the source galaxy is uniquely determined once the other measured parameters are specified, such that its prior can be represented as a delta function. The absolute magnitude of the lens galaxy, M_l , is unaffected by lensing and independent of the source properties, and thus its prior can likewise be treated as a delta function². Moreover, the probability that a galaxy hosts a GW source and that the detected lensed images are genuinely associated does not depend on M_l , Ω_j , or $\mathcal{M}_{\text{SIE}}$, which are omitted in the last term $p(s, l \mid \dots)$.

The LoS redshift prior for the complete catalogue case can be written as:

$$\begin{aligned}
& p(z_s, z_l, \theta_l \mid \Omega_j, H_0, s, l, \mathcal{M}_{\text{SIE}}) \\
&= \frac{1}{p(s, l \mid \Omega_j, H_0)} \frac{1}{N_{\text{Lgal}}(\Omega_j)} \\
&\times \sum_k^{N_{\text{Lgal}}} p(z_s, z_l, \theta_l \mid \hat{z}_{s,k}, \hat{z}_{l,k}, \hat{\theta}_{l,k}) p(s, l \mid z_s, z_l, \theta_l, M_s(z_s, z_l, \theta_l, \hat{m}'_{s,k}, H_0, \mathcal{M}_{\text{SIE}})),
\end{aligned} \tag{11}$$

where N_{Lgal} denotes the number of lensing systems within the sky patch Ω_j . Following the notation of [220], the hat notation denotes the measured value for the k^{th} galaxy-galaxy lensing system, and the corresponding $p(z_s, z_l, \theta_l)$ are modelled as Gaussian distributions centered on these measured values. For z_s and z_l , we adopt the spectroscopic redshift un-

2. Note that, however, in galaxy-galaxy lensing systems, the spatial overlap between foreground lenses and background lensed source-galaxy images leads to blended photometry, which can systematically bias photometric redshift estimates.

certainties introduced in Section 9.2.1, namely $\sigma_z = 0.001(1 + z)$. For the lens parameters, we assume a standard deviation of 0.01, which corresponds to the grid resolution used in the delensing procedure described in [311]. As shown in Eq. (11), the magnitudes of the lens galaxies are not included, which can be neglected when deriving the LoS redshift priors, and thus we will omit M_l and m_l and not explicitly write them in the following.

Since no explicit correlation between GW source redshift and host galaxy luminosity is known, the term $p(s, l | \dots)$ can be factorised as follows:

$$p(s, l | z_s, z_l, \theta_l, M_s, H_0) \propto p(s | z_s) p(s | M_s) p(l | s, z_s, z_l, \theta_l, H_0). \quad (12)$$

For simplicity, one may reduce the complexity of the LoS computation by disabling the luminosity weighting, i.e., setting $p(s | M_s) \propto \text{const.}$. In this case, all source galaxies at z_s are assumed to have equal probability of hosting a BBH merger, and the resulting LoS redshift prior depends on the merger rate and lensing probability as a function of redshift and the distribution of galaxies.

A.2.2 Incomplete catalogue

In practice, galaxy catalogues are often incomplete due to observational limits. In this section, we examine the impact of an apparent magnitude threshold m_{th} , which may cause certain lens galaxies or lensed source-galaxy images to be missing from the catalogue. We consider six possibilities based on the visibility of the lens galaxy and the source-galaxy images: whether the lens is in- or out-of-catalogue, and whether all, a subset, or none of the source images are in the catalogue. Since whether a system is in the catalogue depends on whether the system is identified as lensed (GG) or not ($\overline{GG}$), these six possibilities can be grouped into the two categories (see Table A.1 for details).

With these definitions, Eq. (9) can be rewritten as

$$\begin{aligned} p(z_s, z_l, \theta_l | \Omega_j, H_0, s, l, \mathcal{M}_{\text{SIE}}) &= \iint \sum_{g=GG, \overline{GG}} p(z_s, z_l, \theta_l, M_s, m'_s, g | \Omega_j, H_0, s, l, \mathcal{M}_{\text{SIE}}) dM_s dm'_s \\ &= \sum_{g=GG, \overline{GG}} p(g | \Omega_j, H_0, s, l, \mathcal{M}_{\text{SIE}}) \iint p(z_s, z_l, \theta_l, M_s, m'_s | g, \Omega_j, H_0, s, l, \mathcal{M}_{\text{SIE}}) dM_s dm'_s. \end{aligned} \quad (13)$$

Case	catalogue	z_s, m'_s	z_l, θ_l	Delensing
(G, LG)	In	✓	✓	Very accurate (0-5 %)
(G', LG)	In	✓	✓	Accurate (5-20 %)
$(G, \overline{LG})$	In	✓	✗	Possible (20-50 %)
$(G', \overline{LG})$	Mixed	✓	✗	Poor (50 %-) or Impossible
$(\bar{G}, LG)$	Out	✗	✗	Impossible
$(\bar{G}, \overline{LG})$	Out	✗	✗	Impossible

Table A.1: Information availability for the six possibilities determined by the observational accessibility of the lens galaxy and the lensed source-galaxy images. G denotes the case in which all lensed images are included in the catalogue, $\bar{G}$ denotes the case in which none of the images are included, and G' denotes the case in which only a subset of the images is included. Similarly, LG and $\overline{LG}$ indicate whether the lens galaxy is present in or absent from the catalogue, respectively. A checkmark (✓) and a cross (✗) indicate that the corresponding quantity is observationally accessible or not, respectively. For the $(G', \overline{LG})$ case, if two or three images of a quadruple-image system are observed, the system is identified as lensed and delensing is partially possible, though limited. The accuracy of the delensing depends on the number of accessible observables. The numbers in parentheses denote the relative error ranges of the recovered magnification factors. Conversely, if only one image of a double-image system is observed, the system would not be included in the galaxy-galaxy lensing catalogue, as it may be interpreted as a weak lensing system or a special configuration of an unlensed galaxy. In this case, delensing is not possible.

The integrand of the first term in Eq. (13), corresponding to systems that are in-catalogue, has a form similar to Eq. (10) and can be expanded as

$$\begin{aligned}
& p(z_s, z_l, \theta_l, M_s, m'_s \mid GG, \Omega_j, H_0, s, l, \mathcal{M}_{\text{SIE}}) \\
&= \frac{p(z_s, z_l, \theta_l, M_s, m'_s \mid GG, \Omega_j, H_0, \mathcal{M}_{\text{SIE}})}{p(s, l \mid GG, \Omega_j, H_0)} p(s, l \mid z_s, z_l, \theta_l, M_s, \Omega_j, H_0, \mathcal{M}_{\text{SIE}}) \\
&= \frac{p(M_s \mid z_s, z_l, \theta_l, m'_s, H_0, \mathcal{M}_{\text{SIE}}) p(z_s, z_l, \theta_l, m'_s \mid GG, \Omega_j, H_0)}{p(s, l \mid GG, \Omega_j, H_0)} p(s, l \mid z_s, z_l, \theta_l, M_s, H_0),
\end{aligned} \tag{14}$$

where $p(M_s \mid \dots)$ denotes the conditional probability distribution based on the observed images and the SIE assumption. In the incomplete catalogue case, delensing cannot be assumed fully accurate, and the prior on the intrinsic absolute magnitude of the source galaxy can no longer be represented as a delta function, unlike in the complete catalogue case discussed in Section A.2.1. Nevertheless, the distribution of magnification factors for each source-galaxy image can be inferred through lens reconstruction, using the available information. This information may vary depending on the possibilities in Table A.1, allowing the intrinsic absolute magnitude to be recovered to some extent.

Integrating Eq. (14) over M_s and m'_s yields

$$\begin{aligned} \iint p(z_s, z_l, \theta_l, M_s, m'_s \mid GG, \Omega_j, H_0, s, l, \mathcal{M}_{\text{SIE}}) dM_s dm'_s &= \frac{1}{p(s, l \mid GG, \Omega_j, H_0)} \frac{1}{N_{\text{Lgal}}(\Omega_j)} \\ &\times \sum_k^{N_{\text{Lgal}}} \left[p(z_s, z_l, \theta_l \mid \hat{z}_{s,k}, \hat{z}_{l,k}, \hat{\theta}_{l,k}) \left\{ \frac{1}{N_{\text{samp}}} \sum_n^{N_{\text{samp}}} p(s, l \mid z_s, z_l, \theta_l, M_{s,k}^{(n)}, H_0) \right\} \right], \end{aligned} \quad (15)$$

where $M_{s,k}^{(n)}$ denotes the n^{th} sample among the N_{samp} samples drawn from the conditional distribution $p(M_s \mid \dots, \hat{m}'_{s,k})$, which is generally more informative than a uniform distribution over possible absolute magnitudes of source galaxies. Furthermore, for the source redshift, even if only a single lensed image is observed, z_s can still be determined. Therefore, Eq. (15) retains the same form as Eq. (11) with the conditional sampling over M_s replacing the delta function. Again, if luminosity weighting is not applied, retrieval of the true intrinsic luminosity is not required, and the LoS prior reduces to a simpler form.

Next, the integrand of the second term in Eq. (13), corresponding to systems that are out-of-catalogue, can be expanded in a manner similar to Eq. (2.11) of [220] as follows,

$$\begin{aligned} p(z_s, z_l, \theta_l, M_s, m'_s \mid \overline{GG}, \Omega_j, H_0, s, l, \mathcal{M}_{\text{SIE}}) \\ &= \frac{1}{p(s, l \mid \overline{GG}, \Omega_j, H_0)} p(s, l \mid z_s, z_l, \theta_l, M_s, \Omega_j, H_0, \mathcal{M}_{\text{SIE}}) \\ &\times p(z_s, z_l, \theta_l, M_s, m'_s \mid \overline{GG}, \Omega_j, H_0, \mathcal{M}_{\text{SIE}}) \\ &= \frac{1}{p(s, l \mid \overline{GG}, \Omega_j, H_0)} p(s, l \mid z_s, z_l, \theta_l, M_s, H_0) \\ &\times \frac{p(\overline{GG} \mid z_s, z_l, \theta_l, M_s, m'_s, \Omega_j, H_0, \mathcal{M}_{\text{SIE}}) p(z_s, z_l, \theta_l, M_s, m'_s \mid \Omega_j, H_0, \mathcal{M}_{\text{SIE}})}{p(\overline{GG} \mid \Omega_j, H_0, \mathcal{M}_{\text{SIE}})}, \end{aligned} \quad (16)$$

where the term $p(\overline{GG} \mid \dots)$ in the numerator indicates the probability that a galaxy-galaxy lensing system with the specified properties is not included in the catalogue. In the out-of-catalogue case, the observability of the lens galaxy is less relevant, and only the source-galaxy redshift is required when constructing the LoS redshift prior. Since the criterion for identifying a system as lensed is the detection of at least two lensed images of the source galaxy, the probability $p(\overline{GG} \mid \dots)$ can be expressed as follows,

$$p(\overline{GG} \mid z_s, z_l, \theta_l, M_s, m'_s, \Omega_j, H_0, \mathcal{M}_{\text{SIE}}) = \Theta \left(\left[\sum_{k=1}^{N_{\text{img}}} \Theta(m'_{s,k} - m_{\text{th}}(\Omega_j)) \right] - 2 \right). \quad (17)$$

Here, $\Theta(x)$ denotes the Heaviside step function, defined as $\Theta(x) = 1$ for $x \geq 0$ and $\Theta(x) = 0$ otherwise. For the adopted SIE lens model, the total number of images in a lensing system, N_{img} , is either 2 or 4.

Eq. (16) can then be rewritten as

$$p(z_s, z_l, \theta_l, M_s, m'_s \mid \overline{GG}, \Omega_j, H_0, s, l, \mathcal{M}_{\text{SIE}}) = \frac{\Theta\left(\left[\sum_{k=1}^{N_{\text{img}}} \Theta(m'_{s,k} - m_{\text{th}}(\Omega_j))\right] - 2\right)}{p(s, l \mid \overline{GG}, \Omega_j, H_0) p(\overline{GG} \mid \Omega_j, H_0)} \\ \times p(z_s, z_l, \theta_l, M_s, m'_s \mid H_0, \mathcal{M}_{\text{SIE}}) p(s, l \mid z_s, z_l, \theta_l, M_s, H_0). \quad (18)$$

Since the systems under consideration are galaxy-galaxy lensing systems, the lens properties are explicitly included. The term $p(z_s, z_l, \theta_l, M_s, m'_s \mid H_0, \mathcal{M}_{\text{SIE}})$ corresponds to the prior distributions of redshifts, lens parameters, and magnitudes, which are independent of the sky pixel Ω_j , as the properties of galaxies do not depend on their tangential location. We adopt minimally informative models to predict galaxy properties since not all relevant galaxy observables are directly accessible. Unlike the unlensed-catalogue case, the observed quantities correspond to the lensed source-galaxy properties and the lens properties. We assume that the redshifts of source galaxies follow a uniform distribution in comoving volume. Accordingly, the redshift distribution of lens galaxies is determined jointly by the source redshift distribution and the lensing optical depth.

For the lens parameters, we adopt the distributions described in Section 9.1.1. Note that both the lensing optical depth and the lens parameters are evaluated under the assumption of SIE profiles, and accordingly, the prior term explicitly depends on $\mathcal{M}_{\text{SIE}}$. Lastly, we adopt a Schechter function for the intrinsic absolute magnitudes of source galaxies. Given the source and lens redshifts, the source absolute magnitude, and the lens parameters, the lensed apparent magnitudes of source galaxies can then be computed.

Therefore, the prior can be written as

$$p(z_s, z_l, \theta_l, M_s, m'_s \mid H_0, \mathcal{M}_{\text{SIE}}) = \delta(m'_s - m'_s(z_s, z_l, \theta_l, M_s, H_0, \mathcal{M}_{\text{SIE}})) p(z_s, z_l, \theta_l, M_s \mid H_0). \quad (19)$$

Combining Eq. (18) with Eq. (19) and performing the integration over M_s and m'_s yields

$$\iint p(z_s, z_l, \theta_l, M_s, m'_s \mid \overline{GG}, \Omega_j, H_0, s, l, \mathcal{M}_{\text{SIE}}) dM_s dm'_s \\ = \frac{\int_{M_s(z_s, z_l, \theta_l, m_{\text{th}}(\Omega_j), H_0, \mathcal{M}_{\text{SIE}})}^{M_{\text{max}}(H_0)} p(z_s, z_l, \theta_l, M_s \mid H_0) p(s, l \mid z_s, z_l, \theta_l, M_s, H_0) dM_s}{p(s, l \mid \overline{GG}, \Omega_j, H_0) p(\overline{GG} \mid \Omega_j, H_0)} \quad (20)$$

The nested Heaviside step function in Eq. (17) has been converted into an integration limit over M_s , which depends on the properties of the source and lens galaxies and is determined by the apparent-magnitude threshold of pixel j .

By combining Eqs. (15) and (20), the full expression for the LoS redshift in the incomplete galaxy-galaxy lensing catalogue case (Eq. (13)) can be rewritten as

$$\begin{aligned}
 & p(z_s, z_l, \theta_l \mid \Omega_j, H_0, s, l, \mathcal{M}_{\text{SIE}}) \\
 &= \frac{p(GG \mid \Omega_j, H_0, s, l, \mathcal{M}_{\text{SIE}})}{p(s, l \mid GG, \Omega_j, H_0)} \\
 &\times \frac{1}{N_{\text{Lgal}}(\Omega_j)} \sum_k^{N_{\text{Lgal}}} p(z_s, z_l, \theta_l \mid \hat{z}_{s,k}, \hat{z}_{l,k}, \hat{\theta}_{l,k}) \left[\frac{1}{N_{\text{samp}}} \sum_n^{N_{\text{samp}}} p(s, l \mid z_s, z_l, \theta_l, M_{s,k}^{(n)}, H_0) \right] \\
 &+ \frac{p(\overline{GG} \mid \Omega_j, H_0, s, l, \mathcal{M}_{\text{SIE}})}{p(s, l \mid \overline{GG}, \Omega_j, H_0) p(\overline{GG} \mid \Omega_j, H_0)} \\
 &\times \int_{M_s(z_s, z_l, \theta_l, m_{\text{th}}(\Omega_j), H_0, \mathcal{M}_{\text{SIE}})}^{M_{\text{max}}(H_0)} p(z_s, z_l, \theta_l, M_s \mid H_0) p(s, l \mid z_s, z_l, \theta_l, M_s, H_0) dM_s.
 \end{aligned} \tag{21}$$

By applying Bayes' theorem to $p(g \mid \Omega_j, H_0, s)$ terms in each in-catalogue and out-of-catalogue term, Eq. (21) can be simplified as,

$$\begin{aligned}
 & p(z_s, z_l, \theta_l \mid \Omega_j, H_0, s, l, \mathcal{M}_{\text{SIE}}) \\
 &= \frac{1}{p(s, l \mid \Omega_j, H_0)} \\
 &\times \left[\frac{p(GG \mid \Omega_j, H_0, \mathcal{M}_{\text{SIE}})}{N_{\text{Lgal}}(\Omega_j)} \sum_k^{N_{\text{Lgal}}} \left\{ p(z_s, z_l, \theta_l \mid \hat{z}_{s,k}, \hat{z}_{l,k}, \hat{\theta}_{l,k}) \right. \right. \\
 &\quad \times \left. \left(\frac{1}{N_{\text{samp}}} \sum_n^{N_{\text{samp}}} p(s, l \mid z_s, z_l, \theta_l, M_{s,k}^{(n)}, H_0) \right) \right\} \\
 &\quad \left. + \int_{M_s^{\text{min}}}^{M_{\text{max}}(H_0)} p(z_s, z_l, \theta_l, M_s \mid H_0) p(s, l \mid z_s, z_l, \theta_l, M_s, H_0) dM_s \right],
 \end{aligned} \tag{22}$$

where $p(GG \mid \Omega_j, H_0, \mathcal{M}_{\text{SIE}})$ denotes the probability that a galaxy-galaxy lensing system located on the j^{th} pixel is in-catalogue. It is important to note that this expression does not depend on s , so we must consider not only the host galaxies but also all other galaxies within the given redshift cut that satisfy the magnitude threshold. The explicit definition of

this probability can be written as:

$$\begin{aligned}
& p(GG \mid \Omega_j, H_0, \mathcal{M}_{\text{SIE}}) \\
&= \int d\Xi p(GG \mid \Xi, \Omega_j, H_0, \mathcal{M}_{\text{SIE}}) p(\Xi \mid \Omega_j, H_0, \mathcal{M}_{\text{SIE}}) \\
&= \int d\Xi \Theta \left(2 - \sum_{k=1}^{N_{\text{img}}} \Theta(m'_{s,k} - m_{\text{th}}(\Omega_j)) \right) p(\Xi \mid \Omega_j, H_0, \mathcal{M}_{\text{SIE}}) \\
&= \iiint dz_s dz_l d\theta_l p(z_s, z_l, \theta_l \mid H_0) \int_{M_{\min}(H_0)}^{M_s^{\min}} p(M_s \mid H_0) dM_s,
\end{aligned} \tag{23}$$

where we denoted the full integration domain as $d\Xi \equiv dM_s dm'_s dz_s dz_l d\theta_l$ for brevity, and the integration upper limit as $M_s^{\min} \equiv M_s(z_s, z_l, \theta_l, m_{\text{th}}(\Omega_j), H_0, \mathcal{M}_{\text{SIE}})$. The term $p(z_s, z_l, \theta_l \mid H_0)$ denotes the joint prior on the source and lens redshifts and lens parameters introduced in the out-of-catalogue case, while the term $p(M_s \mid H_0)$ is modelled as a Schechter function describing the intrinsic absolute-magnitude distribution of source galaxies.

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