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Efficient updating of regional supply and use tables with the national-level statistics

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Abstract
Supply and use tables (SUTs) lay out a detailed picture of the entire economy, providing an overview of the production process and use of commodities. The governmental agencies produce these mainly at the national level to derive components related to the calculation of the gross domestic product (GDP). The national SUTs, however, do not capture the heterogeneity of regions within a country. The regional SUTs, on the other hand, are difficult and costly to compile. In the absence of regularly compiled regional SUTs, analysts typically resort to hybrid models based on mechanically updated tables with less extensive data requirements. However, the approaches currently available in the literature do not necessarily guarantee a consistent structure of the SUTs when there is a mismatch in spatial scale at which sectoral output data are available. Building on the multiregional generalized RAS, this paper proposes a modification to the structure of the benchmark matrix that guarantees the supply–use accounting balance as well as the identity of GDP by income and GDP by expenditure at the regional level in the projected matrix. As a result, the procedure allows for efficient production of regional SUTs appropriate for calculating multiplier effects from the national-level statistics.

Keywords: Multiregional generalized RAS, Regional supply and use tables, Supply–use accounting balance

1 Introduction

Supply and use tables (SUTs) lay out a detailed picture of the entire economy, providing an overview of the production process and use of commodities. SUTs are also a building block of models intended for detailed economic impact assessment, extensively applied in many fields, including assessment of the impact of the natural resource use. The governmental agencies produce these mainly at the national level to derive components related to the calculation of the gross domestic product (GDP).

The national SUTs, however, do not capture the heterogeneity of regions within a single country. This deficiency is problematic as the differences between regions and subnational interdependencies can be substantial. It follows from industries' diversification in terms of the production structure that may be related to the location, availability of resources, or ability to attract talent. A policy that is targeting a specific sector when the reliance on that sector varies between regions will produce unevenly distributed economic effects.

While it is clear that regional SUTs have a great potential for policymakers who may be interested in the localized effects of their decisions, these are rarely available. Detailed regional tables are often a product of a specific project with a limited sectoral focus, available for a narrow time frame, and rarely set for routine updating. This is because such products are data-intensive, requiring information on the whole range of industries that comprise the region's economy. Compiling data from all sectors and ensuring its consistency across takes resources and time (Jensen and Macdonald 1982). Values are often available only for an aggregate (Oosterhaven et al. 1986). As a result, timely policy advice based on regional SUTs is rare. Instead, economic impact inputs to policy-making decisions tend to be based on tables updated with limited data using a hybrid approach in which superior information (e.g., focused survey, expert opinion) is incorporated into otherwise mechanically updated tables (Lahr 1993).

The multiregional generalized RAS (MR-GRAS) technique described in Temursho et al. (2020) offers an advanced approach to updating a partitioned matrix that needs to conform to new row sums, column sums and, additionally, non-overlapping aggregation constraints. While using row and column constraints is at the core of more traditional updating methods (e.g., RAS method), adding aggregation constraints provides an opportunity to maximize the utilization of available data by making use of the national-level statistics.

Temursho et al. (2020) application of the MR-GRAS technique to SUTs, however, does not necessarily guarantee a consistent structure of the updated tables. This technical note proposes a simple modification to the structure of the benchmark matrix that guarantees the supply–use accounting balance as well as the identity of GDP by income and GDP by expenditure at the regional level in the output matrix. As a result, the procedure allows efficient production of tables appropriate for calculating multiplier effects and estimating regional economic impacts.

This note's contribution also lies in the empirical application, presenting an example of using the MR-GRAS method. It demonstrates the far-reaching economic impacts of fisheries management policies that alter catch limits for commercial harvesters using the Pacific halibut commercial fishery in Alaska as a case study. The step-by-step instructions on how to apply the approach should be of interest to any researcher working on regional economic analysis, regardless of the focus sector.

2 Materials and methods

The most commonly adopted technique for updating the SUTs is the so-called RAS method method (Stone and Brown 1962; Bacharach 1970; Lahr and de Mesnard 2004). It is a biproportional technique used to estimate a new matrix from an existing one by scaling row and column entries to exogenously given totals. The major shortcoming of this method is that it requires a full set of row and column constraints, something not always available to the analyst (Lenzen et al. 2006). RAS also does not benefit from data available at a higher aggregation level than the original model, while additional information may be available on sums for some submatrices of the projected matrix. Moreover, RAS can only handle non-negative matrices. In the context of SUTs, certain areas of the partitioned matrix may include negative numbers, for example, columns containing values describing changes in inventories or rows with net taxes, which may be negative if subsidies outweigh tax paid.

The generalized RAS (GRAS) method (Günlük-Şenesen and Bates 1988; Junius and Oosterhaven 2003) solves the problem with negative numbers by using reciprocals of the exponential transformations of the related Lagrange multipliers. Approach proposed by Cole (1992); Gilchrist and St. Louis (2004) applies constraints on subgroups of matrix entries. The SUT-RAS extension proposed by Temurshoev and Timmer (2011) applies RAS technique to joint projections of SUTs that does not require the availability of the use and supply totals by products, but still guarantees consistency of the output by construction.

Temursho et al. (2020) MR-GRAS approach combines number of advantages of the extensions to the original RAS method. It allows updating of a partitioned matrix such as SUTs with non-exhaustive row and column totals and non-overlapping aggregation constraints. The updated tables incorporate partial information on its components while continuing to conform to available aggregated data. As a result, this technique can make the multiregional model consistent with aggregated national data and include up-to-date estimates from a limited number of sectors derived from, for example, a focused survey or statistics published by an agency responsible for a specific sector. Thus, the technique maximizes the potential for the use of data that may be supplied at various sectoral and regional aggregation levels. Moreover, it allows for adjusting SUTs' positive and negative entries simultaneously. This accommodates the challenge of higher economic heterogeneity of regions within more aggregated economic system that result in more likely occurrence of negative elements within a multiregional SUTs.

The MR-GRAS approach is based on tri-proportional scaling. The algorithm is set to minimize the weighted logarithm of the relative distance between the entries of the new and the old SUTs, subject to row, column and aggregation constraints. To find the solution that accounts for negative entries, the original benchmark matrix serving as an initial input to the scaling procedure is decomposed to a matrix containing positive elements and a matrix containing the negative entries' absolute values. What follows is the adjustment procedure consisting of a sequence of computations deriving adjustment multipliers that is set to stop when the multipliers converge to a solution conforming to a preset sufficiently low tolerance level.

Adopting the extended MR-GRAS technique, as described in Temursho et al. (2020), however, does not necessarily guarantee the consistent structure of the updated tables. Updated SUTs must continue to satisfy the two SUT framework identities, that is, in the estimated matrix total supply by product should be equal to total use by product, and total intermediate input and value added by industry should be equal to sectoral total output. Temursho et al. (2020) application deals with the challenge of the lack of data on total output by product, but not output by both product and industry. To address this shortcoming, this note proposes a simple modification to the structure of the benchmark matrix that imposes the identity of GDP by income and GDP by expenditure at the regional level in the output matrix. As a result, the updated matrix efficiently accommodates national-level output data, as well as regional data on GDP components that are often produced by statistical agencies even when there is no attempt to derive the full set of regional SUTs.

2.1 MR-GRAS for updating multiregional SUTs

Temursho et al. (2020) describe adopting the MR-GRAS technique to multiregional SUTs that is well suited to situations when the supply (at least partially) is known at the regional level. However, it is more likely that more detailed regional statistics are available for components related to the calculation of the GDP, that is final demand and value added, as well as trade. Thus, the paper proposes a modification of the MR-GRAS setting for R regions that makes the use of these statistics while at the same time guarantees consistent structure of the projected SUTs. It is written as follows:

$$X^0 = \left[\begin{array}{cccc|cccc|cccc} -S_1 & 0 & \cdots & 0 & 0 & 0 & \cdots & 0 & S_1^d & 0 & \cdots & 0 \\ 0 & -S_2 & \cdots & 0 & 0 & 0 & \cdots & 0 & 0 & S_2^d & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & -S_R & 0 & 0 & \cdots & 0 & 0 & 0 & \cdots & S_R^d \\ \hline U_{11} & U_{12} & \cdots & U_{1R} & \mathrm{FD}_{11} & \mathrm{FD}_{12} & \cdots & \mathrm{FD}_{1R} & -S_1^d & 0 & \cdots & 0 \\ U_{21} & U_{22} & \cdots & U_{2R} & \mathrm{FD}_{21} & \mathrm{FD}_{22} & \cdots & \mathrm{FD}_{2R} & 0 & -S_2^d & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots \\ U_{R1} & U_{R2} & \cdots & U_{\mathrm{RR}} & \mathrm{FD}_{R1} & \mathrm{FD}_{R2} & \cdots & \mathrm{FD}_{\mathrm{RR}} & 0 & 0 & \cdots & -S_R^d \\ \hline U_1^M & 0 & \cdots & 0 & \mathrm{FD}_1^M & 0 & \cdots & 0 & 0 & 0 & \cdots & 0 \\ 0 & U_2^M & \cdots & 0 & 0 & \mathrm{FD}_2^M & \cdots & 0 & 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & U_R^M & 0 & 0 & \cdots & \mathrm{FD}_R^M & 0 & 0 & \cdots & 0 \\ \hline \mathrm{VA}_1 & 0 & \cdots & 0 & 0 & 0 & \cdots & 0 & 0 & 0 & \cdots & 0 \\ 0 & \mathrm{VA}_2 & \cdots & 0 & 0 & 0 & \cdots & 0 & 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \mathrm{VA}_R & 0 & 0 & \cdots & 0 & 0 & 0 & \cdots & 0 \end{array}\right] \tag{1}$$

Matrix in Eq. 1 represents purchases only type of regionalized national SUT (Oosterhaven 1984), with its core equivalent to the matrix in Temursho et al. (2020). Here, S_r ($r = \{1, ..., R\}$) is the supply matrix of dimension commodity (C) by industry (I), where the subscript indicates the region within the analyzed country. The supply matrices are introduced here with negative signs so that the columns containing these will sum to zero. $U_{r,s}$ ($r, s = \{1, ..., R\}$) is the domestic use matrix of dimension $C \times I$, where subscripts indicate the commodity origin and where the commodity is used; $\mathrm{FD}_{r,s}$ is the domestic final demand of dimension $C\times$ number of final demand categories (D), with subscripts following these for $U_{r,s}$; U_r^M and FD_r^M are use and final demand matrices of the same dimensions, but related to imported products; VA_r is a square matrix with value added values on the diagonal; and S_r^d is a square matrix with the supply by commodity on diagonal.

Note that the proposed structure implies that rows of the first row section and columns of the first and third column sections sum to zero. Rows of the second row section sum to negative exports by region and commodity, and rows of the third row section sum to imports by region and commodity. S_r^d matrices are introduced with an intention to preserve the SUT framework consistency in the assembled partitioned matrix.

Equations 2 and 3 summarize the described row (vector u) and column (vector v) sums. E indicates vector of export and M indicates vector of imports. Subscripts indicate each vectors' length:

$$\boldsymbol{u} = \left[\, 0_{[RC]} \;\; -E_{[RC]} \;\; M_{[RC]} \;\; \mathrm{VA}_{[RI]} \,\right], \tag{2}$$

$$\boldsymbol{v} = \left[\, 0_{[RI]} \;\; \mathrm{FD}_{[RD]} \;\; 0_{[RC]} \,\right]. \tag{3}$$

3 Application

3.1 Pacific halibut case study

Pacific halibut is distributed on the west coast of the USA and Canada, from California to Alaska. The fish are primarily targeted by the commercial longline fishery and by sport fishers, as well as taken for personal use. The fishery limits are set by the International Pacific Halibut Commission (IPHC) based on annual stock assessment. However, under the Convention establishing the IPHC, the Commission's mandate is optimum management of the Pacific halibut resource, which necessarily includes also an economic dimension.

3.2 Preparing 3-region benchmark SUTs

The model uses as a base the fisheries-focused multiregional social accounting matrix (MR-SAM) model developed by Seung et al. (2020) and describing the US economy in 2014, aggregated to the set of industries and commodities listed in Table 1, and three regions: Alaska (AK), USA West Coast (WC), and the rest of the USA (US).

Equation 4 presents the structure of the benchmark matrix constructed from MR-SAM that is used as an updating function input (X^0). It follows the structure of the matrix proposed in Eq. 1, but specifies regions considered in the model ($r, s = \{\mathrm{ak}, \mathrm{wc}, \mathrm{us}\}$) and separates three value added (VA) categories (employee compensation, proprietor income, other VA components). The final demand (FD) matrices consist of two types of FD, personal consumption expenditures (PCE) and other FD (FD^O).

Table 1 Industries and commodities in the SUTs

	Industry ($i \in I$)	**Primary commodity produced ($c \in C$)**
1	Pacific halibut fishing (AK only)	Pacific halibut landings (c1)
2	Other fish and shellfish fishing	Other fish and shellfish landings (c2)
3	Agriculture and natural resources extraction (excluding fishing)	Agriculture and natural resources (excluding fisheries resources) (c3)
4	Construction	Construction (c4)
5	Utilities	Utilities (c5)
6	Seafood processing	Seafood (c6)
7	Food manufacturing (excluding seafood)	Food (excluding seafood) (c7)
8	Manufacturing (excluding food manufacturing)	Manufactured goods (excluding food) (c8)
9	Transport	Transport (c9)
10	Wholesale	Wholesale (c10)
11	Retail	Retail (c11)
12	Services (including public administration)	Services (c12)

$$X^0 = \left[\begin{array}{ccc|ccc|ccc}
-S_{\mathrm{ak}} & 0 & 0 & 0 & 0 & 0 & S^d_{\mathrm{ak}} & 0 & 0 \\
0 & -S_{\mathrm{wc}} & 0 & 0 & 0 & 0 & 0 & S^d_{\mathrm{wc}} & 0 \\
0 & 0 & -S_{\mathrm{us}} & 0 & 0 & 0 & 0 & 0 & S^d_{\mathrm{us}} \\
\hline
U_{\mathrm{ak,ak}} & U_{\mathrm{ak,wc}} & U_{\mathrm{ak,us}} & \mathrm{FD}_{\mathrm{ak,ak}} & \mathrm{FD}_{\mathrm{ak,wc}} & \mathrm{FD}_{\mathrm{ak,us}} & -S^d_{\mathrm{ak}} & 0 & 0 \\
U_{\mathrm{wc,ak}} & U_{\mathrm{wc,wc}} & U_{wc,us} & \mathrm{FD}_{\mathrm{wc,ak}} & \mathrm{FD}_{\mathrm{wc,wc}} & \mathrm{FD}_{wc,us} & 0 & -S^d_{\mathrm{wc}} & 0 \\
U_{us,ak} & U_{\mathrm{us,wc}} & U_{\mathrm{us,us}} & \mathrm{FD}_{us,ak} & \mathrm{FD}_{\mathrm{us,wc}} & \mathrm{FD}_{\mathrm{us,us}} & 0 & 0 & -S^d_{\mathrm{us}} \\
\hline
U^M_{\mathrm{ak}} & 0 & 0 & \mathrm{FD}^M_{\mathrm{ak}} & 0 & 0 & 0 & 0 & 0 \\
0 & U^M_{\mathrm{wc}} & 0 & 0 & \mathrm{FD}^M_{\mathrm{wc}} & 0 & 0 & 0 & 0 \\
0 & 0 & U^M_{\mathrm{us}} & 0 & 0 & \mathrm{FD}^M_{\mathrm{us}} & 0 & 0 & 0 \\
\hline
\mathrm{VA}^L_{\mathrm{ak}} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & \mathrm{VA}^L_{\mathrm{wc}} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & \mathrm{VA}^L_{\mathrm{us}} & 0 & 0 & 0 & 0 & 0 & 0 \\
\hline
\mathrm{VA}^P_{\mathrm{ak}} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & \mathrm{VA}^P_{\mathrm{wc}} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & \mathrm{VA}^P_{\mathrm{us}} & 0 & 0 & 0 & 0 & 0 & 0 \\
\hline
\mathrm{VA}^O_{\mathrm{ak}} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & \mathrm{VA}^O_{\mathrm{wc}} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & \mathrm{VA}^O_{\mathrm{us}} & 0 & 0 & 0 & 0 & 0 & 0
\end{array}\right] \quad (4)$$

As the MR-GRAS technique requires the consistency of constraints, the original model's trade vectors need to be adjusted. See details in Supplementary data file 1: Table S1 of data file. In the model, fisheries production, including Pacific halibut harvest, is assumed to be supplying the seafood processing industry. This implies a broader scope of the processing sector that also includes product preparation and packaging. Under this assumption, harvested fish are sold to other industries or final users only as a seafood commodity.

3.3 Updating 3-region SUTs

This section demonstrates the adoption of the MR-GRAS technique for updating the multiregional SUTs described in the previous section using the most recent (2019 and 2020) national-level SUTs published by the US Bureau of Economic Analysis (BEA 2021b), complementary regional data on personal consumption and value added by state (BEA 2021c), data on trade in goods by US Census (2020) and fisheries-specific statistics.

First, the BEA tables are aggregated to the same industries and commodities as those listed in Table 1. BEA tables do not specify fisheries as a distinct industry. Fisheries statistics are used to reallocate fisheries production (supply), as well as input to the seafood processing sector, to align BEA tables with the MR-SAM model and incorporate more detailed information on the focus sector. Fisheries production, including landings of Alaskan Pacific halibut, is sourced from commercial fisheries landings database (NOAA 2020).

There is also a mismatch in the allocation of beverages and tobacco production. BEA uses aggregate *Food and beverage and tobacco products*, while MR-SAM includes beverages and tobacco join with other manufacturing products. To accommodate this, the constraints on use and value added by region combine all manufacturing industries (industries 6–8). National supply table is aligned with MR-SAM supply tables using supplementary table *Gross Output by Industry - Detail Level* (BEA 2021a).

MR-GRAS technique is applied to the MR-SAM model (i.e., the matrix in Eq. 4) using the following aggregation constraints built using data for 2019 and 2020:

1 Supply matrices (S_r), summed elementwise and with merged columns for industries 1–3 and 6–8 must equal BEA-derived supply matrix with the same industries merged (S). Production of fisheries commodities derived from fisheries statistics is assigned to the column describing industries 1–3 in aggregate, and production of manufactured commodities is assigned according to supplementary supply data to the column describing industries 6–8 in aggregate.
2 Domestic and foreign use matrices (all $U_{r,s}$ and U_r^M matrices), summed elementwise and with merged columns for industries 1–3 and 6–8 and merged rows for manufactured commodities must equal BEA-derived domestic and foreign use matrix with the same industries and commodities merged (U^d and U_r^M). As fisheries production is assumed to be supplying the seafood processing industry, the fisheries sector's output can be assigned directly as input to production by domestic manufacturers.
3 Final demand matrices (all $\mathrm{FD}_{r,s}$ and FD_r^M matrices), summed elementwise and with merged manufactured commodities (c6–8) must equal the BEA-derived final demand matrices with the same commodities merged (FD^d and FD^M). Note that FD for fisheries commodities is zero by design.
4 Value added matrices (all VA_r^L, VA_r^P and VA_r^O) are included in the same form as in the benchmark matrix with the exception of industries that have to be aggregated to align with BEA-supplied data. Value added components (derived from BEA tables SAGDP2, SAGDP4, and SAINC5) are aggregated for industries 1–3 and for industries 6–8. VA matrices with aggregates are marked with stars (*).
5 Diagonals of the S_r^d matrices summed elementwise must equal BEA-derived vector of supply by commodity (diagonal of S^d). S^{*d} is S^d matrix adjusted for aggregation of commodities in U^d and FD^d.

Equation 5 represents the structure of the final aggregation constraints matrix. The full aggregation matrices are available in the Additional file 1: S2 tab.

$$\boldsymbol{W^1} = \begin{bmatrix} -S & 0 & S^d \\ U & \mathrm{FD} & -S^{*d} \\ U^M & \mathrm{FD}^M & 0 \\ \mathrm{VA}_{\mathrm{ak}}^{*L} & 0 & 0 \\ \mathrm{VA}_{\mathrm{wc}}^{*L} & 0 & 0 \\ \mathrm{VA}_{\mathrm{us}}^{*L} & 0 & 0 \\ \mathrm{VA}_{\mathrm{ak}}^{*P} & 0 & 0 \\ \mathrm{VA}_{\mathrm{wc}}^{*P} & 0 & 0 \\ \mathrm{VA}_{\mathrm{us}}^{*P} & 0 & 0 \\ \mathrm{VA}_{\mathrm{ak}}^{*O} & 0 & 0 \\ \mathrm{VA}_{\mathrm{wc}}^{*O} & 0 & 0 \\ \mathrm{VA}_{\mathrm{us}}^{*O} & 0 & 0 \end{bmatrix} \tag{5}$$

MR-GRAS technique is applied to the original model using the following row and column constraints built based on data for 2019 and 2020:

1 Per model structure, rows of the first row section of X^0 sum to zero.
2 The sum of rows of the second and third row section must equal negative export vectors, and import vectors, respectively, derived from state-level statistics on trade. By fisheries product definition adopted here, the export and import of commodities c1–2 is zero.
3 The sum of rows of the fourth to sixth row sections must equal vectors with value added components by region. No row constraints are applied for rows containing VA related to aggregated industries. These are derived from aggregation constraints defined in W^1 matrix.
4 Per model structure, columns of the first and third column sections of X^0 sum to zero.
5 In the second column section of X^0, the first column of final demand by each region sums to the final demand by households. These are reported by state in BEA's table SAEXP1.

Constraints on row (vector u) and column (vector v) sums are summarized by Eqs. 6 and 7:

$$\boldsymbol{u} = \left[\, 0_{[3C]} \;\; -E_{[3C]} \;\; M_{[3C]} \;\; \mathrm{VA}^{L}_{[3I]} \;\; \mathrm{VA}^{P}_{[3I]} \;\; \mathrm{VA}^{O}_{[3I]} \,\right], \tag{6}$$

$$\boldsymbol{v} = \left[\, 0_{[3I]} \;\; \mathrm{PCE}_{\mathrm{ak}} \;\; \mathrm{FD}^{O}_{\mathrm{ak}} \;\; \mathrm{PCE}_{\mathrm{wc}} \;\; \mathrm{FD}^{O}_{\mathrm{wc}} \;\; \mathrm{PCE}_{\mathrm{us}} \;\; \mathrm{FD}^{O}_{\mathrm{us}} \;\; 0_{[3C]} \,\right]. \tag{7}$$

The output matrix is also adapted to accommodate specific fisheries-related data. Fisheries production statistics are used to constraint the supply of commodities 1 and 2. This is done by setting diagonals of subsection S^d_r of matrix X^0 for commodities 1–2 to zero and fixing the sum of rows related to fisheries output to negative reported fish production. Adopting this constraint requires also adjusting W^1 for consistency.

The updated matrices for 2019 and 2020 are derived using benchmark matrix X^0 and described constraints using the iterative algorithm proposed by Temursho et al. (2020).

3.4 Results

The structure of the updating output (X^{2019} and X^{2020}) is the same as the structure of the X^0 matrix. Imposing consistent structure of the regional SUTs results in minimal mismatch between regional supply and use in the projected matrix. Mean absolute difference amounted to USD 0.03 million for 2019 and USD 0.08 million for 2020. In comparison, mean absolute difference between regional supply and use estimated without imposing consistent structure of the regional SUTs was USD 10,738 million, or on average 1.03% total supply for 2019. For 2020, it was USD 14,926 million and 1.47%.

Table 2 compares results for Pacific halibut fishing in Alaska derived from social accounting matrices built from the updated SUTs. Since Pacific halibut is managed using fisheries limits, the economic impact is estimated using a supply-driven approach (Leung and Pooley 2002), using method developed by Tanjuakio et al. (1996). The results suggest considerable decrease in the Pacific halibut's economic contribution to the United States' economy from 2019 to 2020.

Table 2 Comparison of results derived from updated matrices

	Model for 2019	Model for 2020	% change
Pacific halibut landings [mil. USD]	94.1	66.6	− 29
Economic impact [mil. USD]	325.2	224.1	− 31
In Alaska only [mil. USD]	188.4	132.3	− 30
Multiplier effect - economic impact per 1 USD of Pacific halibut landings	3.46	3.36	− 3

4 Discussion and conclusions

This paper presents a modification of the MR-GRAS method that is making the best use of typically available regional statistics, while guaranteeing consistent structure of the output matrix. The proposed framework focuses on updating regional SUTs when detailed regional statistics are available for components related to the calculation of the GDP, that is final demand and value added, as well as trade. This is a common situation for the analyst to come across. At the same time, the output of the proposed approach guarantees the identity of GDP by income and GDP by expenditure at the regional level. This is a notable advantage as supply–use accounting balance is necessary for deriving any meaningful economic impact assessment estimates.

The paper also offers an elaborate example of updating SUTs for calculating economic impacts at the regional level. While the IPHC's focus is establishing harvest limits that permit the optimum yield from the fishery and maintain the stock at the sustainable level, understanding the human dimension is part of its optimum management of the natural resource.

Few important points regarding the MR-GRAS technique and its potential for informing decision-making need to be noted. First, when adopting exhaustive constraints, that is applying a full set of row, column and aggregation constraints, all constraints have to be mutually consistent and consistent with the benchmark input matrix. In case of discrepancies between sources, it is an analyst's decision what component to adjust instead of the algorithm finding the most efficient solution. Second, the algorithm is only applicable to the cases with non-overlapping aggregation constraints, that is the disaggregated item can be a part of only one aggregated set. While this type of setup represents a prevalent situation the analyst may come across, overlapping and possibly conflicting constraints require adopting an alternative methodology, for example the KRAS (Lenzen et al. 2009) or general-purpose constrained optimization solver. Third, MR-GRAS sign-preserving property should be carefully considered when applying the method. Shifts between positive and negative values may occur from year to year. If such transition or fluctuations are expected, redefining variables may be the best option. For example, one may consider separating taxes and subsidies instead of adopting net tax to guarantee that the signs match.

Abbreviations

BEA	US Bureau of Economic Analysis
FD	Final demand
GDP	Gross domestic product

GRAS	Generalized RAS
IPHC	International Pacific Halibut Commission
MR-GRAS	Multiregional generalized RAS
PCE	Personal consumption expenditures
MR-SAM	Multiregional social accounting matrix
SUTs	Supply and use tables
VA	Value added

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s40008-022-00274-8.

Additional file 1. See details in Supplementary data file, tab S1.

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Author contributions
The author confirms sole responsibility for the following: study conception and design, data collection, analysis and interpretation of results, and manuscript preparation. The author read and approved the final manuscript.

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