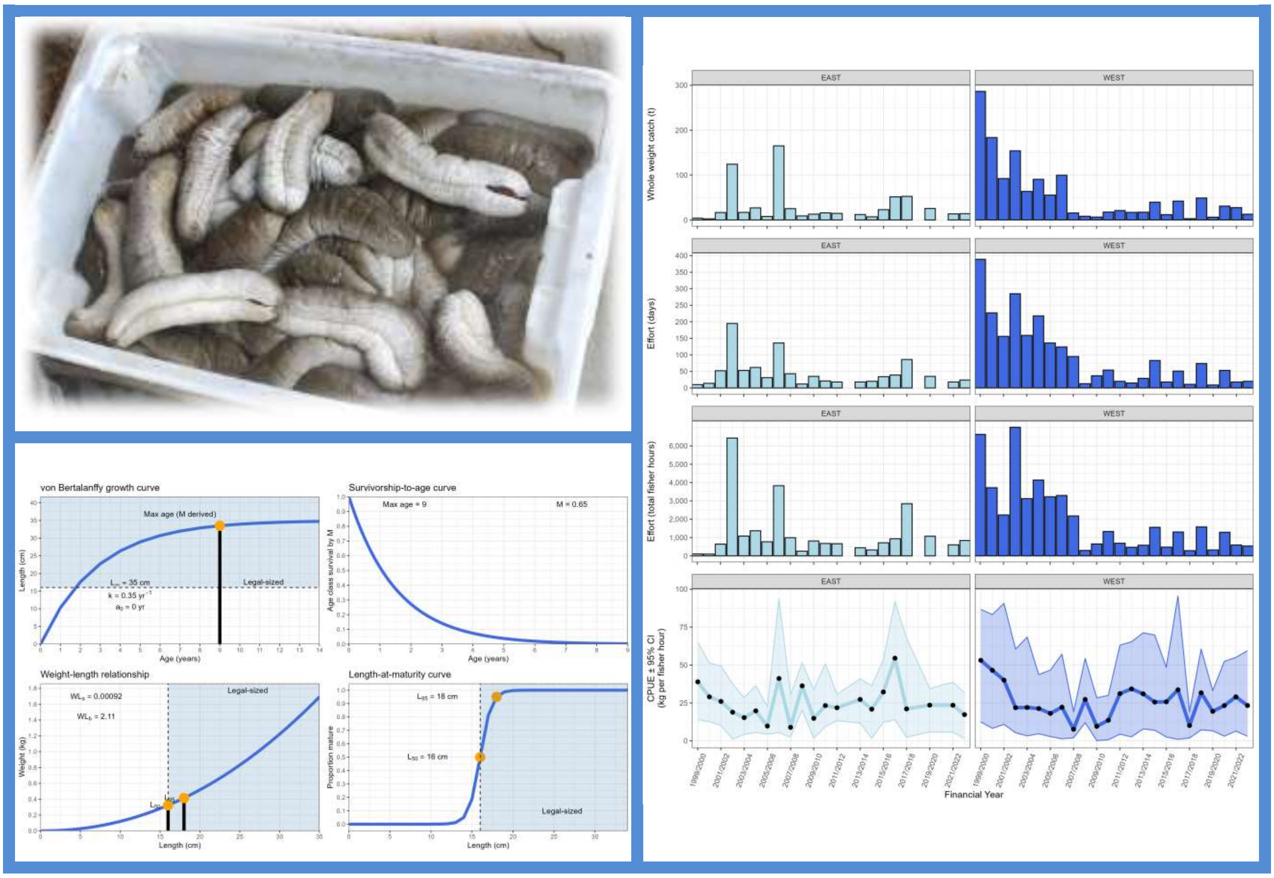
CPUE standardisation and stock assessment scoping report for sandfish (*Holothuria scabra*) in the Northern Territory



Jonathan Smart, Matt Koopman and Ian Knuckey

2025

fishwell

© 2025 Fishwell Pty Ltd.
All rights reserved.

CPUE standardisation and stock assessment scoping report for sandfish (*Holothuria scabra*) in the Northern Territory

Ownership of Intellectual property rights

Unless otherwise noted, copyright (and any other intellectual property rights, if any) in this publication is owned by Fishwell Pty Ltd.

This publication (and any information sourced from it) should be attributed to **Smart, J., Koopman, M. and Knuckey, I. (2025) CPUE standardisation and stock assessment scoping report for sandfish (*Holothuria scabra*) in the Northern Territory. 38pp [CC BY 4.0]**

Creative Commons licence

All material in this publication is licensed under a Creative Commons Attribution 4.0 Australia Licence, save for content supplied by third parties, logos and the Commonwealth Coat of Arms.

Creative Commons Attribution 4.0 Australia Licence is a standard form licence agreement that allows you to copy, distribute, transmit and adapt this publication provided you attribute the work. A summary of the licence terms is available from https://creativecommons.org/licenses/by/4.0/ The full licence terms are available from https://creativecommons.org/licenses/by/4.0/legalcode.en

Enquiries regarding the licence and any use of this document should be sent to: ian@fishwell.com.au

Disclaimer

The authors do not warrant that the information in this document is free from errors or omissions. The authors do not accept any form of liability, be it contractual, tortious, or otherwise, for the contents of this document or for any consequences arising from its use or any reliance placed upon it. The information, opinions and advice contained in this document may not relate, or be relevant, to a reader's particular circumstances. Opinions expressed by the authors are the individual opinions expressed by those persons and are not necessarily those of the publisher or research provider.

Fishwell Contact Details

Name: Ian Knuckey
Address: Queenscliff, VIC, 3225
Phone: 03 5258 4399
Email: ian@fishwell.com.au
Web: www.fishwell.com.au

Contents

Executive Summary

Sandfish (*Holothuria scabra*) are the primary species of sea cucumber harvested in the Northern Territory (NT) Trepang Fishery, constituting more than 99 % of the catch. Sandfish are one of the better studied species of sea cucumber given their high commercial value and aquaculture possibilities. However, many aspects of their biology and population dynamics remain poorly understood, complicating the application of stock assessment approaches. The NT fishery is managed through a series of input and output controls including limited entry, size limits and spatially-explicit catch limits. Evidence of overfishing has not been previously detected for the two NT sandfish stocks comprising the fishery (East and West). However, the 2023 edition of the Status of Australian Fish Stocks defined both stocks as “undefined” citing that there is insufficient information available to detect changes in stock abundance.

Recently, the densities and biomass have been surveyed in three 60 nm x60 nm grids for sandfish, providing some of the first information on stock size for consideration in management. Absolute estimates of biomass are valuable information for stock assessment purposes as they provide an absolute stock size at a given point in time. Although this is a snapshot of the population, it’s value when combined with a reliable index of abundance cannot be understated as it allows stock assessment models to be applied.

In order to provide a complementary abundance index to these recent surveys, this report presents catch-per-unit-effort (CPUE) standardisation for the two NT sandfish stocks, developing an approach for assessing whether localised depletion could be detected within a stock. Catch-per-unit-effort standardisation has benefits over nominal CPUE (i.e. raw CPUE) as it accounts for the effects of changing fleet dynamics, providing an index that can be used to assess changes in population abundance. This can be used as an input to stock assessment models or as a proxy for assigning stock status if the index is considered reliable enough on its own. Furthermore, this report considered whether sufficient data and information now exists to develop stock assessment models for NT sandfish stocks.

The CPUE standardisation analysis was performed using effort units expressed as total fisher hours, which encompasses the entirety of a fishing event, including search time, fishing time and processing time. A generalised mixed effects modelling approach (GLMM) was applied to each stock which standardised for the effects of licence number, fishing grid and the number of crew. Crossed random effects of year (financial year) within grid was used to determine grid level CPUE estimates from a model applied to the entire stock. The benefit of this approach was that grids were treated hierarchically within a stock, such that when limited fishing occurred within certain years for a particular grid, information was provided from other grids to determine abundance. This allowed for evidence of localised depletion to be examined, as each stock was effectively treated as a meta-population within the CPUE standardisation analyses.

The CPUE analyses demonstrated that nominal CPUE at the stock level matched the standardised CPUE across years for the East stock (grids to the East of the Wessel Islands). Similarly, nominal CPUE closely matched standardised CPUE in most years for the West stock (grids to the West of the Wessel Islands), except for the final few years when only one vessel was operating in the fishery. This demonstrates that CPUE standardisation did not meaningfully update the nominal CPUE at the stock level and indicates that CPUE can be used to infer changes in population abundance. At the grid level, several grids had limited catch and effort in recent years which would make detecting possible localised depletion challenging. However, the mixed effects model structure developed in this report overcame this, effectively borrowing information from the stock level CPUE trends to infer what population changes may resemble for grids with limited fishing in certain years. These results showed no evidence that localised depletion has occurred in recent years. However, these analyses must still be treated cautiously, as they maintain the assumption that comparable levels of recruitment occur across grids over time. The recruitment dynamics of sandfish are poorly understood and additional research is required to determine if this assumption is appropriate. Even so, the CPUE analyses show no evidence of localised depletion suggesting that the existing spatial management implemented for the fishery is appropriate.

The CPUE standardisation demonstrated that population has always been stable for the East stock, with appropriate levels of catch throughout the time period. However, for the West stock, initially high catches led to decreases in CPUE, suggesting population declines. A period of lower but stable catches followed which led to CPUE stabilisation and eventual recovery. This synchronicity between catch and CPUE suggests that CPUE provides a meaningful index of population abundance. Although overfishing may have occurred previously, the West stock has recovered, and current catches appear sustainable.

With biomass estimates and CPUE indices available, these can be used in stock assessment models (as applied in Queensland and West Australian sea cucumber fisheries). Approaches to stock assessment using literature values for relevant life history parameters are presented.

Introduction

The Northern Territory (NT) Trepang (sea cucumber) fishery is a limited entry fishery (six licences) with logbook records dating back to 1985 (NT, 2021). Although this is a mixed species fishery, almost all of the catch (99 %) has been sandfish (*Holothuria scabra*). The NT sandfish fishery supplies Asian seafood markets where they are one of the highest value species (Purcell et al., 2018). Sandfish are harvested through hand collection, often in shallow water, and therefore the fishery can be highly selective. Sea cucumber fisheries can therefore operate without any by-catch or undersize individuals being caught and without any habitat disturbances occurring through fishing. This makes them more environmentally friendly than most other fisheries (Purcell et al. 2010). A legal minimum length (LML) of 16 cm is implemented in NT which corresponds to the best available information on sandfish length-at-maturity (Kinch et al. 2008). Since 2016 the fishery has been spatially managed with a 246 t total allowable catch (TAC) distributed over 32 60 nm x 60 nm grids (NT, 2021). There is no evidence of NT sandfish ever being overfished but their stock status currently remains undefined (Hart, 2023). There is little information available to assess population trends or to determine the efficacy of the fishery's spatial management.

Catch-per-unit-effort (CPUE) is often used as a proxy for trends in population abundance and to support stock status determinations in fisheries (Hilborn & Walters, 1992; Maunder & Punt, 2004). CPUE (i.e. catch rates) is valuable as it is low cost, sourced from mandatory logbook data, and can provide a long time series often extending back to commencement of the fishery. However, CPUE can vary with factors other than stock abundance including fishing efficiency (Hoyle et al., 2024). The goal of any successful fishing operation should be to increase CPUE, thereby reducing running costs and maximising profit. This can confound nominal CPUE (i.e. raw CPUE) as an index of stock abundance as fishers seek to increase fishing efficiency (Hoyle et al. 2024). Thus, standardisation of CPUE is generally undertaken to account for factors that influence catchability (e.g. weather, experience) to uncouple efficiency from stock abundance (Hoyle et al., 2024; Maunder & Punt, 2004). Catch-per-unit-effort standardisation can be performed through a variety of techniques but the most common is through generalised linear models, or extended versions of these analyses (Maunder & Punt, 2004). Standardised CPUE is a more valuable indicator of stock heath and is often used to justify stock status assignments in the Status of Australian Fish Stocks (Roelofs et al., 2024). Standardised CPUE is also a key data input into population dynamics modelling for fisheries and is often one of the first steps in the stock assessment process.

A common concern with sea cucumber fisheries is the potential for localised depletion to occur (Friedman et al., 2011). Sea cucumbers are sedentary and spatially dispersed with densities depleted by fishing potentially below effective reproductive thresholds (Bell et al. 2008, Anderson et al. 2011, Eriksson and Byrne 2015). This has unfortunately been well documented in sea cucumber fisheries as these species tend to exhibit meta-population structures. Therefore, spatially isolated subpopulations have high degrees of self-seeding and reduced densities through overfishing can impact the ability of isolated subpopulations to recover quickly (Anderson et al., 2011). This forms the basis for the boom-and-bust archetype that is often used to describe sea cucumber fisheries. Awareness of sea cucumber susceptibility to localised depletion is important, as assessing population trends at too broad a scale can obfuscate localised population declines that need to be addressed. It is for this reason that several Australian sea cucumber fisheries, including the NT sandfish fishery, have spatial management mechanisms designed to spread effort across areas (Skewes et al., 2014; Wickens et al., 2024). Often the development of sea cucumber fisheries and their management needs outpace the science that is required to inform them (Friedman et al., 2011, Eriksson and Byrne 2015). As a result, the spatial management required to avoid localised depletion for Australian fisheries has been implemented preventatively and in advance of the science required to demonstrate its need. That science then occurs following its implementation and is designed to determine its efficacy (Skewes et al., 2014; Wickens et al., 2024).

There are two main objectives of this report: 1) to undertake CPUE standardisation for both NT sandfish stocks that are complementary with the recent biomass surveys undertaken, and 2) to evaluate potential stock assessment options that incorporate these survey estimates and abundance indices. One of the additional aims of the CPUE standardisation analysis was to examine different spatial scales including the 60 x 60nm grids. An approach was therefore developed to determine whether signs of localised depletion could be determined within the CPUE standardisation analysis. Sandfish are one of the best studied species of sea cucumber given their commercial value and their application in aquaculture (Hamel et al., 2022). However, as with other species of sea cucumber, some aspects of their biology remain poorly understood affecting the efficacy of stock assessment. The outputs of this report are intended to support improved stock status determinations and to provide advice for future stock assessment work incorporating fishery-independent surveys. The eventual development of stock assessment models would provide much greater levels of scientific advice that can underpin fisheries management and increase confidence that the fishery is operating sustainably.

CPUE standardisation

Methods

Fishery Dynamics

Operators in the fishery are required to complete daily catch and effort returns that provide information on species, catch in whole weight (kg), time spent fishing (daily hours), number of crew, fishing grid, and fishing method. Logbook data are available from 1985 onwards and were available up to 31/07/2023. Financial year fishing seasons are used for fisheries management. Therefore, the analyses presented in this report consider data from 1999/2000 – 2022/2023. Financial years before this contained confidential data which cannot be presented whereas 2023/2024 was an incomplete fishing season. Some reporting information has changed through time with logbook fields such as date and fishing coordinates becoming available in more recent years. However, the incomplete nature of such fields across years prevents their consideration in CPUE analyses. Species level reporting has also changed through time. As noted in Koopman et al (2024), before 2006 “Echinoderm” was recorded in most logbook records. However, there is strong evidence that most catches were sandfish and were therefore assigned to this species for all further analyses. Records of other species such as black teatfish or prickly redfish were treated as different species and omitted from sandfish analyses. Sandfish are landed as gutted and blanched product which is converted to whole wet weight by NT Fisheries logbook services. During an early period of the fishery, logbooks recorded sandfish numbers rather than catch by weight. These were also converted to whole weight by the NT Fisheries logbook services. Therefore, all catches presented in this report are whole weight catch in kilograms or tonnes.

Fishery effort was expressed in two units: 1) effort days which referred to individual fishing days by vessel and 2) total fisher hours which refers to the total number of hours fished by all fishers in the fishery. This second method is calculated by multiplying the number of hours fished each day (for each vessel) by the number of crew fishing on that day. The data were first inspected and checked to ensure that both fields were reported correctly, removing the outliers identified in Koopman et al. (2024). Total fisher hours represent the full fishing event which includes search time, diving/collection, and product processing. Total fisher hours is therefore the most appropriate and fine-scale unit of effort that can be used to describe the fishery and will support more robust CPUE estimates. The number of licences fishing each year and their relative effort levels were examined for the six active licences fishing between 1999/2000 and 2022/2023. This reveals annual changes in fleet composition and how this can affect CPUE.

Fishery analyses (e.g., catch, effort and CPUE) were undertaken at the fishery, stock, and grid levels to investigate broad and fine scale dynamics. The stocks were separated by Western and Eastern boundary identified at the Wessel Islands and separated using grid locations. Grids 1136,1236, 1336, 1335 and 1436 were assigned to the Eastern stock, with all remaining grids assigned to the Western stock (Figure 1). As noted in Koopman et al. (2024), some records in grid 1136 may be from the Western stock but these include a very low number of catch records (Figure 1).

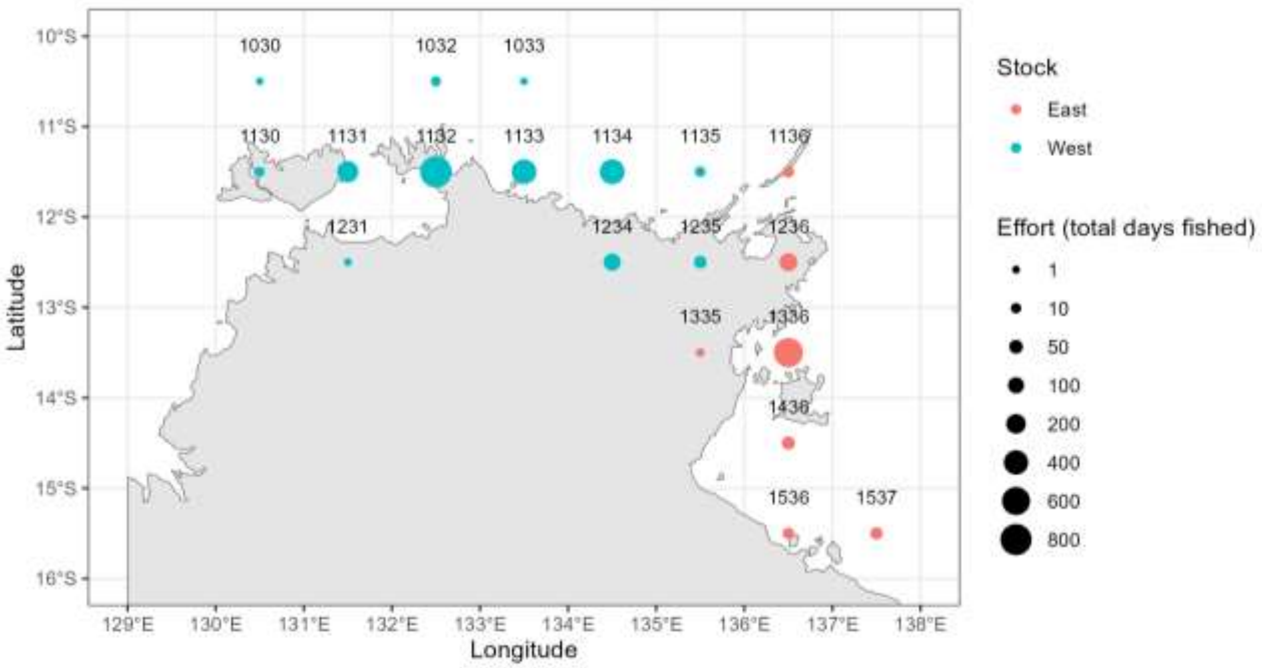


Figure 1: A map of the north coast of Northern Territory showing the stock structure and relative effort associated with each 60nm x 60nm fishing grid (grey lines). The number of total days fished for sandfish (1999/2000 – 2022/2023) is shown by the size of coloured bubbles in each grid centroid (some centroids are on land, but fishing occurs on the corresponding coastline). The colours of the bubbles indicate the stock (West or East) that the fishing effort has been associated with, and the grid label is displayed at the top of each grid.

CPUE standardisation

Nominal CPUE was calculated as the annual arithmetic mean (1999/2000 – 2022/2023) with 95% confidence intervals. Anomalously high CPUE records of more than 100 kg per fisher hour (approximately fifty fishing days) were excluded from the CPUE analysis as these values were unrealistically high and created outliers in the data. These records were maintained in harvest estimates presented so that overall catches were not reduced due to data filtering but were removed from nominal and standardised CPUE analyses.

Catch-per-unit-effort standardisation was performed through a generalised linear mixed effect modelling approach (GLMM) which is a common method for determining indices of abundance from catch and effort information (Hoyle et al., 2024; Maunder & Punt, 2004). The purpose of this approach is to differentiate the effect of catchability parameters (such as licence, number of crew) on CPUE versus changes in population abundance. Any temporal changes in CPUE that are not explained by changing catchability parameters are interpreted as changes to population density, and therefore abundance (Hoyle et al., 2024). Therefore, catch-per-unit-effort standardisation provides two outputs that are valuable for fisheries research. The first is a standardised index of abundance that is predicted from the GLMM while holding all catchability parameters constant. This index of abundance is a key input to fishery population dynamics models and can also be used as a proxy for stock status. The second output is the relative effect sizes of the different catchability parameters which provides valuable insight into fishing dynamics. For example, it may be possible to determine whether certain areas, months, or fishing methods produce higher CPUE. These effects can be valuable for assessing fishing efficiency.

As CPUE standardisation is intended to provide indices of population abundance of NT sandfish, it was applied at the stock and grid level only. Exploration at the fishery level would include two distinct stocks and therefore these outputs would not be valuable for estimating stock status, nor inclusion in a population dynamics model. Catch-per-unit-effort standardisation at the stock and grid level therefore provides population and sub-population level abundance indices, respectively. Only six grids (four for the West stock and two for the East stock) had sufficient levels of effort across years to be considered. Therefore, all remaining grids were excluded from the CPUE analysis.

One of the aims of this analysis was to identify whether localised depletion has occurred and could be identified from CPUE data. This is not a straightforward task, as CPUE data become sparser at increasingly fine spatial scales. This can create noisy and turbulent time series that can often be uninformative given they are based on limited and disaggregated information. Therefore, a new technique was developed to examine spatial depletion which considered populations at the grid level to be deviations away from a global average (i.e., the stock level). This allowed fine scale information in each grid to be used when sufficient data were available but supplemented these data with information from the stock level CPUE in years where limited fishing occurred in a grid. Therefore, this allows CPUE trends from grids that are data rich to be considered in CPUE standardisation for grids that are data poor. This aligns with the Robin Hood paradigm where information is taken from the data rich and used to support analyses for the data poor (Punt et al., 2011).

A localised depletion approach used a GLMM for each stock, with grid as a random effect. Therefore, both the stock and grid level changes in abundance were considered as part of a single model, effectively treating each sandfish stock as a meta-population. The GLMM for each stock was applied using the R programming environment (R Core Team, 2024) using the `glmmTMB` package (Brooks et al., 2017). The GLMM was fitted to catch in kg with financial year (henceforth year), grid, month of fishing, number of crew and licence number treated as independent variables and total fisher hours used as an offset. The GLMM was fitted using a Tweedie distribution with a log-link function and no model intercept. A Tweedie distribution is an extension of the gamma distribution with a key difference being that it can include records where zero catch occurred. This makes it an appropriate error distribution for continuous data that is prone to being right skewed and can include zeroes, which commonly applies to CPUE data. When the gamma distribution is applied for CPUE standardisation, zero catch days must be removed. The Tweedie distribution does not require this, providing a benefit over a standard gamma distribution.

The model GLMM fitting process for both stocks was as follows:

1. A full model with all variables as fixed effects was fitted to the CPUE data using the tweedie distribution. The same model was fitted using a normal distribution and the models were diagnostically compared for appropriate fits using the `performance` R package (Lüdecke et al., 2021) and ranked using Akaike’s information criterion (AIC). The tweedie distribution vastly outperformed the normal distribution for both stocks.

2. Appropriate variables were selected through an AIC ranking analysis performed using the `MuMIn` R package (Bartoń, 2024). This process re-fit the model with different combinations independent variables and ranked the fit of each model. The model with the lowest AIC was selected as the best fitting model and included all independent variables that improved model fit (i.e., were informative about CPUE catchability). Results of this initial model ranking analysis are provided in Appendix A.
3. A further AIC model selection analysis was performed by considering the inclusion of random effects for specific variables that could be included in a hierarchical structure (models with random effects do not get tested through the `MuMIn` package). These candidate mixed effects models (models with fixed and random effects) considered licence and a crossed random effect of year within grid. Licence was included as a random effect; individual fishers are considered to be random CPUE samples and are therefore hierarchical. Grid and year as a crossed random effect treats year as a random sample of the population within each grid level. It suggests that CPUE varies annually within a grid but is also related to other grids. Results of this hierarchical model ranking analysis are provided in Appendix A.
4. The best fitting mixed effects models were again checked to determine if model fits are appropriate. Collinearity was checked in particular, with collinear variables excluded from the final models. Variable collinearity is an indication of insufficient observations across factor levels, leading to CPUE being similarly informed by them. This confounds the model fitting process and is avoided by removing one of a pair of collinear variables. An example of collinearity in CPUE data is licences fishing different areas which therefore means that area and licence provide the same information on CPUE. The diagnostics of the best fitting model for each stock are provided in Appendix A.
5. The best fitting model was used to produce a standardised index of abundance by predicting the year coefficients of the GLMM for each stock and grid while holding all other variables constant. This index is centred on a mean of 1 and can be compared with a nominal CPUE index that has also been centred.
6. The best fitting model was used to determine effect sizes for the catchability variables indicating which variables led to increased fishing efficiency. This was performed using the `visreg` package (Breheny & Burchett, 2017).

Following this process, the best fitting CPUE standardisation model for each stock was:

```
Catch ~ 0 + Year + (1|Grid:Year) + Number of crew + (1|licence) +
offset(log(Total effort hours)
```

for the West stock and,

```
Catch ~ 0 + Year + Grid + (1|Grid:Year) + Number of crew + (1|licence)
+ offset(log(Total effort hours)
```

for the East stock. Note that Month was determined to be a collinear variable for both stocks and was excluded from the final models.

Results

Fishery Dynamics

Catch and effort at the fishery scale have had a general declining trend through time with catch peaking at 291 t in 1999/2000 but averaging 38 t since 2007/2008 (Figure 2). This reduction in catch corresponds with effort reduction (Figure 2). Catch-per-unit-effort had a general declining trend until 2011/2012 when CPUE increased and stabilised (Figure 2). These results suggest that initially high catches may have decreased the population and that lower recent catches have allowed recovery to occur (Figure 2). The average CPUE across the time series was 27 kg per fisher hour (Figure 2).

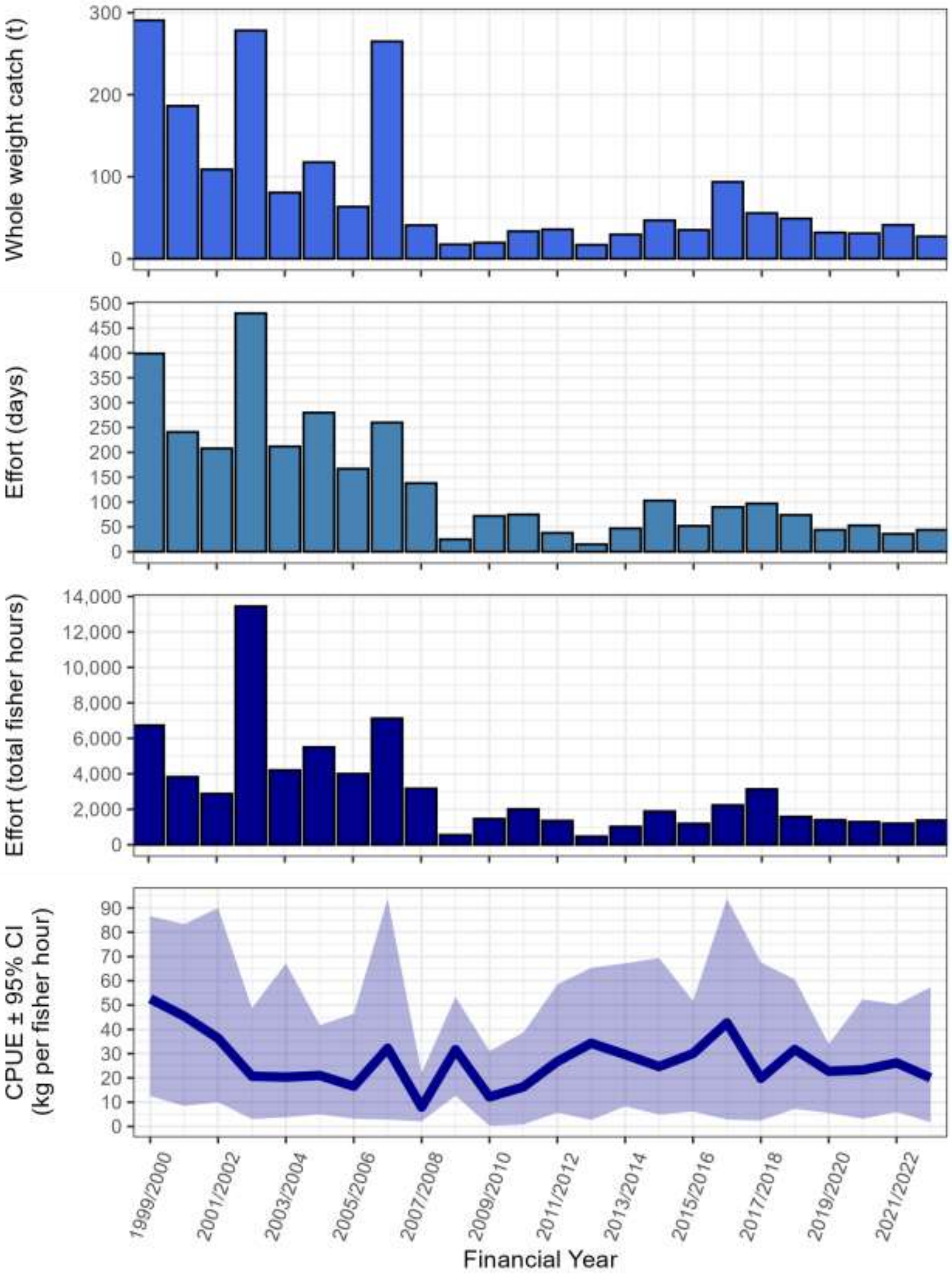


Figure 2: Annual catch and effort statistics at the fishery scale for NT sandfish. Nominal CPUE data were calculated as the annual arithmetic mean. Data prior to 1999/2000 are confidential.

Similar trends in catch and effort apply to both West and East stocks, with declining catch and effort through time (Figure 3). However, the West stock had much higher average catches between 1999/2000 and 2007/2008 at 128 t versus 45 t (Figure 3). From 2007/2008 onwards, catch and effort have been at similar levels with catch averaging 20 t and 21 t for the West and East stocks, respectively (Figure 3). Higher catches in the West stock led to CPUE declines between 1999/2000 and 2009/2010, with recovery occurring from 2010/2011 onwards (Figure 3). The CPUE for the East stock has been relatively stable throughout the time series averaging 25.0 kg per fisher hour from 2000 to 2023, rising to 26.9 kg per fisher hour from 2010/2011 onwards (Figure 3). This is similar to recent CPUE for the West stock which averaged 26.5 kg per fisher hour since 2010/2011 (Figure 3). These results suggest that catches have always remained at appropriate levels for the East stock and have not caused population declines. Conversely, high initial catches for the West stock caused population declines which then recovered and stabilised following catch reductions (Figure 3).

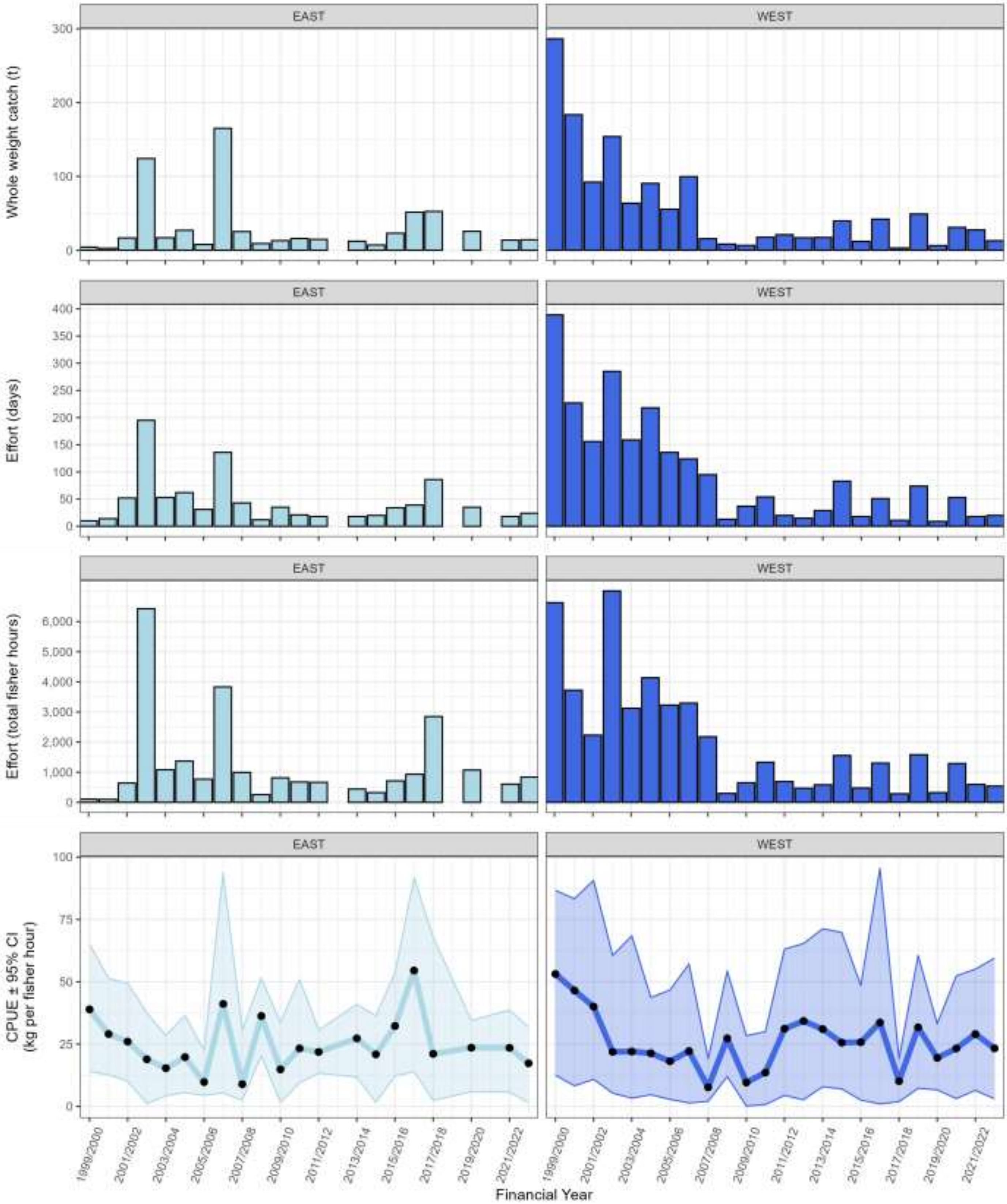


Figure 3: Annual catch and effort statistics at the stock scale for NT sandfish. Nominal CPUE data calculated as the annual arithmetic mean are presented. Data prior to 1999/2000 are confidential. The same y-axis scales are used to allow comparisons.

Grid level CPUE was more variable than fishery and stock level CPUE (Figure 4). Grids 1236 and 1336 from the East stock had an average CPUE of 19.0 and 24.5 kg per fisher hour from 1999/2000 – 2022/2023, respectively (Figure 4). Neither of these Eastern stock grids had notable increases nor decreases to CPUE throughout the time period, indicating stable population levels from 1999/2000 – 2022/2023 (Figure 4). The CPUE for the West stock grids had different trends to one another with grids 1131 and 1134 having a general declining trend through time. However, grid 1134 had an anomalously high CPUE in 2016/2017 (Figure 4). Grids 1132 and 1133 had trends that were similar to the Western stock level CPUE, characterised by declining CPUE until approximately 2009/2010, followed by an increase and stabilisation in CPUE (Figure 4). Given these results are based on nominal CPUE, reasons for different population trends are best considered with standardised CPUE.

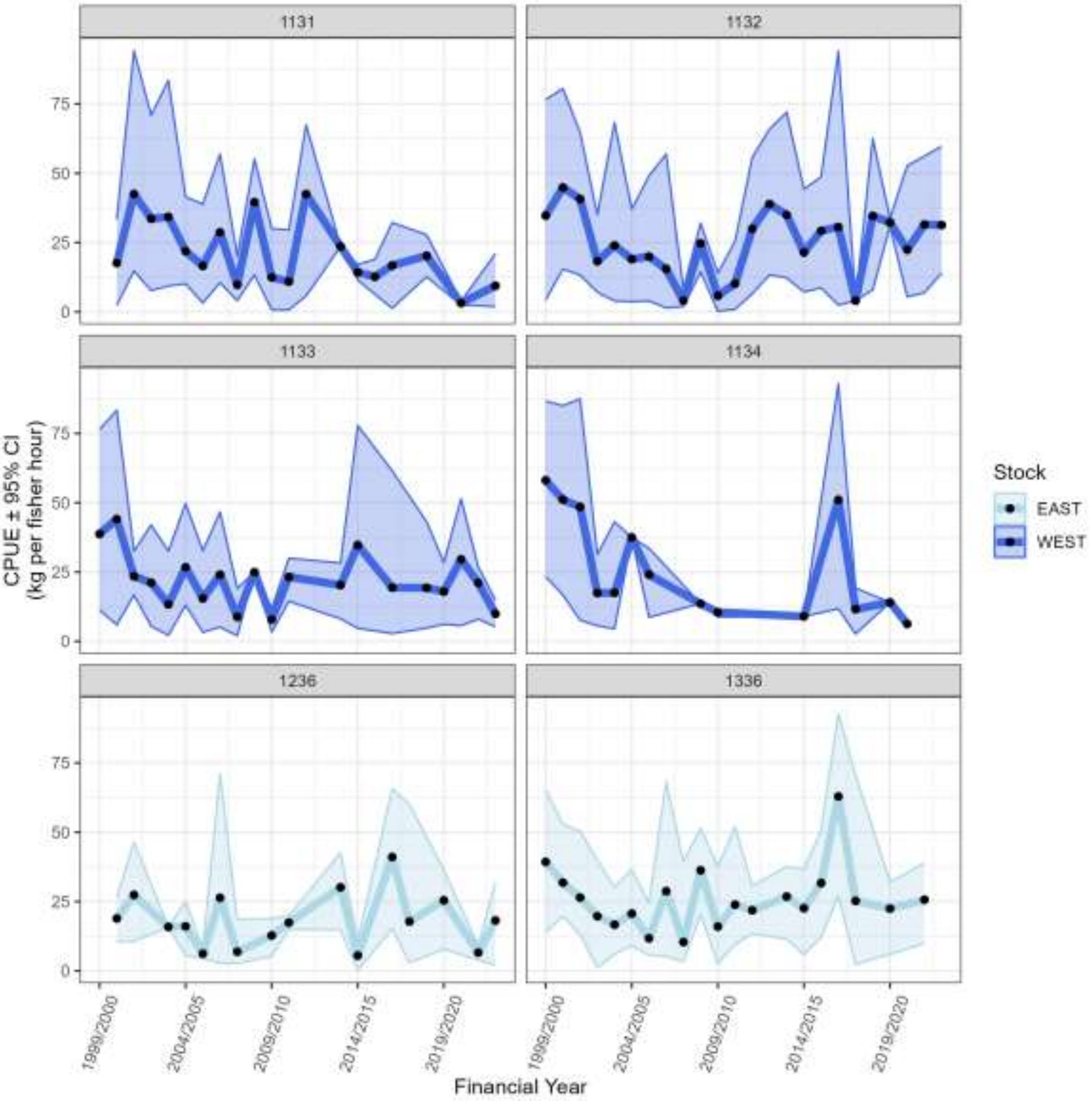


Figure 4: Annual nominal CPUE at the grid scale for NT sandfish. Only grids with catch and effort throughout the time series (i.e., did not incur sporadic fishing) are included. The stock each grid belongs to is indicated by the dark and light blue shading. Data prior to 1999/2000 are confidential.

Fleet changes have occurred through time as different licences have had varying participation rates among years (Figure 5). Between 1999/2000 and 2009/2010 more than three licences fished in all but one year with most fishing for more than 50 days each (Figure 5). However, fewer licences generally were fishing from 2009/2010 onwards with far fewer days being fished by each licence (Figure 5). From 2018/2019 – 2021/2022, only one licence was active in the fishery (Figure 5).

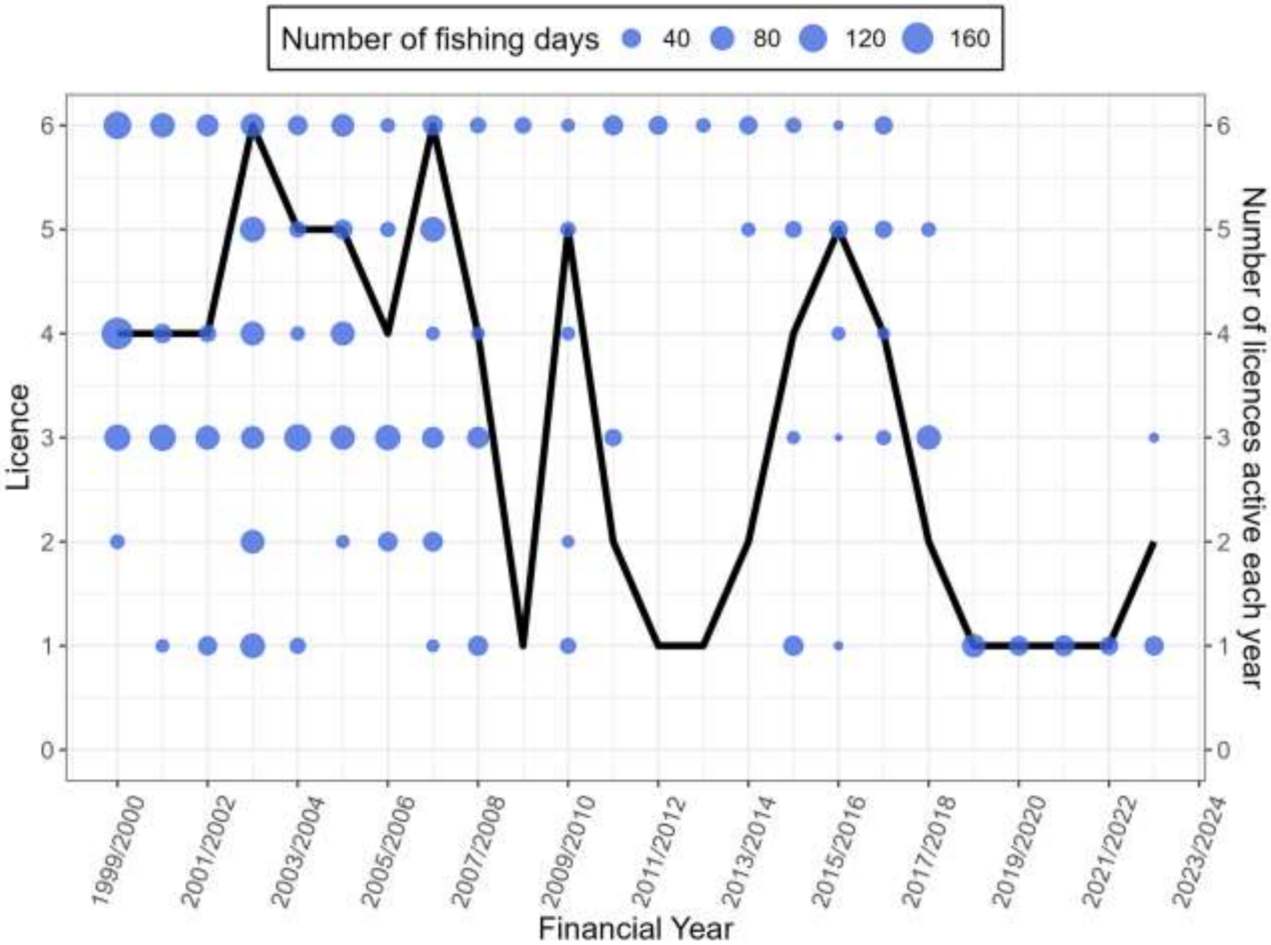


Figure 5: Licence participation for the NT sandfish Fishery from 1999/2000 – 2022/2023. Individual licences are shown on the left-hand y axis and licence numbers are obscured to maintain confidentiality. The size of the blue bubbles indicates the number of annual fishing days for each licence through time. The black line and right-hand y axis represent the number of licences that fished in each year.

CPUE standardisation

West stock

The standardised index of abundance (i.e., standardised CPUE) at the stock level closely follows the nominal CPUE up until 2018/2019 (Figure 6). Following 2018/2019, the nominal and standardised index deviate with the standardised index being higher than the nominal (Figure 6). The timing of this deviation may be related to a single licence fishing in those years, demonstrating an effect of licence on CPUE (Figure 5). Although the standardised and nominal CPUE indices differ slightly in recent years, this analysis shows that CPUE was not substantially changed through standardisation and that nominal CPUE reflects population of abundance for the West stock.

The changes in standardised index strongly align with changes in catch, suggesting that population changes are evident in this index (Figure 6). Catches were initially high, causing declining CPUE, but then substantially reduced by almost 90% from 2007/2008 onwards (Figure 6). Thereafter, the standardised index stabilises before increasing substantially in 2011/2012 (Figure 6). During this period catches remained low and stable, producing a generally increasing trend in the standardised CPUE index (Figure 6). Given this synchronicity with catch, this standardised index could be used for stock assessments performed at the stock scale (i.e., all grids amalgamated), given that it provides plausible indications of the stock's response to different levels of fishing pressure.

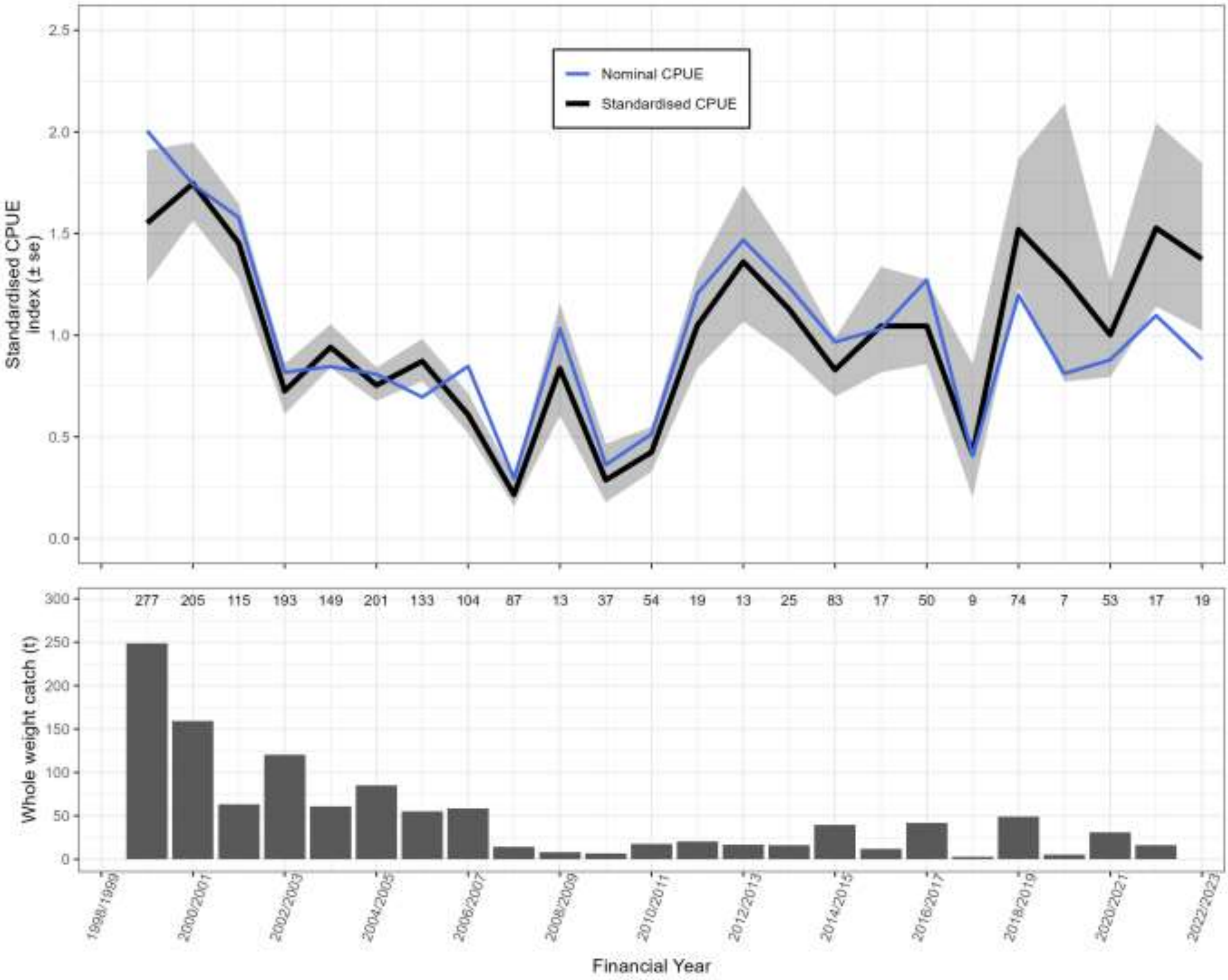


Figure 6: Standardised CPUE index for the West NT sandfish stock (top panel). The black line and grey shaded area show the predicted index of abundance ± standard error from the GLMM. The blue line is nominal CPUE presented in the previous section. Both indices have been centred on a mean of 1 to allow their comparison. The total catch of the West stock is shown by the grey bars in the bottom panel. The values at the top of the bottom panel show the annual number of fishing days.

Grid level standardised indices provided finer scale estimates using the same model to estimate a standardised index at the stock level (Figure 7). Although standardised indices of abundance are presented for each grid, these have been estimated from CPUE data across the stock. Therefore, grids with lower levels of effort have their standardised index of abundance informed by indices from other grids in those same years. This is valuable as some grids have low catch and effort in particular years, leading to nominal CPUE that was highly variable. Grid 1134 is a good example of this, where limited catch and effort occurs in years following 2003/04 (Figure 7). For this grid, the nominal index of abundance was very low in most years with a pronounced increase in 2017/18 (Figure 7). Conversely, the standardised index for grid 1134 shows an increase following 2011/2012 which is higher and more stable (Figure 7). This more closely matches the global standardised index seen at the stock level (Figure 6, Figure 7) which occurs as the predicted abundance in this grid is being informed by the stock level trend when there are limited data in particular years. Examining the catch for grid 1134 shows the plausibility of this standardised index as an extreme level of catch occurs in 2000 which is not repeated. Catches remain low from this point onwards, as does the nominal index but this is based on limited records, whereas the standardised index is reflecting CPUE trends from other grids where fishing is occurring (Figure 7).

Grid 1132 has complementary results, with nominal and standardised indices similar and matching the results of the stock level indices (Figure 6, Figure 7). This occurs as most of the stocks catch and effort comes from this grid. Therefore, the grid is providing the most information to global abundance index estimated at the stock level. A similar result occurs for grid 1133 which has the second highest levels of catch, whereas grid 1131 has a deviation between the standardised and nominal indices following 2012/2013 when minimal fishing effort occurs (Figure 7). The result for grid 1133 is therefore similar to that of grid 1132, and grid 1131 is most similar to 1134 (Figure 7). These results could therefore be used in stock assessments at the grid level, although caution is required given underlying assumptions regarding trends in grid-level recruitment.

The model fitting process determined that ‘month’ was a collinear variable and was excluded from the CPUE standardisation analysis for the West stock. However, all other remaining catchability variables were included in the analysis, indicating that they have an effect on CPUE. The effect sizes for the West stock indicated that CPUE is most influenced by ‘year’ (Figure 8) which is why the nominal index was often similar to the standardised index (Figure 6). Grid 1134 had the greatest effect on CPUE, indicating that sandfish densities could be highest in that grid (Figure 8). The CPUE decreased with the number of crew onboard, although there is no clear explanation for this result from the data available. This could possibly be a reporting effect, where a number of non-fishing crew are listed on logbook returns. If so, then the CPUE standardisation has provided a valuable function by identifying this effect. Licence “1” had the lowest effect size for CPUE (indicated by lower CPUE than other licences) but was the only licence fishing between 2018/2019 and 2021/2022 (Figure 5). This provides further explanation as to why the standardised index was higher than the nominal index in recent years.

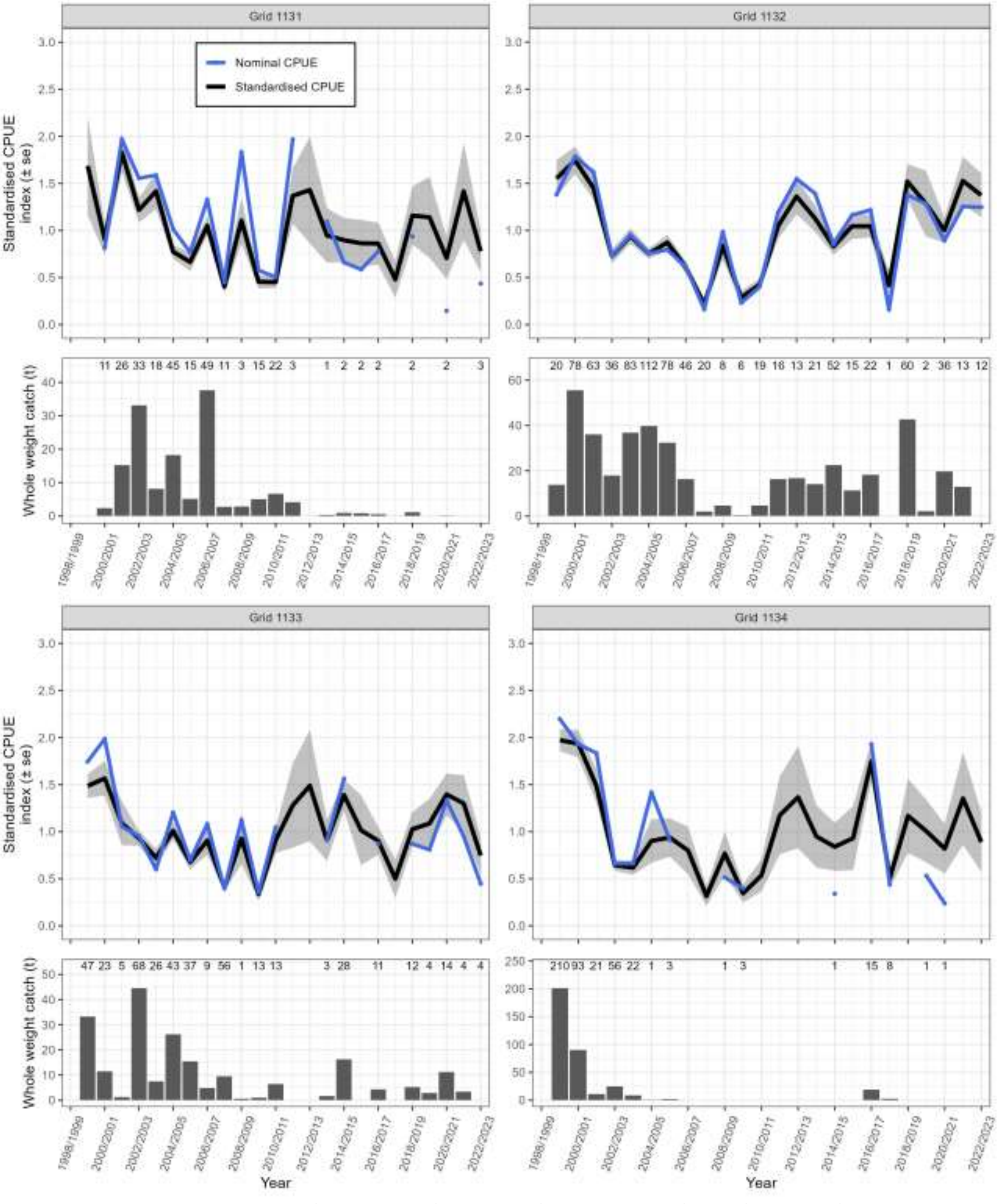


Figure 7: Standardised index of abundance from CPUE for the NT sandfish at four grids from the West stock (top panels). The black lines and grey shaded areas show the predicted index of abundance ± standard error from the GLMM. The blue line is nominal CPUE presented in the previous section for each grid in years where fishing occurred. Both indices have been centred on a mean of 1 to allow their comparison. The total catch of each grid is shown by the grey bars in the panels below each grids standardised index of abundance panels. The values at the top of the catch panels show the number of annual fishing days in each grid.

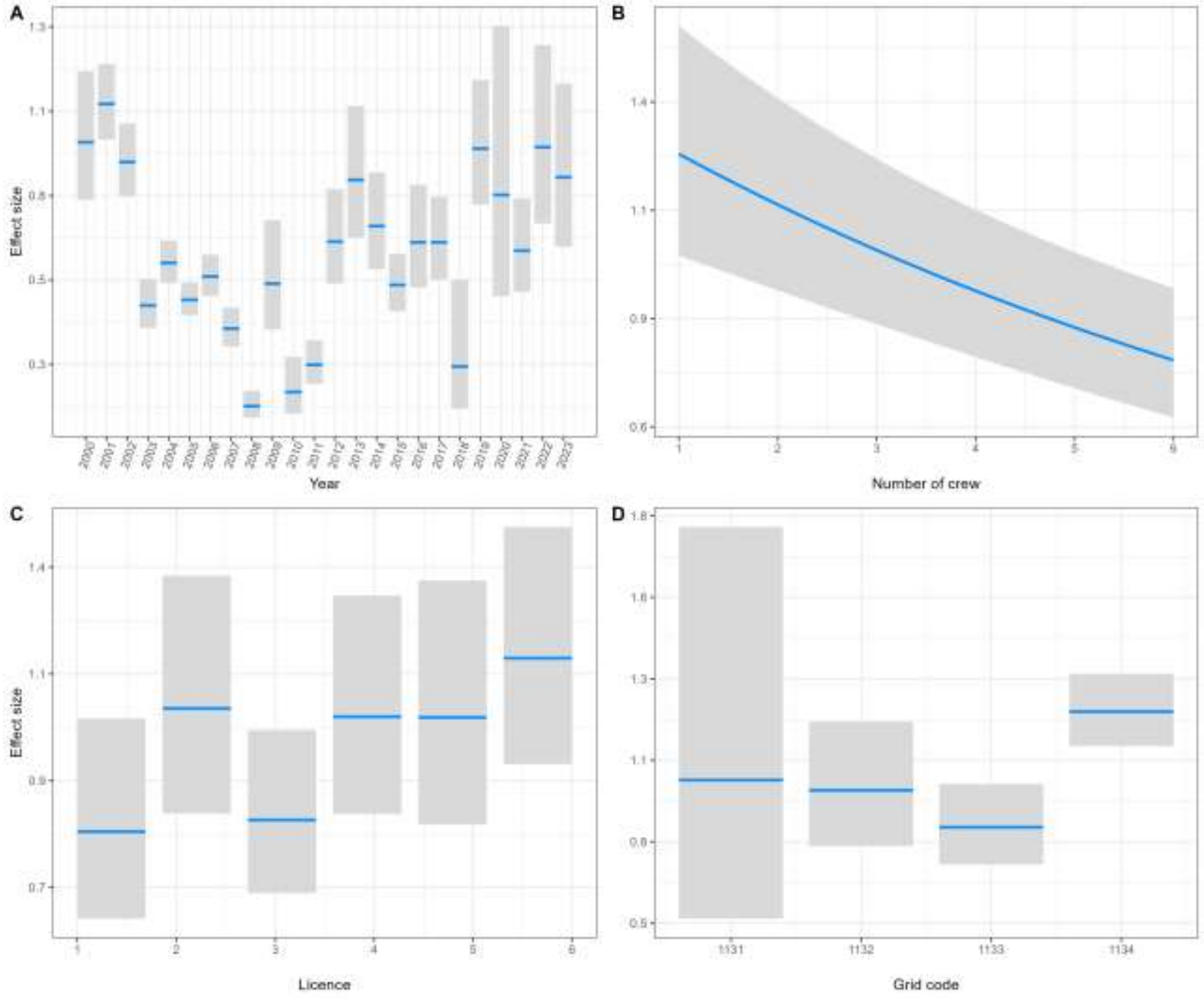


Figure 8: The effect sizes of ‘year’ (Panel A) and the catchability parameters (Panels B – D) from the West stock CPUE standardisation model. Financial years are labelled as integers with ‘2000’ representing ‘1999/2000’. The blue line indicates the mean effect size, and the grey shaded area is the model parameter standard error. Panels with cross bars (A, C, and D) represent variables treated as factors in the model. The ‘number of crew’ variable (Panel B) was treated as a continuous variable. All variables are centred on a mean of 1, allowing their comparability.

East stock

The standardised CPUE for the East stock was more similar to the nominal CPUE than the results shown for the West stock (Figure 9). The CPUE remained stable throughout the time series, suggesting that the sandfish population also remained stable and that catch levels were sustainable through time. Similar to the West stock, this analysis shows that the CPUE index is not substantially updated through a standardisation analysis and that a nominal CPUE reflects population abundance.

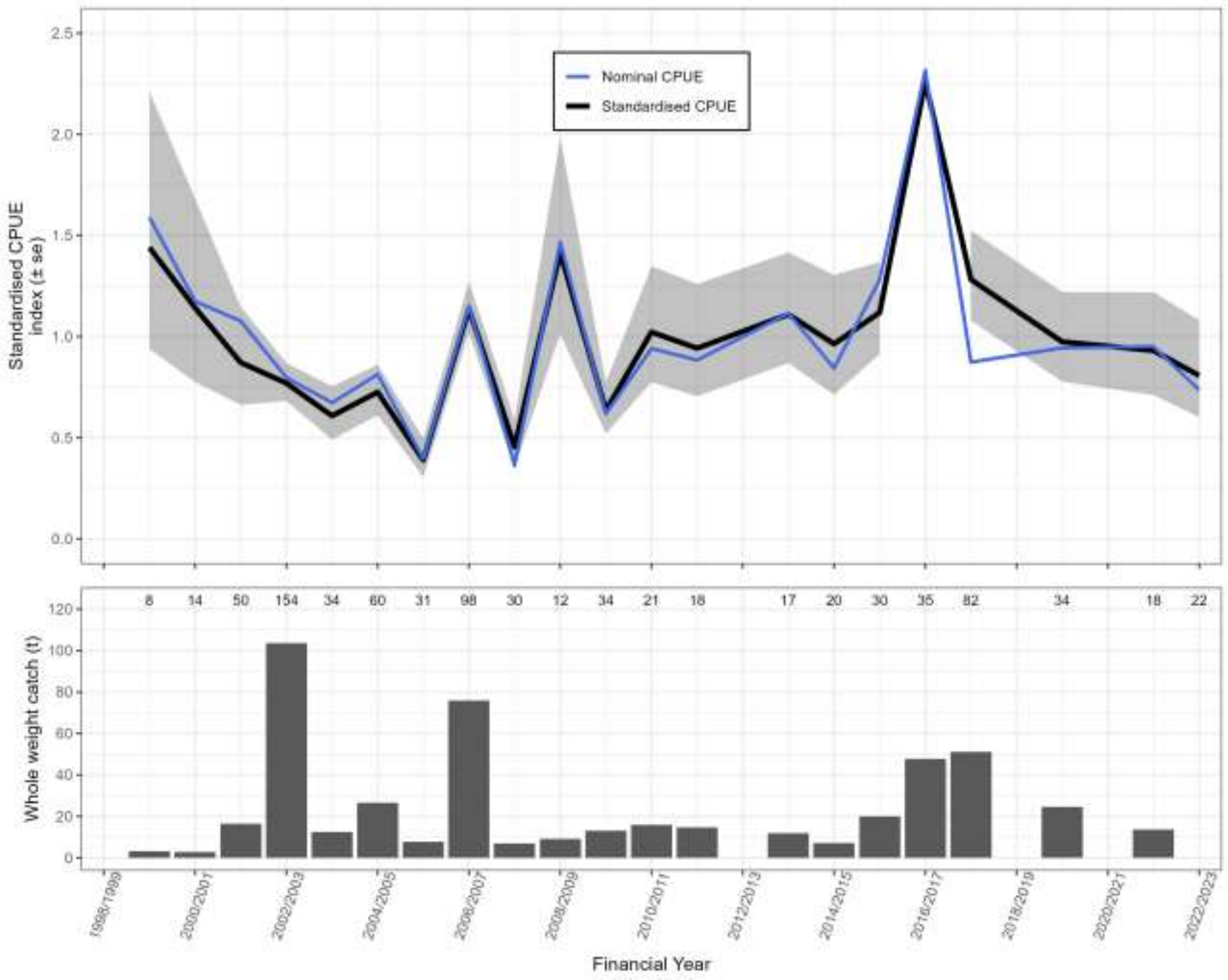


Figure 9: Standardised index of abundance from CPUE for the East NT sandfish stock (top panel). The black line and grey shaded area show the predicted index of abundance ± standard error from the GLMM. The blue line is nominal CPUE presented in the previous section. Both indices have been centred on a mean of 1 to allow their comparison. The total catch of the East stock is shown by the grey bars in the bottom panel. The values at the top of the panel show the annual number of fishing days.

Only two grids were included for the East stock as catch and effort did not occur across sufficient years for the remaining grids. Of the two grids included, grid 1336 had much higher levels of catch (Figure 10). Despite this, stable nominal and standardised CPUE indices were maintained for this grid (Figure 10). Grid 1236 had lower levels of catch with one large year of catch occurring in 2018/2019 (Figure 10). However, nominal and standardised CPUE again remained stable despite some nominal CPUE volatility caused by low numbers of fishing effort in some years (Figure 10).

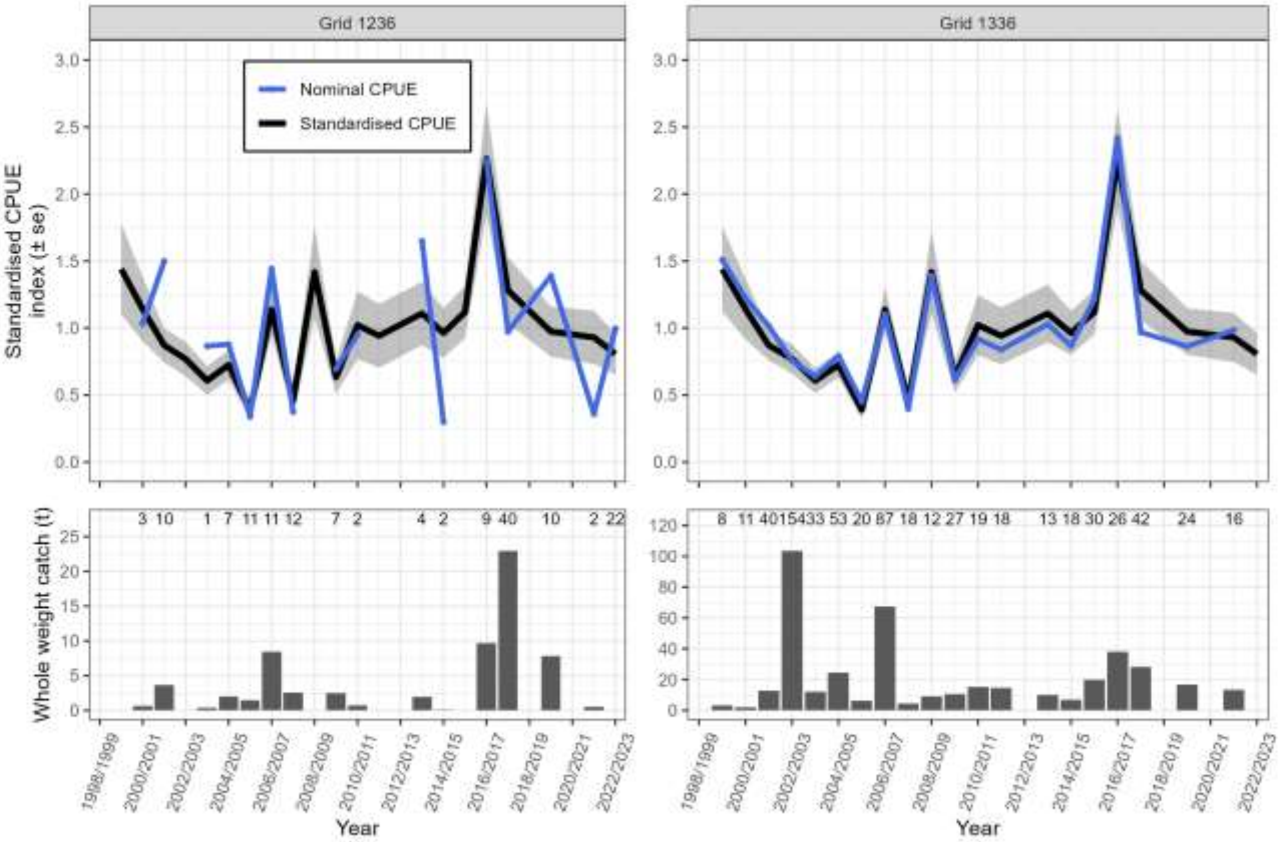


Figure 10: Standardised index of abundance from CPUE for the NT sandfish at two grids from the East stock (top panels). The black lines and grey shaded areas show the predicted index of abundance ± standard error from the GLMM. The blue line is nominal CPUE presented in the previous section for each grid. Both indices have been centred on a mean of 1 to allow their comparison. The total catch of each grid is shown by the grey bars in the panels below each grids standardised index of abundance panels. The values at the top of the catch panels show the number of annual fishing days in each grid.

The model fitting process determined that 'month' was a collinear variable and was excluded from the CPUE standardisation analysis for the East stock. However, all other remaining catchability variables were included in the analysis, indicating that they have an effect on CPUE. 'Year' also had the highest effect size for the East stock, and an increased number of crew had a declining effect (Figure 11). The CPUE of the two grids were more similar than the West stock, as was the licence with the exception of licence "3" which had a lower CPUE for this stock (Figure 11).

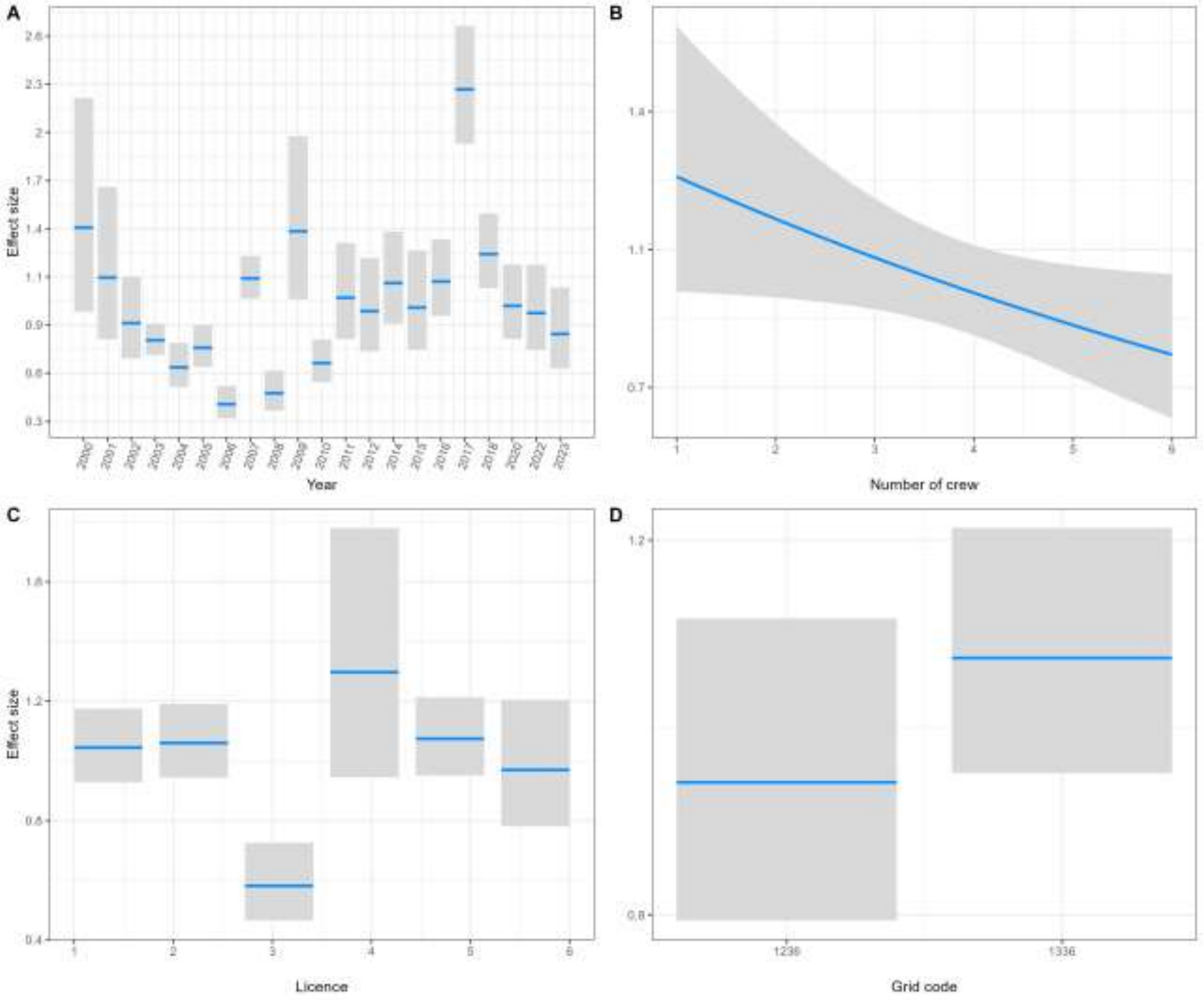


Figure 11: The effect sizes of 'year' (Panel A) and the catchability parameters (Panels B – D) from the East stock CPUE standardisation model. Financial years are labelled as integers with '2000' representing '1999/2000'. The blue line indicates the mean effect size, and the grey shaded area is the model parameter standard error. Panels with cross bars (A, C and D) represent variables treated as factors in the model. The 'number of crew' variable (Panel B) was treated as a continuous variable. All variables are centred on a mean of 1, allowing their comparability.

Stock assessment scoping

Species biology

Growth

Little growth information is available for wild sandfish populations (Hamel et al., 2022) or for sea cucumbers more generally (Kinch et al. 2008). This is because, sea cucumbers cannot be reliably tagged and recaptured and age determination is difficult (Purcell et al. 2016). Some limited growth estimates have been produced through analysis of length frequency distribution. (Dissanayake & Wijeyaratne, 2010) estimated growth of sandfish equivalent to k =0.8 but this estimate may be unreliable as detailed methods were not provided. Long et al (1996) estimated that sandfish in the Torres Strait reached 18 cm in two years of age, based on size frequency data collected during surveys. This suggests that their growth is fast given this is 45 % of their maximum size (~ 40 cm

(Purcell et al., 2023)Maximum age is poorly understood for sandfish but they are thought to be fast-growing and therefore short-lived (Skewes et al., 2014). As no von Bertalanffy (VB) growth estimates are available for sandfish, they must be approximated for stock assessment purposes. A reasonable approximation would be L_∞ = 35 cm based on their maximum length with k = 0.35 yr^{-1} (Table 1; Figure 13). This corresponds to a length of approximately 18 cm at two years of age, matching the estimate of Long et al (1996).

Maturity

Length-at-maturity for sandfish has a degree of plasticity that has been related to region and levels of fishing pressure (Hamel et al., 2022; Yanti et al., 2020). Regional variation in length-at-maturity has been demonstrated across the Pacific Ocean, Indian Ocean and Red Sea and ranges between 13.6 – 23.0 cm (Hamel et al., 2022). The legal minimum length (LML) for NT sandfish is mid-way between this range at 16 cm and corresponds with estimates of length at maturity for sandfish from the Torres Strait and New Caledonia (Conand, 1989; Long et al., 1996). Therefore, a length-at-maturity of 16 cm has the most support for NT populations. Given this, a length-at-maturity is reported, the shape of a maturity ogive has not been described in the literature. Therefore, the length-at-50%-mature (L_{50}) should be treated as 16 cm whereas the length-at-95%-mature (L_{95}) should assigned reasonable values that are sensitivity tested when applied in any stock assessment analysis (Table 1; Figure 13).

Weight-at-length relationships

Weight-at-length relationships were estimated from data collected during recent surveys conducted in grids 1132 (West stock), 1236 (East stock) and 1336 (East stock) (Koopman & Knuckey, in prep). This was performed according to the methods presented in Ogle (2015) where a linear model was fitted to length (cm) and weight (kg) in log10 space, and a bias correction was applied to the intercept parameter (WL_a) when converted back to natural space. This provides the weight-at-length parameters (WL_a and WL_b) which can be used to convert length in cm (L) to weight in kg (W):

$$W = WL_a * L^{WL_b}$$

Reasonable sample sizes of more 70 individuals across a large size range were collected for each grid (Figure 12). Grids 1132 and 1336 had similar weight length relationships despite coming from separate stocks (Figure 12). Conversely, grid 1236 had a flatter weight-at-length relationship than the other grids, despite coming from the same stock as grid 1336. This may be caused by smaller individuals being collected from 1236 as no sandfish larger than 1kg were measured from this grid (Figure 12). However, a difference in weight-at-length between grids is not apparent until sandfish reach a length of 20cm (Figure 12). These results suggest that weight-at-length relationships can vary regionally, but without evidence of this occurring in specific areas a default relationship using WL_a = 0.00092 and WL_b = 2.11439 would be suitable (Table 1).

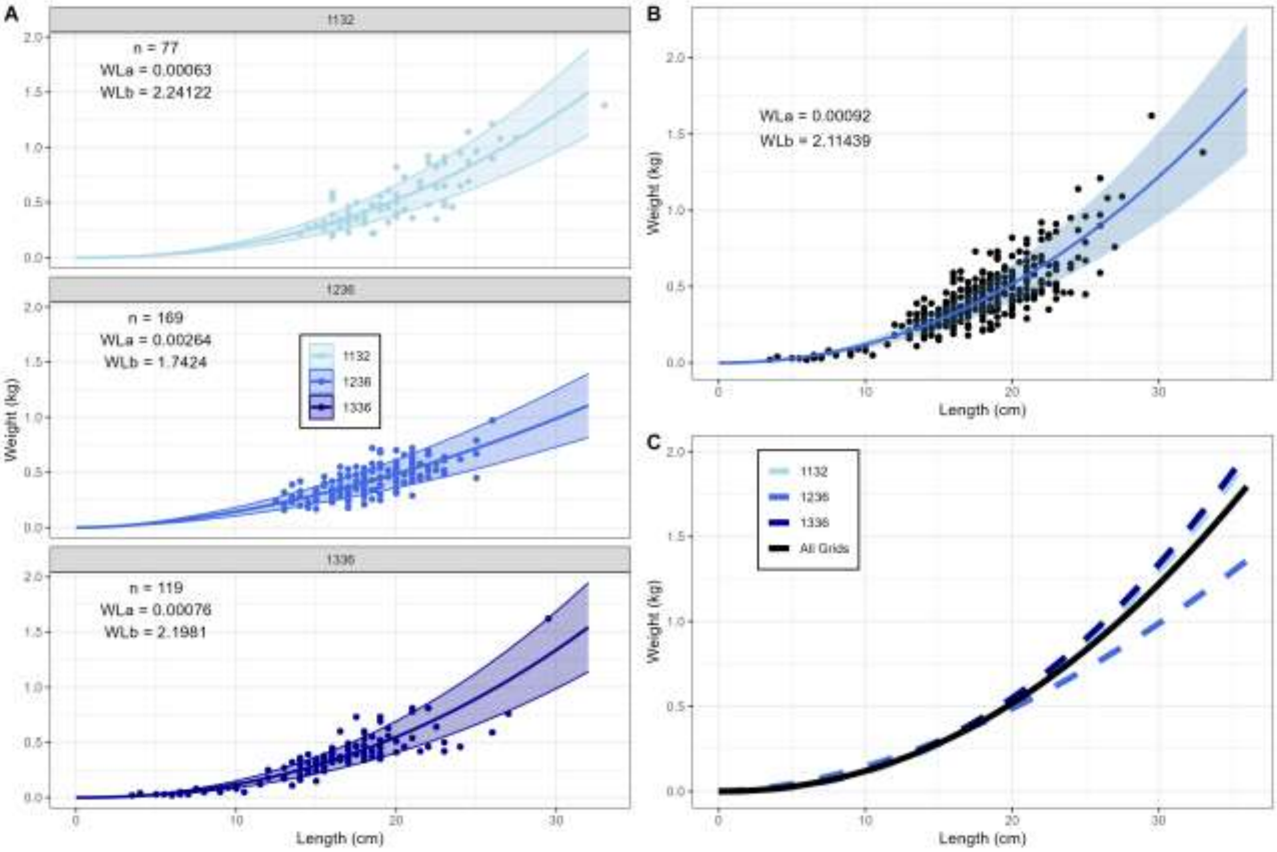


Figure 12: Weight-at-length relationships for NT sandfish surveyed in different grids. The relationships for each grid are shown in the left-hand panels (A). The relationship for all grids combined is shown in the upper right-hand panel (B). The individual relationships and the combined relationships are compared in the bottom right-hand panel (C). Shaded areas represent the 95% confidence intervals of the respective weight-at-length relationship. The parameters relating to each relationship are displayed on the panels, along with the sample size (n) for each grid.

Natural mortality

Natural mortality (*M*) is poorly understood for sea cucumbers. Natural mortality is usually determined from life history correlates such as growth, maturity or longevity through a variety of methods (Hamel & Cope, 2022; Maunder et al., 2023). However, longevity is best considered when determining appropriate *M* values for stock assessment purposes, as a species lifespan will be directly related to its survival rates (Cope & Hamel, 2022). Although *M* may be poorly understood for sandfish, this species is thought to be relatively short lived in comparison with other species (Skewes et al., 2014). Therefore, it is likely to have a higher value of *M* in comparison with less productive species of sea cucumber. An *M* of 0.65yr^{-1} corresponds to a maximum age of 9 (Figure 13) which is a relatively short lifespan for a sea cucumber species, matching assumptions on sandfish biology (Hart, 2023; Skewes et al., 2014). This maximum age also corresponds to the age at which 95% of maximum length (based on L_∞ = 35 cm) according to the VB growth estimates; another accepted proxy for longevity. Therefore, this value produces a coherent life history narrative that suits the known biology of the species. This value of *M* (as well as other approximated) life history estimates should be thoroughly tested within a stock assessment framework given their uncertainty (Smart et al., 2024b).

Recruitment

Two parameters generally apply to Beverton-Holt stock recruitment relationships in stock assessments: steepness (*h*) which corresponds to the proportion of unfished recruitment (R_0) that occurs at 20% of unfished spawning stock biomass (SSB_{20}), and recruitment variability (σ_R) which is the variability about the stock recruitment relationship in log space. Steepness is essentially a measure of recruitment compensation, indicating the degree of increased recruitment that occurs when stock size is reduced, whereas σ_R is a measure of how much recruitment variability occurs according to environmental drivers, rather than stock size. Both of these parameters tend to be poorly understood for sea cucumbers. Recent stock assessments used $h = 0.3$ and $\sigma_R < 0.5$ for several species of sea cucumbers from Queensland (Smart et al., 2024b, 2024a). The justification of these values was that sea cucumber populations are typically slow to recover following over depletion (hence a low *h*) and that σ_R was restricted in a model fitting process to reduce over-fitting to CPUE data (Smart et al., 2024b, 2024a). Similar reasoning and justification can be applied to NT sandfish for stock assessment purposes. Again, these parameters should be sensitivity tested within a stock assessment framework.

Summary

From the information presented for each life history characteristic, a base-case description of species biology can be assembled for stock assessment purposes. Figure 13 shows the growth curve which approximates the known information of sandfish, along with an *M* estimate that aligns with this. These parameters are summarised in Table 1 and variability around growth, mortality, maturity, and recruitment parameters should be explored through sensitivity testing in a stock assessment framework.

Table 1. Summary and justification of best available or approximated life history information for NT sandfish.

Parameter	Value	Reference or justification
Growth		Approximated based on published biological information. Matches maximum size (Purcell et al., 2023). Length-at-age at age two matches (Long et al., 1996)
L_∞	35 cm	
k	0.35 yr^{-1}	
a_0	0 yr	
Maturity		(Conand, 1989)
L_{50}	16 cm	
L_{95}	18 cm	Approximated based on fast growth
Natural Mortality	0.65 yr^{-1}	Produces a longevity that aligns with maximum age from growth parameters used.
Weight-at-length		Estimated from data collected by Koopman & Knuckey (in prep)
a	0.00092	
b	2.11439	
Recruitment		Conservative values used for other sea cucumber assessments (Smart et al., 2024b)
Steepness (h)	0.3	
Variability (σ_R)	< 0.5	

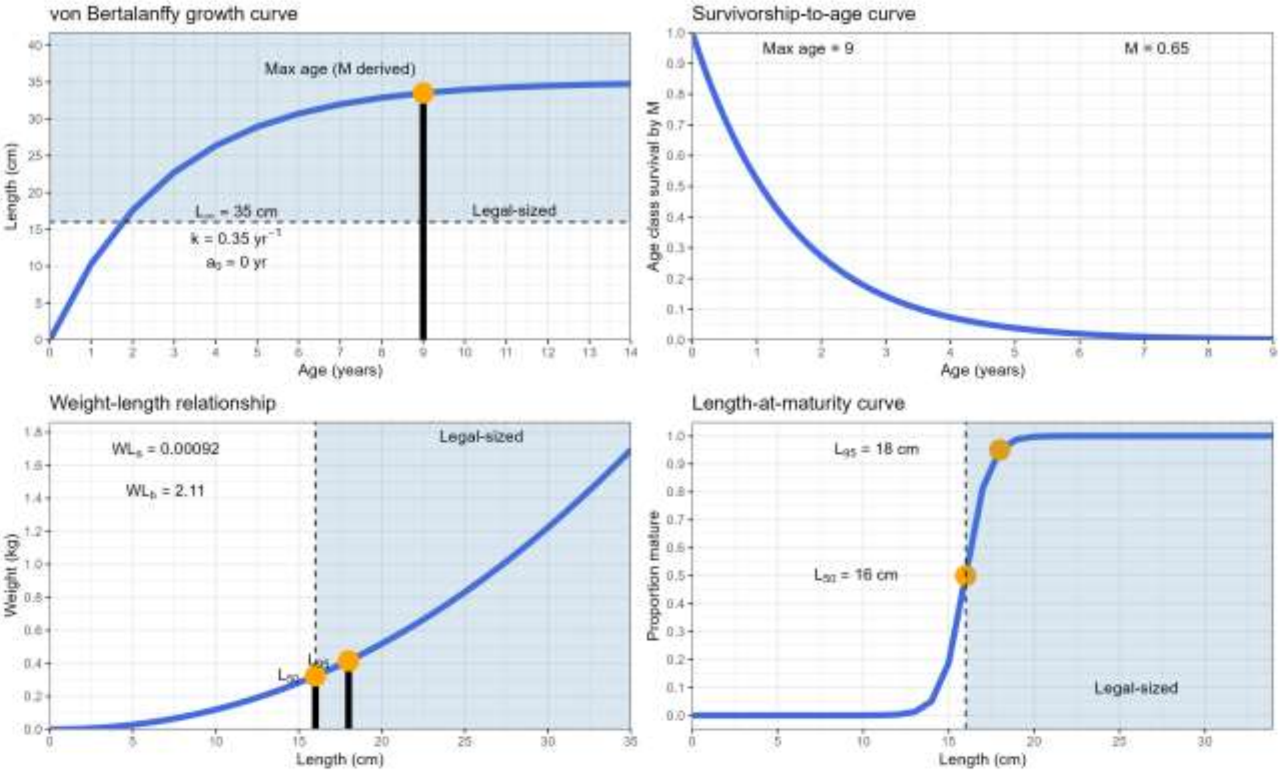


Figure 13: Life history summary of NT sandfish from available information. Note that some values are based on strong assumptions and designed to match best available information on species biology.

Biomass surveys

Three sandfish surveys have been conducted in grids 1132 (West stock), 1236 (East stock) and 1336 (East stock) (Koopman & Knuckey, in prep). These provide density estimates for the areas surveyed together with length and weight compositions of sandfish. The combination of these data allows absolute biomass to be calculated by scaling density by the average weight of individuals applicable to each area (Koopman & Knuckey, in prep). Error estimates for biomass estimates can be produced through bootstrapping procedures. Therefore, absolute estimates of biomass and associated uncertainties are available for the two main grids of the East stock and the main grid of the West stock where the most catch and effort occur. The data from these surveys provide two useful inputs to stock assessment models: 1) Absolute estimates of biomass with uncertainty, and 2) length-compositions that can be used to determine selectivity in age structured models.

Discussion

Current determination of stock status

Both nominal and standardised CPUE indices for the West and East stocks indicate that both stocks are healthy and that recent catch levels have been sustainable. Historical catch and CPUE from 1999/2000 to 2006/2007 indicates that overfishing probably occurred during this period for the West stock. Catches were markedly higher than recent catches during this period and CPUE had a strong declining trend, indicating that stock declines were probable. However, since 2006/2007 catches have been consistently below 50 t whole weight and CPUE has recovered and stabilised over this period.

Catches for the East stock have only exceeded 50 t whole weight in three fishing seasons and have been below 20 t in most years. Both nominal and standardised CPUE have been relatively stable over this period, indicating that these catch levels have been appropriate for the stocks size.

Both stocks were recently classified as ‘undefined’ in the Status of Australian Fish Stocks (Hart, 2023) based on insufficient information being available to assess changes in abundance. However, stocks in Western Australia were assigned stock status definitions given the availability of survey estimates and standardised CPUE. Given that this information is now available for NT stocks, it is likely that a stock status could be assigned in future editions of the Status of Australian Fish Stocks. Based on the evidence provided by the CPUE standardisation here, there is evidence to support a sustainable status for both stocks in 2022/2023. Upcoming publication of biomass estimates from surveys will provide further information that can be used to inform these stock statuses (Koopman & Knuckey, 2025).

Potential for localised depletion

A novel approach was developed in this report to ascertain whether signs of localised depletion could be identified from grid level CPUE. This approach used crossed random effects within a GLMM to share information across grids. The advantage of this approach is that grids with limited fishing effort in certain years receive information on the global (i.e. stock level) CPUE trend to infer abundance. Certain grids for the West stock had low levels of catch and effort in recent years, producing low and often volatile nominal CPUE estimates. However, shared information from other grids with higher levels of fishing activity provided supplementary information that produced standardised CPUE estimates that were higher and less volatile than the nominal values. This represents the greatest level of information that can be provided from a CPUE standardisation analysis on sparse spatial data, but it must also be carefully caveated. An increasing CPUE trend in grids with greater levels of catch and effort indicates that recruitment is outpacing removals (i.e. catch) and therefore the population is increasing. Given low levels of catch in grids with limited fishing effort, one would also expect CPUE to increase at a rate that approximates that of other grids if recruitment rates were spatially comparable. Yet there is currently limited information to verify this as recruitment dynamics remain poorly understood for sandfish and sea cucumbers more generally (Wolfe and Byrne 2022).

The genetic structure of sandfish populations in northern Australia and Papua New Guinea were recently studied and the level of genetic sub-structuring was low (Nowland et al., 2017). However, genetic analyses from Papua New Guinea and Fiji have indicated limited connectivity between subpopulations leading to high rates of self-seeding (Brown et al., 2022; Waldie et al., 2024). Localised depletion of sandfish has been detected on the east coast of Australia where overfishing occurred in Tin Can Bay. There has been restricted gene-flow detected along the east coast, suggesting a low dispersal rate that could have led to this localised depletion (Hamel et al., 2022; Uthicke & Benzie, 2001). This mixture of information indicates that the level of recruitment connectivity for NT sandfish sub-populations is uncertain. Therefore, for the results of this CPUE standardisation to be accepted with confidence, evidence of comparable levels of recruitment between grids needs to be further evaluated.

The standardised CPUE results presented in this report indicate that no localised depletion has occurred for individual grids. However, the contrasting information on sandfish subpopulation connectivity means that this result must still be treated cautiously. Rather than concluding that localised depletion has not occurred, this report concludes that no evidence of localised depletion has been detected. Therefore, the cautious spatial management that is in place for the fishery remains justified but there can be some reassurance that localised depletion is not apparent in the available information and results.

Future stock assessment research

Potential stock assessment approaches

There are two feasible stock assessment modelling options that can be applied to each NT sandfish stock: 1) an age structured population model performed via Stock Synthesis (Methot & Wetzel, 2013), or 2) a biomass dynamics model such as surplus production or delay difference model. Biomass dynamics models are a simpler model framework as they do not consider population structure, instead focusing on the population as a single pool of biomass. Surplus production models are the simplest application of biomass dynamics models, estimating two key parameters: carrying capacity (K) and rate of population increase (r). These models are commonly applied to sea cucumber stocks and have been used in Western Australian sandfish stock assessments (Hart et al., 2022). Delay difference models are an extension of surplus production models which extend beyond estimating K and r by considering limited information on species biology, such that they can better consider recruitment (Hilborn & Walters, 1992). Both surplus production and delay difference models have been applied to sea cucumbers and can be tailored to include estimates of absolute biomass from surveys (Hart et al., 2022; Smart et al., 2024a, 2024b). However, one compromise with biomass dynamics models is that only the legal-sized component of the population can be considered, as this is the only information provided to the models through catch and effort data. Absolute biomass estimates must therefore be truncated to the legal sized component of the surveys for inclusion in these models, making less use of the available data (Smart et al., 2024a, 2024b).

Age structured population models are a more complex model framework than biomass dynamics models as they consider the underlying population structure. Populations can then be summarised according to different biomass definitions such as total, legal-sized, and spawning biomass. These models are able to consider the sub-legal component of the stock which can be valuable when size limits are in place as they consider the component of the population protected from fishing. Both age structured (i.e., Stock Synthesis) and delay different models were recently applied and compared for four sea cucumber species in Queensland which had similar data availability to the NT sandfish fishery (Smart et al., 2024a, 2024b). These comparisons determined that both models could both be effectively applied for sea cucumber stock assessments and produced the same conclusions regarding stock status. However, the age structured models were determined to perform best as they had improved stability, made better use of available data (biomass did not need to be truncated and survey length compositions could be incorporated) and provided more detailed model outputs for consideration in fishery management (Smart et al., 2024a, 2024b). The similarity between recent work undertaken in Queensland and NT means that the same age structured approach would likely be successful. However, the surplus production model applied by Hart et al (2022) could also be successfully applied. The delay difference model applied by Smart et al (2024a, 2024b) remains proprietary software of Fisheries Queensland and is unlikely to be available for use in the NT in the near future. The surplus production model of Hart et al (2022) and age structured model of Smart et al (2024a, 2024b) are therefore the best stock assessment options available for the NT sandfish fishery.

Ideally population models for sea cucumbers should be conducted at the finest spatial scale possible, as meta-population structures exist for many species. However, the finer the spatial scale used in stock assessments, the more data is required, producing an unfortunate trade-off between model specification and data availability. Given that survey estimates are available for the two main grids in the East stock, which also had sufficient levels of catch and effort data to support CPUE standardisation, it may be possible to consider a three-area spatial model for this stock. This would include each surveyed grid and the amalgamation of remaining areas. However, the spatial scale of the West stock makes this less feasible, and it is likely this stock cannot be considered in a spatial stock assessment model. Instead a stock level assessment model could be undertaken with the biomass of grid 1132 scaled to be representative of the remaining grids (Smart et al., 2024b). Full exploration of these options is best considered during the stock assessment process when model stability can be considered as data availability is balanced with spatial structure.

Value of additional research

Standardised CPUE and estimates of absolute biomass are significant steps towards providing sufficient data for stock assessment purposes. Further surveys of grids for the West stock would provide improved spatial coverage, further increasing the level of valuable information for stock assessments. However, additional information on species biology would be particularly valuable for stock assessment purposes. As identified in this report, information on growth is poorly understood, as well as longevity and natural mortality. These are common data limitations for sea cucumber species and have been overcome in stock assessments by careful and judicious decision making by stock assessors, and extensive sensitivity testing of biological assumptions. Nonetheless targeted research into species biology would be particularly valuable and would complement the existing information on biomass estimates and standardised CPUE already available.

Currently, harvest estimates are only available from 1999/2000 onwards as data prior to this are confidential. All available data from logbooks will need to be included in stock assessment modelling. There would also be opportunity to extend the CPUE series back to the commencement of catches.

Acknowledgements

Anton Krsinich and Anthony Hart from Tasmanian seafoods provided valuable input into this report. We thank Ann Schubert from NT Fisheries for provision of logbook data and Michael Usher for providing additional context around catch reporting.

References

Anderson, S. C., Flemming, J. M., Watson, R., & Lotze, H. K. (2011). Serial exploitation of global sea cucumber fisheries. Fish and Fisheries, 12(3), 317–339. https://doi.org/10.1111/j.1467-2979.2010.00397.x

Bartoń, K. (2024). MuMIn: Multi-Model Inference. https://CRAN.R-project.org/package=MuMIn

Bell, J.D., Purcell, S.W., and Nash, W.J. (2008). Restoring small-scale fisheries for tropical sea cucumbers. Ocean and Coastal Management 51, 589-593.

Breheny, P., & Burchett, W. (2017). Visualization of Regression Models Using visreg. The R Journal, 9(2), 56–71.

Brooks, M. E., Kristensen, K., Benthem, K. J. van, Magnusson, A., Berg, C. W., Nielsen, A., Skaug, H. J., Maechler, M., & Bolker, B. M. (2017). glmmTMB Balances Speed and Flexibility Among Packages for Zero-inflated Generalized Linear Mixed Modeling. The R Journal, 9(2), 378–400.

Brown, K. T., Southgate, P. C., Hewavitharane, C. A., & Lal, M. M. (2022). Saving the sea cucumbers: Using population genomic tools to inform fishery and conservation management of the Fijian sandfish Holothuria (Metriatyla) scabra. PLOS ONE, 17(9), e0274245. https://doi.org/10.1371/journal.pone.0274245

Conand, C. (1989). Les holothuries aspidochirotes du lagon de Nouvelle-Cal ́ edonie: Biologie, ́ ecologie et exploitation. PhD Thesis, Universite ́ de Bretagne Occidentale, Brest.

Cope, J., & Hamel, O. S. (2022). Development and considerations for application of a longevity-based prior for the natural mortality rate. Fisheries Research, 256, 106477. https://doi.org/10.1016/j.fishres.2022.106477

Dissanayake, D., & Wijeyaratne, M. (2010). Studies on the sea cucumber fishery in the North Western coastal region of Sri Lanka. Sri Lanka Journal of Aquatic Sciences, 12, 19–38. https://doi.org/10.4038/sljas.v12i0.2212

Eriksson, H., and Byrne, M. (2015). The Sea Cucumber fishery in Australia's Great Barrier Reef Marine Park follows global patterns of serial exploitation. Fish and Fisheries 16, 329-341.

Friedman, K., Eriksson, H., Tardy, E., & Pakoa, K. (2011). Management of sea cucumber stocks: Patterns of vulnerability and recovery of sea cucumber stocks impacted by fishing. Fish and Fisheries, 12(1), 75–93. https://doi.org/10.1111/j.1467-2979.2010.00384.x

Hamel, & Cope, J. (2022). Upgrading from M version 0.2: An application-based method for practical estimation, evaluation and uncertainty characterization of natural mortality. Fisheries Research, 256, 106493. https://doi.org/10.1016/j.fishres.2022.106493

Hamel, J.-F., Eeckhaut, I., Conand, C., Sun, J., Caulier, G., & Mercier, A. (2022). Global knowledge on the commercial sea cucumber Holothuria scabra. In A. Mercier & J.-F. Hamel (Eds.), Advances in Marine Biology (Vol. 91, pp. 1–286). Academic Press. https://doi.org/10.1016/bs.amb.2022.04.001

Hart. (2023). Sandfish (Sea Cucumber) (2023). In Status of Australian fish stocks. Fisheries Research and Development Corporation.

Hart, A. M., Murphy, D. M., & Fabris, F. F. (2022). Western Australian sea cucumber resource assessment report. Department of Primary Industries and Regional Development, Western Australia. Article 324.

Hilborn, R., & Walters, C. J. (1992). Quantitative Fisheries Stock Assessment: Choice, Dynamics and Uncertainty. Chapman and Hall.

Hoyle, S. D., Campbell, R. A., Ducharme-Barth, N. D., Grüss, A., Moore, B. R., Thorson, J. T., Tremblay-Boyer, L., Winker, H., Zhou, S., & Maunder, M. N. (2024). Catch per unit effort modelling for stock assessment: A summary of good practices. Fisheries Research, 269, 106860. https://doi.org/10.1016/j.fishres.2023.106860

Kinch, J., Purcell, S., Uthicke, S., and Friedman, K. (2008). Population status, fisheries and trade of sea cucumbers in the Western Central Pacific. In V. Toral-Granda, A. Lovatelli and M. Vasconcellos. Sea cucumbers. A global review of fisheries and trade. FAO Fisheries and Aquaculture Technical Paper. No. 516. Rome, FAO. pp. 7–55.

Koopman, M., & Knuckey, I. A. (2025). 2024 surveys to estimate the density and biomass of Sandfish (*Holothuria scabra)* at Cobourg Peninsula and Groote Island. (p. 50). Fishwell Consulting.

Koopman, M., Knuckey, I. A., & McShane, P. (2024). Analysis of catches to inform future surveys of Sandfish (Holothuria scabra) in the Northern Territory. Fishwell Consulting.

Long, B., Skewes, T., Dennis, D., Poiner, I., Pitcher, C., Taranto, T., Manson, F., Baxter, I., Polon, P., Karre, B., Evans, C., & Milton, D. (1996). Distribution and abundance of beche-de-mer on Torres Strait reefs.

Lüdecke, D., Ben-Shachar, M. S., Patil, I., Waggoner, P., & Makowski, D. (2021). performance: An R Package for Assessment, Comparison and Testing of Statistical Models. Journal of Open Source Software, 6(60), 3139. https://doi.org/10.21105/joss.03139

Maunder, M. N., Hamel, O. S., Lee, H.-H., Piner, K. R., Cope, J. M., Punt, A. E., Ianelli, J. N., Castillo-Jordán, C., Kapur, M. S., & Methot, R. D. (2023). A review of estimation methods for natural mortality and their performance in the context of fishery stock assessment. Fisheries Research, 257, 106489. https://doi.org/10.1016/j.fishres.2022.106489

Maunder, M. N., & Punt, A. E. (2004). Standardizing catch and effort data: A review of recent approaches. Fisheries Research, 70(2–3), 141–159.

Methot, R. D., & Wetzel, C. R. (2013). Stock synthesis: A biological and statistical framework for fish stock assessment and fishery management. Fisheries Research, 142, 86–99. https://doi.org/10.1016/j.fishres.2012.10.012

Nowland, S. J., Southgate, P. C., Basiita, R. K., & Jerry, D. R. (2017). Elucidation of fine-scale genetic structure of sandfish (Holothuria scabra) populations in Papua New Guinea and northern Australia. Marine and Freshwater Research, 68(10), 1901–1911. Scopus. https://doi.org/10.1071/MF16223

NT. (2021). Northern Territory Trepang Fishery. Ecological risk assessment 2021. (p. 45pp). Department of Industry, Tourism and Trade, Northern Territory Government.

Ogle, D. H. (2015). Introductory Fisheries Analyses in R. Boca Raton, FL, CRC Press.

Punt, A. E., Smith, D. C., & Smith, A. D. M. (2011). Among-stock comparisons for improving stock assessments of data-poor stocks: The “Robin Hood” approach. ICES Journal of Marine Science, 68(5), 972–981. https://doi.org/10.1093/icesjms/fsr039

Purcell, S.W. (2010). Managing sea cucumber fisheries with an ecosystem approach. Edited/compiled by Lovatelli, A.; M. Vasconcellos and Y. Yimin. FAO Fisheries and Aquaculture Technical Paper. No. 520. Rome, FAO. 2010. 157p.

Purcell, S., Lovatelli, A., González-Wangüemert, M., Solis-Marin, F., Samyn, Y., & Conand, C. (2023). Commercially important sea cucumbers of the world (2nd ed., Vol. 1). FAO. https://doi.org/10.4060/cc5230en

Purcell, S.W., Conand, C., Uthicke, S., Byrne, M. (2016). Ecological roles of exploited sea cucumbers: a review. Oceanography and Marine Biology: An Annual Review.

Purcell, S., Williamson, D. H., & Ngaluafe, P. (2018). Chinese market prices of beche-de-mer: Implications for fisheries and aquaculture. Marine Policy, 91, 58–65. https://doi.org/10.1016/j.marpol.2018.02.005

R Core Team. (2024). R: A language and environment for statistical computing [Computer software]. R Foundation Statistical Computing. http://www.R-project.org/.

Roelofs, A., Piddocke, T., Ashby, C., Conron, S., Hartmann, K., Hesp, A., Hone, P., Jacobsen, I., Jesson-Kerr, M., Mayfield, S., Stewart, J., Usher, M., Woodhams, J., & Wright, D. (2024). Status of Australian Fish Stocks Reports 2024. Fisheries Research and Development Corporation.

Skewes, T., Plagányi, É., Murphy, N., Pascual, R., & Fischer, M. (2014). An MSE of the Qld East Coast Sea Cucumber Fishery (FRDC Project No. 2012/200; p. 176). CSIRO.

Smart, J. J., Wortmann, J., & Wickens, M. E. (2024a). Stock assessment of Queensland east coast burrowing blackfish (Actinopyga spinea), with data to June 2023. State of Queensland. https://era.daf.qld.gov.au/id/eprint/13346/

Smart, J. J., Wortmann, J., & Wickens, M. E. (2024b). Stock assessment of Queensland east coast prickly redfish, herrmanni curryfish and vastus curryfish with data to December 2023. State of Queensland. https://era.daf.qld.gov.au/id/eprint/13358/

Uthicke, S., & Benzie, J. (2001). Effect of bêche-de-mer fishing on densities and size structure of Holothuria nobilis (Echinodermata: Holothuroidea) populations on the Great Barrier Reef. Coral Reefs, 19(3), 271–276. https://doi.org/10.1007/s003380000118

Waldie, P., Feary, D. A., Bode, M., Matawai, M., Harrison, H. B., Berumen, M. L., Molai, C., Karo, M., & Hamilton, R. J. (2024). Dispersal patterns of sandfish (Holothuria scabra) larvae in Manus Province, Papua New Guinea. Frontiers in Marine Science, 11. https://doi.org/10.3389/fmars.2024.1380235

Wickens, M. E., Smart, J. J., & Wortmann, J. (2024). Management strategy evaluation of the Queensland east coast sea cucumber fishery, with data to June 2023. State of Queensland. https://era.daf.qld.gov.au/id/eprint/13345/

Wolfe, K., and Byrne, M. (2022). Overview of the Great Barrier Reef Sea Cucumber fishery with focus on vulnerable and endangered species. Biological Conservation 266, 109451. https://doi.org/10.1016/j.biocon.2022.109451.

Yanti, A., Tresnati, J., Yasir, I., Syafiuddin, Rahmani, P. Y., Aprianto, R., & Tuwo, A. (2020). Size at the maturity of sea cucumber Holothuria scabra. Is it an overfishing sign in Wallacea Region? IOP Conference Series: Earth and Environmental Science, 473(1), 012056. https://doi.org/10.1088/1755-1315/473/1/012056

Appendix A

CPUE GLM diagnostics - West Stock

AIC ranking analysis for model variables

Table A1: AIC ranking analysis of models with different fixed effect combinations for the West stock. The model with the lowest AIC value (ΔAIC = 0) is the best fitting model, although models with an ΔAIC less than 2 are equally appropriate. The top ten models according to AIC are shown.

Model formula	df	AIC	ΔAIC
Catch_Kg ~ GRID_CODE + LICENCE_NO + MONTH + NUMBER_OF_CREW + Year + offset(log(Total_hours))	46	27298.99	0
Catch_Kg ~ LICENCE_NO + MONTH + NUMBER_OF_CREW + Year + offset(log(Total_hours))	43	27312.55	13.56
Catch_Kg ~ GRID_CODE + LICENCE_NO + NUMBER_OF_CREW + Year + offset(log(Total_hours))	35	27317.41	18.43
Catch_Kg ~ LICENCE_NO + NUMBER_OF_CREW + Year + offset(log(Total_hours))	32	27329.53	30.54
Catch_Kg ~ GRID_CODE + LICENCE_NO + MONTH + Year + offset(log(Total_hours))	45	27334.68	35.69
Catch_Kg ~ LICENCE_NO + MONTH + Year + offset(log(Total_hours))	42	27348.58	49.59
Catch_Kg ~ GRID_CODE + LICENCE_NO + Year + offset(log(Total_hours))	34	27355.27	56.28
Catch_Kg ~ LICENCE_NO + Year + offset(log(Total_hours))	31	27369.82	70.83
Catch_Kg ~ GRID_CODE + MONTH + NUMBER_OF_CREW + Year + offset(log(Total_hours))	41	27371.64	72.66
Catch_Kg ~ GRID_CODE + NUMBER_OF_CREW + Year + offset(log(Total_hours))	30	27394.44	95.45

AIC ranking analysis for hierachical structure

Table A2: AIC ranking analysis for models with differing hierarchical structures for the West stock. The model with the lowest AIC value (ΔAIC = 0) is the best fitting model, although models with an ΔAIC less than 2 are equally appropriate.

Model formula	df	AIC	ΔAIC
Catch_Kg ~ 0 + Year + (1 | GRID_CODE:Year) + MONTH + NUMBER_OF_CREW + offset(log(Total_hours)) + (1 | LICENCE_NO)	40	27183.17	0
Catch_Kg ~ 0 + Year + (1 | GRID_CODE/Year) + MONTH + NUMBER_OF_CREW + offset(log(Total_hours)) + (1 | LICENCE_NO)	41	27185.25	2.09
Catch_Kg ~ 0 + Year + GRID_CODE + (1 | GRID_CODE:Year) + MONTH + NUMBER_OF_CREW + offset(log(Total_hours)) + (1 | LICENCE_NO)	43	27187.67	4.5
Catch_Kg ~ 0 + (1 | Year) + (1 | GRID_CODE) + (1 | GRID_CODE:Year) + MONTH + NUMBER_OF_CREW + offset(log(Total_hours)) + (1 | LICENCE_NO)	19	27196.61	13.44

Diagnostics of the best fitting model.

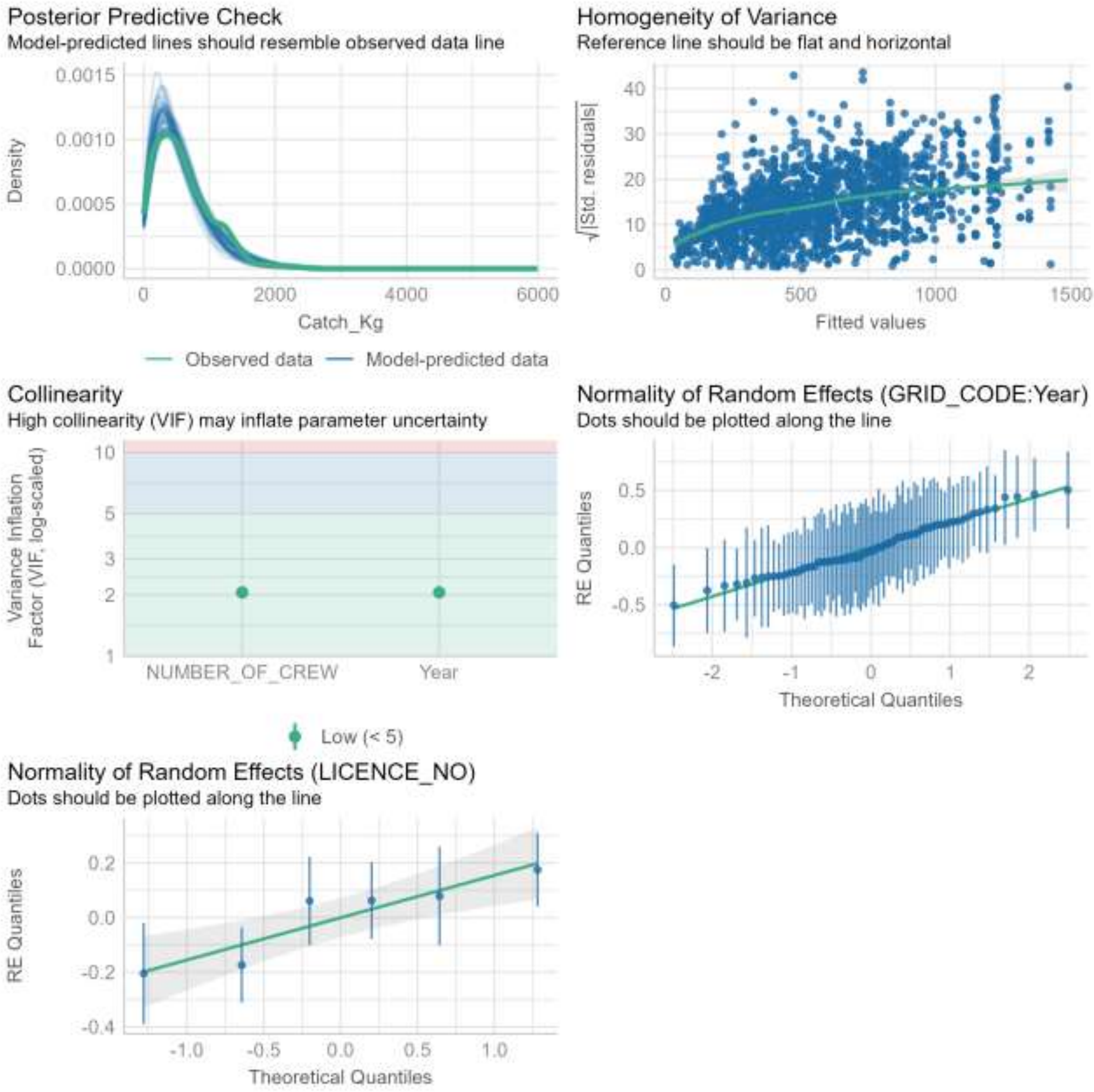


Figure A1: Diagnostic plots for the besting fitting GLMM used in the CPUE standardisation for the West stock. Each panel demonstrates the model performance according to the posterior predictive check, homogeneity of variance, presence of collinearity, and normality of random effects. A description of how each diagnostic plot should look is presented in each panel's subheading. These plots were produced using the `performance` R package (Lüdecke et al., 2021).

CPUE GLM diagnostics - East Stock

AIC ranking analysis for model variables

Table A3: AIC ranking analysis of models with different fixed effect combinations for the East stock. The model with the lowest AIC value (ΔAIC = 0) is the best fitting model, although models with an ΔAIC less than 2 are equally appropriate. The top ten models according to AIC are shown.

Model	df	AIC	ΔAIC
Catch_Kg ~ GRID_CODE + LICENCE_NO + MONTH + NUMBER_OF_CREW + Year + offset(log(Total_hours))	41	11523.64	0
Catch_Kg ~ LICENCE_NO + MONTH + NUMBER_OF_CREW + Year + offset(log(Total_hours))	40	11528.34	4.7
Catch_Kg ~ GRID_CODE + LICENCE_NO + MONTH + Year + offset(log(Total_hours))	40	11528.7	5.06
Catch_Kg ~ LICENCE_NO + MONTH + Year + offset(log(Total_hours))	39	11536.35	12.71
Catch_Kg ~ GRID_CODE + LICENCE_NO + NUMBER_OF_CREW + Year + offset(log(Total_hours))	30	11548.9	25.26
Catch_Kg ~ LICENCE_NO + NUMBER_OF_CREW + Year + offset(log(Total_hours))	29	11550.28	26.64
Catch_Kg ~ GRID_CODE + LICENCE_NO + Year + offset(log(Total_hours))	29	11550.68	27.03
Catch_Kg ~ LICENCE_NO + Year + offset(log(Total_hours))	28	11554.08	30.44
Catch_Kg ~ GRID_CODE + MONTH + NUMBER_OF_CREW + Year + offset(log(Total_hours))	36	11555.82	32.18
Catch_Kg ~ GRID_CODE + MONTH + Year + offset(log(Total_hours))	35	11561.56	37.92

AIC ranking analysis for hierachical structure

Table A4: AIC ranking analysis for models with differing hierarchical structures for the East stock. The model with the lowest AIC value (ΔAIC = 0) is the best fitting model, although models with an ΔAIC less than 2 are equally appropriate.

Model formula	df	AIC	ΔAIC
Catch_Kg ~ 0 + Year + GRID_CODE + (1 | GRID_CODE:Year) + offset(log(Total_hours)) + (1 | LICENCE_NO) + NUMBER_OF_CREW	27	11568.33	0
Catch_Kg ~ 0 + Year + (1 | GRID_CODE:Year) + offset(log(Total_hours)) + (1 | LICENCE_NO) + NUMBER_OF_CREW	26	11570.17	1.84
Catch_Kg ~ 0 + Year + (1 | GRID_CODE/Year) + offset(log(Total_hours)) + (1 | LICENCE_NO) + NUMBER_OF_CREW	27	11571.24	2.91
Catch_Kg ~ 0 + (1 | Year) + (1 | GRID_CODE) + (1 | GRID_CODE:Year) + offset(log(Total_hours)) + (1 | LICENCE_NO) + NUMBER_OF_CREW	7	11605.53	37.2

Diagnostics of the best fitting model.

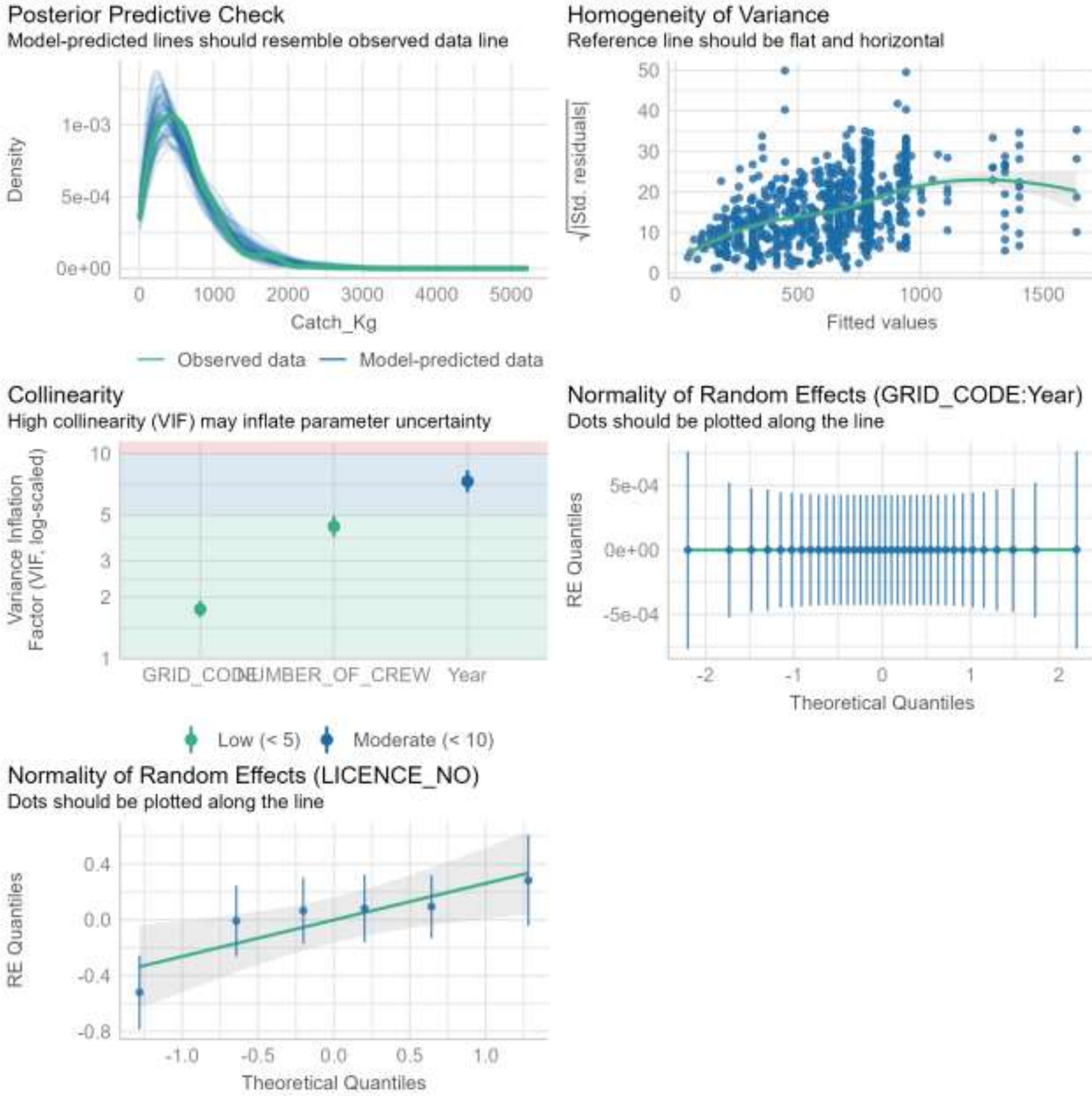


Figure A2: Diagnostic plots for the besting fitting GLMM used in the CPUE standardisation for the East stock. Each panel demonstrates the model performance according to the posterior predictive check, homogeneity of variance, presence of collinearity, and normality of random effects. A description of how each diagnostic plot should look is presented in each panel's subheading. These plots were produced using the `performance` R package (Lüdecke et al., 2021).