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Assessing seasonal nitrogen export to large tropical lakes

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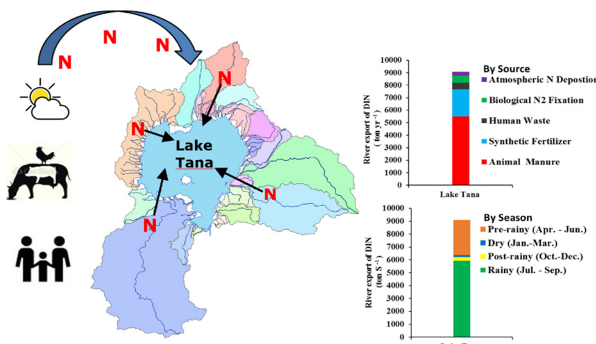
HIGHLIGHTS

- We integrated existing models to capture seasonality in river export of nitrogen to tropical lakes.
- The model was applied to a representative tropical lake: Lake Tana.
- We modelled nutrient exports to Lake Tana, showing good agreement with measured loads.
- We found that river export of nitrogen to Lake Tana is highest in rainy and lowest in dry seasons.
- We found that animal manure is the dominant source of nitrogen in rivers in all seasons.

GRAPHICAL ABSTRACT



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ABSTRACT

Rivers are exporting increasing amounts of nitrogen (N) to lakes, which is leading to eutrophication. However, the seasonality apparent in nutrient loading, especially in tropical areas, is thus far only partially understood. This study aims to better understand the seasonality and the sources of dissolved inorganic nitrogen (DIN) inputs from sub-basins to tropical lakes. We integrated existing approaches into a seasonal model that accounts for seasonality in human activities, meteorology and hydrology, and we applied the model to the sub-basins of a representative tropical lake: Lake Tana, Ethiopia. The model quantifies the river export of DIN by season, source and sub-basin and also accounts for open defecation to land as a diffuse source of N in rivers. Seasonality parameters were calibrated, and model outputs were validated against measured nitrogen loads in the main river outlets. The calibrated model showed good agreement with the measured nitrogen loads at the outflow of the main rivers. The model distinguishes four seasons: rainy (July–September), post-rainy (October–December), dry (January–March) and pre-rainy (April–June). The river export of DIN to Lake Tana was about 9 kton in 2017 and showed spatial and temporal variability: It was highest in the rainy and lowest in the dry seasons. Diffuse sources from agriculture were important contributors of DIN to rivers in 2017, and animal manure was the dominant source in all seasons. Our seasonal sub-basins and rivers model provides opportunities to identify the main nutrient sources to the lake and to formulate effective water quality management options. An example is nutrient application level that correspond to the crop needs in the sub-basins. Furthermore, our model can be used to analyse future trends and serves as an example for other large tropical lakes experiencing eutrophication.

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1. Introduction

Eutrophication occurs in many aquatic systems worldwide, and the problems associated with it such as blooms of harmful algae often have negative consequences for the health of humans and ecosystems alike. Eutrophication in lakes is caused by excessive loads of nutrients delivered by rivers (Hecky, 1993; Lürling and van Oosterhout, 2013). Nitrogen (N) is one of the nutrients driving eutrophication. Nitrogen in rivers can result from diffuse and point sources. Diffuse sources include the use of animal manure, human waste (numerous locations of open defecation in the study basin) and synthetic fertilisers on land; biological N_2 fixation; atmospheric N deposition and erosion of organic N in the top soil. Point sources of N in rivers often include effluents from sewage systems via pipes. In some regions in the world, direct discharges of animal manure to rivers can also be a point source of water pollution (Strokal et al., 2016).

In tropical lakes, N is often the limiting element, thereby governing primary production of phytoplankton (Conley et al., 2009; Jeppesen et al., 2005; Lewis Jr, 1996; Wondie et al., 2007). This is also the case for Lake Tana as the measured ratio DIN:DIP is around eight in most cases. Therefore, we can conclude it is N-limited (Ptacnik et al., 2010). Lake Tana is a representative example of a eutrophicated lake, located in the tropical environment in Ethiopia. Lake Tana is part of the Blue Nile basin and is an important source of water for human activities. Agriculture has been developing rapidly over recent years in Ethiopia and makes a major contribution to the local economy. Socioeconomic development has stimulated agriculture in the Lake Tana basin, which has thus been identified as a major economic corridor by the Ethiopian government (Stave et al., 2017). This growth of agriculture has sparked the release of nutrients to surface and ground waters, leading to severe water pollution (Goshu and Aynalem, 2017; Goshu et al., 2010; Selassie, 2017). Low sanitation conditions, high population pressure and degradation of land in the Lake Tana basin (Goshu and Aynalem, 2017; Yitaferu, 2007) further jeopardise surface water quality in the Lake Tana basin.

Nutrient loading of rivers and lakes is a seasonal event specifically in countries with a highly variable precipitation. Resulting eutrophication effects importantly depend on seasonal cycles of N. Thus, a better quantification of the seasonality in N export to the lake is essential to understand and manage the timing and impact of eutrophication. Another important aspect is the seasonality of human activities (e.g., crop planting periods) and climate (e.g., temperature and hydrology) that influence N export to the lake. Furthermore, for modelling shifts in lake ecosystems, a seasonal N loading has added value compared to an average annual N loading, as it better reflects the seasonality in the effects and the feed-backs (Janssen et al., 2019).

However, the seasonal river export of N in tropical lakes, such as Lake Tana, is still not well understood. This holds especially for the seasonal river export of N by source taking into account spatial variability (e.g., sub-basins). This hampers the formulation of effective management options (de Klein and Koelmans, 2011). Control and early warning systems related to eutrophication need source-, sub-basin– and season-specific data on N loads from sub-basins to rivers and lakes. Such information (monitoring data on N loads) is limited for large tropical lakes such as Lake Tana, especially for ungauged sub-basins. Some studies observed concentrations of N in rivers draining into Lake Tana (Goshu et al., 2017; Wondie et al., 2007), but they focused on a few rivers only and did not provide a systematic overview of N loadings into the lake. They did not address the sources of N in the lake by season. Therefore, the seasonality of eutrophication in the Lake Tana basin remains unknown.

There is a need for modelling tools to quantify the seasonal river export of N to lakes taking into account the seasonality in human activities on the land, climate, hydrology and their spatial variability. Moreover, the models should be able to attribute the sources of N on the scale of sub-basins. Such modelling tools hardly exist for drainage areas of lakes. Different models exist and have been applied to different basins in the world to quantify river export of nutrients (Douglas-Mankin et al., 2010; Schwarz et al., 2006; Mayorga et al., 2010). However, those models are often coarse for lakes and most of them are annual. Others are more detailed, however require a lot of input data implying that they cannot be used in data-poor regions. There are two exceptions. First, a sub-basin model has recently been developed (Strokal et al., 2016) and successfully applied to a few lakes in China (Yang et al., 2019; Li et al., 2019; Wang et al., 2019). This MARINA model (Model to Assess River Inputs of Nutrients to lAkes) considers the spatial variability in human activities and hydrology (sub-basins) for river export of nutrients to lakes. However, this model is annual and does not consider the seasonality. Second, a seasonal modelling approach exists for global rivers: Global NEWS-DIN (Nutrient Export from WaterSheds, McCrackin et al., 2014). This modelling approach is for large basins, however, without considering the spatial variability among basins.

The aim of this study is to assess the seasonality and sources of dissolved inorganic N (DIN) from sub-basins to tropical lakes using Lake Tana as a case study. We focus on the river export of DIN in a spatially explicit manner, by merging the sub-basin scale approach of Strokal et al. (2016) with the seasonal approach of McCrackin et al. (2014). This results in a seasonal model for sub-basins and rivers discharging to tropical lakes such as lake Tana. We implement the seasonal model to examine N exports in Lake Tana sub-basins and we validate the results with measured data in the same area.

2. Methodology

2.1. Study area

The Tana basin has a total drainage area of 16,500 km^2 (Fig. 1). More than six medium- to large-sized tributary rivers and >40 ephemeral streams drain into Lake Tana. Among the rivers, the Gilgel Abay, Dirma, Gumara, Gelda, Rib and Megech rivers contribute >90% of the inflow to the lake (Sirak, 2008). Lake Tana is the source of the Blue Nile, which is the only surface outflow. Lake Tana is a shallow lake, with a maximum depth of 14 m and mean depth of 8 m. This tropical lake is non-stratifying with a mean elevation of 1800 m above sea level. The amount of rainfall is at its maximum during July and August, when it reaches 250–330 mm per month. Mean annual rainfall is nearly 1280 mm (Abebe and Minale, 2017). The rainy season (July–September) receives about two-thirds of the annual rainfall, while the dry season receives 2%; the pre-rainy season (April–June) receives 25% and the post-rainy season 8% of annual rainfall. The average seasonal air temperature reaches its maximum of 21.1 °C in the pre-rainy season and its minimum (18.4 °C) in the rainy season, and it shows a large diurnal but small seasonal change.

Lake Tana is the largest lake in Ethiopia, accounting for 50% of the fresh-water resources of the country (Vijverberg et al., 2009). It has a surface area of 3111 km^2, 28.4 km^3 in volume and a maximum length of 90 km and width of 65 km. There are four administrative zones and eight districts in the Lake Tana basin. Bahir Dar city is a state capital. The population of the basin was projected to be 4.5 million in 2015 (CSA, 2007), with a population density of 228 persons per km^2 in 2007 (Anteneh, 2017), and 70% of the basin is agricultural land (Abebe and Minale, 2017).

In this study, we distinguished 20 sub-basins draining into Lake Tana (Fig. 1).

2.2. Model description

2.2.1. General approach

We developed a seasonal sub-basins and rivers model, setup for the year 2017 by combining two existing modelling approaches with modifications for our study area. The focus of the approach is the sub-basins draining to a lake, without including the lake itself (Fig. 2). The two

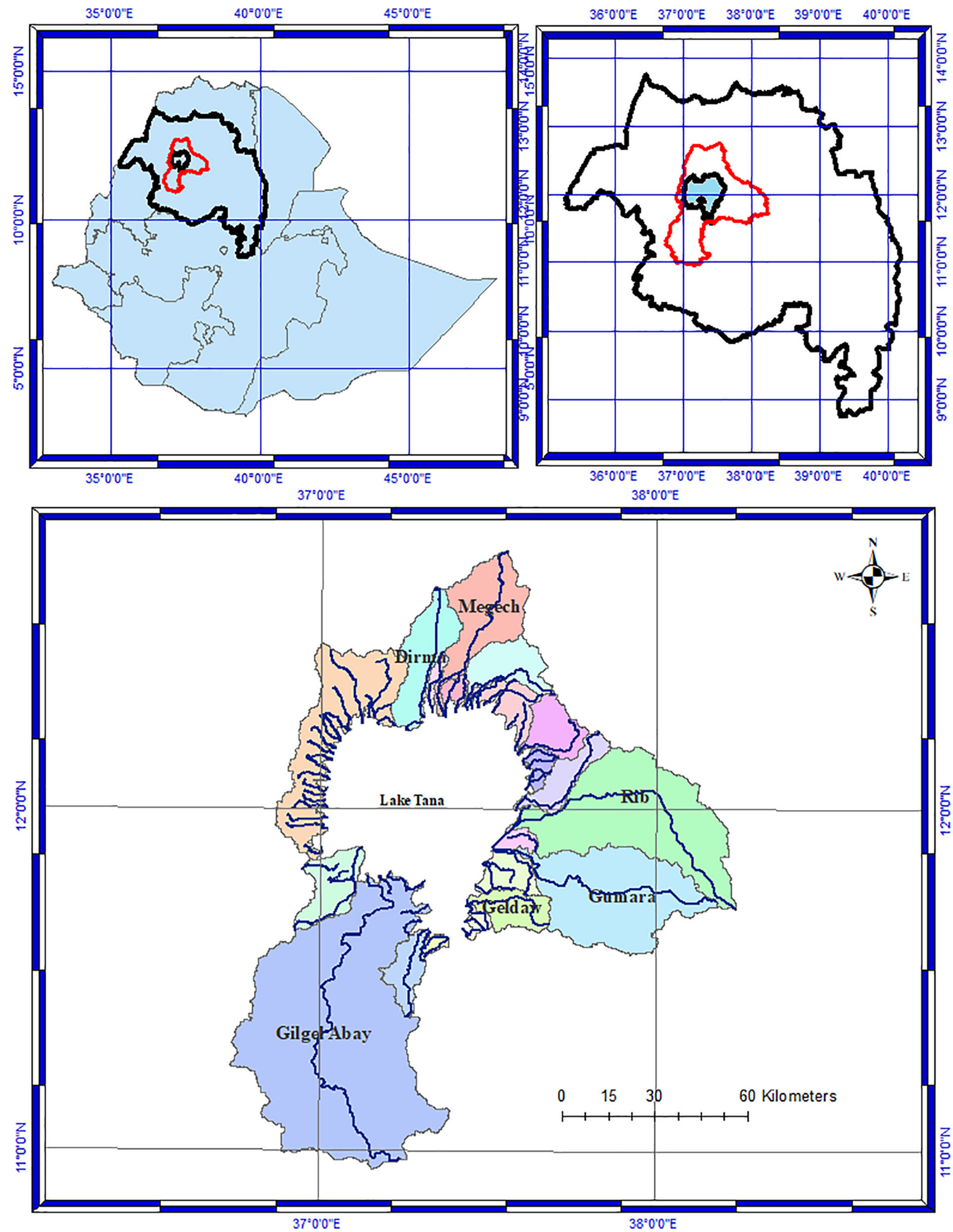

Fig. 1. Ethiopia and the Amhara region (upper left); the Amhara region, the Lake Tana basin and Lake Tana (upper right); the drainage area of the Lake Tana basin and the sub-basins draining into the lake (lower panel).

existing modelling approaches were the sub-basin scale modelling approach of the MARINA model (Strokal et al., 2016; Li et al., 2019; Yang et al., 2019; Wang et al., 2019) and the seasonal modelling approach of the NEWS-DIN(S) model (McCrackin et al., 2014). The MARINA model operates at the sub-basin scale on an annual basis for rivers exporting to lakes, while the seasonal NEWS-DIN(S) model operates at the basin scale for large rivers in the world. These models take a mass-balance approach to quantify nutrient inputs from land to rivers. This includes nutrient inputs to agricultural land (e.g., animal manure, synthetic fertilisers, deposition, fixation) and export from land via crop harvesting and grazing. The net nutrient inputs in soils (inputs minus export) are corrected for nutrient retentions and losses in soils,

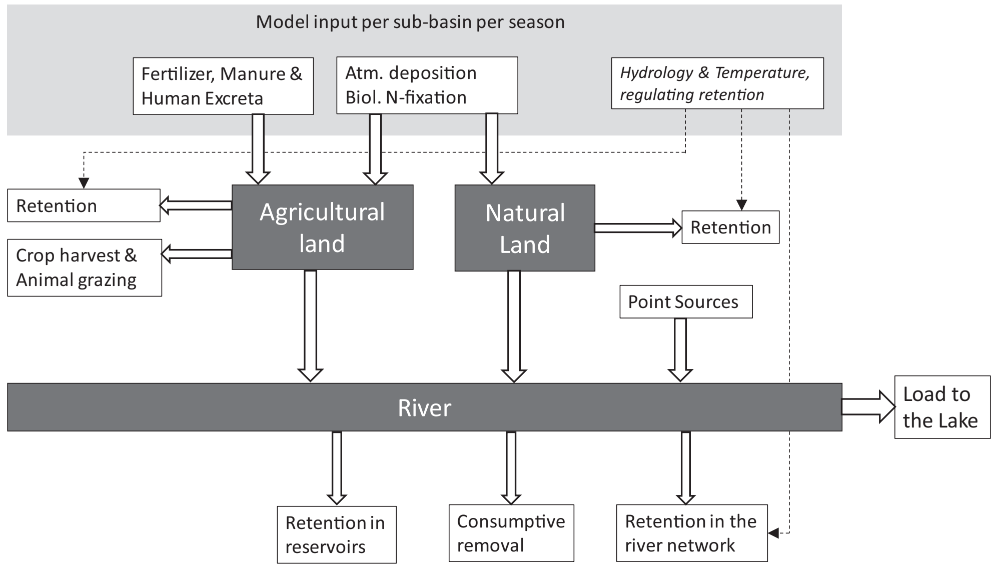

Fig. 2. Conceptual diagram of the seasonal version of the MARINA-model for river export of dissolved inorganic nitrogen from sub-basins discharging into large tropical lakes such as Lake Tana. The seasonal version of the MARINA-model quantifies the river export of dissolved inorganic nitrogen to Lake Tana by season, source and sub-basin for the year 2017. Details are presented in Section 2 and Appendix 3.

and the remainder enters rivers. Some nutrients enter rivers from sewage systems (e.g. from cities) and from natural areas. The human waste not collected in septic tanks and pit latrines but defecated to land was defined as open defecation and we categorized it as a diffuse source of nutrients. Human faeces and urine are defecated at many locations to the soil and eventually leaching N to surface waters in a diffuse way. Nutrients in rivers can be either lost or retained before reaching the river mouth. Retentions and losses of nutrients in rivers are estimated as functions of temperature, associated processes (e.g., denitrification), river damming and water consumption (Fig. 2).

In our study, we added seasonality into the sub-basin scale MARINA model based on the approach of McCrackin et al. (2014), resulting in a seasonal version of the MARINA model for tropical lakes such as Lake Tana. We made the following main modifications for our study area. First, we defined seasons according to the rainfall pattern (Table A.2.1), which differs from the approach of McCrackin et al. (2014) who based it on temperature. Second, we used mainly local sources of data for model inputs to represent the local situations of the Lake Tana basin. Third, we added open defecation as a new source of DIN pollution in rivers of Lake Tana. This is a diffuse source, because people defecate their waste on land and not directly into water. Finally, we recalibrated the model parameters influencing seasonality in the Lake Tana basin. Below, we define seasons (Section 2.2.2) and explain the seasonal model (Section 2.2.3 and A.3).

2.2.2. Definition of seasons

In our study, we defined four seasons in this climate region by rainfall rather than by temperature. Based on the rainfall pattern, our defined seasons were pre-rainy: April, May and June (AMJ), rainy: July, August and September (JAS), post-rainy: October, November and December (OND) and dry: January, February and March (JFM).

2.2.3. Modelling seasonal DIN export

Our seasonal model estimates river export of DIN by season from sub-basins in three steps. First, inputs of N from diffuse and point sources to land and rivers were estimated. Second, the river export of DIN to the outlet of each sub-basin was estimated. Finally, the river export of DIN from sub-basin outlets to river mouths (the point at which DIN was discharged into Lake Tana) was estimated by quantifying retentions and losses of DIN within the river network.

The total load of DIN exported to the lake from each source was determined per sub-basin and per season. The overall equation to quantify annual river export over the four seasons to the river mouth $M_{DIN.\,y.\,j}$ (kg y^{-1}) by source y from sub-basin j was as follows:

$$M_{DIN.y.j} = \sum M_{DIN.y.j.S} \tag{1}$$

where $M_{DIN.\,y.\,j.\,S}$ is the seasonal river export of DIN to the river mouth of Lake Tana by source y from sub-basin j in season S (kg S^{-1}).

$M_{DIN.\,y.\,j.\,S}$ was estimated following the approach of the MARINA model (Strokal et al., 2016), but for seasons (modified from McCrackin et al., 2014) as follows:

$$M_{DIN.y.j.S} = RS_{DIN.y.j.S} \cdot FE_{riv.DIN.outlet.j.S} \cdot FE_{riv.DIN.mouth.j.S} \tag{2}$$

where $RS_{DIN.\,y.\,j.\,S}$ was the input of DIN to rivers in sub-basin j from source y in season S (kg S^{-1}). The DIN in rivers results from both diffuse and point sources, the former of which include DIN that results from N inputs to land (see steps 1 and 2 for details below).

$FE_{riv.\,DIN.\,outlet.\,j.\,s}$ was the fraction of $RS_{DIN.\,y.\,j.\,S}$ that was exported to the outlet of sub-basin j from source y in season S (0–1).

$FE_{riv.\,DIN.\,mouth.\,j.\,S}$ was the fraction of $RS_{DINyj.\,S} \cdot FE_{riv.\,DIN.\,outlet.\,j.\,S}$ that was exported to the river mouth of Lake Tana from source y and sub-basin j in season S (0–1, see details below).

We express the river export of DIN in terms of load to the Lake (kg S^{-1}) or yield (kg km^{-2} of basin area S^{-1}).

Step 1: Quantifying N inputs to land

Nitrogen inputs to land include the use of animal manure, synthetic fertilisers, biological N_2 fixation and atmospheric N deposition on agricultural and natural areas and human waste (faeces + urine). Human waste is not used as fertiliser in the basin. We first estimated inputs of N to land from diffuse sources for 2017. We assumed that human waste (human faeces and urine) that was collected in pit latrines and septic tanks does not reach the surface waters (Van Drecht et al., 2009). To estimate N inputs to land, seasonal data were needed for the following aspects: hydrology, socio-economic development (population density, gross domestic product and sewage connection), sub-basin characteristics (land use and slope), agricultural inputs (fertiliser use and manure excretion, crops, livestock, etc.) and meteorological data (rainfall and temperature). Most model inputs were collected from local information, such as the Ethiopia Central Statistical Authority, Ethiopia Ministry of Water, Electric and Irrigation, Amhara Region Bureaus of Agriculture and Water, Amhara Design and Supervision Enterprise, Blue Nile Water Institute and Bahir Dar University and from zonal and districts Agricultural Offices in the Lake Tana basin. In the absence of locally available data, data for the Nile basin were used from the Global NEWS-2 model (Mayorga et al., 2010). To calculate N inputs to land and rivers at the sub-basin scale by season, model inputs were needed for sub-basins and seasons for 2017. For this, we used an area-weighted method to aggregate local (often district-level) data into the sub-basin scale data.

Annual values for N inputs to land for 2017 were available at the institutions listed above. To allocate annual N inputs to seasons, we took into account crop phenology and climate data (rainfall and temperature) in the natural and agriculture systems (Tables A.4.5 and A.4.7). We allocated to seasons the following inputs for 2017: synthetic fertilisers, atmospheric N deposition and biological N_2 fixation. We assumed that N inputs to land from human waste (open defecation) and animal manure was the same among the four seasons (Appendices A.4.1 and A.4.2).

The seasonal distribution of the use of *synthetic fertilisers* was considered according to the approach of McCrackin et al. (2014). We took into account the planting area, application rate and application pattern of representative crops (see Appendix A.4 and Table A.5).

Annual values for *atmospheric N deposition* on agricultural and natural areas were available from the Global NEWS-2 Model. The annual values are distributed over seasons according to seasonal proportions of rainfall (McCrackin et al., 2014) (see Tables A.4.5 and A.2.1).

Total seasonal *biological N_2 fixation* was calculated by summing the seasonal *biological N_2 fixation* by natural vegetation and seasonal fixation by agricultural area (see Eqs. (A11)–(A15)). The seasonal *biological N_2 fixation* by natural vegetation was calculated from the annual *biological N_2 fixation* by natural vegetation with a formula that defines the relationship between air temperature and nitrogenase activity ((Hijmans et al., 2005) see Eq. (A.16)). To estimate annual *biological N_2 fixation* in natural vegetation, we followed the spatial distribution of non-agricultural land use forms, and only fixation rates of tree cover areas, shrubs cover areas, wetland and lichen/mosses/spare vegetation were considered. The fixation rates of only these land use forms were taken from Global NEWS-2 data (Mayorga et al., 2010).

The seasonal *biological N_2 fixation* in agricultural area was the sum of *biological N_2 fixation* by non-legumes, rice and legumes. For non-symbiotic *biological N_2 fixation* (non-legumes) and grassland, a fixation rate of 5 kg ha^{-1} y^{-1}, and for rice fields, a rate of 25 kg ha^{-1} y^{-1}, as proposed by Smil (1999), was assumed. The seasonal fixation rates were estimated from annual rates by quantifying the annual rates as a function of air temperature based on approach of Hijmans et al. (2005). The details can be found in Annex A.4. We calculated N_2 fixation by legumes as N in biomass harvested multiplied by two (for above- and below-ground biomass), following the approach of Bouwman et al. (2009). The total biological fixation of N_2 thus depends on the total production of legumes, as well as on the areas of grassland and cropland. The seasonal fixation rate was computed as a function of average seasonal temperature standardised by the nitrogenase activity.

The rates were calculated based on crop phenology (Houlton et al., 2008; Sacks et al., 2010) and local information. In addition to local information on crop calendar, the FAO crop data base (http://www.fao.org/agriculture/seed/cropcalendar/cropcal.do) was consulted to determine the planting and harvesting times of crops. Fixation by an individual crop was thus considered only for the period between planting and harvesting. To estimate *biological N_2 fixation* by crops, representative crop phenology was taken into account. We distinguished among rice, legume and non-legume growing areas. Since grassland was not fertilised, it was not part of the agricultural area in our model. We used crop production data compiled at a province level (CSA, 2016) and disaggregated into sub-basins based on an area-weighted method. The data contains crop type, number of holders, area covered, production and crop yield.

Step 2: Quantifying DIN inputs to rivers from diffuse and point sources ($RS_{DIN.\ y.\ j.\ S}$)

$RS_{DIN.\ y.\ j.\ S}$ was the sum of diffuse ($RSdif_{DIN.\ y.\ j.\ S}$) and point sources ($RSpnt_{DIN.\ y.\ j.\ S}$) in (kg S^{-1}).

- Diffuse sources

$RSdif_{DIN.\ y.\ j.\ S}$ for agricultural land was estimated following the approach of the MARINA model (Strokal et al., 2016), but for seasons, as follows:

$$RSdif_{DIN.y.j.S} = WSdif_{N.y.j.S} \cdot G_{N.j.S} \cdot FE_{WS.DIN.j.S} \tag{3}$$

where $WSdif_{N,y,j,S}$ was N input to the land from diffuse source y in sub-basin j and season S (kg S^{-1}). Diffuse sources are specified in step 1; see step 1 how diffuse sources are derived for seasons and sub-basins.

$G_{N.\ j.\ S}$ was the fraction of N that remains in soils after crop uptake and animal grazing in sub-basin j and season S (0–1). This fraction was calculated following the MARINA model approach (Strokal et al., 2016). We use this fraction to estimate the amount of N that reaches rivers after correcting for N losses and retentions in the soils (e.g., denitrification losses as a function of runoff and temperature).

$FE_{WS.DIN.j.S}$ was the export fraction of N from diffuse sources entering the surface water as DIN in sub-basin j and season S (0–1). We followed the seasonal approach of McCrackin et al. (2014) to quantify $FE_{ws.\ DIN.\ j.\ S}$ by season. This approach includes temperature (see Eq. (4)) to account for the effect of temperature on N retention and losses from the soil (e.g., denitrification).

$FE_{ws.\ DIN.\ j.\ S}$ was estimated as follows (McCrackin et al., 2014):

$$FE_{ws.DIN.j.S} = FE_{ro.j.S} \cdot (1 - F_{temp.j.S}) \tag{4}$$

where $FE_{ro,j,S}$ was the fraction of N entering the surface water as DIN in sub-basin j and season S, taking into account the influence of the surface runoff (0–1). $FE_{ro,j,S}$ was calculated as a function of seasonal natural runoff from land to streams in sub-basin j and season S (0–1) (Eq. (5)); $F_{temp,j,S}$ was the fraction of N retention in soils of sub-basin j and season S due to effects of temperature (0–1).

$F_{temp,j,S}$ was estimated using Eq. (6), as follows (McCrackin et al., 2014):

$$FE_{ro.j.S} = b \cdot (Rnat_{j.S} * 4)^a \tag{5}$$

$$F_{temp} = d(T_{j,S}/100)^c \tag{6}$$

where $Rnat_{j,S}$ was the seasonal runoff from land to streams in sub-basin j and season S (m S^{-1}). The natural runoff was multiplied by four, according to McCrackin et al. (2014), to ensure that $FE_{ro.\ j.\ S}$ was consistent with the annual fraction.

The a and b parameters (Eq. (5)) are used to determine the function of runoff (McCrackin et al., 2014). These parameters are recalibrated in for Lake Tana, because seasonality in our study area is driven more by rainfall rather than by temperature, as in the approach of McCrackin et al. (2014).

$T_{j,S}$ was the temperature for the sub-basin j in season S (°C), and the c and d constants (Eq. (6)) reflect the function of air temperature (McCrackin et al., 2014).

In Eq. (6), $T_{j,\ S}$ is divided by 100 to fit the order of magnitude with $Rnat_{j.\ S}$ (McCrackin et al., 2014). $T_{j,\ S}$ for each sub-basin was calculated by taking the average observed temperature of the respective three months in the Lake Tana basin.

- Point sources

The point sources of DIN in rivers ($RSpnt_{DIN.\ y.\ j.\ s}$, kg S^{-1}) include effluents from sewage systems. $RSpnt_{DIN.\ y.\ j.\ s}$ was calculated based on Strokal et al. (2016), but for seasons, as follows:

$$RSpnt_{DIN.y.j.S} = RSpnt_{N.y.j.S} \cdot FEpnt_{DIN.y.j} \tag{7}$$

where $RSpnt_{DIN.y.j.S}$ was DIN inputs to rivers from point source y in sub-basin j and season S (kg S^{-1}).

$RSpnt_{N.\ y.\ j.\ S}$ was the N input from point source y to rivers of sub-basin j in season S (kg S^{-1}).

$FEpnt_{DIN.y.j}$ was the export fraction of N from point source y in sub-basin j that was exported to rivers as DIN (0–1). $FEpnt_{DIN.\ y.\ j}$ was estimated using the approach of the MARINA model (Strokal et al., 2016).

In our model, $RSpnt_{N.\ y.\ j.\ S}$ was zero for 2017, as waste-water treatment plants and other point sources hardly exist in the Lake Tana basin.

Step 3: Quantifying retentions and losses of DIN within the river network

$FE_{riv.\ DIN.\ outlet.\ j.\ S}$ accounts for retentions and losses of DIN within the river network of sub-basins. This fraction was estimated based on Strokal et al. (2016) for sub-basins and on McCrackin et al. (2014) for seasons:

$$FE_{riv.DIN.outlet.j.S} = (1-D_{DIN.j.S}) \cdot (1-L_{DIN.j.S}) \cdot (1-FQrem_{j.S}) \tag{8}$$

where $D_{DIN.j.S}$ is the fraction of DIN retained in dammed reservoirs in sub-basin j and season S (0–1), $L_{DIN.\ j.\ S}$ the fraction of DIN losses by denitrification in the river network of sub-basin j and season S (0–1), and $FQrem_{j.\ S}$ the fraction of nutrients (generic for all nutrients) removed by water consumption in sub-basin j and season S (0–1).

The annual $D_{DIN.\ j.\ i}$ was estimated following Strokal et al. (2016). We assumed the same fractions for all seasons. $D_{DIN.\ j.\ i}$ was calculated as follows:

$$D_{DIN.j.i} = 0.8845 \times \left(\frac{h_{j.i}}{\Delta\tau_{R.j.i}}\right)^{-0.3677} \tag{9}$$

where h_i was the depth of reservoir i in sub-basin j (m), $\Delta\tau_{R.i}$ was the water residence time for reservoir i in sub-basin j (year) (data from Birhanu et al., 2014), and $L_{DIN.\ j.\ S}$ accounts for effects of temperature and was estimated using the approach of McCrackin et al. (2014), as follows:

$$L_{DIN.j.S} = (0.0605 \times \ln(Area_j) - 0.0443) \cdot Q_{10}^{\frac{(T_{j.S} - T_{average.j})}{10}} \tag{10}$$

where $Area_j$ is the total area of sub-basin j (km^2) and Q_{10} the air temperature coefficient that indicates the rate of changes in denitrification as a consequence of increasing the air temperature by 10 °C. The value of Q_{10} is set to 2.54 in this study (Mineau et al., 2015). $T_{j.S}$ is the air temperature for season S in sub-basin j (°C) and $T_{average.j}$ the annual average temperature for sub-basin j (°C). The maximum value of $L_{DIN.j.S}$ is set at 0.65 to avoid extrapolation error (McCrackin et al., 2014).

$FQrem_{j.S}$ is calculated following the approach of Strokal et al. (2016) and McCrackin et al. (2014), as follows:

$$FQrem_j = 1 - \frac{Q_{act.j.S}}{Q_{nat.j.S}} \tag{11}$$

where $Q_{act.j.S}$ is the actual water discharge at the outlet of sub-basin j after water consumption in season S (km^3 S^{-1}). $Q_{act.j.S}$ was collected from the Ethiopian Ministry of Water, Electric and Irrigation for the gauged sub-basins (daily data). The area of the gauged sub-basins comprises about 75% of the total Tana basin. Actual water discharge at the outlets of ungauged sub-basins, $Q_{act.j.S}$, were estimated by taking the actual water discharges of the adjacent or nearest (proximity analysis) gauged station and transferring this actual discharge to a new synthetic discharge for the ungauged sub-basin using the area and rainfall of ungauged catchments based on the approach of (Yarahmadi, 2003) (see Appendix A5 for more detail). $Q_{nat.j.S}$ is the natural water discharge at the outlet of sub-basin j before water consumption in season S (km^3 S^{-1}). $Q_{nat.j.S}$ is estimated by adding water consumption to $Q_{act.j.S}$ for each sub-basin and season. We accounted for water consumption for irrigation, animal watering, and surface water supply. Industries and floriculture farms in the Lake Tana basin mainly use water either from deep wells and/or Lake Tana or by abstracting from rivers not included in the basin. Hence, water consumption by industries and floriculture farms is not accounted for in our model. We obtained the annual water consumption from local data (see Appendix A.4 for details). Seasonal water consumption is the distribution of annual water consumption based on the proportion and use of water in agriculture, industry and residents in seasons.

$FE_{riv.DIN.mouth.j.S}$ accounts for DIN retention and loss during transport from the outlets towards the river mouth (0–1, see Eq. (8)). $FE_{riv.DIN.mouth.j.S}$ is estimated as in Strokal et al. (2016). In our seasonal model, the distance between the hydrometric station (outlets) and the river mouths is reasonably short. Therefore, we assumed that all the DIN that reached the outlet will reach the river mouth, and $FE_{riv.DIN.mouth.j.S}$ was thus assumed to be 1 in our seasonal model.

2.3. Monitoring water quality to estimate actual DIN loads

Water samples were collected on a monthly basis in 2017 in 500 ml polyethylene bottles and were kept in ice and transported to the laboratory for immediate analysis (APHA-AWWA-WPCF, 1981). Chemical analysis of ammonium (NH_4^+ - N), nitrate (NO_3^- - N) and nitrite (NO_2^- - N) was done with colorimetry in accordance with the manufacturer instruction (Palintest transmittance – display photometer 8000). The DIN concentration (g m^{-3}) was calculated by summing NH_4^+ - N (g m^{-3}), NO_3^- - N (g m^{-3}) and NO_2^- - N (g m^{-3}). The DIN load to the lake (g s^{-1}) is a product of DIN concentration (g m^{-3}) and discharge (m^3 s^{-1}). Based on our data set, because discharge and concentration are independent and observed regularly, the average load to the lake can be calculated by multiplying the average discharge and the average concentration, and we thus preferred the straight-forward method (De Vries and Klavers, 1994), as follows:

$$\boldsymbol{L} = \frac{\sum_{i=1}^{m} Q_i}{m} \cdot \frac{\sum_{j=1}^{n} Cj}{n} \tag{12}$$

where

L is the load of DIN (g s^{-1}).

Q_i is the discharge at the gauging stations at time i (m^3 s^{-1}),

C_j is the concentration at different time j (g m^{-3}),

m is the number of discharge measurements,

n is the number of concentration measurements.

2.4. Model calibration and validation

We modified the modelling approach of McCrackin et al. (2014) by re-calibrating the 'a' and 'b' model parameters that determine the runoff function (Table A.6.1 and Eq. (3) above). We found the optimum values for parameters a and b that resulted in the minimum difference between modelled and observed values. To calibrate and validate the integrated model, we used different data sets of observed and modelled DIN loads and yields to the lake. For model calibration, we used the values of seasonal observed and modelled DIN at or near the mouths of the Gilgel Abay, Gelda, Gumara, Rib and Dirma rivers, all of which had DIN observed at or near the river mouth. We used seasonal DIN load and yield data of the Arno-Garno, Megech and Infranz rivers for model validation (see Fig. 1a-c for the location of the rivers and Appendix A.6.3 for observation data). We converted DIN to kg km^{-2} S^{-1} by dividing the observed tons of S^{-1} of a sub-basin by its drainage area.

We assessed the model performance using R^2_P (the Pearson's coefficient of determination, 0–1), R^2_{NSE} (the Nash-Sutcliffe efficiency, $-\infty$-1) (Nash and Sutcliffe, 1970) and RSR, >0, according to Moriasi et al. (2007). R^2_P shows the proportion of the variance in the observed data that is predictable from the modelled data, with higher values representing better performance. R^2_{NSE} evaluates the fitness of the observed and modelled data with the 1:1 line, with higher values representing better performance. RSR is the ratio of root mean square error and standard deviation, with values close to zero showing very good model performance.

3. Results

3.1. Model calibration and validation

Model calibration results showed a good performance, that is, a high agreement between observed and modelled values of DIN load to the lake in ton S^{-1} ($R^2_P = 0.90$; $R^2_{NSE} = 0.88$; RSR = 0.31) and DIN yield in ton km^{-2} S^{-1} ($R^2_P = 0.82$; $R^2_{NSE} = 0.80$; RSR = 0.50; Fig. 3A, B).

For validation the model also performed well against measured data for DIN loadings with $R^2_P = 0.88$, $R^2_{NSE} = 0.81$ and RSR = 0.41 (Fig. 3C). As for DIN yields at the river mouth with observed values, goodness of fit metrics were $R^2_P = 0.86$, $R^2_{NSE} = 0.69$ and RSR = 0.50 (Fig. 3D). The total modelled DIN loading to the lake per season shows a good agreement with the observed loads to the lake (Fig. 3). The abovementioned indicators imply that model performance can be considered good (Moriasi et al., 2007).

3.2. Seasonal nitrogen inputs to land in the Lake Tana basin

The total annual N inputs to land in Lake Tana basin were estimated at 129 kton y^{-1} in 2017 (Fig. 4). The N inputs to land (kg km^{-2} S^{-1}) largely varied among seasons and sub-basins. The inputs were higher in the rainy season and lower in the dry season. The rainy season contributed 36% of the total annual N inputs to land, and the contributions of the post-rainy (21%), dry (21%) and pre-rainy (22%) seasons were lower (Fig. 6). The total annual N inputs to land varied between 0.1 and 51 kton y^{-1} and between 232 and 2464 kg km^{-2} y^{-1} among sub-basins. The highest N inputs to land were delivered by the Gilgel Abay and the lowest by the Infranz-Bahir Dar sub-basin.

The source attribution differs slightly among the seasons. The seasonal N inputs to land for 2017 result from human excreta (open defecation), animal manure, synthetic fertilisers, biological N_2 fixation by crops and natural vegetation and atmospheric N deposition on agricultural and natural land (Table A.4.1; Appendix A.4). Among these diffuse sources, animal manure was the dominant contributor of N inputs to land in all seasons because animal grazing was assumed to occur at the same intensity in all seasons. Synthetic fertiliser was the second dominant N input to land, but only in the rainy season because it is only used during the rainy growing season (Table 1).

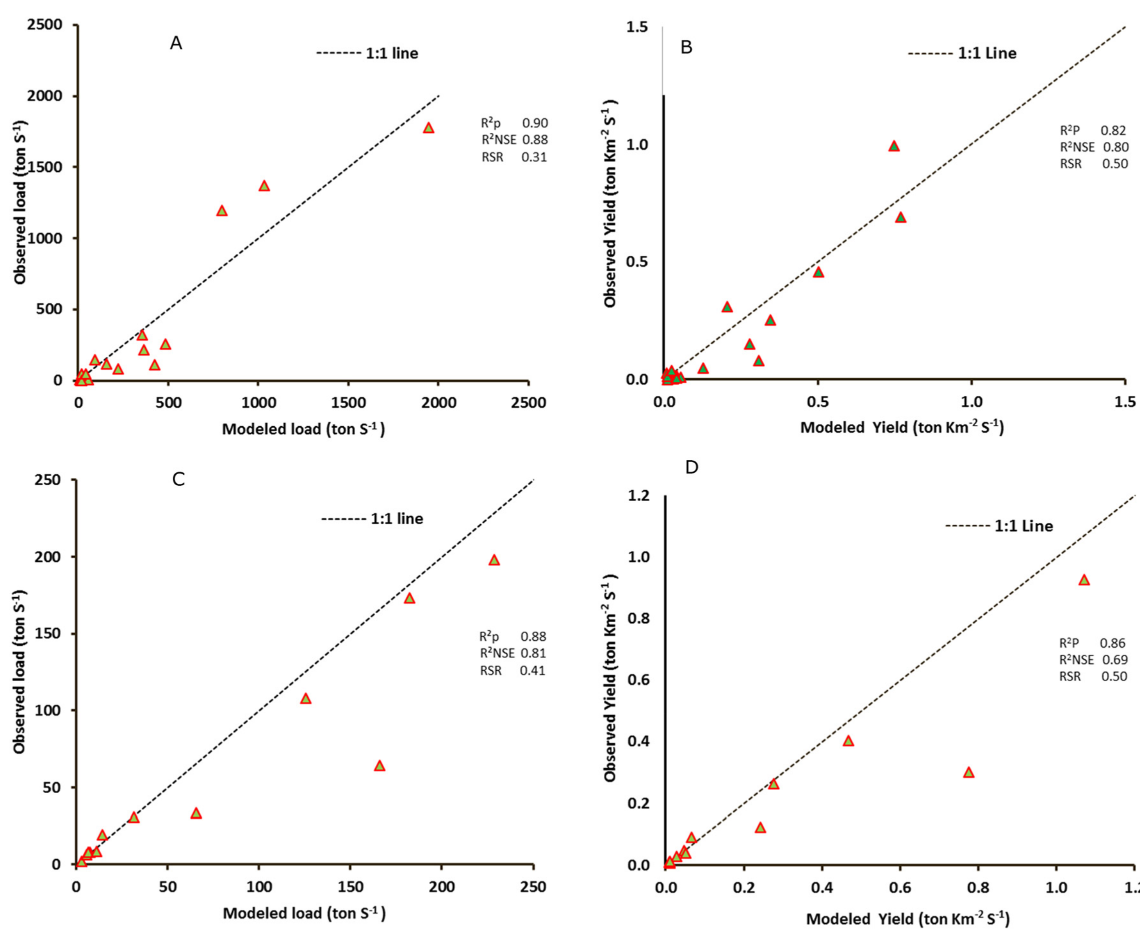

Fig. 3. Model calibration (panels A, B) and validation (panels C, D). Graphs show modelled versus observed DIN load (ton S^{-1}) and DIN yield (ton km^{-2} S^{-1}) from different sub-basins per season. R^2_P, R^2_{NSE} and RSR are the Pearson's coefficient of determination (0–1), the Nash-Sutcliffe efficiency (0–1) and the root mean square error standardised by standard deviation (>0), respectively.

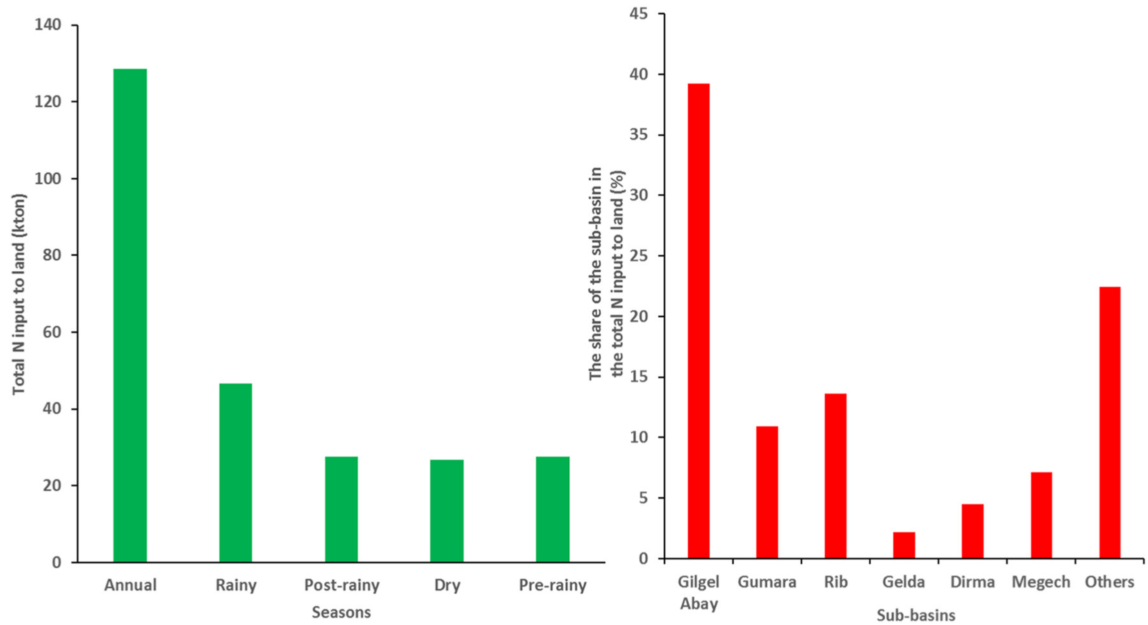

Fig. 4. Modelled Nitrogen (N) inputs to land by season (left) and sub-basin (right) in 2017. The left panel shows the total N inputs to land in kton y^{-1} for the annual and kton S^{-1} for seasons. The right map shows the share of the sub-basins to the total annual N inputs in the Tana basin (% of the total inputs to land in all sub-basins). The seasons in this study are defined based on the rainfall pattern: pre-rainy [April, May and June (AMJ)], rainy [July, August and September (JAS)], post-rainy [October, November and December (OND)] and dry [January, February and March (JFM)]. See Fig. 1 for the location of the sub-basins.

3.3. Seasonal river export of DIN by sub-basin and source to Lake Tana

The model indicated that about 9 kton of DIN was exported by rivers to the lake in 2017 (Fig. 5). In terms of yield, this amount is 802 kg km^{-2} of the total drainage area of the lake y^{-1}. The annual DIN yields from the sub-basins ranged from 232 to 2464 kg km^{-2} y^{-1}. The lowest river export of DIN was delivered by the Gemero Makesegnit and the highest by the Gelda sub-basin.

The six major rivers, namely, the Dirma, Gilgel Abay, Gumara, Gelda, Megech and Rib, together exported over two-thirds of total DIN to Lake Tana (Fig. 5). In the rainy season, about one-third of this export was from the Gilgel Abay sub-basin, 17% from the Gumara, 8% from the Rib, 6% from the Gelda and 6% from the Dirma. Small sub-basins such as the Infranz-Bahir Dar are estimated to export the smallest amounts of DIN to the lake.

River export of DIN to Lake Tana was highest in the rainy and lowest in the dry season. The export of DIN in the rainy season was estimated to be over half of the annual export to the lake. The DIN yields exported in the rainy season ranged from 141 to 1393 kg km^{-2} S^{-1}. The lowest amounts of DIN to the lake were exported from the Gemero-Makesegnit and the highest amounts from the Gelda sub-basin (Fig. 6). The Gilgel Abay sub-basin contributed 504 kg km^{-2} S^{-1}. In the rainy season, the major sources of DIN inputs to the lake were animal manure (49%), synthetic fertiliser (37%) and biological N_2 fixation (6%). Atmospheric N deposition (4%) had the lowest contribution (Fig. 5A).

The DIN load to the lake in the post-rainy season was by far lower than the DIN load in the rainy season (Fig. 5B). The DIN load ranged from 0.5 to 93 ton S^{-1} among sub-basins. Similar to the rainy season, the highest DIN load was exported by Gilgel Abay and the lowest by Infranz-Bahir Dar. By contrast, the highest DIN yield (53 kg km^{-2} S^{-1}) was exported by Gelda and the lowest by Gemero-Maksegnet (5 kg km^{-2} S^{-1}) (Fig. 6).

In the dry season, Bahir Dar-Infranz exported 0.27 ton of DIN, which is much lower compared to the Gilgel Abay sub-basin (43 ton S^{-1}). This sub-basin exported the largest amount of DIN to the lake in the dry season (43 ton S^{-1}). In terms of yield, the river export of DIN ranged from 6 (Infranz _Bahir Dar) to 40 (Gelda) (kg km^{-2} S^{-1}) among the sub-basins in the dry season (Fig. 6).

The pre-rainy season was the second dominant contributor to the annual DIN load after the rainy season (Table 1). In this season, 30% of the annual DIN load was estimated to be exported to the lake. The DIN export ranged from 5.7 to 798 ton S^{-1} among sub-basins. The lowest export was by the Megech-Dirma and Gilgel Abay sub-basins. Animal manure was estimated to be a dominant source of DIN in the lake (82%), and human waste was the second dominant source of DIN, followed by biological N_2 fixation (7%) and atmospheric N deposition (3%).

Table 1
Modelled N inputs to land by season and source for the Lake Tana basin in 2017 (kg km watershed $area^{-2}$ S^{-1}). Ranges indicate minimum and maximum values among sub-basins.

Sources	Rainy	Post-rainy	Dry	Pre-rainy
Animal manure	201–2904	201–2904	201–2904	201–2904
Synthetic fertilisers	260–2873	0	0	0
Human waste	37–249	37–249	37–249	37–249
Biological N_2 fixation[a]	100–334	135–237	11–162	31–181
Atmospheric N deposition[a]	131–196	10–24	2–6	43–77

[a] Over agricultural and natural land.

4. Discussion

4.1. Strengths and weaknesses of the seasonal modelling approach

Our model was applied for 2017, which we consider to be a representative year because we found no significant difference in rainfall and temperature between 2017 and the long term annual average (1952–2015) (Wilcoxon signed-ranked test, $p = 0.61$ for rainfall, $p = 0.18$ for temperature). Furthermore, fertiliser application amounts (the main contributor of DIN) in the basin are fairly constant over the years as they are based on fixed rates (blanket recommendations). From this we assume that 2017 can be seen as a representative year in terms of DIN sources. We also systematically collected observed data for all months of the year 2017, giving us

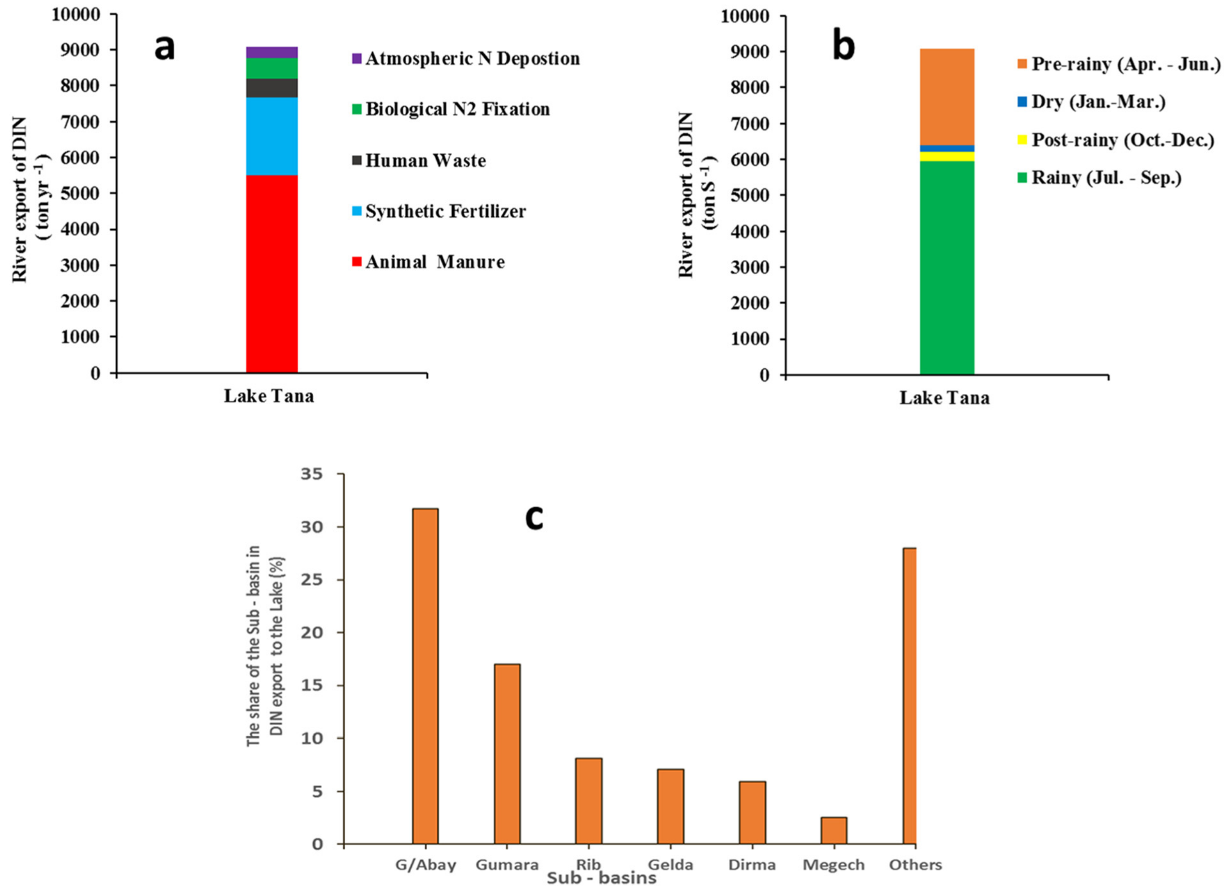

Fig. 5. Total modelled annual river export of DIN by source (ton y^{-1}, a), season (ton S^{-1}, b) and the share of the sub-basins of the total annual river export of DIN (%, c) to Lake Tana in 2017. See Fig. 1 for the location of the sub-basins.

confidence in representativeness of the observed values for different seasons. Although data were only available for one year, this enabled us to calibrate and validate our seasonal model. We realise that more years would be better, but after calibrating the seasonal parameters (Section 2.4), model outputs were generally in good agreement with observed data (e.g., $R^2_{NSE} > 0.65$, see Fig. 3). Nevertheless, our newly developed seasonal approach has some uncertainties that are largely associated with model inputs and parameters. We used Sentinel 2 land cover 2016 imagery to calculate areas of different land cover. Sentinel 2 (20 m–by–20 m resolution) land cover imagery has an overall area weighted accuracy of 65% +/− 1% (Lesiv et al., 2017) but could nevertheless contribute to the uncertainty of our model. The use of global scale data, which has a 0.5° by 0.5° resolution, to local sub-basins of Lake Tana might also introduce some uncertainties. Nevertheless, validation results showed a good performance of the model to quantify seasonal river export of DIN to Lake Tana. Therefore, we consider the model uncertainties to not affect the main messages of our study.

We developed a seasonal version of the MARINA model for large tropical lake sub-basins and rivers by combining the sub-basin modelling approach (Strokal et al., 2016) with the seasonal modelling approach (Chen et al., 2019; McCrackin et al., 2014) and we did this with Lake Tana basin for the first time. The sub-basin scale MARINA model has been widely applied to other lakes, such as the Dianchi (Li et al., 2018), Taihu (Wang et al., 2019) and Guanting (Yang et al., 2019) lakes. These studies all validated the modelling approach against observations. Furthermore, Strokal et al. (2016) tested the sensitivity of model outputs to changes in model inputs and parameters for the sub-basin scale MARINA model. They found that the DIN export by rivers was generally sensitive to changes in animal manure, synthetic fertiliser and hydrology. McCrackin et al. (2014) also validated the seasonal modelling approach against observations for large rivers in the world. The sensitivity analyses of McCrackin et al. (2014) revealed that river export of DIN is also generally sensitive to changes in runoff, particularly in summer. The results of the sensitivity analysis for the sub-basin (from Strokal et al., 2016) and seasonal (from McCrackin et al., 2014) modelling approaches give us insights into the model inputs and parameters that need attention in implementing these approaches in our study area. We therefore used local information to derive model inputs and parameters that reflect best the local situations of the Lake Tana basin (see Section 2).

We argue that our seasonal model is suitable for assessing DIN export from sub-basins to Lake Tana. In general, the main advantage of our approach is that it can provide a relatively accurate way to link water quality with human activities, by quantifying the contribution of separate sources seasonally. Preferably the input is from local data, but if not available, global data can be used as well. Furthermore, the approach enables to estimate DIN export from ungauged sub-basins. The disadvantage is that an accurate assessment needs regional calibration of the seasonal parameters. In addition for local analysis of water quality (e.g., cities), more in-depth model evaluation is needed.

4.2. Seasonal patterns and sources of river export of DIN in the Lake Tana

Our study presents results of the seasonal and sub-basin analyses of DIN export to Lake Tana. Our model enables the identification of which season and sub-basin contributes most to lake pollution, and from which source (e.g., agriculture or city). This provides new insight into the seasonality in river export of DIN, taking into account the socio-economic drivers, human activities, hydrological and

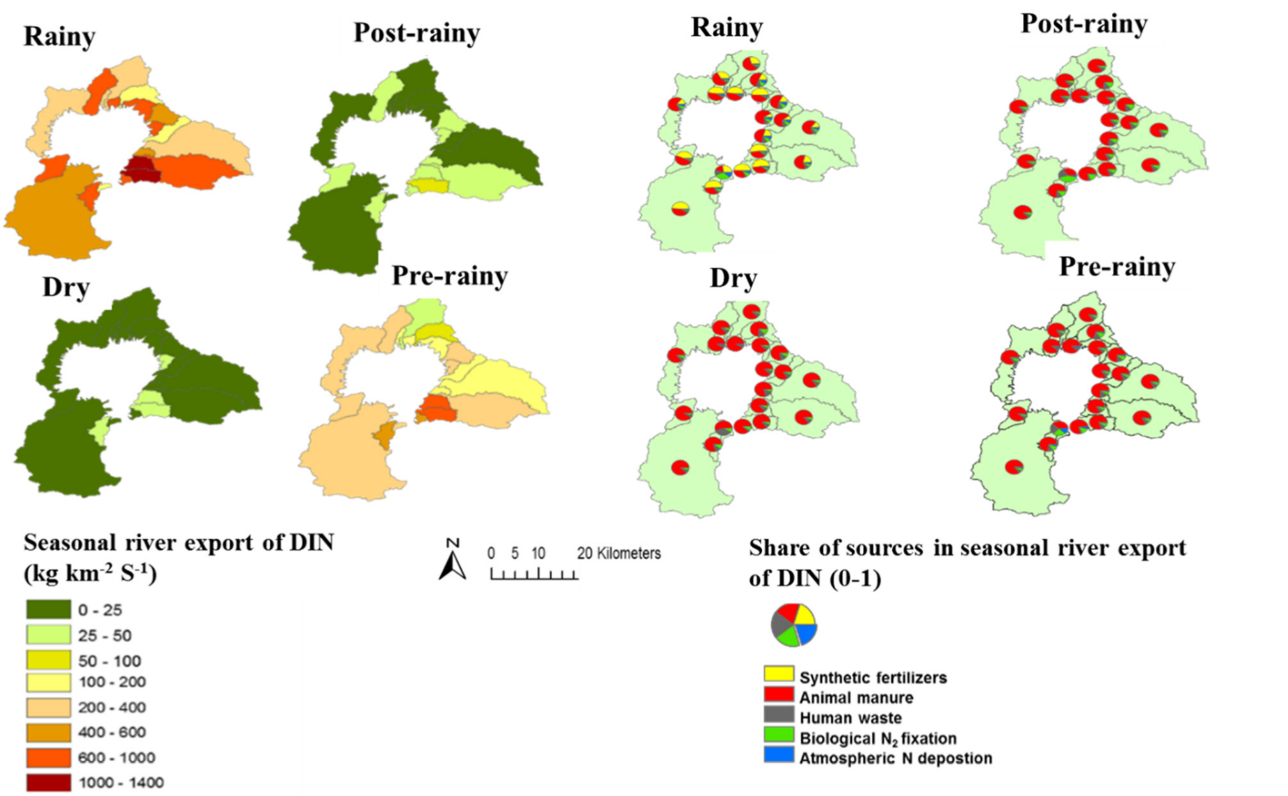

Fig. 6. Modelled seasonal river export of dissolved inorganic nitrogen (DIN) by sub-basin to Lake Tana (kg km^{-2} S^{-1}) and the share of the sources in the seasonal river export of DIN by sub-basin (0–1) in 2017.

climate characteristics. This has not been done before for Lake Tana. Our seasonal model for Lake Tana opens an opportunity to explore solutions and future trends in DIN export by rivers. This is relevant for science and policy-making as we provide a new tool and new insights that can support the formulation of effective water pollution strategies.

Seasonal estimates of the river export of DIN to Lake Tana in Ethiopia are scarcely available. The available studies for the Lake Tana basin and other bodies of water in Ethiopia are mainly based on measurements of DIN concentrations in rivers, river mouths and different parts of the lake. However, the number of observations is very limited. This holds especially for DIN concentrations in rivers of ungauged catchments. For these rivers, water discharges are also often unknown, making it difficult to estimate concentrations of DIN. Our model can help fill this gap.

Our estimates of river export of DIN to Lake Tana were far higher than the estimate for the Nile basin provided by Yasin et al. (2010). We estimated DIN yields that ranged from 232 to 2464 kg km^{-2} y^{-1} among sub-basins of Lake Tana. Yasin et al. (2010) reported DIN yield of 41 to 60 kg km^{-2}y^{-1} for the Nile basin, on average. Our higher estimates could be explained by higher population density (228 people per km^2; Anteneh, 2017) and a larger share of agricultural land (70%) (Abebe and Minale, 2017) of the Lake Tana basin compared to the Nile basin. We think this has to do partly with relatively high N inputs in agriculture. Open animal grazing and open defecation of human excreta likely contribute to higher loads. The Nile basin has a population density of 13 people per km^2 and an agricultural land share of 42% (Yasin et al., 2010). Moreover, the High Aswan Dam in the Nile basin has a high nutrient reduction potential, which could result in lower estimates of river export of DIN, as the DIN outlet point was chosen after the dam site (Yasin et al., 2010).

Our estimates of the DIN loads were generally lower than the estimates of the Yangtze and Pearl River basins and Baiyangdian Lake in China (Liu et al., 2008; Strokal et al., 2016; Yang et al., 2019). This is because our study area is smaller than the basins of those rivers. In undisturbed conditions, the DIN export from a temperate watershed is lower than the DIN export from a tropical watershed (Kosten et al., 2009). However, the lower DIN yields in the Lake Tana basin compared to the Chinese basins could be explained by less human activity (for instance, less intensive application of synthetic fertiliser) and by the tropical climate in the Lake Tana basin (warmer temperature resulting in more N retention). These could contribute to lower DIN export to Lake Tana compared to river export of DIN by Yangtze and Pearl rivers. However, the warmer climate in the Lake Tana basin compared to the Yangtze River basin could favour an increased rate of biological N_2 fixation, though biological fixation is not a major source of DIN to the Lake Tana.

We found the highest DIN export in the rainy season and the lowest in the dry season for the Lake Tana basin, most likely because runoff reaches a maximum in the rainy season and a minimum in the dry season. McCrackin et al. (2014) reported that the seasonal DIN export was positively related to runoff and negatively to temperature. Agriculture in the Tana basin is rain-fed, and most of the agricultural activities have been carried out in the rainy season. Therefore, in the rainy season compared to the dry season, extensive (about two-thirds of the annual rainfall compared to 2% in the dry season), relatively low air temperature (18.4 °C in the rainy compared to 21.1 °C in the pre-rainy) and increased human activity (rain-fed agriculture) likely explain the DIN seasonality in river export of DIN to Lake Tana.

We reported that animal manure and synthetic fertilisers were dominant sources of DIN in Lake Tana. This could be explained by the high livestock density and open-grazing system of animal production in the area. In the Lake Tana sub-basin, livestock production comprises a large portion of farming activities (Alemayehu and Tassew, 2017; Tassew and Seifu, 2007).

Synthetic fertilisers and animal manure together explained about half of the river export of DIN to the coastal waters of Africa (Yan et al., 2010). Liu et al. (2008) reported that synthetic fertilisers were the largest contributor to the basin of Lake Dianchi in China. Wang et al. (2019) reported that diffuse sources contributed >90% of the total dissolved nitrogen (TDN). Strokal et al. (2016) reported that animal manure as a point source (direct discharges to rivers) was the dominant source DIN in Chinese rivers.

4.3. Implications for eutrophication management

Shore areas and river mouths in the north eastern part of Lake Tana have already experienced eutrophication in the form of algal blooms and extensive growth of water hyacinth (Goshu et al., 2017). This is a result of excess N and P from the sub-basins. Negative impacts of the eutrophication problems on ecosystem and public health have been reported (Goshu and Aynalem, 2017; Wondie et al., 2007). So far, attempts to manage eutrophication, for example, by controlling water hyacinth, have been unsuccessful, and controlling water hyacinth and cyanobacterial nuisance have remained key challenges.

Our model provides new insights into seasonal aspects of managing agricultural N inputs to rivers and thus to the lake. We demonstrate that the river export of DIN is highest in the rainy and lowest in the dry seasons. This implies that the risk of N losses during a high runoff season is higher than during a low runoff season. Therefore, farming practices should avoid N losses to rivers, in particular for the rainy season. Conserving the wetlands along the shores may have a nutrient stripping role during high runoff. This will prevent N export to the lake. Since the major source of N is animal manure, increasing reuse possibilities, for instance, by using animal manure as an organic fertiliser is advisable. Precision fertilisation of crops with respect to N demand and timing may reduce N losses from agricultural fields to rivers and thus eutrophication in the lake.

Our study highlights the seasons (e.g. rainy) and sub-basins (e.g. Gilgel Abay, Gumara, Rib, Gelda, Dirma and Megech) where reduction strategies are needed to avoid future lake pollution. Furthermore, our model identifies the causes of the lake pollution (e.g. manure). This can help policy-makers identify adequate reduction policies for Lake Tana.

5. Conclusions

We integrated the two existing modelling approaches into a seasonal model for river export of DIN for large tropical lakes. This resulted in a seasonal version of the MARINA model for sub-basins and rivers discharging to tropical lakes such as Lake Tana. We applied this model for 2017, during which annual river export of DIN to Lake Tana was about 9 kton. River export of DIN to Lake Tana showed spatial and temporal variability, being highest in the rainy and lowest in the dry seasons. For example, two-thirds of the total annual DIN export was exported by rivers in the rainy season, whereas 30%, 3% and 2% of the DIN was exported by rivers in the pre-rainy, post rainy and dry seasons, respectively. Diffuse sources from agriculture were important contributors of DIN in rivers. Animal manure was the dominant source in all seasons. Synthetic fertiliser was the second dominant source in the rainy season. Human waste on land was a substantial diffuse source of N in all seasons in the year 2017. Over two-thirds of the annual river export of DIN was delivered by six of the twenty rivers, namely, the Gilgel Abay, Dirma, Megech, Rib, Gumara and Gelda. The Gilgel Abay sub-basin alone exported about one-third of the annual river export of DIN to the lake.

Our study shows new insights into the seasonality in river export of DIN to Lake Tana. We show the importance of diffuse sources in the lake pollution. This holds especially for wet periods where pollution levels are higher. We also show the areas (sub-basins) where pollution control is needed to avoid further pollution of the lake. This information can contribute to formulate effective management options for Lake Tana that are area-, season- and source-specific. Furthermore, our seasonal model can be applied to analyses of future trends in the lake pollution. We provide a seasonal approach that might be applied to sub-basins and rivers draining into other large tropical lakes that experience similar environmental problems.

For future research, we suggest three main directions. First, we suggest setting up a new project to monitor concentrations of N in rivers draining into the lakes. This will help to apply the model to other years and validate it for those years. Second, we suggest conducting sensitivity and uncertainty analyses to increase trust in the model performance especially for those years for which observations are limited. Third, we suggest applying our model to sub-basins and rivers of other lakes for effective nutrient management. This includes also application of the model to the future. In this future analysis, options to reduce lake pollution can be explored. Our model can also be applied to other sub-basins and rivers of tropical lakes that have comparable characteristics of the sub-basins and rivers of Lake Tana basin (e.g. precipitation, seasons).

CRediT authorship contribution statement

Goraw Goshu: Conceptualization, Methodology, Validation, Writing - original draft, Funding acquisition.**M. Strokal:**Methodology, Validation, Writing - review & editing, Supervision.**C. Kroeze:**Methodology, Validation, Writing - review & editing, Supervision.**A.A. Koelmans:**Conceptualization, Methodology, Validation, Writing - review & editing, Supervision, Project administration, Funding acquisition.**J.J.M. de Klein:** Conceptualization, Methodology, Validation, Writing - review & editing, Supervision, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2020.139199.

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