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An integrated biophysical-ecological assessment of embedded virtual water flows linked to Israel's consumption of agricultural crops

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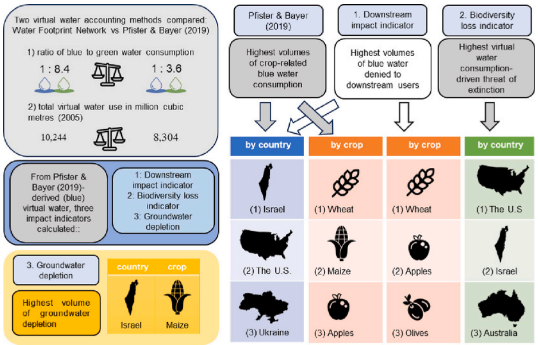
HIGHLIGHTS

- Virtual blue water and water denial volumes can be inconsistent with each other
- Water denial, biodiversity loss and groundwater depletion tend toward consistency
- We delineate regions and watersheds with multiple, overlapping impact hotspots
- Assessment indicates global water consumption databases must converge methods
- Wheat sourcing represents low-hanging fruit of sustainable virtual water consumption

GRAPHICAL ABSTRACT



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ABSTRACT

As populations and affluence grows, increased demand for food drives a concomitant increase in associated water scarcity. A relative and absolute increase in crop-embodied virtual water traded between countries is a geopolitically important component of this scarcity. In addition to biophysical dimensions, blue water consumption can have varying impacts on humans and biodiversity. This study focuses on virtual water trade relating to consumption of crops and crop products, and its related socio-ecological impacts, in a water scarce country with high reliance on virtual water, Israel. The results of two established methodologies are assessed, in calculating consumption associated with the virtual water trade of up to 100 crops. Using virtual water quantifications from the methodology with higher spatial resolution, together with two complementary sets of characterisation factors from life cycle impact assessment methodologies (water scarcity indices and potential disappeared fractions) a novel comparison of impacts on ecosystems relating to loss of species and water denial is facilitated. As an additional impact indicator, groundwater depletion is calculated for the virtual water trade of a narrower set of crops. Israel's crop production was found to be associated with outsized cumulative blue water consumption

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volumes, relative to imports. In addition, regional and country hotspots of blue water consumption, groundwater depletion, downstream user impact and biodiversity loss were identified, including in India, The United States, and the Mediterranean region. Several limitations and suggestions for future application are discussed.

Abbreviations

Acronym	Description
BIV	Biodiversity Impact Value
BW	Blue water
GW	Green water
GWD	Groundwater depletion
MCM	Million cubic metres
PB-BW/GW	Blue water/green water, volumes thereof calculated with the use of water consumption rates sourced from Pfister and Bayer (2019)
PDF	Potential Disappeared Fractions (of species)
SIV	Stress Impact Value
WFN-BW/GW	Blue water/green water, volumes thereof calculated with the use of water consumption rates sourced from Mekonnen and Hoekstra (2011), available on the Water Footprint Network website
WSI	Water Stress Index

1. Introduction

Agriculture is the largest source of water consumption and withdrawal globally, responsible for approximately 60 % of all freshwater withdrawals by 2015 (Wu et al., 2022). There has been a growth in demand for food, and its concomitant trade, over the last few decades. In lockstep with demand growth has been an increase in freshwater withdrawals for irrigation, which increased seven-fold over the course of the 20th century (Gleick, 2000), with water use predicted to grow at approximately 1 % annually until 2050 (UNESCO and UN-Water, 2023). Recent decades have seen an increase in groundwater depletion (GWD), defined as abstraction of groundwater exceeding recharge over time, with GWD having increased by 22 % over a ten-year period, between 2000 and 2010 (Dalin et al., 2017).

An increase in international trade entails that consumption of food products is increasingly associated with distant impacts from unsustainable water withdrawals (Vorosmarty et al., 2015). Roughly one-fifth of the total global water footprint between 1996 and 2005 was attributed to traded goods, with this effective trade of water embodied in goods referred to as virtual water trade (Hoekstra and Mekonnen, 2012). While bottom-up, agricultural commodities-focused water footprint accounting approaches of quantifying virtual water flows designate approximately three-quarters of flows to the agriculture sector (see Hoekstra and Mekonnen, 2012), multi-regional input-output approaches that cover all sectors in detail typically designate lower proportion of shares attributable to the agricultural sector (see Arto et al., 2016; Feng and Hubacek, 2015; Lenzen, 2009; Tukker et al., 2014 for regional and multi-country examples). A large share of blue water is exported from water scarce areas, even as global virtual water trade helps to reduce water scarcity overall (Weinzettel and Pfister, 2019). While international food trade accounted for 11 % of GWD overall in 2010, much GWD occurred in major food-producing regions and global population centres (Dalin et al., 2017). Thus, blue water consumption in general, and GWD in particular, poses potential food and water security risks in producer and importer countries, requiring strategies to reduce dependence on irrigation in water scarce regions.

Recent research exploring the links between trade in food products, crop water consumption, and insecurity of water supplies have, for example: explored the dependence on, and associated vulnerability to water risks of, virtual water imports (Alexoaei et al., 2021); estimated future interregional trade of virtual water water embedded in agricultural products (Graham et al., 2020); and demonstrated the necessity of considering both green and blue water supplies under climate change and population growth (Rockström et al., 2009). Such studies calculate virtual water consumption associated with crop products, which use methodologies incorporating spatially explicit global cropping datasets (Anderson et al., 2015). While some, such as the M3 approach by Monfreda et al. (2008), have a wide coverage of crops, others such as the Monthly Irrigated and Rainfed Crop Areas around the year 2000 (MIRCA) (Portmann et al., 2010) differentiate between irrigated and rainfed production areas.

While water sustainability is often discussed in the context of freshwater provisioning for agriculture, the related diversion of precipitation and the use of surface- and groundwater has detrimental effects on both communities in water stressed regions and biodiversity in both freshwater and on land (IPBES, 2019; Jemmali and Sullivan, 2021). Where plant communities are water-limited, blue water withdrawals can diminish green water supply to plants, with knock-on effects up the food chain (Falkenmark, 2001). The more arid an ecosystem is, the more water quantity represents a limiting factor to biodiversity, with associated biodiversity adapted to low but consistent water availability regimes (Harvey et al., 2007). As an aspect of blue water use, GWD has several impacts, including the water scarcity impacts of depleted aquifers, pauperisation of groundwater-dependent ecosystems, land subsidence and soil salinisation through saltwater intrusion (Aeschbach-Hertig and Gleeson, 2012; Giordano, 2009; Konikow and Kendy, 2005; Sophocleous, 2000).

Notably, Israel can be said to be water secure in that large-scale reuse of wastewater and desalination of seawater, along with national-scale water conveyances and effective regulatory and price signals, have allowed for secure supply while reducing overexploitation of freshwater resources (Marin et al., 2017). To illustrate, in 2016 Israel collected and treated 650 million cubic meters (MCM) of its wastewater and reused 88 % of this stock for irrigation, accounting for approximately 45 % of total irrigation (Fridman et al., 2021a). Though Israel has used water technologies to abate water stress, its current water mix is associated with relatively higher operational costs, higher carbon footprint, and unquantified environmental and health impacts of wastewater reclaimed for irrigation (Becker et al., 2010; Fridman et al., 2021a; Tal, 2018). Thus, by 2016 marginal water accounted for a full 60 % of water consumption for agricultural production (Israeli Water Authority, 2019). Yet, Israel's blue water consumption comprises at least 50 % of its virtual water flow, in contrast to most countries, wherein green water consumption recently accounted for over 90 % of virtual water flows (Shtull-Trauring and Bernstein, 2018; Yang et al., 2006). Crops are associated with varying rates of water consumption and a variety of factors introduce spatial variation in the rate at which water is consumed to produce a standard quantity of harvested crop, including climatic factors, soil type and yields (Mekonnen and Hoekstra, 2011). To capture these factors, several methodologies deriving watershed-, region- and country-specific water consumption rates per ton of crop have been developed. Such methodologies are underpinned by various spatially explicit global cropping datasets, including the aforementioned. The contexts within which they are applied include agriculture-specific water accounting at the sub-national to regional scale i.e., the attribution of green and blue water, and GWD to the growth of specific crops and crop products, as well as to virtual water trade. There have been a few studies surrounding Israel and impacts of its virtual water trade, including: a calculation of crop-specific greenhouse gas emissions associated with the transport of irrigation water (Smolka et al., 2023); an association of the national food supply to soil loss and water availability (Fridman et al., 2021b); and a multiscale analysis of Israel's food supply, including the impact of cropland footprints on species loss (Fridman and Kissinger, 2019). The last of these found that approximately 85 % of overall cropland and calories associated with Israel's food consumption are imported. Some studies have applied a global analysis to terrestrial ecosystem effects of food consumption (Chaudhary and Kastner, 2016; Fridman et al., 2021b) and methods are emerging to link virtual water with terrestrial- and freshwater-related ecosystem impact (see Sandström et al., 2017). Fridman and Kissinger (2019) showed that Israel's food imports exert some degree of impact on biodiversity in exporter countries: deriving species loss from cropland footprint using a method developed by Chaudhary and Brooks (2019), the authors calculated the import-related impact of approximately 0.034 species annual extinctions per ecoregion.

In recent years, novel Life Cycle Assessment-based methodologies that examine biodiversity loss embodied in traded goods have been developed, including through virtual water trade. Two such studies include one focused on water stress concerning generalised ecosystem and human users (Scherer and Pfister, 2016), and another on a combination of aquatic animal and terrestrial plant species (Verones et al., 2020). While using the former gives a generalised account of downstream impact on humans and/or ecosystems, the latter produces an outcome relating to biodiversity loss in two habitat types broadly representative of ecosystems, specifically in terms of probabilities of species loss. Used in tandem, they identify hotspots complementarily.

Sustainability indicators that are often employed in an interregional context, such as those pertaining to virtual water trade, tend to focus on either biophysical or ecosystem aspects and as such, fail to create a holistic and interconnected model of water consumption and the implications thereof (Fridman and Kissinger, 2018). In addition, ecosystem assessments often do not integrate, fully or at all, interregional flows of ecosystem services, one form of which are embodied by traded goods (Pascual et al., 2017).

Methods to combine virtual water trade, and socio-ecological impacts, have not been sufficiently found in the literature. Following the work of Fridman and Kissinger (2018), which focused on the ecosystem disservice of soil loss as a function of agricultural yield and associated water intensity, this study combines a biophysical and an ecosystem approach surrounding Israel's consumption - imports, plus production for local consumption. Thus, Israel serving as a case study of a semi-arid to arid country with relatively high population growth rate projections and water scarcity, despite high water security. Regarding the biophysical dimension, green water (GW) and blue water (BW) consumption are quantified in a spatially explicit manner, through the application of two global water inventory databases, each derived using differing methodologies, as developed: by Pfister and Bayer (2019); and by Mekonnen and Hoekstra (2011), commonly referred to as the Water Footprint Network (WFN) database. Specifically, countries and water-intensive crops that may be depleting blue water stocks are identified, as are watersheds that have high reliance on blue water in relation to green water. Regarding an ecosystem aspect, crop blue water consumption results are used to calculate: spatially explicit impact on: downstream human and ecosystems users (downstream impact indicator); and a set of biodiversity taxa (biodiversity loss indicator) - in exporter countries and in Israel. This is achieved using two methods that fall under the procedure of life cycle impact assessment (LCIA) (International Organization for Standardization, 2006). Lastly, a spatially explicit quantification of GWD – derived directly from production statistics, without requiring blue water consumption values – caused by a narrower range of crops, constitutes a third indicator.

2. Methods

As first step in this study, relating to a biophysical dimension, the virtual water consumption of crop imports and domestic crop production for Israel's final demand were quantified using two databases: Pfister and Bayer (2019) and Mekonnen and Hoekstra (2011). As a second step and relating to an environmental dimension, one set of consumption volumes – calculated from Pfister and Bayer (2019) - were processed to produce two indicators, a downstream impact indicator (stress impact value) and a biodiversity loss indicator (biodiversity impact value). In addition, a third indicator in the environmental dimension, groundwater depletion (GWD), was calculated directly from crop production (Fig. 1). The study combines a variety of heterogenous data sources relating to quantities of produced and traded crops, associated crop-specific rates of water use, and characterisation factors to calculate ecosystem and biodiversity loss indicators of water use. Temporal coverage varies across datasets and spatial resolution harmonised to 5 arc minutes, or approximately 10 km at the equator (Table 1).

2.1. Production and virtual water consumption datasets

To provide more accurate and detailed information about agricultural production at the local or regional level, the spatial production allocation model (SPAM) (You et al., 2009) was used in Fridman and Kissinger (2018, 2019) to downscale Israel's import and domestic production flows into crop production maps at 5 arc minute resolution, based on relative production weights. It is re-used here. This primary crop production dataset represents the year 2005, the most recent year for which such national data had been generated by the time of analysis. It consists of bilateral trade and production data relating to 142 FAO crops, plus 239 processed products. An origin-tracing algorithm assigned supply flows to the original countries of production (including domestic flow from within Israel), with conversion of processed products and livestock products to primary crop equivalents (hereafter referred to as crops), as described in detail in Fridman and Kissinger (2018) and Kastner et al. (2014), Kastner et al., 2011).

From this refined dataset, production data selected for the purposes of this study consist of 100 crops, as they relate to Israel's consumption of all major crops. Using the raster calculator function in ArcGIS (ESRI Inc., 2024), spatially explicit production data (in tonnes) was multiplied by rates of green and blue water consumption of primary crop equivalent in million cubic meters (MCM) per tonne – from each of the two virtual water databases in turn - to derive blue- and green water consumption volumes by crop-country.

Two virtual water databases, developed by Pfister and Bayer (2019) and Mekonnen and Hoekstra (2011), are applied to spatially explicit production data concerning Israel's consumption of crop products, to assess Israel context-specific volumes of virtual water consumption. Both incorporate blue and green water consumption and use globally collected data, and both by necessity exclude the contribution made by relatively well-developed non-freshwater sources in Israel's agriculture sector.

The database (Pfister and Bayer, 2019) of blue and green water consumption rates are at watershed scale, which most closely matched with higher resolution gridded production data. Thus, it is used as the primary database to calculate both virtual water consumption volumes and biodiversity loss and downstream impact indicators, with the text referring to PB-BW (Pfister and Bayer (2019) database-derived blue water) and PB-GW (Pfister and Bayer (2019) database-derived green water) volumes. The water consumption rates in Pfister and Bayer (2019) are derived from the calculation of crop and crop group monthly irrigation water consumption, with the irrigation requirement model CROPWAT underlying their methodology (Smith, 1992). Yield values from the year 2000, sourced from Monfreda et al. (2008), are applied to derive this water consumption.

A second water consumption rates database is sourced from Mekonnen and Hoekstra (2011) which models the green, grey, and blue water consumption of 146 primary crops, as used by the Water Footprint Network, a multi-sector collaboration advancing sustainable water use. The authors used the period 1996 to 2005 at the scale of global crop production to inform parameters. The primary underlying model of crop growing areas used originates from Monfreda et al. (2008), with the MIRCA2000 grid database used to fill gaps (Portmann et al., 2010). Water consumption rates are given for regions divided into subnational

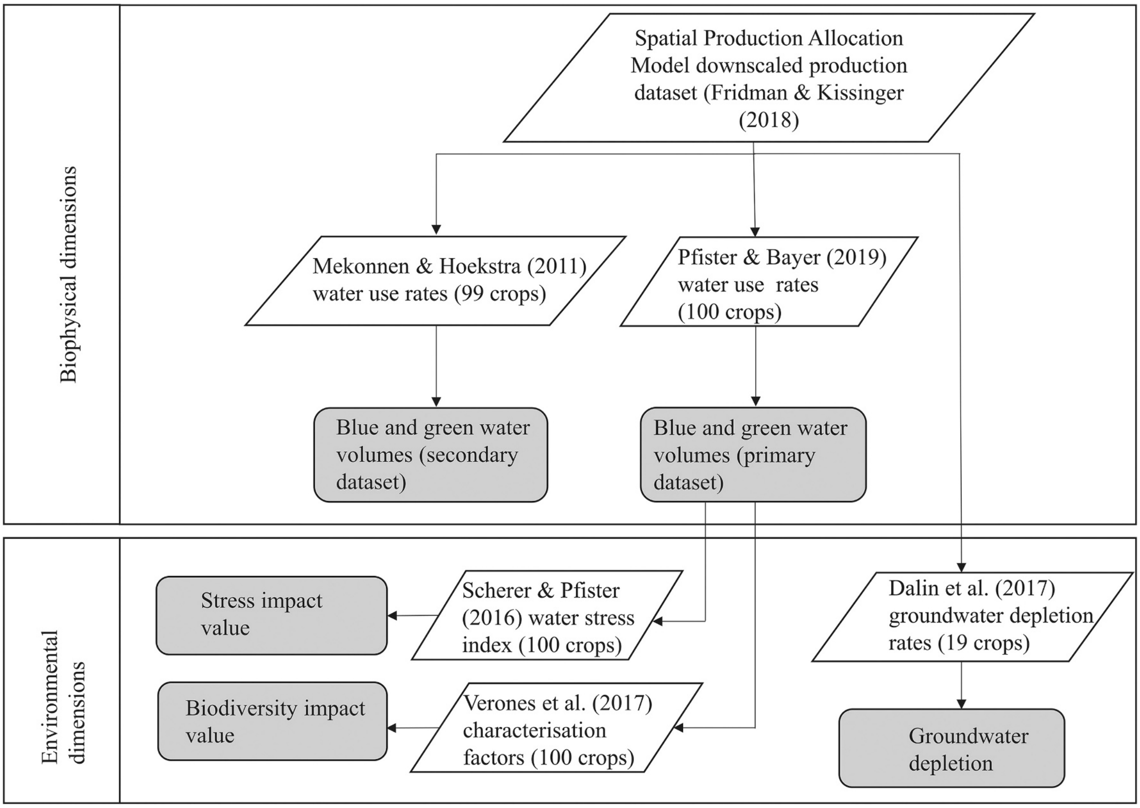

Fig. 1. Flow diagram of the methodological steps of this study, including datasets used as inputs (clear fill), and final outputs (grey-shaded fill). 'Blue and green water volumes (primary dataset)' acts as both input to calculate two indicators within the environmental dimension, and output relating to biophysical virtual water volumes embedded in consumed crops. Studies relating to relevant datasets are referenced.

Table 1
Summary of methods and characteristics thereof, listed by dimension.

Dataset	Spatial coverage & resolution	Temporal resolution	Underlying models & methodologies	Sources
Biophysical dimension				
Israel's crop production & consumption data	Israel & exporter countries; 5 arc minutes	2005	Spatial Production Allocation Model (SPAM); WaterStat; Mekonnen and Hoekstra (2011)	Fridman and Kissinger (2018), Personal Communication
Crop water consumption rates (160 crops/ crop groups), Pfister-Bayer blue water / green water (PB-BW/PB-GW)	Global (watershed level, >11,000 watersheds); 5 arc minutes	2000	CROPWAT	Pfister and Bayer (2019), accessed 03 January 2022
Crop water consumption rates, Water Footprint Network blue water / green water (WFN-BW/WFN-GW)	Global; 5 arc minutes (country level)	1996–2005	CROPWAT; Monfreda et al. (2008)	Mekonnen and Hoekstra (2011)
Ecosystem & biodiversity loss dimension				
Crop-specific groundwater depletion (GWD)	Global; 30 arc minutes (available only per country)	2000	MIRCA2000; PCR-GLOBWB 2.0	Dalin et al. (2017), Supplementary Table 1 (year 2000)
Stress Index Value (SIV)	Global; 5 arc minutes	2001–2010	CROPWAT; Life Cycle Impact Assessment (LCIA)	Scherer and Pfister (2016)
Biodiversity impact value (BIV) as fraction of potential species extinctions/m^3 of water consumed (PDF)	Global; 30 arc minutes	N/A	LCIA	Verones et al. (2020), http://www.lc-impact.eu/. Water stress shapefiles b) ecosystem quality. Accessed 19 July 2022.

political administration units (such as states and provinces), amounting to a global total of approximately 3000 units, as well as for country averages. As political units are incomparable with natural watersheds, country averages were chosen here (as opposed to the watershed scale for the Pfister and Bayer (2019) database), to calculate final blue and green water volumes at country level. In providing a likewise assessment, results of watershed volumes from calculations using the Pfister and Bayer (2019) database were totalled to country level.

The Mekonnen and Hoekstra (2011) database-derived blue and green water volumes are referred to as WFN-BW (blue water) or WFN-GW (green water), with WFN referring to the Water Footprint Network, a recognisable source which provides a standardised framework for calculating water footprints underlain by the methodology and datasets in Mekonnen and Hoekstra (2011). Under this schema, data was available for 99 out of all 100 crops used in the PB-BW/GW schema. For details of the process used to match crop names between methodologies, and with Food and Agricultural Organization (FAO) database crop names and codes, see table A.1.

2.2. Environmental dimension indicators

2.2.1. Downstream impact indicator

Life Cycle Impact Assessment (LCIA), a methodological step within Life Cycle Analysis, assesses environmental impacts of an inventory (the flows of materials and energy), including in specific impact categories such as water-use related impacts. Water Scarcity Indices (WSIs) are used within LCIA to quantify water stress (the ratio of freshwater withdrawals to hydrological availability) experienced by societies as well as ecosystems in a spatially explicit manner.

The first of two datasets used in this study employs WSIs updated by Scherer and Pfister (2016) from those developed by Pfister and Bayer (2014), to derive impacts of virtual water abstraction on downstream ecosystem and human users. Updates include a distinction between surface and groundwater fractions and a more recent base period (Scherer and Pfister, 2016). WSI, ranging between 0.01 and 1, acts as a characterisation factor for application within the midpoint category "water deprivation" in LCIA. This factor is multiplied against actual water use volumes to represent the impact of water scarcity on actual water consumption, in terms of denial thereof.

WSI was calculated globally for two decades by Scherer and Pfister (2016), of which we utilise WSI data for the decade 2001–2010 to match most closely with existing datasets. Data from Monfreda et al. (2008) informed the crop yields and areas underpinning production values in formulating WSI values. In this study, at the scale of 5 arc minutes for unique values, WSI values are multiplied with PB-BW water consumption volumes of all crops in ArcGIS, to derive what is referred to here as Stress Impact Values (SIV). These values are expressed in MCM of blue water deprived of downstream human and ecosystem users. In simple terms, without the presence of agriculture, human activities and natural ecosystems would typically have the quantity of blue water equating to SIV available for use.

2.2.2. Biodiversity loss indicator

The second dataset pertains to LC-Impact, a European Union-funded project that produced a global scale LCIA methodology applicable to the protection of human health, ecosystems, and resources in relation to freshwater consumption (Verones et al., 2020). Regarding water stress in ecosystems, a spatially differentiated approach entails multiplying water use volumes against characterisation factors representing water consumption-driven loss of species. Species loss is divided into animal taxa in surface water- and groundwater-fed wetlands, and terrestrial vascular plants (based on precipitation). These taxa represent proxies for aquatic and riparian ecosystems, and terrestrial ecosystems, respectively, and capture the two general ways in which the water cycle and ecosystems interact.

These biodiversity loss-based characterisation factors are expressed as potential disappeared fraction (PDF) or potential species loss in a year, per cubic metre of water consumed in that year. Thus, spatially explicit values of characterisation factors (in PDF per cubic metre) were multiplied by PB-BW derived water consumption volumes (in cubic metres) associated with Israel's consumption in a single year, at the 5-arcminute scale in ArcGIS, to derive what is referred to as Biodiversity Impact Value (BIV), expressed in units of potentially disappeared fraction of species (PDF) at 5 arc minutes, pertaining to the year under study, 2005.

2.2.3. Groundwater depletion

Groundwater depletion (GWD) captures indirect risk to human societies and to groundwater-fed ecosystems. Here, the results of a methodology devised by Dalin et al. (2017) are utilised, whereby the authors derived the GWD embedded in a set of internationally traded crops. GWD characterises the volume of groundwater abstracted in excess of irrigation return flows and natural recharge rates (Dalin et al., 2017). They derived crop-specific GWD intensities for two years of comparison, using the PCR-GLOBWB global hydrology and water resources model, expressed in litres per kilogram of crop product. In this study, GWD intensities at country-level for the year 2000 (to match with the PB-BW/GW datasets) are multiplied with the same crop production data as described above, for 19 crops, to derive GWD volumes associated with each relevant crop-country combination pertaining to Israel's virtual water consumption (ESRI Inc., 2024).

3. Results

3.1. Virtual water consumption

3.1.1. Primary database calculated-consumption

For production of all crops associated with Israel's consumption for the baseline year 2005 (see fig. 2a) a total of 1806 MCM Pfister and Bayer, 2019 database-derived blue water (PB-BW) and 6498 MCM Pfister and Bayer (2019) database-derived green water (PB-GW) was used at an approximate ratio of 1:3.6 of blue to green water. For the share of blue water (Pfister and Bayer (2019) schema), as a percentage of total (blue and green water) by watershed, for the three highest blue water consuming crops, see fig. B.1. The origins of virtual blue water are spread across the globe, concentrating in Europe and Eurasian regions bordering Europe, in India, with less dense concentrations in North and South America and at highest density in Israel (Fig. 2b). For maps relating to cumulative PB-BW volumes at grid-cell and watershed level respectively, see figs. B.2–3.

Israel's production for local consumption accounts for 1044 MCM or approximately 58 % of PB-BW consumption across all crops (cumulative) – this stands in contrast to the share of Israel's production in tonnes, which stood at 36 %. Share of PB-BW consumption across all crops is followed by the United States and Ukraine, with a 12 % and 7 % share, respectively. 762 MCM or approximately 42 % of PB-BW consumption is taken up by imports is lower than the imported blue water values calculated by Shtull-Trauring and Bernstein (2018), which range from 905 to 1017 MCM/year using two local and two global datasets. Here, the authors used a production quantity dataset as input, ranging from 2007 to 2012, and thus the growth in imports since the 2005 base year this study uses, would account to some degree for this difference.

The seven crops with highest virtual blue water consumption across all watersheds, were from highest, wheat, maize, apples, olives, soybeans, sunflowers, and peaches together with nectarines. For a full list of the PB-BW volumes and associated ranking of all crops under study across all watersheds, see table A.2. As the dominant crop, wheat comprised 22 % of total PB-BW consumption, approximately the same share of total tonnage production. Maize was next dominant, at a 7 % share of PB-BW consumption, with roughly twice as high a share of total production. Wheat and maize are associated with watersheds highly reliant on blue water in Russia and China, respectively.

In addition to production quantities, PB-BW volumes (in MCM) can also be compared with water consumption rates (in cubic metres per tonne (m^3/t) of crop) for PB-BW (Fig. A.1). Water consumption rates are helpful in comparing the intensity of blue water consumption per fixed weight of crop among watersheds, while PB-BW volumes indicate the relative importance for total consumption in Israel. Concerning those watersheds with the highest blue water volumes, the water consumption rates of maize, peaches and nectarines, and wheat are high, while those of apples, olives and sunflower seeds are middling, and that of soybeans (Brazil) is low.

A distinct set of watersheds across exporting regions are shown to be the heaviest users of blue water across up to three high blue water consuming crops per watershed, while it is only in Israel that four or more of these crops with high blue water consumption are associated with single watersheds (Fig. 3). In this case, the watershed IS39269 represented the only watershed associated with six such crops. The U.S.

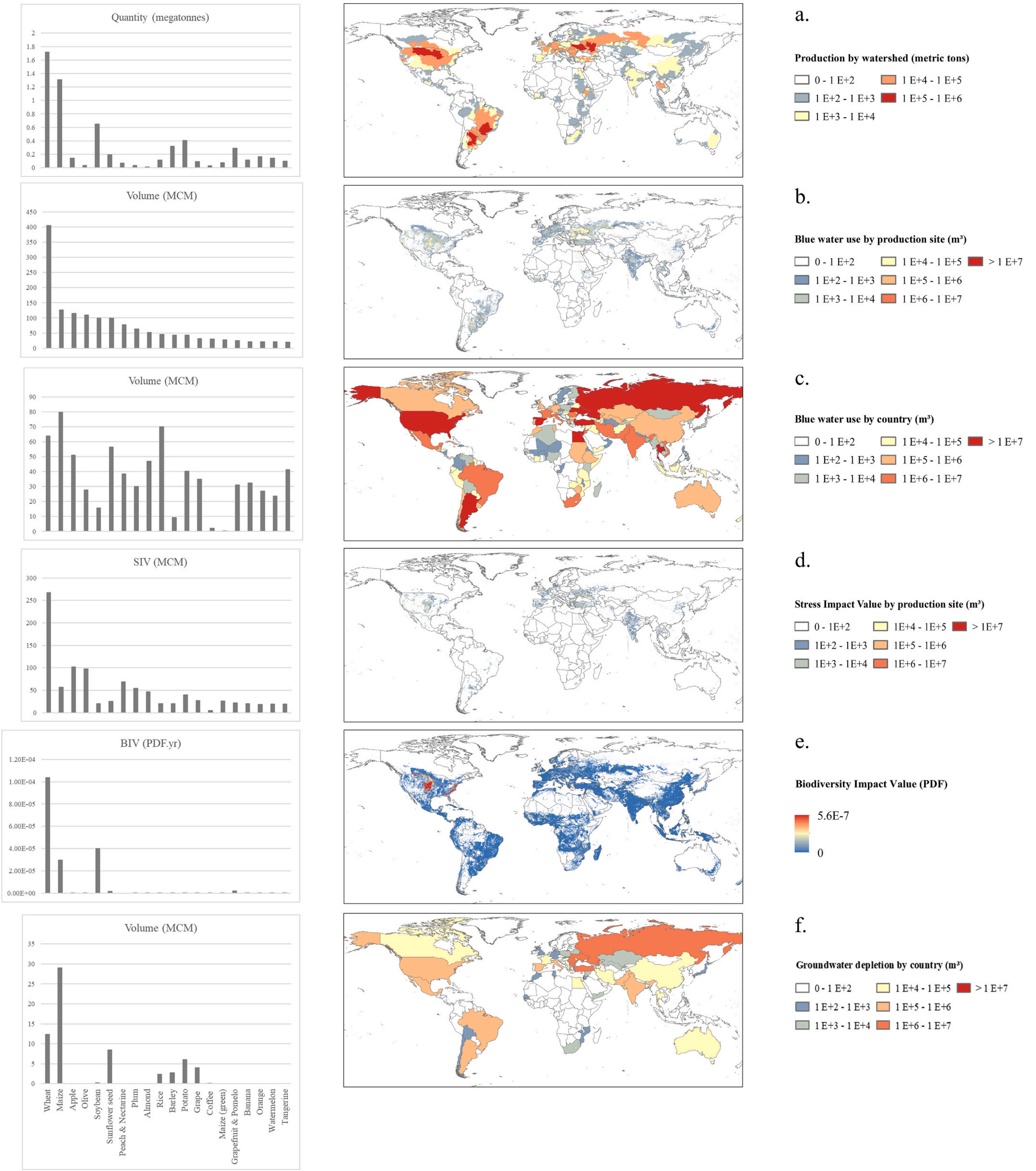

Fig. 2. A comparison of methodological process outputs used to describe biophysical (2a – c), as well as environmental (2d – f) dimensions pertaining to this study. Graphs on the left describe the values associated with the top 20 blue water using crops (as derived from Pfister and Bayer, 2019 dataset). Global-scale figures on the right are expressed either on country or fine-scale level, depending on the spatial resolution of the associated data. a) Production by watershed, for Israel's consumption across all crops (using SPAM data from Fridman and Kissinger (2018)). Quantities of top 20 crops in megatonnes. b) Blue water consumption (derived from Pfister and Bayer (2019) dataset) at site of global crop production (PB-BW), for Israel's consumption across all crops. Volumes of top 20 crops in million cubic metres (MCM). For country scale, see supplementary information. c) Blue water consumption (derived from the Mekonnen and Hoekstra (2011) dataset) by country (WFN-BW), for Israel's consumption across all crops. Volumes of top 20 crops in million cubic metres (MCM). d) Stress Impact Value (SIV) at site of crop production, for Israel's consumption across all crops. Volumes of top 20 crops in million cubic metres (MCM). e) Biodiversity Impact Value (BIV), expressed in potential disappeared fractions over a year for the water consumption in 2005 (PDF), for Israel's consumption across all crops. Impacts of top 20 crops in potentially disappeared fractions (PDF). f) Groundwater depletion (GWD) by country, for Israel's consumption across all crops. Volumes of top 20 crops in million cubic metres (MCM).

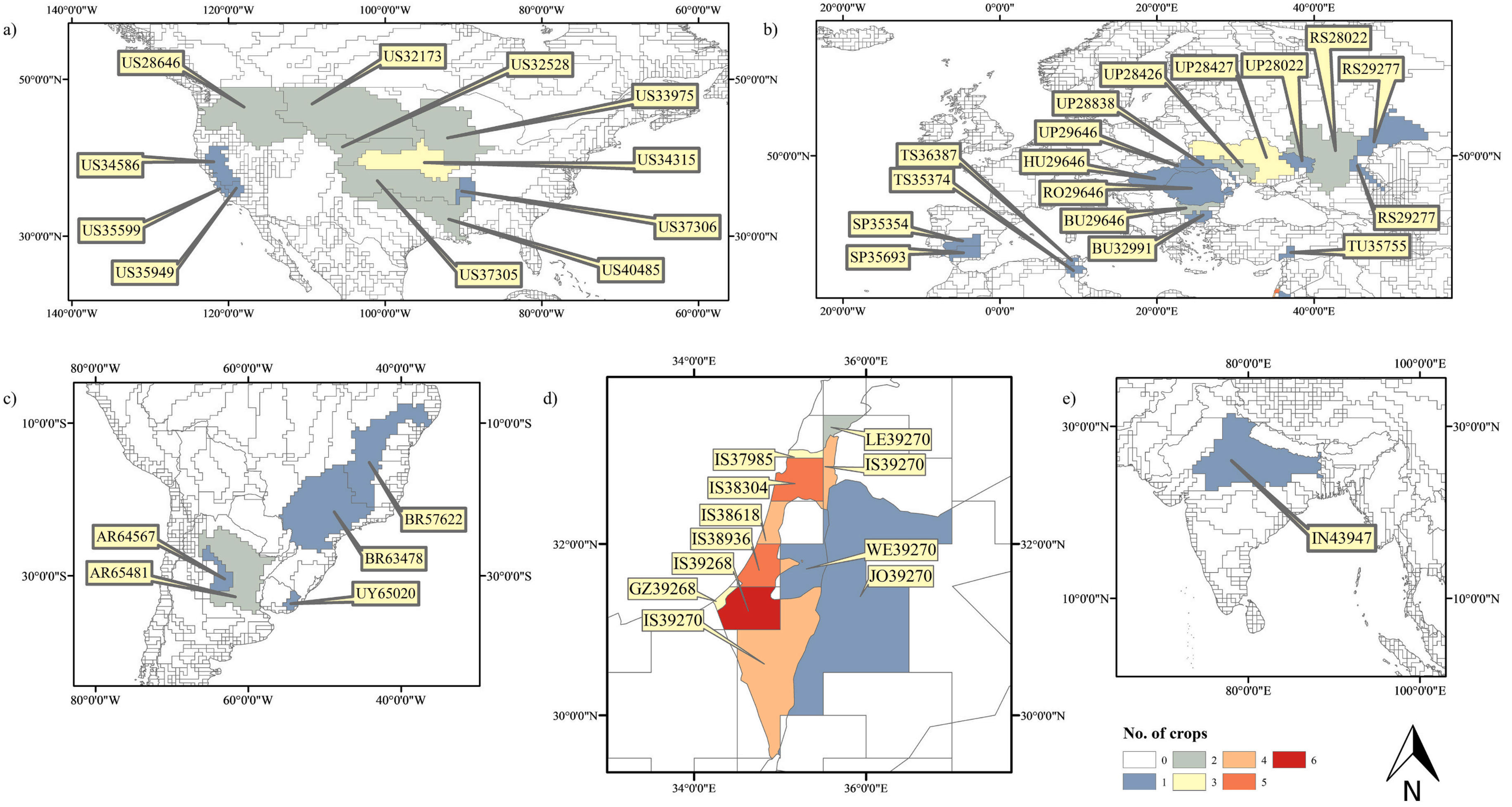

Fig. 3. Number of crops associated with any watershed featuring in the top twelve highest blue water using watersheds (derived from Pfister and Bayer (2019) dataset) for each of the 7 major blue water consuming crops, by region: a) United States, b) Eurasia, c) South America, d) Israel and surrounding countries/regions, e) India. Watersheds (denoted using the watershed classification system from the WaterGAP model (Müller Schmied et al., 2021)) can be traced to crop-specific bar charts in figs. A.1a and A.1b. Legend is common to all five figures.

and Ukraine are recorded as having watersheds featuring in the top 12 lists for three crops. These two countries in addition to Argentina, Russia, Bulgaria, and Lebanon are likewise recorded doing so for two crops, with the U.S. having the highest number of such watersheds, at six. For maps relating to PB-BW consumption of the top 7 PB-BW consuming crops at grid-cell and watershed level respectively, see figs. B.4–6.

Only one country, Brazil, has one crop – soybeans - comprise over 50 % of its share of PB-BW consumption (Fig. A.2). Israel, the United States and Russia, have wheat as the dominant PB-BW consuming crop. Israel has the smallest share of a dominant crop, at 20.4 %, and the largest share of ‘remaining crops’, at close to 40 %.

3.1.2. Assessment of two virtual water accounting datasets

Pfister and Bayer (2019) database-derived blue and green water (PB-BW/GW) and Mekonnen and Hoekstra (2011) database-derived blue and green water (WFN-BW/GW) were both analysed for country- and crop-related volumes, aggregating the former schema's volumes to country level.

Under the WFN-BW/GW schema 10,244 MCM of blue and green water was consumed by agriculture toward Israel's consumption of crop products. Of these totals, the schema entails a cumulative volume of blue water consumption of 1083 MCM, and green water consumption of 9161 MCM. This entails an approximate ratio of 1:8.4 of blue to green water consumption across all crops. In the case of Israel, PB-BW consumption was 780 MCM.

Under the PB-BW/GW schema, blue and green water consumption totalled 8304 MCM, with blue water consumption of 1806 MCM and green water's share at 6498 MCM. This represents a ratio of 1:3.6 of blue to green water consumption across all crops in the schema. For Israel, PB-BW consumption stood at 1044 MCM.

The order of crops regarding cumulative volumes of associated blue water consumption, for both schemas, are given in table 2. Maize is the highest blue water consuming crop under the WFN-BW schema, though consumed approximately five times less blue water as the highest consuming crop (wheat) in the PB-BW schema. Regarding Israel in particular, the WFN-BW schema has a relatively even spread among crops using the highest shares of blue water. A large share is taken up by remaining crops. PB-BW consumption is dominated by wheat, as a single crop, with remaining crops comprising <40 % of total share of blue water (Fig. A.4). For a map of Israel's WFN-BW consumption relating to the highest PB-BW consuming crop, maize, see fig. B.7.

Table 2
Assessments of cumulative blue water volumes for seven crops with highest values under the a) Pfister and Bayer (2019) schema (PB-BW) and b) Water Footprint Network schema (WFN-BW).

a) PB-BW

rank	crop	volume (MCM)
1	Wheat	405.237
2	Maize	125.748
3	Apples	114.221
4	Olives	109.864
5	Soybeans	99.356
6	Sunflower seeds	98.835
7	Peaches & Nectarines	77.659

b) WFN-BW

rank	crop	volume (MCM)
1	Maize	79.543
2	Rice	69.822
3	Wheat	63.886
4	Sunflower seeds	56.347
5	Apples	50.910
6	Almonds	46.902
7	Tangerines etc.	41.330

The top three blue water consuming countries - Israel, the United States and Ukraine (Fig. 2c and Fig. A.3) - have retained their ranking in both schemas. In 11 out of 13 countries, including for the four largest producers, WFN-BW volumes were lower than PB-BW volumes. Only Spain and Thailand possess WFN-BW volumes greater than those of the PB-BW schema. In the case of Thailand, whose WFN-BW volume is over 100 % larger than that of PB-BW, the single crop of rice makes up >99 % of crop imports from the country. Granted differences in scale, diverging results such as this suggest relatively high uncertainty of such global assessments, recognised by Pfister et al. (2011) in reporting that previous studies estimated global blue water consumption in crop production to range from 929 to 1870 $km^3\ yr^{-1}$.

3.2. Environmental dimension indicators

Within its environmental dimension, this study incorporated two indicators relating to the impact of the calculated virtual water volumes, a downstream impact indicator (Stress Impact Value (SIV)) and a biodiversity loss indicator (Biodiversity Impact Value (BIV)).

3.2.1. Downstream impact indicator (stress impact value)

WSI was applied to the PB-BW dataset to produce SIV, an indicator relating to downstream impact, or a measure of the volume of water denied to downstream ecosystem and human users. In Israel, there is little change from PB-BW volumes to those of SIV (Fig. 2d), seeming to indicate that a high proportion of water used in agriculture is diverted from potential use by downstream users. Possibly as a function of relatively higher water stress in Israel's production for local consumption, the drop between PB-BW volumes and SIV indicator is relatively lower than to its two largest blue water importing partners, the United States and Ukraine. For maps relating to cumulative SIV at grid-cell, watershed, and country level respectively, see figs. B.9–11.

Regarding shifts in ranking of countries between the two lists of the top 10 heaviest PB-BW consuming countries and volumes of blue water denied to downstream users (SIV) (Fig. A.5a), the top three countries remained in place – Israel, the United States and Ukraine. Of countries in both lists, Israel, India, and Spain saw the lowest decreases to SIV, as a percent of their overall PB-BW volumes – see Fig. A.5b for a likewise volumetric comparison.

The crops constituting the 12 heaviest PB-BW consuming countries and SIV values remain the same, with only one crop retaining its ranking, wheat, which remains in first place in both top twelve lists (Fig. A.6a, see Fig. A.6b for a likewise volumetric comparison). Wheat, maize, sunflower seeds, and soybeans have the highest relative differences between PB-BW and SIV volumes, indicating a relatively lower impact per fixed volume of water use. Even with wheat experiencing a significant percentage drop, its SIV remained approximately 2.5 times higher than that of the next highest crop, apples. For maps relating to SIV of the three highest PB-BW consuming crops at grid-cell, watershed, and country level respectively, see figs. B.12–14.

Hotspots of high percentage drops between the PB-BW and SIV volumes may indicate potentially high water stress hotspots and require contextualisation with absolute values of blue water consumption. At finer spatial scales, potential hotspots - cumulative across crops - emerge in India, the United States, Spain, China, and the Middle East, among other restricted hotspots. For maps relating to these hotspots of percent decreases cumulatively, as well as for the crops with the two highest PB-BW volumes (wheat and maize), see fig. B.15. For maps providing regional comparisons between PB-BW volumes and SIV, see fig. B.16.

Contrasting the PB-BW volumes and SIV of the three crops with highest cumulative SIV, the crops of apples and olives barely experienced a change in the share of associated water volumes from countries, with Israel being dominant in all cases (Fig. A.7). However, in the case of the SIV of wheat, Israel increases its share of overall volume by close to a third compared to PB-BW, with an associated drop in share of the two next largest contributors, the United States and Ukraine.

3.2.2. *Biodiversity loss indicator (biodiversity impact value)*

Regarding Biodiversity Impact Value (BIV), a measure of the water consumption-driven biodiversity loss or threat of extinction, the highest value of cumulative impacts in a country (across all crops), from the United States, is approximately 16 times larger than that of the next highest value, Israel (table 3). Here, multiple watersheds in the United States possess the highest global cumulative BIVs (Fig. 2e). In all, 83 exporter countries/regions have a BIV above zero, with the majority several orders of magnitude smaller than that of the United States. For maps relating to cumulative BIV use at grid-cell, watershed, and country level respectively, see figs. B.17–19.

Concerning crop-related PDFs, the impact of wheat is 2.6 times higher than that of the crop with next highest impact, soybeans. Peaches and nectarines, ranked seventh, have almost 100 times lower a cumulative impact than wheat. Wheat accounts for 60 % of the total impact of the United States, with impact clustered in the lower Midwest region (coincident with the Mississippi river basin), while soybeans account for 23 % and rice, 17 %. For maps relating to BIV use of wheat, soybeans and maize at grid-cell, watershed, and country level respectively, see figs. B.20–22.

3.2.3. *Groundwater depletion*

As an additional indicator, production statistics were used to calculate groundwater depletion (GWD). Israel is associated with the largest cumulative GWD (40.6 MCM), accounting for approximately 60 % of total GWD, relative to only 12 % of all crop production (by ton) relating to GWD data (Fig. 2f). The country was responsible for GWD approximately four-fold greater than the next heaviest user, Bulgaria. For a list of all countries/regions depleting above 1000 m^3 of virtual groundwater, cumulative GWD volumes per crop, and associated rankings of both, see table A.3. The three highest groundwater depleting crops, maize (29 MCM), wheat (12.4 MCM) and sunflower seeds (8.5 MCM) also featured in the category of the seven largest PB-BW consuming crops. For maps of GWD by country, of the three highest groundwater depleting crops, see fig. B.8.

4. Discussion

Consumption-based studies help establish downstream and upstream impacts of resource use and processing, and as such inform policy that can ameliorate such impacts (Schwarzmueller and Kastner, 2022). Multi-Regional Environmentally Extended input-output models such as EXIOBASE (Tukker et al., 2014) and that developed by Arto et al. (2016), underpin studies focused on environmental impacts associated with the final consumption of products (see Lutter et al. (2016) for calculation of EU final demand water footprints, using EXIOBASE).

Table 3
Ranking in order of the magnitude of cumulative Biodiversity Impact Values (BIV), expressed in potential disappeared fractions (PDF), a) by seven highest countries across all crops, and b) seven highest crops across all countries.

a)

Country	Cumulative BIV (PDF)
United States	1.91E-04
Israel	1.16E-05
Australia	2.31E-06
Jordan	1.27E-06
Canada	1.05E-06
Turkey	7.53E-07
Thailand	4.57E-07

b)

Crop	Cumulative BIV (PDF)
Wheat	1.08E-04
Soybeans	4.03E-05
Maize	3.03E-05
Olives	2.72E-06
Sunflowers	2.11E-06
Apples	1.60E-06
Peaches & nectarines	1.12E-06

While these approaches capture longer supply chains covering economy-wide activities, they provide less detail among water intense products by, e.g. not considering watershed-specific water scarcity (Tukker et al., 2014). Yet, consumption-focused approaches are essential in making the impacts and vulnerabilities of production and trade explicit. The study presented here leverages both global and local datasets in conducting a combined biophysical-ecosystem assessment of the volumes and indicators associated with Israel's virtual water consumption. Such a study relates to: goal 6 of the Sustainable Development Goals, ‘Ensure availability and sustainable management of water and sanitation for all’, and in particular target 6.4 and 6.6, which call for sustainable withdrawals to address water scarcity and for the protection and restoration of water related ecosystems, respectively (United Nations General Assembly, 2015). In addition, regarding virtual water impacts on ecosystems and biodiversity, goal 15 of the Sustainable Development Goals, ‘Protect, restore and promote sustainable use of terrestrial ecosystems, sustainably manage forests, combat desertification, and halt and reverse land degradation and halt biodiversity loss’ is also relevant (United Nations General Assembly, 2015).

4.1. *Biophysical dimensions of water consumption*

The results of this study indicate that much of the consumption-related impact of agriculture on blue water consumption, both in terms of biophysical use and of impacts on ecosystems, can be traced back to Israel's production for local consumption. This trend exists beyond merely an association with high production levels. Attention is also drawn to a handful of other exporting hotspot countries, watersheds, and crops, as shown in Fig. 2.

It is perhaps not surprising that wheat has the highest consumption-related Pfister and Bayer (2019) database-derived blue water (PB-BW) volumes, Mekonnen and Hoekstra (2011) database-derived blue water (WFN-BW) volumes and Stress Impact Value (SIV) volumes, given its prominence in diets globally. In previous studies, it was calculated as being responsible for 14 % of the global water crop impact for the period 1996–2005 (Mekonnen and Hoekstra, 2011) and for 18 % of crop irrigation water consumption in the year 2000 (Pfister and Bayer, 2014). Wheat grown in Israel is associated with a relatively high water consumption rate, while that of maize is relatively lower, with its cumulative production share approximately twice that of its PB-BW share. This is compared to an approximate 1:1 ratio of wheat.

With relatively low blue water to green water ratios for PB-BW/GW, this schema denotes a high reliance on Israel's consumption on blue water stocks, overall and relative to green water consumption. Lower volumes per crop and per country were generally found for WFN-BW. However, a single country figure representing water consumption dynamics has associated a relatively larger scope for imprecision, potentially giving the impression that all watersheds within a country carry equal weight when considering water consumption efficiency or biodiversity impact. Shtull-Trauring and Bernstein (2018), having found large variation in annual water footprint calculations for Israel between local and global data sources (with lower footprints associated with the former), advise the development of high-resolution local datasets based on local crop coefficients.

A degree of overlap of the ranking results of both schemas is found, regarding identification of both water-intensive crops and countries with high blue water consumption. The four countries with the largest cumulative blue water consumption volumes are common to both schemas, with the ranking preserved in both. At the level of individual crops, wheat lost its position as first and there was a large increase in the blue water share of rice under the WFN-BW schema. Differences such as these may serve as a useful starting point to investigate divergences in values.

Regarding grid-level hotspots, at the spatial scale of 5 arc minutes, cumulative PB-BW consumption hotspots are spread over the Indus and Ganges Rivers basins – in the past, responsible for 25 % of global-scale blue water impact alone (Mekonnen and Hoekstra, 2011) - as well as more widely in India. River basins such as these, as well as other major hotspots, could comprise a list of regions to be scrutinised in future sourcing efforts. Those watersheds outlined in Fig. 3 of this study may function as an effective starting point for such a list in the study's context.

The share of blue water impact, relative to green and grey, is highest in arid and semi-arid regions at a global scale (Mekonnen and Hoekstra, 2011). These regions coincide with some of the results of this study: blue water consumption hotspots form in the Western coast of the United States regarding apples; southern Europe regarding all seven major crops, maize, and wheat in particular; northern India regarding all seven major crops, and soybeans in particular; and parts of southeast and southwest Australia regarding all seven major crops.

4.2. *Environmental dimension indicators: Stress impact value, biodiversity impact value, and groundwater depletion*

When analysing the intersection of virtual water trade, water scarcity and the ecosystem impacts of water diversion and withdrawals, watersheds form the natural scale of analysis. In this study and within an environmental dimension, PB-BW data as well as characterisation factors relating to downstream and biodiversity loss impacts were both underlain by watershed-specific data. As an additional indicator in this dimension, GWD is calculated directly from production statistics.

Metrics assessing the environmental impact of water consumption have the potential to be used as the basis for offsetting programs, in turn reducing demand for damaging products and driving the protection of ecosystems and the services they offer (Pfister et al., 2011). Moreover, the European Union has in 2023 introduced EU Deforestation-Free Products Regulation in an attempt to drive sustainable agricultural commodity supply chains and mitigate against biodiversity loss and climate change. Accountability failures of market-based instruments and trade deals, in this case, lead to hard regulation at the supranational level (Berning and Sotirov, 2023), and it may be expected that such regulation increases as resource limitations and associated social and environmental impacts mount. Here, regarding impacts of freshwater consumption, some PB-BW hotspot countries are identified as having high relative impacts from freshwater extraction for irrigation in both socio-ecological and biodiversity loss categories.

Scherer and Pfister (2016) found that water scarcity is highest in regions which overlap with import of blue water for Israel's consumption: The United States, the Mediterranean region, India, and the Beijing region in China. Of exporters of blue water to Israel, Spain, Turkey, and India are particularly affected by water scarcity, while at the same time constituting some of the largest importers. This comes on top of a 50 % likelihood that global consumption-weighted average water scarcity is severe, whereby more than half of water consumed is denied to downstream users (Scherer and Pfister, 2016). This implies that sustainable sourcing may be relatively constrained.

SIV is a valuable additional indicator to give broad socio-ecological context to blue water consumption, even as challenges remain, such as separating human from ecosystem users. While PB-BW volumes may provide an indication of which countries are associated with unsustainable blue water consumption, SIV is a useful measure to home in on which watersheds and countries PB-BW consumption translate into an association with water stress, impacting downstream users and ecosystems. While it is perhaps most straightforward to consider cumulative SIV, isolating crops with a dominant share of SIV can introduce complexity and increase options for sourcing alternative suppliers.

The Mediterranean basin region hosts one of the world's five Mediterranean-type ecosystems (MTEs). This region comprises the third richest plant biodiversity hotspot globally, with Israel in particular incorporating an ecotone and hosting many endemic reptile species (CEPF, 2024; Cox et al., 2006). While BIV is a measure of impact on animal taxa in wetlands (birds, mammals, amphibians, and reptiles) and vascular plant taxa on land, these are meant to act as the ‘canary in the coalmine’, regarding water stress on biodiversity and ecosystems in general (Verones et al., 2017). It should perhaps not be surprising that Israel possesses the 2nd highest cumulative Biodiversity Impact Value (BIV) after the United States, given the scale of its production and associated blue water consumption. This is notable, given the existence of its one partly restored, partly engineered freshwater wetland, comprising the Hula Nature Reserve. However, environmental water guarantees are stated to provide a buffer against wetland biodiversity loss in this case - between 2015 and 2018, on average, Israel allocated 7.9 MCM of freshwater for the reserve every year (Israeli Water Authority, 2019; Marin et al., 2017). Should Israel become vulnerable to disruptions in crop trade due to water scarcity of its trading partners, a concomitant shift to self-reliance might feasibly compromise such environmental water guarantees.

While the results of this study indicate the U.S. and Australia are associated with high biodiversity impact, as Scherer and Pfister (2016) note, there is much scope for improvement of data coverage, for both wetlands and regarding water consumption, and impacts may be either under- or overestimated. Only between 28 % and 63 % of global wetland area reported by Finlayson et al. (1999) is covered, which in turn is less than that estimated by the Global Lakes and Wetlands Database (Lehner and Döll, 2004). Data on animal taxa was lacking in those areas with the largest global blue water consumption figures, including parts of India, Angola, Brazil, Mozambique, and the Iberian Peninsula. This is relevant in this study for India, with relatively high impacts across methodologies in relation to Israel's consumption. Though wetlands fed by groundwater may be rarer than those fed by surface water, data on groundwater consumption was missing from parts of China, India, the United States, South Africa, and Russia. Nevertheless, coverage of terrestrial plants was high, with maximum characterisation factors an order of magnitude higher than those of animal taxa.

Fridman and Kissinger (2019) found that the highest cropland footprint-based impact of Israel's imports on annual biodiversity loss was in ecoregions in South America (Humid Pampas, Araucaria moist forests, Alto Parana Atlantic forests) and Eurasia (East European forest steppe, Pontic steppe). These same regions did not reflect high BIV values, which suggests that virtual water impacts can be complemented by studies that use other indicators of virtual trade impacts, for example using LCA methods in quantifying the impact of cropland use on habitat loss (Schwarzmueller and Kastner, 2022; Semenchuk et al., 2022). A recent review by (Kastner et al., 2021) highlights the range of ways in which trade impacts are measurable, including nutrients, habitat conversion, biodiversity loss and carbon storage. As such, a full suite of indicators can help identify synergies and trade-offs between human wellbeing and biodiversity protection.

As an impact indicator, GWD serves as a useful complement to SIV, with the latter only dealing with surface water discharge. To target consumption-related GWD through import substitution would mean to focus on maize, wheat, and sunflower seeds – responsible for 43 %, 18 % and 13 % of GWD respectively. While the GWD and the PB-BW schema may not be directly comparable, they are nevertheless complementary - lower ratio of GWD to blue water, in countries such as Bulgaria, may or may not indicate rapid depletion of available supplies of blue water. A high proportional reliance on depleting groundwater stocks implies vulnerability to future water shocks such as drought. In terms of agreement, the two schemas share hotspots for wheat such as Ukraine and Russia, as well as the general hotspot of India. Of global GWD hotspots known in the literature, only India had a high volume associated with Israel's consumption in this study (with rice, wheat and millet comprising the highest groundwater depleting crops associated with India, in order), relative to other groundwater depleting countries. Future efforts will most likely focus on teasing apart the share of surface and groundwater, within the same methodological approach and at the same resolution.

4.3. *Limitations and directions for future application*

This study is based on a combination of local data, and global datasets such as MIRCA2000 and SPAM. While global scale analyses offer a broad view of activities, they tend to trade off lower temporal and/or spatial resolution, as has been the case here. Anderson et al. (2015), in comparing global cropping systems models, found that there was significant variation in harvested area and yields, largely driven by input dataset differences and variation in downscaling methodologies. Some differences in input data result from data deficiencies, as well as from attempts to pare down methodological complexity (Pfister and Bayer, 2014).

In this study, a comprehensive investigation into the differing blue and green water volume results between the PB-BW and the WFN data is restricted by the difference in resolution of spatial scales. It is necessary that resolution increases, to account for regional variabilities in irrigation efficiency and environmental impacts, as well as for a likewise comparison of similar databases. Data may lend itself to methods to evaluate uncertainty, which have evolved in this sector in recent years - see Dabrowski et al. (2009); De Girolamo et al. (2019); Mahjabin et al. (2021) for the use of Monte Carlo simulations in a virtual water context.

In addition, such combinations of differing datasets in consumption-based studies are not immediately likely to achieve temporal uniformity. While this is currently an inherent limitation to such studies, including this one, the authors propose to have overcome this through the analysis of multiple lines of evidence, across both biophysical and environmental dimensions. By the date of publication, the population of Israel has grown by approximately 40 % from 2005 (the year pertaining to crop production and consumption data used here) and in addition to higher virtual water volumes and associated impacts, dietary preferences may also have changed.

Due to the dynamic and complex inter-basin water transfer infrastructure underpinning Israel's agriculture, it is not possible to assign virtual water volumes originating from various stocks in any one watershed to an irrigated crop within the same watershed with complete fidelity. For example, in the case of the Northern Negev, reused wastewater originates approximately 50 km away, from the Tel Aviv metropolitan area (Fridman et al., 2021a). Therefore, regarding blue water, the scale of analysis most useful for Israel may be at the country level. Future research might focus on disentangling the origins of water transfers to trace and assign environmental impacts of crop production more precisely.

It is likewise important to note that the global blue water and GWD datasets used in this study may not consider the return to aquifers of treated wastewater, nor the use of other non-freshwater sources of water, including brackish water, flood water, and desalinated water, for irrigation - given the rarity of the practice globally. Here, Fridman, Biran, et al. (2021) focus on variability regarding the mix of Israel's water sources and make a proposal for extended blue water footprint accounting. Should it become feasible for global databases to include the contribution of such non-freshwater sources in a spatially explicit manner in the future, it is expected that crop-related virtual water volumes associated with Israel's production would likely be significantly lower, averaged across years.

Several limitations were present in both biodiversity methodologies deriving characterisation factors. It should be noted that there are potential issues around missing data in the study, specifically characterisation factors, fate factors, wetland data (Verones et al., 2017). The temporal resolution used in deriving WSI characterisation factors was annual, which was taken as the average monthly WSI. There is high seasonal variability of WSIs, therefore, the application of the annual characterisation factor to annual production data to produce SIV in this study, does involve some loss of precision. In addition, these changes are affected by crop types, with differing annual growth patterns. It should be noted that WSI also varies inter-annually, due to population growth, the growth in affluence and changing climates (Núñez et al., 2013). Yet, water stress and water consumption data on the monthly timescale is becoming increasingly available. This allows for effective crop choice management based on growing season, to optimize the use of irrigation water with the aim of minimizing water stress. Tailored responses can include the shifting of crop planting dates or considering the growth calendars of crops with respect to their timing.

Subsequent studies may benefit from making a comparison between WSI - as advanced by Scherer and Pfister (2016) - and the AWARE method, derived from the WULCA Working Group consensus process, as described in (Boulay et al., 2018). This method utilizes a water scarcity midpoint method, for use in Life Cycle Analysis-derived water scarcity impact assessments. Similarly, it gauges the level of deprivation of freshwater consumption (by either humans or ecosystems as users) through consumption of upstream water (Boulay et al., 2018).

5. Conclusion

An agriculture-oriented analysis using the virtual water approach entails the association of crop water consumption with trade flows. A vital further step is to translate crop water consumption into actual impact on human users, ecosystems, and biodiversity. Given the uneven geographic spread of both water consumption and biodiversity richness globally, spatially explicit analysis is vital in identifying hotspots of these impacts from water abstraction. This stands to reduce countries' virtual water-related environmental footprint, and at the same time tease out potential vulnerabilities in food supply, both imported and domestic.

While WSI and other methodologies in this study entail uncertainties pertaining to datasets derived from global-scale data inputs, they provide an important first step in identifying regions which may have water-consumption linked issues. As a combined biophysical-ecosystem assessment relating to virtual water trade improves, the results of this study suggest the scale of analysis should include the Middle East/North African region, southern Europe, the broader Beijing region in China, and northern India. As a crop, wheat represents low-hanging fruit with regards to improvements in its associated virtual water impacts. Lastly, relating to virtual water associated with food consumption, analysis at the watershed scale may indicate an over-reliance on certain watersheds.

This consumption-based case study has shown the vulnerabilities spread across sources of virtual water production and import, across 100 crops consumed in Israel, a water scarce country with high reliance on virtual water imports, typical for the Mediterranean region. It has demonstrated the value of incorporating a groundwater depletion, an ecosystem, and a biodiversity element into an assessment of virtual water use. This incorporation facilitated an understanding of the impacts of virtual water trade, by quantifying the effect of blue water consumption on the environment, using three sets of LCIA characterisation factors, in a spatially explicit manner. Further, it has assessed virtual water consumption of two commonly used water consumption methodologies. A focus on watershed-scale differences at both the biophysical and ecosystem grain across exporter countries and domestically, stands to lower the associated impacts of blue water use. This combination of data provides a useful aide to regional optimisation, a policy strategy which can aide in the alleviating water stress by promoting the trade of crops from water abundant countries to water scarce countries (Yang et al., 2006). Policy to ensure sustainability in virtual water imports as well as in domestic virtual water use will increase the likelihood of arid and semi-arid regions remaining water secure into the future, as well as contribute toward the achievement of Sustainable Development Goals.

CRediT authorship contribution statement

Steven Myburgh: Writing – original draft, Visualization, Formal analysis. **Ervin Kosatica:** Writing – review & editing, Supervision. **Stephan Pfister:** Writing – review & editing, Methodology. **Meidad Kissinger:** Writing – review & editing, Methodology. **Dor Fridman:** Writing – original draft, Visualization, Methodology. **Thomas Koellner:** Writing – review & editing, Supervision, Resources, Conceptualization.

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

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Data availability

Data will be made available on request.

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