

Planning and managing freshwater cage aquaculture in Scotland with combined catchment and lake models of phosphorus loading

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ABSTRACT

Phosphorus (P) is often the main limiting nutrient in freshwater lakes and reservoirs, so it is important to monitor and manage total P (TP) loading to minimise negative impacts on water quality and reduce the risk of eutrophication. In cage aquaculture, P enters the surrounding environment via waste feed, faeces, and excretory products. Static models for predicting P have been used for several decades, yet their capacity to represent the dynamic nature of lake systems remains unclear. There is also a need to consider TP loading from the wider catchment to better represent the range of P inputs to lake systems. This study developed a novel modelling framework by integrating the InVEST Nutrient Delivery Ratio (NDR) to simulate P loading from the catchment with 3 lake models to simulate TP: the static Dillon & Rigler and OECD models, and the dynamic LakeMab model. The approaches were demonstrated using four freshwater lakes (lochs) in Scotland where cages are used to grow Atlantic salmon (*Salmo salar*) smolts: Arkaig, Lochy, Shiel, and Garry. The mean relative errors for the modelled mean TP levels compared to the measured mean values were between: 1.54–2.57 $\mu\text{g L}^{-1}$ for Dillon & Rigler, 1.86–2.74 $\mu\text{g L}^{-1}$ for OECD, and 1.45–3.91 $\mu\text{g L}^{-1}$ for LakeMab. The findings indicate that the three models have similar error rates; despite a slightly poorer fit, the dynamic model successfully captured seasonal fluctuations in TP. This study demonstrates an approach that can strengthen the monitoring, management, and regulation of freshwater aquaculture.

1. Introduction

Water quality issues and eutrophication are among key concerns arising from human activities in lakes and their surrounding catchments (Smith and Schindler, 2009; Ho et al., 2019). Hence, it is important to assess how activities may contribute to nutrient loading and what effects might occur. Cage aquaculture is used to grow fish such as tilapia and salmonids in many lakes throughout the world, and nutrients are released from the farms into the surrounding environment via fish wastes and uneaten feed (Cho and Bureau, 2001; Hua and Bureau, 2006). Phosphorus (P) is the limiting nutrient in many freshwater systems, so P is usually the main nutrient of interest when predicting or monitoring impacts of freshwater fish production in lakes and reservoirs (Beveridge, 2004). P is also an essential mineral for fish, with an important role in metabolic processes and bone development and must be supplied in the diet of farmed fish as uptake from the environment is low (Lall, 2003). Therefore, when determining the amount of fish

production that can take place in a lake system, it is important to assess the potential impact of P loading from aquaculture through laboratory testing and empirical or numerical environmental models.

Empirical-based static models have been used for many years as a way of predicting P levels in lakes and reservoirs (Dillon and Rigler, 1974; Dillon and Rigler, 1975; Vollenweider, 1975; OECD, 1982) and are used to assess the capacity for further P loading through aquaculture (Håkanson et al., 1998; Johansson and Nordvang, 2002; Beveridge, 2004). Decades after their original development, the Dillon and Rigler (1975) and OECD (1982) models are still used to support aquaculture planning and management in freshwater systems, e.g. studies in Brazil (David et al., 2015; Canzi et al., 2017), Indonesia (Taskov et al., 2021), China (Li et al., 2022). In addition, the OECD model is used for regulatory purposes in Scotland (Cromey et al., 2010). While static models are straightforward to use with limited data, they neglect the seasonal and dynamic nature of a lake system. The Dillon & Rigler model uses a mass-balance approach and is applied when long-term datasets are

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available, whereas the OECD model relies on empirical relationships between phosphorus loading and lake nutrient status and is often used for regional assessments or lakes with limited data. An alternative approach is the use of dynamic models to simulate the lake system over time (Mooij et al., 2010; Bhagowati and Ahamad, 2019). The dynamic model LakeMab (Håkanson and Bryhn, 2008), has been suggested as a useful tool for managing water quality in lakes and reservoirs (Roubeix et al., 2020). For aquaculture planning and management, a balance is required between models that have the necessary complexity to simulate a system but are also applicable to the range of freshwater lakes that will be used for aquaculture.

Aquaculture is not the only contributor of P to lake systems, and it is also important to consider P inputs from the surrounding catchment. There are many different models and approaches used to simulate P export and transport through catchments (Wellen et al., 2015; Pferdmenges et al., 2020; Yuan et al., 2020), but many are complex, highly data-intensive, and difficult to apply to different locations. Like the in-lake models, there is a need for simpler catchment models that can be easily applied to new catchments for water management purposes (Jackson-Blake et al., 2017). The InVEST (Integrated Valuation of Ecosystem Services and Trade-offs) Nutrient Delivery Ratio (NDR) model, can simulate P (and nitrogen) inputs to aquatic systems from the surrounding catchment based on land use (Sharp et al., 2020). In comparison to other models such as the Soil and Water Assessment Tool (SWAT) (Arnold et al., 2012), the required data inputs for the NDR model are straightforward to obtain, which increases usability and aids potential applications. The NDR model has been used successfully to consider different nutrient loading scenarios in a catchment with the aim of reducing potential harmful algae events (Rioux and Strong, 2023), to simulate the effects of different land use practices and identify areas in need of attention (Han et al., 2021), and to compare relative differences in nutrient export from catchments in the UK (Redhead et al., 2018).

The aim of this study was to demonstrate a novel approach that combined a catchment model (InVEST NDR) with three different lake models, LakeMab (Håkanson and Bryhn, 2008), and the Dillon and Rigler (1975) and OECD (1982) models, to predict total P (TP) levels in four different Scottish freshwater lake systems used for aquaculture purposes. The first objective was to assess how the predicted TP compared to TP levels measured as part of a routine monitoring program, and the second objective was to evaluate how the three lake models performed against each other.

2. Materials and methods

2.1. Field sites and sampling

Four freshwater lakes in the highlands of Scotland, UK (Lochs Garry, Arkaig, Lochy and Shiel), all containing salmonid cage aquaculture operated by Mowi Scotland, were selected for investigation (Fig. 1). A loch is a Scottish word meaning lake, used here and throughout. The four lochs vary in water volume, area and depth, their catchment areas, and levels of modification (Fig. 1). Loch Arkaig is located upstream of and drains into the deepest of the lochs, Loch Lochy. Loch Garry has a much larger, but heavily anthropogenically modified loch upstream (Loch Quoich). Each of these three lochs have dams at their outflow that controls water released. The fourth, Loch Shiel is a natural loch with no modifications to the outflow. Mean annual precipitation within the loch catchments ranged from c. 2000 mm yr⁻¹ at Loch Lochy to ~2500 mm yr⁻¹, at Lochs Arkaig/Garry and Shiel (Fig. 1).

Each loch has measurements for TP concentrations (µg L⁻¹) from water samples taken at 0 m and 5 m depths from six locations throughout the lochs. An example of this sampling protocol is provided in the Supplementary Information. Samples were collected and analysed by the University of Stirling, since 1987 for Lochs Arkaig and Garry, 2009 for Loch Lochy, and 1991 for Loch Shiel. Initially all lochs were

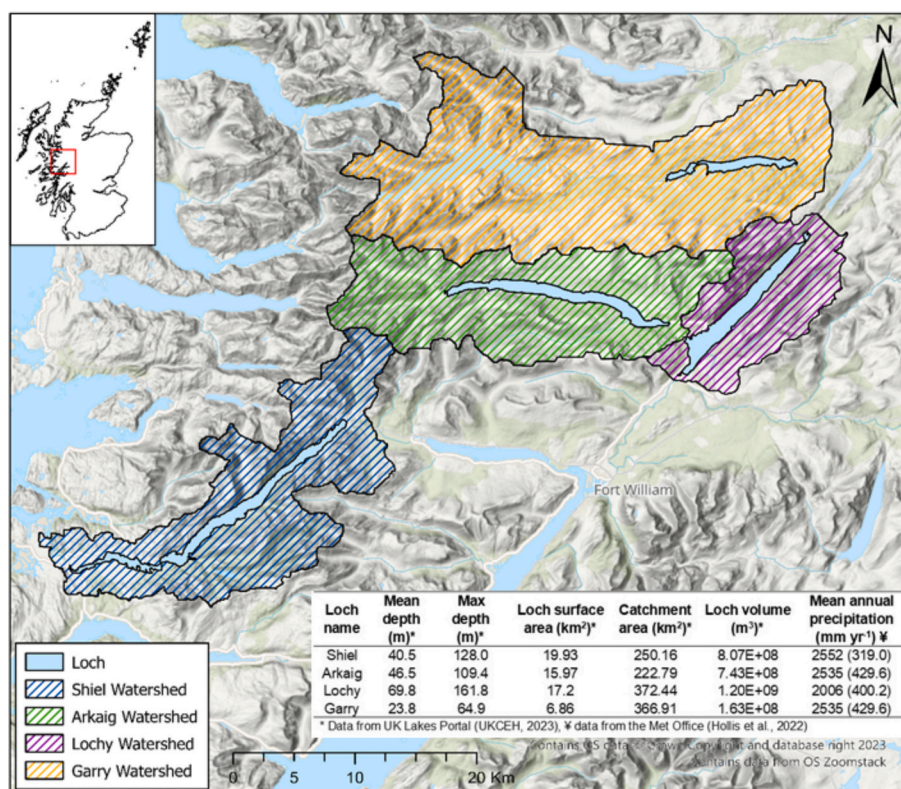


Fig. 1. Map showing locations of the four freshwater Scottish lochs (lakes) and their catchments used for the study; Lochs Garry, Arkaig, Lochy, and Shiel. An inset table summarises the physical characteristics of each loch.

sampled twice per year (summer and winter) to account for seasonal differences, but after 2006 all lochs were sampled 6 times per year (bi-monthly). The annual geometric mean values and mean values for each sampling occasion are provided for each loch in Supplementary Fig. S1.1, showing long-term trends in TP levels over time. Although there are seasonal variations and some fluctuations between annual means, only Loch Shiel shows a consistent change in TP levels, with a gradual increase since 1991. The monthly geometric mean from both depths across the six sampling locations was used for comparison with the LakeMab model, while the annual geometric mean was used for the Dillon & Rigler and OECD models.

On each occasion the water samples were collected using a 5-l capacity Van Dorn water sampler lowered through the water column to the correct depth using a rope marked at 1 m intervals. A 100 mL water sample for TP analysis was decanted from the sampler and transferred into a pre-cleaned pyrex glass Erlenmeyer flask. The mouth of the flask was covered with clean aluminium foil and sealed with a plastic screw cap to prevent phosphorus contamination. TP was determined using a standard perchlorate extraction and molybdenum-blue analysis method (HMSO, 1981).

Mowi Scotland provided data on feed conversion ratio, TP in feed, TP in fish, and fish production, between 2012 and 2022 for Loch Lochy, 2016–2021 for Loch Arkaig, 2015–2021 for Garry, and 2012–2020 for Loch Shiel, which was used in the models. To keep lochs' consistent with measured data, years 2015–2022 were used for analysis, with average farm data used when not otherwise available.

2.2. Modelling methodology

For each loch catchment, the InVEST NDR model provided values of phosphorus export to waterways under differing land use and land cover. These values were then used as inputs to the lake models; i) Dillon & Rigler static model, ii) OECD static model, and iii) LakeMab dynamic model (Table 1). The stages in the modelling and data used are given in Fig. 2. Lake models provided a baseline prediction of loch TP levels with no aquaculture, before caged farming production data of salmon was added into the models and compared to the measured TP values for each loch. Empirical data for model inputs were used where possible (e.g. precipitation data), and variables were predicted where data were unavailable.

2.2.1. Catchment model: InVEST nutrient delivery ratio (NDR)

The InVEST NDR uses a mass balance method to model transport of nutrients through pixels on the same flow path by surface and sub-surface flows under differing Land Use Land Cover (LULC) types and biophysical parameters (e.g. slope, retention efficiency), and P export to waterways (Sharp et al., 2020). The model was used here to map spatial

outputs of P export (in kg y^{-1}) from catchment land parcels to waterways in the drainage basin.

The InVEST NDR model requires spatial inputs of catchment elevation, land use, a nutrient runoff proxy derived from precipitation data, watershed boundaries, a threshold value of flow accumulation and a biophysical table detailing nutrient loading and critical length values for each land use category. A 30 m cell resolution Digital Elevation Model (DEM) was used for elevation (NASA Shuttle Radar Topography Mission (SRTM), 2013). Land Cover Maps (LCMs) were available from the UK Centre for Ecology and Hydrology (CEH) for the years 1990, 2000, 2007, 2015 and annually from 2017 (Rowland et al., 2017; Morton et al., 2000a, b, c; Morton et al., 2021; Marston et al., 2022; Marston et al., 2024). These LCMs cover the entire UK and are high resolution (25 m resolution from 2007 and 10 m resolution from 2020) with 21 UK specific LULC classes. HadUK-Grid raster data were obtained from the Met Office Hadley Centre for the annual nutrient proxy runoff (1 km resolution) (Met Office, 2022), and a standard threshold value of 750 was set for the flow accumulation to create a stream layer that nearly matches real-world stream networks. The Borselli K parameter was left at the default value of 2. The critical length for maximum P retention was set to 9000 m (300 cells). In the biophysical table, values of phosphorus loading ($\text{kg ha}^{-1} \text{y}^{-1}$) and the proportion of load retained were assigned to each of the CEH LULC classes based on Redhead et al. (2018), who collated the values for catchments in England and Wales. Though Scottish catchments have distinct geological characteristics, these values were the closest available sources of data and considered applicable to Scottish catchments.

2.2.2. Catchment model P-export extraction

The InVEST NDR model outputs a raster file of spatial catchment P export (kg y^{-1}) per cell, which was then converted into total P export for each catchment per year. These values were used in both the static and dynamic models. For individual years without LULC data, an average value of catchment annual P export results (between 2015 and 2022) was used.

2.2.3. Estimating fluvial discharge

The static and dynamic models require estimates of mean annual river discharge (Q_A ; $\text{m}^3 \text{yr}^{-1}$) for each loch to make predictions. In this study the equation from (Malmaeus and Håkanson, 2004) was used (Eq. 1), as it has been shown to produce good estimates of Q_A for European rivers.

$$Q_A = ADA \left(\frac{PREC}{650} \right) \times 0.01 \times 60 \times 60 \times 24 \times 365 \times 10^{-6} \quad (1)$$

where, ADA is catchment area in m^2 , PREC is the mean annual precipitation in mm yr^{-1} of the location, and a general value of 0.01 m^3

Table 1

Comparison of the Dillon and Rigler (1975), OECD (1982), and LakeMab (Håkanson and Bryhn, 2008) phosphorus models.

Feature	Dillon and Rigler (1975)	OECD (1982)	LakeMab (2008)
Model type	Empirical steady-state	Empirical steady-state	Dynamic process-based mass balance
Temporal resolution	Annual steady state	Annual steady state	Dynamic (monthly or sub-monthly)
Key compartments	Single water-column compartment including sedimentation/retention	Single water-column compartment	Surface water, deep water, erosion/transport sediments, accumulation sediments
Key driving variables	Areal phosphorus loading, loch depth, water loading rate, retention coefficient, river discharge	Phosphorus loading, residence time, river discharge	Phosphorus loading, hydrology, sediment processes, mixing, burial, diffusion
Sediment processes	Represented by retention coefficient	Embedded in coefficients	Explicit processes (sedimentation, resuspension, burial, diffusion)
Spatial resolution	Loch average	Loch average	Separates water column and sediment zones
Data requirements	Low	Low	High
Strengths	Simple, easy to apply, minimal data	Based on large dataset, widely validated	Can simulate responses to management or loading changes
Limitations	Assumes steady state, limited internal process representation	Assumes steady state, empirical relationships may not fit all loch types	Data intensive, more complex to implement

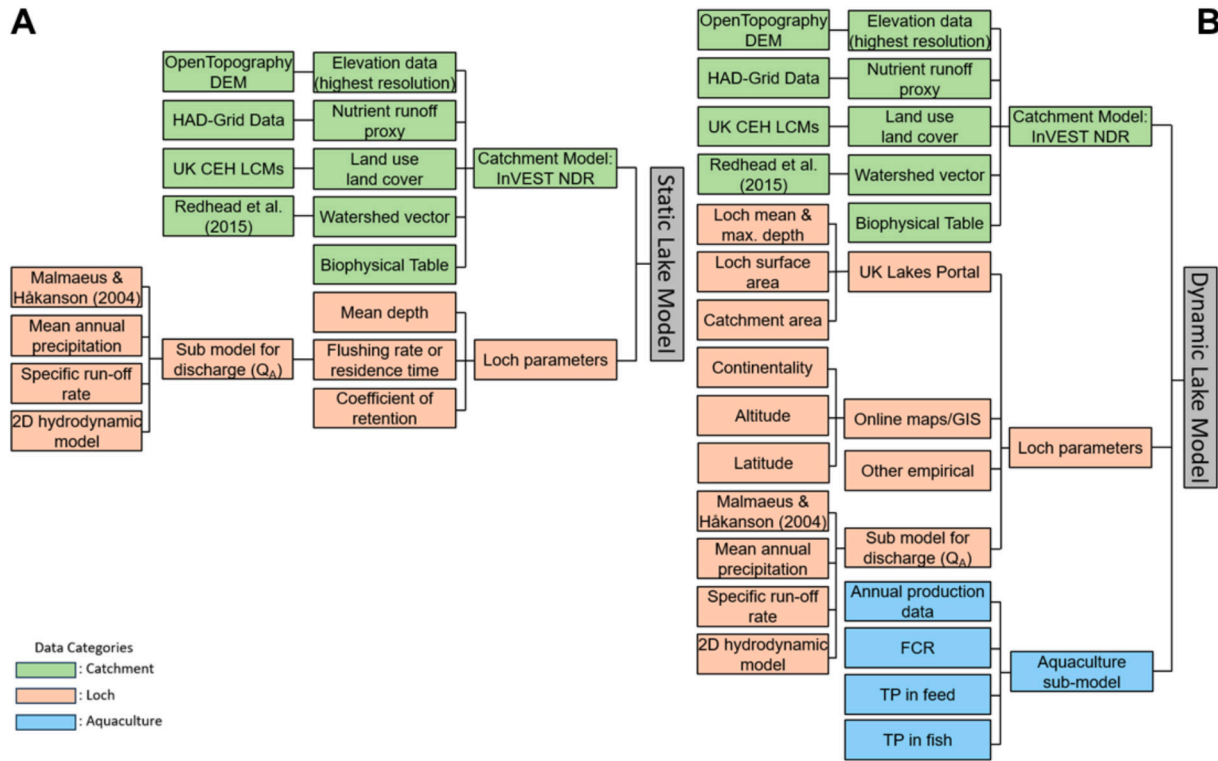


Fig. 2. Conceptual models for using A) InVEST NDR with a static model e.g. Dillon & Rigler and OECD, and B) InVEST NDR with the dynamic LakeMab model. Colours indicate the input data categories for each model type.

$\text{km}^{-2} \text{s}^{-1}$ for specific run-off rate is used (Malmaeus and Håkanson, 2004). The PREC ratio relates to a regression between catchment area of 95 boreal lakes with a mean annual precipitation of c. 650 mm yr^{-1} (Håkanson and Bryhn, 2008). The results were tested against the Shielfoot gauge measurements for outflow data from Loch Shiel. This was the only catchment studied which had a suitably located flow gauge (i.e. downstream of the loch but not after any major river confluences) at Shielfoot Station (ID: 37502) (SEPA, 2022a). Preliminary comparisons showed the basic equation under predicted Q_A for Loch Shiel by c. 50% (Fig. 3). Therefore, to improve the accuracy both the PREC ratio and the run-off rate were modified to better represent Scottish Highland catchments' rainfall, slopes and soil characteristics. The Highlands are dominated by peaty soils (peat, peaty gleys and peaty podzols), which are characterised by lateral flow paths (Soulsby et al., 1998), often existing in thin layers over rock than many areas of Europe, leading to a higher specific run-off rate. Using the annual rainfall (PREC) for Loch

Shiel each year between 2012 and 2021 and the average regional precipitation of 2365 mm yr^{-1} (SEPA, 2022b), a run-off rate of $0.08 \text{ m}^3 \text{ km}^{-2} \text{ s}^{-1}$ was shown to have the best fit to Shielfoot flow data (Fig. 3), giving a more appropriate equation for Q_A for both the static and dynamic models of:

$$Q_A = ADA \left(\frac{PREC}{2365} \right) \times 0.08 \times 60 \times 60 \times 24 \times 365 \times 10^{-6} \quad (2)$$

Although the corrected Malmaeus and Håkanson (2004) formula provides an improved estimate of fluvial discharge under natural hydrological conditions, many lochs are regulated by dams, hydro-electric operations, or other flood-control measures. These interventions can alter the timing and magnitude of outflows relative to natural runoff patterns. As a result, the discharge estimates derived from Eq. (2) should be interpreted as approximations in the absence of direct outflow measurements.

2.2.4. Static model: Dillon & Rigler

A static mass balance model was used by Dillon and Rigler (1975) for predicting the capacity of lakes for caged salmonid culture based on their trophic status by predicting the total P lake concentration. The model was modified from Vollenweider's model (Vollenweider, 1975) to use a coefficient of retention, which is the fraction of phosphorus retained in the lake sediment, rather than the harder to measure sedimentation rate (Beveridge, 2004). Total phosphorus in the lake ($[P]$ in mg m^{-3} or μL^{-1}) is calculated in Eq. (3) by:

$$[P] = \frac{L_{\text{total}}(1 - R)}{q_s} \quad (3)$$

where L_{total} is the annual P loading per loch surface area ($\text{mg m}^{-2} \text{ y}^{-1}$), corresponding to the sum of the P from aquaculture (L_{fish}) and catchment ($L_{\text{catchment}}$), calculated using Eqs. (4) to (7) as follows:

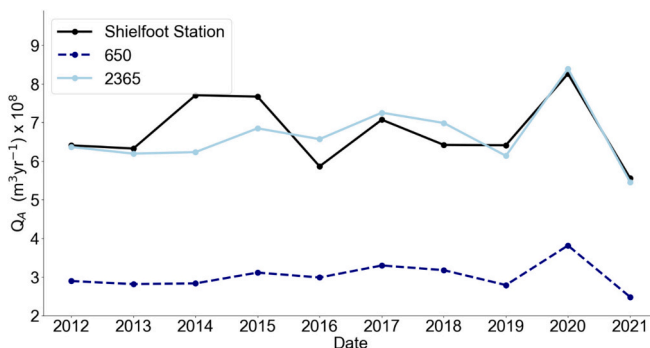


Fig. 3. Q_A calculated using the original precipitation ratio of PREC/650 and the new precipitation ratio of PREC/2365 and run-off of 0.08 using the Malmaeus & Håkanson (2004) equation in comparison to gauged flow data from Shielfoot Station.

$$L_{fish} = \frac{(P_{feed} - P_{harvested})}{Loch\ surface\ area} \quad (4)$$

where

$$P_{harvested} = Annual\ Production * \left(0.48/100\right) \quad (5)$$

and 0.48% is the typical P content found in Atlantic salmon flesh (Gende et al., 2004). P_{feed} is the amount of P (mg) within the food pellets over a year, which can vary between manufacturers, to ultimately determine the P released to the environment. $L_{catchment}$ is calculated by

$$L_{catchment} = \frac{InVEST\ P}{Loch\ surface\ area} \quad (6)$$

where InVEST is the annual P loading from the catchment ($mg\ y^{-1}$), and

$$L_{total} = L_{fish} + L_{catchment} \quad (7)$$

The retention coefficient described by Canfield Jr and Bachmann (1981) can be obtained by

$$R = \frac{v}{(v + q_s)} \quad (8)$$

where

$$q_s = z/\rho \quad (9)$$

and v is settling rate ($m\ y^{-1}$), a constant set to $2.5\ m\ y^{-1}$ from Ulén (2004), z is mean depth of the loch (m), and ρ is the residence time (y) calculated from loch area, A (m^2), mean depth, z (m), and loch outflow, Q_A ($m^3\ y^{-1}$). It is given by

$$\rho = \frac{A * z}{Q_A} \quad (10)$$

2.2.5. Static model: OECD

The OECD model (OECD, 1982) was originally developed from a large database of empirical data of temperate freshwater bodies and is used by the Scottish Environment Protection Agency (SEPA) in freshwater loch aquaculture regulation to ensure the maintenance of trophic status of a loch under the Water Framework Directive (Water Environment and Water Services (Scotland) Act 2003).

The OECD model explains loch TP, [P] ($mg\ m^{-3}$ or $\mu\ L^{-1}$), as a function of the water residence time, ρ (y), in the loch and the annual loading of P from all inflows derived from the InVEST NDR model (L_c , $mg\ y^{-1}$), annual outflow from the system (Q_A , $m^3\ y^{-1}$), and empirically derived constants which vary according to geographic location and depth (Eq. 11). The constants from the combined dataset (OECD, 1982) were used where $a = 1.55$ and $b = 0.82$.

$$[P]_{catchment} = a \left[\frac{L_c/Q_A}{1 + \sqrt{\rho}} \right]^b \quad (11)$$

In terms more suited to aquaculture, to predict change to loch TP from caged farm emissions, the OECD model can be defined as (Johansson and Nordvarg, 2002) in Eqs. (12) to (13):

$$[P]_{farm} = a \left[\frac{L_f/Q_A}{1 + \sqrt{\rho}} \right]^b \quad (12)$$

where L_f is the loading from aquaculture farm emissions as a function of the P discharged to the environment ($mg\ m^{-3}$), the loch volume (V , m^3) and the residence time (ρ , y) as:

$$L_f = \frac{(P_{feed} - P_{harvested})}{V/\rho} \quad (13)$$

The total predicted [P] within the loch combining catchment and farm inputs is given in Eq. (14):

$$[P] = [P]_{catchment} + [P]_{farm} \quad (14)$$

2.2.6. Dynamic model: LakeMab

The dynamic mass-balance LakeMab model (Håkanson and Bryhn, 2008) was used to simulate P levels within the lochs at a resolution of 3 days. For each loch, the LakeMab model was run with measured data of loch area, catchment area, mean and maximum depth (UKCEH, 2023), latitude, altitude, continentality (measured on a map). Time-series variables were also implemented on an annual level for measured mean precipitation from the UK Meteorological Office (Met Office, 2022), catchment P export (from the InVEST NDR model), mean fluvial discharge (Q_A , separately calculated, see Section 2.2.3), measured farm production data, as well as on a monthly level for averaged temperature obtained by the HadUK-Grid dataset produced by the Met Office Hadley Centre between 1991 and 2022 (Hollis et al., 2019; Met Office, 2022).

2.2.7. Model comparisons

The Root Mean Squared Error (RMSE; Willmott et al., 1985) was used to assess the predictive power of each model (OECD, Dillon & Rigler, and LakeMab) compared to the measured TP concentration data for each loch (Bryhn and Håkanson, 2007). This method measures the average difference between values predicted by a model and the actual values, providing a single measure of predictive power. In general, the lower the RMSE the better fit the model is to empirical data. The RMSE is calculated for each model as in Eq. (15):

$$RMSE = \sqrt{\frac{\sum (y - \hat{y})^2}{n}} \quad (15)$$

where \hat{y} and y represent the predicted and observed values respectively, and n is the number of values. The measured TP loch data includes both catchment P loading as well as fish farm emissions. When interpreting comparisons between models, it is important to account for their differing temporal resolutions. While the LakeMab model operates at a finer scale with outputs every 3 days predicting seasonal values, the static models provide predictions on an annual basis. Additionally, due to limited sampling in 2020–2021, measured data for these years were interpolated using previous sampling points using data presented in Fig. S1. In addition to the RMSE, a normalised goodness-of-fit (NGOF) metric was used to examine the model performance in light of the differing temporal resolutions. This metric expresses the mean absolute error as a proportion of the mean observed value. For each variable, NGOF was calculated as:

$$NGOF = \frac{\frac{1}{n} \sum_{t=1}^n |\hat{y}_t - y_t|}{\bar{y}} \quad (16)$$

where \hat{y}_t and y_t are the modelled and observed values at time t , n is the number of paired observations, and \bar{y} is the mean of the observed values. Lower NGOF values indicate closer agreement between model output and measurements.

3. Results

3.1. Catchment model: InVEST nutrient delivery ratio (NDR)

Fig. 4 shows that Loch Garry and Shiel catchments had the largest amount of catchment P export (3675.6 ± 93.1 and $3067.3 \pm 69.4\ kg\ y^{-1}$, respectively) followed by the Arkaig catchment ($2301.3 \pm 75.6\ kg\ y^{-1}$). Loch Lochy had the smallest catchment P export ($1982.2 \pm 65.5\ kg\ y^{-1}$). There were no available land use records for 2016, resulting in the

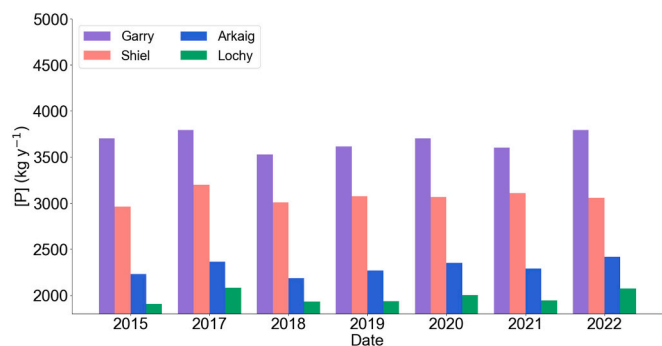


Fig. 4. Yearly time-series of total TP export from each catchment predicted by the InVEST NDR model. No data was available for 2016.

missing output for that year. The mean values for P export between 2015 and 2022 was used for each catchment to model TP inputs in 2016. A sensitivity analysis was carried out for the InVEST NDR model for each of the lake models and outlined in the Supplementary Information.

3.2. Static model: Dillon & Rigler

The results of the Dillon & Rigler model predictions of the P concentrations in the lochs, including catchment and farm emissions are presented in Fig. 5. The model's predictions of TP were generally higher than the measured data for all lochs, except Loch Garry. The average \pm std. predicted values between 2015 and 2022 were $6.1 \pm 1.1 \mu\text{g L}^{-1}$, $6.2 \pm 1.3 \mu\text{g L}^{-1}$, $7.0 \pm 1.3 \mu\text{g L}^{-1}$ for Lochs Arkaig, Lochy, and Shiel, respectively, and $4.8 \pm 1.1 \mu\text{g L}^{-1}$ for Garry. The average mean

measured data was $5.2 \pm 1.0 \mu\text{g L}^{-1}$, $5.7 \pm 0.8 \mu\text{g L}^{-1}$, $6.2 \pm 2.2 \mu\text{g L}^{-1}$ for Lochs Arkaig, Lochy, and Shiel, and $7.0 \pm 2.0 \mu\text{g L}^{-1}$ for Loch Garry.

3.3. Static model: OECD

Fig. 5 shows the OECD model predictions of loch TP, incorporating both catchment P loading and fish farm emissions, in comparison to measured data. Like the Dillon & Rigler model, the OECD model predictions were higher compared to the empirical data for all lochs except Loch Garry. Specifically, between 2015 and 2022, the average \pm std. predicted TP values for Lochs Arkaig, Lochy, and Shiel were $7.0 \pm 1.1 \mu\text{g L}^{-1}$ (measured: $5.2 \pm 1.0 \mu\text{g L}^{-1}$), $7.8 \pm 1.3 \mu\text{g L}^{-1}$ (measured: $5.7 \pm 0.8 \mu\text{g L}^{-1}$), and $7.8 \pm 1.2 \mu\text{g L}^{-1}$ (measured: $6.2 \pm 2.2 \mu\text{g L}^{-1}$), respectively, and $5.5 \pm 1.1 \mu\text{g L}^{-1}$ (measured: $7.0 \pm 2.0 \mu\text{g L}^{-1}$) for Loch Garry.

3.4. Dynamic model: LakeMab

Fig. 6 shows the LakeMab predicted loch TP in the shallow water component, in comparison to measured loch TP data, between 2015 and 2022. The LakeMab model predictions are of high temporal resolution (~ 3 days) showing the effects of modelled seasonality and fluxes on TP in each loch. The predictions were largely similar to the measured data for Lochs Arkaig and Shiel. There was a slight overprediction of levels for Loch Lochy and a considerable underprediction for Loch Garry. The average \pm std. predicted TP values, compared to measured values are: $5.0 \pm 1.1 \mu\text{g L}^{-1}$ (measured: $5.2 \pm 1.0 \mu\text{g L}^{-1}$), $3.3 \pm 0.8 \mu\text{g L}^{-1}$ (measured: $7.0 \pm 2.0 \mu\text{g L}^{-1}$), $5.3 \pm 1.0 \mu\text{g L}^{-1}$ (measured: $6.2 \pm 2.2 \mu\text{g L}^{-1}$) for Lochs Arkaig Garry and Shiel, while $6.7 \pm 1.9 \mu\text{g L}^{-1}$ (measured: $5.7 \pm 0.8 \mu\text{g L}^{-1}$) for Loch Lochy.

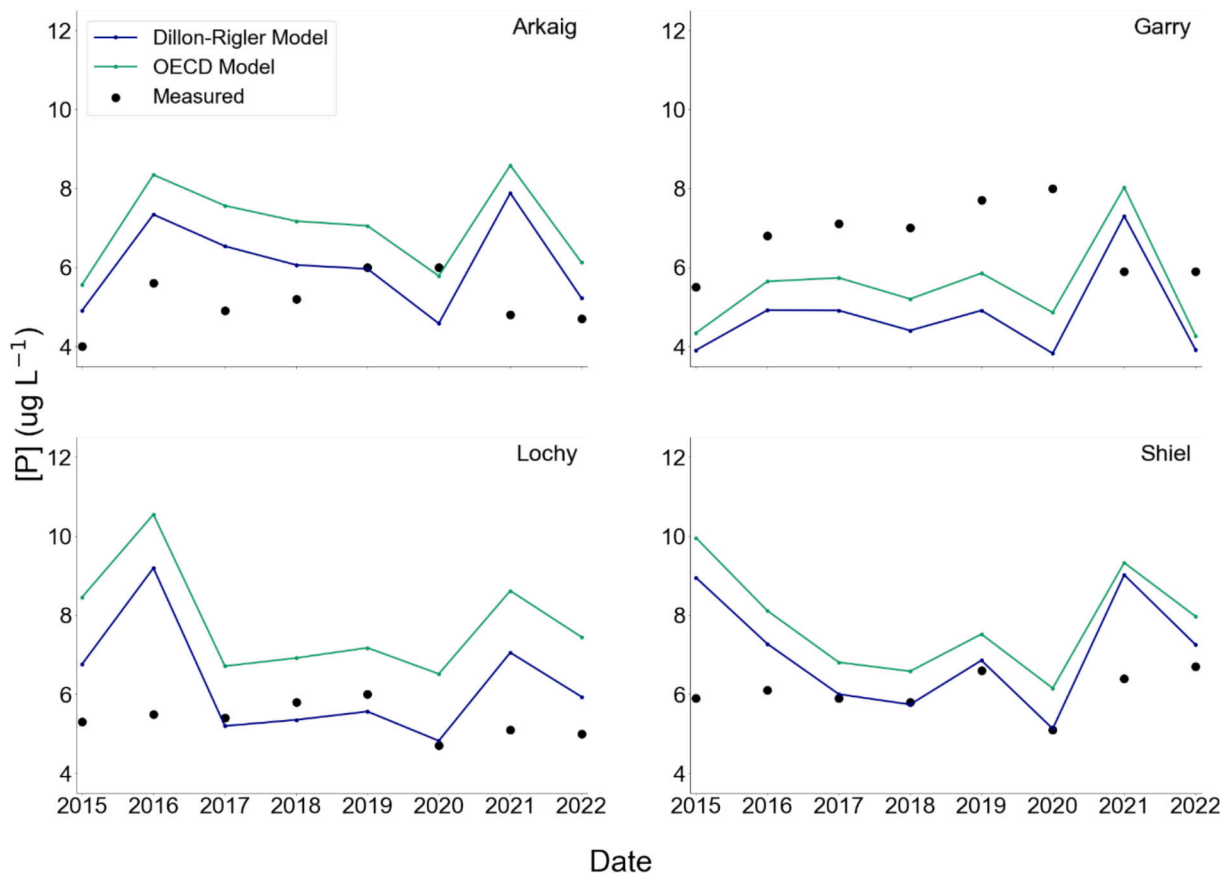


Fig. 5. Loch annual TP predicted by the Dillon and Rigler (1975) model (blue line) and the OECD (1982) model (green line) with input from aquaculture and catchment (InVEST), compared to the mean annual measured observations (black points) for Lochs Arkaig, Garry, Lochy, and Shiel. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

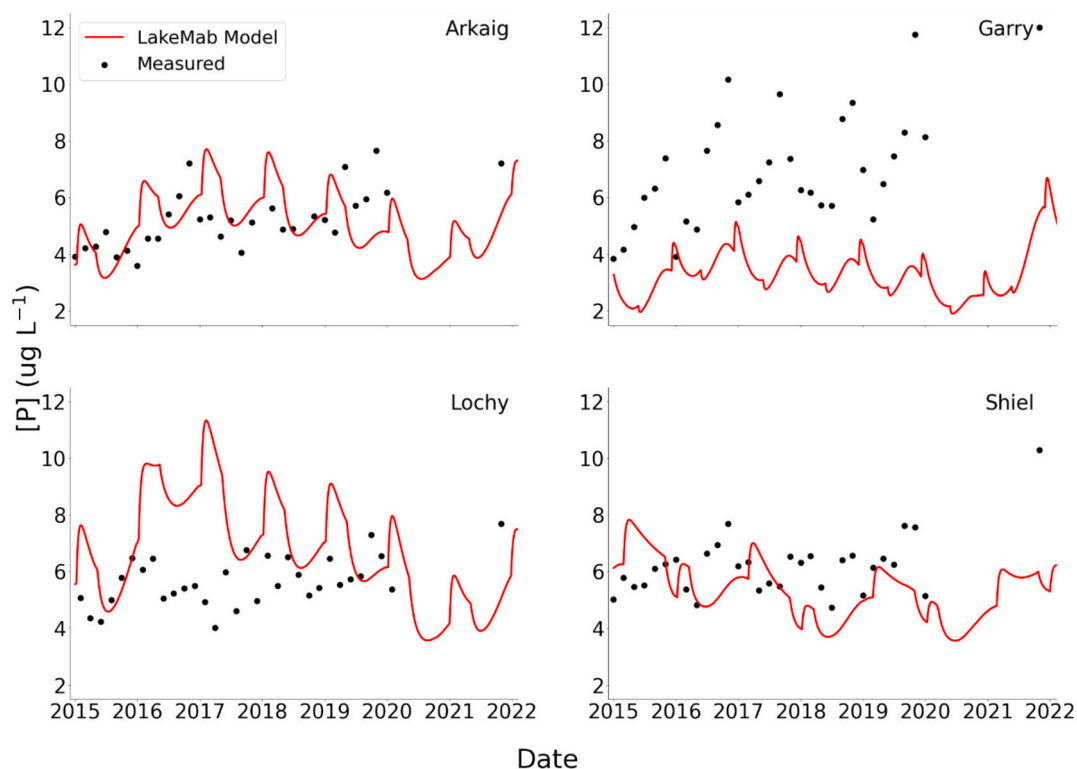


Fig. 6. Loch annual TP predicted by the LakeMab (2008) model with input from fish farm and catchment (InVEST) in comparison to measured data (black points) for Lochs Arkaig, Garry, Lochy, and Shiel.

3.5. Model comparisons

The mean TP loch predictions (Table 2) and relative errors for each model illustrate the differences in predictive performance among the three models. While all 3 performed well, with root mean square (RMSEs) around $2 \mu\text{g L}^{-1}$, there were slight deviations in error rates. Among the models, Dillon & Rigler had the lowest RMSEs (on average an error rate of $1.81 \mu\text{g L}^{-1}$), with comparatively low error rates for Lochy and Shiel ($1.69 \mu\text{g L}^{-1}$ and $1.55 \mu\text{g L}^{-1}$, respectively). OECD had error rates that were slightly higher at an average of $2.22 \mu\text{g L}^{-1}$ and best predicted the measurements for Loch Garry ($1.86 \mu\text{g L}^{-1}$ compared to $2.46 \mu\text{g L}^{-1}$ and $3.91 \mu\text{g L}^{-1}$ for Dillon & Rigler and LakeMab, respectively). LakeMab had the highest error rates at an average of $2.50 \mu\text{g L}^{-1}$, but best predicted Loch Arkaig ($1.45 \mu\text{g L}^{-1}$) compared to Dillon and Rigler ($1.54 \mu\text{g L}^{-1}$) and OECD ($2.22 \mu\text{g L}^{-1}$). All models performed the best for Loch Shiel with errors of $1.55 \mu\text{g L}^{-1}$, $2.05 \mu\text{g L}^{-1}$, and $2.19 \mu\text{g L}^{-1}$ for Dillon & Rigler, OECD, and LakeMab, respectively. When

Table 2

Mean loch TP predictions (standard deviation) and Root Mean Square Error (RMSE) for modelled data using Dillon and Rigler (1975) and OECD (1982), and LakeMab model Håkanson and Bryhn (2008) compared to measured TP concentrations between 2015 and 2022.

Loch	Dillon-Rigler		OECD		LakeMab		Measured ($\mu\text{g L}^{-1}$)
	Mean ($\mu\text{g L}^{-1}$)	RMSE	Mean ($\mu\text{g L}^{-1}$)	RMSE	Mean ($\mu\text{g L}^{-1}$)	RMSE	
Arkaig	6.1 (1.1)	1.54	7.0 (1.1)	2.22	5.0 (1.1)	1.45	5.2 (1.0)
Garry	4.8 (1.1)	2.46	5.5 (1.1)	1.86	3.3 (0.8)	3.91	7.0 (2.0)
Lochy	6.2 (1.3)	1.69	7.8 (1.3)	2.74	6.7 (1.9)	2.45	5.7 (0.8)
Shiel	7.0 (1.3)	1.55	7.8 (1.2)	2.05	5.3 (1.0)	2.19	6.2 (2.2)

normalised to take the relative amounts of data into account (annual vs seasonal), it was shown that overall the LakeMab model gave a better goodness of fit, with values of 0.14, 0.15 and 0.08 for Dillon & Rigler, OECD, and LakeMab, respectively.

4. Discussion

Freshwater lakes and reservoirs are complicated and dynamic ecosystems, and decision support tools can ensure they are used and managed responsibly. This study evaluated a novel combined catchment/lake modelling approach for use in environmental management of freshwater cage aquaculture. The findings suggest that integrating catchment and lake models give good estimates of TP loading, providing valuable insights for future planning, environmental regulation, and resource management.

4.1. Phosphorus monitoring in lochs and aquaculture sites

Long-term monitoring of the lochs over several decades shows some seasonal and annual variation in plotted sampling means and annual geometric means for TP, Fig. S1. The variation in results is due to several factors within loch and associated catchment including changes to land-use over time, short- and long-term precipitation trends, primary productivity within the loch, water exchange, and the level of aquaculture. Though mean annual levels of TP within the loch appear consistent, there are often large differences throughout the year, with ranges varying between lowest at Lochs Lochy and Arkaig (3 to $9 \mu\text{g L}^{-1}$ TP) to highest at Lochy Garry (2 to $12 \mu\text{g L}^{-1}$ TP). The overall trends within the lochs though show a consistent annual mean of TP within Lochs Arkaig, Lochy and Garry, with an increase between 1987 and 2022 at Loch Shiel. All lochs are characterised as oligotrophic; $<10 \mu\text{g L}^{-1}$ TP (OECD, 1982) or $<12 \mu\text{g L}^{-1}$ TP (Carlson, 1977), meaning over time the waterbody has not changed its trophic state, often seen as a threshold of carrying capacity (OECD, 1982; CCME, 2004).

4.2. Catchment modelling

The catchment model used in this study was the InVEST NDR model (Sharp et al., 2020). Other models can simulate P loading from the catchment (Robson, 2014), but the InVEST NDR model was selected as the data requirements were more accessible than other models, it was relatively straightforward to use, and other studies have shown its effectiveness for estimating nutrient loading from catchments, including elsewhere in the United Kingdom (Redhead et al., 2018). However, the InVEST NDR model only considers non-point sources (Sharp et al., 2015), relying primarily on land-use data, which could be a limitation in some areas.

The P export values for different land-uses employed in this study were obtained from Redhead et al. (2018), who undertook an evaluation of the InVEST NDR model, testing against observed values of P and Nitrogen in England and Wales, where it was considered to perform well. Scottish catchments differ in soil type, mineralogy, and precipitation rates, all of which influence phosphorus retention and delivery to the lochs. Because region-specific export coefficients for Scotland are not currently available, the closest published values were used, but more specific Scottish data would refine these assumptions and reduce the associated uncertainty. In addition, continuous data are required in the future to be able to account for the impact of extreme events due to climate driven extreme events (e.g. increased droughts and storminess) on P export from catchments (Whitehead et al., 2009; Forber et al., 2018).

4.3. Fluvial discharge

A major challenge in this study was estimating fluvial discharge (Q_A) for each loch, as there are few flow gauges at suitable locations i.e. at the outflow of lochs prior to any confluences. More accurate and representative models for TP loading in lochs would benefit from better outflow data, particularly lochs that contain aquaculture and activities that require regulatory compliance. This is a common issue (Ruhi et al., 2018) with flow and gauge placement bias leading to data gaps (Krabbenhoft et al., 2022).

In the absence of measurements from flow gauges for three of the lochs, this study used the predicted Q_A as a proxy (Malmaeus and Håkanson, 2004). It was necessary to calibrate this equation for Scotland using a PREC ratio based on regional rainfall and a higher run-off rate ($0.08 \text{ m}^3 \text{ km}^{-2} \text{ s}^{-1}$), than that used in the original formulation, which was developed for European lakes. The calibration was then validated against measurements from a flow gauge located at Shielfoot station on Loch Shiel. This conforms closely to a study by Zhang et al. (2012), who used data from 161 headwater lakes for model calibration and 28 headwater lakes for model validation to show that prediction of TP concentrations was highly sensitive to water flow and upstream catchment features. However, there are limitations to using Q_A for the lochs examined in this study as they are regulated by dams and flood-control structures. Thus, deviations from natural hydrological behaviour may introduce uncertainty into the discharge estimates. Therefore, the discharge estimates derived from the empirical formula should be interpreted as approximations rather than exact representations of regulated flow regimes. Nevertheless, direct measurements of outflow are often unavailable for these systems, meaning that an empirically based approximation provides a practical and necessary alternative. In this context, the corrected formula offers a useful first-order estimate of discharge in situations where no measured data exist.

4.4. Lake modelling: static vs dynamic

The Dillon & Rigler model resulted in more accurate predictions of baseline lake TP overall compared to the other static OECD model, with RMSE values lower for Lochs Arkaig, Lochy and Shiel. The Dillon & Rigler model accounts for TP retention in sediments, whereas the OECD

model relies on a simple water exchange approach, which likely explains the observed differences in goodness of fit to the measured data.

The LakeMab model incorporates a time-series component, allowing for seasonal predictions of TP which is more ecologically relevant. This makes it more representative of annual variations, but more susceptible than the static models to seasonal change. For example, Spears et al., 2012 concluded that internal P loading is likely governed by winds and turbidity particularly in the spring, so including a weather component may increase the seasonal sensitivity of a model. In addition, temperature can have a variety of effects on phosphorus, where warmer temperatures in the summer can increase diffusion rates in both shallow and deep-water sediments giving rise to anoxia driven release of redox-sensitive P complexes in surface sediments (Boström et al., 1988; Spears et al., 2012). It is likely that this led to a poorer model fit to the static models using the RMSE, but better overall fit taking the large seasonal data into account when normalised (Willmott et al., 1985).

All three lake models used in combination with the catchment model had challenges with predicting TP within Loch Garry, underpredicting in each case. This is most likely due to the heavy anthropogenic modifications within both loch and catchment compared to the other lochs making it more challenging to model. Hydrology in Loch Garry is significantly influenced by large scale storage hydro-electric generation operations through the Invergarry power station, with a managed water volume draw down of up to 3.5 m depth (SEPA, 2024). This is significantly more modification than the other lochs modelled during this study. In addition, Loch Garry also has flood control measures, with the release of water during storm events. These factors could explain or contribute to the consistent underprediction of TP within this loch, therefore it is important to consider such modifications when providing recommendations regarding management of Scottish lochs when using predictive environmental models.

4.5. Implications for environmental management

The results from this study suggest that this combined approach that integrates a catchment model with lake models is a useful tool for environmental management of freshwater cage aquaculture. Model testing is an essential step for any modelling approach used in environmental management, but the practical use of the modelling approach by the end-users is also critical, consequently, models and tools are only useful if they can be used for the purpose intended (Hamilton et al., 2019). In the case of aquaculture, multiple lochs or lakes may be under investigation, as in the study here, so approaches must be consistent and have the ability to be set up for new locations. Variations in catchment type and lake conditions may pose a challenge for decision-makers regarding external emissions and limits for new sources, and as shown in this study, have consequences for the models used and predictions made.

For the models used in this study, the static lake models when combined with a catchment model gave a good prediction of annual mean levels of TP. While dynamic models, such as LakeMab, gave better levels of prediction when taking into account seasonal changes and variability. Its higher temporal resolution also suggests that its performance could improve further with the inclusion of more seasonal data, especially relevant in the context of climate change where winters are projected to become warmer and wetter while summers become hotter and drier (Roth et al., 2021). While the annual averages predicted by static models may remain relatively stable, the finer-scale seasonal fluctuations, critical for biological processes, are likely to shift more significantly.

Use of the models and in-situ data allows aquaculture producers and environmental authorities or regulators to assess the cage aquaculture carrying capacity (maximum production capacity while maintaining sufficient ecological integrity) for lake systems and make evidence-based decisions for aquaculture planning and management. Furthermore, the combination of catchment and lake model, as shown here, is a

step towards more integrated catchment management, and a more holistic overview of all P contributions to a freshwater system rather than focusing on individual sources. Accordingly, this modelling approach can be used to simulate ‘what-if’ scenarios such as variations in the amount of fish production, or changes in land use within the catchment. Moreover, the seasonal predictions using the LakeMab model provide useful context for understanding when the system is most sensitive to nutrient loading and for interpreting its assimilative capacity. Monitoring these periods of heightened vulnerability supports longer-term planning, risk assessment, and decision-making, particularly when considering feed formulations with differing phosphorus content. For longer term planning, it would be possible to simulate potential effects of climate change that could influence P loading, for example changes in rainfall and runoff within the catchment.

This study focused on salmon production in freshwater loch systems in Scotland, but the approach could be adapted and tested in other areas where cages are used for freshwater fish production, such as rainbow trout (*Oncorhynchus mykiss*) and tilapia (*Oreochromis* sp.).

5. Conclusions

This study has demonstrated that predicted TP loading calculated with a new approach that combined a catchment model (InVEST NDR) with dynamic and static lake models, is an effective method for predicting long- and short-term phosphorus loading for aquaculture management purposes. Each of the models performed satisfactorily within the limits of their data requirements. While the Dillon & Rigler model provided the most accurate results when fitted to annual data, the dynamic LakeMab model has a higher temporal resolution and can capture seasonality better with a good model fit between predicted and observed data for most of the lochs studied. The integrated modelling framework was demonstrated using Scottish freshwater lochs used for salmon aquaculture but could also be relevant for other locations and cultured species. However, there were still challenges in obtaining sufficient data to model the catchments and lakes at higher temporal resolutions. The study has provided evidence of the effectiveness of combining a catchment and dynamic lake model, and offers a holistic and realistic approach for freshwater management in lakes. Although uncertainties remain, the methods introduced in this study represent a promising framework that can be further refined through expanded data collection and continued validation.

CRedit authorship contribution statement

Meredith Burke: Writing – original draft, Visualization, Investigation, Formal analysis, Data curation. **Lisa Harrison:** Writing – original draft, Methodology, Formal analysis, Data curation. **Lynne Falconer:** Writing – original draft, Supervision, Resources, Funding acquisition, Data curation, Conceptualization. **William Struthers:** Methodology, Investigation, Data curation. **Suleiman O. Yakubu:** Investigation, Formal analysis, Data curation. **Andreas C. Bryhn:** Software, Methodology. **Trevor C. Telfer:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Funding acquisition, Conceptualization.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.aquaculture.2026.744016>.

Data availability

The data that has been used is confidential.

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